Proactive Airline Disruption Management

Increasing Schedule Robustness by Simulating Flexibility Measures

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August 28, 2024

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by

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to obtain the degree of Master of Science
at the Delft University of Technology,
to be defended publicly on September 5th 2024.

Student number:	4368908
Project duration:	July 2023 – August 2024
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TU Delft

Acknowledgements

I would like to express my sincere gratitude to the KLM Operations Control Management Team (in different compositions) for granting me the opportunity to work on my thesis in the dynamic and inspiring environment of KLM Operations Control, and for pointing me to the right people for my questions.

A big thanks to my colleagues at the Operations Control Improvement Team as well for their support. Especially to Jan Morren, who provided me with a lot of valuable knowledge about airline operations, and provided me with the right amount of supervision.

I would like to thank Dr. Alessandro Bombelli for his guidance in the final stages of my thesis project, and his willingness to help, even during his holidays. Dr. Bruno Santos as well for his help during the first half of the project.

Jarem M. Hinsenveld
Delft, August 2024

Contents

List of Abbreviations

A0	Percentage of arrivals at or before the scheduled arrival time
A15	Percentage of arrivals within 15 minutes of the scheduled arrival time
AOG	Aircraft On Ground
ATC	Air Traffic Control
CF	Completion Factor: percentage of scheduled flights which were actually operated
D0	Percentage of departures at or before the scheduled time
D15	Percentage of departures within 15 minutes of the schedule time
FFS	Free Fleet Space: additional ground time on minimum TAT
FIFO	First In First Out
H&S	Hub-and-Spoke
IFR	Instrument Flight Rules
O-D	Origin-Destination
OC	Operations Control
OCC	Operations Control Center
TAT	Turn Around Time
VFR	Visual Flight Rules

Introduction

In airline operations, disruptions are inevitable, and have a large influence on customer satisfaction and direct profit. Costs due to disruptions account for 5-10% or airline revenue, or around $60billion globally.[1] It is possible to account for some disruptions when designing the airline network. This increases the chance of being able to recover the network more effectively, reducing cost, and increasing passenger satisfaction. Sacrificing some flights may increase robustness of the schedule while reducing the total revenue opportunities.

Quantifying robust measures is a challenging task, since the schedule is designed around a year in advance, and there are still many unknowns. This research aims to assess and quantify robust scheduling measures, by simulating different robustness measures in an existing schedule.

This thesis report consists of two parts. The scientific paper is presented in Part I. The it includes a detailed description of the research, case study and results. A more detailed analysis of supporting literature concerning airline planning and scheduling, disruption management, and robust scheduling is shown Part II.

[1] https://www.wipro.com/content/dam/nexus/en/industries/travel-transportation-and-hospitality/offerings/from-chaos-to-harmony-the-future-of-airline-disruption-management.pdf

I

Scientific Paper

Proactive Airline Disruption Management: Increasing Schedule Robustness by Simulating Flexibility Measures

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Abstract

Disruptions in airline operations significantly decrease passenger satisfaction, and have a large influence on the profits of airlines, accounting for an estimated cost of 5 to 10% of yearly revenue. At the same time, disruptions are inevitable and difficult to predict, so should be solved as efficiently as possible when they occur. Solving disruptions and restoring the network to a feasible state requires options for Operations Control of an airline. Options include reserve aircraft and crew, Free Fleet Space (FFS), or swapping opportunities. When designing the timetable, these recovery options should be built in the schedule, and this research aims to quantify the number of reserve aircraft, and the FFS required for robust operations. This was done by building a tool that simulates the effects of extra reserves end FFS. Additional FFS and reserves at the hub airport decreases the total delay times in case disruptions occur at the hub. There is no notable effect of FFS and reserves at outstations. Other airline Key Performance Indicators (KPI's) show little improvement in this research.

1 Introduction

Airlines face many challenges in daily operations. In order to operate all scheduled flights as planned, a synthesis of multiple departments within the airline is required. There should be well maintained aircraft, sufficient cockpit and cabin crew, ground operations such as catering, fuelling, baggage handling and pushback should operate as clockwork, and Air Traffic Control (ATC) should have enough capacity to handle all flights. Furthermore, passengers should arrive at the gate on time, so they must be well informed, and not held up by security for too long. With so many dependencies, delays are inevitable. On top of this, the airline industry is still recovering from the Covid panmdemic. While demand has risen to pre-pandemic levels [1], many airlines face challenges in increasing their capacity. Supply chains of spare parts and new aircraft are disrupted, and there is a shortage of aircraft mechanics [2] and cockpit crew. The Operations Control Team (OCT) is responsible for restoring the schedule if it is disrupted. To do so effectively, the OCT requires options, which may include spare aircraft, crew, or plenty of spare ground time to absorb delays. Lack of options to recover the schedule with, results in propagated delays throughout the day, or cancelled flights. Not only is this undesirable from a financial point of view, but many delays or cancellations may damage the reputation of the airline.

When designing the timetable for next seasons, options for disruption management should be included in the schedule. The responsible scheduling team often takes requirements and wishes from different airline departments into consideration. Requirements are hard and fixed, like the number of available aircraft and slots. These wishes can be a bit more flexible, but not granting them often leads to delays. These include tugdriver capacity, or available maintenance capacity for example. The OCT also delivers Design Criteria to the scheduling department in the form of options to restore the disrupted schedule. There is a fine balance here. A reserve aircraft for example is a cost effective solution if it is used, since there are less cancellations. If it is not used however, it is an expensive solution due to the missed revenue. Another robustness measure could be Free Fleet Space (FFS), which is the extra time on the ground on top of the minimum turnaround. FFS in this reasearch is divided in FFS at the hub airport, and FFS at outstations, since they may be used for different purposes. The aim of this research is to give insights in the effects of different types of robust scheduling measures, to simulate these effects on the airline schedule, and to assess the airline performance using these robust measures. The research question is: *What design criteria should be incorporated in the airline schedule to improve operation robustness and meet the airline Key Performance Indicators?*

The remainder of this paper is divided into the following sections: section 2 gives an overview of relevant literature concerning airline scheduling, disruption management, and robust airline scheduling. The research gap is addresseed here as well. The methods used in this research are described in section 3. This includes an overview of the simulation program, and a detailed

[1] https://www.iata.org/en/pressroom/2024-releases/2024-01-10-01/

[2] https://www.flyingmag.com/the-aviation-mechanic-shortage-is-worse-than-you-might-think/

description of the used models. This simulation was tested in a case study at a large European airline. This case study is described in section 4. Results of the case study are analyzed in section 5. Finally, the conclusions of this research are presented in section 6.

2 Literature Review

This chapter gives a brief overview of the existing literature concerning (robust) airline planning, and disruption management. These are areas applicable to this research. Models and insights in previous research give a valuable basis. First, airline planning is discussed, including some research on robust scheduling. This is followed by literature about disruption management.

2.1 Airline Planning and Scheduling

There is existing literature concerning airline planning and scheduling, robust scheduling, and disruption management. This section gives a brief overview of relevant literature, and background for this research.

2.1.1 Airline Network Design

There are generally two types of airline network designs. In the book by [Belobaba et al., 2009] two network types are explained. The Hub-and-Spoke, and point-to-point networks. Point-to-point networks are the least complicated. A direct flight is offered from one city to the next. The point to point network requires sufficient demand between the two connected cities, as there is no possibility for passengers to transfer to another flight without buying two separate tickets. Most low-cost carriers make use of the point-to-point network.

The more traditional airlines make use of the hub-and-spoke model. Most flights in this network fly to or from one or a small number of large airports. This has the advantage that it requires far less flights to connect the same number of airports than in the point-to-point network. Even very small airports may be served, with the aim of feeding the large, more profitable intercontinental flights, by enabling the passengers to transfer at the hub airport. To be able to transfer between flights, the connection time should be sufficient, but not too long, as the transfer time adds up to the total travel time. Therefore, the hub-and-spoke network is often designed around 'banks'. In a bank, flights operated by wide-body aircraft arrive first, followed by narrow-body aircraft. After passengers have transferred flights, the narrow-body aircraft depart, followed by the wide-bodies. This is the order because wide-body aircraft have a longer turnaround time than narrow-body aircraft. Airlines have several banks at their hub airport(s) every day. Airline networks are designed incrementally, improving the schedule of the previous year [Belobaba et al., 2009].

2.1.2 Frequency Planning and Timetable Design

The airline scheduling process is divided in parts. First, the market is analyzed, the fleet is acquired, destinations are determined, and the initial timetable is constructed. The market share of a routs is mainly dependent on the number of flights, and not necessarily by the size of the used aircraft [Belobaba et al., 2009, Wei and Hansen, 2005]. Designing the timetable is not a simple process [Barnhart and Cohn, 2004], and takes years of preparation.

The timetable is constructed after the destinations, fleet, and frequency of flights is known. If there were no restrictions, most flights would be scheduled at the peak times (banks) to enable as many connections as possible. However, there is always a trade-off to be made between schedule convenience for passengers and fleet utilization [Belobaba et al., 2009]. Additional constraints, such as minimum aircraft TAT, capacity of ground operations, ATC, and required ground time for maintenance are considered in this phase. According to [Belobaba et al., 2009], there is no existent model which makes an optimal timetable, taking into account all factors. The number of possible flight times, combined with airport, aircraft, and crew restrictions, and varying demand through the day is too complex.

There may be new routes created if there is a viable business case, all resources have enough capacity, and there are slots available at both the origin and destination airport.

2.1.3 Fleet Assignment and Aircraft Routing

In this research, the fleet, routes, flight frequencies, and a demand are already known or estimated. Assigning the fleet to the proper flights is one of the challenges. Mathematical optimizations are often used for this, some of which are exact, while others make use of (meta-)heuristics, or more recently, machine-learning. [Abara, 1989] is one of the oldest, and one of the first to use the time-space model. It covers only the flights, and does not consider maintenance requirements, crew, or passenger connections. Later attempts include more of these additions, such as [Subramaninan et al., 1994] who includes maintenance requirements, or [Rushmeier and Kontogiorgis, 1997] who includes passenger connection times. [Hane et al., 1995] makes use of a connection network, and [Clarke et al., 1996] expands this to include crew and maintenance requirements. The models by [Barnhart et al., 2002] and [Lohatepanont and Barnhart, 2004] allow the re-booking of passengers in their itinerary-based fleet assignment model. [Rexing et al., 2000] allows the re-scheduling of flights in order to make use of resources more effectively.

To assign the flights to an aircraft tail, the Aircraft Routing Problem is solved. This minimizes cost, and assigns the most efficient tails to the longest flight, while considering maintenance requirements of all aircraft in the fleet. In this research, assigning flights to aircraft tails in a first-in-first-out manner suffices, because the specific tail characteristics are too complex to predict a year in advance.

Traditionally, the crew is scheduled after the timetable is designed, and the fleet is assigned. More recent research is aimed at integrating multiple scheduling phases into one single model. Some examples of this are integrated fleet assignment and crew pairing models by [Özener et al., 2017] and [Cacchiani and Salazar-González, 2020]. [Glomb et al., 2023] integrates fleet and tail assignment, and [Ben Ahmed et al., 2022] integrates fleet assignment, crew pairing, and tail assignment including maintenance requirements.

2.1.4 Robust Airline Scheduling

Inevitably, disruptions occur in an airline network. During the design phase, some measures are included in the schedule to avoid some disruptions, or to decrease the effect on the network. [Kohl et al., 2007] lists some techniques which could be used by airlines. These include:

- **Slack in the schedule:** Increase the time on the ground to be able to absorb delays.
- **High speed flying:** Try to make up for delays by flying faster. This increases fuel consumption, but decreases delays and crew cost.
- **Crews stay with the aircraft:** Crew does not transfer aircraft. This leads to a decrease in delays due to late crew.
- **Short rotations:** Aircraft fly short rotations, of two flights. If there is a disruption, a maximum of two flights is directly affected, and it is simple to recover as the next flight from the hub is a new rotation.
- **Reserve aircraft and crew:** A costly but effective solution for schedule recovery.

There is existing research in the use of extra buffer in the schedule. [Wu, 2006] did research on how much slack is required in the schedule, but it does not include passenger connections, which is essential for the hub-and-spoke network. Another approach is to re-allocate the slack which is already present in the schedule. By allowing flights to deviate from their originally scheduled departure time, [Aloulou et al., 2010], [Ahmadbeygi et al., 2010], and [Ben Ahmed et al., 2017] investigated the effects on the airline robustness. Their solutions are modelled differently, but the goal of their research is comparable. [Burke et al., 2010] and [Ageeva and Clarke, 2000] optimize for swapping opportunities. By swapping two fleet lines, the propagation of delays may be mitigated.

2.1.5 Design Criteria

For optimal airline operations, many departments should operate like clockwork. Most departments have limitations in their capacity, and this should be considered in the design phase. These design criteria include:

- **Slots:** A slot is the right to take-off or land once from an airport, and is granted for the entire season. If the airline operates more than 80% of flights, they keep the slot for next year. If they don't, they can re-apply for the slot lottery.
- **Fleet availability:** Aircraft have delivery times of multiple years, so it is difficult to increase the number of available aircraft. An expensive option is a wet-lease, which is a bit more flexible, but not an infinite source of aircraft.
- **Crew availability:** There should be plenty of crew, considering the complex CLA's of crew as well.
- **Maintenance requirements:** Aircraft require maintenance to stay airworthy. there should be plenty of time scheduled to perform this maintenance. There are strict regulations for how often maintenance is required. If an aircraft is 'overdue', it can not be used until it is re-certified.
- **Airport Operations:** Airports have a maximum capacity. Capacity of baggage handling, fuelling services, pushback tugs, catering services, airport security and ATC is limited, and this should be considered.
- **Turn Around Time:** The minimum time it takes for the aircraft from arriving at the gate to the next departure should be included in the schedule.
- **Reserve Aircraft and Crew:** For recovery options, reserve aircraft and crew are sometimes requested by Operations Control.

2.2 Disruption Management

Disruptions occur daily for an airline. Reasons could be due to airline errors such as one of the resources being late, or external factors like wind directions. There are three main elements which could be disrupted: the aircraft, passengers, or crew. There is existing literature on all three, but only passenger and aircraft disruptions are covered here. [Clausen et al., 2010] and later [Hassan et al., 2021] did a literature review on disruption management covering all three disruption types. Disruptions include unavailable aircraft and delays. If there is not enough slack in the schedule, delays may propagate throughout the day or week [Wu, 2005], [Wong and Tsai, 2012] and [Arikan et al., 2013] proved this with their models. It is the task of the Operations Control Team to avoid this as much as possible, and to recover the schedule in the most efficient way, with the least affected passengers. The most important tools for disruption management are as follows:

- **Delay the next flight:** There are passengers affected, but you could make-up some time if there is sufficient buffer in the schedule.

- **Cancel flights:** Cancel one flight to save more delays or cancellations. This is only done if there is no other option, since it is expensive and makes passengers unhappy.

- **Swap aircraft:** Swap two fleet lines in order to reduce delay propagation, save some money if a cheaper flight is cancelled, or save slots if there is a risk of losing the slot with a cancellation.

- **Using reserve aircraft and crew:** Effective solution for an AOG or long delays, but expensive if the reserves are not used due to the missed revenue.

- **Increasing flight speed:** Fly faster to reduce block time. More useful for long-haul flights, since there is more distance to make up for lost time.

- **Decrease Turnaround Time:** Some ground operations tasks may be performed faster in order ot marginally decrease turnaround time.

- **Ferry aircraft:** Move an aircraft without passengers. Not preferred, as there is no revenue, but sometimes unavoidable for maintenance or after an AOG.

There are many models foound in literature which solve disruptions. Many solve either disrupted aircraft, crew, or passengers. There are more and more integrated models as well. Models for aircraft recovery include [Teodorovic and Guberinic, 1984], which was the first. It was expanded to include cancellations and airport curfews in [Teodorovic and Stojkovic, 1990] and included crew in [Teodorovic and Stojkovic, 1995]. Some other examples are [Yan and Tu, 1997], [Argüello et al., 1998], [Thengvall et al., 2003], and [Dunbar et al., 2012]. Later research integrates aircraft, crew or passenger recovery. [Arikan et al., 2017] solves the integrated recovery problem optimally. It includes delays, cancellations, aircraft swaps, reserve aircraft, ferrying, cruise control, crew recovery, and passenger itinerary changes. [Vink et al., 2020] is another approach which could be used by an operations control team, as it is a decision support tool. It recovers passengers and aircraft.

