Implementation of an Airline Recovery Model in an Event-Based Simulation

by

Fábio Faizi Rahnemay Rabbani

Submitted to the Department of Aeronautics and Astronautics
in partial fulfillment of the requirements for the degree of

Master of Science in Aeronautics and Astronautics

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

March 2004 [June 2004]

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Abstract

Airlines maximize the use of their resources by minimizing the time between consecutive flight legs in their aircraft and crew schedules. As a result, bad weather or unscheduled aircraft maintenance events can have a significant impact on an airline's operations. The consequences of these disruptions are major costs to airlines, passengers and, ultimately, to the economy itself.

In this thesis, the steps taken to implement an airline schedule recovery model in a realistic simulation of the U.S. airspace system are presented. The MIT Extensible Network Simulation (MEANS), an event based queueing model of the U.S. National Airspace System, can be used for tactical decision making, long term decision making and post priori event analysis. Thus, the addition of a recovery model is critical to obtain accurate simulation results.

The airline recovery model consists of an optimized aircraft re-scheduling model, a crew re-assigning model and a heuristic passenger itinerary search model. The model was used to simulate airline recovery procedures over the course of a day of operations for different scenarios.

Thesis Supervisor: John-Paul Barrington Clarke
Title: Associate Professor

Acknowledgments

This dissertation would have never been written without the help and support of very many people.

First and foremost, I would like to thank my advisor, Professor John-Paul Clarke, who made it possible for me to pursue my education at MIT. I will always be grateful to him. With his knowledge, understanding and kindness, Professor Clarke has among his students a big fan club.

In addition, I wish to thank Terran Melconian, who was of great help during this research in so many levels. No matter if our meetings went smoothly or in-TENSE-ivelly, they were always a step forward in my research.

Also, I would like to extend my gratitude to all of those who helped me during my research and those who enriched my experience at MIT:

My sincere appreciation to all professors with whom I had the pleasure to take classes with, especially Professors Richard de Neufville and Amadeo Odoni.

I would like express thanks to my lab mates at the International Center for Air Transportation, who were of help in finding data and coding: Francis Carr, Tom Gorin, Alex Lee and Jason Loy.

A big "thank you" to the great people I met at MIT. Many of you became dear friends to me and I'm very glad I got to know you.

Finally, I'd like to thank all those at the Aero/Astro Department who are always so attentive to the department's students. I would like to particularly thank Academic Programs Administrator, Mrs. Marie Stuppard and Director of Student Services, Mrs. Barbara Lechner.

My love and gratitude goes to my family and friends:

My always kind, patient and loving parents, Soheil and Simin. I can't express my feelings in a few lines here. But I have thank you for everything that you have done for me and my brothers.

My dearest sister, Emilia and my brother-in-law, Simeon. Thank you for being my "holiday hosts" during great part of the time I was at MIT.

Of course, my younger/older/brother/friend, Roberto; thank you for making the moments we shared together a playground of great memories.

All my relatives: my grandparents, uncles, aunts and cousins. Thank you for reminding me that there is nothing like unconditional love.

Kalina, thank you so much for your friendship and help.

My true friends, who have always been in touch with me. Thank you for the emails, letters and postcards.

To my future niece, with whom I expect to share my birthday parties in the years to come

"...and Owen suspected that to Duddits the past was always last week, the future always next week. It seemed to Owen that if everyone thought that way, there would be a lot less grief and rancor in the world."

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Chapter 1

Introduction

Airlines maximize the use of their resources by setting their schedules with very little slack time between the sequential flight legs flown by each of their aircraft and crew. In addition, airlines have traditionally sought to maximize their appeal to passengers (and thus revenue) by scheduling passenger itineraries with very short connection time between flight legs, so that the elapsed time from origin to destination for each multi-leg itinerary is as short as possible. As a result, disruptions due to bad weather conditions or unscheduled aircraft maintenance can have a significant negative impact in airline operations.

Historically, decisions regarding flight delays and cancellations in response to a disruption, and the post disruption effects on aircraft, crew and passenger schedules, have been made by airline operation controllers on the basis of experience. However, over the past two decades, operations researchers have developed powerful recovery models that generate a near optimal set of flight leg delays and cancellations, aircraft routings, crew pairing and passenger itineraries.

While these recovery models have been gaining greater acceptance, the complexity of the environment in which airlines operate makes it difficult to accurately determine the benefits and/or the weaknesses of specific recovery models a priori. This is also the case in the burgeoning area of robust scheduling, where operations researchers have developed models that generate schedules, which are more robust to disruptions, as the proposed models are even further removed from the airline cost savings and passenger benefits they are designed to achieve. Thus, there is a clear necessity for a simulation tool with sufficient fidelity that researchers and operators alike can use to evaluate proposed scheduling and recovery strategies.

1.1 Motivation

The United States National Airspace System (NAS) is the largest, busiest, and most complex aviation system in the world. Thus, it may be argued that the NAS is the ultimate operating environment for an airline. From an operational perspective, the NAS is composed of the set of airports, air carriers, and air traffic controllers that collectively make safe and efficient air transportation possible within the United States. The Federal Aviation Administration (FAA) is responsible for the safety of civil aviation within the United States and certain ocean areas [1]. This responsibility extends from air traffic control (ATC), aviation safety and security to international coordination. To maintain or enhance current safety and efficiency levels in the face of growing demand, the FAA frequently uses simulations to predict the future interactions of the NAS agents under various scenarios. Other stakeholders of the NAS, such as airlines, invest in the development of simulations to evaluate the response of the system to decisions that affect planned schedules.

According to Wieland et al. [19], there are three primary reasons why a model of the NAS is needed: tactical decision making (predictive modeling), long term decision making (strategic modeling), and post priori event analysis (also a type of strategic model). Tactical decision-making requires an understanding of the NAS in enough detail and with enough fidelity to influence near-term decisions. In other words, tactical decision-making is used in an operational context. Strategic decision-making differs from tactical decision-making in that it is used in a planning context and thus involves decisions made over longer time scales. Post-event analysis is conducted to understand what has happened during some previous event so that useful information can be extracted and applied to future situations.

The MIT Extensible Air Network Simulation – MEANS – is an event based queueing model of the NAS that can be used for all three purposes described by Wieland et al. [19]. The term "event based" refers to the fact that events (e.g. take-offs, arrivals) are scheduled at some point in the future, and once an event has been executed, the simulation time advances to the time of the next event [13]. The model includes queues that intercalate these events to simulate the pattern in which elements (such as aircraft and passengers) are handled during operations.

In general terms, MEANS can be used to analyze current and hypothetical airline network configurations, air traffic rules, and collaboration between airline and air traffic control [12]. MEANS allows the user to simulate the operating conditions and the operational decision of air traffic management and airlines while tracking the movement of every aircraft and passenger in the NAS [4].

Because of its complexity, the behavior of the entire NAS is difficult to predict: each agent has their own objectives and the ability to modify their behavior in response to changes in the operating environment. Modular simulation models are especially desirable for complex systems such as the NAS, because their constituent modules can be modified, if specific modules are either irrelevant or must be enhanced to achieve the desired fidelity, without sacrificing tractability. [4]

In recognition of this, MEANS consists of several modules, divided in three classes. Four of these modules (enroute, tower, taxi and gate) are referred to as state modules because they manage the movement of aircraft through the NAS. Two other modules, the Air Traffic Control System Command Center (ATCSCC) module and the airline module, are referred to as decision-making modules because they do not alter the state of a flight leg directly, but rather, determine the desired changes to the flight schedule that are then executed by the state modules. The weather module represents a third class of modules – informational modules – which provide the data that enables other modules to make decisions or alter their operating conditions. [4]

In real life operations, the FAA restricts the flow of traffic in and around congested areas that may arise from either excessive traffic or poor weather conditions. In MEANS, the ATCSCC module monitors the predicted demand and the predicted capacity (both in terms of arrival rates) for each airport. During simulated bad weather conditions, the capacity of an airport can reduce considerably. If the predicted demand exceeds the predicted capacity, the ATCSCC module, following the FAA regulations, assigns arrival slot times to the incoming flights in order to assure safe distance between consecutive landings. These slot assignments normally result in flight delays and, consequently, changes in the airline schedules that could propagate throughout the system.

Airlines respond to unscheduled variances by gathering all possible information about the current status of the airspace system, concentrating on the events that affect the airline's flights, evaluating the situation of each individual element of their subsystem (e.g. aircraft, crews and passengers), and determining the most beneficial solutions to adapt their schedules. In practice, the airlines manage the process of recovery in what is often referred to as an Airline Operations Control (AOC).

The AOC is the center where most of the tactical decisions of an airline are made by specialized controllers and transmitted to the other agents of the NAS. The operations in an AOC may relate to many elements of the airline. In MEANS, the main role of the AOC module, which is a component of the airline module, is to manage the effects of disruptions on aircraft, crew and passengers. Currently, MEANS' AOC module is very trivial and deals with schedule disruptions by canceling flights with an excessive expected delay.

Additionally, crew schedules are not currently considered by MEANS in the recovering decision, mainly due to the lack of data: airlines typically do not disclose crew schedules due mostly to competitive concerns. Thus, if crews are to be considered in the recovery process, an initial crew schedule is necessary.

1.2 Objective Statement

The main objective of this research was to add an automated AOC module to the existing capabilities of MEANS. In order to do this, airline recovery models were developed, implemented within MEANS and validated. The resulting AOC module was validated through simple recovery procedures in the course of one simulated day for a major U.S. air carrier. To comply with the main objective, a crew schedule generator was built to obtain an initial crew schedule.

1.3 Thesis Outline

This document is divided into seven chapters:

In **Chapter 2**, an overview of airline planning and operation procedures is presented. An outline of disruptions and their effects on airline operations, with emphasis on weather-related disruptions is also presented.

In **Chapter 3**, the details of the MIT Extensible Air Network Simulation are presented in order to state the need for a crew schedule and a more sophisticated AOC module.

In **Chapter 4**, the airline crew schedule generator developed during this research is introduced and preliminary results are presented.

In **Chapter 5**, the airline recovery model and the algorithm that was implemented in MEANS are presented.

In **Chapter 6**, the results obtained during the validation of the AOC module are summarized and the chapter is concluded with the final considerations and future research.

Chapter 2

Overview of Airline Planning and Operations

The profitability of airline operations depends on the generation of good flight schedules. These schedules are created to meet customers' traveling needs while attempting to maximize profits. The development of a flight schedule involves defining the aircraft and crew assignments while transporting passengers from their origin to their destination. The complexity of flight scheduling is attributed to the operational constraints that have to be considered during the process. The influence of constraining factors increases during disruptions, when the flight schedules become erratic and aircraft and crew availability become uncertain. It is then that airlines respond to disruptions by assigning new schedules that still meet the operational constraints and maintain the flow of operations, avoiding major costs.

An overview of airline scheduling is presented in this chapter, along with an assessment of causes to airline disruptions and how airlines respond to these disruptions. Additionally, airline operational decisions and some concepts on airline costs are reviewed. The terminology used in this dissertation is defined throughout the chapter.

2.1 Airline Operational Constraints

Teodorović [18] states that "elaborating a network airline schedule is combinatorial by nature: of the large number of possible alternatives, those must be chosen that satisfy to the greatest extent the interests of the air carrier, the passengers and operational constraints". Among these operational constraints, the following can be highlighted:

- Aircraft Technical Maintenance – for safety reasons, aircraft parts must be inspected or replaced at specific times and at specific locations. In addition, when greater technical work must be done, aircraft are removed from operations for a considerable period of time;

- Meteorological Conditions Prevailing at Airports - some airports might be closed for take off and/or landing operations during intense thunderstorms and snowstorms, and when there is the presence of strong wind gusts in the airport region;

- Crew Regulations – under FAA laws and air carrier agreements, crew regulations impose many restrictions regarding crew rest periods;

- Airport Physical and Operational Limitations – airports have a limited number of gates and, in some instances, limited operation hours to be observed. Operation hours should be particularly constraining for long-haul traffic, due to different time zones.

2.2 Flight Scheduling

In order to build a flight schedule, airlines need a set of inputs, which are commonly classified into physical and non-physical. According to the OECD [14], the main physical inputs are: labor, represented by employed personnel; capital, represented by the fleet of aircraft, buildings, repair/overhaul and maintenance equipment, computer and communication facilities, and airport, aircraft, passenger and baggage service facilities. The main non-physical inputs are the city-pair flying rights, allowed flight system and passenger "loyalty".

For an airline, a *station* is defined as an airport it serves. The flight information composed of an origin station, a destination station, a departure time, and an arrival time is called a *flight leg* or *leg*. The *block time* of a leg consists of the period of time elapsed between the moment the plane is pushed-back from the gate at the origin station and the moment the plane arrives at the gate of the destination station.

Airlines determine the flight schedules more than 3 months prior to the day of operation. The flight schedule includes the origin and destination stations, and the departure and arrival time of each leg. Because the flight schedule is developed so far in advance of the day of operation, it is very likely that there will be minor changes in departure and arrival times.

According to Janić [9], in the framework of a schedule design, an airline should perform the following activities: define the potential markets (routes) to be served; determine the flight frequency on the particular non-stop routes regarding the available network schemes (either point-to-point or hub-and-spoke [1], or both in a mixed scheme); determine the departure and arrival time for each flight and route by the aircraft type; estimate the potential revenues and cost associated with carrying out the preceding steps.

As is to be expected, the cost of operating the flight schedule may be reduced by maximizing the use of capital and labor. Thus, the most important processes in airline scheduling are the building of aircraft rotations and crew schedules. These processes are presented in the following subsections.

---

[1] In general terms, a hub-and-spoke network refers to an airline flight schedule where most of the flight legs start or end in a small subset of stations. The stations with lower activity are called *spokes*. A hub-and-spoke network allows the airline to capture a large number of origin-destination markets with a higher utilization of their aircraft. In order to do this, flight arrivals and departures are grouped into complexes. A *complex* consists of a set of arrival flights called the *arrival bank*, followed by a set of departing flights called the *departure bank*.

Airlines could have in their major hubs as many as a dozen connecting complexes. In this perspective, the smooth operation of the complexes becomes essential for the airline to keep up with their schedules. In the period between the arrival and departure banks, the airlines have to deal with passenger connections, crew briefings and debriefings, baggage transfer, and aircraft servicing.

2.2.1 Aircraft Rotations

After the flight schedule is set, each leg is assigned to an aircraft with a specific passenger capacity. In an airline, the *fleet* is a set of planes of the same type but not necessarily of the same cabin configuration (i.e. planes of the same fleet type can have different passenger capacities). The *tail number* identifies a specific aircraft and is commonly used by the airline planners to assign the aircraft routing. A *rotation* is a sequence of flight legs assigned to a tail number between the aircraft's maintenance checks.

Each rotation must satisfy certain maintenance restrictions that are imposed for safety reasons. Under FAA rules, each airline has to provide the administration with the maintenance plan for each of their aircraft. Each aircraft type has different service requirements, thus, maintenance schedules are fleet specific. It is common that larger airlines have several maintenance bases for their larger fleets, allowing more flexibility in their schedules.

