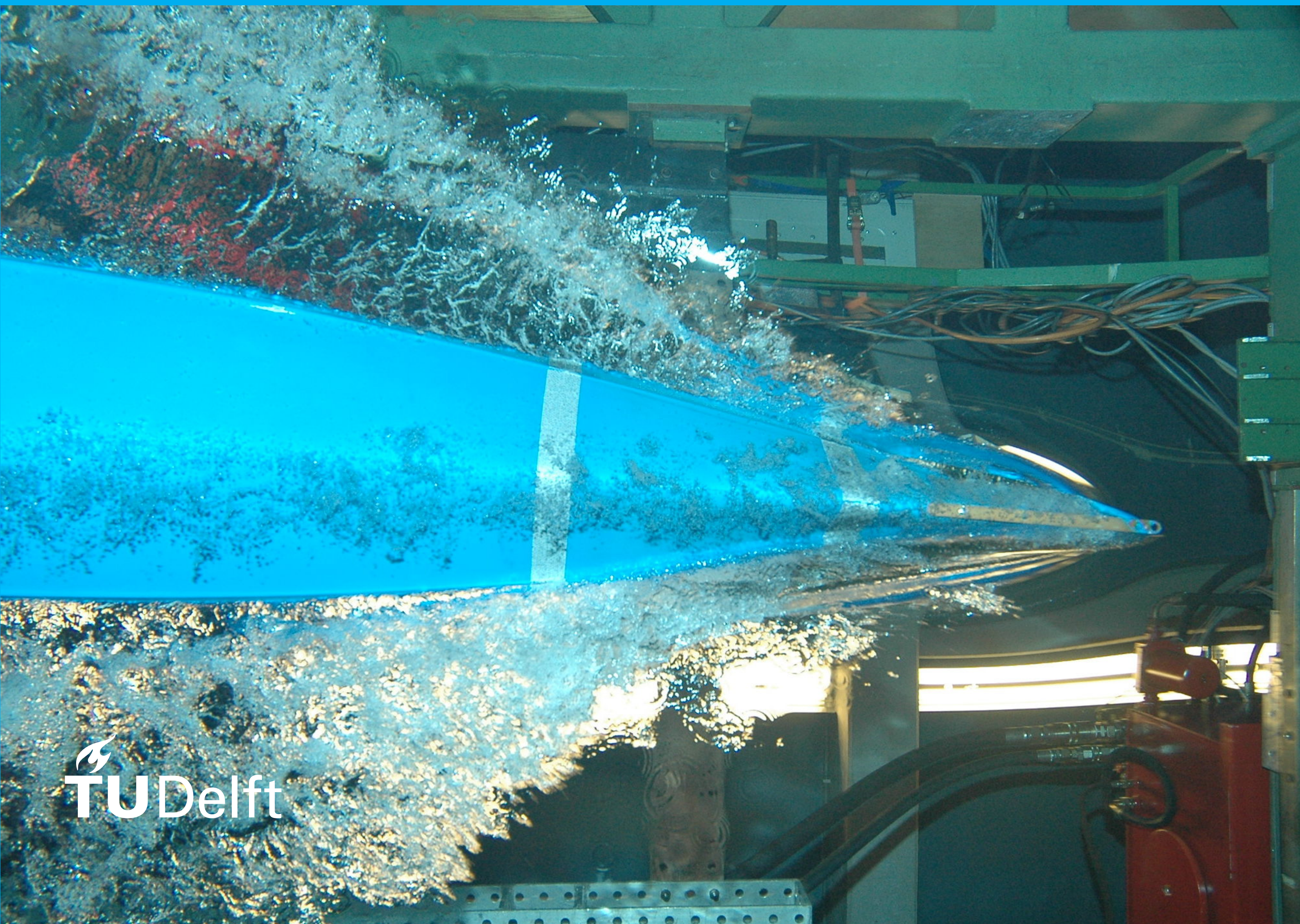
Reserve fleet capacity

Diederick Groeneveld



Reserve fleet capacity

by

Diederick Groeneveld

to obtain the degree of Master of Science
at the Delft University of Technology,
to be defended publicly on 08-06-2021.

Student number:	4372832
Project duration:	16-03-2020 – 05-04-2021
Thesis committee:	Dr. B. Santos
	Dr. H.A.P. Blom

Contents

List of Abbreviations

ARIMA	Autoregression Integrated Moving Average
ARMA	AutoRegression Moving Average
CART	Classification and Regression Trees
CG	Center of Gravity
MILP	Mixed Integer Linear Programming
RF	Random Forests
RM	Revenue Management
SVR	Support Vector Regression
ULD	Unit Load Devices

Introduction

The start of this project was made on the same day as what could be called the official start of the Corona pandemic in the Netherlands. The original idea of the research was very practical, reserve fleet capacity would be deployed from the OCC in different ways to test it's impact. This research project originated from the fact that very little is known about the benefits of reserve fleet capacity. It is clear that having additional capacity is an extremely costly business but still all large airlines have reserve fleet capacity. Most often reserve fleet capacity is sized for coping with aircraft failure but almost all airlines use this capacity for delay mitigation. If reserve fleet capacity is used for delay mitigation the effects on the total system delay are rarely researched. To fill these gaps the research presented in this document was performed. At the start of this project the original research plan was already impossible. The airline industry entered one of the toughest periods ever. Despite all setbacks the project was completed with great thanks to Frank van de Peppel.

This thesis report is organized as follows : In Part I, the scientific paper is presented. Part II contains the relevant Literature Study that supports the research.

I

Scientific Paper

Reserve fleet capacity assessed with a Monte Carlo simulation rule based delay mitigation model

Diederick Groeneveld,*

Delft University of Technology, Delft, The Netherlands

Abstract

Airline reserve fleet capacity is a wide spread phenomenon and is used to limit the impact of delays on the planned flight schedule. This paper focuses on reserve fleet capacity in the form of standby unscheduled aircraft. By means of a Monte Carlo simulation on an existing flight schedule using a rule-based delay mitigation model the effectiveness of reserve fleet capacity is analysed. A method of finding a break even point between fleet size and saved delay costs is proposed and the impact of delay duration on the effectiveness of reserve fleet capacity is analysed. Finally, a comparison is made between grouping reserve fleet capacity into a standby aircraft and spreading the reserve fleet capacity over the flight schedule.

1 Introduction

A think paper of [Eurocontrol, 2019] states that, in anticipation of the high delays in 2018, airlines increased their reserve capacity, either spreading this capacity out over the schedule as buffer time or grouping it in standby aircraft. Eurocontrol estimates that this anticipation of the airlines on air traffic management delays had a negative effect on the growth of air traffic in Europe about three times the size of the effect of the 737 MAX grounding over the same period. This impact on the industry illustrates the value that reserve capacity could bring to lower delays. On the other hand, it also limits the operational possibilities and potential growth. Effective use of available reserve fleet capacity is potentially a key contributor to improve the performance of airlines.

Airline networks are becoming larger and more complex, margins are small and passengers have high demands on time performance. This makes optimisation and network planning essential for airlines. Unfortunately, airline schedules are rarely executed as planned. Bad weather conditions, mechanical failure or

*Msc Student, Air Transport and Operations, Faculty of Aerospace Engineering, Delft University of Technology

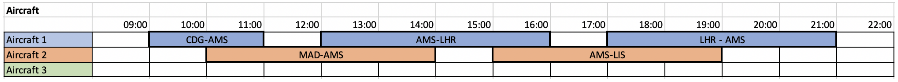


Figure 1: Reserve fleet capacity

crew illness cause disruptions, which influence the planned schedules. In the case of schedule disruption, additional costs start to pile up for the airline. To minimize these costs airlines have three mechanisms: construct robust schedules, aircraft recovery algorithms and the use of reserve fleet capacity. In this paper reserve fleet capacity is defined as all fleet capacity not used for production. Fleet capacity is used for production during flight and the turnaround time before and after the flight. By this definition, reserve fleet capacity can be distributed over a schedule by having additional time between flights on top of the turnaround times or grouped into one or multiple aircraft not scheduled for a day of operations called a standby. Fig. 1 clarifies this definition by illustrating a fake schedule. The colored blocks represent flights. They include the flight time and turnaround time needed to perform the flight. All white blocks are considered reserve fleet capacity, thereby this time is not used for production. For aircraft 1 and 2 this reserve capacity is spread out over their schedule in the form of buffer time. Aircraft 3 is considered reserve fleet capacity, grouped into standby aircraft.

While robust scheduling is a widely researched field, the use of reserve fleet capacity in the form of standbys is not. This paper focuses on the impact of using reserve fleet capacity for delay mitigation. Currently, reserve fleet capacity sizing is based on the amount of unpredicted maintenance or given by other decisions during the fleet sizing process. This paper describes the relationship between fleet size and reserve fleet capacity needed for delay mitigation, which has not yet been studied. Furthermore, it shows the effectiveness of standby aircraft in different delay scenarios and the influence of splitting up a standby aircraft and distributing this capacity over the schedule in the form of buffer time on the effectiveness of this reserve capacity.

First, Section 2 gives an overview of the existing literature on reserve fleet capacity. Subsequently, the problem is defined in Section 3. A description of the used methodology is given in Section 4. Section 5 describes the model validation. Finally, three case studies are explained for which the results are presented in Section 6.

2 Literature Review

In order to place this research in perspective with the existing body of literature, a literature review is performed. Sizing and deploying reserve fleet capacity is a complex multi-step process, which starts with creating a fleet plan. At this stage, the fleet size for the coming years is determined and therefore the total production capacity of the fleet. During the second stage of aircraft scheduling and schedule creation, a decision is made on how much of the available production capacity is used for production and how much for reserve capacity. During the aircraft scheduling phase, reserve capacity can either be deployed as buffer time in between flights or grouped in one or multiple standbys. After determining the division between production capacity and reserve capacity, an effective aircraft disruption should be performed. These steps are discussed in this overview. Additionally, reserve capacity research from other industries is discussed for inspirational purposes.

2.1 Fleet considerations

Fleet selection is based on an iterative process of forecasting demand, considering aircraft types and creating a sustainable financial planning. The decisions made during this process lead to the creation of a fleet plan. The fleet plan describes which aircraft types will be part of the fleet and how many aircraft per type each moment in time. Moreover, it contains a rough planning of aircraft modifications, such as internal layout or the moment of replacement of an aircraft. The determination of the amount of reserve fleet capacity is also part of the creation process of the fleet plan.

Estimating the market size is essential for creating a fleet plan. There are multiple ways of determining market size. For instance, [Zhang and Graham, 2020] considers a macroeconomic approach as it assesses the influence of economic growth on the development of airline markets and [Fiori and Foroni, 2020] analyses reservation to estimate the market size. The availability of reserve fleet capacity could lead to overcapacity when the market size turns out lower than estimated. On the other hand, reserve capacity offers the airline upwards flexibility in case of higher demand than estimated. It could even help to acquire additional market share by increasing frequency on routes due to the S-curve properties [Wei and Hansen, 2005].

The decided upon fleet cannot be seen separate from the eventual schedule in which the fleet will be used. [Lohatepanont and Barnhart, 2004] propose an integrated model for airline schedule design. Larger fleet sizes offer economies of scale in maintenance, crew training and more. The additional capacity will increase the total fleet operation costs. However, the reserve fleet capacity provides more robustness in schedule creation and flexibility during the mitigation of delays. This benefits passenger experience and lowers secondary delay costs such as delay compensation or re-booking of passengers. Eventually, this results in a higher quality of service index (QSI) [Belobaba, 2009].

2.2 Aircraft scheduling

Aircraft scheduling or aircraft routing is the process of optimising all decisions to create an operational schedule. A routing for individual aircraft is determined, crews are assigned to itineraries and maintenance is planned according to regulations.

In 1985, [Etschmaier and Mathaisel, 1985] conclude from the body of literature so far that computers can contribute to aircraft scheduling, but mainly by speeding up the process of checking schedule feasibility. Later research expanded on this and used computers to not only check existing schedules for feasibility but also to create schedules. The research into aircraft scheduling continued, primarily focusing on optimising aircraft utility by improving the efficiency of scheduling maintenance checks. [Gopalan and Talluri, 1998] developed a model that satisfies both the three-day maintenance, as well as the balance-check visit requirements for aircraft whose daily rotations are fixed. [Clarke et al., 1997] proposed a mathematical model with specified maintenance locations, frequency and flight duration. The model addresses sub-tour elimination and uses Lagrangian relaxation. [Barnhart et al., 1998] includes the maximisation of anticipated profits in the proposed string-based model. In this model, strings are defined as a connected set of flights in between maintenance. The model addresses fleet selection and aircraft routing, and presents a single model solution using branch and price algorithm. The research into aircraft scheduling continued to combine maintenance scheduling, crew scheduling and aircraft routing into single problems. Despite the complexity of the separate scheduling problems, there can be great benefit of combining the scheduling problems into single models. [Cohn and Barnhart, 2003] integrate the crew planning process and maintenance scheduling. Their model ensures maintenance feasibility. The model leverages the fact that part of the crew solutions does not influence maintenance. Rather, it offers the user flexibility in the trade-off between time and quality of the solution. [Cordeau et al., 2001] combine the aircraft routing problem and the crew scheduling problem. It uses benders decomposition to limit the run time, which in some cases can save up to half the computational time. The paper proves that significant cost savings can be obtained by simultaneously optimising for aircraft routing and crew planning.

