

Robust Airline Schedule Planning: Review and Development of Optimization Approaches

by
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Ingénieur des Arts et Manufactures
Ecole Centrale Paris, 2003

Submitted to the Department of Civil and Environmental Engineering and the Sloan School of Management in Partial Fulfillment of the Requirements for the Degrees of

Master of Science in Transportation
and
Master of Science in Operations Research

at the
Massachusetts Institute of Technology
June 2004

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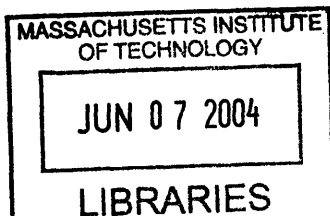
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BARKER

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Abstract

Major airlines aim to generate schedules that maximize profit potential and satisfy constraints involving flight schedule design, fleet assignment, aircraft maintenance routing and crew scheduling. Almost all aircraft and crew schedule optimization models assume that flights, aircraft, crews, and passengers operate as planned. Thus, airlines typically construct plans that maximize revenue or minimize cost based on the assumption that every flight departs and arrives as planned. Because flight delays and cancellations result from numerous causes, including severe weather conditions, unexpected aircraft and crew failures, and congestion at the airport and in the airspace, this deterministic, optimistic scenario rarely, if ever, occurs. In fact, schedule plans are frequently disrupted and airlines often incur significant costs in addition to those originally planned. To address this issue, an approach is to design schedules that are robust to schedule disruptions and attempt to minimize *realized*, and not *planned*, costs. In this research, we review recovery approaches and robustness criteria in the context of airline schedule planning. We suggest new approaches for designing fleet assignments that facilitate recovery operations, and we present models to generate plans that allow for more robust crew operations, based on the idea of critical crew connections. We also examine the impact on robustness of new scheduling practices to debank hub airports.

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Acknowledgments

I cannot possibly express my gratitude for the support of my advisor, Professor Cynthia Barnhart. She has not only provided me with guidance in my research, but she also always helped me when I needed it the most. It has been a great honor to have known her and to have worked with her. Thank you for being such a great person. Thanks also to Professor John-Paul Clarke for his help in my research work.

Many, many thanks to all my friends who made my stay at MIT an experience I will not forget. Thanks to Maya for her numerous advice and her kindness, Yasmine for encouraging me to do a dual degree, Katy for being such a great sport buddy, Amr for these wonderful discussions, Alf for his sense of humour, Sepehr for being such an helpful comrade, and last but not least my French mafia.... Ben I, Ben II and Matthieu.

Of course, I owe my deepest thanks to my parents, and my sisters. They have done the best job of being family when family was needed, friends when friends were needed, and mentors in school, and in life, when mentors were needed.

Finally, I would like to thank Raymond for always being there. I am eternally grateful for his love, support and encouragement.

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Chapter 1

Introduction

The goal in solving the Airline Schedule planning problem is to create aircraft and crew schedules that maximize airline profitability. This problem is large-scale and complex because it is characterized by numerous parameters including dynamic passenger demand, different aircraft types, maintenance requirements and crew work rules. Its size and complexity make it impractical to solve in its entirety, thus it is decomposed into a set of four sub-problems namely Schedule Design, Fleet Assignment, Aircraft Maintenance Routing and Crew Scheduling.

1.1 Airline Schedule Planning: A Sequential Approach

Schedule Design

The output of Schedule Design problem is the flight schedule: the markets to serve and with what frequency, and when to schedule flights to meet these frequencies. The flight schedule is a fundamental to airline profitability and involves strategic decisions of an airline and of its competitors, which are hard to capture in a mathematical model. Therefore the number of optimization models in this area is limited. Nonetheless, mathematical programs have been used in simplified design problems to make incremental changes to existing flight schedules, as described in Berge (1994), Marsten et al (1996) and Lohatepanont and Barnhart (2001). Their approaches are incremental in that the changes from one published flight schedule to the next are limited, but the reported impacts are significant.

Fleet Assignment

Once the flight schedule is determined, the fleet assignment problem is solved to assign a specific aircraft type to each flight in the schedule, while minimizing fleet costs. Fleet costs are comprised of

- 1) Operating costs, representing the cost of flying each flight leg with the assigned aircraft type.
- 2) Spill costs, measuring the revenue lost when passenger demand for the flight leg exceeds the leg's assigned aircraft's seating capacity.

A fleet assignment has to satisfy some constraints such as restrictions on the number of available aircraft of each type, and the balance of aircraft in the network. The aircraft balance constraint requires that each aircraft type is assigned to the same number of strings arriving at a station as departing that station. The fleet assignment problem is often formulated as a multi-commodity flow problem in Abara (1989) and Hane et al (1995). Although this formulation has yielded tremendous savings, it does not address a critical challenge for fleet assignment models. Namely it does not model passenger fares, demands or spill as itinerary-specific, but rather models them as flight-leg specific. The Origin-Destination based fleet assignment approaches by Jacobs, Johnson and Smith 1999, Barnhart, Kniker and Lohatepanont 2002 succeed in modeling more accurately the revenues and spill cost of each fleet.

Maintenance Routing

With schedule design and fleet assignment decisions made, the flight network is decomposed into sub-networks, each one associated with a single aircraft type. The maintenance routing problem is solved to assign individual aircraft to flight legs in a sub-network to create a *rotation* or cycle of flight legs assigned to the same aircraft. Rotations are constructed to ensure that all aircraft are maintained at the right place at the right time, as specified by governmental regulations. The maintenance routing problem is often formulated as a network circulation problem with side constraints. Detailed descriptions can be found in Feo and Bard (1989) and Gopalan and Talluri (1998).

Crew Scheduling

The crew scheduling problem is solved to assign cockpit and cabin crews to flights to achieve minimal operating costs, while satisfying the numerous and complex work rules defining *legal* schedules. This problem is often broken into two problems that are sequentially solved:

- 1) The crew pairing problem to construct minimum-cost, multiple-day work schedules (*crew pairings*) that satisfy all the work rule restrictions;
- 2) The crew assignment problem to assign individual crewmembers to pairings to create equitable and efficient month-long crew schedules. These schedules must satisfy many requirements such as:

- 1) Pilots are qualified to fly only certain types of aircraft
- 2) Flight crews cannot be away from their base or stay on duty for a time period longer than some clearly defined limits.

Because the legality crew pairings structure is very complex, and the cost structure is nonlinear, much of the existing literature formulate the crew pairing problem as a set partitioning problem with one binary decision variable for each pairing. This formulation allows the computation of non-linear pairing costs off-line and eliminates the need for an explicit formulation of complicated work rules. More details can be found in Anbil et al (1991), Gershkoff (1989), Hoffman and Padberg (1993), Barnhart and Sheno (1998) and Klabjan and Schwan (1999).

1.2 Drawbacks of the Basic Sequential Approach

Almost all optimization models in the area of airline schedule planning assume that flight departure and arrival times, as well as the quantity of resources available, such as crews and aircraft, are perfectly known. Unfortunately crew sickness, mechanical failure and adverse weather result in delays, which in turn require necessary changes to the plan, often leading to significantly increased costs. Therefore using mathematical models that ignore such disruptions often result in

- 1) An optimal solution that cannot be implemented
- 2) Increases the costs of operations beyond those planned

Clearly then, the so-called *optimal* schedules that are used today by commercial airlines are far from optimal in practice. One approach to resolve this dilemma is to develop real-time algorithms to re-optimize the schedule after irregularities occur. Another approach is to build robustness in the schedules at the planning stage.

1.3 Thesis Objectives and Contributions

The research documented in this thesis was performed to achieve the following major objectives and make the following contributions:

- 1) Review various approaches to deal with uncertainty in airline schedule planning
- 2) Provide alternative definitions of robustness in the context of airline schedule planning
- 3) Present a model for fleet assignment designed to facilitate recovery operations
- 4) Develop of models generating crew pairings that allow for more robust crew operations

1.4 Thesis Outline

This thesis is organized as follows. In chapter 2, we provide a survey of real-time recovery models and some general robust planning methodologies. In chapter 3, we describe a category of robust models that aims to facilitate recovery in case of disruptions. We also present a robust fleet assignment model that aims to ease the aircraft recovery procedure at spoke airports. In chapter 4, we present a category of robust models that generate schedule that are less prone to disruptions. We propose an alternative definition of robustness for the crew schedule and present a robust crew schedule model with the objective to minimize the number of missed connections for crews. In chapter 5, we assess the robustness of a recent strategic airline policy: the debanking policy. Finally in chapter 6, we summarize these various robust models and discuss possible interactions of these models.

Chapter 2

Strategies to Deal with Uncertainty

2.1 Introduction

There are two ways to deal with the uncertainty in schedule planning resulting from disruptions. One approach is to re-optimize the schedule after disruptions occur during operations; while another more proactive approach is to manage uncertainty by incorporating robustness into the schedules, during the planning stage.

2.2 Irregular Operations

There are many reasons for flight delays and cancellations. Ageeva [2] states that the major causes of disruptions at airports are:

- *Weather*. Wind, fog, thunderstorm, low cloud ceiling, which account for more than 90% of all flight delays at major hubs
- *Equipment failure*.
- *Runway* due to surface repair, unavailability because of construction, etc
- *Volume* Aircraft traffic rate exceeds capacity of the airport at a given time, typically when the weather conditions implies a loss of airport capacity.

These delays and cancellations lead to important internal disruptions to the airline aircraft and crews. But they also lead to significant disruptions to the passengers through delays and missed connections. Lan et al [27] points out that in 2000, about 30% of the flight were

delayed and about 3.5% were cancelled. Unfortunately, the flight delays and cancellations are expected to increase dramatically in the future, with an expected increase of 5% in delays for each 1% increase in air traffic, thus if the air traffic in the US doubles in the next 15 years, as expected, it is important for airlines to incorporate uncertainty in their modeling strategy.

2.3 Real-time Recovery Models

When disruptions occur, airlines must reschedule flight operations. A typical airline's recovery procedure is designed to determine which flight legs to delay or cancel, and how to reroute aircraft, crews and passengers.

As during the planning stage, airlines typically use sequential models to recover from a disruption. In the first stage referred to as *aircraft recovery*, the objective is to reroute aircraft and make flight leg postponement and cancellation decisions. In the second recovery stage referred to as *crew recovery*, the objective is to reroute crews and utilize *reserve crews* as necessary to accommodate changes in the flight schedule. In the final stage referred to as *passenger recovery*, the objective is to reroute passengers whose itineraries are disrupted.

Much of the existing literature in the area of optimization recovery models deals only with the aircraft recovery stage, for two reasons. First, compared to the crews, aircraft are seen as more critical resources, because they are more expensive to reposition and there are fewer "reserve" aircraft than reserve crew available. Second, solving the crew recovery problem optimally in real-time during operations is typically not possible. Finally, the relatively low priority given to passengers helps to explain the scarcity of models dealing with the passenger recovery problem.

Our review of recovery models will be classified on the basis of the objective pursued while trying to recover. The possible objectives are:

- 1) To minimize the effects of disruption as measured by the number of flight delays or cancellations or the amount of passenger delay
- 2) To minimize the increase in operating costs considering crew labor costs, fuel costs or the loss of revenue due to cancellation (that is spill costs)
- 3) To minimize the *disruption duration*, that is, the time before the airline can resume the implementation of the originally planned schedule

2.3.1 Minimizing the Effects of Disruption

2.3.1.1 Aircraft Recovery Models

In 1984, Teodorovic, Dusan and Guberinic [28] discussed the problem of designing a new flight schedule and aircraft routing solution when one or more aircraft experience a technical failure. They determine the solution set of aircraft routings and flight schedule that minimizes overall passenger delay using a branch-and-bound procedure. Their methodology assumes a single fleet type and ignores all maintenance requirements. They implement their model on a simple example involving three aircraft operating a total of eight scheduled flights.

Jarrah et al [16] present a model that is an improvement on the successive shortest path method presented by Gershkoff in 1987. They find a good set of flight cancellations to resolve aircraft shortages. They present two network models each of which allows aircraft swapping among flights and the utilization of spared aircraft to absorb aircraft shortages. The first model, called the delay model, is used to determine a set of flight leg postponement or delays, while the second model (the cancellation model) is used to determine a set of flight leg cancellations. To assess the cost of delaying or cancelling a flight, they used a disutility function that depends on the total number of passengers, the number of passengers that will have a downline connection, lost crew time and disruption of aircraft maintenance (the new schedule might violate for some aircraft their maintenance requirements). They used historical data from United Airlines to determine those disutility functions. The main drawback of this solution framework is that it does not allow for a trade-off between cancelling and delaying a given flight in a single decision process.

In 1997, Cao and Kanafani discussed a real-time decision support tool for the integration of flight cancellations and delays. This work was an extension of Jarrah's work, using many of the modelling concepts presented in [16]. The model considers the airport network as a complete system and traces the effect of delays and aircraft reassignments from one airport at a point in time to the next. They also take into account the issues of *ferrying* (flying an empty aircraft to an airport so that it can cover a flight departing from this airport) and *multiple aircraft type swapping* (if two routings of even different aircraft type meet at more than one

node within a certain time window, an aircraft can be swapped from one routing to the other and then returned to its original routing at a subsequent meeting node).

2.3.1.2 Hybrid Recovery Models

In 1996, Mathaisel [22] presented a software/network application that integrates real-time flight following, aircraft routing, maintenance, crew management, gate assignment and flight planning with dynamic aircraft re-scheduling and fleet re-routing algorithms for irregular operations. The architecture of the system is one server that centralizes all the databases, finds routing alternatives to minimize the effects of disruption, and then distributes the decision support and optimization to various workstations depending on the focus of each workstation. The solution approach is a “what-if” approach in which the controller adjusts parameters using the interactive interface to determine the consequences. The definitive choice remains in the hands of the controllers, who understand that some flights might be more easily cancelled than others.

2.3.2 Minimizing Operating Costs

2.3.2.1 Aircraft Recovery Models

The first model to provide a delay and cancellation plan simultaneously is that of Yan and Young [32]. Their objective is to maximize airline profit, defined as airline revenue minus the cost of cancellation and/or delay. They ignored all maintenance requirements, crew restrictions and passenger connections.

Argüello et al [3] present a time-band optimization model for reconstructing aircraft routings in response to ground delays. The objective is to minimize aircraft operating cost and cancellation revenue lost. In solving the problem, they assume a single fleet type and ignore all crew restrictions and use a greedy randomized adaptive search procedure, called GRASP. From the initial solution in which all flights that are to be flown by the aircraft grounded or delayed are cancelled neighbouring solutions are found by making relatively minor changes to the initial solution. These neighbouring solutions are then costed and only the best are included in a restricted candidate list. Then, randomly selecting a solution in the restricted list,

the algorithm finds new “neighbours” and repeats. Throughout the iterations, the best solution is recorded.

One of the drawbacks of the Arguello et al’s model is that only the next leg each aircraft is scheduled to fly after the disruption is considered and therefore the cost of a cancelled leg or delayed leg is represented as a single value space. However, cancelling a leg can require the airline to cancel several other legs and/or to ferry some aircraft.

In 1997, Clarke [9] presented a model, whose objective was to minimize the operating costs and the lost passenger revenue for a whole sequence of flights. Unfortunately his model is computationally very intensive.

In 2001, Rosenberger et al [24] outlined a model that minimizes the increase in operating costs calculated for each routing, as done in [9], while rerouting aircraft from the same fleet. To make the model tractable and solvable in a limited time, they do not generate all potential new routes, but rather work on a subset of selected aircraft. This subset is selected as follows: For the set of disrupted aircraft, they create a special graph in which for each pair of aircraft (i, j), they check if one can create a new route for j that includes some legs initially covered by i. If this is the case, they add a node for aircraft j in the graph and an arc from i to j. Then for each disrupted flight i, they identify the shortest cycle, in terms of the number of arcs, from i. They then run the model on the set of aircraft that are included in each of the cycles generated for each disrupted flight. According to the authors they are consequently able to solve many large recovery instances quickly.

2.3.2.2 Crew Recovery Models

In 1995, Lettovsky et al [20] presented a crew recovery model that reassigns crews to flight legs, while minimizing the additional cost and operational difficulties to the airlines. The solution strategy is to identify a set of eligible crews, whose original assigned unflown flight legs are used to form new crew pairings, which are then reassigned to individual crew members through a set covering problem.

Given a new flight schedule, including delays and cancellations decisions, the interactive software presented in 2003 by White et al [30] and implemented by Continental Airlines addresses the crew recovery problem. They minimize the overall operating cost of the crews

plus the cost of not covering a flight plus the cost of deadheading plus the cost of having an idle crew. Their methodology is to decompose the problem by fleet type qualification and pilot positions, then to modify only the pairings that are *close* to the disruption. To avoid being *trapped* by crew restrictions they rank the crew constraints in decreasing order of importance and frequency of violation and start by considering only the *top-ranked constraints*. By doing so, the authors are assured to reach sub-optimal solutions within a couple of minutes.

2.3.3 Minimizing the Disruption Duration

2.3.3.1 Aircraft Recovery Models

Yan and Yang [31] propose a strategic model for dealing with temporary aircraft shortages. Their objective is to minimize the length of the perturbed period and to determine the most profitable schedule in that period, using a schedule perturbation model. They consider four strategic models with increasing complexity. In all of the models flight leg cancellations are allowed. In models 2 and 4, ferrying is permitted, and in models 3 and 4, flight leg postponements are allowed. Models 1 and 2 are easily solvable pure network flow problems, whereas models 3 and 4 are NP hard. They use Lagrangian relaxation and subgradient methods to find sub-optimal solutions within 1% of optimality for models 3 and 4.