The time required for a scheduled maintenance is a function of the type of maintenance to be performed. Overnight checks are performed at maintenance stations and are done as often as every two, three or four days, depending on the amount of hours flown by the aircraft. On the other hand, the heaviest maintenance event may take an aircraft out of service for up to 1 month. During this heavy maintenance, the aircraft is almost completely disassembled, each part is checked and repaired or replaced if necessary, and the aircraft is then re-assembled.

2.2.2 Crew Pairings

A set of consecutive flight legs flown by a crew that satisfies rules and contractual restrictions is called *duty*. The time between consecutive flight legs is known as *sit time*. The time difference between the end and the beginning of a duty is the *elapsed time* [16]. Duty time usually includes one hour of briefing before the first flight, when the crew prepares for the flight, plus the length of the flight legs to be flown, in addition to the time crew members spend on the ground between flights and the 15 to 30 minutes after completion of the last flight, for debriefing.

A sequence of flight legs assigned to a crew, usually lasting between 3 and 5 days, starting and ending at the crew's domicile station is called a *crew pairing*. Such stations are called *crew bases*. The time between the departure of the first flight of the first duty and the last flight of the last duty is defined as the *Time Away From Base* (TAFB). A schedule of crew pairings consists of crew members' monthly *bidlines*; that is, a sequence of crew pairings separated by minimum off-duty rest at the crew base. The time spent on the ground by a crew between two nonstop flights is not considered to be rest time. Crew *rest time* comprises the time spent on the ground that is greater or equal to some prescribed time interval, obeying certain rules.

The FAA requires that the crew must receive compensatory rest if they fly more than 8 hours within a 24 hours period. A pairing that violates this planning rule is illegal and cannot be included in a crew schedule. Another FAA rule states that, within any 7 day period, a crew cannot be assigned to fly more than 30 hours and must be given a rest of at least 24 hours [1]. More detailed FAA rules on crew schedules are presented in Chapter 4.

Commonly, the cockpit crew is fleet specific while the flight attendants may be assigned for more than one fleet type, depending on their qualifications. Thus, it is a common practice to consider the cockpit crew the pivot of the crew assignment problem. Still, determining the number of flight attendants in each leg could be complicated: regulations on minimum number of flight attendants are determined by factors such as the size of the plane and the scheduled flying time; whereas the time of the day and the level of service to be offered leave the number of flight attendants dependent to the airline's interests.

After determining the pairings, the next planning stage is to assign pilots to pairings. The crew assignments can be done using either a bidline or a preferential model. A bidline model generates a set of bidlines, and pilots sequentially choose the schedule they prefer in order of seniority. In a preferential model, pilots place weights on duties, which they value in a bidline. [16]

2.3 Airline Schedule Disruptions

Several studies have shown that delays have risen dramatically in the past decade, with especially large increases in gate and taxi delays [7] [15]. One of the primary mechanism through which these delays occur is that, during severe weather and airport congestion, the FAA increases the time between consecutive landings through the so called Ground Delay Programs (GDPs).

In the early 1980s, the FAA started applying GDPs in order to allocate arrival time periods, or *slots*, for each flight leg landing at a specific airport. The primary advantage of a GDP is that those legs arriving at a disrupted airport are delayed prior to takeoff. By taking this measure the ATC avoids airborne holding the aircraft to circle the airspace around the disrupted airport, which might risk passengers' life (aircraft can run out of fuel during lengthy holding on the air) and increase the airline overall operating costs (fuel consumption in the air is greater than on the ground). The drawback of this procedure is that the number of landings and takeoffs at the airport where the GDP was called is reduced, and consequently flights can be significantly delayed during operations.

The consequences of schedule changes during operations are major costs to the passengers, airlines and, ultimately, to the economy itself. According to Lettovsky [11], the main costs contributors are unplanned ferry flights, crew deadheading, extra flying and operating expenses due to extra activities caused by increased congestion, costs related to passengers rebooking, mishandled bags, extra passenger meals and hotel costs, increased passenger overbooking and denied boarding costs, and transfer of revenue to other airlines to accommodate stranded passengers.

Air Traffic Control (ATC) delays cost airlines and their customers an estimated \$6.5 billion in 2000, excluding billions in additional downstream costs to other sectors of the economy. This sum included \$2.3 billion in aircraft operating costs, of which \$220 million was attributable to delays at the gate, \$895 million to delays during taxi-out, \$889 million to airborne delays, and \$333 million to delays during taxi-in. [1]

On-time performance numbers are reported each month to the Department of

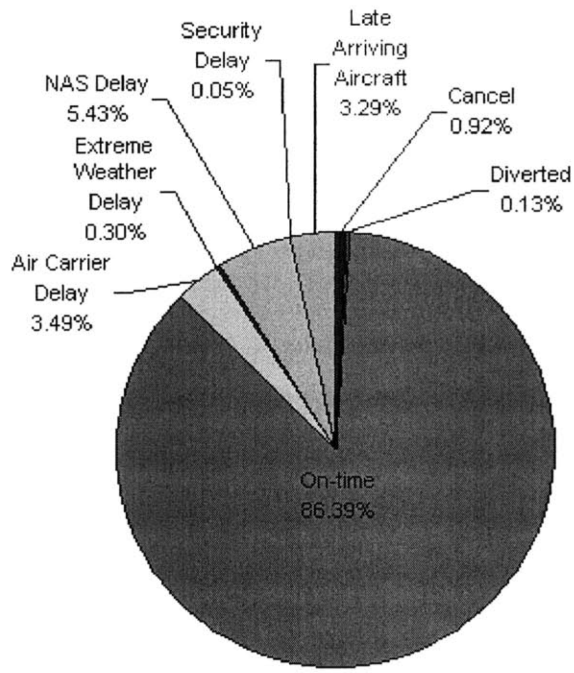

Figure 2-1: Airline On-time Performance: All Airlines - October 2003 [15]

Transportation's Bureau of Transportation Statistics - BTS (Office of Airline Information) by the 16 largest U.S. air carriers. Figure 2-1 illustrates, based on airline reports, how schedule performance is affected by different causes.

There is a fine line between some delays coded as "Extreme Weather" (due to weather conditions that physically endanger an airborne flight) and others coded as "NAS Delay" (where poor weather conditions require precautionary measures). The purpose of the two categories is to identify whether an organization or party could take corrective actions: delays or cancellations coded "Extreme Weather" cannot be reduced by corrective actions, whereas delays or cancellations coded "NAS" could be reduced with corrective actions by the airports or the FAA.

Airlines are not required to report the causes of late-arriving aircraft, but it is likely, given the direct relationship between the time of departure and the time of arrival, that these weather delays are in the same proportion as the weather-caused delays in other categories. The true picture of the impact of weather on airline flights would then consist of the "Extreme Weather" delays, plus the weather portion of the National Airspace System category, plus the weather portion of the Late Arriving

Aircraft category. [15]

Although the numbers above seem small compared to the great number of flights in the U.S., it should be considered that the weather problems are usually concentrated events. These events will inevitably affect all flights entering or leaving the area with bad weather either delaying, diverting, or canceling them; as a matter of fact, as many as 20% of all flights could experience delays or cancellations during bad weather conditions [11]. On the other hand, maintenance problems are spread randomly throughout the airline operation and can often be absorbed through isolated action.

2.4 Airline Schedule Recovery

Even though airlines plan for disruptions during the scheduling stages, the ability of their schedules to absorb delays is limited. Aircraft schedules are usually very tight in order to maximize equipment utilization; crew assignments are set up to minimize flight credit; and hub-and-spoke networks set up short connection time for the passengers. Thus, under isolated incidents or general disruptions, airlines are always subject to major constraints, which need to be treated, sometimes within a very short period of time.

The typical airline recovery procedure is done in stages. In the first stage, the airline reroutes aircraft, and delays and cancels flight legs. During the second recovery stage the airline assigns crews to the remaining flight legs by rerouting the regularly scheduled crews and calling upon reserve crews. In the third stage, the passengers are rerouted. Also, airlines can propose reassigning legs to the specific arrival slots. The airline recovery procedure is managed and executed by the Airline Operations Control.

2.5 The Airline Operations Control

As mentioned before, air carriers usually deal with tactical decisions at command centers known as the Airline Operations Control (AOC). In an AOC, operators keep track and control flights on various aspects. The functional arrangements of the AOC at different airlines are distinct, but the general configuration includes Dispatchers, the Traffic Management Desk, the Operations Desk (which consists of the Operations Coordinator, Crew Scheduler, Costumer Coordinator and Aircraft Router and Planning Coordinator) and the Meteorological Desk. The functions of these operators are briefly described in the following subsections.

2.5.1 Dispatchers

According to the FAA regulations, dispatchers are responsible for monitoring the progress of each flight; issuing necessary instructions and information for the safety of the flight; and canceling or redispatching a flight if, in his/her opinion or the opinion of the pilot in command, the flight cannot operate or continue to operate safely as planned or released.

Their workload is fixed, so each dispatcher is assigned to cover a specific set of flights. The flight plan should be created up to eight hours prior to departure. In order to plan a flight, the dispatchers overview the compliance with safety requirements, seeking minimum operating costs and meeting the overall airline objectives.

Flight aspects such as air speed, flight route, and altitude will have an effect on fuel consumption. The dispatching process involves determining fuel load, maximum payload, total weight and balance. Maximum allowable takeoff and landing weights can be constrained further by runway length, air temperature, and airport elevation. Since the dispatchers have direct contact with the cockpit and with the operations coordinator, they provide pilots with the latest AOC decision updates.

2.5.2 Traffic Management Desk

The Traffic Management Desk (TMD) gathers most of the traffic information to the AOC. The main function of the TMD is to interact with other air carriers, with the FAA and airport ATCs, negotiating GDP calls and slot allocations. Occasionally, the TMD act as dispatchers and keep the rest of the AOC informed about the status of

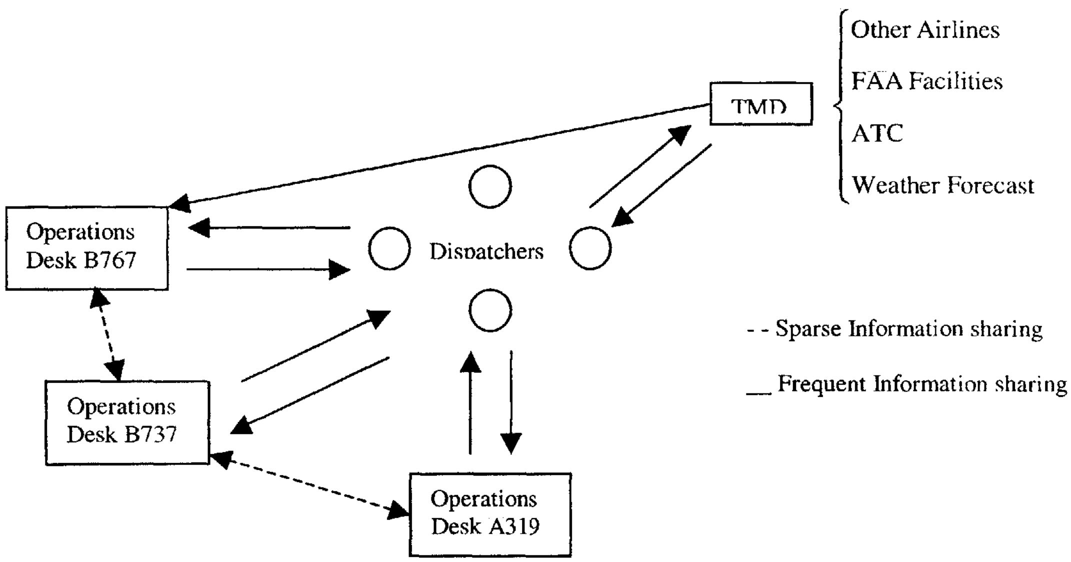

Figure 2-2: Typical AOC Information Flow with Operations Desks Separated by Fleet Type

the airline's flights.

2.5.3 Operations Desk

The Operations Desk consists of the operators that deal with aircraft, crews and passengers. The ways that responsibilities are distributed between the Operation Desks depend on the airline. For some airlines each Operations Desk covers specific flights based on origin and destination (e.g. international, domestic, westbound flights etc.). For other airlines, the criterion is fleet type. As a matter of fact, some U.S. air carriers have recently shifted from the origin-destination to fleet type divisions. The main reason for this shift is that dealing with aircraft of the same fleet type and the corresponding crews for the specific aircraft can reduce considerably the workload of the operators and consequently the time to respond to disruptions.

The AOC information flow sketch in Figure 2-2 is an example of Operations Desk distributed by fleet type. Notice that there still could be some iteration between the Operations Desks: flights could be assigned to a different fleet type or could be delayed for the arrival of connecting passengers.

The *Operations Coordinator* of an Operations Desk mediates the decision process within the desk . He/She also has the function of gathering information and transmitting to the dispatchers the new schedules processed by the desk operators. The main operators of the Operations Desk are Crew Schedulers, Customer Coordinators, Aircraft Routers and Planning Coordinators.

Crew Schedulers

The Crew Schedulers' job involves predicting the work time for each of the crew pairings and their costs, trying as best as possible to keep the planned schedule, despite the inevitable disruptions that occur. Besides the general rules, most airlines still have to comply with their contracts, which usually have more constraints than the labor regulations. In summary, to a crew scheduler, a flight leg is part of a series of work assignments that starts and ends at the crew domicile.

Customer Coordinator

The Customer Coordinator is expected to bring efficiency, low costs and passenger satisfaction together. To a Customer Coordinator, a flight leg is a number of seats for passengers at a specific time, from departure to destination. During their daily activities, the Customer Coordinator receive frequently "flags" sent by the Marketing and Statistics Departments informing them about specific flights that should not be disrupted. These flights might involve those with greater marketing interests or the ones that have been recently cancelled or delayed.

Aircraft Routers

Aircraft routes will often become infeasible during irregular activities. Aircraft Routers monitor and adjust the routing of aircraft in the fleet, while complying with the aircraft maintenance requirements. The Aircraft Routers might swap aircrafts between flights, redirect on-air flights, cancel flights, or create new flights.

Planning Coordinator

The Planning Coordinator does a preplanning job, working on the maintenance checks over ten days prior to the scheduled mechanical evaluation. He/She analyzes the on-location staff numbers and availability in the various maintenance stations and determines the best places for scheduled and non-scheduled maintenance.

2.5.4 Meteorological Desk

The Meteorological Desk deals with one of the most important considerations in planning and executing a flight: the current and anticipated weather en-route and at the destination. Under FAA rules, an airline may not dispatch an aircraft if the weather forecast indicates that the aircraft cannot safely reach its final destination. The weather station in an AOC provides current and anticipated weather conditions and issues early warnings when inclement weather disruptions are expected. The scale of impact on airline operations can often be significantly decreased if an accurate and timely weather forecast is available. Cloud height, horizontal visibility, wind speed and direction, and areas of expected turbulence are included in every flight plan. If the weather changes during a flight, the captain will work with the AOC to adjust the plan accordingly.