2.3 Research gap

There is much research in the areas of airline scheduling, robust scheduling, and disruption management separately. Schedule optimizations which re-allocate scheduled slack for maximum robustness exist. So do decision support tools, which restore a disrupted schedule effectively. There is not much work on how much extra slack is required in the schedule to be able to solve disruptions, or how much reserve aircraft are required for the most robust schedule. This is where this research aims to complement existing literature.

3 Methodology

The aim of this research is to simulate the effects of robustness measures in the airline schedule. This chapter explains the approach of this research. The high-level overview of the simulation is explained in section 3.1. This is followed by a more detailed explanation of the separate simulation modules in section 3.2 to section 3.6.

3.1 Simulation Overview

In order to have a general overview of the methods and simulation, Figure 1 shows a block scheme of the full simulation program.

In Figure 1, the grey circles represent inputs to the system, and the yellow circle represents an output. The blue rounded rectangles represents modules in the complete simulation. All of these modules are explained in the upcoming sections of this chapter. The orange diamond shows a test if all schedule scenarios have been tested, and the simulation stops if this is the case. From left to right in Figure 1, the simulation starts with two inputs. These are an existing base schedule, and scenarios of design criteria for this schedule, from the point of view of Operations Control. scenarios could include reserve aircraft and crew at the hub, or extra free fleet space in any of the fleet types operated by the airline. In the first module of the simulation is an optimization model the base schedule is adjusted to adhere to the defined design criteria. This is done by means of an optimization model, which optimizes for airline profit and connecting passengers. The design criteria are included as constraints for the optimization, as is further explained in section 3.2. The created schedule is then disrupted in the second module, using delays of flights, cancellations, and unavailable aircraft. These disruptions represent events that occur in real life, as there is rarely a day without any delays. There are multiple disruption scenarios, as explained in more detail in section 3.3. The airline Operations Control department is responsible for restoring the schedule to its original form as much as possible when disruptions occur, for the lowest cost possible. The disruption management module aims to do the same by means of an optimization, which minimizes cost. Disruptions in this simulation may be solved using delays, cancellations, or aircraft swaps. See section 3.4 for more details. The recovered schedule is compared to the starting schedule, which yields Key Performance Indicators (KPI's). The KPI's considered in this research are the percentage of on-time departures, the percentage of scheduled flights which were actually operated, the total delay minutes in the network. Schedules may perform better for some disruption scenarios than others. To be able to assess schedules, and determine how much reserve and/or fleet space is best overall, the Determine Schedule Quality module was created. Is multiplies KPI's with the probability of a disruption scenario occuring, and sums all values for each schedule. The result is a table of schedule performance KPI's and

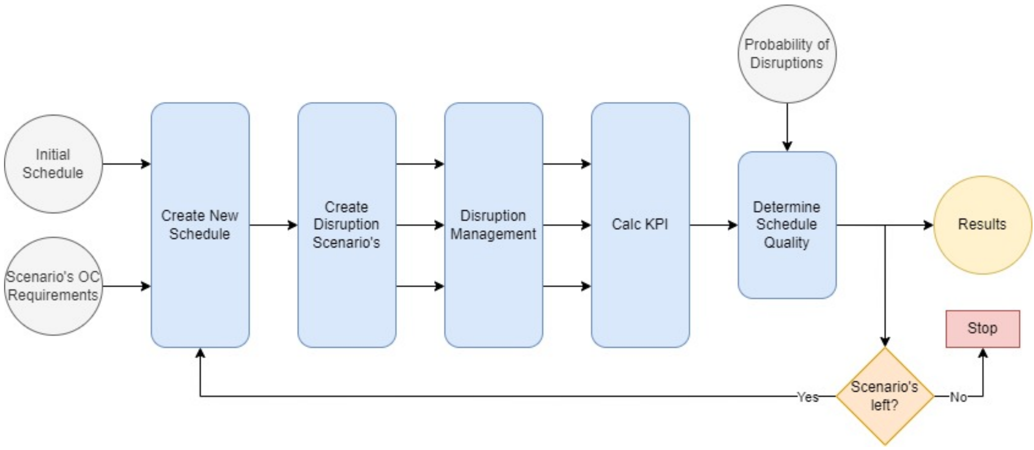


Figure 1: Overview of the Simulation Program

a single metric to assess each schedule, as explained in section 3.6. This result is stored. If there are more design criteria to be tested, the simulation starts again with the same base schedule, and new design criteria, until there are none left.

3.2 Create Schedule Module

The first part of the simulation is made to adjust an existing flight schedule to adhere to the additional design criteria. This represents the airline network planning and scheduling department, who usually create a new timetable by adjusting a timetable for the previously scheduled year and season [Belobaba et al., 2009]. Airline schedules are usually created around a year in advance, and are adjusted in case of major market or political developments. This model assumes the schedule does not change anymore once it is published. The model is designed to assign the fleet to existing flights, while optimizing departure times to ensure valid passenger connections.

$$\min \quad \sum_{i \in FN} \sum_{k \in K} OC_i^k \cdot f_i^k - \sum_{p \in P} \sum_{r \in P} fare_r * t_p^r + \sum_{p \in P} 100 * t_p^0 \tag{1a}$$

s.t.

$$\sum_{v \in V_i} \sum_{k \in K} f_v^k = 1, \qquad \forall i \in \mathbf{F}, \tag{1b}$$

$$\sum_{n \in N^k} y_{n^+}^k + \sum_{i \in O(k,n)} f_i^k - \sum_{n \in N^k} y_{n^-}^k - \sum_{i \in I(k,n)} f_i^k = 0 \qquad \forall k \in \mathbf{K}, \tag{1c}$$

$$\sum_{\dot{a} \in NG^k} f_{\dot{a}}^k + \sum_{a \in NG^k} y_a^k \leq AC^k, \qquad \forall k \in \mathbf{K}, \tag{1d}$$

$$\sum_{v \in V_i} \sum_{k \in K} s^k \cdot f_v^k + \sum_{p \in P} \delta_i^p \cdot t_p^0 \geq Q_i, \qquad \forall i \in \mathbf{FN}, \tag{1e}$$

Table 1: Sets for the change schedule model.

Set	Description
$\mathbf{P}$	Set of Passenger Itineraries.
$\mathbf{F}$	Set of Flights.
$\mathbf{F_{start}}$	Set of Flights at the start of the time window.
$\mathbf{FN}$	Set of Flight Variants, created by moving the departure and arrival time of F.
$\mathbf{V_i}$	Set of variants of flight i.
$\mathbf{K}$	Set of aircraft types.
$\mathbf{G^k}$	Set of Ground Arcs.
$\mathbf{NG^k}$	Set of flight and ground arcs intercepted by the time cut.
$\mathbf{N}$	Set of airports.
$\mathbf{O(k,n)}$	Flight arcs of aircraft type k originating at node n.
$\mathbf{I(k,n)}$	Flight arcs of aircraft type k terminating at node n.
$\mathbf{n^+}$	Ground arcs originating at node n.
$\mathbf{n^-}$	Ground arcs terminating at node n.
$\mathbf{X(i,k)}$	Set of aircraft types k which can not operate flight i.
$\mathbf{R^k}$	Set of maintenance arcs.

Table 2: Parameters for the change schedule model.

Parameter	Description
$\mathbf{OC_i^k}$	Operational cost of flight i with aircraft type k
$\mathbf{fare_r}$	Fare of itinerary r
$\mathbf{AC^k}$	Number of aircraft in fleet of type k
$\mathbf{s^k}$	Number of seats available in aircraft type k
$\delta_\mathbf{i}^\mathbf{p}$	1 if flight i belongs to itinerary p, 0 otherwise
$\mathbf{Q^i}$	Unconstrained demand on flight leg i
$\mathbf{FFS_k}$	Free Fleet Space in aircraft type k

Table 3: Decision Variables for the change schedule module.

Decision Variable	Description
$\mathbf{f_{i,k}} \in \{0,1\}$	1 if flight i is assigned to aircraft type k, 0 otherwise
$\mathbf{y_{a,k}} \in \mathbb{N}_0$	Number of aircraft of type k on ground arc a
$\mathbf{t_{p,r}} \in \mathbb{N}_0$	Number of pax with itinerary p who are re-allocated to itinerary r

$$\sum_{p\in P}\sum_{r\in P}\delta_i^r \cdot t_p^r \leq \sum_{k\in K} s_k \cdot f_i^k, \qquad \forall i \in \mathbf{FN}, r \neq 0, \tag{1f}$$

$$\sum_{p\in P}\sum_{r\in P} t_p^r \leq D_p, \qquad \forall p \in \mathbf{P}, \tag{1g}$$

$$\sum_{v\in V_i}\sum_{k\in K} f_v^k = 0, \qquad \forall \{i,k\} \in \mathbf{X(i,k)}, \tag{1h}$$

$$f_i^k = 1, \qquad \forall \{i,k\} \in \mathbf{R_{i,k}}, \tag{1i}$$

$$\sum_{k\in K} f_i^k = 1, \qquad \forall i \in \mathbf{F_{start}}, \tag{1j}$$

$$\sum_{a\in A} y_{a,k} = FFS_k, \qquad \forall i \in \mathbf{P} \tag{1k}$$

The first module in the simulation assigns the fleet, while optimizing departure times to ensure valid passenger connections. The model is based on the Itinerary Based Fleet Assignment model by [Lohatepanont and Barnhart, 2004]. It deals with the effects of spillage and recapture in a different manner. It does not re-assign passengers to a new itinerary with alternate flights, but it re-schedules flights, and assigns passengers to the corresponding itineraries. The objective function is shown in Equation 1a. The first part minimizes the operational cost of flight variant i with aircraft type k. Variants of the same flight are assumed to have the same operational cost, as the expected block time remains the same, and the departure and arrival times only change by up to 15 minutes. There could be a slight difference in crew cost due to a change in departure times. The second part of the objective function subtracts the fare of itinerary r multiplied by the number of passengers re-allocated from itinerary p to itinerary r from the minimization problem. If there is no change in the flight times, the itineraries do not change, and p and r are the same. The last part of the objective function adds a penalty to the objective if there are more passengers with the desire to travel on itinerary p than seats on the aircraft. This is done to penalize spillage effects, in order to transport as many passengers as possible. Constraint Equation 1b ensures that there is only one variant of each flight scheduled with only one aircraft type, and that all flights are scheduled. In pre-processing, an additional 'cancel' aircraft type is created, with a penalty to the objective function. This ensures that the model is still feasible if there are too many flights for the number of aircraft. To make sure there is an equal number of flights arriving at and departing from all airports, Equation 1c enforces node-balance. At any point in time, there can be no more aircraft in the air or on the ground than the number of aircraft available. This is done using Equation 1d by checking the number of aircraft on flight and ground arcs one minute after every node. To make sure the number of transported passengers does not exceed the capacity of the aircraft, Equation 1e spills passengers exceeding the aircraft capacity to the 0 itinerary. All passengers who want to travel on a flight, are either transported on that flight or its variants, or are spilled to the 0 itinerary. Passengers with the 0 itinerary do not generate any revenue and a penalty is added to the objective function for each spilled passenger. Equation 1f is required to re-assign passengers to a newly created itinerary variant if flights are re-scheduled. To limit the number of passengers on the itineraries in the model, Equation 1g ensures the number of passengers on any itinerary variant of p does not exceed the total demand for itinerary p. All aircraft have performance restrictions, and can not fly to all destinations within the network. Destinations could be too far for the aircraft range, the take-off performance could be insufficient for operations at some airports, or the aircraft could be too large for some airports. Equation 1h prevents flights from being operated by aircraft which can not fly that route. In this model, maintenance slots are assumed fixed, but this could be adjusted in further research. Equation 1i makes maintenance slots fixed for aircraft types, ground times, and locations. Equation 1j is created to make sure the departure time of flights is not moved to a time before the time window. This is required to improve model accuracy. Finally, Equation 1k sets the minimum fleet space in time interval.

3.3 Create Disruptions Module

In an ideal world, all scheduled flights are operated as planned. Unfortunately, this is rarely the case in reality. Even on regular days with nice weather on the majority of routes and destinations, fully staffed cockpit and cabin crew, a well maintained fleet, and ground operations working at full capacity, disruptions in the network occur. Disruptions include minor delays with minimal impact on the network, but also larger disruptions like AOG's where aircraft are unavailable for a longer period of time until they are repaired. Reasons for delays could be reductions in airport capacity, reductions in ground operations capacity, shortage of crew, delays of preceding flights, or late passengers to name a few. This module creates disruption scenarios, in which flights are delayed, cancelled, or aircraft are unavailable for a period of time. It is possible to create scenarios with combination of all types of disruptions. To have a complete overview of different days of operations, scenarios differ from regular days of operations with some minor delays and 1 or 2 AOG's, to major disruptions at the hub or at outstations in case of a storm for example. For now, disrupted flights and aircraft are selected manually to make to problem more traceable, but this could be automated. In the airline industry, changes in the schedule which occur no more than three days before the day of operations are considered as disruptions. Therefore, this module represents changes that occur in the last three days before the day of operations.

3.4 Disruption Management Module

At most airlines, a dedicated Operations Control Team is responsible to restore the disrupted network to a state of feasibility. They have a couple of tools to use to do so. The most important of which is to delay flights, cancel flights, swap aircraft or increase the cost index in order to reduce expected block time. To solve the disruptions created in section 3.3, the optimization model described in this sections is used. Its aim is to restore the disrupted airline schedule to a feasible one. The model has the capability to delay other flights, to cancel them, to swap flights between aircraft tails, or to use a combination of these three disruption management measures. Block-time reduction is not possible in this model to reduce complexity and improve CPU times, but this could be added in follow-up research. The model is based on work by [Vink et al., 2020]. To speed up this part of the simulation with minimal effect on model accuracy, the selection algorithm used in their research is used as well. Table 4 shows the sets of the model, Table 5 the parameters, and Table 6 the decision variables. The optimization model is show in Equation 2a to Equation 2l.

Table 4: Sets for the disruption management model.

Set	Description
$\mathbf{P}$	Set of Aircraft Registrations
$\mathbf{F}$	Set of Flights
$\mathbf{F_p}$	Set of flight arcs currently allocated to aircraft p
$\mathbf{F_{delay_{p,f,d}}}$	Set of delayed flights f of aircraft p with d minutes
$\mathbf{F_{canx_f}}$	Set of cancelled flights.
$\mathbf{F_{unv_{p,f,d}}}$	Set of flights f, or delayed flights f,d affected by unavailable aircraft p.
$\mathbf{D}$	Set of Delayed Flight Arcs
$\mathbf{G}$	Set of Ground Arcs
$\mathbf{N}$	Set of Nodes
$\mathbf{R}$	Set of Maintenance Activities
$\mathbf{R_{fix}}$	Set of Fixed Maintenance Activities
$\mathbf{R_{flex}}$	Set of Flexible Maintenance Activities
$\mathbf{A}$	Set of Airports in F
$\mathbf{E}$	Set of Aircraft Types in P
$\mathbf{O(n,p)}$	Arcs of aircraft p originating from node n.
$\mathbf{T(n,p)}$	Arcs of aircraft p terminating at node n.
$\mathbf{Z(a,e)}$	Number of aircraft of type e at airport a at the end of the time interval.
$\mathbf{X(p,f)}$	Forbidden flight f and registration p combinations.
$\mathbf{U(r,p)}$	Ground arcs corresponding to fixed maintenance activity r of aircraft p.
$\mathbf{V(r,p,m)}$	Ground arcs corresponding to flexible maintenance activity r of aircraft p, starting at time m.

Table 5: Parameters for the disruption management model.

Parameter	Description
$\mathbf{OC_{p,f}}$	Operational Cost of flight f with aircraft p.
$\mathbf{DC_{f,d}}$	Cost if flight f is delayed by d minutes
$\mathbf{DC_{f,d}}$	Cost if flight f is delayed by d minutes.
$\mathbf{CC_{f}}$	Cost of cancelling flight f.
$\mathbf{B_{n,p}}$	Balances all nodes n with aircraft p. 1 at the starting node, 0 at all other nodes.
$\mathbf{K_{a,e}}$	Number of aircraft of type e scheduled to be at airport a at the end of the time window.
$\mathbf{M_{ae_{a,e}}}$	Big M number. Cost of missing an aircraft of type e at airport a at the end of the time window.
$\mathbf{M_{p_p}}$	Big M number. Cost of changing the routing of aircraft p.
$\mathbf{M_{r_r}}$	Big M number. Cost of cancelling maintenance activity r.

Table 6: Decision Variables for the disruption management module.

