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Sustainable Disruption Management

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Summary

The world we live in is globalized. Goods are seldom made in the place where they are used or consumed, and we do increasingly travel to other countries for either business or pleasure. In our everyday lives we rely on well-functioning global transportations systems to continue the standard of living we are enjoying. We rely on airlines being able to transport us safely and efficiently around the globe and may all recall when the Islandic volcano with the difficult name, Eyjafjallajökull, disrupted our ability of doing so.

The backbone of world trade, shipping, does not reach the news in the same way, when operation is disrupted. Never the less, we may recall that the Suez Canal was closed due to riots in Egypt, that the fuel price was impacted by threats of closing of the Strait of Hormuz, and we do from time to time hear about acts of piracy outside the coast of Somalia.

All of these events lead to very severe disruptions to transportation systems. Less severe disruptions do, however, also have a significant impact on transportation systems and on most days, an airline or a shipping company will experience some level of disruption. Most often due to weather, but other issues, such as e.g. technical problems or congestions are also typical causes of delays. Returning a transportation system to its original plan of operation is referred to as *Disruption Management*.

Disruptions are, however, not the only cause of concern to the transportation industry. Fuel is becoming an increasingly expensive resource, and it is being consumed in vast amounts by the transportation industry. The single largest expense for both airlines and shipping companies is fuel, which exceeds both labour costs and capital expenditure.

This thesis addresses how fuel considerations can be taken into account when managing recovery from disruptions. The underlying work of this thesis is carried out as an industrial PhD project in co-operation with the company Jeppesen, which have the airline industry as its primary area of business and the maritime industry as its secondary area. For this reason the thesis has been divided accordingly, with the primary focus being on the airline industry and the secondary being on the maritime industry - more specifically, the liner shipping industry, which in terms of network structure has many similarities with airline networks.

The thesis presents how disruption management fits in to the larger scope of optimization related processes in an airline and provides a brief survey of these. The thesis goes into more detail with disruption management and does as its main contribution describe how this can be combined with *flight planning*. Flight planning is the calculation of the horizontal and vertical flight path, which an aircraft should follow in order to get from airport A to airport B. The objective of this calculation is typically to minimize fuel consumption, while satisfying airspace regulations. To the knowledge of the author the work in this thesis represents the first papers combining disruption management and flight planning through an integrated optimization approach.

An additional contribution of the thesis is to show how flexible flight speeds can be used to improve recovery from disruptions, while at the same time allowing an airline to trade off fuel costs with passenger delay costs. Experimental results show both large cost savings of 5.7% and very large reductions in passenger misconnections of 66% by applying the approach.

This contribution is carried over to the liner shipping industry, which despite being a different industry and having different constraints than the airlines, has sufficient similarities in network structure to benefit from a similar recovery concept. This work has lead to a successful development of an optimization model for the Vessel Schedule Recovery problem (VSRP), which is an area that has not previously been addressed in published literature. Experiments show up to 58% savings in recovery costs compared to manually realized recovery costs for real-life cases.

The thesis does furthermore describe the airspace structure and how flight planning is carried out within the constraints of this structure. In both the US and Europe the flow of flights between different regions is centrally managed in order to reduce the negative impact of airspace congestions. A final contribution of the thesis is an approach and a model, which combines disruption management with flexible flight trajectories. In a situation, where a specific area of the airspace is congested, this approach can help an airline with a more proactive handling of the kind of disruptions, which are caused by congested airspace. This is again an area, which has

not previously been addressed through an approach combining both flight planing and disruption management. The real-world results show considerable yearly savings of above 5.1 million USD for a medium size airline operating in European airspace, which is significantly affected by airspace congestions.

Resumé (Summary in Danish)

Vi lever i en globaliseret verden. Varer bliver sjældent produceret samme sted, som de bliver anvendt eller forbrugt, og vi benytter i stigende grad at rejse til andre lande på ferie eller på forretningsrejse. Den levestandard, som vi i dag nyder, beror i høj grad på velfungerende globale transportsystemer, som kan fragte varer og personer rundt i verden. Vi sætter vores lid til at luftfartsselskaber kan transportere os sikkert og effektivt fra et land til et andet og husker måske alle da den islandske vulkan med den svære navn, Eyjafjallajökull, satte en brat stopper for den mulighed.

Skibsfart udgør rygraden i verdenshandelen, men skaber på trods heraf ikke samme store nyhedsoverskrifter, når den bliver afbrudt eller forsinket. Vi kan dog muligvis alligevel huske, at Suez kanalen blev lukket pga. optøjer i Egypten, at prisen på brændstof blev påvirket af trusler om lukning af strædet ved Hormuz, og vi hører fra tid til anden om piraters kidnapninger ud for Somalias kyst.

Alle disse begivenheder fører til afbrydelser eller store forstyrrelser af transportsystemerne. Mindre forstyrrelser end de ovennævnte kan dog ligeledes have en stor indvirkning på disse systemer og på de fleste dage vil både flyselskaber og shipping firmaer være udsat for en vis grad af forstyrrelser i forhold til den planlagte afvikling. Oftest er det vejret der spiller ind, men andre påvirkninger såsom tekniske problemer eller en form for *trafikpropper (congestions)* er også typiske årsager til forsinkelser. Opgaven med at få et transportsystem tilbage på ret spor og genoptage den planlagte afvikling kaldes *disruption management*. Som regel anvendes det engelske udtryk i Danmark, men i enkelte tilfælde høres den danske oversættelse *genopretning*.

Afbrydelser og forstyrrelser er imidlertid ikke det eneste problem for transport industrien. Brændstof er blevet markant dyrere de seneste år og bliver brugt i store mængder af transport industrien. Den største enkeltstående udgiftspost for både flyselskaber og shipping firmaer er brændstof. Denne post overstiger både lønninger og kapitalomkostninger.

Denne afhandling omhandler hvorledes brændstofomkostninger kan inddrages i disruption management beslutninger når et transportsystem skal bringes tilbage til den planlagte afvikling. Arbejdet, der er beskrevet i denne afhandling, er udført som et erhvervs-ph.d. projekt i samarbejde med virksomheden Jeppesen, der har luftfartsindustrien som sit primære forretningsområde og shipping industrien som sit sekundære område. Af den grund er afhandlingen tilrettelagt herefter, med det primære fokus på luftfartsindutrien og et sekundært fokus på shipping industrien. Mere specifikt er der her tale om container fragt (liner shipping), der i sin netværksstruktur har mange ligheder med flyselskabernes netværk.

Afhandlingen beskriver, hvorledes disruption management passer ind i den samlede struktur af optimeringsrelaterede processer i et flyselskab. Der gives en kort gennemgang af disse processer samt referencer til udvalgt litteratur inden for de enkelte områder. Afhandlingen giver derpå en mere detaljeret gennemgang af disruption management og beskriver som sit hovedbidrag, hvorledes disruption mannagement kan kombineres med *flight planning*. Flight planning er udregningen af både den horisontale og den vertikale rute, som et fly skal følge for at komme fra lufthavn A til lufthavn B. Målet med denne beregning er typisk at minimere brændstof forbruget, givet en lang række myndighedsregler for luftrummet, som skal overholdes. Såvidt forfatteren er bekendt, er artiklerne i denne afhandling de første artikler, som kombinerer disruption management og flight planning i en integreret optimeringsmodel.

Yderligere et forskningsbidrag i afhandlingen er at vise, hvordan fleksibilitet i de hastigheder, hvormed flyvninger er planlagt, kan forbedre de muligheder et flyselskab har for at komme tilbage til den oprindeligt planlagte afvikling. Dette kan gøres samtidig med at omkostninger til brændstof vejes op imod de omkostninger, der er forbundet med forsinkede passagerer. De udførte eksperimenter viser, at der ved at anvende fleksible hastigheder er en stor besparelse på 5.7% af de totale omkostninger forbundet med forstyrrelsen. Hertil kommer en meget stor reduktion på 66% i antallet af passagerer, som undgår at miste deres videre flyforbindelser.

Dette forskningsbidrag er videreført til liner shipping industrien, som på trods af at være en meget anderledes industri med andre begrænsninger end dem vi kender fra luftfartsindustrien,

alligevel har tilstrækkelige ligheder med luftfartsindustrien i netværksstruktur, til at kunne drage fordel af at anvende en lignende tilgang til disruption management. Dette arbejde har ført til en vellykket udvikling af en optimeringsmodel for *the Vessel Schedule Recovery Problem (VSRP)*, hvilket er et område, som ikke tidligere er blevet adresseret i litteraturen. Eksperimenter har vist op til 58% besparelse i genopretningsomkostning i forhold til de omkostninger, der var resultatet af manuel løsning af en række virkelige cases fra Mærsk Line.

Afhandlingen beskriver yderligere de strukturer, der er defineret for at kontrollere trafikken i luftrummet, samt hvorledes flight planning udføres indenfor de begrænsninger, der er givet af disse strukturer. I både USA og Europa er strømme af fly mellem forskellige regioner styret fra centralt hold for at begrænse de negative konsekvenser af congestions i luften. Et sidste forskningsmæssigt bidrag af ph.d.-projektet er en metode og en matematisk model, som kombinerer disruption management med fleksible flyruter. I en situation, hvor et bestemt område af luftrummet er udsat for en stor mængde trafik, kan modellen hjælpe flyselskabet med en mere proaktiv håndtering af den type forstyrrelser, der er forårsaget at sådanne congestions. Dette er tillige et område, der ikke tidligere er blevet adresseret via en metode, der kombinerer både disruption management og flight planning. Resultater fra den virkelige verden viser betydelige årlige besparelser på mere end 5.1 millioner USD for et mellemstort Europæisk flyselskab.

Preface

This dissertation is submitted to the department of Management Engineering at the Technical University of Denmark in partial fulfilment of the requirements for acquiring the PhD degree.

The work has been conducted under the Industrial PhD programme of the Danish Agency for Science Technology and Innovation. The work has been supervised by Professor Jesper Larsen from DTU Management Engineering while it from Jeppesen has been supervised by Jesper Hansen from the Jeppesen office in Copenhagen and Steve Altus from the Jeppesen office in San José.

The thesis consists of an introduction to the project and a collection of four research papers prepared during the period from November 2009 to November 2012.

Kgs. Lyngby, Denmark, November 2012

Bo Vaaben

List of Papers

- **Paper A:** Dominik Dienst, Stefan Røpke and Bo Vaaben (2012). "Realistic models and computational results for disruption management in the airline industry". In: *Central European Journal of Operations Research*
(Submitted)
- **Paper B:** Lavanya Marla, Bo Vaaben and Cynthia Barnhart (2012). "Integrated Disruption Management and Flight Planning to Trade off Delays and Fuel Burn". In: *INFORMS Transportation Science*
(Accepted on condition of minor revision)
- **Paper C:** Bo Vaaben, Jesper Larsen (2012). "Mitigation of Airspace Congestion Impact on Airline Networks". In: *Journal of Air Transport Management*
(Submitted)
- **Paper D:** Berit D. Brouer, Jakob Dirksen, David Pisinger, Christian E.M. Plum, Bo Vaaben (2012). "The Vessel Schedule Recovery Problem (VSRP) - a MIP model for handling disruptions in liner shipping". In: *European Journal of Operational Research*
(Accepted)

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I would also like to thank my co-supervisor, Steve Altus from the Jeppesen office in San José. A discussion with Steve over a beer one evening in Denver back in 2006 was the basis for the idea about using the flexibility, which flight planning provides, in the disruption management optimization. That discussion planted the seed for this project. Steve has also together with Jason Aggarwal from our UK office been a great and patient help in answering every question I have had regarding flight planning in general and regarding the JetPlan product in specific.

I would like to express my gratitude to John Kelly, Heath Bowden and Thomas Wede for their vision and support for this project, which enabled it to be carried through as an industrial PhD with Jeppesen.

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Part I

Background and Synopsis

Chapter 1

Introduction

Uncertainty is an intriguing factor, which influence many aspects of our daily lives. It makes the world unpredictable and interesting, but does at the same time create problems when it comes to creating and executing plans. Whenever an operational system is exposed to an event, which interrupts or delays the planned operation of the system we refer to this as a *disruption*. Managing these disruptions in order to return the system to its planned operation is referred to as *disruption management*.

Many operational systems require complex planning in order to make the system run smoothly and at low cost. Such complex systems with many inter-dependable activities exist in various areas, but are especially pronounced in the world of transportation.

Apart from often being complex with many inter-dependable activities, transportation systems do also have the inherent property of requiring large amounts of fuel, which is becoming an increasingly expensive resource. This is the reason for incorporating energy considerations in disruption management decisions. We refer to this as *Sustainable Disruption Management*.

This thesis addresses the topic of sustainable disruption management for two transportation industries: The airline industry and the maritime industry. This is done by allowing speed and route flexibility in disruption management decisions. For the airline industry in specific, this is achieved by combining flight planning and disruption management.

Flight planning is the calculation of which trajectory an aircraft should follow in order to fly from airport A to airport B. The flight plan determines both the horizontal and the vertical profile of the flight path. The objective it typically to minimize fuel burn, while satisfying a number of physical constraints and legal rules.

1.1 Scope and Thesis Structure

The company Jeppesen, which has supported and sponsored this PhD project, sells products and services to the transportation industry. The primary market segments of Jeppesen are the airline and maritime industries, with the majority of the business being in the airline industry. For this reason the focus of this dissertation has been divided accordingly, with the majority of the work focusing on sustainable disruption management in the airline industry and a smaller part of the work focusing on sustainable disruption management in the maritime industry.

This thesis is divided into two major parts. Part I provides an overview of the operational environment for the airline and maritime businesses together with related research in these areas. Part II consists of four individual scientific papers, which will be published in international scientific journals.

Part I is divided into several chapters. Chapter 1 gives an overview of planning and execution in the airline and maritime industries, with the primary focus being on decision support systems in the airline industry. The chapter also includes the authors view on the direction of OR in the airline industry. Chapter 2 goes into further detail regarding disruption management. It describes the business process in the Operational Control Center (OCC) of an airline and gives an overview of previous work in this area. The OCC of an airline is usually also the entity from which flight planning is conducted by dispatchers. Chapter 3 describes this flight planning process and also the airspace structure and regulations under which flight planning is carried out. Building on the basis of chapters 2 and 3, chapter 4 describes how disruption management and flight planing can be combined to achieve further operational cost savings as well as an increased focus on fuel and CO_2 emissions in the decisions taken on the day of operation.

Part II consists of four scientific papers and constitute the major part of the work in this thesis. The papers are included in their submitted versions to their respective journals. They have, however, been adjusted to the layout of this thesis and may consequently in terms of layout appear slightly different from the published versions.

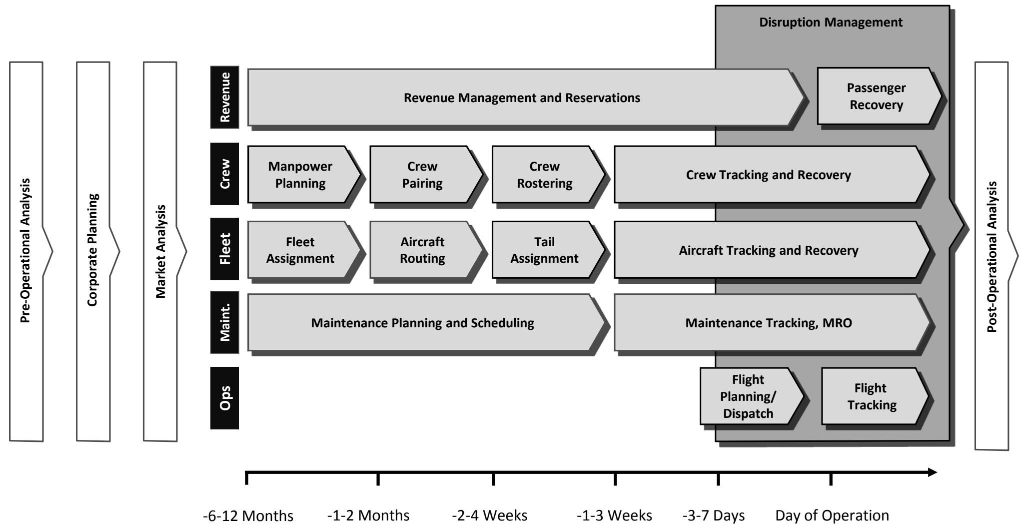

Figure 1.1: Overview of airline business processes

1.2 Planning and Execution in the Airline Industry

In order to place disruption management in a bigger perspective I will in this section provide a very short description of the planning and execution stages in the operation of an airline. Literature describing the operation of an airline is ample. Both in terms of papers and books on this subject. Good surveys are e.g. provided in (Barnhart and Smith, 2011), (Belobaba et al., 2009) and (Yu, 1998).

Figure 1.1 gives a rough overview of the business processes involved in the operation of an airline from year to year. Decisions like e.g. mergers, acquisitions and aircraft purchases should not be neglected as decisions of vital importance for an airline. These are, however not included due to the longer time horizon of these decisions.

As illustrated in Figure 1.1 the airline will look at the operation and profits from the previous year and combine it with the capabilities of the organization in terms of fleet and staffing etc. A market analysis of passenger demand and competition is included as an important input in the overall decisions regarding how the airline should deploy its fleet and with what frequency destinations should be served.

Approximately one year before actual flight operation, different parts of the airline organization will start focusing on planning the operation. A number of business processes are involved in planning the operation as indicated on Figure 1.1. Most of these processes do at larger airlines make use of OR-based Decision Support Systems (DSS). In the following each process is briefly described.

1.2.1 Revenue Processes

The airline will, based on their published schedule, start accepting reservations on their flights. While doing so the *revenue management* department will focus on setting prices in such a way that revenues are maximized and consumer surplus minimized. This is done through continuously opening and closing different fare classes depending on seat availability and historic sales statistics. Each fare class is associated with a specific set of rules in order to limit the demand to specific customer groups. A typical example is to enforce the so-called *Saturday night stay* rule on lower fare class tickets, which requires a passenger to spend Saturday night at the destination, which makes the fare unattractive to business customers, who would like to get home for the weekend.

Revenue management was originally done on a flight-by-flight basis, but many airlines do now use Origin-Destination (OD) pricing, where the price is adjusted based on seat availability and demand for an entire passenger itinerary rather than for the individual flight legs. A good introduction and overview of revenue management can be found in (Belobaba et al., 2009). Revenue management have been celebrated as one of the biggest success stories within the application of OR at airlines and dates back from shortly after the deregulation of the US airline market in 1978.

Once tickets have been sold and passengers embark on their itineraries, things may not go exactly as planned. Bad weather, technical problems, congestions and passengers not showing up for the flight they have checked in on, are all frequent causes for disruptions, which are handled in the disruption management phase on the day of operation. Handling disrupted passengers is referred to as *passenger recovery* or *passenger re-accommodation* and is described in more detail in chapter 2 on page 13. Little research have been published on passenger recovery, but it has been addressed by (Clarke et al., 1999), (Bratu and Barnhart, 2006) and (Vaaben and Alves, 2009).

1.2.2 Crew Processes

Crew management at an airline spans a number of business processes and has for many years been a targeted topic for OR research, due to complicated legal and union rules as well as the high cost of crew. Labour cost did in 2007 account for 23% of operational costs for airlines, which comes in as a close second to fuel cost, which accounts for 26% of operational costs according to Air Transport Association (Belobaba et al., 2009).

Long-term manpower planning is the process of planning the hiring, training and potentially lay-off of pilots and flight attendants in order to make sure that the airline can satisfy its demand for crew with the right qualifications during peak seasons. The process is usually complicated by union agreements requiring that seniority rules must be respected when training is offered for a larger aircraft. This means that the airline's demand for a captain on the 747 fleet cannot be covered by a new hire. It must be offered to a first officer of the 747 fleet, who's position must be offered to a captain from the 767 fleet etc. Covering a captain position on the 747 fleet can consequently require retraining for a large number of pilots and may in some cases need to be planned a couple of years in advance. Long term manpower planing in the airline industry has not been a focus of the OR community. It has, however, recently been addressed in (Holm, 2008).

While long-term manpower planning has received surprisingly little attention in literature, this can not be said about the shorter term manpower planning also referred to as *crew pairing* and *crew rostering*. The problem has been a favourite among OR practitioners for several decades and a survey was published as early as 1969 (Arabeyre et al., 1969). Good introductions and surveys of these problems can be found in (Barnhart et al., 2003) and (Barnhart and Smith, 2011)

The processes of crew pairing and crew rostering serve the purpose of creating crew schedules, which are feasible with respect to legal and union rules, have low cost and often also satisfy crew's requests for time off and trips to specific locations. The two problems would ideally be solved as one, but for most airlines the size of this single problem would be intractable, for which reason it is almost always divided into two problems.

The *pairing problem* takes care of creating *anonymous* round trips, starting at a crew home base, covering a number of flight legs for one to six days and ending at the same crew home base. These round trips are referred to as pairings.

The *rostering problem* takes the generated pairings and assigns these to individual crew members, while again satisfying legal and union, but also respecting commercial requirements such as the required combination of language skills on-board a flight. All pairings need to be assigned to the available crew and each crew member will consequently have a so-called *roster* consisting of a sequence of pairings. A roster typically covers one month of work assignments. For many airlines the rostering stage will also include so-called *preferential bids*. The preferential bids may e.g. include that crew members have requested certain days off, have a desire for short pairings due to family commitments or may prefer trips to certain destinations.

A recent trend in pairing and rostering is to incorporate modelling of pilot alertness into the pairing and rostering processes. This trend has been developed as a consequence of three air traffic incidents from 2006 to 2009 where pilot fatigue played a role, which also increased FAA's focus on this problem (Bohlin et al., 2009), (Moore, 2012). This has now lead to ICAO updating requirements to not only focus on pilot rest rules, but also on fatigue management systems (ICAO, 2011).

When moving from planning crew schedules to executing them, there is one dilemma. In the planning stage the optimization methods vigorously work to get rid of any slack, as this is a typical sign of in-efficiency in the schedules. Slack is, however, exactly what is needed on the day of operation in order to recover schedules. A way of addressing this dilemma is through the introduction of *robust scheduling*. This is surveyed in (Cohn, 2007). An example of robust scheduling for crew are given in (Ehrgott and Ryan, 2002), where the objective function is extended from only focusing on reducing cost to also focus on increasing robustness. This is done by weighting when crew and aircraft should be kept together and when slack should be added to make crew changes less vulnerable to flight delays. Another example of robustness in crew scheduling is given in (Shebalov and Klabjan, 2006), with the consideration of move-up crews in the scheduling phase. Move-up crews are not part of original crew assignments for a given flight, but can in their pairing legally cover the given flight leg. This facilitates recovery in case in-coming crew should be delayed on the day of operation.

Another way of introducing slack in the schedule is suggested in this thesis where the integration of flight planning and disruption management provides slack by allowing flight times to be flexible. This type of slack consequently comes at the cost of increased fuel burn and is addressed further in chapter 4 on page 31.

When crew have been scheduled and their rosters published to them, a time period of typically up to one month goes by, where the airline needs to make sure that the crew rosters continue to cover all flights and are still legal even though smaller changes to both the aircraft and crew schedules may occur: Some crew may be reporting sick, some may have to redo certain training activities and some additional flights may be introduced in the schedule. There are various reasons for smaller changes. This is taken care of in the *crew tracking* phase, which actually extends into the day of operation, where it is often also referred to as *crew recovery*. This will be described further in chapter 2 on page 13 about disruption management.

1.2.3 Fleet Processes

When the corporate planning and market analysis has resulted in a desire for the airline to adjust the previous year's schedule in a certain way and to service specific markets with a desired frequency, the *fleet assignment* process is used to finalize and fine tune the schedule. This is done by solving the Fleet Assignment Model (FAM) which seeks to maximize profits, while covering all scheduled flights and by ensuring that every station has a balance of incoming and outgoing flights of a specific fleet type. FAM has over time been improved and extended in various ways. The fundamental form af FAM is leg-based and an overview of leg-based FAM is provided in e.g. (Hane et al., 1995). One of the shortcomings of leg-based FAM is that it does not incorporate revenue management considerations such as passenger flows from origin to destination (OD-pair) through a hub. This has been addressed in (Barnhart et al., 2002) with a so-called *passenger mix model* combined with FAM. This model incorporates the fact that if a passenger does not find available capacity on his desired OD-pair he will with some probability book a ticket on a subsequent OD-pair of the same airline.

Fleet Assignment determines the flow of fleets through the network, but does not determine how individual aircraft can actually be routed through the network. This is done in the *Aircraft Routing* problem, which can be compared to the pairing problem for crew, where *anonymous* aircraft routes are determined through the network, while respecting turn times and general maintenance opportunity constraints, as every aircraft must undergo certain checks with specific intervals depending on flying hours, number of landings and calendar time. A maintenance opportunity is a gap in the flight schedule at an aircraft maintenance base, where the maintenance department of the airline has the possibility to call the aircraft in for maintenance. Such gaps must be present in each rotation every 3-4 days depending on aircraft type. An overview of maintenance feasible aircraft routing approaches can be found in (Qi et al., 2004) and is further described in (Clarke et al., 1997).

Tail Assignment is the process where the anonymous aircraft routings are assigned to individual aircraft, which are identified by their so-called *tail ID*. The process can thus be compared to the rostering problem for crew. Tail assignment is carried out closer to the day of operation. Typically from 4 to 2 weeks before the day of operation, depending on the scheduling process.

Grönkvist (2005) gives an overview of this process and very successfully implements a combined column generation and constraint programming approach to solve both the aircraft routing and tail assignment problems in one step. Some advantages of this approach is that aircraft specific maintenance requirements can be planned in better time and larger long-term maintenance activities are included in the problem. The approach also enables that more fuel efficient aircraft within a single fleet can be assigned to some of the longer flights in the schedule, which increases their airborne time relative to other aircraft in the fleet. The latter is beneficial as fuel consumption can vary with several percent from aircraft to aircraft even if these aircraft belong to the same fleet. Vice versa it may be that an airline has leased some aircraft on a so-called *power-by-the-hour* contract, where the airline pays according to number of flying hours they are putting on the aircraft. In this case the airline has an interest in reducing the flying hours of the aircraft. Such aircraft can with combined routing and tail assignment be assigned to shorter flights and have more ground time in their rotations. The approach can also give preference to creating so-called *virtual standbys*, where one or more aircraft have larger gaps in their rotations, which allow for covering a round trip flight from the hub to an out-station and back again.

Once individual aircraft have been assigned to flights, the aircraft rotations are moved to the aircraft tracking phase. In this phase changes to the rotations can still occur due to e.g. new charter flights being inserted into the schedule, new maintenance requirements, pilot licenses which have expired for aircraft from certain countries etc. Such events are taken care of in the *aircraft tracking and recovery* phase, which extends into the day of operation and is described further in chapter 2 on page 13.

1.2.4 Maintenance processes

The planning and scheduling processes involved in *Maintenance, Repair and Overhaul (MRO)* is partly addressed by the aircraft routing and tail assignment problems described above as these have to be maintenance feasible. Apart from the shorter term maintenances, which are typically done over-night, aircraft do, after a certain number of flying hours or landings, have to undergo a major overhaul, which requires that it is taken out of service for several weeks. Such larger overhaul activities can be inserted as fixed assignments in the tail assignment problem and are handled somewhat manually in this fashion.

Maintenance activities can be grouped into three types: 1) Gate maintenance, which is typically unscheduled and performed at the gate. 2) Over-night maintenance, which is scheduled and carried out in a maintenance hangar. 3) Major overhauls, which may also include component replacements, such as e.g. landing gear, which needs to be replaced after a certain number of landings. The airline needs to plan when certain components should be replaced as it may be cost beneficial to replace a component when the aircraft is in for maintenance even though the lifetime of the component has not yet expired. The trade-off in this case is the lost lifetime of an expensive component, e.g. the landing gear, when this is replaced before expiration, as opposed to waiting and loosing aircraft productivity due to fact that the aircraft has to be taken out of service once again, when the landing gear expires.

To the knowledge of the author no research has been conducted on the subject of optimizing aircraft maintenance schedules with the objective of minimizing the cost of lost component lifetime and the cost of unnecessary ground time.

1.2.5 Flight operations processes

The flight operation processes take place close to the day of operation and involves *flight planning*. Flight planning is the calculation of a flight plan describing how the aircraft should fly from the origin airport to the destination airport in a safe and fuel efficient way given the current weather, payload and navigational restrictions on the way. This process is described further in chapter 3 on page 21.

A *dispatcher* at an airline is responsible for calculating and filing a flight plan with airspace authorities. After the flight has taken off the dispatcher is responsible for monitoring the flight, including trajectory, inclement weather on the route and fuel burn in order to ensure the safety of the flight. In the US the dispatcher shares the responsibility for the flight's safety with the pilot.

A recent extension of flight tracking is Boeing's recent service offering of *in-flight optimization* (Durham, 2011). This service monitors for individual airborne flight if the planned route can be improved by making small adjustment to the route.

1.3 Liner Shipping versus Airlines

Running an airline and running a liner shipping company may at a first glance seem like two different worlds. The similarities are, however, considerable once we start comparing the transportation networks, vehicles and payload flow within these networks. That the similarities are substantial is further emphasized by the fact that companies operating within one of these two industries have in various cases been seen expanding into the other industry. An example is the Taiwan-based EVA Air, which was founded by the shipping conglomerate Evergreen Group, and has successfully expanded its operation both within air cargo and passenger air transportation. Another example is Maersk Air, which was a part of the Maersk Group from 1969 to 2005. The main business of Maersk Group is Maersk Line, which is the largest shipping company in the world. A final example is Jeppesen, which has its roots and main business in the airline industry. Jeppesen did in 2000 extend its services into the maritime business.

This section describes the similarities and differences between the two industries, with a special focus on the day of operation. The comparison is based on (Christiansen et al., 2007) and personal communication with Christian Plum, Optimization Expert at Maersk Line, and Steffen Conradsen, Director of Maersk Line Situation Room. The Situation Room is the Operational Control Center at Maersk.

1.3.1 Similarities

Regarding the similarities between the two industries it is seen that both larger airlines as well as larger liner shipping companies operate a hub and spoke network, where payload, which in this case is either passengers or containers, may flow from an origin, through one or more hubs to a destination. The vehicles, which the payload is being transported on through the network, is aircraft or vessels. One of the objectives in both industries, when it comes to the day of operation, is that payload arrives with the least possible amount of delay.

For both industries transportation is sold from an origin (air)port to a destination (air)port and payload may connect at one or more hubs. At the hubs connections need to respect a Minimum Connection Time (MCT).

The amount of payload on-board a vehicle do in both industries belong to various itineraries and can within each itinerary group also be subdivided into different value classes. For airline passengers such a value class may be determined by class of service and possibly also fare class, while the value distinction for containers may be based on whether the container is refrigerated - a so-called reefer container - or if it is non-refrigerated. Reefer containers are the most important not to delay. Non-refrigerated containers can be considered to have a lower value and are less important not to delay. An even lower value class is empty containers, which are often left at a port till a subsequent vessel with residual capacity calls the port.

Both industries are heavily impacted by rising fuel cost and fuel constitutes the main part of their operating expenses (Belobaba et al., 2009), (Christiansen et al., 2007). For this reason fuel conservation plays a role in every aspect of their operation, but is still not formally considered in the decision process during disruptions. For aircraft it is possible to increase speeds with 8-10% compared to planned cruise speed. For a vessel, which is originally scheduled to sail at a slow steaming speed of e.g. 16-18 knots, it is possible to speed up with 40% to e.g. 22-24 knots. When considering slowing down in order to conserve fuel, flights soon run into the physical limitation to how much they can slow down. When slowing down, an aircraft will at some point fall down, but before reaching that limit the aircraft will actually increase fuel burn when flying at very low speeds due to increased drag from flap settings. Vessels can decrease speeds significantly without loosing control. The fuel cost and speed flexibility has been one of the main drivers for considering disruption management with speed changes for the liner shipping industry as investigated in the paper in appendix D on page 129.

1.3.2 Differences

Apart from the obvious differences between airlines and liner shipping companies a number of differences are notable in terms of network structure and flows.

One of the main differences in the two industries is the vehicle rotations, which at airlines for each aircraft are planned as rotations starting at a hub, covering a sequence of flights and returning to the hub. Following one rotation the aircraft may continue with a completely different rotation depending on how flights are covered most efficiently. In liner shipping, vessel schedules are like bus schedules, where a cyclic sequence of ports, which is referred to as a *string*, is serviced by various vessels. A sufficient number of vessels are added to the string to typically obtain a weekly departure from every port. The reason for this schedule structure is that payload is more cost sensitive than time sensitive and the structure decreases transportation cost.

The cyclic string structure do, however, also result in vessels never being emptied completely from payload, as it is typically seen following every flight leg for an airline. When considering disruption management this means that the efficient recovery technique of swapping aircraft is not a viable option for the Vessel Schedule Recovery Problem (VSRP). The VSRP does on the other hand allow that the sequence in, which ports are visited can be swapped. This is important in order not be too constrained by quay availability.

Quay space in liner shipping can be compared to gate availability for airlines. Gate availability is typically not a factor, which constrains recovery decision at airlines as gates are often available at many airports and the back-up possibility of *remote positions* are usually always available. Quay space is a far more constraining factor in liner shipping as off-loading and on-loading containers can take many hours, just as loading the tens of tons of bunker fuel, which a vessel can burn per day, can take several hours.

When large delays are experienced at an airline, flight leg cancellations are a frequently used technique for recovering the schedule. The cyclic string structure in the liner shipping industry, does however also eliminate the usage of segment cancellations in the VSRP. An alternative way of recovering schedule time is by not visiting all scheduled ports. This is refereed to as *skipping port calls*. This recovery technique can be used but does leave the problem of handling the containers, which should have been unloaded or loaded in the port, which was skipped. Containers which should have been loaded will be delayed till the next vessel on the string calls the port. Regarding containers, which should have been unloaded, these may be unloaded in the subsequent port and transported back later. In case the decision about skipping a port call is taken early, the vessel can avoid loading containers with the destination of the port, which will be skipped.

Even though there are some clear differences between liner shipping and airline industries, the similarities have been sufficient for making a successful application of some of the recovery methods from the airline world to the liner shipping world. This is emphasized by the statement from Steffen Conradsen at Maersk:

> *"The disruption management study has identified how complex the contingency*

handling process is when something unforeseen happens in the Maersk Line network. Today we are dependant on manual evaluation based on experience and time available to take the right decision. With a disruption tool several options can be identified, downstream consequences assessed and the most efficient solution be presented. This will have a large potential upside and also improve our reaction time to changes which inevitably will happen in our global network. Participating in the project has made it evident to me that we need to identify and develop the right tools for disruption management to reduce our operational expenses." (Enerplan, 2012)

Chapter 2

Disruption Management

This chapter gives a brief description of the workflow and business processes related to disruption management at an airline. The chapter does subsequently review previous work on Disruption Management.

2.1 Introduction

Whenever an event occurs, which makes an airline deviate from its planned schedule or its planned crew rosters, the airline is disrupted. Most larger airlines operate a hub and spoke network, where efficient use of aircraft and crews are causing the airline not to have crew following the aircraft. This is due to the fact that crew work rules are much more restrictive than the rules, which are applied to aircraft. The tight planning of aircraft and crew is causing an airline to become very vulnerable to disruptions, as a delay of a single inbound flight to a hub quickly can propagate to other flights, through delays of both the incoming aircraft and its crew. As this ripple effect in the airline network easily occurs for even small disruptions, it is very important for an airline to manage these in a timely manner.

2.2 Workflow and Business Processes

Most airlines have an Operational Control Center (OCC). Alternative names for this center include Network Operations Center (NOC), System Operations Center (SOC), Airline Operations Center (AOC) and Airline Operations Control Center (AOCC). The term OCC will be used in this paper.

The OCC is by many referred to as "the heart of the airline". It is where *Ops Controllers* monitor the operation of the airline, manage disruptions to the schedule and are responsible for a well-functioning network of flights, crews and passengers on the day of operation. It is jokingly said to be the only place in an airline where the CEO is happy to walk in and see the employees sitting with their feet on the desk without any urgent issues to take care of as this means that the airline is running according to plan.

A smooth execution of all scheduled activities is paramount for an airline as it takes very few disrupted flights on a single day for the airline to go from making a profit to making a loss for that day. The cost of disruptions are estimated to amount to $19 billion annually for airlines in the US alone (Schumer and Maloney, 2008).

The organizational setup of an OCC varies from airline to airline and does to a large extent depend on the size of the airline. There are, however, some typical organizational entities, which are present in virtually any OCC. These are:

- Airline Operations Controllers
  These are sometimes also referred to as just Ops Controllers or Duty Managers and are responsible for the overall operation of the airline's schedule on the day of operation. To

ensure this and to help them in their decisions, they interact with other groups of people in the OCC - mainly the following groups: Aircraft Controllers, Crew Controllers and Customer Service Representatives.

- Aircraft Controllers
  This group of people is responsible for maintaining a feasible schedule and aircraft routing, including that each aircraft is routed back to their scheduled and un-scheduled maintenance activities at one of the maintenance stations. This group of people have a high degree of interaction with the Crew and Maintenance Controllers to ensure the feasibility of un-scheduled maintenance events. The first step in manually solving a disruption is usually that the aircraft controllers come up with a recovery suggestion for the schedule and aircraft rotations. This suggestion is subsequently checked with the crew controllers.

- Crew Controllers
  The Crew Controllers in the OCC receive a suggestion to a schedule change from the aircraft controllers and check if a feasible and acceptable solution for crew can be found. This includes to which extent it is necessary to use standby crews for covering some of the flights in the changed schedule. Early in the day, crew controllers may be reluctant to use their standby crews. If no feasible crew solution is found, this is reported back to the aircraft controllers along with suggestions to schedule adjustments to make the schedule change crew feasible. In this way aircraft and crew controllers may iterate back and forth a few times to find a feasible and acceptable recovery solution.

- Customer Service Representatives
  The Customer Service Representatives in the OCC are responsible for maintaining a proper level of service to the airline's passenger, which is especially important to keep in focus during times of irregular operations as customer service can rapidly deteriorate when the airline starts experiencing even small disruptions. These representatives provide input regarding connections for larger groups of passengers and alerts when VIP passengers are on-board certain flights, which should consequently have a higher focus when handling a disruption.

- Maintenance Controllers
  This group of people are in contact with the maintenance department of the airline and communicate to the Aircraft Controllers in case a maintenance activity will not be finished on time. Vice versa the Aircraft Controllers can also request that a maintenance activity is sped up or shortened in case it severely impacts the operation. The Maintenance Controllers also take care of analyzing any defects, which are being reported to see if these affect the operational performance of the aircraft.

- Flight Dispatchers
  A dispatcher is responsible for a number of individual flights and takes on a flight-by-flight basis care of everything from collecting relevant weather information for a flight to calculating the *flight plan* and monitoring the status and potential risks related to the flight while it is en-route. In many countries dispatchers require a license. In addition to this, the dispatchers in the US share the responsibility for a flight's safety with the pilot.

2.3 Previous work on disruption management

In order to find good recovery solutions in a limited amount of time OR techniques have been applied to the problem. The published models are typically inspired by how the airlines do their manual problem solving, and the models usually address one single resource area each. A few of them focus on one single resource area, while also including aspects of the other areas. A good introduction to disruption management in the airline industry can be found in Yu and Qi (2004) and Belobaba et al. (2009). Kohl et al. (2007) describes a large scale EU-funded project, called Descartes, which addresses various aspects of disruption management. The reader is also referred to an extensive survey of operations research used for disruption management in the airline industry by Clausen et al. (2010).

2.3.1 Aircraft Recovery

Of the 3 resource areas mentioned above, aircraft recovery was the first area to be addressed through the application of OR by Teodorović and Guberinić (1984), who contributed by solving small problems with 3 aircraft and 8 flights, where only delays were considered. This work was later on extended by Teodorović and Stojković (1990), who handled both cancellations and delays for up to 14 aircraft and 80 flights. Jarrah et al. (1993) were the first to publish 2 models, which in combination were capable of producing solutions, which were useful in practice. The models were based on network flow algorithms and were capable of handling fleet swaps, delays and cancellations. The drawback of Jarrah et al. was that cancellations and delays could not be traded off against each other within one single model.

This drawback was later on resolved in the work by Argüello et al. (1997), who formulates the problem as an assignment model, where aircraft resources are assigned to separately generated aircraft routes:

`Minimize:`

$$\sum_{k\in Q}\sum_{j\in P} d_j^k x_j^k + \sum_{i\in F} c_i y_i \tag{2.1}$$

`Subject to:`

$$\sum_{k\in Q}\sum_{j\in P} a_{ij} x_j^k + y_i = 1 \quad \forall i \in F \tag{2.2}$$

$$\sum_{k\in Q}\sum_{j\in P} b_{tj} x_j^k = h_t \quad \forall t \in S \tag{2.3}$$

$$\sum_{j\in P} x_j^k = 1 \quad \forall k \in Q \tag{2.4}$$

$$x_j^k \in \{0,1\} \quad \forall j \in p, \forall k \in Q \tag{2.5}$$

$$y_i \in \{0,1\} \quad \forall i \in F \tag{2.6}$$

$$\tag{2.7}$$

Here F is the set of flights, P denotes the set of generated aircraft routes, Q is the set of available aircraft, while S represents the set of stations. The parameter a_{ij} is 1 if flight i is in route j and 0 otherwise. b_{tj} is a parameter, which is 1 if aircraft route j terminates at station t, otherwise it is 0. The parameter c_i specifies the cost of cancelling flight i, while d_j^k denotes the cost of assigning aircraft k to aircraft route j. Finally does the parameter h_t indicate the number of aircraft, which are required to terminate at station t.

The objective function (2.1) in the model minimizes the total cost of assigning aircraft and possibly cancelling some flights. The constraints (2.2) ensure that all flights are either covered by an aircraft route or cancelled. The aircraft balance constraints (2.3) enforces the requirement that a specific amount of aircraft must terminate at a specific station at the end of the recovery window. The constraints (2.4) ensure that every aircraft is assigned a route. Finally do the constraints (2.5) and (2.6) enforce integrality.

It is observed that the aircraft balance constraints assume that the model only handles a single fleet as the constraint does not enforce fleet specific aircraft to end their routes at a specific station. The model can, however, easily be extended to do so by adding a fleet type index to the variable h_t.

Argüello et al. (1997) uses the model together with a Greedy Randomized Adaptive Search Procedure (GRASP), where this heuristic is used to generate aircraft rotations. In order to evaluate the quality of the heuristic, Argüello et al. apply a time-band approximation scheme and use this for calculating a lower bound for the problems analyzed. The time-band scheme divide the recovery window into time-bands of uniform length and aggregate all activities within each time-band into a single activity. Using this time-band network a lower bound is calculated as an integral minimum cost network flow problem with flight cover side constraints.

Yan and Yang (1996) extends the work of Argüello et al. (1997), but uses a time-line network formulation, without activity aggregation. This has a better handling of especially delays compared to the generate-and-solve heuristic of Argüello et al. (1997). A small example of a time-line network is given in Figure 2.1. Here time is increasing from left to right and each horizontal line represents an airport. Arcs (denoted *flight arcs*) represent planned flights i.e., the arc leaving airport A corresponds to a flight from airport A to B and the horizontal placement of the endpoints represents departure and arrival time. White boxes represent nodes where aircraft start (source nodes) and black boxes represent nodes where aircraft are planned to end their journey within the given time horizon (sink nodes). The small network example in Figure 2.1 could be operated by two aircraft. One starting in airport A, visiting airport B and C before returning back to airport A; and another aircraft starts in airport B, travelling to airport D and back to B before ending at airport D. The network also contains *ground arcs* (not shown) that represent the time spend on the ground, in between flights. As an example, the network in Figure 2.1 would contain four ground arcs for airport B (an arc between node 1 and 2, one between 2 and 3 and so on). Flight delays are represented in the network by so-called *delay arcs*. These are parallel duplicates of the flight arcs and are duplicated with a given frequency interval.

Thengvall et al. (2001) builds upon the work of Yan and Yang (1996) and extends this model to also include so-called protection arcs, which serve the purpose of keeping the proposed solutions somewhat similar to the original schedule. This is important for real-life application of the suggested solutions, as a large number of changes cannot be applied to the schedule last minute.

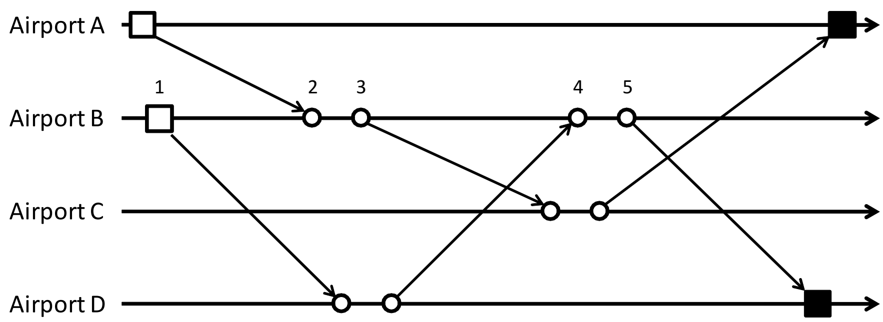

Figure 2.1: Example of time-line network.

Rosenberger et al. (2003) builds on the work of Argüello et al. (1997), where a variable represents a pre-generated aircraft route. Additional constraints are added to ensure that a solution will satisfy airport slot constraints. The model contains a huge number of variables when applied to realistic instances and therefore the authors also propose a heuristic that selects a subset of the aircraft to be included in the model. Computational results show that the approach generates much better recovery plans compared to the short cycle cancellation policy proposed in Rosenberger et al. (2002).

Løve et al. (2005) use a heuristic to solve the dedicated aircraft recovery problem. Good solutions to real life disruption from British Airways are found in less than 10 seconds. The approach focuses on a weighted application of different recovery techniques. The advantage of the approach is that by shifting the weights the approach is capable of producing structurally different recovery options, where some e.g. may have a larger amount of delay propagation, while others e.g. contain more cancellations. The work is described in a larger context in (Kohl et al., 2007)

Andersson and Värbrand (2004) formulate the flight perturbation problem as a set-packing problem. The problem is solved using a Lagrangian relaxation based heuristic and Dantzig-Wolfe decomposition. Problem instances up to 30 aircraft are solved in a few seconds.

Andersson (2006) proposes two meta-heuristics based on simulated annealing and tabu search in order to solve a aircraft recovery problem. Tests are carried out on real-life as well as artificial data. Results show that the tabu search heuristic outperforms the simulated annealing heuristic and that the tabu search heuristic can find high quality solutions in less than a minute.

Recently Eggenberg et al. (2010) proposed a generalized recovery framework using a time-band network, where the same model can be used to solve either an aircraft recovery problem, a passenger recovery problem or a crew recovery problem. They use a column generation approach where the master problem is of the set-partitioning type with side constraints, and the sub-problem is of the resource constrained shortest path type.

2.3.2 Crew Recovery

The second problem, which has been addressed by the OR community is the crew recovery problem. For disruptions, which involve changes to the aircraft schedule, the crew recovery problem is typically solved after the aircraft recovery problem. The objective here is to make sure that all flights are operational with respect to crew. This may involve using incoming crews to operate another flight than the one they were originally supposed to be operating or possibly to use reserve crews on a flight. In other cases it may involve dead-heading crews to another airport, where they are to operate a flight from. Dead-heading means to fly crews passively as passengers to another station, from which they start their active flight.

The crew recovery problem is first addressed in the work by Johnson et al. (1994) in a final report to Northwest Airlines on the crew recovery problem. It is later addressed by Wei et al. (1997), who formulate the problem as set-covering problem with side constraints. The approach is a heuristic depth-first branch and bound search algorithm, where the objective is to minimize the cost of re-assigned pairings. The algorithm starts by identifying originally disrupted crew members and repair their pairings by finding a path back to their home base. It is one of the basic premises of the algorithm, that pairings are maintained legal. After the initial step, some flights are left uncovered and are gathered in a set of uncovered flights, which represent the root of the search tree. An new node in the search tree is created by selecting the first departing flight f from the list of uncovered flights and building a candidate list of crews, which can cover flight f. New legal pairings are generated for these crew members and added to the current set of pairings in the search tree. The pairings and uncovered flights are in each node used as input to an IP model, which minimize the cost of re-assigned pairings.

Yu et al. (2003) present a refined version of the IP model from Wei et al. (1997):

`Minimize:`

$$\sum_{k \in K} \sum_{p \in P_k} c_p x_p + \sum_{f \in F} u_f y_f + \sum_{k \in K} q_k z_k + \sum_{f \in F} d_f s_f \tag{2.8}$$

`Subject to:`

$$\sum_{k \in K} \sum_{p \in P_k} a_{fp} x_p + y_f - s_f = 1 \quad \forall f \in F \tag{2.9}$$

$$\sum_{p \in P_k} x_p + z_k = 1 \quad \forall k \in K \tag{2.10}$$

$$x_p \in \{0,1\} \quad \forall k \in K, \forall p \in p_k \tag{2.11}$$

$$y_f \in \{0,1\} \quad \forall f \in F \tag{2.12}$$

$$z_k \in \{0,1\} \quad \forall k \in K \tag{2.13}$$

$$s_f \in \{0,1,2,...\} \quad \forall f \in F \tag{2.14}$$

Here F represents the set of active flights and P_k is the set of pairings, which crew member k can serve in the recovery window. K is the set of available crew members including both active and reserve crews. The parameter c_p is the cost of assigning pairing $p \in P_k$ to crew member k. u_f is the cost of not covering flight f. The cost of a crew member deadheading on flight f is represented by d_f and q_k denotes the cost of not assigning pairings to crew k. The parameter a_{fp} is 1 if pairing p covers flight f and 0 otherwise. The decision variable x_p is 1 if paring p is part of the solution and 0 otherwise. If flight f is left uncovered the variable y_f takes the value 1 and 0 otherwise. The z_k variable is 1 if crew member k is not assigned any pairing and 0 otherwise. Finally does the variable z_f denote the number of deadhead crew on flight f.

The constraint (2.9) ensures that all flights are either covered by a pairing or penalized in the objective function through y_f being forced to 1. Having excess crew as deadheads on flight f is also penalized in the objective function through the variable s_f. The constraint (2.10) ensures that all crews are assigned a pairing. If not, this is penalized through z_k. Constraints (2.11) through (2.14) ensure integrality.

The model above is presented in the paper by Yu et al. (2003), which also describe the implementation of the CALEB Crew Solver at Continental Airlines. Continental Airlines and CALEB received the Franz Edelman award for this work in 2002.

The approach above is simplified in the way that it assumes a single pairing per set of crew. This can often be used for addressing the pilot recovery problem as the captain and the first officer usually follow the same union agreement and will consequently often have the same pairings. Flight attendants do usually have a different union agreement from the pilots and do consequently often have pairings, which differ from those of the pilots. Individual assignment and preferences can also result in pairings having individual characteristics. Allowing individual pairings is the basis for more efficient rosters and more efficient crew recovery as pairings do not need to be constrained by the most limiting crew member.

The problem, which allows individual crew pairings, has been addressed by Stojković et al. (1998). The approach does, however, only allow modifications to a single pairing per crew member. This single pairing limitation was later addressed by Medard and Sawhney (2007), who handles individual crew pairings and allows changes of multiple pairings per crew member. This is accomplished through a sliding time window.

2.3.3 Passenger Recovery

The third area, passenger recovery, addresses the problem of how to re-accommodate disrupted passengers. The problem requires handling of large amounts of data consisting mainly of so-called Passenger Name Records (PNRs). A PNR describes a booked itinerary for a group of passengers travelling together, where this group often consists of only a single passenger. The PNR data can be modified by a vast number of travel agents all over the world and is maintained in real time by a Global Distribution System (GDS), which also takes care of feeding real-time PNR updates to the airline and their disruption management system.

Passenger recovery has only been addressed by a limited amount of published research. Vaaben (2002) presents a passenger recovery solver. The solver does as part of the objective have the goal of minimizing the expected passenger delays when passengers reach their final arrival destination. This is combined with the *value to the airline* of each passenger as the airline may be particularly interested in minimizing the delay of high-value passengers such as e.g platimun-card holders travelling on first class. An important part of the objective function is consequently to minimize Passenger Value Delay Minutes (PVDM). Other cost aspects, such as hotel accommodation, passenger compensation, upgrade or down grade of service class are also included in the model.

Green and Ande (2005) from American Airlines presents an optimization model, which assigns alternate itineraries to customers who are affected by flight cancellations or delays. The model maximizes the total number of re-accommodated passengers, while giving preference to high value passengers.

