LONG TERM AIRLINE FLEET UTILIZATION AND HEAVY CHECK PLANNING PROBLEM

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ABSTRACT

LONG TERM AIRLINE FLEET UTILIZATION AND HEAVY CHECK PLANNING PROBLEM

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Airlines consistently struggle to make profits. The airline industry is competitive. Industry regulations are strict, and they get more challenging over time. Demand shocks are frequent. Suppliers (fuel companies, aircraft manufacturers, etc.) are powerful against airlines. Most of the time, not the airlines but customers benefit from technological advances via decreased ticket fares. To be profitable, an airline has to reduce its operating costs. Therefore, the planning process of an airline has been of particular interest to operations researchers for decades. Different lines of research focus on various optimization problems arising in the planning process. The aircraft fleet, solely generating revenue for an airline, is the most critical resource for the company. Therefore, an airline has to utilize this resource effectively. Each aircraft in a fleet has different fuel efficiency, different rental fees, and different emission performance. Utilization planning, i.e., determining the aircraft's flight hour and cycle load, is a critical task. While the studies in the literature make aircraft utilization decisions within operational scheduling problems, we propose making long-term rough-cut utilization decisions. The aim is to develop a long-term optimal utilization strategy that minimizes cost and forms a smooth heavy check maintenance schedule for the fleet while considering utilization terms of operating lease contracts. Heavy checks are costly, time consuming (three-four weeks) shop visits which affect an airline's operations. The rough-cut utilization plan can guide operational scheduling decisions and align short-term goals with the long-term strategy. To this end, this thesis formulates a long-term utilization planning and heavy check scheduling problem. We develop a mathematical model and a naive greedy heuristic for the problem. Finally, we present computational experiments for the proposed methods.

Keywords: Airline Planning Process, Aircraft Utilization Planning, Heavy Check Scheduling, Mathematical Modelling

ÖZ

HAVAYOLU FİLO KULLANIM VE BÜYÜK BAKIM PLANLAMA PROBLEMİ

BULAK BİLGEN, Feyza
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Havayolu şirketleri kar etmede sürekli zorluk yaşamaktadır. Havayolu sektörü çok rekabetçidir. Sektörün tabi olduğu düzenlemeler katıdır ve sürekli daha zorlayıcı hale gelmektedir. Sektörde talep şokları ile sık karşılaşılır. Sektörün tedarikçileri (petrol şirketleri, uçak üreticileri, vb.) havayollarına karşı güçlüdür. Teknolojik yeniliklerle elde edilen maliyet iyileştirmelerinden düşen bilet fiyatları ile çoğunlukla yolcular yararlanır. Havayolları kar elde edebilmek için operasyon maliyetlerini düşürmek zorundadır. Yöneylem araştırmacıları havayolu planlama süreçlerine eskiden beri özel ilgi göstermiştir. Planlama sürecinde ortaya çıkan farklı karar verme problemlerine dönük ayrı araştırma alanları ve yazın ortaya çıkmıştır. Bir havayolunun uçak filosu şirketin cirosunu üreten en önemli kaynağıdır. Havayolu bu kaynağı en etkin şekilde kullanmalıdır. Filodaki her uçak için yakıt verimliliği, kiralama ödemeleri ve emisyon performansı farklıdır. Bu nedenle uçakların kullanım planlaması yani hangi uçağın kaç saat uçuş yapacağı ve kaç uçuş yapacağı kararı kritik bir karardır. Literatürdeki çalışmalar uçakların kullanım kararlarını operasyonel seviyedeki çizelgeleme problemlerini çözerken verir. Bu tez ise uzun-dönemli kaba kullanım kararlarını veren bir problem öneriyor. Amaç maliyetleri minimize eden uzun dönemli kullanım planı yaparken aynı zamanda filo için büyük bakım planlaması yapmak ve uçakların kiralama kontratlarından gelen kullanım koşullarına uymaktır. Büyük bakımlar üç dört hafta süren, maliyetli ve havayolunun operasyonlarını etkileyen bakımlardır. Önerilen uzun dönemli plan operasyonel çizelgeleme kararlarını yönlendirerek kısa vadeli çizelgleme amaçları ile uzun vadeli filo kullanım stratejisinin örtüşmesini sağlayacaktır. Bu tez bir uzun dönemli kaba uçak kullanım planlama ve büyük bakım çizelgeleme problemi tanımlamaktadır. Tez problem için bir matematiksel model ve bir basit açgözlü sezgisel önermektedir. Tez son olarak önerilen yöntemlerin hesaplamalı performansını sunmaktadır.

Anahtar Kelimeler: Havayolu Planlama Süreci, Uçak Kullanım Planı, Büyük Bakım Çizelgeleme, Matematiksel Modelleme

To My Beloved Family

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TABLE OF CONTENTS

ABSTRACT v

ÖZ vii

ACKNOWLEDGMENTS x

TABLE OF CONTENTS xi

LIST OF TABLES xiv

LIST OF FIGURES xvi

LIST OF ABBREVIATIONS xvii

CHAPTERS

1 INTRODUCTION 1

2 A BACKGROUND ON THE AIRLINE PLANNING PROCESS 7

  2.1 Passenger Demand and Traffic 7

  2.2 Fleet Planning 8

  2.3 Route Selection 9

  2.4 Timetable Planning 10

  2.5 Aircraft Scheduling 11

  2.6 Crew Scheduling 13

  2.7 Operating Lease 14

  2.8 Maintenance Planning 16

2.9 A Long Term Utilization Planning Approach 17
3 LITERATURE REVIEW 19
3.1 Fleet Assignment Problem 19
3.2 Maintenance Routing or Aircraft Routing Problem 21
3.3 Tail Assignment Problem 23
3.4 Aircraft Heavy Check Planning 25
3.5 Airline Operational Leasing 27
3.6 The Thesis' Contribution to the Airline Schedule Planning Literature 28
4 AIRCRAFT UTILIZATION AND HEAVY CHECK PLANNING PROBLEM 31
4.1 Problem Definition 31
4.2 Notation 33
4.3 Mathematical Model 38
4.4 Numerical Example 42
4.5 A Naive Greedy Heuristic Algorithm 45
5 COMPUTATIONAL RESULTS 49
5.1 Data Preprocessing 49
5.2 Design of Experimental Study 50
5.3 Computational Results 56
5.3.1 Experimental Results for the Mathematical Model 56
5.3.2 Experimental Results for the Heuristic Algorithm 60
5.3.3 Comparison of the Results of Mathematical Model (MM) and Heuristic Algorithm (HA) 63
6 CONCLUSIONS 67

REFERENCES 69

LIST OF TABLES

TABLES

Table 4.1 Flight plan and hangar capacity of numerical example 43

Table 4.2 Utilization and maintenance plan of 5 aircraft fleet mathematical model solution 43

Table 4.3 Utilization and maintenance plan of 5 aircraft fleet real-life scenario solution 44

Table 4.4 Costs of the utilization and maintenance plan 45

Table 5.1 A section of dataset 50

Table 5.2 Experimental Factors 51

Table 5.3 Performance of IBM CPLEX based on fleet size and planning horizon length 57

Table 5.4 Performance of IBM CPLEX based on fleet size, planning horizon length and operating cost variability 58

Table 5.5 Performance of IBM CPLEX based on fleet size and hangar capacity 58

Table 5.6 Performance of IBM CPLEX based on fleet size and planning horizon length 59

Table 5.7 Performance of IBM CPLEX based on fleet size, planning horizon length and operating cost variability 59

Table 5.8 Performance of IBM CPLEX based on fleet size and hangar capacity 59

Table 5.9 Performance of IBM CPLEX based on fleet size and planning horizon length 60

Table 5.10 Performance of IBM CPLEX based on fleet size, planning horizon length and operating cost variability 60

Table 5.11 Performance of IBM CPLEX based on fleet size and hangar capacity 60

Table 5.12 Performance of Heuristic Algorithm based on fleet size and planning horizon length 61

Table 5.13 Quality of solutions based on fleet size, planning horizon length, and operating cost variability 62

Table 5.14 Quality of solutions based on fleet size, and hangar capacity 63

Table 5.15 Comparison of solution performance 64

Table 5.16 Comparison of solution quality 65

LIST OF FIGURES

FIGURES

Figure 1.1 Share of Leased Aircraft in Airline Industry Statista (2022) . . . 3

Figure 4.1 Flight time distribution of Pegasus Airlines - one week in July 2015 . . . 34

Figure 5.1 Flight time distribution of United Airlines - third week in July 2022 . . . 54

Figure 5.2 Solution Performance of Two Methods . . . 66

LIST OF ABBREVIATIONS

CPP	Crew Pairing Problem
CRP	Crew Rostering Problem
FAP	Fleet Assignment Problem
FC	Flight Cycle
FH	Flight Hour
GHG	Greenhouse Gases
HA	Heuristic Algorithm
IATA	International Air Transport Association
MM	Mathematical Model
MRP	Maintenance Routing Problem
N/A	Not Applicable
OMRP	Operational Maintenance Routing Problem
TAP	Tail Assignment Problem

CHAPTER 1

INTRODUCTION

The airline industry is recovering from the effects of the COVID-19 crisis. In 2023, the industry revenues expected to reach \$803 billion (IATA (2023)), which means a 9.7% increase compared to 2022 but which is still 4.1% below the 2019 revenues. IATA (2023) stated that airlines make \$2.25 per passenger on average and many airlines struggle to provide a sustainable return on invested capital to their investors. McKinsey & Company (2022) claims that airlines should maximize the utilization of their aircraft, especially the new ones, to pay the costs and reach profitability. This thesis defines and formulates a utilization and heavy-check maintenance planning problem for airline companies.

An airline's fleet is its primary asset generating all the revenue. Acquisition of each new aircraft requires a considerable capital investment which necessitates operating the aircraft with high utilization to reduce unit operating costs and achieve profitability. Each aircraft in a fleet has different characteristics regarding fuel costs (engine efficiency), leasing (rent and maintenance reserve) payments, etc. An aircraft joins a fleet at a specified time as agreed in purchase or lease contracts and leaves at a preplanned redelivery or retirement time. An aircraft is not available for operation during its shop visits for maintenance checks. This study focuses on heavy checks. A heavy check maintenance visit typically lasts several weeks and occurs once every fifteen months on average. Aircraft must undergo a heavy maintenance check after accumulating a certain flight hours/number of flight cycles or calendar days. Aircraft utilization decisions determine the total operating cost of a fleet and also dictate when each aircraft will have a maintenance check.

Fleet planning, i.e., determining the composition and size of an aircraft fleet, is an airline's long-term, strategic decision. The planning decisions that shape an airline's fleet at a specific time are typically made 2-5 years earlier. An airline can acquire an aircraft by purchasing or leasing it. Each aircraft joins the fleet at a planned time determined by purchase or lease agreements. Similarly, an aircraft leaves the fleet at a specific time. For instance, an airline has to redeliver a leased aircraft to the lessor at the contracted time. Or, an airline may decide to retire or sell an owned aircraft at a specific time. Acquisition, sales, and retirement decisions result in a fleet plan specifying how many aircraft will exist in a fleet during each period in the future. An airline has to operate all flights in its timetable using the available aircraft in the fleet.

In 2021, at the Annual General Meeting of The International Air Transport Association (IATA), the member airlines committed to achieving net zero carbon emissions by 2050. One crucial strategy to achieve this goal is to renew their fleet with the new generation aircraft having higher fuel efficiency and lower carbon and nitrogen oxide emissions. For instance, Airbus A320 Neo offers a 20% reduction in fuel consumption, a 50% decrease in nitrogen oxide emissions, and a 50% reduction in noise compared to classical A320. Nowadays, many airlines publish their fleet renewal plans (Air France (2023), LATAM (2023), and Qantas (2023)). During this gradual transition to new-generation aircraft, different-generation aircraft with different fuel and green house gas (GHG) emission performance operate in the same fleet. Even the same-generation aircraft usually have different fuel (also GHG emission) efficiencies. For instance, an aircraft that recently had an engine overhaul consumes less fuel. Therefore, aircraft utilization decisions, i.e., flight hours and flight cycles operated by each aircraft in each period, influences the fuel consumption, i.e., operating costs and the emission performance of the fleet.

One of the methods to acquire an aircraft is leasing. Specifically, the operating lease is an extensively used aircraft renting method by airlines. IATA (2017) reported that 43% of the aircraft in the aviation industry fly under an operating lease. Statista (2022) and KPMG (2023) report that the share of leased aircraft in aviation industry has exceeded 50% in 2021 (see Figure 1.1).

In the operating lease, the ownership of the aircraft remains with the lessor, and the lessee only gets the right to use the aircraft. Typically, an operating lease contract

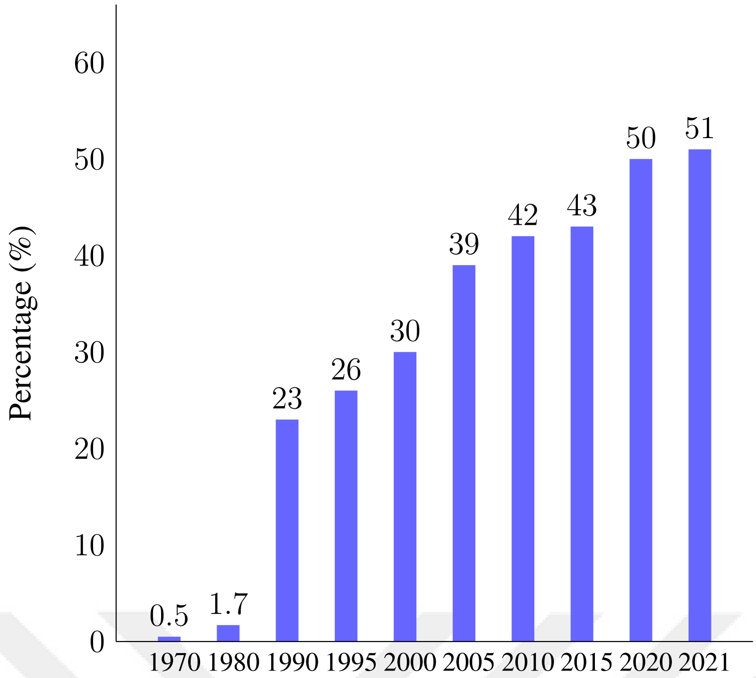

Figure 1.1: Share of Leased Aircraft in Airline Industry Statista (2022)

is made for 5 to 8 years. In an operating lease, along with the rental payments, a lessee has to make regular maintenance reserve payments to the lessor. The money in the maintenance reserve covers the cost of future heavy maintenance checks. Maintenance reserve payments are comparable with rental fees and significantly impact airlines' finances. In addition, operating lease contracts impose some restrictions on the utilization decisions for an aircraft. Violating these restrictions may result in penalty payments made by the lessee. For instance, a leasing contract limits an aircraft's "flight hour/flight cycle" or hour-to-cycle ratio, i.e., the aircraft should operate at certain average flight times throughout the contract period. If the aircraft exceeds this limit in a given year, the lessee must make additional payments to the lessor. Also, an operating lease contract specifies redelivery conditions for an aircraft, i.e., the lessee must return the aircraft to the lessor with a certain amount of flight hours and cycles on it. The lessee must make penalty payments if the accumulated flight hours or flight cycles exceed the agreed levels. Therefore, an airline must consider these leasing contract terms, i.e., payments and utilization conditions, while making aircraft utilization decisions. In the literature, aircraft utilization decisions are considered in operational aircraft scheduling problems. In this thesis, we define a long term aircraft utilization planning problem.

An aircraft is not always available for service, as it has to undergo 3-4 week-long overhauls when required. Predefined maintenance intervals, in terms of calendar months, accumulated flight hours, and flight cycles, determine when an aircraft should visit the shop for a heavy maintenance check. Hence, utilization decisions determine the aircraft's maintenance status. An aircraft has to undergo maintenance as required to stay airworthy. Having too many aircraft under maintenance in the same period is usually not desirable. Airlines need a smooth maintenance schedule to mitigate the risk of failing to operate the flights in the timetable. Otherwise, an airline may have to make expensive short-term aircraft leasing. In addition, an airline usually has a limited workshop capacity for heavy maintenance checks. This also restricts the number of aircraft under maintenance at the same time. These maintenance-related constraints necessitate careful planning of aircraft utilization and heavy check scheduling decisions for a fleet.