2.6 Operational Decisions

In response to disruptions airlines can take corrective measures that involve aircraft, crews or passengers or a combinations of these elements. Decisions such as delaying the departure time of a flight leg and/or rerouting a flight affect more than one airline element; other decisions such as equipment swapping would only involve one element (aircraft). The most common operational decisions for aircraft, crews and passengers are summarized below:

Aircraft

- Cancellations - canceling cycles (a set of flights that start and end at the same station) or segments in the daily schedules can reestablish the original aircraft rotations; the consequences of such decision depend on the time of day, where the aircraft is located and what is its future schedule.

- Ferrying - the procedure of sending an aircraft to a desired location without any passengers is called ferrying. Ferry flights do not produce any revenue but still incur operating costs. Aircraft which were assigned to cancelled flights might have to be sent to another station depending on their original schedule. Also aircraft without scheduled flights (reserve aircraft) might be sent to a location in order to substitute an aircraft under unscheduled maintenance.

- Swapping - when flights are delayed and the future legs flown by the aircraft will be compromised, airlines might search for aircraft of the same characteristics (preferably same fleet) available for swapping in order to minimize the overall system delays or meet other airline objectives. This decision has to be made carefully in order to comply with each of the aircraft maintenance requirements and locations.

- Rerouting - under extreme circumstances such as closed airports, flights might be redirected to other locations. In most cases this decision results in subsequent ferry flights or the adding of an extra flight leg, deadhead crews, and passengers that miss their planned connections at the original destination. Thus, airlines avoid rerouting as much as possible.

- Push Back - the simple act of holding a flight departure can sometimes avoid any of the decisions above, without affecting considerably any of the flight elements.

Crew

- Rescheduling - reconstructing pairings can result in changing more than one crew pairing. The level of complexity of the decision process depends on the recovery models used, the airline size and the length of time available for the decision to be made.

- Compensatory Rest - when a crew has reduced rest time on the previous day (within the boundaries of legality) the airline has to make sure that compensatory time is added to the next rest period.

- Reserve Crews - crews that are not assigned to any flights in day schedule but are expected to be available to cover flights that cannot the flown by active crews. The reserve crews usually are the third line holders after the original scheduled crew and an available crew at the same airport where the scheduled crew is supposed to be. The call for reserve crews depends mainly on when and where they are required and how the performance of the airline will be affected by their presence.

- Deadheading - sending crew members as passengers is commonly done for reserve crews assigned to start the duty at a non-crew base station; also crews which violated legality constraints can be deadheaded back to their home bases. Airlines usually have agreements where their crews can be deadheaded on each other flights.

Passenger

- Push Back - when many passengers with the same itinerary might miss their connections, airlines might pushback the schedule so these passengers do not get stranded at a connecting airport.

- Redirect - changing passenger itineraries is a common practice when cancellations or flight delays occur.

2.7 Airline Incurred Costs

Generally, it is very complex to access airline operational decision costs. According to Holloway [8], there is often no single number that can be identified as the cost of a decision. However, in order to make better decisions in the future, it is necessary to categorize costs into avoidable costs, incremental costs, sunk costs and opportunity costs.

Avoidable costs are the costs that can be prevented by a decision not to do something, to do less of something or to do something in a different way. Incremental costs are additional costs that will flow from a decision to do something, to do more of something or to do something in a different way. According to Holloway [8], both avoidable costs and incremental costs need to be set against the revenue changes associated with each respective decision. Sunk costs are briefly defined as any past expenditure that cannot be recovered; e.g. initial costs of an aircraft in excess of its current market value (actually it is not relevant to decisions going forward). Only elements of past expenditures that are "recoverable" are relevant to current decisions. Opportunity (or economic) is any costs associated with opportunities forgone by not putting a resource into its highest value alternative use; it is not a cash outgoing, but a recognition of the value existing in opportunities that now cannot be taken up. In practice, opportunity costs are everywhere.

Moreover, in the airline industry it is usual to distinguish between operating and non-operating costs. The former are incurred conducting air transport operations, whilst the latter are attributable to activities other than air transport [8]. When dealing with tactical decisions it is reasonable to concentrate cost measures to these direct operating and non-operating costs.

In the following section the airline financial statement, known as Form 41, is presented and the costs considered in the recovery decisions during this research (basically avoidable and incremental costs) are stated.

Delay Type / Cost Category	Permanent	One-Time Airborne	One-Time Ground
Direct Flying Operations			
Pilots			
Fuel			
Flight Maintenance			
Direct			
Burden			
Equipment Ownership			
Depreciation			
Rentals			
Insurance			

Table 2.1: Cost Categories Included in Delay Cost Estimations [12]

2.7.1 Form 41 Costs

All major United States airlines and large regional airlines are required to provide financial statements quarterly to the Department of Transportation. These statements include Balance Sheets Income Statements, Operating Costs by Equipment Type, and Summary Operating Statistics by Equipment [6]. This information is broken down by category and made available in a database. The section of costs that is of most interest is the Flight Operation Cost section. These costs can be separated into Direct Flying Operations (including Pilots and Fuel), Maintenance (including Direct Airframe, Direct Engine, and Maintenance Burden), and Equipment Ownership (including Depreciation, Rentals, and Insurance).

The data in Form 41 is provided in total values for the quarter. But, according to Melconian [12], one may assume linearity for these values provided they are a function of time. For example, for a given quarterly Flying Operating Cost in a fleet, the corresponding value on an hourly basis would be the quarterly value divided by the number of hours flown by the aircraft type. Some of these costs are in fact incurred on an hourly basis. Fuel, for example, is clearly a cost directly related to the number of hours that the aircraft is in use. On the other hand, costs such as ownership costs, do not depend on the number of hours the aircraft in use, but still airlines report them on block-hour-basis.

The inclusion of some of the classifications, shown in Table 2.1, may raise questions. The direct maintenance cost is partly dependent on hours flown (for the short-haul checks) and partly independent (for the long-haul checks). Fuel is not shown as being part of the cost of a ground delay, even though there is some consumption while the aircraft is idling on the ground. The amount of fuel used while on the ground is sufficiently smaller than to the amount of fuel used while airborne that it can be neglected. Finally, it is worth noting that direct maintenance costs are not included for a ground delay, but crew costs are. This is because crew hours are calculated based on block time, whereas aircraft operating hours are calculated based on airborne time. Therefore, a delay on the ground counts as time for the pilots but not for the airframe. [12]

Chapter 3

The MIT Extensible Air Network Simulation

The MIT Extensible Air Network Simulation (MEANS), introduced in Chapter 1, was initially designed to support the exploration, development and evaluation of Air Traffic Management (ATM) concepts for Collaborative Decision-Making (CDM), in particular, and for Traffic Flow Management (TFM) in general. Since then, the capabilities of MEANS have been expanded to allow evaluation of airline scheduling concepts, and the reliability and robustness of airline schedules. Because of its flexibility, modularity, and the ability to simulate operations under uncertainty and other probabilistic phenomena, MEANS is used to simulate the NAS, a complex stochastic system.

The structure and constituent modules of MEANS are described in this chapter. The descriptions are adapted from the forthcoming paper in the journal "SIMULATION: Transactions of the Society for Modeling and Simulation International – Special Issue of Simulation of Air Traffic" entitled "MEANS – MIT Extensible Air Network Simulation" by Clarke, Melconian, Bly and Rabbani [4].

3.1 Model Structuring

As mentioned in Chapter 1, MEANS consists of several Modules, which work together to simulate the NAS. These modules can be classified in three groups: State Modules, Decision Modules and Information Modules as follows:

State Modules are modules that represent the states through which flights pass as they traverse the NAS. The State Modules consist of Tower, Enroute, Taxi and Gate modules;

Decision Modules are modules that do not change the state of a flight leg directly, but rather indicate the changes that need to be made, and then send this information to the modules that will execute the desired changes. They consist of Air Traffic Control System Command Center (ATCSCC) and Airline Module;

Information Modules are modules that provide information to other modules so that they can make decisions or change their operating conditions. The sole information module in MEANS is the Weather Module.

Although each of the seven modules must be provided in order for MEANS to function properly, the user can decide on the level of detail for each module. The user can also select alternative implementations of a module to be used at a specific airport or set of airports, or for a specific airline. It is thus possible to simulate a certain airport or airline for which one has an extensive data with a high-fidelity module, while continuing to apply a lower-fidelity module with fewer data requirements for the remainder of the NAS. For example, in this research an automated AOC module was implemented for one specific airline while the remaining airlines used a trivial AOC module. Figure 3-1 shows the relationships between MEANS' modules.

3.2 Inputs

In MEANS, air traffic flow has been modeled through a network of the major airports in the United States. Each airport in the network is represented as both a source

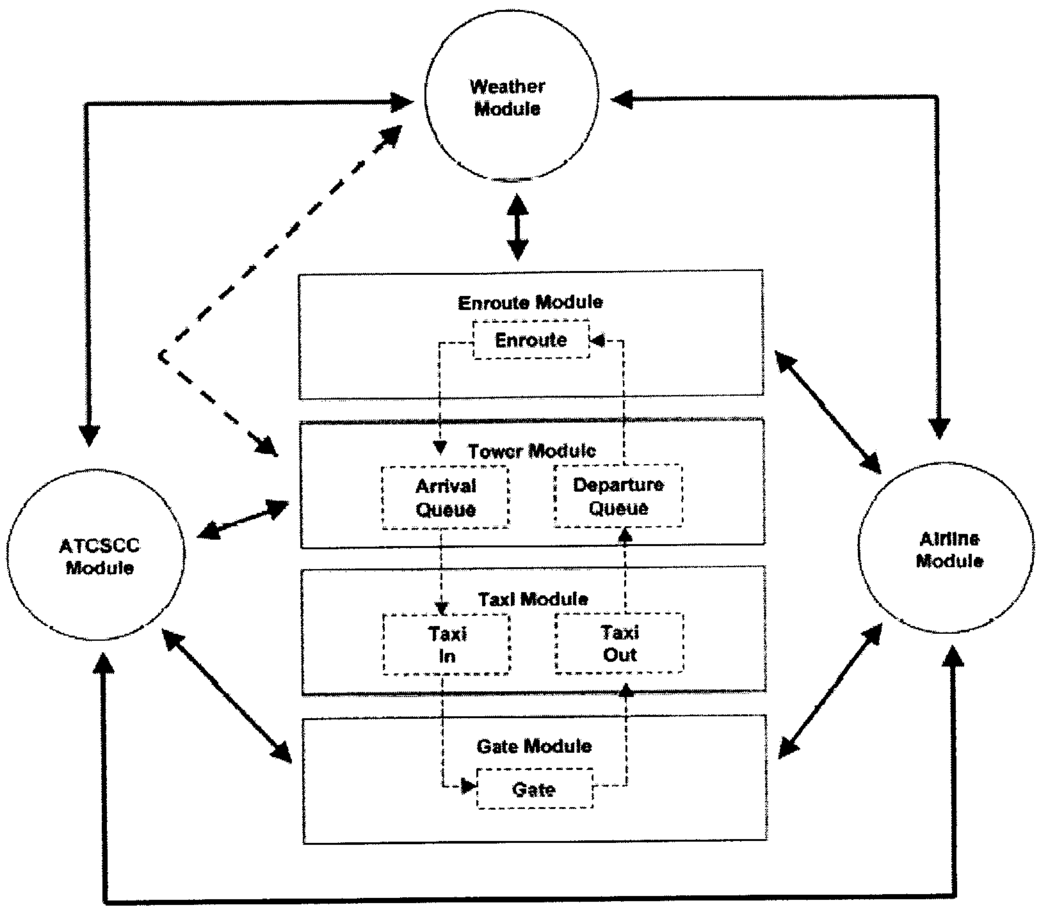

Figure 3-1: MEANS Module Relationships [4]

and a sink for air traffic with a capacity profile that captures the tradeoff between arrival and departure rates, as well as the probabilistic transitions between weather conditions, Visual Flight Rules - VFR and Instrument Flight Rules - IFR, capacities. An artificial source/sink is used to reflect the impact of all other airports in the NAS. The simulation tracks every flight in the NAS, through the network without going down to the detail of secondary dynamics at the individual flight level. For example, only simplified aircraft trajectories are used, and conflict detection/resolution in en-route or terminal area airspace is not simulated. MEANS also tracks each passenger in the NAS individually. The inputs required for MEANS depend on the specific module implementations being used. However, there is a basic set of inputs needed to run any simulation. This basic set of inputs includes the set of information about airports (latitude, longitude, identification code and name) and a complete flight schedule including flight numbers, tail numbers and scheduled arrival and departure times. Additional data that would be required for more detailed simulation includes weather data, distributions for flight and taxi times, and airport capacity curves.

3.3 Outputs

The primary output of MEANS is a set of files containing flow and state transition information for both flights and passengers. The file with flight information contains time stamps for each flight leg, indicating when it pushed back from the gate, when it reached the departure queue, when it left the runway, when it entered the arrival queue at the destination airport, when it landed at the destination airport, and when it arrived at its destination gate. Changes made to the scheduled times during the simulation are also recorded, along with information about ground delay programs that affected the flight. The file with passenger information includes, for each passenger, their originally scheduled flight legs and the flight legs they actually flew.

3.4 Modules

A brief description of the modules and how they operate in MEANS is presented in this section.

3.4.1 Gate Module

When an aircraft arrives at the gate, it enters the gate module. The gate module first determines the time that the aircraft must spend at the gate before it can be used for a subsequent flight leg – this is the minimum turn-around time or the time required to unload passengers and baggage; to clean, fuel and cater the aircraft; and to load the new baggage and passengers. The module then, in consultation with the airline module, selects one of several options. If the aircraft will be continuing on its planned sequence of flight legs, the subsequent departure is either scheduled for its planned time, provided the turn-around process can be completed before the scheduled departure, or delayed. Then, depending on the resulting delay, the subsequent flight leg is either delayed, cancelled or in some cases, another aircraft may be assigned to the subsequent flight leg. Similarly, the sequence of flight legs for a given aircraft may be changed to compensate for a disruption elsewhere in the airline. This decision is made by the airline module, but is executed by the gate module.

3.4.2 Taxi Module

Aircraft enter the taxi module either from the gate module (for departing flights) or the tower module (for arriving flights). The taxi module determines the time that each aircraft spends taxiing-out (the period between gate pushback and entry into the takeoff queue) and taxiing-in (the period between touchdown and arrival at the gate). There is significant uncertainty associated with the duration of these events because aircraft may take multiple paths to or from the runway and/or may have to stop at taxiway intersections to make way for other aircraft. Thus, the passing behavior of aircraft becomes a determining factor in the time required to reach the takeoff queue (departures), and the time required to reach the gate (arrivals).