Bratu and Barnhart (2006) present a Passenger Delay Model for evaluating passenger delay impact on disrupted historic schedules. This is used to argue that the 15 minute on-time performance metric for flights does reflect the delays, which passengers are experiencing due to misconnections.

From our work with airlines, we have observed that most of these use a sequential passenger re-accommodation process rather than re-accommodation of their passengers based on an IP model. Vaaben and Alves (2009) do a comparison of sequential passenger re-accommodation with re-accommodation based on an IP-model.

The models generally group passengers per booked itinerary and apply a path-based approach for re-accommodating the disrupted passengers. Either through maximizing the total amount of re-accommodated passengers or through minimizing passenger delays.

The basic passenger recovery problem can be formulated as a multi-commodity network flow problem, where groups of passengers represent commodities in the network and where columns represent feasible itinerary paths through the network. The model can be expressed as:

```
Minimize:
```

$$\sum_{j \in PG} \sum_{i \in I(j)} c_{ij} x_{ij} \tag{2.15}$$

```
Subject to:
```

$$\sum_{j \in PG} \sum_{i \in I} a_{if} x_{ij} \leq CAP_f \quad \forall f \in F \tag{2.16}$$

$$\sum_{i \in I(j)} x_{ij} = N_j \quad \forall j \in PG \tag{2.17}$$

$$x_{ij} \in \mathbb{Z}_{\geq 0} \quad \forall j \in PG, \forall i \in I \tag{2.18}$$

Here PG is the set of all passenger groups, $I(j)$ is the set of all feasible itineraries for passenger group j. I is the set of all itineraries considered in the network and x_{ij} is the number of passengers from group j, which are assigned to itinerary i. F represents the set of flights with available seat capacity in the network and which are forming part of one of the itineraries in I. CAP_f is the residual seat capacity on flight f and N_j is the number of passengers, in passenger group j. The coefficient a_{if} is 1 in case itinerary i makes use of flight f and 0 otherwise.

Constraints (2.16) ensure that no more passengers can be re-accommodated on flight f than there are seats available on that flight. For each passenger group, constraints (2.17) ensure that all passengers in each group is assigned an itinerary. By adding columns, which represent *unhandled* itineraries, and giving these a high cost it is ensured that all passengers can be assigned an itinerary. The constraints (2.18) ensure integrality.

2.3.4 Integrated Recovery

The recovery processes and solution approaches at an airline are divided according to the traditional structure of airline departments, where each department is responsible for one resource area. The reason for this division is both historical and practical as each area becomes more manageable and the work is broken down into tractable problem sizes.

The down-side of dividing the problem solving into separate resource areas is that the solution to the over-all problem tends to become sub-optimal as each resource area to a large extent considers input data from another resource area as fixed.

The decisions taken in the OCC are never the less, integrated and a result of an interaction between groups of people representing the different resource areas. The very existence of the OCC is to enable integrated decision making and integrated recovery. This is also the ultimate goal from an OR perspective in order to eliminate sub-optimal decisions.

In spite advances in computer technology and mathematical modelling the integrated problem, which simultaneously solves the aircraft, crew and passenger recovery problems, is still hard to overcome and literature, which addresses the fully integrated problem is limited.

Lettovský (1997) formulates the fully integrated recovery problem in his PhD thesis as a MIP-model and suggests a Benders' decomposition scheme for solving it. The master problem is a schedule recovery model focusing purely on the schedule in terms of delays and cancellations. It does consequently not combine this with aircraft rotations as otherwise seen in literature. Aircraft rotations and swaps are addressed in the aircraft recovery problem and is solved for each aircraft type. Swaps between fleets are consequently not addressed. The crew problem is similarly solved for each fleet. Passengers are re-accommodated on available seat capacity in the network. Lettovský does, however, not try to solve the formulated model.

Petersen et al. (2010) have recently tried to solve the integrated problem using Lettovský's Benders' decomposition scheme. The results show that the approach can be used for limited size problems, where 65% of the flights are disruptable and where the time horizon for solving the disruption is limited to one day. Expanding the scope quickly renders the problem size intractable, which is mainly due to the size of the underlying network for the crew problem.

Semi integrated problems have been addressed in more papers in the literature where a paper focuses on one resource area, but include important aspects or constraints from one or more of the other resource areas. This is sometimes referred to as e.g. *passenger-friendly aircraft recovery* or e.g. *aircraft recovery with crew guidance*

Stojković and Soumis (2001) present a crew recovery model, which incorporates flight re-timings to provide more flexibility. The problem is formulated as a multicommodity network flow problem with side constraints and solved using column generation. This work is extended in (Stojković and Soumis, 2005), where the problem addresses usage of multiple crew members with inter-changeable position as seen for some cabin crew positions. This is modelled by using multiple copies of flight arcs, where crew also flow through the network and where additional constraints ensure that only flight arcs copies starting at the same time can be used for a set of crew.

Stojković et al. (2002) presents a real-time model for flight re-timing within given limits. The model is intended for very minor disruptions, where aircraft rotations, crew rosters and passenger connections can be preserved with small re-timing adjustments. The model could be used for checking if a simple re-timing solution to a small disruption exists, but the model would not be capable of suggesting a solution including swaps or cancellations. The interesting contribution of the paper is that the dual of the proposed model is solvable in real time given its linear behaviour with respect to the size of the problem.

The models presented in appendices B and C can also be viewed as semi integrated approaches as they include both aspects of both passenger itineraries and flight planning.

Chapter 3

Airspace, Regulations and Flight Planning

3.1 Airspace and Air Traffic Control (ATC)

Airspace is divided into different classes. One class is *controlled airspace*, where traffic is supervised and managed by Air Traffic Control to increase safety and to facilitate flying in low-visibility conditions according to Instrumental Flight Rules (IFR). This class of airspace is typically at higher altitudes for en-route traffic. Another class of airspace is the *un-controlled airspace*, which typically is restricted to lower altitudes and primarily is intended for smaller aircraft flying according to Visual Flight Rules (VFR), where the responsibility for separation between aircraft lies with the pilots themselves. Airspace around airports is also highly controlled to ensure a safe ascend and descend as terminal areas typically have a high traffic density. This paper focuses on the higher altitude controlled airspace, which services the majority of commercial aviation flights.

The airspace of a country is regulated by the authorities of the country, in the US it is the Federal Aviation Administration (FAA). While the different countries in Europe regulate their own airspace, they have to a large extent agreed on common rules and have also established a common control entity called Eurocontrol. One part of Eurocontrol is the Central Flow Management Unit (CFMU), which from a central location in Brussels is responsible for a smooth operation of flights across the European airspace.

To clearly distinguish who has the authority to control and regulate in specific areas of the airspace, it is divided into Flight Information Regions (FIRs). Any point in the atmosphere belongs to a FIR. Larger countries have various FIRs, while smaller countries only have one single FIR. If a country is adjacent to a sea area their FIR(s) will usually also include a portion of the airspace over that sea. Figure 3.1 shows the division of airspace into FIRs over Europe. The figure shows that e.g. Denmark only has a single FIR with the code EKDK, while e.g. Germany has 5 FIRs. The US has a total of 21 FIRs. Some FIRs entirely consists of oceanic airspace and are regulated by the International Civil Aviation Organization (ICAO). These are also referred to as Oceanic Information Regions (OIR).

Each FIR has a central ATC center who is responsible for air traffic within the FIR. These are internationally called Area Control Centers (ACC) and are in the US also referred to as Air Route Traffic Control Centers (ARTCC). These centers take care of en-route traffic between terminal areas. When a flight passes from one FIR to another FIR the pilot needs to acknowledge his arrival to the new FIR. The responsibility and control of the flight is at this point passed on to the ACC of the new FIR. Regions with a high density of air traffic such as especially Europe and the US do from time to time run into their capacity limits for certain areas of the airspace. As flights can not stop and wait in-air, an ACC will need to put a flight into a holding pattern in case the subsequent ACC does not have the capacity to receive the flight. A holding pattern is either a smaller deviation from the original path of the flight to make the route longer and delay the entry

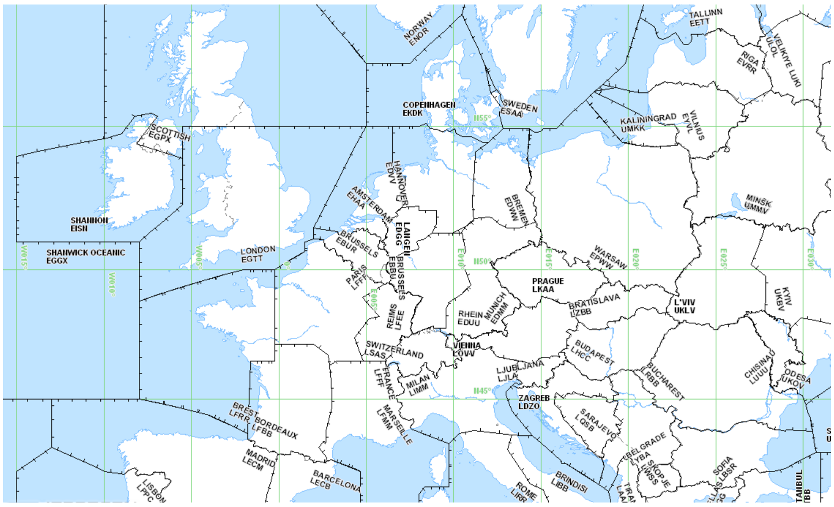

Figure 3.1: Flight Information Regions in Europe. Source: JetPlan, Jeppesen

in to the new ACC or it can even be that the flight is asked to do large circles over the same area. This is in-efficient, creates un-necessary fuel burn and only adds to the congestion of airspace. For this reason Europe and the US have added an additional control layer called Air Traffic Flow Management (ATFM), which coordinates the flow of flights across various FIRs and ensures that holding time does not have to be done in-air but rather can be done on-ground. ATFM will be described further later in this paper.

To coordinate traffic and ensure safety a number of additional elements are defined for the airspace. Among these are *waypoints* and *airways*. A waypoint used to be a physical radio beacon tower which pilots could use as a navigational reference. While radio beacon towers are still in use and still serve as waypoints, additional waypoints have been added with the invention of a more sofisticated navigational system called Area Navigation (RNAV). RNAV allows aircraft to follow a direct path instead of having to fly via a sequence of radio beacon locations. These newer waypoints are simply defined as latitude and longitude points in space.

In the dawn of aviation *airways* were created for some of the US airmail routes as a sequence of lights, which a pilot could follow. Nowadays airways are only marked on maps and are used to maintain air traffic in predefined corridors for ease of coordination from ATC. Together with waypoints the airways create a directed graph, where waypoints represent nodes and airways represent vertices. Figure 3.2 shows airways and waypoints over Frankfurt. Not all airways are available to all flights. Some airways are only open under certain conditions. This is for instance the case with airways traversing military airspace. Such airways are only declared open by ATC, when the military is not requiring usage of the airspace. Other airways are only open to flights, which have previously passed a specific waypoint. The amount of such rules are enormous and does for European airspace at the time of writing constitute approximately 7600 rules in the electronic Route Availability Document (eRAD), which is maintained and published by Eurocontrol (Eurocontrol, 2012). This significantly complicates the process of calculating a legal flight path through the airspace graph from one airport to another airport. This process is called *Flight Planning*.

3.2 Flight Planning

A flight plan describes how the aircraft is going to fly from a Point Of Departure (POD) to a Point Of Arrival (POA) and has to be filed with Air Traffic Control (ATC) before the flight is allowed to take off. The flight plan specifies the intended operation of the flight, which includes:

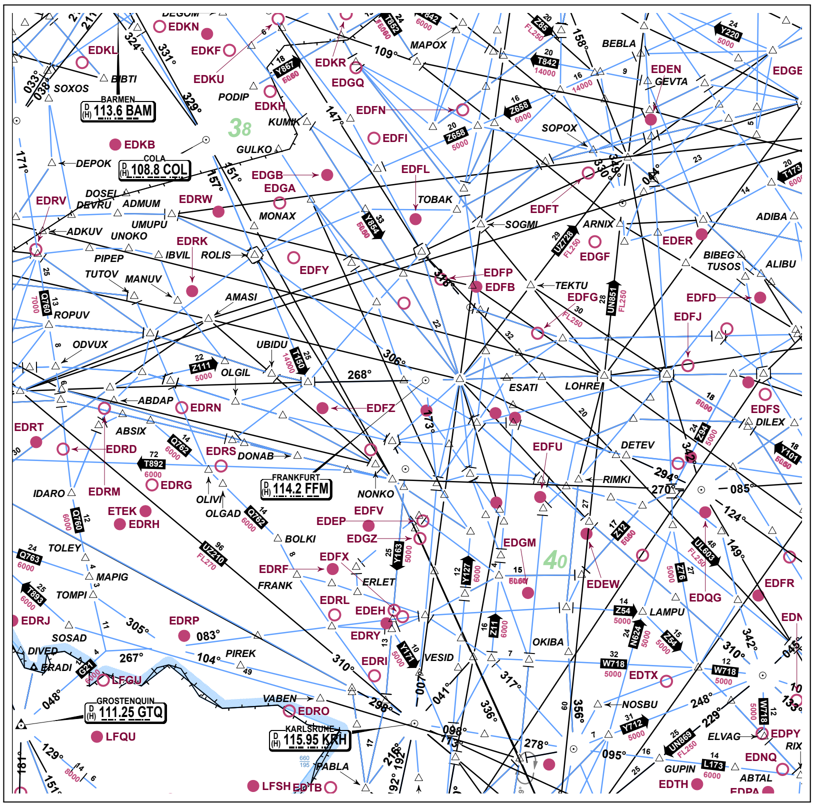

Figure 3.2: Navigational chart of area around Frankfurt, Germany. Source: JetPlan, Jeppesen

Type of aircraft, planned departure time, speed, fuel, route and altitudes. The route is specified as a sequence of waypoints and altitudes. An example of airways and waypoints is given in the navigational chart in Figure 3.2. ATC uses the flight plan to ensure that safety requirements are met. Apart from serving as a guideline to both the pilot and ATC regarding how the flight is going to be conducted, the flight plan also serves as a calculation of how much fuel needs to be loaded onto the aircraft.

Calculating a flight plan is a complex optimization problem in itself. It has, however only been addressed by academia to a rather limited extent compared to other airline related problems. Altus (2012) gives an overview of flight planning related literature and the complexities associated to the problem.

The physical equations of flight motion causes the problem to become a non-linear optimization problem. It has been addressed by (Betts and Cramer, 1995) and (Jardin and Bryson A.E., 2001) using optimal control theory approaches. The disadvantage with these approaches are that once having found the optimal trajectory according to the rules of physics, a complicated correction cycle is needed in order to make the trajectory respect all the regulatory rules. Depending on the logic of the correction cycle the corrected trajectory, which satisfies all regulatory rules may not be the optimal solution to the full problem, which is the one satisfying both physical and regulatory rules (Altus, 2012).

Another approach is to address the problem as a non-linear dynamic network optimization problem, which was first done by (de Jong HM, 1974). An advantage with this approach is that the majority of regulatory rules can be included in the arcs of the network. A challenge with the approach, on the other hand, is that the availability and cost of arcs from a node at time point t to one of the nodes at time point $t+1$ in the network depend on the state of the aircraft in the selected node at time point t. The state of the aircraft at time point t is characterized by a number of variables including: Aircraft weight, altitude, temperature and wind (Altus, 2010). The weight of the aircraft at time point t depends on the amount of fuel initially loaded onto the aircraft and the path taken to time point t. The speed of an aircraft generally varies with aircraft weight. The flight planing algorithm consequently does not only need to decide whether the aircraft should change altitude and direction, but also whether speed should be changed.

3.2.1 Cost Index

An important concept to decide about speed is the *cost index*. All modern aircraft in commercial aviation use cost index as an input to their on-board computer, which is also know as a Flight Management System (FMS). The pilot enters a cost index into the FMS, which basically tells the computer what the value of time is compared to the value of fuel as given in the following definition of Cost Index, where fuel in this definition is measured in kilograms.

$$\text{Cost Index} = \frac{dollars/min}{dollars/kg} \tag{3.1}$$

The definition of the Cost Index consequently expresses the number of kilos of fuel, which the FMS should be willing to burn, in order to save one minute of time. As seen from the definition, a cost index of 0 will minimize the fuel burn by indicating that cost of time is seen as having zero value. In order to calculate the fuel burn correctly, flight planning software also makes use of the cost index definition provided in (3.1). The problem with the cost index definition is that it assumes that the cost of time is linear, which is far from the case in normal airline operation. This is emphasized in (Altus, 2010), where the following sources of cost elements all contribute to the fact that cost of time is not a linear, but rather a piecewise linear function:

- *Subsequent flights.* The risk of delay propagation to subsequent flights makes the cost of time increase significantly once a flight is sufficiently delayed to propagate its delay to a subsequent flight.
- *Operational flexibility.* In case an aircraft is delayed to such an extent that it eliminates a swap possibility with another aircraft, the cost of time increases.
- *Crew connections.* The cost of time increases steeply once a flight gets delayed sufficiently for crew to miss their connections to subsequent flights in their duty.
- *Passenger connections.* Similar to crew connections the cost time for a flight increases steeply if passengers - and especially larger groups of passengers - miss their connecting flights.
- *Goodwill.* Passengers do, among other things, tend to focus on whether scheduled arrival time has been met, when making their internal judgement as to whether they will be returning customers.

The piecewise linear behaviour of passenger misconnections and the associated cost due to loss of goodwill is illustrated in Figure 3.3, which shows how inbound flights to a hub from various locations will incur significantly different passenger misconnections costs depending on the amount of arrival delay and passenger connection possibilities. It is for instance notable that the inbound flight from Mumbai (BOM) will incur a significantly higher cost if arriving 50 minutes late compared to arriving 40 minutes late.

3.3 Air Traffic Flow Management (ATFM)

As previously mentioned the airspace is divided into FIRs, where each FIR has a control center for the area, ACC. In regions with a high density of air traffic an additional coordination layer on top of the ACCs have been established to coordinate the flow of traffic between the FIRs and in this way ensure that air traffic in specific areas do not exceed capacity. The practice of

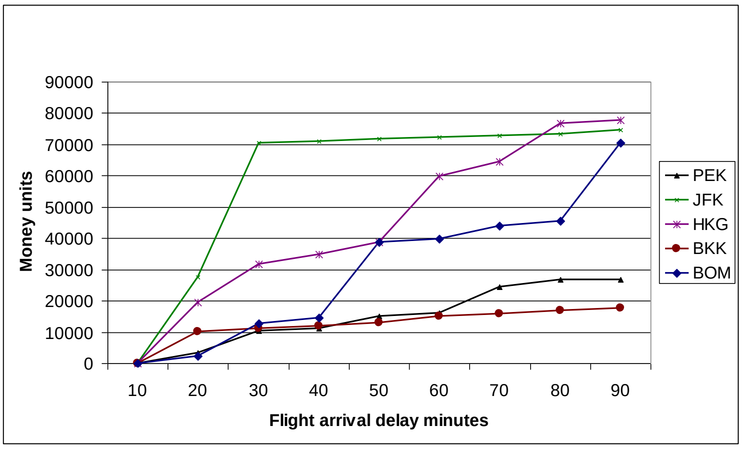

Figure 3.3: Flight delay impact on passenger delay costs.

coordinating air traffic across various FIRs from a system perspective is referred to as *Air Traffic Flow Management (ATFM)*. ATFM is applied both in the US and in Europe, but is not carried out in the same way in the two regions.

3.3.1 ATFM in the US

ATFM in the US is taken care of by the Air Traffic Control Systems Command Center (ATCSCC) located in Northern Virginia. Under nominal operating conditions the ATCSCC does not put special regulation in place in order to restrict the flow of air traffic as the US National Airspace System (NAS) can handle the demand under these conditions. However, when the NAS becomes disrupted due to adverse weather, equipment outages, runway closures or demand surges, the ATCSCC applies special regulations in order to restrict the flow of traffic through the system. One such type of regulation is the Ground Delay Program (GDP) which was initiated in 1998. It is issued when the arrival capacity of an airport is reduced to less than the current arrival demand. In order to match the demand of arrivals with the capacity of the airport the ATCSCC issues a GDP for the airport. Based on an allocation scheme called *Ration By Schedule (RBS)* each airline is granted a number of arrival slots, where the sequence of the arrival slot is the same as in the original schedules of all the airlines. Each airline owns the arrival slots and is able to swap flights between these slots. This is beneficial to the airline as the delay and cancellation costs of one flight may be much higher than the delay and cancellation costs of another flight. It is furthermore possible to sell unused arrival slots to another airline. In order to help dispatchers find good candidates for slot swaps in case of a GDP, Abdelghany et al. (2007) presented a heuristic to do this.

The GDP initiative has been very successful and has according to Metron Aviation avoided 50.000 hours of assigned ground holding since it was initiated (Vossen et al., 2012). Building on this success FAA did in the summer of 2006 implement the *Airspace Flow Program (AFP)* initiative, which extends the GDP procedures to the en-route environment. With the AFP the ATCSCC can enforce a flow restriction across a predefined borderline referred to as a Flow Constrained Area (FCA) and thus restrict the flow of flights in one direction across the FCA. The FCAs which are in effect at any given point in time are published by the ATCSCC as part of the *National Airspace System Status*, which can be found on the website http://www.fly.faa.gov/ois/ This page lists all GDPs and AFPs, which are currently in effect. In the event an AFP is in effect the affected border line FCAs are listed together with the AFP. An example of an FCA is given in Figure 3.4. It shows that East bound flights flying into the New York region across the FCA will have to adhere to the slot times granted by ATCSCC. Each airline is granted a number of slot times according to the Ration By Shedule scheme also used for GDPs. An AFP related slot time is a small time

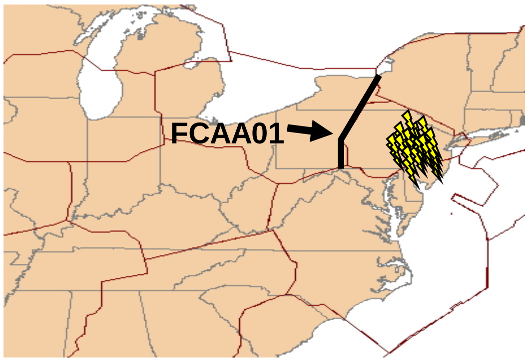

Figure 3.4: A predefined Flow Control Area FCAA01. Source: Principles of AFP for Dispatchers, FAA

window where the airline is granted the right to pass through the FCA with one flight. The airline is allowed to decide which flight should use the slot time and also which time to depart. The constraining element is that the flight will have to arrive to the FCA border line in the granted slot time.

For some flights the carrier may choose to completely avoid this constraint by filing a flight plan, which takes the flight around the FCA. This action will come at the cost of increased flying time and fuel burn.

It is noted that FAA rules ensure that a flight can only be subject to one single ATFM program. It can consequently not be constrained by e.g various AFPs in its flight path even if the direct path takes it through various AFPs. Similarly it can not be subject to both an AFP and a GDP. ATCSCC will in these cases only let the flight be constrained by one of the ATFM programs and thus give the flight priority for the remaining programs in its flight path.

3.3.2 ATFM in Europe

ATFM in Europe is taken care of by the Central Flow Management Unit (CFMU), which is a part of Eurocontrol and located in Brussels. When a flight in Europe flies from point A to point B the pilot - or dispatcher, if the flight belongs to an airline - files a flight plan with the local airspace authorities of point of departure (POD). CFMU receives the flight plan and calculates when the flight will pass through a number of different air sectors on its way. In case any of these sectors have reached their capacity limit, CFMU will issue a *Calculated Take-Off Time (CTOT)*, which is later than the originally intended departure time in the flight plan filed by the carrier. CFMU grants access through the congested air sector on a first-come-first-serve basis in the order of time when flight plans were filed. Based on this policy CFMU issues CTOT-delays to the flights, which have filed flight plans through the congested sector.

In case the dispatcher of an airline determines that the CTOT-delay is too large, he may choose to cancel the flight plan and file another flight plan, which takes the flight around the congested airspace. By doing so he frees up a bit of capacity in the congested air sector. The capacity freed up does, however, not belong to the airline as seen in ATFM in the US. Instead it is now granted to the next flight in line waiting to pass through the congested air sector. All CTOT-delayed flights related to the congested air sector are thus moved up in line.

A dispatcher will consequently only to a limited extent be able to benefit another of his own flights by making the first flight fly around the congested airspace, but the decision may never the less still be beneficial for some of the carrier's flights.

A similar control approach and sequencing for departures is being applied by CFMU when the congestion is not an air sector but the arrival airport of the flight. The main difference in this case is that the dispatcher does not have the option to fly around this airport.

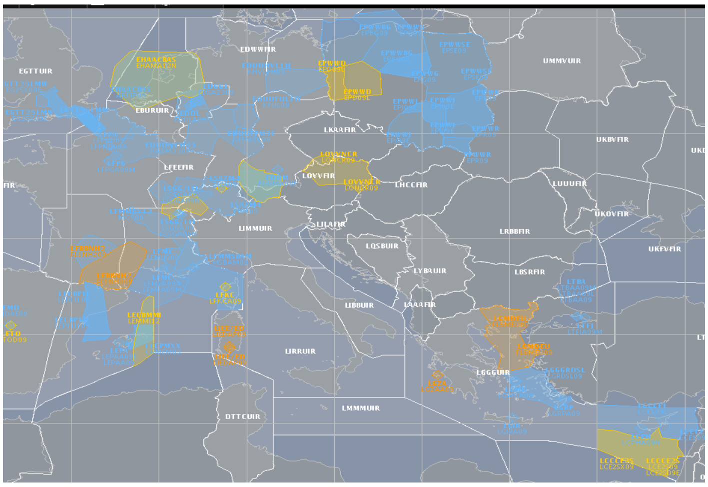

Figure 3.5: Congestions over Europe on September 9th 2012 . Source: CFMU Network Operations Portal

3.3.3 Airspace Congestion

When looking to the sky, airspace may seem plentiful compared to the amount of aircraft manoeuvring in it. Airspace does, however, get congested in areas with a high flight density such as some parts of Europe and the US. Figure 3.6 gives an impression of the severity of the problem, which is seen to be most significant in Europe. Combined with flight density there are two main reasons why airspace gets congested. Both are due to safety regulations (Belobaba et al., 2009):

- ATC needs to keep a large separation between aircraft in their area. Typically 3 to 5 nautical miles horizontally and 1000 to 2000 feet vertically depending on the country and type of airspace.
- ATC is currently based on human controllers, which implies a limitation to how many aircraft a controller can safely monitor at any given point in time. ATC staffing is consequently often seen as a reason to congestions.

Congested areas over Europe can be followed using CFMU's *Network Operations Portal (NOP)*. Not a day passes by without the NOP portal showing various areas in Europe, where en-route and airport delays must be expected. Figure 3.5 displays CFMU's NOP portal at the time of writing on September 9th 2012. The blue, yellow and orange indications are all areas where en-route congestions occurred for some period of time on that day. This gives an impression of how significant the en-route congestion problem is en Europe.

FAA and Eurocontrol have made an interesting comparison of the ATFM related operational performance in the two regions (Eurocontrol and FAA, 2012). While the report shows that en-route congestions is a problem for specific areas in both the US and Europe, it is seen from Figure 3.6 that the problem with en-route congestions is most significant in Europe. The report also states that the risk of getting a departure delay due to en-route congestions is 50 times higher for a flight in Europe than in the US.

Whenever a disruption occurs it typically results in some form of flight delay. A flight delay could for instance be caused by one or more checked-in passengers not boarding the flight and their bags will consequently have to be off-loaded for security reasons, which often results in a delay. This is referred to as a *primary delay*. This delay may have a knock-on effect on a subsequent flight in which case this second flight delay is reported as a *reactionary delay*. The International Airline Travel Association (IATA) have defined a set of delay codes for both primary and reactionary

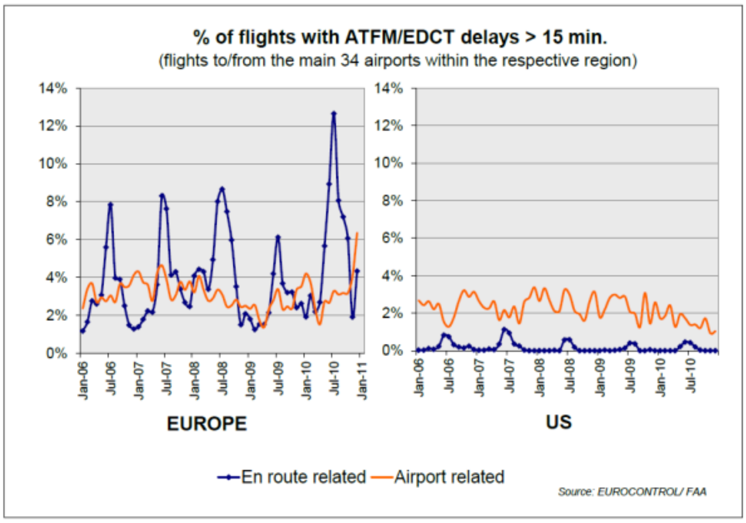

Figure 3.6: US/EU comparison of ATFM delays due to en-route and airport congestions. Source: FAA and Eurocontrol

delays. Airlines use these codes for reporting their delays to Eurocontrol and the delay causes among all airlines are roughly split fifty-fifty between primary and reactionary delays (Eurocontrol, 2010).

It is especially interesting to look at primary delay causes due to the fact that if these are reduced the corresponding reactionary delays will also be reduced correspondingly. In their yearly reports Eurocontrol has published the distribution of primary delays causes for flights in Europe. For 2010 the distribution is shown in Figure 3.7.

In Figure 3.7 it is noted that the majority of the primary delays (41.8%) are caused by factors related to the airline itself, such as technical problems, baggage delays, checked-in passengers not showing up, etc. The second largest portion (32.5%) of primary delays are caused by factors related to Air Traffic Flow Control Management (ATFCM), which is basically the part of Eurocontrol taking care of the flow of flights through different sectors in Europe. The largest subset of the ATFCM-delays are so-called *en-route delays* and correspond to 19.09% of all flight delays.

While en-route delays is not the biggest source of primary delays, it is, however, the fastest growing source of delays as it is seen from Figure 3.8. This source of delays in Europe has increased with an average yearly rate of 17% from 2005 to 2010, which is a good reason to address exactly this kind of delays.

That en-route delays have been rising so sharply in recent years is due to the fact that European airspace is close to reaching its capacity limit. A similar development has also been seen in some areas of the US, especially in the densely populated North East. This is the main reason why both the US and Europe have initiated huge programs called Next Generation Air Traffic Control (NextGen) in the US and SESAR in Europe. Both programs aim at increasing airspace capacity by e.g. enabling more direct flight paths and reduced aircraft separation requirements.

As NextGen and SESAR have not yet been implemented it is on the shorter term important to focus on how disruption management systems can be improved to better address the specific kind of disruptions caused by en-route delays. Even after NextGen and SESAR get implemented the industry will still benefit from more efficient solutions methods, which can properly balance the trade-off between on-time performance and fuel burn.

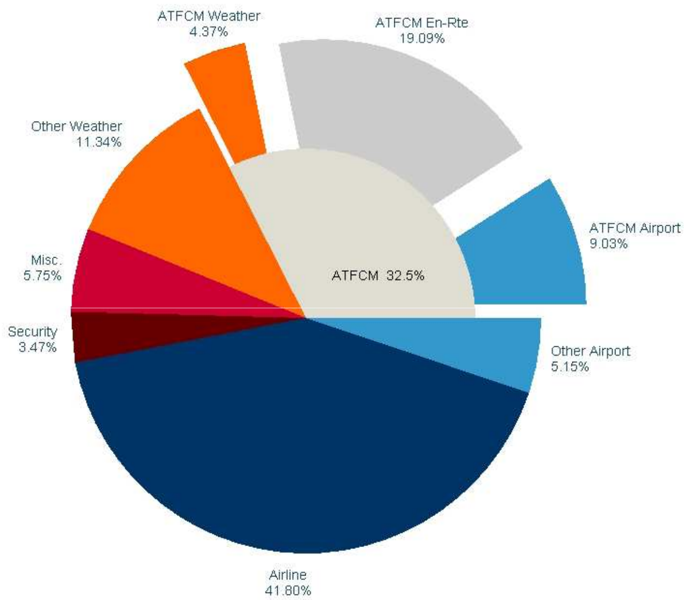

Figure 3.7: Primary Delay Causes in 2010. Source: Network Operations Report for 2010, Eurocontrol

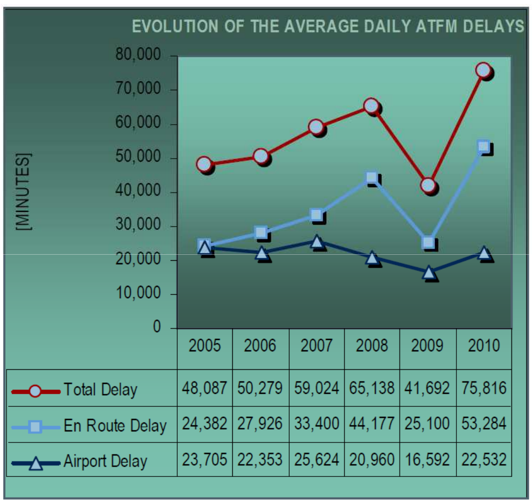

Figure 3.8: Evolution Of Average Daily ATFM Delays. Source: Network Operations Report for 2010, Eurocontrol

Chapter 4

Flight Planning Based Disruption Management

Disruption Management is a rather young research area for OR. The area has, never the less, developed some tradition as to what topics are included in disruption management decisions. Traditionally these areas are:

- Aircraft rotations
- Crew rosters
- Passenger itineraries

This chapter extends these three areas with *flight planning* and describes the purpose of combining flight planning and disruption management.

4.1 Integrated decisions

Any change in schedule of the airline has an immediate and direct impact on other resource areas and can thus quickly affect a large part of the airline operation. Therefore a focal point in disruption management literature is the importance of having integrated decisions on the day of operation.

For this reason the effect on the network of any decision on the day of operation needs to be included in the decision process. The overall supervision and responsibility of such effects lies with the Ops Controllers in the OCC at the airline. Ops Controllers have for decades been supervising airline networks and recovering from disruption by using a combination of three recovery techniques for the aircraft schedule:

- Aircraft swaps
- Flight Delays
- Flight cancellations

One of the primary instruments for monitoring the network effects of disruptions and for recovering from these has been a real-time updated Gantt chart showing the aircraft rotations. In recent years these Gantt charts may also have incorporated visualisation of automated recovery solutions.

The Gantt chart and the three traditional recovery techniques listed above consider flight activities as having a fixed duration of time. One group of people in the airline do, however, not consider flight activities as necessarily having a fixed duration: The dispatchers are responsible for calculating and filing flight plans, and do consequently also have the possibility of speeding up flights to enable connections, or slowing them down to save fuel. They also have the possibility to divert flights around congested areas if needed. The dispatchers do, however, have little interaction with Ops Controllers or Aircraft Controllers in the process of finding recovery solutions to a disruption. Based on the industry experience of the author it is often seen that Ops Controllers and Dispatchers are located in different rooms or different building of the airline. When located close to each other it is rarely seen that Ops Controllers explore the flexibilities in flight planning in the process of finding a good recovery solution.

Finding feasible recovery solutions manually is a difficult task and even more so is the task of finding recovery solutions, which are close to optimal for various resource areas. This may be one of the reasons why ops controllers have not seen the need for introducing an additional level of complexity by adding flight planning as an element of flexibility, when searching for recovery solutions.

With OR-based automated recovery being increasingly applied in the airline industry, the capacity for finding good recovery solutions has been increased significantly. In this light it may be time to increase the solution space by extending the three traditional recovery techniques listed above with the flexibility, which flight planning can provide. The papers related to this thesis is to the author's knowledge the first contributions, which actively incorporate flight planning decisions in disruption management decisions.

The thesis investigates two ways in which flight planning can contribute with increased flexibility in finding recovery solutions. The first is by incorporating *flexible flight speeds* in the recovery decisions. The second is by incorporating *flexible trajectories*. The two approaches can be combined if needed, but have in this thesis been investigated separately. This is mainly due to the fact that flexible cruise speeds mainly are useful for long haul flights, where aircraft spend a relatively long time at cruise altitude. Flexible trajectories on the other hand are mainly interesting to consider where flights are affected by congested airspace. This is most often seen for short haul flights within Europe and in the North East of the US. In the following sections the two approaches are very briefly described.

4.2 Speed Changes

The basic idea behind incorporating flexible flight speeds as a recovery technique is that there is little interaction between Operations Controllers and Dispatcher in the process of finding good recovery solutions. Ops Controllers focus on the larger network and in case of a disruption they come up with a recovery solution based on a combination of swaps, delays and cancellations. They do, however, largely consider flight activities as having a fixed duration of time.

The dispatchers, on the other hand, have the focus on individual flights. They have the possibility of adjusting flight speeds through altering the *cost index* of the flight plans, but it is hard for the dispatchers to determine, what would be the best cost index for an individual flight. One reason why it is hard, is that the cost index input to the flight planning system assumes that the cost of time is linear according to the cost index definition, which is given in equation (4.1).

$$\text{Cost Index} = \frac{dollars/min}{dollars/kg} \tag{4.1}$$

The cost of time in an airline network is, however, not linear, but is very much dependant on connection times as illustrated by a simple example in Figure 4.1 on the next page. The figure shows fuel and passenger re-accommodation costs for a long haul flight with a departure delay of one hour. At normal flight speed for a particular airline using cost index 30, the flight time will be 439 minutes. Speeding up to cost index 300 will reduce the flight time to 435 minutes. The blue line shows that the fuel burn will increase slightly and the magenta line shows that passenger re-accommodation time is not affected as no additional passengers, will be able to make their connection. The red line is the sum of fuel and passenger re-accommodation costs and is

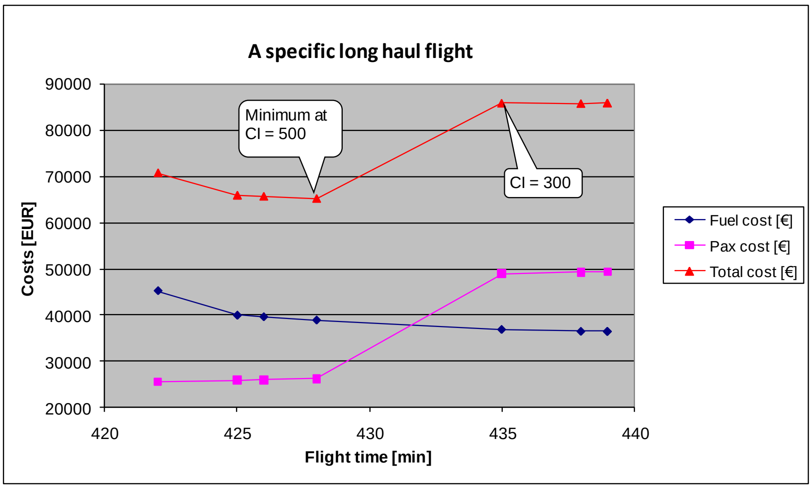

Figure 4.1: Flight time versus fuel and passenger re-accommodation costs.

also unaffected. Speeding up further to cost index 500 will increase fuel burn, but also enable an additional group of passengers to catch their connecting flights. It is also seen that flying at cost index 500 achieves the minimum for the total cost. Speeding up beyond cost index 500 will only increase fuel burn as no additional passengers can make their connections.

The example illustrates the simple logic behind finding the right cost index for a single flight. Even for a single flight the problem may, however, be a bit more complex as the delayed long haul flight may have tight turn time at the arrival airport and may consequently propagate some delay to a subsequent flight. While it can be hard for a dispatcher to determine the best cost index for a single flight, it is even harder for him to determine what would be the best cost index for a number of individual flights given the network dependencies, which connects the flights.

This problem is addressed in the paper in appendix B on page 73. The approach suggests to take a step back and look at the bigger picture by integrating the decisions taken by Ops Controllers and Dispatchers. The approach combines the traditional recovery techniques of swaps, delays and cancellations with cruise speed decisions for long haul flights. The results are promising and show a 66-83% reduction in misconnecting passengers with only a small increase in fuel burn and CO_2 emissions of 0.152 - 0.155%. The total cost saving of the approach is estimated to 5.7 - 5.9% for the airline due to only a small increase in fuel cost and a large saving in passenger re-accommodation cost.

Figure 4.2 on the next page shows an example of a recovery solution with flexible flight speeds. It is noted that the solution contains a number of aircraft swaps within the Airbus 340 fleet. Apart from the swaps the recovery solution also suggests to speed up flight AY068 to cost index 300, which reduces the departure delay of 50 minutes to an arrival delay of 35 minutes. For flight AY030 the recovery solution suggests that the cost index is increased to 900, which reduces the flight time by 40 minutes. This speed-up should be seen in combination with holding flight AY663 as this helps a group of 22 passengers to avoid misconnecting from flight AY030 to AY663.

4.3 Slack On demand

The speed change approach can also be viewed from a slightly different perspective. Recovering from disruptions is not an easy problem to solve, and it has not been made easier in recent years with more and more OR-based tools being applied in the planning phase at airlines. OR-based creation of aircraft rotations and OR-based tail assignment have succeeded in increasing aircraft

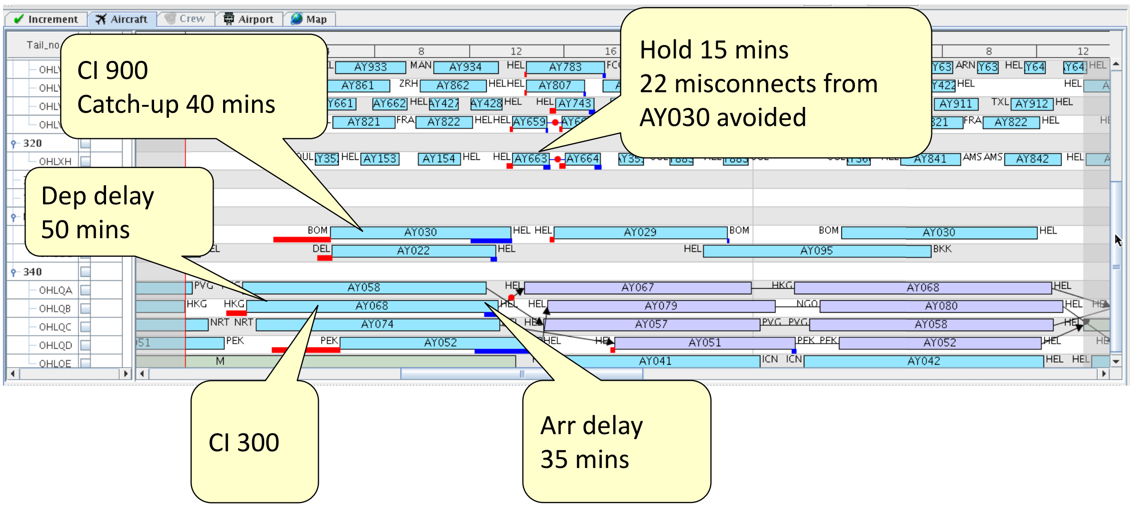

Figure 4.2: Example of recovery solution with flexible flight speeds.

utilization. These advances have come at the cost of aircraft schedules being tighter with less gap between flight activities and generally less slack in the schedule. Robust scheduling have alleviated some of the effect of missing slack and have tried to re-allocate slack to the right places in the schedule.

Allowing flexible speeds as a part of the recovery process can be viewed as a way of having *slack on demand*, where slack to a certain extent for long haul flights can be purchased at the price of the additional fuel required for speeding up.

Similarly when some buffer time have been built into the schedule as a result of robust scheduling the added slack has come at a cost in the scheduling phase and will have no value to the airline once the schedule has been executed without disruptions. By formally calculating, which flights it pays off to slow down, it is possible to trade-in some of the unused slack for a fuel saving.

4.4 Congested airspace

Another area where flight planning based disruption management has a value is in situations when the network of an airline is affected by congested airspace. Also in these situations recovery can benefit from having integrated decisions between Ops Controllers and Dispatchers.

Figure 4.3 on the facing page illustrates how dispatchers may consider filing a flight plan through a congested area or around the congestion. Going through the congestion will result in a departure delay and may cause delay propagation to other parts of the network due to a delayed arrival of the flight. On the other hand, filing a flight plan around the congestion will burn more fuel and may also cause a longer flying time. This decision may consequently also cause a delayed arrival of the flight, but in some situations the delay may be less, than if the direct trajectory was selected. The longer trajectory will, however, burn more fuel. The two different decisions will cause different delay propagation to other parts of the network.

An integrated recovery model including both swaps, delays, cancellations and trajectory selection can help make the proper trade-off between passenger delay cost and fuel cost in congestion situations, where the trajectory selection is of significant importance. This approach is described and analyzed in the paper in appendix C on page 97.

Note that for instance coast-to-coast flights in the US could benefit from a combined approach encompassing both flexible speeds and flexible trajectories as they have a sufficient duration for a

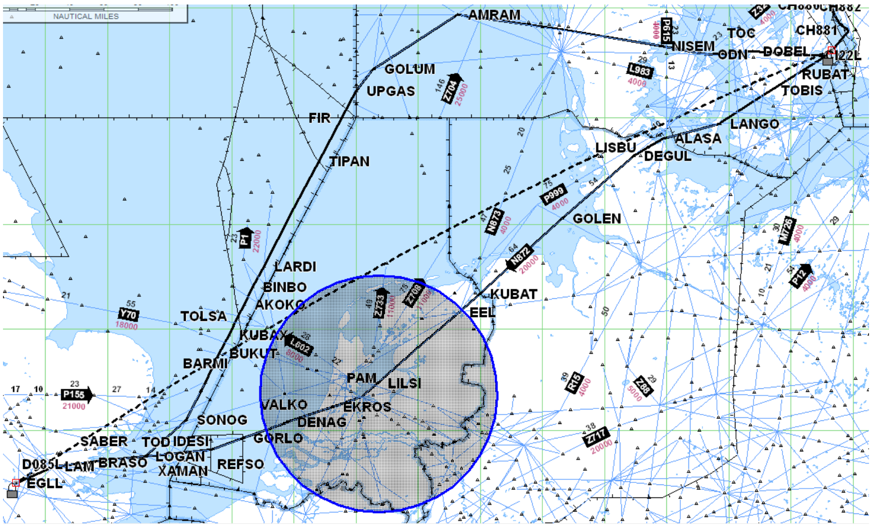

Figure 4.3: Two flight plans going respectively through and around a congested area. Source: Jeppesen

speed change to significantly influence the arrival time and can at the same time be influenced by airspace flow control in the US.

Chapter 5

Summary of Papers

This chapter summarizes the papers, which together constitute the major part of this thesis. For each paper the chapter describes the problem solved, the implemented solution approach, the results and conclusions.

5.1 Paper A: Realistic Models and Computational Results for Disruption Management in the Airline Industry

When recovering from disruptions, it is generally preferred that only a few recovery operations are taken in order to make sure that the recovery solution is implementable in practice. This paper presents and compares two approaches for reducing the number of recovery operations. Both approaches solve the aircraft recovery problem as a multi-commodity network flow problem with side constraints and are based on a time-space network structure.

The first approach uses the concept of so-called *protection arcs*, which covers a sequence of two or more flights in the original flight sequence. The protection arcs can be used at a discount compared to selecting individual flight arcs. This approach was suggested by (Thengvall et al., 2001).

The paper contributes with a second approach, which is the called *Unit Action Penalty (UAP)*. A *unit action* can be either a swap, a delay or a cancellation. UAP is added whenever an action that deviates from the previous schedule is taking place. A low value of the UAP allows the model to choose solutions with few changes among otherwise similar recovery options, while a high value will drive the model to minimize the number of recovery actions even if that means that costly recovery operations, such as cancellations, are needed.

The two approaches are evaluated and compared on two different formulations of the aircraft recovery problem. A fleet based formulation and an aircraft based formulation.

The first formulation is a fleet based formulation, where each fleet represents a commodity type in the multi-commodity network flow model. The fleet based formulation has often been suggested for aircraft recovery as problem sizes are limited with this formulation. The fleet based formulation does, however, not allow modelling of individual aircraft requirements such as e.g. maintenance activities.

The second formulation is the aircraft based formulation, where each individual aircraft represents a commodity type in the multi-commodity network flow formulation. This allows aircraft specific requirements in the model. Maintenance requirements are among the most important individual requirements to model, but various other individual aircraft requirements exist in real-world aircraft recovery problems.

The results show that for a medium size carrier with 200 daily flights it is worthwhile using the aircraft based formulation as it solves to optimality well below a one-minute target. The results also reveal that the UAP is slightly faster than the protection arc approach. It also renders more stable results in terms of running times.

The paper is under review for publication in *Central European Journal of Operations Research.*

5.2 Paper B: Integrated Disruption Management and Flight Planning to Trade off Delays and Fuel Burn

This paper presents an approach, which integrates disruption management and flight planning as the first of its kind. The purpose of the integration is to extend disruption management with the additional flexibility, which flight planning can provide by varying flight speeds. Our key idea in integrating flight planning and disruption management is to adjust the speeds of flights during operations, trading off flying time and fuel burn, and combining with existing mechanisms such as flight holds; all with the goal of striking the right balance of fuel costs and passenger-related delay costs incurred by the airline.

The additional flexibility, which flexible flight speeds provides, helps Ops Controllers find better recovery solutions and it helps dispatchers apply the individual flight speeds, which from a holistic point of view serves the airline network best in order to reduce the combined cost of fuel burn and passenger re-accommodation.

The approach, similarly to one of the approaches in paper A, builds on a time-space network structure and is modelled as a multi-commodity network flow problem with individual aircraft as commodity types in order to satisfy maintenance activities for individual aircraft. The arcs in the network, do, however, not as in previous literature represent *flights*, but rather possible *flight plans* for each flight. The flight plans are calculated through integration with the JetPlan flight planning engine from Jeppesen.

In order to steer the solutions towards an objective, which is not only relevant for the aircraft schedule, we apply passenger misconnection constraints, which drive the solutions towards passenger friendly recovery. This also enables the model to trade off the passenger misconnections costs against fuel burn costs.

A straight forward extension to the approach is to extend the model with crew misconnection constraints.

The approach is evaluated using 3 months of historic disruption data from a mid-size European airline with a relatively large amount of long haul flights. This data is the basis for 60 disruption scenarios and shows that a 66 - 83% reduction in passenger misconnections is possible compared to the traditional sequential recovery without flight plan integration. This is achieved with only a slight increase in fuel burn of 0.152 - 0.155%. The total cost reduction to the airline is estimated to 5.7 - 5.9%.

It is noted that flexible flight speeds mainly contributes to the recovery of long haul flights due to that fact that these flights spend a relatively large amount of their airborne time at cruise altitude.

The paper has been accepted in *INFORMS Transportation Science* on condition of a minor revision. Results from this work has been presented at the *INFORMS annual meeting in Austin, 2010* as well as at *AGIFORS Airline Operations in London, 2011.* It has also been presented at the internal *Jeppesen Operations Research Symposium (JORS) in Denver, 2011*

5.3 Paper C: Mitigation of Airspace Congestion Impact on Airline Networks

This paper presents an approach, which as in paper B combines disruption management and flight planning. But rather than altering the flight speeds, this paper focuses on altering the trajectory in the flight plans. This is relevant in situations with congested airspace, which primarily affects short haul flights within Europe and is also often experienced in the North East of the US.

The approach is an aircraft specific recovery model based on a time-space network and solved as a multi-commodity network flow problem with side constraints. The arcs in the network do also in this case represent *flight plans* calculated through integration with a flight planning engine from Jeppesen. The construction of the underlying time-space network in this approach depends on whether individual flight plans are affected by airspace congestions. In cases where the flight plans are affected by airspace congestions additional flight plan arcs are added to the network in order to allow the model the choice of avoiding the congestion.

For congestions in the US we present an additional constraint which restricts the number of flight through an AFP according to the number of slots granted to the airline.

The paper has been submitted to *Journal of Air Transport Management* and is under review. Results from this work has been presented at *AGIFORS Airline Operations in Atlanta, 2012.* It has also been presented at the internal *Jeppesen Operations Research Symposium (JORS) in Denver, 2012*

5.4 Paper D: The Vessel Schedule Recovery Problem (VSRP) - a MIP model for handling disruptions in liner shipping

Maritime transportation is the backbone of world trade and is accountable for around 3% of the worlds CO_2 emissions. The liner shipping industry is increasingly committed to decrease CO_2 emissions through a *slow-steaming policy* to provide low cost and environmentally conscious global transport of goods. However, more than 70% of all liner shipping round-trips suffer delays in at least one port (Notteboom, 2006).