In this thesis, we study a long-term fleet utilization and maintenance planning problem for a fleet. In the literature, aircraft utilization decisions are given while solving operational aircraft scheduling problems such as the tail assignment problem (TAP) and operational maintenance routing problem (OMRP). TAP and OMRP deal with detailed scheduling decisions considering spatial and temporal constraints, such as maintenance and turnaround time restrictions. Unlike TAP and OMRP, this thesis studies a long-term aggregate utilization planning problem that makes future aircraft utilization decisions and schedules heavy maintenance checks for the fleet.

We formulate an aircraft utilization planning and heavy maintenance check scheduling problem that aims to minimize a fleet's total operating cost, unused maintenance life cost and redelivery penalty cost while ensuring that constraints regarding timetables, aircraft-specific operating conditions due to leasing contracts, and aircraft maintenance programs are satisfied. To this end, we first develop a mathematical model for the problem. Then, we propose a construction heuristic for the problem. We conduct a computational study to demonstrate the performance of proposed solution approaches.

The rest of the thesis is organized as follows. Chapter2 describes fleet planning, timetable development, aircraft and maintenance scheduling processes for a passenger airline. Chapter 3 reviews the related studies on long term maintenance planning and aircraft scheduling. In Chapter 4, we give problem definition and proposed solution approaches. Chapter 5 presents the results of the computational experiments. We conclude the study in Chapter 6.

CHAPTER 2

A BACKGROUND ON THE AIRLINE PLANNING PROCESS

In this chapter, we briefly discuss the airline planning process. We start with defining airline markets and demand and continue with planning decisions made by an airline.

2.1 Passenger Demand and Traffic

Airline passenger demand is the number of passengers wanting to travel at the given ticket price levels. To cover the demand, the airline industry offers flights. The demand is uncertain. The sector may only be able to satisfy some of the demand or offer excess capacity. The number of passengers that boarded flights gives "traffic". In the airline industry, passenger traffic is usually measured by revenue passenger mile (RPM) or revenue passenger kilometers (RPK). For instance, a flight carrying 120 passengers over 1,000 kilometers generates 120,000 RPKs. To cover the passenger demand, airlines provide a capacity measured by available seat miles (ASM) or available seat kilometers (ASK). A flight by an aircraft with 150 seats over a distance of 1,000 kilometers makes 150,000 ASKs of capacity. The ratio of passenger traffic to airline capacity is called the load factor. Load factor is a measure of total flight capacity sold. An airline's profit is calculated by Total RPK × Average Yield - Total ASK × Unit Cost. For an airline, one possible way of increasing its profit is to reduce the unit cost.

Air travel demand is usually estimated for an origin-destination (O-D) market. It can be the number of persons wishing to travel from an origin city A to a destination city B (one-way passenger trip) during a given period. Alternatively, it can be the number of passengers between A and B in both directions. Demand is affected by many factors. Total trip time is an essential factor. For instance, business travelers' demand is sensitive to trip time. They usually prefer non-stop flights. On the other hand, leisure travelers' demand is more sensitive to price. They are usually more willing to get connecting flights as long as the ticket fare is low. The frequency of flights offered in an O-D market also affects demand. Higher frequency increases the demand from business travelers. In a period under consideration, airlines serve an O-D market by scheduling a single flight or offering connecting flights between O-D cities. Therefore, a flight may serve different O-D markets. An airline offers a network of flights that serve many O-D markets. It may operate different types of aircraft for a flight. It depends on which O-D markets a flight serves. Therefore, airlines hold fleets of different aircraft types. Next, we briefly discuss the fleet planning process of an airline.

2.2 Fleet Planning

At a given time, an airline operates a certain number of aircraft. These aircraft may be of different types. Two critical characteristics differ between the aircraft types: capacity and range. For a passenger aircraft, capacity is the number of seats. The range is the maximum flight distance an aircraft can fly carrying its payload (weight of occupants, cargo, and baggage). Airliners, i.e., aircraft manufactured for airlines, are classified as narrow-body and wide-body. Examples of narrow-body airliners are Airbus A320 and Boeing 737, which have a single aisle and around 150 seats. Examples of wide-body airliners are Airbus A340 and Boeing 777, which have two aisles and about 350 seats. Wide-body airliners are often preferred for long-haul international non-stop flights. Different narrow-body airliners exist for short-haul, medium-haul, and long-haul flights. For instance, both Airbus A320 and Being 737 MAX are narrow-body airliners, the latter having a more extended range. The aircraft manufacturers offer various airliners with different seat capacities and range options.

An airline's fleet composition, i.e., the number of aircraft from each aircraft type existing at a given time, is a strategic decision. It affects which O-D markets an airline can serve, operating costs, and revenues. Acquiring an aircraft is a substantial investment and has a significant financial impact on an airline. The list price of an Airbus

A320neo is around $115 million (Reuters (2023)). The investment may require a high upfront payment if the aircraft is purchased. Or, if it is leased, the airline agrees to pay a large sum of money as rental payments in the future. Keeping an aircraft "airworthy", i.e., ready to fly, also has a significant cost.

Fleet planning is determining the fleet size and composition for future periods. An airline's current fleet composition is determined 2-5 years before, which is a long-term, strategic decision. An airline waits six months to 2 years to receive an aircraft. In 2023, Airbus and Boeing announced expected aircraft delivery delays due to supplier delays. An airline can operate a purchased aircraft in the run-up to its retirement or sales. If an operational lease acquires the aircraft, there is typically a planned redelivery time in the contract.

The fleeting decisions affect which O-D markets to serve, i.e., which routes to fly. Next, we briefly discuss route planning decisions.

2.3 Route Selection

Route selection or route planning involves choosing the origin and destination airports to fly between. A flight between two airports serves the local O-D market, i.e., the demand between the flight origin and destination cities and maybe other O-D markets as a connecting flight. An airline decides to fly between two points based on the demand forecast and profitability analysis. For route planning decisions, the fleet composition is a constraint because each aircraft in the fleet has a specific range and operating cost, which affect the feasibility and profitability of a flight by the aircraft. Therefore, fleet and route planning decisions depend on each other.

Route planning decisions can be both strategic and tactical level decisions. An airline can consider selecting a particular route, e.g., Ankara(ESB)-İstanbul(SAW), as a long-term decision. On the other hand, an unexpected increase in the demand in an O-D market or a route selection decision of a competitor airline may open up a flying opportunity on a route. Typically, an airline's route network changes incrementally rather than all at once. An airline adds new routes to its network or removes routes as needed.

Airlines can be categorized as legacy airlines and low-cost carriers. Legacy airlines have been operating for many years since before the liberalization of the air transportation market. Some of the legacy airlines are flag carriers such as British Airways. Low-cost carriers emerged after the liberalization of the market. These airlines focused on decreasing unit costs by improving labor productivity and aircraft utilization. Legacy airlines typically have a hub-and-spoke network pattern in their operations. There is at least one hub airport in a hub-and-spoke network structure. At hub airports, airlines operate connecting banks. A connecting bank at a hub takes one to three hours, during which several flights arrive at a hub airport, and several flights depart. Passengers and baggages connect betwen flights. This structure helps airlines to offer services in many O-D markets other than the local markets of the flights. On the other hand, low-cost carriers are more inclined to provide point-to-point flights, which avoids costly hub operations and long aircraft idle times at hub airports. Airlines typically employ a hybrid strategy. While they operate a banking strategy at some airports, they plan point-to-point flights on some routes.

Passenger demand of an O-D market varies with the time of the day and days of the week. The flight time choices of business travelers and leisure passengers differ. After the selection of routes, timetable planning is the subsequent decision to be made by the airlines.

2.4 Timetable Planning

An airline should decide how often it will fly on a selected route and specifically when these flights will be scheduled. An airline's timetable should capture the demand for the chosen routes. Indeed, increased frequency on a route increases the demand. Therefore, flight frequencies and timetables should be designed to capture and increase the route demand. There are peak periods at which the highest demand is observed. However, an airline has limited aircraft in its fleet and can only schedule limited flights at peak hours. Timetable development is a complex task. It depends on the fleet planning decisions and passenger demand. Usually, it is done incrementally.

While one objective in timetabling is to maximize the captured demand, another goal is to maximize the utilization of the aircraft. As aircraft utilization in a fleet increases, unit operating costs fall, and operations become more profitable. While developing a timetable, planners must also consider turnaround times for the aircraft. Between an aircraft's arrival at an airport and its subsequent departure, a turnaround time is required to disembark the passengers, embark on new passengers, refuel, and cleaning operations. Crew schedules may also bring constraints to timetabling decisions.

The timetable planning problem is a vast sized complex problem. Therefore, the changes to an airline's schedule are incremental rather than radical. To our knowledge, no existing models can handle the problem's complexity. The decision-makers make incremental changes in the timetable manually or by using decision support tools. An airline's fleet is its most important resource to manage. Given a flight timetable, another problematic management problem for an airline is aircraft scheduling, i.e., which aircraft will operate which flights in the timetable.

2.5 Aircraft Scheduling

In timetable planning, an airline designs its flight schedule. A flight schedule specifies the origin-destination airport and departure time of each flight. The next problem to solve is assigning aircraft to the flights in the timetable. A decision-maker needs to consider criteria and constraints when solving the problem. We will mention the most critical ones here.

The first constraint in aircraft scheduling is to ensure that each flight in the timetable is assigned an aircraft. Airlines usually have a limited number of aircraft. It may not be possible to assign an aircraft to each flight. Then, of course, the timetable has to be updated.

The second is the flow balance constraints. If an aircraft operates two flights, one after the other, then the first flight's destination airport and the second flight's departure airport must be the same. Otherwise, the aircraft has to ferry, i.e., fly empty from the first airport to the second, which costs a lot of time and money.

The third is the turnaround time constraint. As mentioned before, passengers are deplaned and enplaned between two successive flights, and the aircraft is refueled and cleaned. Therefore, in an aircraft's schedule, between the arrival time of a flight and the departure time of its succeeding flight, there must be enough time (turnaround time) for these operations.

An aircraft has to undergo periodic light checks every 3-5 days. The frequency of these maintenance events is determined by the number of flight hours and flight cycles operated. These maintenance rules are strict. The aircraft must be grounded unless the aircraft is maintained and inspected as required. Therefore, an aircraft's schedule must include sufficient slack time for these checks. Aircraft can get these checks only in specific airports. The schedule must ensure that the aircraft has adequate slack time at an airport that is a maintenance station.

One of the objectives of aircraft scheduling is profit maximization. Usually, there are different types of aircraft in an airline's fleet. Aircraft-flight assignments should maximize revenue by carrying as many passengers as possible. In other words, passenger demand and ticket fares for each flight and the seat capacities of aircraft should be considered when making assignment decisions. If the seating capacity of an aircraft is short for the demand of an assigned flight, then passenger spill cost occurs and reduces revenue. Similarly, different aircraft have different operating costs due to the size of the aircraft and its engine efficiency. Therefore, aircraft-flight assignment decisions also affect the total operating cost of the fleet.

The scheduling problem is decomposed into two subproblems for airlines with hundreds of aircraft. The first subproblem is called the fleet assignment problem. Given the timetable, the fleet assignment problem (FAP) determines which flight will be operated by which type of aircraft. The FAP considers flow balance constraints by ensuring that the number of aircraft arriving at an airport is equal to the number of aircraft departing in a given period. It seeks profit-maximizing assignment decisions.

The second subproblem is called the maintenance routing problem (MRP). Given the output of the FAP, MRP determines specific routes an aircraft can fly. MRP also ensures that the sequence of flights assigned to an aircraft allows maintenance checks at a maintenance station airport without violating maintenance constraints.

The FAP and MRP are solved well in advance to generate strings of flights. On the other hand, 3-4 days before the day of operation, individual aircraft are assigned to these flight strings. However, at the time of assignment, each aircraft may be in a certain maintenance status, i.e., having certain flight hours and cycles accumulated on it. Also, there might be other operational constraints like a canceled flight or aircraft type change for a flight, etc. FAP and MRP do not consider operational constraints that arise when the final aircraft assignment decisions are to be made. MRP, for instance, uses generic maintenance constraints. However, it is important to consider how many flight hours and cycles have accumulated on a specific aircraft on the day of operation. Also, FAP and MRP fit better with airlines with cyclic schedules that repeat every period. Indeed, each airline has to solve its specific aircraft scheduling problem.

The tail assignment problem (TAP) is the aircraft (tail number)-flight assignment problem. TAP assigns a tail number to each flight in the timetable. The TAP is solved 3-4 days before the operation. It may consider a scheduling horizon of a week, fortnight, or month. The TAP can handle up-to-date status of the aircraft and timetable. The FAP, MRP, and TAP have been studied for decades in the airline planning literature.

2.6 Crew Scheduling

Another essential resource for an airline is its crew members. Crew member work schedules are prepared after developing flight and aircraft schedules. Crew scheduling is a complex optimization problem. Therefore, in the literature, it is solved in two stages. The first stage, called the crew pairing problem (CPP), prepares short schedules for up to 5 days called pairings. A pairing is a string of flights that a crew can be assigned. The crew pairing problem covers all the flights in the flight schedule, i.e., each flight is covered by a pairing. The objective function to minimize in a CPP is the crew cost.

After generating crew pairings, the crew rostering problem (CRP) is solved. The CRP finds strings of pairings that cover a month. Such a string of pairings is called a roster or a bidline. While solving the CRP, one approach is assigning each crew member to a roster. One objective of the crew rostering problem can be maximizing the satisfaction of the crew members. This might be achieved by collecting individual requests from the crew members and seeking rostering decisions that satisfy these requests as much as possible. Another objective is fairness, This might be achieved by a balanced allocation of flight hours among crew members.

In some applications, the crew rostering problem does not assign individual crew members to rosters. The problem just generates generic rosters. After that, a bidding process is implemented. Crew members bid, i.e., express their preferences for the prepared rosters. In such applications, generic crew schedules are called bidlines rather than rosters. First, crew members are sorted by their seniority. Then, each crew member, most senior first, is assigned to its highest-ranked available bidline.

We have described the decision-making problems solved at different stages of the airline planning process. The planning problems mentioned above are not independent of each other. For instance, a solution to a flight scheduling problem may turn out to be infeasible in the aircraft scheduling stage. However, the entire planning problem is too complex to solve using a single model. Yet, models that integrate different planning problems are developed as computing technologies and optimization algorithms improve.

Next, in sections 2.7 and 2.8, we will explain two crucial aviation practices that impact the airline planning process. The following section explains operating lease, which is a popular aircraft acquisition method.

2.7 Operating Lease

The operating lease is an extensively used aircraft acquisition method by airlines. IATA (2017) reported that 43% of the aircraft in the aviation industry fly under the operating lease. In the operating lease, the ownership of the aircraft remains with the lessor, and the lessee only gets the right to use the aircraft. Typically, an operating lease contract is made for 5 to 8 years.

Operating lease brings some advantages to the airlines. First, an airline can add new aircraft to its fleet without the burdens of ownership. While purchasing an aircraft requires a large amount of money to be paid at or before the delivery of the aircraft, an operating lease requires monthly rental payments. Operating lease also has tax advantages. The risk regarding the residual value of the aircraft is on the lessor. The operating lease option is believed to provide more flexibility than ownership. Depending on the aircraft market's situation, returning an aircraft to the lessor might be easier than selling an aircraft.

On average, an aircraft requires expensive heavy maintenance visits (C-checks and D-checks) every 15-18 months. Along with the rental payments, a lessee must make regular maintenance reserve payments to the lessor to finance future heavy maintenance visits. Maintenance reserve payments are made to the bank accounts held by the lessor. The maintenance reserve covers the heavy check expenses. The money remaining in the reserve at the end is usually left to the lessor. Maintenance reserve payments are comparable to rental payments in amount. They impose a significant financial burden on the airlines. Therefore, airlines try to minimize these reserve payments.