In 2000, Thengvall et al [29] outline a model whose objective is to minimize deviation from the original aircraft routing. They use a time-space network that covers a recovery period that can be set arbitrarily. The cost assigned to each flight arc is equal to the revenue generated by flying that flight leg. They augment the original set of flight arcs in the time-space network as follows:

- 1) For each potential delay *copies* of flight arcs are added to the network prior to running the models. The revenue assigned to each of these copy arcs includes a cost of delaying the flight leg. The number of copy arcs generated can be fixed arbitrarily.
- 2) To limit the deviation from the original plan, additional arcs, called protection arcs, are added to the network. If an aircraft is planned to operate 2 legs 1 and 2 in succession, an arc is added to the network that links the departure airport of leg 1 to the arrival airport of

leg 2, with an associated cost equal to the revenue of leg 1 plus the revenue of leg 2 plus an incentive to flight both legs with the same aircraft. This is done for each subsequence of flight legs operated by the same aircraft in the plan. The incentive increases according to the number of legs in the sequence.

3) For each *through-flight*, they add an arc linking the departure airport of the through-flight to the arrival airport of the through-flight is added to the network with an associated cost equal to the sum of the revenue generated by all the legs composing this through-flight. To keep the maximum number of through-flights, the model penalizes the solutions, where different aircrafts cover the flight legs composing a previous through-flight by subtracting to each flight leg revenue the ticket price of the through-flight passengers on this leg.

The objective of the mathematical model is to maximize overall profit, given that each flight should be only covered at most once, either by a regular flight leg, a delayed flight leg, a protection arc or a through-flight arc, and that each node should be balanced. The advantage of this model is that it is flexible, easily incorporating any user preferences.

2.3.4 Recovery Model Drawbacks

The main drawback of dealing with uncertainty at the operations stage is that the airline cannot afford to wait for a solution. This poses serious tractability issues as recovery problems are subject to numerous constraints, including slot availability, gate availability, crew and aircraft restrictions. Because airlines must determine changes to aircraft routings, crew schedules and passenger itineraries rapidly, recovery decisions are often made using rules of thumb developed through years of experience.

2.4 Robust Models

Building robustness into schedules is a proactive way to deal with schedule disruptions. A more robust plan can alleviate the effects of disruptions and yields realized operating costs that are lower than those realized with the *optimal* schedule produced by the sequential approach described in chapter 1. Unfortunately, the robust airline schedule planning problem

is very challenging. First, robustness is difficult to define in general. For example depending on the particular problem instance, a robust plan can be one that yields minimum expected operating costs, or minimum operating costs for the worst case scenario or minimum operating costs while satisfying a certain level of service requirements. Second, it is difficult at the planning stage to define an appropriate trade-off between robustness and cost. Indeed, adding robustness at the planning stage often results in higher planned costs, but it is hoped that the benefits of robust plans that is, reductions in delays, cancellations, should exceed the increase in planned costs. The value of robustness is hard to quantify and thus, it is difficult for airlines to determine how much they should pay to achieve certain levels of robustness.

In the area of robust planning, there are two distinct trends in existing literature. One trend is to capture a uncertainty in the model parameters, and the other is to incorporate robust criteria in the planning models.

2.4.1 Incorporating Uncertainty in Model Parameters

In 2001, Yen and Birge [33] developed a two-stage stochastic integer programming model to minimize total crew costs. Their work is an application to airline scheduling of the general robust planning methodology used in robot design, telecommunications, logistics, etc. Instead of modelling the crew scheduling problem as deterministic, they incorporate uncertainty in the objective data by adding delay costs to the operating costs. These delay costs are characterized by a probability distribution. They aim to find a feasible solution for all possible data instances and to minimize expected overall crew operating costs. In the first stage, they select crew pairings using expected pairing costs. In the second stage, the recourse problem, they test their solution and evaluate the expected recovery cost that it implies. They simultaneously try to find a solution that minimizes the number of times crews have to transfer between airplanes. The main drawback of their approach and of most of stochastic models, is its large size, making it intractable for real size problem.

Also in 2001, Schaefer et al [26] outlined a stochastic extension to the deterministic crew scheduling problem based on the idea that if uncertainty in the flight schedule is assumed, crew costs, which depend on departure and arrival times, cannot be considered to be given any longer. They used a Monte-Carlo simulation to obtain a linear approximation of the

expected crew pairing costs and then solve the resulting deterministic crew scheduling problem incorporating the expected crew pairing costs. Their methodology assumed a single recovery procedure: the push-back recovery procedure in which each flight is delayed until all required resources (crew, aircraft, passengers) are available. This assumption is not overly restrictive only in the case of “small disruptions”.

2.4.2 Incorporating Robust Criteria

Instead of trying to capture uncertainty in model parameters, an alternative approach is to incorporate some added criteria into the model to help achieve robustness. Some metrics that are possible indicators of robustness are:

- *Ease of recovery*: One approach to achieve recovery of aircraft, crews and passengers is to build the schedule such that when disruptions occur, their effects are isolated, preventing important downstream impacts or allowing recovery to be less complex and expensive such that coming up with new aircraft routes or crew duties through basic recovery models is easier. When disruptions occur, airlines must reschedule flight operations. Airline decision makers mainly swap aircraft and crews or cancel a cycle of flights planned to be covered by the disrupted aircraft. In order to ease recovery, a schedule with many crew or aircraft swap opportunities is good, as proposed by Ageeva [2] for aircraft or by Klabjan [18] for crew. Alternatively, ease of recovery is possible if a schedule has small loops out of and into a hub as proposed by Rosenberger [23]. This network structure ensures minimum disruption in the case that a flight has to be cancelled and therefore, the entire loop is disrupted.
- *Slack allocation and Delay propagation*: the effects of aircraft, crew or passenger delays and disruptions in one location are often experienced in locations quite distant from the original disruption. The delay of one flight can cause delays to downstream flights and possible delays and misconnection to crews or passengers assigned to those affected flights. To minimize this propagation of delay Lan et al [27] assign slack times strategically to connections with historically long delays.

In this thesis, we focus on two different approaches. In the next chapter we develop an approach to robustness based on the “ease of recovery” approach. Then in Chapter 4, we

present a model is designed to minimize crew misconnections, with the goal of deriving plans that are less prone to disruption.

Chapter 3

Ease of Recovery Approaches

3.1 Introduction

The following models are designed to build robustness into the schedule by incorporating a criterion that facilitates recovery from disruptions. Insights into the definition of these criteria can be obtained by understanding how airline operations control centers operate and the processes by which schedule plans are recovered. The following models are based on the observation that airlines primarily recover from disruption by canceling flights and/or by swapping aircraft or crews.

3.2 Cancellation Tool

Before introducing the Rosenberger et al robust fleet assignment model [23], we briefly review the fleet assignment problem.

3.2.1 String-based Fleet assignment

After the airline flight schedule has been built, the fleet assignment problem, to find the cost-minimizing assignment of aircraft types, is solved. This problem is usually formulated as a multi-commodity flow problem, in which multiple aircraft types must flow through the network feasibly and with minimum cost. The first formulations of this problem were called *leg-based*, because they assigned to each flight leg a specific aircraft type. Then researchers

introduced string-based fleet assignment models that assigns a sequence of flight legs (referred as a string) to the same aircraft type.

Barnhart et al (1998) [5] extend the leg-based fleet assignment model to a string-based model to ensure that aircraft maintenance requirements can be satisfied for the resulting fleet assignment. We summarize their modeling and algorithmic approach in the next sections.

3.2.1.1 String-based Fleeting Models

The Barnhart et al [5] model represents the airline network using a timeline network for each airport, called a *station*, and for each fleet.

For a given fleet at a given station, a timeline includes:

- 1) *Nodes*. Each node represents the time of a string departure or the arrival time of a string at a particular station.
- 2) *String arcs* and *ground arcs*. A string arc corresponds to a particular string, with its departure node corresponding to the departure station and time of the first flight leg in the string and its arrival node corresponding to the arrival station of the last flight leg in the string. The string arrival time is adjusted to include the minimum amount of time required on the ground for disembarking and embarking passengers, unloading and loading baggage, and refueling. Ground arcs represent the possibility for aircraft to remain idle on the ground between strings.

Side constraints enforce the following requirements and restrictions:

- 1) *Cover*: each flight leg is assigned to exactly one aircraft type
- 2) *Count*: only available aircraft are assigned to the flight network
- 3) *Balance*: each aircraft type is assigned to the same number of strings arriving at a station as departing that station.

3.2.1.2 Model

Before presenting the string-based fleet assignment model, we present the following notations:

- F is the set of flight legs f
- S is the set of strings and $S(f)$ the subset of strings that include flight leg f
- K is the set of fleet types k

- $P(k)$ is the number of planes of type k
- C is the set of airports

To ensure that each fleet assignment uses type $P(k)$ or fewer planes of type k , we count the number of aircraft of type k assigned to each arc spanning a fixed time, called the *plane count time*. Without loss of generality, we select the plane count between the latest arrival at each station on a given day and the earliest departure on the next day. Let t_n be the time that precedes the plane count time and t_1 the one that follows it.

- $O(k)$ is the set of strings of fleet type k whose arcs span the plane count time.
- c_{ks} is equal to the operating cost of fleet k on string s + opportunity cost of spilling passengers (defined in 1.1) if fleet k is assigned to string s
- $x_{ks} = x_{odt}^k$ is the binary string variable that has value 1 if aircraft type k is assigned to string s , and 0 otherwise.
 - o denotes the Origin airport of string s
 - d denotes the Destination airport of string s
- $y_{ot^-}^k, y_{ot^+}^k$ are the ground variables that count the number of aircraft on the ground at each station at every point in time for each fleet. Let t^- be the time of the node preceding node t at the same station o and let t^+ be the time of the node following node t at the same station t .

Given this we write the fleet assignment problem as:

$$\text{Min } \sum_{s \in S} \sum_{k \in K} c_{ks} x_{ks} \quad (3-1)$$

Subject to

$$\sum_{k \in K} \sum_{s \in S(f)} x_{ks} = 1 \quad \text{for all flight leg } f \text{ in } F \quad (3-2)$$

$$\sum_{d \in C} x_{dot}^k + y_{ot^-}^k - \sum_{d \in C} x_{odt}^k - y_{ot^+}^k = 0 \quad \text{for all node } (o, t) \text{ and all aircraft type } k \quad (3-3)$$

$$\sum_{i \in O(k)} x_{ks} + \sum_{o \in C} y_{ot_1}^k \leq P(k) \quad (3-4)$$

$$x_{ks} \in \{0,1\} \quad (3-5)$$

$$y_{ot^-}^k, y_{ot^+}^k \geq 0 \quad (3-6)$$

The objective (3-1) is to minimize the total operating plus spill cost. The cover constraints (3-2) and the binary constraints (3-5) ensure that for each flight leg f , one and only one aircraft type is assigned to it. The node balance constraints (3-3) ensure that for each aircraft type, the number of aircraft flying out of an airport location equal the number into that location. Finally the plane count constraint (3-4) ensures that the number of aircraft assigned in the solution does not exceed the number of aircraft available. This constraint requires the above assumption of when the plane count time was picked.

3.2.1.3 Solution Approach

The disadvantage of the string-based approach compared to the leg-based approach is that there might be many possible strings, and therefore variables. To avoid the complete enumeration of the possible strings, Barnhart et al (1998) [5] describe a column generation method.

3.2.2 Rosenberger et al Model

3.2.2.1 Overview

Regarding flight cancellation, Rosenberger et al [] realized in 2001 that airline decision makers usually cancel a cycle when canceling a flight in order to achieve aircraft balance. Therefore, to minimize the impact of a flight cancellation and make the fleet assignment more robust, they had the idea of designing a fleet assignment with many short cycles.

They contend that the *hub-and-spoke network*, a widely used network structure in which most of the flight legs fly either into or out of a small subset of stations, called *hubs*, is sensitive to disruptions, particularly at hubs. To reduce the impact on other hubs of a disruption at one hub, they design a model that yields reduced *hub connectivity*. Hub connectivity is defined as the number of legs in an aircraft rotation (defined in 1.1) that are in a route that begins in a hub, ends at a different hub and only stops at spokes in between.

Using these two ideas of short cycles and reduced hub connectivity they develop a robust fleet assignment and aircraft routing model.

3.2.2.2 Model

Rosenberger et al present a hub-based fleet assignment model, based on the string-based model presented in 3.2.1, where each string starts and ends at a hub and visits only spokes in between.

They classify strings into two types: those that start and end at the same hub referred to as cancellation cycles; and those that start and end at a different hub referred to as acyclic strings. Then they prove that a decrease in hub connectivity implies an increase in the lower bound on the number of cancellation cycles, and implies an increase in the number of short cancellation cycles.

Using the same notations as used for the string-based model, let us define the connectivity of a string s as:

- $h_{ks} = |F(S)|$ if s is an acyclic cycle, where $F(S)$ is the set of legs included in string s
- $h_{ks} = 0$ if s is a cancellation cycle

Therefore, hub connectivity of a solution to a hub-based fleet assignment model is given by

$$\sum_{s \in S} \sum_{k \in K} h_{ks} x_{ks} .$$

Rosenberger et al present two models:

The first model is designed to minimize fleet assignment costs, with an added constraint to limit hub connectivity. Let χ represent the set of x that satisfy the basic fleet assignment requirements: cover constraints, aircraft count constraints and balance constraints, constraints (3-2) to (3-6) from the string-based fleet assignment. Then the model is:

$$\text{Min } \sum_{s \in S} \sum_{k \in K} c_{ks} x_{ks} \quad (3-7)$$

Subject to

$$\sum_{s \in S} \sum_{k \in K} h_{ks} x_{ks} \leq \zeta \quad (3-8)$$

$$x \in \chi \quad (3-9)$$

The objective is to select the fleet and routing that minimizes fleet assignment operating plus spill costs, subject to a limit ζ on the value of hub connectivity. To ensure feasibility, ζ has to be greater than a computable lower bound on hub connectivity.

The second model is designed to minimize hub connectivity with an added constraint to constrain fleet assignment costs, namely:

$$\text{Min } \sum_{s \in S} \sum_{k \in K} h_{ks} x_{ks} \quad (3-10)$$

$$\sum_{s \in S} \sum_{k \in K} c_{ks} x_{ks} \leq (1 + \varepsilon) c_{fleet-optimal} \quad (3-11)$$

$$x \in \mathcal{X} \quad (3-12)$$

The objective is to select a fleet and routing solution that minimizes hub connectivity, while ensuring that the cost of the solution is within ε of optimal.

3.2.2.3 Solution Approach

Rosenberger et al implement their models and evaluate their approach using three different schedules, one with 2558 flights, one with 910 flights and one with 573 flights. They use column generation and a first-out policy to solve the two models.

3.2.2.4 Results

Rosenberger et al use *SimAir* [25] to assess the robustness of their models. *SimAir* simulates the daily operations of a domestic airline, and is composed of three modules:

- 1) The Event generator module that generates three types of random delay: ground time delays (based on location and time of the day of the departure); additional block time delays (based on the length of the scheduled block time, time of the day of the arrival and on the arrival/departure stations); and unscheduled maintenance delays.
- 2) The Controller module that determines when a disruption prevents a flight from flying as scheduled.
- 3) The Recovery module that proposes a solution to the Controller, who accepts the proposal or requests that a different recovery solution be generated.

They simulate the daily operations over 500 days and demonstrate that the new fleet and routing solutions generated by their models perform better in operations (measuring on time performance, total delay, etc) than those generated with conventional models. Moreover their solutions required fewer aircraft swaps during recovery, also indicating that they are also

more robust. Finally, Rosenberger et al report that the difference between a sub-optimal and an optimal solution in terms of their relative hub connectivity is small: an increase by less than 1% in the number of flight cancellations. From this, they conclude that model I might be the best choice in practice to balance operating costs and robustness.

3.3 Swap Tool

Before describing the approaches of Ageeva and Klabjan, we introduce some fundamental concepts.