Decision Variable	Description
$\delta_{\mathbf{F_{p,f}}} \in \{0,1\}$	1 if flight f is assigned to aircraft p, 0 otherwise
$\delta_{\mathbf{D_{p,f,d}}} \in \{0,1\}$	1 if flight f is delayed by d minutes and assigned to aircraft p, 0 otherwise
$\delta_{\mathbf{C_{f}}} \in \{0,1\}$	1 if flight f is cancelled, 0 otherwise
$\delta_{\mathbf{G_{p,g}}} \in \{0,1\}$	1 if aircraft p uses ground arc g, 0 otherwise
$\mathbf{y_{r,m}} \in \{0,1\}$	1 if maintenance activity r starts at time m, 0 otherwise
$\mathbf{s_{a,e}} \in \mathbb{Z}$	Slack variable to make sure the number of aircraft of type e is the same as expected at airport a at the end of the time window
$\mathbf{s_{r}} \in \{0,1\}$	Slack variable, 1 if maintenance activity r is cancelled, 0 otherwise
$\mathbf{s_{p}} \in \{0,1\}$	Slack variable, 1 if the routing of aircraft p is changed compared to the original routing, 0 otherwise

$$\min \quad \begin{aligned} &\sum_{p\in P}\sum_{f\in F} OC_{p,f}\cdot\delta_{F_{p,f}} + \sum_{f\in F} CC_f\cdot\delta_{C_f} \\ &+\sum_{p\in P}\sum_{f\in F}\sum_{d\in D}(OC_{p,f}+OC_{f,d})\cdot\delta_{D_{p,f,d}} \\ &+\sum_{a\in A}\sum_{e\in E} M_{a,e}\cdot s_{a,e} + \sum_{r\in R} M_r\cdot s_r + \sum_{p\in P} M_p\cdot s_p \end{aligned} \tag{2a}$$

s.t.

$$\sum_{p\in P}\delta_{F_{p,f}} + \sum_{p\in P}\sum_{d\in D}\delta_{D_{p,f,d}} + \delta_{C_f} = 1, \qquad \forall f\in\mathbf{F}, \tag{2b}$$

$$\begin{aligned} &\sum_{f\in F\cap O(n,p)}\delta_{F_{p,f}} - \sum_{f\in F\cap T(n,p)}\delta_{F_{p,f}} \\ &+ \sum_{(f\in F,d\in D)\cap O(n,p)}\delta_{D_{p,f,d}} \\ &- \sum_{(f\in F,d\in D)\cap T(n,p)}\delta_{D_{p,f,d}} \\ &+ \sum_{g\in G\cap O(n,p)}\delta_{G_{p,g}} - \sum_{g\in G\cap T(n,p)}\delta_{G_{p,g}} = B_{n,p} \end{aligned} \qquad \forall p\in\mathbf{P}, \tag{2c}$$

$$\begin{aligned} &\sum_{p\in(P\subset e)}\sum_{f\in F\cap Z(a,e)}\delta_{F_{p,f}} \\ &+ \sum_{p\in(P\subset e)}\sum_{(f\in F,d\in D)\cap Z(a,e)}\delta_{D_{p,f,d}} \\ &+ \sum_{p\in(P\subset e)}\sum_{g\in G\cap Z(a,e)}\delta_{G_{p,g}} = K_{a,e} - s_{ae_{a,e}} \end{aligned} \qquad \forall a\in\mathbf{A},\forall e\in\mathbf{E}, \tag{2d}$$

$$\sum_{f\in F_p}\delta_{F_{p,f}} + \sum_{f\in F_p}\sum_{d in D}\delta_{D_{p,f,d}} \geq |F_p|\cdot(1-s_p), \qquad \forall p\in\mathbf{P}, \tag{2e}$$

$$\sum_{g\in U(r,p)}\delta_{G_{p,g}} \geq |U(r,p)|\cdot(1-s_r), \qquad \forall r,p\in\mathbf{R_{fix}}, \tag{2f}$$

$$\sum_{g\in V(r,p,m)}\delta_{G_{p,g}} \geq |V(r,p,m)|\cdot y_{r,m}, \qquad \forall r,p,m\in\mathbf{R_{flex}}, \tag{2g}$$

$$\sum_{m\in V(r,p,m)} y_{r,m} = 1 - s_r, \qquad \forall r,p\in\mathbf{R_{flex}}, \tag{2h}$$

$$\sum_{f\in F\cap X(p,f)}\delta_{F_{p,f}} + \sum_{(f\in F,d\in D)\cap X(p,f)}\delta_{D_{p,f,d}} = 0, \qquad \forall p\in\mathbf{P}, \tag{2i}$$

$$\delta_{F_{p,f}} + \delta_{D_{p,f,d}} = 0 \qquad \forall p,f,d\in\mathbf{F_{unv}}, \tag{2j}$$

$$\delta_{D_{p,f,d}} = 1 \qquad \forall p,f,d\in\mathbf{F_{delay}}, \tag{2k}$$

$$\delta_{C_f} = 1 \qquad \forall f\in\mathbf{F_{canx}} \tag{2l}$$

The disruption management module minimizes cost. The first part of the objective function in Equation 2a represents the operational cost of an operated flight without delay. The second part includes the delay cost, while the third part adds the cost of a cancellation. Only one of theese actually contributes to the objective function. The fourth part of the objective function is to penalize the objective in case of missing aircraft at the end of the time window. This may happen if there is an unexpected AOG. The penalty represents the cost to ferry the aircraft back to the hub. Similarly, the fifth part includes a penalty if a maintenance slot is missed due to delays or cancellations. Finally, changing an aircraft routing has financial consequences as well. It may for example be required to unload all luggage or catering in case of a type swap. This is dependent on the time before departure this change is known. Because this is a model which looks up to a year ahead in time, so disruptions do not occur on the spot, this penalty is summarized into one single value. This should be enough to discourage aircraft swaps if it is not required. Constraints if the disruption management model include flight coverage in Equation 2b. This ensures all flights are either operated as scheduled, delayed, or cancelled. Only one option with one aircraft type is valid. Equation 2c makes sure all nodes have an equal number of incoming and outgoing aircraft on regularly scheduled flight arcs, delayed flight arcs and ground arcs. At the start of the interval, there may already be an aircraft at one node. The right side of Equation 2c makes sure this is possible. At the end nodes, there may be an imbalance as well. Equation 2d ensures that at the end of the time interval, the number of aircraft equals that of the initial schedule, or the slack variable $s_{a,e}$ is activated, penalizing the objective. Slack variable s_p is activated if the aircraft routing is changed. This is done by means of Equation 2e. There are three constraints which enforce maintenance requirements. Equation 2f makes sure the aircraft is at the correct airport where the maintenance is performed, by activating the ground arcs. If there is no other option due to delays or cancellations, slack variable s_r is activated. Flexible maintenance activities require two constraints. The first of which is Equation 2g. It links flexible maintenance activities and start times to the associated ground arcs. Equation 2h activates slack variable s_r if there is no way of scheduling the flexible maintenance activity due to delays or cancellations. Not all aircraft are capable of flying to every destination. This is sometimes even tail dependent. Equation 2i makes sure aircraft are not assigned to flights it is unable to perform. In the full simulation, there are pre-defined delayed flights, cancellations, or unavailable aircraft. Because the disruption management model is based on a decision support tool, this requires additional constraints. Equation 2j makes sure that there are no flights performed by the unavailable aircraft during its unavailability. Pre-defined delays are enforced by Equation 2k, and cancelled flights are enforced by Equation 2l.

3.5 Calculate KPI Module

After solving the imposed disruptions in the network, the recovered schedule is compared to the undisrupted schedule. The KPI's considered are shown in Table 7. For each KPI, a table is created with the performance of each schedule for all disruption scenarios. See Table 7 for an example of two schedules and three disruption scenarios. Each row represents the performance of one schedule. The disruption scenarios are the columns. The SQ column is explained in section 3.6. It is worth noting that KPI's resulting from this simulation are subject to a lot of uncertainty due to the program using data from previous years, and the stochasticity of disruptions occuring in the future. Hence the KPI's from this simulation should not be used as an accurate representation of reality. It can be used to compare performance of multiple schedules for multiple disruption scenarios.

Table 7: Key Performance Indicators used to assess the schedule performance.

KPI	Description
D0 [%]	Percentage of flights departed within one minute or before the scheduled departure time at D-3.
CF [%]	Percentage of scheduled flights at D-3 which were actually operated.
Delay [min.]	Total delay minutes in the network.

3.6 Determine Schedule Quality Module

As the number of simulated schedules and disruption scenarios grows larger, the comparison between schedule performances becomes more complicated quickly. To counter this, the performance of schedules is summarized in one single metric, based on the probability of disruption scenarios happening in reality, and the schedule performance for each KPI. Equation 3 shows the how this value for schedule quality is calculated. SQ is the Schedule Quality, p_j is the probability of disruption scenario j occurring, and $S_{i,j}$ is the performance of schedule i for disruption scenario j. This method is similar to how the Expected Monetary Value (EMV) is calculated for the Expected Value of Perfect Information (EVPI) from decision theory.

$$SQ = \sum_j p_j \cdot S_{i,j} \tag{3}$$

The schedule quality is determined for all schedules, and this is added as a new column in the tables described in section 3.5. The schedule with the best SQ may perform the best overall in multiple disruption scenarios. In the example of Table 8, this is schedule

1. The outcomes of the best schedule may be different for the different KPI's. It is up to the airline to decide which of the KPI's are the most important.

Table 8: Example of performance assessment table for the Completion Factor.

Schedule	Sc1 (p=0.6)	Sc2 (p=0.2)	Sc3 (p=0.2)	SQ
1	1	0.99	0.99	**0.996**
2	0.98	0.96	0.97	0.974

4 Description of the Case Studies

This section describes a case study for a real a. This case study was performed in collaboration with a major European airline, who provided the data and insights in the schedule development process and operational challenges.

4.1 Data Used and Pre-Processing

The basis of this research is a schedule of the intercontinental network as planned assuming all resources operate at full capacity. There is some slack already built in the schedule, including some reserve aircraft. Overall there is no room for extra flights with the available fleet and there is a little, but not much FFS. This is considered the base schedule, which is edited in the simulation. In order to keep CPU times reasonable, and not run into memory errors, only three days of the full schedule are simulated, as the number of variables and constraints grows exponentially.

4.1.1 Data and Assumptions for the Create New Schedule Module

The Create New Schedule module re-schedules flights, and optimizes for passenger revenue minus the operational cost. The basis for this model is an existing schedule, with flights assigned to a fleet type. The model is allowed to change flights to different aircraft types, but only if flights to that destination are feasible with the selected aircraft type. Turnaround times vary by aircraft type, and this is taken into account in the model. Block times of all flights are assumes constant, even though some aircraft are capable of flying at a higher cruise speed. This makes the schedule more flexible on the day of operations, since more aircraft can be used on routes without introducing extra delays. The operational cost for each aircraft type on each route was provided by the collaborating airline. It is the average of operational cost in the current season. There are some new destinations in the schedule for which there was no operational cost data available. Operational cost for these destinations were estimated based on destinations in the same area with similar flight distance. Operational costs are not always precisely accurate for future operations, as flying times may change due to airspace restrictions, crew may become more expensive due to a new CLA, and fuel price fluctuations. For the use of this model this introduces some inaccuracy. This will not influence the model too much however, since all flights are affected by cost rise, and when creating the real schedule, not all changes in airspace regulations are known in advance.

Data regarding the passenger numbers on all O&D's and the corresponding revenue was provided by the collaborating airline as well. Again, this is data from the current season, and passenger numbers of new destinations were estimated using similar routes, or numbers of partner airlines. From this data, the passenger itineraries were created. All intercontinental to intercontinental connections at the hub airport are shown as multi-flight itineraries. Intercontinental to European and European to Intercontinental flights are assumed to have a local origin or destination at the hub. This is a valid assumption, since the European/Domestic network is usually built around the more profitable intercontinental network. Only connections at the hub airport on flights operated by the airline providing the data are considered, since these account for the majority of passenger connections. In future research, connections at the hubs of partner airlines, or passengers travelling on code-share/interline flights could be considered as well. This will improve model accuracy, but introduces a lot of extra complexity. Revenue is averaged over an entire season. The effects of peaks in the schedule, or other market effects are not considered. As the airline schedule is for the largest part the same on a weekly basis during an entire season, this is an assumption with a small influence on the model outcome. The result is a flight schedule which is assigned to a fleet type, but not yet to an aircraft tail. This generally does not happen until a week to a day before the day of operations. In this model, the aircraft routing is done by assigning flights to aircraft tails in a first in first out manner.

4.1.2 Data and Assumptions for the Disruption Management Module

The disruption management module uses the schedule created in the first module of the simulation, and the disruptions created in the second module. In order to restore the disrupted schedule to a feasible schedule Operational cost data is the same as used for the Create Schedule module. Delay cost is in the form of a large matrix with one row per flight, and a column for the delay cost for an incremental delay of five minutes. Every five minutes of delay adds cost. There are three main driving factors for this delay cost. The first of which is a cost component to crew, who earn extra time off when working longer than scheduled. The second cost component is the future value, since delayed passengers get a more negative sentiment towards an airline if they are delayed, and may be inclined to book a flight with a different airline. The last component is the missed connection cost. Sometimes this is not much if there are few critical connections, but sometimes five minutes of delay may create many missed connections, and this may be the difference between a profitable and loss-generating flight. The model optimizes for this, by delaying other flights, swapping flights between aircraft tails, or cancelling less profitable flights. Delay data is an average of one week of the current season, and considers missed connections in the intercontinental network. This is all done in preprocessing. To improve the accuracy of this model, connections to and from European destinations could be included. In their paper, [Vink et al., 2020] show an example of how the delay costs are determined, which is similar to the method used in this research. Cancellation costs are the average of one week of flights during the summer peak. These numbers are representative of a busy week in the schedule. In this model, if a flight is delayed by more than 180 minutes, it is cancelled.

4.2 Scenarios for Schedule Design Criteria

The provided schedule and underlying data are constants in all the simulations. The only variable are the OC design criteria. In this research, two types of design criteria are tested in the simulation. The first is the effects of Free Fleet Space in the schedule on the performance of an airline. In the base schedule, there is some FFS at both the hub and outstations. In this case study, the effects of increasing FFS at the hub by 10 to 100% in 10% increments are analyzed, and this is distributed equally in all aircraft types. Secondly, the effects of reserve aircraft and crew are tested in the simulation. These reserves are stand-by at the hub, and can be used when required. This is generally an expensive solution, because of the missed revenue of the reserve aircraft. In the base schedule, there is already a reserve aircraft in the largest fleet type with long range. This gives the most flexibility in operations, as it can be used to replace most flights scheduled in other fleet types. The extra reserves will be placed in different aircraft types, from largest range to smallest. When the range of two aircraft types is comparable, the aircraft with the highest capacity is selected first as reserve. An overview of all simulation inputs is shown in Table 9. A total of 24 schedule scenarios are tested in this case study.

4.3 Disruption Scenarios

In everyday operations, disruptions occur as a stochastic process. In order to give a complete overview of schedule performance, multiple disruption scenarios were tested. In real life there could be an infinite number of disruption scenarios since everyday is different. In this case study however, five scenarios were tested which represent some of the most common types of disruptions. In this case study, all disruptions are imposed on the first day of the simulation. The days fol-

Table 9: Design Criteria Scenarios for the Change Schedule Module

Scenario	Reserve Aircraft + Crew	Hub FFS % of base	Outstation FFS % of base
Base	1	100%	100%
Hub+10%	1	110%	100%
Hub+20%	1	120%	100%
Hub+30%	1	130%	100%
Hub+40%	1	140%	100%
Hub+50%	1	150%	100%
Hub+60%	1	160%	100%
Hub+70%	1	170%	100%
Hub+80%	1	180%	100%
Hub+90%	1	190%	100%
Hub+100%	1	200%	100%
Out+10%	1	100%	110%
Out+20%	1	100%	120%
Out+30%	1	100%	130%
Out+40%	1	100%	140%
Out+50%	1	100%	150%
Out+60%	1	100%	160%
Out+70%	1	100%	170%
Out+80%	1	100%	180%
Out+90%	1	100%	190%
Out+100%	1	100%	200%
Reserve+1	2	100%	100%
Reserve+2	3	100%	100%
Reserve+3	4	100%	100%
Reserve+4	5	100%	100%

lowing the disruptions are used to see what is required to recover the schedule to a feasible state. The disruption scenarios, also listed in Table 10, include a regular day of operations, scenarios with major disruptions at the hub airport, maintenance delays, and AOG's. The first scenario is a regular day, without many irregular circumstances. So there is good weather, there are no strikes whatsoever, staff is at normal capacity, and there is nothing else out of the ordinary. In the simulation, there is a seemingly high number of departure and arrival delays, but most of these are 15 minutes or less, as this occurs often. Total delay time is slightly less than the average observed delay time per in the first half of 2024. There are no unavailable aircraft in this scenario. The second scenario represents a severe arrival capacity reduction during the morning arrival bank, due to a storm for example. Some flights are diverted, and arrive at the hub with a delay of over 2 hours. In the intercontinental network, this is an extreme scenario, since usually the domestic/European network is more affected by capacity reductions. In the third scenario, all departing flights in one bank are delayed severely. This could occur with dense fog, strikes, or IT outages. Delayed departures at the hub lead to delayed arrivals at outstations. This scenario therefore tests the effects of delays at outstations as well. At the time of writing, there are shortages in aircraft mechanics and disrupted supply chains for spare parts. This may influence the time it takes to perform the required maintenance. Therefore the fourth scenario has some maintenance slots exceeding the planned time. This is modelled as the aircraft being unavailable directly after the scheduled maintenance slot. The delays are that of an average day. The final scenario includes five unavailable aircraft at outstations, in addition to regular delays. When this happens, it is often unavailable for a long time, since spare parts and a hangar in which to perform the repairs are not always available at outstations. In this scenario there are a few quick repairs, and a few more complex repairs.