An operating lease contract for an aircraft usually imposes a specific "flight hour/flight cycle" ratio for aircraft usage. An aircraft should operate at a certain hour-to-cycle ratio. If an aircraft exceeds this agreed level in a calendar year, the lessee must make additional payments to the lessor.

Also, an operating lease contract usually imposes redelivery conditions for the aircraft. For instance, the lessee must return the aircraft to the lessor with a certain amount of flight hours and cycles. If the accumulated flight hours or flight cycles exceed the agreed levels, the lessee must make penalty payments. Therefore, an airline needs to carefully plan aircraft utilization to minimize the maintenance reserve payments (along with other costs) and to ensure the hour-to-cycle and redelivery terms in the lease contract.

2.8 Maintenance Planning

An aircraft has to undergo different maintenance operations throughout its life. This ensures that the aircraft operates safely, reliably and cost-effectively. Aircraft maintenance expenses account for 10%-15% of total operating costs (Ackert (2011)). While the utilization of an aircraft is critical for the profitability of its operations, it has to be grounded during those maintenance activities.

There are different categories of maintenance events for an aircraft. These categories are named after the first four letters of the alphabet: A, B, C, and D. A and B checks are considered light maintenance operations. C and D checks are called base or heavy checks. Over the years, the B-check tasks have been merged into A-checks. Similarly, aircraft manufacturers and airlines merged C and D checks. The tasks in D-checks are allocated to C-checks.

In an A-check, an aircraft receives routine service (oil, filter replacement, lubrication, etc.), interior/exterior inspection, troubleshooting operations, and corrective actions so that it can be dispatched to flights. An aircraft needs an A-check for every 300-600 flight hours or 200-300 flight cycles, meaning an A-check occurs every 15 days to one month. The time required for an A-check is 6 to 10 hours. Airlines typically schedule an A-check during an overnight stop at an airport where facilities and labor for A-check exist. The MRP and TAP consider A-check requirements and insert A-check visits into the schedules. Maintenance programs of aircraft are strictly regulated. An aircraft has to undergo maintenance within mandatory intervals specified in terms of usage parameters such as flight hours, flight cycles, and calendar days. An aircraft may have to be grounded if the airline fails to perform maintenance checks on time.

C-cheks typically repeat every 15-18 months and take three or four weeks. These are called base or heavy maintenance checks. During a C-check, an aircraft is parked at a hangar and unavailable for operation. A C-check may include tasks such as airframe structural inspection, landing gear overhaul, engine performance restoration, replacement of life-limited parts in the engine, and auxiliary power unit restoration. An aircraft's exterior is inspected for signs of damage, tear, or wear in airframe structural inspection. This may require stripping the exterior paint and uncovering the airframe, wings, etc. Landing gear overhaul is disassembling, inspecting, repairing, and replacing the components of a landing gear system. It is also possible to entirely replace landing gear, saving an airline time. In engine performance restoration, the engine is disassembled, inspected, and repaired. A life-limited part must be replaced after a specific lifetime measured in flight hours, cycles, or calendar years. During an engine overhaul, airlines typically replace all life-limited parts. Different tasks in C-checks may have different intervals. For instance, APU unit restoration is necessary every 5,000-7,000 flight hours, but a landing gear overhaul is needed for every 18,000 flight cycles or ten years, whichever comes first. Of course, these intervals differ for different aircraft models. Airlines package these heavy maintenance tasks into C-checks.

Preparing C-check schedules for the aircraft in its fleet is essential for an airline. There are several reasons. First of all, an airline has a timetable and needs to know how many aircraft will be operable in each period in the future. Second, an airline has a specific hangar capacity, limiting the number of aircraft that can simultaneously have heavy maintenance. Third, airlines should avoid early maintenance visits. Replacing parts and materials, inspecting and repairing equipment earlier than required wastes resources.

2.9 A Long Term Utilization Planning Approach

During the planning process described above, airlines make aircraft utilization decisions while solving operational aircraft scheduling problems such as OMRP and TAP, which assign individual aircraft to the flights in the timetable. These decisions have long-term impacts. First, operational aircraft scheduling decisions affect the fleet's long-term operating cost performance. Second, the airline's heavy check maintenance scheduling performance is affected.

This study proposes a long-term aircraft utilization planning and heavy check scheduling model, which makes a rough-cut utilization plan for each aircraft and a heavy check maintenance schedule jointly with the utilization decisions. A long-term utilization plan can provide input to the operational aircraft scheduling process and helps to improve the airline's cost performance while enabling a smooth heavy check maintenance plan. It also helps the airline to comply with the leasing contract terms on aircraft usage.

The proposed approach is analogous to the rough-cut capacity planning in the manufacturing industry. Rough-cut capacity planning ignores operational restrictions such as material availability and setup times. With a similar approach, aircraft utilization planning determines aircraft usage for future periods. Aircraft usage in a period is the total flight hours and number of cycles the aircraft operates. An aircraft utilization plan must consider several factors. The first is the airline's timetable. Second is the fleet plan, which includes the delivery-redelivery schedules of new and existing aircraft. The third is the heavy maintenance check requirements. The last is the usage-related contract terms, such as hour-to-cycle ratio restrictions and flight hour/cycle-based redelivery conditions for each leased aircraft.

A utilization plan also determines a heavy check maintenance schedule for the aircraft in a fleet. This helps an airline prepare for maintenance checks. Also, an airline can foresee possible aircraft lease requirements in the future. Since each aircraft in a fleet has different operating costs, a utilization plan helps minimize the entire fleet's total operating cost. Operating cost includes fuel costs, rental payments for aircraft on lease, ownership costs, maintenance reserve payments, etc. This study also considers maintenance costs, i.e., the penalty for unused maintenance intervals.

The next chapter reviews the related literature on airline planning process.

CHAPTER 3

LITERATURE REVIEW

This thesis proposes a long-term fleet utilization and maintenance planning problem which minimizes the total operating cost of the fleet while making long-term heavy check maintenance scheduling decisions. In this chapter, we give a review of the studies related to aircraft scheduling decisions, operational leasing and heavy chek maintenance planning problems.

3.1 Fleet Assignment Problem

As discussed in Chapter 2, one can view the airline planning process as a series of decision-making problems. As said, this process is iterative rather than linear. The first step of the planning process is designing a flight schedule (developing a timetable). The output of this stage is a set of flights with origin-destination and departure-arrival time information.

Airline scheduling starts with solving the fleet assignment problem. Given a timetable, each flight is assigned an aircraft type. In the fleet assignment problem, a basic assumption is that the flight schedule repeats daily or weekly. Most of the fleet assignment studies in the literature maximize revenue. Estimated demand and the average ticket fare for a flight, together with the seating capacity of the assigned aircraft type, give the flight's revenue. Studies on fleet assignment problem date back to the 1970s. The pioneering study by Levin (1971) models a flight scheduling and aircraft routing problem as an integer program considering the selection of departure times from sets of discrete time points. The objective to minimize was the fleet size.

Abara (1989) formulated the fleet assignment problem using a connection network structure. In a connection network, each node represents a time point for the departure or arrival of a leg. An arc between two nodes may represent a flight, a connection between the arrival of a flight and the departure of another flight, or the beginning of the day at an airport or the end of the day at an airport. Hane et al. (1995) proposed a mathematical formulation using a time-space-network. Time-space networks are often used in formulating vehicle routing-scheduling problems. The routing and scheduling problems contain both time and space decisions. For instance, an aircraft may be scheduled to arrive at an airport (ESB) on a particular day and time. In a time-space network, this arrival time is represented by a node. From one node to another, the airport or time or both change so that the fleet assignment problem can be viewed as a network flow problem. Network representations of the problem led to efficient mathematical formulations. However, fleet assignment is an NP-hard optimization problem for which heuristic solution methods were also developed. For example, Dožić et al. (2019) proposed a variable neighborhood search algorithm for the fleet assignment and fleet sizing problem.

A standard objective function of fleet assignment problems is revenue maximization. In the fleet assignment problem, assigning an aircraft type with sufficient seat capacity to cover the passenger demand of each flight increases revenue. However, it is only usually possible to cover part of the demand due to fleet constraints. Also, as discussed before, passenger demand usually occurs for O-D pairs, i.e., itineraries rather than individual flights. Barnhart et al. (2002) solved the fleet assignment problem with itinerary-based demand.

Airline operations are subject to disruptions. Rosenberger et al. (2004) showed that aircraft schedules with short cycles, i.e., with flight strings that frequently visit the same airport, are more robust against flight cancellations.

Recent studies on fleet assignment problems attempt to integrate the problem with other decisions of the airline planning process. Wei et al. (2020) studies combined timetable development and fleet assignment problem. They make joint flight scheduling and fleeting decisions. They also incorporate passenger choice via discrete choice models. Yan et al. (2022) studied an extension of the same problem and proposed an exact solution method. Xu et al. (2021) considered an integrated robust airline scheduling problem that makes joint flight scheduling, fleet assignment, and aircraft routing decisions. They aim to develop a schedule that permits possible departure time changes and flight selection decisions to recover from disruptions or to increase profits. They propose a column generation method and a variable neighborhood search algorithm. Ben Ahmed et al. (2022) studied an integrated fleet assignment, aircraft routing, and crew pairing problem for which they proposed a metaheuristic algorithm. Unal et al. (2021) proposed a mathematical formulation for the integrated fleet assignment and aircraft routing problems. Glomb et al. (2023a) studied a scheduling problem that jointly considers fleet assignment, tail assignment, and turnaround handling decisions. Turnaround handling is the scheduling of ground operations between flights. The authors developed an exact algorithm for the problem.

3.2 Maintenance Routing or Aircraft Routing Problem

After solving the flight scheduling and fleet assignment problems, the next step is determining which aircraft will operate which flight. Given a set of flights assigned to a specific fleet type, the problem is constructing a route for each aircraft of that fleet type. It is called the maintenance routing problem because the aircraft routes should satisfy maintenance constraints. In this problem, light or line maintenance checks, called A-check and B-check, are considered. An A-check of an aircraft is performed approximately every 400-600 flight hours and needs 6 hours or more. Usually, A-checks take place during an overnight stay. Therefore, the aircraft route should include the required time for maintenance during its stay at an airport, i.e., between two successive flights' arrival and departure times. Also, maintenance location is a constraint. Maintenance checks can occur only at those airports designated as maintenance stations.

Many studies on the maintenance routing problem assume a cyclic schedule. Rather than constructing a route for individual aircraft, these studies generate generic routes which satisfy maintenance constraints so that, at the time of operation an aircraft can be assigned to these routes.

Feo and Bard (1989) was the first study considering aircraft scheduling maintenance constraints. They proposed locating the maintenance stations to minimize maintenance costs while developing the aircraft schedule. Clarke et al. (1997) formulated the aircraft rotation problem, which constructs the routes for aircraft given the maintenance constraints (locations, durations, and frequencies). They showed the similarities of the problem with the asymmetric traveling salesperson problem and developed a Lagrangian relaxation-based solution approach.

Barnhart et al. (1998) developed a flight-string-based formulation for an aircraft scheduling problem that makes fleet assignment and maintenance routing decisions. A flight string-based formulation can easily handle maintenance-related constraints. In this formulation approach, each decision variable represents a flight string. All maintenance-related constraints can be easily implemented while generating a flight string, i.e., a decision variable. Liang et al. (2011) proposed a time-space-network-based formulation for the maintenance routing problem. Khaled et al. (2018) extended this formulation to include accumulated flight hour and flight cycle calculations for the aircraft. Haouari et al. (2013) developed a connection network-based formulation for the aircraft routing problem that considers maintenance constraints. While string-based formulations include exponentially many decision variables, connection networks allow a compact formulation. Haouari et al. (2013) also presented the computational efficiency of their proposed modeling approach.

Another formulation approach developed for the maintenance routing problem is based on the concept of “line of flights”. A line-of-flights is a string of flights that start and end at maintenance airports. Generating line-of-flights helps to achieve compact formulations for the problem. Kabbani and Patty (1992), Gopalan and Talluri (1998), and Talluri (1998) developed solution methods based on line-of-flights.

Başdere and Bilge (2014) studied an operational aircraft routing problem that considers maintenance constraints for each aircraft. The model aims to avoid early maintenance visits by minimizing the unused flying times of aircraft before maintenance.

Elthouky et al. (2017) and Zhou et al. (2020) review the maintenance routing studies published until 2017 and 2020, respectively. Recent studies on maintenance routing problems focus on robustness, integration with other planning problems, and cruise speed control. Ma et al. (2022) give a review of the maintenance routing studies that focus on uncertainties in airline operations. Airline operations are subject to disruptions such as delays, flight cancellations, airport closures, etc. Developing aircraft schedules considering anticipated disruptions is an approach to cope with uncertainties. Eltoukhy et al. (2020) propose a turnaround time reduction approach as a robustness approach and develop a mathematical model. Ben Ahmed et al. (2022) integrate fleet assignment, maintenance routing, and crew pairing problems for a daily flight schedule and consider robustness. They propose a mathematical model. Wen et al. (2022) developed an aircraft rerouting approach in an operational setting to fulfill aircraft maintenance requirements.

Another line of research is considering cruise speed control in aircraft scheduling. In most of the studies, flight times are assumed to be constant. However, in practice, flight time can be controlled by the captain. First Aktürk et al. (2014) proposed using cruise speed control in aircraft rescheduling problems. Gürkan et al. (2016) have employed the idea in an integrated aircraft fleeting and routing problem. Zhang et al. (2022) have considered cruise speed control in an operational maintenance routing problem.

Saltzman and Stern (2022) studied minimum fleet size problem jointly with the maintenance routing problem. They proposed an alternative network representation and a new mathematical formulation for the problem. Their approach reduces the model size compared to the existing models. Bulbul and Kasimbeyli (2021) developed a new solution algorithm for the maintenance routing problem. Their algorithm was based on augmented Lagrangian relaxation.

3.3 Tail Assignment Problem

A maintenance routing problem usually refers to generating aircraft routes that satisfy general maintenance restrictions without making specific aircraft-route assignments. Maintenance routing problems are solved months before the operation time, but individual aircraft-flight assignments are made days before the operation. The studies in the literature name this problem as “operational maintenance or aircraft routing” or “tail assignment”. The word “tail” refers to the tail numbers of aircraft. Each flight is assigned a tail number, i.e., an aircraft. Grönkvist (2003) and Grönkvist (2005) introduced the tail assignment problem. The problem is solved at the very last stage of the airline planning process. It assigns individual aircraft to flights considering all operational constraints such as maintenance intervals of aircraft, etc.

Given a flight schedule and a fleet, the tail assignment problem schedules aircraft so that the schedule covers all flights. Each aircraft is located at a certain airport at the beginning of a scheduling horizon, and each aircraft has a specific remaining maintenance (light check) life. Maintenance visits are also scheduled as required. Most of the studies on tail assignment problems focus on developing exact solution algorithms. Gabteni and Grönkvist (2009) combines column generation and constraint programming approaches to develop an exact solution method. A group of studies are dedicated to improving column generation-based exact algorithms for the tail assignment problem. Enarsson and Jeganathan (2022) proposed using machine learning approaches to decide starting strategy while solving the restricted master problem in each iteration of the branch and price algorithm. Danielsson and Karlsson (2018) used an integer-quality column-generation approach and proposed new preprocessing methods that eliminate arcs in the flight network to enhance the computational performance of the exact algorithms. Thorén (2022) implemented a multidirectional dynamic programming algorithm to solve the resource-constrained shortest path problem, which arises as a subproblem in column-generation-based methods. Hult (2022) proposed a new Lagrangian relaxation-based approach to find lower bounds and improve the computational performance of exact solution approaches. Blomgren (2018) proposed a heuristic that finds initial solutions, i.e., upper bounds, to improve the performance of exact solution methods. Khaled et al. (2018) proposed an alternative formulation approach that does not use network representation of flight schedules. They presented the computational performance of the approach. Fuentes et al. (2021) employed the line-of-flights concept to achieve a mathematical formulation. They presented computational results for a case study from Vueling Airlines.