Consider the following two aircraft and their assigned flight legs:

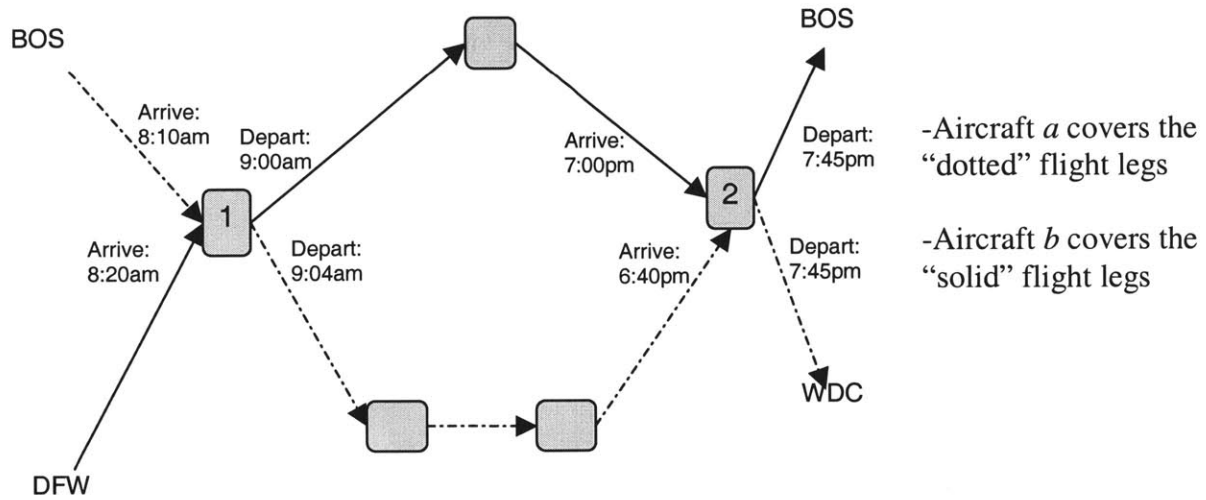


Figure 3.1 Illustration of aircraft swapping

Aircraft *a* lands at airport 1 at 8:10 am and departs at 9:04 am from 1, whereas aircraft *b* lands at aircraft 1 at 8:20 am and departs at 9:00 min. Therefore aircraft *a* and aircraft *b* are together on the ground for 40 minutes at airport 1. We then say that aircraft 1 and aircraft 2 *overlap* at airport 1. Later in the day, they are again on the ground at airport 2 for 45 minutes, resulting in a second overlap this time at airport 2. Moreover if these two overlaps occur between two successive maintenance visits of aircraft *a* and *b*, we say that we can *swap* aircraft *a* and *b*. If we swap them at airport 1: aircraft *a* covers the solid flight legs between 1 and 2, and aircraft *b* covers the dotted flight legs between 1 and 2.

3.3.1 Ageeva's Approach

Ageeva [2] introduced the idea that flexibility, and therefore, robustness of an airline schedule can be improved by increasing the number of overlapping routes, and hence the number of swaps, in the aircraft maintenance routing solution. Note that after a swap, the new aircraft routings still satisfy maintenance requirements. This follows by definition, because swaps are allowed only between aircraft routings that intersect at least twice between successive maintenance visits of the affected aircraft. Ageeva's algorithm to generate robust maintenance routing solutions consists in generating several alternative cost-optimal maintenance routing solutions. Then for each cost-optimal maintenance routing solution, she evaluates the number of overlapping routes, indicator of the number of aircraft swapping opportunities. Finally her robust maintenance routing solution is the one with the biggest number of overlapping routes.

Klabjan and Chebalov [18] suggest a similar approach to the problem of crew scheduling in which they achieve crew schedule robustness by providing opportunities to swap crews. Before introducing the robust crew schedule model, we briefly review the basic crew pairing model.

3.3.2 Crew Pairing Problem

3.3.2.1 Overview

As described in chapter 1, the crew scheduling problem is typically divided into two sub-problems. First, the crew pairing problem is solved. In this problem, we want to find a minimum cost subset of the feasible pairings such that each flight segment is covered by exactly one chosen pairing. Second, the crew assignment problem is solved. In this problem, the chosen pairings are combined with rest periods and vacations to create extended, typically monthly, individual work schedules.

3.3.2.2 Model

The crew pairing problem, usually formulated as a set partitioning problem, utilizes the following notation:

Parameters:

- F : the set of flight legs i
- P : the set of pairings p
- c_p : the operating cost of pairing p
- δ_{ip} : equals 1 if pairing p includes flight leg i , else 0

Variables:

- y_p : equals 1 if pairing p is selected, 0 otherwise

The crew pairing problem is formulated as:

$$\text{Min } \sum_{p \in P} c_p y_p \quad (3-13)$$

Subject to

$$\sum_{p \in P} \delta_{ip} y_p = 1 \quad \text{for each flight leg } i \text{ in } F \quad (3-14)$$

$$y_p \in \{0,1\} \quad (3-15)$$

The objective (3-13) of this crew pairing model is to minimize the cost of the chosen set of pairings. The *cover constraints* (3-14) and the binary constraints (3-15) ensure that each flight leg i is covered by exactly one selected pairing.

3.3.2.3 Solution Approach

The crew pairing formulation requires the explicit enumeration of all pairings. Unfortunately, enumerating pairings can be difficult. First, numerous work rules and regulations must be checked to ensure legality and therefore, feasibility of each pairing. Second, even for relatively modest-sized networks, the number of potential pairings is huge. For instance, a network composed of several hundred flight legs typically has billions of potential pairings (Barnhart et al [6]). Finally, the integrality requirements on each pairing variable further complicates the solution process.

Therefore, this problem is solved either by heuristic local optimization approaches or by column generation methods (Anbil et al. [1]).

3.3.3 Klabjan Model

3.3.3.1 Key Ideas

Klabjan and Chebalov [18] introduce the idea of move-up crews. A move-up crew is defined for each flight leg f as the number of crews:

- 1) with the same crew base as the crew pre-assigned to cover f ;
- 2) located at the departure station of flight leg f and available to depart at the departure time of f ;
- 3) with the same number of remaining days until the end of their pairings as the crew pre-assigned to f .

The objective of Klabjan and Chebalov's model is to maximize the number of move-up crews for each flight leg departing a hub, while ensuring the usual flight cover constraints as seen in 3.2.2.2. Because of their modified objective, the selected solution will likely cost more than the total minimum cost solution. To circumvent this problem, first they solve the usual pairing problem, which gives them a planned crew cost. Second, they include in their model a constraint limiting crew cost to some pre-defined tolerance above the planned crew cost.

3.3.3.2 Model

Before presenting the Klabjan and Chebalov model, we present the following notation:

Parameters:

- L : the set of all legs
- HL : the set of all legs originating at a hub
- CB : the set of all crew bases
- CBL : the set of all legs originating at a crew base

We assume that each crew base is a hub therefore CBL is included in HL .

- $P_{i,cb,d}$: the set of pairings covering leg i , starting at crew base cb and having d days remaining after leg i .

- $\bar{P}_{i,cb,d}$: the set of all pairings covering i that yield a move-up crew if a pairing beginning at crew base cb with d days remaining after leg i is in the solution
- P_i : the set of pairings covering i
- P^i : the set of pairings whose first leg is i
- M : an arbitrary number usually 2 or 3

Variables:

- y_p : equals 1 if pairing p is included in the solution, 0 otherwise
- $x_{i,d}^{cb}$: equals 1 if for flight leg i , i departs from a hub airport, it is not the first leg of the pairing and it is covered by a pairing with crew base cb and d days remaining after leg i , and 0 otherwise
- w_i : equals 1 if flight leg i is covered by a pairing whose first leg is i , for all $i \in CBL$
- $z_{i,d}^{cb}$ the number of move-up crews for flight leg i , given i is covered by a pairing p , beginning at a crew base cb with d days remaining after leg i
- c_{OPT} : the optimal planned crew cost from the basic crew pairing problem
- r : the “robustness” factor measuring the maximum additional crew cost beyond c_{OPT} allowable in the move-up crew solution.

The move-up crew model is:

$$\text{Max } \sum_{i,cb,d} z_{i,d}^{cb} \quad (3-16)$$

Subject to

$$\sum_{p \in P_i} y_p = 1 \quad i \in L\&H\&L \quad (3-17)$$

$$\sum_{p \in \bar{P}_{i,cb,d}} y_p = x_{i,d}^{cb} \quad \text{for legs } i \in HL, cb \in CB \text{ and } d \quad (3-18)$$

$$\sum_{p \in P^i} y_p = w_i \quad \text{for legs } i \in CBL \quad (3-19)$$

$$w_i + \sum_{cb,d} x_{i,d}^{cb} = 1 \quad \text{for legs } i \in CBL \quad (3-20)$$

$$\sum_{cb,d} x_{i,d}^{cb} = 1 \text{ for legs } i \in \text{HLACBL} \quad (3-21)$$

$$\sum_{p \in P_{i,cb,d}} y_p \geq z_{i,d}^{cb} \quad \text{for legs } i \in \text{HL} \quad (3-22)$$

$$z_{i,d}^{cb} \leq M * x_{i,d}^{cb} \quad \text{for legs } i \in \text{HL}, cb \in \text{CB and } d \quad (3-23)$$

$$\sum_p c_p x_p \leq (1+r).c_{opt} \quad (3-24)$$

The objective (3-16) is to maximize the number of move-up crews over all flight legs. Constraints (3-17) ensure that each leg originating at a spoke is covered exactly once. Constraints (3-18) characterize for each flight leg i , the crew that covers i by their crew base and the numbers of days left before the end of the pairing. Klabjan and Chebalov do not assign move-up crews to a flight leg if it is first in the crew's pairing. Therefore constraints (3-19) and (3-20) partition the flight legs out of a crew base: each flight leg is either the first leg of a pairing or it is characterized by: cb and d . These two constraint sets also ensure that each flight leg originating at a crew base is covered exactly once. Constraints (3-21) ensure that each flight leg originating at a hub which is not a crew base is covered exactly once. Constraints (3-22) and (3-23) count and limit the number of move-up crews. And finally constraint (3-24) ensures that the sub-optimally in terms of crew cost is bounded.

3.3.3.3 Solution Approach

Klabjan and Chebalov develop a solution method based on Lagrangian decomposition in which they relax the constraints associated with counting the number of move-up crews: that is, constraints (7) and (8). This relaxed problem has similar tractability characteristics as that of the set partitioning problem in 3.3.2.2. Using column generation methods, Klabjan and Chebalov solve the move-up crew model on a relatively small problem containing 123 flight legs. Klabjan and Chebalov however did not evaluate the robustness of their model because existing simulators, such as SimAir (see section 3.2.2.4), do not include crew swapping as a recovery option (Rosenberger et al[25]).

3.4 Robust Fleet Assignment Model

3.4.1 Motivation

Pilots are qualified to operate all aircraft with a specific equipment type *rating*. Typically, each equipment type rating coincides with an aircraft type, for instance the Boeing 777 has one type rating, and the DC 9 has one type rating. There are exceptions, however. The Boeing 757 and the Boeing 767 have a common rating and the Boeing 737 has several ratings. The 737-100 and the 737-200 have the same type rating but different from the single type rating 737-300, 737-400 and 737-500. All of these types have a different rating from that given collectively 737-600, 737-700, the 737-800 and the 737-900. For the remainder of this thesis, we define an *aircraft family* to be the set of aircraft with a common type rating. Hence the 737-600, 737-700, 737-800 and 737-900, for example all belong to the same aircraft family.

In theory, airline operation centers can swap aircraft of different types. But if the two swapped aircraft are not from the same family, the airline operation centers must modify the crew schedule to assign qualified crew to the swapped aircraft. To limit the crew schedule modifications implied by aircraft swaps, recovery policies commonly swap only among aircraft of the same family. Figure 3.2 illustrates this restriction. Assume that we are monitoring the airline operation at Airport B. The solid lines with arrows represent the planned schedule of family 1 aircraft and the double lines with arrows represent the planned schedule of family 2 aircraft. Therefore the aircraft assigned to f_2 can be swapped with the aircraft assigned to f_7 but not the aircraft assigned to f_3 .

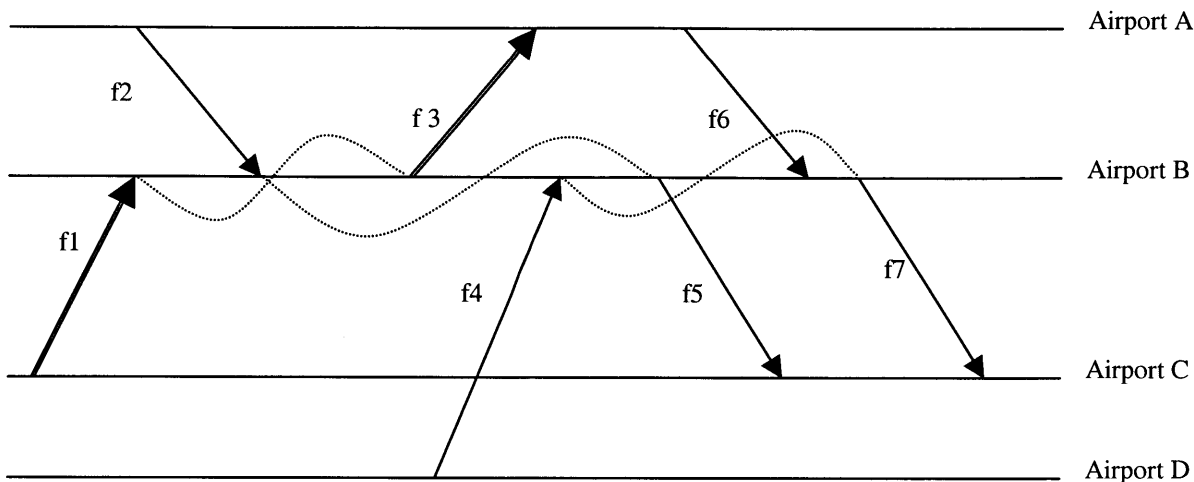


Figure 3.2: Illustration of aircraft rating restrictions on swap recovery procedure

This restriction of swapping among aircraft of the same family, combined with the fact that typically there are only a limited number of flight legs at spoke airports, leads us to conclude that the greater the number of aircraft families at spoke stations the more difficult the recovery. To validate this idea, we conduct the following analysis:

Consider the operations of a major U.S. airline at one of its spoke airports, namely San Francisco. The airline operates five different aircraft types at this airport, namely: Boeing 737-600, Boeing 737-800, Boeing 757, Boeing 767 and MD-90. The associated passenger capacities are: 109-150 passengers, 180 passengers, 200-250 passengers and 150 passengers, respectively. This translates to three different aircraft families, specifically: the 737-600 family, the 757-767 family and the MD-90 family. In Table 3.1, we depict departures and arrivals of this airline at San Francisco.

Based on this flight schedule, our objective is to evaluate the impact on passengers of an aircraft shortage at San Francisco airport. To this end, we consider the following scenarios. Suppose that one day, exactly one of the 18 incoming flight legs at the San Francisco Airport has to be cancelled for technical reasons, implying that the airline operations control center at San Francisco has to operate with a shortage of one aircraft. Our aim is then to try to swap aircraft of the same family at San Francisco to reduce the overall passenger delay.

Table 3.1: Arrivals and departures from San Francisco for a major airline

ARRIVAL				DEPARTURE			
From	flight number	arrival time	aircraft type	to	flight number	departure time	aircraft type
Atlanta	523	10:40am	737	Salt lake city	1692	06:30am	M90
Cincinnati	509	11:23am	757	Cincinnati	338	06:35am	757
Dallas	2137	11:51am	MD90	Atlanta	632	07:00am	767
Salt Lake city	1137	12:08pm	737	Dallas	514	07:00am	737
Atlanta	251	12:19pm	757	Atlanta	1946	08:00am	767
Atlanta	633	01:42pm	737	Salt lake city	2206	09:25am	737
Salt Lake city	1008	01:50pm	737	Cincinnati	1040	10:30am	757
Cincinnati	1176	02:58pm	757	Dallas	1570	11:05am	MD90
Atlanta	219	03:27pm	767	Atlanta	670	11:30am	737
Salt Lake city	1035	04:00pm	737	Salt lake city	1172	01:00pm	737
Dallas	905	05:23pm	737	Dallas	2014	01:10pm	MD90
Atlanta	1949	06:27pm	767	Atlanta	250	01:19pm	757
Cincinnati	660	06:48pm	757	Cincinnati	946	02:40pm	757
Salt Lake city	1895	07:35pm	737	Salt lake city	1025	03:00pm	737
Dallas	1571	07:40pm	MD90	Atlanta	1449	03:15pm	757
Atlanta	2089	08:20pm	757	Salt lake city	866	04:55pm	737
Salt Lake city	971	09:17pm	MD90	Atlanta	2148	09:40pm	757
Atlanta	305	10:02pm	757	Atlanta	1804	11:40pm	737

We provide an estimate of the impact on passenger delays by making the following simplifying assumptions:

- 1) Among aircraft of the same family, aircraft routings are based on a first-landed-first-departed policy.
- 2) If a flight leg is cancelled, we assume that we can always accommodate the passengers on the following flight unless it is also cancelled.
- 3) The recovery policy allows only aircraft swaps among aircraft of the same family and minimizes the overall delay incurred by passengers.
- 4) Disruptions do not exceed 12 hours, implying that 12 hours after the beginning of the disruption all resources, aircraft and crews, are available.

We evaluate the impact of an unavailable aircraft for selected flight legs and report the results in Table 3.2.

We observe that only one scenario has a big impact on passengers, namely if flight 2137 from Dallas is disrupted, then flight 2014 has to be cancelled because no other MD-90 is on the ground at that time and its passengers have to wait more than 17 hours for the next flight

for Dallas. Performing the same analysis, assuming that flights currently covered by the MD-90 family are covered by the 737 family, which has similar passenger capacity, then the delay incurred by passengers on 2014 drops to zero.

Table 3.2: Impact on passengers of various aircraft shortage scenario

Scenario: Aircraft unavailable for leg	delay/pax
No 523	0 minute
No 509	0 minute
No 2137	2014 cancelled
No 1137	0 minute
No 251	0 minute
No 633	0 minute
No 1008	0 minute
No 1176	0 minute
No 219	0 minute
No 1035	0 minute
No 905	0 minute
No 1949	0 minute
No 660	0 minute
No 1895	0 minute
No 1571	0 minute
No 2089	0 minute
No 971	0 minute
No 305	0 minute

This simple analysis illustrates the impact on passengers of fleeting solutions with a limited number of fleet families. If the airline decreases the number of aircraft families at San Francisco by replacing MD-90 aircraft by Boeing 737 aircraft, the resulting fleet assignment is more robust with respect to passenger delays.