There are currently three available taxi module implementations. A trivial implementation assigns constant taxi-out and taxi-in times that may vary based on airport if the user desires. A historical implementation uses historical taxi-out and taxi-in data in the form of taxi time distributions for different airports. The third implementation is based on a strong correlation between aircraft passing behavior and taxi times, both for a given aircraft being passed by or passing other aircraft on the way to (or from) the runway and taxi times. Hence, this implementation uses an estimation model that determines unimpeded taxi times and then incorporates the effects of aircraft passing. The amount of passing is found based on historically derived probability distributions that are functions of the number of aircraft on the ground either at gate pushback for departures or touchdown for arrivals.

3.4.3 Tower Module

Each airport has a single instance of the tower module which processes all arrivals and departures through the shared runway resource. The tower module does this by determining arrival and departure rates for each airport and based on these rates determines the time aircraft must spend in the arrival or departure queue. There are four tower module implementations two of which are currently available and two that are under development: historical playback, historical pareto frontier, simulated pareto frontier and controller agent.

In the already implemented historical playback, the hourly rates at which arrivals and departures are served are set equal to the hourly rates at which arrivals and departures were processed during the same hour on the day of interest. This implementation thus allows the user to evaluate the impact of changes in the NAS that do not effect airport tower operations in any way.

Also present in MEANS is the historical pareto frontier which determines the arrival and departure rates from pareto frontiers that are generated from historically observed airport operation points. Each pareto frontier – a curve that describes the tradeoff between the number of arrivals and the number of departures that can be conducted at an airport in a given time period – describes the situation of possible operating conditions (arrival-departure mix) for a given airport. In this implementation, each airport tower has two pareto frontiers, one for Instrumented Meteorological Conditions (IMC) and one for Visual Meteorological Conditions (VMC). The module first selects the appropriate pareto frontier based on local ceiling and visibility conditions as provided by the weather module. The specific operating point is then selected based on the ratio of arrivals to departures waiting to be served at the start of the time period, which approximates first-come-first-serve behavior. Because the pareto frontiers used in this implementation are based on historical data, the capacities are essentially weighted averages of the capacities obtained from the most often used runway configurations. Hence, these curves do not directly reflect the changing capacity due to utilization of different runway configurations.

One of the tower implementations currently being developed is the simulated pareto frontier implementation. Unlike the historical pareto frontier implementation, the pareto frontiers correspond to specific runway configurations and fleet mixes as well as different weather conditions.

In the controller agent implementation, rather then using arrival and departure rates, arrivals and departures are served on a case-by-case basis using the FAA spacing regulations and the same event sequencing methods used to generate the simulated pareto frontiers. While this method does not allow for arrival and departure stream re-sequencing, it does more accurately reflect the realizable airport capacity for a given schedule.

3.4.4 Enroute Module

The enroute module receives aircraft from the departure queue of their origin airport and schedules the time that each aircraft will enter the arrival queue at their destination airport. Currently, a detailed model of the enroute airspace is not part of MEANS. The enroute time for a given aircraft is determined by randomly selecting a time from the flight time distribution for the corresponding pair of departure and arrival airports. Airport-to-airport flight time distributions were derived empirically via analysis of historical data excluding flights that experienced significant holding at their destination, thus leaving a distribution which includes only the effects of enroute delays. Should it be desired, users may also use deterministic enroute times.

3.4.5 ATCSCC Module

The primary function of the ATCSCC module in MEANS is to initiate and manage GDPs and ground stops. The ATCSCC module monitors the predicted demand and the predicted capacity (both in terms of arrival rates) for each airport, up to six hours ahead of the current time. If the predicted demand exceeds the predicted capacity by a specified margin, a GDP is initiated for all flights scheduled to arrive at that airport during the period when this excess demand is predicted to occur. As an alternative to this automatic initiation, a list of GDPs can be specified by the user. Ground stops and GDPs affecting only flights arriving from certain airports or tiers of airports are not currently generated by the automatic predictor, but they can be specified by the user as an input.

Once a decision has been made, or an input received, the actual GDP must be put into effect. This is done with a procedure based on the Ration by Schedule and Compression algorithms used by the FAA. First, a list of slots is generated with spacing determined from the arrival rate of the GDP. Flights are then assigned to slots in the order in which they occur in the original schedule. Once this initial slot allocation is completed, each airline is then allowed to swap flights between its own slots, as well as to cancel flights, reassign aircraft, or any of a number of other changes that may be accomplished within an airline. If an airline cannot fill a slot which it has been given, either in the initial assignments or as a result of a subsequent cancellation, a flight from another airline will be moved forward into the vacant slot. The original airline's schedule will then be searched for a flight that can fit in the newly emptied slot. This procedure is repeated until a slot has been found that can be given to the original airline.

3.4.6 Airline Module

The airline module has three sub-modules: the schedule sub-module, the AOC sub-module and the passenger sub-module. The schedule sub-module is used to develop the initial airline schedule. The AOC sub-module manages flight delays and cancellations. The passenger sub-module tracks the delay for each passenger and supplies the AOC sub-module with the data required to access the impact of decisions on passengers.

Schedule Sub-Module

MEANS uses a baseline schedule of flights as an input. This schedule includes the planned departure and arrival time of each flight leg, and the specific aircraft (in the form of its registration number) assigned to each flight leg. This data is taken largely from the Airline Service Quality Performance (ASQP) database. However, the ASQP database does not contain information for all flights, and in order to simulate the actual system demand, hourly aggregate flight count information from the Enhanced Traffic Management System (ETMS) CODAS database is used to determine the ASQP demand shortfall. This shortfall is made up by generating artificial flights for each hourly block, so that the system demand reflects the ETMS CODAS demand. These flights are then added to the schedule by scheduling them at even time intervals during their assigned hourly block.

AOC Sub-Module

The AOC sub-module has three implementations: simple rule based, human-in-the-loop, and automated AOC. The first two implementations have been completed. In this work, an airline recovery model is implemented in order to automatically respond to schedule disruptions. The details of this implementation are presented in Chapter 5.

The first step in all three implementations is to determine the departure times of all flight legs if nothing is done in response to the incurred delays. In the case of a GDP or ground stop, the AOC sub-module determines the delay that each affected flight would incur if it were to use its assigned controlled arrival slots.

In the first implementation, the simple rule based implementation, flight leg cancellation decisions are made using a simple rule; if the expected delay for a flight is greater than a user specified limit, e.g. two hours, flight is cancelled. Aircraft are then assigned to the subsequent flight legs based on aircraft availability. No accommodation is made for aircraft maintenance or crew constraints.

In the human-in-the-loop implementation, the decisions regarding which flights to cancel and which aircraft to swap are made by human operators via a graphical-user-interface (GUI). The GUI provides both the expected flight delays and some limited feedback on the effects of decisions in terms of how later flight legs will be effected if a selected flight leg is cancelled or delayed. While aircraft maintenance and crew constraints are not explicitly considered within the implementation, these constraints may be considered by the human operator in making his/her decision.

Passenger Sub-Module

Passengers are an important part of the air transportation system, and direct assessment of the effects of NAS disruptions on passengers is becoming an increasingly important metric. Thus, MEANS supports the tracking of individual passengers and passenger itineraries. The passenger model takes into account both aircraft passenger capacities and minimum required connections times for passengers to make subsequent flights, therefore enabling the assessment of the number of connecting passengers disrupted as a consequence of late arrivals and the resulting delay due to the re-accommodation process. The passenger module can be disabled entirely if passenger results are not of interest for the scenario being considered, or if passenger itinerary data are unavailable.

3.4.7 Weather Module

The weather module provides both current and predicted weather conditions for an airport to other MEANS modules that request such data. In the context of the weather module, weather conditions are the wind, ceiling, and visibility for the airport in question. No enroute weather is currently implemented. This module currently supports two weather implementations: a trivial implementation and a historical implementation.

The trivial weather implementation assumes VMC for all airports in the simulation. In addition, all predictions will be VMC. This provides the ability for the user to remove weather as a consideration when running the simulation.

The historical weather implementation relies on a user supplied data file that contains weather information for the time period being simulated. The weather module processes requests for current conditions by performing a table lookup. The module handles requests for predictions in a similar manner.

It should be noted that the weather implementation used during this research had perfect weather predictions (although more recent versions of MEANS already include weather predictions based on historical forecasts). For example, a request for the predicted weather at an airport four hours in the future will return the same values as a request for the current weather at that same airport made four hours later in the simulation.

3.5 Implementation Considerations

One of the design goals in MEANS has been to create a flexible structure that allows complex modules to be implemented without requiring changes to the core interfaces. There are several mechanisms in place to support this design goal including a modular architecture, the use of general and extensible framework types, the implementation of an extensible modular interface, and a remote communication capability.

An emphasis has been made on providing MEANS with an easily extended modular interface, and this has been accomplished by using the object-oriented capabilities of C++. The clear distinctions and interfaces between the modules of MEANS allows each individual module to be replaced without changing the others. This makes it possible to select modules based on the scenario being run, using simple modules where data is not available or sensitivity to changes is low, and using sophisticated modules in the area under investigation. This modularity also reduces the learning curve by allowing developers to write new modules without becoming experts on the entire simulation.

Using the virtual inheritance mechanisms of C++, modules can extend the capabilities of many base types without changing the type definitions. For example, MEANS being a discrete event simulation has an event queue that is populated by actions scheduled to occur at discrete times. By providing an event base class with virtual interface functions, modules can create custom events that inherit from the provided base class and take any sort of actions desired and then insert these events into the event queue. Similarly, a virtual interface is provided for stochastic distributions which any module can use to create any sort of custom distribution. This distribution can then be passed to other modules that know nothing about it and it can still be evaluated to obtain the required values.

The same inheritance mechanism allows modules to define new interfaces without requiring changes to the basic interface and thereby all other versions of the module. For example, suppose a MEANS user is designing an airline agent that requires more detailed weather information than is available through the basic interfaces. The user can create a new weather module with its own interfaces. The airline module under development can then detect the presence of this new weather module and use the extended interfaces to obtain the additional required data, all without requiring any changes to the basic MEANS framework, and thereby avoiding affecting other users.

3.6 Limitations of the Airline Module

In any modeling exercise, there is always a trade-off between fidelity and tractability. If too little detail is included, one runs the risk of missing relevant interactions and the resulting model would not provide results that match observed behavior. If too much detail is included in the model, it may become intractable or actually make it more difficult to understand and interpret key relationships.

The initial version of MEANS' airline module neglected details for the sake of tractability: aircraft and passenger recovery are very trivial and crews are not considered in the process. This research represents an effort to overcome these particular setbacks of the simulation by building initial crew schedules and implement an automated AOC module.

In the following chapters, the development and the results of a crew schedule generator (Chapter 4) and the study of a cost-based airline recovery model (Chapter 5), its implementation as an AOC module in MEANS and its validation (Chapter 6) are presented.

Chapter 4

The Crew Schedule Generator

Crew schedules are a major constraint in the airline recovery problem: the options that may be exercised by an airline during a disruption greatly depend on crew availability. Thus, if crew constraints are to be considered in the airline recovery problem, there must be a baseline crew schedule to properly account for the effects of disruptions. However, airlines do not publish their crew schedules because of security concerns and competitive reasons. Consequently, it was necessary to generate a crew schedule.

Crew scheduling may be defined as the problem of finding a set of well-defined tasks (duties, pairings, bidlines) that satisfy legality rules and resource constraints. The main objective in crew scheduling is to cover all scheduled flights with the necessary crew members, while minimizing the airline costs. The problem is computationally hard due to the large number of variables, complex feasibility rules (which are evolving through time) and nonlinear costs.

In this chapter, the crew scheduling problem is addressed and solved with enough detail that it can be used during the simulation of airline recovery in MEANS. Background on crew scheduling is first presented (Section 4.1), followed by the general regulations that govern crew schedules (Section 4.2). In Section 4.3, the costs considered in the crew scheduling problem are discussed. Finally, the formulations and algorithm used to generate and solve the crew scheduling problem, the assumptions made to ensure tractability and the preliminary results obtained are presented (Sections 4.4 – 4.7).

4.1 Background and Previous Work

4.1.1 Branch-and-Price in Crew Scheduling

Branch-and-price is a generalization of branch-and-bound[1] with LP relaxations where columns can be generated and applied throughout the branch-and-bound tree. In branch-and-price, sets of columns are left out of the LP relaxation because there are too many columns to be handled efficiently; in fact, most of the variables associated with these columns will be equal to zero in an optimal solution. In order to check the optimality of the LP solution, the pricing problem is called. The pricing problem is basically a separation problem for the dual LP, which when solved, identifies the next columns to include in the basis. If additional columns are found, the LP relaxation is reoptimized. If no additional columns are found in the pricing problem and the LP solution is not integral, then a branching has occurred. [2]

For crew scheduling specifically, Barnhart et al. [2] suggest that all feasible pairings are enumerated and then a set partitioning problem is formulated in which each column corresponds to a pairing and the objective is to partition all of the segments into a set of minimum cost pairings. The drawbacks with this approach are that the number of pairings included needs to be fixed and that it can be very hard to find a good feasible solution due to the complexity of the integer problem. Branch-and-price would implicitly consider all of the pairings while pricing out the non-basic columns in a simplex algorithm. It is crucial though that columns are generated during the

[1]Branch-and-bound is an exact algorithm for solving integer optimization problems. As the name suggests, the algorithm explores sets of feasible integer solutions by dividing a large problem into smaller sub-problems (branching) and then determining the optimal value for each sub-problem (which provide a bound on the optimal value for the larger problem). Because the so-called sub-problems themselves can be as hard to solve as the original problem, they might also have to be split into yet smaller sub-problems using the same algorithm. These consecutive branches form the branch-and-bound tree. Each level of the tree has a lower bound which might be the smallest LP relaxation cost among the sub-problems (which are a lot easier to solve). If a sub-problem is solved to optimality the solution has to be smaller than the lower bound in order to be considered a candidate for the optimal solution of the original problem.

solution of the initial LPs throughout the tree.

4.1.2 Crew Scheduling under Uncertainty

Schaefer et al. [17] present a method for finding crew schedules that may perform well in operations. This method searches pairing costs that would more accurately represent the cost of a pairing during operations under disruptions. With these costs, a set partitioning model is solved. In order to find a reasonable value for these operational costs, a linear approximation of the expected crew cost was used.

In their formulation they defined the variable $\bar{c}(C)$, the expected cost in operations for crew C and assumed that if the costs χ_q of pairing q exist such that $\bar{c}(C) = \sum_{q \epsilon C} \chi_q$ for all crew schedules, then an optimal solution to the stochastic crew scheduling problem can be found by solving a set partitioning problem.

The drawback in this approach is that in general χ_q are not available. Schaefer et al. [17] describe a method to search for χ_q that satisfies the equation. In order to find the pairing cost they used a Monte Carlo simulation of at least 50 days of operation using an event-based simulation and the termination criterion being a 99% confidence level. The computational results presented indicated that the schedules developed using the approximate expected cost performed better in operations with disruption than those using planned cost.