Despite these figures and that the liner shipping industry has a network structure, which - in terms of container flow - resemble the hub-and-spoke structure found in airline networks, we found no research addressing OR-based disruption management in this industry.

The slow-steaming policy used by many liner shipping companies creates a large amount of "slack on demand" in this industry and makes the concept of dynamically managing the speeds - as proposed in paper B - very attractive for liner shipping.

This paper presents an analysis of the recovery techniques, which are available on the day of operation in a liner shipping company, and a comparison of these to the techniques used in the airline industry. Based on this analysis we propose a model for solving the *Vessel Schedule Recovery Problem (VSRP).* The model is evaluated based on computational results for four real-life cases representing common disruptions. The cases have been selected by experienced Ops Controllers from the OCC at Maersk Line. The recovery options identified by the mathematical model are comparable or superior to the decisions implemented in real life with cost savings of as much as 58%. The model is solved by a MIP solver within seconds for the selected cases.

The paper also presents a set of generic test instances with an increased number of vessels and ports affected by a disruption. This provides insight into the network sizes, which can be handled in real time by the solution approach.

The paper has been accepted in *European Journal of Operational Research.* In addition to this the work has been presented at the *European Conference on Operational Research in Vilnius, 2012*

Chapter 6

Conclusion

In the following the main findings of the thesis are summarized and the contributions are highlighted. This is followed by a final section with reflections on trends in Airline OR and ideas for future work in the context of this thesis.

The thesis has addressed real-life applications of disruption management and has more specifically described, how it is possible to integrate fuel, speed and trajectory considerations in the decision support systems for disruption management. This has been addressed for two different areas of the transportation industry, primarily for airlines and secondarily for liner shipping. The thesis has described how disruption management fits into the broader context of airline operations and has for liner shipping described the similarities and differences in how disruption management can be carried out in the liner shipping industry compared to how it is done at airlines.

The thesis has addressed different aspects of disruption management for the two industries. This has been done through four specific projects, where three of the projects concerned the airline industry and one project related to the liner shipping industry. In the following the main findings for each of these projects are summarized:

In paper A we compare two exact aircraft recovery models based on multi-commodity network flow representations. The first model is a fleet based formulation, where the commodities in the network are anonymous aircraft belonging to a specific fleet. The second model is an aircraft based formulation, where the commodities are individual aircraft. In real-life applications it is important to find solutions to the aircraft specific recovery problem. Some of the reasons are:

- Planned maintenance activities are aircraft specific.
- It is important to be able to control the number of aircraft swaps within the same fleet in order to ensure that the recovery solution is implementable in practice.
- Even though aircraft belong to the same fleet they do often have individual characteristics such as, auxiliary tanks, differences in in-flight entertainment systems and type of lease contracts.
- Finally may an aircraft get minor deficiencies, which do not leave the aircraft in-operational, but does limit it to specific routes.

Even though the aircraft specific model is significantly slower than the fleet specific model we concluded that it is feasible to find optimal aircraft specific recovery solutions for a medium sized carrier with approximately 200 daily flights, as solution time stay well below the one minute target. We also compare two different techniques for limiting the number of recovery actions in a solution. One of these techniques is the Unit Action Penalty, which was found to be slightly faster and more stable in terms of solution times, compared to the Protection Arc method.

For larger carriers, it may be necessary to use additional techniques in order to reach practically useful solution times. Such techniques could include application of an arc reduction technique, which is described in one of the papers in the thesis, or applying column generation to solve the problem. It should also be said that reaching an optimal solution to this problem on the day of operation is not strictly necessary in practice. Being within a few percent from optimality after one or two minutes of running time will be satisfactory.

One of the primary contributions of the thesis is presented in paper B where we integrated disruption management with flight planning. To the knowledge of the authors this is the first paper, which addresses this integration. The idea behind the proposed optimization model is to use *flight plans* instead of *flights* in the aircraft recovery model. Penalties for broken passenger connections are added to the model in order to drive the trade-off between the additional fuel burn cost caused by speeding up some flights and the passenger delay costs caused by misconnecting passengers. The approach is mainly applicable to long haul flights, where the flight time can be significantly influenced by changing the speed. The proposed model creates a basis for making more informed decisions regarding flight speed and fuel burn and thus avoid speed change decisions, which are simply based on gut feeling or basic rules of thumb.

By allowing flexibility in long haul flight speeds as a part of the disruption management process, a total cost saving of 5.7% was achieved. Apart from benefiting the airline in terms of reduced costs, a large reduction of more than 65% fewer misconnecting passengers was also seen and does consequently increase the service reliability, which airline passengers are experiencing. These results are achieved with only a small increase in fuel burn of 0.15%.

Another of the primary contributions is presented in paper C, where we identified the opportunity of using the flexibility, which the dispatchers at an airline can provide in the recovery process, when airspace is congested. This paper does, as in the previous paper, integrate flight planning and disruption management, but does so by focusing on the flight plan trajectory, rather than the speed. Many short haul flights in especially Europe, but also in the North East of the US, operate in airspace, which is severely affected by airspace congestions. In European airspace congestions are the fastest growing source of delays and have over the previous five years shown an average yearly increase of 17%. One of the main contributions of this paper is how airspace congestions are integrated in the underlying network structure of the optimization model. As a special case for airspace congestions in the US, we do as another contribution propose a method and a model extension, which allows prioritization of, which flights should use the few available slot times, which an airline has been granted, for traversing a Flow Constrained Area in an Airspace Flow Program. The model allows this prioritization to be made as an integrated part of the disruption management decision.

Experimental results indicate a lower bound yearly saving of 5.1 millon USD for a single fleet of a medium size European carrier, despite the fact that the hub of the carrier is located outside the central part of Europe.

The last paper (D) takes the application of decision support for disruption management to the industry of liner shipping and does to the knowledge of the authors represent the first literature on decision support for disruption management in a liner shipping network.

The main contribution of this paper is a model for handling the Vessel Schedule Recovery Problem (VSRP) and incorporates the specific recovery constraints, which are encountered in this industry. The work is inspired by the disruption management solution methods used for the airline industry and does in this initial work already incorporate fuel and speed considerations.

The model is applied to four real-life cases from Maersk Line and results are achieved in less than 5 seconds with solutions comparable or superior to those chosen by operations managers in real life. Cost savings of up to 58% were achieved by the optimization based solutions compared to the manually realized recovery costs for the real-life cases.

6.1 Main contributions

The main contributions of this thesis are primarily the contributions related to the individual projects and are consequently also discussed in the corresponding papers. The list below contains the most important contributions.

- The idea of using *flight plans* in stead of *flights* as arcs in the network of the aircraft recovery problem.
- The additional recovery technique of adding speed changes as a recovery technique in addition to the traditional techniques of swaps, cancellations and delays.
- A further addition to the recovery techniques: An integrated recovery approach for handling diversions around congested airspace.
- A model and an approach for prioritizing, which flights should use the few available slot times for traversing a Flow Constrained Area in an Airspace Flow Program.
- A concept and an initial business value analysis for an integrated disruption management and flight planning system. Such a system can support increased interaction between dispatchers and ops controllers and can in this way benefit from the value, which the dispatch function can contribute with in the recovery process.
- A method for limiting the amount of recovery actions, which can occur in an aircraft recovery solution.
- A comparison of two approaches for limiting the amount of recovery actions in aircraft recovery solutions.
- An arc reduction technique for the aircraft specific recovery problem. The Constraint Programming based technique ensures that aircraft, which are present in one area of a network at a given point in time, will not be represented by arcs leaving a flight departure node, if it can be concluded that the aircraft cannot propagate through the network in order to reach the departure node.
- To the knowledge of the authors, we contribute with the first model and experimental results for the Vessel Schedule Recovery Problem (VSRP). This model addresses disruption management for liner shipping.

6.2 Trends in Airline OR and Future work

This section contains a short reflection on trends in Airline OR and describes how the work of this thesis fits into this trend and where the author sees how future research can continue this trend.

The airline industry has benefited from OR for several decades and OR practitioners have vice versa been benefiting from the willingness of airlines to accept new methods and supply data for research. This has taken place since the 1960s with crew pairing and rostering, and later on also revenue management and fleet assignment. There has been a trend in Airline OR where the problem focus have slowly been moving from left to right when looking at Figure 1.1 on page 5. This is very pronounced in the crew areas where research started with pairing and moved onto rostering. The efficiency and compact schedules obtained through this optimization started the focus on robust optimization and has continued to the day of ops, where we still experience challenges in getting fully integrated solutions on the day of operation and where airlines are also still hesitant to replace manual recovery with OR-based automated recovery.

A similar development from left to right has been seen in fleet related OR research, where planning problems have been addressed for several decades and are also widely adopted by the industry. Aircraft recovery itself is reaching a more mature level and I do with the work in this thesis hope that we can reach further into the actual flight operation by integrating recovery and flight planning. This supports the trend in airline related OR and the movement from left to right in the previously mentioned figure, as the problems addressed are getting closer and closer to the actual flight operation.

A step further into the actual flight operation has already been taken with the recently launched *Boeing In-flight Optimization* (Durham, 2011). This work focuses on creating trajectory adjustments for an aircraft while it is in flight. This is based on weather updates and verified for conflicting en-route traffic before being proposed to pilots and ATC for approval. The current in-flight optimization is, however, done on a per-flight basis and does not take network considerations into account.

As future work it would be very interesting to combine the current in-flight optimization of Boeing with the two projects, which integrate flight planning and disruption management, in this thesis. This would allow in-flight optimization to not only be performed on a per-flight basis, but rather on a network basis.

An additional area, which would be very interesting to take further, is the combined flight planning and disruption management approach for congested airspace. What still needs to be evaluated is how this approach performs in a US airspace setting, where Air Traffic Flow Management (ATFM) is regulated slightly different from in Europe. ATFM in the US grants a number of slot times through a Flow Controlled Area (FCA) to an airline and lets the airline decide how to use the slot times. In Europe ATFM grants the slot to a specific flight plan for a flight. If the flight plan is not used, the slot time is lost. The airline side of the congested airspace problem in the US consequently becomes a bit more interesting as there is more to decide in terms of flight prioritization.

The topic of simultaneously solving the aircraft and crew recovery problem is still a research area, which deserves attention. Valuable research contributions have been done in this area, but for real-life disruptions the problem of finding integrated recovery solution for especially aircraft and crew remains one of the primary challenges for disruption management in the airline industry. Using flexible flight speeds and adding crew connection constraints may for long haul flights help in generating more crew-friendly solutions with less misconnecting crews.

A final area, which would be interesting to investigate further is the Vessel Schedule Recovery Problem, which could be extended with additional recovery techniques, which have been identified as sometimes being applied in the current manual recovery operation. These include the decision of only *unloading* containers in a port, but not *loading*, in order to reduce the port call time of a delayed vessel.

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Part II

Research Papers

Appendix A

Realistic Models and Computational Results for Disruption Management in the Airline Industry

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Abstract It is important for an airline to manage disruptions in order to ensure that the airline returns to its original planned schedule as quickly and cost efficiently as possible. A central part of disruption management is the aircraft recovery problem. This paper presents and compares two models for the aircraft recovery problem. The comparison is done with an emphasis on solving real world problems with the corresponding constraints, such as ensuring that an unlimited number of changes to the aircraft schedule cannot be implemented last minute or that maintenance and other aircraft specific constraints have to be respected.
Keywords: Disruption Management, Aircraft Recovery, Flight Delays, Flight Cancellations, Aircraft Swaps, Airline Industry

A.1 Introduction

Flight delays and other disruptions in the airline industry have been estimated to cost the US economy alone more than $41 billion in 2007 (Schumer and Maloney, 2008). Of these, $19 billion was estimated to be costs to the airlines, while the remaining cost was partly due to the passenger's cost of time and partly due to cost incurred in related industries. Running an airline is a costly business. The fixed expenditure on capital equipment is very high, while margins often are relatively low. At the same time the industry is exposed to a high degree of uncertainty due to e.g. weather, airspace congestions and technical problems. In order to turn a profit, airlines have for many years been using Operational Research (OR) to optimize their planned operation with respect to yield, crew and aircraft. The problem is that a substantial amount of all flights do not operate according to their planned schedule. This creates the need for also having efficient recovery techniques for the day of operation.

A.1.1 Disruption Management

Whenever an event occurs, which makes an airline deviate from its planned schedule or its planned crew rosters, the airline is disrupted. Most larger airlines operate a hub and spoke network, where efficient use of aircraft and crews are causing the airline not to have crew following the aircraft. This is due to the fact that crew work rules are much more restrictive than the rules, which can be applied to aircraft. The tight planning of aircraft and crew is causing an airline to become very vulnerable to disruptions, as a delay of a single inbound flight to a hub quickly can propagate to other flights, through delays of both the incoming aircraft and its crew. As even small disruptions in this way quickly can propagate to a large part of the airline's network, it is very important for an airline to manage disruptions in a timely manner.

Most airlines have an Operational Control Center (OCC), where people from different areas of the airline are gathered in order to ease communication and be able to take decisions fast. These people are often referred to as Ops Controllers.

A.1.2 Observations from Operational Control Centers

When solving a disruption it is important to find a solution, which brings the airline back to its original plans as quickly and cost efficiently as possible. The Ops Controllers often only have a limited number of minutes to come up with a solution. One of the authors of this paper has been employed at one of the leading providers of software and services for operational planning of commercial airlines for 11 years. Working closely with OCCs of several airlines has led to the observations that when solving disruptions manually, the Ops Controllers typically only have time to come up with a single solution to a disruption. For complex disruptions the manually found solution is usually far from the optimal solution. In the manual solutions the Ops Controllers often chose to cancel flights, which did not necessarily have to be cancelled or they opt for a simple solution approach, where flight delays are propagated to the subsequent flights until the slack in the schedule allows the airline to return to normal operation. Simple solutions with flight delay propagation will typically lead to a slower recovery with many more passengers being affected than if you are able to find a solution, which makes use of the aircraft swap possibilities in the schedule.

Even though flight delay propagation does usually not result in the most efficient kind of solution for passengers and crew, it does posses the property that it is easy to figure out manually and easy to implement when it comes to the actual communication ot the required changes to the affected areas in the airline. A theoretically more efficient solution which involves many swaps is often more difficult to implement as it may require many operational changes in a very short period of time, such as e.g. physical aircraft tows between gates, fuelling instruction changes, catering changes and communication of gate changes to passengers. For this reason Ops Controllers need to strike a balance between the cost effectiveness of a solution and the practical implementability of a solution. The solution approach suggested in this paper help controlling this balance.

All of the airlines we have been in contact with separate their manual solving of disruptions into three main resource areas: aircraft recovery, crew recovery and passenger recovery. The solution process typically initiates in the aircraft resource area, where problems in the flight schedule are resolved. If this is causing some crew members to have assignments, which are either impossible for them to reach or conflict with legal or union rules then these crew problems are solved subsequently. For disruptions, which only affect the crew area, such as for instance a crew member reporting in sick, the solution process typically initiates in the crew resource area. The passenger resource area is usually the last one being resolved. This is due to the fact that even though passengers are the reason for an airline operating its flight, the passengers never pose a hard constraint for a recovery solution. A recovery solution needs to be feasible for both aircraft and crew in order to be operational for the airline. This solution may not be a particularly good solution for the passengers, but it does not prohibit the operation.

A.1.3 Previous work on Disruption Management

In order to find good recovery solutions in a limited amount of time OR techniques have been applied to the problem. The full problem of recovering all 3 resource areas of aircraft, crew and passengers is, however, so complex that no work has been published so far, which cover all 3 areas in one single integrated model. The published models are typically inspired by how the airlines do their manual problem solving, and the models usually address one single resource area each. A few of them focus on one single resource area, while also including aspects of the other areas. A good introduction to disruption management in the airline industry can be found in Yu and Qi (2004) and Belobaba et al. (2009). Kohl et al. (2007) describes a large scale EU-funded project, called Descartes, which addresses various aspects of disruption management. The reader is also referred to an extensive survey of operations research used for disruption management in the airline industry by Clausen et al. (2010).

Of the 3 resource areas mentioned above, aircraft recovery was the first area to be addressed through the application of OR by Teodorović and Guberinić (1984). This work was merely academic in its scope and only considered flight delays. It did not consider cancellations and aircraft swaps. Over the years more practically applicable models were developed. These will be addressed later in this paper, in section A.2.

The second problem, which has been addressed by the OR community is the crew recovery problem, which was initially addressed in the work by Johnson et al. (1994). Later work include Wei et al. (1997), Stojković et al. (1998), Lettovsky et al. (2000) and Medard and Sawhney (2007). For disruptions, which involve changes to the aircraft schedule, the crew recovery problem is typically solved after the aircraft recovery problem. The objective here is to make sure that all flights are operational with respect to crew. This may involve using incoming crews to operate another flight than the one they were originally supposed to be operating or possibly to use reserve crews on a flight. In other cases it may involve dead-heading crews to another airport, where they are to operate a flight from. Dead-heading means to fly crews passively as passengers to another station, from which they start their active flight.

The third area, passenger recovery, has only been addressed by a very limited amount of published research. The main contribution in this area is done by Bratu and Barnhart (2006), who present a Passenger Delay Model. From our work with airlines, we have observed that most of these use a sequential passenger re-accommodation process rather than re-accommodation of their passengers based on an IP model. Vaaben and Alves (2009) does a comparison of sequential passenger re-accommodation with re-accommodation based on an IP-model.

In this work we are focusing on aircraft recovery as this is the central part of disruption management, due to the fact that changes here affect both crew and passengers through changes to the schedule. The work does not address the subsequent process of recovering crew and passengers.

A.2 Aircraft Recovery

Aircraft recovery is the task of returning an airline's schedule back to normal operation as quickly as possible, while incurring a minimal amount of cost. The operations available to an ops controller in order to complete this task are: delaying flights, canceling flights or swapping flights. A recovery solution will typically consist of a combination of these operations. In rare cases an ops controller may also chose to *ferry* a flight, which is to fly an aircraft from airport A to airport B without passengers in order for that aircraft to be able to carry out a scheduled flight from airport B.

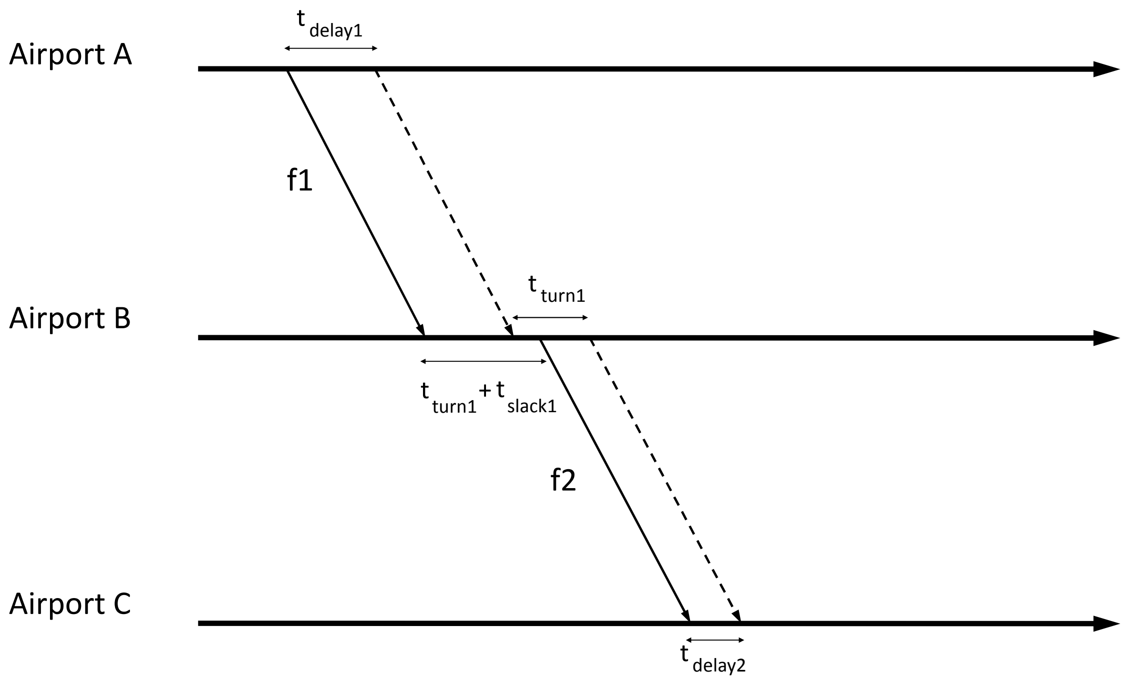

Figure A.1: Delay Propagation

Delaying one or more flights is an operation, which is frequently used when doing manual recovery in an OCC. A simple solution to a small delay of a flight is to propagate some of this delay to the subsequent flights, which are already assigned to that same aircraft X. Delay propagation is illustrated in Figure A.1, where flights $f1$ and $f2$ both are assigned to the same aircraft. Flight $f1$ is experiencing an inbound delay of t_{delay1}. Since the aircraft has to respect a turn time of t_{turn1} this is going to delay flight $f2$ by $t_{\text{delay2}} = \max(0, t_{\text{delay1}} - t_{\text{slack1}})$ where t_{slack1} is the slack time built into the schedule.

Adding slack to a schedule in the planning stage usually has a cost. The trade-off between a more robust schedule with slack and a less robust schedule without slack is handled in the planning phase and is referred to as robust scheduling as decribed in e.g Ahmadbeygi et al. (2010). Observation from the industry show that the degree to which robust scheduling is used varies widely from airline to airline. Some airlines, like the one which has provided data for this paper do, however, add rather little slack between flights. In such cases an inbound delay of a flight does usually not have to be very large before simple delay propagation leads to a bad recovery option, where many affected passengers as well as several subsequent flights can be affected before the schedule is recovered.

As an alternative to simply propagating delays it is often a good choice to combine delays with *swapping*. An aircraft swap is illustrated in Figure A.2. In the illustration the flights $f1$ and $f2$ are in the original schedule assigned to aircraft X, while flights $f3$ and $f4$ in the original schedule are assigned to aircraft Y. We now assume the same input problem as in the previous delay propagation example from Figure A.1, where flight $f1$ has an inbound delay of t_{delay1}. The swapping technique implies that aircraft X is re-scheduled to fly $f1$ and $f4$, while aircraft Y is rescheduled to fly $f3$ and $f2$. By using the swapping technique we can avoid propagating the delay of t_{delay2} (on figure A.1) to flight $f2$. The illustration is a simple 2-way swap involving only 2 aircraft, but a swap may also be a 3-way or N-way swap, where N is the number of aircraft involved

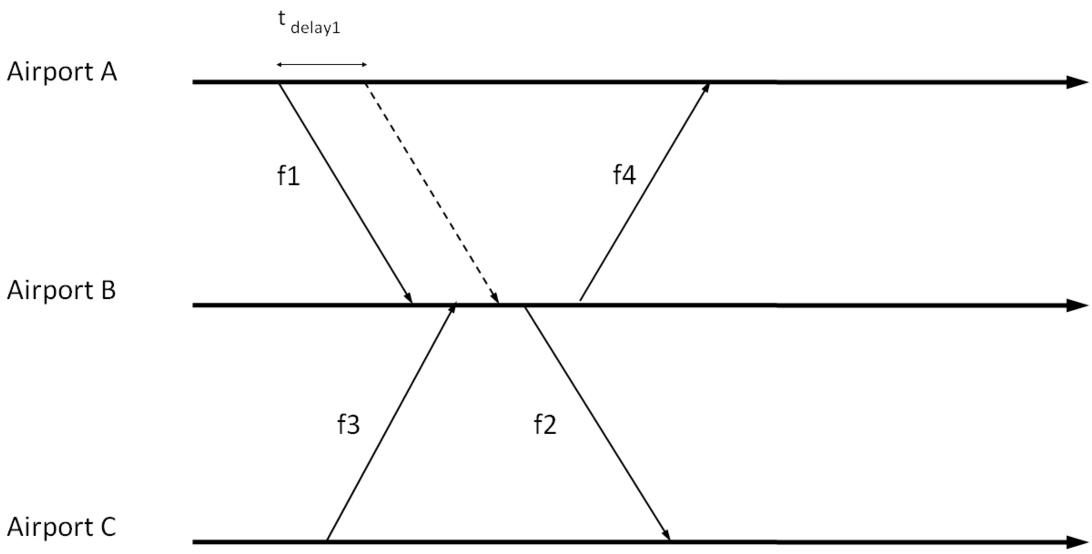

Figure A.2: Swapping

in the swap operation. Our observations from OCCs show that OR-based recovery usually has a significant advantage over manually based recovery, when it comes to finding efficient swaps with $N \geq 3$.

Two types of swaps exists: 1) *tail swaps* where the swap occurs between aircraft of the same aircraft type. In the swapping example above this would be if aircraft X and aircraft Y both belong to the same aircraft type. 2) *fleet swaps* where the swap occurs between aircraft of different types. Tail swaps are preferred to fleet swaps due to the fact that they do not add to the complexity of the crew recovery problem as a pilot, who is qualified for aircraft X, will also be qualified for aircraft Y, if X and Y are of the same type. If Y had been of a different type than X, this would add to the complexity of the crew recovery problem and would possibly require the need for the availability of reserve crews at the departure station of flights X and Y.

It should be noted that for some types of aircraft such as e.g. Airbus 318, 319, 320 and 321 crew can be cross qualified, due to the fact that authorities such as e.g. the FAA can grant a combined type certificate for these types if the cockpit layouts are maintained the same. In such a case, one may consider swaps between these 4 types as having a low cost due to the fact that these swaps will not add to the complexity of the crew recovery problem.

The third normal recovery technique is *canceling*. This is usually the last resort for an ops controller. Canceling can often be avoided by making extensive use of the swapping and delay possibilities, which often exist in an airline's disrupted schedule. On the other hand a couple of cancellations may sometimes be a better alternative than a recovery solution with extensive delay propagation, as the cancellations will affect relatively few passengers severely, while delay propagation can end up affecting a very large number of passengers in a way where many of these will lose their onward connections and thus end up being severely delayed at their final arrival.

There is a final recovery technique, named *ferrying*, available to an ops controller. A ferry flight is a flight, which is flown without passengers from one airport to another. The purpose of this is to make the aircraft available for another flight, which could otherwise not be covered in the schedule. Ferrying is a very expensive technique, which is seldom used. In some cases an ops controller will, however, be forced to use it. This is for instance the case when a flight is diverted to an an alternate airport due to bad weather at its original arrival destination. In this case a ferry flight will typically be used to return the aircraft to the normal operating schedule.

An additional element, which needs to be taken into account regarding aircraft recovery, is the existence of so-called *through-flights*. These are also referred to as *multi-leg flights*. Through-flights are flights, which make a stop-over in one or more airports on their way from an origin airport to a destination airport. The reason for the existence of these flights is that it can be attractive for an airline to sell an "almost direct" service from airport A to airport C, where the only inconvenience to passengers traveling from A to C is that a short stop-over in airport B is made. Passengers traveling from A to C do, however, not need to disembark the aircraft at airport B. A through-flight is typically instated on routes, where the main demand is from A to C, while there are smaller demands from A to B and B to C. As less passengers will be getting on and off at airport B, the turn time at this airport can typically also be reduced slightly. When solving the aircraft recovery problem it is preferred that the individual flight legs of a through-flight are all assigned to the same aircraft in the recovery solution.

A.2.1 Previous work on aircraft recovery

In the literature the initial work in the field of aircraft recovery was done by Teodorović and Guberinić (1984), who contributed by solving small problems with 3 aircraft and 8 flights, where only delays were considered. This work was later on extended by Teodorović and Stojković (1990), who handled both cancellations and delays for up to 14 aircraft and 80 flights. Jarrah et al. (1993) were the first to publish 2 models, which in combination were capable of producing solutions, which were useful in practice. The models were based on network flow algorithms and were capable of handling fleet swaps, delays and cancellations. The drawback of Jarrah et al. was that cancellations and delays could not be traded off against each other within one single model.

This drawback was later on resolved in the work by Yan and Yang (1996) whose model were capable of trading off delays, swaps and cancellations in one single model based on a time-line network. Thengvall et al. (2001) later on extended this model to also include so-called protection arcs, which serve the purpose of keeping the proposed solutions somewhat similar to the original schedule. This is important for real-life application of the suggested solutions, as an unlimited number of changes cannot be applied to the schedule last minute.

Rosenberger et al. (2003) present a model based on the set packing problem. The model contains a huge number of variables when applied to realistic instances and therefore the authors also propose a heuristic that selects a subset of the aircraft to be included in the model. Computational results show that the approach generates much better recovery plans compared to the short cycle cancellation policy proposed in Rosenberger et al. (2002). Andersson (2006) proposes two metaheuristics based on simulated annealing and tabu search in order to solve a aircraft recovery problem. Tests are carried out on real-life as well as artificial data. Results show that the tabu search heuristic outperforms the simulated annealing heuristic and that the tabu search heuristic can find high quality solutions in less than a minute. Recently Eggenberg et al. (2010) proposed a generalized recovery framework using a timeband network, where the same model can be used to solve either an aircraft recovery problem, a passenger recovery problem or a crew recovery problem. They use a column generation approach where the master problem is of the set-partitioning type with side constraints, and the sub-problem is of the resource constrained shortest path type.

A.2.2 Aircraft specific recovery

Previous literature concentrates on doing a so-called *fleet specific recovery*. In the cases where the underlying model is a multi commodity network flow model, the commodities are aircraft belonging to a specific fleet. The solutions provided will consequently specify that e.g. an aircraft from the Boeing 737 fleet must be assigned to flight $f1$ and will arrive at LHR airport at 22:00 in the evening. But the solution will not specify, which Boeing 737 will arrive at LHR. This is problematic as the maintenance department of the airline needs to know, which specific 737 will arrive in the evening for over-night maintenance. Furthermore they need to be able to set as a constraint in the model, that a specific aircraft must arrive for maintenance at a specific airport at a specific point in time. For this reason it is important to solve the *aircraft specific recovery problem.* There are a number of other reasons, why it is important to solve the aircraft specific problem rather than the fleet specific problem. Some examples are:

- To make specific aircraft respect their assigned maintenance activities.
- To control the number of tail swaps within the same fleet and penalize these in a solution.
- Within the same fleet there may be differences between individual aircraft. Some may have auxiliary tanks.
- There may be differences in in-flight entertainment systems on individual aircraft within the same fleet, which means that certain aircraft are preferred on longer routes.
- There may be differences in the terms of the leasing contract for different aircraft within the same fleet. As an example the airline may have leased one aircraft on a so-called *power-by-the-hour*-contract, where the airline pays according to the number of flying hours the airline puts on the aircraft. Other aircraft in the same fleet may be leased and paid for entirely based on calendar time.
- An aircraft may experience a deficiency, which does not require it to be grounded, but may require that it is not being used on certain routes. E.g. with a malfunctioning GPS it is preferred not to use that aircraft on routes over water.
- In case of a malfunctioning Auxiliary Power Unit (APU) an aircraft can only fly to airports where external power connection is available.

The list above is not exhaustive, but makes it clear why it is important to solve the *aircraft specific recovery problem* as opposed to the *fleet specific recovery problem* for real-life disruptions.

To summarize, the main contribution of this paper is to show that the multi-commodity network flow model presented by Thengvall et al. (2001) can be used to model individual aircraft, and that the model thereby is able to capture more of the constraints that occur in real-life situations. Through extensive tests we furthermore show that it is, from a running-time perspective, realistic to use the model to handle disruptions for a medium sized carrier with around 200 daily flights. Another contribution of the paper is to show that the so called *unit-action-penalties* can be used to reduce the number of recovery actions taken by the model as an alternative to the protection arcs proposed in Thengvall et al. (2001). We believe that the unit-action-penalties are easier to understand and lead to more compact models.

A.3 Modeling

In this section we describe the time-line network representation of the aircraft recovery problem, as well as the mathematical model that is based on the network. The model is derived from the one proposed by Thengvall et al. (2001). Thengvall et al. (2001) modeled the problem on a fleet level, meaning that individual aircraft within a fleet are anonymous and decisions are of the form: "an aircraft from fleet x is carrying out flight y". In this paper we propose to model the problem at the aircraft level such that decisions are of the form: "aircraft x is carrying out flight y". This is advantageous due to the reasons mentioned in the previous section, but compared to a fleet based model it also results in a much larger mathematical model for a similar problem instance.

A.3.1 Network representation

The basic layout of the network is shown in Figure A.3. Here time is increasing from left to right and each horizontal line represents an airport. Arcs (denoted *flight arcs*) represent planned flights i.e., the arc leaving airport A corresponds to a flight from airport A to B and the horizontal placement of the endpoints represents departure and arrival time. White boxes represent nodes where aircraft start (source nodes) and black boxes represent nodes where aircraft are planned to end their journey within the given time horizon (sink nodes). The small network example in Figure A.3 could be operated by two aircraft. One starting in airport A, visiting airport B and C before return back to airport A; and another aircraft starts in airport B, travelling to airport D

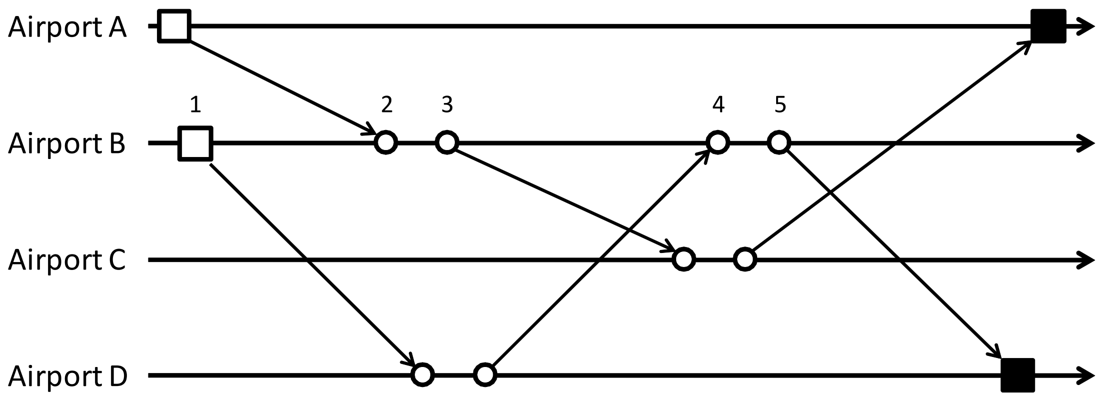

Figure A.3: Flight arcs

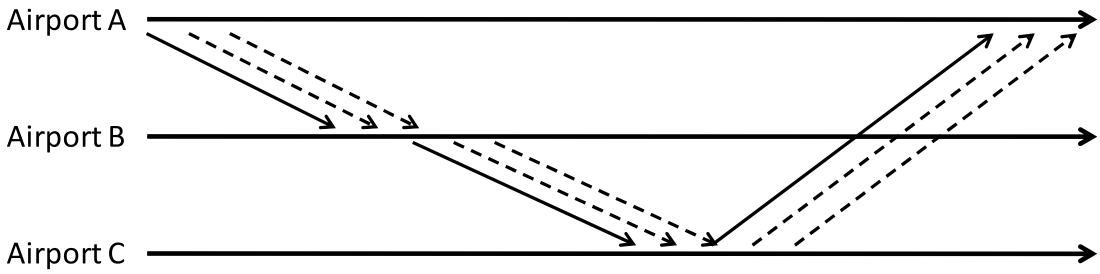

Figure A.4: Delay arcs

and back to B before ending at airport D. The network also contains *ground arcs* (not shown) that represent the time spend on the ground, in between flights. As an example, the network in Figure A.3 would contain four ground arcs for airport B (an arc between node 1 and 2, one between 2 and 3 and so on). The network also contains *maintenance arcs* which, like ground arcs, connect two nodes associated with the same airport. However, maintenance arcs represent planned repairs and/or inspections and are usually mandatory, where ground arcs are optional.

Extra arcs (*delay arcs*) are introduced to allow delays (shown in Figure A.4). Here each dashed arc represents a delay of the original flight (drawn with a solid line). Each dashed arc represents a particular amount of delay. A fine granularity of possible delays is obviously going to result in a large number of additional arcs. Another recovery option is to use ferry flights to transport an aircraft flying without passengers from one airport to another, this option is represented by *ferry arcs.* In principle, an arc representing a ferry flight could depart from every node in the network to allow a ferrying operation at every location and every instant. However, in this paper we have only included three types of ferry arcs, illustrated on figure A.5. The three types are: 1) ferry arcs from source nodes to hub airports, leaving the source node immediately (solid arcs), 2) ferry arcs from hub nodes to sink nodes, reaching the sink node at the latest possible instant (dashed arcs) and 3) ferry arcs from source to sink nodes (dotted arcs). Ferry arcs are associated with a very high cost and should only be used when it is impossible to obtain a feasible recovery plan otherwise.

When recovering from disruptions, it is generally preferred that only a few recovery operations are taken in order to make sure that the recovery solution is implementable in practice. One way of ensuring this is to introduce *protection arcs.* Protection arcs span several flight arcs that, according to the original plan, were supposed to be flown by the same aircraft. Protection arcs are associated with a certain "bonus" such that it is more profitable to take one protection arc instead of the individual flight arcs that it covers. The idea is that this will prevent the model from

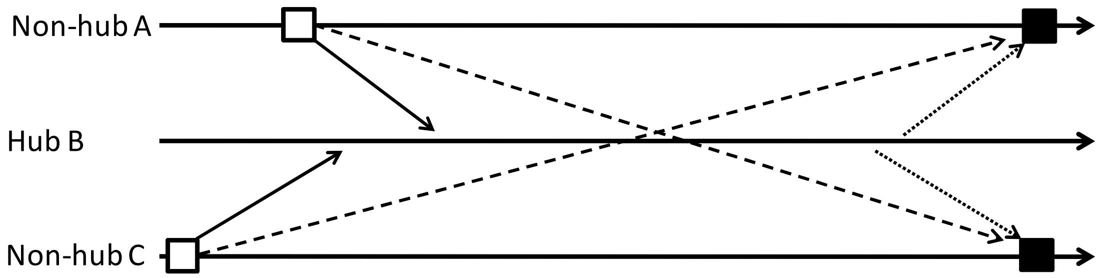

Figure A.5: Ferry arcs

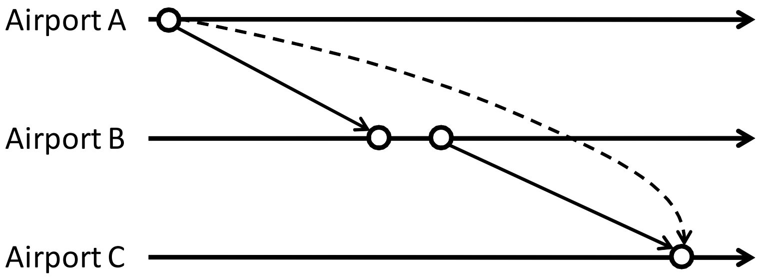

Figure A.6: Protection arcs

switching aircraft on the series of flight arcs that the protection arc covers, unless it is essential to the recovery operation. A related concept is that of *through-flight arcs*. As mentioned earlier, through flight arcs, for example, represent flights visiting airport A, B and C. Passengers from airport A can disembark in airport B or they can stay on the aircraft in airport B and get to destination C without leaving the aircraft. If a leg in the through-flight is disrupted it will affect the entire through-flight. Therefore a through flight arc is introduced that covers both flights and it has a lower cost than the sum of the two individual arcs in order to encourage assigning a single aircraft to both flights.

A.3.2 Model

Let $G = (V, A)$ be a graph representing the network described above, let I be the set of available aircraft and N the set of flights to be carried out in the recovery period. Define $\alpha_n \subset A$ as the set of arcs that cover flight $n \in N$ (if an arc $a \in \alpha_n$ is selected then flight n is carried out). For example, the original flight arc, derived delay arcs and protection arcs could all cover the same flight. Each vertex $v \in V$ is associated with balance or demand parameters $d_{iv} \in \{-1, 0, 1\}$ for each aircraft $i \in I$. A value of one (minus one) means that i aircraft is consumed (appearing) at node v and a value of zero means that an aircraft i entering the node also must leave it again. The plus/minus one values are used at sink/source nodes. We define binary decision variables x_{ia} that take the value one if aircraft i serves arc a and zero otherwise, and binary decision variables y_n that are one if flight n is canceled and zero otherwise. We notice that some combinations of arcs and aircraft are infeasible, and the corresponding variables x_{ia} must be fixed to zero. The infeasibilities belong to three categories: 1) maintenance arcs can only be carried out by the aircraft it was created for, 2) some combinations of flights and aircraft are infeasible. There can be several reasons for this, e.g. size of aircraft, range of flight, restrictions at the origin or destination airport or requirements for certain navigation equipment on board, 3) we do not allow an aircraft to use the protection arc for a series of flights that it was not scheduled to fly. When an aircraft is incompatible with a certain flight n it has an impact on all the arcs covering that flight (all arcs in α_n) and they must all be fixed to zero. Similarly, if a maintenance tasks must be carried out we will have to fix the corresponding variable x_{ia} to one. We let the set $S_v, v \in \{0,1\}$ contain all pairs (i,a) of arcs a and aircraft i such that x_{ia} has to be fixed to v. Let c_{ia} be the penalty of assigning aircraft i to arc a (more on that later) and γ_n be the penalty of canceling flight n. Also, let $\delta^+(k) = \{(i,j) \in A : i = k\}$ (and $\delta^-(k) = \{(i,j) \in A : j = k\}$) be the set of arcs originating in (respectively, ending in) node $k \in V$. The aircraft recovery problem can now be formulated as follows:

$$\min \sum_{i \in I} \sum_{a \in A} c_{ia} x_{ia} + \sum_{n \in N} \gamma_n y_n$$

subject to

$$\sum_{a \in \delta^-(v)} x_{ia} = \sum_{a \in \delta^+(v)} x_{ia} + d_{iv} \quad \forall i \in I, v \in V \tag{A.1}$$

$$\sum_{i \in I} \sum_{a \in \alpha_n} x_{ia} + y_n = 1 \quad \forall n \in N \tag{A.2}$$

$$x_{ia} = v \quad \forall v \in \{0,1\}, (i,a) \in S_v \tag{A.3}$$

$$x_{ia} \in \{0,1\} \quad \forall i \in I, a \in A \tag{A.4}$$

$$y_n \in \{0,1\} \quad \forall n \in N \tag{A.5}$$

Here constraint (A.1) ensures aircraft balance at each node $v \in V$. Constraint (A.2) ensures that each flight is either carried out or canceled. Constraint (A.3) fixes incompatible or mandatory aircraft-arc pairs to zero or one, respectively. Constraints (A.4) and (A.5) define the domain of the decision variables. We note that the integrality requirement on the x_{ia} variables corresponding to ground arcs can be relaxed. This is because the value of these arcs will be given by the values of the remaining arcs. We also note that we do not need to represent the variables involved in the fixing constraint (A.3) in an actual implementation of the model. Variables fixed to 0 can be omitted and variables fixed to one can be dropped by setting d_{iv} to one for the origin vertex to minus one for the endpoint of the arc.

An abundance of information is encoded in the cost coefficients c_{ia} as the type of arc is encoded in this parameter. Costs are set as follows:

- a is a **flight arc:** if i is the aircraft planned to carry out the flight then c_{ia} is set to zero. Other aircraft are assigned a positive cost dependent on how similar the aircraft is to the intended aircraft: aircraft from the same fleet has a low cost while aircraft from a different fleet has a higher cost.
- a is a **ground arc**: we set c_{ia} to zero for all $i \in I$.
- a is a **maintenance arc:** if the arc is mandatory a cost of zero can be applied. If the maintenance can be cancelled or postponed we can assign a negative cost to the arc to encourage the model to carry out the planned maintenance (in the computational tests we have only used mandatory maintenance tasks).
- a is a **delay arc:** the cost structure is similar to the one for flight arcs, but now even the aircraft intended for the flight will be assigned a penalty, dependent on the amount of delay. Other aircraft will be assigned an even higher penalty.
- a is a **ferry arc:** ferry arcs are assigned a high penalty. The penalty is dependent on the aircraft class.
- a is a **protection arc:** protection arcs have a negative cost coefficient to encourage their use. The more flights the protection arc spans the higher is the applied bonus. We remind that we only allow that the intended aircraft use the protection arc.
- a is a **through-flight arc:** are handled in the same way as protection arcs. Here we allow aircraft other than the intended one to carry out the flight, but the cost coefficient may be positive in that case, dependent on how desirable it is to change the aircraft for the flights covered.

We also propose a variant of the model where all protection arcs are removed. Instead we introduce a *unit action penalty* (UAP) π that is added whenever an action that diverts from the original plan is taking place. π is simply added to all the appropriate cost coefficients. A low value of π allows the model to choose solutions with few changes among otherwise similar recovery options while a high value will drive the model to minimize the number of recovery even if that means that costly recovery operations are needed (like cancellations).

A.3.3 A fleet based model

We also perform experiments with a fleet oriented model similar to the one proposed by Thengvall et al. (2001). The model is easily derived from the aircraft model. It reuses the network structure of the aircraft model and uses parameters and variables similar to the aircraft model: let F be the set of fleets, let $\bar{c}_{fa}$ be the cost of serving arc $a \in A$ using an aircraft from fleet $f \in F$ and let $\bar{d}_{fv} \in \mathbb{Z}$ be a parameter that specifies the balance at node $v \in V$ for fleet $f \in F$. Also, let $\bar{S}$ be a set of pairs (f, a) such that fleet f cannot handle the flight represented by a. We define a new binary variable $\bar{x}_{fa}$ that takes value one if an aircraft from fleet $f \in F$ is serving the flight represented by arc $a \in A$. We let N, F_n, γ_n and y_n have the same meaning as in the aircraft model. The fleet model can now be written as:

$$\min \sum_{f \in F} \sum_{a \in A} \bar{c}_{fa} \bar{x}_{ia} + \sum_{n \in N} \gamma_n y_n$$

subject to

$$\sum_{a \in \delta^-(v)} \bar{x}_{fa} = \sum_{a \in \delta^+(v)} \bar{x}_{fa} + \bar{d}_{fv} \qquad \forall f \in F, v \in V \tag{A.6}$$

$$\sum_{f \in F} \sum_{a \in \alpha_n} \bar{x}_{fa} + y_n = 1 \qquad \forall n \in N \tag{A.7}$$

$$\bar{x}_{fa} = 0 \qquad \forall (f, a) \in S \tag{A.8}$$

$$\bar{x}_{fa} \in \{0, 1\} \qquad \forall f \in F, a \in A \tag{A.9}$$

$$y_n \in \{0, 1\} \qquad \forall n \in N \tag{A.10}$$

The cost coefficients $\bar{c}_{fa}$ should be interpreted in a similar way as in the aircraft model. We notice that the fleet model cannot handle maintenance tasks as they are associated with a specific aircraft.

A.4 Computational experiments

In this Section we present computational results. These are based on real life data from a medium sized carrier with approximately 200 daily flights served by 65 aircraft and belonging to 6 different fleet types. The data set has 56 airports and contains on average 14 maintenance tasks per 24 hour period. All tests are carried out on an Intel Core2, 2.66 GHz computer running Windows XP with 3 GB memory installed. The models are implemented using OPL studio version 6.3, and CPLEX 12.1 is used as the solver. A Java front end is implemented, which both allows creation of various disruption scenarios and the verification of solutions.

We wish to investigate two questions through the computational experiments:

1. *Fleet Model versus Aircraft Model.* How do solutions from the aircraft model compare to those of the fleet model in terms of usability and running times?

2. *Unit Action Penalty versus Protection Arcs.* Are the unit action penalty and the protection arc approach both able to provide simple recovery options?

A.4.1 Fleet Model versus Aircraft Model

We start by investigating the running time of the different models for a single disruption scenario. We run the fleet model and aircraft model with both the unit action penalty and protection arc approach, and varying recovery period length on an instance where three aircraft are grounded for 10 hours.

In Figures A.7 and A.8 we show the solution time to optimality as a function of the length of the recovery period for the fleet and the aircraft model, respectively. As expected the fleet model solves much faster than the aircraft model and easily solves a scenario with a planning horizon of two days in less than 10 seconds. While the aircraft model is slower, it still manages to solve scenarios with a one day planning horizon within 60 seconds. We consider this a reasonable amount of time to wait for a recovery option (the 60 second limit is marked by the horizontal dashed line in the figure).

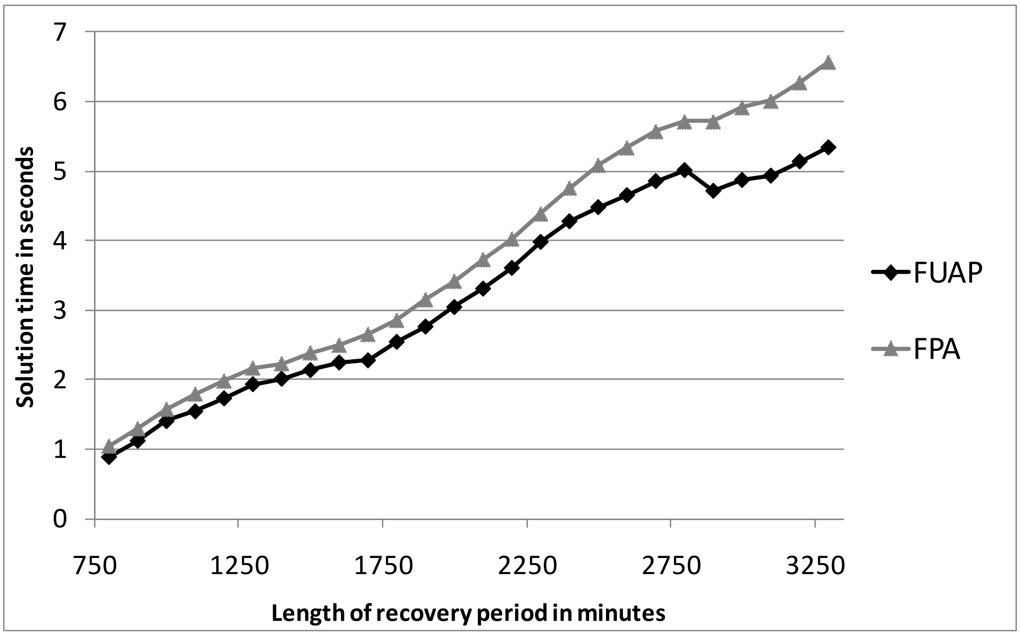

Figure A.7: The solution times for the different fleet models with varying recovery period lengths with 3 aircraft grounded for 10 hours

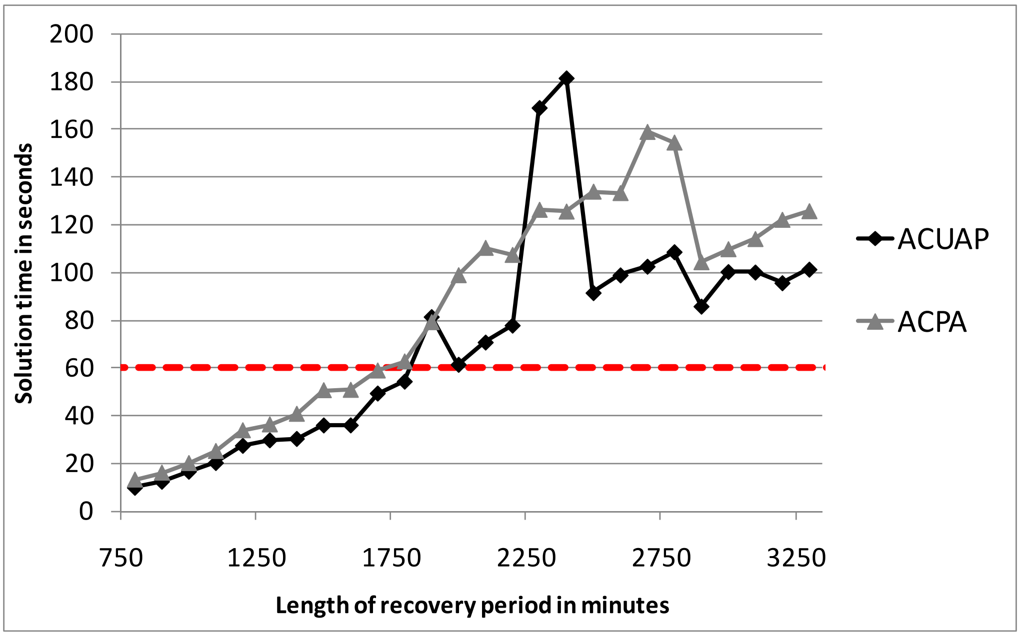

Figure A.8: The solution times for the different aircraft models with varying recovery period lengths with 3 aircraft grounded for 10 hours.