Sanchez et al. (2020) focus on scheduling maintenance decisions for a given flight schedule for 30 days. They propose a two-stage solution approach. In the first stage, maintenance opportunities are identified and planned for each aircraft. If the first stage returns infeasible, then in the second stage, tail reassignment decisions are made to achieve a feasible schedule. They consider multiple objectives to optimize. Glomb et al. (2023b) solve the tail assignment problem with predictive maintenance considerations via part failure scenarios. They propose a benders decomposition-based exact algorithm. Maher et al. (2018) studied the daily tail assignment problem considering 3-day maintenance plans.

Ruther et al. (2017) proposed reoptimizing integrated aircraft routing, crew pairing, and tail assignment decisions close to the day of operation using up-to-date information. They developed a branch-and-price method to solve the problem.

Hottenrott (2015) proposed an adaptive large neighborhood search algorithm for the tail assignment problem. Some studies attempt to use quantum computing approaches for solving tail assignment problems. Martins (2020) reformulated the problem as a quadratic unconstrained binary optimization problem and applied a quantum annealing heuristic. Vikstål et al. (2020) simplified the tail assignment problem as an exact cover problem and used a quantum approximate optimization algorithm to solve the problem. These studies have concluded that further research is needed for using quantum computing techniques on this problem.

3.4 Aircraft Heavy Check Planning

As discussed in Chapter 2, the maintenance routing problem considers maintenance check restrictions when developing aircraft routes (flight strings) to use. The tail assignment problem deals with the individual maintenance status of each aircraft and either schedules maintenance visits or takes preplanned maintenance visits as constraints when making aircraft-flight assignment decisions. However, these problems consider the lighter checks (A-check, B-check), i.e. line maintenance events, which occur more frequently. While an A-check can be done during an overnight stay at an airport, B-check requires a couple of days. Indeed, in practice, the tasks in B-checks are usually planned within A-checks.

Aircraft also require heavy checks (C-check and D-check). C-checks repeat every 15-20 months on the average, and D-checks repeat every 6-8 years. These checks take longer times (2-3 weeks) during which the aircraft is parked at a hangar and unavailable for operations. Similar to B-checks, in practice, D-check tasks are allocated to C-checks.

The literature has extensively studied aircraft scheduling problems with A-check planning decisions/constraints. However, few recent papers looked at an aircraft fleet's long-term maintenance or heavy-check planning problem. An exception is Boere (1977), which developed a simulation-based planning approach for Air Canada to schedule A and C checks. The author reported that a 5% reduction in labor and material costs was achieved as a result. Other exceptions are two references of AGIFORS (The Airline Group of the International Federation of Operational Research Societies) Symposium presentations (Etschmaier and Franke (1969) and Bauer-Stämpfli (1971)), both of which study long-term airline overhaul scheduling problems.

After a long time, recently Deng et al. (2020) studied a long-term heavy maintenance check scheduling problem for a heterogeneous fleet to minimize wasted maintenance interval, i.e., to reduce premature heavy-check visits. They assumed that the number of flights and flight hours an aircraft will operate is known. They also presented a case study from a European airline which demonstrated a 7% decrease in maintenance check visits in 4 years and a $9.8 million estimated increase in revenue due to increased aircraft availability. For the same problem, Andrade et al. (2021) proposed a reinforcement learning approach.

Different than Deng et al. (2020), Deng and Santos (2022) considered uncertainty in aircraft utilization (flight hours, flight cycles operated) and in maintenance check durations. They proposed an approximate dynamic programming method to minimize wasted maintenance intervals. van der Weide et al. (2022) considered the same uncertainties as Deng and Santos (2022) and proposed to develop a robust heavy maintenance check schedule to minimize unused maintenance intervals, extra hangar slot costs, and grounding costs for aircraft. They proposed a mathematical formulation and a genetic algorithm to solve the problem.

Aircraft maintenance checks include many tasks. These tasks can be assigned to different check visits. As mentioned, airlines can plan B-check tasks in A-checks by making task allocation decisions to increase aircraft availability. The problem is called the task allocation problem. Witteman et al. (2021) proposed a bin-packing approach to solve the problem. Deng et al. (2021) presented a decision support system that jointly makes aircraft maintenance check scheduling, task allocation, and shift planning decisions.

Hu et al. (2021) proposed a reinforcement learning approach for the maintenance scheduling problem. Different from the previous studies, they considered the output of an aircraft's prognostic and health management system when making these decisions. A prognostic and health management system is onboard equipment that predicts the remaining useful life of main aircraft components. Hu et al. (2021) used the system's output as an input to their method, along with planned aircraft utilization, repair costs, and spare component inventory levels.

3.5 Airline Operational Leasing

The most critical resource of an airline is the aircraft fleet. One of the most popular aircraft acquisition methods is operational leasing. Guzhva et al. (2019a) gives an overview of the aircraft market and the leasing industry. Operational leasing is preferred over other methods for several reasons mentioned in Chapter 1. However, a leasing contract usually poses certain restrictions on the utilization of the aircraft and also dictates maintenance reserve payments to be made by the lessor (Guzhva et al. (2019b)).

A leasing contract specifies the delivery and redelivery dates of an aircraft. Also, the contract stipulates that an aircraft should be redelivered in certain conditions. Delayed redelivery results penalized rental payments. At the time of redelivery, the aircraft should have certain flight hours and cycles on it, i.e., it should be in certain maintenance status. Violation of this condition may result in penalty payments. Saltoğlu (2019) gives a detailed discussion of redelivery-related cost risks arising in leasing contracts for an aircraft lessee.

Another restriction imposed by a leasing contract on aircraft utilization regards the hour-to-cycle ratio. In a certain period, the hour-to-cycle ratio of an aircraft is the ratio of total hours flown to total cycles made by the aircraft. A lessor usually requires hour to cycle ratio to stay in a specific interval during every period. Otherwise, the rental/maintenance reserve payments increase in the following periods. Therefore, airlines try to control the hour-to-cycle ratio of aircraft to avoid extra payments to the lessors.

In operational leasing, the ownership of the equipment stays with the lessor. The useful lives of aircraft components depreciate during the leased period. To protect the asset value, a lessor usually requires a regular (typically monthly) maintenance reserve payment from lessees. Maintenance reserve payments pose a financial burden on airlines. Maintenance reserves are deposited in a bank account held by the lessor. The accumulated amount is used for heavy-check maintenance costs. For the lessee, getting back the leftover amount is usually impossible after maintenance payments are made. Since each aircraft in a fleet may have different maintenance reserve payment rates, an airline has to consider these payments in utilization planning.

3.6 The Thesis' Contribution to the Airline Schedule Planning Literature

This thesis proposes a long-term fleet utilization and heavy check planning model. Given the planned and estimated timetable information for future periods, the model finds a rough-cut aircraft utilization plan. Furthermore, the model considers maintenance status (accumulated flight hours, flight cycles, and calendar days) on each aircraft and plans heavy check maintenance visits as required. As each aircraft has a different operating/rental cost, the objective to minimize is the total cost which also includes early maintenance costs.

As reviewed in this chapter, the studies on the planning process for airlines need to consider long-term utilization decisions. This thesis does not propose making aircraft-flight assignment decisions for a long-term period. These decisions are subject to many constraints, some unfolding a short time (a few days) before the operation. Instead, analogous to the rough capacity planning decisions in production, we propose to develop a utilization plan for each aircraft in the fleet. The model outputs how many hours and cycles each aircraft will fly in each period and a heavy-check maintenance visit plan for the whole fleet. The model plans future operation load (in terms of flight hours and flight cycles) for each aircraft. The planned workload for each period can be an input to the tail assignment problem, a target utilization level for that period. In the long term, this reduces total operating and premature maintenance costs and achieves a smooth heavy check plan.

The proposed model also considers contract restrictions on aircraft utilization. The redelivery and delivery periods, redelivery conditions, and hour-to-cycle constraints are included in the model. To our knowledge, these issues were not considered in airline planning studies before.

CHAPTER 4

AIRCRAFT UTILIZATION AND HEAVY CHECK PLANNING PROBLEM

Aircraft utilization decisions are made at the operational level in the airline planning and scheduling literature. Heavy checks are costly maintenance operations that require grounding an aircraft for 2-3 weeks. These checks are due when the aircraft utilization since the last heavy check reaches a certain threshold. Existing studies on heavy check planning problems assume either each aircraft has a specific utilization every month or they assume future aircraft utilization is uncertain. In this thesis, we propose to prepare a utilization plan for an aircraft fleet for a certain period. We make utilization planning and heavy check maintenance planning decisions jointly and consider leasing contract-based delivery-redelivery conditions and utilization restrictions on the leased aircraft. This chapter will first give a detailed description of the problem, present a mathematical model and illustrative example. Then, a naive heuristic algorithm will be given.

4.1 Problem Definition

The problem considers a fleet of aircraft. The problem makes utilization planning and heavy check scheduling decisions for each aircraft in the fleet within a certain planning horizon. The aircraft in the fleet are of the same type, i.e., they have similar seating capacities. An aircraft joins and leaves the fleet at specific times determined by the leasing or purchasing contracts and retirement decisions. Of course, an aircraft may stay in the fleet through the entire planning horizon. Each aircraft has a specific operating cost performance. An aircraft operates a flight at a particular cost determined by a fixed cost (cost per flight cycle) and a variable cost (cost per flight hour).

The model of the aircraft, its engine efficiency, and maintenance status affect its cost performance. For a leased aircraft, rental and maintenance reserve fees also realize for each flight. Airlines usually pay these fees to the lessor every month. There might be fixed rental fees as well as utilization dependent fees (maintenance reserve and rental fees).

Each aircraft must get a heavy check service following the maintenance interval determined by its manufacturer. Airlines schedule a heavy check for an aircraft after a certain number of flight hours, a certain number of flight cycles, or a certain number of calendar days, whichever comes first. During the shop visit, an aircraft cannot operate any flights. Consistent with the industry practice, we assume that D-checks' tasks are allocated in C-checks. Therefore, in the problem, we consider C-check scheduling decisions only. Each C-check includes a different set of tasks requiring a different duration. Within the planning horizon under consideration, multiple C-checks can be scheduled for an aircraft. By regulations, an aircraft's operations and maintenance events must be closely monitored and recorded. At the beginning of the planning horizon or at the time an aircraft joins the fleet, the maintenance status of an aircraft is known. To be specific, the flight hours, number of flight cycles and calendar days accumulated on an aircraft since its last heavy check is given. As utilization plan is prepared, the accumulated flight cycles, flight hours and calendar days are recorded.

An airline typically has a limited hangar capacity for heavy checks. Therefore, the maximum number of aircraft under heavy maintenance is limited in a given period. An airline can also impose a limit on this number, especially to make more aircraft available during peak demand periods.

An airline usually sells a flight's tickets one year before at the earliest. At a given time, the flight schedule of an airline for the following year is known. As discussed in the previous chapters, the timetable of an airline remains relatively the same and the changes to a timetable usually occur incrementally. Therefore, we assume that an airline has a reasonable estimate of flight legs and frequencies for each period (week or month) in the next couple of years. In the proposed problem, aircraft utilization decisions are made based on the fixed timetable for the next year and estimated plans for the following years.

In an airline's flight schedule, a number of flights are planned in each period. Utilization planning involves allocating those scheduled flights in a period among the available aircraft in the fleet. One approach is assigning each flight to an aircraft by considering the operational constraints, as in the tail assignment problem. Another method is considering aggregate flight hours and cycles in a period and allocating them among the aircraft. Since utilization planning is a long-term decision, the first approach is extensively detailed and impractical. Aggregating all flight hours in a period and, similarly, the flight cycles and allocating among aircraft is much more practical. However, this approach ignores the differences between long-haul and short-haul flights. Therefore, to make a more realistic utilization plan for each period, we propose working with the frequency distribution of flight cycles over the ranges of flight times.

Figure 4.1 shows a frequency distribution of Pegasus Airlines' scheduled flights in a selected one-week period in July 2005. There are 12 flight time intervals in the figure, and the number of flights is given for each time interval. As can be seen in the example, there are a small number of extremely short flights lasting between 15 to 45 minutes. Also, there are four flights in the interval of 345 to 375 minutes. Many of the flights are between 75 to 105 minutes long. In utilization planning, we propose a model to decide how many flights an aircraft will be assigned from each interval in each period. This allows allocating longer flights to more cost-efficient aircraft, i.e., aircraft with higher fuel efficiency or lower operating costs per flight hour. This approach also helps to make utilization decisions that comply with the contract terms regarding hour-to-cycle ratio and utilization restrictions.

We define the utilization planning and heavy check scheduling problem the following few years. We divide the planning horizon into weeks and make utilization and maintenance decisions for each week. We next give the notation used in our model.

4.2 Notation

In this problem, we consider a fleet of aircraft and the set of aircraft in the fleet is denoted by I. We denote the periods in the planning horizon by T. If T is one year

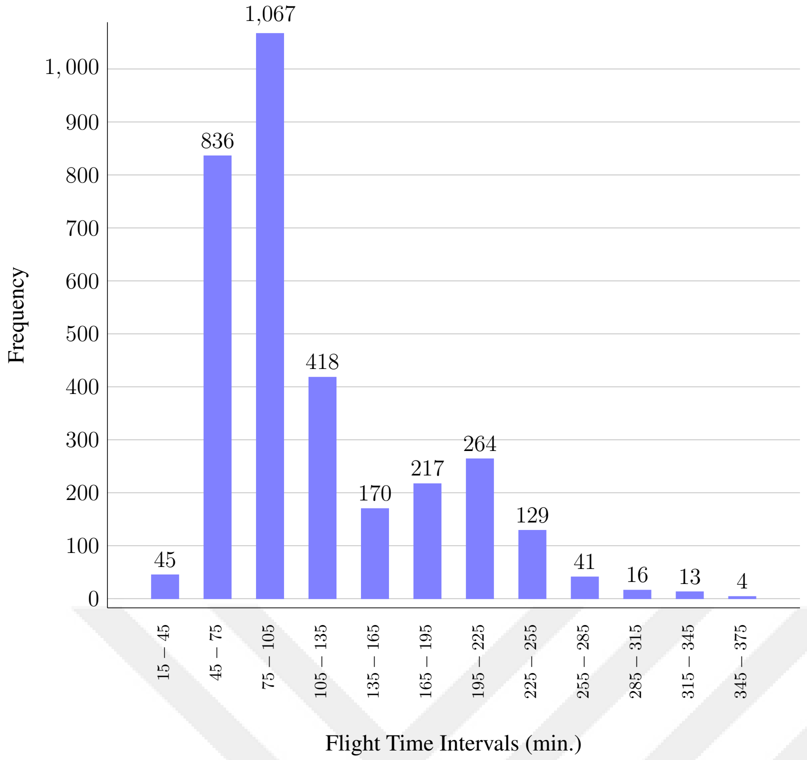

Figure 4.1: Flight time distribution of Pegasus Airlines - one week in July 2015

and each period is one week, then $T = \{1, 2, \ldots, 52\}$. Each aircraft i joins the fleet in period T_i^P. If aircraft i is already in the fleet at the beginning of the planning horizon, then $T_i^P = 1$. An aircraft is redelivered or retired at the end of period T_i^R. If an aircraft i stays in the fleet until the end of the planning horizon, then $T_i^R = |T|$.

Each aircraft has certain maintenance intervals. Aircraft i has to undergo a heavy check after $\bar{H}_i$ hours of flight, $\bar{C}_i$ flight cycles and $\bar{D}_i$ calendar days whichever comes first. $H_{i(T_i^P-1)}$ is the flight hours on the aircraft before joining the fleet, i.e., at the end of period $T_i^P - 1$. Similarly, we define the accumulated flight cycles ($C_{i(T_i^P-1)}$) and calendar days ($D_{i(T_i^P-1)}$) on aircraft i before joining the fleet. If $T_i^P = 1$, then $H_{i(T_i^P-1)}$ gives the flight hours on aircraft i at the beginning of the planning horizon. Similar interpretation is valid for $C_{i(T_i^P-1)}$ and $D_{i(T_i^P-1)}$.