4.2 Crew Legal Requirements

In order to build a crew schedule, it is necessary to comply with certain regulations. Chapter I - Part 121 of the Code of Federal Regulations specifies flight time crew limitations, rest requirements, and air carrier obligations to crewmembers. The Crew Schedule Generator developed here followed all of the general regulations in this Code that applied to the time periods considered. The following is a transcript of this Legal Statement:

Flight time limitations and rest requirements: All flight crewmembers.

(a) No airline may schedule any flight crewmember in scheduled air transportation or in other commercial flying if that crewmember's total flight time will exceed:

(1) 1,000 hours in any calendar year;

(2) 100 hours in any calendar month;

(3) 30 hours in any 7 consecutive days;

(4) 8 hours between required rest periods.

(b) Except as provided in paragraph (c), no airline may schedule a flight crewmember during the 24 consecutive hours preceding the scheduled completion of any flight segment without a scheduled rest period during that 24 hours of at least the following:

(1) 9 consecutive hours of rest for less than 8 hours of scheduled flight time.

(2) 10 consecutive hours of rest for 8 or more but less than 9 hours of scheduled flight time.

(3) 11 consecutive hours of rest for 9 or more hours of scheduled flight time.

(c) An airline may schedule a flight crewmember for less than the rest required in paragraph (b) of this section or may reduce a scheduled rest under the following conditions:

(1) A rest required under paragraph (b)(1) of this section may be scheduled for or reduced to a minimum of 8 hours if the flight crewmember is given a rest period of at least 10 hours that must begin no later than 24 hours after the commencement of the reduced rest period.

(2) A rest required under paragraph (b)(2) of this section may be scheduled for or reduced to a minimum of 8 hours if the flight crewmember is given a rest period of at least 11 hours that must begin no later than 24 hours after the commencement of the reduced rest period.

(3) A rest required under paragraph (b)(3) of this section may be scheduled for or reduced to a minimum of 9 hours if the flight crewmember is given a rest period of at least 12 hours that must begin no later than 24 hours after the commencement of the reduced rest period.

(4) No airline may assign any flight time to a crewmember unless the flight crewmember has had at least the minimum rest required under this paragraph.

(d) Each airline shall relieve each flight crewmember engaged in scheduled air transportation from all further duty for at least 24 consecutive hours during any 7 consecutive days.

(e) No airline may assign a crewmember to any duty with the air carrier during any required rest period.

(f) Time spent in transportation (deadheads), not local in character, that an airline requires of a flight crewmember and provides to transport the crewmember to an airport at which he is to serve on a flight as a crewmember, or from an airport at which he was relieved from duty to return to his home station, is not considered part of a rest period.

(g) A flight crewmember is not considered to be scheduled for flight time in excess of flight time limitations if the flights to which he is assigned are scheduled and normally terminate within the limitations, but due to circumstances beyond the control of the airline (such as adverse weather conditions), are not at the time of departure expected to reach their destination within the scheduled time. [1]

In addition, airlines have their own agreements with their employees, regarding working conditions, rest periods and salaries. Airlines do not publish these agreements openly because of competitive reasons. In the current implementation of the Crew Schedule Generator, specific airline rules were not considered.

4.3 Duty and Pairing Costs

When scheduling crews, airlines do not normally measure their crew costs in monetary terms. Rather, crew costs are usually expressed in terms of minutes of pay and credit. For a given duty, the difference between the total cost in minutes of pay and credit and the total block time is referred to as the flight-time-credit (FTC). FTC for entire pairings is also calculated in a similar way. The derivation of the FTC for both duties and pairings is described below.

Let p be any pairing that is composed of duties $d_1, \ldots, d_k$. For any duty d_i, where $i \in \{1, \ldots, k\}$ consisting of legs $l_{i,1}, \ldots, l_{i,m(i)}$ the cost $c(d_i)$ will be:

$$c(d_i) = max\{\sum_{j=1}^{m(i)} block(l_{i,j}), f_d * elapsed(d_i), mgp_d\}$$

where:

$block(l_{i,j}) = arrivaltime(l_{i,j}) - departuretime(l_{i,j})$;

$elapsed(d_i) = arrivaltime(l_{i,m(i)}) - departuretime(l_{i,1}) + briefingtime + debriefingtime$;

f_d is a fraction smaller than 1 that represents the rate of pay for elapsed time in terms of minutes of pay and credit;

mgp_d is the minimum guarantee pay for a duty.

The flight-time-credit of a specific duty ($FTC(d_i)$) is given by:

$$FTC(d_i) = \frac{c(d_i) - \sum_{j=1}^{m(i)} block(l_{i,j})}{\sum_{j=1}^{m(i)} block(l_{i,j})}$$

The pairing cost c_p is given by:

$$c_p = max\{\sum_{i=1}^{k} c(d_i), f_p * TAFB(p), mgp_p * k\}$$

where:

$TAFB = arrivaltime(l_{k,m(k)}) - departuretime(l_{(1,1)}) + briefingtime + debriefingtime$;

f_p is a fraction smaller than 1 that represent the average rate of pay of time away from base;

The FTC of pairing p is defined by:

$$FTC(p) = \frac{c_p - \sum_{i=1}^{k} \sum_{j=1}^{m(i)} block(l_{i,j})}{\sum_{i=1}^{k} \sum_{j=1}^{m(i)} block(l_{i,j})}$$

4.4 The Crew Schedule Generator

The Crew Schedule Generator is composed of two separate scripts: the Duty Generator and the Pairing Generator. The results obtained from the Duty Generator are used in the Pairing Generator as part of the initial schedule. Throughout this Chapter, any reference to the "Crew Schedule Generator" applies to both scripts.

The Crew Schedule Generator was written in the object-oriented language C++. All elements (flights, duties and pairings) are placed into objects, enabling easy storage and access to data through the C++'s structures and classes. A *structure* is basically a set of diverse types of data that may have different lengths when they are grouped together under a unique declaration. A *class* is a logical method to organize data *and* functions in the same structure. Objects were grouped and sorted using containers available in the C++ Standard Library. For example, flights were grouped by departure and arrival airports, and ordered by departure time. This allowed a faster search for connecting flights and a more convenient way to build duties and pairings.

The Crew Schedule Generator performs in two basic steps: generation of a large number of feasible crew schedules; and finding a set of crew schedules that cover all flights using optimization procedures to minimize costs. The algorithm for generating duties and pairings are presented in the following two subsections. The formulation for the optimization procedure is presented in the subsequent section.

4.4.1 Duty Generation

The sole data input for the Duty Generator script is a set of flight schedules. The output of the script is a set of one-day duty lines. The flight segments were stored in a *Flight* structure that contains the basic information about the flight's origin and destination, and scheduled departure and arrival times. To build the duties from these flight segments a class type *Duty* is set up, which contains all the information about the duties created as well as legality check functions. The information available in the *Duty* class includes generation data (total flying time, total duty time and a pay-and-credit function) as well as optimization variables (reduced cost, number of iterations in which the duty was included) to be used during the optimization segment of the code. Also, a container includes pointers to the flight segments (structure Flight) that are associated with the duty.

The generator starts off by selecting one flight segment and setting it as a *base flight* for a set of duties, i.e. all these duties would start with the base flight. A *base duty* is created with the base flight as its single element. Then, flights are connected to the base flight to create new duties. The process of generating duties is repeated by connecting flights to the existing duties. Thus, the process consists basically of extending duties with feasible flight segments. The candidate connecting flights are determined based on minimum allowable connection times and location. The user can set different minimum connection times for crewmembers that continue in the same aircraft and crewmembers that have to change planes.

As soon as a new duty is generated, legality checks are made. If found to be illegal, the duty is immediately deleted, avoiding unnecessary memory usage. After all possible duties for one base flight are generated the process is repeated with another flight until all flights have been set up as a base. Figure 4-1 shows an example of the crew schedule generation algorithm.

It is worth noting that longer flights might exceed time limitations assumed by the user. Thus, no legality checks are made in the base duties as all scheduled flights have to be covered. Not complying with this assumption would result in infeasible solutions in the optimization process.

4.4.2 Pairing Generation

The Pairing Generator follows the same scheme as of the Duty Generator: the class *Pairing* inherits all the information from the structure *Flight* and class *Duty*. Similar

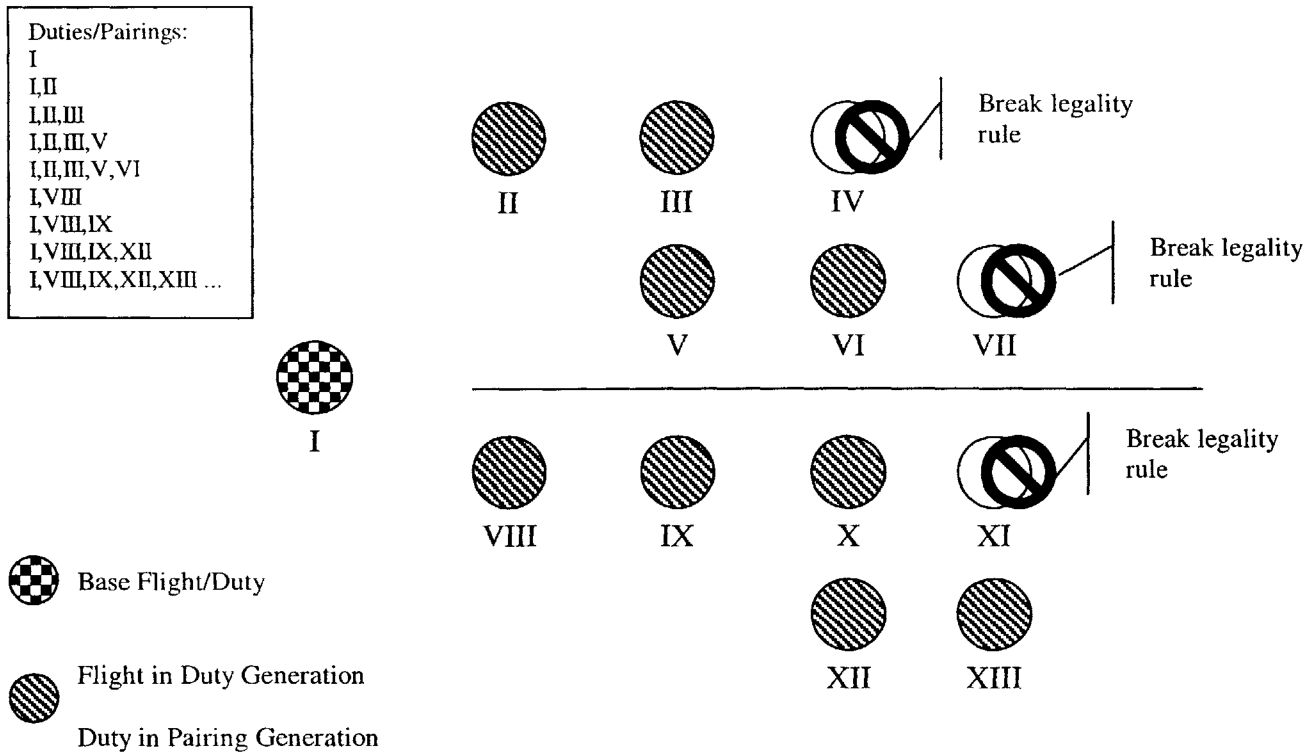

Figure 4-1: Crew Schedule Generation Algorithm

to the *Duty* class, generation and optimization variables were included in the *Pairing* class.

For a specific day, the generator selects a duty and sets it as the *base duty.* A set of pairings is then generated, where all of these pairings start with the base duty. The user can determine for how many days a pairing can be extended, by setting the maximum number of duties.

To form pairings of various days, duties are connected based on required rest periods and location. Only when these requirements are fulfilled, duties are added to the existing pairings forming new pairings. After all possible pairings for one base duty are generated the process is repeated with another duty, until all duties have been set up as a base.

During the pairing generation, as it was in the duty generation, the objects that did not comply with the regulatory restrictions were eliminated. The pairing generation has an important distinction in relation to the duty generation: it starts and ends at the same city. This constraint was considered even before generating a new Pairing object in order to save memory and time, since the pairing generation problem is much larger and more time consuming when compared to the duty generation.

4.4.3 Solving the Crew Scheduling Set Partitioning Problem

After generating the duties/pairings, the Crew Schedule Generator starts to search for a crew schedule that covers all flights and minimizes costs, measured in FTC. The optimization procedure in both the Duty Generator and the Pairing Generator script is very similar, and thus, they are presented together as a generic set partitioning problem[2].

The solver used in this work was the GNU Linear Programming Kit - GLPK, Version 2.0. The model was written in the mathematical programming language AMPL. The basic formulation for the crew scheduling problem is presented below.

Given the following indices:

r_j – pairing/duty (j=1,2,...,n)

n – number of pairings/duties

c_j – the cost of pairing/duty r_j

m – number of flights to be made according to the given airline schedule

and the following binary variables:

$$a_{i,j} = \begin{cases} 1 & if\ flight\ i\ is\ part\ of\ pairing/duty\ j, \\ 0 & otherwise \end{cases}$$

$$x_i = \begin{cases} 1 & if\ pairing/duty\ r_j\ exists\ in\ the\ crew\ schedule, \\ 0 & otherwise \end{cases}$$

[2]For more details in this subject, please refer to Bertsimas [3] pages 456 and 457

the crew scheduling problem can be formulated as follows:

$$min \sum_{j=1}^{n} c_i x_j$$

subject to:

$$\sum_{j=1}^{n} a_{ij} x_j = 1, i = 1, 2, \ldots, m$$

$$x_i = \{0, 1\}, j = 1, 2, \ldots, n$$

In the above formulation, flight segments are set as the rows and the duties/pairings as the columns. The number of variables for the crew scheduling problem is very large, thus column generation procedure is used to guarantee tractability. The initial basis for this procedure is the diagonal matrix, i.e. start with a solution where each duty is assigned to one flight. If a crew schedule is previously available the user can start the procedure from that schedule. In order to solve the crew scheduling problem through column generation, the Crew Schedule Generator algorithm has two main phases.

The first phase involves the LP relaxation of the crew scheduling problem. The LP is solved to the optimality of a subset of variables determined by the column generation procedure. The LP relaxation is solved numerous times, where new columns are added, some are kept from previous iterations, and some are eliminated. The basis from the previous solution is always kept, so the solution of following iterations is always better or equal to the previous one. The criteria for eliminating/keeping the variables for future iterations were reduced cost of the previous iteration, and the number of consecutive times that the variable was included in the basis on past iterations. The order in which the pairing/duties were included in the master problem was based on minimum FTC and flight covering, which guaranteed a user-specified number of columns as covering options for each flight leg. The LPs are solved until the solution converges and no significant improvement is observed over a certain number of iterations. In the second phase, the IP is solved using the last LP relaxation solution as a lower bound. The Integer Problem is solved using branch-and-bound.