3.4.2 Modeling idea

Based on the previous analysis, a fleeting solution can facilitate recovery and yield shorter passenger delays if a limited number of aircraft families are operated at spoke airports.

Additionally, there is a clear trade-off between minimizing the total fleeting cost, that is, operating costs plus spill costs as defined in section 1.1, and minimizing the number of aircraft families at spoke stations. A fleet assignment model minimizing the number of aircraft families at spoke stations can reduce the number of possible fleeting solutions, which

in turn can result in higher fleet costs. To limit this effect, we first solve the basic fleet assignment model, to determine the minimum fleet costs, and then we solve a modified fleet assignment model with the objective to minimize the number of aircraft families at the spoke stations with an additional constraint that bounds the associated fleet costs as a function of the minimum fleet costs.

3.4.3 Formulation

In this section, we use the above observations to guide our development of models for robust fleet assignment. Before presenting our fleet assignment model with limited aircraft families at spoke airports, we present the following notation:

Parameters:

- F : set of flight legs f
- C : set of airports
 - o denotes the Origin airport of a flight leg
 - d denotes the Destination airport of a flight leg
- S is the set of spoke airports
- K : set of fleet types k
- M : set of fleet families m
- c_{kf} : the operating cost of fleet k assigned to flight leg f + cost of spilling passengers if fleet k is assigned to flight leg f , as defined in 1.1
- c_{OF} : fleet cost associated with the optimal solution to the basic fleet assignment model
- r : the “robustness” factor measuring the maximum additional fleet cost beyond c_{OF} allowable in our solution
- δ_k^m : equals 1 if fleet type k is in fleet family m , and 0 otherwise.

Variables

- M_s : the number of fleet families at spoke airport s
- z_s^m : equals 1 if fleet family m is assigned to spoke airport s , else 0.

- $x_{kf} = x_{odt}^k$: equals 1 if aircraft type k is assigned to flight leg f , else 0

We used notation similar to the one defined for the string-based fleet assignment model in 3.2.1.2, to restrict the number $P(k)$ of planes of type k , to represent the ground variables, $y_{ot^-}^k$ and $y_{ot^+}^k$, and to model the plane count time constraint

Our robust fleet assignment model formulation is:

$$\text{Min } \sum_{s \in S} M_s \quad (3-25)$$

$$\sum_{k \in K} x_{kf} = 1 \quad \text{for all flight legs } f \text{ in } F \quad (3-26)$$

$$\sum_{d \in C} x_{dot}^k + y_{ot^-}^k - \sum_{d \in C} x_{odt}^k - y_{ot^+}^k = 0 \quad \text{for all nodes } (o, t) \text{ and all aircraft } k \text{ in } K \quad (3-27)$$

$$\sum_{f \in O(k)} x_{kf} + \sum_{o \in C} y_{ot, t_1}^k \leq P(k) \quad \text{for all fleet type } k \quad (3-28)$$

$$\delta_k^m x_{sdt}^k \leq z_s^m \quad \text{for all destinations } d \text{ at any time } t \quad (3-29)$$

$$\sum_m z_s^m \leq M_s \quad \text{for all spoke station } s \quad (3-30)$$

$$\sum_{f \in F} \sum_{k \in K} c_{kf} x_{kf} \leq (1+r) \cdot c_{OF} \quad (3-31)$$

The objective (3-25) is to minimize the number of aircraft families at each spoke stations. Constraints (3-26), (3-27) and (3-28) represent the usual fleet assignment model constraints, specifically: the flight cover constraints, the balance constraints and the plane count constraints, respectively. Constraints (3-29) and (3-30) state that M_s is exactly equal to the number of aircraft families at the spoke s . Finally (3-31) bounds the model's value as a function of the optimal basic fleet solution cost.

3.4.4 A Variant

A possible variation to this model is to change the objective function to: $\text{Min } \sum_{f \in F} \sum_{k \in K} c_{kf} x_{kf}$ while keeping the same constraints, (3-26) to (3-30). In this case, M_s is no longer a variable, but rather, a parameter. This implies that we now have to determine an appropriate value for each M_s , which might be difficult in practice. One idea is to look at

historical data and to enforce a small allowable number of aircraft families at spoke stations that historically face numerous aircraft disturbances.

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Chapter 4

Approaches to Reduce Likelihood of Disruption

4.1 Introduction

The models that are typically used to solve the sequential airline schedule planning problem, as shown in chapter 1, maximize airline profit by minimizing crew and aircraft operating costs. To achieve this goal, a finely tuned optimization solution increases resource utilization through the removal of *slack*, providing crews with less time to connect between flight legs and aircraft with reduced time on the ground between flying. Slack is defined for aircraft as the difference between the planned *turn-time*, time between the arrival of the aircraft at the gate and the time this aircraft is scheduled to depart on the next flight, and the minimum turn-time. Similarly, slack for crews is defined as the difference between the planned *crew connection time*, that is, the elapsed time from crew arrival at the gate and the time the crew is scheduled to depart on the next flight, and the minimum crew connection time. Less slack time, although economical in theory, may translate in practice into more missed crew and aircraft connections, higher operating costs and less robustness. To address these issues, researchers have begun to accept more costly airline schedule solutions, compared to minimum cost solutions, with reduced susceptibility to disruption. Next, we will present the aircraft routing model developed by Lan et al [27], which places slack judiciously, that is, where it is needed to minimize the disruptive effects on passengers of delays.

4.2 Robust Aircraft Maintenance Routing

4.2.1 Key Ideas

Lan et al [27] partition flight delays into two different types of delays:

- *Propagated delay*: Flight delay caused by waiting for an incoming aircraft, which is a function of aircraft routing.
- *Independent delay*: Delay caused by all other sources, including bad weather conditions, late passengers, absent or delayed crews, etc.

To minimize the overall flight delays and make the aircraft maintenance routing solution more robust, the idea of robust aircraft maintenance routing is to reduce propagated delay by intelligently routing aircraft and optimally allocating slack to absorb the propagated delay to the greatest extent. Obviously by increasing slack for certain aircraft connections, the resulting solution might be less cost effective. To try to circumvent this issue, the idea is to reduce slack where it is less needed which has no impact on the robustness of the solution but makes the solution more cost effective.

The aircraft maintenance routing problem, as in fleet assignment, can either be formulated as a leg-based model or a string-based model. Here a *string* is defined to be a sequence of connected flights that begins and ends at a maintenance station and has elapsed time that does not exceed the maximum time-between-maintenance limits required by law and by airline policy. Because delays propagate along the aircraft routes, to track delay propagation it is more appropriate to use a string-based model.

First we present the basic string-based routing model, then the robust aircraft maintenance routing model, and finally we will compare them in terms of tractability and robustness.

4.2.2 Basic String-based Routing Model

The aircraft maintenance routing problem can be solved separately for each fleet type. The structure underlying each of these problems is a time line network, seen in 3.2.1.1. For this model, we use notation similar to that used for the basic string-based fleet assignment model in 3.2.1.2.

Parameters

- F: set of flight legs f
- S: set of strings and $S(f)$ the subset of strings that include flight leg f
- P: number of planes
- C: set of airports
- M: set of nodes located at a maintenance stations
- O: set of strings whose arcs span the plane count time.
- c_s : the operating cost of string s

Variables:

- $x_s = x_{odt}$ is the binary string variable that has value 1 if string s is used in the solution, and 0 otherwise. o denotes the Origin airport of string s and d denotes the Destination airport of string s
- $y_{ot^-}^k, y_{ot^+}^k$: the ground variables that count the number of aircraft on the ground at each station at every point in time for each fleet. See 3.2.1.2 for a detailed description of t^- and t^+ .

To ensure that the aircraft maintenance routing uses P or fewer planes, as we did for the string-based fleet assignment, we count the number of aircraft assigned to each arc spanning a fixed time, called the *plane count time*. See 3.2.1.2, for a detailed description of t_n and t_1 .

Given this we write the fleet assignment problem as:

$$\text{Min } \sum_{s \in S} c_s x_s \quad (4-1)$$

Subject to

$$\sum_{s \in S(f)} x_s = 1 \quad \text{for all flight legs } f \text{ in } F \quad (4-2)$$

$$\sum_{d \in C} x_{dot} + y_{ot^-} - \sum_{d \in C} x_{odt} - y_{ot^+} = 0 \quad \text{for all nodes } (o, t) \in M \quad (4-3)$$

$$\sum_{s \in O} x_s + \sum_{o \in C} y_{ot, t_1} \leq P \quad (4-4)$$

$$x_s \in \{0, 1\} \quad \text{for all strings } s \quad (4-5)$$

$$y_{ot^-}, y_{ot^+} \geq 0 \quad \text{for all nodes } (o, t) \in M \quad (4-6)$$

The objective (4-1) minimizes total operating cost. The cover constraints (4-2) and the binary constraints (4-5) state that for each flight leg f , one and only one aircraft is assigned to it. Because by definition all strings start and end at a maintenance location, the node balance constraints are only needed at maintenance station nodes, that is why (4-3) ensure that the number of aircraft flying out of an maintenance location equal the number into that location. Finally the plane count constraint (4-4) ensures that the number of aircraft assigned in the solution does not exceed the number of available aircraft.

4.2.3 Model

The objective of Lan et al [27] is to minimize expected propagated delay while satisfying conventional aircraft maintenance routing constraints, that is, cover constraints, balance constraints and plane count constraint. To achieve this goal, they first determine the propagated delay distribution for every flight leg in the airline schedule. Based on historical data from the ASQP (Airline Service Quality Performance) database, they show that for more than 80% of flights, the distribution of propagated delay follows a log-normal distribution. Before introducing the Lan et al's model, we provide the following additional notation:

- ξ represents the set of strings that satisfy the basic aircraft maintenance routing requirements:(4-2) through (4-6).
- pd_{ij}^s is the delay propagated from flight i to flight j if flight i and flight j are in string s

The robust aircraft maintenance routing model (Lan et al) is:

$$\text{Min } E\left(\sum_{s \in S} \sum_{(i,j) \in s} pd_{ij}^s x_s\right) \quad (4-7)$$

$$\text{Subject to } x \in \xi \quad (4-8)$$

The difference between the basic string-based aircraft routing model (4-1)-(4-6) and this model (4-7)-(4-8) is the objective function. In both cases, the models are deterministic mixed integer linear programming problems. The main difference is that in the robust model, for each string s , we need to estimate $\sum_{(i,j) \in s} E(pd_{ij}^s)$ instead of c_s . As a result both problems have similar tractability.

4.2.4 Results

Lan et al use a *Branch and Price* approach to solve the robust aircraft maintenance routing model. This technique can be described as the branch-and-bound algorithm with linear programming relaxations solved at nodes of the branch-and-bound tree using column generation (see Barnhart et al [7] for a detailed description of this algorithm). Lan et al implemented their model on four different networks, composed of 20, 59, 97 and 102 flights, respectively. Using historical data in July 2000 to determine the expected propagated delay and generate routings they apply their routing solutions on August 2000 operational conditions, they compute the expected resulting delays in August 2000. They then compare their result with actual delays in August 2000. The total propagated delay generated by Lan et al solution is 44% less than that actual experienced in August 2000, implying an 11% decrease in passenger misconnections.

4.3 Motivation: Critical Crew Connection

One restriction on a valid crew pairing is that two sequential flight legs cannot be assigned to the same crew unless the time between these flights (known as *crew connection time*) is sufficient for the crew members to travel through the terminal, from the arrival gate of one flight to the departure gate of the next. This restriction does not hold if both flights have been assigned to the same aircraft; in that case the crew connection time can be as short as the minimum required time for the aircraft (known as the *minimum turn time*) before its next departures, which includes disembarking and embarking passengers, refueling, etc. We refer to a *short connect* as a connection in which the same crew and the same aircraft are assigned to a pair of successive flight legs. In this chapter, we assume that the minimum crew connection time is equal to 45 minutes and the minimum aircraft turn time is 30 minutes.

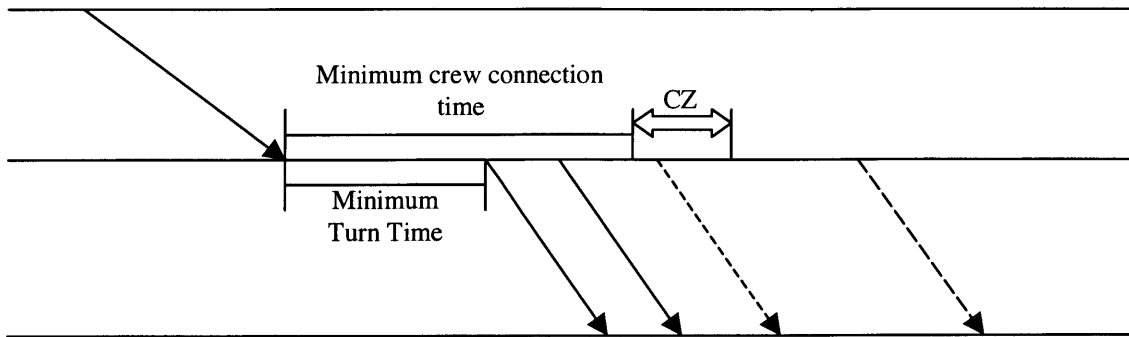


Figure 4.1: Definitions related to crew connections

Bratu and Barnhart (2002) compute flight delays in August 2000 using data from a major US airline and found that the airlines flight legs have an average delay of 16 minutes. These short delays, although seemingly contained can lead to crew misconnections if the planned crew connection time is close to the minimum crew connection time. Repeated delays can then snow ball into significant delays and disruptions for the crews, resulting in the use of reserve crews and increased crew operating costs. We call *critical connects* those connections in which the connection time is *close* to the minimum connection time, making them more prone to disruptions. We assume that critical connects have a connection time between 45 minutes and 1 hour. Figure 4-1 illustrates these definitions; the double arrow represents the *critical zone*, if a crew connects to a flight, is assigned to different aircraft and the departure is in that zone, the crew connection is a critical connect.

As discussed above, critical connects cause the crew schedule to be more prone to disruptions and misconnects even when the delays are short. One solution is to disallow critical connects in the crew schedule. Of course this is not cost effective, because crews and especially cockpit crews are expensive, being the second-largest operating expense after fuel. To be cost-effective, airlines need to maintain a high level of crew utilization. It is possible however to limit the costs and reduce the fragility of the crew schedule simultaneously by intelligently minimizing the number of critical connects. One approach is to reschedule and postpone departure corresponding to critical connections (illustrated in our first model). A

second approach is to integrate aircraft routing and crew scheduling decisions in order to keep aircraft with crews, when crew connections are critical (illustrated in our second model).

4.4 Robust Crew Schedule with Time Windows

4.4.1 Time Windows and Crew Connections

We assume that the minimum crew connection time (MCCT) is a constant for all crews independent of the type of airport at which they connect. As discussed above, for a connection to be feasible, the planned crew connection time must be greater than the minimum crew connection time, with the difference between the two referred to as *slack*. The ACCT refers to the actual crew connection time, defined as the actual departure time minus the actual arrival time of the departing and arriving flight legs, respectively, in the crew connection.

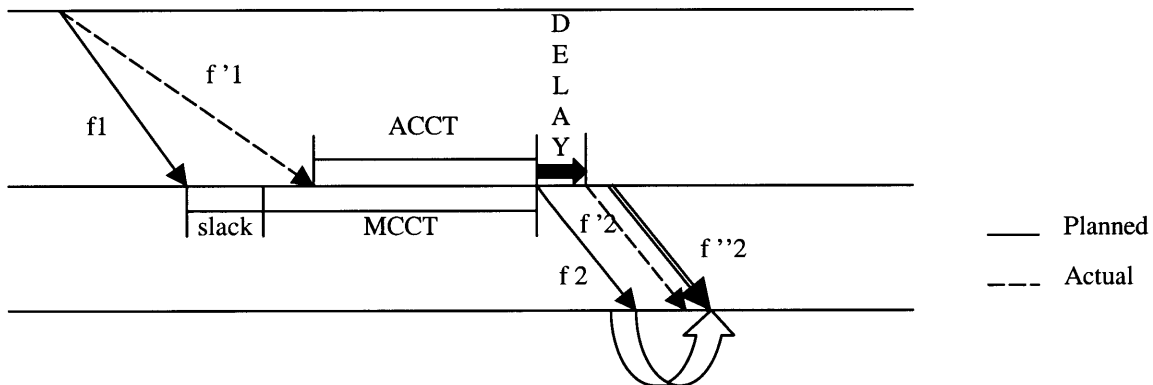


Figure 4.2: Illustration of flight schedule retiming

If ACCT is smaller than the MCCT, the crew is considered *disrupted*.

Figure 4.2 illustrates the idea of our crew schedule with time windows model. Assume that the same crew is assigned to flight leg $f1$ and flight leg $f2$. The solid lines with arrows represent the planned schedule. The connection between $f1$ and $f2$ is a critical connects because the slack for this connection is 5 minutes. Suppose that according to historical data, $f1$ is often delayed to the position of $f'1$. In that case, the ACCT is shorter than the MCCT and the airline must decide to either call on reserve crews, which is expensive and can only be done in a limited number of airports, or delay $f2$ to the position $f'2$, in order to enable the

scheduled crew to make its connection. If in the planning stage, we had moved the departure time of flight f_2 to f'_2 , then even if f_1 is delayed to the position f'_1 , the crew is not disrupted.

