Joana Filipa Silva Fernandes Carreira

AIRLINE FLEET COMPOSITION: ANALYSIS AND PLANNING

PhD Thesis in Doctoral Program in Transport Systems supervised by Professor António Pais Antunes and Professor Morton O'Kelly, presented to the Department of Civil Engineering of the Faculty of Sciences and Technology of the University of Coimbra

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ABSTRACT

This Thesis' focus is the airline fleet composition problem, particularly in terms of its planning and modeling features. More specifically, this work investigates the best way for an airline to decide how to plan its aircraft fleet, in order to accomplish a pre-determined number of goals and to comply with the inevitable reality constraints. Whether the airline should acquire or lease the aircraft, how many aircraft models should the airline choose to compose its fleet, what would be the best fleet mix in order to minimize the airline's costs (or maximize the airline's revenues) and to fulfill the predicted demand, are some of the questions that this work will try to answer.

An extensive review of the existing literature in terms of fleet planning problems, in general, and airline fleet planning problems, in particular, is presented. The most relevant fleet planning optimization models are identified and classified. An analysis on the currently existing literature in terms of leasing of aircraft is also included in this work. And the major gaps existing in this research field are identified, as a starting point for the work developed.

Furthermore, the major aircraft manufacturers in the aviation market are enumerated and a description and characterization of the most relevant aircraft types is provided, focusing on its most relevant features, such as seat capacity, range and aircraft size dimensions. An analysis of the evolution throughout time of aircraft models and aviation in general is included. Additionally, this work presents a rank of the world's largest airlines, as well as a general review on airlines' efficiency, productivity and costs. Four airlines were chosen (American Airlines and Delta Air Lines, from the United States; and Ryanair and Lufthansa, from Europe) to be examined in terms of their fleets' evolution. American Airlines and Delta Air Lines are two of the biggest airlines in the world, and offer a fleet mix of mainly Airbus, Boeing, and McDonnell Douglas models. In Europe, Ryanair and Lufthansa are two of the largest airlines. Ryanair currently existing fleet is an only-Boeing 737-800 (next Generation) fleet, while Lufthansa's fleet is predominantly composed by Airbus models (although it also includes some Boeing aircraft).

Two airline fleet planning models were developed: one focused on airline long-distance operations, whereas the other model's focal point is an airline short-distance network and fleet. For the first model, a strategic fleet planning problem faced by TAP Air Portugal, the Portuguese legacy carrier, was presented, with the aim of shedding light on the aircraft models to select, as well as on the mix of aircraft to purchase (or financially lease) and the aircraft to operationally lease in order to cope with the forecasted passenger demand between Lisbon and Brazil (TAP long-distance operations), in the year of 2020. The developed approach was based on an optimization model that can be cast in the class of two-stage stochastic integer programs. The results of the study provided clear insights on how TAP should renovate its fleet, depending on the available resources. The leasing of aircraft is an option that should definitely be taken into consideration by TAP, since it allows the carrier to deal with demand uncertainty without investing large amount of resources in the purchase of new aircraft.

Regarding the short-distance model, an integer static and deterministic optimization model was developed and applied to a TAP Europe inspired case study. The demand was considered deterministic, and the study was conducted considering a specific time period. The results of the study helped providing some understanding on how TAP could benefit by performing some changes in its short-distance fleet. The optimization model developed, integrated within an overall application methodology, proved to be a useful tool that could be used by airlines when planning their short-distance fleet.

This Thesis work, in particular the two optimization models developed, can certainly contribute as a fairly helpful tool for airlines when dealing with fleet planning decisions.

RESUMO

O foco central desta Tese é o problema da composição de frotas aéreas, em particular, no que diz respeito ao seu planeamento e modelação. Especificamente, este trabalho investiga a melhor forma de uma companhia aérea planear a sua frota, a fim de cumprir um determinado número de objetivos e lidar com as inevitáveis restrições da realidade. Algumas das questões às quais este trabalho irá tentar responder são: se a companhia aérea deve comprar ou alugar os aviões; quantos modelos de avião deve a companhia aérea escolher para compor a sua frota; qual seria a melhor frota possível tendo em vista minimizar os custos para a companhia aérea (ou maximizar os seus lucros) e respeitar a procura prevista.

Este trabalho apresenta uma revisão extensa sobre a literatura existente na atualidade no que diz respeito a problemas de planeamento de frotas, em geral, e planeamento de frotas aéreas, em particular. São identificados e classificados os modelos de otimização de planeamento de frotas mais relevantes. Adicionalmente, é efetuada uma análise dos trabalhos de investigação anteriormente realizados sobre aluguer de aviões, e identificadas as principais lacunas existentes neste campo de investigação, ambas servindo de ponto de partida para o trabalho desenvolvido na presente Tese.

Será apresentada uma descrição e caracterização dos principais modelos de aviões existentes no mercado de aviação, bem como uma análise dos maiores fabricantes de aviões no mundo. A caracterização dos aviões é feita com base em algumas das suas características técnicas, como o número de lugares (capacidade), o alcance e as dimensões. A evolução dos modelos de aviões e da aviação ao longo do tempo é também estudada de um modo geral. Mais especificamente relacionado com companhias aéreas, é apresentado um ranking das maiores companhias aéreas do mundo e é feita uma revisão em termos de eficiência, produtividade e custos. Foram examinadas quatro companhias aéreas (American Airlines e Delta Air Lines, dos Estados Unidos; e Ryanair e Lufthansa, da Europa) em termos de evolução de frotas. As duas companhias americanas são duas das maiores companhias aéreas em todo o mundo e apresentam uma frota composta por modelos Airbus, Boeing e McDonnell Douglas. A Ryanair e a Lufthansa são duas das maiores companhias aéreas Europeias. A frota atual da Ryanair é constituída exclusivamente por Boeing 737-800 (next Generation), enquanto a frota da Lufthansa é maioritariamente composta por modelos Airbus (embora também inclua alguns modelos Boeing).

Foram desenvolvidos dois modelos de planeamento de frotas aéreas: um direcionado para operações de longa distância, e outro mais focado em redes e frotas de curta distância. Para o primeiro modelo, foi apresentado um problema estratégico enfrentado pela TAP Air Portugal, a principal companhia aérea Portuguesa. O objetivo foi o de determinar os modelos de aviões que a companhia deve adquirir (ou alugar financeiramente) para constituir a sua frota aérea, de forma a dar resposta à procura prevista entre Lisboa e o Brasil (operações de longa distância da TAP) no ano de 2020. A abordagem apresentada baseou-se num modelo de otimização da classe dos programas lineares estocásticos de duas etapas. Os resultados obtidos neste estudo permitiram obter uma visão clara sobre como a TAP deveria renovar a sua frota aérea, considerando os seus recursos financeiros disponíveis. O aluguer de aviões é uma opção que deve, definitivamente, ser tida em conta pela TAP, uma vez que permite que a companhia dê resposta à incerteza da procura sem ter de investir montantes significativos na aquisição de aviões.

No que diz respeito ao modelo de curta distância, foi desenvolvido um modelo de otimização estático e determinístico que foi aplicado a um estudo de caso inspirado nas operações da TAP na Europa. A procura foi considerada determinística e o estudo foi conduzido tendo em consideração um período de tempo específico. Os resultados do estudo ajudam a entender de que forma a TAP poderia beneficiar de algumas mudanças na sua frota aérea de curta distância. O modelo de otimização desenvolvido, aplicado no âmbito de uma metodologia integrada, provou ser uma ferramenta bastante útil para as companhias aéreas planearem as suas frotas.

O trabalho desta Tese, em particular os dois modelos de otimização desenvolvidos, são, sem dúvida, ferramentas que podem tornar-se um contributo relevante para as companhias aéreas aquando da tomada de decisões relativamente ao planeamento das suas frotas.

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1 INTRODUCTION

The work of this Thesis is focused on airline fleet planning – in particular, on the best way for an airline to decide how to plan its aircraft fleet, in order to accomplish a pre-determined number of goals and to comply with the inevitable reality constraints. Whether the airline should acquire or lease the aircraft, how many aircraft models should the airline choose to compose its fleet, what would be the best fleet mix in order to minimize the airline's costs (or maximize the airline's revenues) and to fulfill the predicted demand, are some of the questions that this work will try to answer.

1.1 Scope of the Thesis

In a world that is becoming increasingly connected and a fast developing global economy, air transportation plays a crucial role from several different perspectives. Aviation is undoubtedly an industry capable of providing a quick worldwide transportation network, which significantly influences and contributes to economy growth and tourism expansion, and additionally enables world trade (ATAG, 2010; Statista, 2017).

In 2016, the arrivals of international tourists increased around 0.04 billion (in comparison to the previous year), and more than 50% of the tourists use air transportation to travel to their destinations. Furthermore, air transportation improves people's quality of life in innumerous ways. The air transportation industry is also responsible for generating over 62.7 million jobs all around the world, between airlines, air navigation services providers and airport operators, as well as jobs related to the freight transportation supply chain (Statista, 2017).

During the year of 2016, commercial airlines were responsible for carrying over 3.8 billion passengers, all over the world, and the global revenue produced was around 501 billion $. In Figure 1.1, the evolution of the number of aircraft passengers carried (both domestic and international), in the world, between 1970 and 2016, is displayed. It is clear the strong increase in the number of passengers, growing from 0.5 billion to over 3.5 billion in nearly 50 years. It is also noticeable some periods when this growth was more accentuated, like some years before 2000, around 2005, and a couple of years after 2010.

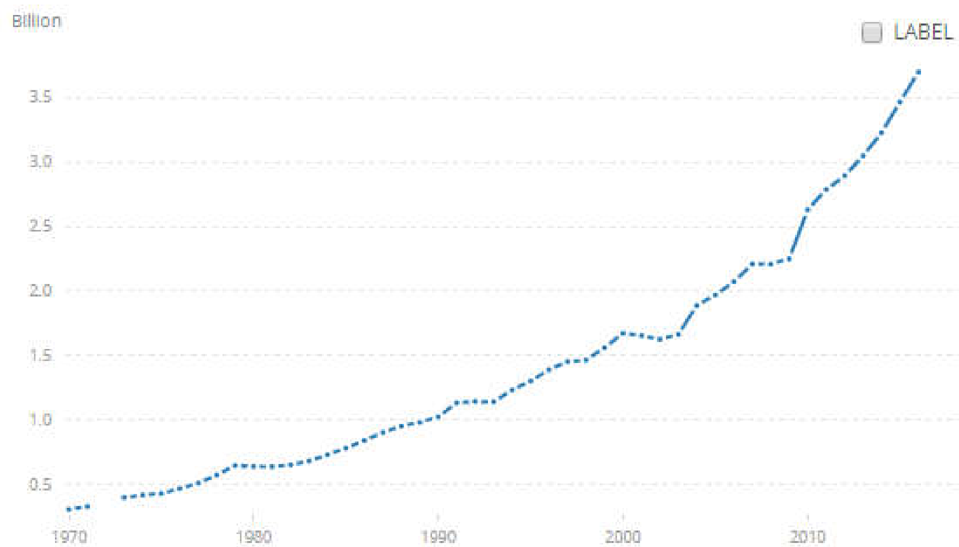

Figure 1.1 – Evolution of passengers carried by air transportation, in the world (1970-2016) (sources: ICAO, 2017b; The World Bank, 2017)

Nevertheless, there were some phases with a lot of stability and even a slight decrease, such as during the early 1980s, a couple of years after 1990, also after 2000, and some years before 2010. Especially around 2000 and 2010, it is notorious that periods of more stability and with no major changes were precedent of sharp increases (ICAO, 2017b; Statista, 2017; The World Bank, 2017).

In a more particular analysis, focused only in Europe (specifically on the 28 Member States of the European Union), in 2016, the total number of passengers carried by air was 973 million, which represents an increase of 5.9%, in comparison to 2015.

In Figure 1.2, it is possible to observe the countries where the growth in terms of air transportation passengers was more significant, between 2015 and 2016 (Eurostat, 2017). Bulgaria, Romania and Cyprus were the three countries that suffered a higher increase in terms of air transportation passengers, between 2015 and 2016 (over 18%). In Slovenia and Belgium there was even a decrease in terms of air passengers' traffic. On average, for all the 28 Member States of the European Union, the number of air passengers transported increased around 5.93%, from 2015 to 2016.

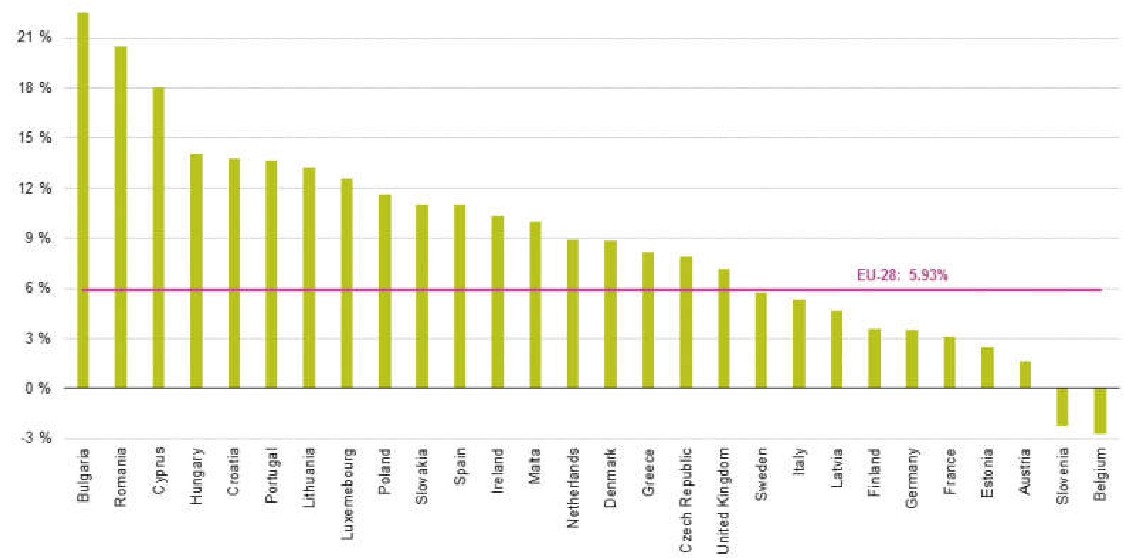

Figure 1.2 – Growth in total air passengers transported, in 2015/2016 by member states of the European Union (source: Eurostat, 2017)

This past substantial increase in terms of air transportation passengers is predicted to continue in the future. Figure 1.3 shows the historical trends (1960 and 1990) and a future projection (2020 and 2050) for modal traffic volume for automobiles, buses, railways, and high-speed transportation (predominantly aircraft) in the world. As it is possible to observe from the data in the figure, in 2020, the world passenger traffic volume will more than duplicate (in comparison to the values of 1990), while in 2050, it is expected to quadruplicate. The high-speed transportation will play a progressively more important role within all transportation fields, and it is expected that more than 1/3 of the world passengers' traffic volume (≈36%) will be accounted by air transportation, in 2050. In 1960, air travel was responsible for only

2% of world passengers' traffic, while in 1990 this number increased to 9%. The projection for 2020 is that 25% of world passengers will travel by air (Lee et al., 2001).

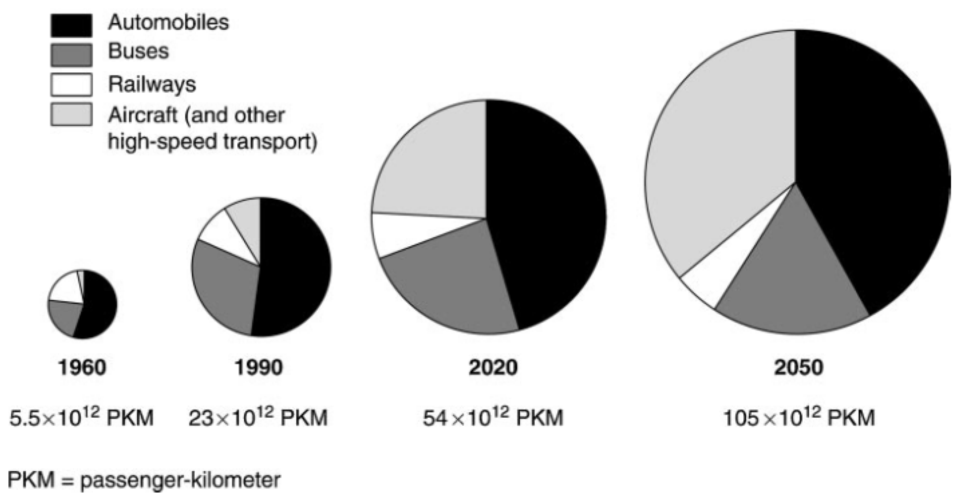

Figure 1.3 – Passenger traffic volume, by major mode of transport (in 1960 and 1990, and projections for 2020 and 2050) (source: Lee et al., 2001)

Hand in hand with this substantial increase in terms of air transportation demand and passengers carried by air, it is also important to address the evolution and changes in terms of aircraft models and their characteristics, which have a major impact when it comes to planning an airline fleet. It is expected that the commercial passenger aircraft fleet will double from today's size (Airbus, 2017c; Boeing, 2016).

One of the most important planning decisions that an airline faces is related to its fleet planning. Airline fleet planning is, precisely, the main focus of this work. According to Belobaba et al. (2015, pp. 153), the fleet planning step tries to answer the following questions: "*What type of aircraft to acquire, when and how many of each?*". It is one of the major long-term strategic decisions for an airline, both in terms of planning and operations. These fleet composition and mix decisions will have a great impact in terms of the overall financial position of the airline, as well as in its operating costs and its capability of operating in a profitable manner, and being able to increase its revenues.

1.2 Objectives of the Work

In accordance with what was described previously, it is possible to define some main goals for this work. In a more generic way, the goals of this work can be enumerated as follows:

- Review the existing literature in terms of fleet planning problems, in general, and airline fleet planning problems, in particular; Analyze and classify the several methods and optimization models developed and presented in the current literature;
- Understand and describe how the aircraft leasing is included (or not) in the literature and how it may be included in airline fleet planning studies;
- Analyze the different aircraft manufacturers existing in the current aviation market and review the principal aircraft models' characteristics, as well as its evolution throughout time;
- Investigate and rank the world's largest airlines and study efficiency, productivity and costs of airlines in general; Examine the evolution of some airlines' fleet, throughout the years;
- Develop some tools (define methodological approaches that can include, for instance, mathematical models) to help airlines to take decisions regarding their fleet planning for the future.

More specifically, the main practical objectives of this research work may be described as follows (these objectives are mainly focused on the methodologies, methods and models that can be developed to achieve some of the previously mentioned generic goals):

- Develop a long-distance airline fleet planning optimization model (taking into account the uncertainty of the future demand – stochastic model – and considering the problem as a dynamic fleet planning problem);
- Develop a short-distance airline fleet planning optimization model – deterministic and static model (although it is possible to admit some variations within the year, for instance, per season);

- Apply the optimization models to the real case study of TAP Air Portugal (or smaller and partial case studies inspired in the reality of TAP, adjusted to the long or short-distance features) and analyze the obtained results from the airline point of view;
- Understand how the fleet of an airline may evolve throughout time and, more specifically, how TAP may take decisions concerning the evolution of its fleet, both in long and short-distance operations;
- Investigate whether the leasing of aircraft could be an advantageous option for an airline, when planning its fleet;
- Study the impact of some elements, such as uncertainty of the demand, load factors or investment costs, in an airline fleet planning process.

1.3 Structure of the Thesis

This Thesis is organized in six chapters. This Chapter 1 introduces the research work. The main subject of the Thesis is introduced and an explanation on the scope of the work is provided. Furthermore, the main objectives of the work are enumerated and described in detail.

In Chapter 2, an extensive literature review on fleet planning, in general, as well as in airline fleet planning, in particular, will be provided. The most relevant authors and work will be enumerated and described. A review on the main fleet planning optimization models and airline fleet planning models will be presented. These models will be characterized in terms of model type, decision variables included, solving methods used, the inclusion (or not) of uncertainty, whether the model is static or dynamic, and the incorporation (or not) of leasing options (only for the airline fleet planning models).

Chapter 3 will provide an analysis on aircraft types and the evolution of airlines' fleets. The main aircraft manufacturers will be reviewed and the aircraft models currently existing in the aviation market will be presented and characterized, based on its most relevant features, such as seat capacity, range and aircraft size dimensions. An historical evolution of aviation and aircraft types will also be presented. Furthermore, the focus of this chapter will be on airlines' efficiency, productivity and costs. A review of some literature on these subjects will be completed. Finally, the composition and evolution of the fleet of some of the world's major airlines will be presented (American Airlines, Delta Air Lines, Ryanair, and Lufthansa were the airlines chosen for the analysis).

In Chapter 4, a strategic fleet planning problem faced by TAP Air Portugal, the Portuguese legacy carrier, will be presented. This work is intended to shed light on the aircraft models to select, as well as on the mix of aircraft to purchase (or financially lease) and to operationally lease in order to cope with the forecasted passenger demand between Lisbon and Brazil (TAP long-distance operations), in the year of 2020. The presented approach for addressing the problem is based on an optimization model that can be cast in the class of two-stage stochastic integer programs. The results of the study will provide clear insights on how TAP should renovate its fleet, depending on the available resources. According to the obtained results, the leasing of aircraft is an option that should definitely be taken into consideration by TAP, since it allows the carrier to deal with demand uncertainty without investing a large amount of resources in the purchase of new aircraft.

Chapter 5 will include a study on the planning of an airline short-distance fleet. An integer static and deterministic optimization model is presented and applied to a TAP Europe inspired case study. The demand will be considered deterministic and the study will be conducted considering a specific time period. The results of the study will provide some understanding on how TAP could benefit from performing some changes in its short-distance fleet. This optimization model, integrated within an overall application methodology, will prove to be a useful tool that could be used by airlines when planning their short-distance fleet.

In Chapter 6, the final conclusions of the work will be presented, as well as some potential improvements and future work that might be possible to develop, based on the work presented in this Thesis.

1.4 Publications and Presentations

Some of the work included in this Thesis has already been published and presented in several occasions. The work presented in Chapter 4 was published in the European Journal of Operational Research, in 2017 (Carreira et al., 2017).

Furthermore, some parts of the work of this Thesis were also presented both in Portugal and internationally. The conferences where the work was presented are listed below:

- 14th GET Conference (Transports Study Group) – February 2017 / Fátima, Portugal
  - Title: Airline Fleet Planning – TAP Case Study
  - Authors: Joana Silva Carreira (University of Coimbra, Portugal), António Pais Antunes (University of Coimbra, Portugal), Guglielmo Lulli (Lancaster University, United Kingdom), Amedeo Odoni (MIT, United States)
  - Best presentation award

- 2016 MIT Portugal Conference – June 2016 / Braga, Portugal (poster session)
  - Title: Airline Fleet Planning – TAP Case Study
  - Authors: Joana Silva Carreira (University of Coimbra, Portugal), António Pais Antunes (University of Coimbra, Portugal), Amedeo Odoni (MIT, United States), Guglielmo Lulli (Lancaster University, United Kingdom)

- 13th GET Conference (Transports Study Group) – January 2016 / Figueira da Foz, Portugal
  - Title: A Study on the Long-Distance Fleet of an Airline – The Case of TAP Service to Brazil
  - Authors: Joana Silva Carreira (University of Coimbra, Portugal), António Pais Antunes (University of Coimbra, Portugal), Guglielmo Lulli (Lancaster University, United Kingdom)

- 2015 MIT Portugal Conference – June 2015 / Lisbon, Portugal (poster session)
    - Title: A Study on the Long-Distance Fleet of an Airline
    - Authors: Joana Silva Carreira (University of Coimbra, Portugal), António Pais Antunes (University of Coimbra, Portugal), Amedeo Odoni (MIT, United States), Guglielmo Lulli (Lancaster University, United Kingdom)
    - Best poster award

- 18th ATRS World Conference – July 2014 / Bordeaux, France
    - Title: A Study on the Long-Distance Fleet of an Airline
    - Authors: Joana Silva Carreira (University of Coimbra, Portugal), Guglielmo Lulli (Lancaster University, United Kingdom), António Pais Antunes (University of Coimbra, Portugal), Amedeo Odoni (MIT, United States)

- 11th GET Conference (Transports Study Group) – January 2014 / Covilhã, Portugal
    - Title: Airline Fleet Composition – Analysis and Planning
    - Authors: Joana Silva Carreira (University of Coimbra, Portugal), António Pais Antunes (University of Coimbra, Portugal), Morton O'Kelly (University of Ohio, United States)

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2 RESEARCH BACKGROUND

This chapter of the Thesis presents a review on fleet planning issues and optimization models developed to deal with them, being divided into three large sections. The first section introduces the progress made throughout the years on general fleet planning, as well as the most relevant research developed on optimization models. In the second section, more specifically, the existing studies and optimization models on airline fleet planning are discussed. The last section of this chapter includes the description of the main research gaps identified in the literature related to airline fleet planning.

2.1 Fleet Planning Problem

This first section of the Research Background is organized as follows: first, the terminologies 'fleet sizing' and 'fleet composition' are distinguished; secondly, a general overview of the evolution of the literature on fleet planning problems is provided; thirdly, a summary on the most relevant work existing on fleet planning in combination with other fleet management problems is presented; and finally, the most significant optimizations models developed to solve fleet planning problems are enumerated and described.

2.1.1 Fleet Sizing vs. Fleet Composition

When it comes to fleet planning, there are two different terminologies that can be found in the literature: fleet size and fleet composition. According to Etezadi & Beasley (1983), in the fleet sizing problems, the types of vehicles available are already known and the decisions to be made concern only the number of vehicles to choose to constitute the fleet. This usually happens when there is only one type of vehicle available, which means the fleet is homogeneous – more common, for instance, in maritime transportation, where usually there is only one type of ship to choose (e.g. Kirby, 1959; Wyatt, 1961; Du & Hall, 1997; Imai & Rivera, 2001; Lai & Lo, 2004; Vis et al., 2005; Diana et al., 2006). On the other hand, fleet composition problems relate to decisions concerning both the number and the types of vehicles to be selected, among a given sample. This mainly occurs when the fleet is heterogeneous (e.g. Etezadi & Beasley, 1983; Leung et al., 2002; Loxton & Lin, 2011; Loxton et al., 2012). Sometimes, these two expressions are used together, describing the final objective of these types of problems as the determination of the size and composition of a certain fleet (e.g. Gould, 1969; Gheysens et al., 1986; Couillard & Martel, 1990; Couillard, 1993). Nevertheless, in the majority of the literature, the expression "composition" is used to refer both to the size and composition of the fleet.

There is also other terminology that commonly appears whenever the fleet planning problem is associated to other fleet management problems (especially to the vehicle routing problem), which is the fleet mix. It often appears as "fleet size and mix", being the word mix used to refer to the composition of the fleet (e. g. Golden et al., 1984; Ulusoy, 1985; Dullaert et al., 2002; Hoff et al., 2010; Steffensen, 2012; Pasha et al., 2016). The vehicle fleet mix is also the shorter expression used to refer to the vehicle routing and fleet composition problem (Salhi et al., 1992).

2.1.2 General Overview

Fleet planning problems have been gaining increasing importance and relevance, playing nowadays a significant role among researchers' work. It is definitely a problem that affects many companies, since they frequently rely on a private vehicle fleet to transport people, goods or equipment. Generally, fleet planning problems focus on the balanced and efficient correlation between supply and demand: supply of transportation capacity and demand for transportation services. Therefore, the composition of a company's fleet is a crucial decision that must be taken prudently, so the company's demand can be satisfied and the total transportation costs minimized.

One of the first researchers to study fleet planning problems was Kirby (1959). He considered a very simple problem in the context of a small railway system and took into account a homogeneous vehicle fleet (all vehicles of the same type). He tackled the problem from two different sides: prevent a low utilization of owned wagons and conversely avoid the frequent hire of costly extra wagons. Kirby (1959) obtained an equation for the total expected cost per day, based on the relative cost of owned and hired wagons per day, along with a probability distribution for the number of wagons required in each day. The demand was considered to be stationary with seasonal variation. Taking into account the final objective of minimizing the total costs for the rail company, it was possible to determine the number of owned and hired wagons. A couple of years later, the approach developed by Kirby (1959) was extended by Wyatt (1961).

The assumption of a homogeneous fleet when developing fleet planning models was also made by other researchers besides Kirby (1959) – for instance, Dantzig & Fulkerson (1954), Jin & Kite-Powell (2000) and Ghiani et al. (2004). However, several other authors have considered in their studies a heterogeneous fleet (with multiple vehicle types) when addressing fleet planning problems, notably Etezadi & Beasley (1983), Powell & Carvalho (1997), Redmer et al. (2003), Wu et al. (2005), Loxton & Lin (2011), and Loxton et al. (2012).

In addition to the distinction between homogeneous and heterogeneous fleet, it is also worth mentioning that fleet planning is a generic and broad subject studied within a number of different areas. There are several relevant fields in which fleet planning is a crucial step of the decision-making process for the transportation companies.

One of the most common fields where fleet planning problems are addressed is road transportation, mainly concerning general vehicles (e.g. Beaujon & Turnquist, 1991; Couillard, 1993; Zak et al., 2011), but also trucks (e.g. Wu et al., 2005), ambulances (e.g.

Chong et al., 2016), paratransit services (e.g. Fu & Ishkhanov, 2004), and snow or coal disposal vehicles (e.g. Perrier et al., 2007; Zeng & Yang, 2007). Still regarding inland transportation, the fleet planning problems have also been studied within rail systems, by deciding on the number of rail wagons to use (e.g. Kirby, 1959), and intermodal freight transportation, combining both road and rail as transportation modes (e.g. Powell & Topaloglu, 2003). In respect to maritime transportation, there is literature related to the study of fleet planning for tankers (e.g. Dantzig & Fulkerson, 1954), ferries (e.g. Lai & Lo, 2004), and maritime containers (e.g. Imai & Rivera, 2001; Lun & Browne, 2009). Likewise, the air transportation field has been one of the central subjects where fleet planning issues have arisen. Several studies have been carried out regarding airlines' fleet planning (e.g. Listes & Dekker, 2005; Harasani, 2006; Sun et al., 2008) and helicopters' fleet planning problems have also been investigated (e.g. Thomson & Tiplitz, 1979; Brown et al., 1991; Norddal, 2013).

2.1.3 Fleet Planning Problem Combinations

Fleet planning problems are usually studied in combination with other types of fleet management problems, such as fleet scheduling, replacement, assignment and/or routing. Much of the research that has been developed associates these types of problems, since they are frequently related and the inputs and features of a problem may be the inputs and features of another problem. Therefore, it makes sense that they can be studied and analyzed in an integrated way.

One of the very first papers to appear on the fleet planning problem combined with other management problems was from Dantzig & Fulkerson (1954). They looked into the Navy fuel oil tankers scheduling problem and determined the minimum number of tankers while guaranteeing a shipping service with a fixed schedule.

Although replacement problems appear more frequently in industrial engineering and operations literature (Hartman, 1999, 2001, 2004; Rajagopalan, 1998), this is also a problem that can arise within the fleet planning in transportation.

One of the first authors to study fleet planning issues alongside with replacement problems was Ahmed (1973). According to this author, a given truck (or any other vehicle) reaches its maximum economic life when its repair cost is higher than its replacement cost. Therefore, the main challenge when it comes to fleet replacement problems is to find the optimal economic life of a vehicle. Ahmed (1973) developed an optimal equipment replacement policy to select an optimal policy capable of minimizing the average annual cost of each truck in the long run. The case study included the trucking operations (fleet of 18 trucks aged from 1947 to 1963 models) of a motor transportation firm from Texas, USA. According to the results of this research, the optimal policy indicates that a 2-year-old truck was the most economical option for small trips (around 125 miles per day ≈ 200 km per day). Later, in the early 2000s, Jin & Kite-Powell (2000) studied the replacement problem by determining optimal strategies for using, building and scrapping ships while maximizing the profit for the company. They assumed a homogenous fleet and a uniform demand. Both Ahmed (1973) and Jin & Kite-Powell (2000) considered the fleet planning problem as a dynamic problem, which means that the results refer to different periods, thus describing the evolution of the fleet throughout time.

When it comes to studies regarding fleet planning combined with fleet assignment, for instance, Beaujon & Turnquist (1991) developed an approach to optimize both the decisions regarding the size of a vehicle fleet and the decisions on the utilization of that same fleet, offering a framework that covers both fleet planning and fleet assignment. Similar to Ahmed (1973) and Jin & Kite-Powell (2000), these authors also considered the fleet planning problem as a dynamic problem, taking into account different periods of time.

The approach of Sherali & Tuncbilek (1997) to the fleet sizing problem of a railway transportation system also combined fleet sizing and fleet assignment problems. These authors used the multilevel rail-car fleet management problem faced by RELOAD (a branch of the Association of American Railroads, AAR) as a case study, and dealt with the problem considering it static, at first, and dynamic, in a second phase. In this same year, and also incorporating fleet assignment in their work, Du & Hall (1997) studied both fleet sizing and empty equipment distribution. They proposed the utilization of inventory theory to redistribute vehicles among terminals, by using decentralized stock control policies. The authors analyzed these utilization policies considering different fleet sizes and determined the least cost tradeoff.

Wu et al. (2005) studied a fleet sizing problem in the context of the truck-rental industry and integrated tactical (asset purchases and sales) and operational (truck allocation and empty truck repositioning) decisions. The authors determined the optimal fleet size and mix, considering the customer travel time as uncertain and the customer demand as non-stationary (dependent on geographical location, time, and the economic cycle of the industry).

Another fleet management problem that is usually studied alongside with fleet planning is the vehicle routing problem (which is usually related to the fleet assignment problem too). Gheysens et al. (1984; 1986) were among the first authors to address these two problems combined. In 1984, these authors presented a formulation for the fleet size and mix vehicle routing problem, which is an extension of the standard vehicle routing problem formulation, but the objective function includes a term that represents the acquisition cost of the vehicle fleet. Two years later, in 1986, these same authors developed a two-stage heuristic, based on the lower bound procedure developed in their previous work, for the fleet size and composition vehicle routing problem. They first used the vehicle mix solution from the lower bound procedure described in the work of Golden et al. (1984) to determine the fleet composition, to be used in a generalized heuristic in a second phase. The previously determined vehicle mix was used as a set of seed points, and these seed points were then positioned at some costumers' location. The next step of these authors was to allocate the vehicle types to the seed points, and then assign costumers to the different vehicles. The assignment of the costumers was made by solving a generalized assignment problem.

Ulusoy (1985) studied the fleet size and mix problem in capacitated arc routing. He considered a heterogeneous fleet and included the fixed and variable costs associated to the fleet into the objective function. The solution procedure applied by the author consisted of four phases: 1) find a giant tour (minimum total distance travelled); 2) partition the giant tour into sub tours; 3) select the least-cost set of vehicle tours satisfying the demands from the set of vehicle tours generated; 4) repeat until some stopping criterion is satisfied (in this case, the generation of tours will stop when the decrease in total cost drops below a pre-defined value).

Desrosiers et al. (1988) studied the multiple travel salesman problem, which is a much studied network flow problem within the transportation field, being a special case of the vehicle routing problem. The multiple travel salesman problem tries to find the shortest possible route, given a list of cities and the distances between them, that visits each city exactly once and returns to the origin city. Desrosiers et al. (1988) examined the Lagrangian methods to determine the minimal fleet size for the multiple travel salesman problem with time-window constraints. They considered a homogeneous fleet of vehicles located at a common depot.

The research of Larson (1988) also included fleet sizing and routing problems. This author studied the problem of transporting sludge from city-operated wastewater treatment plants in the city of New York to a new ocean dumping site 106 miles offshore. He developed a simulation tool that combined different strategic planning problems, such as fleet sizing, choice of vessel size, sizing local inventory holding capacities, and analyzing system behavior with and without transshipment. His work was later extended by Richetta & Larson (1997), in order to adapt the simulation tool to the changes occurred in the marine transportation system, as a result of new environmental regulations and technologies.

In Salhi & Rand (1993), an overview of papers in fleet composition and state of the literature combining fleet composition and routing of vehicles is presented. These authors developed a seven-phase heuristic, based on a route perturbation procedure. At each phase, the heuristic would try to improve the current solution. Their work was later upgraded by Osman & Salhi (1996). They developed a method based on some modifications of the route perturbation procedure presented by Salhi & Rand (1993). Their major innovation was to adapt the tabu search heuristic, originally developed by Osman (1993) to solve the vehicle routing problem, to the fleet management problem (more specifically to the fleet size and mix vehicle routing problem). Although with larger computing times, these authors were able to obtain some new and good results for their problem.

Powell & Carvalho (1997) formulated the fleet management problem with multiple equipment types and limited substitution as a multicommodity network flow problem. They formulated the problem as a dynamic control problem. Their results showed that it is possible to obtain solutions within 4 or 5% of a linear relaxation, and they were also able to solve larger and more complex problems, with assumptions of multiple vehicles and load types.