The fleet has to operate the flights in the timetable. Set J denotes the number of flight hour intervals as exemplified in Figure 4.1. T_{tj}^c is the number of flight cycles in flight interval j in period t. In a given period, all flights in all flight hour intervals must be assigned to aircraft in the fleet. B_{tj} is the average flight hour of flight interval j in period t.

As mentioned before, this problem does not consider A- and B-checks decisions. For heavy check decisions, each C-check includes a different set of tasks requiring a different duration. We can denote these tasks as C1, C2, C3, etc. So, during the planning horizon an aircraft can have at most K heavy checks. As discussed, aircraft i can fly at most $\bar{H}_i$ hours between check k and check $k+1$. Heavy checks must be scheduled in ascending order, i.e., check $k+1$ cannot be scheduled before check k. Heavy check k takes O_i^k periods during which the aircraft is grounded and overhauled at a hangar slot. In period t at most A_t aircraft can be under maintenance due to hangar capacity or peak demand concerns.

An aircraft may be subject to hour-to-cycle limitations. $\underline{h/c}_i$ and $\overline{h/c}_i$ give lower and upper bounds, respectively, on the hour-to-cycle ratio for aircraft i. There may be upper limits on the flight hours and cycles an aircraft can operate in a period. These limits are denoted by $\bar{h}_i$ and $\bar{c}_i$. Following the contract terms, an airline may aim to utilize an aircraft at a certain level before its redelivery period. H_i^{red} and C_i^{red} are the target flight hours and cycles for aircraft i. If the airline does not comply with the redelivery targets, then a penalty payment will be incurred. $C_i^{red/h}$ and $C_i^{red/c}$ denote the penalty costs due to the deviation from targets.

Flight operation costs differ between aircraft. Fuel cost is a significant portion of the flight cost. Fuel cost depends on aircraft type, model, engine efficiency, maintenance status, etc. Two aircraft of the same type may have different fuel cost performance. The depreciation cost of an owned aircraft or the rental fee of a leased aircraft also changes from aircraft to aircraft. For a leased aircraft, maintenance reserve payment is made for each flight operated by the aircraft. The leasing contract of each aircraft specifies maintenance reserve payments. An aircraft emits GHGs during its operation. The emission quantities are different for different aircraft as their fuel efficiency are different. Therefore, GHG emission costs are different for different aircraft. Landing costs may also differ between aircraft based on noise and emission performance. Some flight operating cost items depend on flight hour, e.g., fuel cost, rental fees paid for each flight hour, maintenance reserve payments made for each flight hour, etc. Some cost items are fixed for each flight cycle, e.g., rental and maintenance reserve payments per flight cycle, landing fees, etc. In this study, for each aircraft i, flight cost per hour is denoted by $C_i^{o/h}$, and flight cost per cycle is $C_i^{o/c}$. These two unit costs include all the above items that depend on flight hour and cycle, respectively.

Due to hangar capacity restrictions, an airline may overhaul an aircraft before its maintenance interval ends. Premature maintenance increases maintenance costs and causes life-limited parts to be replaced earlier than required. Therefore, when an aircraft enters a heavy check procedure, we penalize unused maintenance life in the model. $C_i^{em/h}$, $C_i^{em/c}$, and $C_i^{em/d}$ give denote the penalty costs for unused flight hours, cycles and calendar days.

Utilization planning and heavy check scheduling problem basically makes two types of decisions. The first is how much each aircraft will be utilized in each period and the second is during which periods an aircraft will be under maintenance. Utilization decisions will be given based on flight hour intervals. Therefore, we define decision variable x_{itj}^c, the number of flight cycles in interval j assigned to aircraft i in period t. Another decision variable schedules maintenance periods. y_{it}^k is a 0-1 decision variable which indicates if heavy check k for aircraft i starts in period t. For each aircraft, maintenance intervals must be imposed for maintenance decisions. The decision variable H_{it} holds for the total flight hour accumulated on aircraft i in period t. Similarly, C_{it} and D_{it} hold the accumulated flight cycles and calendar days on aircraft i in period t.

Below, we give the list of notation described above:

Sets:

I : Set of aircraft that exist in the airline's fleet in planning horizon

J : Set of flight hour intervals

T : Set of periods included in the planning horizon

Parameters:

K : Maximum number of overhaul checks for an aircraft

T_i^P : the period in which aircraft i joins the fleet,
equals 1 if the aircraft is already in the fleet before planning period

T_i^R : the period at the end of which aircraft i will be redelivered,
$|T|$ if aircraft is not delivered in planning horizon

$\bar{H}_i$: Flight hour interval between two overhauls for aircraft i

$\bar{C}_i$: Flight cycle interval between two overhauls for aircraft i

$\bar{D}_i$: Calendar day interval between two overhauls for aircraft i

$\bar{h}_i$: maximum flight hours aircraft i can fly in a period

$\bar{c}_i$: maximum number of cycles aircraft i can fly in a period

$\overline{h/c}_i$: maximum hour to cycle ratio of aircraft i for a period

$\underline{h/c}_i$: minimum hour to cycle ratio of aircraft i for a period

$H_{i(T_i^P-1)}$: flight hours on aircraft i at the beginning of T_i^P

$C_{i(T_i^P-1)}$: number of flight cycles on aircraft i at the beginning of T_i^P

$D_{i(T_i^P-1)}$: calendar days on aircraft i at the beginning of T_i^P

H_i^{red} : target flight hours on aircraft i at at redelivery time

C_i^{red} : target number of flight cycles accrued on aircraft i at redelivery period

O_i^k : Duration (# of periods) for check k of aircraft i

A_t : Maximum number of aircraft overhauled in period t

T_{tj}^c : Total number of cycles planned in timetable in flight hour interval j in period t

B_{tj} : Average flight hour for planned/estimated in timetable in inteval j and period t

$C_i^{o/h}$: Operating cost of aircraft i per flight hour

$C_i^{o/c}$: Operating cost of aircraft i per flight cycle

$C_i^{em/h}$: Cost of early maintenance per flight hour

$C_i^{em/c}$: Cost of early maintenance per cycle

$C_i^{em/d}$: Cost of early maintenance per calendar day

$C_i^{red/h}$: Penalty cost of deviation from target redelivery flight hours

$C_i^{red/c}$: Penalty cost of deviation from target redelivery flight cycles

t_p : Number of days in a period

Decision Variables:

x^c_{itj} : Number of flight cycles assigned to aircraft i from interval j in period t

x^d_{it} : Number of days accrued on aircraft i in period t

y^k_{it} : 1 if heavy check k of aircraft i starts in period t, 0 otherwise

H_{it} : Total flight hour accumulated on aircraft i in period t

C_{it} : Total cycles accumulated on aircraft i in period t

D_{it} : Total calendar days accumulated on aircraft i in period t

U^{FH}_{it} : Unused maintenance life in flight hours in period t for aircraft i

U^{FC}_{it} : Unused maintenance life in flight cycles in period t for aircraft i

U^{CD}_{it} : Unused maintenance life in calendar days in period t for aircraft i

Δh_i : Deviation of accumulated flight hours from redelivery target for aircraft i

Δc_i : Deviation of accumulated flight cycles from redelivery target for aircraft i

4.3 Mathematical Model

This section gives the mathematical model of the problem.

Constraints:

Flight Load Constraints:

$$\sum_{\substack{i \in I: \\ T_i^P \leq t \leq T_i^R}} x^c_{itj} = T^c_{tj} \quad \forall j \in J, \;\; t \in T \tag{4.1}$$

In each period, the fleet has to operate the flights in the timetable. Constraint (4.1) ensures that flight cycles in each interval and period in the timetable are allocated to the aircraft in the fleet.

Overhaul planning constraints:

$$H_{it} \geq H_{i(t-1)} + \sum_{j \in J} B_{tj} x^c_{itj} - \bar{H}_i \sum_{k=1}^{K} y^k_{it} \quad \forall i \in I, T_i^P \leq t \leq T_i^R \tag{4.2}$$

$$H_{it} \leq H_{i(t-1)} + \sum_{j \in J} B_{tj} x^c_{itj} \quad \forall i \in I, T_i^P \leq t \leq T_i^R \tag{4.3}$$

$$H_{it} \leq \bar{H}_i \left(1 - \sum_{k=1}^{K} y^k_{it} \right) \quad \forall i \in I, T_i^P \leq t \leq T_i^R \tag{4.4}$$

$$0 \leq H_{it} \leq \bar{H}_i \quad \forall i \in I, t \in T_i \tag{4.5}$$

Each aircraft, is allowed to fly a certain number of hours ($\bar{H}_i$) before an overhaul. For each time period, constraint (4.2) and (4.3) calculates flight hours accrued by an aircraft so far. Constraint (4.4) resets accumulated flight hours on an aircraft to zero if the aircraft's heavy check starts at period t. Constraint (4.5) imposes lower and upper bounds on H_{it}. Note that $H_{i(T_i^P-1)}$ is the flight hours accumulated on aircraft i before the aircraft joins the fleet.

$$C_{it} \geq C_{i(t-1)} + \sum_{j \in J} x_{itj}^c - \bar{C}_i \sum_{k=1}^{K} y_{it}^k \quad \forall i \in I, T_i^P \leq t \leq T_i^R \tag{4.6}$$

$$C_{it} \leq C_{i(t-1)} + \sum_{j \in J} x_{itj}^c \quad \forall i \in I, T_i^P \leq t \leq T_i^R \tag{4.7}$$

$$C_{it} \leq \bar{C}_i \left(1 - \sum_{k=1}^{K} y_{it}^k\right) \quad \forall i \in I, T_i^P \leq t \leq T_i^R \tag{4.8}$$

$$0 \leq C_{it} \leq \bar{C}_i \quad \forall i \in I, T_i^P \leq t \leq T_i^R \tag{4.9}$$

$$D_{it} \geq D_{i(t-1)} + x_{it}^d - \bar{D}_i \sum_{k=1}^{K} y_{it}^k \quad \forall i \in I, T_i^P \leq t \leq T_i^R \tag{4.10}$$

$$D_{it} \leq D_{i(t-1)} + x_{it}^d \quad \forall i \in I, T_i^P \leq t \leq T_i^R \tag{4.11}$$

$$D_{it} \leq \bar{D}_i \left(1 - \sum_{k=1}^{K} y_{it}^k\right) \quad \forall i \in I, T_i^P \leq t \leq T_i^R \tag{4.12}$$

$$0 \leq D_{it} \leq \bar{D}_i \quad \forall i \in I, T_i^P \leq t \leq T_i^R \tag{4.13}$$

Similar to constraints (4.2) and (4.5), constraints (4.6)-(4.9) update the number of flight cycles on an aircraft. Constraints (4.10)-(4.13) keeps track of the number of days on an aircraft.

Aircraft unavailability constraints:

$$\sum_{j \in J} x_{itj}^c \leq \bar{c}_i \left(1 - \sum_{k=1}^{K} \sum_{r=0}^{\min\{O_i^k - 1, t - T_i^p\}} y_{i(t-r)}^k\right) \quad i \in I, T_i^P \leq t \leq T_i^R \tag{4.14}$$

$$x_{it}^d = t_p \left(1 - \sum_{k=1}^{K} \sum_{r=0}^{\min\{O_i^k - 1, t - T_i^p\}} y_{i(t-r)}^k\right) \quad i \in I, T_i^P \leq t \leq T_i^R \tag{4.15}$$

Constraint (4.14) ensures that an aircraft cannot fly if it is under maintenance during a period. If a maintenance check starts at period t and takes o periods, then the aircraft cannot fly during periods $t, t+1, \ldots, t+o-1$. x^d_{it} is the number of days assigned on an aircraft i, in period t. Constraint (4.15) determines the value of x^d_{it}.

Upper bound on number of aircraft overhauled in a period:

$$\sum_{i \in I} \sum_{k=1}^{K} \sum_{r=0}^{\min\{O_i^k - 1, t - T_i^p\}} y^k_{i(t-r)} \leq A_t \ \ \forall t \in T \tag{4.16}$$

Constraint (4.16) ensures that in a given period the number of aircraft overhauled cannot exceed A_t which may be due to the number of hangars available or due to some other operational restrictions.

Hour to cycle constraints:

$$\underline{h/c}_i \leq \frac{\sum_{j \in J} B_{tj} x^c_{itj}}{\sum_{j \in J} x^c_{itj}} \leq \overline{h/c}_i \ \ \forall i \in I, T_i^P \leq t \leq T_i^R \tag{4.17}$$

Constraint (4.17) requires a certain balance between the number of flight hours and number of cycles assigned to an aircraft in a period. This might be due to contract terms or due to operational constraints.

Bound on flight hours in a period

$$\sum_{j \in J} B_{jt} x^c_{itj} \leq \bar{h}_i \ \ \forall i \in I, T_i^P \leq t \leq T_i^R \tag{4.18}$$

Similarly, constraint (4.18) imposes an upper bound on the number of flight hours an aircraft can make in a period.

Redelivery Constraints:

$$H_i^{red} - \Delta h_i \leq H_{iT_i^R} \leq H_i^{red} + \Delta h_i \ \ \forall i \in I, T_i^R < |T| \tag{4.19}$$

$$C_i^{red} - \Delta c_i \leq C_{iT_i^R} \leq C_i^{red} + \Delta c_i \ \ \forall i \in I, T_i^R < |T| \tag{4.20}$$

Unused Life due to Premature Maintenance

$$\text{IF } \sum_{k=1}^{K} y_{it}^{k} = 1 \text{ THEN } U_{it}^{FH} = \bar{H}_i - H_{i(t-1)} \quad \forall i \in I, T_i^P \le t \le T_i^R \tag{4.21}$$

$$\text{IF } \sum_{k=1}^{K} y_{it}^{k} = 1 \text{ THEN } U_{it}^{FC} = \bar{C}_i - C_{i(t-1)} \quad \forall i \in I, T_i^P \le t \le T_i^R \tag{4.22}$$

$$\text{IF } \sum_{k=1}^{K} y_{it}^{k} = 1 \text{ THEN } U_{it}^{CD} = \bar{D}_i - D_{i(t-1)} \quad \forall i \in I, T_i^P \le t \le T_i^R \tag{4.23}$$

Constraints (4.21)-(4.23) calculate unused maintenance intervals at those periods when maintenance starts.

Overhaul check precedence constraints

$$\sum_{t=T_i^P}^{\bar{t}-1} y_{it}^{k-1} \ge y_{i\bar{t}}^{k} \quad \forall i \in I, k = 2 \ldots K, T_i^P \le \bar{t} \le T_i^R \tag{4.24}$$

$$\sum_{t=T_i^P}^{T_i^R} y_{it}^{k} \le 1 \quad \forall i \in I, k = 1 \ldots K \tag{4.25}$$

Overhaul checks of an aircraft must follow a certain order and each check may have a different durations. Therefore, the model ensures that this order is followed, i.e., check k must be scheduled before check $k+1$ via constraint (4.24). By constraint (4.25), heavy check k of aircraft i can only be scheduled to start in one period, i.e., a heavy check can only be done once to an aircraft.