Time window specifies how much time a given flight can be shifted. Clearly, if departure time can be rescheduled in a “large” window, even longer delays will not disrupt crews, and our model will produce even more *robust* solutions. Obviously, there is a trade-off between robustness and cost. Adding more slack by retiming departures, can be good for connecting crews, but result in reduced productivity for the aircraft and the crews and maybe also for the fleet. The challenge is to determine where to postpone departure and add slack so as to maximize the benefit for connecting crews, without requiring additional crews or aircraft to fly the schedule, while maximizing robustness of crew connections.

Levin [21] was the first to propose the idea of adding time windows to aircraft routing and scheduling models. In that paper, time windows were used to allow departures to occur at discrete time intervals. Because the scheduled time of some flights is more flexible than others, the width of each time window, defining the set of possible departure times, is a parameter that can be different for every flight. Here we assume a uniform departure time window for each flight and do not discretize the time window; any time within the window is an allowable departure time.

4.4.2 Crew pairing and Departure Re-timing Model

In our work, we consider the fleet assignment and aircraft routings as fixed, and ensure that any crew pairing solution with retimed flight legs that our model produces does not violate the current fleet and routing solutions.

To make the trade-off between robustness and cost, we first solve the conventional pairing problem, which gives us a minimum planned crew cost, denoted c_{OC} . Then, we include in crew pairing and re-timing model a constraint limiting the crew cost to some specified amount greater than the minimum cost. Next we solve Lan et al’s model [27], which generates the *robust* routing solution input to our model, with its associated planned connecting time for each aircraft connection (i,j) referred to as $RobustTurn_{ij}$. We include in our crew pairing and departure re-timing model’s objective function a term to minimize for

each aircraft connection, the absolute decrease after retiming in the connection time $RobustTurn_{ij}$, for each aircraft connection (i,j) .

Before introducing our robust crew model with time windows, we present the following notation.

Parameters:

- F : set of flight legs i
- P : set of pairings p
- C : set of aircraft connections (i,j) included in the robust aircraft routing solution
- \tilde{c}_p : penalty cost that represents for each pairing p the weighted number of connections included in the pairing p that are critical for the crew.
- δ_{ip} : equals 1 if pairing p includes flight i , else 0
- α_{ij} : weight attributed to the aircraft connection (i,j)
- r : the “robustness” factor, as previously defined

Variables:

- y_p : equals 1 if pairing p is in the solution, 0 otherwise

For each connection $(i, j) \in C$, we define:

- t_i^+ : equals the arrival time of flight i
- t_j^- : equals the departure time of flight j
- e_{ij} : equals the difference between the planned re-timed aircraft connection time and $RobustTurn_{ij}$
- Δ_{ij} : equals the absolute value of e_{ij} , if $e_{ij} < 0$; 0 otherwise

The robust crew schedule with time windows model is:

$$\text{Min } \sum_{p \in P} \tilde{c}_p y_p + \sum_{ij} \alpha_{ij} \Delta_{ij} \quad (4-9)$$

Subject to

$$\sum_{p \in P} \delta_{ip} y_p = 1 \quad \text{for all flight legs } i \text{ in } F \quad (4-10)$$

$$\sum_{p \in P} c_p y_p \leq (1+r).c_{OC} \quad (4-11)$$

$$\sum_{p \in P} t_j^- \delta_{jp} y_p - \sum_{p \in P} t_i^+ \delta_{ip} y_p \geq MinTurn \quad \text{for all aircraft connection } (i, j) \in C \quad (4-12)$$

$$\sum_{p \in P} t_j^- \delta_{jp} y_p - \sum_{p \in P} t_i^+ \delta_{ip} y_p = RobustTurn_{ij} + e_{ij} \quad \text{for all aircraft connection } (i, j) \in C \quad (4-13)$$

$$-e_{ij} \leq \Delta_{ij} \quad \text{for all aircraft connection } (i, j) \in C \quad (4-14)$$

$$0 \leq \Delta_{ij} \quad \text{for all aircraft connection } (i, j) \in C: \quad (4-15)$$

The objective (4-9) is to minimize the sum of the weighted number of critical connects and the positive deviation of each aircraft connection from its robust turn time. Constraints (4-10) ensure that each flight leg is covered exactly once. Constraint (4-11) guaranties that planned crew costs are close to the minimum possible. Constraints (4-12) ensure that the current routing solution is still feasible, with each aircraft turn longer than the minimum required. Constraints (4-13)-(4-15) state that for each aircraft connection (i,j) included in the current routing solution, Δ_{ij} is equal to 0 if the planned connection time is greater than the robust connection time and is the robust connection time minus the planned connection time otherwise.

We attribute different weights to the Δ -term in the objective function to ensure that our retimed solution does not undo the robustness gains achieved by solving the Lan et al model. For example if a flight leg is important to the airline due to its revenue, or if based on historical data, a specific aircraft connection is often missed, it might be interesting to assign a higher weight on these connections.

4.5 Robust Integrated Routing and Crew Planning

4.5.1 Integration

As discussed above, critical connects make the crew pairing solution more susceptible to disruptions. To ensure a more robust schedule, we minimize the number of critical connects, by keeping the aircraft and crew together, if connection times are in the critical zone

Figure 4.3 illustrates the idea of our integrated robust routing and crew pairing model. Assume that the same crew is assigned to flight leg $f1$ and flight leg $f2$ and the same aircraft is assigned to flight leg $f1$ and flight leg $f3$. The solid lines with arrows represent the planned

schedule. The connection between $f1$ and $f2$ is a critical connect. Suppose that according to historical data, $f1$ is often delayed to the position of $f'1$. In that case, the crew is disrupted as seen in 4.4.1 because ACCT is shorter than MCCT. Now let's consider that the aircraft routing is changed to $f1$ followed by $f2$. In this case even when $f1$ is delayed, crew and aircraft are not disrupted. This solution is therefore more robust than the original one.

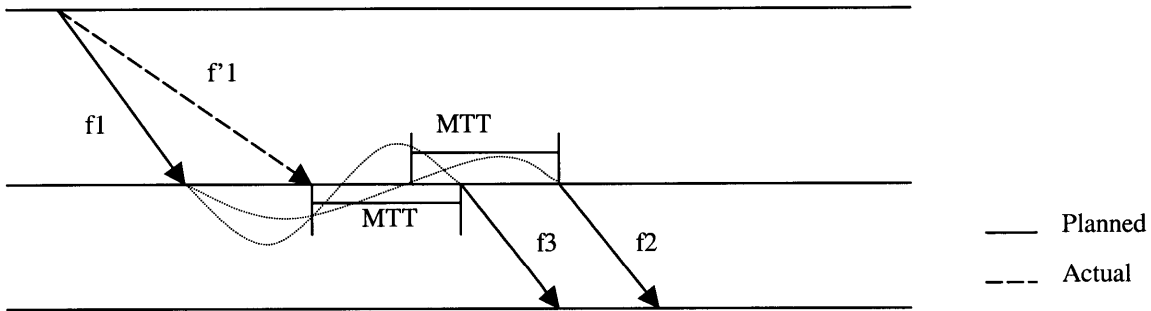


Figure 4.3: Illustration of robust extended crew scheduling

The challenge here is therefore to integrate and solve the aircraft routing and crew pairing problems in order to minimize the number of critical connects.

Cohn and Barnhart [11] were the first to propose the idea of integrating aircraft routing and crew scheduling decisions. They notice that short connects reduce crew costs by increasing the crew utilization. But, because the feasible short connects are determined by the aircraft maintenance routing solution, they develop an approach in which the crew pairing problem is solved simultaneously with the aircraft routing problem. In their model, they add to the basic crew pairing model a collection of variables, ensuring that the crew solution generated has an associate feasible aircraft routing solution. By integrating these decisions, crew pairing solution costs can be reduced because more short connects can be utilized in the crew solutions.

4.5.2 Integrated Robust Routing and Crew Model

In our integrated robust routing and crew model, we use a similar idea to that introduced by Cohn and Barnhart [11]. Our objective is modified, however, to choose an aircraft routing solution and a crew pairing solution that minimizes the number of critical connects used while

keeping crew costs close to minimum. In this model, a critical connection is a crew connection, in which the planned connection time is comprised between 45 minutes and 1 hour and the sequential flight legs are not assigned to the same aircraft. Again, to balance crew costs and the number of critical connects, we first solve the usual crew pairing model, which gives us a planned crew cost, referred as c_{oc} . Then we include in our model a constraint limiting crew costs.

Before describing our robust extended model, let's introduce the following notation:

Parameters

- F : set of flight legs f
- P : set of pairings p
- S : set of maintenance solutions s . A maintenance solution s is a set of aircraft strings that satisfy the basic aircraft maintenance routing requirements:(4-2) through (4-6), it determines the feasible short connects and the number of critical connects.
- R_s : set of route strings included in maintenance solution s
- \tilde{C} : set of critical connections annulled by S
- \tilde{S} : set of short connections allowed by S
- b_{cr} : equals 1 if route string r includes (that is, assigns the same aircraft to) critical connect c , else 0
- β_{hr} : equals 1 if route string r allows short connect h , else 0
- δ_{fp} : equals 1 if pairing p includes flight f , else 0
- a_{cp} : equals 1 if pairing p includes critical connect c , else 0
- α_{hp} : equals 1 if pairing p includes short connect h , else 0
- r : the “robustness” factor, previously defined

Variables:

- x_s : equals 1 if maintenance solution s is in the solution, 0 otherwise.
- y_p : equals 1 if pairing p is picked, 0 otherwise
- α_c, β_c : equal to (0, 0) if critical connect c is covered by one crew and one aircraft or if critical connect c is not included in the maintenance routing solution and is not in the

crew pairing solution; (0, 1) if critical connect c is not in the crew pairing solution included and is included in the maintenance routing solution; (1, 0) if critical connect c is included in the crew pairing solution and not in the maintenance routing solution.

The integrated robust aircraft routing and crew pairing problem is:

$$\text{Min } \sum_{c \in \tilde{C}} \alpha_c \quad (4-16)$$

Subject to

$$\sum_{s \in S} x_s = 1 \quad (4-17)$$

$$\sum_{p \in P} \delta_{fp} y_p = 1 \quad \text{for all flight legs } f \text{ in } F \quad (4-18)$$

$$\sum_{s \in S} \sum_{r \in R_s} \beta_{hr} x_s - \sum_{p \in P} \alpha_{hp} y_p = 0 \quad \text{for all short connections } h \text{ in } \tilde{S} \quad (4-19)$$

$$\sum_{s \in S} \sum_{r \in R_s} b_{cr} x_s - \sum_{p \in P} a_{cp} y_p - \beta_c + \alpha_c = 0 \quad \text{for all critical connections } c \text{ in } \tilde{C} \quad (4-20)$$

$$\sum_{p \in P} c_p y_p \leq (1+r).c_{OC} \quad (4-21)$$

The objective (4-16) is to minimize the number of critical connects in the selected crew pairings. Constraint (4-17) ensures that exactly one maintenance solution is selected. Constraints (4-18) guarantee that each flight leg is covered by exactly one crew. Constraints (4-19) ensure that only feasible short connects are included in the crew pairing solution. Constraints (4-20) count the number of critical connects in the pairing solution that are not in the aircraft maintenance routing solution. Constraint (4-20) ensures that the cost of the selected crew pairings is close to minimum crew pairing costs.

4.5.3 Ensuring Robust Maintenance Routings

An important challenge associated with this model is the issue of how to ensure robustness of the aircraft routing solutions. Our idea is to generate routing solutions in our model using the robust aircraft routing model of Ageeva, which ensures aircraft swapping opportunities and ease of recovery in case of disruption. Alternatively we could use Lan et al's robust routing model 4.2, which limits delay propagation. Because in our integrated robust crew and aircraft routing model we are merely *selecting* an aircraft routing solution, we will not alter the robustness proprieties of the routing solution selected in solving our model.

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Chapter 5

Hub Debanking

5.1 The Airline Industry

5.1.1 Birth of the Hub-and-Spoke Network

Before 1978, the Airline Industry was regulated. Two agencies, namely the Civil Aeronautics Board and the Civil Aeronautics Authority, set fares and determined which airlines could serve which cities. Because several carriers often served the same markets, the competition in the industry already existed. To preserve their market share, carriers competed on service, such as the number of passengers per flight attendant, good quality in flight service and more frequent flights. In 1978, the Airline Deregulation Act deregulated the airline industry and dissolved the Civil Aeronautics Authority. The airlines were now free to decide the fares to charge and which routes to serve.

Bogush [8] notices that after deregulation, established carriers decided to mainly compete not on fare but on service, for example better meals, more frequent flights, more itineraries. The establishment of the *hub-and-spoke* network is the result of the desire to offer more destinations, and therefore stimulate more demand. In this strategic policy, flight schedules are built with a focus on the hub airports and a goal of trying to maximize the number of itineraries that can be offered by connecting flights into and out of the hubs. Thus hubs allowed carriers to expand service networks for less cost than *point-to-point* services for each of the routes. Hubs also allowed airlines to survive for post-deregulation competition by consolidating passengers destined to multiple locations at spoke stations, and redistributing them on connecting flights at the hub. Figure 5.1 illustrates the difference between the hub and spoke network design and the point-to-point network design. To serve n^2 O-D pairs with

the point-to-point, one need n^2 flight legs but with the hub-and-spoke one can do it with n arcs

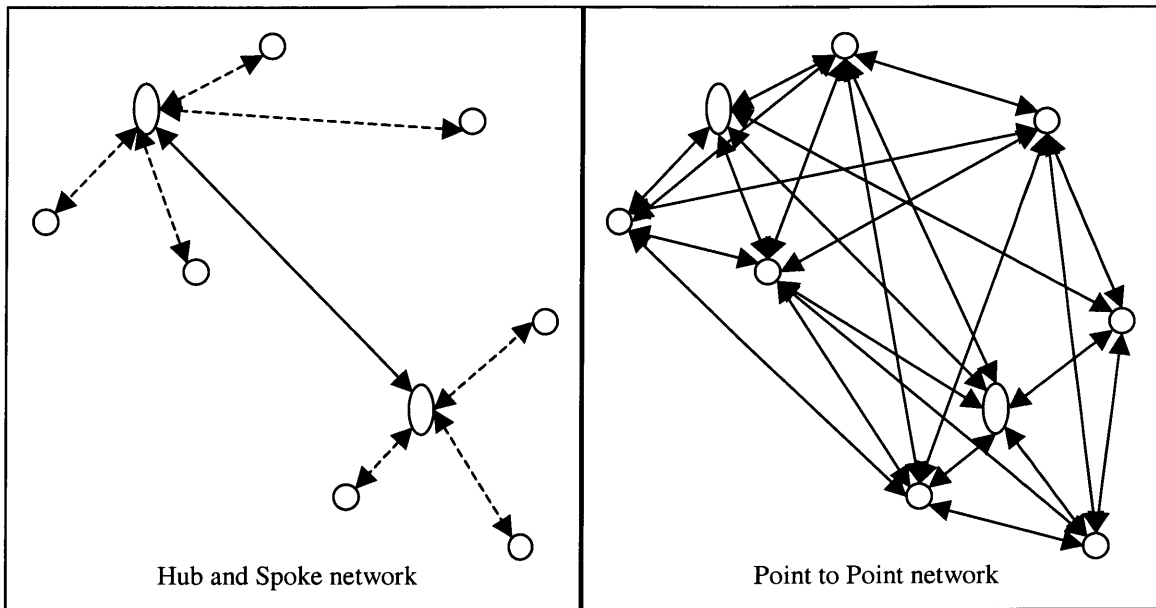


Figure 5.1: Illustration of two schedule operating networks for the airlines

The potential benefits of the hub and spoke strategy are numerous: greater frequency and travel options, access to small cities, and better resource utilization through consolidation. To achieve these benefits, however, it requires a high-degree of operating efficiency at the hubs.

5.1.2 Changes in Competition

According to Bogusch [8], prior to the advent of the Internet, most flight reservations were booked through travel agencies via the Customer Reservation System (CRS). Flights for a given origin-destination city pair appeared ranked by departure time and total elapsed time. Appearing on the “first screen” of the CRS search was an important factor in the number of bookings an airline received and hence was a key determinant to market share. Competition to appear on the first screen was fierce and airlines scheduled flights to coincide with the most popular departure times, and to achieve the shortest planned connection time. This led to *banking* of flight legs at hubs, that is, a sequence of flight leg arrivals followed closely by flight legs departures. Banks result in planned periods of peak activity followed by limited activity at the hub airports.

As the number of tickets sold on the Internet increased, customers gained more knowledge about their travel options. Moreover, because the majority of Internet travel sites display itineraries in order of increasing price and not increasing elapsed time, itinerary elapsed time became less important in influencing passenger buying decisions. At the same time, an increasing number of carriers started to enter the industry. These new entrants, called low-cost carriers, compete based on low fares. Their principal advantage is their low operating cost, which they achieve with strategies such as: minimum service in single-class flight legs, acquisition of used and refurbished aircraft, fleet commonality and a cheaper but more productive labor force. These new carriers are not locked into expensive labor contracts, as the legacy carriers with their heritage of regulation.

These two factors, near perfect customer information and low cost carrier entrance in the market, led to an emerging unwillingness from the customers to pay high fares. The large network legacy carriers were pressured to lower their costs or face bankruptcy. The first step was to analyze to what their high operating costs were attributable.