5 Results

As described in section 4, there were two different types of proactive disruption management tested. The first is extra FFS, the second extra reserve aircraft and crew. The results of the created schedules are analyzed with three metrics, which are the Completion Factor, D15, and total delay minutes. These metrics represent some of the the most important KPI's for passengers, but there are more that could be considered, such as arrival performance or the number of feasible/missed PAX connections. In this research however, arrival performance is equal to the departure performance since the block times are unchanged. PAX connections are represented in the departure performance to some extent.

5.1 Effects of Free Fleet Space and reseerve aircraft

Adding extra fleet space in the schedule could yield some improvements in performance. As there is more time on the ground, there is more time to recover delays, which should result in a lower number of delays, as well as less total delay minutes, and less cancellations. This may come at the price of less scheduled flights, which results in less revenue. This section describes the results of the case study with extra FFS. Using reserve aircraft and crew is also a common way of solving a disrupted network, as the reserve can be used for flights on short notice. This is not a perfect solution however, since there may be additional costs for downgrading passengers, empty seats, or catering issues.

5.1.1 Number of Flights

When looking at the number of flights, the results show a predictable pattern. Figure 2(a) shows the trend for the number of flights dependent for extra FFS scenarios. With more FFS, there is less room for flights in the schedule. This effect is greatest at the hub airport. This could be explained by the extra hours of FFS already present at the hub, which is more than the FFS at outstations. The initial schedule, without additional FFS or reserves consists of 396 flight legs in three days. These are all the intercontinental flights of the collaborating airline in their five largest wide-body aircraft (sub-)types. Extra reserve aircraft and crew reduces the number of available aircraft for operations. Figure 2(b) shows the number of flights in the network for scenarios with additional reserves. The trend is decreasing, although there was a decrease in flights expected between the second and third reserve. The reason for this could be that the simulation randomly chose a registration as a reserve, which might have been scheduled for maintenance. This avoids removing flights, but should be improved in future research, as scheduled maintenance is essential for keeping the fleet airworthy.

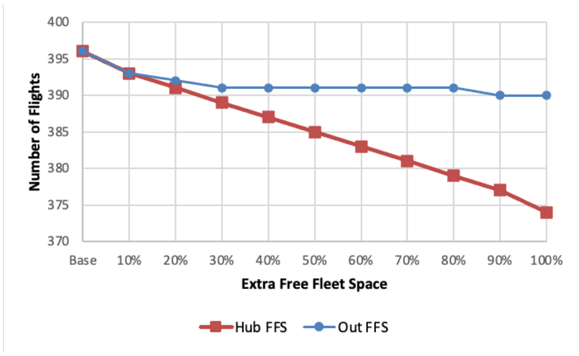
5.1.2 On Time Departure Performance

The results are less predictable when looking at the D15. Figure 3(a) shows the effects on on time departure for FFS design criteria schedules. This is the weighted average of all five disruption scenarios. The results show a lot of variability, but when looking at the actual percentages, the differences are within 1.2%. This accounts to approximately one daily flight. Results are even closer when looking at the reserve aircraft schedules, with all schedules have an expected D15 within 0.5%. This is shown in Figure 3.

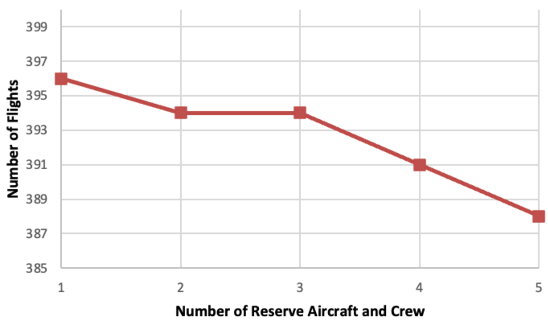
So overall, there are no large differences in on time departure, and this number does not change significantly when looking at the individual disruption scenarios. Table 11 shows the full table of all schedules and their performance for the five disruption scenarios. For scenarios with disruptions at the hub (scenario 1

Table 10: Disruption Scenarios to assess Schedule Performance

Scenario	Disruption	Hub Arrival Delays	Hub Departure Delays	Unavailable aircraft
1	Regular day of operations	18 delays of 5-40 minutes, 315 delay minutes total	16 delays of 5-40 minutes, 335 delay minutes total	None
2	Reduced capacity during morning arrival bank	20 delays, 1000 delay minutes	0 additional delays	1 at hub after 1st arrival for 20 hours
3	Reduced capacity during morning departure bank	0 additional delays	14 delays, 1050 delay minutes	1 at outstation after 1st arrival for 20 hours
4	Maintenance exceeds scheduled time	17 delays, 300 delay minutes	15 delays, 325 delay minutes	5 aircraft unavailable, 120 to 750 minutes
5	AOG's at outstations	17 delays, 300 delay minutes	15 delays, 325 delay minutes	5 unavailable, 3 to 20 hours

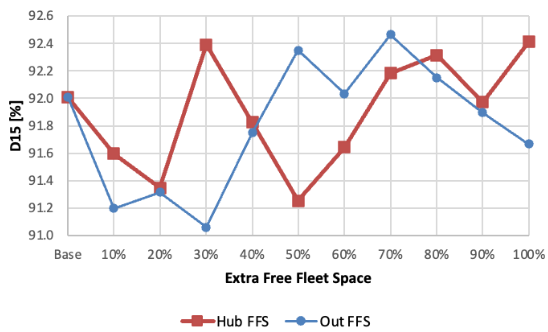


(a) Number of flights for Free Fleet Space scenarios.

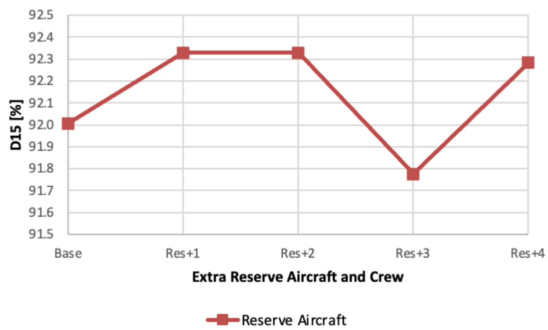


(b) Number of flights for reserve aircraft scenarios.

Figure 2: Number of flights for different network design criteria.



(a) On time performance for Free Fleet Space scenarios.



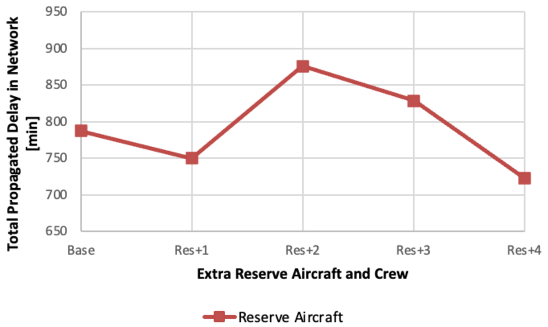
(b) On time performance for reserve aircraft scenarios.

Figure 3: Flights departing within 15 minutes of the schedule.

and 2), additional reserve aircraft marginally improve the on time departure, but this fluctuates, and does not appear to improve with even more reserves. This could be explained if swapping aircraft is more expensive than propagating the delay to the next flight.

5.1.3 Total Delay Minutes

(a) Total delay minutes in the network Free Fleet Space scenarios.

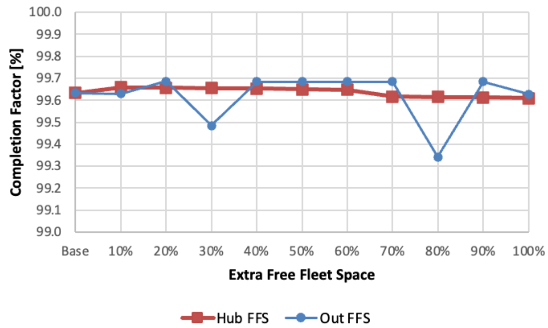


(b) Total delay minutes in the network for reserve aircraft scenarios.

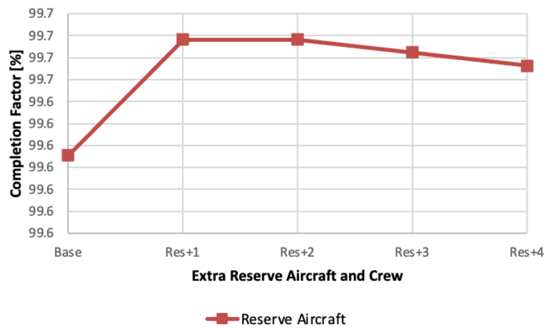
Figure 4: Flights departing within 15 minutes of the schedule.

Figure 4(a) shows the weighted average of the total propagated delay minutes in the network. The disruptions that were imposed on the network were subtracted from this number, in order to better analyze the effects of delays on consecutive flights. The weighted average of total propagated delay time shows a lot of variability for both FFS scenarios. When looking at separate disruption scenarios, there are larger differences. Variability could be caused by the differences in the schedule creation module. Flights are scheduled at a different time, or different flights are removed from the schedule in order to find optimality. Not all flights are scheduled in the same registration in each schedule, since tails are assigned in a FIFO manner. If a flight following a delayed flight has little connecting passengers, or long transfer times, the impact of a delay may not be that large compared to swapping fleet lines. Therefore, the model will prefer delaying these flights, leading to lower on time performance. The other way around is also possible. If a flight with many short connections is scheduled after a delayed flight, there will most likely be a tail swap, and the total delay minutes decrease. In the model, a tail swap is penalized to reflect the true cost of swapping aircraft at a late stage, and this penalty is only assigned once. When the routing changes, the following swaps are not penalized since there is plenty of time to prepare for the next flight. Similarly, extra reserve aircraft also does not show a trend, as shown in Figure 4(b). Considering the variability in the data, there is no clear conclusion of the effect of FFS on the total delay minutes. One trend can be observed in the scenarios with delays at the hub, which are DS1 and DS2. Then the FFS at the hub becomes sufficiently large, the propagated delays seem decrease. This is not clearly visible in the graphs, but looking at the numbers in Table 12, which shows the full table of schedules, and their performance when disrupted.

5.1.4 Completion Factor



(a) Total delay minutes in the network Free Fleet Space scenarios.



(b) Total delay minutes in the network for reserve aircraft scenarios.

Figure 5: Flights departing within 15 minutes of the schedule.

Cancellations remain nearly constant for these schedules and scenarios. Figure 5(a) shows the number of scheduled flights that were actually operated for the FFS schedules. From the base scenario, all schedules with extra fleet space improve the CF by around 0.1%, which accounts for one flight in one disruption scenario. All other scenarios have an equal number of cancellations, but a slightly decreasing CF, since the total number of flights decreases and the cancelled flights account for a larger percentage of the total. The same effect is observed for the extra reserve aircraft schedules,

Table 11: On time performance of disrupted schedules with different design criteria

Schedule	DS1	DS2	DS3	DS4	DS5	Weighted Average
Base	92.4	93.8	91.8	91.2	89.3	92.0
Hub+10%	91.7	93.2	91.5	91.2	89.2	91.6
Hub+20%	92.0	94.0	90.3	90.8	89.7	91.3
Hub+30%	92.5	94.2	92.2	91.4	90.2	92.4
Hub+40%	92.8	93.6	91.0	91.3	90.1	91.8
Hub+50%	92.1	92.4	90.7	91.0	89.8	91.3
Hub+60%	91.8	93.5	91.2	90.6	90.3	91.6
Hub+70%	92.3	93.8	92.0	91.7	89.7	92.2
Hub+80%	92.3	93.8	92.3	91.7	90.2	92.3
Hub+90%	92.5	94.0	91.6	90.7	89.3	92.0
Hub+100%	92.8	94.6	91.9	91.9	90.1	92.4
Out+10%	92.3	92.0	91.2	90.0	88.6	91.2
Out+20%	91.1	92.3	91.7	89.4	90.0	91.3
Out+30%	91.7	92.6	90.8	90.5	88.3	91.1
Out+40%	91.7	92.6	91.7	91.1	91.1	91.7
Out+50%	92.8	93.7	92.0	91.4	91.1	92.3
Out+60%	92.6	93.7	91.4	92.3	90.0	92.0
Out+70%	93.1	92.8	92.6	91.7	90.8	92.5
Out+80%	92.0	94.6	92.0	91.4	89.1	92.1
Out+90%	92.2	93.7	91.4	91.4	90.2	91.9
Out+100%	92.2	93.4	91.4	91.4	88.5	91.7
Res+1	92.6	94.0	92.0	91.8	90.1	92.3
Res+2	96.9	94.0	89.8	91.5	90.9	92.3
Res+3	92.0	94.0	91.4	90.8	89.4	91.8
Res+4	92.8	93.9	92.2	90.5	90.2	92.3

Table 12: Total delay minutes of disrupted schedules with different design criteria

Schedule	DS1	DS2	DS3	DS4	DS5	weighted Average
Base	470	190	1280	585	845	787
Hub+10%	450	230	1295	525	825	789
Hub+20%	475	145	1435	550	790	832
Hub+30%	505	105	1225	605	835	756
Hub+40%	490	250	1370	515	820	829.5
Hub+50%	510	255	1420	625	775	861
Hub+60%	565	175	1380	600	860	846
Hub+70%	485	110	1300	525	775	769
Hub+80%	510	210	1275	555	750	784.5
Hub+90%	510	135	1360	605	785	812
Hub+100%	370	40	1235	530	675	696.5
Out+10%	425	360	1340	670	1150	875
Out+20%	595	360	1365	760	790	892
Out+30%	505	235	1420	585	1245	899
Out+40%	480	285	1285	640	660	797
Out+50%	360	155	1305	575	660	748.5
Out+60%	475	170	1335	430	845	790.5
Out+70%	375	285	1240	520	705	750.5
Out+80%	515	100	1325	625	925	808
Out+90%	525	160	1400	555	865	839
Out+100%	540	190	1420	525	1160	882.5
Res+1	455	175	1235	535	765	750
Res+2	560	160	1515	645	610	875.5
Res+3	530	180	1355	630	815	828.5
Res+4	420	170	1210	585	620	722.5

shown in Figure 5(b). One additional reserve lead to one less cancelled flight for the chosen disruptions. For schedules with more reserves, containing less flights, the completion factor decreases more sharply than for the extra FFS schedules. This can be explained by the fact that extra reserve aircraft have a larger effect on the number of flights in the schedule than increasing the total FFS. Therefore the cancelled flights are a larger percentage of the total scheduled flights. The completion factor shown in Figure 5 are the completion factor excluding the imposed cancellations in disruption scenarios.

6 Conclusions

The aim of this research is to give insights in the effects of different types of robust scheduling measures, to simulate these effects on the airline schedule, and to assess the airline performance using these robust measures in the schedule. Results of this research did not highlight a clear best-performing strategy when it comes to increasing robustness, but provided useful insights and showcased potential for further research.

Increasing the number of reserves or FFS in the schedule leads to a reduction in the number of scheduled flights. This does not necessarily lead to an improvement in performance. Results showed a lot of variability in airline performance in all assessed KPI's. This represents reality, since there are many variables contributing to disrupted operations. Scheduling for the unexpected does not eliminate disruptions completely, but might decrease the propagation effects. If scheduling extra FFS, adding it to the hub TAT appears to be the best for schedule robustness, as it is easier to swap fleet lines for recovery. Improving the simulation model presented in this paper could give better recommendations to the airline.