Sign Restrictions: The constraints below give the sign and domain restrictions for the decision variables.

$$y_{it}^{k} \in \{0,1\} \quad \forall i \in I, T_i^P \le t \le T_i^R, k = 1 \ldots K \tag{4.26}$$

$$x_{itj}^{c} \quad \text{integer} \quad \forall i \in I, \forall j \in J, T_i^P \le t \le T_i^R \tag{4.27}$$

$$H_{it} \ge 0 \quad \forall i \in I, T_i^P \le t \le T_i^R \tag{4.28}$$

$$C_{it} \ge 0 \quad \forall i \in I, T_i^P \le t \le T_i^R \tag{4.29}$$

$$D_{it} \ge 0 \quad \forall i \in I, T_i^P \le t \le T_i^R \tag{4.30}$$

$$x_{it}^{d} \ge 0 \quad \forall i \in I, T_i^P \le t \le T_i^R \tag{4.31}$$

Objective Function:

$$\sum_{i\in I}\sum_{t=T_i^P}^{T_i^R}\left(C_i^{o/h}\sum_{j\in J}B_{tj}x_{itj}^c + C_i^{o/c}\sum_{j\in J}x_{itj}^c\right)+$$
$$\sum_{i\in I}\sum_{t=T_i^P}^{T_i^R}\left(C_i^{em/h}U_{it}^{FH}+C_i^{em/c}U_{it}^{FC}+C_i^{em/d}U_{it}^{CD}\right)+$$
$$\sum_{i\in I}\left(C_i^{red/h}\Delta h_i + C_i^{red/c}\Delta c_i\right) \tag{4.32}$$

In the objective function the first two terms give the total cost of operating aircraft for the assigned flight hours and cycles. The next three cost terms give the cost of underutilized maintenance life. The last two terms are penalty costs for not meeting redelivery conditions regarding accumulated flight hours and flight cycles on the leased aircraft.

As the problem size of mathematical models grows, the computational complexity and difficulty of finding solutions increase exponentially. This phenomenon is particularly evident in optimization problems, where larger problem instances often involve a vast search space of potential solutions. With each additional variable, constraint, or decision factor, the number of possible combinations to explore multiplies, rendering the problem increasingly intricate and demanding on computational resources. In line with the above-mentioned decision variables and constraints and depending on the size of our problem, the model is hard to solve. In the next section, we give an illustrative example of the problem solved with the mathematical model.

4.4 Numerical Example

In this section, we prepared an instance of 5 aircraft 12 weeks to demonstrate the solution output of the mathematical model. Operating costs are randomly generated from the High class-High variability interval that will be defined in Section 5.2. Since the problem size is small, we solve the instance without the relaxation of x_{itj}^c. The instance was optimally solved in 3196 seconds. The flight plan and hangar capacity (A_t) of the instance are showed in Table 4.1.

Period (t)	1	2	3	4	5	6	7	8	9	10	11	12
FC	103	84	77	76	82	94	92	83	90	102	90	98
FH	287	237.2	212.8	216	195.2	226.9	231.9	210.7	221.8	253.3	236.7	263.7
A_t	1	1	1	1	1	0	0	0	1	1	1	1

Table 4.1: Flight plan and hangar capacity of numerical example

This instance has 5 aircraft in the fleet and 1 more aircraft that joins the fleet at period 1 and leaves at period 8. Additionally, 2 aircraft (aircraft 7 and 8) can be short-term leased to fulfill the flight plan. The solution output, i.e., utilization and maintenance plan of the fleet is demonstrated in the Table 4.2. "X" shows overhaul periods in the tables.

Aircraft (i) / Period (t)	1	2	3	4	5	6	7	8	9	10	11	12
1	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	X	14 FC 32.2 FH	14 FC 30.9 FH	14 FC 35.8 FH	14 FC 20.9 FH	14 FC 37.9 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH
2	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	X	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH
3	14 FC 38 FH	X	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH
4	X	14 FC 38 FH	14 FC 37.9 FH	14 FC 38 FH	14 FC 37.9 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH
5	4 FC 20 FH	5 FC 24.6 FH	X	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 37.8 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH
6	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	13 FC 38 FH	-	-	-	-
7	40 FC 111.9 FH	23 FC 60.6 FH	6 21.9 FH	6 26 FH	12 11.1 FH	10 6 FH	8 FC 6.1 FH	0	20 31.9 FH	31 60.9 FH	20 46.7 FH	27 70.5 FH
8	3 FC 3.1 FH	0	1 FC 1 FH	0	0	0	0	0	0	1 FC 2.4 FH	0	1 FC 3.2 FH

Total number of aircraft in overhaul at period t	1	1	1	1	1	0	0	0	0	0	0	0

Table 4.2: Utilization and maintenance plan of 5 aircraft fleet mathematical model solution

We also solved the problem with a scenario that we think is highly likely to be used in real life, with which we can compare the mathematical model solution. In this scenario, the constraints defined in our problem, i.e., unused maintenance life, hangar capacity (A_t) and redelivery penalty cost constraints and flight hour intervals approach, are not considered. We assigned flight cycles in the flight plan are evenly distributed among the available aircraft in the fleet. The flight hours are distributed according to the average flight hour in the period. Also, we considered the maintenance limits ($\bar{H}_i$, $\bar{C}_i$, $\bar{D}_i$), and flight hour and cycle bounds an aircraft can operate in a period ($\bar{h}_i$, $\bar{c}_i$) while assigning the flights. The solution output is demonstrated in Table 4.3. Since the flight distibution is not done regarding the hangar capacity, aircraft 4 and 5 had to be grounded, showed as "0" in the table. This situation has increased the use of short-term leased aircraft which has high operating costs, so the total operating cost has increased.

Aircraft (i) / Period (t)	1	2	3	4	5	6	7	8	9	10	11	12
1	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	13 FC 36.4 FH	X	14 FC 33.6 FH	14 FC 35 FH	14 FC 35 FH	14 FC 35 FH	14 FC 35 FH	14 FC 36.4 FH	14 FC 37.8 FH
2	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 33.6 FH	14 FC 33.6 FH	14 FC 35 FH	12 FC 30 FH	X	14 FC 35 FH	14 FC 36.4 FH	14 FC 37.8 FH
3	14 FC 38 FH	X	14 FC 38 FH	14 FC 38 FH	14 FC 33.6 FH	14 FC 33.6 FH	14 FC 35 FH	14 FC 35 FH	14 FC 35 FH	14 FC 35 FH	14 FC 36.4 FH	14 FC 37.8 FH
4	6 FC 16.8 FH	0	0	X	14 FC 33.6 FH	14 FC 33.6 FH	14 FC 35 FH	14 FC 35 FH	14 FC 35 FH	14 FC 35 FH	14 FC 36.4 FH	14 FC 37.8 FH
5	9 FC 25.2 FH	0	X	14 FC 38 FH	14 FC 33.6 FH	14 FC 33.6 FH	14 FC 35 FH	14 FC 35 FH	14 FC 35 FH	14 FC 35 FH	14 FC 36.4 FH	14 FC 37.8 FH
6	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 38 FH	14 FC 33.6 FH	14 FC 33.6 FH	14 FC 35 FH	14 FC 35 FH	-	-	-	-
7	32 FC 92.9 FH	42 FC 123.2 FH	21 FC 60.8 FH	7 FC 27.5 FH	12 FC 27.2 FH	10 FC 25.2 FH	8 FC 21.8 FH	1 FC 5.7 FH	34 FC 81.8 FH	32 FC 78.3 FH	20 FC 54.7 FH	28 FC 74.7 FH
8	0	0	0	0	0	0	0	0	0	0	0	0

Total number of aircraft in overhaul at period t	0	1	1	1	1	0	0	0	1	0	0	0

Table 4.3: Utilization and maintenance plan of 5 aircraft fleet real-life scenario solution

The operating costs, early maintenance costs, and redelivery penalty costs are calculated as in Table 4.4. According to the cost comparision of the two models, approximately $2M gain is achieved in total cost with the Mathematical Model.

	Mathematical Model			Real-Life Scenario		
Aircraft (i)	Operating Cost	Early Maint. Cost	Redelivery Penalty Cost	Operating Cost	Early Maint. Cost	Redelivery Penalty Cost
1	\$3,145,473	\$310,789	-	\$3,181,538	\$296,090	-
2	\$3,181,030	\$257,091	-	\$3,070,894	\$201,097	-
3	\$3,116,300	\$353,719	-	\$3,036,386	\$353,719	-
4	\$3,240,663	\$263,130	-	\$2,403,117	\$254,622	-
5	\$2,876,558	\$268,709	-	\$2,722,369	\$272,300	-
6	\$2,346,965	-	\$16,425	\$2,303,987	-	\$17,240
7	\$10,625,333	-	-	\$14,147,800	-	-
8	\$276,167	-	-	-	-	-
Overall	\$28,808,489	\$1,453,438	\$16,425	\$30,866,091	\$1,377,828	\$17,240
Total Cost	\$30,278,352			\$32,261,162		

Table 4.4: Costs of the utilization and maintenance plan

4.5 A Naive Greedy Heuristic Algorithm

This section explains the heuristic algorithm developed for this problem. We designed the algorithm by evolving the logic of the Heuristic Algorithm to minimize the same objective value defined in Section 4.3. Steps followed in the algorithm can be given as follows:

1. Sort aircraft in the fleet based on their operating cost per hour in ascending order.

2. Calculate the operating cost of one flight cycle for each flight range and period.

3. For each period, calculate the operating cost gains of each aircraft and the next aircraft in aircraft order. Sort flight ranges in each period for each aircraft accordingly.

4. **For each aircraft in the aircraft order,**

    4.1. Initiate the counters (accumulated flight cycles, hours, days on the aircraft, total cost of aircraft).

4.2. **For each period that the aircraft is in the fleet** (between T_i^P and T_i^R), If there is a flight to assign in period t (T_t^c > 0),

  4.2.1. **For each flight range regarding the order,**

    4.2.1.1. **If accumulated flight cycles, hours, and calendar days on aircraft are in the maintenance limits,** If there is a flight to assign in flight range (T_{tj}^c > 0),

      (a) Determine the maximum assignable flight cycles by remaining within the maximum flight cycles and hours an aircraft can operate. After that, calculate the assignable flight hours according to the average flight hour in the range.

      (b) Determine the maximum assigned flight cycles,

        - If accumulated flight cycles and hours with the assignable flight cycles and hours are in the maintenance limits, use the assignable flight cycles and hours determined in the previous step.
        - Otherwise, determine the maximum assigned flight cycles by remaining within the maintenance limits.

      (c) After that, calculate the assigned flight hours according to the average flight hour in the range.

      (d) Update the counters. Calculate the operating cost in the flight range and add to the cost of each aircraft in each period.

      (e) If one or more of the accumulated values is on the maintenance limit,

        - If the hangar is available in the next period and during overhaul, return to step 4.2.1.
        - Otherwise, check the previous periods until find the first period in which the aircraft can undergo premature maintenance.
          * Specify the maintenance in the schedule.
          * Reupdate counters retrospectively.
          * Calculate the penalty cost of unused life and add to the cost of each aircraft in each period.

        - ∗ Set accumulated flight cycles, hours, and days to zero.
        - ∗ Break the flight range loop and return to step 4.2 with the period at the end of the overhaul duration.

    4.2.1.2. **Else, the aircraft undergoes maintenance:**

        - If a flight assignment is made in the current period, skip to the next period, and specify the maintenance in the schedule.
        - Calculate the penalty cost of unused life and add to the cost of each aircraft in each period.
        - Zeroize accumulated flight cycles, hours, and days.
        - Break the flight range loop (step 4.2.1).

  4.2.2. If an aircraft leaves the fleet before the end of the planning horizon, calculate the redelivery penalty cost.

  4.2.3. Calculate the total cost for each aircraft.

  4.2.4. If the aircraft undergoes maintenance in step 4.2.1.2, return to step 4.2 with the period at the end of overhaul duration.

4.3. Calculate the objective function value, i.e., the total cost of the fleet.

In the first step, sorting is made based on the flight cost per hour to determine the optimal assignment order since the flight cost per hour has a greater impact on the objective value than the flight cost per cycle. Also assigning flights to the aircraft with the minimum operating cost is important. Hence, in steps 2 and 3, the algorithm determines which flight range in period will be assigned to the aircraft.

The algorithm iterates through each aircraft, its planning periods, and flight ranges as seen in steps 4, 4.2, and 4.2.1. The counters for each aircraft in each period in the algorithm are initialized to monitor through the processes. Before each assignment process, the algorithm checks whether the aircraft's accumulated values are within the maintenance limits as in step 4.2.1.1. Otherwise, it proceeds to the maintenance step 4.2.1.2.

In the assignment steps (a) and (b), the algorithm determines the assigned flight cycles and hours regarding the flight limits per period $\bar{c}_i$ and $\bar{h}_i$, and the maintenance limits $\bar{C}_i$ and $\bar{H}_i$. After the designation of the assigned flight cycles and hours, the algorithm checks whether the aircraft will undergo maintenance in the next period. If so, the limit of the maximum number of aircraft that can be in maintenance is checked for overhaul duration of the aircraft. If the next period is available, the algorithm continues in the setup. Otherwise, it checks the previous periods until finds the first period in which the aircraft can undergo premature maintenance.

In the premature maintenance step, the algorithm reverses the assignments and updates the counters accordingly. The rest is the same as the maintenance step as follows.

In the maintenance step, the algorithm schedules maintenance periods according to the overhaul duration, updates variables and counters accordingly.

After each assignment or maintenance activity, the algorithm calculates associated costs, i.e., operating cost, and penalty cost for unused flight hours, cycles, and days.

If an aircraft leaves the fleet before the end of the planning horizon, the algorithm calculates the deviation from the redelivery targets, H_i^{red} and C_i^{red}, and the associated redelivery penalty cost.

In the end, the objective function value is calculated by summing the operating costs, penalty cost of unused life, and redelivery penalty cost of each aircraft.

CHAPTER 5

COMPUTATIONAL RESULTS

This chapter presents the computational results for the Mathematical Model and Heuristic Algorithm. For this study, it is hard to get flight data and constraints of the leasing contracts from airline companies, and there is limited source to obtain the flight data. We used the database provided by the Bureau of Transportation Statistics US (BTS, 2023) for gathering recent flight data for a selected airline. After that, the input data of the study is composed by narrowing down the obtained data. The data processing, experimental design process, and computational results are discussed below.

5.1 Data Preprocessing

To generate problem instances for the computational study, we need the planned flights data for an airline. So we used past flight data provided by BTS. The Bureau of Transportation Statistics (BTS), part of the U.S. Department of Transportation (DOT), is a unique source of commercial aviation and transportation economics statistics. Also, the BTS database provides a context for understanding statistics on transportation for decision-makers and the public.

We queried raw flight data for all airlines in the BTS database, including flight date, operator ID, tail number, origin and destination airport ID, and airtime in minutes for the year of 2022 month-by-month. Also, we obtained a list of aircraft models and ages for tail numbers from BTS. We merged both lists and chose United Airlines among all airlines. Subsequently, we made the following decisions for the computational study. We filtered the dataset to include narrow-body aircraft flights exclusively. Then, we filtered tail numbers that have flights in all months in the considered time interval. As a result, we obtained a list of Boeing 737, 757 family, and Airbus 319 family. We decided to proceed with Boeing 737-924 type aircraft flight data because the number of aircraft is more than other types. Even though we studied with one type of aircraft, the aircraft are of different generations and different ages so that each aircraft has different characteristics, i.e., operating costs, initial values.

A section of the dataset obtained is shown below in Table 5.1. Each column represents respectively month, week, day, tail number of aircraft, operator carrier flight number, origin and destination airports ID, flight time in minutes, aircraft model, and age. Each flight cycle is in each row day by day.

M	W	D	Tail Num.	Op. Carrier Fl. Num.	Origin Airport ID	Dest. Airport ID	Air Time	Model	Age
1	1	1	N64844	1761	14679	14771	64	Boeing 737-924ER (W)	8
1	1	1	N64844	2114	14771	14107	90	Boeing 737-924ER (W)	8
1	1	1	N64844	1896	14107	14771	98	Boeing 737-924ER (W)	8
1	1	1	N64844	2440	14771	13204	273	Boeing 737-924ER (W)	8
1	2	12	N57439	1151	12266	15304	91	Boeing 737-924ER	14
1	2	12	N57439	2603	15304	12264	109	Boeing 737-924ER	14
1	3	16	N36476	343	14679	14771	64	Boeing 737-924ER (W)	10
1	3	17	N36476	2440	14771	13204	283	Boeing 737-924ER (W)	10
1	4	24	N45440	1284	12892	12264	243	Boeing 737-924ER	14
1	4	25	N45440	461	12264	11618	42	Boeing 737-924ER	14

Table 5.1: A section of dataset

Since we propose rough-cut utilization planning, we focused on flight cycles and flight time in the data. We composed flight schedules from the data set for different sized fleets. As we mentioned before, we defined the period in this problem as week. Hence, we combined our daily flight data as weekly. As stated in the previous chapters, an airline is assumed to have a reasonable estimate of flight legs and frequencies for each period (week or month) in the next few years. So, we used the weekly flight plan repeatedly to create a flight schedule for a planning horizon longer than 48 weeks.