Concerning the fleet size and mix vehicle routing problem, Dullaert et al. (2002) developed and presented new heuristics for solving this problem. They considered a heterogeneous fleet, and defined time windows so that the costumer could be served at minimal costs (both routing and vehicle costs). They obtained good results in terms of the performance of the heuristics in comparison to other heuristics presented in the literature.

Also presenting an integrated study of different fleet management problems, Lai & Lo (2004) formulated a ferry service network design problem by considering the optimal fleet size, routing, and scheduling for both direct and multi-stop services. In order to solve the problem, Lai & Lo (2004) used a heuristic algorithm exploiting the polynomial-time performance of shortest path algorithms. The performance of the algorithm was discussed based on the study of two different scenarios for ferry services in Hong Kong.

Some years later, Perrier et al. (2007) presented a survey on models and algorithms for winter road maintenance. In their paper, the authors addressed the vehicle routing and fleet sizing and replacement problems for the case of plowing and snow disposal. Concerning specifically the fleet sizing issues, Perrier et al. (2007) presented a review only regarding optimization models, specifically for snow disposal and hauling snow to disposal sites. Still in 2007, Zeng & Yang (2007) wanted to determine both the number and types of ships and the ship routing, while minimizing the total coal shipping costs. Three outbound ports were considered, to where the coal was transported by rail, and from there the coal would be shipped to demand ports.

Lee et al. (2008) focused their work on the heterogeneous vehicle routing problem that is characterized by the existence of different types of vehicles (usually in terms of their capacity) that may compose the fleet. They developed a heuristic for determining the composition of a vehicle fleet and travelling routes, by using tabu search and by solving set partitioning problems. Both fixed and variable cost problems were tested for evaluation of the heuristic.

Regarding the maritime transportation system, Yang et al. (2009) developed a ship routing and fleet planning model, combining the short-term scheduling and long-term planning of the fleet. Using as a starting point the state at a certain time of an existing fleet, the authors' approach would predict the optimal fleet composition and fleet planning for several years in the horizon. Also focused on maritime transportation, as well as on road-based transportation, Hoff et al. (2010) presented a paper containing a review on optimization models combining fleet composition and routing problems, focusing mainly on their industrial aspects. The fleet size vehicle routing problem was the central topic of their work. They, first, presented a classification of the problems, and then described and categorized the current literature on more extended and related problems.

2.1.4 Fleet Planning Optimization Models

Fleet planning problems can be addressed using several different techniques. According to a brief summary presented by Zak et al. (2011), it is possible to find in the literature numerous solution procedures to solve these fleet planning problems, such as exact algorithms (e.g. Sherali & Tuncbilek, 1997; Wu et al., 2005), approximate algorithms, like specialized heuristics (e.g. Ball et al., 1983) and metaheuristics (e.g. Perrier et al., 2007) for optimization problems. It is also possible to find simulation techniques (e.g. Etezadi & Beasley, 1983; Du & Hall, 1997) for simulation problems, decomposition techniques, combined approaches and multi-stage procedures for complex formulations (e.g. Fagerholt, 1999; Imai & Rivera, 2001; List et al., 2003; Vis et al., 2005).

Fleet planning problems can also be formulated as optimization models and, when so, they usually present an objective function composed by one single criterion. The most used method to solve these optimization models is by applying single objective optimization techniques, such as linear programming (e.g. Gould, 1969; Wu et al., 2005), integer programming (e.g. Ball et al. 1983; Vis et al., 2005), transportation methods (e.g. Sherali & Tuncbilek, 1997), dynamic programming (e.g. Fagerholt, 1999), network algorithms (e.g. Beaujon & Turnquist, 1991), single objective specialized heuristics (e.g. Salhi & Sari, 1997), and metaheuristics (e.g. Perrier et al., 2007).

In this section of the Thesis, the focus is on optimization models, as an approach to solve fleet planning problems. An enumeration and description of the most relevant papers on fleet planning optimization models that have been written throughout the years is hereby presented.

Some of the first authors to present some work related to optimization models used to solve fleet planning problems are Avramovich et al. (1982). They described an implementation of a decision support system to help managing the fleet configuration of North American Van Lines, one of the largest truck transportation companies in the United States. The system was based on a large linear programming model, designed to help on the decisions regarding what types of tractors should be sold to owners/operators or should be traded in each week. The authors considered the demand as deterministic, that is, they did not take into account any uncertainty associated to the demand.

Couillard & Martel (1990) formulated a stochastic programming model to address the vehicle fleet planning problem in the road transportation industry, more specifically for truck companies. The model was developed by taking into account tax allowances, and considering a heterogeneous fleet and the demand as a non-stationary stochastic seasonal process. In terms of the available alternatives for acquiring new vehicles for the fleet, the authors included the possibility of vehicle rental or leasing, and also considered a replacement/expansion policy. The final step of the model would be to generate a minimal discounted cost plan that would include the purchase, replacement, sale and/or rental/lease of the vehicles required to respond to a seasonal stochastic demand. Couillard & Martel (1990) also presented an efficient algorithm to solve the model.

As mentioned previously, Beaujon & Turnquist (1991) studied the fleet planning problem alongside with fleet assignment issues, presenting a framework that covers both fleet planning and fleet assignment problems. They formulated a model to optimize both decisions on defining the size of vehicle fleet and decisions on using that same fleet. The model included interactions of fleet size with loaded/empty movements. The formulation of the problem was presented in terms of expected values for random demand and travel times, thus the optimization model was stochastic. Beaujon & Turnquist (1991) also took into consideration the dynamic aspects of the network and maximized the total profit (difference between revenues and transportation costs) generated by the fleet. The authors first transformed the stochastic model into a deterministic one (nonlinear network optimization problem) and then solved it through the application of a decomposition procedure dealing alternatively with the inventory and vehicle allocation problems. The approach of Beaujon & Turnquist (1991) led to interesting results on small examples, and the authors concluded that the model is useful in identifying good strategies for the vehicle sizing fleets and for the allocation of empty vehicles.

Similarly to Beaujon & Turnquist (1991), Sherali & Tuncbilek (1997) also presented a dynamic optimization model to determine loaded and empty railcar movements, a fleet management problem faced by RELOAD (a branch of Association of American Railroads, AAR). These authors' approach to the fleet sizing problem combined both fleet sizing and fleet assignment problems. They proposed two decision models, one static and one dynamic. The static model is solved taking into account a time-independent typical month of the year data and it deals with a homogeneous fleet. The authors determined the optimal number of empty flows for all empty routes, considering a given demand for loaded flows between given origin-destination pairs, and taking into account the transportation times in the network. They defined the fleet size as a "*ratio of a cycle time (total daily transportation time in a network) and the estimated time of expected daily number of trips (loaded and empty) per car*" (Zak et al., 2011, pp. 323). For the alternative dynamic model proposed by Sherali & Tuncbilek (1997), the authors used the concept of time-space network to represent the movements of both loaded and empty railcars for a certain planning horizon. The dynamic model was used to determine the fleet size, as well as to provide guidelines for the storage and retrieval of cars, and to assist in calibrating the static model. To solve the problem, they used a decomposition heuristic procedure.

Also taking into account the dynamic features of the fleet planning problem, Jin & Kite-Powell (2000) combined fleet planning and fleet replacement problems in their work. They determined optimal strategies for using, building and scrapping ships, while maximizing the profit for the company, over the planning period. The model developed by these authors optimized vessel utilization and replacement schedules. They assumed a homogenous fleet and a uniform demand, therefore only the deterministic case is studied and presented. Their work emphasized the importance of combining different fleet planning problems, such as utilization and replacement. Still related to the maritime transportation, Xinlian et al. (2000) presented an algorithm which combined the linear programming technique with the dynamic programming, in order to improve the solution of the standard linear model for fleet planning. In their work, these authors defined three main objectives: 1) to determine the optimal number and type of ships to add to a given fleet; 2) the optimal time to acquire the ships; and 3) the optimal deployment of the ships. Xinlian et al. (2000) first solved the problem for different time periods independently, and then, by using dynamic programming, they determined the fleet evolution over sequential years. The authors considered a heterogeneous fleet and a fixed demand, and optimized the fleet of ships needed to give response to the demand, while minimizing the total costs for the company.

Two years later, Leung et al. (2002) proposed a robust optimization model to solve a logistics problem faced by a Hong Kong manufacturer, in an environment of uncertainty. The authors stated that by adjusting some penalty parameters it is possible to determine an optimal long-term transportation strategy, which includes the determination of optimal delivery routes and the definition of an optimal vehicle fleet composition. The underlying goal was to minimize the total costs for the company under different economic growth scenarios. In their paper, and by using a Hong Kong-based manufacturing company example, Leung et al. (2002) also demonstrated the robustness and effectiveness of the model (a robust solution is one that provides “good” results for a large variety of possible scenarios, but may not be optimal for any of them).

Similar to the work of Leung et al. (2002), List et al. (2003) also considered a stochastic component integrated in an optimization model for fleet sizing, to account for the uncertainty in future demand and productivity of individual vehicles. These authors also focused on robust optimization issues. They developed a two-stage stochastic model, combining two different objectives (minimizing the total costs and maximizing the quality of the service – the latter is included in the objective function as a minimization of a penalty related to service quality), for the fleet sizing problem in a freight transportation system. The first stage of the model includes the decisions regarding the fleet sizing (number of vehicles), and in the second stage the vehicles are assigned to certain routes. The second stage decisions are based on demand forecast values that are modeled according to random variables. The authors used a stochastic decomposition as a solution procedure. Through a numerical example, List et al. (2003) have shown the importance of including uncertainty in the fleet sizing problem formulation. On the other hand, their focus on robust optimization allowed the creation of a fundamental tradeoff between the level of fleet investment and the level of risk in the solution.

Zak et al. (2011) presented an extension of their previous work (Redmer et al., 2003) and considered a fleet sizing problem in a medium-size road freight transportation company operating a heterogeneous fleet of vehicles. They took into account the technical back-up facilities of the company, the interests of different stakeholders and technical and economic criteria, and formulated a mathematical model of the decision problem in terms of multiple objective mathematical programming based on queuing theory. The proposed methodology to solve the fleet sizing problem consisted in a two-step procedure: 1) generation of a set of efficient (Pareto-optimal) solutions through a software called MEGROS; 2) revision and evaluation of the solutions, through the use of an interactive multiple criteria analysis method, called Light Beam Search (LBS), and according to preferences of the decision makers. Finally, the trade-offs between criteria would be analyzed and the most satisfactory solution on the fleet size for the company would be selected.

A few years later, Wu et al. (2005) presented a linear programming model to determine the optimal fleet size and mix of a truck-rental company, considering uncertain parameters (customer travel time) and dynamic conditions (non-stationary customer demand). The authors built the model for a time-space network served by a heterogeneous fleet. To solve the fleet planning problem, Wu et al. (2005) developed a two-phase procedure. First, they applied Benders decomposition (Benders, 1962) to allocate customer demand according to the available trucks, and then they used Lagrangian relaxation (Hillier & Lieberman, 2005) to improve the solution convergence. This two-phase method was presented as an efficient tool to solve large-scale instances of the problem.

Yang et al. (2009) developed a ship routing and fleet planning model, considering the maximization of the total profit for the company as the objective function. The model presented by the authors combined both short-term scheduling and long-term planning of fleet. These authors considered two inputs for the model: 1) a certain existing fleet at a certain time, as a starting point; 2) the transportation demands for a continuous period of time. Based on this information, the model predicted and calculated the optimal ship fleet composition and the fleet planning for a number of years. The authors used a simplex algorithm to solve the linear programming model, and the validity of the model was illustrated by the performance of some numerical tests. Their model showed satisfactory results, and the system could easily find the optimal fleet planning decisions according to the initial inputs.

More recently, and similarly to some papers mentioned above, also with considerations regarding the uncertainty of the demand (stochastic component of the model), Loxton et al. (2012) presented an extension of their previous work (Loxton & Lin, 2011), discussing the problem of assembling a new fleet by taking into account the uncertainty of future vehicle requirements, considering a heterogeneous fleet. The objective of the model was to minimize the total expected transportation costs (fixed, variable driving and hiring costs), while determining the optimal vehicle fleet required to fulfil the stochastic demand. These authors used a combination of the golden section method with dynamic programming to find the optimal composition of the fleet. Loxton et al. (2012) presented some numerical results that show the effectiveness of the algorithm.

When dealing with large databases and big problem instances, one can find in the literature several papers that use heuristics to solve fleet planning optimization models. The heuristics will help to simplify and reduce the size of the problems and the computation times of the models. According to Pearl (1983, pp. vii), "*heuristics stand for strategies using readily accessible though loosely applicable information to control problem-solving processes in human beings and machine*".

It is possible to find in the literature numerous authors who developed heuristic techniques to help solving fleet planning problems. Some examples of these authors are Gheysens et al. (1984, 1986), who reviewed some existing heuristics to solve the fleet size and mix vehicle routing problem, as well as a lower bound procedure, based on which the authors developed a new heuristic; Salhi et al. (1992) proposed some simple modifications for standard heuristics used to solve the combined vehicle routing and vehicle fleet composition problem; Salhi & Sari (1997) developed a multilevel composed heuristic to solve the combined problem of allocating customers to depots, finding the delivery routes and determining the vehicle fleet composition of a company; Dullaert et al. (2002) developed heuristics for the fleet size and mix vehicle routing problem with time windows; Fu & Ishkhanov (2004) proposed a heuristic procedure to identify the optimal fleet mix that maximizes the operating efficiency of a paratransit service system, based on its specific operating conditions and environments; Lee et al. (2008) developed an efficient heuristic for determining the composition of a vehicle fleet and travelling route, by using tabu search and solving set partitioning problems; and Pasha et al. (2016) implemented simple heuristics incorporating tabu search to find the best fleet composition that fulfils the customer demands, and the best routing using that fleet, for each period in the planning horizon.

In Table 2.1, a summary of the papers described in this section is presented. The studies were analyzed in terms of type of optimization model used, the decision variables included in the model, the method used to solve the model, whether the authors took into consideration the uncertainty of the fleet planning problem (deterministic vs stochastic) and if the problem was considered to be static or dynamic.

Table 2.1 – Fleet planning optimization models

Reference	Model Type	Decision Variables	Solving Method	Uncertainty	Dynamic
Avramovich et al. (1982)	Linear programming	.Number of tractors to sell .Number of trade pack tractors	-	Yes	Yes
Couillard & Martel (1990)	Stochastic programming	.Number of purchased vehicles .Number of sold vehicles .Number of brokers with vehicles hired	Grid refinement technique for the "Δ" form of separable programming	Yes	Yes
Beaujon & Turnquist (1991)	Stochastic programming	.Number of loaded vehicles .Number of empty vehicles .Number of vehicles initially allocated	Network programming techniques	Yes	Yes
Sherali & Tuncbilek (1997)	Dynamic programming	.Number of car-load trips	Heuristic	No	Yes
Jin & Kite-Powell (2000)	Dynamic programming	.Number of ships retired .Number of new ships purchased	-	No	Yes
Xinlian et al. (2000)	Linear/Dynamic programming	.Number of ships to buy .Number of ships to replace	Two step algorithm (linear and dynamic programming techniques)	Yes	Yes
Leung et al. (2002)	Integer linear programming	.Volume of products loaded by lorry .Lorry operating a certain route (binary)	-	Yes	No
List et al. (2003)	Stochastic programming	.Number of shipments carried, deferred and delayed .Number of vehicles moving .Number of acquisitions and retirements in the fleet	Stochastic decomposition	Yes	No
Zak et al. (2011)	Multiple objective, nonlinear, integer (combinatorial) programming	.Number of vehicles in a homogeneous group	Two step solution procedure (generate a set of efficient solutions; evaluating those solutions)	Yes	No

Wu et al. (2005)	Linear programming	.Empty truck flow .Number of trucks purchased .Number of trucks sold .Number of trucks in inventory .Loaded truck flow	Two phase solution approach	Yes	No
Yang et al. (2009)	Linear programming	.Number of ship for a certain route .Number of laid-up ships .Number of ships added to the fleet	Simplex algorithm	No	Yes
Loxton et al. (2012)	Dynamic programming	.Number of vehicles to include in the fleet	Novel algorithm (dynamic programming and golden section search)	Yes (demand) No (costs)	No

From the previous table, it is possible to observe that the fleet planning optimization models used in the literature vary between linear, integer, stochastic or dynamic programming models. The majority of the decision variables used are related to the number of vehicles/ships to purchase/sell/keep in the fleet of the company. Regarding the methods used to solve the optimization models, it is possible to find a large variety of methods, such as heuristics, simplex algorithm, two step algorithms or network programming techniques.

One can also remark that most of the work developed on fleet planning optimization models already takes into account the uncertainty associated to fleet planning problems. The majority of the authors considered the problems to be stochastic (for instance, in terms of travel demand and costs) and included this uncertainty when modelling the problem. Regarding the planning horizon for the authors' analysis, some of them studied the fleet planning problem as static (for a specific time period), whereas others took into consideration different time periods for their research, dealing with fleet planning as a dynamic problem.

2.2 Airline Fleet Planning Problem

In this section of the Research Background, the airline fleet planning problem and its most important characteristics will be discussed, as well as the most commonly used approaches to address it. First, a general overview of the problem and the existing literature in this regard is provided. Secondly, the leasing of aircraft as a way of airlines acquiring their aircraft with (supposedly) smaller costs is discussed, and a description of the research that has already been done on aircraft leasing related with the airline fleet planning processes is given. Finally, a review of the most relevant optimization models developed throughout the years for airline fleet planning problems is presented.

2.2.1 General Overview

The airline fleet planning problem consists essentially in determining the aircraft types and the number of aircraft of each type that an airline needs in order to achieve its goals. Clark (2007, pp. 1) provides a more complex definition, defining airline fleet planning as "*the process by which an airline acquires and manages appropriate aircraft capacity in order to serve anticipated markets over a variety of defined periods of time with a view to maximizing corporate wealth*".

As mentioned previously, the decisions concerning the general fleet composition problem are closely interrelated with decisions regarding other fleet management problems, such as fleet replacement, assignment, routing, or scheduling. When it comes to air transportation, the routing problem becomes simpler since a flight route can be defined only by the leg (origin-destination pair) and the flight distance between the origin and destination points will always be the same. Thus, the planning of the composition of an airline fleet presents some differences with respect to general planning problems. According to Kilpi (2008), the choice between a uniform or a diversified fleet can be a challenging task for an airline. With a uniform fleet, maintenance, training and labor cost will be lower. On the other hand, a fleet composed by different aircraft types presents the possibility of choosing an aircraft that can more efficiently respond to market conditions and travel demand.

Airline fleet planning is a complex decision-making process which has been dealt with by several authors, particularly in recent years. For instance, Harasani (2006) proposed a system for the evaluation and selection of a fleet of aircraft for an airline in Saudi Arabia, with operations in domestic and international routes. The types of aircraft were chosen according to the aircraft range and payload for a certain route network. The results, in terms of aircraft efficiency and its contribution to the net profit of the airline, were obtained through an Excel application created by the author. Along the same lines, Sun et al. (2008) developed a method to evaluate the fleet composition of an airline integrating fleet planning and fleet assignment components. They calculated the planned direct cost (POC) for several different fleet composition alternatives, in which they simulated the airline operation according to information on flight schedules, expected reservation demand, and mean price of each flight. The best alternative was the one with the lowest POC.

Various authors have studied the airline fleet planning problem in different ways. Several took into consideration the close connection between flight frequencies and aircraft size, considering identical factors. For instance, Pai (2010) studied the influence of certain factors on flight frequencies and aircraft size on US airline routes. This author took into account market demographics, airport characteristics, airline characteristics and route characteristics. His research showed that flight frequency and aircraft size increase with population and income. He also concluded that an increase in runway length leads to a higher frequency and larger aircraft sizes, as well as an increase in delay at the route endpoints results in lower frequencies and smaller aircraft, among other things. Givoni & Rietveld (2009) used regression analysis in over 500 routes in the US, Europe and Asia, to investigate the effects of route characteristics (distance, level of demand, level of competition) and airport characteristics (number of runways, being hub or not) on aircraft selection. They concluded that the choice of aircraft size is mainly influenced by route characteristics and almost not at all by airport characteristics.

Wei & Hansen (2005) developed a nested logit model to study the influence of aircraft size on the airline's demand and market share in competitive duopoly markets, considering one major airport as an origin and another as a destination. They also incorporated the service frequency, seat availability and fares on their analysis. These authors concluded that airlines demonstrate better market share by increasing frequencies rather than increasing the aircraft size (seat availability per flight). Later, Wei & Hansen (2007) performed an integrated analysis on aircraft size and service frequency in a competitive environment. They developed and applied three game-theoretic models to analyze the impact of these decisions on cost and demand for air transportation. The authors studied the aircraft size influence in an individual airline's market share, as well as in a market including values for a total air travel demand. Wei & Hansen (2007) emphasized that the aircraft size is an important factor to take into account during the process of decision-making in airlines' fleet management. Also related to the relationship and influence between selection of aircraft and air travel demand, Bhadra (2003) investigated if it was possible to obtain the selection of aircraft and fleet mix for an origin and destination pair, based on passenger demand.

More recently, Ozdemir et al. (2011) studied the selection of aircraft for the largest Turkish airline company, by using the Analytic Network Process, a multicriteria decision support technique. They considered cost (purchasing, operating, maintenance, and salvage cost), time (delivery and use), physical attributes and other factors (dimensions, security, reliability and suitability for service quality) as the main criteria for the aircraft selection. Gomes et al. (2014) investigated the selection of aircraft for a company investing in regional charter flights in Brazil. In order to find a solution for their problem, they used a multicriteria decision aid method named NAIADE (Novel Approach to Imprecise Assessment and Decision Environments), and took into consideration three types of criteria: financial, logistics and quality.

An interesting paper about airline fleet composition is due to Kilpi (2007). He performed an analysis on the history of all jet aircraft operated by commercial passenger or cargo airlines worldwide in the period between 1952 and 2005, particularly with respect to uniformity and scale. He examined developments in airline fleet composition using a Fleet Standardization Index (from Pan & Santo, 2004)[1] with the aim of analyzing the evolution of airlines fleet

[1] Pan & Santo (2004) presented a study on airlines' fleet standardization (fleet commonality issues) taking into account the factors that influence that standardization and the benefits that can be extracted from it. They

composition globally. His study shows that uniformity in airline fleets has been gradually decreasing, while their size has been progressively increasing. Almost a decade before Kilpi (2007), Adrangi et al. (1999) also made an analysis of the change in the fleet composition of nine major operators in the US during a period of 13 years. In Seristö (1995), a data snapshot of one year is analyzed, regarding 42 major airlines worldwide.

One of the major concerns of an airline when deciding the composition of its fleet is definitely the minimization of costs. Therefore, one of the key issues in finding an optimal fleet composition for an airline is the clear definition of which types of costs should be taken into account and what value do they have in reality. The work of Seristö & Vepsäläinen (1997) and Swan & Adler (2006) provide insightful information on this subject. In Seristö & Vepsäläinen (1997), the factors that offer cost reduction possibilities in airline operations are identified, and the impact of different cost reduction measures are evaluated. They concluded that fleet composition, route network, and company policies on remuneration and work rules are the factors that most affect the total costs of an airline. Swan & Adler (2006) present the aircraft operating costs disaggregated into cost categories and, in addition, they establish and evaluate a generalized cost function for commercial passenger aircraft operating costs. Also regarding aircraft operating costs, Wu & Caves (2000) investigated the connection between flight schedule punctuality and aircraft turnaround efficiency at airports. Their goal was to minimize system operating costs and, at the same time, maintain a certain level of schedule punctuality. These authors considered the system operating costs to include departure delay costs, passenger delay costs and schedule time costs. They took into consideration the stochastic effects of schedule punctuality and the aircraft performance in terms of turnaround time, and applied a mathematical model to simulate aircraft turnaround operations. Their results showed that a proper use of schedule buffer time has a great significance in maintaining schedule punctuality performance.

developed an index (Fleet Standardization Index) that can be used to compare different fleets and also to evaluate the implications from maintaining or renewing fleets.

The airline fleet planning problem has also been studied in the environmental perspective. Koch et al. (2009) and Braun et al. (2010) used multi-objective optimization models to analyze trade-offs between airline operations and environmental impact. Koch et al. (2009) investigated the effects of variations in flight altitude and speed on operating costs and climate change, whereas Braun et al. (2010) discussed the climate benefits achievable for a single airline from changes in network design. Morrell (2010) used a net present value model to investigate environmental trade-offs in (long term) fleet planning. He explored the economic viability of early aircraft retirements and the introduction of new technology into an airline fleet. This author only considered a single fleet decision (replacing one aircraft type by a different one), and neither network nor fleet effects (e.g., fleet composition, commonality with existing fleet) were taken into account.

More recently, based on Morrell (2010) and using an approach similar to the ones adopted by Koch et al. (2009) and Braun et al. (2010), Rosskopf & Luetjens (2012) developed a methodology for balancing economic and environmental goals in airline fleet planning. Through the use of a multi-objective optimization model, they analyzed three different components of the airline fleet management problem considering a 10-year planning horizon: fleet composition (number and type of aircraft), fleet development (timing of aircraft purchases and retirements) and fleet employment (assignment of aircraft to routes in the network). The model was capable of determining the trade-offs between an economically and an environmentally optimal fleet. Their results indicate that lowering the environmental footprint involves higher costs for the airline. Givoni & Rietveld (2010) also analyzed the environmental consequences of airlines' choice on service frequency and aircraft size. They compared the environmental impacts of operating large or small aircraft in short-haul routes, and considered local air pollution, climate change and noise impacts on their analysis. Givoni & Rietveld (2010) concluded that airlines prefer to increase frequency instead of increasing aircraft size (capacity), particularly on short routes. These authors also mentioned that, in order to conserve the airline position on the market, flight frequency is a key factor.

One of the most recent and relevant research work within the airline fleet planning field is from Dožić & Kalić (2013, 2015). In 2013, they proposed a two-stage model for airline fleet planning. In the first stage of the model, the authors determined an approximate fleet mix in terms of aircraft size, by using fuzzy logic[2]. After this first step, the obtained results were two sets of routes, one covered by small aircraft, and the other by medium size aircraft. These outputs were then used as inputs for the second stage of the model, where the fleet sizing problem was solved by using a heuristic procedure. Dožić & Kalić (2013) illustrated the model by using an example of an airline based at Belgrade airport. Two years later, the same authors (Dožić & Kalić, 2015) improved their previously developed work and added one more stage to the airline fleet planning model. Their goal was to develop a model capable of helping airlines operating on short and medium haul routes. Besides addressing fleet composition/mix and fleet sizing problems (in which they focused their previous work), in their most recent research, these authors also incorporated the aircraft type selection decision process in their fleet planning model. In each one of the three stages, Dožić & Kalić (2015) used different techniques to obtain the intended results, such as fuzzy logic, heuristic and analytic approaches, and multi-criteria decision making. They again used a hypothetical airline based at Belgrade airport, as an example for illustrating the three-stage airline fleet planning model.

[2] The idea of fuzzy logic was first mentioned by Dr. Lotfi Zadeh (University of California, Berkeley, USA), in the 1960s. In Zadeh (1975, p. 407), the author refers that fuzzy logic can be characterized as "*a logic of approximate reasoning*". Zadeh (1975, p. 407) also enumerates the most significant characteristics of fuzzy logic: "*(i) fuzzy truth-values expressed in linguistic terms, e.g., true, very true, more or less true, rather true, not true, false, not very true and not very false, etc.; (ii) imprecise truth tables; and (iii) rules of inference whose validity is approximate rather than exact*". In other words, fuzzy logic can be described as an approach to computing, based on "degrees of truth" instead of the more common "true or false" logic (1 or 0 – Boolean logic), on which the modern computing depends (WhatIs.com, 2017). According to Singh et al. (2013, pp. 1), fuzzy logic can deal with "*uncertain, imprecise, vague, partially true, or without sharp boundaries*" information that usually results from "*computational perception and cognition*". The fuzzy logic approach can be used in several fields, such as control theory, artificial intelligence, pattern recognition, and optimization.

2.2.2 Aircraft Leasing

According to Zuo (2010, pp. 4), leasing can be defined as "*a contract between a lessor and a lessee where the lessor provides the lessee with the right to use assets, property owned by the lessor*". The contract is usually set up for a particular time period (lease term), during which the lessee is obliged to periodically pay a certain rent, agreed to between the lessor and the lessee.

There are two different types of lease: the operating lease and the capital (or financial) lease. Oum et al. (2000, pp. 19) provide a simple but clear explanation about the crucial distinction between these two types of lease: "*if the term of a lease covers a major portion (e.g. 75%) of the economic life of the equipment under the lease, the lease is a capital lease; anything shorter is an operating lease*". It is worth mentioning that in the aircraft leasing market, although the economic lives of aircraft may be around 20-30 years, the operating leases are usually for a short period (5 years or less). Wensveen (2012) gives a more complex explanation, affirming that operating lease is a short-term lease that cannot be cancelled, and one of its characteristics is that, at the end of the lease contract, the lessor maintains full title of the asset and accepts any market risk as to its value at the time. On the other hand, in a financial lease, after the ending of the lease contract, the title of the asset passes to the lessee, in exchange of a certain amount of money, usually pre-agreed. Thus, there is no market risk for the lessor on the value of the asset.

According to Wensveen (2012), before the 1980s, the majority of the airlines would consider purchasing as the only option to acquire new aircraft for their fleet. In 1984, only approximately 20% of the world's commercial aircraft were leased. But around two decades after, in 2006, aircraft leasing accounted for over half of all aircraft acquisitions. Therefore, lease of aircraft has become an increasingly important tool for the airline industry, and nowadays the costs associated to aircraft leasing definitely represent a significant portion of airlines' total costs. The purchase price of an aircraft and the operating expenses associated with it are very high. Therefore, airlines increasingly consider aircraft leasing as an interesting alternative to obtain new aircraft. As reported by Gritta et al. (1994), for a sample of major US carriers, the percentage of aircraft leased increased from 19% in 1969 to 54% in 1991, and the percentage of aircraft under operating leases to total leased aircraft increased from 13% in 1969 to 82% in 1991.

From the point of view of airlines, one of the major advantages of leasing an aircraft is that it gives them flexibility in capacity management, which is a major issue when demand for air transportation service is uncertain. Morrell (2013) enumerates the advantages and disadvantages for an airline of the aircraft leasing process. Some of the more significant advantages are the conservation of the airline's working capital and credit capacity, the provision of up to 100% of finance with no deposits or prepayments, and the shift of the obsolescence risk of aircraft to the lessor. In relation to the disadvantages, some of them are the profit from the eventual sale of the aircraft going to the lessor and the aircraft specification not being tailor-made for the lessee airline.

One of the first authors to investigate aircraft leasing was Pulvino (1998). He used commercial aircraft transactions to determine the magnitude of the discount at which distressed airlines liquidate assets. The market of used commercial aircraft has many participants besides the airlines, such as governments, air cargo companies, and financial institutions, like leasing companies. Pulvino (1998) analysis was made through a comparison between financially constrained and unconstrained airlines. The author's results indicate that constrained airlines receive lower prices than their unconstrained rivals when selling used narrow-body aircraft and that they are more likely to sell used aircraft to industry outsiders. He also concluded that unconstrained airlines significantly increase their buying activity when aircraft prices are depressed, a fact that was not observed for the financially constrained airlines.

Santos (2011) studied aircraft leasing in Brazil. He modeled Brazilian airlines' leasing costs, according to the Brazilian market characteristics, airlines' features, and aircraft attributes. The exchange rate was used as a variable in the model, since the leasing cost is significantly associated with exchange rate fluctuations, due to the fact that the majority of the leasing contracts is made with foreign companies.

Aircraft leasing has already been incorporated by some researchers in fleet composition analyses, especially regarding optimization models (Oum et al., 2000; Hsu et al., 2011; Bazargan & Hartman, 2012; Khoo & Teoh, 2014; Repko & Santos, 2016). The approaches and findings of these authors are described in the following section.

2.2.3 Airline Fleet Planning Optimization Models

In terms of optimization models, probably the first researcher to study the airline fleet planning problem was New (1975). He discussed airline fleet planning when old aircraft become obsolete and new aircraft types with improved performance become available, and considered a dynamic environment. This author presented a review of previous models, and developed a viable model for planning the acquisition and disposal of aircraft, defining the fleet composition for a commercial airline.

Jenkins (1987) studied the fleet planning problem from the airlines point of view, and was also one of the first authors to develop an optimization model within this field. He used an advanced planning methodology to select aircraft types and to plan an aircraft fleet. He formulated the problem of finding an optimal mix of an air transport fleet as an integer linear program in which the objective function includes, for each type of aircraft, a fixed operating cost for having that type of aircraft in the fleet and an operating cost that varies with the number of aircraft. Jenkins (1987) analyzed real data, from the Canadian Forces Air Transport Fleet, in order to illustrate the usefulness of parametric procedures in identifying robust solutions (optimal or near optimal over a wide range of parameter variation).

Similarly to Jenkins (1987) work, there are other examples of studies on the subject of airline fleet planning that incorporate concerns about the robustness of solutions. For instance, Listes & Dekker (2002, 2005) developed a scenario aggregation based approach for determining a robust airline fleet composition. The authors addressed the problem by using the dynamic allocation concept, which accounts for the stochastic nature of passenger demand, in supporting decisions related to fleet composition. Their results show that a stochastic approach is much more beneficial when compared to a deterministic approach, and also that their approach's implementation was feasible. Wesolkowski et al. (2012) developed a multi-objective optimization model for the airline fleet mix problem. They pointed out that for a company transporting cargo and/or people (for instance, an airline), when dealing with fleet planning decisions, a few different objectives can arise (for instance, cost and performance), which implicates that sometimes fleet planning problems should be considered multi-objective. Based on this premise, Wesolkowski et al. (2012) proposed an alternative model, inspired by the Stochastic Fleet Estimation – Robust (SaFER) model[3], to solve the fleet planning problem within a multi-objective optimization framework. They used an artificial air mobility dataset to demonstrate the advantages of the alternative model over the SaFER model, in terms of computational time and accurate estimation of schedule costs.

In recent years, there have been several authors presenting optimization models as a possible approach to deal and solve airline fleet planning problems. For instance, Wang (2014) developed a model to minimize the fleet planning costs for an airline, by incorporating the passenger mix problem into the fleet composition problem. According to this author, the traditional methods for determining an airline fleet composition do not take into consideration the network effects. Therefore, in order to present a solution for this problem, Wang (2014) studied the network effects (regarding airlines operating in a hub and spoke network), and incorporated the passenger demand transfers from one airport to another into his work. He used three different decision variables in his model: 1) the purchasing number of aircrafts in each fleet type; 2) the frequencies of each aircraft type flying on legs; and 3) the spilling

[3] The Stochastic Fleet Estimation – Robust (SaFER) model was previously developed by Wesolkowski and Wojtaszek (2012), and it uses scheduling heuristics and optimization to estimate a fleet capable to give response to a certain scenario requirements. However, the application of SaFER model to real problems, especially when dealing with multi-objective frameworks, is not computationally feasible.

number of passengers from each itinerary. This author demonstrated the feasibility and effectiveness of the model through the use of a numerical example.

Majka (2015) presented a multi-objective mathematical model for planning a fleet of a regional European airline. This author's research focused on developing a regional transportation system using light aircraft. He considered that the aircraft would efficiently compete with cars on distances over 200 km (shorter travelling times and acceptable level of costs). The objective was to determine the optimal fleet for the airline, while minimizing the transportation costs and maximizing the transportation efficiency.

As mentioned in the previous section, there are some authors who have developed optimization models to solve airline fleet planning problems, incorporating aircraft leasing into their work. For instance, Oum et al. (2000) developed a model for the airlines to determine the optimal mix of leased and owned capacity, taking into consideration that the demand for air transportation is uncertain and cyclical. The empirical results they obtained suggest that the optimal leasing demand for the airlines would range between 40% and 60% of their total fleet for a reasonable range of operating lease premiums. These results indicate a huge market potential for leasing companies. Oum et al. (2000) also concluded that the financial status of the airline and passenger demand are critical factors when it comes to lease versus own capacity decisions.

More recently, Hsu et al. (2011) developed a stochastic dynamic programming model to optimize airline decisions regarding the purchase, the lease, or the disposal of aircraft over time, and applied it to an airline in Taiwan. The results of their study show that severe demand fluctuations would make the airline lease rather than purchase aircraft, which would allow greater flexibility in fleet management. This may be a reference work for the airlines that they can use in their replacement decision-making process, while taking into consideration the fluctuations in the market demand and the status of the aircraft.

Similar to Hsu et al. (2011), Bazargan & Hartman (2012) also presented an aircraft replacement model that minimizes the discounted costs of owning or leasing and operating a fleet, by identifying which aircraft to buy, sell and lease over the planning horizon. The model was applied to two US airlines with different business models. The results show that aircraft leasing was in both cases the best alternative.