There are a couple of ways the simulation model can be improved. To start off, the extra FFS is now randomly assigned as a percentage of the original FFS. It could be interesting to analyze the effect of FFS during the peak periods at the hub airport, as these are the moments where most flights arrive/depart, and many passengers transfer flights. A big opportunity is to include medium-haul to long-haul transfers and vice versa, since this is a large percentage of the airport transfers. Effects of re-timing flights on crew and ground operations were not considered, and all maintenance is considered fixed. This could have a large influence on model performance. The disruption management model can be improved by including crew requirements, re-assigning maintenance slots to different tails, and medium-haul to long-haul passenger transfers. Adjusting block time could improve the model as well, and would make it a more realistic simulation. Finally, re-booking passengers would improve model performance as well. As there were only five disruption scenarios, which were weighted using quite some bias, there is room for improvement here as well. Every day is different, so there could be many more disruption scenarios. These scenarios could be weighted using historic analysis of the airline to give a realistic overview.

Based on the results of the case study, it would be inadvisable to increase the FFS or the number of reserve aircraft in the schedule, There are no conclusive benefits, and it comes with the price of scheduling less flights, decreasing revenues. Based on existing literature however, there is most likely a connection between FFS or reserves and the KPIs of the airline. Therefore, improving this simulation model may result in a different conclusion. This research gives a solid basis for determining the FFS and reserves required for robust operations. Improving this simulation to be even closer to reality might show different results.

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Table 13: Completion factor of disrupted schedules with different design criteria

Schedule	DS1	DS2	DS3	DS4	DS5	weighted Average
Base	100.0	100.0	99.4	100.0	98.6	99.6
Hub+10%	100.0	100.0	99.4	100.0	98.9	99.7
Hub+20%	100.0	100.0	99.4	100.0	98.9	99.7
Hub+30%	100.0	100.0	99.4	100.0	98.8	99.7
Hub+40%	100.0	100.0	99.4	100.0	98.8	99.7
Hub+50%	100.0	100.0	99.4	100.0	98.8	99.7
Hub+60%	100.0	100.0	99.4	100.0	98.8	99.6
Hub+70%	100.0	100.0	99.4	100.0	98.5	99.6
Hub+80%	100.0	100.0	99.4	100.0	98.5	99.6
Hub+90%	100.0	100.0	99.4	100.0	98.5	99.6
Hub+100%	100.0	100.0	99.4	100.0	98.5	99.6
Out+10%	100.0	100.0	99.4	100.0	98.6	99.6
Out+20%	100.0	100.0	99.4	100.0	99.1	99.7
Out+30%	100.0	100.0	99.4	100.0	99.1	99.7
Out+40%	100.0	100.0	99.4	100.0	99.1	99.7
Out+50%	100.0	100.0	99.4	100.0	99.1	99.7
Out+60%	100.0	100.0	99.4	100.0	99.1	99.7
Out+70%	100.0	100.0	99.4	100.0	99.1	99.7
Out+80%	100.0	100.0	99.4	100.0	99.1	99.7
Out+90%	100.0	100.0	99.4	100.0	99.1	99.7
Out+100%	100.0	100.0	99.4	100.0	98.6	99.6
Res+1	100.0	100.0	99.4	100.0	98.9	99.7
Res+2	100.0	100.0	99.4	100.0	98.9	99.7
Res+3	100.0	100.0	99.4	100.0	98.9	99.7
Res+4	100.0	100.0	99.4	100.0	98.8	99.7

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II

Literature Study
previously graded under AE4020

1

Introduction

Since the Covid pandemic, air travel demand has grown, and is nearly back at the level of 2019 [46]. The pressure on the fleet of the airlines has grown. Even though the number of flights is still a bit lower than in 2019, airlines still face problems which are a result of the worldwide pandemic. The supply chain of components is disrupted, which results in delays in the Maintenance, Repair an Overhaul (MRO) activities of airlines. Furthermore, the aircraft manufacturers face the same problems in the supply chain for new aircraft, which leads to delays in aircraft delivery dates. Not only fleet maintenance, but many other departments of airlines face challenges. There is often a shortage of personnel in many departments, such as baggage handling, catering services, cabin/cockpit crew, and engineering. In order to operate a route network without delays, all departments should have enough capacity to perform their task at the required moment, and all aircraft should be available as planned. In reality however, the occurrence of disruptions in the airline network is inevitable. The Operations Control Team (OCT) is responsible for minimizing the impact of disruptions, and restoring the network when disruptions occur. To do so effectively, the OCT requires options to resolve delays. If there are no options left, delays may propagate through the day, or flights have to be cancelled. Therefore, disruptions have to be accounted for in the network planning phase. The average delay of all European flights in the first quarter of 2023 was almost 15 minutes. The largest part of this was caused by previous delays, followed by airline caused delays [37].

When designing the timetable for next season, the responsible team has to take into consideration the requirement and wishes from other departments within the airline. For instance, maintenance is often restricted in the available hangar space, or the number of mechanics available, and crew planning takes into consideration the often complex regulations and agreements regarding crew rest times. There are hard, constraining requirements, such as the number of available aircraft, or the airport capacity. There are softer requirements, or wishes as well, which likely cause delays or cancellations if ignored. An example could be the capacity of the towing department. If there are too many flights scheduled in a short time window, this could lead to delays due to late pushback. From the perspective of the OCT, requirements could be a number of reserve aircraft and crew, or buffer in the schedule. A reserve aircraft often has a significant effect on the KPI's of the airline, such as the Completion Factor (CF), departure at the scheduled time (D0), departure within 15 minutes of scheduled time (D15), and consequently the on time arrival performance (A0 and A15). Reserve aircraft are expensive, and an additional reserve may not be an attractive option from a commercial point of view, and does not always result in the airline meeting the operational targets. In order to keep the network controllable on the day of operations, additional network design criteria may be required. The aim of this research is to define and substantiate these criteria. Aircraft routing and crew considerations are taken into account in this literature review. Due to the size and complexity of the problem, maintenance constraints are not considered in depth. The area is of importance to the airline operations, but detailed analysis is left for future research.

To be able to plan ahead for inevitable disruptions and network recovery options, more knowledge is required about the network scheduling process, the disruptions in airline networks, and possible measures to improve the network reliability. Therefore, this literature review consists of three subjects. In Chapter 2, the design process of an airline network is explained. This includes route and frequency planning, fleet assignment, aircraft routing, and crew assignment. Chapter 3 explains airline network disruptions, and how airlines recover from these disruptions. Finally, the proactive measures which could be taken by airlines in order to increase network robustness are discussed in Chapter 4.

2

Airline Network Design, Planning and Scheduling

In order to design an airline network effectively, an airline first defines its business model, then makes other strategic decisions concerning destinations and fleet. This is used to create the schedule, which is divided in four consecutive steps (Barnhart and Cohn, 2004). The first step is Schedule Design. In this step, a market analysis is performed, and used to determine the routes, flight frequency, and flight schedule to fly these frequencies. The second step is the Fleet Assignment, in which the fleet of an airline is assigned to the designed flight schedule, taking into account the aircraft performance characteristics, and maximizing profit. The third step is the aircraft maintenance routing. This ensures that all aircraft meet all maintenance requirements. The final step is crew scheduling, where cabin and cockpit crew is assigned to all flights with a minimum cost objective. In this chapter, the airline network design, planning and scheduling is explained. In Section 2.1, the types of networks used in the airline industry are explained. This is followed by the steps of network planning and scheduling in Section 2.2. The final part of Section 2.2 integrates the different steps in airline network design. Section 2.3 summarizes the findings in this chapter.

2.1. Airline Network Design

There are generally two types of airline network designs. Hub-and-Spoke, and point-to-point networks. Point-to-point networks are the simplest. A direct flight is offered from one city to another. No transfer options are given, and if a passenger would like to transfer, two separate tickets have to be acquired. If the second flight is missed due to a delay of the first flight, there is no compensation or rebooking policy by the airline. The point-to-point network is only profitable if there is sufficient demand for travel between the origin and destination airports. Low-cost carriers exclusively make use of the point-to-point network, sometimes creating demand by offering very low fares.
The hub-and-spoke (H&S) network is more complex, offering passenger transfer services, which includes moving luggage from one aircraft to another at the transfer airport. In case of a missed connection due to delay, the passenger is rebooked to the next available flight, usually at no additional cost for the passenger. The main advantage of the H&S network, is that more markets are connected with the same number of flights. Not all routes have to be profitable, since there is value in the feeder function from less dense routes in order to fill the more profitable larger aircraft. The H&S network only works when the passenger connections at the hub airport are not too long. Therefore, H&S carriers design their network around "banks", in which first the wide-bodies (which have a longer TAT) arrive, followed by the arrival of narrow-bodies. After a short transfer period, the narrow bodies depart, followed by the wide-bodies. Airlines have multiple banks in a day. Legacy carriers like Delta Airlines, Lufthansa or KLM mainly use the H&S network, but have a few point-to-point routes for destinations with exceptionally high demand.

2.2. Airline Network Planning and Scheduling

The airline scheduling process is traditionally divided in parts (Belobaba et al., 2009). Fleet planning is the first step, followed by route and frequency planning. To determine the flight routes, an important element is the balance of demand and supply between an Origin-Destination (O-D) pair, where parallel markets are taken into account (Lohatepanont and Barnhart, 2004). Airlines generally use an incremental approach, building on the network of the previous year.

2.2.1. Frequency Planning and Timetable Design

Airline schedules are designed with a maximum profit objective, and designing a schedule is very complex (Barnhart and Cohn, 2004). Schedule development begins over a year before the flight departures (Belobaba et al., 2009). According to Belobaba et al. (2009) and Wei and Hansen (2005), the market share of an airline is strongly dependent on the frequency share of the route, so flying more frequently with smaller aircraft leads to a higher market share than flying once with a large airplane. With the fleet, routes, and frequency known, the timetable is designed. An airline prefers to plan departures at the peak periods, but a trade-off is made between maximum fleet utilization, and schedule convenience for passengers (Belobaba et al., 2009). Additional constraints, like minimum aircraft turnaround time, capacity of ground services, Air Traffic Control, and maintenance requirements are taken into account in this step. According to Belobaba et al. (2009), there is no existent model which makes an optimal timetable, taking into account all factors. The number of possible flight times, combined with airport, aircraft, and crew restrictions, and varying demand through the day is too complex.

For most airlines, there is a summer, and winter schedule. With the exception of rare cases, like fleet constraints observed by some Embraer E2 operations (e.g. by KLM Cityhopper and Air Astana), or by the 737-Max fleet grounding in 2019 (e.g. by American Airlines and Southwest), schedules are designed by adjusting the schedule from previous years. The current schedule serves as a basis for the new schedule. It is common for airlines to divide the network in sectors, and each sector has its responsible scheduler. The scheduler analyzes the flights in the sector, and checks whether it is beneficial to adjust the departure and/or block times. Reasons to do so may be to accommodate an additional connection, to reduce operating costs, or a slight change in airport slot times. New routes may be created when there is a viable business case, slot availability is checked with the slot coordinators, and other resource restrictions are taken into account.

2.2.2. Fleet Assignment

Generally, fleet is assigned to flights after the timetable is made. The objective is to capture as much demand as possible, while minimizing the operational costs. Most airlines use a mathematical optimization model such as Abara (1989), which is often expanded to represent the timetable as a closed-loop time-space network (Hane et al., 1995, Subramaninan et al., 1994). Rushmeier and Kontogiorgis (1997) presents the Fleet Assignment Model including the connect time rules.

Abara (1989) is one of the first works to solve the fleet assignment problem. The objective is to maximize the benefits of flights minus the costs of e.g. airports, or fuel usage. It has five constraints. The first is flight coverage, which ensures all flights are covered exactly once. Continuity of equipment makes sure that aircraft can be in only one place at a time. Schedule balance is included in order to make sure that all stations have an equal number of inbound and outbound flights per aircraft type. Cost minimization was considered by constraining the number of aircraft used. There are possibilities to add extra operational constraints for purposes like limits on the number of slots, number of overnight stays at outstations, operating costs and more. In the model, all aircraft turn combinations are decision variables. Abara (1989) models the network as a time-space model, and it is capable of solving full size airline networks.

Similarly, Subramaninan et al. (1994) model the airline network as a time-space model. In this model, all later departures from an airport can be paired with an arriving airplane. This model may be expanded with maintenance arcs, crew requirements. The objective is to minimize operating cost, spill cost, and applicable penalties. Operating cost depend on the aircraft type used, crew, landing fees, etc. Spill cost is the number of passengers which can not be transported due to a fully booked flight. The authors report an a large cost saving, but note that the difference in revenue is hard to predict due to the variance in demand, and the lack of record of spill and recapture. Contrary to Abara (1989), Subramaninan et al. (1994), which make use of a time-space network model, Hane et al. (1995) make use of a connection network. The work describes a daily, short to medium haul network, and describes methods to solve the fleet assignment problem more efficiently. Rushmeier and Kontogiorgis (1997) expand the time-space model with passenger connection requirements, and includes an estimation for profits generated by allowing transfers.

Clarke et al. (1996) expand the model of Hane et al. (1995), and include maintenance and crew considerations. Maintenance requirements are included by adding a constraint that makes sure all aircraft stay overnight at an airport with maintenance facilities, and maintenance arcs for longer maintenance checks. Crew requirements are included by adding constraints for the minimum rest times of the crew. This may either be done by having the aircraft remain with the crew, or using midday breakouts, in which the crew is switched halfway the day. This minimizes the time the crew is away from base.

The Itinerary-based Fleet Assignment Model, created by Barnhart et al. (2002), integrates passenger itineraries with spilling and recapture rates with the fleet assignment model. The authors concluded that their model improved profits compared to the fleet assignment model without the effects of passenger recapture. Including this improved the model further, but the actual recapture rate is difficult to quantify, making the exact improvement from the complete model hard to predict. This has no large effect on the fleet assignment. Lohatepanont and Barnhart (2004) extend this model by assuming markets are independent, which gives the capability to adjust demand for all individual markets. The model takes an existing schedule, evaluates some new flights with pre-defined candidates for deletion, creates the net flight schedule, and assigns the fleet. The authors make some assumptions compromising the model accuracy, but results from the model may be compared with other models using the same assumptions. Integrated Schedule Design and Fleet Assignment Model is computationally expensive. Therefore, the authors created an Approximate Schedule Design and Fleet Assignment Model, where the interaction between supply and demand is approximated. This runs significantly faster, and may be used for full-size airline schedules.

Kenan et al. (2018) combines the Flight Scheduling and Fleet Assignment Problems. The authors create a time-space model with a two-stage objective function which maximizes profit. To reduce the problem size, a Sample Average Approximation algorithm is used. The authors perform a trade-off between the problem size, and accuracy. After analyzing the results, the optimality gap was less than 1% using 100 scenarios. Demand, spill and recapture rates are not included in the model, and neither are crew pairing and scheduling, and maintenance requirements.

Rexing et al. (2000) extended a simple version of the fleet assignment model, and added time windows by creating copies of flight arcs within a specified window. This allows departure times to change slightly, in order to give a more optimal use of resources. The the model takes a long time to run, but compared to the standard fleet assignment model, less aircraft were required to fly the existing network, and fleet assignment costs were reduced. The model did not take into account crew considerations, or maintenance requirements, so the model results are most likely a bit overestimated.

2.2.3. Aircraft Routing Problem

The aircraft routing problem, or maintenance routing problem (Belobaba et al., 2009) is solved after the fleet assignment problem, and before the crew scheduling problem. In the fleet assignment problem, the aircraft type was assigned to flights, and in the ARP, the registration is appointed to a sequence of flights. Maintenance slots are assigned to aircraft as well.

There is vast literature about the aircraft routing problem. Earlier research optimized considering maintenance opportunities, such as Abara (1989), Barnhart et al. (1998) and Sriram and Haghani (2003). Later, more aircraft-specific requirements were investigated by Lagos et al. (2020), Sarac et al. (2006) and Sanchez et al. (2020). The aircraft routing problem is integrated with the fleet assignment problem frequently in literature, see for example Barnhart et al. (1998), Li and Wang (2005) and Shabanpour et al. (2023). Integration of robust measures are a common area of interest as well (Eltoukhy and Mostafa, 2022, Froyland et al., 2014, He et al., 2023). Since the scope of this project is to plan in advance for disruptions, the aircraft routing problem is of less relevance. It is therefore not considered in depth, but the references stated in this section give an overview of the current state of the art.