The created schedules face many challenges, such as bad weather conditions, mechanical failure or crew illness. The need arouses to create schedules that are better able to cope with these disruptions. The creation of schedules more resilient to disruption is called robust scheduling.

[Wu, 2005] gives a method for analysing the inherent delays of a schedule. The model simulates the turnaround times by using a Markov chain algorithm to describe the stochastic nature of aircraft routing in a network. The combination of a turnaround model and an en-route-model simulates the inherent delays and the propagation through the schedule. [Lonzius and Lange, 2017] propose a robust aircraft scheduling approach by limiting hub connectivity and implementing swap opportunities.

[Wong and Tsai, 2012] proposes a survival model of flight delay propagation. In this model, two types of delay are considered: arrival delays and departure delays. Based on this division, the survival time is calculated for delays. The survival time is defined as the number of minutes from the start of a delay to the end of that delay. The distribution of these delays is used to create a survival function and a hazard function. The survival function indicates the probability that a delay survives or takes longer than a certain time t. The hazard function gives the instantaneous probability that a delay of duration t will occur. The paper offers a way to investigate individual factors that contribute to delay and identifies if these delays originate from arriving or departing. [Wang et al., 2019] concluded that flight buffer time has higher influence on delay propagation than ground buffer time.

It becomes clear that deployment of reserve fleet capacity can only be done when fulfilling all maintenance requirements. Existing maintenance opportunities might change or new opportunities might arise by the deployment of reserve capacity. The crew planning needs to be extended to fit the deployment of reserve fleet capacity. Depending on the type of disruption, different choices need to be made. In case of a mechanical failure, the scheduled crew will still be available to operate the reserve aircraft. In the case of delay exceeding the next departure time, additional standby crew will be needed to operate the reserve aircraft. The combined scheduling models provide an insight into how optimisation can be done while optimizing for multiple objectives. These models could serve as an example for a fleet reserve deployment model. Considering schedule robustness gives an insight into where the schedule is most vulnerable to disruptions. This helps estimate where and when the reserve fleet capacity is most likely needed.

2.3 Aircraft disruptions

Airlines face many types of disruptions. Decisions on how to cope with disruptions are made in the operations control center of the airline, where operations of aircraft, crews and passengers are managed centrally. A more general description of recovery and the organization is given by [Kohl et al., 2007]. In essence, the operations control center has four different schedule recovery strategies: delay propagation, aircraft swapping, flight leg cancellations and the use of reserve fleet capacity in the form of a hot-standby.

All flights scheduled to be performed by one aircraft are called a fleet line. During schedule creation, reserve fleet capacity can be used to create additional time in between flights. This way, a buffer for absorbing delays is created inside the fleet line. The mitigation strategy of delay propagation uses this time to absorb delays. For this method, no active action is taken to solve the delay. It is most effective for schedules with sufficient buffer time in place in the fleet line [Belobaba, 2009].

Aircraft swapping is an often used delay mitigation strategy. The strategy aims at redistributing the existing buffer time over different fleet lines. A delayed aircraft is switched with a different aircraft so that the total delay of the system goes down.

Flight leg cancellation can have many different reasons. Most often this is caused by mechanical problems, shortage of crew or reduced departure/landing capacity. In these cases, reserve capacity could be needed to fill the gap in the schedule. Flight legs can also be canceled because of downstream delays. In this case, the cancellation is used to create ad-hoc additional reserve capacity. If a flight leg is canceled, aircraft flow conservation needs to be maintained. This usually leads to the cancellation of multiple legs as the canceled aircraft is not able to perform the downstream flights [Belobaba, 2009].

If available, airlines can use the reserve fleet capacity in the form of a hot-standby to mitigate the disruption. A hot-standby is an aircraft that is not scheduled to perform any flights during that day or during multiple consecutive days, but is parked on a nearby location on the hub airport to be used in the schedule when needed. In the case where there is a hot-standby available, a swap between the hot-standby and the disrupted aircraft could be performed. The standby aircraft will perform the next flight of the disrupted aircraft. In turn, the disrupted aircraft becomes the new hot-standby.

The combined effort of solving the aircraft routing problem and the flight scheduling problem is called the aircraft recovery problem (ARP). For these problems it is not only necessary to provide a (near) optimal solution, but also to limit calculation time in order for the solution to be of use in operational situations. In case of a disruption, first the aircraft recovery needs to be considered. Secondly, crew recovery is regarded and finally passenger recovery. Models created for this problem can be expanded to incorporate deployment of reserve fleet capacity.

[Chen et al., 2020] uses a multi-objective evolutionary approach to solving the integrated aircraft routing and crew paring problem under disruptions. The problem with this approach is that it is not time efficiently solvable. Nevertheless, it will always find an answer or multiple good alternatives as genomes are saved. [Vink et al., 2020] provides a real-time operational solution using a dynamic algorithm. The paper addresses the dynamic nature of the problem, i.e. the recovered schedule from the earlier disruption is taken as input for a subsequent disruption. Aircraft are selected according to their contribution to solve the disruption. [Abdelghany et al., 2008] creates a rolling horizon model, in which disruptions are anticipated based on a function of severity. A list of flights is created that is not able to serve as a resource for disrupted flights, called resource-independent flights. The input for the model is the available resource bank of flights, excluding the resource-independent flights and the disrupted flights at that stage. If an available flight is used to mitigate a disruption, the flight is placed in the disruption list. [Bratu and Barnhart, 2006] considers the aircraft recovery problem from the passenger perspective. Often aircraft delay is not a good measure for passenger delay. A trade-off between airline operating costs and passenger delay costs is modelled. [McCarty and Cohn, 2018] takes the passenger-centric model even further. Instead of considering the possibility of changing the aircraft schedule to mitigate disruptions, they create a model to preemptive rerouting of passengers in case of a disruption. The idea is to proactively reroute passengers in case of a delay, instead of waiting until connections are missed.

3 Problem statement

Reserve capacity is a costly business in all industries. For the airline industry, having reserve fleet capacity would mean having an extremely expensive aircraft on the ground not generating any revenue. This might seem as an illogical decision, but for high quality service airlines the benefits of on time performance might outweigh the costs of having reserve fleet capacity. Currently, the reserve fleet capacity is based on unpredicted down time of aircraft, such as mechanical failure. Although this reserve fleet capacity is often used to lower total system delays, no research has been done with regard to the benefits of having reserve fleet capacity to mitigate delays.

Data analysis of the planned schedules and executed schedules prohibits drawing conclusion about the deployment of reserve fleet capacity. The initially planned optimal or near-optimal schedule is changed due to disruptions occurring during operations. Delay mitigation measures taken on day one might prevent the operations on day two from starting at the planned optimum. Due to choices made during the day of operations, it becomes difficult to assess the impact and effectiveness of reserve capacity deployment based on the difference between planned and operated schedules. The planned schedule was never executed, therefore it will always be unknown what the outcome would have been if no other delay mitigation actions were taken. To analyse the impact of the taken mitigation measures, a baseline needs to be used in which the planned schedule was performed without the deployment of the standby aircraft.

The aim of the research is to identify the added value of reserve fleet capacity and in which way it can best be used. The research was based on the planned and executed schedules of a large European airline. The analysis is mainly based on the total system delay defined as the sum of all input and consequential propagation of those delays. Linked to this total delay the total delay costs were calculated. These delay costs include the future value loss, passenger reallocation costs and passenger compensation costs. The height of these costs depends on the duration of the delay and the importance of the flight in the overall network. These costs were taken as input and were provided by the same airline.

During operations, decisions on using reserve fleet capacity need to be made within a short time span, i.e. between the moment a delay first occurs and the next possibility to mitigate that delay. The created model aims to mimic the decisions of the airline.

The model created during this research can be used to quantify the effectiveness of reserve fleet capacity for a given operation. It gives an insight on how much additional reserve fleet capacity is needed on top of the existing buffer time in the schedule for different fleet sizes. By using different delay scenarios the impact of delays on the effectiveness of standby aircraft is shown and the effect of splitting up a standby aircraft into additional buffer time is investigated.

During the creation of the model the following assumptions were made. Flight cancellation is a complex issue for airlines. During extreme delays or technical failure an aircraft can be grounded for multiple hours. In such a case, a flight can be canceled from the schedule. This can either be done by canceling flights in the same fleet line or flights in other fleet lines. Doing so frees up capacity that can be allocated to other flights in the schedule. This research assumes that no flights are canceled.

In addition, the assumption was made that crew would not pose any restrictions on the executed schedule. Hereby, we lower the complexity of the model. The model tries to stay as close to the original schedule as possible. Flights are only re-timed because of delays, therefore crew will be able to perform the originally scheduled flight in most cases.

Although the European airline providing the input schedules has a hub and spoke network, the model was based on a part of this network, namely the part that only performs out and back operation. This means that all flights are from the hub airport to an outstation and back. The combination of a flight from the hub to an outstation and back is called a rotation. Because of this property, one rotation is always performed with one aircraft.

The original fleet on which the input schedule is based contains multiple sub-types of the same aircraft. These sub-types have different passenger capacities. During the model creation all aircraft were deemed to have the same passenger capacity and therefore all flights could be performed by all aircraft.

During operations airlines have the opportunity to change flight times by changing flight speed in order to make up for delays. During model creation flight times were assumed to be fixed.

These assumptions impact the results of the model. Due to the fixed flight times a higher number of delays will need to be mitigated as the option of flying faster was not incorporated into the model. Assuming no crew restrictions and the interchangeability of all aircraft sub-types increased the flexibility in aircraft swaps. The impact of on time performance on passenger delay costs in an out and back network is lower than in a hub and spoke network, where missing connection flights significantly increases delay costs.

4 Methodology

This research uses a Monte Carlo simulation of the original planned schedule with and without delay mitigation measures and compares it to Monte Carlo simulations of the planned schedule with additional fleet capacity. To perform these simulations a rule-based model was developed based on the input of a large European airline. The simulation consists of multiple steps, shown in Fig. 2.

The first part of the model generates delays based on delay predictions. These delay predictions are taken from an existing European airline database. The delay predictions are based on external influences on the schedule, such as airport congestion delays and weather or traffic intensity. Moreover, they are uncorrelated to earlier rotations. The delay predictions are split into percentiles. The predicted delays for rotations are drawn from these percentiles using a uniform distribution. After sampling from the delay predictions, an updated schedule is created incorporating the original generated delays and the propagation of these generated delays.

After sampling the delays the rule-base model is activated. Although the delays are sampled for a full month, the model is created to mimic the approach taken by an operations control center. This means that the model works chronologically and deals with delays when they occur. The model only considers the delays at the hub airport. If a delay occurs, the model only considers the propagation of the delay in that fleet line for the next time steps. The model uses two delay mitigation strategies: let the delay propagate trough the schedule or perform a swap between two aircraft.

The choice between letting the delay propagate and swapping is based on two sequential rules: step size and a propagated delay threshold.

Step size: The step size was used as input for the model and determines which input delays would be sufficiently large to consider an aircraft swap. This implies, e.g., that with a step size of 30 minutes all delays below 30 minutes would not be considered for swapping. For these cases no mitigation action was taken and the delay will propagate through the schedule.

If the step size was exceeded, the second rule was checked. The second rule was put in place to take into account the existing buffer time in the schedule. The next rotation of a delayed flight should not be swapped if sufficient buffer time is already in place in the schedule to mitigate the delay. Future implications of the delay could be calculated by summing the input delay and the delays that will follow from it for that fleet line, each time decreased by the existing buffer time in between the rotations. This summed delay was named calculated total delay.

Propagated delay threshold: The threshold was constructed as a moving average of the total delay per rotation based on all past days of the simulated month. If the calculated total delay of the fleet line for that day exceeded the threshold, a short list with all possible swap opportunities was created. If the threshold was not exceeded, the delay will be left to propagate through the schedule.

A swap opportunity is defined as follows: the propagated arrival time of the delayed flight should be 45 minutes before the departure of the rotation of the to swap with aircraft. Moreover the last arrival time of the to swap with aircraft should be 45 minutes before scheduled departure time of the next rotation of the delayed aircraft. Swaps are only performed at the hub airport. If multiple swap opportunities are available, the model will select the aircraft with the longest unscheduled time before the rotation to be taken over from the delayed aircraft. If a swap is performed, all rotations starting on that day of operations are swapped.

A run consists of generating the delays, combining them with the schedule and using this as input for the simulation model. By performing multiple runs the impact of reserve capacity can be studied.