Also incorporating aircraft leasing into their research, Khoo & Teoh (2014) proposed a methodology to find optimal solutions for a fleet planning decision model, and considered the demand as a stochastic parameter. These authors' approach comprised a five-step modeling framework (developed to quantify the uncertainty of the demand for each operating period), a probabilistic dynamic programming model (formulated to determine the optimal number and types of aircraft to be purchased and/or leased, in order to meet the stochastic demand), and a probable phenomenon indicator (defined to ensure that the airlines own a fleet suitable for a certain service level under uncertainty). In order to demonstrate the applicability of the methodology proposed, Khoo & Teoh (2014) used an illustrative case study.

Repko & Santos (2016) proposed a multi-period scenario tree methodology, to help solve the airline fleet planning problem, taking into account the uncertainty of the demand. They considered that the tree was composed by nodes and branches. Nodes representing the decision points in different stages of the planning horizon, and branches representing the scenarios with variations of the demand. Repko & Santos (2016) developed a mixed-integer linear programming model, to optimize the fleet composition of an airline in multiple periods, and assumed that the aircraft can be owned or leased by the airline. These authors presented two real-world based case studies to prove the validity of the model.

In Table 2.2, a summary of the existing research on airline fleet planning optimization models is presented. The type of optimization model, the decision variables defined, the solving method used, the consideration of a stochastic problem (with uncertainty), a static or dynamic approach, and the integration of aircraft leasing were some of the characteristics analyzed in the papers.

Table 2.2 – Airline fleet planning optimization models

Reference	Model Type	Decision Variables	Solving Method	Uncertainty	Dynamic	Leasing
New (1975)	Linear programming	.Number of owned aircraft .Number of aircraft operating in a certain route .Number of aircraft purchased .Number of aircraft sold	-	No	Yes	No
Jenkins (1987)	Integer programming	.Number of aircraft in the fleet	Parametric analysis	Yes	No	No
Oum et al. (2000)	Integer programming	.Number of owned aircraft .Number of leased aircraft	-	Yes	Yes	Yes
Listes & Dekker (2002, 2005)	Integer programming	.Aircraft flying a certain leg (binary)	Scenario aggregation-based approach	Yes	Yes	No
Hsu et al. (2011)	Stochastic dynamic programming	.Number of purchased aircraft .Number of leased aircraft .Flight frequency on a certain route performed by a certain aircraft	Backward dynamic programming	Yes	Yes	Yes
Wesolkowski et al. (2012)	SaFER (Stochastic Fleet Estimation - Robust)	.Number of sorties that a platform of a certain type is used to perform a certain task	Multi-objective optimization	Yes	No	No
Bazargan & Hartman (2012)	Binary-integer linear programming	.Number of aircraft to buy .Number of aircraft to lease .Number of owned aircraft	-	No	No	Yes
Wang (2014)	Linear programming	.Number of aircrafts to purchase .Aircraft flight frequencies	Passenger mix problem (PMP) based	No	No	No
Khoo & Teoh (2014)	Probabilistic dynamic programming	.Number of aircrafts to purchase .Number of aircrafts to lease	Decomposition into simpler sub problems (backward working method)	Yes	Yes	Yes

Majka (2015)	Linear programming	.Number of aircraft to perform a certain task	Multi-objective optimization	Yes	No	No
Repko & Santos (2016)	Mixed-integer linear programming	.Number of aircraft owned .Number of acquired aircraft .Number of disposed aircraft .Weekly frequency of a certain aircraft in a certain route .Number of passengers transported in a certain route	Scenario tree approach	Yes	Yes	Yes

Similarly to what was observed in terms of general fleet planning optimization models, when it comes to airline fleet planning, it is also possible to find in the literature different optimization models. Some examples of models are the linear and integer programming, or mixed-integer, as well as stochastic dynamic and probabilistic dynamic programming. Regarding the decision variables used by the authors, the majority comprise the number of aircraft to own, purchase or lease. The flight frequency of a certain route performed by a certain type of aircraft is also a common decision variable that is possible to find in the airline fleet planning optimization models literature.

In the majority of the papers analyzed, it was possible to find the inclusion of uncertainty when modeling travel demand and/or costs. Some of the authors considered the airline fleet planning problem to be static, and other dealt with the problem as dynamic. Finally, the inclusion of leasing options when planning an airline fleet was also a characteristic included in some of the analyzed work included.

2.3 Research Gaps

From the preceding section, one can conclude that issues related with airline fleet planning have already been widely investigated. There is a lot of previous research about this topic, in general, as well as concerning the optimization analysis and modelling of the fleet planning problem from the airlines point of view, in particular.

Considering all the references described previously, it is possible to enumerate some of the more relevant and complete papers on this subject, that can be used as a research basis for the work developed: regarding general fleet planning, List et al. (2003); specifically related to airline fleet planning, Listes & Dekker (2005), Oum et al. (2000), Bazargan & Hartman (2012), and Hsu et al. (2011).

As mentioned previously, List et al. (2003) developed an optimization model for a general fleet sizing problem, having as a final goal the minimization of the total costs. They integrated into their model a stochastic component, referent to the uncertainty in future demands and productivity of individual vehicles. They also focused their research on robust optimization. However, there are some issues that can definitely be explored and improved. For instance, they did not consider the possibility of including in the fleet composition model the option of vehicle’s leasing, and the consequent costs associated to it. Furthermore, another aspect that was not included in List et al. (2003) approach, and may improve the analysis and the results, is the consideration of a dynamic problem, so that the results can be obtained for different time periods and a path of the evolution of the fleet may be designed. This is an improvement recognized by the authors at the end of the paper.

Regarding Listes & Dekker (2005) work, their approach was to maximize the total profit of an airline, while determining their robust fleet composition. They presented a scenario aggregation based approach and considered the stochastic nature of passengers’ demand, by integrating a dynamic allocation of the fleet’s capacity to the flight schedule. The possible improvements that could be done in this research are similar to the ones referred in the previous paragraph. The authors did not consider the fleet composition problem as dynamic in terms of time, either; and the costs associated to the aircraft leasing were also not taken into account.

Oum et al. (2000) developed a model for the airlines to determine the optimal mix of leased and owned capacity. They took into consideration that the demand for air transportation is uncertain and cyclical, by including a stochastic component into the model. One of the most valuable aspects of this work is the fact that it presents a method of forecasting the airlines' demand for operating lease of the aircraft. Nevertheless, once again, the authors' approach does not consider the fleet composition problem as a dynamic problem, and the model is run and the solutions are found for a specific period of time. Besides, Oum et al. (2000) research does not present any concern with the robustness of the model, which is an aspect that can definitely be improved.

In the opposite side of the papers mentioned before, Bazargan & Hartman (2012) dealt with the aircraft replacement problem as a dynamic problem, and incorporated a time component in their analysis. They developed a model that minimizes the discounted costs of owning, or leasing, and operating a fleet, over the planning horizon, while defining which aircraft the airline should buy, sell and lease, for different periods in time. However, on the other hand, Bazargan & Hartman (2012) work does not take into account the stochastic component related to the passengers' demand and operating costs, which is positively a downside of their work. Furthermore, the model's robustness is another aspect that is not taken into account by the authors.

One of the most complete works regarding the airline fleet composition problem is from Hsu et al. (2011). They developed a stochastic dynamic programming model to optimize airline decisions regarding the purchase, the lease, or the dispose of aircraft, over time. Thus, their approach considered both dynamic and stochastic components in the model, which are indispensable characteristics when dealing with the airline fleet planning subject. However, it is noteworthy that the authors deal with the stochastic component of the model in a very simple way. Although Hsu et al. (2011) present a very relevant research work in this field, there are some weaknesses in their study. For instance, one of the inputs of the model is the flight frequencies. However, the flight frequencies depend, at least to some extent, on the airline fleet composition, so this dependency should be considered in the model. Another limitation of their model is the fact that it does not take into consideration the variability of the demand within a year time period. Furthermore, the case study in Hsu et al. (2011) only includes 8 different city-pair routes, so the efficiency of the dynamic programming approach in more realistic problems is questionable.

Although the airline fleet composition problem has been widely investigated, there are undoubtedly some gaps in this research field. One of the aspects that have already been taken into consideration in a lot of the work developed under this subject is the uncertainty of the air transportation demand. However, the uncertainty associated to the operating costs, and its evolution during different time periods, is still scarcely considered in the literature.

A relevant part of the work developed does not incorporate a dynamic approach, and the models are usually defined for a specific time period. However, the schedules of the decisions and their consequent impacts, as well as the evolution of the fleet composition over time, are crucial issues when planning a fleet of an airline. Another major gap is definitely on air cargo demand. Although it represents a big part of air transportation demand, the literature including demand from freight companies is very limited.

The major goal of this work is to fill some of the gaps that currently exist within the airline fleet composition research field. Two optimization models are going to be developed to determine the optimal fleet composition of an airline, while minimizing its total costs. One of the models will be focused on long-distance airline operations, whereas the second model will deal with short-distance movements. How many, and which type of aircraft should the airline purchase, dispose or lease, and when should these actions take place, for a given time horizon, are some of the questions that this research work will try to answer.

3 AIRCRAFT TYPES AND EVOLUTION

In this chapter of the Thesis, an analysis of the different currently existing aircraft models will be presented, as well as the main current aircraft manufacturers in the market. The characteristics of each type of aircraft will be enumerated and described, and its mechanical and technological evolution will also be analyzed. Furthermore, a study on the evolution of the fleet of some of the largest airlines in the world will be presented, and a description of some of the crucial characteristics of an airline, such as airline efficiency, productivity and costs, will also be performed.

3.1 Types of Aircraft

It is possible to find the definition of aircraft in any dictionary: "*any machine capable of flying by means of buoyancy or aerodynamic forces, such as a glider, helicopter, or airplane*" (Collins English Dictionary, 2017). In other words, and in simpler terms, an aircraft can be defined as "*a vehicle used for traveling through the air*" (Your Dictionary, 2017).

There are aircraft types of all shapes, sizes and price range. Furthermore, aircraft categorization may be based in several different features, such as lighter or heavier than air, civil (business or commercial) or military, aircraft configurations, for example, wing types, takeoff and landing gear, and propulsion systems (Encyclopædia Britannica, 2017).

Some general examples of aircraft types may be: 1) helicopter – represents an easier way to reach locations that would be more difficult to access otherwise; 2) twin piston – more economical and appropriate to short-distance flights, with a seat capacity between 3-8 passengers; 3) executive jet – a small aircraft in terms of number of seats, ranging between 4-16 passengers, and suitable for medium or long-distance flights, being one of the most efficient ways of flying; 4) turboprop – more used to fly for short and medium-distance destinations, representing 2-4 hours of flight time, and with a range of seats between 4 and 70 passengers; 5) airliner – a larger aircraft appropriate to all distance flights, and seat capacity going from 50 to 400 passengers; or 6) cargo aircraft – suitable for any kind of cargo transportation, which can vary from short notice flights transporting small items, to large cargo aircraft carrying more bulky parcels (Aircraft Charter World, 2009).

3.1.1 Aircraft Manufacturers and Aircraft Type Characteristics

The main focus of this work is on commercial aircraft and the size and composition of the fleet of an airline. Nowadays, when it comes to commercial aviation, it is possible to find in the aviation market at least 4 major and well known civil aircraft manufacturers (these represent some of the companies from which an airline can choose the types of aircraft to include in its fleet):

- Airbus
- Boeing
- Embraer
- Bombardier

Airbus

Airbus is one of the world's top aircraft manufacturers and the largest space and aeronautic company in Europe. It was established in 1970. It is responsible for fulfilling more than half of the orders for airliners with more than 100 seats, being its aircraft recognized for its comfort, economics and versatility. In 2017, Airbus received more than 17,200 aircraft orders, in total, and delivered over 10,500 aircraft. Airbus is based in Europe and although the company's headquarters are located in Toulouse, France, it has grown internationally to approximately 180 locations and 12,000 suppliers. The company maintains both aircraft and helicopter final assembly lines across Asia, Europe and America. It has around 133,000 employees from 85 different nationalities. Delta Air Lines, United Airlines, US Airways and Virgin America are some examples of US airlines that include Airbus aircraft models in its fleet. Besides passenger aircraft, Airbus also offers aircraft models for cargo and express operators (Airbus, 2017a).

Airbus is currently producing 12 different aircraft types for passengers – 4 in A320 family, 4 in A330 family, 3 in A350 XWB family and 1 A380. In Table 3.1, a summary of the main characteristics of the Airbus aircraft types is presented.

Table 3.1 – Airbus aircraft characteristics
(sources: Airbus, 2017a, 2017b)

Aircraft Type	Seats		Range [km]	Wing Span [m]	Overall Length [m]	Height [m]
	Typical	Max				
A318	107	103	5,750	34.10	31.44	12.56
A319neo	140	160	6,950	35.80	33.84	11.76
A320neo	165	189	6,500	35.80	37.57	11.76
A321neo	206	240	7,400	35.80	44.51	11.76
A330-200	247	406	13,450	60.30	58.82	17.39
A330-300	277	440	11,750	60.30	63.66	16.79
A330-800neo	257	406	13,900	64.00	58.82	17.39
A330-90neo	287	440	12,130	64.00	63.66	16.79
A350-800	276	440	15,270	64.75	60.54	17.05
A350-900	325	440	15,000	64.75	66.80	17.05
A350-1000	366	440	14,750	64.75	73.78	17.08
A380	544	853	15,200	79.75	72.72	24.09

Boeing

Boeing is the world's largest company in the aerospace field and the leading manufacturer considering commercial and military aircraft in combination. It was created in 1916, and it is considered a top company in designing and manufacturing satellites, missiles, weapons, defense, space and security systems, and also advanced information and communication systems. This company is based in the United States (US) and its headquarters are located in Chicago, Illinois. Boeing is a top US exporter company and employees more than 147,000 people both in the US and in another 70 countries. It is known for being one of the most diversified, pioneer and innovative, as well as talented and capable companies in the world. Nearly 50% of the world existing commercial fleet (approximately over 10,000 aircraft) is composed by Boeing airliners in service all around the world. Also in terms of freight air transportation, Boeing is the top company in the market, offering a large and diverse family of freighters. Around 90% of the world's cargo is transported in Boeing aircraft models. Some of the companies using Boeing aircraft as part of its fleet mix are, for instance: Alaska Airlines, Air New Zealand, Delta Air Lines, Etihad Airways, and KLM Royal Dutch Airlines (Boeing, 2017).

Currently, Boeing manufactures 5 different families of commercial aircraft: 737 Next Generation (3 passenger aircraft models), 747 (1 passenger and one freight aircraft models), 767 (1 freight aircraft model), 777 (3 passenger and one freight aircraft models) and 787 (3 passenger aircraft models), and it also offers a Boeing Business Jet range. Some of Boeing's most recent aircraft include the 737 MAX (4 aircraft models), the 787-10 Dreamliner and the 777X (2 passenger aircraft models). In Table 3.2, it is possible to find some of the general characteristics of the Boeing passenger aircraft families.

Table 3.2 – Boeing aircraft characteristics
(sources: Boeing, 2012, 2014, 2015, 2017; Trimble, 2015)

Aircraft Type	Seats		Range [km]	Wing Span [m]	Overall Length [m]	Height [m]
	Typical	Max				
737-700	126	149	5,575	35.80	33.60	12.50
737-800	162	189	5,436	35.80	39.50	12.50
737-900ER	178	220	5,463	35.80	42.10	12.50
737 MAX 7	138-153	172	7,080	35.90	35.56	12.50
737 MAX 8	162-178	200	6,510	35.90	39.52	12.42
737 MAX 9	178-193	220	6,510	35.90	42.16	12.40
737 MAX 10	188-204	230	5,960	35.90	13.80	12.40
747-8	410	467	14,816	68.40	76.30	19.40
777-200ER	313	-	13,084	60.90	63.70	18.50
777-200LR	317	-	15,843	64.80	63.70	18.60
777-300ER	396	-	13,649	64.80	73.90	18.50
777X-8	350	375	8,700	72.00	70.00	19.50
777X-9	400	425	7,600	72.00	77.00	19.70
787-8	242	359	13,620	60.70	56.69	17.00
787-9	290	406	14,140	60.70	63.00	17.00
787-10	330	440	11,910	60.70	68.27	17.00

Bombardier

Bombardier is an international transportation company spread all over the world, in more than 60 countries along 5 continents. It was established in 1942 and it is a world leading manufacturer in two different businesses: aerospace and rail transportation. In the aerospace sector, Bombardier represents one of the top four major civil aircraft manufacturers and it is one of the major companies contributing for the evolution of worldwide mobility. Innovation, efficiency and sustainability are the key priorities of the company, when designing and manufacturing aviation products and services. Bombardier is based in Canada and its headquarters are located in Montréal. The company employees more than 28,500 people worldwide. Bombardier aircraft and aviation products are present in several and diversified markets, such as business aircraft, commercial aircraft, aero structures and engineering services, specialized aircraft solutions, and aircraft services and training. Lufthansa, Gulf Air, Odyssey Airlines, Korean Air, Iraqi Airways, and airBaltic are some of the airlines using Bombardier aircraft models in its fleet (Bombardier, 2017).

Regarding the commercial aircraft market, Bombardier manufactures 3 different series of aircraft: the C series (2 aircraft models), the CRJ series (3 aircraft models), and the Q series (1 aircraft model). In Table 3.3, the main characteristics of these commercial passenger aircraft produced by Bombardier are presented.

Table 3.3 – Bombardier aircraft characteristics
(sources: Bombardier, 2017; Bombardier Commercial Aircraft, 2017a, 2017b, 2017c, 2017d, 2017e, 2017f)

Aircraft Type	Seats		Range [km]	Wing Span [m]	Overall Length [m]	Height [m]
	Typical	Max				
CS100	108	135	5,741	35.10	35.00	11.50
CS300	130	160	6,112	35.10	38.70	11.50
CRJ700	66	78	12,497	23.20	32.30	7.60
CRJ900	81	90	12,497	24.90	36.20	7.50
CRJ1000	97	104	12,497	26.20	39.10	7.50
Q400	74	90	2,040	28.40	32.80	8.40

Embraer

Embraer is considered the direct rival of Bombardier – both companies compete intensively and closely for the 3rd place in terms of the aircraft manufacturing market. It was created in 1969, in São José de Campos, Brazil, and its main focus is on commercial, defense and executive aviation, mainly on some particular market sections with high growth potential. Embraer employees around 18,000 people, being roughly 87% people from Brazil. This company is nowadays spread all over the world, with factories, offices, and centers of distribution in the Americas, Africa, Asia, and Europe. Some of the airlines that use Embraer aircraft models in their fleet are, for example: Air Canada, Alitalia, Finnair, Kenya Airways, KLM Royal Dutch Airlines, Saudi Arabian Airlines, Lufthansa, Virgin Australia, and US Airways (Embraer, 2017a).

Embraer manufactures aircraft for three different markets: commercial aviation, defense systems and executive aviation. Regarding the commercial aviation, Embraer offers 2 aircraft families: E-JETS (4 passenger aircraft models), and ERJ 145 Family (4 passenger aircraft models). For the next few years, Embraer will launch a new family of aircraft, E-JETS E2, with 3 new aircraft models (E175-E2, E190-E2 and E195-E2). In Table 3.4, some of the key aircraft characteristics of Embraer models are presented.

Table 3.4 – Embraer aircraft characteristics (sources: Embraer, 2005, 2007, 2008, 2015a, 2015b, 2015c, 2015d, 2017b)

Aircraft Type	Seats		Range [km]	Wing Span [m]	Overall Length [m]	Height [m]
	Typical	Max				
E170	66	78	3,982	26.00	29.90	9.85
E175	76	88	4,074	26.00	31.68	9.86
E190	96	114	4,537	28.72	36.24	10.57
E195	100	124	4,260	28.72	38.67	10.57
ERJ135	30	37	3,243	20.04	26.33	6.76
ERJ140	44	-	3,058	20.04	28.45	6.76
ERJ145	50	-	2,873	20.04	29.87	6.75
ERJ145XR	50	-	3,706	21.00	29.87	6.75

3.1.2 Evolution of Aviation and Aircraft Models

Nowadays, aviation companies like Airbus and Boeing are well known and internationally established within the aviation market, offering an extensive variety of aircraft models. Therefore, airlines, cargo or mail companies, and other private corporate and business groups are able to benefit from a large selection of aircraft models when planning their fleets.

It is possible to say that the history of modern aviation and aircraft models' evolution comes from approximately 100 years ago. In Table 3.5, a summary timeline of the historical landmarks of air transportation evolution and aircraft developments, progresses and improvements is presented.

Table 3.5 – Aviation and aircraft evolution and historical landmarks (source: Greatest Engineering Achievements, 2017)

1901	First successful flying model propelled by an internal combustion engine
1903	First sustained flight with a powered, controlled airplane
1910	First take off from a ship
1914	Automatic gyrostabilizer leads to first automatic pilot
1914-1918	Dramatic improvements in structures and control and propulsion systems
1915	National Advisory Committee for Aeronautics
1917	The Junkers J4, an all-metal airplane, introduced
1918	Airmail service inaugurated
1919	U.S. Navy aviators make the first airplane crossing of the North Atlantic
1919	Passenger service across the English Channel introduced
1925-1926	Introduction of lightweight, air-cooled radial engines
1927	First nonstop solo flight across the Atlantic
1928	First electromechanical flight simulator
1933	Douglas introduces the 12-passenger twin-engine DC-1
1933	First modern commercial airliner
1935	First practical radar
1935	First transpacific mail service
1937	Jet engines designed
1939	First practical single rotor helicopters
1939-1945	World War II spurs innovation
1947	Sound barrier broken
1949	First jet-powered commercial aircraft
1950	B-52 bomber
1952	Discovery of the area rule of aircraft design
1963	First small jet aircraft to enter mass production
1969	Boeing 747
1976	Concorde SST introduced into commercial airline service
1986	Voyager circumnavigates the globe (26,000 miles) nonstop in 9 days
1990	B-2 bomber developed
1995	First aircraft produced through computer-aided design and engineering
1996-1998	Joint research program to develop second-generation supersonic airliner

From the previous table, it is worth noting the improvements in propulsion systems that occurred between 1914 and 1918. These developments took place due to the World War I, since there was the need for aircraft with higher speed and altitude, as well as better aircraft flying and driving flexibility. These demands were the key drivers of the achieved progresses in aerodynamics, structures and control and propulsion systems design. Furthermore, in 1933, the first modern commercial aircraft was launched, by Boeing. It was a Boeing 247, a twin-engine for 10 passengers. Later on, during World War II (1939-1945), once again a war was an influence for progress in aircraft technology. The aircraft radar-detector was developed by the British, and the Germans introduced new radio-wave navigation techniques. From both sides, the airborne radar was developed, which was a useful tool for attacking aircraft at night. In 1949, the first jet-powered commercial aircraft was introduced. Two decades later, the Boeing 747 is produced, being the first wide-body turbofan-powered commercial aircraft of the market. In 1995, it is produced the first aircraft through computer-aided design and engineering, by Boeing. The company introduced the Boeing 777, the biggest two-engine jet aircraft flying (Greatest Engineering Achievements, 2017).

The timeline presented above includes both events concerning the air transportation and aviation evolution in general, and also historical landmarks related to aircraft models' progresses and improvements. The current review will now focus on the aircraft's evolution in terms of its technological features (such as size and design) and environmental and efficiency aspects (such as CO_2 emissions and fuel efficiency).

Air traffic volumes and air transportation demand have been increasing for the last several years. Furthermore, the leading aircraft manufacturers also predict that the demand for air transportation services will continue to grow in the next 10 to 15 years. Their predictions also foresee that the commercial passenger aircraft fleet will double from today's size (Airbus, 2017c; Boeing, 2016). It is expected that this growth would be associated to an increasing in vehicles' overall capacities, that is, higher demand would be directly correlated to the augmentation in size of the aircraft. In the work of Givoni and Rietveld (2009), the authors defend that the average aircraft size will depend on the balance between two points: the increase of the demand in already existing routes (possible use of larger aircraft), and the opening of new routes (possible use of new smaller aircraft). They investigated the choice of aircraft size in traditional markets.

The historical evolution of different aircraft models was analyzed by Kilpi (2008). Figure 3.1 displays the increase of the aircraft types available between 1960 and 2004. Due to the airline industry growth, the number of aircraft models highly expanded. In the 1960s, all the aircraft models in the market were narrow-bodies and only a small number of manufacturers existed. A decade later, both the wide-body aircraft and jets with less than 100 seats (regional jets) were introduced. In the 1980s, aircraft families started to emerge and a new generation of aircraft started to be produced (such as Boeing 757, 767, 737 Classic, Airbus A320 Series). The 1990s were the decade when a new group of wide-bodies started to appear, which contributed for the dominance of the twin-engine aircraft in the long-haul traffic. From the mid-1990s on, new types of aircraft have been produced and launched mainly in regional jets.

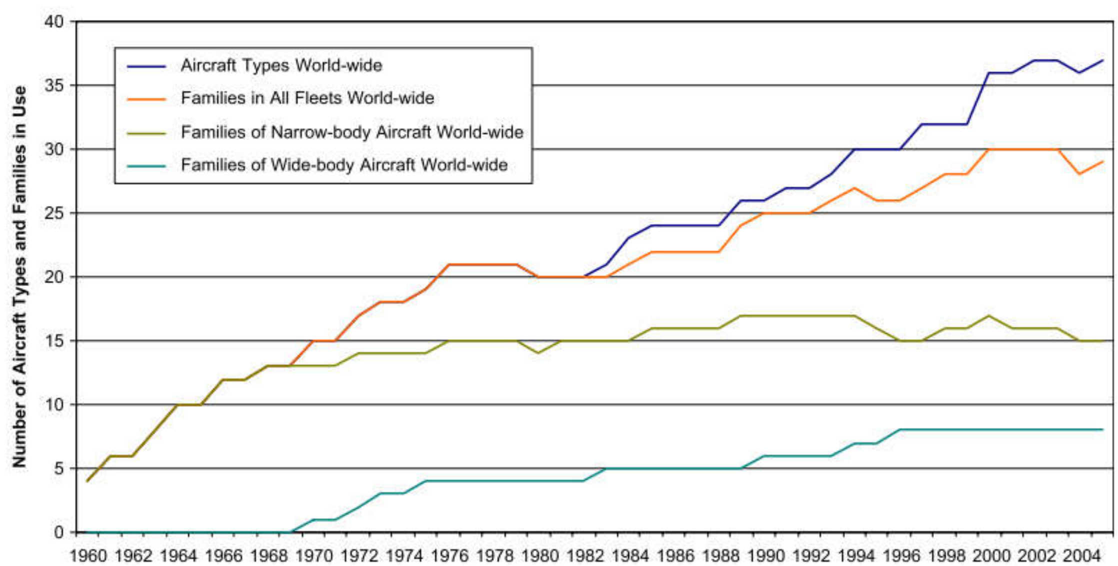

Figure 3.1 – Number of aircraft types and families in use (source: Kilpi, 2008)

There is a fairly recent paper (Bejan et al., 2014) in which the evolution of aircraft is also addressed, from a physics point of view. It is an interesting work in which the authors advocate that the evolution of airplanes can be related to the evolution of birds and other animals. For instance, similar to what happens with animals, the engine mass of an aircraft is proportional to its body size (for the animals, the vital organs like heart, lungs and muscle in general, represent a % proportional to the total body size). Therefore, as stated in Bejan et al.

(2014) the aircraft design, whether it is a large or a small aircraft, will show proportionality between wing span and fuselage length, and between fuel load and body size.

In Figure 3.2, a representation of the different aircraft models in terms of size, and the years when they were put in service, is displayed. One can observe that the size of the aircraft models has been increasing year over year. Nevertheless, smaller and lighter new aircraft models are still being produced in the present. Note that in the decade of 2000 a diverse range of new aircraft models were created, from lighter to heavier. However, throughout the years, always new and bigger models have been released.

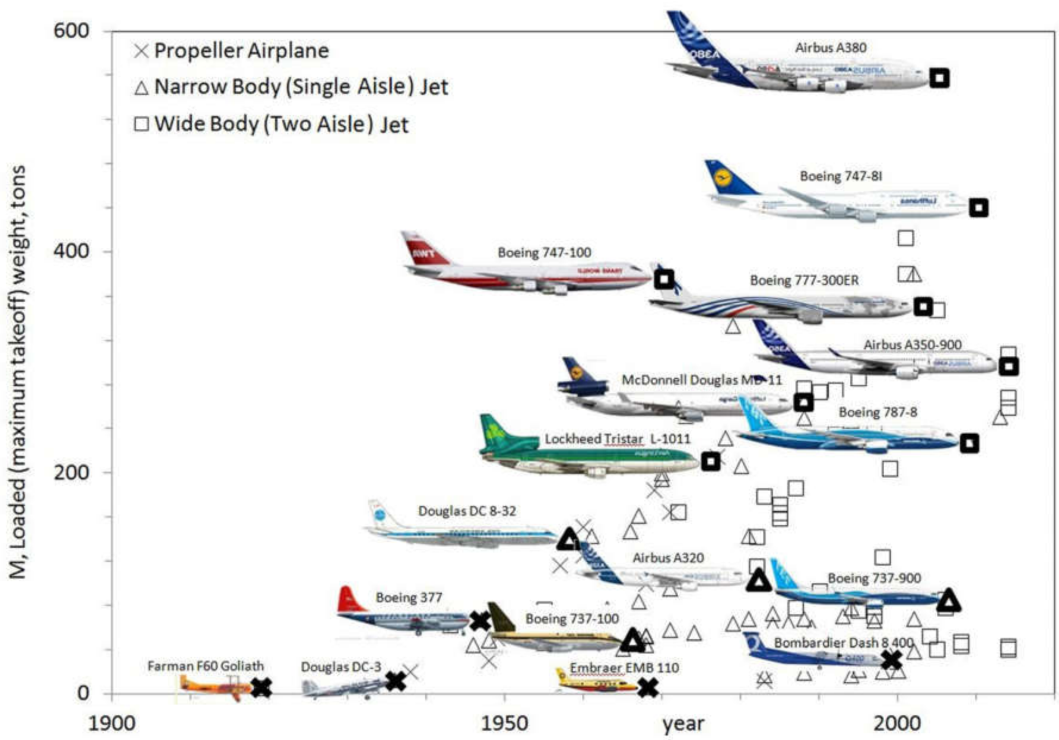

Figure 3.2 – The evolution of the major airplane models during the 100-yr history of aviation (source: Bejan et al., 2014)

According to Bejan et al. (2014), the previous figure represents the evolution and changes in aircraft design, which will necessarily and consequently influence the movement of people around the world. This growing movement gets faster, more efficient, and will be able to reach farther in no time.

Bejan et al. (2014) also demonstrated that, during the evolution of aircraft, the aircraft heat engine sizes have increased nearly proportionally to the aircraft sizes (see Figure 3.3). This is, for small aircraft, the major components of the aircraft (such as pipes, heat exchangers, pumps, compressors, and turbines) will also be small, while for large aircraft all these mechanisms will be larger. The author proved that this relation between the mass of the engines and the mass of the whole aircraft was statistically significant.

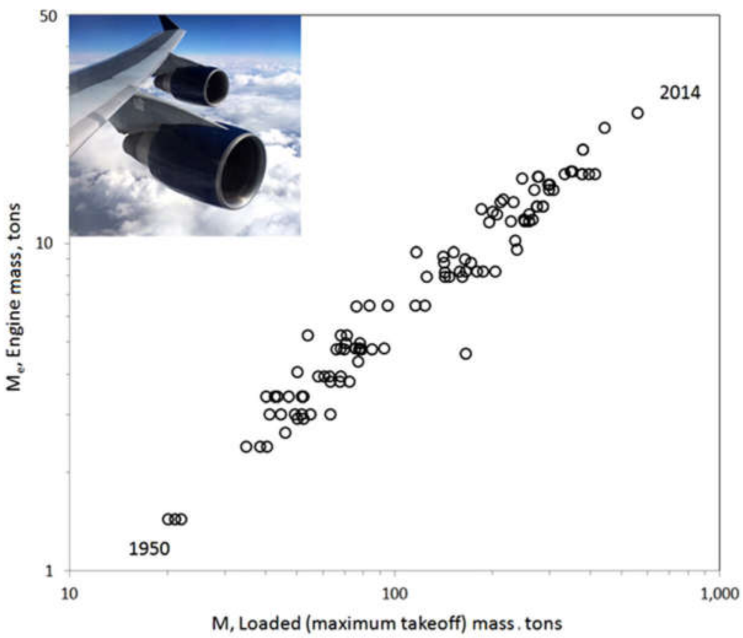

Figure 3.3 – The evolution of the engine size in comparison to the evolution of the aircraft size (source: Bejan et al., 2014)

Alongside with this proportionality on size, Bejan et al. (2014) also verified the proportional relation between the size of the engine, the size of the fuel used, and the mass of the aircraft (see Figure 3.3 and Figure 3.4). The author defended that larger aircraft are more efficient, because of two different aspects: they operate with less friction, due to more spacious openings for fluid flows, and with less heat transfer irreversibility, since the heat transfer is made through larger surfaces.

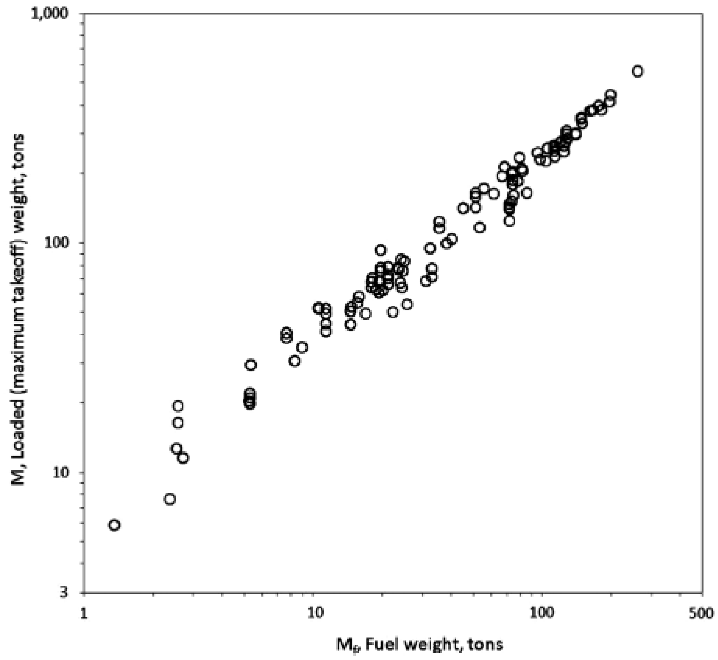

Figure 3.4 – The proportionality between fuel mass and aircraft mass (source: Bejan et al., 2014)

In addition to size and fuel mass, this author also analyzed the relation between the size of the aircraft and the distance they can travel (range). In a similar way to the information presented previously, Bejan et al. (2014) proves that larger aircraft will travel farther (see Figure 3.5).

In terms of efficiency, Bejan et al. (2014) defends that commercial air travel is becoming more efficient and less costly, which is shown through the evolution of aircraft. By analyzing the unit cost (expressed as liters of fuel spent per seat and 100 km flown), this author observed the decreasing tendency of these values for the past 50 years, representing a decrease of around 1.2% fuel burnt per seat, per year.

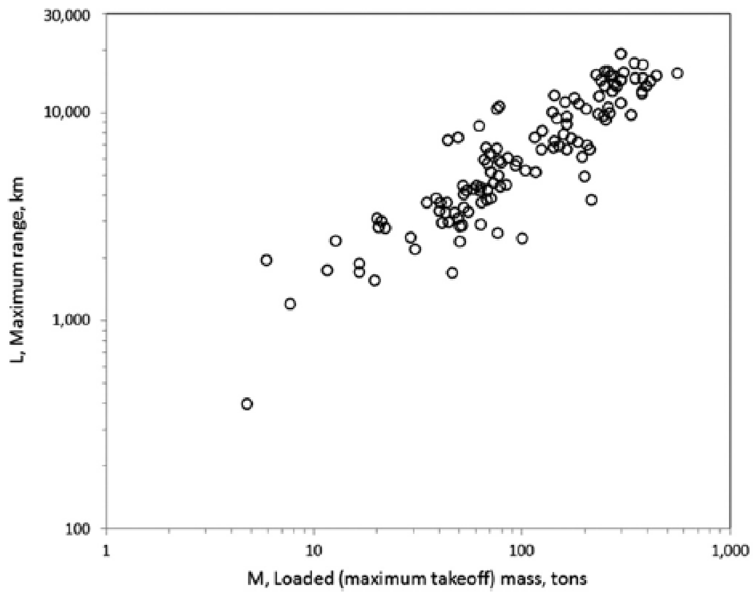

Figure 3.5 – The effect of the size of the aircraft and its range (source: Bejan et al., 2014)

This analysis was based on the work of Peeters et al. (2005), who evaluated the evolution of fuel efficiency of commercial aircraft since 1930. This author compared several large aircraft with piston engines with both old and new jet aircraft (aircraft with jet engine)[4], in terms of aircraft fuel efficiency, and concluded that "*the last piston-powered aircraft were as fuel-efficient as the current average jet*" (Peeters et al., 2005, pp. 3). In comparison to the first jet-powered aircraft, this author's analysis indicated that the last piston-powered aircraft were at least twice as fuel-efficient. In conclusion, and considering what was mentioned previously, it is possible to state that the evolution in the direction of larger aircraft models goes side by side with greater aviation efficiency. This means that larger aircraft are expected to perform better in terms of environmental costs (per passenger km), that is the larger the aircraft, the lower the costs.