2.2.4. Crew Scheduling

After the timetable is designed, and the aircraft are assigned to flights in the timetable, the crew schedules are constructed. There are many rules which have to be taken into account, such as work and rest times. Furthermore, the airline takes crew requests into account, such as holidays, and consistency in the flight times. Crew is usually scheduled in two steps: crew pairing, in which the schedules are created, and crew assignment, in which pairings are assigned to crew members (Belobaba et al., 2009). Most earlier research make use of a linear relaxation and column generation algorithm, with a minimum crew cost objective. See for example Hoffman and Padberg (1993), Klabjan et al. (2001) and Barnhart et al. (1998). Constraints include coverage of all flight legs exactly once. Flights in pairings are sequential in time and space, and subsequent flights take into account the required connection time. In the model in Belobaba et al. (2009), this column generation algorithm is solved repeatedly to find the optimal subset of variables for the column generation algorithm.

Barnhart and Cohn (2004) explain the discussed models, and suggest research in combining the sequential models in order to improve model results. Models become large, and take a long time to solve. To reduce the problem size, there are a few options. Variable elimination is one of the options. Many constraints are redundant in the model. These do not contribute to the model outcome, but are used in the model anyways. Removing these redundant constraints is possible by node consolidation or arc consolidation. Another problem reduction method is exploitation of dominance. Some variables are dominated by others, hence they have a little to no influence on the model results. Variable disaggregation is another possibility. Some variables may be disaggregated into other variables with fewer decisions. Many of these variables may be eliminated, resulting in a smaller problem. Another approach to reduce the problem size is the use of heuristics. Cohn and Barnhart (2003), Levine (1996) or more recently Azadeh et al. (2013).An exact solution can not be guaranteed in these approaches. Cohn and Barnhart (2003) compares their heuristic model with an exact solution, and give flexibility to trade-off solution time and quality of the results.

Recent developments show more research in using machine learning techniques for the crew pairing and scheduling problems. Yaakoubi et al. (2020) for example used ML to create clusters of flights which are likely to be performed by the same crew, which were later assembled and modified to form pairings. Morabit et al. (2021) and Tahir et al. (2021) used ML to improve the column generation algorithm by selecting the most promising columns. There is relevant literature from other research area's related to transport, such as Gattermann-Itschert et al. (2023) who included a ML model to learn preferences of a railway crew planner. This could work for airline crew planning as well.

2.2.5. Integrated Models

To integrate the fleet assignment and crew pairing problems, Özener et al. (2017) created an integrated fleet assignment and crew pairing model. To be able to do so, the fleet assignment and tail assignment problems were integrated. The objective function has two parts, where flight profit minus crew cost is maximized. Compared to a sequential and iterative optimization, the integrated model of Özener et al. (2017) showed significantly faster CPU times, while giving an overall lower cost, and higher profit. The model disregards maintenance constraints.

Cacchiani and Salazar-González (2020) present four models which retime flights in a schedule. Fleet assignment, aircraft routing, and crew pairing is considered. The authors make use of heuristics, and column generation algorithms. The first model considers all flight retiming and rerouting options while the second model keeps the routing fixed, but does allow all retimings. The third model selects a subset of the flight copies, which limits the set of retiming options. The fourth model also selects a subset of flight copies, but uses a column generation algorithm to select the flight retiming options. The first model is the slowest, but gives the best improvement overall. The authors conclude that the best performing model in the improvement vs CPU-time trade-off is the fourth model which uses column generation for selecting flight copies.

Ben Ahmed et al. (2022) integrates the fleet assignment, maintenance routing, and crew scheduling problems in one single model. In the model, all flights are covered exactly once, the schedule is periodic, maintenance constraints are taken into account, crew pairings comply with all regulations, the number of crew used does not exceed the available crew, and there are robustness measures incorporated (see Chapter 4). The model objective is to maximize the overall profit, which is given by revenue minus fleet assignment cost minus some non-robustness penalties given to critical connections, critical crew connections, and connections where crew do not follow the aircraft. The constraints ensure route feasibility, itinerary feasibility, pairing feasibility including duty, and short connections. It is a non-linear model, which is linearized. To solve it, a restricted master problem was constructed bu dropping the robustness constraints and variables. A relaxed version was solved, and the problem decomposed. A reduced aircraft routing and crew pairing problem was solved for each aircraft family. Finally, a proximity search algorithm was used, which searches for an improved solution. This model takes a long time to run, if solved exactly, with one instance taking 10 hours, while still not optimal. The decomposed method is considerably faster, but still not very fast. The proximity search is in many instances the fastest. The decomposed and proximity search methods are accurate, with most results being within 1% of the optimum.

Glomb et al. (2023) integrated the fleet assignment and tail assignment problems, and alternately solved the model with a model that optimizes turnaround handling. The objective of the first model is to minimize the assignment cost of fleet and flight combinations. It is modeled as a connection network. The second model minimizes aircraft assignment cost, and cost for delays and turnaround options. This model takes into account all ground operations between flights, and ensures that subsequent activities start after the previous activity is completed. Post-flight processes which are considered are taxi, deboarding, cargo unloading, and cleaning. This is followed by the pre-flight processes: Fuelling, catering, boarding, cargo loading, finalisation, de-icing, and taxi. The integrated model takes into account scarce resources. It is solved using an island decomposition approach. This approach shows faster, and more accurate results compared to other methods such as benders decomposition, waterfall or lbf.

2.2.6. Design Criteria

When designing the network, many aspects have to be considered. In addition to the hard constraints of finite resources, such as the number of available aircraft, there are different "design criteria" which are set up by all departments. Constraints and design criteria include:

- **Airport Capacity/Slots:** Many airports have capacity constraints for ATC, runway capacity, or gate capacity. Therefore the number of arrivals and departures is often regulated. Most large European airports are level 3 slot regulated, meaning that an airline needs the rights to land and take-off at a certain time. If more than 80% of the scheduled flights are performed in a season, the airline keeps the slot rights for the next year. Otherwise slots are assigned randomly to interested parties. Slots are the most important assets of airlines operating in slot constrained airports. Slots may be traded with other airlines, but acquiring new slots is often difficult.
- **Aircraft availability:** The number of available aircraft is known in advance. It is difficult to acquire more aircraft in a year, although it is possible to wet lease to capture seasonal demand.
- **Crew availability:** Aircraft require cockpit and cabin crew. Especially cockpit crew is currently a scarce resource, so this could be considered as a hard constraint.
- **Maintenance requirements:** To keep their airworthiness, aircraft are required to undergo maintenance after a number of days/flight cycles/flight hours. Maintenance checks are traditionally divided in A-, B-, C-, and D-checks. A- and B-checks are frequent, relatively quick checks which are planned a few weeks in advance. It is possible to defer these maintenance checks to some (limited) extent, so they could be considered as soft constraints. C- and D- checks are complex, occur once in a few years, and are planned years in advance. Due to their complexity and the large amount of resources required, C- and D-Checks are considered as hard constraints.
- **Ground Operations:** There is a maximum capacity of all airport ground operations. There is a limited capacity of pushback tugs/crew, baggage handling, fuelling services, and catering services.
- **Turn Around Time:** There is a minimum time required to unload and load the aircraft between flights. The time depends on the type of aircraft, and to some extent the ground equipment used (using two jet bridges, or extra stairs speeds up the minimum TAT slightly).
- **Reserve Aircraft and Crew:** In order to have options to recover the network in case of disruptions, there are reserve aircraft and crew scheduled.

2.3. Concluding Remarks

The different parts of airline network design: route and frequency planning, fleet assignment, maintenance routing, and crew scheduling has been researched extensively. To reduce computational time in the models, column generation is widely used. Due to the sequential nature of the scheduling process, the final solution is not likely to give the highest operating profit. Therefore, recent research is more focused on the integration of the different scheduling parts. If all variables of all scheduling parts are taken into account, there are too many variables to give reasonable solutions within reasonable time. Hence, an optimal solution does not exist yet. There are existing models which make use of (meta-)heuristics, in order to give an approximation with a small expected gap to the optimal solution. Another more recent development is the increase in research about robust scheduling, where disruptions in the network, which inevitably occur, are taken into account. Robust airline scheduling is explained in Chapter 4. Most of the airline network is the same as the year before. Since many airports, especially in Europe and Asia, are heavily slot constrained, slots are the most important consideration when creating new routes, extending existing routes, or changing departure times.

3
Disruption Management

If all scheduled flight depart and arrive exactly on time, there are not many challenges to operating the network. In reality however, this is rarely the case. There are a couple of reasons a flight might be delayed or cancelled. Su et al. (2021) classifies flight disruption sources in two categories: Airline Resource Disruption, and External Environmental Disruption. The main factors for airline resource disruptions are the availability of aircraft, and crew. There might be a mechanical breakdown, in which case the aircraft can not be used, and needs unplanned maintenance. Planned maintenance could take longer than expected, due to shortages in personnel, or a disrupted supply chain for components. Other reasons for aircraft disruptions could be fuel shortages, personnel shortages/strikes. Flight crew could be absent due to illness, personal emergencies, or due to disrupted flights. This chapter discusses the disruptions of the airline network in Section 3.1, the recovery of aircraft in Section 3.2.2, crew in Section 3.2.4, and Section 3.2.6 discusses integrated recovery methods.

3.1. Disruptions in Airline Schedules

The airline network may be disrupted by external, environmental factors such as wind direction and strength at the hub or outstation, en-route head wind for longer flights, extreme cold, fog, or snow at the hub or an outstation. Other external factors include Air Traffic Control (ATC) capacity reductions, runway closure due to maintenance.

3.1.1. Types of disruptions

Since the use of airline resources is optimized using the models described in Chapter 2, the impact of a disruption may be severe for the continuity of the network. Filar et al. (2001) describes causes for air traffic delays due to airport, and airspace capacity. When the weather conditions require Instrument Flight Rules (IFR), the airport capacity is significantly lower compared to Visual Flight Rules (VFR). The airspace has a maximum capacity as well, which is usually, but not always higher than the airport runway capacity. Aircraft are sometimes delayed at the originating airport because of airspace or destination airport capacity. This is easier to do for short- to medium-haul flights, as they are often still on the ground when capacity issues become evident. Long-haul flights are often already flying when capacity issues occur. Filar et al. (2001) discusses the papers by Teodorovic and Guberinic (1984), Teodorovic and Stojkovic (1995) which aim to find circumstances in which aircraft are suddenly not available, and to minimize the number of cancelled flights. These are limited models in the sense that the problem is made small, and ferry movements are not allowed. In the model of Jarrah et al. (1993), this is included. Filar et al. (2001) discusses more research on aircraft unavailability, such as Argüello et al. (1997), Yan and Tu (1997), Yan and Yang (1996), Yan and Young (1996). These models make use of a time space network, and do not take into account crew requirements. Teodorovic and Stojkovic (1995) consider the challenges of crew planning, and suggests a first in first out (FIFO) approach for the completion of crew rotations and aircraft schedules, but better solutions could be found with a dynamic programming heuristic. Filar et al. (2001) discusses models from Richetta and Odoni (1993), Terrab and Odoni (1993), Terrab and Paulose (1992) about solutions for reduced airport capacity, and discusses the effects of ground delays due to the arrival slot regulation (Luo and Yu, 1997, Vasquez-Marquez, 1991). Kohl et al. (2007) investigated airline disruption management. Airline Disruption Management is an ongoing process, with several goals: deliver customer promise, minimize excess costs, and get back to the original schedule as quickly as possible. Disruption management is complex, and human experience is required to solve some cases. This may be done by planning for disruptions in early stages, avoiding operational complexity, exploiting probability of events occurring, and planning for alternative scenario's. This is called "Robust Scheduling" and it is explained in Chapter 4.

Summarizing, there are three main subjects considering airline disruptions, which are all connected: aircraft disruptions, crew disruptions, and passenger disruptions. Disruptions include delays, and unavailability of resources.

3.1.2. Delay Propagation

Delays propagate, because multiple resources, such as aircraft, crew, and passenger connections have to by in synchronization (Wu, 2012). Models were created to identify the causes and impact of delay propagation, such as Wu (2005). This paper suggests that delays are inherent, and have stochastic causes. Hence, there should be buffer time embedded in the network schedule to ensure network robustness.

Wu (2005) uses a model to simulate operations, which models aircraft turnaround operations, and en-route operations in separate modules. The turnaround operations model was developed by Wu and Caves (2002, 2004). It is a combination of a Markov Chain algorithm, and discrete-event simulation. Passenger processing, and cargo processing were modelled as parallel Markov chains, and this was simulated using a Monte Carlo simulation. Processes which are independent from passenger and cargo processing were modelled using a discrete-event simulation, because of the uncertainty of these processes. To model the delay of a flight, the en-route module uses random variables for the departure time, and block time of a flight. When compared to the data from a real airline, the model of Wu (2005) shows lower delays than they actually were in real life. The model is capable of following trends, but underestimates propagated delay, even in the case where a longer TAT (Turn Around Time) was planned.

The delay propagation model of Wong and Tsai (2012) uses a model for the survival of delays. A Cox proportional hazards model is used to model flight delays. This delay is used in a survival function to model how long the delay will last. For departure delays, cargo mail handling has the highest influence on delays, as the chance of recovery is lowest. This is followed by flight operations and crewing, passenger and baggage handling, and aircraft type. ATC restrictions have the lowest influence. Weather also has a high impact, but this is beyond control of airlines. For arrivals delays, the block buffer time, and weather have the highest influence.

The models of Wong and Tsai (2012), Wu (2005) both are focused on individual aircraft rotations, and do not take into account the entire network. Arikan et al. (2013) models delay propagation in a stochastic model. It determines the actual block time, and compares this to the scheduled block time, by using a log-Laplace distribution. This is used for the delay propagation model.

The concluding remark of this section is that delays occur in the airline industry, and they should be solved to avoid delay propagation. There are several methods of doing so, which are explained in upcoming sections.

3.2. Airline Network Recovery

When a disruption in the airline network has occurred, the objective of an airline is to minimize the impact of the disruption. Disruptions include flight delays, airport disruptions, crew disruptions, or aircraft unavailability due to an AOG (Aircraft On Ground) for example. Clausen et al. (2010) did a literature review about airline disruption management. Until the year of writing, most research was done in the area of aircraft recovery, with some papers describing passenger, crew, or integrated models (Hassan et al., 2021). Hassan et al. (2021) did a literature review more recently, and found that research attention shifted more towards integrated models. However, aircraft recovery is still the most researched topic.

Delays are not the only form of network disruption. There may be aircraft or crew unavailability due to other reasons such as mechanical failures, illness, or airport closures. When it is not possible to absorb disruptions in a schedule, airlines try to recover the network to the planned schedule. Previous research makes the distinction in three area's: Aircraft Recovery, Crew Recovery, and Passenger Recovery. Combinations, and integrated recovery has been researched as well. This section deals with the methods used for network recovery.

3.2.1. Network Representation

In the findings of Clausen et al. (2010), the airline network is most commonly represented in three different ways: a connection network, time-line network, and a time-band network.

In the connection network, flight legs correspond to nodes in the network, and connections between flight legs correspond to the arcs between the nodes. The origin and destination nodes represent the possible airports at which an aircraft is located in a set time window. The path between origin and destination nodes shows the feasible paths of an aircraft as part of a rotation. Advantages are that maintenance is easily incorporated, but the drawback is that the number of nodes grows exponentially, hence larger models are computationally expensive.

In the time-line network, all airports are listed vertically, and time horizontally. Nodes are the times that either a departure or and arrival occurs at an airport. The edges are the flights between airports. There are ground arcs as well, which represent aircraft which stay at the airport overnight for example. A direct path is a feasible rotation for an aircraft. Arguello (1998) proposes the time-band network, in which the activities at an airport within a certain time band are represented in a node. This model is constructed dynamically whenever a disruption occurs.

3.2.2. Recovery Options

An airline OCT has several options to restore the network. These strategies include:

- **Flight delay:** Delays propagate in the network, but this may be mitigated if there is buffer time in the network
- **Flight cancellation:** An expensive but effective solution for network recovery. Passengers are unhappy, and may have to be compensated.
- **Aircraft swaps:** This might be a good option if there is buffer time, or when it is cheaper to cancel a different flight, which is not fully booked, or less slot constrained.
- **Reserve aircraft and crew:** Generally, a reserve aircraft is expensive, since it does not generate revenue when it is not used, but this is preferred over flight cancellation.
- **High speed flights:** To reduce flight block time, an airline may chose to fly faster. The aircraft uses more fuel, but delays in the network may be mitigated. This is more effective for longer flights, since the flying time is a larger percentage of the total block time.
- **Faster ground operations:** Sometimes, TAT mat be reduced when some ground operations are executed faster. A lighter catering product reduces loading time for example.
- **Ferry flights:** To move an aircraft from an outstation back to the hub without passengers. This is only done to fly an aircraft back after unplanned maintenance at an outstation, or in order to perform the required maintenance at the hub airport where facilities are better.