The intention of increasing the length of the recovery period is to give the model the opportunity to use less drastic recovery options by looking further ahead instead of just at the near future. This is analyzed in more detail in the Figures A.9 to A.12, which present the proposed solutions of all 4 models for the disruption case with three grounded aircraft for 10 hours using various lengths of recovery periods. The y axis shows the number of actions performed of the particular type and the x-axis shows the recovery period in minutes. Comparing the fleet models in Figures A.9 and A.10 to the aircraft models in Figures A.11 and A.12, one sees that the fleet models are pretty steady when it comes to increasing the recovery period. Looking further ahead does not offer many new possibilities for improvement (at least in this scenario). The aircraft models, which have more detailed information about individual aircraft re-assignments, do on the contrary show that increasing the recovery period does lead to solutions with less recovery actions. It is also noted that the fleet models give solutions containing a significantly lower number of recovery actions (ranging from 4 to 6 actions) than the aircraft models (ranging from 15 to 35 actions). This is due to the fact that the fleet models have no possibility of registering necessary tail swaps and do not have the possibility of respecting maintenance activities. This shows that the fleet models are underestimating the needed number of recovery actions and that these solutions consequently will require some additional processing in order to become feasible for usage at the airline.

Note that for the fleet models (e.g. figure A.9) it may seem strange that the number of actions equals the number of delays, while there also are fleet swaps taking place. This is because the fleet swaps also include a delay and therefore also count towards the number of delays.

The results show that it is possible for a medium sized carrier to use the aircraft based recovery model, which from an operational point of view is more desirable than the fleet based model. The aircraft model allows the airline to respect maintenances, tail swaps and other individual aircraft related aspects in a one-shot solution approach, where subsequent processing of the aircraft recovery solution is not needed in order to respect e.g. individual maintenance assignments. In the following section we provide further evidence that shows that the aircraft model can be solved fast enough to be useful in an environment where decisions should be made within minutes.

A.4.2 Unit Action Penalty versus Protection Arcs

In this section we assess if either the Unit Action Penalty or the Protection Arc method serve better in the purpose of reducing the number of changes to the schedule in a recovery solution. This is important in order for the recovery solutions to be implementable in practice on the day of operation at an airline. From Figures A.7 and A.8 we observe that the unit action penalty approach overall is slightly faster than the alternative protection arcs method, but that the difference is minor.

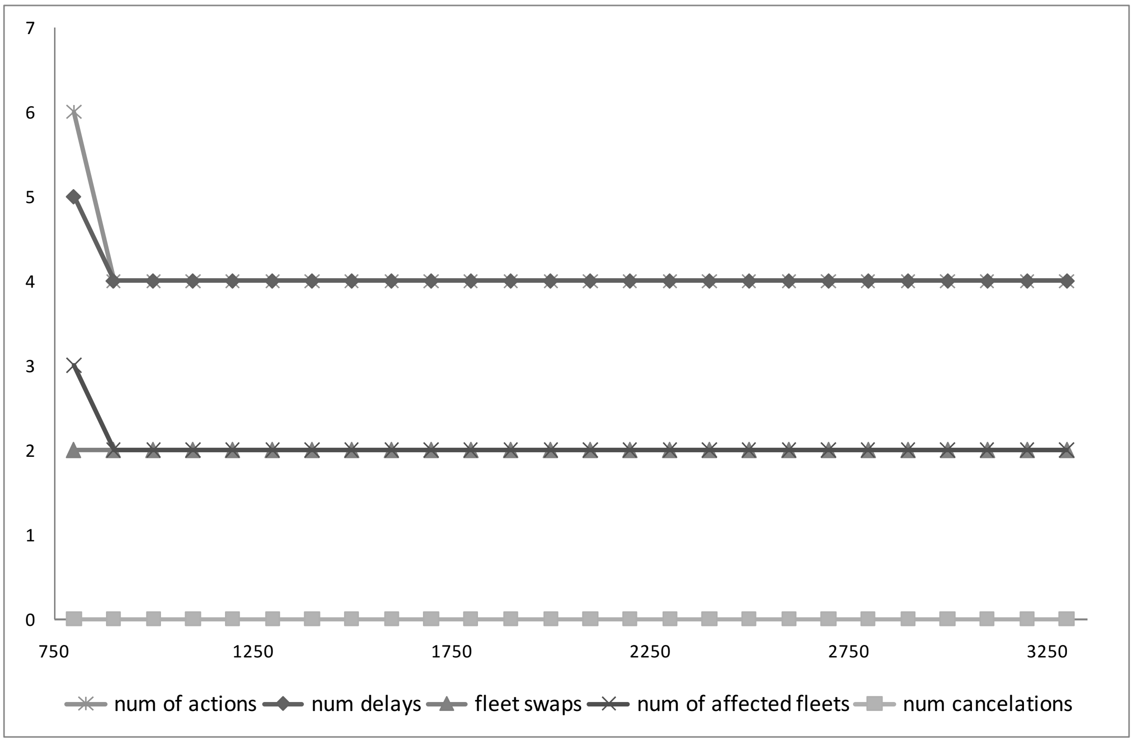

Figure A.9: The number of different actions for different lengths of the recovery period for the fleet model with unit action penalty and 3 aircraft grounded for 10 hours.

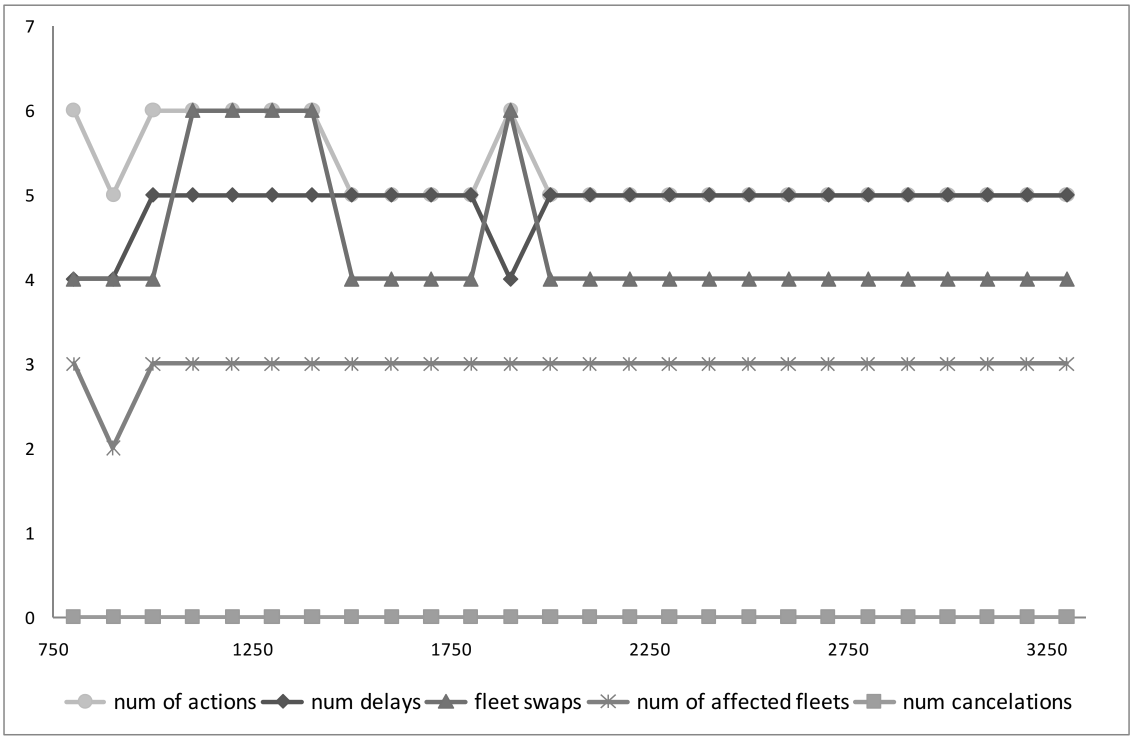

Figure A.10: The number of different actions for different lengths of the recovery period for the fleet model with protection arcs and 3 aircraft grounded for 10 hours.

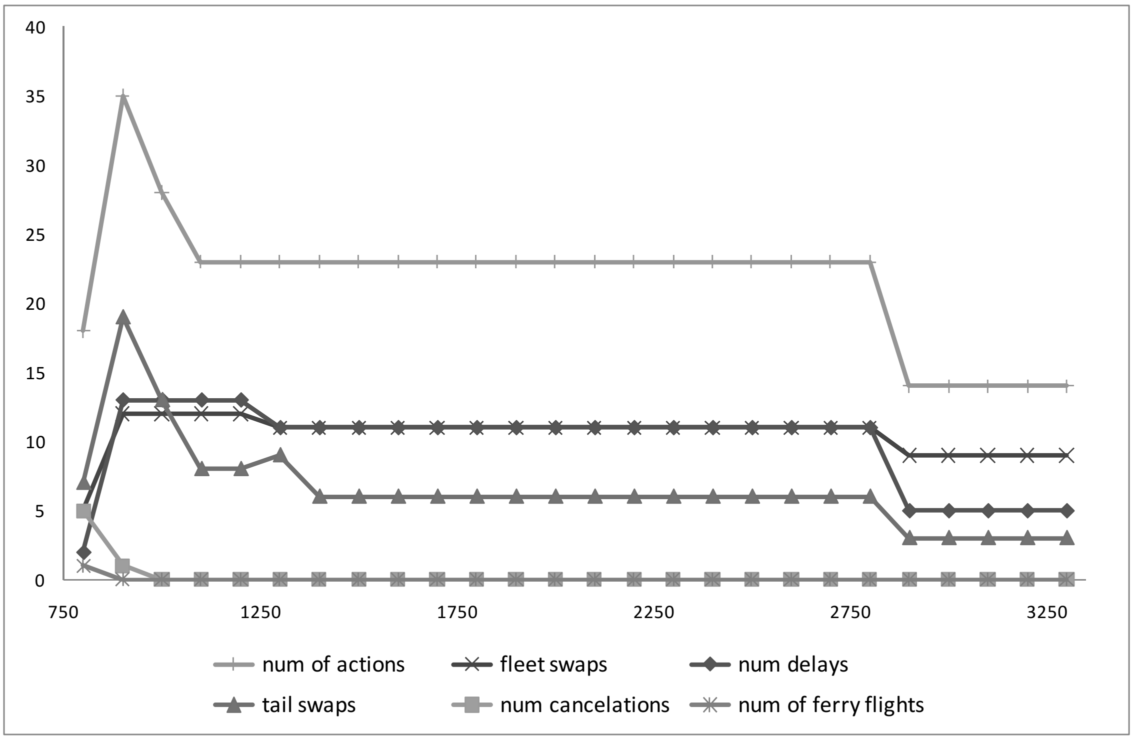

Figure A.11: The number of different actions for different lengths of the recovery period for the aircraft model with unit action penalty and 3 aircraft grounded for 10 hours.

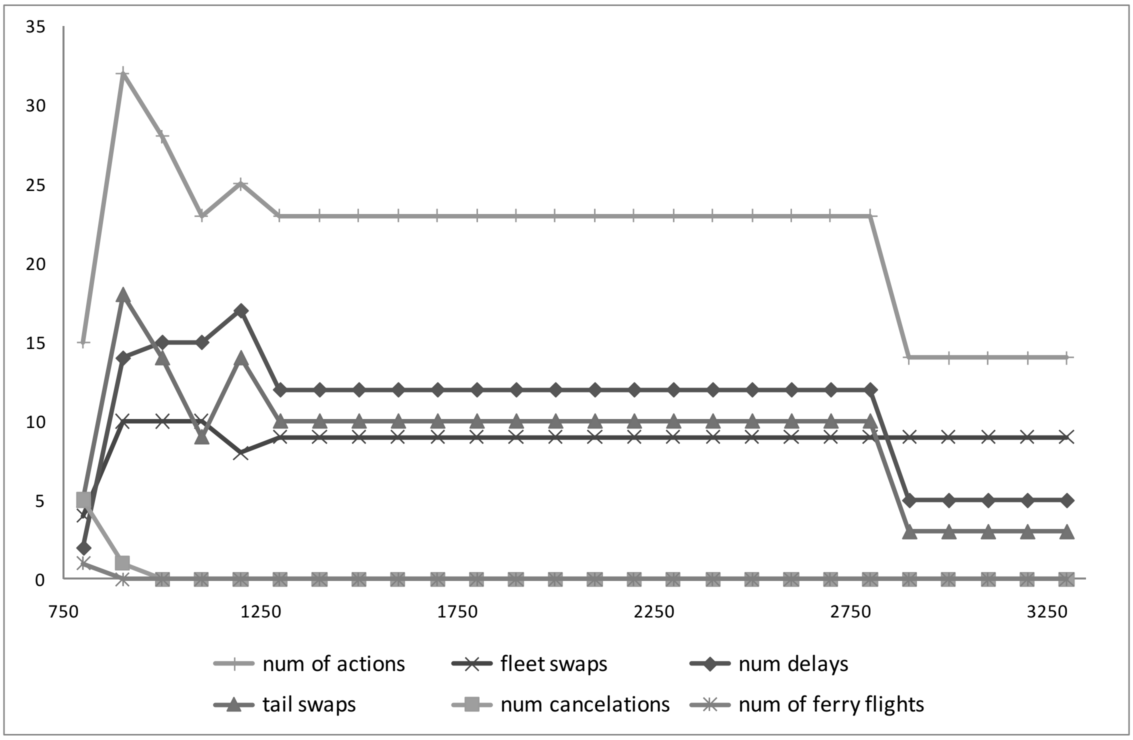

Figure A.12: The number of different actions for different lengths of the recovery period for the aircraft model with protection arcs and 3 aircraft grounded for 10 hours.

Comparing the unit action penalty approach to the protection arc approach shows that the approaches produce comparable results. Figures A.13 and A.14 compare the behavior of the two approaches in more detail for the aircraft model. In these figures the number of changes of a particular type is drawn as a function of the unit action penalty (Figure A.13) and the protection bonus (Figure A.14). For both models the number of actions taken decreases as the penalty/bonus increases, which is as expected. It is also observed that the number of expensive actions (e.g. cancellations) increases as the penalty/bonus increases. It is noticeable that the two models provide different results, but the overall structure of the solutions is similar. We note that, in a real-life situation, it may be useful to solve the model with several settings of the unit action penalty or protection arc bonus in order to produce a number of recovery plans that the Ops Controller can choose from. The solution of the models could take place in parallel on several computers, such that the Ops Controller does not have to wait longer for acquiring alternative solutions.

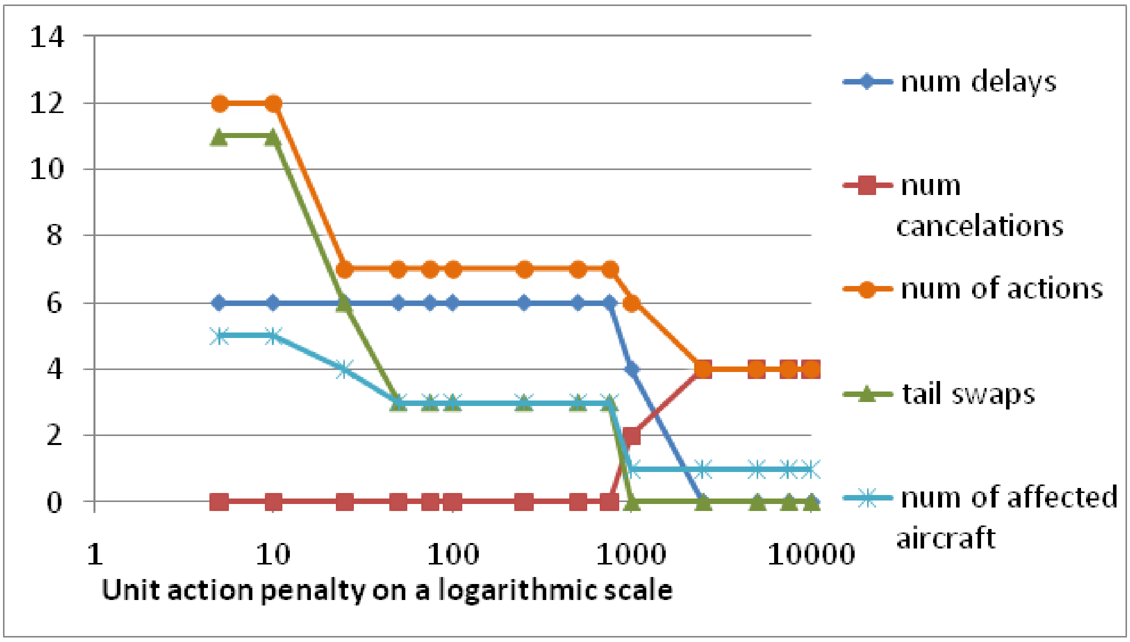

Figure A.13: The number of changes for the ACUAP for scenario *1GR_10_24*.

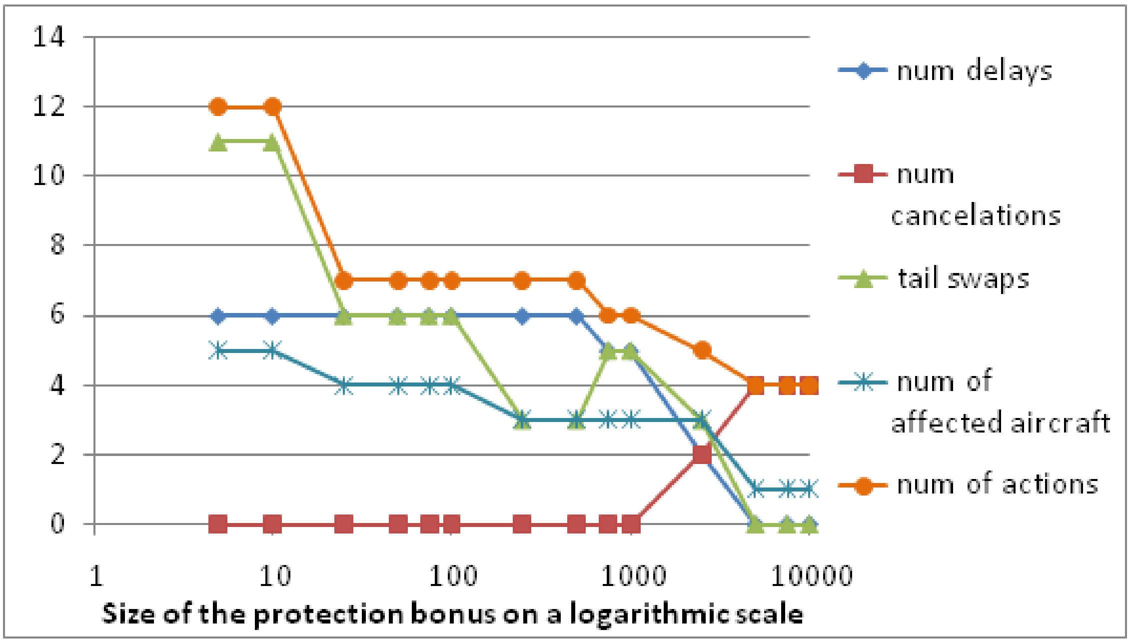

Figure A.14: The number of changes for the ACPA for scenario *1GR_10_24*.

In order to test the stability of running time for the aircraft models more extensively, we have created a large number of disruption scenarios and solved them with the two aircraft models. The scenarios were created by considering 17 basis scenarios and creating 1000 instances of each of these by varying the day of the disruption (different schedules are followed on different days) and the aircraft involved in the disruption. Figures A.15 and A.16 shows the results from the unit action penalty and the protection arc approaches, respectively. The basis scenario is shown on the x-axis. The first three scenarios are grounding of 1, 2 or 3 aircraft for 10 hours, the next three scenarios are for delaying 1,2 or 3 aircraft for 2 hours. The following three scenarios are for canceling 1,2 or 3 aircraft, the next two scenarios are for closing a hub for 2 or 4 hours. Then follows two scenarios for closing a less significant airport for 2 or 4 hours, then four scenarios simulating fog for 2 and 4 hours over a hub and a less significant airport. In the fog scenarios all aircraft that depart during the fog interval will experience a delay of between 5 and 60 minutes. In the airport closure scenarios all aircraft departing and arriving in the closure interval will be canceled and all aircraft located at the start of the closure interval will be grounded. All scenarios are solved with a recovery period of 24 hours. On the y-axis we show the solution time. The figures illustrate the maximum and minimum solution time, the 95-percentile, the mean solution time as well as the standard deviation. For the unit action penalty approach we see that in the worst case (out of 17000 experiments) we experience a running time of 80 seconds and that 95 percent of the test cases for each scenario are solved in less than 40 seconds. The protection arc approach shows similar results, albeit with slightly longer running times. For both models there is some variation over the different scenarios, but overall the performance is very stable. The test results show that both aircraft models, for medium size airlines and with a reasonable recovery period, are applicable in practice. We note that a substantial fraction of the solution time actually is consumed loading the models into OPL studio. This means that the running time could be improved, with a modest effort, by bypassing OPL studio and implementing the models directly in a language like C++ or Java in order to avoid the overhead of OPL studio.

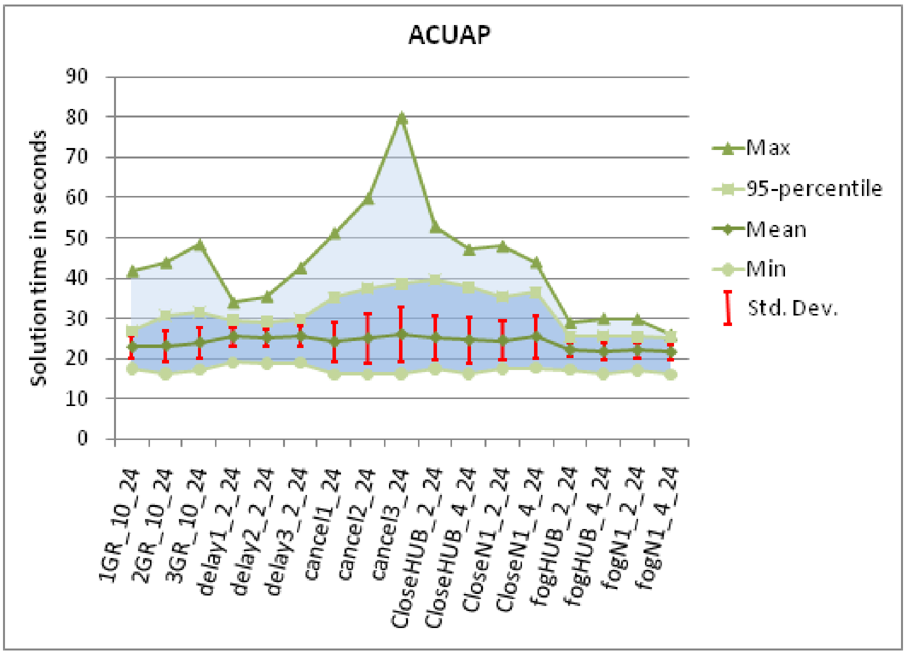

Figure A.15: probability distribution of the solution times of 1000 runs per disruption scenario, ACUAP.

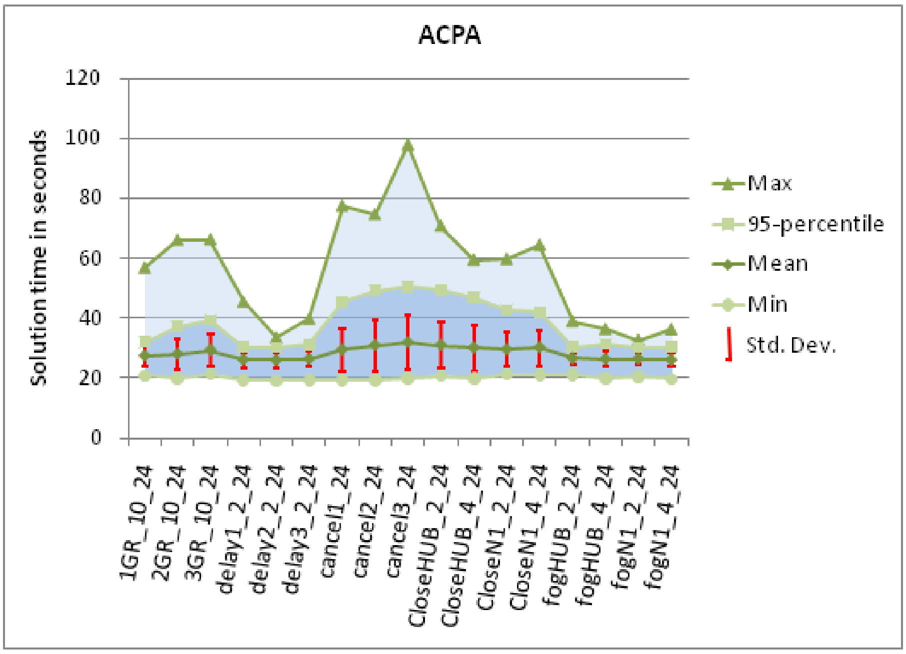

Figure A.16: probability distribution of the solution times of 1000 runs per disruption scenario, ACPA.

A.5 Conclusions

This paper has compared exact aircraft recovery models based on a multi-commodity network flow representation, where the commodities in a fleet based formulation are anonymous aircraft belonging to a specific fleet, while the commodities in an aircraft based formulation are individual aircraft. For both models we have done experiments with two different mechanisms for reducing the number of changes to the original schedule, which is suggested by the recovery solutions. Even though the aircraft based model takes significantly longer time to run than the fleet based model, we do conclude that for a medium sized carrier with approximately 200 daily flights it is worthwhile using the aircraft based model as this still solves to optimality well below a one-minute target, which is set as an acceptable waiting time. The advantage of the solutions obtained using this model is that all maintenance activities are respected and that individual aircraft preferences can also be modeled.

When it comes to a comparison of the two methods for reducing the number of recovery actions in a solution, we have found the Unit Action Penalty to be slightly faster and more stable compared to the Protection Arc method. We recommend using the Unit Action Penalty approach, as it is simpler to understand its impact on the proposed recovery plans.

A possibility for future work in order to improve the solution speed would be to combine the advantages of the fleet based model and the aircraft based model. This could be done by having a fleet-based representation of aircraft, which do not have scheduled maintenance activities in the time window, while using an aircraft based representation for aircraft with scheduled maintenance activities in the time window. Some of the other mentioned aircraft preferences from section A.2 could also lead to additional aircraft being moved from the "fleet group" to the "aircraft group". Moving more aircraft to this group would naturally reduce the speed-up effect.

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Appendix B

Integrated Disruption Management and Flight Planning to Trade off Delays and Fuel Burn

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Abstract

In this paper we present a novel approach addressing airline delays and recovery. Airline schedule recovery involves making decisions during operations to minimize additional operating costs while getting back on schedule as quickly as possible. The mechanisms used include aircraft swaps, flight cancellations, crew swaps, reserve crews and passenger rebookings. In this context, we introduce another mechanism, namely *flight planning*, which enables flight speed changes. Flight planning is the process of determining flight plan(s) specifying the route of a flight, its speed and its associated fuel burn. Our key idea in integrating flight planning and disruption management is to adjust the speeds of flights during operations, trading off flying time and fuel burn, and combining with existing mechanisms such as flight holds; all with the goal of striking the right balance of fuel costs and passenger-related delay costs incurred by the airline. We present models for integrated aircraft and passenger recovery with flight planning, both exact and approximate. From computational experiments on data provided by a European airline, we estimate approximately that reductions in passenger disruptions on the order of 66-83%, accompanied by small increases in fuel burn of 0.152 - 0.155% and total cost savings of 5.7 - 5.9% for the airline, may be achieved using our approach. We discuss the relative benefits of two mechanisms studied - specifically, flight speed changes and intentionally holding flight departures, and show significant synergies in applying these mechanisms. The results, compared to recovery without integrated flight planning, are increased swap possibilities during recovery, decreased numbers of flight cancellations, and fewer disruptions to passengers.

Keywords: airline schedule recovery, flight planning, enhanced disruption management

B.1 Introduction

Inherent uncertainty in airline operations makes delays and disruptions inevitable. Because the airline system operates as a closely interconnected network, it is subject to 'network effects', that is, a disruption in one place can quickly propagate to multiple other parts of the network. Therefore, managing these delays as they arise is crucial. *Disruption management* is the process by which, on the day of operation, when a disruption occurs, airlines try to bring operations back on schedule as quickly as possible, while incurring minimal costs. Measures such as flight cancellations, flight holds, aircraft swaps, crew swaps, reserve crew and passenger re-accommodation are used as part of the disruption management process. In this work, we integrate *disruption management* and *flight planning*. *Flight planning* is the process of determining, at the pre-departure stage of each flight, its three-dimensional trajectory, involving its path, altitude(s), speed and fuel burn as the aircraft flies from its origin to its destination. Our goal is to reduce flight delays and disruptions to passengers using disruption management combined with flight planning, to achieve the appropriate trade-off of passenger service with fuel burn and additional operating costs incurred during recovery. To our knowledge, this is the first work that integrates these aspects of airline operations.

The ability to change a flight's speed directly impacts its block (or flying) time, and thus, its arrival time; which in turn can impact network connectivity of the flight's aircraft, crew and passengers to downstream flights. Therefore, through changes to block times, to trade-off the costs of changing a flight's arrival time (including, for example, network connectivity costs capturing the costs associated with resulting delays and disruptions to the flight's aircraft, crews and passengers) with the change in fuel burn costs (associated with the flight's block time adjustment).

To illustrate our *integrated disruption management and flight planning* approach, consider, for example, a flight experiencing a departure delay at its origin. The choices are to: (1) operate the flight at increased speeds (and increased fuel burn), and employ techniques such as aircraft swaps and flight cancellations as necessary, to absorb delays at the flight destination and to decrease costs associated with passenger delays and misconnections; or (2) reduce the flight's speed using flight planning to decrease fuel burn and emissions if connectivity is unaffected. Our overarching goal is to decrease costs incurred during airline operations by identifying the operational trade-offs between (i) aircraft and passenger delay costs; and (ii) fuel burn costs.

B.1.1 Disruption Management

During operations, operational recovery procedures of dynamic scheduling, routing and disruption management vary among carriers. The first priority for most airlines facing disrupted operations is to bring operations back to the plan. For this, operations controllers re-assign the resources of the airline in order to minimize the costs associated with the disruption. Three types of decisions are made: (i) whether or not to cancel a flight, (ii) what the rescheduled departure time is of flights that are to be operated, and (iii) which aircraft and crew is assigned to each operated flight. Typically, following aircraft and crew recovery, passenger recovery and re-accommodation is performed.

For an in-depth study of airline recovery, we recommend the reader to Barnhart (2009), Yu and Qi (2004), Barnhart et al. (2006), Kohl et al. (2007) and Clausen et al. (2010). Other relevant studies are Dienst (2010) and Thengvall et al. (2001).

B.1.2 Flight Planning

A flight plan is a document prepared by an operator (usually an airline) indicating the movement of the concerned aircraft in time and space, from its origin to its destination. The flight plan specifies the route (ground track) of the aircraft, its profile (altitudes along the route), its speed (which varies along the route) and the fuel burned in operating the flight plan. For an example of a flight plan, we refer the reader to Altus (2007).

The relationship between fuel burn and flying time (and consequently, block time) for a given flight leg is highly non-linear. Figure B.1 illustrates the relationship between flying time and fuel burn for a long-haul flight. The flexibility in speed changes is the highest for long-haul flights and least for short-haul flights. Each point on this curve represents a specific flight's flight plan with the associated flying time and fuel burn.

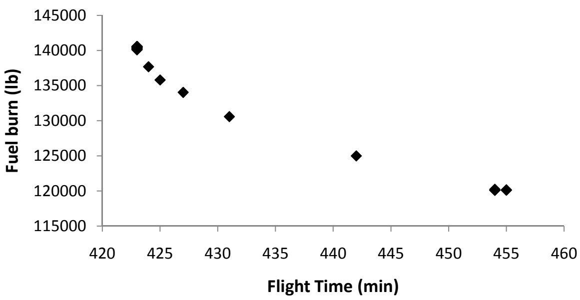

Figure B.1: Relationship between flight time and fuel burn

B.1.3 The Problem

We briefly describe the problem setting in this section. We consider scenarios in which a flight is delayed at its origin due to a disruption in the network. Our decision time frame is from one hour to one half-hour prior to flight departure, when we know the expected departure time of the flight and are in a position to select the flight plan and satisfy the necessary fueling requirements related to the choice of flight plan. We consider disruption management techniques that combine flight planning with aircraft swaps, flight cancelations and passenger recovery. Through this process, we trade-off network connectivity costs and delay costs associated with flight arrival times, with the fuel costs associated with flight speed changes. The effect is to re-allocate slack in block and ground times by: (i) increasing aircraft speed to reduce block times and add ground time at the destination, thereby preserving connections; (ii) decreasing aircraft speed to increase block time and save on fuel costs if fuel costs dominate airline delay costs (especially those related to passengers); and (iii) intentionally delaying (or holding) downstream flights to preserve passenger connections, without increasing the speed of the arriving flight and incurring increased fuel costs.

B.1.4 Contributions

The contributions of our research are as follows. First, we introduce an *enhanced disruption management* tool with integrated flight planning, and provide exact and approximate optimization models that combine flight planning with traditional disruption management models. In particular, we focus on two aspects of flight planning, speed changes and flight departure holding, and trade-off fuel costs and passenger delay costs. Our approach represents an integration of two aspects of airline operations hitherto studied separately, namely, disruption management and flight planning.

Second, through dialogue with multiple airlines, we provide a synopsis of the current state-of-the-practice with regards to flight planning approaches. We also discuss the current practices of flight planning and disruption management. We identify opportunities for improving disruption management through integration with flight planning and show the need for optimization-based decision support.

Third, we evaluate our approach on scenarios based on data from an international airline. Our experiments focus on hub operations and opportunities for improved trade-offs between passenger costs and fuel costs, with the goal of minimizing total realized costs. Based on our assumptions, we estimate approximately that in comparison with conventional disruption management, our integrated flight planning and disruption management strategy could result in decreases in passenger misconnections of about 66-83%, decreases in passenger-related delay costs for the airline of 60-73%, increases in fuel costs of 0.152-0.155%, and total cost savings of 5.7 - 5.9% for the airline under consideration. Additionally, passenger delay costs over the two-month period of our experiments are estimated approximately to decrease by $17.5-17.9M. By demonstrating the dynamic nature of the trade-off frontier between passenger costs and fuel burn costs and discussing this trade-off for different disruption scenarios, we make the case for dynamically selecting aircraft speeds during operations. We also discuss the relative benefits of the two types of mechanisms studied - that of flight speed changes and that of holding flight departures - and show significant synergies in applying the two mechanisms simultaneously.

B.1.5 Organization of the paper

In §B.1.1, and §B.1.2, we presented an overview of disruption management and flight planning, respectively. In §B.2 we introduce some terms relevant to flight planning and a summary of the practice of operational flight speed changes via dialogue with six airlines. In §B.3 we illustrate, with an example, opportunities for integrating flight planning and disruption management to minimize costs; and indicate shortcomings in the state-of-the-practice that motivate our *integrated flight planning and disruption management* approach. We then present a diagrammatic description of our approach. In §B.4, we present our modeling architecture to integrate flight planning with disruption management. Our models provide a way to trade-off passenger delay costs and fuel burn costs, and minimize total realized costs. We provide models in §B.5 that capture passenger connectivity costs exactly and approximately, thereby facilitating solution. We describe our experimental setup in §B.6. In §B.7, we present our results and compare them with the current state-of the practice to estimate cost savings to the airline under consideration.

B.2 Flight Planning: Current Practice

As illustrated in Figure B.1, each point on the flight time-fuel burn curve for a given flight represents a flight plan from the origin to the destination of that flight. A flight plan on this curve may be identified based on multiple metrics, among which the two most common ones are: (i) a fixed flight cruise speed, and (ii) *cost-index* (CI). Flight cruise speed, as its name suggests, identifies the flight plan based on how fast the aircraft flies, and its associated flying time. It does not include a notion of fuel burn in its specification. CI, on the other hand, is a measure that has been introduced to capture explicitly both flight time (speed) and fuel burn in its definition; as detailed in the following subsection.

B.2.1 Cost Index (CI)-based flight planning

Cost Index (CI) is an assumed ratio of the time-related costs of a flight divided by the fuel cost; that is, it is the ratio of cost per unit time divided by the cost per mass unit fuel. Time-related costs are defined as those that are related to (i) the duration of the flight, examples include aircraft maintenance costs per minute and crew duty costs per minute; and (ii) the arrival time of the flight, examples include aircraft connectivity, crew connectivity, and passenger connection and delay costs per minute. CI is expressed in units of 100lb/hr (Boeing) or kg/min(Airbus) and can be interpreted physically as the amount of additional fuel worth burning (relative to the minimum fuel burn to operate the flight) to save one unit of time. CI thus captures within it a notion that time-related costs and fuel burn costs can be balanced. The use of CI is now standard practice in the industry, and is used as a rule-of-thumb, capturing the notion that associated with flight speed changes are both fuel impacts and network connectivity impacts.

Typically, an airline selects the 'right' CI value at which to build and operate its schedule by analyzing its historical operations, and computing the ratio of the total realized cost of fuel and the total realized cost of time-related effects (delays, connectivity, etc.). This can be done at a network, fleet or market level, resulting in 'network CI', or 'fleet CI', or 'market CI'. Airlines typically create their flight schedules such that flights are assumed to operate at the historically derived CI value (referred to as the 'normal' CI) and its associated speed. The speed associated with the 'normal CI' is the speed for which the fuel burn rate equals the CI value. To the estimated flying time for the selected speed, additional time is added for taxiing, transiting, delays, etc. to finalize the block time, and schedule for the flight. Compared to flying by simply determining a speed, CI is a more balanced measure that is meant to account for delay- and fuel-related costs.

A CI value of zero means that relative to fuel costs, time-related costs are zero; or the additional fuel worth burning to save one unit of time relative to the minimum fuel burn speed is zero. In this case, the aircraft should be operated at its most fuel-efficient cruise speed, called the *maximum range cruise speed* (and minimum fuel burn speed). When operating at a high CI, the value of time is greater than the associated fuel burn cost, and to minimize the sum of fuel and connectivity costs, the aircraft is sped up, incurring higher fuel costs and lower delay costs.

B.2.2 State-of-the-practice at airlines

In this section, we discuss the current state-of-the-practice involving operational flight planning, for six international carriers.

In practice, computing the CI values using historical data (as described in §B.2.1) is time-consuming, costly, and requires the use of dedicated software (Altus, 2010). As a result, typically a single 'average' CI value (equal to the 'normal' CI value) is used to determine flight plans and the speeds at which to operate flights. Operationally, airlines also specify a *range* of CI values that serve as the operating bounds on a given flight. The dispatcher or pilot is allowed, at his or her discretion, to speed up or slow down within this range in the event of schedule disturbances. (The max CI in the range does not mean that further speed up is not physically possible, instead it is the allowable upper limit at which the flight can be operated at the pilot's discretion.) The min CI value in the range is 0, that is, the minimum fuel burn speed. The max CI value in the range is typically set as a percentage cap on excess fuel burnt beyond the 'normal' CI, which can differ from carrier to carrier. The max CI value is at least limited by the fuel tankering policies of the airline, which do not allow speed up to an extent that requires the use of emergency fuel (this should occur only in emergency situations.) The max CI value can also be more conservatively set, reflecting the fact that the marginal cost of fuel burn per minute of flying time saved is increasing. Yet another consideration in setting the maximum CI value is the objective of airline management to prevent pilots from 'flying too fast' to reach their destinations early and cut their work day short, without regard to the high fuel costs incurred in the process. These guidelines result in pilots or dispatchers filing a faster flight plan prior to departure (at higher CI) if delayed at departure and a slower flight plan if departing early. Note, again, that this is with the intention of minimizing the sum of fuel and time-related costs, as operating at a higher CI (speeding up) means that time-related costs dominate and operating at a lower CI means fuel costs dominate.

Pilots are also given the latitude, if tailwinds are encountered or if the aircraft has an early start, to operate the flight at a CI value lower than the 'normal CI' value. And, in cases of headwinds or late starts, pilots may adjust the flight speed during the flight to operate at higher CI values within the range. Typically, these guidelines are issued with the caution that speeding up will consume excess fuel, and such decisions should be taken judiciously.

A trend that has been observed in the industry during the recent fuel price spike in 2007 is increased use of speed changes during flight. Operational speed changes were used as a mechanism to save on fuel costs by utilizing slack in the flight schedule. Associated Press articles (Associated Press, May 1, 2008) and (Associated Press, May 2, 2008) reported that airlines slowed down flights, resulting in longer flying times but lower fuel burn. As a result, airlines reported savings of about $20 million in one year.

The prevalence of CI as a measure for choosing flight speeds and plans indicates that airlines give significant consideration to the trade-off between time-related connectivity costs and fuel costs. Current practices, however, have some shortcomings. A major issue, one we address in this work, is that the CI values and ranges do not capture the dynamics of operations and thus do not model the true time-fuel tradeoff. To illustrate this point, consider for example, that the 'right' choice of aircraft speed can differ for the same flight on different days, based on the network state, and aircraft and passenger connectivity of that flight on that day. We will demonstrate this further using an example in §B.3. No airlines, to our knowledge, make flight speed decisions that optimize the trade-off in passenger delay costs and fuel costs using *current* flight *network* information, taking into account downstream impacts involving flight and passenger misconnections. In the following sections, we describe how we enhance and extend current practices to capture these dynamics and network effects.

B.3 Our Integrated Flight Planning and Disruption Management Approach

Figure B.2 provides a schematic of our basic concept. Consider a flight a into hub H, delayed by Δ at departure. If the aircraft flies at the scheduled speed, flight a reaches H Δ time units later than scheduled. This decreases connecting time available to passengers at H by Δ time units, and results in disruptions to passengers with connection time consequently reduced to less than the minimum connecting time $MinCT$. Using the following mechanisms, however, passenger connections may be preserved.

Flight speed changes: By changing the speed at which flight a is operated, block time can be decreased and ground time at H increased or vice versa. Figure B.2(ii) shows how using alternate flight plans that operate at different speeds can create different amounts of slack in the schedule, with faster speeds on a allowing passengers adequate time to connect to flights b, c, d, and e.

Flight departure re-timing: In Figure B.2(iii), we illustrate another strategy in which speed change decisions are complemented with flight holding decisions. In the example, it might be more cost efficient to speed up a to a lesser extent than is necessary to preserve passenger connections to b, c and d, and then to hold the departures of flights b, c, d to allow downstream connections from a.

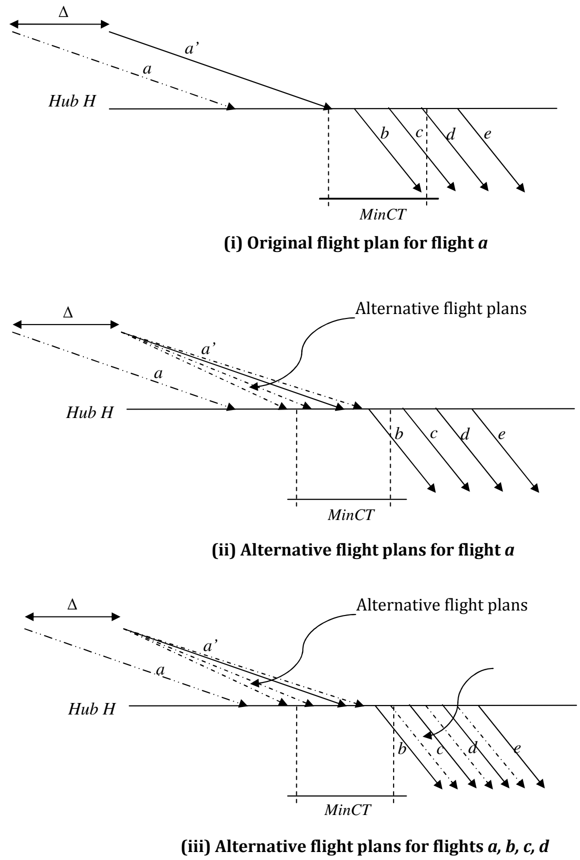

Figure B.2: Flexibility provided in disruption management by choosing alternate flight plans

B.3.1 Example

We illustrate the advantage provided by optimizing flight speeds in the disrupted scenario shown in Figure B.2. We evaluate, for each flight speed possible, the fuel cost and the passenger-related delay costs to the airline. To do this, we use the tools described in §B.3.1 and §B.3.1.

Flight Planning Engine

Flight plans used in our experiments are generated using JetPlan (Jeppesen, 2010), a flight planning tool developed by Jeppesen Commercial and Military Aviation. Jeppesen's flight planning engine uses information about each flight, its planned (or current) schedule, airways, weather patterns, possible aircraft and engine configurations, and payload during the day of interest. It then generates flight plans corresponding to different speeds and travel times for each flight. The flight plan generator takes into account the fuel burn due to the payload consisting of cargo, passengers, luggage hold, and fuel weight. Included in fuel are contingency and reserve fuel.

Passenger Delay Evaluation Module

For each possible choice of flight plan and the schedule associated with that choice, we evaluate the impacts on passengers using an airline disruption management simulator (Davis et al., 2002) (Vaaben, 2009). The purpose of this simulator is to compute the estimated true *realized* passenger delay costs of a set of delayed flights and the corresponding recovery actions on the day of operations. A passenger is defined to be *disrupted* if they cannot take their originally planned itinerary due to cancelations or misconnections. The simulator performs passenger re-accommodation for disrupted passengers by solving the passenger recovery problem with the actual cost values experienced by the airline. Summed with the delay costs experienced by passengers on delayed (but not disrupted) flights, this provides an estimate of the true passenger-related delay cost *to the airline*. These are computed using the delay cost specified in §B.6.3, which include passenger-delay related costs to the airline, hotel, meal reimbursements and goodwill costs.

Results

Table B.1 shows the changes in (i) fuel costs of flight a (taken from the actual operation of a major European airline), and (ii) the corresponding realized passenger-related delay costs to the airline; by operating a at different speeds, given Δ equal to one hour. The flight speeds and fuel costs in columns 1, 2 and 3 are generated using the Flight Planning Engine. Passenger-related delay costs in column 4 are computed for the schedule specified in column 2, using the Passenger Delay Evaluation Module. Table B.1 and Figure B.3 summarize the fuel costs and the passenger-related delay costs to the airline, corresponding to the different flight plans (or CI values), thus depicting the trade-off between the flying time and total cost.

Cost Index (CI)	Flight Time	Fuel burn ($)	Passenger-related delay cost ($)	Total Cost ($)
20	455	53772.80	103396.50	157179.30
40	454	53776.10	103337.10	157113.20
60	454	53777.00	103337.10	157114.10
80	453	53838.80	103337.10	157175.90
100	451	53957.80	103396.50	157354.30
300	442	55962.10	102010.00	157972.10
500	431	58401.00	42715.30	101116.40
700	427	60013.00	41308.60	101321.60
900	426	60551.60	41249.20	101800.80
1100	424	61651.30	38361.60	100012.90
1500	423	62942.70	38302.20	101244.90

Table B.1: Flight time - cost trade-offs associated with different flight plans

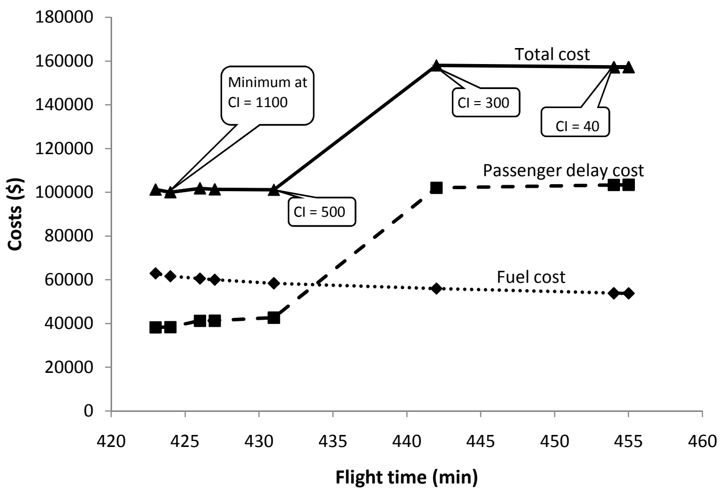

Figure B.3: Trade-off between flight time and associated costs

Compared to the flying time of 431 minutes (at CI 500), the originally planned flight time of 454 minutes (or CI 40) results in many more disrupted passengers, more extensive delays and increased need for re-accommodation. At CI 500, there is a sharp reduction in the passenger cost function as several passengers can make their planned connections, while at CI 40, these passengers mis-connected. More fuel is burned with the faster speed, but not so much as to offset the improvements in passenger-related delay costs to the airline. The sum of passenger delay and fuel burn costs is minimized at a flight time of 424 minutes (at CI 1100). However, the airline from which this example is extracted, typically operates at CI 30 and allows its dispatchers and pilots to speed up to a maximum of CI 300. It is clear from the figure that neither of these CI values truly minimizes costs. While speeding up the flight from CI 40 to CI 300 may be viewed by the pilot as 'making up time', in fact it simply burns excess fuel and increases total cost.

The example illustrates that it is possible to optimize (minimize) total costs by increasing (or decreasing) aircraft speeds relative to those planned. The appropriate speed change and the realized benefit depends on both Δ and on the degree and structure of passenger itinerary connectivity, and is not well-captured using the static rule-of-thumb approach currently used in practice. There has been growing understanding of the shortcomings of current practice, as discussed in Burrows et al. (2001) and Altus (2010), but models to overcome these limitations have not been built.

The example further illustrates that a more effective way to choose a flight speed is to optimize costs in real-time. We present in the following section an optimization-based framework that allows us to optimize operating fuel costs and performance costs as measured by passenger service reliability, thereby minimizing total costs incurred.

Traditional disruption management practice does not capture elements of speed changes as a means to enable planned (but delayed) connections during operations. Flight planners also do not capture the network impacts of the schedule during operations as described in Altus (2010). Our work serves to illustrate that by combining these elements, improvements in total costs are achievable.

Our integrated flight planning and disruption management approach uses at its core, an optimization model that requires input information about possible flight plans in a disrupted scenario and combines them with existing mechanisms of swaps, cancelations and holding flights. Our optimization model is schematically shown in Figure B.4. The flight planning engine that feeds into this module has been described earlier in §B.3.1.

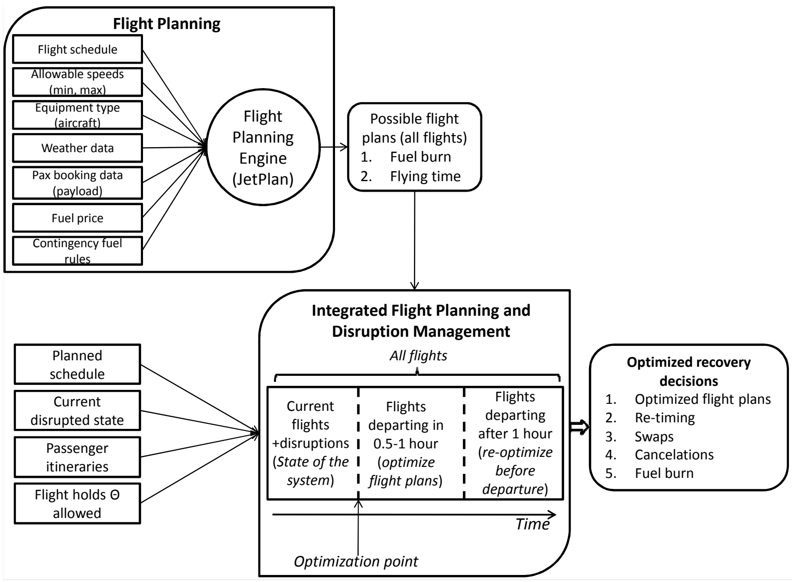

Figure B.4: Optimization module for integrating flight planning and disruption management

Our experimental approach is described in Figure B.5. The optimization module is integrated with a data analysis module that analyzes historical data to generate statistically significant scenarios. This serves as input into the optimization. We evaluate the solutions from the optimization using an independently built simulator, described previously in §B.3.1, to compute *true* delay and disruption costs.