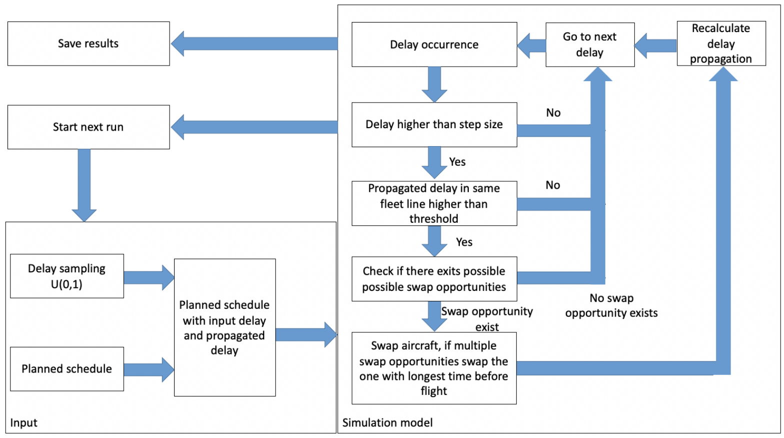


Figure 2: Flow chart of the model simulation

5 Model validation

In order to draw a conclusion about the use of reserve fleet capacity, the model needs to be validated to ensure that it could reach the same solution quality as the solution of the airline to which it is compared. The delay sampling method was validated by comparing the total minutes of delay as input to the model with the actual total delay of actual executed schedules of the same airline. Secondly, it was validated if the distribution of those delays was the same as with the actual executed schedules. In both these validations only the first occurrence of the delay is taken into account, not the propagation as this propagation is highly influenced by the way the airline takes mitigation actions.

Month	**Total external delay reference**	**Average total sampled delay**	Difference
March 2019	30050 minutes	28500 minutes	-5%
June 2019	35030 minutes	34650 minutes	-1%
September 2019	21060 minutes	22544 minutes	+7%
December 2019	20060 minutes	20661 minutes	+3%

Table 1: Total external delays as validation of the delay sampling based on 100 runs.

After determining if the total delay of the delay sampling was within range of the validation data, the distribution of delay duration was compared.

Table 1 shows that the delay sampling method provides results within an acceptable range of those of the validation data. Because only comparing the total delays says nothing about the way these sampled delays are distributed,

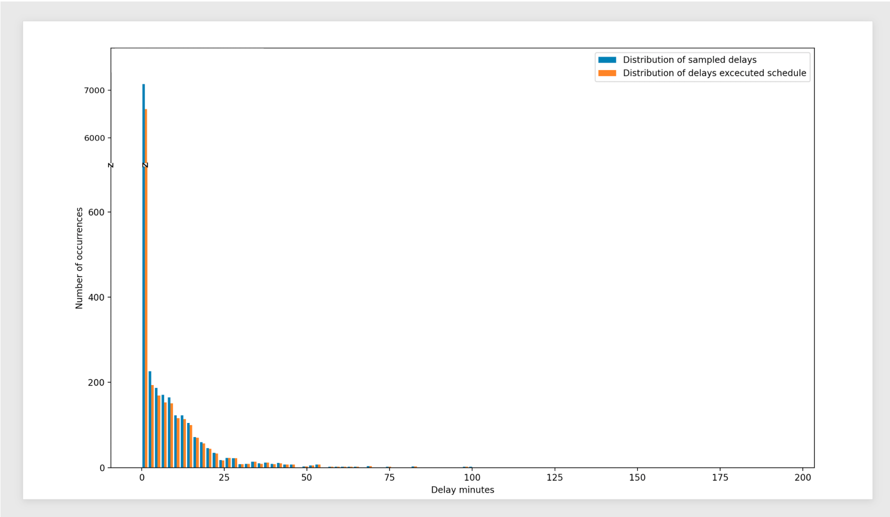


Figure 3: Distribution of sampled delays compared with input delays of an excecuted schedule

Fig. 3 is needed to verify if the sampled delays are in fact similarly distributed as the delays of the validation data. It was concluded that the total value of delays sampled from the distribution of the sampled delays was within acceptable range of the validation data.

6 Case Studies

During the research three case studies were performed. Each case study was created to consider a single effect of having reserve fleet capacity. The first case study was performed to find the needed reserve fleet capacity for different fleet sizes. The second case study aimed at distinguishing which type of delay scenarios reserve fleet capacity is most useful for. The third case study looks at the effect of splitting up a standby aircraft and distributing this capacity over the schedule in the form of buffer time. During these case studies the results of having additional fleet capacity is compared to a baseline. This baseline exists of running the same model with the same input schedule, delays and criteria for delay mitigation actions but without the additional standby aircraft.

6.1 The impact of fleet size on the payoff of reserve capacity

The first case study aims to analyse the impact of fleet size on the payoff of reserve fleet capacity. Adding reserve capacity logically lowers total delay of the system and therefore delay costs, but it comes at a price. This case study was performed to see at which fleet size the added costs of having extra fleet capacity was surpassed by the delay or delay cost it saved.

The original fleet size of 50 aircraft was taken with a packed schedule and a medium delay scenario, see Section 6.2. With this as input, the model was than run for the original fleet size, the original fleet size with one standby reserve aircraft and the original fleet size with two standby reserve aircraft. This was done for all fleet sizes between 5 and 50. The new fleet size was obtained by dropping one of the fleet lines of the schedule at random. The total delay of the schedule with the original fleet size was taken as a baseline to compare to the results of the total delay with one or two reserve standbys.

The case study considered adding a full aircraft to the fleet, which means 10 hours per day of possible production. If a flight is scheduled on this standby, the added reserve fleet capacity will go down and the scheduled production capacity goes up. This way, it is possible for airlines to add reserve fleet capacity without adding a complete aircraft to their fleet. This was not considered during this case study, however the impact of scheduling flights on a standby is further elaborated on in case study Section 6.3.

Fig. 4 shows the capacity increase as a percentage of the fleet size when one (blue line) or two (orange line) reserve aircraft are added to the fleet. Secondly, the figure shows the decrease of the delay as a percentage of the total delay for the fleet without reserve for one (green line) or two (red line) reserve aircraft. The intersection of the green and blue line shows the break even point for one reserve aircraft. For a fleet size of 5 aircraft the prevented delay becomes higher than the added capacity. The intersection of the red and the orange line at 8 shows the break even point for two reserve aircraft.

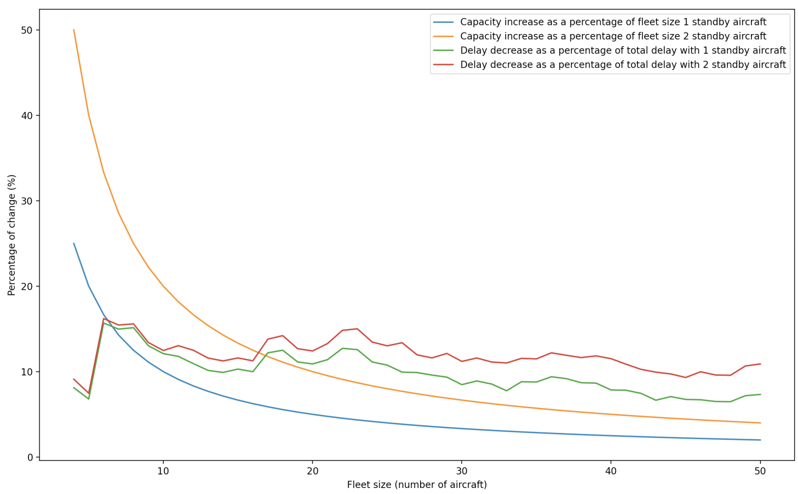


Figure 4: Break even points of adding reserve capacity based on percentage of capacity increase and percentage of delay saved.

Fig. 5 shows the total delay saved by deploying one or two reserve aircraft compared to the added production capacity in minutes. The dark blue line shows the total capacity added by one standby aircraft based on an average 6.6 block hours per day [Zhou, 2019] which comes down to 11880 minutes per month. The light blue line shows the total delay minutes saved with one reserve standby aircraft and the orange line shows the total delay saved by adding two reserve standby aircraft to the fleet.

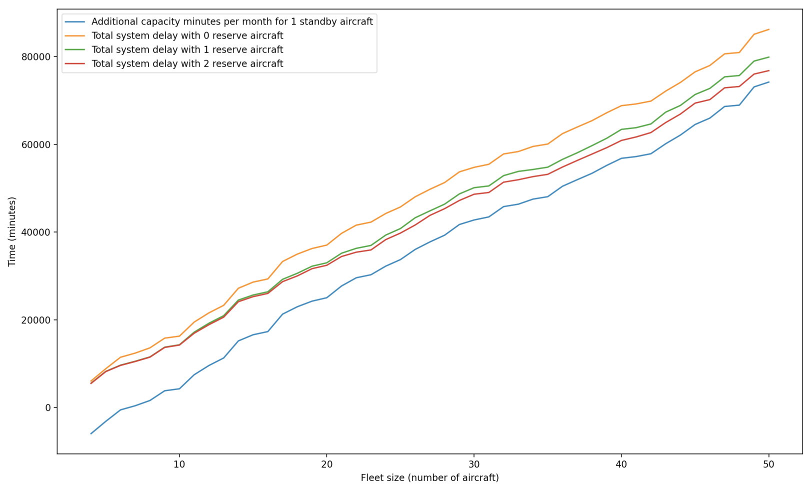


Figure 5: Total system delay for varying fleet size with zero, one or two standby aircraft

A third analysis was performed to find the break even points based on the total delay costs. For this analysis first the added costs of having an additional aircraft in the fleet needed to be determined. These additional costs were calculated using the operational costs excluding fuel. Based on [Planestats et al., 2021] and [Crew et al., 2005] the operational costs excluding fuel were estimated to be between 2000 and 2250 per block hour. The fuel costs are excluded because the use of additional fleet capacity does not increase the total flight hours. Crew costs are included in the operational costs as additional crew might be needed. Flights shifted to the reserve might be performed before crew from an earlier flight is available.

Fig. 6 shows in yellow the range of additional costs for one reserve aircraft per month. The blue range shows the additional costs per month of two reserve aircraft. The blue line shows the total delay costs per month save compared to the fleet without the additional reserve aircraft and the orange line shows the total delay costs saved compared to the fleet without two additional reserve aircraft. The intersection of the blue line with the yellow range indicates when the costs of having an additional reserve aircraft are lower than the delay costs that the reserve aircraft saves. The possible intersection of the orange line with the blue range would be the break even point for having two reserve aircraft.

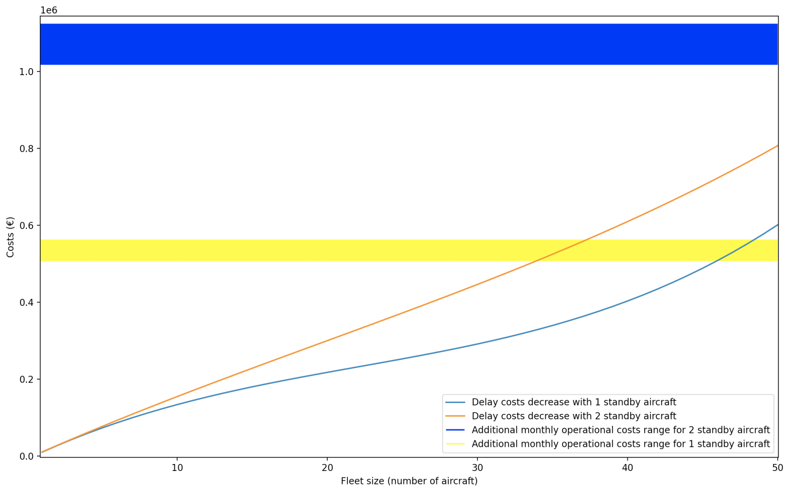


Figure 6: Break even points of adding reserve capacity based on total system delay costs.

Fig. 6 shows the break even point between fleet size and reserve fleet capacity. The break even point for having one standby reserve was around a fleet size of 48 aircraft. For two standby aircraft the results were extrapolated, thereby ending up at a fleet of 85 aircraft. It was concluded that for a fleet of 50 aircraft having one standby aircraft would actually save the airline more than the added operation costs. Considering the costs or the on time performance having more than one standby for a fleet of 50 aircraft does not payoff. Fig. 5 shows that by having two standby aircraft the total delay and therefore on time performance only increases marginally. This limited impact of the second standby can be explained by the fact that for a second standby aircraft to be effective large delays should occur simultaneously, the chance of that happening increases with fleet size. Although having more than one standby is not cost efficient, it could be part of an airline strategy. Having additional reserve capacity allows the airline to quickly expand their network or increase the frequency on existing routes by scheduling it for production.

It should be noted that calculations were performed on an out and back operation. This out and back operation is a small part of a hub and spoke network. A hub and spoke network might even benefit more from the on time performance, therefore results from this study should be considered on the low side of the actual benefit to the total network.

6.2 The impact of delay on the effectiveness of reserve fleet capacity

The second case study was performed to see if reserve fleet capacity is as effective in all types of delay scenarios. Using Monte Carlo simulation, delays are sampled from the different delay scenarios. The scenarios are split into high delay, mid delay and low delay. All scenarios are based on the same distribution of delays, but the mean is shifted by multiplying all values by 0.6 for the low delay scenario, 1 for the medium delay scenario and 1.3 for the high delay scenario. After considering these results a fourth scenario was added. In the fourth delay scenario, the medium delay was taken and the distribution of delays was changed by adding an additional 20 minutes to all input delays higher than 20 minutes. By doing this, the distribution of delays was altered and not only the influence of the length of delays could be investigated but also the impact of the distribution of delays.

This case study uses the total system delay and the total delay costs. These delay costs include the future value loss, passenger reallocation costs and passenger compensation costs. The height of these costs depends on the duration of the delay and the importance of the flight in the overall network. These costs were taken as an input and were provided by a large European airline.