[4] According to the dictionary (Merriam-Webster, 2017), a jet engine can be defined as "*an engine that produces motion as a result of the rearward discharge of a jet of fluid*", in more specific words "*an airplane engine that uses atmospheric oxygen to burn fuel and produces a rearward discharge of heated air and exhaust gases*". On the other hand, a piston engine is "*an engine utilizing pistons working in cylinder and usually involving reciprocating motion*".

Furthermore, and still related to aircraft performance and efficiency, Lee et al. (2001) developed an investigation on jet aircraft fuel consumption since 1960, and provided some predictions on future trends. This author analyzed the historical influence of aircraft performance on cost, with the objective of investigating the potential evolution of future efficiency improvements and reduction of emissions. He used analytical and statistical models (applied to historical data from US airlines) to correlate the quantification of technological and operational influence on aircraft energy, and the direct operating cost and aircraft pricing. Some of the most relevant conclusions of Lee et al. (2001) were: 1) 69% of overall efficiency improvements in aircraft, between 1960 and 2000, were due to progresses in engine fuel per unit thrust; 2) improvements related to aerodynamic features represent 27%; 3) the remaining 5% are related to other factors, such as scale effects of larger aircraft; 4) improvements on aircraft structural efficiency (e.g. weight reduction) did not contribute to improve energy efficiency; and 5) the estimation of the fleet-average annual improvement, per available seat-kilometer, was 2.4% (between 1971-1998).

More recently, Kharina and Rutherford (2015) also developed some work on aircraft fuel efficiency. In August 2015, these authors, from the International Council on Clean Transportation, published a white paper on “Fuel efficiency trends for new commercial jet aircraft: 1960 to 2014”. In Figure 3.6, it is possible to observe the historical changes in fuel efficiency for commercial jet aircraft from 1960 to 2014. The ICAO (International Civil Aviation Organization) metric value refers to the CO_2 standard metric value of fuel efficiency trends under this organization. This metric value was developed within ICAO’s Committee on Aviation Environmental Protection, as part of the effort to establish a CO_2 emission standard for new aircraft.

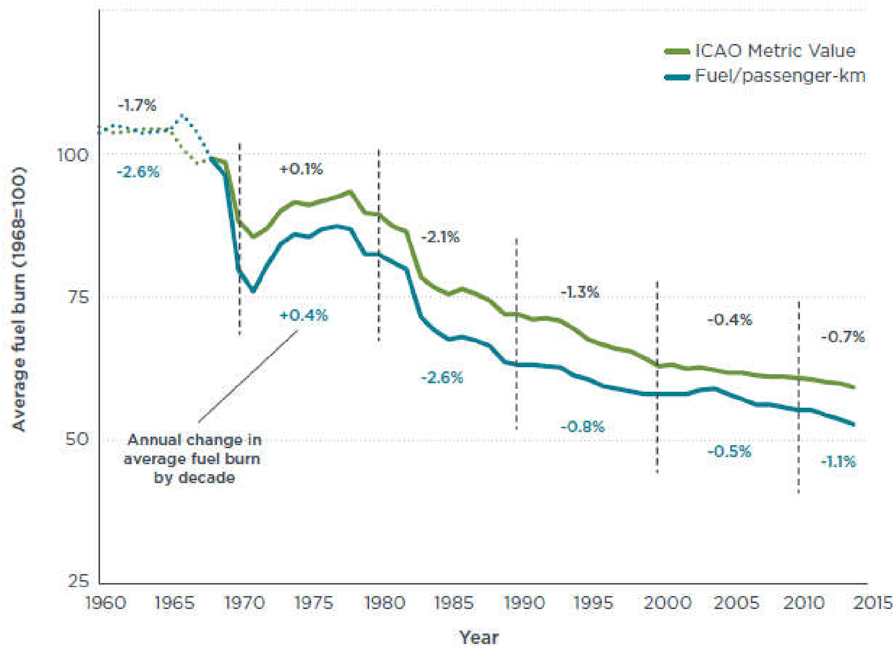

Figure 3.6 – Average fuel burn for new commercial jet aircraft (1960-2014)
(source: Kharina and Rutherford, 2015)

Kharina and Rutherford (2015) presented this study, proving that the fuel burn of new aircraft fell around 45%, on average, from 1968 to 2014. In terms of annual rate, this represents an annual reduction rate of 1.3%. However, as it is possible to assess from the previous figure, this annual reduction rate suffered significant variations throughout the decades. For instance, around the 1980s, it is possible to note a considerable improvement in fuel efficiency (approximately 2.6% annually), which was caused by the adoption of new technologies and more efficient aircraft principles. On the other hand, during the 1970s, very little progress in terms of fuel efficiency was observed.

3.2 Composition and Evolution of Airlines' Fleets

The characterization of an airline is closely related to its fleet size and mix, as well as to the evolution of the fleet throughout the years. From a more general point of view, Kilpi (2008) presented an analysis on the history of all jet aircraft operated by commercial passenger or cargo airlines worldwide in the period between 1952 and 2005. The author focused on uniformity and scale, and the analysis involved the fleet of the top 20 airlines in the world. He examined developments in airline fleet composition using a Fleet Standardization Index (from Pan & Santo, 2004) with the aim of analyzing the evolution of airlines fleet composition globally.

Figure 3.7 shows the global aircraft fleet throughout the years, by aircraft category. It is clear that the production of aircraft has grown quite constantly, even though some international crises occasionally occurred. Between 1971 and 2005, the world wide-jet aircraft fleet has grown on an average of 4.7% per year.

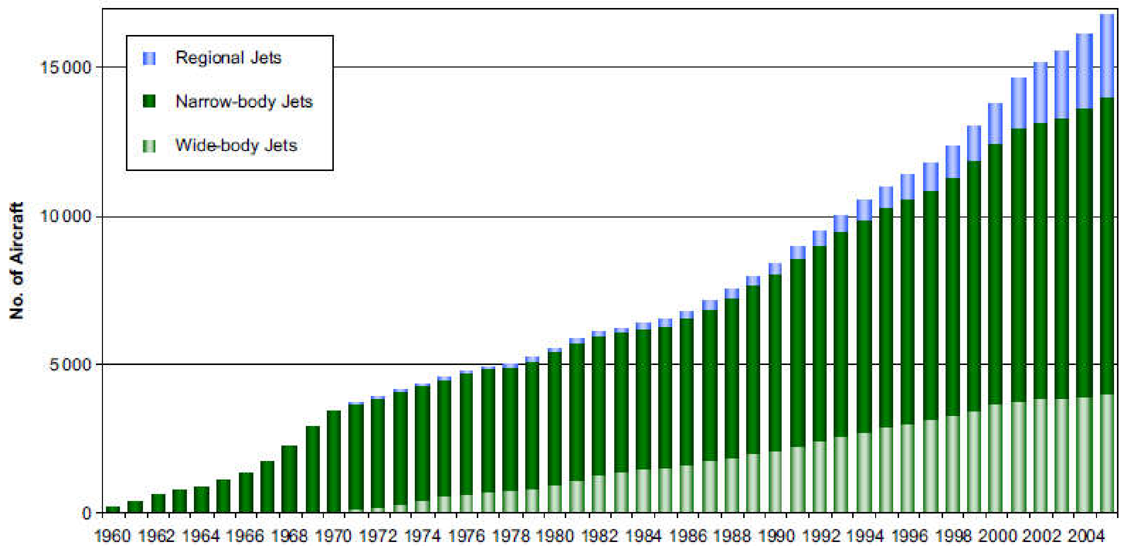

Figure 3.7 – Global fleet by aircraft category
(source: Kilpi, 2008)

Kilpi (2008) also compared the average fleet for narrow-bodies aircraft, from 1960 to 2005, by geographic region (Figure 3.8). The region which experienced the largest average fleet size, since the beginning, was North America. An even bigger difference would be noticeable if the analysis was in terms of total fleet of the airlines, since North American airlines have usually kept their aircraft much longer than airlines in Europe and Asia.

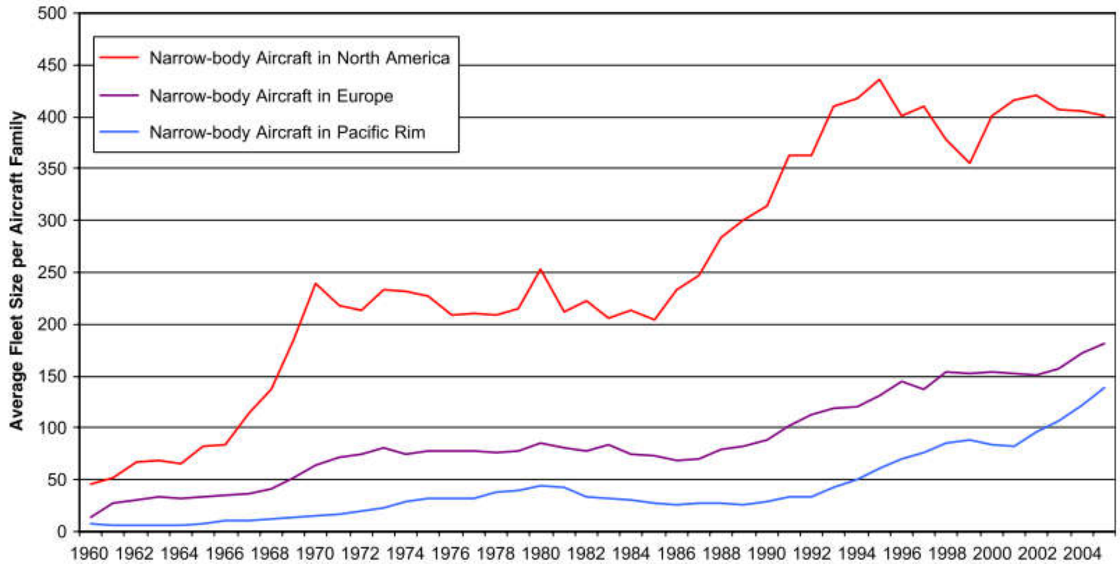

Figure 3.8 – Average fleet size per narrow-body aircraft family by main region (source: Kilpi, 2008)

The sudden increase in average fleet size in North American airlines, around 1966, was due to the introduction of the first generation of jets. Approximately two decades later, the second generation of jets had already been launched into the aviation market, and the North American airlines gradually introduced these new aircraft models into their fleets, in order to give response to the emergent demand after the deregulation period. The average size of the fleets continued to grow during the 1990s, even with the retirement of older aircraft models. It is possible to see the same trend in the other regions (Europe and Pacific Rim), although on a smaller scale.

As mentioned previously, the work of Kilpi (2008) focused on uniformity and scale, and the author performed an analysis concerning the fleet of the top 20 airlines in the world. Figure 3.9 shows the trend of the average fleet scales[5] of the top 20 airlines, during the period between 1976 and 2005. From the figure, one can observe that the general trend has been ascending

[5] Fleet scale is a measure developed by Kilpi (2008), based on the work of Pan & Santo (2004) – Fleet Standardization Index – that combines information on fleet size and structure. It is calculated using three levels of detail for fuselage and engines.

almost during the whole time. According to Kilpi (2008), in 1976, the average fleet size of a top 20 airline was 130 aircraft while in 2005 it was 300 aircraft.

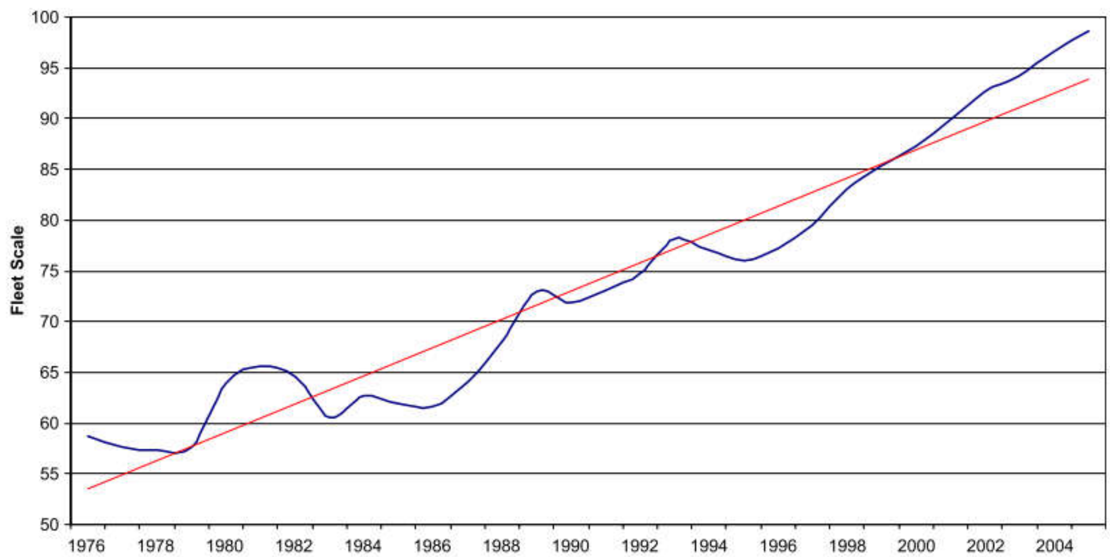

Figure 3.9 – Fleet scale: average of the world top 20 operators (1976-2005)
(source: Kilpi, 2008)

One of the most relevant conclusions of this author was that uniformity in airline fleets has been gradually decreasing, while in terms of size airline fleets have been progressively increasing.

3.2.1 World's Largest Airlines

The definition of world's largest airline may be regarded from several different perspectives. For instance, American Airlines Group is considered the world's largest airline when it comes to fleet size, revenue, profit, passengers carried and revenue passenger mile. On the other hand, if the classification is per assets value and market capitalization, Delta Air Lines comes in first place. Lufthansa Group is the world's largest airline by number of employees, while Ryanair wins by number of international passengers carried. Turkish Airlines is the airline that serves a higher number of countries, and on the freight air transportation side, FedEx Express is the airline responsible for the largest freight ton-kilometers scheduled.

As stated previously, air traffic volumes and air transportation demand will continue to grow in the next 10 to 15 years (Airbus, 2017c; Boeing, 2016). In Figure 3.10, the airline traffic by region, in 2016, is displayed. Asia-Pacific is the leading region, representing 31.2% of the world's total airline traffic, closely followed by Europe (27.4%) and North America (25.9%). Africa represents only 1.4% of the world's airline traffic, while Latin America and the Middle East together correspond to around 14%.

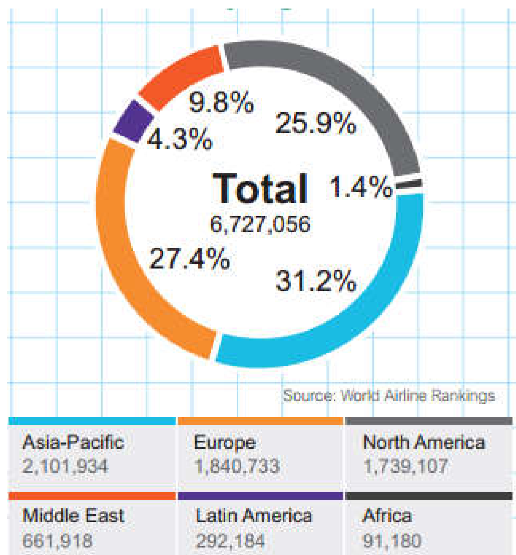

Figure 3.10 – Airline traffic by region
(source: Flight Global, 2017)

In order to analyze and sort the world's largest airlines, one characteristic that it might be taken into account is the total number of passengers carried by the airline. A rank of the top 10 world's largest airlines, in terms of boarding passengers (in millions) is presented in Table 3.6. The data refers to 2016.

In 2016, the number of total passengers carried across the leading 150 airlines increased nearly 6% (approximately 3.4 billion passengers). This increase was caused mainly by a 10% jump in numbers among the low-cost-carrier sector (Flight Global, 2017).

Table 3.6 – World's largest airlines, by number of passengers carried (in millions) (source: Flight Global, 2017)

Rank	Airline	Country	Passengers (2016)
1	American Airlines Group	USA	198.7
2	Delta Air Lines	USA	183.7
3	Southwest Airlines	USA	151.8
4	United Airlines	USA	143.2
5	Ryanair	Ireland	119.8
6	China Southern Airlines	China	84.9
7	China Eastern Airlines	China	80.9
8	EasyJet	United Kingdom	73.1
9	Turkish Airlines	Turkey	62.8
10	Lufthansa	Germany	62.4

Another crucial feature when analyzing the ranking of world's largest airlines is the revenue of the company. In Table 3.7 the ranking of the top 10 airlines, in terms of revenue, in 2016, is presented.

Table 3.7 – Top 10 airlines, by revenue (in billion \$) (source: Flight Global, 2017)

Rank	Airline	Country	Revenue (2016)
1	American Airlines Group	USA	40.18
2	Delta Air Lines	USA	39.64
3	United Continental	USA	36.56
4	Lufthansa	Germany	34.91
5	Air France - KLM	France	27.40
6	FedEx	USA	27.36
7	Emirates Group	United Arab Emirates	25.78
8	IAG	United Kingdom	24.88
9	Southwest Airlines	USA	20.42
10	Air China	China	17.30

Although an air travel development was verified in 2016, the combined revenues of the 150 leading airlines in the world decreased around \$4 billion. This was essentially due to lower profits and continued exchange-rate volatility, which led to a limited turnover growth (Flight Global, 2017).

More relevant to this work is the rank of airlines in the world by fleet size, which refers to the number of aircraft operated by the airline. In order to meet high and increasing passengers' demand, several airlines expanded their fleet size. In Table 3.8, a list of the top 10 largest airlines in the world, in terms of fleet size, is presented. The data refers to June 2016.

Table 3.8 – World's largest airlines, by fleet size (source: Air Spotting, 2016)

Rank	Airline	Country	Fleet (June 2016)
1	American Airlines	USA	1556
2	Delta Air Lines	USA	1330
3	United Airlines	USA	1229
4	Southwest Airlines	USA	720
5	FedEx Express	USA	688
6	China Southern Airlines	China	515
7	China Eastern Airlines	China	429
8	Air Canada	Canada	404
9	Air China	China	384
10	Ryanair	Ireland	349

The top largest airlines, in terms of fleet size, are from the United States and China. The largest European airline is Ryanair. In this top 10 it is also possible to find a Canadian Airline, Air Canada, which appears in 8th place.

American Airlines is the largest airline in the world, in terms of fleet size, with a total of 1556 aircraft. It is also considered the world's major airline by revenue and destinations served. Together with its regional partners, this American airline operates about 6700 flights per day to over 350 destinations. In terms of fleet, American Airlines works with a fleet of 1556 aircraft, a mix between Airbus, Boeing, McDonnell Douglas, and Embraer (American Airlines, 2017).

Delta Air Lines operates over 5400 international and domestic flights daily, alongside with its subsidiaries. This airlines' network includes 319 destinations to 54 different countries. Its fleet is composed by 1330 aircraft, among Airbus, Boeing and McDonnell Douglas aircraft manufacturers. Delta Air Lines uses some of the biggest Boeings in the world (such as, Boeings 717, 757, 767), and its fleet mix includes both more recent and older aircraft as a strategy for using less expensive aircraft (Delta Airlines, 2017).

United Airlines comes in third place of the world's largest airlines, with a fleet of 1229 aircraft in total. It is also one of the biggest airlines in the world when it comes to revenues. Its international and domestic network comprises 235 destinations spread among 60 different countries in Asia, America and Europe. United Airlines fleet is constituted by both Airbus and Boeing aircraft (United Airlines, 2017).

Also from North America, Southwest Airlines is the largest low-cost airline in the world. It operates almost 4000 flights per week during the peak season. This airline network is spread over 101 destinations in the United States plus another 8 countries. The fleet of this airline is composed by 720 aircraft, and it is an exclusively Boeing fleet, being the largest Boeing 373 operator in the world (Southwest Airlines, 2017).

3.2.2 Airlines' Efficiency, Productivity and Costs

As discussed on the previous section, some of the characteristics that have been largely evolving during the past years, when it comes to aircraft models, are related to efficiency and productivity. Connected to these two features is inevitably the cost. In addition to analyzing these three items in terms of aircraft models, it is also important to understand how changes and improvements in aircraft characteristics will impact the overall efficiency, productivity and costs of an airline.

Windle (1991) was one of the first authors to perform an analysis on airlines' cost and productivity. This author measured the productivity and unit cost of a group of airlines, both from the US and not (he used annual data from 1989, for 14 US and 27 non-US airlines), and compared the results. He concluded that US airlines have a greater level of productivity (12% more, in 1983), in comparison to a sample of non-US airlines, even though in the US the labor cost is higher. According to Windle (1991), this higher productivity level is the result of higher density of air traffic. If the analysis is decomposed, the level of productivity of the US airlines is 19% bigger than a sample of European airlines, 1% over a sample of Canadian operators, and 48% larger than a sample of other non-US airlines. Regarding the assessment in contrast to a sample of East Asian airlines, the latter present a productivity advantage of 15% in relation to US airlines' sample. This productivity disadvantage of non-Us airlines has been partially overcome through lower labor prices, which contributed to the approximate equality of the unit costs between US and non-US airlines (e.g. US operators present around 7% higher unit cost than European airlines).

A couple of years later, Good et al. (1993) compared the growth of technical efficiency and productivity of four of the largest European airlines and eight of the largest American companies, during the period between 1976 and 1986. The authors predicted possible efficiency improvements for the European aviation liberalization, by comparing efficiency differences between the two airline's groups. Figure 3.11 shows the technical efficiency scores for the European airlines and the average for the US carriers, as well as the projection values until 1996.

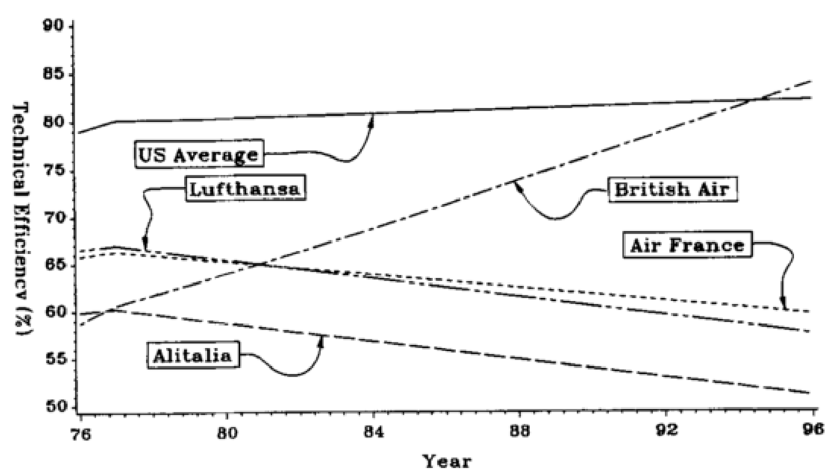

Figure 3.11 – Estimated and projected levels of technical efficiency (1976-1996) (source: Good et al., 1993)

From the previous figure, one can note that the airlines Air France, Lufthansa and Alitalia show a decrease in terms of technical efficiency levels, which, according to Good et al. (1993), can be explained by the increase of international service offered by US airlines. It is also worth noting that British Airways largely increased its technical efficiency, presenting values over Air France, Lufthansa and Alitalia.

In line with the work presented previously, Oum and Yu (1995, 1998a) developed some work on productivity and cost competitiveness of the world's major airlines, which ended up being published as a book (Oum and Yu, 1998b). Chapter 6 of the book is fully dedicated to the examination of airlines' overall productive efficiency, using diverse methods, such as Total Factor Productivity (TFP), residual TFP, and stochastic frontier method. In this section, only the Total Factor Productivity and residual TFP methods are going to be addressed For more information on the stochastic frontier methods, see Oum and Yu (1998b).

The TFP is a measure of productivity of all inputs. It is able to recognize that a variety of inputs will generate several outputs. The gross TFP can be defined as "*the amount of aggregate output produced by a unit of aggregate input*" (Oum and Yu, 1998b, pp. 93) and expresses the airline productivity (the term 'gross' is used since the index may not indicate the real productive efficiency). The gross TFP can be influenced by several factors, such as stage length, composition of outputs, and state of economy, all of these being largely outside of administrative control. Therefore, in order to be able to make an accurate analysis and draw relevant conclusions on airline productive efficiency, there is the need to calculate the residual TFP index.

The residual TFP index can be computed in two phases: first, the gross TFP index is regressed against a set of explanatory variables, and second, the residual TFP is computed by removing the effects of variations in the variables beyond administrative control from the gross TFP measure. Then, this residual TFP can be used to make comparison of productive efficiency between different airlines, and over time within a certain a carrier (Oum and Yu, 1998b). The residual TFP index, for European, Asian, and American airlines, is displayed in Figure 3.12, Figure 3.13 and Figure 3.14.

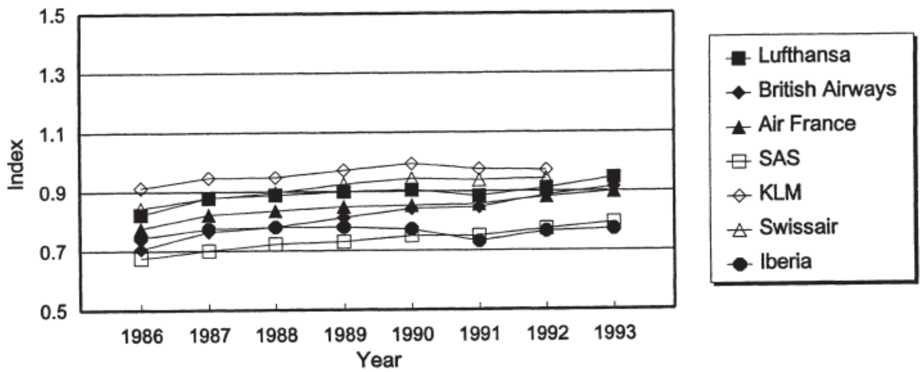

Figure 3.12 – Residual TFP index (European airlines)
(source: Oum and Yu, 1998b)

From Figure 3.12, one can observe that the European airlines have improved productive efficiency and reach much higher growth rates than North American airlines. Particularly worth of mention is British Airways that achieved the largest productivity growth, around 4% per year (Oum and Yu, 1998b).

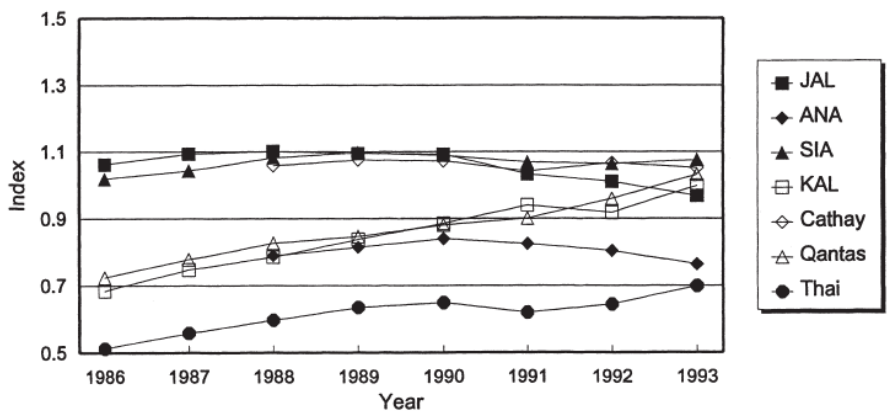

Figure 3.13 – Residual TFP index (Asian airlines)
(source: Oum and Yu, 1998b)

In terms of the Asian airlines (Figure 3.13), it is possible to divide them into groups: Korean Air (KAL), Qantas, and Thai Airways, which showed a significant increase of productive efficiency (5.6%, 5.2% and 4.6% respectively); Japan Airlines (JAL), All Nippon Airways (ANA), and Cathay Pacific, which are airlines that present a slow growth in residual TFP; and Singapore Airlines (SIA), which, although having also experienced an increase in its productive efficiency, it was a rather small one, around 0.8% per year (Oum and Yu, 1998b).

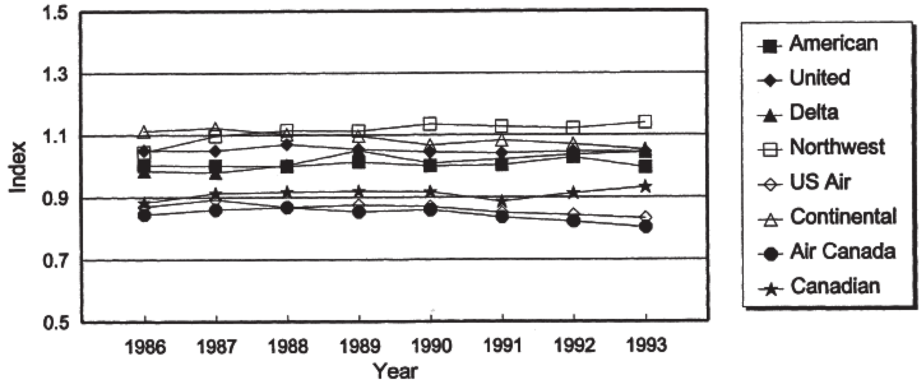

Figure 3.14 – Residual TFP index (North American airlines)
(source: Oum and Yu, 1998b)

Regarding the North American airlines (Figure 3.14), one can note that Continental Airlines and US Airways suffered a minor decrease in productive efficiency. On the other hand, Northwest Airlines, Delta Air Lines and Air Canada slightly increased their values of productivity (0.3-1.9%, 0.8-1.3%, and 1%, respectively). Other North American airlines did not experience any relevant variations in the productive efficiency. From the three previous figures, it is also noticeable that the efficiency levels of the top airlines in each region were very similar (for instance, American, United, and Delta in the US; and Singapore, Korean Air, Cathay, and Qantas) in Asia (Oum and Yu, 1998b).

In summary, the main conclusions of Oum and Yu (1998b) were that US airlines are usually more efficient that Asian carriers (4% more, in 1993), and these are more efficient than European airlines (8% more, in 1993). In their study period, European and Asian airlines experienced higher growth in productivity than its North American counterparts, which caused a significant decreased in the productivity gap between North American and the other airlines. British airways, Lufthansa and KLM changed from a gap of 20% to 9%, in comparison to North American airlines. And SIA, Cathay and KAL started with a productivity gap of 16% (in the beginning of the study period) and ended up (in 1993) with similar productivity levels to the US top airlines. Oum and Yu (1998b) concluded that throughout the time, the airlines productive efficiency, if competing in similar types of market, tend to converge.

In relation to airline's costs, in particular airlines' cost competitiveness, Oum and Yu (1998a) investigated the cost competitiveness subject, by making a comparison on the performance of 22 major airlines in the world, for the period of 1986-1993. The authors decomposed the unit cost differentials into potential sources, like input prices, attributes related to network and outputs, and efficiency. Afterwards, these results were used to build a cost competitiveness indicator. Figure 3.15, Figure 3.16 and Figure 3.17 show the variations over time of the cost competitiveness factor for the airlines in study (American, European, and Asian airlines). The comparison is made taking into consideration the values for the American Airlines, in the same year. Thus, the changes also reflect, to some extent, the fluctuations in American Airlines' unit costs.

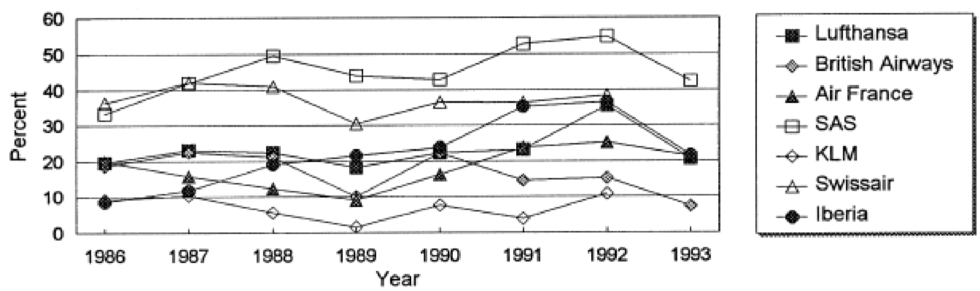

Figure 3.15 – Cost competitiveness (European airlines)
(source: Oum and Yu, 1998a)

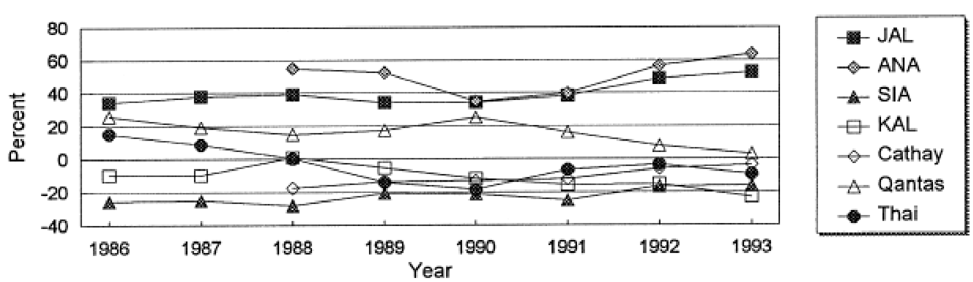

Figure 3.16 – Cost competitiveness (Asian airlines)
(source: Oum and Yu, 1998a)

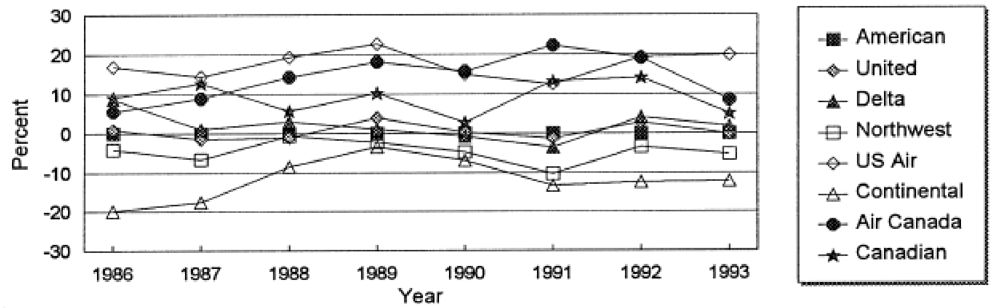

Figure 3.17 – Cost competitiveness (North American airlines)
(source: Oum and Yu, 1998a)

From the previous figures, one can note that the relative rankings among the airlines in the study remained quite stable over time, even though it is possible to observe some significant variations of the relative cost competitiveness for the airlines individually. The most obvious changes occur with British Airways and Qantas. In both cases, the airlines improved their relative cost competitiveness positions (in relation to American Airlines), essentially due to progresses in efficiency. By contrast, in the case of Air France, one can see that its performance had declined since 1993, as a consequence of higher input price and inferior efficiency. In Figure 3.15, it is noticeable that the cost competitiveness positions of Swiss Air and KLM did not present significant changes. This could be explained by the neutral result caused by the contrary effects of improvement of their level of efficiency and the increase of their input prices Oum and Yu (1998a). In a more general analysis, it is possible to say that the European airlines are less cost competitive than the US airlines, mainly because they present higher input prices and lower efficiency. The Asian airlines (with exception of Japan Airlines and All Nippon Airways) are more cost competitive that US airlines. This result is caused by Asian airlines' low input prices.

The main conclusions of Oum and Yu (1998a) work, in relation to 1993, can be enumerated in four points: 1) the Asian airlines (except Japan Airlines and All Nippon Airways) showed in general more cost competitive levels than the major US carriers, mainly because of their considerably lower input prices; 2) the Asian Airlines' exceptions, Japan Airlines and All Nippon Airways, were more than 50% less cost competitive than American Airlines, largely due to their high input prices; 3) the major European airlines were between 7% (British

Airways) and 42% (Scandinavian Airlines Systems) less cost competitive than American Airlines, because of both higher input prices and lower efficiency; 4) in relation to the US airlines, American Airlines, United Airlines, and Delta Air Lines presented analogous cost competitiveness levels, whereas Northwest Airlines and Continental Airlines reached 5% and 12% higher cost competitiveness that American Airlines, respectively.