5.2 Design of Experimental Study

In this thesis, we propose to prepare a utilization plan for an aircraft fleet for a certain period. Utilization planning and heavy check maintenance planning decisions are made jointly by considering leasing contract-based delivery/redelivery conditions and utilization restrictions on the leased aircraft.

For the computational study, we have selected the following experimental factors: length of planning horizon (T), fleet size (I), operating cost parameters, hangar capacity (A_t). These factors affect the objective function, the schedule and the difficulty of the planning problem. We determined the values as a summary in Table 5.2. Next, we discuss the experimental factors in detail.

Experimental Factors	Values
Fleet Size (I)	20, 40, 80 aircraft
Planning Horizon (T)	52, 104 weeks
Operating Cost ($C_i^{o/h}$) Class	High: \$3750 Low: \$2750
Operating Cost Variability	High: \$250 Low: \$50
Hangar Capacity (A_t)	max=Ix0.1 min=Ix0.05 seasonal effect=revise min with zero hangar capacity in high season (21-32 weeks)

Table 5.2: Experimental Factors

We first tested the computational performance of IBM CPLEX on the mathematical model. We tried to solve different size problem instances to find the problem size that can be solved in a reasonable time by using IBM CPLEX. Within this framework, we decided to proceed with three fleet sizes (I) of 20, 40, and 80 aircraft and two planning horizons (T) of 1 and 2 years (52 and 104 weeks). As we specify the period in this study as a week, the number of days in a period (t_p) is 7.

As stated in Chapter 4, the problem incorporates redelivery conditions for leased aircraft. The number of leased aircraft is 20% of the fleet size, i.e., 4, 8, and 16 aircraft are leased. Each leased aircraft i joins the fleet in period T_i^P and leaves the fleet in period T_i^R. Each leased aircraft has a redelivery condition regarding accumulated flight hours and flight cycles on the aircraft. These H_i^{red} and C_i^{red} values are defined as 3,000 flight hours and 1,000 flight cycles for each aircraft i. If the airline misses the redelivery targets, there will be a penalty for deviation from the target. Generally, penalty costs derive from leasing contracts. This study assumes the penalty cost per flight hour and cycle ($C_i^{red/h}$ and $C_i^{red/c}$) as \$50 and \$75 for each aircraft i, respectively.

Each aircraft in the fleet can operate different limited flight hours and cycles in a period due to operational constraints. In this case, the average flight hours and cycles an aircraft operates in a week are calculated from the obtained data. Afterward, the maximum flight hours and cycles in a week are determined as 64 hours and 25 cycles according to flight data.

Each aircraft i has specific operating cost performance and maintenance status.

- An aircraft operates a flight at a particular cost determined by a fixed cost (cost per flight cycle, $C_i^{o/c}$) and a variable cost (cost per flight hour, $C_i^{o/h}$).
- Each aircraft has a certain maintenance status at the beginning of the planning horizon (T_i^P = 1) or at the time T_i^P an aircraft joins the fleet, i.e., initial values: the flight hours ($H_{i(T_i^P-1)}$), flight cycles ($C_{i(T_i^P-1)}$), and calendar days ($D_{i(T_i^P-1)}$).

We researched approximate operating cost values, and we made an inference through United Airlines Fourth Quarter and Full Year 2022 Financial Results. In our study, to define the operating costs and initial values of each aircraft in the fleet, we used the random number generator of Java.

As in Table 5.2, we determined high and low operating cost per flight hour ($C_i^{o/h}$). And, we defined operating cost variability to determine the interval width for generating the random $C_i^{o/h}$. Hence, the intervals in which we randomly generated $C_i^{o/h}$ for each aircraft i are as follows:

- High class-High variability: U(3500, 4000)
- High class-Low variability: U(3700, 3800)
- Low class-High variability: U(2500, 3000)
- Low class-Low variability: U(2700, 2800)

We calculated the operating costs per flight cycle for each aircraft ($C_i^{o/c}$) as three times of randomly generated $C_i^{o/h}$.

We chose the range of initial flight cycles and calendar days on the aircraft to be randomly generated between 200-2000 cycles and 150-1500 days which are 10$\%$ and 100$\%$ of $\bar{C}_i$, and $\bar{D}_i$ maintenance limits. We assumed $\bar{H}_i$ as the product of $\bar{C}_i$ by the approximate average flight hours (2.5 hours) of an aircraft in the fleet. Operating costs and initial values are randomly generated in the abovementioned intervals for 5 replications with five specific seeds.

As stated in Chapter 4, each C-check includes a different set of tasks, and we assumed that an aircraft can undergo maintenance 12 times at maximum throughout the planning horizon. Each C-check task requires a different overhaul duration for each aircraft i, O_i^k, which is determined as follows:

- for k = 12; O_i^k = 3 weeks,
- for k = 3, 6 and 9; O_i^k = 2 weeks,
- for other values of k; O_i^k = 1 week.

Maintenance limits, i.e., flight hour, flight cycle, and calendar day limits vary for each aircraft type. Regarding the maintenance interval of Boeing 737-924 type, $\bar{H}_i$, $\bar{C}_i$, and $\bar{D}_i$ values for each aircraft i are determined as 6000 hours, 2000 cycles, and 1500 days. When an aircraft undergoes a heavy check; unused maintenance lives, i.e., flight hours, cycles, or days on the parts create a penalty cost. The unused flight hour and cycle costs ($C_i^{em/h}$, $C_i^{em/c}$) are 5$\%$ of $C_i^{o/h}$ and $C_i^{o/c}$. The unused calendar day cost ($C_i^{em/d}$) is set to \$100.

Since the airline has a limited hangar capacity for heavy checks, at most A_t aircraft can be under maintenance in period t. An airline can impose a limit on A_t, to make more aircraft available during peak demand periods. Three scenarios are set for this study as follows:

1. For each period t, high hangar capacity A_t is determined as 10$\%$ of the fleet size I,
2. For each period t, low hangar capacity A_t is determined as 5$\%$ of the fleet size I,

3. High-season weeks in a year, $t = \{21, 22, \ldots, 32\}$, A_t is chosen to be zero. Rest of the weeks in each year planning horizon T, hangar capacity is set the same as the minimum number of hangar capacity. The third scenario in this study is called the seasonal effect.

Figure 5.1 shows a frequency distribution of United Airlines' scheduled flights in the third week of July 2022. The figure shows eight flight time intervals, and the number of flights is given for each time interval. As shown in Figure 5.1 , there are a small number of short flights lasting between 15 to 45 minutes and long flights lasting between 300 to 375 minutes. Many of the flights are between 75 to 120 minutes long. For each week in our data set, we have a similar distribution. Therefore, we used flight ranges as in the distribution in our instances.

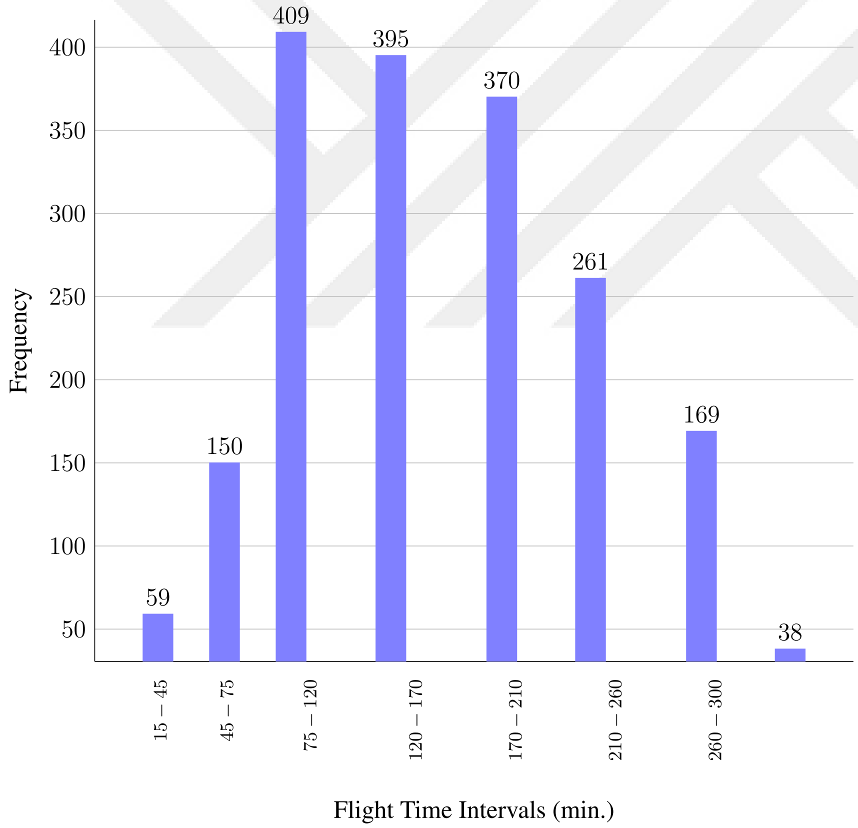

Figure 5.1: Flight time distribution of United Airlines - third week in July 2022

By this approach, the flight hour intervals (J) for each period t in the planning horizon T are specified as eight flight ranges. So, the flight schedule for each fleet is designed as consisting of flight cycles (T^c_{tj}) and the average flight hour (B_{tj}) in flight range j

in period t. We combined the daily flight data as weekly data and calculated T^c_{tj} and B_{tj} for each flight range j in period t.

During the overhaul, an aircraft cannot operate any flights. The flight data here is obtained from a real fleet schedule. The schedule does not include maintenance events. However, our model will force some aircraft to undergo maintenance and become unavailable. This may result in infeasibility. In the computational study, we assume that the airline can lease some aircraft for the short term to fulfill scheduled flights in the timetable and avoid infeasibilities. Therefore, we extended the fleet size by 20% to consider those short-term lease opportunities. It is assumed that,

- These aircraft are always available on the planning horizon with zero initial values at the beginning.
- These aircraft can operate 20 hours and 20 cycles a day and 7 days a week.
- These aircraft have much higher $C_i^{o/h}$ and $C_i^{o/c}$ values than the aircraft in the fleet. It is determined as \$10,000 per flight hour and \$30,000 per flight.
- The airline is not responsible for maintaining the short-term leased aircraft. So, we separately set the maintenance limits as 100,000 flight hours, flight cycles, and calendar days. Because in our computation, we do not want them to undergo maintenance. Correspondingly, we specify the costs of early maintenance as zero.
- Penalty costs are the same with aircraft in the fleet as they are not one of the aircraft to be redelivered.

To sum up, in this computational study we solved 360 problem instances for three different fleet sizes, two different planning horizons (52, 104 weeks), three different hangar capacities (max, min, seasonal effect), with five replications of two operating cost classes (high, low), and two operating cost variability (high, low).

In the computational study, we did not use the constraint (4.17) as it was defined in Section 4.3, since the flight time interval approach also helps to make utilization decisions that comply with the constraint.

5.3 Computational Results

We have solved 360 problem instances with the mathematical model and the heuristic algorithm described in Section 4.3 and Section 4.5. In this section, we discuss the results of the solution approaches and the impacts of experimental factors on the solutions.

5.3.1 Experimental Results for the Mathematical Model

We used Java programming language with the IBM CPLEX optimization software package to solve the mathematical model. IBM CPLEX provides solutions to optimization problems, including variable values that optimize the objective function and information about the status of the optimization process, e.g., whether a feasible solution was found, whether the problem is infeasible.

The experiments are conducted on a computer with 16 GB RAM and an Apple M1 Pro 8-core 3.2 GHz processor. Due to the size of the problem, CPLEX may find an optimal or feasible solution for an instance in many hours, even days. Since there are 360 instances to be solved for this study, the CPLEX computation time for each instance is limited to 1,800 seconds. We identified the x_{itj}^{c} value as an integer in section 4.3. However, for the purpose of CPLEX finding a solution faster and easier, we relaxed the x_{itj}^{c} value and used as double. This is also because we are trying to get a rough-cut plan.

To be able to interpret the CPLEX solution performance and quality, we observed the solution statuses of instances and the gap values. CPLEX calculates the gap value of a feasible or optimal solution as follows:

$$\text{Gap} = (\text{Objective Value} - \text{Best Bound})/\text{Objective Value}$$

In Table 5.3, we gave performances and qualities of solutions based on fleet size and length of planning horizon. As seen, 1 out of 360 instances could be optimally solved. Across 360 instances, the result statuses of the CPLEX model are as follows: 87.22% feasible solution, 0.28% optimal solution, 5.83% no solution with Best Bound value and 6.67% no solution. 45 instances has no solution which means CPLEX does not find a feasible solution for these instances in limited computation time. However, 24 out of 45 instances have Best Bound value. As the size of the problem increases, CPLEX solution quality worsens. CPLEX founds approximately 93% feasible solutions for instances of 20 and 40-aircraft fleets, regardless of the planning horizon length. However, this rate drops to around 58% for larger problems like 80-aircraft 104-week instances. An increase in the fleet size or the planning horizon length increases problem size and complexity, leading to poorer solution quality.

		Solution Status			Solution Quality		
I	T	Feasible	Optimal	No Solution	Max Gap(%)	Min Gap(%)	Avg Gap(%)
20	52	56	0	4	0.89	0.27	0.57
	104	56	0	4	4.82	0.62	1.41
	Overall	112	0	8	4.82	0.27	0.99
40	52	55	1	4	1.25	0.0	0.88
	104	56	0	4	71.59	1.12	41.28
	Overall	111	1	8	71.59	0.0	21.08
80	52	56	0	4	27.07	0.84	7.27
	104	35	0	25*	78.66	49.13	66.23
	Overall	91	0	29	78.66	0.84	29.95
Overall		314	1	45	78.66	0.00	16.50

*: 21 of them have a Best Bound value.

Table 5.3: Performance of IBM CPLEX based on fleet size and planning horizon length

To analyze the operating cost variability effect on solutions, we studied small-sized instances, i.e., 20 aircraft fleet and 40 aircraft 52 weeks, since their solutions are of higher quality. There is no effect on solution status. Besides, as seen in Table 5.4, the average gap value has slightly improved in samples with low variability in operating cost.

The hangar capacity effect is demonstrated in Table 5.5. We observed that the seasonal effect increased the number of no-solution results. However, according to the average of gap values, solution quality has increased in the solved instances.

I	T	Op. Cost. Var.	Max Gap(%)	Min Gap(%)	Avg Gap(%)
20	52	High	0.89	0.42	0.63
		Low	0.80	0.27	0.51
	104	High	4.82	0.67	1.57
		Low	3.28	0.62	1.26
40	52	High	1.25	0.0	0.91
		Low	1.21	0.56	0.85

Table 5.4: Performance of IBM CPLEX based on fleet size, planning horizon length and operating cost variability

		Solution Status			Solution Quality		
I	A_t	Feasible	Optimal	No Solution	Max Gap(%)	Min Gap(%)	Avg Gap(%)
20	max	40	0	0	4.82	0.27	1.06
	min	40	0	0	4.44	0.31	1.03
	seasonal effect	32	0	8	2.74	0.31	0.86
	Overall	112	0	8	4.82	0.27	0.99
40	max	39	1	0	70.88	0	23.7
	min	40	0	0	71.59	0.61	26.90
	seasonal effect	32	0	8	43.72	0.64	10.52
	Overall	111	1	8	71.59	0	21.08
80	max	32	0	8*	78.66	1.12	31.65
	min	32	0	8*	71.56	1.08	29.84
	seasonal effect	27	0	13**	67.33	0.84	28.06
	Overall	91	0	29	78.66	0.84	29.95
Overall		314	1	45	78.66	0	16.50

*: All have a Best Bound value.