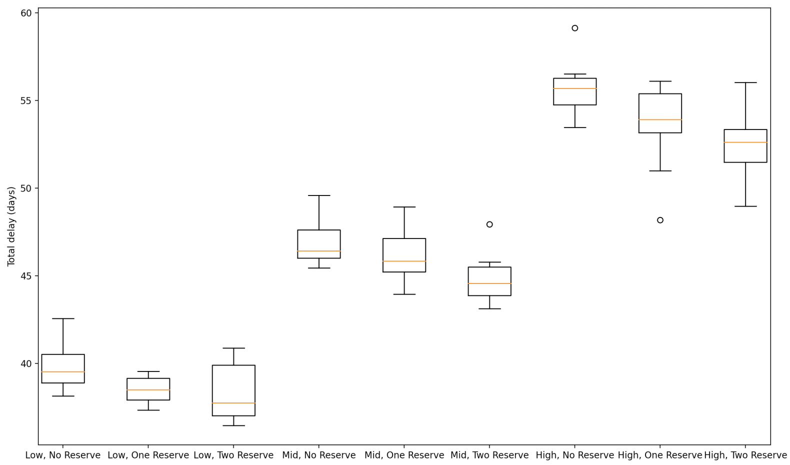


Figure 7: Result of the Monte Carlo simulation showing total system delay for the high, mid and low scenarios

Figure 7 shows the results of the Monte Carlo simulation with a fleet size of 50 aircraft with zero, one or two reserve standby aircraft. The results show that having a standby reserve aircraft lowers the total system delay for all delay scenarios but the decrease is proportional. Table 2 shows the total system delay and delay costs. It can be seen that in the low scenario the added value of a second reserve is almost negligible considering the decrease in total system delay, yet it almost doubled the saved delay costs. In the medium and high delay scenario, the effectiveness of having only one reserve aircraft increases slightly and the effectiveness of having two reserve aircraft becomes higher. Higher delays increase the percentage of delay costs saved. In the forth delay scenario the reserve capacity is more effective in terms of delay saved and the related delay costs saved.

Delay scenario, # reserves	**Total system delay time**	**Diff. with 0 reserve (%)**	**Total system delay costs**	**Diff. with 0 reserve (%)**
Low, reserve 0	39days19:45:00		€ 6.448.784	
Low, reserve 1	38days12:01:00	3,32	€ 6.140.395	4,78
Low, reserve 2	38days08:09:00	3,72	€ 5.909.372	8,36
Medium, reserve 0	46days20:33:00		€ 7.273.745	
Medium, reserve 1	45days03:17:00	3,66	€ 6.518.172	10,38
Medium, reserve 1	44days19:23:00	4,37	€ 5.820.176	19,98
High, reserve 0	55days15:04:00		€ 10.595.431	
High, reserve 1	53days13:46:00	3,69	€ 8.561.149	19,19
High, reserve 2	52days14:43:00	5,41	€ 7.809.419	26,29
Distribution shift, reserve 0	51days00:31:00		€ 7.609.673	
Distribution shift, reserve 1	48days21:21:00	4,17	€ 6.925.708	8,98
Distribution shift, reserve 2	47days20:39:00	6,22	€ 6.340.739	16,67

Table 2: Total system delay and delay costs per delay scenario for a fleet size of 50 aircraft with 0 reserve, 1 reserve and 2 reserve aircraft.

From these results it can be concluded that standby aircraft are most effective in mitigating long delays, as shown in scenario 4. This is a logical consequence of the fact that smaller delays can also be absorbed by buffer times in the schedule. Interestingly, one standby saves approximately the same amount of delay for the for high, mid or low delay scenarios, but the saved costs increase significantly. This is caused by the exponential nature of the delay costs. Having a second standby aircraft becomes more sensible for an airline expecting delays similar to the high delay scenario or delay scenario 4.

6.3 The effectiveness of having reserve fleet capacity grouped in a standby

The last case study takes the same approach as the second case study. Again, three different delay scenarios were compared to see the impact of longer delays on the effectiveness of reserve fleet capacity. In this case the reserve fleet capacity was no longer grouped in a standby but spread out over the schedule in the form of additional buffer time. The redistribution of rotations over the 50 aircraft and the additional standby(s) was done based on the results of the case study illustrated in Section 6.2. After each simulation the final schedule was saved. It is counted how often the rotation was performed by the standby. A new schedule was created in which each day the rotation most often performed by the standby was reallocated from the original aircraft to the standby aircraft. The newly created schedules where then used as input for the simulations. The results of these simulations can be compared with the case study of Section 6.2 and with the baseline of the schedule without additional reserve capacity.

Table 3 shows the results of the simulation using the newly created schedules in which one rotation per day was reallocated to the standby aircraft. The data show that having two additional aircraft on top of the fleet becomes more effective in higher delay scenarios. The same effect was observed in the case study of Section 6.2. The effect of having one additional aircraft stays almost the same with increasing delay, but decreases in the high delay scenario. The saved delay costs almost doubles for all scenarios when two instead of one additional aircraft is added to the fleet.

Delay scenario, # reserves	**Total system delay time**	**Diff. with 0 reserve (%)**	**Total system delay costs**	**Diff. with 0 reserve (%)**
Low, reserve 0	39days19:45:00		€ 6.448.634	
Low, reserve 1	38days13:01:00	3,30	€ 6.240.988	3,220
Low, reserve 2	38days11:09:00	3,31	€ 6.000.366	6,951
Medium, reserve 0	46days20:33:00		€ 7.273.745	
Medium, reserve 1	45days04:00:00	3,52	€ 6.718.562	7,633
Medium, reserve 2	45days00:00:00	3,96	€ 6.220.198	14,484
High, reserve 0	55days15:04:00		€ 10.595.431	
High, reserve 1	53days19:46:00	3,24	€ 8.991.156	15,141
High, reserve 2	52days20:43:00	4,97	€ 8.204.817	22,563

Table 3: Total system delay and delay costs per delay scenario for a fleet size of 50 aircraft with 0 reserve, 1 reserve and 2 reserve aircraft redistributed over the schedule.

The performance of the reserve fleet capacity is almost similar to the results of case study Section 6.2 shown in table Table 2. In general, the effectiveness of the reserve capacity becomes lower when one rotation per day is already scheduled on the standby. By reallocating a rotation, time is freed up on one other aircraft of the fleet. This split up time can be used less effectively than when this time was grouped in a standby. This slightly lower performance aside, splitting up the standby does offer possibilities for an airline. Having the reserve fleet capacity already incorporated in the schedule would lower the number of times the standby unexpectedly needs to be brought into rotation from a far away parking spot. Not having to do so will lower the operational costs significantly.

7 Conclusion

Research into reserve fleet capacity has been very limited. Choices about fleet size are made years before schedule execution. Therefore a better understanding of the impact of reserve fleet capacity and its effectiveness in different delay scenarios can contribute to a better on time performance, higher airline margins and better fleet plan creation.

In Section 6.1 the break even point for fleet size and reserve capacity was found. Based on a general delay case and the given schedule the break even point for having one standby reserve was around a fleet size of 48 aircraft. It should be noted that calculations were performed on point to point operation. This out and back operation is a small part of a hub and spoke network. A hub and spoke network might even benefit more from the on time performance, therefore results from this study should be considered on the low side of the actual benefit to the total network.

In the second case study Section 6.2 the effectiveness of reserve fleet capacity was analysed during different delay scenarios. It was found that having one reserve aircraft on top of a fleet of 50 aircraft saved approximately the same amount of delay for high, mid or low delay scenarios. The effect on the delay costs doubled from a low to mid delay scenario and doubled again from mid to high delay. The added value of having two standby aircraft on top of a fleet of 50 aircraft increased when the delay increased. The delay costs saved are double that of having one standby aircraft. Reserve fleet capacity becomes more effective if the input delays of the schedule have more outliers.

In the third case study Section 6.3 resulting schedules from the case study presented in Section 6.2 were used to generate a new schedule in which one flight per day would be reallocated to the standby aircraft. The model was then rerun. This resulted in fairly similar but a bit lower performance of the reserve capacity in terms of efficiency. From this result it could be concluded that there is an opportunity for airlines to save on their operational costs by scheduling their standby aircraft at the position in their schedule where they have predicted to need this capacity. Doing this for one rotation per day would still offer the flexibility of having grouped reserve capacity, but lower the costs of having to bring the standby unexpectedly into rotation from a far away parking spot.

This paper presents a Monte Carlo simulation based approach to analysing fleet reserve capacity. In this way a trade-off between additional operational costs and saved delay costs could be made. Indications were found that reserve fleet capacity becomes more effective in high delay scenarios with high outlier delays. Grouping reserve fleet capacity into a standby aircraft is efficient and offers flexibility on the day of operations, but if confidence in delay predictions increases operational costs can be lowered by spreading reserve fleet capacity over the schedule.

References

[Abdelghany et al., 2008] Abdelghany, K. F., Abdelghany, A. F., and Ekollu, G. (2008). An integrated decision support tool for airlines schedule recovery during irregular operations. *European Journal of Operational Research*, 185(2):825–848.

[Barnhart et al., 1998] Barnhart, C., Boland, N. L., Clarke, L. W., Johnson, E. L., Nemhauser, G. L., and Shenoi, R. G. (1998). Flight string models for aircraft fleeting and routing. *Transportation Science*, 32(3):208–220.

[Belobaba, 2009] Belobaba, P. (2009). *Fundamentals of Pricing and Revenue Management*. John Wiley Sons, Incorporated, Chichester, West Sussex.

[Bratu and Barnhart, 2006] Bratu, S. and Barnhart, C. (2006). Flight operations recovery: New approaches considering passenger recovery. *Journal of Scheduling*, 9(3):279–298.

[Chen et al., 2020] Chen, C. H., Chou, F. I., and Chou, J. H. (2020). Multi-objective Evolutionary Scheduling and Rescheduling of Integrated Aircraft Routing and Crew Pairing Problems. *IEEE Access*, 8:35018–35030.

[Clarke et al., 1997] Clarke, L., Johnson, E., Nemhauser, G., and Zhu, Z. (1997). The aircraft rotation problem. *Annals of Operations Research*, 69:33–46.

[Cohn and Barnhart, 2003] Cohn, A. M. and Barnhart, C. (2003). Improving crew scheduling by incorporating key maintenance routing decisions. *Operations Research*, 51(3):387–396.

[Cordeau et al., 2001] Cordeau, J. F., Stojković, G., Soumis, F., and Desrosiers, J. (2001). Benders decomposition for simultaneous aircraft routing and crew scheduling. *Transportation Science*, 35(4):375–388.

[Crew et al., 2005] Crew, F., Lease, A., and Services, P. (2005). A d. o. pages 2005–2007.

[Etschmaier and Mathaisel, 1985] Etschmaier, M. M. and Mathaisel, D. F. X. (1985). Airline Scheduling : An Overview. (October 2020).

[Eurocontrol, 2019] Eurocontrol (2019). Effects on the network of extra standby aircraft. *EUROCONTROL*, (October).

[Fiori and Foroni, 2020] Fiori, A. M. and Foroni, I. (2020). Prediction accuracy for reservation-based forecasting methods applied in Revenue Management. *International Journal of Hospitality Management*, 84(July 2019):102332.

[Gopalan and Talluri, 1998] Gopalan, R. and Talluri, K. T. (1998). Operations Research. (August 2020).

[Kohl et al., 2007] Kohl, N., Larsen, A., Larsen, J., Ross, A., and Tiourine, S. (2007). Airline disruption management-Perspectives, experiences and outlook. *Journal of Air Transport Management*, 13(3):149–162.

[Lohatepanont and Barnhart, 2004] Lohatepanont, M. and Barnhart, C. (2004). Airline Schedule Planning: Integrated Models and Algorithms for Schedule Design and Fleet Assignment. *Transportation Science*, 38(1):19–32.

[Lonzius and Lange, 2017] Lonzius, M. C. and Lange, A. (2017). Robust Scheduling: An Empirical Study of Its Impact on Air Traffic Delays. *Transportation Research Part E: Logistics and Transportation Review*, 100:98–114.

[McCarty and Cohn, 2018] McCarty, L. A. and Cohn, A. E. (2018). Preemptive rerouting of airline passengers under uncertain delays. *Computers and Operations Research*, 90:1–11.

[Planestats et al., 2021] Planestats, A., Wyman, O., and Narrowbodies, S. (2021). About nOW Arriving Reported Operating Cost and Utilization of More Than 3 , 000 Narrowbody Aircraft Cost Per Block Hour Cost Per Block Hour (US $) Cost Per ASM (US Cents) Indicies and Monthly Ownership Cost Average Daily Aircraft Utilization Recent Arrivals September 11 Terrorist Attack Rebound Example - IATA World Passenger Analysis - June 2019 Related Oliver Wyman Insights Mobility 2040 - Staying Ahead of Disruption. page 2040.

[Vink et al., 2020] Vink, J., Santos, B. F., Verhagen, W. J., Medeiros, I., and Filho, R. (2020). Dynamic aircraft recovery problem - An operational decision support framework. *Computers and Operations Research*, 117:104892.

[Wang et al., 2019] Wang, Y., Zhu, J., and Liu, C. (2019). The analysis of the influence of delay absorbing sequence on flight delay propagation. *IOP Conference Series: Materials Science and Engineering*, 688(2).

[Wei and Hansen, 2005] Wei, W. and Hansen, M. (2005). Impact of aircraft size and seat availability on airlines' demand and market share in duopoly markets. *Transportation Research Part E: Logistics and Transportation Review*, 41(4):315–327.