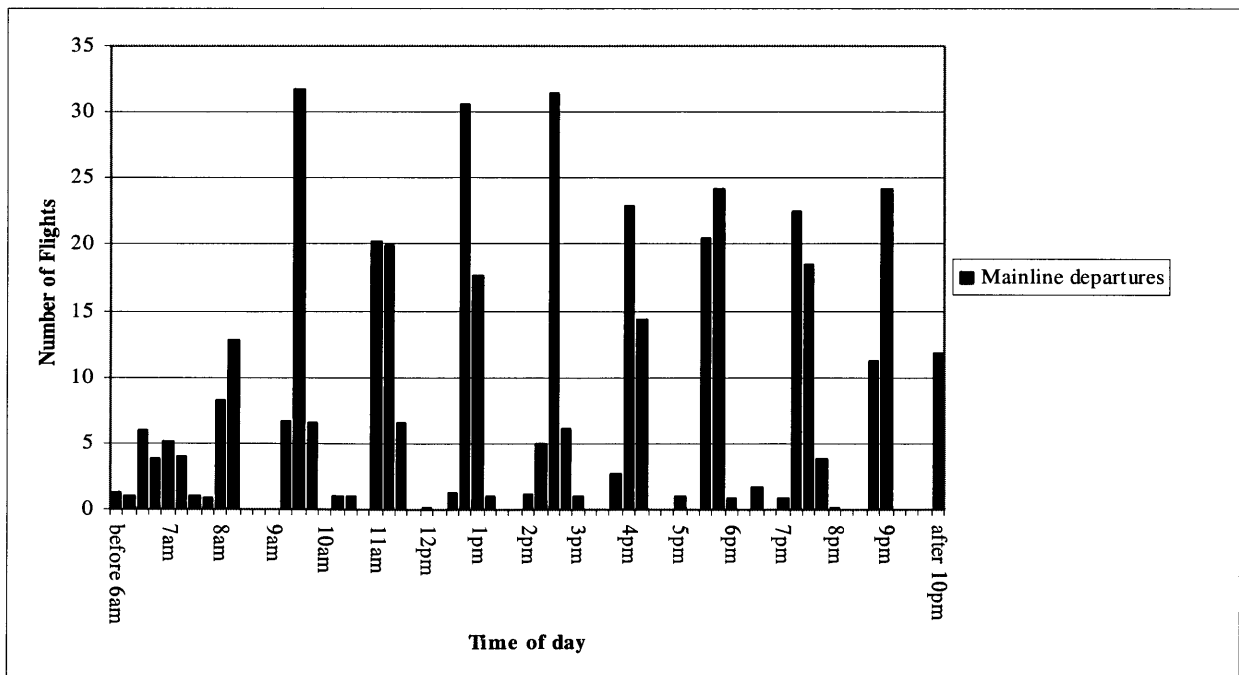
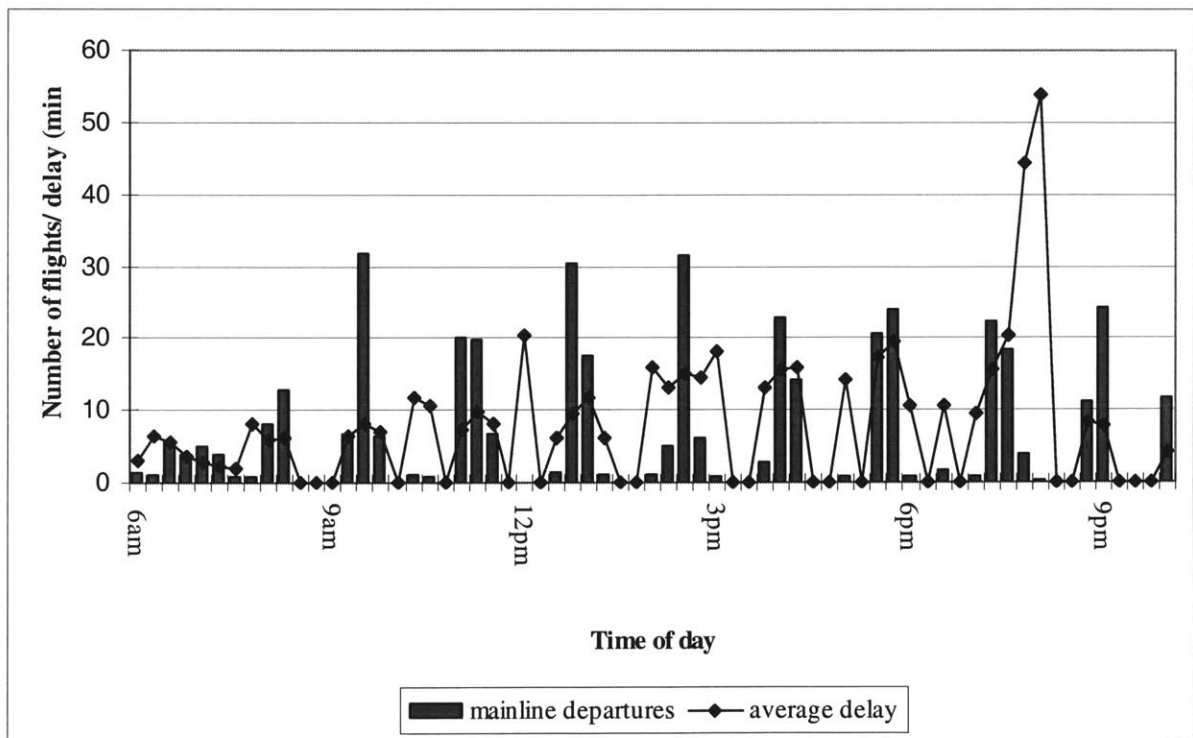


Figure 5.2 American Airlines scheduled mainline departures in 15-minute intervals at DFW, March 2002

The high operating cost of large network carriers is not only due to high labor costs but also to low operating efficiency at the hubs. Motivated by the desire to offer customers the shortest connection times and departures at popular times, carriers such as American Airlines (AA) had banked schedules to enable very short passenger connections. Figure 5.2 depicts AA's scheduled mainline departures over fifteen minute intervals out of Dallas Fort Worth (DFW) for March 2002. It is evident that there are 8 departure banks in this schedule at DFW. As a result of these *peaks* in ground and airport resources, hubs are periodically congested over the day, leading to significant delays. Figure 5.3 depicts the correlation between AA's average delay per departure flight and flight departure frequency over fifteen intervals out of Dallas Fort Worth (DFW) for March 2002.



significant impacts on airline operations and on passengers. Flight delay at hub airports is only one of the drawbacks of the hub-and-spoke banked network. Banking also leads to:

- 1) **Uneven aircraft utilization:** Aircraft must wait at spoke airports until an appropriate time to depart and meet the scheduled arrival bank at the hub station;
- 2) **Low resource utilization:** Increased numbers of ground employees must be present in order to process passengers, luggage, etc during the banks. Employees are then mostly must be present idle between banks

5.1.3 American Airlines Debanking Policy

In April 2002, American Airlines moved toward a more continuous flow of arrivals and departures at their hub in Chicago, O'Hare International Airport (ORD). In November 2002, they decided to extend this policy of de-banking to their hub in Dallas Fort Worth (DFW). While a debanked schedule runs the risk of reduced revenue potential, a steady flow of departures and arrivals should have a favorable effect on operating costs.

In the remainder of this chapter we analyze the debanking policy of American Airlines at Dallas Fort Worth. First, we examine at a high level, the schedule changes compared with a banked AA schedule. Then, we assess the robustness of the debanked schedule in terms of on-time performance, passenger connections and ease of aircraft recovery, compared to a banked AA schedule.

5.2 Analysis of American Airline Policy of Debanking at Dallas Fort Worth airport

5.2.1 Analysis Methodology

When isolating the effects of a schedule change, one must take into account a variety of additional factors that might influence the analysis, such as:

- Seasonality: seasonal effects can occur in both passenger demand and traffic patterns;
- One-time shocks;
- Industry trends: fluctuations in demand and changes in certain airline policies; and
- Incremental changes: small changes such as block time adjustments, boarding procedure changes that the airline makes to its schedule.

To address the seasonality effects, we choose to compare data from March 2002, before the debanking policy, to data from March 2003, after the debanking policy. We use historical data from the Airline Service Quality Performance (ASQP) database. The ASQP database provides flight information for all domestic flights served by jet aircraft by major airlines in the U.S.. For each flight leg, ASQP provides the following flight operation information: airline, flight number, origin and destination airports, planned departure time and arrival time, actual departure time and arrival time, *taxi-out* time, that is, the time between the aircraft departure from the gate and the actual take off, and aircraft tail number.

Dallas Fort Worth is a hub for Delta Airlines, American Airlines and American Eagle. American Eagle is a partner of American Airlines. This partnership enabled American Airlines to offer more frequent service to various regional locations at DFW. American Eagle serves 133 regional destinations. American Airlines and its commuter sister American Eagle both depeaked their schedule at DFW, therefore we assess the effects of this conjoint policy change.

5.2.2 Dallas-Fort Worth Airport

To address the effects of industry trends at Dallas Fort Worth, we first assess the position of American Airlines and its partner American Eagle by comparing the numbers of flights per day they operate with the numbers operated by other airlines at Dallas-Fort Worth (DFW).

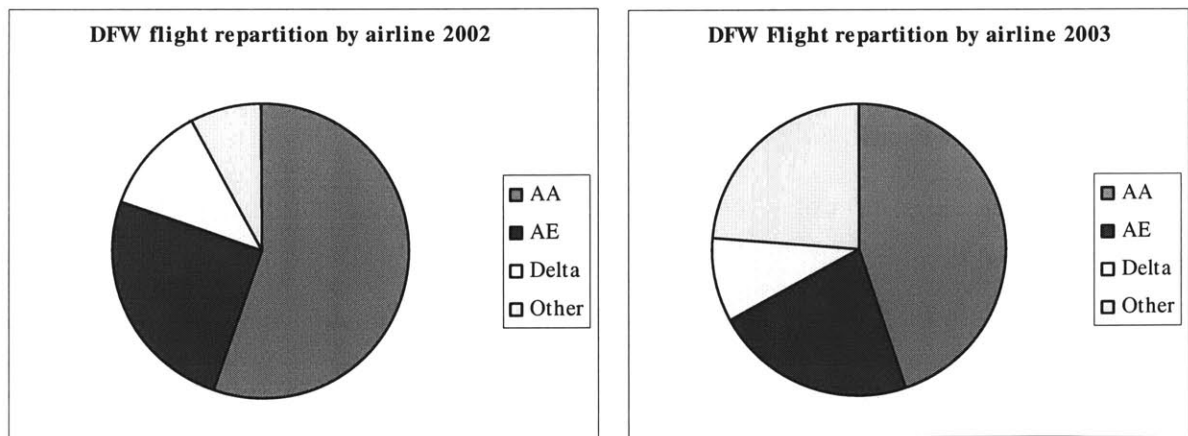


Figure 5.4 Flight repartition by airlines in March 2002 and March 2003 at DFW

Figure 5.4 illustrates the number of departure flights per airline at DFW. We can see that for both years, American Airlines is the dominant airline at DFW, even though the relative proportion of other airlines has increased from 2002 to 2003 Table 5.1 lists the number of mainline departures per airline at DFW for March 2002 and March 2003.

Table 5.1 Number of mainline departures per airline at DFW

	March 2002	March 2003
AA	414	404
AE	190	196
Delta	89	84
Other	59	212

The number of flights operated by American Airlines, American Eagle and Delta Airlines is roughly the same in March 2002 and March 2003, while the number of flights for the other airlines has more than tripled. This increase is attributable to two new airlines operating in March 2003 compare to March 2002 at DFW, namely Skywest and Atlantic Southeast. Skywest offers 42 flights and Atlantic Southeast offers 96 flights, both as Delta connection partners.

Skywest and Atlantic Southeast operate small aircraft, for example the Canadair regional jet. At DFW, there are two different runways, one is dedicated to the take-off and landing of medium to large aircraft, such as those used by American Airlines, Delta Airlines, Continental Airlines, etc, and the other one is dedicated to the take off and landing of smaller aircraft, such as those operated by American Eagle, Skywest, Atlantic Southeast, etc. Therefore, levels the two new regional carriers' operations at DFW affect congestion levels only for American Eagle, and not American Airlines.

5.2.3 Overview of Schedule Change

As seen in section 5.2.2, the variation in the number of mainline departures for American Airlines and American Eagle at DFW in March 2002 and in March 2003 is negligible.

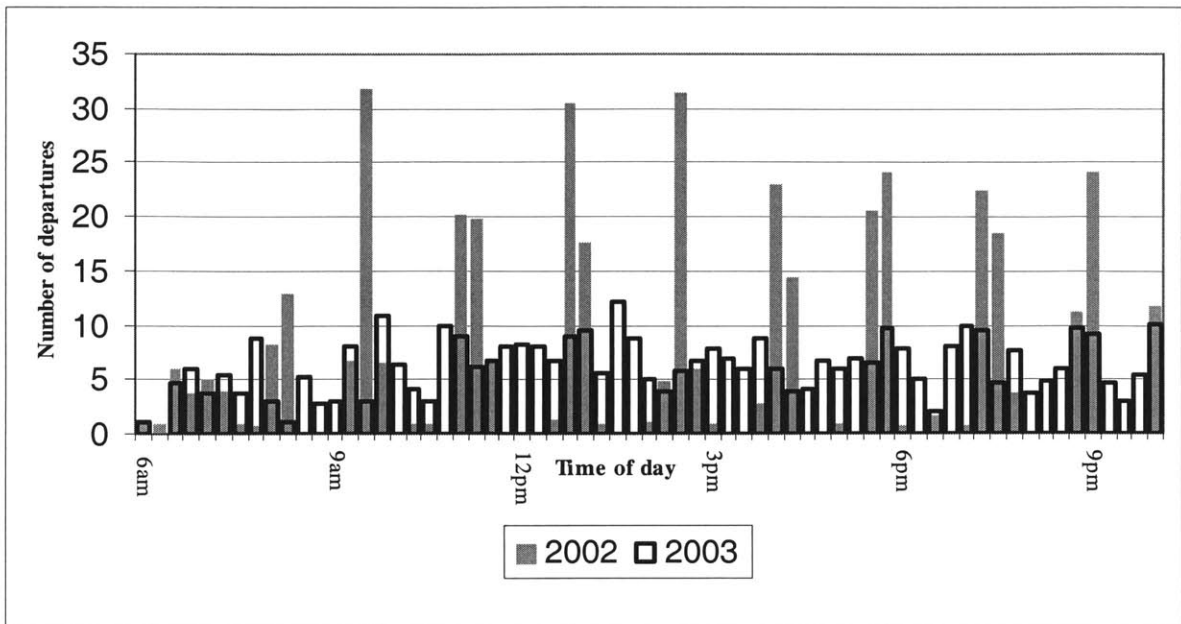


Figure 5.5 Comparison of domestic mainline scheduled departures per 15 minute interval, for American Airlines at DFW, March 2002 and March 2003

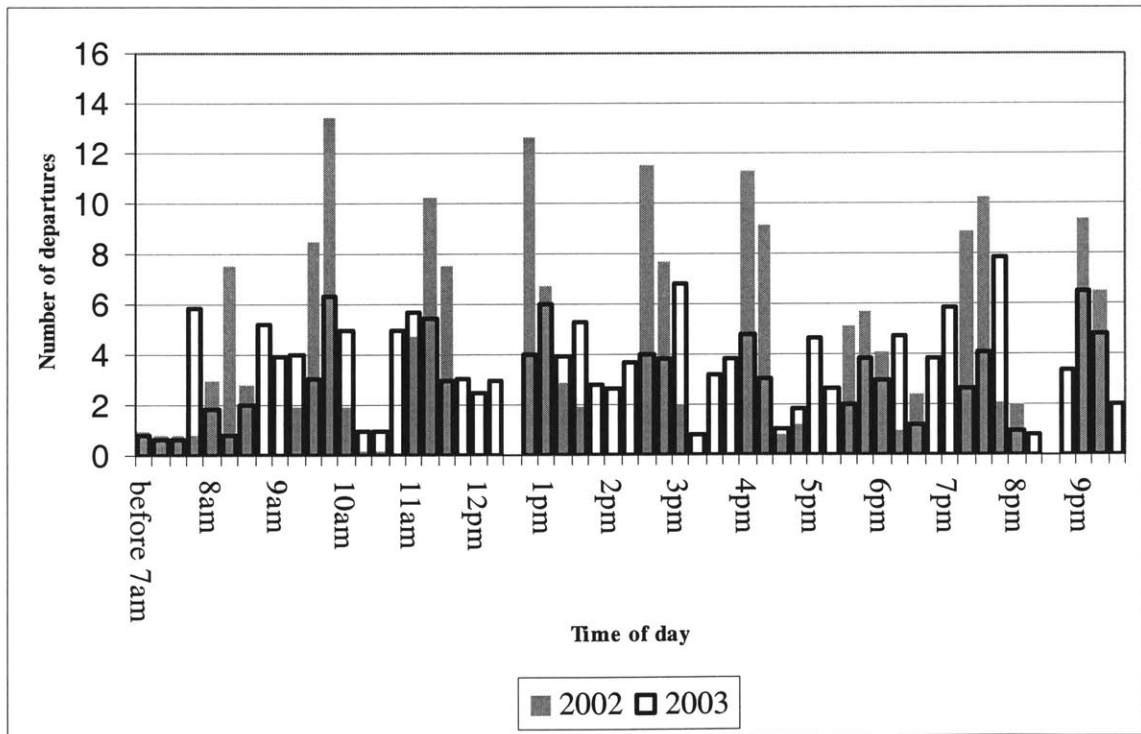


Figure 5.6 Comparison of domestic mainline scheduled departures per 15 minute interval, for American Eagle at DFW, March 2002 and March 2003

Figure 5.5 shows a direct comparison of the American Airlines (AA) domestic mainline scheduled departures from Dallas Fort Worth in March 2002 and in March 2003. In this graph, one can see that AA’s new scheduling policy essentially cuts off the tops of the eight previously distinct peaks and redistributes flights into the surrounding time intervals. As a result, the maximum number of departures per 15-minute interval has gone from 32 in March 2002 to 12 in March 2003. We conduct the same analysis for American Eagle. The results are shown in figure 5.6. The maximum number of departures per 15-minute interval has gone from 13 in March 2002 to 8 in March 2003. Although American Eagle’s policy also has cut-off the top of the previously distinct peaks, but not to the same extent as American Airlines. We define the *degree of peaking*, as the maximum percentage of flights departing in a given interval. Figures 5.7 and 5.8 show the mainline departures for AA and AE respectively, scheduled per 15 minute interval as a percentage of total mainline departures at DFW for AA and AE respectively. The degree of peaking for AA has gone from 7.68% in March 2002 to 2.99% in March 2003. During the same period, the degree of peaking for AE has gone from 7.06% to 4%.