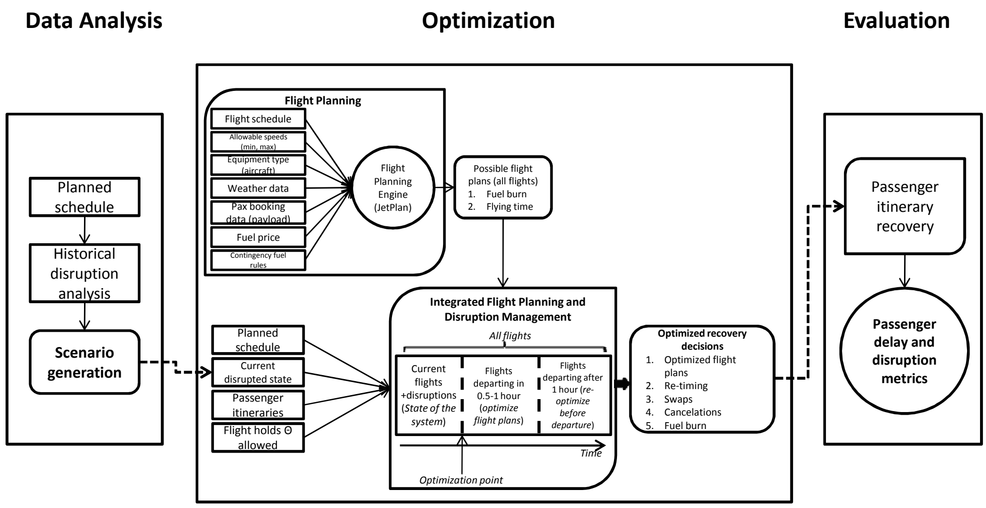

Figure B.5: Experimental approach for integrated flight planning and disruption management

B.4 Modeling Framework

In our enhanced disruption management approach incorporating flight planning, schedule and flight plan optimization is performed prior to each flight, at the time just before the flight plan is filed for the flight. This provides the ability to produce different flight planning solutions during operations; solutions designed to capture the features of aircraft and passenger connectivity for that flight given current schedules, and further network effects that propagate throughout the network. We focus on aircraft and passenger disruption management. With suitable modifications, this can be extended to include crew disruption management also.

Given a disrupted schedule, an airline defines a recovery time-window of duration T, starting from the current time on the day of operations, beyond which normal operations should be resumed. The time-window is defined to begin at least one hour prior to departure of the long-haul flights that are delayed at departure to their hub. It consists of both the arrival and departure banks of long-haul flights and extends over 48 hours, or even 72 hours in case of a very large disruption.

At the start of the time window, we assume that we have a snapshot of the airline's schedule and resource allocations at that point in time. That is, we assume knowledge of: (i) current aircraft locations, planned aircraft rotations and maintenances; (ii) currently delayed flights, and (ii) planned passenger itineraries (and therefore disrupted itineraries). We refer to this information as the *airline system state* at time t.

Knowing the airline system state, estimated times of departure for flights delayed at departure, and scheduled times for non-disrupted flights, we create time-space network representations (described in §B.5) for aircraft and passenger movements. We create appropriate copies (also described in §B.5) representing possible arrival and departures of flights in the time-space networks, allowing for re-scheduling as well as speed changes for flights. With these networks underlying the model, we solve the enhanced disruption management and flight planning formulation(s) (presented in §B.5) which provides a schedule that minimizes the sum of passenger delay and fuel burn costs.

B.4.1 Assumptions

The following assumptions are considered when building our models: (i) A flight cannot be cleared for departure prior to its scheduled departure time; (ii) The decrease in payload (and hence the decrease in fuel burn) due to passengers mis-connecting is negligible; and (iii) If a flight plan with a significantly different arrival time at the destination airport is used, there is a landing slot available at that time.

B.5 Mathematical Models

B.5.1 Time-space networks

Our model is based on *time-space network* representations of the airline's schedule. The nodes in a time-space network are associated with both time and location, and an arc between two nodes indicates a possible movement between the two locations (or same location) and times. Given the state of the system at time t, we create time-space networks within the time-window T whose arcs are based on (i) estimated departure and arrival times of disrupted flights in the system, and (ii) scheduled departure and arrival times of non-disrupted flights, and (iii) possible re-timings and speed changes of flights. In fact, we create two different types of time-space networks: (i) an aircraft flow network for each aircraft and (ii) a passenger flow network for the passengers.

We introduce some notation useful for building our network representations. Let F be the set of flights f that have both departure and arrival within the time window T. Among these, let $F^{'}$ be the set of long-haul flights, for which we consider speed changes, re-timing and swaps; and F - $F^{'}$ be the set of short-haul flights for which we consider flight re-timings alone but no speed changes (speed changes are not significant for short-haul flights). Let A be the set of aircraft a available and $A^{'}$ be the set of aircraft that operate long-haul flights. Let Π be the set of fleet types available, and $\pi(a)$ denote the fleet type assigned to aircraft a in the original schedule. Let $F_{\pi(a)}$ represent the set of flights of the same fleet type as aircraft a, and $F_{FML(a)}$ the set of flights of the same fleet family as aircraft a. For aircraft $a \in A^{'}$, we allow tail swaps (swaps within $F_{\pi(a)}$) and fleet swaps (swaps within $F_{FML(a)}$). Let P be the set of passenger itineraries operated within the time window T, and n_p represent the number of passengers on itinerary $p \in P$. Let D_L and D_S represent the set of long-haul and short-haul flights, respectively, that are immediately downstream of any long-haul flight $g \in F^{'}$ in a passenger itinerary $p \in P$.

Aircraft flow networks

For each aircraft $a \in A$, we create a time-space network N_a to track its movement over the flight schedule. N_a spans the length of the time window T and consists of flights that can be operated by aircraft a, that is, N_a contains $F_{\pi(a)}$ and $F_{FML(a)}$. The operations of these flights are captured by multiple arc copies for each flight, that represent possible departure and arrival times of each flight, as we will describe below. Each node in the aircraft flow network represents either a possible departure time of a flight f, or a possible arrival time of the flight *plus* the minimum turn time of aircraft a. We represent the set of nodes in N_a as $N_a^{'}$. In N_a for each aircraft a, a supply $s^n = 1$ is associated with the node n where the aircraft is known to start at the beginning of the time window T, and a demand of $s^n = -1$ where it completes the last flight in the network. All changes to aircraft a's path and schedule are thus limited within the time-window.

For each flight leg f, we denote the set of flight copies (over all networks N_a) as C_f. Each flight leg copy $k \in C_f$ connects a possible departure time of flight f to a possible arrival time (corresponding to a specific flight plan) plus the minimum turn time of aircraft a. N_n^- is the set of incoming arcs to each node $n \in N_a^{'}$ and N_n^+ is the set of outgoing arcs from each node $n \in N_a^{'}$. A ground arc exists from each node to the next (time-wise) node at each location, and allows feasible aircraft paths to be defined. We refer to the set of ground arcs in N_a as G_a.

Because we consider disruptions to long-haul flights, we create flight copies to model recovery for these flights. For each long-haul flight, that is, for all $f \in N_a$ where $a \in A^{'}$, we create copies of the following types. The first represents the originally scheduled (or estimated, in the case of delayed flights) time of departure and arrival. The second represents alternative departure times of the flight (compared to the original) without speed changes. For this, we generate copies of the flight every 5 minutes until a maximum departure delay of R minutes after its estimated departure time. The third represents flight plans that involve speed changes (created using the Flight Planning Engine), and therefore, represent block time changes to the original flight, but with the same departure time as that of the original flight. The fourth type represents flight plans involving speed changes for the different departure times of flights specified is a combination of the second and third types, representing both a different departure time and a different speed (block time) of operation.

Additionally, copies are created to model the holding of downstream flights in passenger itineraries. Let Θ (in minutes) be the maximum extent to which downstream flights departures are allowed to be intentionally held or delayed in order to facilitate passenger connections. That is, downstream connections are allowed to arrive at most Θ minutes late at their destination. Then, in each network N_a, we have the following cases. First, for all long-haul flights $f_1 \in D_L$ (that is, f_1 follows a long-haul flight in a passenger itinerary) we will capture possible speed changes as well as delaying departure times for this flight. Let the maximum decrease in block time possible due to speeding up f be δ. We create possible departure nodes of flight f every 5 minutes until a maximum departure delay of $\Theta + \delta$ (if such nodes are not already created in previous steps), and corresponding flight copies representing speed changes due to alternative flight plans for each possible departure time. Thus, we ensure that the arrival delay of the downstream flight copies at the destination is no more then Θ minutes. Second, for all short-haul flights $f_2 \in D_S$, we simply make copies of the flight with its scheduled block time and departure arcs at 5 minute intervals until a maximum departure delay (and a corresponding arrival delay) of Θ. However, from the short-haul flights held for passengers, delay can be propagated further downstream to other short-haul flights due to aircraft arriving late. Therefore, for flights $f_3 \in F - F^{'}$ downstream of f_2, we again create copies of the flight with its scheduled block time and departure arcs at 5 minute intervals until a maximum departure delay (and a corresponding arrival delay) of Θ.

In our experiments, we choose values of Θ to be 0, 5, 10 and 15 minutes. We impose a limit of 15 minutes on Θ so that arrival delay of a downstream flight f due to delay propagated to it from an upstream flight via passenger connections is limited to 15 minutes. This is so that the on-time performance of the system (determined by delays greater than 15 min) is not deteriorated.

Scheduled maintenance for an aircraft a, if scheduled within the time window T, is modeled by creating an artificial 'flight leg' in N_a, beginning at the start of maintenance at the maintenance station and ending at the end of the scheduled maintenance at the same station. If maintenance can be delayed, we capture it by creating copies of this arc. Maintenance arcs for aircraft a are only present in N_a and not in other networks.

Three types of costs are associated with each flight copy in the aircraft flow networks. First is the incremental fuel cost c_f^k, for each flight copy $k \in C_f$ for each flight f, compared to the 'normal' CI of operation. c_f^k can be positive or negative, and is obtained from the flight planning engine. Second are aircraft swap costs of operating the flight with an aircraft other than that planned. Let s_f^a denote the swap cost of operating flight f with aircraft a (equals zero if a is the originally planned aircraft routing). Let $\zeta_{(a,f)}^k$ be an indicator that is 1 for all copies $k \in C_f$ that belong to N_a. Then with flight copy $k \in C_f$, a swap cost of $s_f^a \zeta_{(a,f)}^k$ is associated. Third are incremental costs d_f^k of delayed departure, of \$10 per minute, associated with each minute a flight is delayed beyond its scheduled departure.

The above description of construction of N_a for each aircraft a is equivalent to creating a single aircraft flow network, with flight copies for each aircraft exactly as described above; and modeling it as a multi-commodity network flow problem with each aircraft as a commodity. However, for ease of exposition, we have described it as an aircraft flow network for each individual aircraft. Our model differs from previous literature, where typically, each fleet has been modeled as a commodity (Thengvall et al. (2000), Andersson and Varbrand (2004), Yan and Young (1996) and Bratu and Barnhart (2006)).

Passenger flow networks

Similar to aircraft flow networks, we also construct a *passenger flow network* N_P that captures all passenger itineraries. Each node in the passenger flow network represents either a (scheduled or possible) departure of flight f, or an arrival of flight f for a passenger on that itinerary. N_P contains flight copies combined from aircraft flow networks N_a for all a (the minimum turn time for each aircraft, however is not included in defining the nodes in N_P), with the exception of maintenance arcs. Thus, the flight copies represent the operation of the flight with differing departure and arrival times, and by different aircraft. Connection arcs at each location connect successive flight legs, when feasible (exceeds the minimum connecting time) in a passenger itinerary. On this network, each passenger is modeled as a commodity, with its origin at the departure node of the first flight leg on their itinerary, and its destination as the latest node of the passenger's destination airport in the time-window. The destination node of passenger p is set in this manner to capture potential disruptions, and re-accommodation.

Let $N_p^{'}$ be the set of nodes on itinerary p and G_p be the set of ground arcs for p in the passenger flow network N_P. To model passenger re-accommodation, first, we generate candidate itineraries $R(p)$ for each passenger type p. If passenger itinerary p is not disrupted at time t, $R(p)$ consists only of the originally scheduled itinerary. If passenger itinerary p is disrupted in the scenario considered, $R(p)$ is a list of candidate itineraries or paths on the passenger flow network from the origin of p to its destination, with each starting after p's original departure, by at least the amount of disruption of p. $R(p)$ also includes a virtual itinerary to indicate re-accommodation to another airline's network, or perhaps, cancelation of the passenger trip at its origin. d_p^r represents the arrival delay of passengers originally on itinerary p who are re-accommodated on itinerary r. Passenger-related costs c_p^r denote the cost of using itinerary r to accommodate passenger p. This is based on the actual arrival time of itinerary $r \in R(p)$ at the destination, and includes delay costs and goodwill costs. Parameters Cap_f are the number of seats on flight f and parameter δ_f^r is 1 if flight f is on itinerary r and zero otherwise.

Variables

Let x_f^k be a binary variable that takes on value 1 if copy k of flight leg f is present in the solution and 0 otherwise, y_g be a binary variable that is 1 if ground arc g is present in the solution and 0 otherwise, and z_f be a binary variable that is is 1 if flight f is canceled in the solution and 0 otherwise. Let ρ_p^r be the number of passengers originally on itinerary p who are re-accommodated on itinerary r (ρ_p^p equals the number of non-disrupted passengers traveling on their originally scheduled itinerary).

B.5.2 Aircraft Recovery and Passenger Re-accommodation Model

We propose models to minimize the sum of multiple operating costs, including incremental fuel costs, swap costs and passenger-related delay costs (for re-accommodation and recovery). The following is our formulation for combined aircraft recovery and passenger re-accommodation including flight planning opportunities.

$$\min \sum_{f \in F} \sum_{k \in C_f} (c_f^k + s_f^a \zeta_{(a,f)}^k + d_f^k) x_f^k + \sum_{p \in P} c_p^r \rho_p^r \tag{B.1}$$

$$\text{s.t.} \sum_{k \in C_f} x_f^k + z_f = 1 \qquad \forall\, f \in F \tag{B.2}$$

$$\sum_{g \in N_n^-} y_g + \sum_{(f,k) \in N_n^-} x_f^k + s^n = \sum_{g \in N_n^+} y_g + \sum_{(f,k) \in N_n^+} x_f^k \qquad \forall\, n \in N_a^{'}, \forall\, a \in A \tag{B.3}$$

$$\sum_{r \in R(p)} \rho_p^r = n_p \qquad \forall\, p \in P \tag{B.4}$$

$$\sum_{p \in P} \sum_{r \in R(p)} \delta_f^r \rho_p^r \le Cap_f(1 - z_f) \qquad \forall\, f \in F \tag{B.5}$$

$$x_f^k \in \{0, 1\} \qquad \forall\, k \in C_f, \forall\, f \in F \tag{B.6}$$

$$\rho_p^r \in \mathbb{Z}^+ \qquad \forall\, r \in R(p), \forall\, p \in P \tag{B.7}$$

$$y_g \ge 0 \qquad \forall\, g \in G_a, \forall\, a \in A \tag{B.8}$$

The objective (B.1) is to minimize the sum of incremental fuel costs, swap costs, incremental delay costs and passenger delay costs. Constraints (B.2) ensure that a flight is either operated using one of the copies created, or canceled. This flight cover constraint is also applied to the copies of maintenance arcs (described in §B.5.1) with the corresponding z variable set to 0 to disallow cancelation of maintenance. Thus we ensure that compulsory maintenance is carried out, and to exactly the aircraft to which it is assigned. Constraints (B.3) require flow balance for each aircraft. Constraints (B.4) ensure that all passengers reach their destinations either on their original itinerary or an alternate one. Constraints (B.5) ensure that no passengers are assigned to a canceled flight leg, and restrict the number of passengers assigned to a flight leg to its capacity. Constraints (B.6), (B.7) and (B.8) restrict variable values to appropriate binary or integer values. The constraint that y_g is binary can be relaxed to $y_g \ge 0$ because x variables are binary.

B.5.3 Approximate Aircraft and Passenger Recovery Model to Trade-off Fuel Burn and Passenger Cost

Solving the aircraft and passenger recovery model with passenger re-accommodation described in (B.1) - (B.8) can require excessive time for real-time decision making. Feasible solutions obtained when the model is stopped after 5 minutes result in high operating costs. This is likely due to the large sizes of the problem caused by the aircraft-specific networks, flight copies from alternate flight plans, departure times and the corresponding copies to model aircraft swaps, and capacity constraints (B.5) that often result in fractional solutions (as observed in Barnhart et al. (2002) and Bratu and Barnhart (2006)). Thus (B.1) - (B.8) may not suitable for application when decisions have to be made in a few minutes. To address this, we introduce an alternative model that captures approximately the trade-off between fuel burn and passenger delays.

In addition to the notation in (B.1) - (B.8), let $IT(p)$ be the set of flight legs in itinerary p, $IT(p,l)$ the lth flight leg in itinerary p. Let n_f be the number of booked passengers whose itineraries terminate with flight leg f; δ_f^p equal 1 if itinerary p terminates with flight leg f, and 0 otherwise. We let $MC(p,f,k)$ denote the set of flight leg copies $f^{'}$ (the flight to which f connects in itinerary p) in the passenger flow network N_P, to which there is insufficient time to connect from copy k of flight leg f. Let λ_p be a binary variable that is 1 if itinerary p is disrupted and 0 otherwise, and let $\tilde{c}_p$ be the approximate cost of disruption per passenger on itinerary p. $\tilde{c}_p$ is an *approximate* costs of re-accommodation for each disrupted itinerary $p \in P$, because we assume that if passenger itinerary p is disrupted, the passengers on itinerary p are re-accommodated on the next available itinerary to the destination in the next flight bank. Based on this assumption, we compute the per passenger estimated arrival delay cost to the airline for passengers on itinerary p. c_p estimates the costs incurred *by the airline* due to passenger delays, including recovery costs and goodwill costs corresponding to the arrival delay. Setting a cost per itinerary p also allows the capture of non-linearity in costs, where higher delays incur disproportionately higher costs compared to smaller delays. Our modified aircraft recovery model with passenger disruptions is as follows:

$$\min \sum_{f\in F}\sum_{k\in C_f}(c_f^k + s_f^a\zeta^k_{(a,f)} + d_f^k)x_f^k + \sum_{f\in F} c_f z_f + \sum_{p\in P}\tilde{c}_p n_p \lambda_p \tag{B.9}$$

$$\text{s.t.} \sum_{k\in C_f} x_f^k + z_f = 1 \qquad \forall\, f\in F \tag{B.10}$$

$$\sum_{g\in N_n^-} y_g + \sum_{(f,k)\in N_n^-} x_f^k + s^n = \sum_{g\in N_n^+} y_g + \sum_{(f,k)\in N_n^+} x_f^k \qquad \forall\, n\in N_a^{'}, \forall\, a\in A \tag{B.11}$$

$$x^k_{IT(p,l)} + \sum_{m\in MC(p,IT(p,l),k)} x^m_{IT(p,l+1)} - \lambda_p \leq 1 \qquad \forall\, k\in C_{IT(p,l)}, \forall\, l\in 1,..,|IT(p)|-1, \forall\, p\in P \tag{B.12}$$

$$\lambda_p \geq z_f \qquad \forall\, f\in IT(p), \forall\, p\in P \tag{B.13}$$

$$x_f^k \in \{0,1\} \qquad \forall\, k\in C_f, \forall\, f\in F \tag{B.14}$$

$$z_f \in \{0,1\} \qquad \forall\, f\in F \tag{B.15}$$

$$\lambda_p \in \{0,1\} \qquad \forall\, p\in P \tag{B.16}$$

$$y_g \geq 0 \qquad \forall\, g\in G_a, \forall a\in A \tag{B.17}$$

The objective function (B.9) sums up the the incremental fuel costs of flights, swap costs, the incremental costs of flight delays, costs of flight cancelations and the costs to the airline of passenger itinerary disruptions. Constraints (B.12) ensure that itineraries with insufficient connection time are classified as disrupted. Because the value of c_p is greater than zero, this constraint ensures that λ_p is 1 if and only if both terms in (B.12) are 1, that is, if passengers on itinerary p cannot connect from one leg on their itinerary to the following leg on their itinerary. Constraints (B.13) similarly ensure that if a flight leg is canceled, all itineraries containing the flight are classified as disrupted. Constraints (B.16) can be relaxed to $0 \leq \lambda_p \leq 1$ because x and z variables are binary. In all other cases, λ variables will be zero because of the positive cost associated with them in the objective. Constraints (B.10), (B.11), (B.14), (B.15) and (B.17) ensure flight cover (or scheduled maintenance as described in §B.5.2), aircraft balance, and binary values of variables x, z and y respectively, as discussed for (B.1) - (B.8).

B.6 Experimental Setup

B.6.1 Network Structure and Experiment Design

In this section, we demonstrate the potential impact of disruption management enhanced with flight planning, using data obtained from a major European airline (specified in §B.3.1). The airline operates a hub-and-spoke network with about 250 flights per day serving about 60 cities daily and multiple continents. (This does not include feeder airline flights.) The airline operates a banked schedule at its hub. About 243 flights, or 93% of the flights operated by the airline are into or out of the hub. 10% of the flights (approximately 30 arrivals and departures per day) operated are long-haul, and present significant opportunities for speed changes. The remaining 90% of flights are medium-haul and short-haul. Aircraft rotations on this network are typically designed as cycles originating from and ending at the hub, with each cycle consisting of 2 to 4 flights. This is particularly true of short- and medium-haul flights that operate within Europe, which are operated as short cycles around the hub. Long-haul flight operations comprise more than 30% of the flying hours of the airline per day. About 40% of the passengers have at least one long-haul flight on their itinerary. Because these itineraries bring in more revenue than itineraries with only short-haul flights, we estimate that about 50% of the revenue is associated with passenger itineraries containing long-haul flights.

In our experiments, we focus on disruptions of long-haul flights inbound to the hub. The first reason for this focus is a significant percentage of passengers connect at the hub from international locations into Europe and vice versa, and therefore the hub presents the best opportunity to affect passenger connectivity. A second reason is flight planning opportunities, in particular, speed changes, are significant for long-haul flights.

Our models are implemented in C++ and use Xpress. Computational experiments are conducted on a server using a 64 bit Intel Xeon E5440 2.83 GHz processor with 4 cores and 16 GB RAM. Because our models are designed for real-time application, we limit the solve time to 2 minutes and evaluate the best solution found.

B.6.2 Historical Delay Analysis and Scenario Generation

We describe here our scenario generation process, depicted in the Data Analysis module of Figure B.5. We conduct an analysis of delays of long-haul flights that are inbound to the hub and generate distributions of these delays. Our historical delay analysis is conducted for data available for the months of June and July 2008. Unfortunately, passenger information for this period is not available. We have passenger data only for a period of two weeks in November 2008 (for which we do not have flight delay data). We replicate each instance of disruption for each day for which the same schedule occurs and passenger data is available. Thus, each delay scenario may be solved multiple times, once for each day a similar schedule re-occurs for the two weeks in November 2008 for which passenger data is available. We test and evaluate a total of 60 scenarios.

B.6.3 Parameter assumptions

We assume the following values for the parameters in the model:

- Passenger-related delay costs to the airline = \$1.09/passenger per minute, for 2008. This number is the airline's estimate of *its own cost* incurred for passenger delays, including recovery, re-accommodation and goodwill cost.
- Fuel cost = \$3.65/gal or \$0.478/lb. This estimate is a result of the airline AOCC's reported costs (including taxes) of €700 - €800 per metric ton of fuel in February 2010. We assume an average cost of €750 per metric ton. This value is converted to €0.34/lb or \$ 0.43/lb in February 2010. (with density 0.82 kg/litre, 3.6 gal/litre, €1 = \$1.27 European Central Bank (2010) for Nov 2008). Further, guided by the IATA fuel price development charts (International Air Transport Association, 2010), a ratio of 0.903 for costs in November 2008 to February 2010 is applied, to convert the price to \$0.478/lb in November 2008.
- T = approximately 1.5 days or the end of the propagation boundary, encompassing at least two successive arrival banks at the hub to allow for aircraft swaps.
- Normal CI = 30; rule-of-thumb maximum CI specified by the airline = 300
- c_p = Cost per disrupted passenger in model (B.9) - (B.17) = \$457.8. This cost is calculated assuming that disrupted passengers are re-accommodated in the next bank, with an average re-accommodation time of 7 hours, by calculating the average time to the next connecting flight for different passenger itineraries.
- swap cost s_k^f = \$500 per tail swap, \$1000 per fleet swap
- flight cancelation cost = \$20,000

B.6.4 Models being compared

For the evaluation module used in Figure B.5, we compute passenger delay and disruption metrics for solutions to the following optimization models.

Baseline for comparison: Sequential recovery

We use as a basis for comparison the solution to our model allowing aircraft recovery with possible departure delays but no flight changes and passenger disruptions not accounted for. We accomplish this by solving formulation (B.9) - (B.17), with $c_k^f = 0 \,\forall\, k \in K, \forall\, f \in F$ and $c_p = 0 \,\forall\, p \in P$. The objective in this model is to minimize the sum of flight departure delay costs, swap costs and cancelation costs.

Airline rule-of-thumb with flight planning

In this case, we generate solutions allowing flights to be delayed intentionally and allowing flight speeds at the normal flight speed or at the maximum speed specified by the rule-of-thumb. To generate these solutions, we solve the formulation (B.9) - (B.17) without passenger connection constraints (B.12), (B.13) and (B.16); with only two arc copies per flight representing the normal flight speed and the maximum speed specified by the rule-of-thumb, and with $c_p = 0$. The objective in this model is to minimize the sum of fuel costs, flight departure delay costs and cancelation costs.

Aircraft-centric (sequential) recovery with speed changes, with flight planning.

In this case, we generate solutions allowing flight holding and flight speed changes, but ignore the resulting passenger disruption costs. To generate these solutions, we solve formulation (B.9) - (B.17) without passenger connection constraints (B.12), (B.13) and (B.16) and with $c_p = 0$. The objective in this model is to minimize the sum of fuel costs, flight departure delay costs and cancelation costs.

Passenger-centric disruption management approach without flight planning

In this case, the problem is to find the best solutions to (B.9) - (B.17) but to disallow flight arcs corresponding to speed changes. We let $\Theta = 0, 5, 10,$ and 15 minutes and solve the corresponding formulation (B.9) - (B.17)

Enhanced disruption management with flight planning

We solve the complete model (B.9) - (B.17), as described in §B.5, with $\Theta = 0, 5, 10,$ and 15 minutes.

B.6.5 Evaluation - passenger recovery and delay estimation

Each solution generation model described in §B.6.4 produces a schedule which we evaluate for passenger delays in the evaluation module depicted in Figure B.5 and detailed in §B.3.1. Note that the simulated costs obtained using this approach are different from the objective function values for the models in §B.6.4, because the models approximate passenger disruption costs based on mis-connections, whereas the simulator estimates the *actual* passenger costs to the airline based on actual re-accommodation. Details of our experiments are presented in §B.7.

B.7 Results and discussion

B.7.1 Case study 1

To illustrate the tradeoffs occurring in these problems, we first consider a simple case: one flight f is delayed by Δ minutes into the hub, while all other flights operate as scheduled. We consider different levels of delay Δ, on each of 12 days of operation of f, in November 2008. Flight f is representative of the other flights in the network in that the trends and trade-offs observed with this flight are also seen in the case of other flights. In this case, we vary Δ from 10 minutes to 60 minutes in intervals of 10 minutes.

Figure B.6 shows the change in fuel burn and passenger cost curves for different levels of Δ, for selected representative days of operation. The horizontal axis represents the arrival delay of flight f and the vertical axis represents costs incurred. For each value of Δ, the fuel cost curve can be plotted to reflect speed changes in f, resulting in different arrival delays and corresponding fuel burn. Fuel cost curves are marked by Δ values from 10 to 60 in the upper portion of the figure. As the value of Δ increases, the fuel cost curve itself does not change shape, but shifts to the right to reflect increased arrival delay.

In the case when downstream flights are not held for passengers ($\Theta = 0$), the passenger-related airline costs incurred for different levels of flight arrival delay are shown, for instances across five days of data.

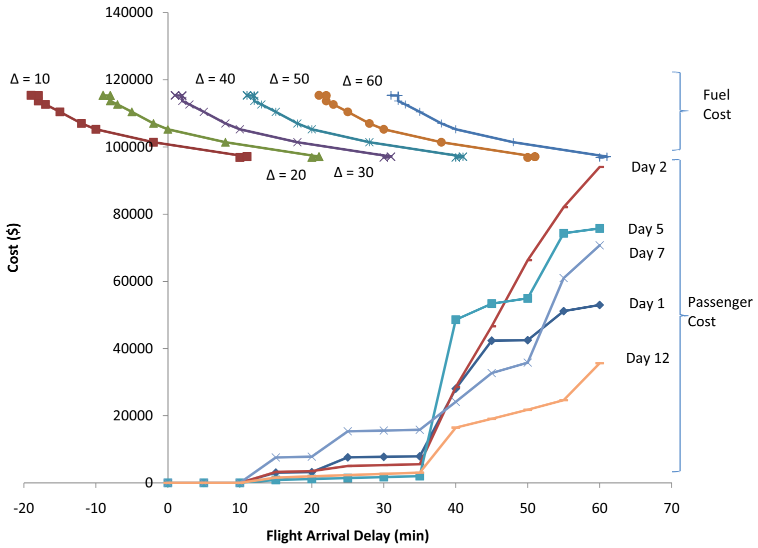

Figure B.6: Trade-offs between fuel burn and passenger delay costs over multiple days

(These are indicated in the lower part of Figure B.6.) As arrival delay increases, passenger delay increases and more passenger misconnects occur. The delay cost curve incurs a 'jump' when a set of passengers misconnect and require recovery and re-accommodation. The total cost curve that is a sum of fuel costs and passenger costs changes dynamically with changes in the delay Δ of flight f. This we illustrate using Figure B.7, which demonstrates the changes in the total cost curve for different Δ, for one day of operations (represented by Day 2 in Figure B.6).

Figure B.7 serves to illustrate that total costs can differ dramatically with changes in Δ. During operations, the propagation impacts of Δ can be adjusted when the departure times of downstream flights are allowed to be altered (or are altered in the course of the day, due to plans not operating exactly as planned) so that passengers can make connections. Holding downstream passenger connections opens up the possibility of the upstream flight speeding up to a smaller extent and burning less fuel, but incurring fewer misconnections. The network interactions now become more interesting, as we have the flexibility of changing speeds and departure times of inbound delayed flights as well as the outbound flight departure times.

We now describe the phenomena that occur when flight speeds and departure times are simultaneously modified to mitigate the effects of disruptions. We do so by solving the model (B.9) - (B.17), with different values of Θ. $\Theta = 0$ results in the phenomenon so far discussed and described in Figures B.6 and B.7. Now we present the fuel burn and passenger-related airline costs (costs estimated via simulation) when (B.9) - (B.17) is solved for $\Theta = 0$, 10 and 15, for the specific flight f and each value of Δ; and compare them to our baseline results. The results presented in Table B.2 are over a 12-day period for which data is available for this flight. The costs presented are the percent savings related to the baseline disruption management model described in B.6.4. We present the fuel burn, passenger (pax) misconnections and associated savings in costs experienced by the airline, for results from five different strategies of disruption management: (1) Column 1: The baseline disruption management strategy described in Section B.6.4, which does not allow for speed changes; (2) Column 2: A disruption management strategy that combines the baseline disruption management strategy with the airline's rule-of-thumb speed up strategy specified in §B.6.4; (3) Column 3: Our enhanced disruption management strategy that combines flight planning with disruption management using (B.9) - (B.17), as described in §B.6.4, with Θ set to 0; (4) Column 4: Our enhanced disruption management strategy that combines flight planning with disruption management using (B.9) - (B.17), as described in §B.6.4, with Θ set to 10 minutes; (5) Column 5: Our enhanced disruption management strategy that combines flight planning with disruption management using (B.9) - (B.17), as described in §B.6.4, with Θ set to 15 minutes.

From our analysis, we present the following findings:

1. The rule-of-thumb that is sometimes adopted by dispatchers, of speeding up to the allowable speed

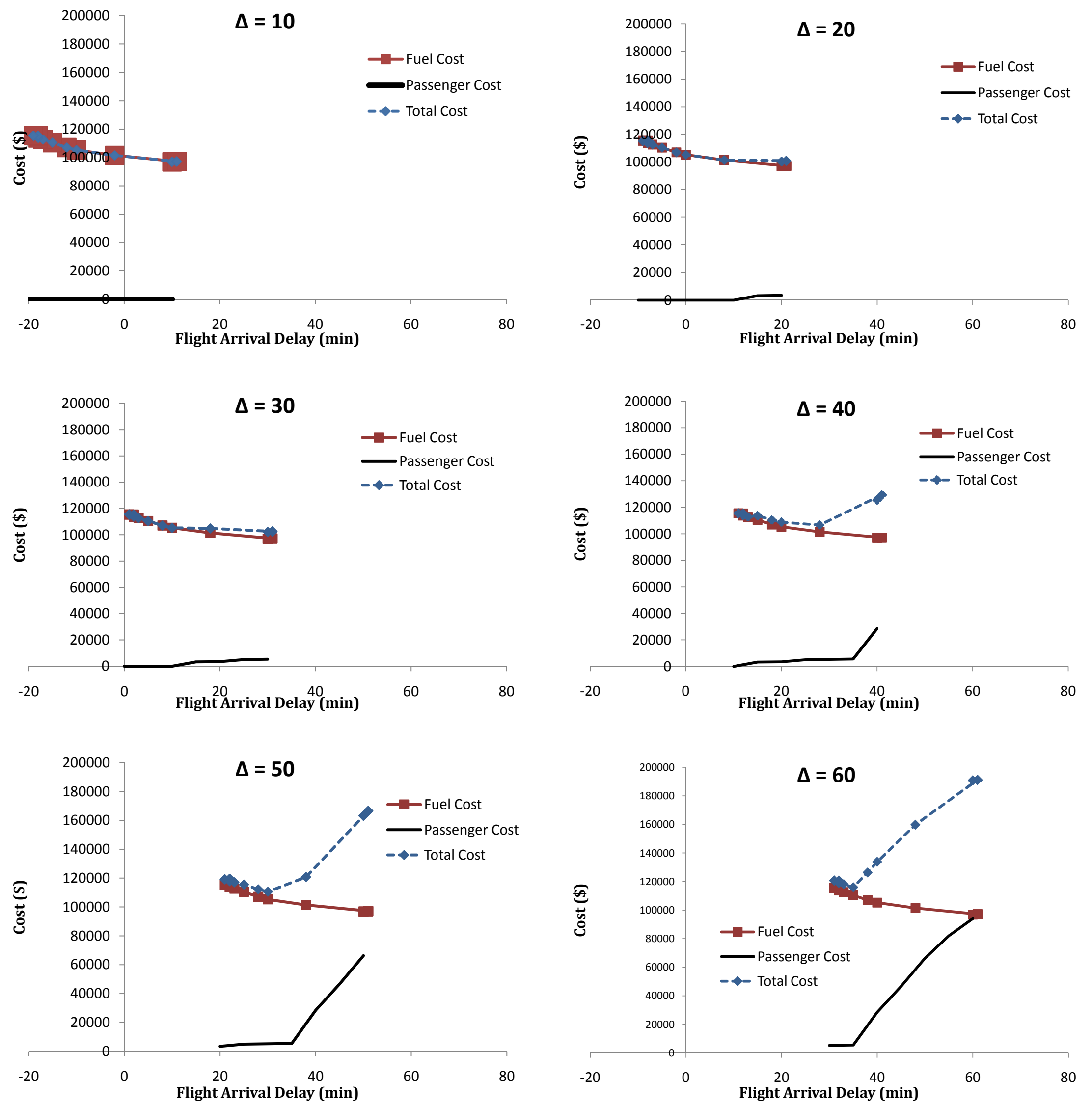

Figure B.7: Changing optimal trade-off point between fuel and passenger cost with departure delay Δ

(Column 2 solutions), results in improved passenger costs compared to the baseline recovery model, as it improves the on-time performance of the flight. However, for medium levels of disruption, such as 20-30 minutes, it results in increased fuel consumption even in cases where it may not be required. This rule-of-thumb-based policy may be able to recover passengers for $\Delta = 10$ and $\Delta = 20$, but may fall short for larger disruptions. In comparison with our optimization-based models, the rule-of-thumb speed-up policy almost always results in higher costs.

2. Our enhanced recovery approach compared to the baseline and rule-of-thumb-practices generally reduces total costs and passenger-related delay costs for the airline significantly (except for some scenarios as explained below).

   (a) For all levels of disruption, recovery models enhanced using flight planning will hold constant or decrease total passenger-related delay costs compared to the baseline approach. For the example in Table B.2, the total cost improvements ranged from 0 to 15%.

   (b) Depending on the itineraries of passengers, both flight speed changes as well as holding of downstream flights might be necessary to reduce the number of misconnected itineraries. For

	Baseline recovery	Rule-of-thumb speed up (to CI 300)	Enhanced recovery: don't hold connecting flights	Enhanced recovery: hold connecting flights up to 10 min	Enhanced recovery: hold connecting flights up to 15 min
Δ = 10 min					
Fuel savings per operated LH flight %	-	-4.69	0.05	0.05	0.05
pax disruption savings %	0 disruptions	N/A	N/A	N/A	N/A
delayed pax cost savings %	0 disruptions	N/A	N/A	N/A	N/A
Total cost savings %	-	-4.69	0.05	0.05	0.05
Δ = 20 min					
Fuel savings per operated LH flight %	-	-4.69	-2.72	-2.72	0.05
pax disruption savings %	-	99.72	93.45	96.58	99.72
delayed pax cost savings %	-	93.66	80.30	82.80	93.66
Total cost savings %	-	-0.22	1.05	1.17	4.30
Δ = 30 min					
Fuel savings per operated LH flight %	-	-4.69	-3.40	-2.73	-2.73
pax disruption savings %	-	42.17	71.23	93.73	96.58
delayed pax cost savings %	-	39.32	57.94	68.64	70.61
Total cost savings %	-	-2.54	-0.40	0.75	0.85
Δ = 40 min					
Fuel savings per operated LH flight %	-	-4.69	-5.95	-4.33	-4.33
pax disruption savings %	-	56.45	70.35	94.29	94.42
delayed pax cost savings %	-	73.20	72.57	85.73	85.49
Total cost savings %	-	7.53	6.37	9.80	9.76
Δ = 60 min					
Fuel savings per operated LH flight %	-	-4.69	-6.24	-8.66	-6.24
pax disruption savings %	-	13.72	70.70	71.35	72.40
delayed pax cost savings %	-	22.54	84.56	85.45	64.43
Total cost savings %	-	3.87	22.31	20.94	15.98

Table B.2: Single flight delay: simulated percentage *savings* for different recovery strategies, averaged over 12 days of operation

example, in the case of a 20-minute initial disruption, simply allowing speed changes without holding downstream flights is sufficient to recapture 93% of the disrupted passengers back onto their original itineraries compared to the baseline case. In the case of 30- and 40-minute delays, however, only about 70% of passenger misconnects can be prevented by allowing speed changes without holding flights. By also allowing downstream flight departures to be delayed by 10 minutes, the misconnects are decreased by about 95%.

(c) Because the objective function of the model (B.9) - (B.17) estimates costs approximately, and hence differently, from those calculated in the simulation, discrepancies may be (rarely) observed in cases for which passenger delay costs calculated in the simulation are not well approximated by the passenger disruption costs in the objective function of (B.9) - (B.17). For example, note the negative value of realized total cost for $\Delta = 30$ in column 3 of Table B.2. The simulated passenger delay cost savings are not as high as indicated by the objective function value when (B.9) - (B.17) is solved, resulting in increased costs instead of savings.

3. Low levels of disruption:

(a) For very low levels of disruption (for example, 10 minutes), enough slack is present in the system to absorb the disruption, and flight planning mechanisms such as speed increases and holding downstream flights are not required. Instead, we might be able to slow down the flight without incurring disruptions. However, for even fairly low levels of disruption such as 20 minutes, the interaction between speed changes and passenger delays can come into play. In the case of the flight demonstrated in Table B.2, some passenger connections have a small amount of slack for which delays of 20 minutes cannot be absorbed, resulting in misconnections if the flight is not sped up. In the 20-minutes of delay case, however, almost all disruptions can be absorbed by speeding up the flight, and/or delaying downstream flights to the appropriate extent.

(b) For low levels of disruption, fuel burn costs dominate and drive the trade-off between fuel burn and passenger delay costs, as seen in the cases of 10 - 20 minutes of delay. In these cases, because fewer passengers are impacted, the balance in the optimization model tilts in the favor of decreasing fuel costs. The decision in such cases is to slow down the flight because passengers are not disrupted by the slow down. Occurrences of these levels of delays provide an opportunity to save fuel in comparison to the baseline recovery approach.

4. Intermediate levels of disruption:

   (a) For intermediate levels of delay, such as 20 - 40 minutes, holding downstream flights to wait for connecting passengers can have significant benefits. In Table B.2, the number of passenger misconnections decreases significantly from Column 3 to Columns 4 and 5. With the decrease in the number of misconnections, there is a corresponding decrease in passenger-related costs, for $\Delta = 20$ and $\Delta = 30$.

5. High levels of disruption:

   (a) For higher levels of initial disruption (more than 30 minutes in the case shown above), passenger delay costs dominate the trade-off between fuel burn and delay costs. This is because many more downstream flight connections are impacted by a large initial disruption. To reduce the number of passenger disruptions, the optimal least total cost decision is to speed up the long-haul flight. If allowed, downstream flights are also held in order to facilitate passenger connections.

   (b) We also observe from Table B.2 that for departure delay levels less than 40 minutes, the number of passenger misconnections and the corresponding passenger costs significantly decrease when downstream flights are held compared to the case when only flight speeds are changed. For higher levels of delay, as shown for $\Delta = 60$, the decrease in the number of misconnections and in the passenger costs is less significant when flights are held compared to when only speed changes are allowed. (In fact, passenger delay costs increase for $\Theta = 15$.) The increase in passenger-related costs connected with holding downstream flights begins to exceed the decrease in passenger-related costs associated with re-accommodation and recovery of disrupted passengers. Thus the benefits of holding downstream flights decrease as the level of the initial disruption Δ increases to large values, because many more flights are held, and delay times for passengers on the downstream flights are increased.

B.7.2 Case study 2

In this section, we present a more comprehensive set of experiments and results, derived from the airline specified in §B.6. We consider 60 scenarios derived from the airline's historical data to test our models. In each scenario, typically, 12-14 long-haul flights are inbound to (and outbound from) the hub in each bank, among which 1-6 flights may be delayed by varying degrees from their origin into the hub. Based on the degrees of delay experienced, we categorize the scenarios, as described in Table B.3. In the time-window T for which recovery is performed, there are 26-40 long-haul flights depending on the length of T. Our model formulation sizes are of the order of 200,000 rows and 200,000 columns.

If all inbound delays to the hub in the scenario are less than 20 minutes, we refer to it as a small-delay scenario; if the longest delay is greater than 20 but less than 50 minutes, we refer to it as a medium-delay scenario; if the longest delay among all flights is greater than 50 but less than 120 minutes, we refer to it as a large-delay scenario; and if there exists a delay in the scenario greater than 120 minutes we refer to it as a very large-delay scenario. Table B.3 also shows the frequency of occurrences of these disruptions in June-July 2008.

Disruption type	Number	Frequency
small delays	6	0.18
medium delays	12	0.28
large delays	14	0.25
very large delays	28	0.29

Table B.3: Disruption scenarios

In this section, we compare a larger set of disruption management strategies, as described in §B.6.4: 1. Column 1: Baseline disruption management without speed changes and not explicitly capturing passenger disruptions from §B.6.4; 2. Column 2: Aircraft-centric recovery that includes speed changes enabled by flight planning but does not explicitly capture passenger disruptions, described in §B.6.4; 3. Columns 3-6: Passenger-centric (pax-centric) disruption management approach without flight planning, with downstream departure holds set to $\Theta = 0$, 5, 10 and 15 minutes in columns 3-6 respectively. The models are described in §B.6.4; and 4. Columns 7-10: Our enhanced disruption management strategy that combines flight planning with disruption management ((B.9) - (B.17)) with downstream departure delays set to $\Theta =$

0, 5, 10 and 15 minutes respectively. We do not include the airline rule-of-thumb as it is a more costly option, as illustrated in §B.7.1.

As specified earlier, we impose a maximum solve time of 2 minutes for the models, and evaluate the best solution obtained thus far. MIP gaps (the ratio between the objective of the best integer solution obtained and the best linear program) equaled zero for the baseline disruption management, aircraft-centric recovery with flight planning, and passenger-centric recovery without flight planning models (except for the $\Theta = 15$ case for which small MIP gaps occurred). Our enhanced disruption management models with flight planning resulted in MIP gaps up to 50% when the disrupted scenario contained a very large number of highly delayed flights, due to the larger number of flight copies required.

Table B.4 summarizes our results over the 60 scenarios. We report the *simulated* values of the passenger disruption savings, delayed passenger costs to the airline, fuel savings per operated long-haul (LH) flight in T, total cost savings, short-haul (SH) flights intentionally held, number of flights canceled, number of swaps, on-time performance (OTP) for the long-haul fleets, and MIP gap for different models of interest.

		Baseline recovery	Speed change	Pax Centric $\Theta = 0$	Pax Centric $\Theta = 5$	Pax Centric $\Theta = 10$	Pax Centric $\Theta = 15$	Enhanced Recovery $\Theta = 0$	Enhanced Recovery $\Theta = 5$	Enhanced Recovery $\Theta = 10$	Enhanced Recovery $\Theta = 15$
Pax disruption savings %	average	–	6.06	20.29	38.64	55.64	60.79	65.91	76.53	77.96	79.14
Delayed pax cost savings to airline %	average	–	-15.40	26.43	41.09	53.58	57.90	64.26	77.77	78.52	79.56
Fuel savings per operated LH flight %	average	–	-0.082	-0.158	-0.163	-0.163	-0.167	-0.254	-0.252	-0.251	-0.249
Total cost savings to airline %	average	–	4.95	1.29	2.26	2.48	2.86	9.18	9.02	9.01	9.00
SH flights held	average	–	0.00	0.00	4.00	6.20	7.23	0.00	3.52	4.57	5.45
Nr. canceled	average	1.60	1.23	0.57	0.53	0.53	0.50	0.10	0.10	0.10	0.10
Nr. swaps	average	3.75	3.77	4.00	3.80	3.80	3.83	3.47	3.40	3.33	3.33
OTP	average	0.88	0.92	0.90	0.90	0.90	0.90	0.94	0.94	0.94	0.94
MIP gap %	average	0.00	0.00	0.00	0.00	0.00	0.33	7.13	7.21	7.12	7.87

Table B.4: Simulated *savings* per day for different recovery strategies and holding policies Θ, over all scenarios

In Table B.4 we show that relative to the (traditional) sequential recovery model, the enhanced recovery models perform better than: (i) the model that uses speed changes alone (column 2); and (ii) passenger-centric recovery models (columns 3-6) without flight speed changes but with different levels of flight holds Θ. The enhanced recovery models essentially capture the flexibility exhibited by both classes of models and thus exhibit superior performance.

These results show an improvement of 66-79% in the number of passengers disrupted, compared to a sequential recovery approach. Passenger delay costs (incurred by the airline) can be decreased by 64-79%. This comes at a cost of additional fuel burn costs of about 0.25% per operated flight, and results in an overall cost savings of about 9% for the airline. The enhanced recovery models with flight planning also decrease significantly the number of flight cancelations (from 1.6 to 0.1 per scenario) by allowing an increased number of swaps, thereby increasing flexibility in recovery. Also, the possibility of speed-ups and the decreased numbers of cancelations help improve the on-time performance of the airline from 0.88 to 0.94 for the long-haul fleet. However, we also observe a high degree of variability in the savings from our enhanced recovery models. This follows from our discussion in §B.7.1 concluding that different delay scenarios and different levels of passenger connectivity result in very different trade-offs in fuel and delay costs (Figures B.6 and B.7). Thus, to gain further insight, we present Tables B.5 - B.8 detailing the performances of the different models for different levels of disruption.

From these tables, we conclude the following:

Small disruptions: Our enhanced recovery models can recover a significant fraction (82-98%) of disrupted passengers. For small disruptions these are few in number, so most can be recovered using speed changes and by holding downstream flight departures. A very small increase in fuel burn costs of 0.007% is observed due to speed increases (and speed reductions, where appropriate). The result is an overall cost savings of 1.64 - 1.72 % for the small delay scenarios.

Medium disruptions: A significant number of passengers (61-86%) are prevented from missing their connections. The fraction is not as large, however, as in the case of small-disruptions. Compared to the small-disruption case, a larger number of passengers are negatively impacted by the medium-disruptions, and fewer affected connections can be re-connected using flight speed changes and departure holds. As expected, higher speed ups are required compared to the small-disruption cases, thus burning more fuel (0.014 %) on average. The higher speed up per LH flight, combined with the fewer passengers saved

		Baseline recovery	Speed change	Pax Centric $\Theta = 0$	Pax Centric $\Theta = 5$	Pax Centric $\Theta = 10$	Pax Centric $\Theta = 15$	Enhanced Recovery $\Theta = 0$	Enhanced Recovery $\Theta = 5$	Enhanced Recovery $\Theta = 10$	Enhanced Recovery $\Theta = 15$
Pax disruption savings %	average	–	0.00	0.00	48.01	98.05	98.05	82.18	98.79	98.79	98.79
Delayed pax cost savings to airline %	average	–	-108.70	23.01	39.94	58.87	62.31	57.84	67.69	67.69	68.53
Fuel savings per operated LH flight %	average	–	-0.007	0.000	0.000	0.000	0.000	-0.007	-0.007	-0.007	-0.007
Total cost savings to airline %	average	–	0.03	0.00	0.47	1.36	1.36	1.64	1.67	1.66	1.72
SH flights held	average	0.00	0.00	0.00	3.20	4.20	4.20	0.00	1.40	1.40	1.40
Nr. canceled	average	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Nr. swaps	average	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OTP	average	0.93	1.00	0.93	0.93	0.93	0.93	1.00	1.00	1.00	1.00
MIP gap %	average	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table B.5: Small delay scenarios: Simulated *savings* per day for different recovery strategies and different holding policies Θ

		Baseline recovery	Speed change	Pax Centric $\Theta = 0$	Pax Centric $\Theta = 5$	Pax Centric $\Theta = 10$	Pax Centric $\Theta = 15$	Enhanced Recovery $\Theta = 0$	Enhanced Recovery $\Theta = 5$	Enhanced Recovery $\Theta = 10$	Enhanced Recovery $\Theta = 15$
Pax disruption savings %	average	–	0.00	0.00	35.01	70.38	77.07	61.40	86.76	86.76	86.76
Delayed pax cost savings to airline %	average	–	-60.91	0.00	32.07	57.80	68.28	57.15	85.69	85.69	85.69
Fuel savings per operated LH flight %	average	–	-0.013	0.000	0.000	0.000	0.000	-0.014	-0.013	-0.013	-0.013
Total cost savings to airline %	average	–	0.04	0.00	-0.01	-0.08	-0.11	0.35	0.10	-0.08	-0.08
SH flights held	average	0.00	0.00	0.00	2.83	4.58	4.92	0.00	2.58	2.58	2.58
Nr. Canceled	average	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
Nr. Swaps	average	5.83	4.83	5.83	5.83	5.83	5.83	4.83	4.83	4.83	4.83
OTP	average	0.95	1.00	0.95	0.95	0.95	0.95	1.00	1.00	1.00	1.00
MIP gap %	average	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table B.6: Medium delay scenarios: Simulated *savings* per day for different recovery strategies and different holding policies Θ

		Baseline recovery	Speed change	Pax Centric $\Theta = 0$	Pax Centric $\Theta = 5$	Pax Centric $\Theta = 10$	Pax Centric $\Theta = 15$	Enhanced Recovery $\Theta = 0$	Enhanced Recovery $\Theta = 5$	Enhanced Recovery $\Theta = 10$	Enhanced Recovery $\Theta = 15$
Pax disruption savings %	average	–	0	5.53	23.78	45.53	55.84	57.41	72.03	76.74	81.15
Delayed pax cost savings to airline %	average	–	0.6	6.58	21.17	37.03	43.89	46.72	66.85	69.8	74.17
Fuel savings per operated LH flight %	average	–	-0.008	-0.011	-0.011	-0.011	-0.011	-0.032	-0.032	-0.033	-0.028
Total cost savings to airline %	average	–	0	0	0.11	0.56	0.44	1.47	1.24	1.09	1.15
SH flights held	average	0.00	0.00	0.00	5.57	10.29	12.00	0.00	5.21	6.00	7.79
Nr. Canceled	average	0.14	0.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Nr. Swaps	average	3.75	3.79	3.86	3.57	3.57	3.57	3.57	3.57	3.57	3.57
OTP	average	0.90	0.93	0.91	0.91	0.91	0.91	0.94	0.94	0.94	0.93
MIP gap %	average	0.00	0.00	0.00	0.00	0.00	0.81	3.41	2.36	2.03	1.72

Table B.7: Large delay scenarios: Simulated *savings* per day for different recovery strategies and different holding policies Θ

from misconnecting cause the total cost savings *for the airline* to be small, as to be almost negligible in these cases. However, significant benefits are observed in costs experienced by passengers as a significant number are saved from misconnecting.