[Wong and Tsai, 2012] Wong, J. T. and Tsai, S. C. (2012). A survival model for flight delay propagation. *Journal of Air Transport Management*, 23:5–11.

[Wu, 2005] Wu, C. L. (2005). Inherent delays and operational reliability of airline schedules. *Journal of Air Transport Management*, 11(4):273–282.

[Zhang and Graham, 2020] Zhang, F. and Graham, D. J. (2020). Air transport and economic growth: a review of the impact mechanism and causal relationships. *Transport Reviews*, 1647.

[Zhou, 2019] Zhou, D. (2019). Airline fleet planning and utilization hours comparison studies.

II

Literature Study

previously graded under AE4020

Contents

Acronyms

ADI average demand interval. 16

ARP aircraft recovery problem. 13

ASK available seat kilometers. 5, 6

ATK available tonne-kilometers. 5

ATM air traffic management. 3

BELF break even load factor. 6

CV coefficient of variation. 16

DOC Direct operating costs. 6, 7

IOC indirect operating costs. 6

MA moving average. 16

MMILP multi-objective mixed integer linear programming. 9

MTOW maximum take-off weight. 6

OCC operation control center. 12

OEW operating empty weight. 6

QSI quality of service index. 6, 7

RASK revenue per ASK. 6

SA simulated annealing. 9

SES single exponential smoothing. 16

1 Introduction

The airline networks become larger and more complex, margins are small and passengers have high demands on time performance. This makes optimisation and network planning essential for airlines. Unfortunately airline schedules are rarely executed as planned. Bad weather conditions, mechanical failure or crew illness cause disruptions which influence the planed schedules. In the case of schedule disruption additional cost start to build up for the airline.
To minimize these cost airlines have three mechanisms. Airlines proactively construct robust schedules that are less affected by disruptions or that can better absorb delays. Although robustness methods have proven effectively in lowering delay costs it introduces inefficiencies into the system and increases the operational costs. At the moment of disruption airlines use aircraft recovery algorithms to resolve the disruption as quick as possible. In practices airlines have reserve fleet capacity to cope with disruptions.
Eurocontrol [1] states that in July 2019 only 32.9% of the departing flights and 21.9% of the arriving flights was on time. This was a significant increase from July 2018. A think paper of Eurocontrol [2] states that as in anticipation of the high delays in 2018 airlines increased there reserve capacity, either spreading this capacity out over the schedule as buffer time or grouping it in hot stand-by aircraft. Eurocontrol estimates that this anticipation of the airlines on air air traffic management (ATM) delays had a negative effect on the growth of air traffic in Europe about 3 times the size of the effect of the 737 MAX grounding, over the same period. This impact on the industry illustrates the value that reserve capacity could bring to lower delays but on the other hand limits the operational possibilities and potential growth. Effective use of available reserve fleet capacity is potentially key contributor to improve the performance of airlines.
Reserve capacity has traditionally treated as a given based on historical agreements within a planning department or by what capacity is available to use as reserve. Flight schedules are optimised without considering reserve fleet capacity.
To create a model that structurally incorporates reserve fleet capacity into the planning process an overview of the existing literature was made. A start was made by analysing the state of the practice at KLM chapter 2. Further the literature concerning the fleet planning process and the impact of reserve capacity on fleet planning will be discussed (chapter 3). In chapter 4 aircraft scheduling and robustness scheduling is discussed. To consider the possibilities of reserve fleet capacity during disruptions the aircraft recovery problem (chapter 5) is discussed. For inspiration and current practices an overview of existing reserve capacity planning models from outside the airline industry are given in chapter 6. In chapter 7 an overview is heuristics is given to choose from during the model creation.
The aim of research will be to form a basis to answer the following research question and sub questions:

In what way can reserve fleet capacity best be used?

- Is reserve fleet capacity needed?
- If needed, how can the optimal reserve capacity be determined?
- How can reserve fleet capacity best be used to ensure continuations of the regular schedule in case of disruptions?

2
State of practice

The current state of the practice at KLM was analysed by interviewing colleagues employed at the planning department and planning software development department. Based on these experiences the following can be said about the current practise at KLM.

The use of reserve resources such as towing trucks, fueling trucks or crew are widely spread throughout airline operations. But the use of reserve aircraft is also wide spread.
Reserve aircraft capacity can be thought of as additional production capacity not used for production. Instead this additional production capacity is used to create flexibility in the schedule by either grouping the capacity in a standby resource or by spreading the capacity over the schedule creating slack time in between operations. Having an aircraft as standby reserve often decreases slack time in between flights of non-reserve aircraft. This has the benefit that crews can operate more flights without switching aircraft. A second upside of using a reserve aircraft over having more slack in between flights is that the additional capacity can be used where needed instead of being spread out over the full system.
KLM uses two different reserve indicators. Planned reserve, one aircraft which is designated to be reserve as agreed by a convention between the planning department creating the schedule two weeks in advance and the operational department managing the day of operations.
The second type of reserve is used for over capacity which is also labeled in the system as reserve. This is done to prevent the model from spreading the downtime over multiple aircraft. This is an operational limitation caused by Schiphol regulations concerning limiting gate parking time. When overcapacity is spread out over the system the maximum parking time at a gate might be exceeded resulting the aircraft being towed away from the gate to a parking spot. This operations increases the number of delays.
Currently KLM uses a tool called Sentry to determine the deployment of reserve capacity. This tool uses opportunity costs to determine whether to use the reserve capacity. The tool gives a 1,5 block hour penalty for using the reserve capacity as it will no longer be available for the next schedule disruption. The model considers 3 to 6 hours into the future. The limitation of this model is that it only takes into account a single reserve aircraft as given by the agreement in the planning department. If more reserve capacity is present the model will not be able to make efficient use of it.
In KLM's current fleet plans reserve fleet capacity is addressed per aircraft type. This creates the risks that reserve capacity cannot be effectively used or that there is overcapacity for one type but insufficient capacity for another type.

3

Fleet considerations

Fleet selection a is an integral part of the long-term decision for airlines. The topic is addressed here because of the influence of acquiring additional aircraft to be used as reserve capacity on an airline. Fleet selection is based on an iterative process of forecasting demand, considering aircraft types and creating a sustainable financial planning. The decisions made during this process lead up to the creation of a fleet plan. Creating a fleet planning is basically the process of matching capacity and demand of the markets the airline anticipates to serve right now and in the future. A fleet plan states the long term planning for all aircraft types and individual aircraft, it contains the rough planning of modifications or replacement of the aircraft.

3.1. Fleet selection

During the fleet selection process a fleet plan is created. The fleet plan describes which aircraft types will be operated and the number of aircraft per type for each moment in time. Decisions for this plan are done based on aircraft type, capacity, range and age. Selection of the fleet heavily influences the operational possibilities of the airline. Therefore an airlines fleet plan should reflect a strategy for multiple periods into the future. A fleet plan should incorporate the possible constraints and opportunities of a certain fleet and it should offer the airline sufficient flexibility to overcome unexpected external or internal changes. Although choices for fleet selections are highly influenced by irrational factors such as marketing and environmental issues or political and international trade concerns, we will only focus on the rational part of the decision concerning performance characteristics, the economics of operations and revenue generation. This section focuses on a traditional flag carrier airline

Supply and demand

Fleet planning is the process of matching capacity and demand of the markets the airline anticipates to serve right now and in the future. Supply in the airline market is usually measured in two ways, available seat kilometers (ASK) and available tonne-kilometers (ATK). One ASK or ATK is the amount of seats or tonne freight transported for one kilometer. During the creation of a fleet plan it is extremely important to have a reliable forecast of how the demand of the to serve markets will develop in the coming years. Forecasting demand for the airline industry is a very complex problem. It can be addressed by considering macro-economics as done by Zhang and Graham [3] who discuss the influence of economic growth on the development of airline markets or by analysing reservation data as done by Fiori and Foroni [4]. To decrease the problem size for these forecasts it is possible to convert ASK to ATK so that the total supply and demand of the market can be given as one measure. The difference in seat price (business,comfort and economy) can than be used as a weight to create a standard ASK. In more complex forecast models ASK and ATK per seat type are considered individually.

The supply and demand of the aircraft market can best be seen as a perishable goods market. Aircraft seats are only available at the moment of departure, if the supply of seats is not filled at that moment spillage occurs. The provided supply of seats is not consumed. On the demand side the same phenomenon exists. For instance passengers are only prepared to travel at a certain time or day of the week, if at that time or day the required seats can not be provided demand is spoiled.

During the analysis of the demand of the to serve markets it becomes important to consider the market share

that can be acquired. Market share in the airline industry can in general be described by an S-curve. The S-curve describes the relationship between the market share and the frequency share for an origin destination market. The curve forms an S shape as increases in frequency results in less than proportional increase in market share in the tips of the curve. Wei and Hansen [5] proves that increase in frequency gives higher market share returns than an increase in aircraft size. Confirming that market share behaves like an S-curve. This leads to the fact that short range origin-destinations usually be operated by smaller aircraft at higher route frequencies. Although this phenomena is proven by studies it has it's shortcomings. Markets will behave different if they are less frequency related like leisure markets or heavily relies on peak moments Clark [6].
A second estimation of market size can be done by using the quality of service index (QSI), it models demand based on the preference for minimum travel time, minimum number of stops on a route, frequency of service and airline image. Lohatepanont and Barnhart [7] propose an integrated model for airline schedule design. The model distinguishes between different fare classes, incorporates recapture of passengers and identifies the non-observed demand. Observable demand in an airline market is usually constrained by the supply currently provided in a market. An extensive model is created that illustrates one of the possibilities of airline schedule design, the importance of matching supply and demand is very clear in this approach.
When considering the supply and demand for the to serve markets, seasonality effects can play a very important role for certain origin-destination markets.

AIRCRAFT PERFORMANCE

After assessing the future origin-destination markets a decision needs to be made on what aircraft types to operate. Aircraft performance is the main driver for this decision, this section briefly discusses the most important criteria.
Range is one of the important selection criteria for an aircraft. Far destinations can only be flown if the aircraft type allows such range. For short range destinations a wider selection of aircraft can be used. A trade-off needs to be made between long range jets with, usually, higher seat capacity and smaller short range jets. For smaller jets or oversea operations extended twin operations (ETOPS) regulations are limiting the operational range.
Aircraft performance is a very important part of the fleet selection process. As for almost everything in the airline industry weight is one of the main factors driving the decision making process. Two main weight classifications are of most importance considering the operations of the aircraft. The operating empty weight (OEW) and the maximum take-off weight (MTOW). The OEW is the weight of the aircraft ready for service, it does not include the payload or fuel weight. The MTOW is the maximum weight at which the aircraft is allowed to take-off. The difference between OEW and MTOW can, depending on the type of flight, be filled with fuel or payload. Increasing the amount of fuel will lower the amount of payload but will expand the operational range and vise versa
Less concrete but just as important requirements are: en route performance, environmental impact, produced noise and fuel consumption. These requirements can be driven by the airlines wishes but can also be driven by the regulations of governments or airports.

ECONOMICS AIRCRAFT OPERATIONS

All decision made during the creation of a fleet plan are driven by the prospects of generating profit. Passenger airlines have two main sources of income, passenger transportation and freight transportation. In this section only the passenger transportation will be treated.
The main indicator of cost and revenue generation of a route or network is revenue per ASK (RASK) is a combination of yield and load factor. Yield is the amount of revenue generated for 1 ASK and load factor is the percentage of ASK sold. During the fleet selection a balance between the required ASK by passengers, the demand, and the provided ASK by the airlines, the supply, needs to be created [6]. An important parameter for this balance is break even load factor (BELF) which is the load factor needed to generate sufficient revenue to cover all costs. This can be calculated for a network, origin-destination market or per aircraft type.
The costs of aircraft operations can be split into two parts: Direct operating costs (DOC) and indirect operating costs (IOC). The DOC vary based on the selected aircraft type. The IOC are independent from the selected aircraft type and are contributed to the organisation needed for operating the aircraft. The DOC consist of crew costs, fuel costs and maintenance costs. Airlines aim to lower costs by creating fleet commonality. In theory operating few different aircraft types lowers maintenance costs as fewer different spare components need to be in stock. In practices this proves to be difficult to realise. There is however a significant cost saving component due to easier crew and maintenance team training. [6]

Ownership charges, depreciation and interest can be seen as a part of DOC as the size of these investments differ per aircraft type. To model ownership charges multiple investment appraisals such as the payback model, return on investment and net present value exist. The payback model considers the initial investments and compares the forecast of the profits it is going to generate. It is then calculated how much time it is going to take to payback the initial investment. Shortcomings of this model are that value of money is not taken into account or that profits after the payback period are uncertain. The return on investment method converges the forecast of profits into a percentage of the initial investment. A downside is that the size of the investment and therefore the risk can not be traced back. The final method is net present value of money. Prices depreciate overtime because of inflation. This method takes this into account, an objective comparison can be made between different investments at two different moments in time. This method can be expanded to incorporate the risk of not reaching the predicted profits.
Depreciation of the aircraft is based on one of the investment appraisals. An important factor is the residual value of an aircraft at the end of its financial life. Age and production line status lower residual value, residual value is important as it offers some confidence into the planning procedure IATA [8].