**: 5 of them have a Best Bound value.

Table 5.5: Performance of IBM CPLEX based on fleet size and hangar capacity

Additional to the 1800 sec. computational time, we solved 20 aircraft instances with 3600 sec. computation time limit. The results are showed in Tables 5.6, 5.7 and 5.8. There is no optimal solution as with 1800 sec. When we compare the results (Tables 5.6, 5.7 and 5.8) with Table 5.3, 5.4 and 5.5;

- The solution statuses and effect of experimental factors are not affected by the computation time.
- With longer computation time, the gap values of 52 week instances have slightly improved whereas 104 week instances' gap values have greatly improved.

		Solution Status			Solution Quality		
I	T	Feasible	Optimal	No Solution	Max Gap(%)	Min Gap(%)	Avg Gap(%)
20	52	55	0	5*	0.9	0.25	0.55
	104	56	0	4	1.42	0.51	0.79
	Overall	111	0	9	1.42	0.25	0.67

*: 1 of them gave memory error and has a Best Bound value.

Table 5.6: Performance of IBM CPLEX based on fleet size and planning horizon length

I	T	Op. Cost. Var.	Max Gap(%)	Min Gap(%)	Avg Gap(%)
20	52	High	0.81	0.38	0.60
		Low	0.9	0.25	0.50
	104	High	1.42	0.62	0.85
		Low	1.16	0.51	0.72

Table 5.7: Performance of IBM CPLEX based on fleet size, planning horizon length and operating cost variability

		Solution Status			Solution Quality		
I	A_t	Feasible	Optimal	No Solution	Max Gap(%)	Min Gap(%)	Avg Gap(%)
20	max	39	0	1*	1.34	0.25	0.72
	min	40	0	0	1.24	0.3	0.63
	seasonal effect	32	0	8	1.42	0.27	0.66
	Overall	111	0	9	1.42	0.25	0.67

*: 1 of them gave memory error and has a Best Bound value.

Table 5.8: Performance of IBM CPLEX based on fleet size and hangar capacity

We increased the computation time to 7200 sec. to resolve 20 aircraft 52 week instances. The solution results are showed in Tables 5.9, 5.10 and 5.11. The solution quality got better with 7200 sec. computation time.

		Solution Status			Solution Quality		
I	T	Feasible	Optimal	No Solution	Max Gap(%)	Min Gap(%)	Avg Gap(%)
20	52	51	0	9*	0.8	0.21	0.49

*: 5 of them gave memory error and has a Best Bound value.

Table 5.9: Performance of IBM CPLEX based on fleet size and planning horizon length

I	T	Op. Cost. Var.	Max Gap(%)	Min Gap(%)	Avg Gap(%)
20	52	High	0.8	0.35	0.57
		Low	0.71	0.21	0.41

Table 5.10: Performance of IBM CPLEX based on fleet size, planning horizon length and operating cost variability

		Solution Status			Solution Quality		
I	A_t	Feasible	Optimal	No Solution	Max Gap(%)	Min Gap(%)	Avg Gap(%)
20	max	18	0	2*	0.8	0.21	0.5
	min	18	0	2*	0.73	0.28	0.5
	seasonal effect	15	0	5**	0.72	0.25	0.47
	Overall	51	0	9	0.8	0.21	0.49

*: All gave memory error and has a Best Bound value.

**: 1 of them gave memory error and has a Best Bound value.

Table 5.11: Performance of IBM CPLEX based on fleet size and hangar capacity

5.3.2 Experimental Results for the Heuristic Algorithm

The Heuristic Algorithm (HA) explained in Section 4.5 is coded using Java programming language. The experiments are conducted on a computer with 16 GB RAM and an Apple M1 Pro 8-core 3.2 GHz processor.

This algorithm solves an instance in a short time. In this experiment, solving an instance took 0.16 sec. at maximum. All 360 instances are solved in 5 seconds.

To observe the qualities of the solutions, we calculated the Heuristic Algorithm's gap values according to the Best Bound value of the Mathematical Model (MM), the same way as CPLEX:

$$\text{Gap} = \frac{(\text{Objective Value of Heuristic Solution} - \text{Best Bound of Mathematical Model})}{\text{Objective Value of Heuristic Solution}}$$

As we mentioned in Section 5.3.1, there is no solution and no Best Bound value for 24 out of 360 instances solved with MM. Apart from these 24 instances, the solution found by HA for 1 instance is not feasible. Hence, we analyzed the solution quality of HA according to 335 instances. The performance and the quality of HA solutions are demonstrated in Table 5.12. There are 2 instances noted as 'no feasible' in table due to the incomplete flight assignments. The algorithm assigns flights aircraft by aircraft, so a situation may arise where the number of aircraft, including short-term lease aircraft is insufficient to assign all flights in the schedule due to the daily flight hour and cycle constraints. According to Table 5.12, HA performance is not significantly affected by the problem size whereas HA quality has slightly improved for big-sized problems.

		Solution Status		Solution Quality		
I	T	Feasible	No Feasible	Max Gap(%)	Min Gap(%)	Avg Gap(%)
20	52	60	0	22.60	13.35	17.90
	104	58	2	22.11	13.48	17.71
	Overall	118	2	22.60	13.35	17.81
40	52	60	0	23.66	14.70	19.27
	104	60	0	23.68	14.50	19.19
	Overall	120	0	23.68	14.50	19.23
80	52	60	0	22.96	14.74	18.82
	104	60	0	22.66	14.66	18.76
	Overall	120	0	22.96	14.66	18.79
Overall		358	2	23.68	13.35	18.61

Table 5.12: Performance of Heuristic Algorithm based on fleet size and planning horizon length

HA solution status is not affected by experimental factors. We showed operating cost variability and hangar capacity effects on the solution quality of HA in Tables 5.13 and 5.14. While the solution quality worsens with low operating cost variability, the quality has increased slightly with the seasonal effect in hangar capacity.

			Solution Quality		
I	T	Op. Cost Var.	Max Gap(%)	Min Gap(%)	Avg. Gap(%)
20	52	High	22.60	13.35	17.33
		Low	22.50	15.42	18.47
	104	High	22.04	13.48	17.22
		Low	22.11	14.60	18.21
		Overall	22.60	13.35	17.81
40	52	High	23.29	14.70	18.74
		Low	23.66	15.88	19.81
	104	High	22.83	14.50	18.53
		Low	23.68	15.61	19.84
		Overall	23.68	14.50	19.23
80	52	High	22.46	14.74	18.65
		Low	22.96	15.36	18.98
	104	High	22.29	14.66	18.56
		Low	22.66	15.45	18.96
		Overall	22.96	14.66	18.79
		Overall	23.68	13.35	18.61

Table 5.13: Quality of solutions based on fleet size, planning horizon length, and operating cost variability

		Solution Quality		
(I)	A_t	Max Gap(%)	Min Gap(%)	Avg. Gap(%)
20	max	22.6	13.35	17.78
	min	22.47	13.45	17.87
	seasonal effect	22.45	13.48	17.75
	Overall	22.60	13.35	17.81
40	max	23.66	14.54	19.23
	min	23.68	14.55	19.25
	seasonal effect	23.61	14.50	19.20
	Overall	23.68	14.50	19.23
80	max	22.94	14.66	18.79
	min	22.96	14.67	18.79
	seasonal effect	22.94	14.67	18.79
	Overall	22.96	14.66	18.79
	Overall	23.68	13.35	18.61

Table 5.14: Quality of solutions based on fleet size, and hangar capacity

5.3.3 Comparison of the Results of Mathematical Model (MM) and Heuristic Algorithm (HA)

In this part, we compared the objective values of both approaches to check the solution performances. Both approaches could not find a feasible solution for only one instance. In the first two columns of Table 5.15, we showed the solution performance comparison of 314 instances that both approaches have found a feasible solution. The next column shows 44 of the 45 instances that MM found no solution were solved by HA. The last column shows that MM solved 1 of the 2 instances that HA found “not feasible” solution.

For larger instances, i.e., 40 aircraft-104 weeks and 80 aircraft-104 weeks Heuristic Algorithm found better solutions. Especially for 80 aircraft-104 weeks instances, we observed that MM has not found a solution better than HA. In the overall evaluation, the success of MM in 314 instances is 72%.

			Number of Instances			
			Both found a solution		MM found no Solution	HA found no Solution
(I)	(T)	A_t	HA<MM	MM<HA	HA found a solution	MM found a solution
20	52	max	0	20	0	0
		min	0	20	0	0
		seasonal effect	0	16	4	0
		Overall	0	56	4	0
	104	max	0	19	0	1
		min	0	20	0	0
		seasonal effect	0	16	3	0
		Overall	0	55	3	1
		Overall	0	111	7	1
40	52	max	0	20	0	0
		min	0	20	0	0
		seasonal effect	0	16	4	0
		Overall	0	56	4	0
	104	max	18	2	0	0
		min	19	1	0	0
		seasonal effect	8	8	4	0
		Overall	45	11	4	0
		Overall	45	67	8	0
80	52	max	4	16	0	0
		min	2	18	0	0
		seasonal effect	1	15	4	0
		Overall	7	49	4	0
	104	max	12	0	8	0
		min	12	0	8	0
		seasonal effect	11	0	9	0
		Overall	35	0	25	0
		Overall	42	49	29	0
		Overall	87	227	44	1

Table 5.15: Comparison of solution performance

The solution qualities of MM and HA, i.e., the gap values calculated regarding to Best Bound value have been shown separately in Section 5.3.1 and 5.3.2. Here in Table 5.16, we compared the gap values of 314 instances that have a feasible solution by both approaches.

		Heuristic Algorithm			Mathematical Model		
I	T	Max Gap(%)	Min Gap(%)	Avg. Gap(%)	Max Gap(%)	Min Gap(%)	Avg. Gap(%)
20	52	22.6	13.35	17.90	0.89	0.27	0.57
	104	22.11	13.48	17.71	4.82	0.62	1.42
	Overall	22.6	13.35	17.81	4.82	0.27	0.99
40	52	23.66	14.7	19.27	1.25	0	0.88
	104	23.68	14.5	19.19	71.59	1.12	41.28
	Overall	23.68	14.5	19.23	71.59	0	21.08
80	52	22.96	14.74	18.82	27.07	0.84	7.27
	104	22.54	14.66	18.66	78.66	49.13	66.23
	Overall	22.96	14.66	18.76	78.66	0.84	29.95
Overall		23.68	13.35	18.59	78.66	0	16.55

Table 5.16: Comparison of solution quality

HA solution quality is more stable than MM's. However, MM has much better solution quality for small instances, i.e., 20-aircraft fleet, 40-aircraft 52-week, and 80-aircraft 52-week instances. While the problem size increases, MM's solution quality worsens.

In general evaluation, according to the Best Bound values found by CPLEX, the HA solutions' gap value could be calculated for 335 instances, and the MM solution's gap value could be calculated for 315 instances. We showed the number of instances distributed according to certain gap intervals in Figure 5.2. The advantage of HA is having a high solution-finding rate and finding a solution in a short time. HA solution quality is more stable regardless of problem size. However, it is an undeniable fact that the solution quality of MM is much better for small problems.

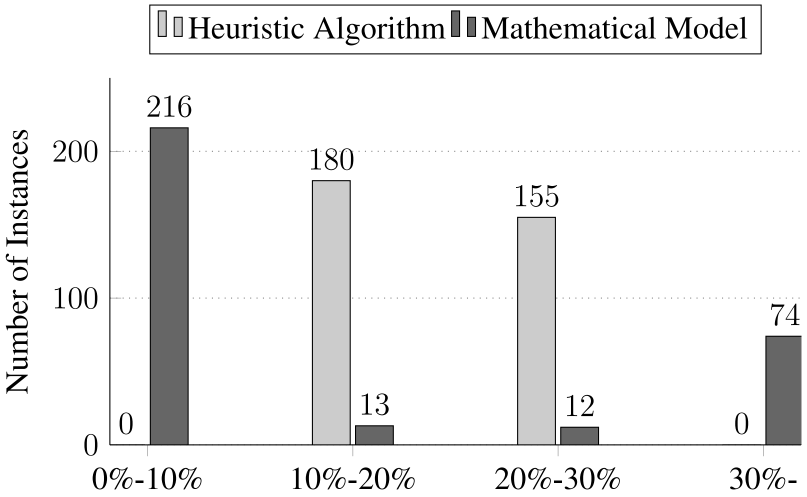

Figure 5.2: Solution Performance of Two Methods

CHAPTER 6

CONCLUSIONS

In this thesis, we studied utilization planning and heavy check maintenance planning for an aircraft fleet considering leasing contract-based delivery-redelivery conditions and utilization restrictions on the leased aircraft. In Chapter 4, we presented a detailed problem definition, highlighting the multifaceted nature of the aircraft fleet management problem. We have clarified the challenges and complexities inherent in the leased aircraft fleet utilization planning and heavy check scheduling. The challenge lay in developing a coherent utilization plan that effectively allocated flights to aircraft, considering flight durations and specific aircraft characteristics, while adhering to maintenance schedules and contractual agreements. We have gained valuable insights into crafting strategies that balance operational efficiency, cost-effectiveness, and compliance with industry regulations.

Throughout this thesis, we explored various methodologies to address the complexity of aircraft utilization planning and heavy check scheduling. The aggregation of flight hours and cycles for allocation proved to be a pragmatic approach, with considerations for flight duration distributions. This approach allowed for a balanced distribution of flight characteristics across aircraft, enabling the optimization of cost-efficiency and compliance with contractual stipulations. We prepared a flight schedule leveraging the frequency distribution of flight cycles over various time intervals. This innovative approach not only optimizes aircraft allocation based on operational costs and efficiency but also facilitates compliance with contractual hour-to-cycle ratios and utilization restrictions. By dividing the planning horizon into manageable time units, we provide a structured framework for decision-making, ensuring effective utilization and maintenance planning every week.

We developed two approaches, a Mathematical Model and a Heuristic Algorithm, that harmonizes flight allocation and maintenance schedules, we offer a comprehensive solution that balances operational efficiency, cost-effectiveness, and contractual compliance. We used 2022-year flight data of narrowbody aircraft in United Airlines' fleet for experimental design. We prepared 360 instances for the computational study. Instances are solved by both approaches and their solutions' performance and quality are analyzed. According to the solutions of instances, among the 3 fleet groups of instances, MM has better quality and performance for small instances. While increasing the fleet size or planning horizon HA gets better results. For big-sized problems, HA competes with MM about the solving rate and the quality of solutions.

The insights and methodologies presented here contribute to the ongoing evolution of aircraft fleet management practices and lay the groundwork for further advancements in this critical field. Our research provides airlines to improve operational performance and save costs by utilizing a proposed utilization planning and heavy check scheduling model with a systematic approach. Further exploration is needed to refine the model and incorporate advanced optimization algorithms.

The proposed utilization planning and heavy check scheduling model offer a foundation for enhancing decision-making processes, fostering adaptability to changing circumstances, and optimizing aircraft utilization. However, as with any complex problem area, some areas need further exploration. Future research endeavors might focus on refining the model and developing a better heuristic or meta-heuristic to accommodate more nuanced factors, such as dynamic flight schedule changes and unforeseen disruptions. Also, our model can be merged with aircraft scheduling by using the solution output of our model as an input of aircraft scheduling. Additionally, we believe that the integration of advanced optimization algorithms and real-time data could enhance the accuracy and applicability of the proposed approach.

As the aviation industry continues to evolve, the strategies and principles outlined in this thesis can serve as a compass for airlines seeking to optimize their fleet operations. By embracing innovation, technology, and strategic planning, airlines can confidently navigate the dynamic aviation landscape, achieving higher efficiency and performance.

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