More recently, Arjomandi and Seufert (2014) used data envelopment analysis (DEA) models to investigate both environmental and technical efficiencies of airlines. The authors chose 48 major airlines in the world, both full-service (35 airlines) and low-cost (13 airlines), from six different regions, and studied their performance over the period of 2007-2010. The organization of the airlines, per region, was as follows: Europe and Russia (13 airlines), North America and Canada (11), Latin America (1), China and North Asia (13), Asia Pacific (6), and Africa and the Middle East (4). This split had the goal to include in the same group the major airlines of the region and a representative sample of low-cost carriers.

From their work, Arjomandi and Seufert (2014) concluded that the most technically efficient airlines were from China and North Asia, and a significant part of the best environmental airlines were from Europe and Russia. The authors also determined that, in general, low-cost airlines are usually more environmentally oriented that the others, even though the number of full-service airlines environmentally responsible is increasing. Another conclusion that arose from their investigation was that the majority of the low-cost carriers were technically operating under increasing returns to scale, in all the period of study (2007-2010). This might indicate that there is room for these airlines to improve their technical efficiency, by increasing their capital and staff. On the other hand, the opposite result was found for the largest airlines, which could imply that these airlines can economize on their inputs, in order to overcome their both technical and environmental inefficiencies.

The International Civil Aviation Organization (ICAO, 2017a) performed a recent comparative analysis in terms of American airlines' costs and productivity (time period of 1993-1999). The results of their findings are presented in Figure 3.18 and Figure 3.19, in terms of unit cost ($ per available seat mile - ASM).

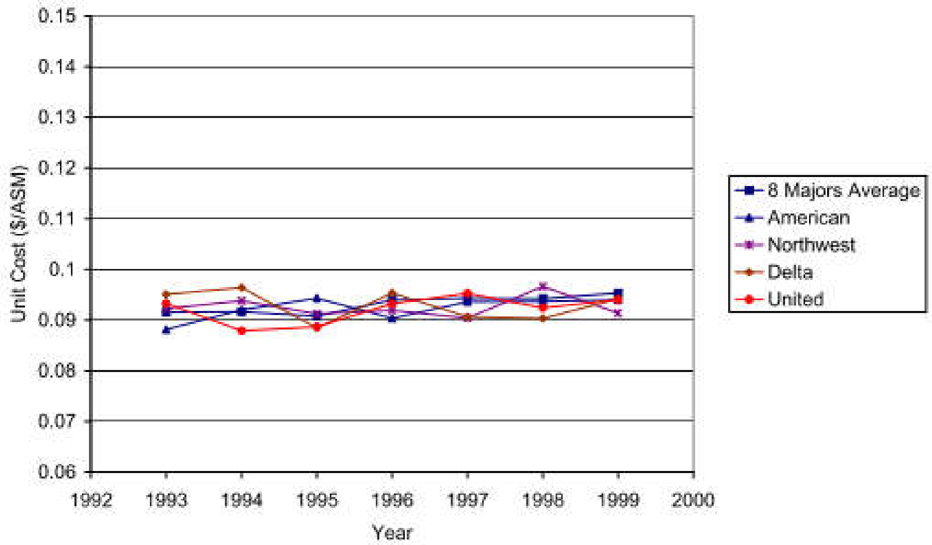

Figure 3.18 – Unit cost (available system operating expense/ASM)
(source: ICAO, 2017)

From the previous figure, it is possible to observe that the average unit cost for eight of the major American airlines increased around 4% during that same period. One can also note that the top 4 airlines in the US (American Airlines, Northwest Airlines, Delta Air Lines, and United Airlines) presented very similar unit costs during the time period of study.

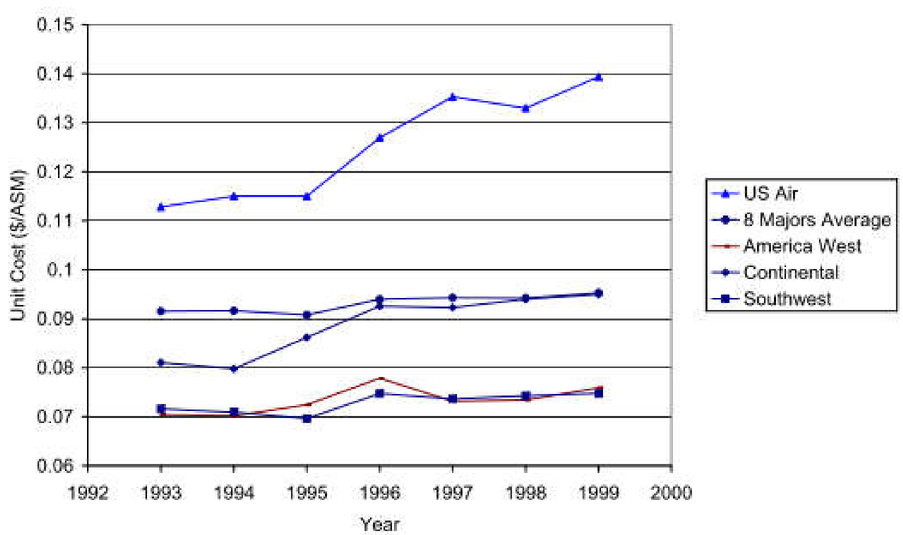

Figure 3.19 – Unit cost (available system operating expense/ASM)
(source: ICAO, 2017)

In Figure 3.19, which displays the same unit cost results, but for different American airlines, it is possible to see the significant increase of unit cost that Continental Airlines and US Airways suffered between 1993 and 1999 (17% and 24%, respectively). In respect to Southwest Airlines and America West Airlines, these were the airlines with lower values for the unit costs, while US Airways was the one with higher results.

In terms of aircraft productivity (which will have a significant impact in the overall airline productivity), from ICAO (2017), three main conclusions were inferred in terms of how to increase aircraft productivity (and consequently decrease the unit costs for the airline): 1) increase flight departures per day (by reducing turnaround times or using off-peak departure times); 2) extend stage lengths (average stage length is positively correlated with increased aircraft utilization); 3) add more seats in same aircraft type (by eliminating the first class seating, for example).

3.2.3 Evolution of Airlines' Fleets

Another interesting aspect when dealing with airline fleet size and mix is the evolution it has suffered throughout the years, for a specific airline. How does the fleet changes throughout the years? And why does it change? What are the main reasons of an airline behind the decision of acquiring, selling or leasing new aircraft for its fleet?

To perform this analysis, some of the major airlines in the world (enumerated in a previous section) were chosen: American Airlines and Delta Air Lines (from the United States), and Ryanair and Lufthansa (from Europe).

American Airlines

American Airlines is the largest airline in the world, in terms of fleet size, revenue, and destinations served. It is now based in the Fort Worth, Texas, and it was founded in 1926. Its parent company is American Airlines Group, which was formed in 2013, as a merger between AMR Corporation (the parent company of American Airlines) and US Airways Group (the parent company of US Airways). The American Airlines Group is responsible for operating around 6700 flights per day to more than 350 different destinations, being 10 of them hubs across the continental US (American Airlines, 2017).

Table 3.9 shows the current fleet of American Airlines and its respective age. This airline has a total of 945 active aircraft, with an average age of 10.2 years. It is a fleet composed by Airbus, Boeing, McDonnell Douglas, and Embraer aircraft, being almost 70% of the fleet constituted by the Airbus A319, the Airbus A321-200, and the Boeing 737-800 (Next Generation). According to the information in Airfleets (2017), the airline has no new aircraft models ordered for the future.

Table 3.9 – Active aircraft in the current fleet of American Airlines (source: Airfleets, 2017)

Aircraft	Number of Active Aircraft in the Fleet	Age of the Fleet (years)
Airbus A319	125	13.5
Airbus A320-200	48	16.5
Airbus A321-200	218	5.2
Airbus A330-200	15	10.0
Airbus A330-300	9	
Boeing 737-800 NextGen	301	8.0
Boeing 737 MAX 8 NextGen	2	
Boeing 757-200	36	18.6
Boeing 767-300	25	19.8
Boeing 777-200	47	12.9
Boeing 777-300	20	
Boeing 787-800	20	1.4
Boeing 787-900	13	
Embraer 190	20	9.8
McDonnell Douglas MD-82	10	21.5
McDonnell Douglas MD-83	36	
TOTAL	**945**	**10.2**

The most recent models in the fleet are the Boeing 787 family (800/900) with an average age of 1.4 years, and the Airbus A321-200 aircraft models, with an average age of 5.2 years.

Some of the oldest aircraft in the fleet belong to the McDonnell Douglas manufacturer, and the Boeing 757-200 and 767-300 are also some of the models that were acquired almost two decades ago, on average.

In Table 3.10, the aircraft retired from American Airlines fleet, in the past, are enumerated, as well as the years of retirement. This information can help understanding the history and evolution of the fleet of American Airlines.

Table 3.10 – Retired aircraft from the fleet of American Airlines (source: Airfleets, 2017)

Aircraft	Number of Retired Aircraft	Date when the Aircraft was Retired
Airbus A300-600	2	2011
Airbus A320-200	5	2016/2017
Airbus A321-200	13	2015
Boeing 717	28	2002/2003
Boeing 737-100	2	1988/1989
Boeing 737-200	32	1988/1989/1990/1991/1992/1994
Boeing 737-300	17	1988/1991/1992
Boeing 737-400	1	2016
Boeing 747-100	24	1974/1975/1976/1978/1981/1983/1984/1985
Boeing 747-200	1	1984
Boeing 747-SP	2	1994
Boeing 757-200	42	2003/2004/2005/2007/2008/2010/2011/2012/ 2013/2014/2015/2016/2017
Boeing 767-200	6	2005/2007/2008/2008
Boeing 767-300	16	2003/2004/2017
Bae 146	14	1988/1989/1992/1993/1994
McDonnell Douglas DC-10	42	1987/1988/1989/1994/1995/1996/1997/ 1999/2000/2001
Fokker 100	65	2003/2004/2005/2006/2007/2008
McDonnell Douglas MD-11	21	1994/1996/1997/1998/2000/2001/2002
McDonnell Douglas MD-82	38	1986/2002/2004/2007/2008/2009/2010/2011/ 2012/2013/2014/2015/2016/2017
McDonnell Douglas MD-83	30	2001/2002/2003/2004/2005/2007/2010/ 2011/2012/2013/2014/2015/2016/2017
McDonnell Douglas MD-87	5	2000/2001/2002/2003
McDonnell Douglas MD-90	5	2005
TOTAL	**411**	**-**

In total, American Airlines removed 411 aircraft models from its fleet, throughout the years (since 1974 until 2017). For instance, the Boeing 747-100 was a model that was totally removed from the fleet between 1974 and 1985, and it is an aircraft type that no longer makes part of the composition of the fleet. Still during the 1980s and early 1990s, models like Boeing 737-100/200/300, Boeing 747-200, Boeing 747-SP, and Bae 146 were completely eliminated from the American Airlines fleet. As it is possible to see from Table 3.9, nowadays, the company only operates with more recent Boeing models, such as Boeing 757, 767, 777, and the newest ones from Boeing 787 family (800/900).

Regarding the Airbus models, some of them currently in the fleet have more than one decade of existence. Nevertheless, almost 20 of Airbus models were already retired from the fleet, in more recent years (2011-2017). Also some Boeing 757-200 and McDonnell Douglas MD-82/83 were only retired from the fleet for the last decade.

Delta Air Lines

Delta Air Lines was founded in 1924 and it is a US airline based in Atlanta, Georgia. Delta operates to more than 300 destinations in 6 continents (in 54 different countries). The average number of flights performed by Delta is around 5400 every day, both international and domestic destinations. Its fleet is constituted by 1330 aircraft, in total, including Airbus, Boeing, and McDonnell Douglas aircraft models (Delta Airlines, 2017).

Table 3.11 presents a summary of the current fleet of Delta Air Lines, as well as the average age of the fleet. Delta's current active fleet is composed by 856 aircraft, in total (194 Airbus models, 490 Boeing, and 172 McDonnell Douglas). Opposite to what happens with American Airlines, more than 50% of Delta's fleet is constituted by Boeing models. In terms of the future, Delta has 1 Airbus A321-200, 1 Airbus A350, 2 Boeing 737-700, and 3 Boeing 737-800, the 5 models from Next Generation c

Table 3.11 – Active aircraft in the current fleet of Delta Air Lines (source: Airfleets, 2017)

Aircraft	Number of Active Aircraft in the Fleet	Age of the Fleet (years)
Airbus A319	57	15.6
Airbus A320-200	64	22.3
Airbus A321-200	28	0.8
Airbus A330-200	11	9.7
Airbus A330-300	31	
Airbus A350	3	0.3
Boeing 717	91	15.7
Boeing 737-700 NextGen	10	8.9
Boeing 737-800 NextGen	74	
Boeing 737-900 NextGen	87	
Boeing 747-400	5	26.3
Boeing 757-200	108	20.0
Boeing 757-300	16	
Boeing 767-300	60	20.3
Boeing 767-400	21	
Boeing 777-200	18	12.6
McDonnell Douglas MD-88	111	24.8
McDonnell Douglas MD-90	61	
TOTAL	**856**	**17.1**

The average age of Delta Air Lines' fleet is 17.1 years (7 more years than the average age of American Airlines' fleet). The newest models in the fleet, with less than 1 year old, on average, are the Airbus A321-200 (28 aircraft in total) and the Airbus A350 (3 aircraft in total). In terms of the oldest aircraft in the fleet, there are several models with more than 20 years old, such as Airbus A320-200, Boeing 747-400, Boeing 757 family (200/300), Boeing 767 family (300/400), and McDonnell Douglas MD 88/90.

In Table 3.12, the list of aircraft that were removed in the past from Delta's fleet is presented. In addition, the years of removal of the aircraft models are also indicated.

Table 3.12 – Retired aircraft from the fleet of Delta Air Lines (source: Airfleets, 2017)

Aircraft	Number of Retired Aircraft	Date when the Aircraft was Retired
Airbus A310-200	8	1992/1995
Airbus A310-300	23	1994/1995/1996/2000
Airbus A321-200	1	2017
Boeing 737-200	65	1987/1988/1990/1993/1995/ 2003/2005/2006/2007/2008/2009
Boeing 737-300	25	1993/1994/2005/2006/2007/2008/2011
Boeing 737-800 NextGen	2	2002
Boeing 747-100	5	1974/1975/1977
Boeing 757-200	51	2003/2004/2005/2006/2009/2011/2012/2015
Boeing 767-200	14	2005/2006/2007
Boeing 767-300	8	2000/2006/2007/2008/2010
McDonnell Douglas DC-10	14	1975/1988/1989
Lockheed L-1011 TriStar	33	1980/1984/1985/1991/1997/1998/2000/2001/ 2002/2003/2004/2005/2006
McDonnell Douglas MD-11	17	1993/1994/2003/2004/2005/2006/2007
McDonnell Douglas MD-90	3	2009/2011
TOTAL	**269**	**-**

Since 1974, Delta Air Lines has already eliminated 269 aircraft from its past fleet. It is interesting to notice that, although American Airlines and Delta Air Lines were founded with only two years of difference (1926 and 1924), the number of discarded aircraft throughout the years is very different (411 for American Airlines, and 269 for Delta). Nevertheless, the current fleet of American Airlines is constituted by more 226 aircraft models than Delta's fleet.

The model Boeing 747-100 completely disappeared from the fleet still during the 1970s. In the 1980s and early 1990s, a lot of aircraft models were also totally removed from the fleet, such as Airbus A310-200, as well as some Boeing 737-200, and Lockheed L-1011 TriStar. None of these models are included in the current fleet of Delta. Furthermore, Airbus A310-300, Boeing 737-300, Boeing 767-200, McDonnell Douglas DC-10, and McDonnell Douglas MD-11, were also eliminated from the fleet, although the process had been more continuous throughout the years, than for the models referred ahead.

During the 2000s, a lot of new aircraft models were included in the fleet, for example, Airbus A319, some of Airbus A330 family (200/300), Airbus A350, and also Boeing 717, Boeing 737 Next Generation (700/800/900), and Boeing 777-200. Simultaneously, some old aircraft were being removed from the fleet, although the models themselves were still part of Delta's final fleet, for instance, Airbus A321-200 (1 aircraft), Boeing 757-200 (51 aircraft), Boeing 767-300 (8 aircraft), and McDonnell Douglas MD-90 (3 aircraft).

In more recent years (from 2010 until now), it is possible to see from Table 3.12 that only aircraft Boeing 737-300, Boeing 757-200, Boeing 767-300, and McDonnell Douglas MD-90 were removed from the fleet.

Ryanair

Ryanair was created in 1984 and it is based in Dublin, Ireland. It is a low-cost airline and it is considered one of the largest European Airlines, mainly due to the number of international passengers carried. In 2017, Ryanair became the first European airline to have carried over one billion customers. It operated over 2,000 daily flights, for 205 different destinations, in 33 countries (Ryanair, 2017).

In Table 3.13, the current fleet of Ryanair is summarized. As it is possible to observe from the table, Ryanair is an only-Boeing 737-800 Next Generation airline, with exception to one only Boeing 737-700 Next Generation aircraft, which was acquired in 2015. The average age of the 421 aircraft in Ryanair's fleet is 6.7 years. The fact that this airline only uses one type of aircraft is an advantage in terms of costs, helping the company to keep costs down, doing justice to its low-cost profile.

Table 3.13 – Active aircraft in the current fleet of Ryanair (source: Airfleets, 2017)

Aircraft	Number of Active Aircraft in the Fleet	Age of the Fleet (years)
Boeing 737-700 NextGen	1	6.7
Boeing 737-800 NextGen	411	
TOTAL	**412**	**6.7**

According to the information presented in Ryanair's website, the airline has already ordered more 183 Boeing 737-800, and it plans to expand its fleet to more than 520 aircraft in 2024.

Although nowadays Ryanair possesses only one aircraft model in its fleet composition, it was not always like that. Table 3.14 shows the number and model of aircraft that were removed from Ryanair's fleet in the past, and the year of the respective removal.

Table 3.14 – Retired aircraft from the fleet of Ryanair (source: Airfleets, 2017)

Aircraft	Number of Retired Aircraft	Date when the Aircraft was Retired
Airbus A320-200	2	2015
ATR 42	4	1989/1990/1991/1992
Boeing 737-200	14	2005/2006/2007
Boeing 737-400	6	2014/2015
Boeing 737-800 NextGen	75	2004/2007/2008/2009/2010/2011/2012/2013/2014/2015/2016/2017
TOTAL	**101**	**-**

Initially, Ryanair had 4 ATR 42 aircraft as part of its fleet, but these models were eliminated during the late 1980s and early 1990s. In the 2000s, some other aircraft models were being retired from the fleet, such as Airbus A320-200, Boeing 737-200, and Boeing 737-400. Nevertheless, all these models were always represented in small quantities in the overall fleet.

Even though the Boeing 737-800 Next Generation is the aircraft model of choice of Ryanair, throughout the years a lot of these aircraft were also removed from the fleet (75 aircraft in total).

Lufthansa

Lufthansa was created in 1953 and it is one of the largest European airlines. Its headquarters are located in Dublin, Ireland. This airline operates to 301 different destinations, in 100 countries around the world. In 2016, Lufthansa performed a total 1,021,919 flights, and carried around 109 million passengers (Lufthansa, 2017).

Table 3.15 presents the current fleet of Lufthansa (287 aircraft in total), and the average age of the fleet (11.4 years). The fleet is composed mainly by Airbus models (238 aircraft in total, which corresponds to more than 80% of the fleet), and some Boeing and McDonnell Douglas aircraft too. Lufthansa's fleet is rather young (no aircraft model has more than 20 years). The more recent aircraft in the fleet are the Airbus A350 (6 aircraft in total), the Boeing 777-Freighter (5 aircraft), and the Airbus A380 (14 aircraft), being the older ones the McDonnell Douglas MD-11 (12 aircraft) and the Airbus A319 (30 aircraft). According to Airfleets (2017), Lufthansa has 1 Boeing 747-800 ordered for the future.

Table 3.15 – Active aircraft in the current fleet of Lufthansa (source: Airfleets, 2017)

Aircraft	Number of Active Aircraft in the Fleet	Age of the Fleet (years)
Airbus A319	30	15.7
Airbus A320 Neo	9	9.6
Airbus A320-200	68	
Airbus A321-100	20	12.7
Airbus A321-200	43	
Airbus A330-300	19	10.3
Airbus A340-300	13	14.4
Airbus A340-600	16	
Airbus A350	6	0.5
Airbus A380	14	5.9
Boeing 747-400	13	9.9
Boeing 747-800	19	
Boeing 777-Freighter	5	3.5
McDonnell Douglas MD-11	12	18.0
TOTAL	**287**	**11.4**

In Table 3.16, a summary of the number of aircraft retired from Lufthansa's fleet is presented, as well as the years of retirement of the aircraft models.

Table 3.16 – Retired aircraft from the fleet of Lufthansa (source: Airfleets, 2017)

Aircraft	Number of Retired Aircraft	Date when the Aircraft was Retired
Airbus A300 B2/B4	11	1979/1981/1983/1984
Airbus A300-600	15	2005/2008/2009/2010/2012
Airbus A310-200	17	1993/1994/1995
Airbus A310-300	18	1989/1992/1993/1996/1998/1999/2004/2005/2006
Airbus A319	21	2001/2004/2005/2009/2010/2013/2014
Airbus A320-200	35	1993/2002/2003/2013/2014/2015/2016
Airbus A321-200	1	2000
Airbus A330-200	5	2004/2006
Airbus A340-200	9	1993/1994/1996/2003/2004
Airbus A340-300	12	2005/2006/2011/2012/2015
Boeing 737-100	22	1969/1981/1982/1983
Boeing 737-200	57	1983/1985/1987/1988/1990/1992/1993/1994/1995/1996/1997/1998/1999/2000
Boeing 737-300	27	1991/1993/1997/2001/2002/2003/2004/2014/2017
Boeing 737-400	7	1993/1997/1998
Boeing 737-500	19	1990/1993/1994/2003/2004/2015/2016/2017
Boeing 737-700 NextGen	2	1999/2011
Boeing 747-100	3	1977/1978/1979
Boeing 747-200	30	1978/1979/1984/1990/1991/1992/1994/1995/1999/2000/2002/2003/2004/2005
Boeing 747-400	2	1993/2013
Boeing 767-300	3	1995/2004
Bae 146	1	2000
McDonnell Douglas DC-10	16	1989/1990/1992/1994/1995/1996
McDonnell Douglas MD-11	2	2015/2016
TOTAL	**335**	-

In total, there were already 335 aircraft removed from the fleet, between 1969 and 2017. It is interesting to observe that this is a higher number than the number of aircraft currently existing in the fleet of Lufthansa. This means that the renewal of aircraft has been quite intense over the years. Some models, such as Airbus A300 B2/B4, Boeing 737-100, and Boeing 747-100 were removed from the fleet still in the 1970s and early 1980s. During the 1990s, it is possible to identify a lot of models that were completely eliminated from the fleet, and were no longer acquired by the airline (for instance, Airbus A310-200, Boeing 737-400, and McDonnell Douglas DC-10).

The Airbus A300-600, Airbus A310-300, Airbus A330-200, Airbus A340-200, as well as all the models from Boeing 737 family, the Boeing 747-200, Boeing767-300, and the Bae 146 were also removed once and for all from Lufthansa’s fleet, although in a more continuous time period or more recently (1980s, 1990s and 2000s).

Similar to what happens with American Airlines, Lufthansa also operates mainly with the most recent Boeing models, like Boeing 747-400 and Boeing 747-800. Furthermore, although there had been a significant number of Airbus aircraft models removed from the fleet (144 aircraft in total, almost 50% of the total retired aircraft), as mentioned previously, Lufthansa’s fleet is predominantly composed by Airbus aircraft models.

In more recent years (after 2010), the retirement of aircraft happened more significantly with Airbus A300-600, Airbus A319, Airbus A320-200, Airbus A340-300, and Boeing 737-300/500, and 1 McDonnell Douglas MD-11 aircraft.

4 LONG-DISTANCE MODEL

4.1 Introduction

Strategic fleet planning is a crucial process within any transportation company. It relates to decisions on the fleet size and, in the case of a fleet with different types of vehicles, on the fleet composition. In the aviation industry, these decisions are extremely critical, being undoubtedly among the most important ones that administrators of commercial airlines have to make. Buying a (new) wide-body aircraft like the Airbus 330-200 or the Boeing 787-8 requires an investment of more than $200M (200 million USD), and even rather small aircraft like the Bombardier CRJ700 or the Embraer 170 cost over $20M.

Investment costs are certainly a major factor in a fleet planning process but are not the only drivers. As part of this process, airlines must decide which aircraft suit their network; when they are needed; how many are required; and whether they are needed for replacement or for enlarging the fleet size. There are several criteria – partly conflicting – that need to be considered in addition to the investment costs, such as, technical, operational and environmental performance, and cabin comfort. Another important influencing factor is fleet commonality, i.e., the number of aircraft of the same type, the same aircraft family, or the same manufacturer in a fleet. The relevance of one criterion with respect to the others is specific of the air carrier. For instance, at Lufthansa operating costs are of more concern than investment costs because they are "for the rest of the asset's life" (Baldwin, 2012). As such, the focus is put on fuel burn, and carbon and noise emissions. Moreover, fleet planning decisions reflect the adopted business model. In general, low-cost air carriers operate a fleet consisting of one model or family of aircraft. The choice delivers operational simplicity and economies of scale vital to budget airlines. On the other side, large network air carriers operate several different aircraft types to better meet customer requirements and serve different markets.

The study herein presented deals with fleet planning issues currently being faced by TAP Air Portugal, the Portuguese legacy carrier. Some 20 years ago, TAP defined the expansion of service to/from Brazil to be its foremost strategic direction. This direction has been pursued rather successfully since then, and in 2014 TAP was by far the leading carrier in the Europe-Brazil market offering 65 weekly flights each way between Portugal and 9 Brazilian cities, 61 based in Lisbon and the other 4 in Oporto, against only 11 flights per week serving 3 cities in the mid-1990s. Twelve aircraft Airbus 330-200 are currently used to operate the flights to/from Brazil, seven of which are aged 15 years or more. The main scope of the Brazil TAP study was to analyze fleet planning decisions, which depend on the aircraft to replace, to cope with the forecasted passenger demand between Portugal and Brazil in the year 2020. Specifically, the study was intended to shed light on the aircraft models to be selected, as well as on the mix of aircraft to be bought (or financially leased) and aircraft to be operationally leased. The latter alternative is certainly costlier but avoids TAP to invest in aircraft that will be unnecessary in case the evolution of demand is below expectations. In the study, it is assumed that, in the future, all TAP long-haul operations will be based in one single airport, Lisbon, to avoid the very high costs involved in the Oporto-based flights.

The main component of the methodology developed for this study is a stochastic mixed-integer optimization model. Fleet planning problems have often been approached with integer programs as attested by the extensive literature quoted in a recent review paper by Hoff et al. (2010). However, none of the works cited there presents models that deal specifically with commercial aviation. Due to the lack of models devoted to the subject or not, and as stated in an authoritative textbook by Belobaba et al. (2015, Ch. 7), in practice airlines primarily rely on spreadsheet-based financial methods when making fleet planning decisions. The authors of the textbook manifest their surprise that the tools airlines employ for supporting such expensive decisions are far from being as sophisticated as the ones they apply to, for example, flight scheduling or revenue management problems. The mathematical model developed for this study can be a valuable alternative or complement to the methods currently used in practice, notably because it allows an in-depth screening of the decision space.

This chapter is structured as follows. In the next section, a detailed description of TAP service to Brazil and on the fleet planning problem TAP faces with regard to this market is provided. This is followed by the presentation of the methodological approach adopted to tackle this problem. The two key components of this approach are subsequently dealt with: first, the procedure used to forecast demand; and then, the optimization model developed to address long-haul fleet planning problems under uncertain demand (represented by means of scenarios). The results obtained through the application of the model to the reference planning case considered in the Brazil TAP study are described afterwards, together with an analysis of their sensitiveness to changes in a number of key features. The final section of the chapter summarizes the contents of the study and indicates some directions for the fleet planning work that would be possible to carry out in the future.

4.2 Study Background

In this section, essential background materials about the Brazil TAP study are provided. In particular, detailed information is given about the network of long-haul flights, the demand for TAP flights between Portugal and Brazil, and the aircraft fleet that makes these flights. All the information provided refers to the first part of 2014, the time when the study was initiated.

4.2.1 Flight Network

The network of TAP Air Portugal includes long-haul flights to 14 destinations in Africa and the Americas (Table 4.1). The vast majority of these destinations correspond to either Portuguese-speaking countries (namely, Angola, Brazil and Mozambique) or important immigration countries for Portuguese nationals (the United States and Venezuela). The share of Brazil in this network is substantial, as this country accounts for 9 of the 14 destinations served by TAP (64%) and for 65 of the 84 long-haul flights (77%) it operates every week.

Table 4.1 – TAP Air Portugal long-haul destinations (source: TAP, 2014)

Continent	Country	City
Africa	Angola	Luanda
	Mozambique	Maputo
America	Brazil	Belo Horizonte
		Brasília
		Fortaleza
		Natal
		Porto Alegre
		Recife
		Rio de Janeiro
		Salvador
		São Paulo
	USA	Miami
		New York - Newark
	Venezuela	Caracas

The 9 Brazilian destinations served by TAP correspond, in general, to the metropolitan regions with a population of at least 2.5 million (Figure 4.1 and Table 4.2). The only exceptions are Curitiba, which is not served by TAP flights despite its 3.1 million inhabitants, and Natal, which is home to only 1.3 million people but is located close to seaside resorts that are considered to be among the best in Brazil and became quite popular in Portugal in the late 1990s.

Figure 4.1 – Main metropolitan regions of Brazil

Table 4.2 – Population of the main metropolitan regions of Brazil

Region	Population (million)		Growth rate (%/year)
	2000	2010	
Belém	1.839	2.102	1.35
Belo Horizonte	4.819	5.415	1.17
Brasília	2.051	2.570	2.28
Cuiabá	0.726	0.834	1.39
Curitiba	2.768	3.174	1.38
Florianópolis	0.816	1.012	2.17
Fortaleza	3.057	3.616	1.69
Goiânia	1.743	2.173	2.23
Londrina	0.678	0.764	1.21
Maceió	0.989	1.156	1.57
Manaus	1.646	2.106	2.50
Maringá	0.517	0.613	1.70
Natal	1.125	1.351	1.85
Porto Alegre	3.719	3.959	0.63
Recife	3.338	3.691	1.01
Rio de Janeiro	10.869	11.836	0.86
Salvador	3.120	3.574	1.37
São Luís	1.092	1.331	2.00
São Paulo	21.694	24.145	1.08
Vitória	1.439	1.688	1.61

4.2.2 Passenger Demand

The total (leg-based) demand served by TAP Air Portugal through its flights from Portugal to Brazil is in the order of 730,000 passengers per year, approximately 45% of which initiate or finish their journey in Portugal (naturally, demand for the opposite direction is similar). Almost all other passengers travel to Brazil through Lisbon from European countries, notably Italy and France. This traffic is spread across seasons in a well-balanced manner, being the number of passengers in the most loaded trimester only 28% above the equivalent figure for the less loaded trimester (Summer and Winter in Europe, respectively).

The distribution of passenger demand across the main Brazilian metropolitan regions is shown in Table 4.3, where is made the distinction between the 9 regions that are served by TAP flights and the other 11 most populated regions of Brazil (altogether, these 20 regions generate 707,500 passengers annually each way, thus accounting for 97% of the total demand). The analysis of the table shows that São Paulo and Rio de Janeiro are by far the most important TAP destinations in Brazil, generating over 125,000 trips, followed by Fortaleza, Salvador and Recife (beach tourism), Belo Horizonte (third-largest metropolitan area) and Brasília (capital city), which generate between 50,000 and 70,000 trips.

Table 4.3 – TAP passenger demand for the main metropolitan regions of Brazil (source: OAG, 2014)

Region served by TAP flights	Demand (10^3 pax/year)	Region not served non-stop by TAP flights	Demand (10^3 pax/year)
Belo Horizonte	61.52	Belém	3.31
Brasília	54.86	Cuiabá	1.89
Fortaleza	62.05	Curitiba	7.07
Natal	38.73	Florianópolis	4.36
Porto Alegre	42.61	Goiânia	5.00
Recife	65.86	Londrina	1.60
Rio de Janeiro	125.04	Maceió	1.36
Salvador	60.18	Manaus	4.51
São Paulo	158.65	Maringá	1.36
		São Luís	1.71
		Vitória	5.87
Total	669.49	Total	38.04

The relationship between passenger demand from the 20 metropolitan regions and the population resident in these regions is shown in Figure 4.2. The visual analysis of this figure clearly indicates that demand and population are strongly positively correlated if metropolitan regions are separated according to whether they are served by TAP flights or not. In the latter case, passengers need to make part of their trips in flights offered by Brazilian airlines, as cabotage is not allowed in Brazil. The examples of Porto Alegre and Curitiba, two metropolitan regions with population between 3 and 4 million relatively close by Brazilian standards (distance by road is approximately 700 km), illustrate the impact of non-stop service on traffic in a striking manner: Porto Alegre is served by TAP flights and generates about 42,600 yearly trips from Portugal; Curitiba is not and generates less than 1/5 of that number of trips.

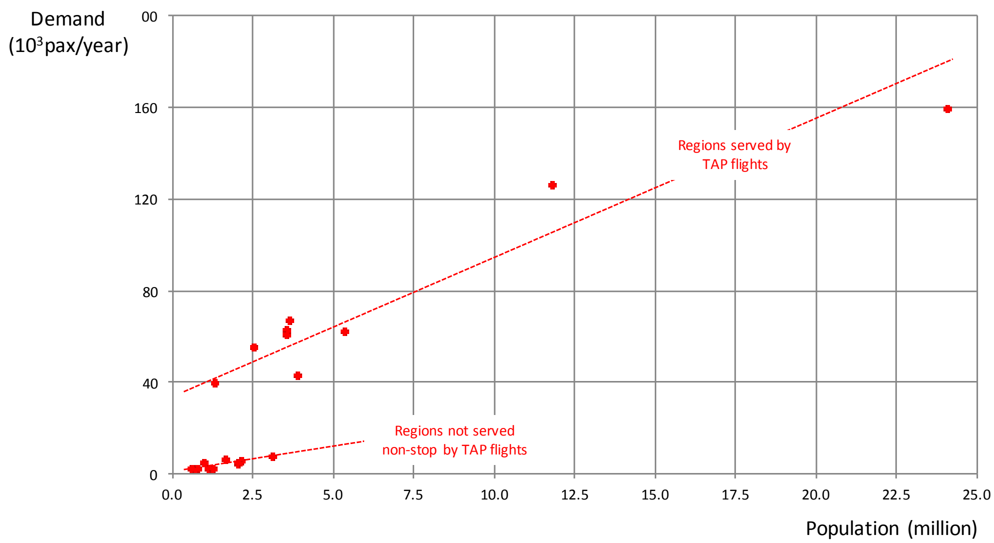

Figure 4.2 – Relationship between TAP passenger demand and population for the main metropolitan regions of Brazil

The connecting airports (or airport systems) for trips with destination to the 11 metropolitan regions that are not served by TAP flights are presented in Table 4.4. First of all, this table reveals that, as one could expect, the most important connecting airports correspond to São Paulo, Rio de Janeiro and Brasília, which are in the itineraries of trips to 7, 6 and 5 regions, respectively (the fact that Brasília performs a significant connecting role is due to its capital city status, as well as to its relatively central location in Brazil). It also reveals that only two regions resort to a single connecting airport. These regions are Londrina and Maceió, respectively served through São Paulo and Salvador. The airports of Belo Horizonte, Natal, Porto Alegre and Recife are not used by TAP passengers for connections, therefore they are not represented in the table.

Table 4.4 – Connecting airports for metropolitan regions not served non-stop by TAP flights

Metropolitan region	Demand through connecting airport (%)				
	Brasília	Fortaleza	Rio de Janeiro	Salvador	São Paulo
Belém	17.3	67.2	15.5	0	0
Cuiabá	42.8	0	10.7	0	46.5
Curitiba	0	0	37.4	0	62.6
Florianópolis	0	0	49	0	51
Goiânia	70.8	0	0	0	29.2
Londrina	0	0	0	0	100
Maceió	0	0	0	100	0
Manaus	0	71.9	0	28.1	0
Maringá	0	0	21.5	0	78.5
São Luís	24.9	75.1	0	0	0
Vitória	16.5	0	48.1	13.6	21.7

4.2.3 Aircraft Fleet

The long-haul fleet of TAP Air Portugal consists of 16 Airbus aircraft, 4 of the A340-300 type and 12 of the A330-200 type. All aircraft are operated in the two-class configuration, with 300 seats in the case of the A340 and 246 seats in the case of the A330. Therefore, the total capacity of the fleet is 4,644 seats, 63% of which corresponds to the A330. Most of the TAP flights to Brazil are performed with the A330, being the other aircraft essentially used for flying to the other long-haul destinations. This means that 63% of the long-haul seat capacity of TAP is assigned to 64% of its destinations and to 77% of its weekly flights.