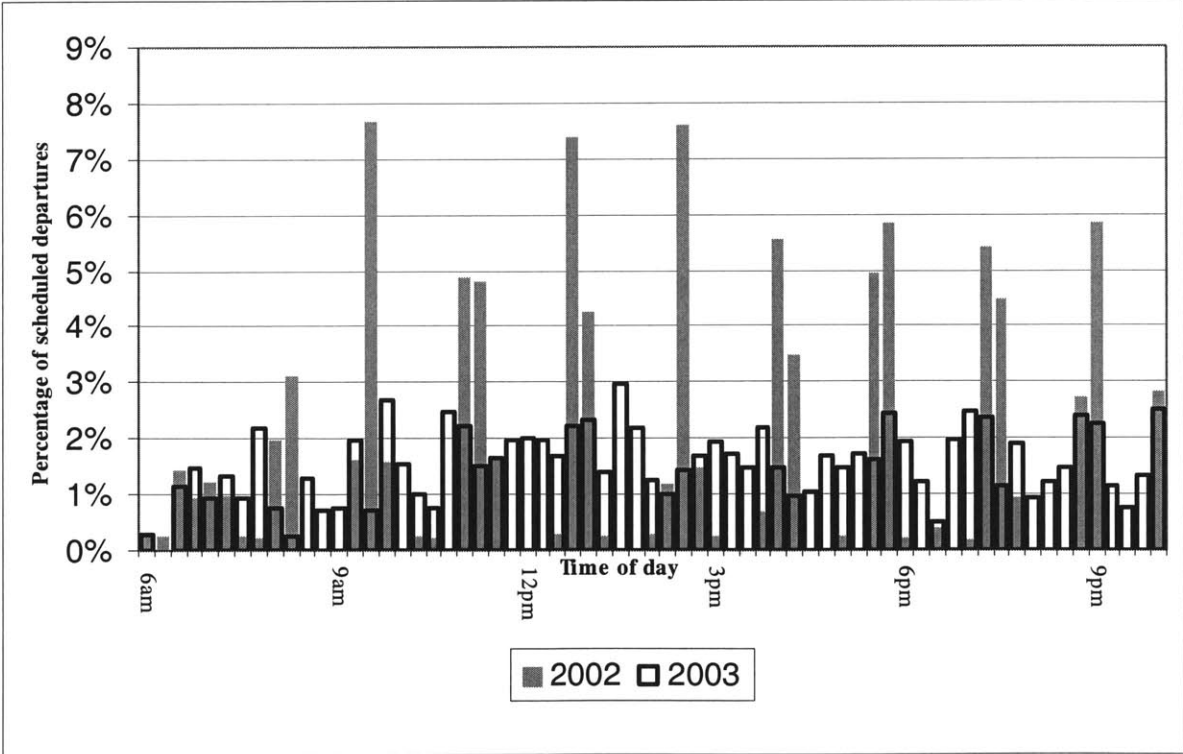


Figure 5.7 American Eagle at DFW scheduled departures in 15 minute intervals, March 2002 and March 2003, normalized by number of flights

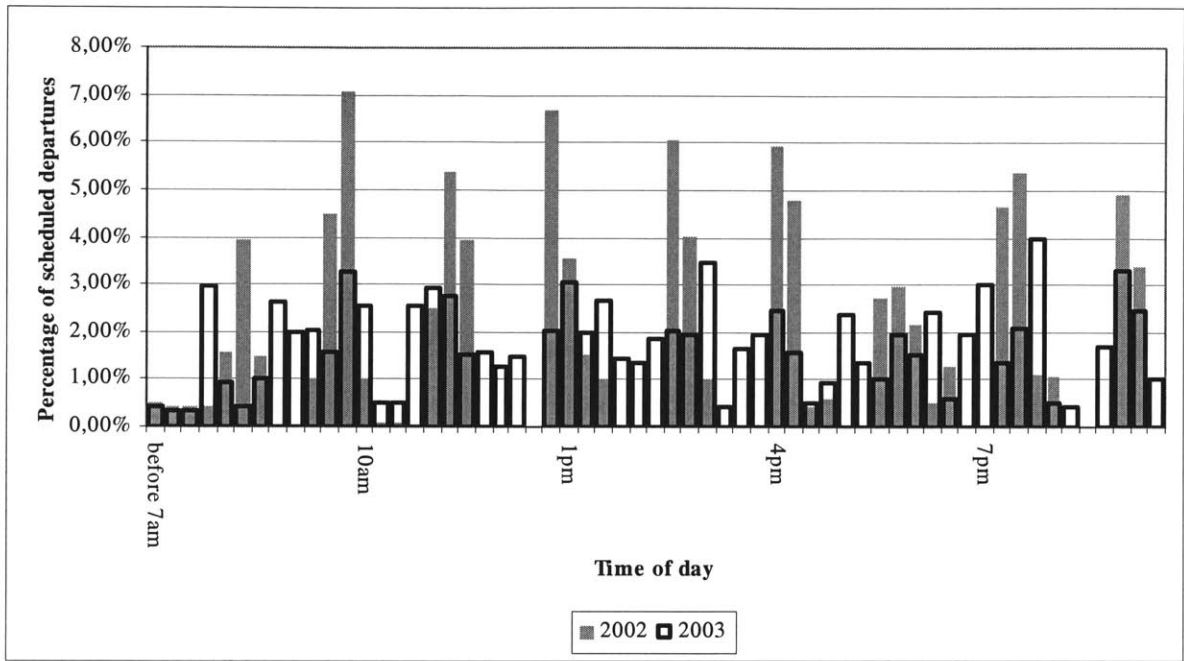


Figure 5.8 American Eagle at DFW scheduled departures in 15 minute intervals, March 2002 and March 2003, normalized by number of flights

From figures 5.7 and 5.8, we observe that American Airlines and American Eagle reduced by more than 50% their degree of peaking while operating essentially the same number of flights in 2003 as 2002 at DFW.

5.3 Robustness Analysis

In this section we attempt to estimate the effects of the changes made in American Airlines and American Eagle’s schedules at Dallas Fort Worth. We consider three different criteria to evaluate the robustness of a schedule:

- 1) **Operational performance:** average delay per flight and the degree of congestion at the airport ;
- 2) **Passenger connection:** scheduled passenger connections and the number of passenger misconnections; and
- 3) **Aircraft ease of recovery:** average number of swapping opportunities among the same aircraft family

5.3.1 Operational Performance

5.3.1.1 Delay Minutes

The monthly average delay per mainline flight departure, as shown in Table 5.2, for American Airlines, American Eagle and the other airlines in March 2002 and March 2003, at Dallas Fort Worth.

Table 5.2 Average delay for mainline departures per airline at DFW, March 2002 and March 2003

	AA		AE		Others	
In March	2002	2003	2002	2003	2002	2003
Delay per flight(min)	11.5	5.5	10.0	5.3	9.4	6.3

We can see that for all airlines, average delay decreased from 2002 to 2003 even though the total number of mainline departures, as seen in section 5.2.2, increased. Average delay decreased by 50% for AA flights, by 47% for AE flights and by 32% for the other airline flights.

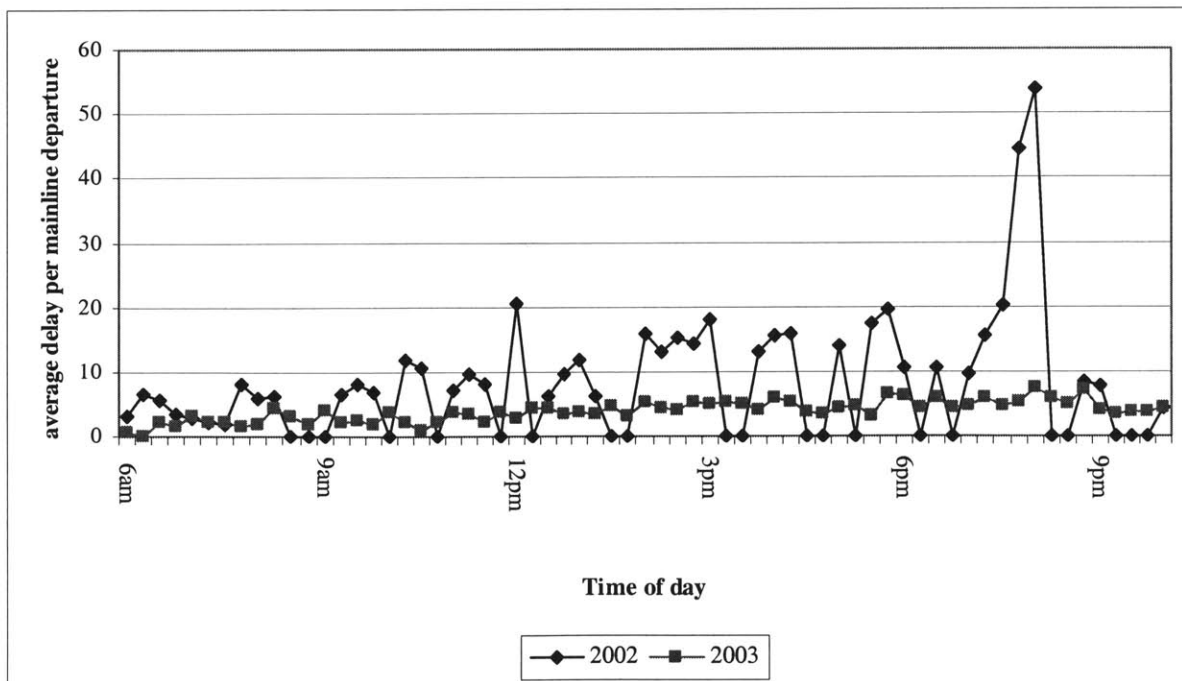


Figure 5.9 Average delay minutes per mainline departure for American Airlines in 15 minute intervals, March 2002 and March 2003 at DFW

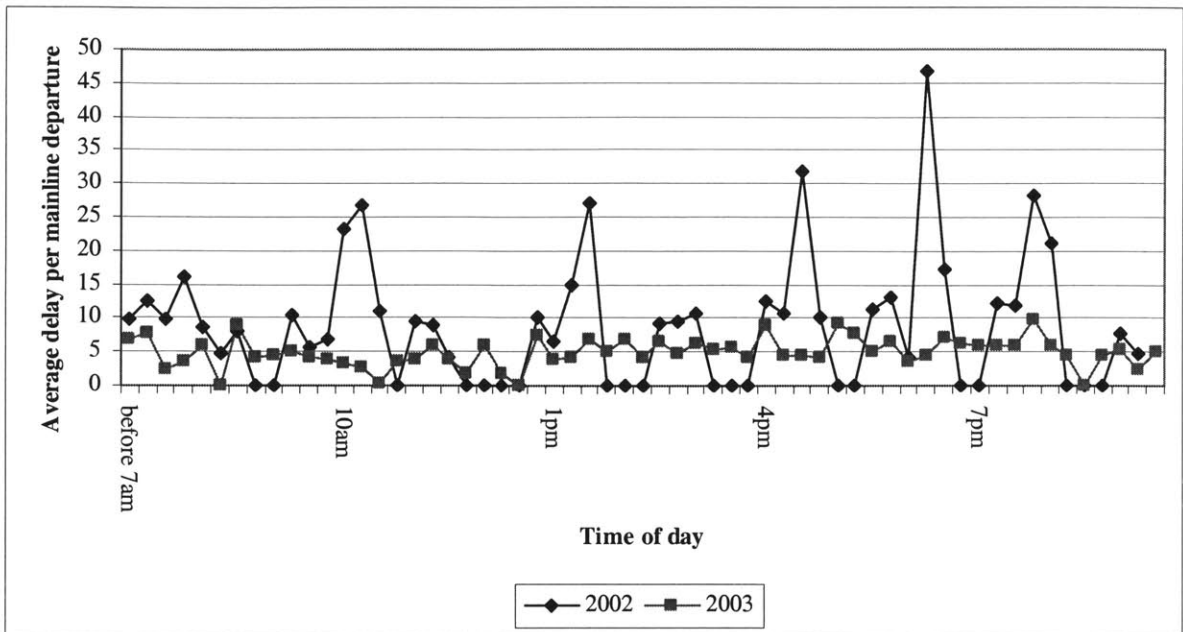


Figure 5.10 Average delay minutes per mainline departure flight for American Eagle in 15 minute intervals, March 2002 and March 2003 at DFW

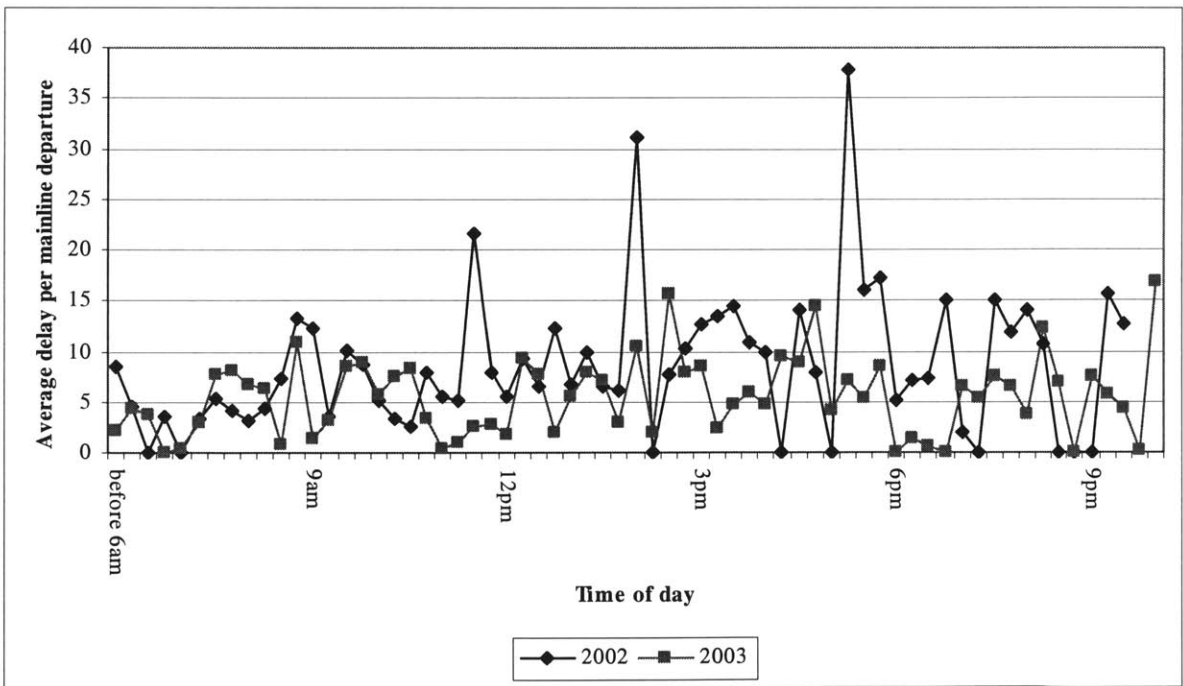


Figure 5.11 Average delay minutes per mainline departure flight for other Airlines (not AA or AE) in 15 minute intervals, March 2002 and March 2003 at DFW

The average departure delay minutes per flight for AA at DFW in March 2002 and March 2003 is shown in Figure 5.9. One can see that in March 2002 not only were more delays occurring as the day progressed, but the average delays were getting longer. In March 2003,

this increasing delay trend has disappeared with the average delay remaining between 0 and 10 minutes throughout the day. A similar delay evolution for AE from March 2002 to March 2003 is shown by Figure 5.10. Interestingly, although the other airlines did not debank, they reaped the benefits of AA's and AE's debanking. Figure 5.11 illustrates a decrease in delay per flight for the other airlines from March 2002 to March 2003. Note, however, that even in March 2003 the average departure delay for other airlines is not consistent and still reaches levels experienced in 2002.