Delays are not the only form of network disruption. There may be aircraft or crew unavailability due to other reasons such as mechanical failures, illness, or airport closures. When it is not possible to absorb disruptions in a schedule, airlines try to recover the network to the planned schedule. Previous research makes the distinction in three area's: Aircraft Recovery, Crew Recovery, and Passenger Recovery. Combinations, and integrated recovery has been researched as well. This section deals with the methods used for network recovery.

3.2.3. Aircraft Recovery

Early research in disruption management was mainly about aircraft recovery. Teodorovic and Guberinic (1984) first investigated aircraft recovery. In this model, one or more aircraft are unavailable, and the flights may be re-assigned or re-timed. Maintenance is ignored in their model. This model was extended to include cancellations as a possible solution, and airport curfews as constraint (Teodorovic and Stojkovic, 1990). The same authors extended the model with crew considerations (Teodorovic and Stojkovic, 1995). These models make use of a connection network, generated data, and a single fleet type.

Jarrah et al. (1993) created network models for cancellation and delaying of flights. They are separate models, and do not allow for a trade-off between the two options. Rakshit et al. (1996) reports the effects of the models of Jarrah et al. (1993). Cao and Kanafani (1997a,b) extend these models, and allows for a solution of combining delays and cancellations. Ferry flights and options for aircraft swapping are also included in their model. Mathaisel (1996) created a model which uses cancellations and re-timing, but does not discuss crew considerations, and multiple fleet types. It gives an interactive tool which shows re-routing alternatives. All models mentioned in this paragraph make use of a Network Flow Model.

A second approach is the modelling with a time-line network, introduced by Yan and Yang (1996). The time-line model was completed with ferrying arcs, and time-shifted copies of arcs to allow for delays. Maintenance and crew are not taken into account, and a single fleet type is used. The constraints in some models in Yan and Yang (1996) were relaxed, and heuristics were used to speed up the algorithm significantly, while still giving near-optimal results. Yan and Tu (1997) presents a similar model, with the inclusion of a multi-type fleet. Yan and Lin (2005) includes temporary closures of airports, and Yan and Young (1996) includes multiple stops for aircraft. The modelling of perturbations in these papers is slightly different, but solution methods are similar. They are time-line modelled networks using real-life data. Thengvall et al. (2000) extends previous models with the addition of protection and through-flight arcs, which enables the model to deviate from the original schedule. Aircraft delays, swaps and cancellations are permitted. Crew and maintenance are disregarded, and a single fleet type is used. LP relaxation is used to speed up the model, but it gives near-optimal solutions. Thengvall et al. (2001, 2003) extend the earlier work with the addition of hub closure, and multiple fleets. Three models were created, of which the first two had a maximum profit objective, and one a minimal delay and cancellation cost.

Arguello (1998) introduced the time-band model. Bard et al. (2001) used this model to discretize the time line, and create a minimum cost model to reassign aircraft. The constraints in the model ensure all aircraft can be at one place at a time, minimum TAT is adhered to, recovery extends to the end of the day, at the end of the day all aircraft are positioned for the next day, airport curfew is adhered to, and no changes to the maintenance schedule are allowed. The model is initialized by using the current schedule, identifying the grounded and delayed aircraft, and setting the time-band length for all stations. The network is transformed to a time-band network, and the mathematical program is created. It solves the LP relaxed program, and use it in the MILP solver. Finally the schedule is created and checked for feasibility. Eggenberg et al. (2007) uses a column generation algorithm, where each aircraft has an independent recovery network. Maintenance arcs are introduced in be able to incorporate maintenance requirements.

Rosenberger et al. (2003) shows another approach to the aircraft recovery problem, and models it as a set partitioning model on a connection network. For all disrupted aircraft, the feasible swaps are determined by a preprocessing heuristic. Flight legs in the new routes are used as columns for the set partitioning problem. This is a fast algorithm as reported by Rosenberger et al. (2002). Andersson and Värbrand (2004) also makes use of a set partitioning problem in a connection network, with a shortest path problem as subproblem with linear node costs and time windows. Program run time with a Lagrangian relaxation-based heuristic is manageable, and the results are comparable to the results of the Dantzig-Wolfe based decomposition.

Some models make use of (meta-)heuristics. The first of which was Argüello et al. (1997). Their model uses a greedy approach to reconstruct the network when one or more aircraft are grounded. This initial approach is then altered by changing the flight routes, swapping aircraft, or cancellation. It is built for a single fleet type, and disregards maintenance.
Løve et al. created a heuristic to generate a feasible revised flight schedule. Delays, cancellations, and aircraft swaps and fleet swaps are possible solutions. The model makes a trade-off to find the best solution. Weights

for this trade-off may be changed if required. According to Kohl et al. (2007) confirmed the results of Løve et al.. Andersson (2006) uses tabu search and simulated annealing meta-heuristics. The heuristics use a tree-search algorithm to find new aircraft schedules, and tries to relink paths between different solutions. It allows delays, cancellations and aircraft swaps. The tabu search method often produces better results, and both methods give good solutions in a short time. The model by Andersson (2006) is capable of using a multiple type fleet. The model by Liu et al. (2006) allows delays and aircraft swaps, but uses a single fleet type, and does not allow cancellations. It was extended for multiple fleet type use (Liu et al., 2008).

In order to decrease delay propagation, Ahmadbeygi et al. (2010) suggests re-allocating scheduled slack to flights which are often delayed. Propagated delays are not modeled perfectly, and are sometimes over- or underestimated.
Similarly, Wu (2006) suggests a sequential modelling approach to ensure network robustness, in which only flight times were adjusted, while routing remained the same. In this model, a significant cost saving was achieved. The drawback of a sequential approach is that the solution might be sub-optimal, since results or constraints of one problem might restrict feasible solutions later in the process.

Weide et al. (2010) attempts to counter this, and concludes that the integrated aircraft routing and crew pairing is computationally expensive. Therefore it uses an iterative approach. First the crew pairing problem is solved, followed by a the aircraft routing problem, in which the number of restricted connections that are operated by the crew pairing solution are maximized. The next step is to minimize the number of restricted aircraft changes in the crew pairing problem. This is done until a crew penalty exceeds the maximum value.

Lan et al. (2006) created models to minimize passenger disruptions, by rerouting aircraft, or changing departure times, based on a stochastic delay distribution. Their model does not take into account the effects of crew and passenger connections on delay propagation.

Dunbar et al. (2012) aims to improve the models from Ahmadbeygi et al. (2010), Lan et al. (2006), Weide et al. (2010), in which simplified delay propagation models from Wu (2005, 2006) are used. Results show an improvement of the routing and crewing Integrated, Propagated Delay model compared to the routing and crewing Sequential, Propagated Delay model.

Where previous mentioned models make use of Independent and Identical Distribution assumptions, Wu and L. (2019) researched the delay propagation effects of multiple resource connections in an airline network, without using this assumption. It uses the Delay Propagation Tree models from earlier research (Ahmadbeygi et al., 2010, Dunbar et al., 2012, Lan et al., 2006), and combines this with a Bayesian Network model. Bayesian Network models were used before by Cao et al. (2008), Liu and Ma (2008), Liu et al. (2008), Xu et al. (2005) for limited problems.

Lee et al. (2022) applied a reinforcement learning approach for the aircraft recovery problem. Multiple fleet types are considered. The only disruption considered is the temporary closure of airports. In reality, there may be many more disruptions. Recovery options are delaying and swapping aircraft. Options for cancellation and ferrying are not included in the model. Compared to a more traditional method, the reinforcement learning method was faster, but gave overestimated results. The model is designed in such a way that it does not avoid unnecessary aircraft swaps. Unnecessary swaps may have consequences for the crew scheduling, in addition to ground operations such as gate availability and catering.

3.2.4. Crew Recovery

With disrupted flights, the crew schedules are inevitably disrupted as well. To recover crew schedules, airlines have a few options, including re-assignment, dead heading, and cancellation. Since crew schedules have to adhere to strict regulations, union agreements, and airline-specific policies, the crew recovery problem is considered more difficult than aircraft recovery (Hassan et al., 2021).

Crew schedules may be disrupted by flight delays, cancellations, and crew unavailability. Castro and Oliveira (2007, 2009) consider crew unavailability as a disruption, and apply a multi-agent system to the crew recovery problem. They report significantly faster, and better solutions compared to manual recovery operations. There is no sample size reported. The model uses sub models, which optimize parts of the problem.

(Meta-)heuristics are also used to solve the crew recovery problem. Chang (2012) created a Genetic Algorithm for the crew recovery problem. The objective is to minimize the number of deadheads, unconnected flights, schedule changes and number of affected crews due to schedule changes. The algorithm has reasonable run time, giving results in 10 minutes when analyzing over 650 flights, with 70 crews and 18 recovery days. The model takes into account rest time regulations, and connection feasibility. Since heuristics are used, it is not an optimal solution, and the author does not state the optimality gap.

Liu et al. (2013) created an interfleet and intrafleet model, which were solved using different methods. For difficult models, a simulated annealing algorithm was created. Costs were not taken into account, as the objective is to cover all flights. Hence, when taking into account costs, solutions may be very different. The problem size was limited by using a time window of 24 hours, and crew size of 6. The interfleet model gives consistently better results than the intrafleet model. The authors take into account both delays and crew unavailability as disruption types.

The approach by Novianingsih et al. (2015) is to identify all possible crew swaps, and apply this if possible. If this is not possible, a new crew schedule is created with the use of heuristics. This schedule is then improved with another module. The model was applied to a network with 214 flights and 48 crews. The model gives fast results with a maximum tested run time of under three minutes, but it only takes into acocunt disruptions due to delays. By only considering legal pairings, all regulations are taken into account. The model optimizes for minimum cost of crew changes.

Zhu et al. (2014) use a constraint programming model, minimizing recovery cost. Constraints include temporal-spacial requirements, deadheading and time legalities. Their model is applied to a small problem with a two-pilot flight crew on a single day of operations (Hassan et al., 2021). This is a small representation of a complete airline schedule, so it might be interesting to see how the model performs in a large-scale airline network, with multiple days.

3.2.5. Aircraft and Crew Recovery

There are a few papers which research the integration of aircraft and crew recovery, the first of which was Aguiar et al. (2011). The authors use multiple meta-heuristic approaches such as a genetic algorithm, hill climbing and simulated annealing. The genetic algorithm outperforms the others in the case study of the authors, although the other heuristics perform well. The simulated annealing and hill climbing methods were applied to the crew recovery problem as well, with the simulated annealing having a slight edge. Aguiar et al. (2011) only take into account disruptions due to aircraft unavailability. Solutions of the models are not compared to the global optimum. Therefore, it can not be determined whether the results of these heuristics are of sufficient quality.

Le and Wu (2013) use an iterative tree growing algorithm with node combination. A time-space network is used to describe the heuristic method. Maintenance requirements, and crew scheduling regulations are taken into account.

Zhang et al. (2015) use a two-stage heuristic algorithm for aircraft and crew recovery. The first stage is the integrated aircraft recovery and flight re-scheduling with crew consideration. This is followed by integrated crew recovery and flight-rescheduling with partial aircraft consideration. For the aircraft recovery model, constraints for maintenance, slots, and crew satisfaction are included. The use of reserve aircraft is a possible schedule recovery method. Crew regulations and connection feasibility are included in the second model. Although the model is a bit slower than the model of Abdelghany et al. (2008), the results are better, with a lower overall cost.

Maher (2016) used a column-and-row generation algorithm to solve the integrated recovery problem. It builds on existing column generation models, and allows delays and cancellations as recovery options. Crew regulations are taken into account, but aircraft swaps are not. The results is a faster model than a standard column generation model, and it was tested on both a P2P and H&S network.

Shortcomings to the models in this section is that none of the models take into account all common disruptions. Crew unavailability was not considered as a disruption, and the use of reserve crew was not possible. Future research could improve in these areas.

3.2.6. Integrated Recovery

Modelling for aircraft, crew, and passenger recovery simultaneously is challenging, but there are some papers addressing integrated recovery. Some papers consider two of the three recovery options while modelling the third one indirectly by applying penalties. Vink et al. (2020) for example, solves the aircraft recovery problem including maintenance requirements and passenger itineraries, and penalizes solutions which might have crew implications.

An exact method of solving the integrated recovery problem was created by Arikan et al. (2017). In the model, all disruption types are considered, except crew unavailability. Recovery options include flight delays, cancellations, aircraft swaps, use of reserve aircraft, aircraft ferrying, cruise speed control, crew deadheading, and itinerary changes. Is is therefore a complete model, and gives solutions within 20 minutes in their case study.

Vink et al. (2020) created a model which is suitable for operational use. There are four solutions to the aircraft recovery problem given in the paper. The first and quickest one is the trivial solution, which only takes into account the disrupted aircraft. The selection algorithm gives solutions in about 20 seconds, and tries to improve the trivial solution by considering more aircraft iteratively. The third solution is the static global solution. This is the optimal solution if all disruptions for the day are known in advance. The dynamic global solution gives the global optimum for the entire fleet in the dynamic environment. The static and dynamic global solutions are not suitable for operational use, since CPU times are too long (in the order of 10-20 minutes). In the worst case scenario, the selection algorithm presented a solution which was 39% more expensive than the dynamic solution. In this scenario, there was unexpected maintenance required. In most other cases, the results were the same, or within a few percent. The model by Vink et al. (2020) uses a parallel time-space network, in which all aircraft are modelled in a separate network, but flight arcs of other aircraft are included to be able to swap flights.

3.3. Concluding Remarks

Recent development show an increase in research about models that integrate aircraft, crew, and passenger recovery. Furthermore, recent models have more recovery options such as aircraft type swaps, or cruise speed control. The main challenge in disruption management is the required CPU time for optimal solutions. The airline OCT requires solutions to network disruptions within a few minutes, and models lose their usefulness if this is not guaranteed. By making use of heuristics or large servers, models which solve disruptions accurately in an operational environment already exist, however there is no model that gives an exact solution which considers all possible disruption scenarios, with all possible recovery strategies within reasonable time.

4

Robust Airline Network Planning

In the design process of the airline network, airlines try to plan for the unexpected. Kohl et al. (2007) list a few techniques which are used by airlines. These include:

- **Slack in the schedule:** Add some time to the minimum TAT, in order to be able to absorb delays.
- **High speed flying:** Increase speed, and therefore fuel costs, in order to decrease passenger delays, and crew costs. This is an effective way to absorb delays, especially on longer flights.
- **Crews follow the aircraft:** Crew stays with the aircraft. This eliminates transfer times for the crew, and makes for easy monitoring of the operations.
- **Out and back:** Aircraft fly to a destination, and directly back to the same hub airport. In case of a disruption, only two flight legs are directly affected, so delay absorption and recovery is straightforward.
- **Stand by crews and aircraft:** May be used in case of a disruption. Effective for recovery, but costly.

This chapter explains the possible actions airlines may take to improve network robustness. Section 4.1 explains measures which may be taken to absorb delays, and avoid delay propagation. Section 4.2 explains measures which are required in case of more severe disruptions. Finally, Section 4.3 explains the proactive measures to recover the crew in case of disruptions.

4.1. Schedule Absorption Capacity

The schedule of airlines is often disrupted by delays or cancellations. In the network planning phase, small disruptions are taken into account, and should not have a large impact on the network. By including more buffer in the schedule, more disruptions are resolved with a minor impact. However, when the buffer is not used, there is more ground time, so the resources are used less efficient, which leads to an increase in cost (Clausen et al., 2010).

4.1.1. Retiming of Flights and Buffer

According to Clausen et al. (2010), there are two challenges in absorption robustness planning: how much slack should be incorporated in the schedule, and where should this slack be scheduled. The first who addresses this issue in literature is Wu (2006). He follows a sequential approach, In which the schedule is first created, and then fine-tuned. Flights are modelled with two modules: the turnaround, and enroute modules. In these modules, the time taken for all airport and flight operations are simulated using stochastic disruptions, and a Monte-Carlo simulation with 1,000 runs to reduce simulation noise levels. The turnaround module includes all airport ground operations such as passenger (de)boarding, cargo and baggage (un)loading, catering (un)loading, and fuelling. Because many activities should be performed sequentially, and disruptions are stochastic, semi-Markov Chains are used to model the ground operations, and disrupting events are modeled as disrupting states in the Markov model. The enroute module also uses stochastic functions to simulate the total block time. It considers airport layout, runway congestion, queues on taxiways, and ATC delays, and historic flight block times between airports. In the following step, all flight rotations in the schedule were analyzed for delays, and the flight and buffer times were adjusted in order to have an expected delay of less than 15 minutes. The use of the model resulted a reduction in departure delays of 30%. The overall schedule reliability increased form 37% to 52%. The model does not take into account airport restrictions due to slots for example. Furthermore, passenger connections are not included in the model, which reduces the usefulness for for H&S airlines.