3.2. EFFECTS OF HAVING RESERVE CAPACITY ON THE FLEET PLAN

The effects of having reserve fleet capacity on the fleet plan are multiple. Larger fleet sizes offer economy of scale in maintenance, crew training and more. As discussed in section 3.1 demand in the airline industry is difficult to predict. Reserve fleet capacity gives the airline an opportunity to scale up in case of higher demand, additional the risk of having overcapacity in case of decreasing demand increases. The market share of an airline depends on the QSI this is highly influenced by on time performance of the airline. The reserve fleet capacity will provide more robustness in schedule creation and flexibility during the mitigation of delays. This will benefit passenger experience and lower secondary delay costs such as delay compensation or re-booking of passengers. The additional capacity will increase the total fleet operation costs.

4

Aircraft scheduling

The scheduling phase of the planning process is divided into 3 parallel scheduling processes: Maintenance scheduling, Crew scheduling and Aircraft scheduling 4.1. Scheduling these processes interactively leaves inefficiencies in the planning process. Section 4.4 discusses the literature into robustness planning.

4.1. Aircraft scheduling

Aircraft scheduling or aircraft routing is the process of optimising all decisions to create an operational schedule. A routing for individual aircraft is determined, crews are assigned to itineraries and maintenance is planned according to regulations.

In 1985 Etschmaier and Mathaisel [9] conclude from the body of literature so far that computers can contribute to aircraft scheduling but mainly by speeding up the process of checking schedule feasibility. Only the human mind was capable enough to recognise patterns and to come up with new solutions. The research into aircraft scheduling continued mainly focusing on optimising aircraft utility by improving the efficiency of scheduling maintenance checks. Gopalan and Talluri [10] developed a model that satisfies both the three-day maintenance as well as the balance-check visit requirements for aircraft whose daily rotation are fixed. Clarke *et al.* [11] proposed a mathematical model with specified maintenance locations, frequency and flight duration. The model addresses sub-tour elimination and uses Lagrangian relaxation. Barnhart *et al.* [12] includes the maximisation of anticipated profits in the proposed string-based model. In this model strings are defined as a connected set of flight in between maintenance. The model addresses the fleet selection and aircraft routing and presents a single model solution using branch and price algorithm.

Clausen *et al.* [13] describes three main network representations: time-line network, connection network and time-band network. In a time-line network each departure or arrival is represented by a node. Time is displayed horizontally, and locations are located vertically. In this way all activities at a location can be seen from left to right, all flight legs are represented by the arcs between the nodes. In a connection network flights are represented by nodes the arcs between nodes represent the feasible connection between flights. In a time-band network, locations are displayed horizontally and time vertically. Station-time node represents activities at an airport called a time band, the time label corresponds to the available time (arrival time and turn-around time) of the first available aircraft in the time band. A station-sink node represents the end of the recovery period at each station. The edges between the nodes represent flights.

The research into aircraft scheduling continued to combine maintenance scheduling, crew scheduling and aircraft routing into single problems. Despite the complexity of the separate scheduling problems there can be great benefit of combining the scheduling problems into single models.

Cohn and Barnhart [14] integrate the crew planning process and maintenance scheduling. Their model ensures maintenance feasibility. The model leverages the fact that part of the crew solutions does not influence maintenance and offers the user flexibility in the trade-off between time and quality of the solution. Cordeau *et al.* [15] combine the aircraft routing problem and the crew scheduling. It uses benders decomposition to limit the run time which can save in some cases up to halve the computational time. The paper proves that significant cost savings can be obtained by simultaneously optimising for aircraft routing and crew planning. As the model complexities and calculations increase more heuristics are used. Jamili [16] uses a model that is composed of two parts, a set partitioning problem and a time constrained multi-commodity network flow formulation. In the proposed model, flight times take independently values according to a symmetric distribution to account for disruptions. Using this the model is able to add minimum buffer times at the best sections of the schedule. The model assumes that passengers can either fly direct or indirect, the model routes the aircraft and determines optimal arrival/departure times. Because of the size of the problem Jamili [16] uses a hybrid algorithm that combines simulated annealing (SA) and particle swarm optimization. Simulated annealing is a method, based on the cooling of material, which explores solutions outside the local optimum with which the global optimum can be found more efficiently. Particle swarm optimisation is a method in which candidate solutions move to a better solution based on their own and neighbours experience.

4.2. MAINTENANCE SCHEDULING

Maintenance scheduling is of great importance and highly influences the profitability of the airline. Performing maintenance involves two types of costs. Primary cost, directly related to the maintenance such as material costs or personal costs and secondary costs, the cost of not being able to operate the aircraft while the maintenance takes place. Maintenance exists of short, medium and long-term interventions. Short-term maintenance, or otherwise called line maintenance, does not need to be scheduled. Due to it's short nature it can usually be performed as part of the gate procedure or overnight. Long-term larger maintenance needs to be modeled and included into the schedule making process. Maintenance and checks need to be performed after a regulated number of months (MO), flight hours (FH) or flight cycles (FC). The first threshold to be reached will determine when the maintenance needs to be performed. These thresholds vary per check and are aircraft specific.
Sanchez *et al.* [17] proposes a multi-objective mixed integer linear programming (MMILP) model to solve the maintenance scheduling problem. The model exists of two parts, the first algorithm checks if sufficient maintenance opportunities (MOPs) are available. MOPs exist were large turn-around times offer the opportunity to perform needed maintenance. When the schedule does not have enough MOPs, so the schedule is unfeasible,the second model combines the tail assignment problem with the maintenance problem based on the restriction violations. This then explores the optimal options across an aircraft journey.

4.3. CREW SCHEDULING

Crew is defined as cockpit and cabin crew. Crew scheduling is, due to the complexity of the problem, split up into two stages. First the crew pairing problem is solved. The crew pairing problem defines the set of feasible crew pairings with the minimal amount of costs. Secondly the crew rostering problem is solved. The rostering problem assembles the pairings into longer schedules, these could either be rosters or bidlines. Rosters are work schedules created for individual crew members based on his or her preferences, bidlines are generic schedules assigned to crew members based on a bidding process Belobaba [18].
Performance indicators used to evaluate the output of the processes at this stage; total person-days, number of overnight stays, deadhead times, and ground time. It is highly desired that the values of these parameters be as low as possible.

4.4. ROBUST SCHEDULING

Schedules created are rarely executed as planned. Bad weather conditions, mechanical failure or crew illness cause disruptions which influence the planned schedules. Airlines try to mitigate these disruptions as will further be elaborated on in chapter 5 or to anticipate them by creating schedules better able to absorb disruptions. The creation of schedules more resilient to disruption is called robust scheduling.

To create more robust schedules multiple models are developed to find the weaknesses of schedules. For instance Wu [19] gives a method for analysing the inherent delays of a schedule. The model simulates the turnaround times by using a Markov chain algorithm to describe the stochastic nature of aircraft routing in a network. The combination of a turnaround model and an en-route-model simulates the inherent delays and the propagation through the schedule. Lonzius and Lange [20] propose a robust aircraft scheduling approach by limiting hub connectivity and implementing swap opportunities.
Wong and Tsai [21] proposes a survival model of flight delay propagation. In this model two types of delay are considered, arrival delays and departure delays. Based on this split up the survival time is calculated for delays the survival time is defined as the number of minutes from the start of a delay to the end of that delay. The

distribution of these delays is used to create a survival function and a hazard function. The survival function indicates the probability that a delay survives or takes longer than a certain time t. The hazard function gives the instantaneous probability that an delay of duration t will occur. The paper offers a way to investigate individual factors that contribute to delay and identifies if these delays originate from arriving or departing.
When considering robustness of a schedule a second division between types of delay can be made. This is analysed by Marla *et al.* [22]. In this paper three models are proposed: domain-specific model, a probability distribution-free model and probability-distribution based model. During construction of these models delays are split up as follows. Independent delay, delays that first occur during the flight. Note that these delays can be statistically dependent of each other but are independent of aircraft routing. Propagated delays, delays that find their origin in the previous flights of the schedule. It was found that the probability distribution-free models and probability-distribution based models have intractability problems but do offer a better solution than the string based domain-specific models.
The same approach is taken by Wang *et al.* [23]. A detail view of the split up of delay used is shown in figure Figure 4.1. Random forest tree algorithm ranks the importance of the features influencing the propagation of delay. They concluded that flight buffer time has higher influence on delay propagation than ground buffer time.

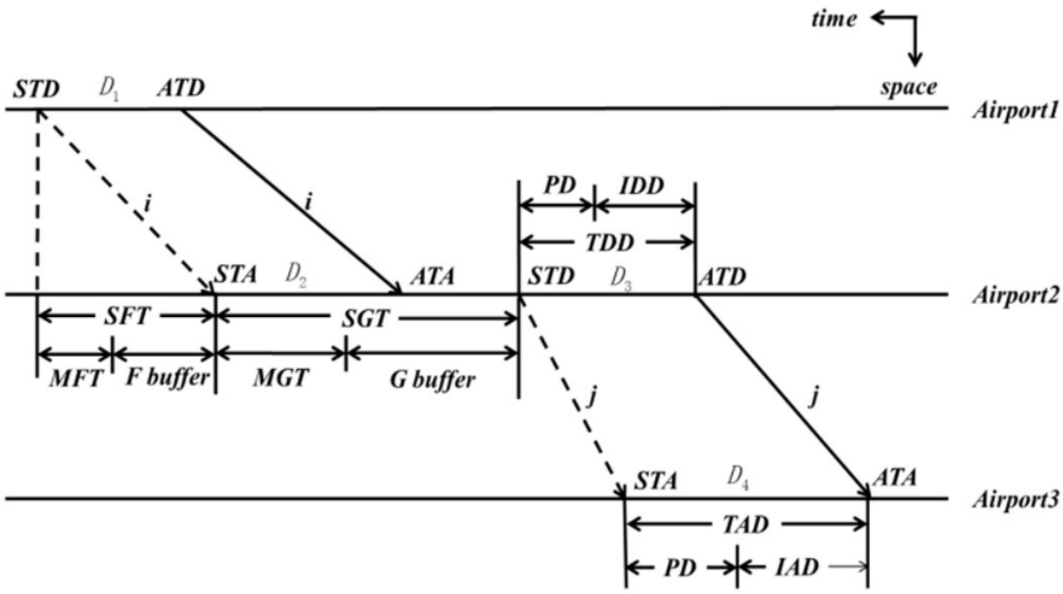


Figure 4.1: *Picture taken from Wang* et al. *[23] shows two sequential flights i and j. Explanation of the symbols is given in Table 4.1*
.

Symbol	Meaning	Symbol	Meaning
STD	Schedule departure time	SFT	Schedule flight time
STA	Schedule arrival time	MFT	Minimum flight time
ATD	Actual departure time	ATA	Actual departure time
IAD	Independent arrival delay	TDD	Total departure delay
SGT	Scheduled ground turnaround time	MGT	Scheduled ground turnaround time
G buffer	Ground buffer time	F buffer	Flight buffer time
PD	Propagated delay	TAD	Total arrival delay
IDD	Independent departure delay		

Table 4.1: *List of symbols used by Wang* et al. *[23] to describe the different time intervals between the arrival and departure time of two consecutive flights.*

These methods point out the existing weaknesses in planned schedules and offer the operator a perspective on how to improve it's robustness. Other methods aim at improving the schedule by optimising robustness in the schedule. Like Lee *et al.* [24] who use a multi-objective genetic algorithm to optimize an existing flight schedule in terms of operational costs and robustness. The algorithm provides the user with a set of possible good compromises between the multiple objectives from which the user can choose. The genetic algorithm mimics the natural process of genetic reproduction. In this model flight schedules are defined as chromosomes of individuals. From a Poole of chromosomes, a parent selection is done. From this parent generation a new child and elite population is created by means of a roulette wheel matching approach. Crossover in the chromosomes is done by arithmetic crossover and point crossover. The algorithm optimizes for % delay given as number of late flights + canceled flights divided by total number of flights and flight time credits (FTC) the difference between the number of minutes paid and the number of minutes flown as a percentage of number of minutes flown.

4.5. IMPACT OF SCHEDULING ON RESERVE CAPACITY

This chapter gives an overview of how schedules are generated and what different processes play a role. It becomes clear that deployment of reserve fleet capacity can only be done when fulfilling all maintenance requirements. Existing maintenance opportunities might change or new opportunities might arise by the deployment of reserve capacity. The crew planning needs to be extended to fit the deployment of reserve fleet capacity. Depending on the type of disruption, different choices will need to be made. In case of a mechanical failure, scheduled crew will still be available to operate the reserve aircraft. In the case of delay exceeding the next departure time, additional standby crew will be needed to operate the reserve aircraft. The combined scheduling models provide an insight into how optimisation can be done while optimizing for multiple objectives. These model could serve as an example for a fleet reserve deployment model. Considering schedule robustness gives an insight into where the schedule is most vulnerable to disruptions, this helps estimate where and when the reserve fleet capacity is most likely needed.

5

Disruptions in aircraft routing

Disruptions are happenings in which it is not possible to operate the predetermined optimised schedule. Disruptions can have many different causes, most often: weather or unpredicted maintenance. But also resource shortage, such as crews illness or congestion around airports can cause disruptions. Disruptions are a part of the daily operations in the airline industry. Eurocontrol [1] states that in July 2019 only 32.9% of the departing flights and 21.9% of the arriving flights was on time. This was a significant increase from July 2018. A think paper of Eurocontrol [2] states that as in anticipation of the high delays in 2018 airlines increased there reserve capacity, either spreading this capacity out over the schedule as buffer time or grouping it in hot stand-by aircraft.