The oldest aircraft in the fleet are the 4 A340, all of them with first flights made in 1994 or 1995. Since then, TAP only purchased A330, 7 from the period 1996-2000, thus being now 15 years old or more, and 5 from the period 2006-2010 (Figure 4.3).

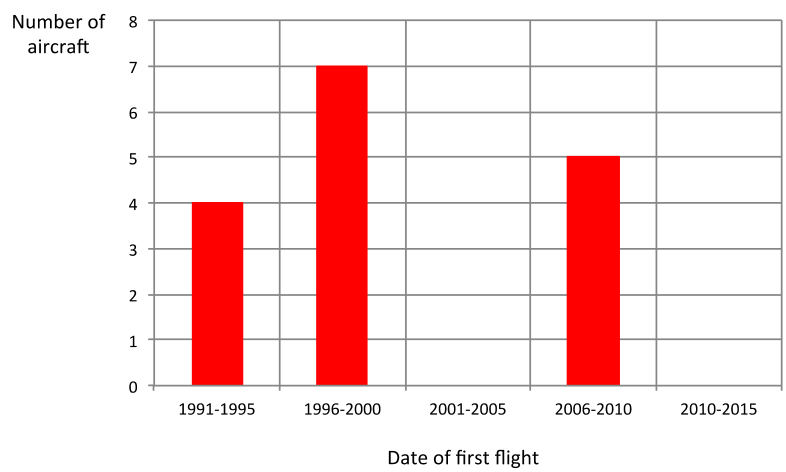

Figure 4.3 – Date of first flight for the aircraft of TAP's long-haul fleet (source: Airfleets, 2017

The need to replace the older aircraft employed in Brazil operations was the main driver behind the study herein described. Specifically, the study aims to address the following two questions: first, which types of aircraft should replace the older ones; second, for each aircraft type, how many new aircraft should be bought and how many should be (operationally) leased.

With respect to the first question, it is worth noting that TAP is, and wants to remain, an all-Airbus airline. This means that the new aircraft must be chosen among the three long-haul aircraft series that Airbus is currently producing: A330; A350; and A380. However, the latter series is not a real option because Lisbon's airport cannot operate A380 aircraft at present, and it is highly unlikely that this situation will change at least in the next 10 years. The possible series from where the new aircraft should be selected are therefore the A330 and the A350.

Regarding the second question, the responses naturally depend on the characteristics of the aircraft, described in Table 4.5. Observe that the seat capacity refers to the two-class configuration, as TAP offers in the flights to Brazil. It is also worthy to notice that the cruise speed vary only slightly across aircraft types and that flight range for all aircraft types clearly exceed the great circle distance between Lisbon and Porto Alegre, the farthest destination served by TAP in Brazil, which is 8774 km. Therefore, seat capacity and costs are the two features that really matter. As for seat capacity, the use of A350 would allow TAP to offer flights with up to 50% more seats than the A330 currently used to serve Brazilian destinations. The use of A350 aircraft might therefore be helpful to provide more seat capacity particularly for trips to the main metropolitan regions. As for the costs, based on the information available at TAP, there are two aspects to underline: (a) the A350 have higher capital cost per seat than the A330, but this is compensated by lower operating cost (essentially due to lower fuel consumption); (b) the option of leasing aircraft is approximately 20% more expensive than the purchasing option, but of course has the advantage of being more flexible, avoiding TAP to make investments that will not be necessary if the demand for Brazilian destinations grows below expectations.

Table 4.5 – Aircraft costs and operational characteristics (source: TAP, 2014)

Aircraft type	Seat capacity	Cruise speed (km/h)	Flight range (km)	Costs ($M)		
				Investment	Leasing (per year)	Operating (per year)
A330-200	246	871	13400	216	13.0	54.0
A350-800	276	903	15300	254	15.3	59.8
A350-900	315	903	14350	288	17.3	67.6
A350-1000	369	903	14800	332	19.9	78.0

4.3 Methodological Approach

The problem faced by an airline when making fleet planning decisions is extraordinarily complex when all its components are taken into account. First of all, the airline needs to look at future demand, which is by nature uncertain, and to its variability across seasons (and months, and days of the week). Generally, this is done considering the long-haul destinations separately from the short- and mid-haul destinations, because they need to be served by fleets with different characteristics (regarding aircraft size and, especially, flight range). Part of the uncertainty airlines have to cope with relates to the demographic and economic evolution of the markets served by the airline, and another part relates to competition from other airlines, including from possible new entrants in those markets. Furthermore, future demand is dependent on the flight frequencies and schedules that the airline will offer in each market, as well as on the many other factors that affect quality of service (seat space and legroom, courtesy of employees, on-time performance, etc.). Finally, airlines need to look at financial issues. Replacing older aircraft is in principle advantageous from the standpoint of operating costs because new aircraft are generally more efficient with regard to fuel consumption. However, purchasing new aircraft requires substantial capital outlays. The alternative is the operational leasing of aircraft, but, in the long term, leasing is more expensive than purchasing.

The methodological approach adopted in the Brazil TAP study to handle such complex problem, summarized in the diagram of Figure 4.4, is based on the recognition that it is not realistically possible to achieve practical results without making simplifications. The first task performed essentially consisted in deciding the simplifications to make and structuring the fleet planning problem faced by TAP regarding its flights to Brazil. This task included discussions with TAP officials to establish the essential components of the problem in hand.

The first and foremost simplification that was made was to separate the demand side of the problem from the supply side. Specifically, it was assumed that the fleet should be planned to respond to the passenger demand in 2020. This demand was estimated taken into account the factors explaining the current demand for TAP flights between Portugal and Brazil. The next task consisted therefore in the realization of a demand forecast. In order to account for uncertainty, several scenarios for future demand were generated.

Practically in parallel with the previous task, it was developed the optimization model for determining the least cost fleet that TAP should use in its flights to Brazil, while taking into account all the relevant demand and cost information, as well as the operational constraints involving the possible aircraft to include in the fleet.

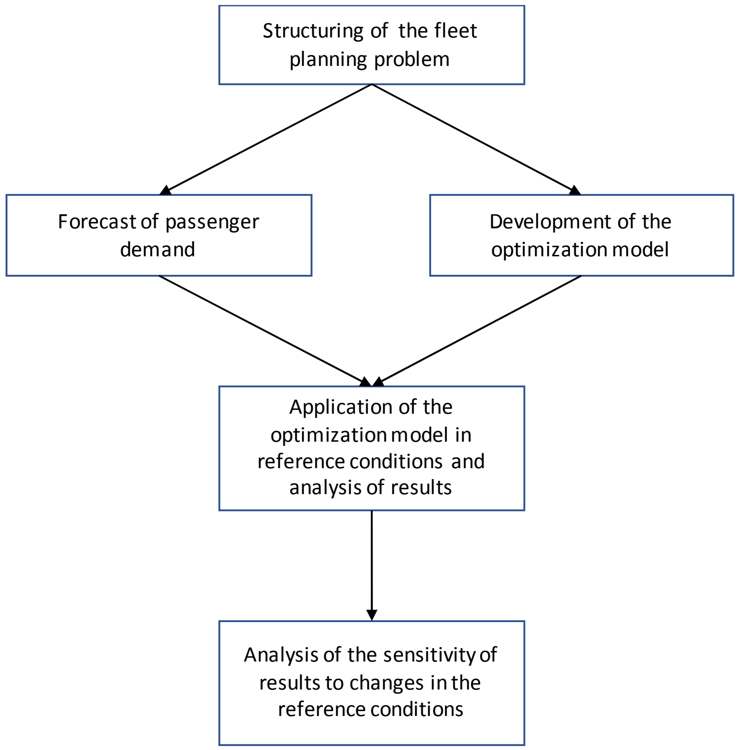

Figure 4.4 – Methodological approach adopted in the study

The final task performed consisted in getting the results for the study by solving the optimization model for the demand forecasted in 2020. This task was carried out in two stages: in the first, based on the indications provided by TAP officials, there was defined a set of reference conditions and determined the best solution for these conditions using the optimization model developed in the previous task. Second, a sensitivity analysis to assess the implications on the solution of changes in the reference conditions was conducted.

Details about the various tasks are provided in the subsequent sections.

4.4 Demand Forecast

As stated in the previous section, passenger demand forecast was an important component of this study. It was performed for the reference year of 2020 based on the idea, formed by the observation of Figure 4.2 (previous section), that the evolution of this demand for each metropolitan region of Brazil would be properly explained by only two variables: the population resident in the region; and the existence or not of non-stop service to that region (indicator variable). This idea was confirmed through multiple regression analysis. Other possible explanatory variables, such as GDP, international business and tourism, and ticket prices, were considered in the analysis (in addition to the variables mentioned above), but they were never statistically significant. In the case of ticket prices this was not surprising because they are in general very similar no matter the destination.

Among the specifications used for the relationship between demand and population, the one that provided the best results (probably because, by using logarithms, the "size effect" associated with São Paulo and Rio de Janeiro was circumvented), was as follows:

$$\ln Q = a + b.\ln P + c.X + \varepsilon \tag{4.1}$$

Where Q is the demand from a metropolitan region; P is the population of the metropolitan region; $X = 1$ if the metropolitan region is served non-stop, and $X = 0$ otherwise; a, b and c are regression coefficients; and ε is a normally-distributed error term with zero mean and standard deviation σ, that is, $\varepsilon \sim N(0, \sigma)$.

The regression results that were obtained for this equation are summarized in Table 4.6. One can see there that almost 96% of the variation in data is explained by the equation above (R^2_{adj} = 0.958), and that all regression coefficients are significantly different from zero (t stat >> 2). The demand modeled by the regression equation fits the observed demand data rather well as also evidenced by the diagram of Figure 4.5. The apparent exception is for small traffic volumes, whose lower and higher values are overestimated and underestimated, respectively. The regression residuals, i.e. the differences between observed and modeled demand, which can be seen as realizations of the error term, have a zero mean as expected and a standard deviation of 0.327, and, according to the histogram presented in Figure 4.6, appear to follow a normal distribution (the number of observations is too small for formal normality testing).

Table 4.6 – Summary of regression results

Adj. *R* square	0.958			
Standard error	0.346			
Coefficient	Value	Standard error	*t*-stat	*p*-value
a	0.865	0.111	7.814	0.000001
b	0.655	0.119	5.487	0.000040
c	2.333	0.213	10.945	0.000000

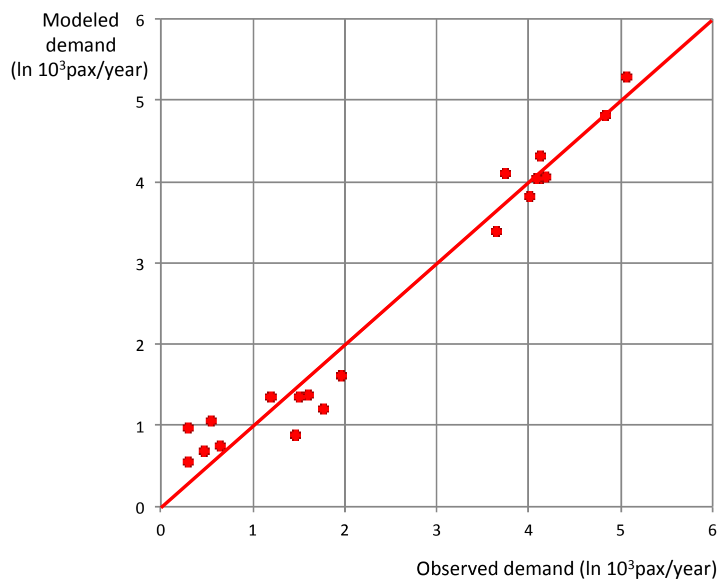

Figure 4.5 – Observed demand vs. modeled demand

Based on the regression results, it is possible to generate equally-probable scenarios for future passenger demand using the following expressions:

– Metropolitan regions served by TAP flights

$$Q_f = e^{(a+c+\varepsilon)} P_f^b = e^{(3.198+\varepsilon)} P_f^{0.655} \tag{4.2}$$

– Other metropolitan regions

$$Q_f = e^{(a+\varepsilon)} P_f^b = e^{(0.865+\varepsilon)} P_f^{0.655} \tag{4.3}$$

Where Q_f and P_f represent future demand and future population, respectively, and $\varepsilon \sim N\,(0, 0.327)$.

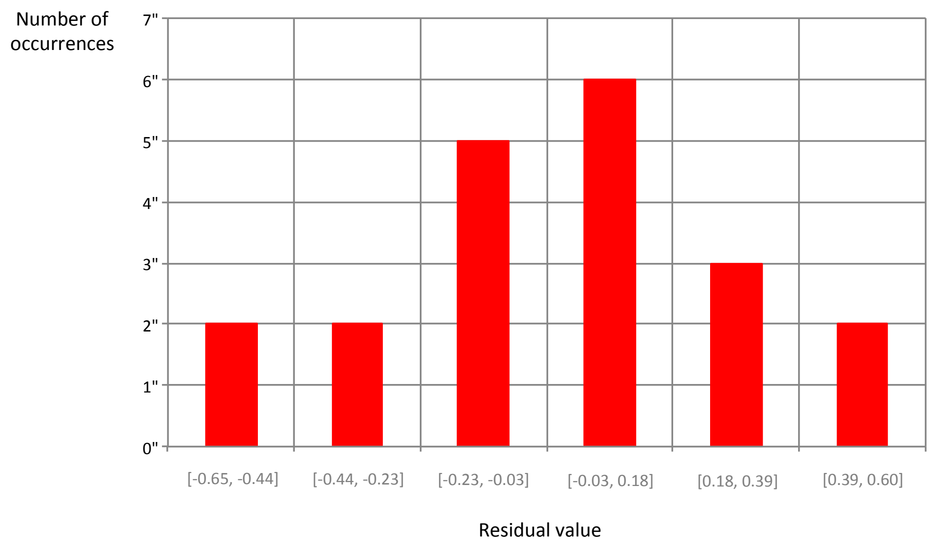

Figure 4.6 – Histogram of regression residuals

4.5 Optimization Model

In this section, after a brief overview of the existing literature on airline fleet planning models, the stochastic mixed-integer optimization model developed for this study is presented. The model was designed with the case of TAP Air Portugal in mind, but could apply to the long-haul fleet of any airline (no matter the number of bases it operates).

4.5.1 Literature Overview

Fleet planning problems have been widely studied in maritime and road transport, especially in combination with vehicle routing problems. As described in Hoff et al. (2010), who provided a comprehensive literature review on strategic fleet planning, the mathematical modeling of the problem should include, as detailed as possible, all relevant revenues and costs related to the purchase and operation of the fleet. The models should also take possible long-term contracts and spot markets into account. On the other hand, the inclusion of (detailed) routing aspects is usually meaningless, unless transportation demand is highly predictable.

In air transportation, research in fleet planning problems has been much more limited and has attracted the interest of the scientific community only in recent years. The principal features of the problems are presented in Belobaba et al. (2015, Ch. 7), together with a brief description of the decision support methods used by airlines to address them. In a recent paper, Clegg (2015) described the fleet planning process within British Airways. While economic/financial evaluations and technical/ performance characteristics of alternative aircraft types tend to dominate the fleet planning process within most of the airlines, there are several additional aircraft selection criteria that cannot be overlooked.

The economic and financial assessment of the available aircraft alternatives to support fleet planning can be either top-down, i.e., based on high-level aggregate analysis, or bottom-up, based on much more detailed data analysis and forecasts by flight and route. From a financial perspective, Gibson (2010) reviewed many of the current practices in fleet planning, examining the validity and usefulness of financial valuation models from both theoretical and practical perspectives.

Few works that combine both the economic and the business aspects of fleet planning have been carried out. Hsu et al. (2011) developed a stochastic dynamic programming model to optimize airline decisions regarding the purchase, the lease, or the disposal of aircraft over time, and applied it to EVA Airline (Taiwan). The results of their study show that severe demand fluctuations would make the airline lease rather than purchase aircraft, which would allow greater flexibility in fleet management. This can be a reference work for the airlines' replacement decision-making process, as it takes into account both the fluctuations in the demand and the status of aircraft. Along the same lines, Bazargan and Hartman (2012) presented an integer programming model to compute the number of aircraft to buy, lease or sell in order to minimize the total discounted costs over the planning horizon. The authors applied their approach to two United States airlines with different business models. The results show that aircraft leasing was in both cases the best alternative.

From a more operational perspective, Listes and Dekker (2005) studied the fleet planning problem with the goal of determining a robust airline fleet composition with respect to the concept of dynamic allocation of the fleet to routes, in response to short-term fluctuations in demand. By mean of a stochastic programming model solved with the progressive hedging algorithm, the authors determine the most appropriate fleet given the flight schedule. Thus, the results obtained in this setting should be regarded only as input for the analysis, in which, clearly, many more aspects need to be taken into account before an actual decision is made.

The optimization model presented below combines features from the fleet composition model proposed in Listes and Dekker (2005), which does not consider leasing options, with features from the fleet replacement models proposed in Hsu et al. (2011) and Bazargan and Hartman (2012), which consider the various financing options but disregard important operational issues (e.g. the actual flights that the fleet has to make). The main innovation in this model relates to the fact that it combines both types of features, thus capturing the essential components of a long-haul fleet planning problem (without going into details that would compromise its applicability in practice). Moreover, it accounts for seasonal variations of demand and determines endogenously the number of flights for each origin-destination pair (in the Listes and Dekker (2005) model flights are made according to a predefined schedule).

4.5.2 Model Formulation

The optimization model developed for the airline fleet planning problem belongs to the class of two-stage stochastic integer programs (SIPs). The SIP modeling framework was chosen because it explicitly represents uncertainty and models a sequence of decision stages that are coherent with the airline decision-making process. Indeed, uncertainty affects many of the problem parameters, especially those referring to passenger demand and to cost structure, i.e., investment (capital), leasing and operating costs. At each stage, the SIP model allows to revise decisions already made based on the new information available. Therefore, it grants more flexibility in the decision-making process and provides solutions hedged against uncertainty, which are not too conservative.

The proposed model formalizes the following sequence of decisions and observations, i.e., realizations of the multivariate random variable representing uncertainty. The first stage decisions relate to the fleet size. More specifically, they concern with the number and the type of aircraft to purchase. Once the realization of the uncertain parameters is observed – e.g., demand for each destination, investment, operating and leasing costs of each aircraft, etc. – the recourse actions are implemented. In this specific model, the recourse actions are decisions about the leasing of aircraft.

The model was restricted to two stages because both buying and leasing decisions will be taken into account. Moreover, the two-stage SIPs have been widely studied, are more compact than their multi-stage extensions, and several algorithmic approaches are available in the literature for solving them, see e.g. Schultz (2003) and Sen (2005). Therefore, the practical use of these models is in a rolling horizon fashion, which allows updating the parameters of the instances as soon as new information becomes available.

The optimization model developed is based on three key assumptions:

(a) The long-haul flights leave from or arrive to a base (or hub) of the airline that operates them (in the case of TAP it is assumed that there will be only one base, Lisbon). That is, the aircraft serving the long-haul destination, first flies the out-bound route from a base airport to the destination, and then flies back to that base airport.

(b) The total duration of a round-trip flight, measured in days, to serve a specific destination can be restricted to one of the following values {1.0, 1.5, 2.0}. This assumption, which simplifies the model, represents with good fidelity long-haul operations within airlines in general and TAP in particular. Indeed, airlines typically operate cyclic schedules (i.e. flights take place every day, or regularly, at the same time of the day over a season or a year). The reason is because such schedules help to manage the fleet and the crews, and take advantage of the slot allocation priority rules applied by all the main airports worldwide outside the United States, including Lisbon (IATA, 2017). For instance, for the flights between Lisbon and Brasília, the aircraft leaves from Lisbon at 9:30 am, lands in Brasília at 5:20 pm, and flies back to Lisbon at 6:55 pm where it arrives at 6:05 pm, in order to be ready to leave again to Brasília 2h 25m later.

(c) The costs of long-haul flights can be taken as a function of the number and type of aircraft that make them, according to TAP officials. This is because the number of aircraft of each type is closely correlated to the number of flights operated by that type of aircraft. However, the proposed model could easily be transformed to account for costs dependent not only on the number and type of aircraft but also on the origin-destinations pairs they serve (as indicated below, a set of its decision variables refers to the number of weekly flights for each origin-destination pair made by each type of aircraft).

In what follows, it is assumed that the random vector q, corresponding to passenger demand, has a finite support; that is, $\Xi = \{q^1, \ldots, q^S\}$ with probabilities $p_1, \ldots, p_S$. This hypothesis allows us to represent uncertainty by means of scenarios. A scenario is a realization of the vector of random variables corresponding to an elementary atom $q \in \Xi$.

The model's formulation requires definition of the following notation:

<u>Sets</u>

A: set of aircraft types;

D: set of origin-destination pairs;

S: set of scenarios;

P: set of periods of the year (seasons or months).

<u>Parameters</u>

r: discount rate (/year);

ci_a: discounted investment cost of an aircraft of type a (\$/year);

co_a: operating cost of an aircraft of type a ($/year);
p_s: probability of scenario s;
cl_a: leasing cost of an aircraft of type a ($/year);
s_a: capacity (number of seats) for an aircraft of type a (pax);
f_{ad} = 1 origin-destination pair d is within the range of aircraft a; f_{ad} = 0 otherwise;
q_{dps}: demand for origin-destination pair d in period p and scenario s (pax/week);
α: level of risk protection, i.e., the probability of the scenarios accommodated in the optimal solution;
t_d: total duration of a round-trip flight for origin-destination pair d, including the turnaround time (days). By assumption (b) above, this parameter may assume one of the following values {1.0, 1.5, 2.0}, depending on the distance to the destination;
n_a: number of aircraft of type a in the current fleet of the airline that will not be replaced;
$i_{\max}$: maximum investment in new aircraft ($);
$i_{\min}$: minimum investment in new aircraft ($).

Decision Variables

X_a: the number of aircraft of type a to buy;
Z_{as}: the number of aircraft of type a to lease in scenario s;
Y_s = 1, if scenario s is accommodated in the optimal solution; Y_s = 0, otherwise;
V_{adps}: the number of weekly flights for origin-destination pair d in period p and scenario s, using aircraft of type a.

X_a and Y_s are the first stage decision variables, while Z_{as} and V_{adps} are the recourse actions (second stage decision variables).

The annual expected total costs of the airline (C) was considered as a criteria of performance to set the decision variables. The total costs, to be minimized, account for the discounted investment costs, the leasing costs and the operating costs. Given the notation introduced above, the objective-function of the proposed airline fleet planning model can be formulated as follows:

$$\text{Min}\, C = \sum_{a\in\boldsymbol{A}} \left(r.ci_a + co_a\right) X_a + \sum_{a\in\boldsymbol{A}} \sum_{s\in\boldsymbol{S}} p_s \left(cl_a + co_a\right) Z_{as} \tag{4.4}$$

The minimization of the objective-function is subject to the following set of constraints:

$$\sum_{a \in \boldsymbol{A}} s_a\, f_{ad}\, V_{adps} \geq q_{dps}\, Y_s \quad \forall d \in \boldsymbol{D}, p \in \boldsymbol{P}, s \in \boldsymbol{S} \tag{4.5}$$

$$\sum_{s \in \boldsymbol{S}} p_s Y_s \geq \alpha \tag{4.6}$$

$$\sum_{d \in \boldsymbol{D}} t_d V_{adps} \leq 7.\left(n_a + X_a + Z_{as}\right) \qquad \forall a \in \boldsymbol{A}, p \in \boldsymbol{P}, s \in \boldsymbol{S} \tag{4.7}$$

$$\sum_{a \in \boldsymbol{A}} ci_a X_a \leq i_{\max} \tag{4.8}$$

$$\sum_{a \in \boldsymbol{A}} ci_a X_a \geq i_{\min} \tag{4.9}$$

$$X_a, Z_{as}, V_{adps} \in \boldsymbol{Z}_0^+ \quad \forall a \in \boldsymbol{A}, d \in \boldsymbol{D}, p \in \boldsymbol{P}, s \in \boldsymbol{S} \tag{4.10}$$

$$Y_s \in \{0,1\} \qquad \forall s \in \boldsymbol{S} \tag{4.11}$$

Constraints (4.5) are the demand constraints. For each origin-destination pair, period of the year and scenario, these constraints guarantee that passenger demand is satisfied, meaning that the airline will provide enough seat capacity to accommodate the forecasted demand of passengers (and that this capacity is made available in flights that are within the range of the aircraft that make them). Seat capacity depends on the number of connections and the type of aircraft in the airline fleet used to serve a specific origin-destination. Observe that these constraints are enforced only for a subset of scenarios, i.e., those scenarios whose decision variable Y_s is set to one. Indeed, in conjunction with constraint (4.6), which is a probabilistic constraint, not all scenarios are necessarily accommodated in the optimal solution. The rationale for this modeling approach is that satisfying the demand constraints for all possible scenarios can be deemed uneconomical by the airline management. Indeed, if all the scenarios would be accounted in the solution, the first stage decisions of the SIP recourse model would lead to a seat capacity large enough to cover all possible demand outcomes in the next stage. The probabilistic constraint (4.6) limits the number of scenarios accommodated in the optimal solution thus overcoming the potential drawback described above. If airline managers are willing to avoid the risk of not satisfying the demand even in the most demanding scenarios, then they should choose α =1. For 0 < $\alpha \leq$ 1, the larger the value of α, the smaller will be the risk that demand will not be served.

Constraints (4.7) are the time constraints. They impose that the total flight time (measured in days per week) does not exceed the total available flight time (measured in days), for each type of aircraft, period of the year and scenario. These constraints set the size of the fleet in order to accommodate all the long-haul flights.

Constraints (4.8) and (4.9) set the maximum and minimum investment the airline is willing to make in the purchase of aircraft. The reason for including a minimum investment constraint in the model is because the accounting value of an airline depends on the aircraft it owns, and not on the leased aircraft used in its operations (which correspond to a service that the airline purchases). This is an issue that airline managers will certainly not neglect when making fleet planning decisions.

Finally, expressions (4.10) and (4.11) define the domain for the decision variables included in the model.

The model presented above was developed assuming that the airline has the goal of satisfying all the demand taken as reference for the planning of its fleet. The case where the airline considers not satisfying a fraction of that demand (because the corresponding benefits would not compensate for the additional fleet costs), can be easily accommodated in the model. In fact, this is possible by adding a term in the objective-function representing the loss of revenues ensuing from the loss of demand, and changing constraint (4.5) so that seat capacity will cover the reference demand deducted from the lost demand. The formulation of the new objective function (4.4') and demand constraints (4.5') would therefore be:

$$\text{Min}\, C = \sum_{a \in \boldsymbol{A}} \left(r.ci_a + co_a \right) X_a + \sum_{a \in \boldsymbol{A}} \sum_{s \in \boldsymbol{S}} p_s \left(cl_a + co_a \right) Z_{as} - \sum_{d \in \boldsymbol{D}} \sum_{p \in \boldsymbol{P}} \sum_{s \in \boldsymbol{S}} p_s\, n_p\, cu_{dp}\, U_{dps} \qquad (4.4')$$

$$\sum_{a \in \boldsymbol{A}} s_a\, f_{ad}\, V_{adps} \geq q_{dps}\, Y_s - U_{dps} \qquad \forall d \in \boldsymbol{D}, p \in \boldsymbol{P}, s \in \boldsymbol{S} \tag{4.5'}$$

Where:

n_p: number of weeks in period p;

cu_{dp}: cost of lost demand for origin-destination pair d in period p (\$/pax);

U_{dps}: lost demand for origin-destination pair d in period p and scenario s (pax/week).

4.6 Study Results

In this section, the main results for the TAP Air Portugal strategic fleet planning study are presented. As mentioned before, TAP is currently operating flights to Brazil with 12 Airbus A330-200, 7 of which are 15 years old or older. The study was developed to assist the fleet renovation process, considering the (uncertain) passenger demand from the 20 main Brazilian metropolitan regions expected in the year 2020. More specifically, the study aimed to respond to the following two key questions: (a) which types of aircraft should replace the older ones; (b) for each aircraft type, how many new aircraft should be bought and how many should be (operationally) leased. The aircraft types considered were the A330-200 and the models in the A350 series (800, 900 and 1000), whose key characteristics are shown in the previously presented Table 4.5.

As stated when describing the methodological approach adopted in the study, the results were obtained in two stages. First, the model was solved for reference conditions defined with the help of TAP officials. Second, a sensitivity analysis was performed to analyze how the solution would vary in response to changes in those conditions. For solving the model, it was used FICO Xpress, a top-market general-purpose integer optimization software, on a PC equipped with a 2.50 GHz Intel Core i5-3210M CPU.

Specifically, the reference conditions taken into consideration in this study were:

(a) Minimum investment costs: $648M (corresponding to the purchase of 3 A330-200);

(b) Number of A330-200 to replace: 5 (out of the 7 older aircraft of this type operated by TAP);

(c) Operational leasing costs: 20% higher than (discounted) investment costs;

(d) Number of demand scenarios: 20 (all equally likely);

(e) Level of risk protection (as measured by the percentage of demand scenarios that are accommodated in the solution): 90%.

With respect to passenger demand, this study relied on three important assumptions. The first one was that the population of the various metropolitan regions of Brazil would grow in the period 2010-2020 at the same rate it has grown in the period 2000-2010. The second assumption was that trips made to the 11 metropolitan regions not served by TAP flights would follow the same itineraries as today, and in the same proportions, as shown in the previously presented Table 4.4 (e.g., 17.3% of the trips between Lisbon and Belém would be made through Brasília, 67.2% through Fortaleza, and 15.5% through Rio de Janeiro). Finally, the third assumption was that demand variations across the year could be neglected (that is, the model was applied without considering different periods of the year). This assumption is reasonable because seasonality in the flights between Portugal and Brazil is low and may be handled through revenue management practices.

The total weekly demand for the 20 scenarios considered (Scenarios 1-20), as well as for the next 20 scenarios, is depicted on Figure 4.7. These data were obtained through expressions (4.2) and (4.3) using the random number generator of FICO Xpress (random seed equal to 1). The scenarios were considered to be equally probable, but demand for a large number of scenarios should be relatively close to the average as the error term in those expressions follows a normal distribution. It should be noticed that, by a matter of chance, the demand for the first 20 scenarios (and especially for the first 10) is, on average, below the population mean. This has implications on results that will be discussed later in this section.

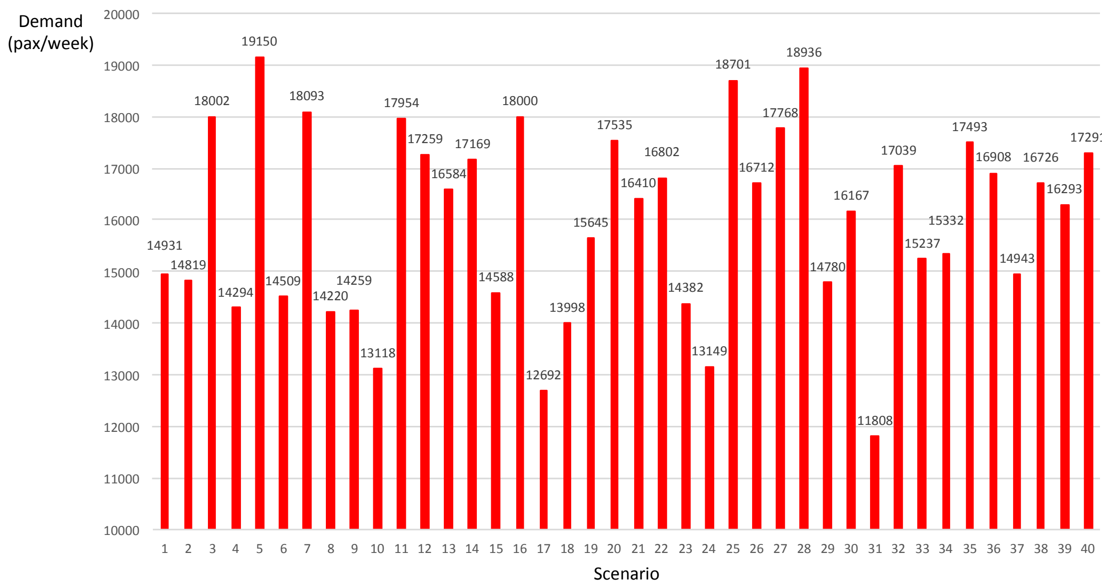

Figure 4.7 – Total weekly demand for 40 scenarios

To model instances corresponding to the various demand scenarios were solved through the branch-and-cut algorithm implemented in FICO Xpress. Although they were difficult to solve to proven optimality, computational experiments on small-scale instances showed that the algorithm finds the optimal solution in short computational times and then takes a comparatively long time to close the optimality gap. Quite often, solvers show this behavior when tackling integer programs. In view of these experiments, a time limit of one hour was imposed to the computations. For this reason, in the remaining of this section, it will always be referred best solutions (or best solutions found), and never of optimal solutions.

The results obtained by solving the model in the reference conditions and for the sensitivity analysis are presented and discussed below in separate sections. The focus is on fleet composition and size, as well as on costs for the airline and their distribution across categories (investment, leasing, and operating).

4.6.1 Reference Case

The best solution for the reference case is summarized in Table 4.7 and Table 4.8. Table 4.7 displays the number of aircraft to purchase for each type considered (i.e., value of the first stage decisions), the range for the number of aircraft to lease (which is the sum of the second stage decisions and therefore depend on the scenario realization), the investment costs, the expected leasing, operating and (annual-equivalent) total costs. Table 4.8 reports the value of the second stage decision variables, i.e., the number of leased aircraft for each type. However, for the sake of readability, only the values for Scenario 9 (low demand, i.e., 14,259 passengers per week), Scenario 13 (average demand, i.e., 16,584 passengers per week) and Scenario 11 (high demand, i.e., 17,954 passengers per week) are reported. These scenarios correspond respectively to the first, second and third quartile of the total demand distribution.

Table 4.7 – Fleet and costs in the reference case solution (Scenarios 1-20)

Indicator		
Number of new aircraft		3-8
Purchased	A330-200	2
	A350-800	0
	A350-900	1
	A350-1000	0
Leased		0-5
Number of existing aircraft		7
Total number of aircraft		10-15
Investment costs ($M)		720.0
Expected leasing costs ($M/year)		30.6
Expected operating costs ($M/year)		679.0
Expected total costs ($M/year)		745.6

The reference case solution points to the purchase of three aircraft, namely two A330-200 and one A350-900, for a total investment of $720M. This means that only three of the older five aircraft to dismiss are replaced by new purchased aircraft. The required investment exceeds the minimum investment of $648M – imposed by constraint (9) of the formulation – by 11.1%. The total expected costs amount to $745.6M per year. For the discount rate of 5% considered in the calculations, the depreciation of the investment costs is 4.8% of the total expected costs. (Alternatively, observe that, the annual quota of the investment costs amounts to 4.8% of the total expected costs). The far-reaching component of the total costs is the operating costs (91.1%).

Table 4.8 – Purchased and leased aircraft in the reference case solution (Scenarios 1-20)

Type of aircraft	Number of new aircraft			
	Purchased	Leased		
		S11	S13	S9
A330-200	2	1	2	0
A350-800	0	3	1	0
A350-900	1	0	0	1
A350-1000	0	0	0	0
Total	3	4	3	1

As mentioned above, leasing decisions depend on the realization of the demand scenario. If Scenario 9 occurs, only one aircraft is leased (A350-900), while in the case of Scenario 11 four aircraft – one A330-200 and three A350-800 – are leased. The number and the types of leased aircraft clearly depend on the realization of the air traffic demand. Even though the leasing of aircraft is more expensive, it grants the airline of the flexibility to adjust its own fleet according to the demand realization in all the considered destinations.

Since, by a matter of chance, the demand for the first 20 scenarios generated is, on average, clearly lower than population mean, the calculations were repeated for Scenarios 21-40. As shown in Table 4.9, the expected total costs are higher (by almost 3.0%), but only the leasing and the operating costs increase (14.1% and 2.6%). Indeed, the key decisions, the ones concerning the number and the types of aircraft to purchase, are exactly the same (that is, two A330-200 and one A350-900), and therefore the investment costs are also the same.

Table 4.9 – Fleet and costs in the reference case solution (Scenarios 21-40)

Indicator		
Number of new aircraft		3-8
Purchased	A330-200	2
	A350-800	0
	A350-900	1
	A350-1000	0
Leased		0-5
Number of existing aircraft		7
Total number of aircraft		10-15
Investment costs ($M)		720.0
Expected leasing costs ($M/year)		34.9
Expected operating costs ($M/year)		696.9
Expected total costs ($M/year)		767.8

4.6.2 Sensitivity Analysis

In what follows, an analysis of the sensitivity of the best solution found to (one-at-a-time) changes in the conditions that characterize the reference case was executed.