4.5 Data and General Airline Information

The flight schedule used as input for the duty and pairing generation in this research was the domestic flight schedule of Continental Airlines from August 16th, 2000. The domestic traffic of Continental was composed of 1120 flights, 8 of which started on August 16th and ended on the 17th. The pairings were generated as if the flight schedule on the 16th was repeated for consecutive days in Continental's schedule. Thus, the overnight flights were not included in the final computation.

Some relevant Continental Airlines flight and crew information are listed below (Yu et al. [20]):

- Operates more than 2,000 daily departures to 123 domestic and 93 foreign destinations with its subsidiaries Continental Express and Continental Micronesia.
- Has 4,000 pilots and 8,000 flight attendants with crew bases at Cleveland, Houston and Newark.

4.6 Assumptions and Computational Issues

During the crew schedule generation, the following assumptions were made to ensure tractability:

- The crew is homogeneous and unsplitable, that is the whole fleet was treated as if it were one aircraft type and pilots and copilots would fly an entire pairing together. This assumption avoids that the availability of reserve crews to be considered separately for each fleet type, reducing the number of parameters that need to be defined during the operations simulation.
- As the number of duties considered in the pairing generation increases, the number of pairings generated increases exponentially. Due to limited computer memory and limited ability of the GLPK to handle large problems, the duties considered for the pairing generation were restricted to the ones obtained from the solution of the Duty Generator.

- For the pairing generation it was assumed that the flight schedule considered for the duty generation was repeated on consecutive days.

The Crew Schedule Generator allows the user to set numerous values that largely depend on the capability of the software used. The values below were used to obtain the preliminary results shown in the following section:

- Minimum crew connection time: 1 hour
- Minimum crew connection time between flights with the same tail number: 30 minutes
- Maximum daily duty flying time: 8 hours
- Maximum total duty time in one pairing (flying time + sit time): 12 hours
- Rate of pay for elapsed time in terms of minutes of pay and credit (f_d): 0.60
- Rate of pay for TAFB in terms of minutes of pay and credit (f_p): 0.30
- Minimum daily payment: equivalent to 4:30 flying hours
- Maximum number of days in a pairing: 3 days

4.7 Preliminary Results

The main objective of this segment of the research was to create a baseline crew schedule with which the airline performance can be evaluated by comparing it to the schedule after the recovery. Thus, once reasonable results were found, the LP iterations were interrupted.

The duties and pairings for the schedule selected shown in Section 4.5 were generated following the restrictions imposed by the values and assumptions presented in Section 4.6.

For the duty generation, the number of duties initially generated was of approximately 780,000 duties. The Duty Generator obtained the following results:

Number of Duties : 476

Average Duty Total Time : 9.79 hours

Average Flight Time : 6.31 hours

Average Number of Legs : 2.32

Number of LPs Solved : 125

Approximate Number of Duties Included in the Column Generation : 120,000

For the pairing generation, the same flight schedule was assumed to repeat over the course of 3 days. The Duty Generator results were then combined through feasible connections, considering the necessary rest times. Since only the optimized duty schedules were included (due to memory limitations), no more than 10,000 pairings, composed of 1 to 3 duties, were generated. With this small set of pairings the LP convergence was very slow, and the solution included many one-day pairings used in the initial basis. As a result, the number of pairing average legs compared to the duty average legs per crew (2.32) is very low as can be seen below:

Average FTC : 2.21

Number of Pairings : 902

Average TAFB : 43.15 hours

Average Number of Legs : 3.70

Average Flight Time : 10.12 hours

Number of LPs Solved : 51

Approximate Number of Pairings Included in the Column Generation : 8,500

The results above show the average FTC for a crew schedule CS composed of crew pairings $p \in CS$ given by:

$$FTC(CS) = \frac{\sum_{p \in CS} c_p - block(CS)}{block(CS)}$$

This formulation was used by Schafer et al. [17] to calculate the performance of crew schedules under disruptions. In the referred work, the planned FTC varied between 2.51 through 3.92 for schedules with 119-342 legs. Thus, the FTC value obtained in this crew scheduling for a schedule of 3336 legs (3 days with 1112 legs per day) can be considered small. The fact that no distinction was made between the crews allowed to fly specific fleet types influenced this low average FTC. Without this distinction the Crew Schedule Generator, being restricted by only time and location, was able to choose any flight legs for any crew.

The assumptions as well as the results presented in this Chapter were part of the input data during the simulation of the Airline Operations Control Module in MEANS.

Chapter 5

The Airline Operations Control Module

Realistic simulation of airline recovery requires detailed information about different aspects of its operations. Among these are flight, aircraft, crew and passenger information, as well as airport and route weather forecasts, gate availability, and airline ground activities. The model presented in this Chapter uses the information provided by MEANS and the crew schedule obtained by the Crew Schedule Generator to investigate the airline recovery process.

The details of the automated Airline Operations Control module are presented below. In Section 5.1, an overview of the airline recovery models, on which this module is based on, is presented. This is followed by Sections 5.2 through 5.6 with detailed descriptions of the module job flow and the models and algorithms used in the module.

5.1 Overview

The core of the MEANS automated AOC module is the airline recovery problem formulation developed by Clarke [5], simplified using the heuristic assumptions presented by Rosenberger [16] and the problem segmentation decoupling presented by Lettovsky [11].

The Airline Schedule Recovery Problem presented by Clarke [5] is a path-based formulation where the decision variable corresponds to the assignment of a specific aircraft to a predetermined sequence of flights. In this formulation, each aircraft must satisfy its maintenance requirements, and reach an appropriate maintenance station, before the remaining legal time expires. The aircraft rerouting subproblem uses a specialized tree-searching algorithm to generate the feasible sequence of flights. Clarke's formulation is summarized below:

Indices:

F - set of all flights ij

N - set of all feasible flights arriving at station i in time period p

K - set of all aircraft k in the fleet

Parameters:

D_{ij} - actual passenger demand for flight (i,j)

f_{ij} - average fare per passenger on flight (i,j)

r_{ij} - goodwill value per passenger on flight (i,j)

t_{ij} - flight time for flight segment (i,j)

C_{ijk} - operating cost of assigning aircraft k to flight (i,j)

C_{ij0} - cost of canceling flight (i,j)

CAP_k - seating capacity of aircraft k

$TIME_k$ - legal flight time remaining on aircraft k before maintenance is required

α_{ijn} - equals one if flight sequence n contains flight segment (i,j)

C_{nk} - cost of assigning flight sequence n to aircraft k

S_{ij} - amount of spilled passengers from flight (i,j)

Decision Variables

$X_{nk} = 1$, if flight sequence n is assigned to aircraft k, 0 otherwise

$Y_{ij} = 1$, if flight (i,j) is cancelled, 0 otherwise

Objective Function

$$min \sum_{n \in N} \sum_{k \in K} C_{nk} X_{nk} + \sum_{(i,j) \in F} C_{ij0} Y_{ij}$$

where:

$$C_{nk} = \sum_{ij \in n} \{C_{ijk} + r_{ij} S_{ij} - min[D_{ij}, CAP_k] \cdot f_{ij}\}, \ \forall k$$

subject to:

flight covering - ensures that each flight is either covered by one aircraft at a given time, or is cancelled.

$$\sum_{n \in N} \sum_{k \in K} \alpha_{ijn} \cdot X_{nk} + Y_{ij} = 1, \ \forall ij \in F$$

aircraft covering - ensures that each aircraft is assigned to no more than one sequence at a given time

$$\sum_{n \in N} X_{nk} \leq 1, \ \forall k \in K$$

aircraft utilization - ensures that for each aircraft, the potential sequence of flights does not exceed the number of available flight time left on the aircraft before scheduled maintenance.

$$\sum_{n \in N} \sum_{(i,j)} t_{i,j} \alpha_{ijn} X_{nk} \leq TIME_k, \ \forall k$$

leg based demand covering - accounts for the accommodation of passengers on each flight segment

$$\sum_{n \in N} \sum_{k \in K} \alpha_{ij} \cdot CAP_k \cdot X_{nk} + S_{ij} - D_{ij} \geq 0 \forall ij, S_{ij} \geq 0$$

In addition, several auxiliary operational constraints for crew availability, slot allocation, gate allocation, aircraft balance and maintenance resource allocation are presented. Each auxiliary operational constraints could have its own reassignment sub-problem of the given resource to each operational flight. The constraints on aircraft utilization and passenger demand covering are not included in the main problem, rather they are included in the aircraft rerouting sub-problem.

Clarke's model is very complex, and many of the formulas rely on a large set of candidate options. Thus, solving this problem as formulated is computationally very expensive. Rosenberger [16] simplifies the formulation by selecting candidate routings (a subset of the entire set of routings) and eliminating the sub-problems. The aircraft recovery model to be presented in Section 5.4.1 follows the same approach to simplifying Clarke's formulation by selecting candidate routes heuristically for flights that were affected by GDPs.

Lettovsky [11] presents an integrated model that uses a linear mixed-integer mathematical program that maximizes total profit to the airline while capturing the availability of aircraft, crews and open seats. His formulation has three large parts corresponding to crew assignment, aircraft routing and passenger flow. Linking these parts lends to very large problems that would be intractable even for small disruptions. The model is, thus, decomposed, where the master problem is solved and the crew, aircraft and passenger problems are decoupled. The decomposition scheme is as follows:

- a master problem, where cancellations, delays, and equipment substitution are found to recover the disrupted schedule;

- one aircraft sub-problem for each equipment type, that restores aircraft routings;

- one crew sub-problem for each equipment type that rebuilds crew pairings for the revised schedule;

- one sub-problem, that allocates passengers to flight legs with respect to the seating capacity of the revised schedule to minimize overall impact on passengers

The solution algorithm is derived applying Benders decomposition to a mixed-integer linear programming formulation of the problem. The basic idea of Benders decomposition is that a problem may be separated when decisions can be made in consecutive stages, i.e. where the second stage is known after the first one is solved and fixed[1].

5.2 The AOC Module Job Flow

Airline Recovery is usually performed in stages: in the first stage, aircraft are rerouted and flights and delayed or cancelled; in the second stage, pilots are reassigned to flights and reserve pilots are called if necessary; in the third stage passenger itineraries are rescheduled and non-accommodated passengers are supported by "on-location" staff. In recognition of this, the AOC module consists of an optimized aircraft re-scheduler, a heuristic crew re-assigner and a passenger re-accommodation model.

The main model of the module is the aircraft re-scheduler, which takes the current schedule and the control times determined by the MEANS ATCSCC module and computes the operating costs associated with the aircraft and crew, and the expected passenger disruption in various candidate scenarios. The outcome of the aircraft re-scheduler is a new schedule with delays, cancellations, ferry flights and new aircraft routings.

The crew re-assigner uses the schedule determined by the aircraft re-scheduler to find the crews whose schedules become infeasible and the crews that would break regulatory constraints. It also identifies the ferry flights not yet covered by any crews and assigns inactive crew to those flights. Flight schedules can only be changed incrementally during this stage, and if no crew can be found to cover a flight without a major rescheduling, the flight is cancelled.

If a flight is cancelled or an aircraft is full, causing a passenger's current schedule to be infeasible, the passenger accommodation model searches for alternative itineraries to the passenger's destination. For misconnected passengers, the model determines new itineraries starting from where the passenger misconnects. Because

[1]For more details in this subject, please refer to Bertsimas [3] pages 254-260

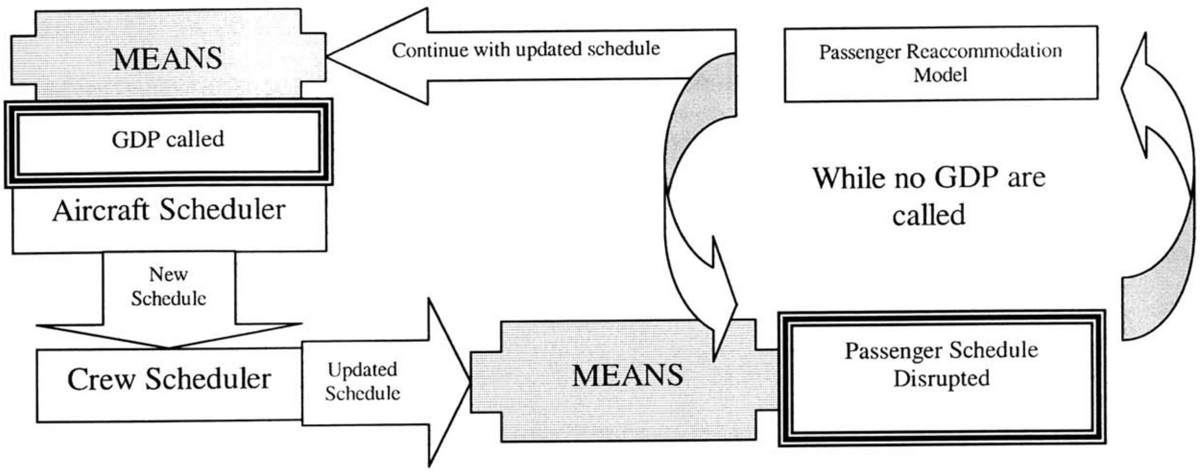

Figure 5-1: Automated Airline Operations Center Module Job Flow

the passengers can be re-accommodated at any time during simulation, the passenger re-accommodation model may be called numerous times between disruptions. The AOC module job flow is shown in Figure 5-1.

5.3 The AOC Module Initialization

Before each disruption, legs are set to an initial flight schedule F_i. The set of aircraft A is assigned to F_i, where each $\alpha \in A$ is assigned to one leg $f \in F_i$. The module is called if, upon a disruption, F_i becomes infeasible. For the AOC module, a disruption ψ, identified by the ATCSCC module, is considered a continuous period of time in a specific airport where the reduced capacity changes the initial schedule of flight legs incoming to that airport and, causing the initial schedule F_i to be infeasible.

Once ψ occurs, the module loads flight, aircraft and passenger data into parallel schedules, with the necessary information to be used during the recovery process. The parallel flight schedule has the basic flight and aircraft information and is uploaded once, right after ψ is called, avoiding time consuming searches throughout the recovery stage. This parallel flight schedule has updated information that gathers data, such as rescheduled and control times, current aircraft tail number assigned to the flight leg, present available seats as well as aircraft hourly flight and ground costs. It also includes the list of flights that are candidate for swaps and the corresponding costs to be used during the optimization.

The same principle is applied to the passenger data. Instead of dealing with each passenger individually, passengers who have the same itinerary and have paid the same fare are clustered into a parallel passenger schedule, reducing considerably the search time for affected passengers during the cost calculations. After generating the parallel schedules, the module maps the flight schedule into tree-searching containers sorted by keys such as airline, departure city and aircraft tail numbers.

Flights delayed directly or indirectly due to ψ form a new temporary schedule F_ψ. If the estimated delay for a flight in F_ψ is over a threshold value then the AOC module considers changing the aircraft assigned to that flight. The threshold value chosen was 15 minutes beyond the scheduled arrival time, as the U.S. Department of Transportation considers a flight to be "on time" if it arrives less than 15 minutes after the scheduled arrival time.