5.1. Operational options for disruption recovery

Airlines face many types of disruption. Decisions on how to cope with disruptions is made in the operation control center (OCC) of the airline where operations of aircraft, crews, and passengers are managed centrally. A more general description of recovery and the organization is given by Kohl *et al.* [25]. In essence the OCC has four different schedule recovery strategies: Delay propagation, aircraft swapping, flight leg cancellations and the use of reserve capacity.

Delay propagation is the most simple way of delay mitigation. For this method no active action is taken to solve the delay. This method is most effective for schedules with sufficient slack (time between arrival en departure). In such a case delay will be absorbed by the schedule overtime. Consider the following example shown in Figure 5.1: Aircraft 1 has a delay of three hours on it's flight form CDG to AMS, because of this the next flight of aircraft 1 needs to be postponed by one hour. In this example the delay propagates through the schedule until the end of the day of operations. The example shows that the slack between the flights absorbs part of the delay (two of the three hours).
Aircraft swapping is an often used delay mitigation strategy. The strategy assesses the arrival times of the incoming aircraft and considers the next planned departures of those aircraft. In the case of one of the aircraft having a delay which prevents it from meeting the next departure an assessment of all available aircraft able to meet this departure time is done. If one of these aircraft is able to meet the departure time of the delayed aircraft and the delayed aircraft is able to meet the next departure time of the other aircraft both schedules could be swapped. An example is given in Figure 5.1. For this swapping to function properly all maintenance, crew rotation/certification and passenger capacity constraints must be fulfilled for both aircraft.
A flight leg can be cancelled for many different reasons. Most often this is caused by a mechanical problems, shortage of crew, upstream schedule delays or reduced departure/landing capacity. If a flight leg is canceled aircraft flow conservation needs to be maintained. This usually lead to the cancellation of multiple legs as the canceled aircraft is not able to perform the downstream flights. [18]
If available, airlines can use the reserve fleet capacity to mitigate the disruption. In this case a swap between the reserve and the disrupted aircraft is performed. The reserve aircraft will perform the next flight of the disrupted aircraft, the disrupted aircraft becomes in turn the new reserve. Figure 5.1 shows an example of the use of reserve capacity.

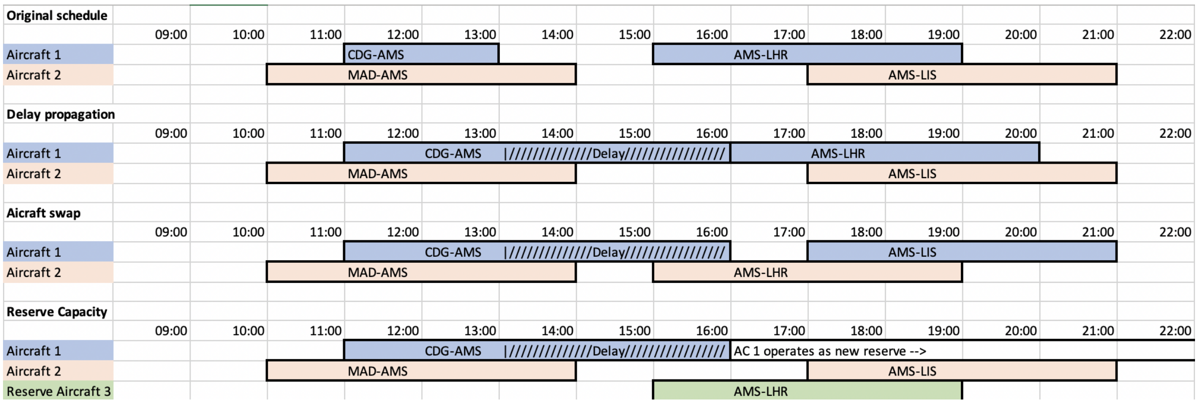


Figure 5.1: *This figure shows an fictitious flight schedules. The top schedule is the original, the bottom three show measures to cope with a disruption of the original schedule. Each line shows the scheduled operations for that specific aircraft.*

5.2. AIRCRAFT RECOVERY MODELS

In the application of the disruption mitigation measures described in section 5.1 multiple models are developed. These models aim to solving the aircraft routing problem as well as the flight schedule problem. This combined problem is called the aircraft recovery problem (ARP). For this problem it is not only necessary to provide a (near) optimal solution as well as limited calculation time to be of use in operational situations. In case of a disruption first the aircraft recovery needs to be considered, second crew recovery and finally passenger recovery.

Hu *et al.* [26] present a integer programming model that integrates the aircraft and passenger recovery after a schedule disruption. the paper considers scenarios in which aircraft are grounded and flights have to be rescheduled. The objective is to minimize disruptions and consequential costs.
Chen *et al.* [27] uses a multi-objective evolutionary approach to solving the integrated aircraft routing and crew paring problem under disruptions. It uses the NSGA-II method, a genetic algorithm that per definition uses: initialization, fitness computation, selection, crossover, and mutation to generate offspring. The chromosome genes represent the aircraft, and in the pairing segment, chromosome genes represent the splitting positions of aircraft flight legs to form different pairs. The problem with this approach is that it is not time efficiently solvable but it will always find an answer or multiple good alternatives as genomes are saved.
Vink *et al.* [28] provides a real time operational solution using a dynamic algorithm. The paper addresses the dynamic nature of the problem, the recovered scheduled from the earlier disruption is taken as input for a next disruption. The model uses a defined time window in which return to original schedule should be realized. Non-feasible solutions are addressed by including slack variables in the model. To limit the search space a selection algorithm is used to determine which part of the fleet is needed to mitigate the disruption. The selection is based on rules and split up into three algorithms. Each algorithm expands the search space in a step-wise manner to lower the cost with each additional aircraft. Algorithm 1 only considers the disrupted aircraft, algorithm 2 considers all aircraft at the airport at which the disruption occurs and algorithm algorithm 3 is activated if long aircraft unavailability is experienced and considers aircraft that are not present at the disrupted location. In this way aircraft are selected according to their contribution to solve the disruption.
Abdelghany *et al.* [29] creates a rolling horizon model in which disruptions are anticipated and as a function of severity. A list of flights is created that is not able to serve as a resource for disrupted flights called resource-independent flights. The input for the model is the available resource bank of flights excluding the resource-independent flights and the disrupted flights at that stage. If an available flight is used to mitigate a disruption the flight is placed in the disruption list. By doing this the horizon is shifted further in time, the model is rerun to again determine the disrupted flights and available resources. Adding flights in the disruption list increases run time but allows for more swap opportunities to be found.
Bratu and Barnhart [30] considers the aircraft recovery problem from the passenger perspective. Often aircraft delay is not a good measure for passenger delay. A trade off between airline operating costs and passenger delay costs is modeled. Two models are created, one considering the disrupted passenger costs and one considering the delayed passenger costs. Both models incorporate maintenance feasibility and crew recov-

ery. They concluded that while decreasing passengers delay, airline resources and schedules can be recovered and operating costs can be controlled.
McCarty and Cohn [31] takes the passenger-centric model even further. Instead of considering the possibility of changing the aircraft schedule to mitigate disruptions they create a model to preemptive reroute of passengers in case of a disruption. During the creation of the model a fictitious case of one disrupted flight is used. The idea is to proactively reroute passengers in case of a delay instead of waiting until connections are missed. A two stage stochastic model is used, the first stage preemptively reassigns passengers to other itineraries in anticipation of the delay, the second stage considers the passengers that still miss connections after the delay has been realized

6
Reserve Capacity in other industries

Reserve fleet capacity is a topic widely used in practise but is little discussed in literature. Therefore the research was extended to see how the topic is addressed in other industries. During this search it was tried to answer the questions: how can the optimal reserve capacity be determined and how is reserve capacity used?

Public transportation networks are in many ways comparable to airline networks. Cats and Jenelius [32] considers the metro network of Stockholm and proposes a way of using given reserve capacity to lower overall passenger delay in case of a disruption. The proposed model is divided into two parts, the first part identifies the links available for capacity enhancement based on their initial saturation level and the second part considers the overload in case of increased saturation. The method integrates stochastic supply and demand, dynamic route choice and limited operational capacity. This dynamic agent-based modelling enables Cats and Jenelius [32] to capture the adaptive redistribution of passenger flows as well as cascading network effects.
In the airline industry rerouting of passengers is complicated as later flights or additional transits are bad for customer experience. Still a similar approach is discussed in section 5.2 by Vink *et al.* [28] in which the third selection algorithm considers the full fleet which could result in canceling non-disrupted flight legs to better accommodate disrupted passengers.

An extensive research topic into reserve capacity is that of reserve crew planning. Crew planning as discussed in section 4.3 is a complex multistage process. Sohoni *et al.* [33] propose a model to integrate the crew planning and the rostering problem while optimizing for reserve crew. The common approach is to generate legal feasible schedules, use set covering algorithm to select a subset of reserve work schedules. Crew is divided into two main groups, regular crew and reserve crew. The crew is scheduled by using a bid-line process that optimises for bidding conflicts to ensure sufficient reserve crews can be scheduled. Subsequently a set of reserve duty periods is selected that covers all trips in the disrupted time period. Finally the required number of reserve duty periods are selected to generate reserve work schedules, a sequence of reserve duty periods including idle days. Sohoni *et al.* [33] optimise the use of the reserve crew as well as the amount of reserve crew needed. Bayliss *et al.* [34] consider the reserve crew problem in revers. It approaches the reserve crew problem by considering the probability of crew unavailability based on the number of available reserve crews. For this method the input probabilities are extremely important to the outcome of the model. To improve calculation times multiple heuristics are considered.
By optimising for maximum conflict Sohoni *et al.* [33] ensure that sufficient reserve crews are available. In an airline flight schedule the same can be done by optimizing for maximum swap opportunities. In this way it can be ensured that sufficient aircraft can serve as mitigation resource. The link between the needed capacity and the effective use of the capacity is also applicable to the reserve fleet capacity problem.

van den Broek d'Obrenan *et al.* [35] address the problem of having buffer hospital beds. Patients are placed on a waiting list for surgery and prioritised based on the need for medical aid. Surgery time is modeled as a stochastic process. By optimising the scheduling, the needed reserve hospital beds can be limited to a minimum.

This way of minimising reserve hospital beds can be linked to robust scheduling. By spreading out the events with high probability of delay, a more effective use can be made of reserve hospital beds or reserve fleet capacity.

The paper of Abedi and Rahimiyan [36] gives an insight into reserve capacity in the energy market. In the traditional carbon based energy production the energy market was mainly influenced by demand uncertainties and supply could be managed quite accurately. By adding more renewable energy sources to the market, supply becomes more uncertain because of the unpredictable nature of weather and the influence on solar or wind power. Abedi and Rahimiyan [36] consider correlation of power output between nearby wind farms and the effect of this on the planned reserve capacity in the day ahead energy market. The paper uses a stochastic model which schedules energy and reserve in the first stage. In the second stage schedules energy and reserve based on the scenario proposed for the realised wind energy. The paper concludes that by not considering the correlation between nearby wind farms less reserve capacity is scheduled. This offers a lower operational costs but makes the system vulnerable and offers high financial risks on real-time operations. The same parallel between lowing operational costs and increasing system vulnerability exist also in the reserve fleet capacity problem.
The difference with reserve fleet capacity is that in the energy market reserve capacity is either scheduled or not, airlines have a third option by incorporate reserve fleet capacity as additional robustness in the schedule.

An extensive research field in the aerospace industry is spare part inventory management. The inventory needed for a spare part is often determined by forecasting the expected demand for that specific part. To find the correct forecasting method, demand is categorised in four groups: smooth, erratic, lumpy and intermittent demand. This categorisation is done based on the average demand interval (ADI) and coefficient of variation (CV) as explained in the paper of Costantino *et al.* [37]. A second way of determining the needed stock in inventory is by using a stochastic model. Patriarca *et al.* [38] uses a discrete Weibull distribution for simulating the stochastic demand. Syntetos *et al.* [39] consider the spare parts demand for business aircraft. This demand is highly unpredictable and uncertain. In this paper forecast algorithms like: Croston, Croston TSB, Croston SBJ, Croston SNB, moving average (MA), single exponential smoothing (SES) are compared with bootstrapping. Same procedure can be applied to forecasting the need of reserve fleet capacity.
A parallel between the fleet reserve capacity and inventory management can be made. An aircraft can be seen as one spare part on a storage location. In case of a disruption the aircraft is called upon and the inventory is reduced by one part. In the case that no reserve aircraft are left in the inventory, the inventory is out of stock. The reserve inventory is replenished when the delayed aircraft arrives and can be used as spare, see section 5.1 (reserve capacity). In spare part management these moments are priced based on the probability and the costs of additional demand for a spare part during this stock out moment. In the case of fleet reserve capacity an optimisation can be done of the prevented delay cost by using a spare aircraft and the costs of the stock out situation. This example illustrates how a spare part model could be used to determined which delays to mitigate using the reserve capacity.