Large and very-large disruptions: A phenomenon different from those in small- and medium-disruption cases comes into play. Large disruptions propagate downstream in the long-haul schedule, affecting many flights and passengers, and requiring flight speed-ups for a large number of flights (0.033% for large disruptions and 0.5% for very large disruptions). Flight speed changes in enhanced recovery enable a larger number of swap possibilities in the network as schedule recovery is performed, and the added flexibility also decreases the number of cancelations that might be needed in a traditional recovery model. Due to this added flexibility, a significant percentage of passengers (57-81% for large delay and 69-71% in very-large delay scenarios) can be prevented from missing their connections. The result is a

		Baseline recovery	Speed change	Pax Centric $\Theta = 0$	Pax Centric $\Theta = 5$	Pax Centric $\Theta = 10$	Pax Centric $\Theta = 15$	Enhanced Recovery $\Theta = 0$	Enhanced Recovery $\Theta = 5$	Enhanced Recovery $\Theta = 10$	Enhanced Recovery $\Theta = 15$
Pax disruption savings %	average	–	12.53	39.31	45.69	47.11	50.01	69.08	70.63	71.31	71.64
Delayed pax cost savings to airline %	average	–	11.79	51.52	56.30	56.89	58.16	77.18	78.07	78.21	78.24
Fuel savings per operated LH flight %	average	–	-0.159	-0.322	-0.332	-0.332	-0.341	-0.504	-0.500	-0.497	-0.496
Total cost savings to airline %	average	–	10.21	2.66	4.65	4.90	5.76	18.11	18.01	18.15	18.10
SH flights held	average	0.00	0.00	0.00	3.86	5.24	6.41	0.00	3.45	5.24	6.21
Nr. Canceled	average	3.21	2.45	1.14	1.07	1.07	1.00	0.17	0.17	0.17	0.17
Nr. Swaps	average	3.38	3.97	4.00	3.72	3.72	3.79	3.45	3.31	3.17	3.17
OTP	average	0.83	0.87	0.87	0.87	0.87	0.88	0.91	0.91	0.91	0.91
MIP gap %	average	0.00	0.00	0.00	0.00	0.00	0.29	13.11	13.79	13.75	15.46

Table B.8: Very large delay scenarios: Simulated *savings* per day for different recovery strategies and different holding policies Θ

total cost savings of 1.1-1.4% for large-delay and 18% for very large-delay scenarios.

Due to the high amount of delay propagation that occurs in the large and very large disruption scenarios, propagation to several flights has to be modeled, and a longer time-window T may have to be used, along with more flight copies, as needed. Because of the two minute limit on solution time, the larger-size integer program solutions are not optimal, with MIP gaps shown in Tables B.7 and B.8. Nonetheless, the solutions to our enhanced recovery models achieve significant improvements relative to the sequential recovery, speed change and passenger-centric models.

From tables B.4, B.5, B.6, B.7, B.8, we see that flight speed changes alone with no passenger-centric costs do not add much value. Once passenger centric-costs are added into the objective, the models add much more value, as seen in the columns 'Enhanced Recovery $\Theta = 0$'. Moreover, enhanced recovery models perform better than those with passenger-centric costs and objectives for all values of Θ. The improvement is greatest for small values of Θ(such as 0 and 5), that is, when downstream passenger connections are not allowed to be held or are held only briefly. This occurs because the enhanced recovery model allows speed changes, while the passenger-centric models do not. Our enhanced recovery models also add progressively more value relative to passenger-centric recovery as the size of the initial disruption increases and more flights are impacted.

Neither speed changes alone (column 4 in Tables B.4, B.5, B.6, B.7, B.8), nor passenger-centric recovery with flight holds alone (columns 5 through 8 in the tables) can generate savings as great as those of the enhanced recovery models (columns 9-12 in the tables) in which these mechanisms are combined.

To put these results in context, we weight the average savings from Tables B.5 - B.8 by the frequency of occurrences of such delays described in Table B.3. This results in a total cost savings to the airline of about 5.7 - 5.9%, decrease in passenger disruptions of 66 - 83% and increase in fuel burn over the long-haul fleet of 0.152-0.155%. The decrease in passenger-related cost savings to the airline is about 60 - 73%. Though the cost savings to the airline are highest for very-large-delay cases and are of the order of 1-2% for other types of scenarios, in all types of scenarios, there are significant savings in passenger misconnections and disruptions. Savings in delay minutes experienced by passengers (computed using the evaluation module) are of the order of 474,823 - 485,254 minutes per disrupted scenario compared to baseline recovery, resulting in decreased passenger-delay costs of $17.5 - 17.9 M over the June-July period in 2008 (using a passenger-value-of-time equal to $37.56 per hour (Air Transport Association, 2008)).

B.7.3 Summary

Our enhanced recovery approach integrating flight planning into disruption management allows the capture of speed changes of flights and captures the interaction between fuel burn and delay costs. We show significant synergy between flight speed changes and existing mechanisms of disruption management, such as flight holds. Compared to the current state-of-the-practice at airlines, our enhanced recovery approach provides a more accurate way of dynamically quantifying the tradeoff between time-related costs and fuel-burn related costs. The rule-of-thumb policy in practice is almost always costlier than our enhanced recovery approach. Our enhanced recovery models reduce total costs and passenger-related delay costs for the airline, compared to existing approaches in practice and in the literature. For very low disruption levels, fuel costs dominate over passenger-related delay costs to the airline, and as the extent of disruption increases, passenger-related delay costs dominate. The ability to change flight speeds also contributes to higher cost savings for the airline as the extent of the initial disruption increases. Flight speed changes in combination with flight holds mitigate delay propagation effects by providing more aircraft swap opportunities and decreasing the number of required cancelations.

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Appendix C

Mitigation of Airspace Congestion Impact on Airline Networks

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Abstract In recent years European airspace has become increasingly congested and airlines can now observe that en-route capacity constraints is the fastest growing source of flight delays. In 2010 this source of delay accounted for 19% of all flight delays in Europe and has been increasing with an average yearly rate of 17% from 2005 to 2010. This paper suggests and evaluates an approach to how disruption management can be combined with flight planning in order to create more proactive handling of the kind of disruptions, which are caused by congested airspace. The approach is evaluated using data from a medium size European carrier and estimates a lower bound saving of several million USD.
Keywords: Disruption Management, Congested Airspace, Aircraft Recovery, Flight Delays, Flight Cancellations, Aircraft Swaps, Airline Industry

C.1 Introduction

Running an airline is a complex business where hundreds of aircraft need to be scheduled and maintained. Thousands of flights need to be dispatched every day. Tens of thousands of crew members need to be rostered and millions of passengers need to be transported from one location to another every year. To accomplish this enormous task airlines have for several decades relied on Operations Research (OR) to stay competitive and conduct careful and efficient planning of every single activity in their operation. Unfortunately these efficient plans are hardly ever being executed as originally intended.

In 2010 24% of all flights in Europe and 18% of all flights in the US were delayed more than 15 minutes and consequently experienced some sort of disruption (Eurocontrol and FAA, 2012). Bad weather, technical problems, crew reporting sick and in recent years to an increasing extent also airspace being congested are all examples of uncertainty elements, which will force an airline to deviate from their detailed and optimized plans.

To manage these deviations there has during the last couple of decades been a move in airline related OR research from purely being focused on the planning phase of an airline to also being focused on the real-time execution of the airline. This move has as a first step involved robust planning and later on also disruption management. In this paper we take OR based disruption management one step further in the direction toward the actual flight operation as we combine disruption management and flight planning. As flight planning is a little researched field by the OR community the paper includes an extensive description of flight planning and the airspace rules under which flight planning is conducted.

C.1.1 Outline of Paper

The paper initially gives a short introduction to disruption management and the main work processes, which exists in an *Operational Control Center (OCC)* in an airline. This continues with a brief comparison of planning versus day of operation processes and argues why it is crucially important to have integrated decisions on the day of operation.

The paper provides a literature review on disruption management with a special focus on integrated disruption management. Whereas previous work on disruption management often addresses the integration between aircraft recovery, crew recovery and passenger recovery, we do in this paper consider flexible flight trajectories as an integrated part of the recovery process, which is particularly useful in disruption situations involving congested airspace. For this reason the paper provides an introduction to airspace and Air Traffic Control (ATC). Airspace and ATC provides the structure and regulations under which flight planning is conducted.

The paper briefly describes flight planning and previous literature in this area in order to give a better understanding of how flight planning is incorporated into the recovery decisions.

The paper goes into further detail with Air Traffic Flow Management (ATFM) and describes the differences in ATFM regulation procedures between the US and Europe. This is important as ATFM plays a central role when authorities regulate congested airspace.

With disruption management, flight planning and ATFM in place we suggest a network representation and a model, which handles integrated recovery decision with flexible flight trajectories. We decribe a framework for using the integrated decision approach and use this to evaluate our suggested approach. Finally we present our findings in terms of a lower bound for the annual saving, which can be obtained by using the approach. Some suggestions to future work are also presented.

C.1.2 Contributions

As congested airspace in recent years has become the fastest growing source of delays in Europe (Eurocontrol, 2010) a first contribution of this paper is to suggest and evaluate an approach to how disruption management can be combined with flight planning in order to create more proactive handling of the kind of disruptions, which are caused by congested airspace.

A second contribution of this paper is to suggest a method for increased interaction between Ops Controllers and flight planners in order to make sure that the network effects of any trajectory selection is properly incorporated in the decisions.

A third contribution is a flight planning based aircraft recovery model, which takes into account both passenger misconnections and congested airspace constraints.

C.2 Disruption Management

Whenever an event occurs, which makes an airline deviate from its planned schedule or its planned crew rosters, the airline is disrupted. Most larger airlines operate a hub and spoke network, where efficient use of aircraft and crews are causing the airline not to have crew following the aircraft. This is due to the fact that crew work rules are much more restrictive than the rules, which can be applied to aircraft. The tight planning of aircraft and crew is causing an airline to become very vulnerable to disruptions, as a delay of a single inbound flight to a hub quickly can propagate to other flights, through delays of both the incoming aircraft and its crew. As even small disruptions in this way rapidly can propagate to a large part of the airline's network, it is very important for an airline to manage disruptions in a timely manner.

Most airlines have an Operational Control Center (OCC). Alternative names for this center include Network Operations Center (NOC), System Operations Center (SOC), Airline Operations Center (AOC) and Airline Operations Control Center (AOCC). The term OCC will be used in this paper. The OCC is by many referred to as "the heart of the airline". It is where *Ops Controllers* monitor the operation of the airline and manage disruptions to the schedule and are responsible for a well-functioning network of flights, crew and passengers on the day of operation. It is jokingly said to be the only place in an airline where the CEO is happy to walk in and see the employees sitting with their feet on the desk without any urgent issues to take care of as this means that the airline is running according to plan.

A smooth execution of all scheduled activities is paramount for an airline as it takes very few disrupted flights on a single day for the airline to go from making a profit to making a loss for that day. Estimates for the cost of disruptions to airlines are estimated to $19 billion annually in the US alone (Schumer and Maloney, 2008).

The organizational setup of an OCC varies from airline to airline and does to a large extent depend on the size of the airline. There are, however, some typical organizational entities, which are present in virtually any OCC. These are:

- Airline Operations Controllers
  These are sometimes also referred to as just Ops Controllers or Duty Managers and are responsible for the overall operation of the airline's schedule on the day of operation. To ensure this and to help them in their decisions, they interact with other groups of people in the OCC - mainly the following groups: Aircraft Controllers, Crew Controllers and Customer Service Representatives.

- Aircraft Controllers
  This group of people are responsible for maintaining a feasible schedule and aircraft routing, including that each aircraft is routed back to their scheduled and un-scheduled maintenance activities at one of the maintenance stations. Aircraft Controllers have a high degree of interaction with the Maintenance Controllers to ensure the feasibility of un-scheduled maintenance events. In some cases disruption events can be recovered entirely by the Aircraft Controllers. This is often the case when a disruption can be recovery by only performing aircraft swaps within a single fleet of aircraft. In other cases more coordination with other areas is required.

- Crew Controllers
  When the recovery of the schedule and aircraft routings inflict changes to the schedule, these changes need to be verified for feasibility with the Crew Controllers, who will verify if the pilots and flight attendants can carry out the changed schedule while still respecting legal and union rules or if the schedule can be recovered by swapping assignments within the crew rosters. If necessary they can activate standby crew in this process. In case the changed schedule can not be covered with crew, this information is returned to the Aircraft Controllers, usually together with suggestions to how the schedule change can be adjusted to make the crew rosters feasible.

- Customer Service Representatives
  The Customer Service Representatives in the OCC are responsible for maintaining a proper level of service to the airline's passengers, which is especially important to keep in focus during times of irregular operations as customer service can rapidly deteriorate when the airline starts experiencing even small disruptions. These representatives provide input regarding connections for larger groups of passengers and alerts when VIP passengers are on-board certain flights, which should consequently have a higher focus when handling a disruption.

- Maintenance Controllers
  This group of people are in contact with the maintenance department of the airline and

communicates to the Aircraft Controllers in case a maintenance activity will not be finished on time. Vice versa the Aircraft Controllers can also request that a maintenance activity is sped up or shortened in case it severely impacts the operation. The Maintenance Controllers also take care of analyzing any defects, which are being reported to see if these affect the operational performance of the aircraft.

- Flight Dispatchers
  A dispatcher is responsible for a number of individual flights and takes on a flight-by-flight basis care of everything from collecting relevant weather information for a flight to calculating the *flight plan* and monitoring the status and potential risks related to the flight while it is en-route. In many countries dispatchers require a license and in the US the responsibility for a flight's safety is shared between the pilot and the dispatcher.

C.2.1 Planning versus Day of Operation

An airline may be viewed as one single complex system, where various resources need to interact smoothly in order for the airline to stay competitive and profitable. To facilitate the planning and coordination of these resources, planning is typically divided into resource areas, where one part of the airline organization takes care of crew planning, another makes plans for the aircraft resource and yet another focus on coordinating the passengers.

Within each resource area, problems are decomposed into e.g. manpower planning, crew pairing, crew rostering etc. This division of the planning process between resources and the subsequent decomposition makes the planing problems tractable, even though we in this process inherently do suboptimization when viewing the planning problem of an airline as one single complex system.

In the planing phase of an airline, this division into resource areas and the subsequent decomposition into tractable problems is typically not a huge concern as each problem is usually feasible and a large coordination effort between the resource areas is not needed in order to ensure feasibility of the larger problem, which includes various resources. The situation is very different on the day of operation, where every decision in one resource area potentially has a direct impact on the feasibility of the operation of another resource area, and time for coordination between resource areas is getting equally limited. The delay of a flight to ensure turn time feasibility may for instance immediately cause a misconnection for some passengers and a duty time violation for a pilot, where the latter could quickly inhibit the operation of various flights. For this reason it is important to quickly be able to find integrated solutions, which are feasible for all resource areas on the day of operation.

C.2.2 Previous work on disruption management

In order to find good recovery solutions in a limited amount of time OR techniques have been applied to the problem. The full problem of recovering all 3 resource areas of aircraft, crew and passengers is, however, so complex that no work has been published so far, which cover all 3 areas in one single integrated model, while staying within practically applicable solution times. In order for a solution approach to be applicable in real life it needs to stay within a couple of minutes (Dienst et al., 2012). For fully integrated solutions a few more minutes may be allowed. The published models are typically inspired by how the airlines do their manual problem solving, and the models usually address one single resource area each. A few of them focus on one single resource area, while also including aspects of the other areas. A good introduction to disruption management in the airline industry can be found in Yu and Qi (2004) and Belobaba et al. (2009). Kohl et al. (2007) describes a large scale EU-funded project, called Descartes, which addresses various aspects of disruption management. The reader is also referred to an extensive survey of operations research used for disruption management in the airline industry by Clausen et al. (2010).

Of the 3 resource areas mentioned above, aircraft recovery was the first area to be addressed through the application of OR by Teodorović and Guberinić (1984). This work was merely academic in its scope and only considered flight delays. It did not consider cancellations and aircraft swaps. Over the years more practically applicable models were developed. Jarrah et al. (1993) were the first to publish 2 models, which in combination were capable of producing solutions, which were useful in practice. The models were based on network flow algorithms and were capable of handling fleet swaps, delays and cancellations. The drawback of Jarrah et al. was that cancellations and delays could not be traded off against each other within one single model.

This drawback was later on resolved in the work by Yan and Yang (1996) whose model were capable of trading off delays, swaps and cancellations in one single model based on a time-line network. Thengvall et al. (2001) later on extended this model to also include so-called protection arcs, which serve the purpose of keeping the proposed solutions somewhat similar to the original schedule. This is important for real-life application of the suggested solutions, as an unlimited number of changes cannot be applied to the schedule last minute.

Rosenberger et al. (2003) present a model based on the set packing problem. The model contains a huge number of variables when applied to realistic instances and therefore the authors also propose a heuristic that selects a subset of the aircraft to be included in the model. Computational results show that the approach generates much better recovery plans compared to the short cycle cancellation policy proposed in (Rosenberger et al., 2002). Andersson (2006) proposes two metaheuristics based on simulated annealing and tabu search in order to solve a aircraft recovery problem. Tests are carried out on real-life as well as artificial data. Results show that the tabu search heuristic outperforms the simulated annealing heuristic and that the tabu search heuristic can find high quality solutions in less than a minute. Recently Eggenberg et al. (2010) proposed a generalized recovery framework using a timeband network, where the same model can be used to solve either an aircraft recovery problem, a passenger recovery problem or a crew recovery problem. They use a column generation approach where the master problem is of the set-partitioning type with side constraints, and the sub-problem is of the resource constrained shortest path type.

The second problem, which has been addressed by the OR community is the crew recovery problem, which was initially addressed in the work by Johnson et al. (1994). Later work include Wei et al. (1997), Stojković et al. (1998), Lettovsky et al. (2000) and Medard and Sawhney (2007). For disruptions, which involve changes to the aircraft schedule, the crew recovery problem is typically solved after the aircraft recovery problem. The objective here is to make sure that all flights are operational with respect to crew. This may involve using incoming crews to operate another flight than the one they were originally supposed to be operating or possibly to use reserve crews on a flight. In other cases it may involve dead-heading crews to another airport, where they are to operate a flight from. Dead-heading means to fly crews passively as passengers to another station, from which they start their active flight.

The third area, passenger recovery, has only been addressed by a very limited amount of published research. The main contribution in this area is done by Bratu and Barnhart (2006), who present a Passenger Delay Model. From our work with airlines, we have observed that most of these use a sequential passenger re-accommodation process rather than re-accommodation of their passengers based on an IP model. Vaaben and Alves (2009) does a comparison of sequential passenger re-accommodation with re-accommodation based on an IP-model.

Whereas previous work in the area of disruption management often focus on the integration between aircraft, crew and passenger recovery, we do in this paper focus on the integration between operations control and the dispatch functions in the OCC of an airline. We do so by incorporating flexible flight path in the recovery decisions. To the knowledge of the authors, no previous work has addressed this integration.

In this work we are focusing on extending disruption management with flight planning to reduce the impact, which congested airspace can have on an airlines operation. In order to do so we first provide some background on airspace and air traffic control, which forms the basis for carrying out flight planning in congested airspace situations.

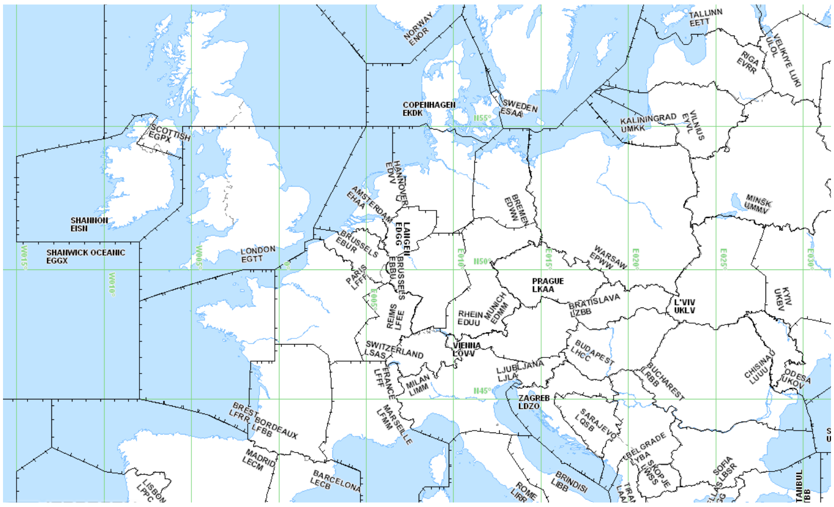


Figure C.1: Flight Information Regions in Europe. Source: JetPlan, Jeppesen

C.3 Airspace and Air Traffic Control (ATC)[1]

Airspace is divided into different classes. One class is *controlled airspace*, where traffic is supervised and managed by Air Traffic Control to increase safety and to facilitate flying in low-visibility conditions according to Instrumental Flight Rules (IFR). This class of airspace is typically at higher altitudes for en-route traffic. Another class of airspace is the *un-controlled airspace*, which typically is restricted to lower altitudes and primarily is intended for smaller aircraft flying according to Visual Flight Rules (VFR), where the responsibility for separation between aircraft lies with the pilots themselves. Airspace around airports is also highly controlled to ensure a safe ascend and descend as terminal areas typically have a high traffic density. This paper focuses on the higher altitude controlled airspace, which services the majority of commercial aviation flights.

The airspace of a country is regulated by the authorities of the country, in the US it is the Federal Aviation Administration (FAA). While the different countries in Europe regulate their own airspace, they have to a large extent agreed on common rules and have also established a common control entity called Eurocontrol. One part of Eurocontrol is the Central Flow Management Unit (CFMU), which from a central location in Brussels is responsible for a smooth operation of flights across the European airspace.

To clearly distinguish who has the authority to control and regulate in specific areas of the airspace, it is divided into Flight Information Regions (FIRs). Any point in the atmosphere belongs to a FIR. Larger countries have various FIRs, while smaller countries only have one single FIR. If a country is adjacent to a sea area their FIR(s) will usually also include a portion of the airspace over that sea. Figure C.1 shows the division of airspace into FIRs over Europe. The figure shows that e.g. Denmark only has a single FIR with the code EKDK, while e.g. Germany has 5 FIRs. The US has a total of 21 FIRs. Some FIRs entirely consists of oceanic airspace and are regulated by the International Civil Aviation Organization (ICAO). These are also referred to as Oceanic Information Regions (OIR).

Each FIR has a central ATC center who is responsible for air traffic within the FIR. These are internationally called Area Control Centers (ACC) and are in the US also referred to as Air Route Traffic Control Centers (ARTCC). These centers take care of en-route traffic between terminal areas. When a flight passes from one FIR to another FIR the pilot needs to acknowledge his

[1]The reader is advised that if reading this thesis from one end to the other, the following three sections about Airspace and ATC, Flight Planning and Air Traffic Flow Management, are identical to the corresponding sections already read in chapter 3.

arrival to the new FIR. The responsibility and control of the flight is at this point passed on to the ACC of the new FIR. Regions with a high density of air traffic such as especially Europe and the US do from time to time run into their capacity limits for certain areas of the airspace. As flights can not stop and wait in-air, an ACC will need to put a flight into a holding pattern in case the subsequent ACC does not have the capacity to receive the flight. A holding pattern is either a smaller deviation from the original path of the flight to make the route longer and delay the entry in to the new ACC or it can even be that the flight is asked to do large circles over the same area. This is in-efficient, creates un-necessary fuel burn and only adds to the congestion of airspace. For this reason Europe and the US have added an additional control layer called Air Traffic Flow Management (ATFM), which coordinates the flow of flights across various FIRs and ensures that holding time does not have to be done in-air but rather can be done on-ground. ATFM will be described further later in this paper.

To coordinate traffic and ensure safety a number of additional elements are defined for the airspace. Among these are *waypoints* and *airways*. A waypoint used to be a physical radio beacon tower which pilots could use as a navigational reference. While radio beacon towers are still in use and still serve as waypoints, additional waypoints have been added with the invention of a more sofisticated navigational system called Area Navigation (RNAV). RNAV allows aircraft to follow a direct path instead of having to fly via a sequence of radio beacon locations. These newer waypoints are simply defined as latitude and longitude points in space.

In the dawn of aviation *airways* were created for some of the US airmail routes as a sequence of lights, which a pilot could follow. Nowadays airways are only marked on maps and are used to maintain air traffic in predefined corridors for ease of coordination from ATC. Together with waypoints the airways create a directed graph, where waypoints represent nodes and airways represent vertices. Figure C.2 shows airways and waypoints over Frankfurt. Not all airways are available to all flights. Some airways are only open under certain conditions. This is for instance the case with airways traversing military airspace. Such airways are only declared open by ATC, when the military is not requiring usage of the airspace. Other airways are only open to flights, which have previously passed a specific waypoint. The amount of such rules are enormous and does for European airspace at the time of writing constitute approximately 7600 rules in the electronic Route Availability Document (eRAD), which is maintained and published by Eurocontrol (Eurocontrol, 2012). This significantly complicates the process of calculating a legal flight path through the airspace graph from one airport to another airport. This process is called *Flight Planning*

C.4 Flight Planning

A flight plan describes how the aircraft is going to fly from a Point Of Departure (POD) to a Point Of Arrival (POA) and has to be filed with Air Traffic Control (ATC) before the flight is allowed to take off. The flight plan specifies the intended operation of the flight, which includes: Type of aircraft, planned departure time, speed, fuel, route and altitudes. The route is specified as a sequence of waypoints and altitudes. An example of airways and waypoints is given in the navigational chart in Figure C.2. ATC uses the flight plan to ensure that safety requirements are met. Apart from serving as a guideline to both the pilot and ATC regarding how the flight is going to be conducted, the flight plan also serves as a calculation of how much fuel needs to be loaded onto the aircraft.

Calculating a flight plan is a complex optimization problem in itself. It has, however only been addressed by academia to a rather limited extent compared to other airline related problems. Altus (2012) gives an overview of flight planning related literature and the complexities associated to the problem.

The physical equations of flight motion causes the problem to become a non-linear optimization problem. It has been addressed by (Betts and Cramer, 1995) and (Jardin and Bryson A.E., 2001) using optimal control theory approaches. The disadvantage with these approaches are that once having found the optimal trajectory according to the rules of physics, a complicated correction cycle is needed in order to make the trajectory respect all the regulatory rules. Depending on the

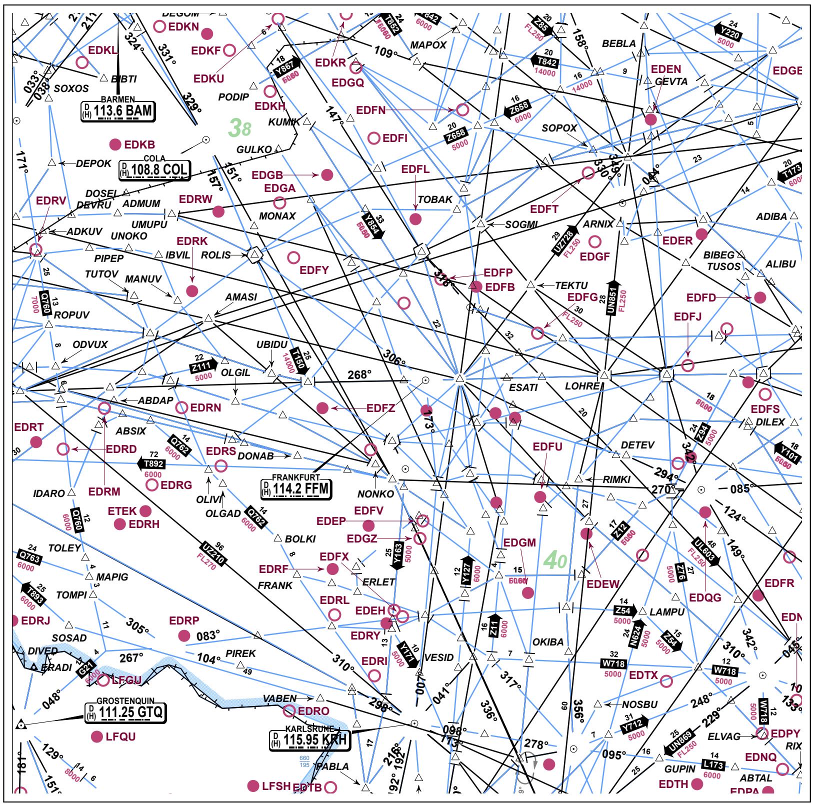


Figure C.2: Navigational chart of area around Frankfurt, Germany. Source: JetPlan, Jeppesen

logic of the correction cycle the corrected trajectory, which satisfies all regulatory rules may not be the optimal solution to the full problem, which is the one satisfying both physical and regulatory rules (Altus, 2012).

Another approach is to address the problem as a non-linear dynamic network optimization problem, which was first done by (de Jong HM, 1974). An advantage with this approach is that the majority of regulatory rules can be included in the arcs of the network. A challenge with the approach, on the other hand, is that the availability and cost of arcs from a node at time point t to one of the nodes at time point $t+1$ in the network depend on the state of the aircraft in the selected node at time point t. The state of the aircraft at time point t is characterized by a number of variables including: Aircraft weight, altitude, temperature and wind (Altus, 2010). The weight of the aircraft at time point t depends on the amount of fuel initially loaded onto the aircraft and the path taken to time point t. The speed of an aircraft generally varies with aircraft weight. The flight planing algorithm consequently does not only need to decide whether the aircraft should change altitude and direction, but also whether speed should be changed.

C.4.1 Cost Index

An important concept to decide about speed is the *cost index*. All modern aircraft in commercial aviation use cost index as an input to their on-board computer, which is also know as a Flight Management System (FMS). The pilot enters a cost index into the FMS, which basically tells the computer what the value of time is compared to the value of fuel as given in the following definition of Cost Index, where fuel in this definition is measured in kilograms.

$$\text{Cost Index} = \frac{dollars/min}{dollars/kg} \tag{C.1}$$

The definition of the Cost Index consequently expresses the number of kilos of fuel, which the FMS should be willing to burn, in order to save one minute of time. As seen from the definition, a cost index of 0 will minimize the fuel burn by indicating that cost of time is seen as having zero value. In order to calculate the fuel burn correctly, flight planning software also makes use of the cost index definition provided in (C.1). The problem with the cost index definition is that it assumes that the cost of time is linear, which is far from the case in normal airline operation. This is emphasized in (Altus, 2010), where the following sources of cost elements all contribute to the fact that cost of time is not a linear, but rather a piecewise linear function:

- *Subsequent flights.* The risk of delay propagation to subsequent flights makes the cost of time increase significantly once a flight is sufficiently delayed to propagate its delay to a subsequent flight.
- *Operational flexibility.* In case an aircraft is delayed to such an extent that it eliminates a swap possibility with another aircraft, the cost of time increases.
- *Crew connections.* The cost of time increases steeply once a flight gets delayed sufficiently for crew to miss their connections to subsequent flights in their duty.
- *Passenger connections.* Similar to crew connections the cost time for a flight increases steeply if passengers - and especially larger groups of passengers - miss their connecting flights.
- *Goodwill.* Passengers do, among other things, tend to focus on whether scheduled arrival time has been met, when making their internal judgement as to whether they will be returning customers.

The piecewise linear behaviour of passenger misconnections and the associated cost due to loss of goodwill is illustrated in Figure C.3, which shows how inbound flights to a hub from various locations will incur significantly different passenger misconnections costs depending on the amount of arrival delay and passenger connection possibilities. It is for instance notable that the inbound flight from Mumbai (BOM) will incur a significantly higher cost if arriving 50 minutes late compared to arriving 40 minutes late.

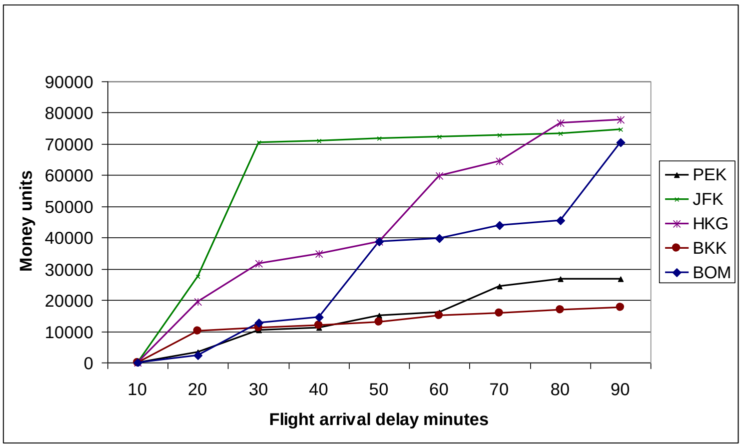


Figure C.3: Flight delay impact on passenger delay costs.

C.5 Air Traffic Flow Management (ATFM)

As previously mentioned the airspace is divided into FIRs, where each FIR has a control center for the area, ACC. In regions with a high density of air traffic an additional coordination layer on top of the ACCs have been established to coordinate the flow of traffic between the FIRs and in this way ensure that air traffic in specific areas do not exceed capacity. The practice of coordinating air traffic across various FIRs from a system perspective is referred to as Air Traffic Flow Management (ATFM). ATFM is applied both in the US and in Europe, but is not carried out in the same way in the two regions.

C.5.1 ATFM in the US

ATFM in the US is taken care of by the Air Traffic Control Systems Command Center (ATCSCC) located in Northern Virginia. Under nominal operating conditions the ATCSCC does not put special regulation in place in order to restrict the flow of air traffic as the US National Airspace System (NAS) can handle the demand under these conditions. However, when the NAS becomes disrupted due to adverse weather, equipment outages, runway closures or demand surges, the ATCSCC applies special regulations in order to restrict the flow of traffic through the system. One such type of regulation is the Ground Delay Program (GDP) which was initiated in 1998. It is issued when the arrival capacity of an airport is reduced to less than the current arrival demand. In order to match the demand of arrivals with the capacity of the airport the ATCSCC issues a GDP for the airport. Based on an allocation scheme called *Ration By Schedule (RBS)* each airline is granted a number of arrival slots, where the sequence of the arrival slot is the same as in the original schedules of all the airlines. Each airline owns the arrival slots and is able to swap flights between these slots. This is beneficial to the airline as the delay and cancellation costs of one flight may be much higher than the delay and cancellation costs of another flight. It is furthermore possible to sell unused arrival slots to another airline. In order to help dispatchers find good candidates for slot swaps in case of a GDP, Abdelghany et al. (2007) presented a heuristic to do this.

The GDP initiative has been very successful and has according to Metron Aviation avoided 50.000 hours of assigned ground holding since it was initiated (Vossen et al., 2012). Building on this success FAA did in the summer of 2006 implement the *Airspace Flow Program (AFP)* initiative, which extends the GDP procedures to the en-route environment. With the AFP the ATCSCC can enforce a flow restriction across a predefined borderline referred to as a Flow Constrained Area (FCA) and thus restrict the flow of flights in one direction across the FCA. The FCAs which are in effect at any given point in time are published by the ATCSCC as part of the *National Airspace System Status*, which can be found on the website http://www.fly.faa.gov/ois/ This page lists all GDPs and AFPs, which are currently in effect. In the event an AFP is in effect the affected border line FCAs are listed together with the AFP. An example of an FCA is given in Figure C.4. It shows that East bound flights flying into the New York region across the FCA will have to adhere to the slot times granted by ATCSCC. Each airline is granted a number of slot times according to the Ration By Shedule scheme also used for GDPs. An AFP related slot time is a small time window where the airline is granted the right to pass through the FCA with one flight. The airline is allowed to decide which flight should use the slot time and also which time to depart. The constraining element is that the flight will have to arrive to the FCA border line in the granted slot time.

For some flights the carrier may choose to completely avoid this constraint by filing a flight plan, which takes the flight around the FCA. This action will come at the cost of increased flying time and fuel burn.

It is noted that FAA rules ensure that a flight can only be subject to one single ATFM program. It can consequently not be constrained by e.g various AFPs in its flight path even if the direct path takes it through various AFPs. Similarly it can not be subject to both an AFP and a GDP. ATCSCC will in these cases only let the flight be constrained by one of the ATFM programs and thus give the flight priority for the remaining programs in its flight path.

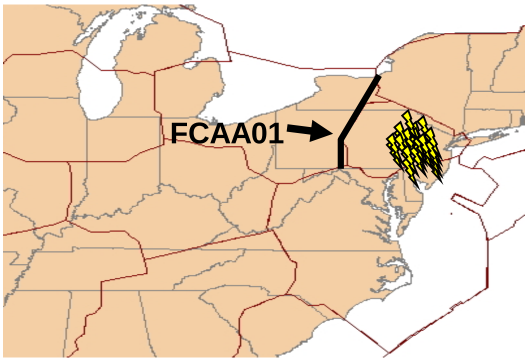


Figure C.4: A predefined Flow Control Area FCAA01. Source: Principles of AFP for Dispatchers, FAA

C.5.2 ATFM in Europe

ATFM in Europe is taken care of by the Central Flow Management Unit (CFMU), which is a part of Eurocontrol and located in Brussels. When a flight in Europe flies from point A to point B the pilot - or dispatcher, if the flight belongs to an airline - files a flight plan with the local airspace authorities of point of departure (POD). CFMU receives the flight plan and calculates when the flight will pass through a number of different air sectors on its way. In case any of these sectors have reached their capacity limit, CFMU will issue a *Calculated Take-Off Time (CTOT)*, which is later than the originally intended departure time in the flight plan filed by the carrier. CFMU grants access through the congested air sector on a first-come-first-serve basis in the order of time when flight plans were filed. Based on this policy CFMU issues CTOT-delays to the flights, which have filed flight plans through the congested sector.

In case the dispatcher of an airline determines that the CTOT-delay is too large, he may choose to cancel the flight plan and file another flight plan, which takes the flight around the congested airspace. By doing so he frees up a bit of capacity in the congested air sector. The capacity freed up does, however, not belong to the airline as seen in ATFM in the US. Instead it is now granted to the next flight in line waiting to pass through the congested air sector. All CTOT-delayed flights related to the congested air sector are thus moved up in line.

A dispatcher will consequently only to a limited extent be able to benefit another of his own flights by making the first flight fly around the congested airspace, but the decision may never the less still be beneficial for some of the carrier's flights.

A similar control approach and sequencing for departures is being applied by CFMU when the congestion is not an air sector but the arrival airport of the flight. The main difference in this case is that the dispatcher does not have the option to fly around this airport.

C.5.3 Airspace Congestion

When looking to the sky, airspace may seem plentiful compared to the amount of aircraft manoeuvring in it. Airspace does, however, get congested in areas with a high flight density such as some parts of Europe and the US. Figure C.6 gives an impression of the severity of the problem, which is seen to be most significant in Europe. Combined with flight density there are two main reasons why airspace gets congested. Both are due to safety regulations (Belobaba et al., 2009):

- ATC needs to keep a large separation between aircraft in their area. Typically 3 to 5 nautical miles horizontally and 1000 to 2000 feet vertically depending on the country and type of airspace.

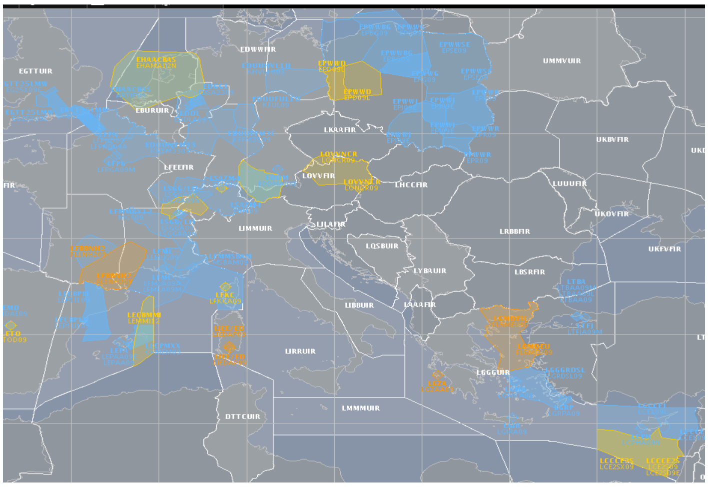


Figure C.5: Congestions over Europe on September 9th 2012 . Source: CFMU Network Operations Portal

- ATC is currently based on human controllers, which implies a limitation to how many aircraft a controller can safely monitor at any given point in time. ATC staffing is consequently often seen as a reason to congestions.

Congested areas over Europe can be followed using CFMU's *Network Operations Portal (NOP)*. Not a day passes by without the NOP portal showing various areas in Europe, where en-route and airport delays must be expected. Figure C.5 displays CFMU's NOP portal at the time of writing on September 9th 2012. The blue, yellow and orange indications are all areas where en-route congestions occurred for some period of time on that day. This gives an impression of how significant the en-route congestion problem is en Europe.

FAA and Eurocontrol have made an interesting comparison of the ATFM related operational performance in the two regions (Eurocontrol and FAA, 2012). While the report shows that en-route congestions is a problem for specific areas in both the US and Europe, it is seen from Figure C.6 that the problem with en-route congestions is most significant in Europe. The report also states that the risk of getting a departure delay due to en-route congestions is 50 times higher for a flight in Europe than in the US.

Whenever a disruption occurs it typically results in some form of flight delay. A flight delay could for instance be caused by one or more checked-in passengers not boarding the flight and their bags will consequently have to be off-loaded for security reasons, which often results in a delay. This is referred to as a *primary delay*. This delay may have a knock-on effect on a subsequent flight in which case this second flight delay is reported as a *reactionary delay*. The International Airline Travel Association (IATA) have defined a set of delay codes for both primary and reactionary delays. Airlines use these codes for reporting their delays to Eurocontrol and the delay causes among all airlines are roughly split fifty-fifty between primary and reactionary delays (Eurocontrol, 2010).

It is especially interesting to look at primary delay causes due to the fact that if these are reduced the corresponding reactionary delays will also be reduced correspondingly. In their yearly reports Eurocontrol has published the distribution of primary delays causes for flights in Europe. For 2010 the distribution is shown in Figure C.7.

In Figure C.7 it is noted that the majority of the primary delays (41.8%) are caused by factors related to the airline itself, such as technical problems, baggage delays, checked-in passengers not showing up, etc. The second largest portion (32.5%) of primary delays are caused by factors related to Air Traffic Flow Control Management (ATFCM), which is basically the part of Eurocontrol

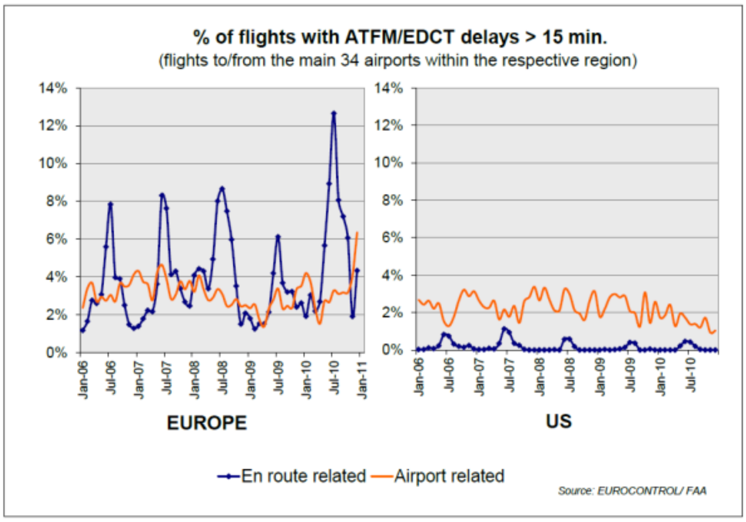


Figure C.6: US/EU comparison of ATFM delays due to en-route and airport congestions. Source: FAA and Eurocontrol

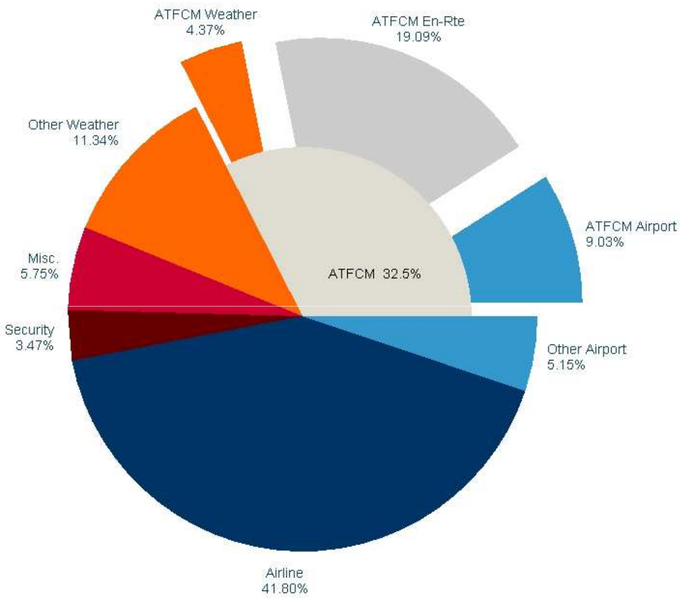


Figure C.7: Primary Delay Causes in 2010. Source: Network Operations Report for 2010, Eurocontrol

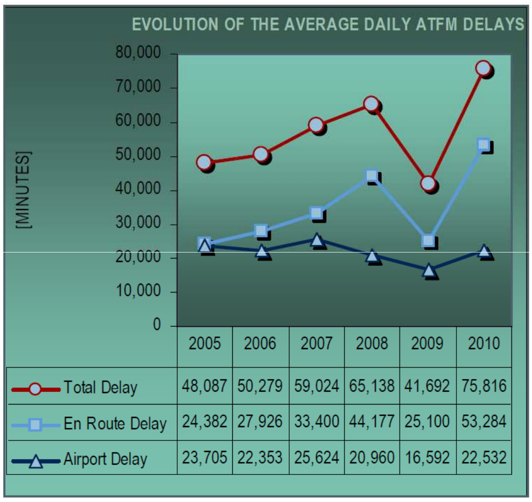


Figure C.8: Evolution Of Average Daily ATFM Delays. Source: Network Operations Report for 2010, Eurocontrol

taking care of the flow of flights through different sectors in Europe. The largest subset of the ATFCM-delays are so-called *en-route delays* and correspond to 19.09% of all flight delays.

While en-route delays is not the biggest source of primary delays, it is, however, the fastest growing source of delays as it is seen from Figure C.8. This source of delays in Europe has increased with an average yearly rate of 17% from 2005 to 2010, which is a good reason to address exactly this kind of delays.

That en-route delays have been rising so sharply in recent years is due to the fact that European airspace is close to reaching its capacity limit. A similar development has also been seen in some areas of the US, especially in the densely populated North East. This is the main reason why both the US and Europe have initiated huge programs called Next Generation Air Traffic Control (NextGen) in the US and SESAR in Europe. Both programs aim at increasing airspace capacity by e.g. enabling more direct flight paths and reduced aircraft separation requirements.

As NextGen and SESAR have not yet been implemented it is on the shorter term important to focus on how disruption management systems can be improved to better address the specific kind of disruptions caused by en-route delays. Even after NextGen and SESAR get implemented the industry will still benefit from more efficient solutions methods, which can properly balance the trade-off between on-time performance and fuel burn.

C.6 Combining flight planning and disruption management

In section C.2 the work flow in the OCC is described. This show that there is a high degree of interaction between Ops Controllers and people in the related areas of aircraft, crew and customer service. Based on the experience of the first author and his 14 years in the airline industry, there is little interaction between Ops Controllers and dispatchers, who at some airlines are not even located in the same room.

Ops Controllers take care of the overall network of flights and use a combination of swaps, delays and cancellations in order to recover from a disruption. Dispatchers on the other hand, look at individual flights and make local decisions about trajectory and speed.

There is little focus on the flexibility which flight planning can provide when searching for good recovery solutions, especially when it comes to disruptions related to airspace congestions. The flexibility, which flight planning can provide to the overall network recovery problem lies in

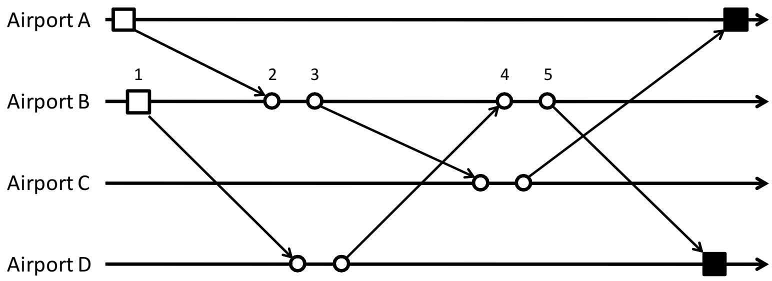


Figure C.9: Basic layout of time-space network.

changing the speed and trajectory of the flight in order to avoid a congested airspace sector, which may cause delays.

The proposal of this paper is a model, which does exactly this. It includes both speed and trajectory flights in disruption management decisions in order to change flight planning decisions from being local decisions for individual flight to being decision which serves the entire airline network in the best possible way in terms of both fuel burn and passenger connections.

C.7 Modelling

In this section we describe the network representation of the problem as well as the mathematical model, which is based on the network. The model is based on a *time-space network* representation of the airline's schedule and planned maintenance activities. The nodes in a time-space network represent both time and location. In the current application the locations are airports.

C.7.1 Network representation

In the aircraft recovery literature the modelling is generally based on different variants of three network representations as surveyed in (Clausen et al., 2010). 1) A *connection network*, where the flight activities are represented by nodes in the network. 2) A *time-line network* where each node represents a point in time and a location, while flights are represented as arcs in the network. 3) Finally a *time-band network* has been used as a variant hereof, where points in time are aggregated into so-called time-bands. The latter two representations both belong to the *time-space* class of representations, where nodes represent both a point in time and space. As the purpose of this paper is to alleviate the problems of congested airspace by combining flight planning and disruption management, we have made the choice of a time-line network. This representation has the advantage of an exact representation of time and location at an airport together with an intuitive and logical way of representing flight plans as arcs in this network.

The basic layout of the network is shown in Figure C.9. In this network time is increasing from left to right and each horizontal line represents an airport location. A white square node represents a source node for a specific aircraft. This is the current location of this aircraft at the start of the *recovery window*. The recovery window is a time window where the algorithm is allowed to make changes to the aircraft schedule. A black square node is a sink node for a specific aircraft and represents a time where this aircraft must be present at the specified airport. The sink nodes are located at the end of the recovery window. An arc represents an actual flight movement from one airport to another.

The small network example in Figure C.9 could be operated by two aircraft. One starting in airport A, visiting airport B and C before returning back to airport A; and another aircraft starting in airport B, travelling to airport D and back to B before ending at airport D. The network also contains *ground arcs* (not shown) that represent the time spend on the ground, in-between flights. As an example, the network in Figure C.9 would contain four ground arcs for airport B (an arc between node 1 and 2, one between 2 and 3 and so on). The network also

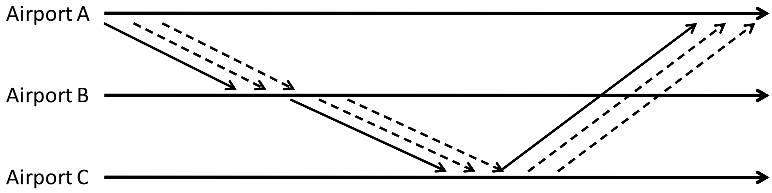


Figure C.10: Delay arcs.

contains *maintenance arcs* which, like ground arcs, connect two nodes associated with the same airport. However, maintenance arcs represent planned repairs and/or inspections and are usually mandatory, where ground arcs are optional.

In order to produce a valid recovery solution where no additional post-processing is required it is important to have complete control over which specific aircraft will perform each activity. This is obvious for maintenance activities, where a mandatory maintenance of an aircraft requires that this specific aircraft arrives at the maintenance hangar. It is not sufficient to have any aircraft belonging to the same fleet arrive at the hangar. Similarly aircraft deficiencies, such as e.g. a non-functional Auxiliary Power Unit will not leave the aircraft in-operational, but will constrain which airports the aircraft can visit. For this reason we have opted for solving the aircraft specific recovery problem as opposed to the fleet specific recovery problem. The difference between these two problems have been analyzed in (Dienst et al., 2012).