The three components of the AOC module (aircraft re-scheduler, crew re-assigner, and passenger re-accommodation model) are presented in detail in the following sections.

5.4 Aircraft Re-scheduler

The purpose of the aircraft re-scheduler is to manage the airline's aircraft routing during F_ψ, while minimizing the immediate costs. The core of the aircraft re-scheduler is the aircraft recovery model. The model adjusts the formulation presented in Section 5.1 to the available data: gate resources are assumed to be infinite and remaining time for each aircraft is not considered for the simulation day. The aircraft re-scheduling algorithm is shown in Figure 5-2. The model is stated below with the appropriate limitations on aircraft and candidate route selection.

begin

Update Flight and aircraft information and store in parallel schedule

Update the passenger itinerary and store in parallel schedule

Read the current crew duty

Load the searching containers for the parallel schedules

for all flights set to control times due to ψ flown by aircraft $\alpha \in A$

  if control arrival time – schedule arrival time < threshold

    continue

  else

    Define a cancellation plan for flights flown by α.

    Choose among the candidate sequence of flights flown by α that could be cancelled the one with least operational cost impact.

    Determine the Ferry Flights necessary to meet selected requirements

    for all candidate route *r* chosen

      Compute costs associated with assigning aircraft α to route *r* and assigning the aircraft originally scheduled to fly *r* to α's current schedule

    end for all

end for all

optimize for all routes and aircraft considered

end

begin *crew rescheduling*

begin *passenger reassignment*

Figure 5-2: AOC Initialization and Aircraft Re-scheduling Algorithm

5.4.1 The Aircraft Recovery Model

Consider a flight leg f in the initial disrupted schedule F_ψ. Let $R_{(\alpha,F_\psi)}$ be a set of routes that are considered feasible for aircraft $\alpha \in A$. This set is heuristically chosen depending on the recovery procedure selected, as will be presented in Chapter 6. For each $f \in F_\psi$, let C_{f0} be the cost associated with canceling leg f and

$$Y_f = \begin{cases} 1 & if\ leg\ is\ cancelled, \\ 0 & otherwise \end{cases}$$

For each route $r \in R_{(\alpha,F_\psi)}$ the cost of assigning aircraft α to route r is $C_{\alpha,r}$, and

$$X_{\alpha,r} = \begin{cases} 1 & if\ route\ r\ is\ assigned\ to\ aircraft\ \alpha, \\ 0 & otherwise \end{cases}$$

Then the following set packing formulation can be stated:

$$min \sum_{\alpha\in A} \sum_{r\in R_{(\alpha,F_\psi)}} C_{\alpha,r}X_{\alpha,r} + \sum_{(f\in F_\psi)} C_{f0}Y_f \tag{5.1}$$

subject to:

$$\sum_{r\ni f} X_{\alpha,r} + Y_f = 1, \ \forall f \in F_\psi \tag{5.2}$$

$$\sum_{r\in R_{(\alpha,F_i)}} X_{\alpha,r} \leq 1, \ \forall \alpha \in A \tag{5.3}$$

$$Y_f \in \{0,1\}, \ \forall f \in F_\psi \tag{5.4}$$

$$X_{\alpha,r} \in \{0,1\}, \ \forall \alpha \in A, \ r \in R_{(\alpha,F_\psi)} \tag{5.5}$$

Notice that the first part of the objective function 5.1 considers only the set of routes $R_{(\alpha,F_\psi)}$, reducing considerably the number of variables. The packing constraints 5.2 ensure that each leg is either in a route or is cancelled, and the assignment constraints 5.3 assigns a route r to no more than of one aircraft. Constraints 5.4 and 5.5 set the integral solutions.

5.4.2 Cost Assessment for the Aircraft Recovery Model

The objective function 5.1 requires the assessment of the cost of assigning routes to aircraft and canceling flight legs. The costs for aircraft rerouting are not predetermined because these values partially depend on F_{ψ}. The crew costs are included in the aircraft operation costs and the passenger accommodation is evaluated in an expected scenario where the flights schedules would belong to F_{ψ}. The assessment of the cancellation and aircraft assignment costs is present below.

Cancellation

Consider flights $[f_0(\alpha), \ldots, f_d(\alpha), \ldots, f_k(\alpha), \ldots] \in F(\alpha)$ to be flown by aircraft α, where $f_d(\alpha) \in F(\alpha)$ is disrupted and let $F_{d,k}(\alpha)$ be a subset of $F(\alpha)$ starting with $f_d(\alpha)$ and ending at a $f_k(\alpha) \in F(\alpha)$.

The module examines all legs scheduled to be flown by aircraft α after the disrupted flight $f_d(\alpha)$ and calculates the costs associated with canceling flights that belong to $F_{d,k}(\alpha)$, $\forall f_k(\alpha)$. Ferry flight costs are included from the departure station of $f_d(\alpha)$ to the arrival station of $f_k(\alpha)$. The model then heuristically selects the cancellation cycle with the least cost and sets it as the cancellation option for aircraft α.

It is worth noting that, specifically for disruptions due to GDPs, one leg cancellations of disrupted flights incoming to airports with reduced capacities are not reasonable, thus, $d > k$, and the second part of objective function 5.1, $\sum_{(f \in F_{\psi})} C_{f0} Y_f$, could be rewritten as $\sum_{\alpha \in A} C_{F_{d,k}(\alpha)} Y_{F_{d,k}(\alpha)}$.

The cost associated with canceling a sequence of flights is:

$$C_{F_{d,k}(\alpha)} = \sum_{f \in F_{d,k}(\alpha)} [Rc_f - (OA_f - CC_f)] + FF_{(d,k)}$$

where:

$C_{F_{d,k}(\alpha)}$ - Cost of canceling flight legs f_d through f_k with $[f_d, \ldots, f_k] \in F_d(\alpha)$

Rc_f - Revenue lost from passengers whose itinerary included $f_d(\alpha)$ and are not expected to be recovered.

OA_f - Flight One-time airborne costs for flight f

CC_f - Crew costs for flight f, which are still incurred even if a flight is cancelled

$FF_{(d,k)}$- Cost of a ferry flight from the departure city of f_d to the arrival city of f_k. This cost includes the ground cost incurred from the extra periods of time on ground. The ground costs per unit of time are assumed equal at any station for each fleet type.

The revenue loss due to passengers who were not re-accommodated is calculated as follows: for passengers whose itinerary include any flights $[f_d(\alpha), \ldots, f_k(\alpha)]$ the modules assumes F_ψ as true (except for flights considered for cancellation) and searches for possible itineraries by which the passengers can reach their final destination. If no itineraries are found for these passengers, the module assumes that they will not fly with the airline on that day, and the fare paid by them is considered lost revenue.

Passengers are sorted by fare, and no considerations are made for the possible delays incurred on a new itinerary. The schedule assumed during the calculations F_ψ will most likely change in real time due to common operation conditions. Thus, there is no guarantee for how close the estimated cost will be to the actual cost after operations.

Aircraft Reassignment

The module does not consider reserve aircraft. Thus, the set of aircraft rerouting options is created by swapping aircraft between routes. Consider again the disrupted flight $f_d(\alpha)$ which belongs to route $r*$. For a candidate route r, currently scheduled to be flown by aircraft β, the cost associated with assigning α to r ($C_{\alpha,r}$) also includes the cost of assigning β to $r*$, consequently:

$$C_{\alpha,r} = \sum_{f \in r}(Rc_f + OA_f + OG_f) + \sum_{f \in r*}(Rc_f + OA_f + OG_f)$$

where:

$C_{\alpha,r}$ - Cost of assigning aircraft α to route r

Rc_f - Revenue lost from passengers who misconnected due to delays implied in the aircraft reassignment, and are not expected to be re-accommodated

OA_f - Flight One-time airborne costs for flight f

OG_f - One-time ground costs due to aircraft extra time on ground

The revenue lost due to passenger misconnections is calculated in a similar way to the passengers scheduled to fly cancelled legs. For passengers whose itineraries become infeasible, the module assumes F_ψ as true and searches for possible itineraries by which the passengers can reach their final destination and if no alternative itineraries are found, the passenger fare is considered to be lost revenue. Here, passengers are also sorted by fare. The difference between misconnected passengers and those in cancelled flights is that only passengers whose itineraries will become infeasible are considered. Otherwise, passengers are expected to remain on their original itineraries regardless of the delays incurred.

5.5 Crew Re-assigner

Finding a good set of crews to cover all missed connections is a challenging task. Johnson et al. [10] used a predefined time window to limit the search for suitable crews to swap at an airport where a misconnection occurs. The authors observed that this method often fails to involve enough crews at spoke airports and includes too many crews at hubs. This behavior is caused by a low flight frequency at spoke airports and a high flight frequency at hub airports. Lettovsky [11] proposed a limit on the search by a maximum number of involved crews per misconnection, regardless of the type of the airport.

The crew re-assigner developed for this module is in fact a rather primitive implementation of what could be applied in MEANS when crews are tracked in the simulation. The crew re-assignment model implemented basically assumes that either crews will continue their assigned schedules even after disruptions or reserve crews would be called to cover the flights that cannot be flown by the crews assigned to them.

For crews who cannot arrive on time for their following flight leg, χ_M, the module considers two options. First, it estimates the cost associated with incrementally pushing back a flight so the crew can continue with their schedule. Legality checks are made to evaluate the feasibility of this option. For the second option, the module searches available reserve crews that can be deadheaded from different crew bases to the departure location of χ_M before its scheduled departure time. The reserve crew with the shortest deadhead time is selected. The cost of deadheading χ_M to its final duty destination is added to the cost associated with the second option. The option with the lowest FTC is then selected.

For a crew χ_C scheduled to fly a cancelled flight, the module follows a similar procedure. However, in order to χ_C continue its schedule it is necessary for it to be deadheaded to the destination of the cancelled flight. Reserve crews are also selected based on minimum deadheaded time and the cost of this option includes the cost of χ_C being sent to its final destination.

One difficulty in solving the crew recovery problem is that crews can fly on other air carriers; so realistic crew recovery models may include every flight leg on other airlines. Here, an optimistic assumption was made. If deadhead segments are found for a crew from a station to another, the segment that results in the shortest deadheading period is chosen, and all flight legs included in this deadheaded segment would have seats available, regardless of which airlines are involved. Figure 5-3 summarizes how the module deals with crews who cannot make it on time to their following scheduled flight legs (χ_M) and crews assigned to cancelled flights (χ_C).

For every option considered, crew legality is checked and if illegal, the option's FTC is set to infinity. No considerable effort was made to cover ferry flights and flights which were assigned to crews whose available legal time had expired. For both situations reserve crews are called, and if not found, the flights involved are cancelled. The module does not allow significant changes in the flight schedule during the crew recovery, because of the model's limitations and assumptions.

5.6 Passengers Re-accommodation

The passenger re-accommodation model implemented in this module is part of on-going research to minimize overall passenger delays. The passenger function is called after the aircraft and crew segments of the module to re-accommodate passengers with infeasible itineraries because of cancelled and full flights. For passengers misconnected due to flight time changes the re-accommodation is done as passengers arrive at the airport where they misconnect.

The module finds the quickest set of flight legs from the location where the passenger itinerary was disrupted to the passenger's final destination, using an $A*$ search algorithm. If it is able to find a complete set of flight legs to the final destination, these new legs are added to the passenger itinerary, and the passenger is accommodated on the flights. Since the overall objective of the module is to reduce costs, passengers to be re-accommodated are arranged from highest to lowest fare, reducing the chances of high fare passengers being stranded.

begin
Find crews scheduled to cancelled flights, crews that missed their connections due to flight delay, and crews that would become illegal
for all misconnected crew χ_M
    Compute the cost C_M of holding the flights so the crew continues the scheduled duty
    Evaluate χ_M legality for continuing schedule
    if continuing schedule with χ_M illegal
        set $C_M \rightarrow +\infty$
    Find the closest reserve crew available χ_R with feasible deadheading flights
    Compute cost C_R of deadheading crew to χ_M misconnected location and continuing duty from that point on
    Evaluate χ_R legality for continuing the χ_M duty schedule
    Compute the cost of deadheading χ_M to final duty destination C_{MD}.
    if deadheading χ_R is infeasible
        set $C_R \rightarrow +\infty$
    if $C_M \rightarrow +\infty$ and $C_R \rightarrow +\infty$
        cancel infeasible flights
    else if $C_M > C_R + C_{MD}$, χ_M will continue its schedule and flights can be incrementally rescheduled
    else χ_R will be assigned to flights and χ_M is sent to final duty destination
end for all
for all crew that is scheduled to a cancelled flight leg χ_C
    if cancelled flight is the last flight of the duty
        Compute cost of deadheading crew to final duty destination and break loop
    else
        Compute the cost C_C of deadheading the crew to continue duty after the cancelled flight
        Evaluate χ_C legality for continuing schedule
        if continuing χ_C duty illegal
            set $C_C \rightarrow +\infty$
        Find the closest reserve crew available χ_R with feasible deadheading
        Compute cost C_R of deadheading crew to χ_C arrival station of cancelled flight and continuing duty from that point on
        Evaluate rule regulation for χ_R to continue the χ_C duty
        Compute the cost of deadheading χ_C to final duty destination C_{CD}.
        if deadheading χ_R is infeasible
            set $C_R \rightarrow +\infty$
        if $C_C \rightarrow +\infty$ and $C_R \rightarrow +\infty$
            cancel flight sequence
        if $C_C > C_R + C_{CD}$, χ_C will continue its schedule and flights can be incrementally rescheduled
        else χ_R will be assigned to flights and χ_C is sent to final duty destination
end for all
Update crew information
end

Figure 5-3: Crew Recovery Heuristic Algorithm

Chapter 6

Validation and Final Considerations

The AOC module presented in Chapter 5 was implemented in MEANS and the resulting version of the simulation was evaluated. The steps to validate the AOC module are presented in this Chapter. The inputs, including the assumptions and the information data used, the scenarios considered, along with the analysis of the results obtained from a sample day in the operations of a major U.S. carrier are shown below.

6.1 Implementation

The flexibility of MEANS allows complex modules to be implemented without requiring changes to the core interfaces. The AOC module, written in C++, relied on the virtual inheritance mechanisms of this programming language to reduce the effort required to add the module to the simulation. The optimization tool employed was the GNU Linear Programming Kit v.2.0.

The automated AOC module was implemented for Continental Airlines. A trivial airline module was assigned to the other major air carriers, where flights delayed more than 2 hours were cancelled. The flight schedule used during the simulations was the domestic schedule of August 16th, 2000.

6.1.1 Input Data and Assumptions

As was presented in Chapter 4, the flight schedule for the 10 major U.S. air carriers was obtained from the ASQP database and the smaller airlines and general aviation traffic was obtained from CODAS.