7
Optimisation methods

As a new model will be created for aircraft reserve capacity it is important to consider possible heuristics, during the discussion in earlier chapters some of these heuristics are already discussed. This chapter aims to give a clear overview so that in a later stage of constructing a model a choice can choice can be made between different heuristics to improve calculations times. As Francisco [40] states in his book, heuristics are specific for the model used and the problem solved. A heuristic approach should be chosen that exploits a specific property of the problem.

Exact methods

The most common optimisation method used is the branch-and-bound method. The Branch-and-bound is a search method that will yield the optimal solution, if it exists. The focuses on limiting the search space by only branching on possible more optimal solutions. Branching is the process of adding additional constraints. Bounding refers to fathoming branches if no better solution can be found in that part of the sub-problems. The limitation of this technique is that in extreme cases the heuristic will branch on all decision variables making it still very time consuming.

If the problem can be formulated as a multistage process, a process in which a decision can be split up into multiple steps, dynamic programming can offer an efficient way to solve the problem. Dynamic programming starts in the last stage of the problem and assumes that all previous stages have already been performed. Then, the algorithm moves backwards trough the problem and recursively determines the best policy for leaving a state. In order for this heuristic to work the final stage must be solvable and given the current state the optimal decision for each of the remaining states does not depend on the previous states or decisions.

Heuristics can be split into two: Construction heuristics and improvement heuristics. Construction heuristics start without a solution and fixate the solution with each step taken. Improvement heuristics start with a solution and improve this solution by iteration.[40]

Local search methods

Variable neighbourhood search is a local search algorithm it dynamically shifts the searched neighbourhood and checks for local optima. The neighbourhood is then updated based on the search. A guided local search works quite similar but instead of changing the neighbourhood structure the fitness of solutions near the local optima is changed to escape the local optima. Based on the same principles two methods stand out: Simulated annealing and tabu search. Simulated annealing is a method, based on the cooling of material. The method will except new inferior solutions to escape from the local optimum. The probability of excepting better solutions called T is changed during the run. During the run time, T determines which solutions are excepted, as more runs are done the probability of selecting worse solutions will go down as the search space gets more narrow. Tabu search is an often used heuristic. It stores solutions for a short time in a tabu list. The local search adds new solutions to the list and cannot add any solutions that are already on the list hereby forcing the algorithm to leave the local optimum.[40]

Population based heuristics

The genetic algorithm mimics the natural process of genetic reproduction. The algorithm starts off with a population of solutions. The solutions are valued based on the objective value and are then changed based on the combination of parameters. The first generation of solutions is then used to create a child population of solutions with the same properties as the parent generation. More optimal solutions are more likely to be selected to form the new generation, the new generation is formed based on crossover between different solutions. Additionally mutation within a solution can be created to investigate solutions that otherwise would not be found. [40]

Ant colony optimisation is done by mimicking the behavior of an ant colony. Each individual ant of the colony starts out to find a shortest path to a food source. It communicates indirectly with other members of the colony by leaving a pheromone trail, this trail evaporates over time. At first ants will choose randomly from to upcoming possibilities but as pheromones build up, the probability for other ants to choose the same path increases. This heuristic works very well for traveling salesmen problems as described by Dorigo and Gambardella [41].

Particle swarm optimisation was originally based on the behavior of bird flocks. The algorithm is started with a random population of solutions. Each particle has a starting velocity and keeps track of the best local optimum it has visited so far. The flock as a whole keeps track of the best global optimum visited so far. Each time step the velocity of the particles is changed randomly towards the local and global optimum. An overview of applications and discussion of the method is given by Eberhart and Shi [42].

8 Conclusion

Airlines experience delay on a daily basis. Customer satisfaction and profitability highly depend on a smooth daily operation. Throughout fleet planning phase this is first addressed by including reserve capacity. During the scheduling phase, it is tried to create robust schedules to prevent delays. During disruptions algorithms are used to mitigate delays. Reserve capacity is a valuable asset during this phase.
During the fleet planning phase of an airline decisions concerning reserve fleet capacity are made. Fleet planning is a complex phase with great implications on the operations of the airline. Predicted demand for a to serve origin destination market highly influences the decisions an airline needs to make. Having additional reserve capacity can be a benefit in a growth market but offers extra risk in a market with decreasing demand.
Scheduling is the last part of the airline planning process. In this part of the planning process multiple processes come together: maintenance, crew and aircraft scheduling. It has been tried to combine these processes to optimize them simultaneously or to plan them sequentially. Planning them simultaneously offers the possibility of more optimal solutions but increases computational complexity. An important research topic of airline planning is robustness scheduling. The method of creating schedules that are better resistant against disruptions. It can be concluded that reserve fleet capacity is an essential part of robustness planning. Reserve fleet capacity can either be grouped in hot standby aircraft or spread out over the network to increase buffer times.
Although robust scheduling can improve a schedule significantly still disruptions will occur. Four often used methods of mitigating these delays are discussed: delay propagation, aircraft swapping, flight leg cancellation and reserve fleet capacity. Current decisions for the use or size of reserve capacity are based on old agreements. It is time to challenge these beliefs and find a scientific basis.
Reserve capacity is a wide spread phenomena in all types of industries, although there are great differences, lessons can be learned such as rerouting of passengers, effective use of reserve capacity or spreading out events with high probability of delay.
Different heuristics are treated to create a mathematical basis for the creation of a real time aircraft recovery problem incorporating reserve fleet capacity.
Two effective ways of using reserve fleet capacity are: to use the additional reserve to increase buffer times or to group the aircraft in hot standbys. To predict the needed amount of reserve capacity, a stochastic model or forecast model could be used. The way reserve fleet capacity is implemented influences the number of aircraft needed for optimal use. To efficiently use reserve fleet capacity a better integration of the aircraft recovery models and reserve fleet capacity is needed.

Bibliography

[1] Eurocontrol, *All-Causes Delay and Cancellations to Air Transport in Europe,* EUROCONTROL (2019).

[2] Eurocontrol, *Effects on the network of extra standby aircraft,* EUROCONTROL (2019).

[3] F. Zhang and D. J. Graham, *Air transport and economic growth: a review of the impact mechanism and causal relationships,* Transport Reviews **1647** (2020), 10.1080/01441647.2020.1738587.

[4] A. M. Fiori and I. Foroni, *Prediction accuracy for reservation-based forecasting methods applied in Revenue Management,* International Journal of Hospitality Management **84**, 102332 (2020).

[5] W. Wei and M. Hansen, *Impact of aircraft size and seat availability on airlines' demand and market share in duopoly markets,* Transportation Research Part E: Logistics and Transportation Review **41**, 315 (2005).

[6] P. Clark, *Buying the Big Jets* (Ashgate Publishing Company, Burlington, 2017).

[7] M. Lohatepanont and C. Barnhart, *Airline Schedule Planning: Integrated Models and Algorithms for Schedule Design and Fleet Assignment,* Transportation Science **38**, 19 (2004).

[8] IATA, *Airline Disclosure Guide Aircraft acquisition cost and depreciation,* IATA (2016).

[9] M. M. Etschmaier and D. F. X. Mathaisel, *Airline Scheduling : An Overview,* (1985).

[10] R. Gopalan and K. T. Talluri, *Operations Research,* (1998).

[11] L. Clarke, E. Johnson, G. Nemhauser, and Z. Zhu, *The aircraft rotation problem,* Annals of Operations Research **69**, 33 (1997).

[12] C. Barnhart, N. L. Boland, L. W. Clarke, E. L. Johnson, G. L. Nemhauser, and R. G. Shenoi, *Flight string models for aircraft fleeting and routing,* Transportation Science **32**, 208 (1998).

[13] J. Clausen, A. Larsen, J. Larsen, and N. J. Rezanova, *Disruption management in the airline industry-Concepts, models and methods,* Computers and Operations Research **37**, 809 (2010).

[14] A. M. Cohn and C. Barnhart, *Improving crew scheduling by incorporating key maintenance routing decisions,* Operations Research **51**, 387 (2003).

[15] J. F. Cordeau, G. Stojković, F. Soumis, and J. Desrosiers, *Benders decomposition for simultaneous aircraft routing and crew scheduling,* Transportation Science **35**, 375 (2001).

[16] A. Jamili, *A robust mathematical model and heuristic algorithms for integrated aircraft routing and scheduling, with consideration of fleet assignment problem,* Journal of Air Transport Management **58**, 21 (2017).

[17] D. T. Sanchez, B. Boyacı, and K. G. Zografos, *An optimisation framework for airline fleet maintenance scheduling with tail assignment considerations,* Transportation Research Part B: Methodological **133**, 142 (2020).

[18] P. Belobaba, *The Global Airline Industry* (John Wiley Sons, Incorporated, Chichester, West Sussex, 2009) pp. 253–274.

[19] C. L. Wu, *Inherent delays and operational reliability of airline schedules,* Journal of Air Transport Management **11**, 273 (2005).

[20] M. C. Lonzius and A. Lange, *Robust Scheduling: An Empirical Study of Its Impact on Air Traffic Delays,* Transportation Research Part E: Logistics and Transportation Review **100**, 98 (2017).

[21] J. T. Wong and S. C. Tsai, *A survival model for flight delay propagation,* Journal of Air Transport Management **23**, 5 (2012).

[22] L. Marla, V. Vaze, and C. Barnhart, *Robust optimization: Lessons learned from aircraft routing,* Computers and Operations Research **98**, 165 (2018).

[23] Y. Wang, J. Zhu, and C. Liu, *The analysis of the influence of delay absorbing sequence on flight delay propagation,* IOP Conference Series: Materials Science and Engineering **688** (2019), 10.1088/1757-899X/688/2/022006.

[24] L. H. Lee, C. U. Lee, and Y. P. Tan, *A multi-objective genetic algorithm for robust flight scheduling using simulation,* European Journal of Operational Research **177**, 1948 (2007).

[25] N. Kohl, A. Larsen, J. Larsen, A. Ross, and S. Tiourine, *Airline disruption management-Perspectives, experiences and outlook,* Journal of Air Transport Management **13**, 149 (2007).

[26] Y. Hu, B. Xu, J. F. Bard, and H. Chi, *Computers & Industrial Engineering Optimization of multi-fleet aircraft routing considering passenger transiting under airline disruption q,* COMPUTERS & INDUSTRIAL ENGINEERING **80**, 132 (2015).

[27] C. H. Chen, F. I. Chou, and J. H. Chou, *Multiobjective Evolutionary Scheduling and Rescheduling of Integrated Aircraft Routing and Crew Pairing Problems,* IEEE Access **8**, 35018 (2020).

[28] J. Vink, B. F. Santos, W. J. Verhagen, I. Medeiros, and R. Filho, *Dynamic aircraft recovery problem - An operational decision support framework,* Computers and Operations Research **117**, 104892 (2020).

[29] K. F. Abdelghany, A. F. Abdelghany, and G. Ekollu, *An integrated decision support tool for airlines schedule recovery during irregular operations,* European Journal of Operational Research **185**, 825 (2008).

[30] S. Bratu and C. Barnhart, *Flight operations recovery: New approaches considering passenger recovery,* Journal of Scheduling **9**, 279 (2006).

[31] L. A. McCarty and A. E. Cohn, *Preemptive rerouting of airline passengers under uncertain delays,* Computers and Operations Research **90**, 1 (2018).

[32] O. Cats and E. Jenelius, *Planning for the unexpected: The value of reserve capacity for public transport network robustness,* Transportation Research Part A: Policy and Practice **81**, 47 (2015).

[33] M. G. Sohoni, E. L. Johnson, and T. G. Bailey, *Operational airline reserve crew planning,* Journal of Scheduling **9**, 203 (2006).

[34] C. Bayliss, G. De Maere, J. Atkin, and M. Paelinck, *Probabilistic airline reserve crew scheduling model,* OpenAccess Series in Informatics **25**, 132 (2012).

[35] A. van den Broek d'Obrenan, A. Ridder, D. Roubos, and L. Stougie, *Minimizing bed occupancy variance by scheduling patients under uncertainty,* European Journal of Operational Research **286**, 336 (2020).

[36] A. Abedi and M. Rahimiyan, *Day-ahead energy and reserve scheduling under correlated wind power production,* International Journal of Electrical Power and Energy Systems **120**, 105931 (2020).

[37] F. Costantino, G. Di Gravio, R. Patriarca, and L. Petrella, *Spare parts management for irregular demand items,* Omega (United Kingdom) **81**, 57 (2018).

[38] R. Patriarca, T. Hu, F. Costantino, G. D. Gravio, and M. Tronci, *A System-Approach for Recoverable Spare Parts Management Using the DiscreteWeibull Distribution,* Sustainability (Switzerland) **11** (2019), 10.3390/su11195180.

[39] A. A. Syntetos, M. Zied Babai, and E. S. Gardner, *Forecasting intermittent inventory demands: Simple parametric methods vs. bootstrapping,* Journal of Business Research **68**, 1746 (2015).

[40] A. R. L. Francisco, *Design of Modern Heuristics* (Springer Heidelberg, Leiden, 2011).

[41] M. Dorigo and L. M. Gambardella, *Ant colony system: A cooperative learning approach to the traveling salesman problem,* IEEE Transactions on Evolutionary Computation **1**, 53 (1997).

[42] R. C. Eberhart and Y. Shi, *Particle swarm optimization: Developments, applications and resources,* Proceedings of the IEEE Conference on Evolutionary Computation, ICEC **1**, 81 (2001).

Bibliography