Minimum investment costs

Here, the effect of the minimum investment costs parameter (i_{min}) on the best solution is analyzed. For this parameter there are two aspects of interest. One concerns with the number of aircraft to purchase when $i_{\text{min}} = 0$, i.e., constraint (4.8) is relaxed; the second is to analyze the effect of this parameter on the mix of aircraft to purchase.

With respect to the first aspect, and as evidenced in Table 4.10, the number of aircraft to purchase to minimize the expected total costs (in the absence of a minimum investment constraint), is zero. Indeed, as depicted in Figure 4.8, the expected total costs tend to decrease as investment decreases (and leasing increases). This result, although it may be somewhat surprising, is consistent with the opinions expressed for instance in Wojahn (2012) and by experts of the field with whom this results were discussed (e.g. De Neufville, 2015). It finds explanation in the level of flexibility that airline managers will have for adjusting the fleet mix to the realization of the passenger demand. Indeed, if the airline does not purchase any new aircraft the mentioned level of flexibility will be the maximum possible. However, as highlighted by TAP officials, aircraft ownership increases the financial value of the airline, and this is a factor that cannot be neglected in fleet planning decisions.

Table 4.10 – Impact of changes in the minimum investment costs

Indicator		Minimum investment costs ($M)					
		0	216	432	648	864	1080
Number of new aircraft		3-7	3-6	3-7	3-8	4-8	5-7
Purchased	A330-200	0	0	0	2	2	4
	A350-800	0	1	2	0	2	1
	A350-900	0	0	0	1	0	0
	A350-1000	0	0	0	0	0	0
Leased		3-7	2-5	1-5	0-5	0-4	0-2
Number of existing aircraft		7	7	7	7	7	7
Total number of aircraft		10-14	10-13	10-14	10-15	11-15	12-14
Investment costs ($M)		0.0	254.0	508.0	720.0	940.0	1118.0
Expected leasing costs ($M/year)		71.4	58.5	42.8	30.6	20.3	11.9
Expected operating costs ($M/year)		660.5	668.4	670.5	679.0	688.3	702.0
Expected total costs ($M/year)		731.9	739.6	738.7	745.6	755.7	769.8

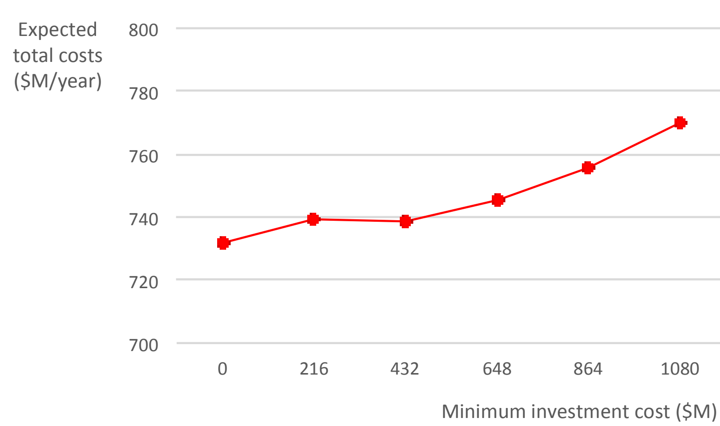

Figure 4.8 – Impact of minimum investment costs on expected total costs

As for the mix of aircraft to purchase, when the parameter $i_{\min}$ is strictly smaller than $648M (which is the investment required by three A330-200), the best option is the purchase of aircraft of the A350 series, i.e., aircraft with larger seat capacity and larger investment costs, but smaller operating costs per seat. On the other hand, when the minimum investment increases, the solution points to the purchase of smaller size aircraft. Again, these results are consistent and they can be explained by the flexibility of adjusting the fleet mix to the realization of the future demand. In fact, in the former case ($i_{\min}$ < \$648M), at most two aircraft can be purchase and the fleet size is of at most nine aircraft. Under all the scenarios, it is necessary to lease at least one aircraft in order to meet the demand. Therefore, the airline has a certain degree of flexibility given by the reduced size of the fleet and can take advantage of the opportunity of diversifying its fleet. It is also interesting to observe that increasing the amount of investments, i.e., increasing the size of fleet, there are scenarios for which the leasing of aircraft is not needed. This situation may signal the case of unused seat capacity; situation that would be even more likely and exacerbated if larger aircraft were purchased. Summarizing, the purchase of four aircraft or more is not economically convenient.

Number of A330-200 to replace

In the reference case, five of the older A330-200 in TAP's fleet are dismissed. In Table 4.11 the solutions for the cases that consider a number of dismissed aircraft equal to four and six are also reported.

Table 4.11 – Impact of changes in the number of A330-200 to replace

Indicator		Number of A330-200 to replace		
		4	5	6
Number of new aircraft		3-7	3-8	4-9
Purchased	A330-200	0	2	1
	A350-800	3	0	2
	A350-900	0	1	0
	A350-1000	0	0	0
Leased		0-4	0-5	1-6
Number of existing aircraft		8	7	6
Total number of aircraft		11-15	10-15	10-15
Investment costs (\$M)		762.0	720.0	724.0
Expected leasing costs (\$M/year)		18.2	30.6	43.9
Expected operating costs (\$M/year)		685.4	679.0	676.2
Expected total costs (\$M/year)		741.8	745.6	756.4

In all the cases, the number of aircraft to purchase is three, which is somewhat imposed by the minimum investment constraint. Increasing the number of dismissed aircraft, the fleet size shrinks and consequently increases the number of leased aircraft. Therefore, exists a direct relationship between the number of leased aircraft and the number of A330-200 dismissed. Obviously, increasing the number of leased aircraft, so do the leasing costs. However, the larger number of leased aircraft has a positive effect on the operating costs as a result of a better adjustment of the fleet mix to the realization of the demand and the inclusion in the fleet of more efficient aircraft. The decrease in operating costs is nevertheless not enough to compensate for the additional leasing costs, and the expected total costs increase with the number of aircraft dismissed.

It is also interesting to note the effect of the number of aircraft to replace on the investment costs. Given the limited “budget” of the airline, reducing the number of dismissed aircraft with the consequent contraction of the leasing costs the airline has the capability to invest more on the purchasing of new aircraft and diversify the fleet, as TAP has already a fleet of 8 (=12-4) A330-200. Again, fleet diversification is a key point for an effective demand response. On this subject, it should also be recalled that the demand is multidimensional, as there is one demand value for each destination in each scenario.

Operational leasing costs

For the analysis of the impact of variations in leasing costs, these were taken to be 10% or 30% higher than (discounted) investment costs, in addition to the 20% considered in the reference case. The main conclusion was that the increase of leasing costs has a modest impact on the expected total costs, which is not surprising since they account for only a small fraction of the total costs (Table 4.12). However, because of the interrelations between investment, leasing and operational costs, the variations of one of the listed costs lead to a different cost structure with the consequent change in the fleet mix used to meet demand.

Table 4.12 – Impact of changes in operational leasing costs

Indicator		Operational leasing costs (% above discounted investment costs)		
		10	20	30
Number of new aircraft		3-7	3-8	3-8
Purchased	A330-200	1	2	2
	A350-800	2	0	0
	A350-900	0	1	1
	A350-1000	0	0	0
Leased		0-4	0-5	0-5
Number of existing aircraft		7	7	7
Total number of aircraft		10-14	10-15	10-15
Investment costs ($M)		724.0	720.0	720.0
Expected leasing costs ($M/year)		28.9	30.6	33.5
Expected operating costs ($M/year)		678.5	679.0	679.3
Expected total costs ($M/year)		743.6	745.6	748.8

When leasing costs are 10% higher than the discounted investment costs, i.e., in the case of most inexpensive leasing costs, TAP has the opportunity to invest a larger budget on the purchasing of new aircraft. Even if the increment of the investment costs is rather small with respect to the total budget invested, it allows purchasing two A350-800 and one A330-200. Observe that, the total seat capacity of this combination of aircraft is of 798 seats and is smaller than the one obtained with the mix proposed by the solutions of the other two cases (e.g., 20% and 30%). In this situation, the airline has more flexibility to adjust the fleet to the different demand scenarios and may operate with better seats occupancy rate. Indeed, this mix is also particularly suitable for scenarios with high demand, as the purchased A350-800 aircraft will be used to serve destinations like Fortaleza and Recife, and larger aircraft will be leased to serve destinations with the higher demand, i.e., São Paulo and Rio de Janeiro.

When the leasing of aircraft is more expensive, e.g., 20% higher than the discounted investment costs or even more, to compensate the higher leasing costs the airline reduces the investment in new aircraft, purchasing two A330-200 and one A350-900. The obtained fleet mix, though flexible to accommodate most of the demand scenario, may require a larger number of leased aircraft in the scenario with highest demand, which is somewhat counterintuitive – higher leasing costs and larger number of leased aircraft. However, this is due to the combination of demand at the different destinations, the fleet owned by the airline and the related interdependencies between the different components of the cost structure.

Number of demand scenarios

The reference case was built upon 20 demand scenarios. This number may look small, but by augmenting it, it was verified that for 30 or 40 scenarios (and even for 60) the best solution found is exactly the same, both with respect to the number and the types of aircraft to purchase and to the range of aircraft to lease (Table 4.13). In contrast, if only 10 scenarios were considered, the solution would involve a smaller fleet, and one of the aircraft to purchase could be of a smaller size (an A350-800 instead of an A350-900). This indicates that 20 scenarios are enough to deal properly with uncertainty.

Table 4.13 – Impact of changes in the number of demand scenarios

Indicator		Number of demand scenarios			
		10	20	30	40
Number of new aircraft		4-7	3-8	3-8	3-8
Purchased	A330-200	2	2	2	2
	A350-800	1	0	0	0
	A350-900	0	1	1	1
	A350-1000	0	0	0	0
Leased		1-4	0-5	0-5	0-5
Number of existing aircraft		7	7	7	7
Total number of aircraft		11-14	10-15	10-15	10-15
Investment costs ($M)		686.0	720.0	720.0	720.0
Expected leasing costs ($M/year)		26.9	30.6	33.6	34.9
Expected operating costs ($M/year)		653.5	679.0	692.4	697.0
Expected total costs ($M/year)		714.7	745.6	762.0	767.9

Another feature of these results that deserves to be mentioned is the increase of expected total costs with the number of demand scenarios. Normally, the expected total costs should oscillate around the mean while converging to it. This does not occur in this case because, as stated earlier, the average demand for the first 20 scenarios is rather low. Hence, instead of oscillating around the mean, expected total costs converge to the population mean from below, and progressively less quickly as the number of demand scenarios increases.

Level of risk protection

By increasing the parameter level of risk protection (α), it was imposed that the optimal solution will also accommodate scenarios with the largest air traffic demand (Table 4.14). Obviously, the higher the level of protection, the higher will be the expected total costs. For instance, in the case of α=1, the first stage decisions are also hedged against scenarios with the highest demand. This requires higher investment costs and, in case of realization of the highest demand scenario, higher leasing costs. Moreover, for scenarios with large demand the operating costs will be larger as the airline will operate a larger number of flights in order to meet the demand.

Table 4.14 – Impact of changes in the level of risk protection

Indicator		Level of risk protection (%)		
		80	90	100
Number of new aircraft		3-7	3-8	3-8
Purchased	A330-200	2	2	1
	A350-800	1	0	2
	A350-900	0	1	0
	A350-1000	0	0	0
Leased		0-4	0-5	0-5
Number of existing aircraft		7	7	7
Total number of aircraft		10-14	10-15	10-15
Investment costs ($M)		686.0	720.0	724.0
Expected leasing costs ($M/year)		26.3	30.6	37.8
Expected operating costs ($M/year)		653.1	679.0	705.9
Expected total costs ($M/year)		713.7	745.6	779.9

On the other hand, considering a value of α=0.8 means that the highest demand scenarios are disregarded and the fleet planning is accomplished by holding a more prudent position with respect to the possibility of increasing the Brazilian air traffic market. Consideration that is also signalled by the reduced amount of investments and the smaller seat capacity, gained with the new purchased aircraft, with respect to the other two cases.

4.7 Conclusion

In this chapter, a study on the renovation of the long-haul fleet used by TAP Air Portugal to serve the (uncertain) passenger demand between Portugal (Lisbon) and Brazil, in the year 2020, was presented. At present, the fleet serving this very important TAP market is rather old, as 7 of the 12 Airbus A330-200 that usually perform the flights are more than 15 years old. The objective of the study was to shed light on the number and the types of aircraft that should replace the older aircraft, and on whether they should be purchased or operationally leased.

To solve TAP's fleet planning problem, a stochastic mixed-integer optimization model was developed, and it can be considered to be a relevant addition to the airline planning toolbox currently available. Indeed, despite being relatively simple, the developed model captures the essential constituents of the problem under analysis, and the results provide very clear insights into how TAP should renovate its fleet. In particular, it has shown that the leasing of aircraft is an option that should definitely be taken into consideration by TAP, since it allows the carrier to deal with demand uncertainty without spending the large amount of resources associated to the purchase of new aircraft.

As recognized by the TAP Air Portugal officials who accompanied the study and discussed its results, the model proposed can be useful in its present form. However, there are some improvements that could increase its value for airlines. One of the possible improvements relates to decisions on the destinations to serve non-stop by an airline. In the application to TAP, these markets were defined exogenously (they were the same TAP currently serves), but it would not be difficult to extend the model so that these markets were defined endogenously. After this extension, the model would become an integrated network design and fleet planning optimization tool. As far as one can tell, this type of tool does not exist today, and could be of great utility in airline planning processes.

Because the proposed model can be used by airlines with much larger networks than TAP, some effort has also to be devoted to the implementation of more efficient solution algorithms. On this subject, it would be possible to take advantage of the most advanced features of optimization software (Klotz and Newman, 2013) and of specialized algorithms for stochastic integer programs, see e.g. Schultz (2003) and Sen (2005). For instance, because the proposed model is a stochastic integer program with complete fixed recourse, it can be solved by the Scenario Updating Algorithm (Lulli and Sen, 2006). The Scenario Updating Algorithm has the additional feature that can also be used as a tool for post-optimality analysis, i.e., to explore the influence of out-of-sample scenarios on the solution of the stochastic program, similarly to the Contamination Method first proposed by Dupacová (1995) for stochastic linear programs.

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5 SHORT-DISTANCE MODEL

5.1 Introduction

A fleet composition model applied to a short-distance fleet presents some differences, in comparison to the long-distance model. When it comes to a short-distance network, the airline fleet routes are also an aspect that should be taken into account. Instead of a leg-based demand, it is more common to deal with origin-destination (OD) pairs and the demand between those origin and destinations.

One of the major differences of this short-distance model, in comparison with the long-distance model presented previously, is the inclusion of the weekly flights performed by the airline as a term in the objective function. This means that the distance and time of each flight will also have an impact on the total costs for the airline, which is an assumption that is closer to what happens in reality. Associated to each flight completed by an aircraft, there is a cost depending on the distance flown, as well as on the capacity of the aircraft that operated that same flight.

The initial problem that will be addressed in this chapter can be described as follows: an airline needs to define the fleet for accommodating a given daily demand between several airports. The demand varies across the year from season to season. The flight distance between the airports is known. The type of aircraft that will make the flights is to be chosen among a given set of aircraft types. For each one of these aircraft types, the number of seats, the range, the maximum speed, and the turn time (the time required to unload an aircraft after its arrival at the gate and to prepare it for departure again) are known. The objective is to determine the fleet size and mix that minimizes the total costs of the airline or that maximizes its revenues (knowing the average airfares for each trip segments). The pursuit of this objective needs naturally to take into account budget constraints that may limit the extent of fleet changes that the airline can carry out, as well as the alternatives the airline has with respect to finance these changes (buying vs. leasing/renting).

In order to address this problem, a case study inspired in TAP's European operations was constructed, based on its short-distance fleet and network. The main goal is to define whether or not TAP Air Portugal would benefit in making some changes in its short-distance fleet. In the case of positive answer, what changes should TAP perform? Should they expand their fleet, by adding some new aircraft to their already existing fleet? Or, instead, should they replace some old aircraft, and maintaining the size of the fleet? Which option would be more advantageous for the airline? These are some of the questions that will be answered in the following sections.

5.2 Case Study

In this section, a case study inspired in TAP Europe market and operations is presented. The short-haul flights' network of TAP is described, as well as the passengers' demand for several destinations in Europe served by TAP is determined. The airline's short-distance fleet is also characterized. All the information presented is referred to the year of 2013, especially due to the major changes in TAP's short-distance fleet that have occurred in 2014, and that will not be taken into account into this study. Furthermore, the study of this TAP Europe case was initiated in 2013, which means that the data was collected at that time.

5.2.1 Flight Network

In 2013, TAP Air Portugal operated short-haul flights for 49 different destinations in Europe: 7 cities in Portugal, continental and islands (in addition to TAP hubs, Lisbon and Oporto), and 40 other destinations around Europe (see Table 5.1 and Figure 5.1).

Table 5.1 – TAP Air Portugal destinations in Europe (source: TAP, 2017)

CONTINENT	COUNTRY	CITY
Europe	Austria	Vienna
	Belgium	Brussels
	Croatia	Zagreb
	Czech Republic	Prague
	Denmark	Copenhagen
	Finland	Helsinki
	France	Bordeaux
		Lyon
		Marseille
		Nice
		Paris
		Toulouse
	Germany	Berlin
		Dusseldorf
		Frankfurt
		Hamburg
		Munich
	Hungary	Budapest
	Italy	Bologna
		Milan
		Rome
		Venice
	Luxembourg	Luxembourg
	Netherlands	Amsterdam
	Norway	Oslo

CONTINENT	COUNTRY	CITY
Europe	Poland	Warsaw
	Portugal	Faro
		Funchal
		Horta
		Lisbon
		Pico
		Ponta Delgada
		Porto
		Porto Santo
		Terceira
	Romania	Bucharest
	Russian Federation	Moscow
	Spain	Barcelona
		Bilbao
		Coruña
		Madrid
		Malaga
		Seville
		Valencia
	Sweden	Stockholm
	Swuitzerland	Geneva
		Zurich
	United Kingdom	London
		Manchester

The short-distance network of TAP has suffered some changes in the last few years. Some destinations were terminated (such as Zagreb, Budapest and Bucharest), whereas some new destinations were added to the network (for example, Nantes and Vigo). Therefore, the currently TAP short-distance network presents some substantial changes in comparison to the one the airline operated in 2013. Nevertheless, the network described here is the one TAP operated in 2013, and this is the one in which this case study is going to be based on.

Figure 5.1 – TAP Air Portugal: routes within Europe
(source: Airline Route Maps, 2017)

As it is possible to observe from Table 5.1 and Figure 5.1, presented above, the European destinations to where TAP flies are the capitals of the other European countries, and other major European cities. Furthermore, and as expected, TAP also operates to other cities in Portugal, mainly to the Portuguese archipelagos, Azores and Madeira. Some of the European destinations are highly populated, such as London and Paris, whereas other destinations present lower population, for example, Venice, Luxembourg and Geneva, as well as the Portuguese destinations in the islands.

5.2.2 Passenger Demand

TAP is responsible for operating around 700 weekly short-haul flights to several destinations in Europe, with origin in Lisbon, and around 150 weekly flights from Oporto. These numbers regard only direct flights (with non-stop). In 2013, around 6.530 million passengers flew with TAP, only in Europe.

Considering the destinations mentioned previously, the passengers' demand for each one of the destinations, from Lisbon and Oporto, was obtained through the Eurostat database (Eurostat, 2013): Database by themes → Transport → Air transport → Air transport measurement - passengers → Detailed passenger transport by reporting country and routes. The obtained data was presented per quarter of the year of 2013, and the daily average passengers' demand was calculated accordingly.

Since the data from the Eurostat database concerns the passengers' movements between two different airports, it was then necessary to calculate the demand only related to TAP flights. Based on a flights' schedule from the airports of Lisbon and Oporto (ANA, 2014a, 2014b), in which the information regarding the airlines performing the flights was also presented, it was possible to obtain the proportion of passengers' daily demand representative of TAP flights. These final values are displayed per quarter of the year of 2013, in Table 5.2 (flights with origin in Lisbon) and Table 5.3 (flights with origin in Oporto).

Table 5.2 – TAP passengers' daily demand from Lisbon (2013)

	1st qtr	2nd qtr	3rd qtr	4th qtr
Lisbon	0	0	0	0
Oporto	365	469	539	419
Vienna	78	138	133	123
Brussels	189	252	315	206
Zagreb	0	0	0	0
Prague	55	144	206	92
Copenhagen	208	297	356	262
Bordeaux	75	81	90	71
Lyon	145	222	241	172
Marseille	0	0	0	0
Paris	543	765	895	685
Toulouse	76	122	134	97
Berlin	108	147	156	135
Frankfurt	301	445	497	361
Hamburg	90	129	149	112
Munich	119	163	184	145
Budapest	95	119	151	81
Milan	208	240	251	229
Rome	353	448	516	358
Venice	163	198	236	166

	1st qtr	2nd qtr	3rd qtr	4th qtr
Luxembourg	57	63	68	70
Amsterdam	321	461	511	396
Oslo	115	124	199	111
Faro	235	242	291	215
Funchal	600	883	968	846
Horta	40	76	129	45
Ponta Delgada	68	107	129	85
Porto Santo	0	0	0	0
Terceira	116	151	216	133
Barcelona	399	471	493	427
Bilbao	56	123	145	128
Madrid	439	501	530	458
Valencia	59	98	110	96
Stockholm	106	119	127	112
Geneva	298	313	386	302
Zurich	303	421	495	319
London	577	735	788	635
Manchester	66	83	119	78

Table 5.3 – TAP passengers' daily demand from Oporto (2013)

	1st qtr	2nd qtr	3rd qtr	4th qtr
Lisbon	421	479	552	435
Oporto	0	0	0	0
Vienna	0	0	0	0
Brussels	51	106	117	73
Zagreb	0	0	0	0
Prague	0	0	0	0
Copenhagen	0	0	0	0
Bordeaux	61	75	88	70
Lyon	0	0	0	0
Marseille	0	0	0	0
Paris	222	274	336	268
Toulouse	0	0	0	0
Berlin	0	0	0	0
Frankfurt	0	0	0	0
Hamburg	0	0	0	0
Munich	0	0	0	0
Budapest	0	0	0	0
Milan	0	0	0	0
Rome	0	0	0	0
Venice	0	0	0	0

	1st qtr	2nd qtr	3rd qtr	4th qtr
Luxembourg	56	54	80	64
Amsterdam	31	95	95	79
Oslo	0	0	0	0
Faro	0	0	0	0
Funchal	134	184	277	167
Horta	0	0	0	0
Ponta Delgada	0	0	0	0
Porto Santo	0	0	0	0
Terceira	0	0	0	0
Barcelona	172	199	211	189
Bilbao	0	0	0	0
Madrid	128	144	158	138
Valencia	0	0	0	0
Stockholm	0	0	0	0
Geneva	187	198	243	213
Zurich	122	131	181	116
London	70	84	93	79
Manchester	0	0	0	0

In order to work on the side of safety and to assure that the solution found (in terms of the airline fleet composition) can give response to the demand in the majority of the possible scenarios, a peak factor of 25% was applied to the obtained passengers' demand values.

As it is possible to observe, in regards to all the destinations enumerated in the previously presented Table 5.1, it was not possible to obtain demand information for all of them, from the Eurostat database. Therefore, and being this a case study inspired in TAP European operations, some of the destinations were not took into consideration, such as Helsinki (Finland), Nice (France), Dusseldorf (Germany), Bologna, Warsaw (Poland), Pico (Portugal), Bucharest (Romania), Moscow (Russia), and Coruña, Malaga and Seville (Spain). For all the other destinations, it was possible to obtain passengers' demand information for the year of 2013.

5.2.3 Aircraft Fleet

In 2013, the short-haul fleet of TAP Air Portugal included 39 aircraft of TAP and 14 aircraft from Portugália (Companhia Portuguesa de Transportes Aéreos, S.A. – PGA), which is a subsidiary carrier of TAP Air Portugal, founded in 1988. TAP's fleet has been the same since 2010. In a total of 53 aircraft, the fleet is composed mainly by aircraft type Airbus (19 of type A319, 17 of type A320-200, and 3 of type A321-200, of TAP), and 14 other aircraft, from PGA (8 of type Embraer 145, and 6 Fokker 100), plus 2 aircraft in wet lease (Aircraft, Crew, Maintenance and Insurance – ACMI)[6] of OMNI Aviation[7].

From Figure 5.2, one can observe that the great majority of the fleet is more than 15 years old (first flight before the year 2000), more specifically, the fleet older than 15 years old corresponds to 75% of the total short-haul fleet. Furthermore, some of the aircraft are more than 25 years old (4 aircraft performed their first flight before 1990). Thus, the short-haul fleet of TAP can be considered quite old. Furthermore, and because of the continuous evolution of technology, some new and more technologically advanced models of aircraft have been developed in the last years. Additionally, older aircraft frequently present higher values for fuel consumption, as well as more tendency to develop technical problems and eventually breakdowns, which can obviously represent large amounts of spending for the airline, in order to keep its fleet working safely and efficiently.

[6] A wet lease is a leasing arrangement in which one airline or aircraft company (the lessor) provides an aircraft, complete crew, maintenance, and insurance (ACMI) to another airline or other type of business acting as a broker of air transportation (the lessee). The lessee pays by hours operated, and is responsible for providing fuel and covering airport fees, and any other duties or taxes. The flight number is also the flight number of the lessee. A wet lease generally lasts 1–24 months, and it is typically utilized during peak traffic seasons or annual heavy maintenance checks, or even to initiate new routes (see also 2.2.2 Aircraft Leasing).

[7] The OMNI Aviation is a Portuguese private group that offers expertise and know-how in almost every areas of aviation (helicopters operation, commercial and business aviation, emergency medical air services, and aviation support areas). The segment of OMNI that deals with operation of commercial aircraft in Portugal is the White Airways that manages and regulates all the options of Full Charter, Wet Lease or ACMI for the clients. More information in Omni Aviation (2017).

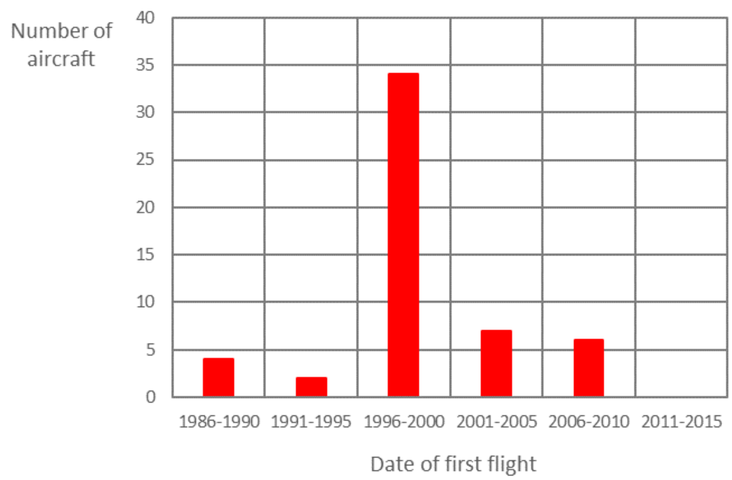

Figure 5.2 – Date of first flight for the aircraft of TAP's short-haul fleet (source: Airfleets, 2017)

Bearing in mind the facts mentioned previously, TAP Air Portugal could definitely study the hypothesis of making some changes in its fleet. Thus, the main goal of this case study is to see whether or not it would be beneficial for the airline to perform those changes in its short-haul fleet. And in case of a positive answer, how should those changes occur? Should the older aircraft be replaced for new aircraft? If yes, which ones would be better to replace? And which new models would be the best option for TAP to purchase? Or instead of replacing older aircraft, should TAP keep all the existing fleet and acquire some new models to enlarge its short-distance fleet?

In order to answer all these questions, this study was developed taking into consideration that the demand of 2013, for the European destinations served by TAP, does not suffer major changes. So, in this study the demand was considered to be stationary, so the changes on the fleet would occur in that same year.

In terms of the sample of available aircraft models, from which the new models can be chosen, the same models that currently exist in TAP's short-haul fleet were considered to be part of that sample (see Table 5.4). Although there are already some new models in the market (particularly from Airbus), these are the ones more adequate to perform short-haul flights, especially because of their capacity and range.

Table 5.4 – Aircraft characteristics (models in TAP's short-haul fleet) (source: TAP, 2016; Embraer, 2007)

Type of Aircraft	Seats	Speed [km/h]	Range [km]	Turn Round Time [min]	COSTS	
					Capital [M$]	Operating [$/seat/km]
A319	124	828	6950	36	83.6	0.0437
A320-200	150	828	6100	43	91.5	0.0401
A321-200	185	828	5950	51	107.3	0.0385
ERJ145	50	828	2873	20	21.0	0.0516

Based on all the information provided in this section, the case study presented is going to be developed under two major distinctive objectives: 1) should TAP replace older aircraft in its short-distance fleet, and acquire some new models? And how many of each type?; and 2) should TAP keep the already existing short-distance fleet, and enlarge it by acquiring new models of aircraft? And how many of each type?.

5.3 Fleet Planning Optimization Model

In this chapter, an optimization model representing the essential ingredients of an airline fleet planning problem is provided. The main objective of this model is to determine the optimal fleet composition for a given airline, while minimizing the total costs associated to that fleet composition. The model was developed with inspiration on the work of Fresco (2012).

The main purpose of the model is to define how many aircraft of each type should the airline own so that its total costs are minimized. The total costs can be divided into capital costs (associated to the ownership of the aircraft) and operating costs (labor, fuel, insurance, maintenance, etc.).

5.3.1 Model Formulation

For formulating the model the following notation will be used:

<u>Sets</u>

N = *{1,...,N}*: set of origin and destination nodes (airports);

K = *{1,...,K}*: set of types of aircraft;

M = *{1,...,M}*: set of time periods.

<u>Parameters</u>

Q_{ijm}: demand faced by the airline in route *ij*, in period *m* (passengers/day);

D_{ij}: distance (great circle) for a flight between airports *i* and *j* (km);

s_k: number of seats of an aircraft of type *k*;

r_k: range of an aircraft of type *k* (km);

v_k: maximum speed of an aircraft of type *k* (km/h);

t_k: turn time of an aircraft of type *k* (min);

$c^c{}_k$: capital cost of an aircraft of type *k* (M$);

$c^o{}_k$: operating cost of an aircraft of type *k* ($/seat/km);

ρ: discount rate (%/year);

δ_m: number of days in period *m*;

β: peak factor.

<u>Decision variables</u>

X_k: number of aircraft of type *k* owned by the airline;

Z_{ijkm}: number of daily flights in route *ij* made by an aircraft of type *k* in period *m*.

Given this notation, the model can be formulated as follows:

$$\min C = \sum_{k \in K} \rho . c_k^c . X_k + \sum_{i,j \in N} \sum_{k \in K} \sum_{m \in M} \frac{\delta_m}{10^6} . c_k^o . d_{ij} . s_k . Z_{ijkm} \tag{5.1}$$

Subject to:

$$\sum_{k \in K} s_k . Z_{ijkm} \geq \beta . Q_{ijm}, \forall i, j \in \mathrm{N}, m \in \mathrm{M} \tag{5.2}$$

$$\sum_{i,j\in N}\left(\frac{d_{ij}}{v_k}+t_k\right).Z_{ijkm}\leq 12.X_k,\forall k\in \mathrm{K},m\in \mathrm{M} \tag{5.3}$$

$$Z_{ijkm}\leq a_k,\forall i,j\in \mathrm{N},k\in \mathrm{K},m\in \mathrm{M},a_k=\begin{cases}1000\leftarrow D_{ij}\leq r_k\\ 0\leftarrow D_{ij}\rangle r_k\end{cases} \tag{5.4}$$

$$\sum_{j\in N}Z_{jikm}=\sum_{j\in N}Z_{ijkm},\forall i,j\in \mathrm{N},k\in \mathrm{K},m\in \mathrm{M} \tag{5.5}$$

The objective function (5.1) of this integer optimization model minimizes the discounted annual costs incurred by the airline (expressed in M$/year). Its first term represents the capital costs and the second term represents the operating costs. The division by 10^6 included in the second term is used to convert $ into M$.

Constraints (5.2) are capacity constraints and guarantee that, in each route and period (e.g., month or season), the total number of aircraft seats is enough to accommodate the demand. Constraints (5.3) are time constraints, stipulating that the time spent with flights and turnaround operations cannot exceed the maximum daily operation time (assumed to be 12 hours – Airline Data Project, 2013) for each aircraft type. Constraints (5.4) guarantee that the distance flown by an aircraft does not exceed its flight range. Finally, constraints (5.5) are continuity constraints, stating that the number of aircraft of each type arriving daily to each airport is the same as the number of aircraft of that type departing from the airport.

5.4 Study Results

The application of the optimization model to the TAP Europe inspired case study presented previously, revealed some detailed and interesting results, which are going to be presented in this section.

5.4.1 Initial Solution

The main goal of this study is to shed some light on how would it be more beneficial for TAP Air Portugal to plan, arrange and adjust its short-distance fleet, taking into account a certain given demand for some of the its most important destinations in Europe. The first analysis performed consists on defining the optimal solution for the airline, considering that the airline is planning its fleet from the very beginning (no initial fleet), and can freely choose the aircraft to compose its short-distance fleet. The sample of aircraft from where the airline can choose its fleet is presented in Table 5.5. As it is possible to observe, besides the aircraft models currently present in TAP short-distance fleet, a model Bombardier CS100 was also taken into account, since this is an aircraft type that can clearly compete with the others models from the sample, especially in terms of seat capacity and costs.

Table 5.5 – Aircraft characteristics (initial solution)
(source: TAP, 2016; Embraer, 2007; Bombardier Commercial Aircraft, 2017b)

Type of Aircraft	Seats	Speed [km/h]	Range [km]	Turn Round Time [min]	COSTS	
					Capital [M$]	Operating [$/seat/km]
A319	124	828	6950	36	83.6	0.0437
A320-200	150	828	6100	43	91.5	0.0401
A321-200	185	828	5950	51	107.3	0.0385
ERJ145	50	828	2873	20	21.0	0.0516
CS100	108	829	5741	30	76.5	0.0396

The model was solved using FICO Xpress (a top-market optimization software) on a Samsung equipped with a 2.50 GHz Intel Core i5-3210M CPU. After several hours of computation, the initial solution found was not yet a guaranteed optimal solution, but the optimal gap obtained was however rather small (≈ 1%). The fleet composition obtain for this initial analysis is presented in Table 5.6.The total annual-equivalent cost for this solution is 447.16 M€/year. In terms of the distribution between capital and operating costs, the former corresponds to 2487.00 M$ (= 124.35 M$/year), and the latter to 322.81 M$/year.

Table 5.6 – Initial fleet composition

Aircraft Type	Number
A319	1
A320-200	5
A321-200	8
ERJ145	19
CS100	9
Total	42

The dominant type of aircraft is the Embraer ERJ145, followed by the Bombardier CS100 and then the Airbus models. The total number of aircraft in the fleet is 42, corresponding to 4276 seats. As stated before, the total number of aircraft in the short-distance fleet of TAP was 53, in 2013 (see previous section 5.2.3 Aircraft Fleet), which is reflected in a total seat capacity of 6503. This differences in terms of number of aircraft in the fleet (and, consequently, in terms of seat capacity) can be explained by the fact that an airline always needs to have more aircraft in tits fleet than only the ones required to satisfy the demand. This extra number of aircraft allows the airline to deal with possible and unexpected immobilization of aircraft due to maintenance issues, damages, inspections, etc. Therefore, there is always the need to include an additional number of aircraft in an airline fleet mix. In this case, these aspects are not being addressed, which can explain the lower number of aircraft in the fleet obtained in this initial solution.

Furthermore, according to TAP's report form 2013, 61% of their total carried passengers in that year had their final destination in Europe. This percentage corresponds to a total of approximately 6.5 million passengers, who have flown with TAP. From the previously presented Table 5.2 and Table 5.3, and considering a 25% peak factor, it is possible to calculate that, for this case study, the total number of passengers carried by TAP, in Europe, corresponds to about 4.8 million. In comparison to what happened in reality, for the year of 2013, one can conclude that in this TAP Europe inspired case study, the demand being considered is around 80% of TAP's real demand, which also helps explaining the lower number of aircraft in the fleet obtained with the model. Additionally, and by analyzing the obtained results in terms of fleet composition, the seat capacity of this initial solution (Table 5.6) corresponds to 4276 seats, in total. This number represents a portion of approximately

66%, in comparison to the real seat capacity of TAP's short-distance fleet. Although these values present a quite significant difference, this disparity can be explained by the distribution of weekly flights by the airline and its final timetable. If the existing fleet presents lower seat capacity, the number of flights that the airline will have to perform will be higher, in order to give response to the passengers' expected demand.