The passenger data was derived from the aggregate passenger information of Continental Airlines for the third quarter of 2000. No posterior effects of passenger disruptions were taken into consideration. That is, if passengers were disrupted by the airline and not re-accommodated, no indirect effects, such as loss of goodwill, were considered. In addition, the simulation considers passengers who were stranded at the end of the day as lost revenue. These passengers could, in fact, continue their trip with the airline on the next day or could choose another air carrier for the remainder of their trip.

The crew schedule was created using the pairing generator presented in Chapter 4. This crew schedule includes crews with pairings that were a maximum of 3-days in duration, where each pairing was flown by a pair of pilots. Each pair of pilots was assumed to stay together during the entire pairing. By including the entire pairings, it was possible to capture the effects of the disruptions on the required rest periods. The remaining days of the crew pairings were assumed to run without disruptions to their schedule. Reserve crew bases were created in Cleveland, Newark and Houston. The total number of reserve crews was set to be 30% of the total active crews on the day. The distribution of reserve crews among the crew bases was proportional to the number of domestic departures from the base during the whole month of August 2000.

Aircraft information, such as fleet type and seating capacity was obtained from the JP Fleet Database. The aircraft ground, airborne and crew costs were acquired from Form 41. The taxi and airspace traffic were obtained from distributions derived from historical data for 2000.

Scenario 1		
Airport	GDP Begin	GDP End
CLE	10:00	18:00
Scenario 2		
Airport	GDP Begin	GDP End
CLE	10:00	18:00
IAH	8:00	15:00
EWR	12:00	18:00
Scenario 3		
Airport	GDP Begin	GDP End
CLE	10:00	18:00
BOS	7:00	16:00
LAX	13:30	23:30

Table 6.1: Scenarios Evaluated (all times in EST)

6.1.2 Scenarios

Continental Airlines (CO) is the seventh largest domestic air carrier in terms of traffic. Its domestic schedule forms a hub-and-spoke network where 99.5% of the schedule either arrives or departes from a hub station. Continental's major hubs are Cleveland (CLE), Houston (IAH) and Newark (EWR). The network is composed of 76 stations, served by 1112 daily domestic flights (not considering overnight flights). The 300 aircraft in the domestic fleet are of five aircraft types.

During the validation of the AOC module, three scenarios with disruptions at different CO stations were considered. The scenarios are presented in Table 6.1. Scenario 1 and Scenario 2 consider solely disruptions at hub stations, whereas Scenario 3 includes disruptions at two spoke stations – Boston (BOS) and Los Angeles (LAX). Disruptions were obtained by setting airport capacities equivalent to those in IFR conditions. When the demand exceeded capacity at an airport, the ATCSCC module called GDPs, causing delays in the inbound traffic to the airport.

6.2 Procedures

Flight legs which had slot times assigned to them during a GDP, were considered to be *directly affected flights.* Flight legs that, due to aircraft or crew unavailability, needed to be rescheduled were considered *indirectly affected flights.*

The two simple cancellation rules that were used to validate the AOC module operations and evaluate the module in different scenarios are presented below .

Rule 1 : For an aircraft route containing a directly affected flight, the candidate cancellation subroutes always start with this flight. That is, if a cancellation subroute is selected for the aircraft, the directly affected flight is definitely cancelled.

Rule 2 : For an aircraft route containing a directly affected flight, the candidate cancellation subroutes may begin with either the directly affected flight or any other subsequent flight leg indirectly affected.

In addition to these rules, two assumptions were made on aircraft rerouting:

Unconstrained Aircraft Rerouting (UAR) : assumes that, in the simulated day, any aircraft can meet maintenance requirements by reaching the arrival location of any other aircraft in their fleet. This implies that aircraft of the same fleet can interchange assigned routes without considering where the daily final destination will be.

Constrained Aircraft Rerouting (CAR) : assumes that all aircraft must be at the scheduled final destination by the end of the day. This assumption considers that, in order to meet maintenance requirements, it is necessary for the aircraft to be at a specific location

COSTS ($)	
Flight Cost	3874167
Passenger Cost	46800
Total Operating Cost	3920967
DELAYS (min)	
Total Flight Delay	8056
Average Flight Delay	7.24
Total Passenger Delay	229000
Passenger Average Delay	2.52
PERFORMANCE	
Cancelled Flights	0
Ferry Flights	0
Crew FTC	2.21
Number of Active Crews	476
Non-Accomodated Passengers	0.27%

Table 6.2: Results of a simulated normal day of operations for CO

6.3 Simulation of a Normal Day Airline Operations

During normal operating conditions, airlines can operate their flight networks according to schedule. Thus, to simulate a normal day of operations for CO, a base case was generated where the capacity at all airports was above the demands throughout the entire day. Table 6.2 shows the results of the base case simulated.

The *Flight Costs* include direct operating costs for scheduled and ferry flights, along with crews costs (including unassigned crews originally scheduled to fly on that day). The aircraft operating costs associated with the cancelled flights are subtracted from this value. The *Passenger Cost* accounts for the revenue loss due passengers who did not arrive at their destinations at the end of the day (based on the fare they paid). The *Total Operating Cost* is the sum of the two previous values, and represents the monetary expenses during operations. The *Flight Delay* accounts for the discrepancy between the scheduled arrival times and the actual arrival times (excluding cancelled flights). The *Passenger Delay* accounts for the difference between the scheduled and the actual arrival time at the passenger's final destination (excluding passengers that are not re-accommodated at the end of the day).

Procedures	I	II	III	IV
COSTS ($)				
Flight Cost	3887399	3877313	3875275	3869763
Passenger Cost	382077	598022	488620	746452
Total Operating Cost	4269476	4475335	4363895	4616215
DELAYS (min)				
Total Flight Delay	9511	9049	9526	9137
Average Flight Delay	8.44	7.99	8.42	8.03
Total Passenger Delay	527000	401000	547000	438000
Passenger Average Delay	5.81	4.42	6.03	4.82
PERFORMANCE				
Cancelled Flights	43	55	58	70
Ferry Flights	15	21	20	26
Crew FTC	2.58	2.71	2.70	2.81
Number of Active Crews	496	503	504	511
Non-Accomodated Passengers	3.02%	4.70%	3.78%	5.67%

Table 6.3: Scenario 1 – Disruption at CLE

6.4 Analysis of the Simulation during Irregular Operations

The results of four procedures that combine the rules and aircraft rerouting constrains explained in Section 6.2 in the scenarios shown in Section 6.1.2 are presented below.

The procedures simulated were the following:

Procedure I - Rule 1 + UAR

Procedure II - Rule 1 + CAR

Procedure III - Rule 2 + UAR

Procedure IV - Rule 2 + CAR

Analysis and considerations about the results shown in Tables 6.3 through 6.5 are presented below.

Estimated Arrival Times

Comparing Procedures I and III (UAR) and Procedures II and IV (CAR) in Scenarios 1 and 2, there is a clear increase on the number of passengers who are not

Procedures	I	II	III	IV
COSTS ($)				
Flight Cost	3899282	3913242	3906637	3898868
Passenger Cost	483141	551097	506930	596279
Total Operating Cost	4382423	4464339	4413567	4495147
DELAYS (min)				
Total Flight Delay	11879	11727	12143	11379
Average Flight Delay	10.51	10.31	10.72	9.97
Total Passenger Delay	796000	560000	892000	601000
Passenger Average Delay	8.78	6.17	9.84	6.62
PERFORMANCE				
Cancelled Flights	62	69	70	84
Ferry Flights	18	25	21	29
Crew FTC	2.82	3.01	2.85	3.04
Number of Active Crews	510	511	515	535
Non-Accomodated Passengers	3.55%	4.27%	3.70%	4.66%

Table 6.4: Scenario 2 – Disruptions at CLE, IAH, EWR

Procedures	I	II	III	IV
COSTS ($)				
Flight Cost	3862742	3883327	3872853	3883101
Passenger Cost	819723	571924	644040	645758
Total Operating Cost	4682465	4455251	4516893	4528859
DELAYS (min)				
Total Flight Delay	9697	9626	9628	9610
Average Flight Delay	8.61	8.50	8.52	8.45
Total Passenger Delay	607000	480000	601000	552000
Passenger Average Delay	6.70	5.30	6.63	6.08
PERFORMANCE				
Cancelled Flights	51	58	58	69
Ferry Flights	14	21	18	25
Crew FTC	2.72	2.90	2.85	3.02
Number of Active Crews	521	532	530	541
Non-Accomodated Passengers	5.74%	4.36%	4.60%	4.94%

Table 6.5: Scenario 3 – Disruptions at CLE, BOS, LAX

re-accommodated at the end of the simulated day. In many cases, using the control times determined during the slot allocation as the sole source of information for the arrival times leads to an overestimation of the expected re-accommodated passengers by the module. Take for example Scenario 1: the actual arrival times at CLE were, on average, 25 minutes beyond the control times, even after cancellations were made in the schedule. The delays affect particularly passenger connections in hubs, where bank times might be missed by the delayed incoming flights.

Affected Passengers in Hub and Spokes

In Scenarios 2 and 3, the disruptions occur at very distinct airports. The simulation results show that, as expected, the number of directly affected flights in Scenario 2 was considerably larger than in Scenario 3. As a result, the number of cancellations and the average delay in Scenario 2 are greater than in Scenario 3. Still, the number of disrupted passengers in the latter scenario is greater than in the former scenario because of the distinction in flight frequencies. For passengers stranded at spoke stations, the chances of not being re-accommodated on the same airline are greater because of the restricted number of outbound flights at these locations.

Comparing the number of cancellations between CAR and UAR

In all scenarios, it was observed that with CAR (Procedures II and IV) the number of cancellations is greater compared to the equivalent procedures with UAR (Procedures I and II). There are two correlated reasons found that justify this observation. First, the number of feasible candidate routes for an aircraft is reduced considerably with CAR, thus, in some cases where indirectly affected flights would be considerably delayed, canceling subroutes became more attractive. Second, in order to comply with CAR, the cancellations subroutes were sometimes extended through the last flight assigned to the aircraft, increasing the number of cancellations.

The number of cancellations directly affects the delay measures, such as Flight Delays and Passenger Delays. These values were smaller in the procedures with CAR for all scenarios, because the delays calculated exclude cancelled flights and passengers who are not re-accommodated at the end of the day. There is one exception to this rule, which is addressed in the following observation.

Passenger Re-accommodation in Scenario 3

There is a particular observation to be made about the passenger revenue loss in Scenario 3 (Table 6.5), when comparing Procedures I and II. Unlike the other procedures, the procedure with CAR was better at re-accommodating passengers. In a more detailed analysis it was observed that 2 inbound flights to LAX and 1 outbound flight from LAX, which were cancelled in Procedure I, were not cancelled in Procedure II because the aircraft scheduled to these flights were scheduled to be at LAX at the end of the day. The same happened to 2 inbound flights to BOS that were not cancelled in Procedure II. Thus, less passengers going to those locations were disrupted and consequently, fewer were not accommodated.

Crew Recovery

Little analysis can be done on the performance of the crew recovery since it is still a very primitive model. As it can be observed, the number of reserve crews is proportional to the number of ferry flights, which were exclusively flown by reserve crews. Also the flight delays and cancellations due to crew unavailability were insignificant. There were no cancellations due to the absence of crews. The small number of disruptions due to crew unavailability can be explained by three factors: (1) knowledge of the disruption well in advance, allowing the module to search for reserve crews at least 6 hours ahead of time; (2) optimistic deadheading connections, where any of the major airlines allowed CO crew members to fly any of their flights without seat restrictions; and (3) there were no fleet restrictions on the reserve crews that were called.

6.5 Drawbacks of the Module

The fact that the module is activated only once when a GDP is called, does not represent the true activity of an AOC. In reality, there is constant sharing of information within the center and with other airlines. This drawback is visibly clear for long GDP programs where the uncertainty increases as the time period between the decisions of the module and the time of the disruptions increases.

The passenger re-accommodation model did not consider all possible routings for stranded passengers: it searched for the best alternative itineraries in term of passenger delay. If all flights in the chosen itinerary were full, these passengers were not re-accommodated. Another drawback of the passenger re-accommodation model is that the model did not re-accommodate passengers before they misconnected; they were assigned to new itineraries only when they reached the airport where they misconnect (only passengers scheduled to fly cancelled flights were re-accommodated in advance).

While estimating the impacts of disruptions, airlines acknowledge that they are dealing with very unpredictable conditions. Currently, the AOC module considers control times as the only estimate for flight delay. As presented before, setting a deterministic value for the expected delay could lead to the underestimation of the revenue loss due to misconnected passengers.

The heuristic crew reassignment model applied here is very simplistic and does not represent an optimal approach to the problem. Intensive studies have been made by Lettovsky [11] and Yu [20] describing how to address the crew rescheduling problem, by searching for crews involved in disruptions and finding near-optimal recovered crew schedules.

Various sources of data were used during the simulation. As might be expected, information from different sources did not always match. Also, in some cases, data was not available. Thus, some assumptions were made, which although logical, might have influenced the final result.

6.6 Future Research

The aircraft recovery formulation presented in this research uses operating costs as the driving factor behind decision-making. The application of other objective functions to solve problems related to airline irregular operations, such as minimizing passenger delay, increasing profit margins and reducing crew FTC, have been the source of study of other researchers. These decision criteria can also be applied to an AOC module and adapted to the dynamic environment of MEANS.

The passenger re-accommodation model used in this research is simplistic in the sense that searching heuristically for the best alternative itinerary for disrupted passengers does not represent the airline's approach to handle their customers. Overall, compared to aircraft and crews recovery, passenger re-accommodation has been considerably less studied. Currently, there is a research being developed and implemented in MEANS to minimize passenger disruptions.

In real system operations, the Collaborative Decision Making (CDM) process allows airlines to interact with each other and with the FAA in order to find better solutions for delays [7]. Independent implementations of AOC modules for different airlines would allow the application of a realistic CDM in MEANS.

The weather forecast considered in this thesis had a 100% accuracy. Given that, the airline responses to disruptions did not have to be adapted to changes caused by inaccurate weather forecast. With an imprecise weather prediction, an airline module in MEANS would have to update decisions according to forecast and scheduled changes. AOC decision latency and information flow would then be relevant issues to be addressed.

The results presented were obtained considering only one day of operations. Simulation for longer periods of time would result in a considerable increase of the airline recovery problem: searches for candidate aircraft routes would require more time and memory, crew regulatory checks would have to be extended accordingly to the time period considered, and passengers who are not re-accommodated at the end of the day, could be accommodated in flights on the following day. Nonetheless, simulating operations over continuous days would allow for a better picture of aircraft rotations and the maintenance constraints, as well as the influence of crew regulatory issues during the recovery process.

Another point to be addressed during simulations of airline operations would be disruptions due to unscheduled maintenance. The recovery process for such disruptions is considerably simpler than those due to weather-related disruptions. The current version of MEANS does not consider such disruptions, but this feature could be included through random occurrences based on probabilistic distributions.

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