Additional arcs (*delay arcs*) are introduced to allow delays (shown in Figure C.10). Here each dashed arc represents a delay of the original flight (drawn with a solid line). Each dashed arc represents a particular amount of delay.

In more traditional aircraft recovery as presented by e.g. (Yu and Qi, 2004) arcs would have presented flights. The arcs introduced so far allows traditional recovery, where a multi-commodity network flow model can decide how to best recover the schedule using a combination of the three traditional recovery techniques: Swapping flights, delaying flights and maybe cancelling some flights.

In the current network representation the arcs do not just represent flights but rather *flight plans*. These flight plans are calculated using a flight planning system and include more detailed information regarding how the flight will be conducted. This includes trajectory, speed and fuel burn. The fuel burn calculation from the flight planning system allows detailed calculation of the fuel cost of the flight. For a given flight, a number of different flight plans can be produced, where each flight plan is calculated using different input parameters. This gives rise to the introduction of additional arcs.

Speed change arcs

By providing a different *cost index* as input to the flight plan calculation the cruise speed and consequently the fuel burn will change. Compared to the normal cost index for the airline and aircraft type a lower cost index will result in increased flying time and a lower fuel burn, while a higher cost index results in shorter flying time and increased fuel burn. The network representation of speed change arcs are illustrated in Figure C.11. The solid arcs indicate flight plans where a flight is flown at the standard cost index of the airline, while the dashed lines indicate flight plans with either lower or higher cost index setting. The figure illustrates in a very simplified example the additional flexibility, which the speed change arcs provide with respect to recovery. For flight f1, which departs with a delay, the schedule can be recovered by either selecting a faster flight plan for flight f1 or by maintaining flight f1 at standard speed and delaying the departure of flight f2 while at the same time selecting a faster flight plan for f2. In (Marla et al., 2011) they analysed the speed change arcs in detail and they will consequently not be investigated further in this paper. The paper by Marla et al. concludes that speed change arcs are mainly of benefit to long haul flight as these spend significant amount of time at cruise speed. For short haul flights the speed change arcs can only affect the arrival time with a couple of minutes, which may easily be eliminated by the uncertainty related to taxi time.

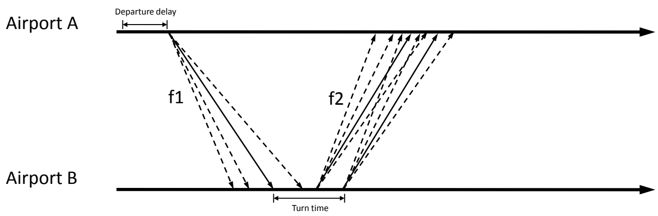


Figure C.11: Speed change arcs.

Congestion related arcs

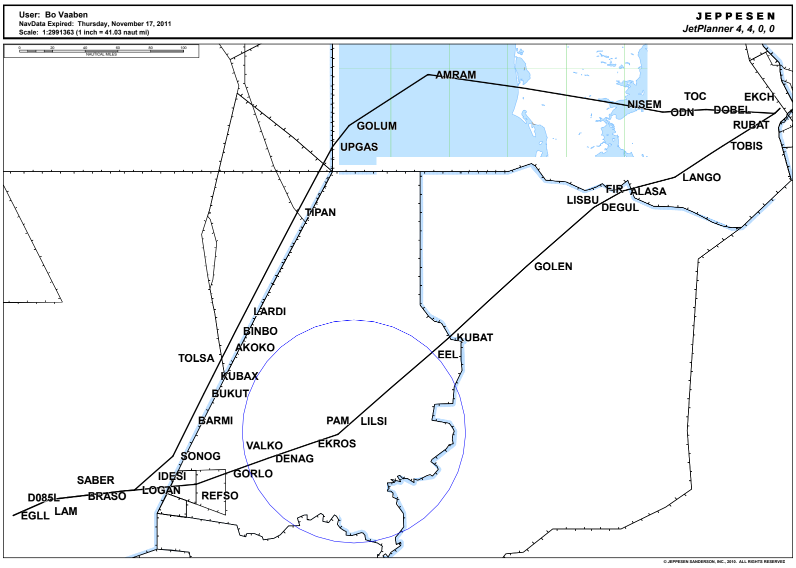
While speed change arcs are mainly interesting for long haul flights, another kind of arcs are relevant for short haul flights. A large amount of short haul flights in Europe and the North East of the US operate in congested airspace. For this reason it is interesting to extend the network with flight plan arcs, which alter the trajectory of flights in order to avoid congested airspace. This is illustrated in Figure C.12, where the first part of the figure (a) shows two flight plans. One flight plan traversing a congested volume of airspace, which will result in an estimated departure delay, and another flight plan following a sequence of waypoints taking the flight around the congested volume of airspace. Part (b) of the figure shows the corresponding arcs for flight f1. The leftmost solid arc represents the flight plan taking the flight around the congested airspace. The dashed arcs illustrate that it may be relevant to speed up the flight for this trajectory due to the longer route. The second solid arc for flight f1 represents the direct flight plan, where the route traverses the congested airspace with the consequence that the flight will depart with a calculated departure delay (CTOT). The figure also illustrates that the en-route delay can lead to propagation of the entire delay or parts of the delay to subsequent flights. It is only necessary to generate the additional congestion related arcs for the subset of flights, where the flight plan generation using the most direct trajectory has revealed that this trajectory takes the flight through a volume of congested airspace.

Arc reduction techniques

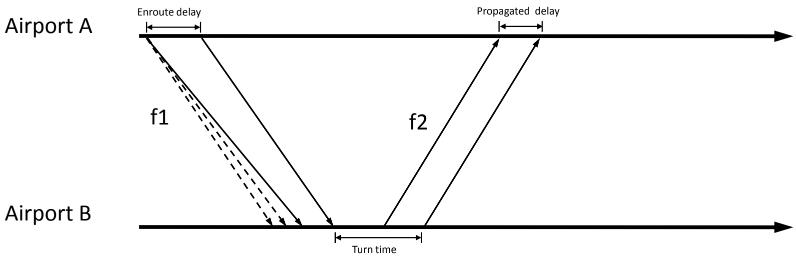
As previously mentioned we solve the aircraft specific recovery problem, which results in a multi-commodity network flow problem where each aircraft is modelled as a commodity. This results in a large number of flight plan arcs which are candidates for being present in the the network. In order to reduce the solution time of the resulting MIP problem, an arc reduction technique is applied. This technique is inspired by the constraint programming world, as combining methods from Constraint Programming (CP) and Linear Programming (LP) can often lead to improved solution times (Vaaben, 1998).

In CP a variable describing a set is referred to as a *Constrained Set Variable*. We denote the Constrained Set Variable X. The domain of X is defined by two sets. (1) A *possible set* of elements P and (2) a *required set* of elements R where $R \subseteq P$. Given this definition of X it is possible to reduce the domain of X by either expanding R or reducing P. X is determined when $R = P$.

Inspired by the constraint propagation technique used in CP we distinguish between *departure nodes* and *arrival nodes* in the time-space network and let all the departure nodes have a Constrained Set Variable of aircraft. When building the network we apply forward domain propagation of possible aircraft from departure node to departure node as illustrated in Figure C.13. In this illustration white squares indicate source nodes, which are departure nodes. Black squares



(a) Flight plans through and around congested airspace



(b) Arc representation of congestion related flight plans

Figure C.12: Network representation of congested airspace arcs

indicate sink nodes, which are arrival nodes. White circles indicate departure nodes for flight plans. In order to simplify the illustration the following arcs are not visualized on the figure: Delay arcs, speed change arcs, congestion avoidance arcs and ground arcs.

Node 1 in the top left corner on the figure is the source node of aircraft a. No other aircraft than aircraft a can reach this node and aircraft a is also required in this departure node. We do consequently have $P = R = \{a\}$ for this node. In a similar fashion we have for node 2, the source node for aircraft d that $P = R = \{d\}$. For node 3 on the illustration we have that the possible set of aircraft, which can reach this node are $P = \{a, b\}$, where aircraft b is reaching the node from the source node of this aircraft. It can also be observed that aircraft d cannot reach the possible set of departure node 3. For a real life size airline network covering for instance the US this propagation eliminates the construction of arcs for e.g. aircraft situated on the US West coast in the morning, which do not need to be represented for flights departing in the morning on the US East coast.

Propagation of the required sets R are done backwards in the network starting at the sink nodes. And from the departure nodes of the maintenance activities where a specific aircraft is required. This can help predetermining that certain aircraft are required on certain arcs and reduce the need for arc and consequently flight plan generation. It can also pre-determine certain infeasibilities in case $R \nsubseteq P$ for a departure node.

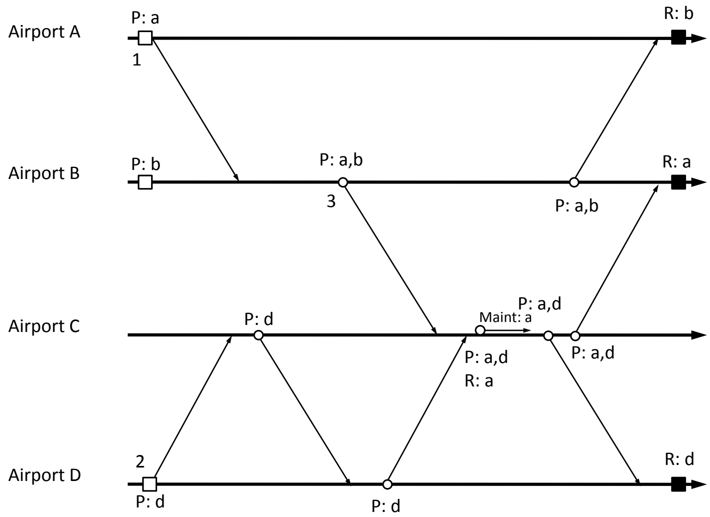


Figure C.13: Illustration of possible sets in time-line network.

C.7.2 Passenger Misconnection protection

When airspace congestions occur the airline is typically faced with the decision whether it should accept a departure delay or file a flight plan with a trajectory, which takes a flight around the volume of congested airspace. Accepting a departure delay may result in some passengers missing an onward connection at the destination airport, which is very costly to the airline. A longer route on the other hand will incur additional fuel cost and may even still result in an arrival delay and passenger misconnections. A tight turn time at the destination airport may additionally result in knock-on delays to subsequent flights, which again could result in more passenger misconnections. In order to have the airline make the right trade-off between the additional fuel burn cost, which the longer route incurs, and the cost of having some passengers loose their connection due to the delayed departure we introduce passenger misconnection constraints as also used in the work by (Marla et al., 2011). The actual constraints are given in the modelling section C.5. It is noted that equivalent misconnection constraints can be used for crew connections, which would be introduced with a higher violation penalty.

C.7.3 AFP slot constraints

In the US, Air Traffic Flow Management is carried out by ATCSCC by imposing AFPs, where the AFP activates one or more FCA's and control the flow of flights through these border lines as described in section C.5. When an AFP is imposed, airlines will receive a number of slot times where they are allowed to pass through an FCA. The airlines decide themselves, which flights will make use of these slot times. This gives the US airlines increased control over their flights in a congestion situation compared to their European counterparts, but does also introduce some additional complexity as they need to prioritize, which flights should use which time slots through the FCA. To help with this prioritization we propose the AFP Slot Constraints as illustrated in Figures C.14 and C.15.

Figure C.14 shows possible trajectories for two flights to Newark airport (EWR) departing from Chicago (ORD) and Detroit (DTW) respectively. Before the departure of these flights ATCSCC has issued an AFP, which activates the Flow Controlled Area FCAA01 as indicated with solid bold line on the figure. When the AFP is issued the airline in question is granted a number of timeslots for passing through the FCA. In this example we assume that two such time slots are granted.

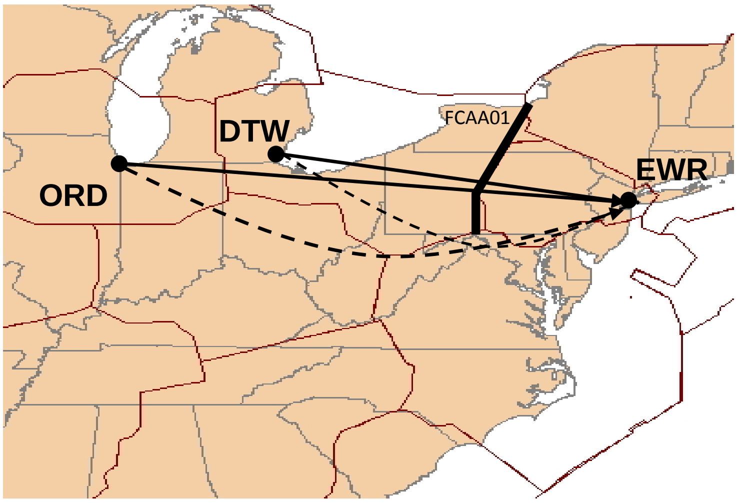


Figure C.14: Arc representation of trajectories through and around FCA.

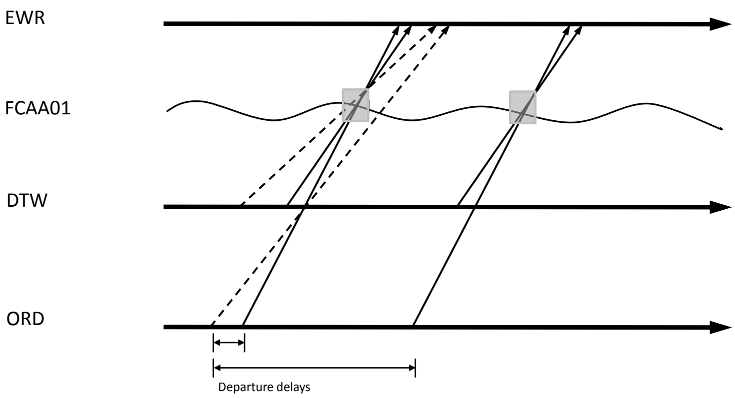


Figure C.15: Illustration of AFP constraint.

The solid arrows indicate direct trajectories from ORD and DTW to EWR. These trajectories need to respect the time slots granted by ATCSCC. The dashed arrows on the other hand indicate trajectories taking flights around the FCA. For these flight plans the airline is not restricted by the timeslots for passing through the FCA.

Figure C.15 shows the corresponding flight plan representation as arcs in the time-space network. The FCA area is here represented as a wave line to indicate that the FCA is not one single point in space but rather a border line or an area. The two time slots granted for passing through the FCA are marked as grey shades on the FCA. The solid trajectories from the Figure C.15 are represented as solid arcs. It is noted that the same direct trajectory taking a flight through the first time slot can also be used in a later flight plan taking the flight through the second time slot. The dashed arcs on the graph indicate flight plans using trajectories taking the flight around the FCA. The dashed arcs are consequently not restricted by the FCA.

With the example provided in figures C.14 and C.15 it is noted that there are 3 possible decisions for each flight, which is affected by and AFP on its most direct trajectory:

- *Direct trajectory.* Chose a direct trajectory through the FCA at one of time slots provided. In the example this results in 2 solid arcs in the network. The usage of these arcs will typically also result in a departure delay. Combined with the possibility of changing speed it can result in some additional speed change arcs through the time slots. These speed change arcs are not shown on the figure.

- *Alternate trajectory.* Choose a trajectory around the FCA. This is represented by a single dashed arc for each affected flight. Again, combined with the speed change possibility it can result in some additional speed change arcs, which are not depicted on the figure.

- *Flight cancellation.* Choose to cancel a flight. This would typically also result in another flight cancellation in order to cancel a complete round trip from the hub to a destination and back again.

C.7.4 Mathematical Model

Let $G = (\mathcal{N}, \mathcal{A})$ be a graph representing the network described above. Let $\mathcal{N}$ be the set of nodes in the network, where these are divided into departure nodes $N_d \in \mathcal{N}$ and arrival nodes $N_a \in \mathcal{N}$. Let A be the set of available aircraft and F the set of flights to be carried out in the recovery period T.

Arcs in the network are either flight plan arcs $C \in \mathcal{A}$ or ground arcs $G \in \mathcal{A}$. Every flight f has a set of possible flight plans denoted $C_f \in C$. Each flight plan $k \in C_f$ connects a possible departure node $n \in N_d$ with an arrival node in N_a. From each arrival node a ground arc is created to the first subsequent departure node respecting the turn time between the two corresponding flights. From each departure node for a flight plan there exists additional outgoing ground arcs to the subsequent departure node on that airport location in order to ensure cancellation capability of the model.

To control the creation of feasible aircraft paths through the network we define N_n^- as the set of incoming arcs to each node $n \in \mathcal{N}$ and N_n^+ is the set of outgoing arcs from each node $n \in \mathcal{N}$. For each aircraft $a \in A$, a supply $s^n = 1$ is associated with the node n where the aircraft is known to start at the beginning of time window T, and a demand of $s^n = -1$, where it starts the next flight just outside the time window T.

Let x_f^k be a binary variable, which takes the value 1 if flight plan $k \in C_f$ of flight $f \in F$ is used in the recovery solution and 0 otherwise. Similarly the binary variable y_g takes on the value 1 if ground arc $g \in G$ is present in the solution and 0 otherwise. We let the binary variable z_f denote if flight $f \in F$ is cancelled. It that case it takes the value 1 and 0 otherwise.

Let $\mathcal{P}$ be the set of passenger itineraries operated within the recovery period, and n_p represent the number of passengers on itinerary $p \in \mathcal{P}$. Let $IT(p)$ be the set of flight legs in itinerary p, $IT(p, l)$ the lth flight leg in itinerary p. Let $MC(p, f, k)$ denote the set of onward flight plans following flight f in passenger itinerary p to which there is insufficient time to connect from flight plan k of flight f. This set consequently corresponds to the set of flight plans, which in combination with the selection of flight plan k will cause a misconnection for the passengers on itinerary p. Let λ_p be a binary variable, which takes the value 1 if the passengers on itinerary p are disrupted and 0 otherwise.

To control the usage of flight plans traversing an AFP and consequently consuming the slot time resource in the AFP we define the binary constant d^k_{fb}, which takes the value 1 if flight plan k of flight f makes use of time slot b and 0 otherwise. In case the airline network is affected by various AFPs we let the enumeration sequence of AFP2 continue from the end of the enumeration sequence of AFP1 etc.

The problem can now be formulated as follows:

`Minimize:`

$$\sum_{f\in F}\sum_{k\in C_f} c^k_f x^k_c + \sum_{f\in F} c_f z_f + \sum_{p\in\mathcal{P}} \tilde{c}_p n_p \lambda_p \tag{C.2}$$

`Subject to:`

$$\sum_{k\in C_f} x^k_f + z_f = 1 \qquad \forall f \in F \tag{C.3}$$

$$\sum_{g\in N^-_n} y_g + \sum_{(f,k)\in N^-_n} x^k_f + s^n = \sum_{g\in N^+_n} y_g + \sum_{(f,k)\in N^+_n} x^k_f \qquad \forall n \in \mathcal{N}, \forall a \in A \tag{C.4}$$

$$x^k_{IT(p,l)} + \sum_{m\in MC(p,IT(p,l),k)} x^m_{IT(p,l+1)} - \lambda_p \leq 1 \qquad \forall k \in C_{IT(p,l)}, \; \forall l \in 1,...,|IT(p)|-1, \forall p \in \mathcal{P} \tag{C.5}$$

$$\lambda_p \geq z_f \qquad \forall f \in IT(p), \forall p \in \mathcal{P} \tag{C.6}$$

$$\sum_{f\in F}\sum_{k\in C_f} d^k_{fb} x^k_f \leq 1 \qquad \forall b \in B \tag{C.7}$$

$$x^k_f \in 0,1 \qquad \forall k \in C_f, \forall f \in F \tag{C.8}$$

$$z_f \in 0,1 \qquad \forall f \in F \tag{C.9}$$

$$\lambda_p \in 0,1 \qquad \forall p \in \mathcal{P} \tag{C.10}$$

$$y_g \geq 0 \qquad \forall g \in G \tag{C.11}$$

Here constraints (C.3) ensure that every flight is either carried out and thus assigned a flight plan or cancelled.

Constraints (C.4) are referred to as either *flow conservation constraints* or *aircraft balance constraints*. It requires that if an aircraft flows into a node, it must also leave it again except for the source and sink nodes in the network where we in the source node have a supply of the aircraft, $s^n = 1$, while the sink node has a demand of an aircraft $s^n = -1$. For all other nodes we have $s^n = 0$. The constraints thus ensures that for sure for every aircraft a path is found from source to sink in the network.

Constraints (C.5) enforce λ_p to be 1 for every combination of flight plan arcs which will result in one or more passenger itineraries misconnecting. λ is penalized in the objective function proportionally to the number of passengers on this itinerary, who will lose their connection when this combination of arcs are in basis.

Constraints (C.6) ensure that if a flight is cancelled then passengers onboard that flight will also be counted and penalized as misconnecting.

Constraints (C.7) ensure for every AFP time slot that only a single flight plan is allowed to traverse the corresponding FCA in the time slot.

Constraints (C.8), (C.9), (C.10) and (C.11) are all integrality constraints for respectively: Flight plan selection, flight cancellations, passenger misconnections and the usage of ground arcs.

To respect maintenance activities, which are aircraft specific, we model these as special "flights" where the possible set of aircraft, which can carry out this activity, is only one single aircraft.

Regarding the objective function (C.2) this is divided into 3 parts:

- *Flight plan cost.* The cost parameter c_f^k is a sum of the following cost elements: Incremental fuel cost, flight delay cost and aircraft swap cost.

  The incremental fuel cost is calculated compared to the fuel burn of the original flight plan, which is calculated as the cheapest possible trajectory flow at the standard cost index of the airline. In case the original flight plan is selected the incremental fuel cost will consequently be zero. In case a flight plan with a lower speed is selected the incremental fuel cost will give a negative contribution to the cost function. It is noted that in a congested airspace setting the cheapest possible trajectory will typically require a departure delay and it may thus be cheaper to select a flight plan avoiding the congested airspace even though this flight plan will have a higher incremental fuel cost.

  Flight delays are in the model driven mainly by the balance between fuel burn cost and passenger misconnection cost, but a smaller flight delay cost is introduced to steer the solutions away from too often delaying flights with a low load factor as such delays may look beneficial from an emediate cost saving perspective, but airlines do generally not like many smaller delays as they are hurting the airlines ranking in the 15-minutes On Time Performance (OTP) statistics.

  An aircraft swap cost is introduced to penalize swaps between aircraft with a significant difference in seat capacity, as this may lead to denied boarding of some passengers, even though these passengers do not necessary miss their connections time wise. The swap penalty increases with the difference between seat capacities.

- *Cancellation cost.* The cost parameter c_f specifies the cost penalty for cancelling a flight or a maintenance activity, which is modelled as a special kind of "flight". The cost for cancelling a flight is also penalized as the passengers on that flight will be counted as misconnecting. The flight cancellation cost is consequently set rather low. The cancellation cost for maintenance activities is set very high to make the cancellation of a maintenance activity correspond to an infeasible solution. We refer to this practice as a *soft constraint*. The advantage of modelling a maintenance cancellation as a soft constraint is that an infeasible input disruption caused by maintenance activity, which is impossible to cover, will not just result in an infeasibility, but rather pinpoint the infeasible maintenance activity to the user.

- *Passenger misconnection cost.* The parameter $\tilde{c}_p$ is an approximate cost of re-accommodation for each disrupted itinerary $p \in P$, because we assume that if a passenger itinarary p is disrupted, the passengers are re-accommodated on the next available itinerary to the destination in the next flight bank. Based on this assumption, we compute the per passenger estimated arrival delay cost to the airline. Setting a cost per disrupted itinerary p also allows the capture of the piece-wise linearity in cost, where higher delays incur disproportionately higher costs compared to smaller delays.

As we do not include a complete passenger re-accommodation in this model, but only an approximation of the passenger impact, we measure the full impact of the flight plan selection by subsequently running the resulting solutions from this model through a commercially available re-accommodation tool called the Jeppesen Passenger Re-accommodation Solver (Vaaben and Alves, 2009), which takes the full passenger itineraries and aircraft capacities into account and calculates the passenger re-accommodation cost.

C.8 Experimental Framework

In this section we describe the data and experimental framework used to evaluate the proposed solution approach. The airline data, which is used for the experiments, have generously been made available to us by a medium sized European carrier. The carrier operates a hub-and-spoke network with approximately 250 daily flights serving 60 cities on multiple continents. About 10% of the flights are long-haul, while the remaining 90% are medium and short-haul within Europe. The airline is consequently severely impacted by airspace congestions in the European region. In our experiments we focus on fleets covering short haul flying within Europe, which are the flight mainly exposed to airspace congestions. The data received from the airline contains its historic flight schedule covering 3 months and including both planned and actual times. Along with this we have also received matching passenger reservations with complete itineraries for a period of 2 weeks.

Data concerning airspace congestions are collected from the Network Operations Portal of Eurocontrol (http://www.public.cfmu.eurocontrol.int) and replicated into the flight planning engine on a per disruption basis.

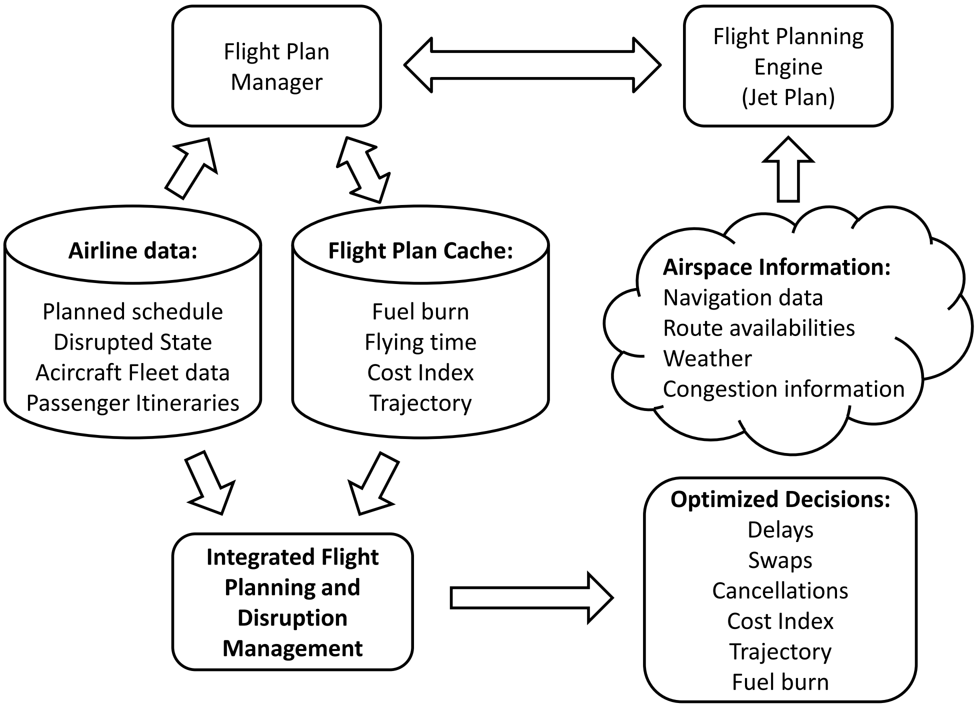


Figure C.16: Framework for Integrated Flight Planning and Disruption Management.

The framework of software modules and data used for the experiments are illustrated in Figure C.16. The framework contains a Flight Plan Manager, which have been developed for the experiment. The Flight Plan Manager reads the planned schedule and disrupted state from a database along with passenger loads for each flight. Based on this information the Flight Plan Manager calls the flight planning engine, which is a commercial software tool from Jeppesen and ensures that flight plans are continuously updated for all flights in the time period observed. For flight plans, which are affected by congested airspace, an alternative flight plan avoiding the congestion is also calculated. All flight plans are stored and continuously updated in the flight plan cache to enable fast retrieval, when a disruption needs to be solved.

The Integrated Flight Planning and Disruption Management module, contains the implementation of the optimization model formulated in section C.7. When a disruption needs to be solved this module retrieves schedule, disruption state, fleet information and passenger itineraries along with relevant and updated flight plans from the Flight Plan Cache. The optimization run leads to a simultaneous decision on: Delays, Swaps, Cancellations, Trajectory and fuel burn.

The recovery solution from this process is subsequently evaluated by a commercially available *passenger re-accommodation solver*, which calculates the actual passenger re-accommodation cost. This final evaluation step is carried out due to the fact the proposed recovery model in section C.7 does not take the full passenger itineraries into account, but only passenger connections.

C.8.1 Parameter assumptions

For input parameters in the model we assume the following values:

- The airline's own cost for a delayed passenger is assumed to be $1.09 per minute. This input is based on the airline's own internal calculations of this cost for year 2008 and includes passenger re-accommodation and loss of goodwill.

- Fuel is assumed to be $0.478 per lb, which is equivalent to $3.65 per gallon. This is based on the airlines own reported cost of approximately €750 per metric ton in February 2010. This price has been converted to 2008 numbers using a conversion rate of €1 = $1.27 in November 2008 according to the European central bank and according to IATA charts indicating that the fuel cost in February 2010 was 0.903 times the cost in November 2008.

- The normal Cost Index for the airline is assumed to be 30. All flight plans are calculated at this speed since no speed changes are considered in this experiment.

- The cost per disrupted passenger c_p is based on the assumption that misconnecting passengers will be re-accommodated in the next bank of flights, which gives an average delay of 7 hours for the flight schedule of this airline. Using the cost per passenger delay minute of $1.09, this gives a misconnection cost of $457.8.

- A swap cost of $500 is assumed for swaps within the same fleet. Swaps between fleets is not used in these experiments. The cost is based on parameter calibration with airline Ops Controllers.

- A flight cancellation cost c_f of $20.000 is assumed and is also based on parameter calibration with Ops Controllers.

- For the purpose of flight plan calculations an average passenger weight, including luggage, of 100 kgs has been used.

C.9 Computational experiments

In this section we present the results of the computational experiments, which have been carried out in order to evaluate the proposed model from section C.7.

Our models are implemented in C++ with a direct interface to the MIP solver Xpress version 19.00. The experiments are conducted on a server running Linux and equipped with a 64 bit Intel Xeon E5440 processor with 4 cores and 16 GB of RAM.

The cases used to evaluate the model is based on 3 months of historical disruption data combined with a subset of airspace congestions. As previously illustrated in Figure C.5, the number of congested areas over Europe is large and it has unfortunately not been possible to replicate all airspace congestions to the flight planning engine for the purpose of the evaluation. For this reason the results should be seen as a conservative lower bound for the savings which can be achieved by applying the approach.

The evaluation is based on 28 scenarios distributed over the seven days of the week in order to capture the varying flight schedule and passenger flows during the course of a week. The seven days have, however not been selected from the same week, but have been evenly distributed over the three months in order to even out some of the traffic variations from month to month.

C.9.1 Example: Heavy fog over the Netherlands

In this example heavy fog over the Netherlands is causing increased separation requirements, which reduces the ATC capacity in the area. This is resulting in a volume of airspace experiencing congestions during a course of 5 hours. The area has an extension of approximately 15.400 square nautical miles (nm^2), where the congestion in average have caused a 15 minute estimated departure delay for flights traversing the congested area. The recovery time window has been set to 48 hours, which leaves 93 flights belonging to the Airbus 320 fleet, consisting of 12 aircraft, in the window. Of the 93 flights 14 pass through the congested airspace during the presence of the congestion. Figure C.17 shows the recovery solution for the example. It is noted that flights marked with a blue dot in the lower left corner have been assigned a flight plan, which takes the flight around the congested area, which would otherwise have caused a departure delay of approximately 15 minutes. These are the 5 flights: 875, 876, 892, 891 and 811. These flights have been assigned a flight plan, which deviates from the lowest cost flight plan, in order to avoid the congested area.

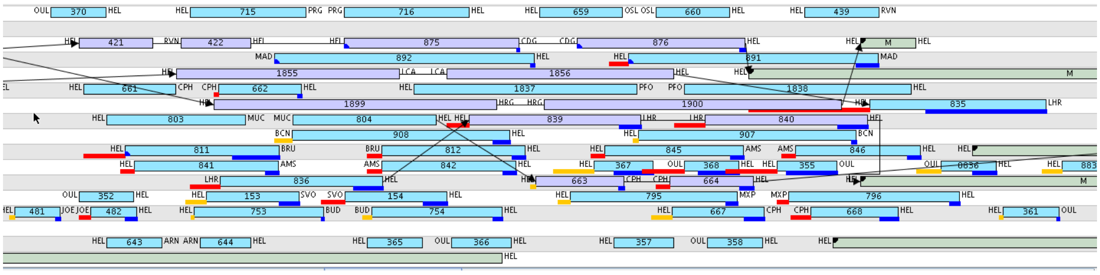


Figure C.17: Gantt display showing recovery solution for the example.

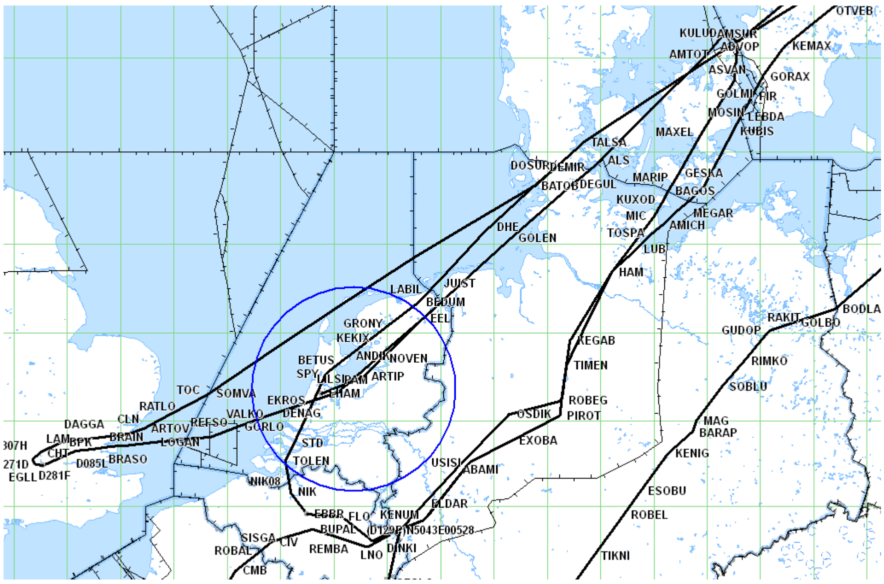


Figure C.18: Gantt display showing recovery solution for case 1.

Figure C.18 shows a trajectory view of the same solution as displayed in the Gantt view in Figure C.17. It is notable that the flights going to and from Amsterdam (AMS) airport are forced to enter the congested area and depart with a 15 minutes delay. Less obvious is it that for flights to and from London it is cheapest to select a trajectory through the congested area and accept the departure delay. For the flight to Brussels (BRU) a trajectory around the congestion is selected, while the flight from Brussels should go through the congestion. It is worth noting that the hub of the airline is located in the periphery of Europe and in spite the fact that the congestion occurs far from the hub, it does have a significant impact on the network operation of the airline.

Weekday	**Flights in recovery window**	**Congestion affected flights (%)**	**Congestion affected flights diverting around congestion (%)**	**Additional fuel pr. diverted flight (%)**	**Re-accommodation cost saving (%)**	**Total cost saving (%)**	**Total cost saving (USD)**
Monday	93	15.1	35.7	3.87	23.61	22.90	30,135
Tuesday	100	17.0	64.7	3.89	2.94	1.89	3,131
Wednesday	102	14.7	40.0	3.96	12.35	10.41	5,251
Thursday	78	16.7	46.2	4.15	1.24	0.56	853
Friday	79	17.7	42.9	4.33	3.12	1.79	1,297
Saturday	64	14.1	55.6	3.48	20.72	19.11	8,493
Sunday	82	19.5	56.3	3.32	23.61	22.54	29,662
Average	85.4	16.4	48.7	3.86	12.51	11.31	11,260

Table C.1: Result of approach for same congestion on different days.

Table C.1 shows the variations in results over the different days of the week, where the week day selection has been distributed evenly over the course of the 3 months of schedule data, which has been available. It can be observed that the same congestion results in a large difference in the number of congestion-affected flights, which are diverted around the congestion. This is due to three factors:

- Day-to-day variations in the schedule
- Differences in passenger flows
- Differences in historical disruptions

The day to day variations in the schedule is estimated to have less impact on the variations as there is a rather high re-occurrence of the same flights each day. The majority of the variation stems from the differences in passenger flows from day to day and the differences in level and type of disruption each day. The differences in passenger flows affect the extent to which passenger connections influence the solution due to constraints C.10. Similarly, an input disruption with various larger flight delays will already have used up the aircraft turn time and passenger Minimum Connection Time (MCT) buffers in the schedule. These disruptions are consequently more likely to render solutions, where flights are diverted around congested airspace as an additional departure delay will immediately lead to delay propagation through constraints C.4 and C.10.

The interesting observation from Table C.1 is the large variation in the percentage of flights, for which it is cost beneficial to select a trajectory around a congested area. There is furthermore an even larger variation in how cost beneficial it is to divert these flights around the congestion. This emphasizes the fact that it is difficult for a dispatcher, who does not have the entire network overview and does not have individual passenger connection information, to decide when he should select a trajectory around a congested area of airspace and when he should rather accept a departure delay and take the most fuel efficient trajectory. This is the reason, why it is important to have integrated decisions between ops controllers and dispatchers.

Table C.1 shows an average saving of \$11,260 per day when this airspace congestion occurs. In order to obtain a lower bound estimate of a yearly saving by applying the approach, the statistics department of Eurocontrol were kind to provide us with a list of their most frequently congested areas in year 2008, combined with the number of days where each of these locations were imposed an en-route regulation with more than 15 minutes of departure delays. The approach has been evaluated on a selection of some of the most frequently congested areas in Northern Europe, which provides a lower bound for the saving, which can be achieved by applying the approach of using flexible flight plans in the recovery decisions, when congested areas of airspace are involved. Each of the four evaluated areas have been evaluated over seven days as for the case with the Netherlands in the previous Table C.1. The lower bound estimate is consequently based on 28 scenarios, which all solve to optimality in less than 1 second.

Airspace area	**Average regulation duration (minutes)**	**Number of days with en-route regulation above 15 minutes**	**Average daily saving with flexible trajectories (USD)**	**Yearly saving with flexible trajectories (kUSD)**
North West of Poland	235	333	2,309	769
Holland	301	5.1 318	11,260	3,581
South Baltic Sea	106	81	6,254	507
East of Denmark	247	79	3,109	246
Lower bound saving	-	-	-	5,103

Table C.2: Selection of en-route congested areas of Northern European airspace with savings estimate for flexible trajectories.

As mentioned previously, the airline, which has contributed data to this research, does not have its hub in a central part of Europe and is somewhat retracted from the main congested areas of the continent. Despite that fact, it is notable that airspace congestions over the Netherlands are one of the most contributing areas to the savings potential of the approach. Based on that observation it is assumed that airlines, which are more centrally located in Europe, would be able to benefit considerably more from the approach.

The results in table C.2 show an estimated lower bound of yearly savings of 5.1 million USD for the the airline's Airbus 320 fleet consisting of 12 aircraft. This is however also the fleet of this airline, which is mainly used on routes covering central European airspace. Other fleets of the airline would contribute to increasing the lower bound for the savings potential of the approach, but would not do so to the same extent as the Airbus 320 fleet does. Other areas of airspace, would with their congestion frequencies also contribute to increasing the lower bound for the savings potential, but based on the route structure, hub location and congestion frequencies the four areas in Table C.2 are the main contributors.

C.10 Conclusions and future work

The main conclusion from this work is that it is possible to integrate dispatch decisions regarding flight trajectories in the recovery decisions. An optimization based recovery system, which integrates traditional recovery with flexible flight trajectories, can in an environment, which is severely impacted by airspace congestions, contribute with a yearly saving of several million USD. For a medium size European carrier, with a hub located outside of central Europe, a lower bound yearly savings potential of 5.1 million USD is estimated compared to traditional recovery without flexible trajectories.

For future work it would be relevant to apply the approach to a US-based airline, preferable one with a significant part of its operation in the North East of the US, where most US airspace congestions occur. Such work would contribute to quantifying the benefit of having the AFP slot selection integrated into the recovery and trajectory selection approach.

C.11 Acknowledgements

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Appendix D

The Vessel Schedule Recovery Problem (VSRP) - a MIP model for handling disruptions in liner shipping

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Abstract Containerized transport by liner shipping companies is a multi billion dollar industry carrying a major part of the world trade between suppliers and customers. The liner shipping industry has come under stress in the last few years due to the economic crisis, increasing fuel costs, and capacity outgrowing demand. The push to reduce CO_2 emissions and costs have increasingly committed liner shipping to *slow-steaming policies*. This increased focus on fuel consumption, has illuminated the huge impacts of operational disruptions in liner shipping on both costs and delayed cargo. Disruptions can occur due to adverse weather conditions, port contingencies, and many other issues. A common scenario for recovering a schedule is to either increase the speed at the cost of a significant increase in the fuel consumption *or* delaying cargo. Advanced recovery options might exist by swapping two port calls or even omitting one. We present the Vessel Schedule Recovery Problem (VSRP) to evaluate a given disruption scenario and to select a recovery action balancing the trade off between increased bunker consumption and the impact on cargo in the remaining network and the customer service level. It is proven that the VSRP is $\mathcal{NP}$-hard. The model is applied to four real life cases from Maersk Line and results are achieved in less than 5 seconds with solutions comparable or superior to those chosen by operations managers in real life. Cost savings of up to 58% may be achieved by the suggested solutions compared to realized recoveries of the real life cases.

Keyworks: disruption management, liner shipping, mathematical programming, recovery

D.1 Introduction

Disruptions occur often in a global liner shipping network. According to Notteboom (2006) approximately 70-80% of vessel round trips experience delays in at least one port. The common causes are bad weather, strikes in ports, congestions in passageways and ports, and mechanical failures. More exceptional causes include piracy and crew strikes on the vessels.

Example: The vessel Maersk Sarnia is deployed on a scheduled service providing transport of container cargo between South-East Asia and the west coast of Central America, see Figure D.1. During the pickup of cargo in South-East Asia the weather conditions cause Maersk Sarnia to suffer a 30 hour delay when leaving Kwangyang in South Korea. The delay can cause the vessel to miss an important scheduled port call in the transhipment port of Balboa in Panama. As a result large parts of the cargo will miss their onward connections and most cargo will not be delivered on time.

In order to mitigate the negative effects of the delay on Maersk Sarnia the operations center at Maersk Line has several options:

- Omit the upcoming port calls at Yokohama, Lazaro Cardenas, or Balboa.
- Speed up significantly to try to reach Balboa on time.
- Swap the port calls of Lazaro Cardenas and Balboa.
- Accept the delay and catch up the schedule returning to South-East Asia from Balboa.

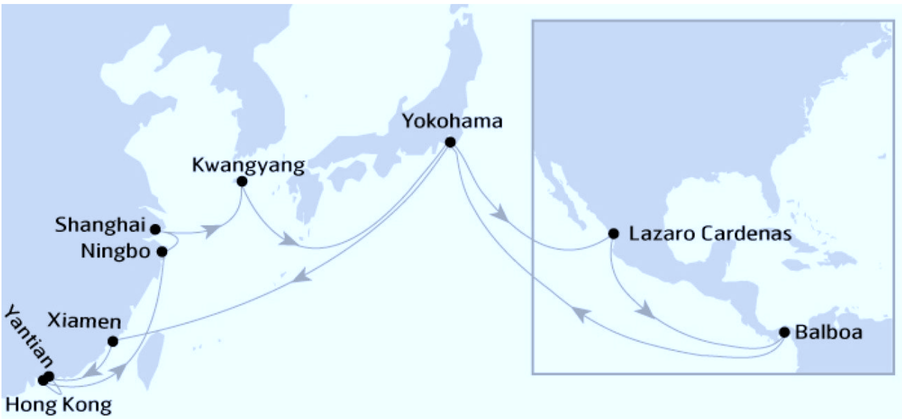


Figure D.1: A trans-pacific round trip is depicted. Cargo is collected in transshipment ports in Asia and sailed to transshipment ports in Central America. The round trip takes 56 days implying that 8 vessels is required to maintain a weekly service. Feeder vessels are used to connect all ports in a geographical area.

Figure D.2: A feeder service collect containers in the hub in Bremerhaven and transport them to their destinations in Norway.

Currently when a disruption occur, the operator at the shipping companies manually decides what action to take. For a single delayed vessel a simple approach could be to speed up. However, the cost of bunker fuel is a cubic function of speed (Alderton, 2004) and vessels' speeds are limited between a lower and upper limit. So even though an expensive speed increase strategy is chosen, a vessel can arrive late for connections, propagation delays to other parts of the network.

In recent years liner companies have had an increased focus on minimizing the bunker consumption in order to provide environmentally friendly transport and to minimize the operational costs (Maersk, 2010). On the other hand, on time delivery is very important for a global liner shipping company as delayed cargo carries a high cost by customers and key clients. Nevertheless, the negative effects of miss-connections or delaying a key clients merchandise can be hard to measure against a concrete cost of for example bunker. Furthermore, the ripple effect of the recovery on to the remaining network is very complex to overview for a human. In the considered example Maersk Sarnia recovered the situation by a general speed increase with a high bunker cost, but nevertheless the speed increase did not ensure timely delivery of containers to the hub port of Balboa, and final recovery was done returning to Asia. As a result all the cargo was delayed and some cargo missed the onward connection at the hub. The mathematical model presented in this paper suggested omitting the last port call in Asia reaching the transhipment port without increasing the vessel speed and on time. The cost saving, including a delay penalty, of the suggested solution is more than 20 %.

A standardized way of handling disruptions based on mathematical grounded decision support may significantly lower the cost of handling disruptions as seen in the airline industry (Rakshit et al., 1996; Yu et al., 2003) and simplify implementation of strategic decisions among stakeholders. According to UNCTAD (2010) *slow-steaming* has resulted in a significant increase in delays and they expect carriers to resume higher speeds in order to increase reliability and productivity. According to Notteboom (2006) reliability is generally achieved by introducing sufficient buffer time into a service. We believe that a mathematical decision support tool as the one presented in this paper may result in sustaining a *slow-steaming* policy, while increasing reliability of service without the need to introduce additional buffer time. In this paper, we introduce a mathematical model for handling the most common disruptions in liner shipping called the Vessel Schedule Recovery Problem, VSRP.

We make four contributions: First, we propose a novel formulation for the VSRP inspired by similar models within the airline industry. To the best of our knowledge the present article is the first to apply optimization to handle disruption management within the domain of liner shipping networks. Secondly, We prove the VSRP to be NP-complete. Third, we report computational results for four cases representing common disruptions, selected by experienced personnel at Maersk Line Operations Center. The recovery options identified by the mathematical model are comparable or superior to the decisions implemented in real life with cost savings of as much as 58%. The model is solved by a MIP solver within seconds for the selected cases. Fourth, a set of generic test instances is used to provide insights into the network sizes that may be handled in seconds by the current model and solution methods.

The remainder of the paper is organized as follows. Section D.2 introduces disruption management in the liner shipping business. Section D.3 describes related literature. In Section D.4 we introduce the *Vessel Schedule Recovery Problem (*VSRP*)*, the graph topology, and a mathematical model for the VSRP along with proofs of the $\mathcal{NP}$- completeness of the problem. In Section D.5 we introduce the four real life cases and the generic test instances and report computational results. Following this section we conclude that a decision support tool based on mathematical optimization of a disruption scenario could greatly aid an operations manager in evaluating the different recovery options.

D.2 The Liner Shipping Business

Liner shipping of containers is the backbone of world trade. Even though containerization simplifies the operations and reduces the cost per transported unit, the earned return is less than 10% on assets (Stopford, 2009). Customers demand fast and reliable delivery, while the shipping companies constantly search to cut costs. These issues have motivated major investments in improving the daily operations at large shipping companies (Notteboom, 2006). The liner shipping company referred to as a *carrier* has a public schedule of services. A service consists of a cyclic route with a scheduled time for each port call en route. Containers travel through the network as passengers in a public transit network, often combining several services. The port calls of a service, must usually happen at a predefined time and place in the port, often called the *berth slot*. This is defined by the physical place that the vessels moors, the berth, and a time window where the vessel is serviced. Most carriers provide weekly frequency of port calls. In recent years major companies are using slow-steaming to lower the variable cost and the CO2 emission (Løfstedt et al., 2011; Rosenthal, 2010; Maersk, 2010). To stay competitive, research has been focused on designing the network to operate as efficiently as possible. For shipping companies, a division of the ports into *hubs and spokes* is common(Christiansen et al., 2007). The network is not a traditional *hub and spoke network design* with direct links between two hubs or a spoke and a hub. As an alternative large vessels operate *main lines* between a set of hub ports and smaller vessels operate *feeder lines* connecting a set of spokes to a hub. An example of a *main line* service between hub ports is given in Figure D.1 and an example of a *feeder* service servicing a hub and several spokes is given in Figure D.2.

The motivation for this hub-and-spoke network design is to benefit from the economies of scale on container vessels (Stopford, 2009). The majority of containers are transhipped at least once during transport adding to the operational complexity and the impact of a disruption. Liner shipping companies operate with a head haul and a back haul direction. In the head haul direction vessels are almost full as opposed to the back haul direction. The head haul generally generates the majority of the revenue retrieved by operating the full service. As described above disruptions are accounted for and handled in the network by adding buffer time. Customer demand for fast delivery results in increased speeds and nearly no buffer time on the head haul, whereas the back haul is slower and has more buffer time. Due to the complexity of recovering from a disruption additional buffer time is included on the back haul with the option of a slight speed increase to catch up with the schedule on the back haul.

The most important variable costs in a liner shipping network is the bunker cost, the cost of using passageways such as the Suez and Panama canals, and the cost of calling ports to load and unload cargo. The fixed cost of operating a network in terms of asset costs on vessels, containers, and equipment are significant. Whenever a vessel fails to operate in accordance with the original schedule it is hurting the shipping company's business (and the business of their customers) (Notteboom, 2006). The utilization of vessels will often be affected negatively as containers miss-connect, resulting in a higher cost per transported unit. Furthermore, it might be necessary to arrange alternative transport for the miss-connected units also adding to the cost. Finally, the customers demand a reliable service and expect on time delivery. A major concern is therefore how to handle disruptions when they occur.

For larger liner shipping companies the information about disruptions are gathered in the company's Operational Control Center (OCC), from where decisions are also taken with respect to how the disruptions should be handled. Decisions here are taken in real-time and any system to support this process should support real-time decision making. The reason for this is two-fold. 1) Weather is changing quickly in some parts of the world, which may cause a port to close for a period of time. In such a case it is important to make a reasonable quick decision regarding whether the port should be skipped, which typically will lead to a change of course and the possibility of slowing down and saving on bunker fuel. 2) The other and more important reason is that controllers working in the OCC are in some periods faced with the need for taking many decision and evaluating various alternatives. This is where the requirement for a quick response becomes imperative. For this reason controllers at Maersk have stated 10 seconds as a reasonable response time for a disruption management system.

D.2.1 From airline disruption to liner shipping disruption

Operations research has for many years been applied extensively in the airline industry (Barnhart, 2009). Initially OR was mainly used in the planning phase, but during the last two decades OR has also found its way into the disruption management tools, which are used on the day of operation where the planned schedule is being executed.

This paper focuses on utilizing the findings in disruption management tools for the airline industry in order to construct a mathematical model of the VSRP to handle disruptions in the context of the liner shipping business. The airline and liner shipping businesses have evident similarities, but also some core differences (Christiansen et al., 2004). Larger airlines and larger liner shipping companies both operate a hub and spoke network, where either passengers or containers need to flow from an origin, through one or more hubs to a destination. Here, they need to arrive with the least possible amount of delay. In this way vessels resemble aircraft and containers resemble passengers. While crew recovery is a significant part of disruption management for an airline, this is not the case for a liner shipping company, as crew always follow the vessel and do not have work rules, which significantly limit the utilization of the vessel. Traditional aircraft recovery as described by Thengvall et al. (2001) or Dienst et al. (2012) makes use of 3 recovery techniques: *Delays*, *Swaps* and *Cancelations*. In addition to these techniques Marla et al. (2011) show that a large improvement in the number of passenger miss-connections can be obtained if *speed-changes* are included as a fourth recovery technique. In the following we discuss how each of these techniques can be applied to disruption management in a liner shipping network:

- *Delays*. For an airline the most straight forward way of handling a disruption is to delay flights and let the delays propagate to the subsequent flights of an aircraft. After a number of delay propagations the initial delay will have disappeared due to the fact that the gap between flights is usually a bit longer than the required turn time and most aircrafts are idle over night. For an airline this recovery technique is unfortunately also the one which, when applied alone, often ends up causing a lot of miss-connections (Dienst et al., 2012). In liner shipping it is also possible to delay the departure of a vessel, but port calls do not have additional slack built into them and container vessels are constantly in service, which means that delay propagation will not be able to resolve a disruption on its own. It will need to be combined with some of the techniques presented below in order to have the desired effect of recovering from a disruption.