In Table 5.7 and Table 5.8, it is possible to observe the results obtained in terms of the average daily flights for each type of aircraft (flights with origin in Lisbon and Oporto), for the initial solution described above. Since the demand varies according to four different periods, there was the need to calculate the average number of daily flights, in order to better analyze the results as a whole, for the entire year of 2013. The average number of TAP daily flights to Europe is 108.5, from Lisbon (34 destinations in total), and 22.75, from Oporto (11 destinations in total). As expected, destinations with higher demand values are the ones served by a higher number of flights (more than 5 daily flights, in average), such as Oporto, Paris, Funchal, Madrid and London, with origin in Lisbon. From Oporto, Geneva and Zurich are the cities served by a higher number .flights (more than 3 daily flights, in average).

From this results, it is also possible to observe that larger aircraft, with higher seat capacity (the Airbus models), are more used to operate flights in longer legs, such as Lisbon-Copenhagen. Furthermore, they can also be used in shorter legs, but with higher demand values, such as Lisbon-Paris, Lisbon-Hamburg, Lisbon-Rome, and Porto-Paris. The Embraer ERJ145, with only 50 seat capacity is most frequently used in shorter legs, for instance, Lisbon-Oporto, Lisbon-Faro, and Lisbon-Madrid.

From Table 5.7, it is possible to observe, for instance, that the flights between Lisbon and Oporto are performed by the aircraft models Airbus A321-200 (8 in total in the fleet), Embraer ERJ145 (19 in total in the fleet) and Bombardier CS100 (9 in total in the fleet). One curious aspect that is also possible to see in Table 5.7 is that every model of aircraft in the fleet operates flights in the legs Lisbon-Copenhagen and Lisbon-Paris. The average total number of daily flights from Lisbon to Paris is quite large (7.25). However, for the leg Lisbon-Copenhagen this value is not that high (only 3), in comparison to other legs. This result, although it may seem quite strange initially, it can possibly be explained by the distribution of flights per period (week/month). For example, the aircraft A319, A320-200, A321-200 and ERJ145 operate less than one flight per day (0.25 or 0.5), which means that each one of this models of aircraft perform only one flight in every four days, on average.

Table 5.7 – Average daily flights for each type of aircraft – origin in Lisbon

	A319	A320-200	A321-200	ERJ145	CS100	TOTAL
Oporto	0	0	0.5	7.5	1	9
Vienna	0	0	0.5	0.25	0.5	1.25
Brussels	0	0.5	0.25	0	1.75	2.5
Prague	0.25	0.25	0.25	0	0.5	1.25
Copenhagen	0.25	0.5	0.5	0.5	1.25	3
Bordeaux	0.25	0	0	0.5	0.5	1.25
Lyon	0	0	0.5	1.5	0.75	2.75
Paris	0.25	0.75	1.75	0.75	3.75	7.25
Toulouse	0.5	0	0	0.5	0.5	1.5
Berlin	0	0.5	0.5	0.25	0	1.25
Frankfurt	0	1.25	0.75	1	1.25	4.25
Hamburg	0.25	0.5	0.25	0.25	0	1.25
Munich	0	0.25	0.5	0.75	0.25	1.75
Budapest	0.25	0.5	0	0.25	0.25	1.25
Milan	0	0.5	0.25	0.75	1.25	2.75
Rome	0	1	1.25	0.5	1.25	4
Venice	0	0.75	0	0.5	1	2.25
Luxembourg	0	0	0	1	0.5	1.5
Amsterdam	0	0.75	1	1	1.75	4.5
Oslo	0	0.75	0	0.75	0.25	1.75
Faro	0	0.5	0	4.5	0.25	5.25
Funchal	0	0.75	1.75	4.75	3.5	10.75
Horta	0	0	0.25	0.75	0.25	1.25
Ponta Delgada	0	0.25	0.25	0	0.5	1
Terceira	0	0.5	0.5	0.75	0	1.75
Barcelona	0	0.75	1	1.75	1.75	5.25
Bilbao	0	0	0.25	1.25	0.5	2
Madrid	0	0	1	5.5	1.5	8
Valencia	0.5	0	0	0.75	0.25	1.5
Stockholm	0	0.75	0.25	0	0	1
Geneva	0	0.25	0.75	2	1.25	4.25
Zurich	0	0.5	1.5	1	0.75	3.75
London	0	0.5	3.25	0	1.75	5.5
Manchester	0	0.25	0	0	0.75	1
TOTAL	2.5	13.75	19.5	41.5	31.25	108.5

Table 5.8 – Average daily flights for each type of aircraft – origin in Oporto

	A319	A320-200	A321-200	ERJ145	CS100	TOTAL
Brussels	0	0.5	0	0	0.5	1
Bordeaux	0.25	0	0	0.5	0.5	1.25
Paris	0	0.25	1.25	0.5	0.5	2.5
Luxembourg	0	0	0	0.5	0.75	1.25
Amsterdam	0.5	0	0	0.25	0.25	1
Funchal	0	0	0.5	2	0.5	3
Barcelona	0	0.5	0	0.75	1.25	2.5
Madrid	0	0	0.75	1	0	1.75
Geneva	0	0	0.5	3	0.25	3.75
Zurich	0.25	0	0	2.5	0.25	3
London	0	0	0	1.25	0.5	1.75
TOTAL	1	1.25	3	12.25	5.25	22.75

The previous tables present the average number of daily flights, for each type of aircraft. However, it is also possible to calculate the average daily flights performed by each aircraft (42 in total in the fleet). These results are presented in Table 5.9, for flights departing from Lisbon and Oporto.

Table 5.9 – Average daily flights per aircraft in the fleet

	Lisbon	Oporto
A319	2.50	1.00
A320-200	2.75	0.25
A321-200	2.44	0.38
ERJ145	2.18	0.64
CS100	3.47	0.58

For flights with origin in Lisbon, one can see that the Bombardier CS100 (9 in total in the fleet) is the model performing a higher average number of daily flights, followed by the Airbus A320-200 (5 in total in the fleet). The Embraer ERJ145, although being the model with a higher representation in the fleet (19 in total), is the aircraft operating a lower average number of daily flights. For the case where the flights depart from Oporto, the average number of daily flights is more evenly distributed, being the aircraft A319 responsible for operating an average of 1 flights per day, while all the other models of aircraft perform an average of less than 1 flight per day.

5.4.2 Complementary Analysis

The complementary analysis performed is based on the assumption that the initial fleet of the airline is the one obtained with the previous analysis, and that the airline wants to make some changes in its initial fleet composition, in order to meet some requirements. In general terms, with this analysis, some key questions for the airline will try to be answered, such as: which aircraft should the airline keep, and which ones should be replaced; how many and which type of aircraft should the airline buy.

In order to answer these questions, the complementary analysis was developed considering three different possibilities, which were elaborated as new cases:

a) The airline wants to keep the more recent aircraft models in the fleet, and replace the older ones;
b) The airline wants to replace all the Embraer aircraft existing in the fleet, since these are the ones with a lower seat capacity;
c) The airline wants to uniform the fleet to an all-Airbus fleet, so they will replace all the Embraer and Bombardier models, and will only buy new Airbus.

Although this analysis is based on some new possible changes that TAP can make considering its initial fleet, the results in terms of costs will be presented considering that the fleet is again constituted from zero, in order to allow the comparison with the initial solution found and presented previously (best solution found to meet the existing demand).

Case 1) Replacement of the older aircraft in the fleet

For this first analysis, and based on the information about the age of the short-distance fleet of TAP, it was assumed that approximately half of the number of each type of aircraft existing in the fleet would be replaced for new aircraft types. That means that the initial fleet for the airline is 0 A319, 2 A320-200, 4 A321-200, 9 ERJ145 and 4 CS100. The obtained results in terms of the new fleet composition and costs, regarding the best solution found in 0.5h of computation, are presented in Table 5.10.

Table 5.10 – Costs and fleet composition (case 1)

Total Expected Costs (M$/year)			452.43
Capital Costs (M$)			2570.60
Operating Costs (M$/year)			323.90
Aircraft Type	Existing Fleet	New Fleet	Total Fleet
A319	0	2	2
A320-200	2	3	5
A321-200	4	4	8
ERJ145	9	10	19
CS100	4	5	9
Total	19	24	43

From Table 5.10, it is possible to observe that, by replacing some of the older aircraft in the fleet, the choice of the new aircraft models will be similar to the ones being replaced. This is an expected result, since the demand is considered to be static. The only difference, in terms of fleet composition, is the number of A319 models, which is equal to 2 for this case, and in the initial solution was equal to 1, being the total number of aircraft in the fleet higher in this case than in the initial solution. In terms of costs for the airline, this solution presents higher total expected costs, as well as higher capital and operating costs, being the last ones the costs that present a lower increase in relation to the initial solution.

Regarding the distribution of the average daily flights, from Lisbon and Oporto, these results are present in Table 5.11 and Table 5.12.

Since the number of A319 in the fleet is higher, as expected, the number of average daily flights, in total, performed by this aircraft model is also higher, in comparison to the initial solution. In terms of the average number of TAP daily flights to the European destinations, in total, the value for this solution is exactly the same as in the initial solution. From Lisbon, TAP operates an average of 108.75 daily flights, to a total of 34 destinations, and 22.75 daily flights, from Oporto, with 11 destinations in total. Also similar to the obtained results for the initial solution, in this case, larger aircraft are also used to operate longer legs, or shorter legs but with high demands. And smaller aircraft models are used to fly in shorter legs.

Table 5.11 – Average daily flights for each type of aircraft – origin in Lisbon (case 1)

	A319	A320	A321	E145	CS100	TOTAL
Oporto	0.25	0.25	0.25	7.5	0.75	9
Vienna	0.25	0	0.25	0.5	0.5	1.5
Brussels	0	0.5	0.25	0.5	1.5	2.75
Prague	0.25	0.25	0.25	0	0.5	1.25
Copenhagen	0	0.25	0.75	0.5	1.5	3
Bordeaux	0.25	0	0	0.5	0.5	1.25
Lyon	0	0	0.5	1.5	0.75	2.75
Paris	0.25	0.25	2	3	3.25	8.75
Toulouse	0.5	0	0	0.5	0.5	1.5
Berlin	0	0.5	0.5	0.25	0	1.25
Frankfurt	0.25	0.75	1.25	0.25	1.25	3.75
Hamburg	0.25	0.5	0.25	0.25	0	1.25
Munich	0	0.25	0.5	0.75	0.25	1.75
Budapest	0.25	0.5	0	0.25	0.25	1.25
Milan	0	0.5	0.25	0.75	1.25	2.75
Rome	0	1.5	1.25	0	0.75	3.5
Venice	0	0.75	0	0.5	1	2.25
Luxembourg	0	0	0	1	0.5	1.5
Amsterdam	0	0.75	1	0	2.25	4
Oslo	0	0.75	0	0.75	0.25	1.75
Faro	0	0.5	0	4.5	0.25	5.25
Funchal	0	0.75	2.25	5	2.5	10.5
Horta	0	0	0.25	0.75	0.25	1.25
Ponta Delgada	0	0.25	0.25	0	0.5	1
Terceira	0	0.5	0.5	0.75	0	1.75
Barcelona	0	0.25	0.5	1.75	3.25	5.75
Bilbao	0.25	0	0	1.5	0.5	2.25
Madrid	1	0	0.75	3.75	1.5	7
Valencia	0.5	0	0	0.75	0.25	1.5
Stockholm	0	0.75	0.25	0	0	1
Geneva	0	0.25	0.5	1.5	2	4.25
Zurich	0	0.5	1.5	1	0.75	3.75
London	0	0.25	3.25	0.25	2	5.75
Manchester	0	0.25	0	0	0.75	1
TOTAL	4.25	12.5	19.25	40.75	32	108.75

Table 5.12 – Average daily flights for each type of aircraft – origin in Oporto (case 1)

	A319	A320	A321	E145	CS100	TOTAL
Brussels	0	0.5	0	0	0.5	1
Bordeaux	0.25	0	0	0.5	0.5	1.25
Paris	0	0.25	1.25	0.5	0.5	2.5
Luxembourg	0	0	0	1	0.5	1.5
Amsterdam	0.5	0	0	0.25	0.25	1
Funchal	0.25	0	0.25	1.75	0.75	3
Barcelona	0	0.5	0	0.75	1.25	2.5
Madrid	0	0	0.75	1	0	1.75
Geneva	0.25	0	0.25	3.25	0.25	4
Zurich	0.25	0	0	2.5	0.25	3
London	0.25	0	0	0.5	0.5	1.25
TOTAL	1.75	1.25	2.5	12	5.25	22.75

From Table 5.11 and Table 5.12, one can also observe that the legs Lisbon-Oporto, Lisbon-Paris, and Lisbon-Frankfurt are operated by all the types of aircraft in the fleet, at some point. In the initial solution, this happened only for the legs Lisbon-Copenhagen and Lisbon-Paris. This results may be explained by the distribution of the daily flights per period (week/month), and the possible convenience in terms of schedule and fleet availability, for the airline, to assign different aircraft to the same flight, depending on the day the flight will occur.

In terms of the average daily flights per aircraft in the fleet (Table 5.13), in this case, and considering the origin in Lisbon, the Bombardier CS100 is the aircraft model that performs a higher average number of daily flights, followed by the Airbus models (specially A320-200 and A321-200). For flights departing from Oporto, the A319 model is the type of aircraft more used to fly.

Table 5.13 – Average daily flights per aircraft in the fleet (case 1)

	Lisbon	Oporto
A319	2.13	0.88
A320-200	2.50	0.25
A321-200	2.41	0.31
ERJ145	2.14	0.63
CS100	3.56	0.58

Case 2) Replacement of all the Embraer aircraft models

In this second case, the airline wants to replace all the Embraer models in the fleet, since these are the ones presenting lower seat capacity (only 50 seats). Furthermore, the airline does not want to but any more of these models of aircraft, so the sample of available aircraft will be reduced to the three Airbus models and to the Bombardier CS100. The obtained results, in terms of costs and fleet composition, for this case, are presented in Table 5.14.

Table 5.14 – Costs and fleet composition (case 2)

Total Expected Costs (M$/year)			461.81
Capital Costs (M$)			2928.00
Operating Costs (M$/year)			315.41
Aircraft Type	Existing Fleet	New Fleet	Total Fleet
A319	1	2	3
A320-200	5	2	7
A321-200	8	1	9
ERJ145	0	0	0
CS100	9	5	14
Total	23	10	33

This solution presents a lower total number of aircraft in the fleet (33 in comparison to 42 in the initial solution). Nevertheless, in terms of individual aircraft models, all of them will be included in the new fleet in a higher number. Since there is no possibility of buying new Embraer ERJ145 models, and taking into consideration that in the initial solution there were 19 of this aircraft model, this new solution shows that the Bombardier is an adequate option to replace the old Embraer aircraft (5 new Bombardier CS100, in comparison to 2 and 1 for the Airbus models). Although in this case, the total expected and capital costs are higher than the initial solution, it is possible to observe that in terms of operating costs, this solution presents lower operating costs (315.41 M$/year for this case, in comparison to 322.81 M$/year, in the initial solution). This can be explained by the fact that, as mentioned previously, the total number of aircraft in this new fleet is lower (only 33, in comparison to the 42 in the initial solution).

The number of average daily flights performed by the aircrafts of this fleet is presented in Table 5.15 and Table 5.16.

Table 5.15 – Average daily flights for each type of aircraft – origin in Lisbon (case 2)

	A319	A320	A321	CS100	TOTAL
Oporto	0	1.25	0.75	2.5	4.5
Vienna	0	0	0.75	0.25	1
Brussels	0	0.5	0.25	1.75	2.5
Prague	0.25	0.25	0.25	0.5	1.25
Copenhagen	0.25	1.25	0.5	0.5	2.5
Bordeaux	0.25	0	0	0.75	1
Lyon	0.25	0	0.75	0.75	1.75
Paris	0.25	0.75	3	2	6
Toulouse	0.25	0	0.5	0.25	1
Berlin	0	0.25	0.5	0.5	1.25
Frankfurt	0	1	1.25	1.25	3.5
Hamburg	0.25	0.25	0.25	0.5	1.25
Munich	0.25	0.25	0.25	0.75	1.5
Budapest	0.25	0.25	0	0.75	1.25
Milan	0	0.5	0.5	1.25	2.25
Rome	0.75	1.25	0.75	1	3.75
Venice	0	0.75	0	1.25	2
Luxembourg	0	0	0	1	1
Amsterdam	0	0.5	1.5	1.75	3.75
Oslo	0	0.75	0.25	0.25	1.25
Faro	0.25	1	0	1.25	2.5
Funchal	0	0.25	2.25	5.5	8
Horta	0	0	0.25	0.75	1
Ponta Delgada	0	0.25	0.25	0.5	1
Terceira	0.25	0.5	0.25	0.5	1.5
Barcelona	0	0.5	0.5	3.75	4.75
Bilbao	0	0	0.75	0.25	1
Madrid	0.25	0.25	1.75	2	4.25
Valencia	0.5	0.25	0	0.25	1
Stockholm	0	0.75	0.25	0	1
Geneva	0	0.5	1	1.5	3
Zurich	0	0.5	0.5	3	4
London	0	0.25	3.75	1.25	5.25
Manchester	0	0.25	0	0.75	1
TOTAL	4.25	15	23.5	40.75	83.5

Table 5.16 – Average daily flights for each type of aircraft – origin in Oporto (case 2)

	A319	A320	A321	CS100	TOTAL
Brussels	0	0.5	0	0.5	1
Bordeaux	0.25	0	0	0.75	1
Paris	0	0.5	1.25	0.5	2.25
Luxembourg	0	0	0	1	1
Amsterdam	0.5	0	0	0.5	1
Funchal	0.25	0.25	0.25	1.25	2
Barcelona	0.25	0.75	0	1	2
Madrid	0	0	0.75	0.5	1.25
Geneva	0.25	0.75	0	1.25	2.25
Zurich	0.25	0.25	0.5	0.25	1.25
London	0.25	0	0	0.75	1
TOTAL	2	3	2.75	8.25	16

The results presented show that the number of total daily flights operated is lower than in the initial solution and in Case 1. From Lisbon, there are an average of 83.5 flights departing to Europe, and from Oporto, only 16 flights per day. In terms of the legs that are performed by every type of aircraft in the fleet, in this case, there are a lot more than in the previous solutions: Lisbon to Prague, Copenhagen, Paris, Hamburg, Munich, Rome, Terceira, and Madrid. And from Porto to Funchal and Zurich. It is worth noting that, in this case, there is one less model of aircraft in the fleet, since it is considered that the airline does not want to buy new Embraer models. Therefore, it is expected that, with lower number of aircraft models in the fleet, there are more legs being operated by several types of aircraft.

Regarding the average daily flights per aircraft in the fleet (Table 5.17), the Bombardier CS100 is the type of aircraft in the fleet responsible for a larger number of flights, when Lisbon is the origin node, whereas from Oporto, the A319 is the model used to operate a larger number of daily flights.

Table 5.17 – Average daily flights per aircraft in the fleet (case 2)

	Lisbon	Oporto
A319	1.42	0.67
A320-200	2.14	0.43
A321-200	2.61	0.31
CS100	2.91	0.59

Case 3) Standardization of the fleet: all-Airbus

In this last case, the airline wants to uniform the fleet, to an all-Airbus fleet. Therefore, all the existing Embraer and Bombardier are going to be replaced, and the sample of available aircraft will only include the three Airbus models. The initial fleet will consist on 1 A319, 5 A320-200, and 8 A321-200. The obtained results for this case are presented in Table 5.18.

Table 5.18 – Costs and fleet composition (case 3)

Total Expected Costs (M$/year)			479.66
Capital Costs (M$)			2983.30
Operating Costs (M$/year)			330.50
Aircraft Type	Existing Fleet	New Fleet	Total Fleet
A319	1	10	11
A320-200	5	7	12
A321-200	8	1	9
ERJ145	0	0	0
CS100	0	0	0
Total	14	18	32

In terms of costs for the airline, it is possible to see that this is a solution substantially more expensive that the initial one (479.66 M$/year for this case, in comparison to 447.16 M$/year for the initial solution). And, as opposed to case 2, in this case, the operating costs are also significantly higher than the initial solution. The aircraft model A320-200 is the one presenting higher representation in the total fleet, and the A319 is the type of aircraft that suffers a higher increase, in terms of the new acquired fleet. For the A321-200, the result is exactly the contrary.

In Table 5.19 and Table 5.20, the average number of daily flights per type of aircraft in the fleet is presented. Although from Lisbon, the total number of daily flights departing, in average, is lower than in all the cases before (77.5 flights per day), the number of daily flights operated from Oporto is similar to case 2 (15.5 flights per day, in comparison to 16 in case 2).

Table 5.19 – Average daily flights for each type of aircraft – origin in Lisbon (case 3)

	A319	A320	A321	TOTAL
Oporto	1.25	1.75	1	4
Vienna	0.25	0	0.75	1
Brussels	1.25	0.75	0.25	2.25
Prague	0.75	0.25	0.25	1.25
Copenhagen	1	1.25	0.25	2.5
Bordeaux	1	0	0	1
Lyon	0.75	0.5	0.5	1.75
Paris	0.5	2.25	2.75	5.5
Toulouse	0.5	0	0.5	1
Berlin	0.5	0.25	0.5	1.25
Frankfurt	1.5	1.25	0.75	3.5
Hamburg	0.75	0.25	0.25	1.25
Munich	1	0.25	0.25	1.5
Budapest	1	0.25	0	1.25
Milan	0.25	1.5	0.25	2
Rome	0.25	2.75	0.5	3.5
Venice	1.5	0.5	0	2
Luxembourg	1	0	0	1
Amsterdam	1	1.25	1.25	3.5
Oslo	0.25	0.75	0.25	1.25
Faro	1.25	0.75	0.25	2.25
Funchal	0.75	4.25	1.75	6.75
Horta	0.75	0	0.25	1
Ponta Delgada	0.5	0.25	0.25	1
Terceira	0.75	0.5	0.25	1.5
Barcelona	0.5	1.25	1.75	3.5
Bilbao	0.25	0	0.75	1
Madrid	1	2	1	4
Valencia	0.75	0.25	0	1
Stockholm	0	0.75	0.25	1
Geneva	1.5	1.25	0.25	3
Zurich	0.75	1.5	1	3.25
London	0.75	0.5	3.75	5
Manchester	0.75	0.25	0	1
TOTAL	26.5	29.25	21.75	77.5

From the analysis of these tables, it is also possible to observe that there are some legs operated by only one type of aircraft, such as from Lisbon to Bordeaux, and Luxembourg, and from Oporto to Bordeaux, Luxembourg, Amsterdam, and London. All these legs are operated only by A319 aircraft, with an average of 1 daily flight.

Since the fleet is composed by only 3 Airbus models, the distribution of the flights by each type of aircraft is more homogeneous than in the previous cases, where the airline's fleet was composed by several different models of aircraft.

Table 5.20 – Average daily flights for each type of aircraft – origin in Oporto (case 3)

	A319	A320	A321	TOTAL
Brussels	0.5	0.5	0	1
Bordeaux	1	0	0	1
Paris	0.25	1.25	0.75	2.25
Luxembourg	1	0	0	1
Amsterdam	1	0	0	1
Funchal	1	0	0.75	1.75
Barcelona	1.5	0.5	0	2
Madrid	0.5	0	0.75	1.25
Geneva	1.5	0.25	0.25	2
Zurich	0.5	0.25	0.5	1.25
London	1	0	0	1
TOTAL	9.75	2.75	3	15.5

In terms of the average daily flights per aircraft in the fleet, these results are presented in Table 5.21. It is possible to observe that, also as mentioned previously, the distribution of flights across the type of aircraft is more consistent, especially in the case where the flights depart from Lisbon. For flights operated form Oporto, the A319 is clearly the aircraft more used to fly.

Table 5.21 – Average daily flights per aircraft in the fleet (case 3)

	Lisbon	Oporto
A319	2.41	1.25
A320-200	2.44	0.36
A321-200	2.42	0.40

5.5 Possible Improvements to the Model

The model presented above captures some of the essential ingredients of airline fleet planning problems, but does not account for other important features of such problems.

In the first place, the model focuses on cost minimization. A more relevant objective for airlines can definitely be the maximization of profit. This objective could be easily coped with by considering a revenue term in the objective function, consisting in the multiplication of the average airfare in each leg by the demand for that leg. This demand could be made a function of airfare (and possibly also of market share), but this would make the model nonlinear (in addition to being integer), thus more difficult to solve.

A second shortcoming of the model relates to the fact that it does not take budget constraints into account, in particular constraints related to the investment capabilities of the airline. These constraints could be easily incorporated in the model, either directly or indirectly by considering an upper limit on the number of aircraft of each type (wide body, large, small) to replace. In addition to this upper limit, a lower limit could also be consider, to reflect the fact that some aircraft may be too aged and have to be retired from operations for technological reasons.

Another significant extension of the model would be to consider that the airline can own or lease/rent the aircraft used for its operations. This would in particular be useful for the airline to cope with demand in peak seasons, probably paying more for the leased aircraft in such seasons than they would pay for owned aircraft, but avoiding the costs of having owned aircraft idle in the remaining seasons. This extension of the model would also be easy to handle.

An additional improvement of potential interest relates to the fact that, as formulated, the model tends to favor the use of large aircraft over small aircraft in a given leg because, unless demand is too low, large aircraft are less costly per passenger. This signifies that the beneficial effect of increasing flight frequencies (thus reducing schedule delays), is not taken into account. To avoid this, it would be helpful to consider the total number of flights (in the whole network or in the most competitive legs) as a second objective of the model.

The model can also be enhanced with respect to the way demand is handled. Indeed, it works with leg based demand whereas origin/destination based demand is a more meaningful way of handling demand. The consideration of O/D based demand would allow network design (including hub location) and fleet composition issues to be dealt with in an integrated manner, but would make the model clearly more complicate.

A final important improvement to the model would consist of considering the dynamic and uncertain features of the fleet composition problem. The essential decisions to be made refer to the medium term – what should the fleet be in, for instance, 5 years. However, these decisions have long-term implications, and should be made considering the evolutions of demand, costs and possibly also airfares in the next 20 or 25 years. Over such long time horizons, these evolutions are highly uncertain, and it is doubtful that they can be approached without considering different possible states of the world (scenarios) and the respective probabilities. In such circumstances, more than seeking expected minimum cost or maximum profit solutions, airlines will probably look for robust solutions – solutions that will perform well in all or most scenarios, but are not necessarily optimal in any of them.

An improved model combining all these features at the same time would certainly help airlines to make well informed decisions with respect to the composition of their fleet. However, it is unlikely that, except for very small instances, it could be solved to optimality or even near-optimality within reasonable computation effort using FICO Xpress. Therefore, specialized exact algorithms or, alternatively, efficient heuristic algorithms may have to be developed for handling the improved model.

5.6 Conclusion

The previous study presented an airline fleet planning optimization model, applied to a TAP Europe inspired case study. The initial problem was presented as the determination of an airline fleet for accommodating a given daily demand between several airports, considering that the demand will vary across the year, from season to season. The flight distance between the airports was known, as well as the type of aircraft (and its characteristics) of the sample from which the airline could choose the new aircraft models to compose its fleet. The objective was to determine the best fleet composition that would minimize the costs for the airline.

The application of the model to a case study inspired in TAP Europe operations provided some clear insights on how TAP could benefit in making some changes in its short-distance fleet. Furthermore, it was possible to conclude that the model could be a helpful tool for airlines, when dealing with fleet planning problems, providing good results and solutions for short-distance fleets and operations.

The obtained results show that, in a case where it is possible to acquire a fleet from zero (considering that there is no initial fleet), the total number of aircraft would be similar to the one TAP already has in its short-distance fleet. However, in terms of fleet mix, there would be some significant changes, since the majority of the aircraft would be Embraer models, while, in reality, TAP has a larger percentage of Airbus models. This can be explained by the fact that Embraer acquisition (or capital) costs are way smaller than for Airbus models (even though Embraer operating costs are higher than for Airbus models), which means that for an initial investment in new aircraft, the best option would be to choose cheaper aircraft models. Nevertheless, the Airbus models would allow the airline to fulfill the demand for more distant destinations with lower operating costs.

In reality, it is not feasible for TAP to simply build a new whole fleet from scratch, due to budget and investment constraints. Therefore, one of the possibilities would be to replace some of the older aircraft and keep the most recent models. The results show that, in comparison to other types of solutions (for instance, replace all the Embraer models, or become an all-Airbus fleet), replacing the older aircraft regardless of their type, would be a better option in terms of costs for the airline.

The proposed model and application described in this chapter are definitely a good starting point for airlines to use when planning their fleets. It can provide good results in some specific circumstances, such as in case of short-haul operations, and when applied for a particular static time period. Nevertheless, there are certainly some improvements that could be implemented, in order to ameliorate this tool. One of these improvements would be, for instance, to use an objective function that would take into account the profit for the airline, instead of minimizing the airline's costs. Furthermore, including the option of leasing aircraft would also be a significant and more realistic change. Finally, a more relevant improvement could definitely be to include the uncertain features and dynamic of the airline fleet problem. Several possible future scenarios could be considered, which would represent the possible future demand in a more accurate way. Additionally, different time periods could be taken into account, in order to perform a more close to the reality fleet planning, considering several time stages for the planning horizon.

6 CONCLUSION

In this final chapter of the Thesis, the main conclusions of the work will be drawn, and some suggestions of possible improvements and future work will be enumerated.

6.1 Main Conclusions

The objectives that were initially defined for this work were mostly achieved, and it is possible to say that the work of this Thesis, in particular, the two optimization models developed, can certainly contribute as a fairly helpful tool for airlines when dealing with fleet planning decisions.

An extensive review on the existing literature in terms of fleet planning problems, in general, and airline fleet planning problems, in particular, was successfully carried out. It was possible to identify and classify the most relevant optimization models developed under these topics. The leasing of aircraft was also a subject under study, and a broad investigation on the existing research on aircraft leasing was provided. Although issues related with airline fleet planning have already been widely investigated, both in terms of optimization analysis and modelling of the fleet planning problem (from the airlines point of view), there are still some gaps in the research field. Some of the developed and presented papers do not consider the option of aircraft leasing, while others do not take into consideration the dynamic and/or the uncertain features of the fleet planning problem.

It was possible to identify the different aircraft manufacturers existing nowadays and a description and characterization the aircraft types currently present in the aviation market was provided. It was also performed an analysis on the evolution of aircraft models throughout time. Furthermore, this work also includes a rank of the world's largest airlines, as well as a general review on airlines' efficiency, productivity and costs. Four airlines were chosen (American Airlines and Delta Air Lines, from the United States; and Ryanair and Lufthansa, from Europe) to be examined in terms of their fleets' evolution, throughout the years. American Airlines and Delta Air Lines are two of the biggest airlines in the world, and present a fleet mix of mainly Airbus, Boeing, and McDonnell Douglas models. In Europe, Ryanair and Lufthansa are two of the largest airlines. Ryanair currently existing fleet is an only-Boeing 737-800 (next Generation) fleet, while Lufthansa's fleet is predominantly composed by Airbus models (although it also includes some Boeing aircraft).

Two different airline fleet planning optimization models were developed, presented and applied to real case studies. The first model is a long-distance optimization model, developed to understand how TAP Air Portugal could renovate its long-haul fleet to serve the (uncertain) passenger demand between Portugal (Lisbon) and Brazil, in the year 2020. Being its long-distance fleet rather old (the majority of the fleet is more than 15 years old), the objective was to clarify and help on TAP decisions on the number and types of aircraft that should replace the older aircraft, and on whether they should be purchased or operationally leased. The stochastic mixed-integer optimization model developed captures the essential constituents of the problem under analysis, and the results provide very clear insights into how TAP should renovate its fleet. Therefore, it can be considered to be a relevant addition to the airline planning toolbox currently available in the market. The results have shown that the leasing of aircraft is an option that should definitely be taken into consideration by TAP, since it will allow the airline to deal with uncertain demand without having to spend a large amount of resources in the purchase of new aircraft.

The second optimization model developed is more adequate to solve short-distance airline fleet planning problems. The objective was to calculate the optimal fleet for an airline, while minimizing its total costs. The fleet needs to accommodate a certain daily demand between several airports (considering some variation of the demand, from season to season), and the fleet mix will be chosen among a sample of aircraft models. The model was applied to a case study inspired in TAP Europe operations. The results show that TAP could benefit in making some changes in its short-distance fleet, mainly by replacing some of the older aircraft, while keeping the more recent ones.

It is fair to say that the work here presented, mainly the two optimization models developed, can certainly contribute as a legitimately helpful tool for airlines when dealing with fleet planning decisions. Both fleet planning optimization models allow the airline to answer some key questions, such as how many, and which type of aircraft should the airline purchase, dispose or lease, and when should these actions take place, for a given time horizon.

6.2 Possible Improvements and Future Work

Although the work presented in this Thesis proves to be valuable for airlines and aviation sector in general, there is still room for improvements and some future work that can be developed based on what was already presented.

In order to complement and further develop the work presented in Chapter 3, it would be interesting to explore some other subjects, such as fleet planning and evolution of fleets in air cargo companies. This subject was not address in this Thesis and there is not much research already developed on the topic. Although in terms of demand, freight companies represent a big part of air transportation, the literature including demand cargo airlines is very scant. It would be interesting to investigate which are the major airlines responsible for the freight transportation in the world, which are their most important routes, and how do they manage their fleets, when thinking about retiring old aircraft and acquiring new ones. Another aspect that could be explored in terms freight airlines would be the comparison between the different features that passengers and freight airlines take into consideration, when taking decisions about their fleets' management. For instance, find out which aspects (costs, safety, quality, comfort…) are more important for each type of airlines. In addition, the evolution of freight airlines' fleet would also be a topic of interest to devote further investigation.

From Chapter 4, where a long-distance fleet planning optimization model was applied to TAP Brazil case study, there is some future developments than can be applied. The model presented is already a valuable and useful tool by itself, and can be used by airlines when planning their long-distance fleet. However, there are some improvements that could increase its value for airlines. One simple change would be to include decisions concerning whether to serve the destinations with direct flights. In the case study presented, this was a decision based on what happens in reality with TAP flights to Brazil, but it would not be difficult to extend the model formulation in order to accommodate this decision. After this extension, the model would become an integrated network design and fleet planning optimization tool, which is a type of tool that, as far as one can tell, does not exist today.

Furthermore, in order to allow airlines with larger networks to use the developed model, some effort would also need to be devoted to the implementation of more efficient solution algorithms. For instance, some further research could be done on the most advanced features of optimization software, and on specialized algorithms for stochastic integer programs (e.g. Scenario Updating Algorithm, and/or Contamination Method).

In relation to the short-distance fleet planning optimization model presented in Chapter 5, although this is a model that captures some of the essential ingredients of an airline fleet planning problem, there are still some other important features that could be included, in order to improve the model. For instance, in terms of the objective function of the model, it was used the minimization of the costs for the airline. However, it would be more relevant to define it as a maximization of the airline profit. This would be a quite easy change to include, by simply adding a revenue term in the objective function (average air fare of each leg times the demand in that specific leg).

Another weakness of the model is the fact that budget constraints are not taken into account, which would be a way of representing the investment capacity of the airline. Again, this would be simple to incorporate in the model, by considering an upper bound of the number of aircraft type to replace. Moreover, and somehow related to the budget constraints, a relevant improvement would be to include the leasing of aircraft as an option for the airline's operations. This addition would allow the airline to more efficiently cope with demand, especially during peak seasons.

Finally, an important and more relevant improvement to this short-distance model would be to take into account the dynamic and uncertain features of the fleet composition problem. Fleet planning airlines' decisions usually refer to the medium term (e.g. 5 years), however these mid-term decisions have implications also in the long-term horizon, and should consider the evolutions of demand, costs and possibly also airfares in the next 20 or 25 years. Therefore, the inevitable uncertainty of future demand is something that needs to be taken into account, by the means of different possible future scenarios that would represent the diverse states of the world. Furthermore, in terms of demand, some changes could also be implemented, especially in relation to the way it is handled. Instead of leg based demand, it would be more meaningful to work with origin/destination demand, which would also allow to integrate network design issues into the fleet composition initial problem. Nevertheless, a problem with these characteristics would clearly become more complex.

An ameliorated and improved model combining all these previously mentioned features would certainly help airlines to make well informed decisions with respect to the composition of their fleet. However, it is doubtful whether a problem with this complexity (especially in the case of larger instances) could be solved to optimality or even near-optimality within reasonable computation effort using FICO Xpress. For that reason, and in order to handle the improved model, there would be the need to develop some specialized exact algorithms or, alternatively, efficient heuristic algorithms.

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