The second challenge defined by Clausen et al. (2010) is where to implement a buffer in the schedule. Aloulou et al. (2010) tries to allocate the scheduled slack to flights by allowing flights to deviate from their planned departure time slightly. The model takes into account the required time between flights, and the time required for passenger connections. Fleet and crew assignment does not change in their model. The model objective is to maximize robustness, with constraints which ensure passengers are able to make their connection, in addition to the network flow conservation, and the coverage of all flights exactly once. The model selects flights from a set of possible departure times. Multiple scenario's were tested with different discretization times, and different departure time windows. The most accurate simulation with the smallest discretization of 5 minutes, and largest time window of 15 minutes resulted in a 35% lower number of delays, and a 30% reduction in total delay time.

In a similar approach, Ahmadbeygi et al. (2010) presented a model which minimized delay propagation by re-allocating the slack already present in the schedule. Connecting passenger itineraries are unaltered, and flight times do not change significantly in order to keep projected demand levels accurate. One of the limitations of the model is that recovery decisions, which could have a high impact on delay propagation, are not considered. Furthermore, interactions from two delays are not taken into account, but are both counted as a delay. Ahmadbeygi et al. (2010) present two models: a single- and multi-layer model. The single-layer model considers the effects of delays on a flight's immediate connections. The multi-layer model takes into account propagated delays, until the delay is completely absorbed. The delay propagation tree is introduced, which shows propagated delays over the entire routing. Both models were tested with different optional time windows, and gave fast results. The most accurate model gave a reduction in delay propagation of around 50%. With this model however, some crew connections may become infeasible, because the time between flights becomes too short. The model does not allow changes to the aircraft routing.

Ben Ahmed et al. (2017) first solves the aircraft routing problem. Flights in the network are then retimed, with a maximum On Time Performance objective. Delays are simulated using a Monte-Carlo simulation. Results show an increase in on time performance of 9.8-16%, a reduction in total delay of 25-33%, and a reduction in delayed passengers of 8-21%. The average change of flight departure time was between 13.5 and 15%. This is the average, so there are larger time changes. These changes in departure time have a significant impact on the network, and since the aircraft routing problem is usually performed at most a week before a flight, this is not always feasible as tickets are sold way in advance.

A drawback of buffer scheduling and retiming is that research in this area is focused on maximizing slack in order to increase the robustness of the network. This is not always possible however, since the already scheduled slack is often there to make the schedule feasible. Ben Ahmed et al. (2017) suggests research in the direction of integrated flight retiming, aircraft maintenance routing, and crew pairing in a single model.

4.1.2. Routing for Flight Delays

Lan et al. (2006) created two models. The first model solves the aircraft routing problem, and incorporated robust measures by optimizing aircraft and maintenance routing. The objective is to minimize propagated delay of selected aircraft routings. The delays are taken from historic data, or created using stochastic methods. Aircraft routings are all possible sequences of flights a single aircraft registration may fly. The problem is solved with the branch-and-price algorithm. By using these robust measures, the simulated number of propagated delays of the case studies reduced by 27 to 54%, or 44% on average. Furthermore, the on time performance increased by a few percent. The second model by Lan et al. (2006) uses an existing schedule and retimes flights in order to reduce passenger missed connections. The objective is to minimize the expected number of delayed passengers. There are additional constraints that enable the current routings and itineraries. This model is solved with the branch-and-price algorithm as well. The model creates copies of flights, and chooses the most optimal for the smallest number of passenger disruptions. The number of copies was varied from one every minute, and one every five minutes, with time windows from 5 to 15 minutes before and after the originally scheduled time. The effect of a larger time window was larger than the effect of more copies, while the extra copies increased the size of the problem by at least 10 times. It would be interesting to see the integration between the two models.

4.2. Schedule Recovery Capacity

In case of a more severe disruption, the network is usually not recoverable by absorption. To be able to recover from severe disruptions, due to technical issues for example, multiple recovery measures may be incorporated in the schedule. Examples are: swapping opportunities, station purity, use of short cycles, and the use of sub-networks. Increasing recovery capacity generally leads to a reduction in maximum revenue, but a reduction in total cost due to recoveries.

4.2.1. Swapping Opportunities

Swapping opportunities may be used by airlines to switch aircraft rotations, in order to decrease delay propagation further in the network. An aircraft which has more buffer in the schedule may be assigned to a delayed flight. Due to the additional buffer, the delay is absorbed, rather than propagated to the next flight.

Burke et al. (2010) used a multi-objective approach, in which botch schedule reliability and flexibility are optimized. The model is built on a time-space network simulating a week of operations. Flexibility in the flight times of the model is created by constructing copies of the flight arcs in a predefined time window, which is small enough to have a negligible effect on passenger demand, and a small effect on passenger connections. The schedule reliability is modeled by simulating stochastic delays which results in the probability a a flight departs on time. The flexibility of the schedule is modeled by simulating the probability a flight departs on time which used one of the three types of swapping opportunities. The methodology is based on genetic algorithms combined with local search. The model was applied to data from KLM, and achieved an improvement in on time performance in nearly all cases. A drawback of the model by Burke et al. (2010) is that while it is capable of swapping aircraft of the same type, it is unable to simulate aircraft type changes. This is more expensive and complex than a singe type aircraft swap because different aircraft types require different crew, and different aircraft types usually have a different passenger and cargo capacity and performance. It is still used sometimes to for the continuation of the network. The swapping of maintenance slots is also not included in this model.

Ageeva and Clarke (2000) researched robust airline schedule planning, and concentrated on subroute switching. An initial set of routings was created, which was used to generate multiple alternatives. Alternative solutions were created by adding constraints. When applied to the test data, the author concluded that in some cases a 35% increase in robustness could be achieved. The model gave the best results when two aircraft were allowed to depart within 30 to 40 minutes of each other. This results in a maximum delay of 40 minutes, which may be acceptable. This model does not take into account crew considerations, which might result in infeasible, or very expensive solutions.

4.2.2. Station Purity

Smith and Johnson (2006) suggests applying station purity to the network. Station purity ensures that the number of fleet types, which serve an airport, does not exceed a specified limit. This makes it easier to move up crew assignments to cover operational disruptions. The model of Smith and Johnson (2006) is a standard fleet assignment model, with extra constraints which ensure station purity. This extra constraints increased program run time significantly, especially using scenario's with more flights and fleet types. The authors developed methods to reduce the required computation time. When assuming there are only flights between hub airports, or between hub and spoke airports in the H&S network, computation time is reduced. Spoke airport are modelled as hubs, or grouped with other spoke airports, which is easier to solve. Results showed a lower profitability, but a faster computation time. This station decomposition method is further improved by using dual stabilization. The station decomposition method is faster with station purity, but it sometimes gives higher MIPgaps. This was solved using a fix-and-price heuristic. Crew costs are reduced by using station purity, but Smith and Johnson (2006) does not elaborate on the effects of station purity on recovery operations, such as swapping opportunities.

4.2.3. Hub Isolation and Short Cycles

By applying hub isolation and reducing the size of cycles, the number of cancellations is reduced, since less consecutive flights have to be canceled in case of one cancellation. Rosenberger et al. (2004) use the fleet assignment model in a time-space network, and use this to create two separate models. One constrains hub connectivity and minimizes cost, and the second constrains cost, and minimizes hub connectivity. Results from the models show an improvement in on time performance, a reduction in cancellations, and a reduction in aircraft swaps in most cases. The model by Rosenberger et al. (2004) is only applicable for multiple hub airlines.

4.2.4. Reserve Aircraft

An additional measure for schedule recovery is the scheduling of reserve aircraft. Airlines do this regularly in its operations. This is an expensive solution, but it gives the freedom to use the reserve immediately when a flight is very late, or in case of technical problems. Varenna (2023) investigated the effects of an additional reserve, and results showed that it is commercially not an attractive option, as the missed revenues exceed the cost of a cancellations.

4.3. Proactive Crew Recovery

When disruptions occur in the airline network, there may be an additional challenge in rescheduling or repositioning the crew.

In order to increase the robustness in the crew schedules, Ehrgott and Ryan (2002) created a model which is a bi-criteria optimization. It minimizes costs, and maximizes robustness at the same time. These two measures are usually in conflict. The authors assign a non-robustness measure to all "Tours of Duty", and penalize crews which have to switch aircraft. The size of this penalty is based on the transfer time, and expected delay. Ehrgott and Ryan (2002) conclude that for a small increase in cost, there is a significant gain in schedule robustness. The increase in cost is mainly in the form of increased number of overnights, while the increase in robustness is due to a reduction in aircraft switches. For some cases the median ground time tends to decrease. This bay be because of the decreased number of aircraft switches, or the increase in overnights.

Schaefer et al. (2005) present a model which creates crew schedules, while remaining traceable. The model determines the expected pairing costs, based on the assumption that planes are always available, and all flights are delayed until crew is available. This means the model is restricted in the recovery options, since airlines have more options to recover the schedule than only delaying flights. The pairing costs are estimated using a Monte Carlo simulation. Crew rest, and transfer times are included in the model. To ensure the model is able to absorb delays without recovery actions, there are penalties given to the crew schedules if there are short sits, or short rest times. The best set of penalties is found using local search. The penalties are used to create an objective functions, which is solved using a set partitioning approach. The problem is solved by LP relaxation over the generated parings, and a random column generation algorithm.

Schaefer and Nemhauser (2006) use an existing airline schedule, and create perturbations. These perturbations do not alter crew paring or route feasibility. In the model, the assumptions of aircraft availability, and push-back recovery were made, similarly to the model of Schaefer et al. (2005). By introducing perturbations, the authors define lateness, and prove that with a larger perturbation, the lateness decreases. This means there is a better on time performance. Furthermore, larger perturbations lead to lower operational crew costs, since the planned cost, and operational flying time remain the same, and duty time, and the lateness are not larger than the original schedule. Results from the model show an increase in operational performance, while not increasing crew costs. The assumption of push-back recovery limits the model severely, since airlines use more tools to recover the schedule.

Yen and Birge (2006) try to solve the crew assignment problem with a stochastic model in stead of a more traditional deterministic model. The objective is to minimize the cost of crew parings, and delay costs due to crews switching planes. The model augments crew schedules, allows or disallows crew switches between flight pairs, and uses a branching approach. Yen and Birge (2006) restrict the problem by making plane assignment static, having a homogeneous ground time for aircraft and crew, and bounding the delay times. All crew members fly the scheduled flights regardless of delay circumstances. In reality this gives legal issues. The authors conclude that the model finds solutions with fewer plane changes, and an increase in connection times in case of a plane change. This leads to less costly schedule disruptions. In reality, the assumptions made are not completely realistic. The plane assignment is not static, and different planes may have a different ground time. The operations control team may also chose to reduce TAT. Furthermore, the actual delay may exceed the maximum delay as used in this model. Taking all these factors into account may lead to a more expensive solution. However, this approach can be used in comparison to reality, and gives some insights.

While Schaefer et al. (2005) and Schaefer and Nemhauser (2006) minimize the costs associated with crew swaps, Shebalov and Klabjan (2006) try to maximize swapping opportunities in addition to minimizing crew costs. This has two advantages: the possibility of a crew to cover one of a few flights, and the opportunity for an airline to chose which flight to cancel in case of a disruption. The only pairing feasibility rules which are taken into account by the model are that crews start at the same base, and have the same number of days left in the pairing. This might give issues with crew work and rest times in reality. The model of Shebalov and Klabjan (2006) has two steps. The first step is to solve the crew pairing problem for minimum cost. Then the number of move-up crews is maximised, with a constrained increase in crew cost. The problem is solved by Lagrangian relaxation and column generation. In most cases, the model gives lower operational flight time credit, and uncovered flight legs. Number of deadheads (crew flying as passengers) and reserve crew decreased in all test cases. The trade-off between robust and traditional solutions should be made carefully, but a robust solution within 1% of the optimal solution may reduce total crew cost.

Previous described models try to minimize crew cost, and maximize swapping opportunities. Sohoni et al. (2006) researched the effects of reserve crew for airlines. Demand of reserve crew is estimated by evaluating the bidding-invoked conflicts, and demand for daily operations. The model succeeds in increasing reserve availability. Improvements could be made in simulating the daily network, to forecast disruptions.

The model of Ben Ahmed et al. (2022), explained in Chapter 3 has robustness measures incorporated in the objective function. A penalty is applied if resource connections are short. This applies to both crew and aircraft. Schedules where the crew follow the aircraft are promoted bu restricting the number of crew changes. In the relaxed versions of the model, there is a fixed penalty whenever crew changes aircraft. Ben Ahmed et al. (2022) analyze their models, and compare the results of the model with and without robustness measures incorporated. Robustness measures resulted on average in 88% reduction in short crew connections, 81% reduction in critical crew connections, 55% reduction in critical aircraft connections, and the crew followed the aircraft more often. Aircraft assignment cost increased with 0.17%, and passenger revenue decreased with 0.01%. This reduction in profit is most likely offset by the reduction in delays on the day of operations.

4.4. Concluding Remarks

The largest part of robust scheduling takes an existing schedule, and improves this by adding robustness measures. This always leads to a decrease in potential operating profit compared to the schedule without robustness measures. Recent developments integrate robust measures in the scheduling phase, decreasing this additional cost effect. Initially, research focused on the performance improvement in one area. Similar to the trend of the "regular" airline scheduling research, recent and future developments focus on the integration of multiple areas. A robust aircraft schedule may have costly implications for crew. By integrating these areas, both may be optimized.

5
Conclusion

This aim of this literature review is to give an overview the methods which are used to create the airline network and schedule, how disruptions are countered, and what measures may be taken to plan for disruptions. Analysis of the airline planning and optimization papers indicates that exact methods exist for the classical sequential approach in frequency planning, fleet assignment, maintenance routing, and crew scheduling. Some models integrate two or more of these. No exact methods exist which integrate all four parts, as the number of variables is too large, even for relatively small airlines, but the trend in operations research is the increase in research about integrated models.

Solving a disrupted airline network is often a challenging task. Originally, most research was focused on aircraft recovery, followed by passenger recovery, and crew recovery. Following the same trend as airline schedule design, recent research focuses more on integrated models. As the OCT often has to make decisions within minutes, models which aid in making recovery decisions have to give fast results. There are existing models which consider most disruption and recovery types and give exact solutions. These models however, take a long time to give results. Therefore more and more models make use of heuristics, multi-agent systems, and there is potential for research using machine learning models.

The airline network schedule is designed with a maximum profit objective. This usually means flying as much as possible, and reducing ground time to a minimum. To avoid many cancellations on the day of operations due to inherent delays, the schedule should be robust. Most research about robust scheduling is focused on aircraft routing, but robust crew and passenger scheduling is also covered in literature. Similar to the trend of the other research areas, there is more research about integrated robust scheduling.

When looking at the existing literature, most robustness assessment models are aimed at the effect of robustness measures. There are tools that re-allocate existing slack, but there are no tools that asses the actual slack that is required to achieve predefined KPI's. When creating a schedule for a new season, it is useful to determine the required slack and reserve aircraft/crew before creating the schedule. There is a gap in literature for a simulation tool which assesses the performance of schedules with different operational design criteria from the OCT point of view. Therefore the MSc thesis has the following objective:

To develop a network scheduling simulation model which adheres to, and evaluates design criteria such as schedule buffer, swapping opportunities, and reserve aircraft, in order to improve airline performance on the day of operations.

The main, and supporting research questions which aid in meeting the MSc thesis objective are listed below:

What design criteria should be incorporated in the airline schedule to improve robustness and meet the airline Key Performance Indicators?

1. How is the airline schedule currently created?

2. To what extent is it possible to model the airline scheduling process, considering design criteria of all airline departments?
3. What options does the Operations Control Team have to solve network disruptions?
4. How is a disruption management tool used to solve disruptions?
5. What are the current design criteria from all airline departments?
6. How will a tool help in improving the OCT design criteria?
7. What Key Performance Indicators are important to the airline, and what are the targets?

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