- *Swaps*. This is a very efficient recovery technique for an airline, as it can be used to eliminate a lot of delay propagation to subsequent flights. Swaps are possible as an aircraft becomes empty after each flight. As a result one aircraft may be substituted for another. Unfortunately, this technique is not applicable to a liner shipping company, as a container vessel servicing a certain service is never empty and it is both extremely costly and time consuming to empty it completely. While vessels cannot be swapped in the VSRP it is for a liner shipping company possible to swap the order in which ports are being visited, whenever these ports are located geographically close to each other.

- *Cancellations*. This technique is usually not preferred in the aircraft recovery problem, but it is an efficient way of recovering, whenever the airline experience large delays or reduced runway capacity. For a liner shipping company this technique is unfortunately not directly applicable as it would interrupt the service operation of the vessel. In the VSRP it is however possible to cancel or omit a port call. In this case containers, which are destined for the omitted port, are then off-loaded at a subsequent nearby port and containers for on-loading in the omitted port are being held for the next vessel on that service, or another service covering the same ports, which often results in a delay of up to a week.

- *Speed changes*. Including speed changes from a network perspective as an integrated part of disruption management turns out to be a very effective way of balancing passenger delays versus fuel burn for an airline (Marla et al., 2011). This is in spite of the fact that a flight usually can only be sped up with 8-10% compared to its planned speed. For a vessel, which is originally scheduled to sail at a slow steaming speed of e.g. 16-18 knots, it is possible to speed up with 40% to e.g. 22-24 knots. This additional speed flexibility may be promising for the application of this technique in a liner shipping network.

As it is seen there are some clear similarities in the techniques, which can be applied in recovering a disruption in an airline network, and the techniques, which can be applied in recovering a disruption in a liner shipping network. The aircraft swapping technique available to an airline provides increased interaction between aircrafts in an airline network as opposed to vessels in a liner shipping network. An additional complication in a liner shipping network is that vessels operate around the clock and cannot naturally recover by using some of the overnight slack, which is often available in an airline network. For this reason recovering from a liner shipping disruption may take days and even weeks as opposed to a typical maximum of 48 hours for airlines. If a container fails to connect to a succeeding vessel the impact will often be more severe in liner shipping. International airports have a number of daily departures for a given destination presenting the option to re-accommodate passengers with a slight delay on a subsequent flight. For liner shipping a missed connection will normally result in a major delay.

We must estimate the effect on the cargo onboard with regards to missed onward connections and delays in order to assess a given recovery plan. Ideally the container groups would be reflowed on the residual capacity of the entire liner shipping network simultaneously with a recovery plan for the delayed vessels. This would significantly increase the graph of our instance as the containers onboard will include services, not considered in the disruption scenario. Additionally, reflowing the cargo is a large scale multicommodity flow problem. Mathematical models incorporating a large multicommodity flow problem such as capacitated network design (Frangioni and Gendron, 2009) and liner shipping network design (Álvarez, 2009) are severely restrained by the size of the problem and excessive solution times for general MIP solvers. We expect similar issues if incorporating the reflow of miss-connected containers into the VSRP and most certainly the application will no longer be able to provide real time suggestions when considering reflowing containers on the residual capacity of the network in a joint optimization. This is furthermore supported by findings in the airline literature where Bratu and Barnhart (2006) concludes that a combined model for solving a combined aircraft recovery and passenger re-accommodation model is too complex to solve to make it useful for real time optimization. Similarly the review Clausen et al. (2009) shows that full passenger re-accommodation is always handled in a subsequent optimization phase. An approach, which has been useful in the airline industry (Marla et al., 2011) is not to solve the full passenger re-accommodation problem together with aircraft recovery, but rather let the aircraft recovery be guided towards passenger friendly solutions by penalizing misconnecting passengers. A similar approach could be deployed for disrupted containers.

D.3 Literature review

Notteboom (2006) analyze the negative effects of disruptions in liner shipping and the actions taken by liner shipping companies to mitigate them. The recent paper by Notteboom and Vernimmen (2009) demonstrates how the increased bunker price has a significant impact on the liner shipping business. The cost of fuel is a dominant cost driver when transporting containers, nevertheless shipping companies are willing to burn extra fuel to arrive according to the schedule. Disruption management is a major concern for liner shippers given this trade-off. Notteboom and Vernimmen (2009) argue that the increased price on bunker has resulted in lowering the speed of vessels to save fuel, which in turn gives the vessels more buffer time and the operators more possibilities to recover from a disruption.

Even though the research within maritime transportation has gained increased focus during the last decades, we have encountered no journal papers devoted to disruption management in (liner) shipping. This can be caused by various things; firstly as mentioned the usage of mathematical modeling in maritime transportation is still in its infancy and secondly the market of liner shipping is extremely competitive. The development of decision support software will often be carried out for a major player in the market and therefore not necessarily published. After the submission of this article another model on disruption management in liner shipping was published in the thesis of Kjeldsen (2012). A heuristic is presented for solving a relaxed version of the model and computational results are provided for a set of generated disruption scenarios. The work by Yang et al. (2010) and Li et al. (2009) addresses disruption management for berth allocation in container terminals. Their papers are focused on how to recover the berthing schedules when vessels are delayed from the terminal point of view. Yang et al. (2010) presents an MIP Model and a heuristic solution approach. The problem handled is very different from the VSRP dealing with disruptions from the carriers point of view. The work of Du et al. (2011) allocates berths considering fuel consumption and has a good review on other Berth allocation literature. Well-established OR departments at many airlines have addressed the severe economical impact of flight delays and how to mitigate the effects of delays through disruption management based on OR. In 2008 the Joint Economic Committee under the U.S. Congress published a report estimating the infused cost to the American society to more than \$40 billion (JEC, 2008). The order of magnitude of the cost of disruptions has later been confirmed in a more theoretically profound study by Ball et al. (2010) even though their final estimate is $\approx 20\%$ lower. Both Rakshit et al. (1996) and Yu et al. (2003) document significant savings by implementing real-time decision support systems to handle the disruptions at major US airlines where the later estimates the annual saving to amount to \$40 million for Continental Airlines.

Disruption management research for airlines generally deals with recovering the 3 resource areas aircraft, crew and passengers. The full problem of optimizing all of these areas simultaneously is, however, so complex that no work has been published so far, which cover all 3 areas in one single integrated model. Most of the published models address one single resource. A few of the models focus on one resource area, while including specific aspects of other areas. For a good general introduction to disruption management in the airline industry the reader is referred to Yu and Qi (2004) and Barnhart (2009). The paper of Kohl et al. (2007) describes a large scale EU-funded project, called Descartes, which addresses various aspects of disruption management for all 3 resource areas. The reader is also referred to an extensive survey of operations research used for disruption management in the airline industry by Clausen et al. (2009). In order to adapt disruption management techniques applied to the airline industry to the liner shipping industry the aircraft recovery problem resembles vessel recovery and the recovery of passenger itineraries resembles container recovery. Since liner shipping companies do not have to deal with crew recovery, this literature review will only focus on aircraft and passenger recovery.

The first model on the *Aircraft Schedule Recovery Problem*, presented in the literature, is a network flow model by Teodorović and Guberinić (1984), who contributed by solving small problems with 3 aircraft and 8 flights. This work was extended by Teodorović and Stojković who extended the model in later papers. The solvable problem sizes still remained small with 14 aircraft and 80 flights. Jarrah et al. (1993) presented the first work, which were applicable in practice based on instances from United Airlines. They published 2 models, which in combination were capable of producing solutions handling all 3 traditional recovery techniques delays, swaps and cancelations. The drawback of handling this in 2 separate models was that delays and cancelations could not be traded off against each other. This drawback was resolved in the work by Yan and Yang (1996) who were capable of trading off delays, swaps and cancelations in one single model based on a time-line network. Thengvall et al. (2001) extended this model to also include so-called protection arcs, which serve the purpose of keeping the proposed solutions somewhat similar to the original schedule. This is important for real-life application of the suggested solutions as an unlimited number of changes cannot be applied to the schedule last minute. The work by Dienst et al. (2012) extends this model to also cover aircraft specific maintenances and preferences in an aircraft specific recovery model.

The *Passenger Recovery Problem* is an area of disruption management, which has been addressed to a rather limited extent by published research. Our observation from airlines show that most of these use a sequential re-accommodation process, which is carried out after an aircraft recovery schedule has been decided upon. Vaaben and Alves (2009) do a comparison of sequential passenger re-accommodation with re-accommodation based on an MIP-model. The main contribution in the area of passenger recovery is done by Bratu and Barnhart (2006), who present two models. Both are basically aircraft recovery models with some crew recovery guidance. One of them also includes passenger recovery, but is not solvable in real time. The other one is solvable but does not include complete passenger recovery. Instead it penalizes passenger miss-connections.

The work by Marla et al. (2011) extends on the work by Dienst et al. (2012) and Bratu and Barnhart (2006) by doing aircraft specific recovery with penalized passenger miss-connections, while at the same time also introducing the additional recovery technique of *speed changes*, which enables the model to balance the trade-off between passenger delay cost and fuel burn cost in a network perspective. The purpose of the present paper is to investigate if the application of similar disruption recovery techniques in a liner shipping context will be beneficial.

D.4 The Vessel Schedule Recovery Problem - (VSRP)

A given disruption scenario consists of a set of vessels V, a set of ports P, and a time horizon consisting of discrete timeslots $t \in T$. The time slots are discretized on port basis as terminal crews handling the cargo operate in shifts, which are paid for in full, even if arriving in the middle of a shift. Hence we only allow vessels arriving at the beginning of shifts. Reducing the graph to timeslots based on these shifts, also has the advantage of reducing the graph size, although this is a minor simplification of the problem. For each vessel $v \in V$, the current location and a planned schedule consisting of an ordered set of port calls $H_v \subseteq P$ are known within the recovery horizon, a port call A can precede a port call B, $A < B$ in H_v. A set of possible sailings, i.e. directed edges, L_h are said to *cover* a port call $h \in H_v$. Each L_h represent a sailing with a different speed.

The recovery horizon, T, is an input to the model given by the user, based on the disruption in question. Inter continental services will often recover by speeding during ocean crossing, making the arrival at first port after an ocean crossing a good horizon, severe disruptions might require two ocean crossings. Feeders recovering at arrival to their hub port call would save many missed transhipments giving an obvious horizon. In combination with a limited geographical dimension this ensures that the disruption does not spread to the entire network.

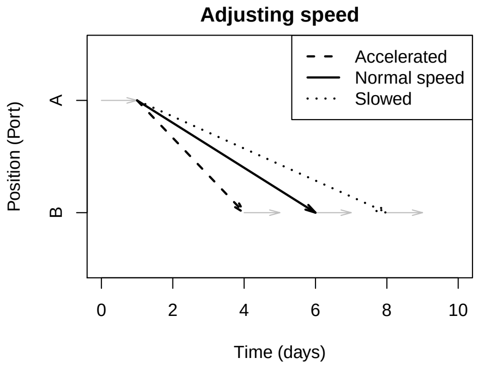
The disruption scenario includes a set of container groups C with planned transportation scenarios on the schedules of V. A feasible solution to an instance of the VSRP is to find a sailing for each $v \in V$ starting at the current position of v and ending on the planned schedule no later than the time of the recovery horizon. The solution must respect the minimum and maximum speed of the vessel and the constraints defined regarding ports allowed for omission or port call swaps. The optimal solution is the feasible solution of minimum cost, when considering the cost of sailing in terms of bunker and port fees along with a strategic penalty on container groups not delivered “on-time” or misconnecting altogether.

D.4.1 Graph topology

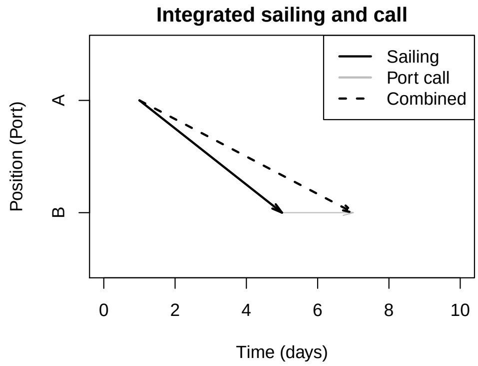
A disruption scenario is conceptualized as a directed graph in a time-space network similar to the one used by Thengvall et al. (2000, 2001, 2003), Marla et al. (2011) and Dienst et al. (2012). The horizontal axis corresponds to a point in time within the given planning horizon, and the vertical axis corresponds to a geographical position; a port in the context of VSRP. A simple example of a time-space network is presented in Figure D.3(a). Here, two geographical positions are given and a vessel can connect from the initial position A to the next position B with three different speeds.

A directed graph $G = (N, E)$ with node set $N = \{p^t \in N | p \in P, t \in T\}$ where p^t denotes port p at time t representing the time-space network. n^- and n^+ denotes the in- and out-going edges of node $n \in N$ respectively. $N_v \subseteq N$ is the set of all nodes for vessel $v \in V$. The set consists of a source node n_s^v corresponding to the current position of the vessel and a sink node n_t^v corresponding to the scheduled position at the end of the recovery horizon. Additional nodes are created for the set of port calls $h \in H_v$ within a time window of $\{a_v^h, b_v^h\}$ defining the earliest and latest arrival time respectively given the vessels minimum and maximum speed, the current position and the remaining set of port calls.

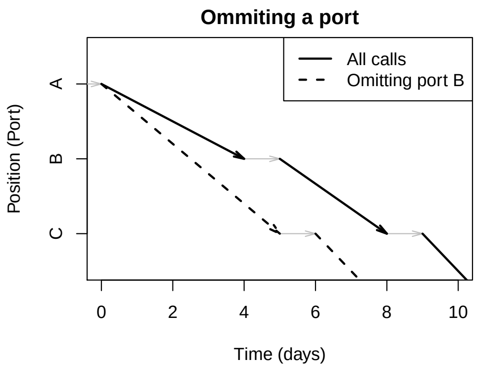
Define the edge set $E = E_s \cup E_g$ where E_s represents a sailing of a vessel $v \in V$ such that $E_s = \{(p^t, q^{t'})|p^t, q^{t'} \in N, p \neq q, t \leq t'\}$ and $E_g = \{(p^t, p^{t'})|p^t, p^{t'} \in N, t < t'\}$. The duration of a port call is fixed for each vessel $v \in V$ according to the scheduled port call duration from the original schedule. Because the port call duration is fixed port call edges E_g are included in the sailing edges E_s, thereby removing the set E_g as seen in Figure D.3(b). Including the edge set E_g in E_s reduces the number of columns in the mathematical model. For illustrative purposes the port call edges are still visualized in Figures D.3(c) and D.3(d), while the remainder of the figures in this paper only visualize the combined edges.



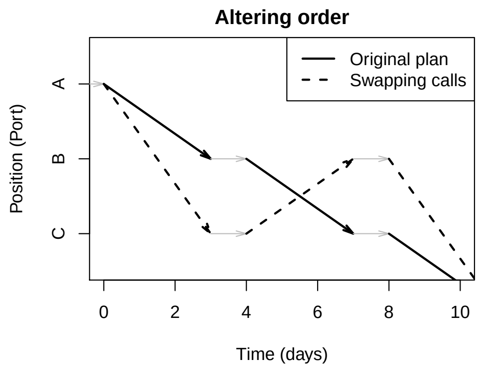
(a) Edges connecting two ports with various sailing speed.



(b) An edge combining sailing and port call edge.



(c) Edge corresponding to omitting a port call and decreasing speed.



(d) Edges corresponding to changing the order of port calls.

Figure D.3: Possible moves in the time-space network model. Port call edges are gray.

The edge sets $E_v \subseteq E_s$ are the edges that define feasible sailings among the nodes of N_v for a given vessel $v \in V$. $c_e^v \in \mathbb{R}_+$ is the cost of using edge $e \in E_v$ for vessel type $v \in V$ consisting of the bunker cost at a given speed and port fee for port $p = target(e)$. t_e^v is the time it takes to traverse edge $e \in E_s$ given speed, distance and port call time. The edge set $E_s = \bigcup_{v \in V} E_v$ is defined according to the planned schedule and the possible recovery actions defined below:

- **Adjusting vessel speed** (Figure D.3(a))
  In the span of the minimum and maximum speed of vessel $v \in V$ several edges may connect ports A and B. Define the set of edges $L_h \subset E_v$ covering port call $h \in H_v$ as $L_h = \{(A^t, B^{t'})|A, B \in H_v, A < B, t \leq b_v^A, a_v^B \leq t' \leq b_v^B, t < t', \forall t' = a_v^B + K \cdot \delta_B\}$ where K is a positive integer denoting the shift and δ_B is the duration of a shift at terminal B.

- **Omitting a port call** (Figure D.3(c))

Vessels might omit port calls to recover a delay or simply to save the port cost. Omitting port calls will result in miss-connected containers. Allowing to omit port B on a sailing from port A via port B to port C corresponds to having an edge (A^{t_A}, C^{t_C}) where $t_C - t_A$ corresponds to the sailing time. Edges L_h with differing sail speeds must be created as described in above bullet.

- **Swap order of calls** (Figure D.3(d))
  In some cases, a delayed vessel needs to call a number of ports close to each other. It might be possible to swap port calls within a designated geographical area. In the time-space network a swap is included by adding, first an omitting edge, followed by an edge back to the original port call. Again this must be executed for differing vessels speeds, as described in first bullet.

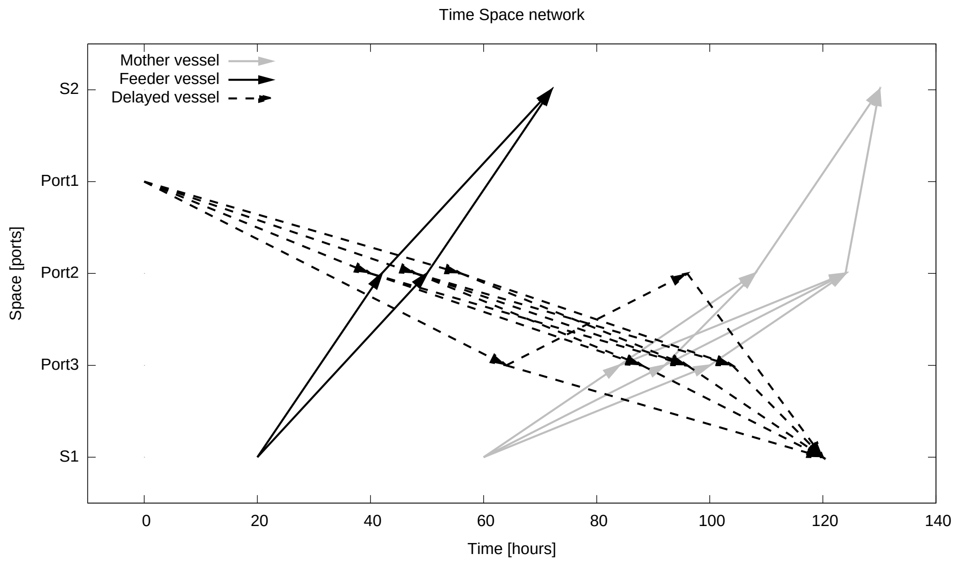


Figure D.4: Example of a time-space network for a test problem with three vessels, sinks and sources, three ports, speed adjusting edges, and port swap for the *delayed* vessel. In the network only the edges taking part in a feasible path are shown.

Figure D.4 gives an example of a full time-space network for a small test instance. Three vessels are affected by the delay of the *delayed* vessel.

The set of vessels is

$$V = \{delayed, feeder, mother\} = \{d, f, m\}$$

and for each vessel a set of port calls is given. These are

$$\begin{aligned} H_d &= \{P_1, P_2, P_3, S_1\} \\ H_f &= \{S_1, P_2, S_2\} \\ H_m &= \{S_1, P_3, P_2, S_2\} \end{aligned}$$

where P_i is Port i and S_i corresponds to onward sailing according to schedule. For each of the port calls $h \in H_v$ a set of possible sailings L_h covering the call is given. As an example vessel d has the set of four possible sailings/legs covering the call in Port 2:

$$\begin{aligned} L_{(d,P_2)} = \{ \quad & (P_1, 0) \to (P_2, 38) \quad , \quad (P_1,\ 0) \to (P_2, 48) \quad , \\ & (P_1, 0) \to (P_2, 58) \quad , \quad (P_3, 62) \to (P_2, 98) \quad \} \qquad . \end{aligned}$$

The cost of each of these edges is the sum of the bunker cost from sailing with the necessary speed between the ports and the cost of calling Port 2. The cost of using leg $(P_1, 0) \rightarrow (P_2, 38)$ is higher than the cost of using leg $(P_1, 0) \rightarrow (P_2, 58)$ as the sailing time is smaller $(38 < 58)$ resulting in a higher sailing speed and consequently an increased bunker fuel burn.

The problem has characteristics that are not directly reflected in the graph. These are the flow of containers, extended port stays due to omissions, limits on the capacity of a port, and port closure in a period of time. The extended port stay due to an omission can readily be handled in the graph construction by adjusting the duration of the set of sailing edges in E_s, that represent the omission. This has not been done to simplify modeling, as the effect will small. The port capacity issue can be modeled by constraining the number of vessels arriving (or used legs) at each port in each given time interval. Port closures are included by removing all edges corresponding to arriving at a port while it is closed.

D.4.2 Transportation scenarios - the impact of a recovery on the affected cargo

In order to evaluate which container groups will suffer from missed onward connections and delays we define a transportation scenario for each container group in terms of their origin, destination and planned transhipment points. $B_c \in H_v$ is defined as the origin port for a container group $c \in C$ and the port call where vessel v picks up the container group. Similarly, we define $T_c \in H_w$ as the destination port for container group $c \in C$ and the port call where vessel w delivers the container group. Intermediate planned transshipment points for each container group $c \in C$ are defined by the ordered set $I_c = (I_c^1, \ldots, I_c^m)$. Here $I_c^i = (h_v^i, h_w^i) \in (H_v, H_w)$ is a pair of calls for different vessels $(v, w \in V | v \neq w)$ constituting a transshipment. Each container group c has m^c transshipments. M_c^e is the set of all non-connecting edges of $e \in L_h$ that result in miss-connection of container group $c \in C$. $c_c^d \in \mathbb{R}_+$ is the cost of a delay to container group $c \in C$ exceeding a day of the planned arrival and $c_c^m \in \mathbb{R}_+$ is the cost of one or several misconnections to container group $c \in C$, which is added to the delay penalty in the model.

The cost of delaying the arrival of a container at its destination is to a large extent related to the loss of goodwill from the affected customers. This may vary by the type of container and the importance of the customer to the liner shipping company. In general refrigerated containers are more costly to delay than non-refrigerated, but more detailed classification by container type and customer value may be applied. The cost classifications used in the case-studies in this paper have been supplied by Maersk Line and are based on their internal approximations of these costs.

D.4.3 Mathematical model

The mathematical model is inspired by the work within aircraft recovery with speed-changes by Marla et al. (2011). Like others before Marla et al. (e.g. Marla et al. (2011) and Dienst et al. (2012)) we use a time space graph as the underlying network, but reformulate the model to address the set of available recovery techniques, which are applicable to the VSRP.

Define binary variables (x_e) for each edge $e \in E_s$ set to 1 iff the edge is sailed in the solution. Define binary variables (z_h) for each port call $h \in H_v \quad \forall v \in V$ set to 1 iff call h is omitted. For each container group c we define binary variables $o_c \in \{0, 1\}$ indicating whether the container group is delayed or not and y_c to account for container groups misconnecting. $O_e^c \in \{0, 1\}$ is a constant set to 1 iff container group $c \in C$ is delayed when arriving by edge $e \in L_{T_c}$. $M_c \in \mathbb{Z}_+$ is an upper bound on the number of transshipments for container group $c \in C$.

$$S_v^n = \begin{cases} -1 & , n = n_s^v \\ 1 & , n = n_t^v \\ 0 & \text{Otherwise} \end{cases}$$

is applied to the flow conservation constraints.

`Minimize:`

$$\sum_{v\in V}\sum_{h\in H_v}\sum_{e\in L_h} c_e^v x_e \quad + \quad \sum_{c\in C}\left[c_c^m y_c + c_c^d o_c\right] \tag{D.1}$$

`Subject To:`

$$\sum_{e\in L_h} x_e + z_h = 1 \qquad \forall v \in V, h \in H_v \tag{D.2}$$

$$\sum_{e\in n^-} x_e - \sum_{e\in n^+} x_e = S_v^n \qquad \forall v \in V, n \in N_v \tag{D.3}$$

$$y_c \leq o_c \qquad \forall c \in C \tag{D.4}$$

$$\sum_{e\in L_{T_c}} O_e^c x_e \leq o_c \qquad \forall c \in C \tag{D.5}$$

$$z_h \leq y_c \qquad \forall c \in C, \forall h \in B_c \cup I_c \cup T_c \tag{D.6}$$

$$x_e + \sum_{\lambda\in M_c^e} x_\lambda \leq 1 + y_c \qquad \forall c \in C, e \in \{L_h | h \in B_c \cup I_c \cup T_c\} \tag{D.7}$$

$$x_e \in \{0,1\} \qquad \forall e \in E_s \tag{D.8}$$

$$z_h \in \mathbb{R}_+ \qquad \forall v \in V, h \in H_v \tag{D.9}$$

$$y_c, o_c \in \mathbb{R}_+ \qquad \forall c \in C \tag{D.10}$$

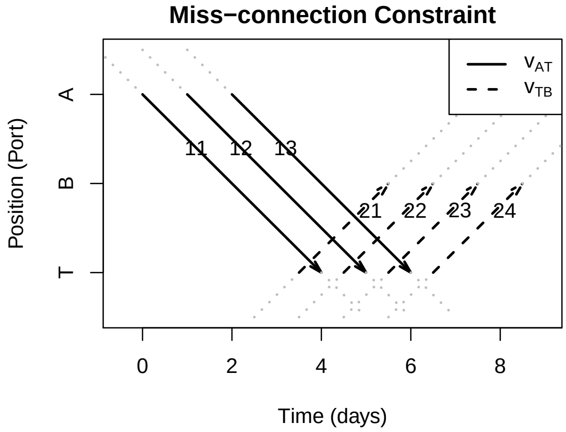
The objective function (D.1) minimizes the cost of operating vessels at the given speeds, the port calls performed along with the penalties incurred from delaying or misconnecting cargo. The weighted sum scalarization (Ehrgott, 2005), the ϵ-constraint method (Ehrgott, 2005), and variable fixing has been implemented for the VSRP with promising results in the thesis by Dirksen (2011).

Constraints (D.2) are *Set-Partitioning* constraints ensuring that each scheduled port call for each vessel is either called by some sailing or omitted. (D.3) are *Flow-Conservation* constraints. Combined with the binary domain of variables x_e and z_h they define feasible vessel flows through the time-space network. A misconnection is by definition also a delay of a container group and hence the misconnection penalty is added to the delay penalty. This is expressed in (D.4).

Each container group has a planned arrival time upon which it can be decided whether or not a given sailing to the destination will cause the containers to be delayed. Constraints (D.5) ensure that o_c takes the value 1 iff container group c is delayed when arriving via the sailing represented by edge $e \in E_s$. The right hand side does not have to be multiplied despite the number of summed variables may be larger than one due to the cover constraint (D.2) as this constraint ensures that only one incoming edge $x_e, e \in L_{T_c}$ can have flow. Constraints (D.6) ensure that if a port call is omitted, which had a planned (un)load of container group $c \in C$, the container group is misconnected. Constraints (D.7) are coherence constraints ensuring the detection of container groups' miss-connections due to late arrivals in transshipment ports. For each of the possible inbound sailings of a container transshipment a constraint is generated. On the left-hand side the decision variable corresponding to a given sailing, x_e, is added to the sum of all decision variables corresponding to having onward sailing resulting in miss-connections, $\lambda \in M_c^e$.

The constraint is illustrated in Figure D.5. When implementing the constraint the variables corresponding to inbound sailings are summed.

The variable x_e is required to be binary, whereas the remaining variables are only required to be non-negative. Binary x_e combined with constraints (D.2) implies z_h to be binary. Given the binary domains of x_e and z_h combined with constraints (D.6), (D.7) and a minimization implies y_c to be binary. Finally, Minimization, binary domains of x_e and y_c combined with constraints (D.4) and (D.5) imply that o_c is binary.



A container group transship from vessel v_{AT} to vessel v_{TB} at port T. It has three inbound (x_{11}, x_{12}, x_{13}) and four outbound $(x_{21}, x_{22}, x_{23}, x_{24})$ opportunities. The miss-connection constraint gives the following three equations:

$$\begin{aligned} &x_{11} && + x_{21} \leq y + 1 \\ &x_{12} && + x_{21} + x_{22} \leq y + 1 \\ &x_{13} + x_{21} + x_{22} + x_{23} \leq y + 1 \end{aligned}$$

Figure D.5: Example of the miss-connection constraint (D.7).

D.4.4 Model extensions

The model can be extended to incorporate additional features of a given problem instance such as the berth occupation constraint.

$$\sum_{v \in V} \sum_{h \in H_v} \sum_{e \in L_h} U_e^{pt} x_e \leq 1 \qquad \forall p \in P, t \in T \tag{D.11}$$

$U_e^{pt} \in \{0, 1\}$ is a constant set to 1 iff edge $e \in L_h$ occupy a berth in port $p \in P$ in time slot $t \in T$. The constraint ensures that only a single vessel can enter and use a berth at a given time. This constraint will not handle berth allocation in general, which specified methods exist for, as mentioned in literature review. But when several vessels have to compete for a single berth available at a terminal, this constraint can be used to model the liner shipping company's choice of prioritization, irrespective of the terminal's options.

D.4.5 Complexity

The VSRP is NP-hard if omissions of ports is allowed, or if port swaps are allowed. Even if only one of the recovery actions is allowed, the problem is NP-hard as shown in the following: If ommissions of ports are allowed in VSRP, the NP-hardness can be proved by reduction from the *0-1 Knapsack Problem (KP)*. Given an instance of the KP with a knapsack of capacity c, and n items having profit p_i and weight w_i, we transform it to an instance of the VSRP by using a single vessel and n ports which can be omitted. The cost of omitting a port is set to $-p_i$ and the duration of a port call is set to w_i. Sail times between ports are set to zero, and the recovery horizon is set to c, ensuring that a maximum profit subset of the items is chosen satisfying the capacity of the knapsack.

If port swaps are allowed in VSRP, the NP-hardness is shown by reduction from the *Traveling Salesman Problem* (TSP). Given an instance of TSP with n nodes and edge costs c_{ij}, we construct an instance of the VSRP by introducing n ports which can be visited in arbitrary order. Port calls and travel times are set to zero, while the sail cost between ports is c_{ij}. The cost of omitting a port is set to infinity ensuring that all ports are visited following the shortest Hamiltonian cycle.

The above reductions prove that the VSRP with allowed omissions is weakly $\mathcal{NP}$-hard and the VSRP with multiple omissions to be strongly $\mathcal{NP}$-hard. Extended proofs for the $\mathcal{NP}$-completeness of the VSRP may be found in Dirksen (2011).

D.5 Computational results

The program has been run on a MacBook Pro with 2.26 GHz processor and 2 GB of memory running Mac OSX using IBM ILOG CPLEX 12.2.0.0 as MIP solver. To test the performance and applicability of the developed model, it has been run on four real instances and a number of auto generated instances.

D.5.1 Real-life Cases from Maersk Line

The cases used to evaluate the VSRP are based on historical events at Maersk Line (ML). They are selected to represent the most common disruption scenarios and recovery options. Each case includes information about vessel schedules, port distances, container movements, recovery options, vessel speeds, and costs. ML handles these types of disruptions on a daily basis. The purpose of the cases is to test the suggested model, but also to clarify typical disruptions and how they are currently handled. An overview of the cases is given followed by a detailed presentation. The cases are

1. **A Delayed Vessel**
   The vessel Maersk Sarnia is delayed out of Asia due to bad weather. The vessel is, filled with cargo, about to cross the Pacific Ocean and unload in Mexico and Panama.

2. **A Port Closure**
   The port Le Havre in France is closed due to a strike. The vessel Maersk Eindhoven arriving with cargo from Asia can either wait for the port to open (giving an expected 48 hour delay) or omit the call in Le Havre.

3. **A Berth Prioritization**
   The port in Jawaharlal Nehru (India) does not have the capacity for a ME3-service vessel and a MECL1-service vessel to port at the same time. As the MECL1-service vessel is delayed and the vessels will arrive at the port simultaneously, it is necessary to decide which vessel to handle first.

4. **Expected Congestion**
   The feeder vessel Maersk Ravenna is planned to call three Colombian ports. Due to port maintenance at the last port to call, a delaying congestion is expected if arriving as planned. ML has to decide if the plan should be changed to avoid the congestion.

D.5.2 Case results

The computational results for the cases are promising. Good recovery strategies have been generated within 5 seconds, which proves the model applicable as a real-time decision support tool for liner shipping companies. The optimization based recovery strategies are generated with a strategic penalty for delaying and misconnecting containers. The two penalties are given the same value, i.e. $c_c^m = c_c^d$. For each of the cases discretization of the time horizon is $\delta = 3$ hours. Table D.1 shows different size measures for the four cases. The results from the optimized runs (**OPT**) have been compared to the real life solution (**RS**). **RS** is the realized sailings for the affected vessels and the realized impact on containers. All presented costs are relative to the real cost to preserve the relativeness of bunker, port fees and container impact of a solution. However, the costs have no relation to real life costs.

An overview is given in Table D.2. The results clearly show potential in the mathematical model. The experts at ML have indicated that in two out of the four cases they would prefer **OPT**, in one **OPT** is the same as **RS**, and in the last **RS** is preferred. However, in the case where **RS** is preferred, the recovery strategy is based on re-flowing cargo, which is not considered by the VSRP. The tendency is clearly that the model generates competitive solutions and would be a substantial support to the operator resulting in better recovery solutions using significantly less time. However, based on just four cases it is not reasonable to conclude that the optimized solutions are generally superior. The computational times are less than 5 seconds with CPLEX consuming roughly half the execution time, while graph generation consumes the rest. Please note that Case 1 (A Delayed Vessel) has a much longer planning horizon than the remaining cases, which accounts for the increase in running times. Even for Case 1 the solution time is indeed acceptable for a operational application.

D.5.3 Case 1 (A Delayed Vessel)

Within the planning horizon of Case 1 Maersk Sarnia delivers containers to a single ML vessel in Lazaro Cardenas and seven ML vessels in Balboa. Each vessel may be delayed to the originally planned arrival time. The vessel Maersk Sarnia is allowed to omit Yokohama and either Lazaro Cardenas or Balboa. The **OPT** is structurally different to **RS**. Both are plotted in Figure D.6. ML has chosen to call all ports with a speed increase (**RS**). However, the speed-up is not sufficient to reach the head haul ports in time. The optimized solutions (**OPT**) is to omit the call in Yokohama resulting in 400 misconnected containers while the remaining ports are called in time. The combined costs and penalties of **RS** are 24% higher than the costs and penalties of **OPT**. The experts at ML confirm that omitting Yokohama was a superior solution and note, that they were unable to convince a single important stakeholder of the superiority of this solution. It is very clear that the generalized mathematical assessment provided by a decision support tool would have been a strong argument in the discussion.

D.5.4 Case 2 (A Port Closure)

In Case 2 (A Port Closure) either Le Havre is called 48 hours delayed, or Rotterdam is called at the planned time. In Le Havre 649 containers need to be loaded and 1911 need to be unloaded. The time-space network of the case is presented in Figure D.7.

Again **OPT** is different in structure compared to **RS** (Figure D.8). However, as noted earlier **RS** is based on re-flowing containers not considered by the VSRP. Surprisingly, the data for the suggested solutions show that **OPT** is a better alternative with respect to cost. In real life the delay turned out to be 72 hours and a solution was obtained by allowing to merge two port calls. This option was not available to the model and hence the results are not comparable.

D.5.5 Case 3 (A Berth Prioritization)

In the third case, the additional berth occupation constraint (D.11) is added to ensure that the vessels call the port in India one at a time. The berth prioritization case is interesting as four of the connecting ML vessels may be delayed significantly and still reach their next port to call. **OPT** and **RS** result in the same solution presented in Figure D.9. The runs confirm the decision of **RS** and verify the applicability of a decision support system in an operational setting, providing fast solutions. In this case the decision would have been reached in a matter of seconds as opposed to hours.

Case	V	PC	CG	C	RH	N	E	x_e	z_h	y_c / o_c	Constraints
1	8	26	23	5145	961	301	7073	7073	10	23	1706
2	6	22	19	12358	969	118	290	290	10	19	122
3	10	33	24	5671	548	171	411	411	13	24	221
4	1	5	6	838	166	103	416	416	3	6	300

Table D.1: An overview of the relative sizes of the cases in terms of the number of vessels **(V)**, the number of port calls in the scenario **(PC)**, the number of container groups included **(CG)**, the total number of containers **(C)**, the recovery horizon in hours **(RH)**, the size of the graph (N, E), and the number of variables (x_e, z_h, y_c, o_c).

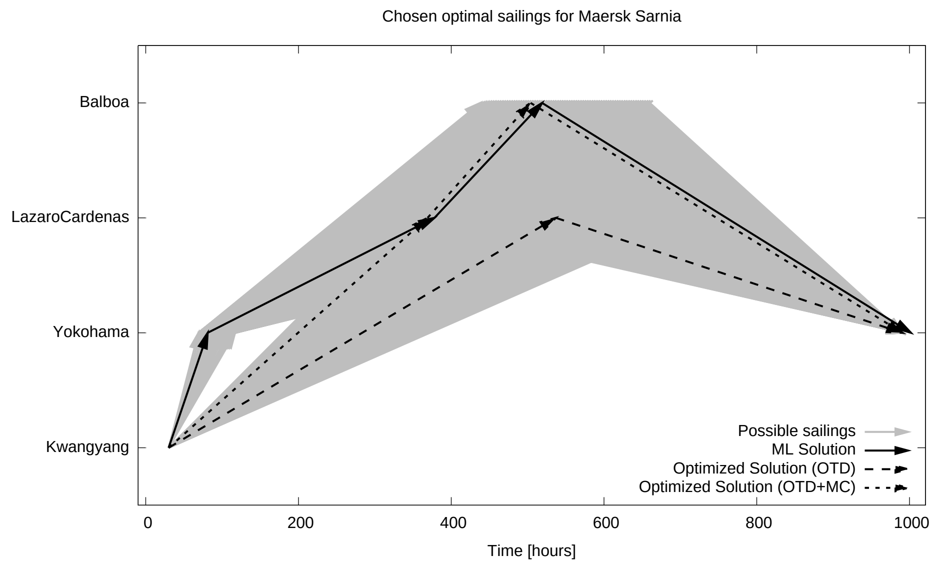


Figure D.6: Case 1: Suggested recovery solutions for Case 1 (A Delayed Vessel).

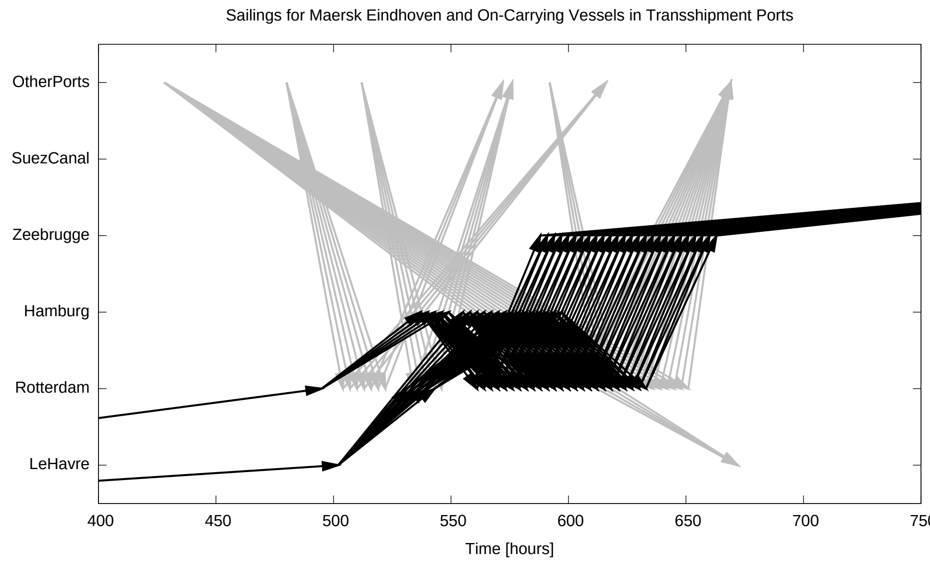


Figure D.7: Time-space network for Case 2.

		Sailing Cost		Delays		Misconnections		Solve	
		RS	OPT	RS	OPT	RS	OPT	Time	Best
Case	1	1,000,000	914,063	(2449)	(0)	(26)	(400)	4.529	OPT
	2	1,000,000	977,392	(3111)	(3111)	(58)	(58)	0.718	RS
	3	1,000,000	1,000,000	(687)	(687)	(0)	(0)	0.681	Equal
	4	1,000,000	1,033,334	(222)	(0)	(0)	(0)	0.518	OPT

Table D.2: Overview of results for the cases. The costs are relative, the container impact in units, and the time to solve in seconds. The best-column shows which solution the ML experts would prefer today.

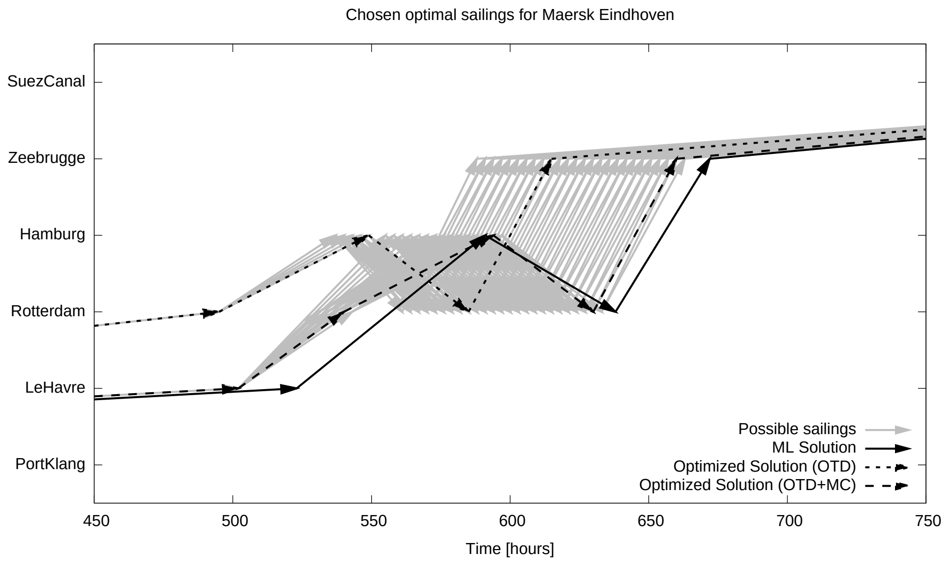


Figure D.8: Suggested recovery solutions for Case 2.

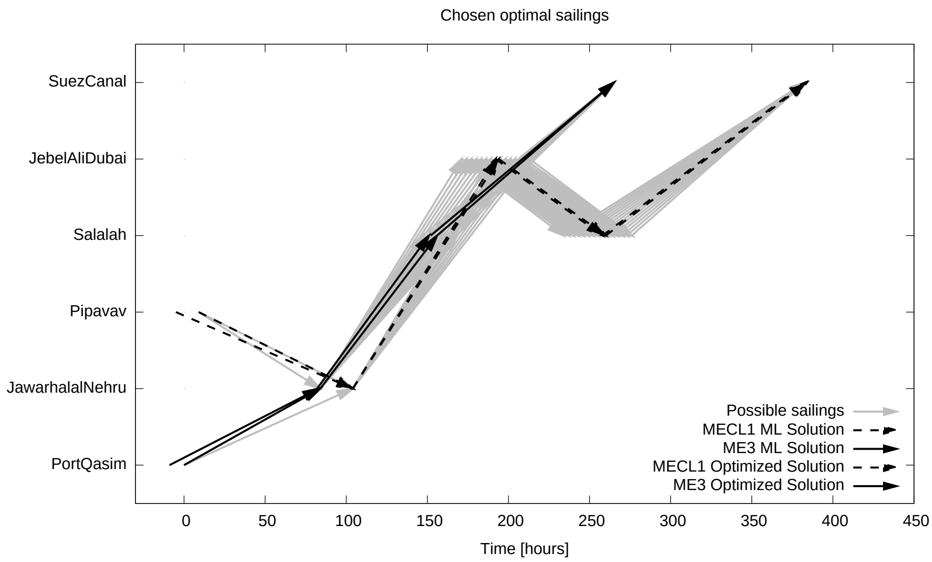


Figure D.9: Time-space network and solution for Case 3. The ME3-vessel (full line) or the MECL1-vessel (dashed line) calls Jawaharlal Nehru in India first.

D.5.6 Case 4 (Expected Congestion)

The last case where a feeder vessel is expecting port congestions in the last port differs completely from the former cases. The feeder only carries direct import and export cargo to and from Colombia, meaning that no additional vessels need to be taken into account and that a single run is generated as misconnections are not possible. The expected port delay (of 24 hours if Santa Marta is called after $t = 100$) combined with the possibility of calling the three ports in Colombia in any order defines the problem. The time-space network of possible sailings along with the solutions is given in Figure D.10. **RS** was to alter the order of the port calls to ensure that Santa Marta was visited long before the expected congestion. This resulted in a delay to the cargo in Cartagena. Contrary to **RS**, **OPT** suggests continuing as planned, but speeding up to arrive at Santa Marta before the expected congestion. This solution displays slightly increased bunker cost but ensures that all containers are delivered on time. According to the experts at ML, the optimized solutions should have been implemented. The costs and penalties reveal a saving amounting to a stunning 58%.

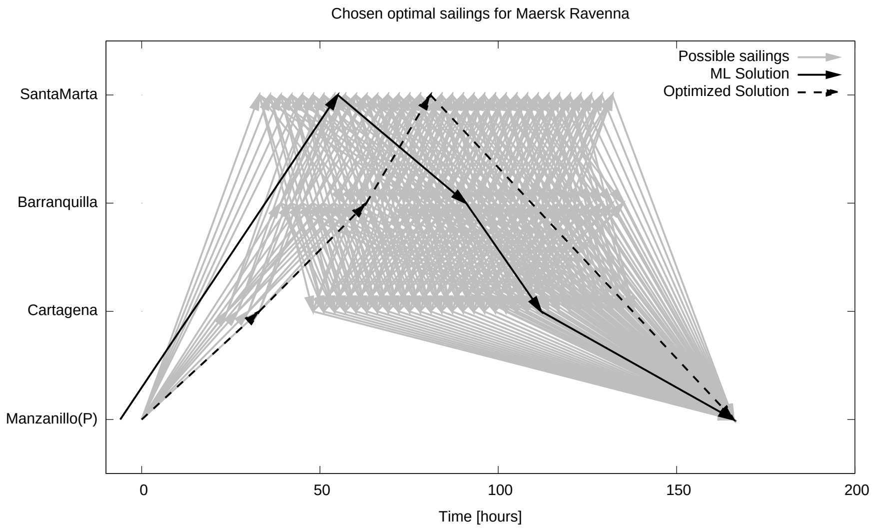


Figure D.10: Suggested recovery solutions for Case 4 (Expected Congestion) in the time-space network.

D.5.7 Auto generated test instances

The four cases utilize different parts of the solution space satisfactorily, but lack in size and are thus relatively fast to solve. To test the scalability of the model, a set of random instances have been generated, refer to Figure D.11 for an example. η^2 ports are placed in a squared grid, where distances and sailing times are proportional to Euclidean distances. Vessels are generated with a random schedule of $\kappa < \eta^2$ ports to call. Container itineraries are generated such that each intermediate call for each vessel and arriving container group is added with some probability. For these instances the computational time grow with increasing number of calls per vessel and number of vessels in instance as seen in Figure D.12. It can be seen that the computational time handles an increased number of vessels well, but is impacted harder by an increased number of port calls. It seems viable that the model will solve in minutes for instances with up to 10 vessels and port calls making it viable for use in a wide range of real world problems. For more details on how the instances are generated and details on computational time please refer to the thesis by Dirksen Dirksen (2011).

D.6 Conclusion and future work

To the best of our knowledge this paper is the first literature on decision support for disruption management in a liner shipping network. We have presented a novel mathematical model for the Vessel Schedule Recovery Problem (VSRP). The model addresses frequently occurring disruption scenarios in the liner shipping industry. The model is based on disruption management work from airline industry and adapted to liner shipping. We show the VSRP to be NP-complete. The model is solved using a MIP solver and computational experiments indicate that the model can be solved within ten seconds for instances corresponding to a standard disruption scenario in a global liner shipping network. Computational results for four real-life cases show similar or improved solutions to historic data. The solutions have been verified by experienced planners. A set of generic test instances have been provided and computational results indicate that the model

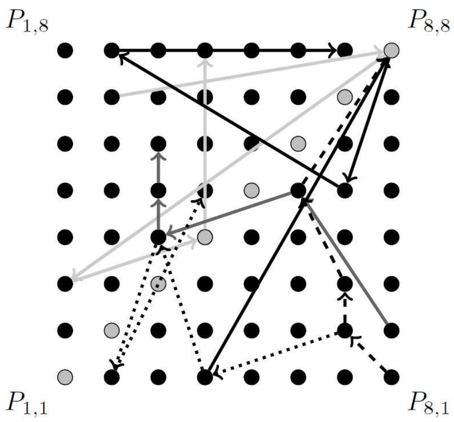
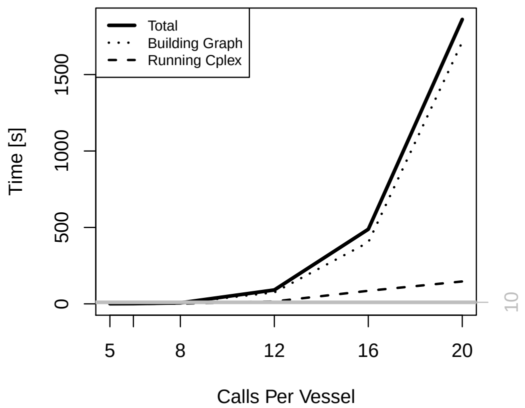
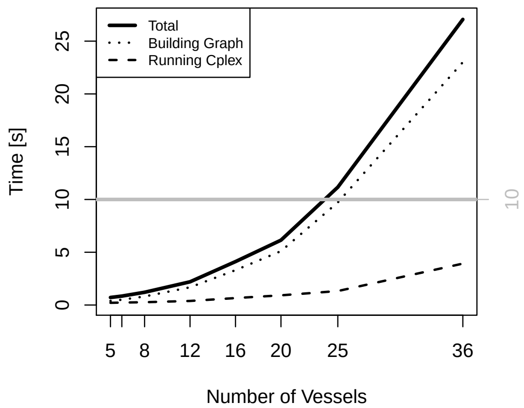


Figure D.11: Graphical explanation of the standard way random instances of the VSRP are generated.



(a) Computational times increasing the number of port calls per vessel, with 5 vessels



(b) Computational times increasing the number of vessels, with 5 port calls

Figure D.12: Computational times for generic generated problems with varying number of ports and vessels respectively. The times are average values based on 5 repeated runs.

is capable of handling larger disruption scenarios than the real-life cases in seconds. However, with an increasing number of vessels, the computational time show exponential growth and can no longer reach an optimal solution within ten seconds, for larger instances. An analysis of the four real life cases, show that a disruption allowing to omit a port call or swap port calls may ensure timely delivery of cargo without having to increase speed and hence, a decision support tool based on the VSRP may aid in decreasing the number of delays in a liner shipping network, while maintaining a *slow steaming* policy. This initial work on disruption management in liner shipping show potential for interesting extensions. Other recovery modes than the three considered (speed adjustment, port call omission and port call swap) could be investigated, e.g. reducing the time spent at port by unloading but not loading, merging port calls or adding protection arcs. Another extension would be to reroute the non-satisfied cargo on the remaining, or even third party network. The connection with berth scheduling problems with disruption of fixed scheduled services as considered here could also be explored further.

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