5.3.1.2 Taxi-out Time

Taxi-out time, the time between the aircraft departure from the gate and the actual take off is influenced by a number of factors (Idris et al [14]) namely:

- 1) *Ruaway configuration*: determines the flow pattern on the airport surface;
- 2) *Airline/ terminal configuration*: determines for each airline, the distance between the gate and the runway;
- 3) *Weather and downstream restrictions*; and
- 4) *Departure Demand and Queue Size*: large queues of departing aircraft form on the airport surface due to imbalances between demand and (reduced) capacity

We report the average taxi-out time per mainline departure for AA, AE and the other airlines in March 2002 and 2003 at DFW in Table 5.3. Average taxi-out time for AA departures decreased by 20%, for AE by 12% and for the other airlines by 13%. This decrease in taxi-out time, assuming that in March 2002 and in March 2003, the runway, the airline/ terminal configurations and the weather conditions are the same, is explained by a decrease in queue size and hence, congestion, due to the debanking policy of AA and AE.

Table 5.3 Average taxi-out time per airline at DFW, March 2002 and March 2003

In March	AA		AE		Others	
	2002	2003	2002	2003	2002	2003
Taxi-out(min)	18,1	14,9	18,5	16,3	19,5	16,9

The runway configuration at DFW, presented in section 5.2.2, combined with the fact that departure demand remained the same for medium and large aircraft, and increased for small aircraft, explains the larger decrease in taxi-out time for AA than for AE. Interestingly

although Skywest and Atlantic Southeast increased demand for capacity on the runway used by AE, average taxi-out times were decreased for each of these airlines because of AE's debanking policy.

5.3.2 Passenger Connections

Table 5.4 Top five passenger destinations departing from DFW, March 2002

Carrier	Destination	Origin	# passengers
AA	LAX	DFW	44041
AA	ORD	DFW	42951
AA	MIA	DFW	39788
AA	LAS	DFW	35843
AA	SAT	DFW	34809

Table 5.5 Top five passenger origins arriving to DFW, March 2002

Carrier	destination	Origin	# passengers
AA	DFW	LAX	44729
AA	DFW	ORD	44236
AA	DFW	MIA	39422
AA	DFW	LAS	35231
AA	DFW	STL	35138

Identifying the origins/destinations served through DFW with large passenger demands in March 2002 (see tables 5.4 and 5.5) we select four AA itineraries through DFW with high demand and compare their planned connection times and the numbers of misconnections in March 2002 and March 2003. The four itineraries are: Los Angeles to Chicago (LAX-ORD), Miami to Los Angeles (MIA-LAX), Chicago to Las Vegas (ORD-LAS) and Saint Louis to San Antonio (STL-SAT). To conduct this analysis we make the following simplifying assumptions:

- 1) A *smooth passenger connection* requires at least 35 minutes of *actual connection time*, between the actual arrival time and the actual departure time of the two connecting flight legs. A *tight passenger connection* is one in which the actual connection time is between 35 minutes and 20 minutes. A *missed passenger connection* has actual connecting time less than 20 minutes; and
- 2) If a passenger misses his/her connection, we assume that the airline can accommodate him/her on the next flight to his/her destination.

As illustrated in Table 5.6, the planned passenger connection time after the debanking policy has increased for the four itineraries. Nonetheless the maximum increase is 15 minutes which represents a 37 % increase in connection time and the average increase in connection time for these four itineraries is 6.75 minutes. This result is consistent with that reported by Bogusch [], who shows that the average increase in connection time induced by AA's debanking policy at Chicago (ORD) is 5 minutes.

Table 5.6 Planned passenger connection times for American Airlines for selected O-D pairs, March 2002 and March 2003

	Planned connection time(min)	
	2002	2003
LAX-ORD	40	55
MIA-LAX	51	53
ORD-LAS	47	57
STL-SAT	48	48

Table 5.7 summarizes the distribution of the actual passenger connection time for our four itineraries, in March 2002 and March 2003. The number of missed connections and tight connections decreases from 2002 to 2003 for all itineraries except MIA-LAX. A closer look to the data, reveals that the missed connections for this itinerary are due to large delays at Miami. The departure delay at Miami in March 2003 was over 20 minutes for 10 days. Note also that from March 2002 to March 2003 the average departure delay at Miami airport increased by more than 86%, that is, from 6.3 minutes to 11.7 minutes. Therefore we can assume that this increase in missed connections is due to an increased in congestion at Miami. For the other three itineraries the decrease in missed connections is indicative of an increased robustness of the debanked flight schedule, experienced by connecting passengers.

Table 5.7 Distribution of actual passenger connection times for American Airlines for selected O-D pairs, March 2002 and March 2003

	2002			2003		
	Missed (%)	Tight (%)	Smooth (%)	Missed (%)	Tight (%)	Smooth (%)
LAX-ORD	11	37	52	0	3	97
MIA-LAX	0	6	94	19	16	65
ORD-LAS	16	20	64	8	4	88
STL-SAT	17	17	66	0	3	97

Table 5.8 Distribution of passenger tight connections for American Airlines for selected O-D pairs, March 2002 and March 2003

	2002			2003		
	30-35 min (%)	25-30 min (%)	20-25 min (%)	30-35 min (%)	25-30min (%)	20-25 min (%)
LAX-ORD	80	20	0	0	100	0
MIA-LAX	100	0	0	80	20	0
ORD-LAS	60	20	20	0	100	0
STL-SAT	80	20	0	0	100	0

Table 5.8 summarizes the distribution of the tight connections for these itineraries.

5.3.3 Aircraft Ease of recovery

As seen in section 3.4.1, to recover from an aircraft shortage or disruption, airline operations centers typically swap among aircraft of the same fleet family. Banked Hub-and-Spoke networks, with departure and arrival banks, have the advantage of ensuring that every couple of hours, significant number of aircraft of the same fleet family is on the ground at the same time. This provides a large number of potential swapping opportunities. We are interested therefore, to assess if a debanking policy of spacing arrivals and departures throughout the day, reduces these swapping opportunities and therefore reduces the robustness of the flight schedule.

Based on aircraft tail number from the ASQP database, data from JP international fleet [15] and the simplifying assumption that flight legs operated on multiple days are assigned to the same equipment type, we conclude that American Airlines in their domestic network operates two different aircraft families at DFW: the DC-9 family and the Boeing 757-767 family. We estimate the number of aircraft of each of these families on the ground at DFW per 15-minute interval in March 2002 and March 2003, and illustrate our results in Figure 5.12 and 5.13.

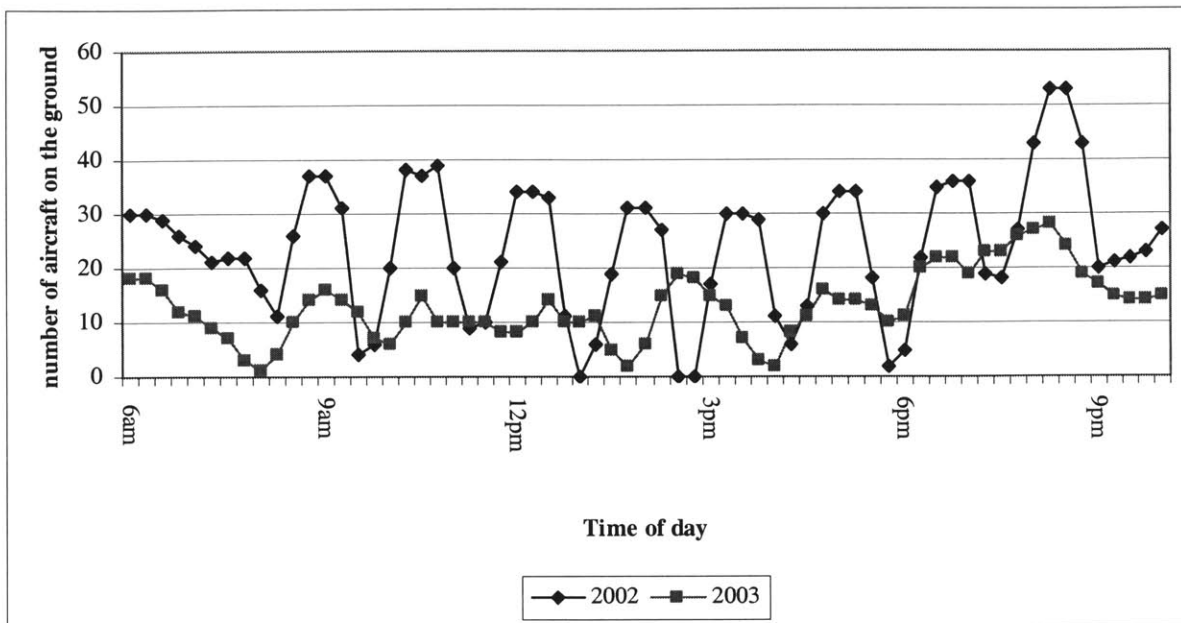


Figure 5.12 Number of DC-9 on the ground at DFW for American Airlines per 15 minute interval, March 2002 and March 2003

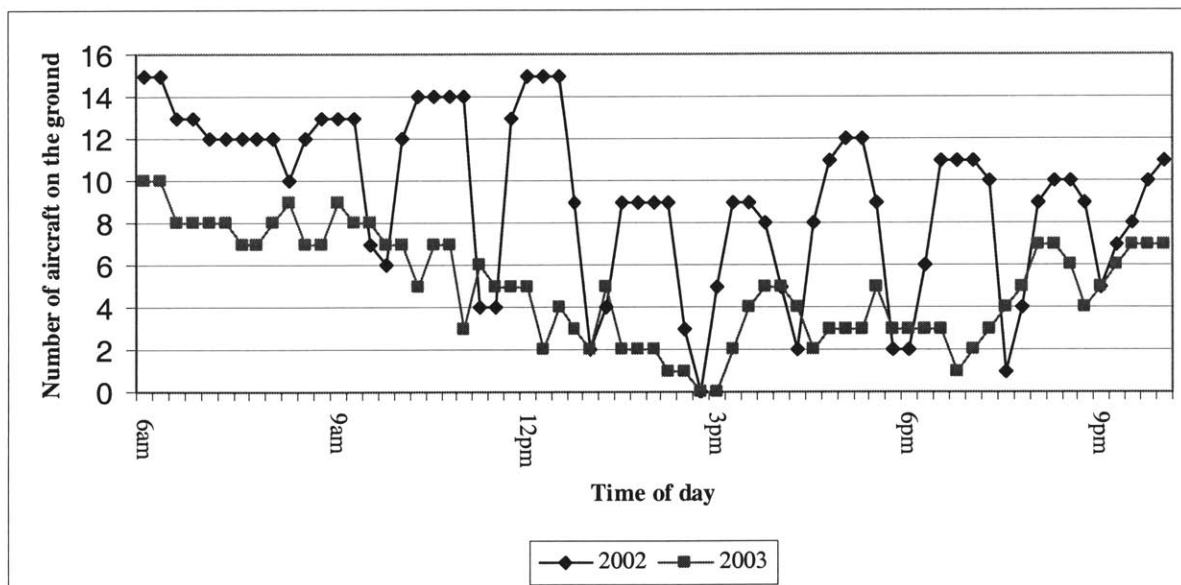


Figure 5.13 Number of Boeing 757 and Boeing 767 on the ground at DFW for American Airlines per 15 minute interval, March 2002 and March 2003

As expected, the number of aircraft on the ground is more constant throughout the day in 2002 than in 2003. In figure 5.12, even without the banking the number of DC-9 on the ground in March 2003 is at least 5, for more than 90% of the time. Hence an adequate number of swapping opportunities exist for DC 9's throughout the day. For the Boeing 757-767

family, however, roughly from 1pm to 3pm the number of aircraft on the ground at DFW is below three. During that period the number of swapping opportunities is limited and in the event of an aircraft disruption, the debanked schedule might not be robust enough.

Table 5.9 Average ground time (in hours) per aircraft for American Airlines at DFW, March 2002 and March 2003

	Ground time per aircraft (hour)	
	2002	2003
DC-9	2.015	2.95
757-767	1.26	2.28

The reduction in swaps opportunities is offset to some degrees by the increases in aircraft productivity achievable with debanking. The average ground times per aircraft type at DFW for American Airlines in 2003 compared to 2002 are summarized in Table 5.9. The average decrease in ground time is 37% for the DC-9 family, and 23% for the 757-767 family. This clearly illustrates the increased aircraft utilization achieved by debanking policy.

Chapter 6

Conclusions

6.1 Summary

In airline operations, flight delays and cancellations are common and often lead to passengers, crews and aircraft delays and disruptions. Fundamentally, there are two distinct approaches to deal with these uncertainties.

One is to deal with uncertainty at the operations stage, that is, using recovery procedures. Recovery procedures aim to reschedule flights, crews and passengers rapidly after disruption. In chapter 2, we present several of these recovery models. The main challenge of this approach is that the airline must generate solutions rapidly. This poses serious tractability issues, as recovery problems have many decision options and are subject to numerous constraints, including slot availability, gate availability, crew and aircraft restrictions, etc. As a result, most of these recovery models only tackle one aspect of the airline scheduling problem, that is, they address aircraft, or crews, or passengers.

Another approach to deal with the problem of stochasticity of operations is to build more *robust* schedules at the planning stage. We review methodologies for incorporating robustness in airline schedule planning. We examine robust airline schedule planning methods that strive to achieve ease of recovery, or to reduce susceptibility to disruption. In figure 6.1, we summarize the robust models reviewed and presented in this thesis.

In chapter 3, we present new models for robust scheduling that focus on facilitating recovery when disruptions occur. After estimating the effects on passengers of limited aircraft swap opportunities during recovery, we design a robust fleet assignment model that generates

fleeting solutions with a limited number of aircraft families at spoke airports. This fleeting solution facilitates recovery and yields shorter passenger delays when aircraft shortages arise.

In chapter 4, we introduce two new models:

1. **The robust crew pairing problem with time windows:** First we generate an aircraft routing solution based on Lan et al's [27] model. Then, by rescheduling and postponing flight departures corresponding to critical (tight) crew connections, we generate a feasible crew pairing solution with a minimum number of critical crew connections, translating to fewer crew misconnections during operations.
2. **The integrated robust aircraft and crew pairing model:** Here we integrate aircraft routing and crew scheduling decisions in order to keep aircraft with crews, when crew connections are critical. This helps to contain disruptions and mitigate their propagation throughout the network. It also reduces the likelihood that crews will misconnect when they have tight connections.

We examine in chapter 5 the impact of scheduling policies on robustness. We analyze the debanking policy at Dallas-Fort Worth, initiated in November 2002 by American Airlines and American Eagle. As expected, spacing out departure and arrival times allows increased aircraft utilization and hence, lower operating costs. Debanking also results in less congestion on airport taxi-ways, runways and at gates, even with increasing numbers of departures and arrivals. Moreover, debanking allows for more robust operations, as measured by improved on-time performance.

Interestingly, debanking does not have to result in large average increases in passenger connection times, and moreover, significant reductions in the numbers of misconnecting passengers can be achieved. The only robustness drawback to debanking that we identified is the resulting reduction in aircraft swapping opportunities. This reduction, however, is problematic only if the total number of flights operated by an aircraft family at a hub airport is small.

Finally, to build robust airline schedules, there are two difficulties:

- a. Tractability; and

- b. Validation, which is the issue of how to assess the quality of a solution and how to measure the degree of robustness of a solution. One way is to use simulators, but the ability to model human decisions made during recovery is still often limited. This issue is directly linked to the issue of assessing the economic value of schedule robustness and finding the optimal trade-off between schedule robustness and operating costs.

6.2 Future Research: Robust Framework

The robust models reviewed in figure 6.1 incorporate a robustness criterion for at most two of the airline schedule planning subproblems: schedule design, fleet assignment, maintenance routing and crew pairing. Because the airline scheduling problem is solved sequentially and decisions taken for upstream subproblems often restrict the feasible choices to downstream subproblems, one possible future research topic is to estimate the impact of the use of a robustness criterion at one step of the sequential airline schedule planning process on the subsequent subproblems as measured by the changes in costs and robustness levels. The goal and challenge is to construct a robust framework that generates the “most” robust airline schedule plan over all the scheduling subproblems. For example, this framework could be:

- 1) As a first step toward a more robust schedule, debank the flight schedule at the hub airports to provide a more balanced schedule at the hubs and thus, reductions in airport congestion and flight delays.

- 2) For each sub problem, choose one robustness criterion in order to avoid conflicts. For instance, choose from Figure 6.2, [3] and [6] or [2], [4] and [7], to generate robust fleet assignments, aircraft routings and crew pairings.

Authors	American Airlines [1]	This thesis [2]	Rosenberger [3]	Lan Barnhart [4]	Ageeva Clarke [5]	Klabjan [6]	This thesis [7]
Robust criteria	Reduce hub operational inefficiencies	Aircraft ease of recovery	Aircraft ease of recovery	Aircraft routing less prone to disruptions	Aircraft ease of recovery	Crew ease of recovery	Crew pairing less prone to disruptions
Schedule design	Debanking			Time window reschedule			
Fleet assignment		Min number of aircraft families at spokes	Short cycles Min hub connectivity				
Maintenance Routing				Slack allocation	Creating overlapping aircraft routings		Select aircraft routing solution and crew pairings to minimize the number of tight connections
Crew Scheduling					Create overlapping crew pairings		
Comments	Better on-time performance	Increase aircraft swapping opportunities	Isolation of disruptions	Min flight propagation delay	Increase aircraft swapping opportunities	Increase crew swapping opportunities	

Figure 6.1 Robust model summary

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