
# Congestion in a competitive world: a study of the impact of competition on airline operations

**Niklaus Eggenberg**

**Lavanya Marla**

**STRC 2009** **September 2009**

TRANSP-OR

ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

# Congestion in a competitive world: a study of the impact of competition on airline operations

Niklaus Eggenberg
Transp-or
EPFL
1015 Lausanne
phone: +41 21 693 24 32
fax: +41 21 693 80 60
niklaus.eggenberg@epfl.ch

Lavanya Marla
Civil And Environmental Engineering
MIT
Cambridge, MA
phone:
fax:
lavanya@mit.edu

September 2009

## Abstract

Air transport is a fast developing area. Airlines compete for a limited resource, namely airport capacity. The consequence is an increase in airport congestion, which generates huge delays that are enhanced due to delay propagation through the whole network. Currently, in the US, the Federal Aviation Association (FAA) only controls operational capacity allocation when disruptions occur with Ground Delay Programs (GDPs), and airlines are free to schedule their operations. In this paper, we propose a theoretical framework allowing to evaluate different regulations or incentives.

## Keywords

air traffic, congestion, revenue management, competition, airline scheduling, simulation

# 1 Introduction

In the US, the market is mainly competition-driven, and the US government works hard to ensure fairness of the competition. This holds for the airline business as well as for many other. The airline business has, as the energy supply or the health care, a capital socio-economic impact: both industry and people's daily life depend on air transportation, whether it is for business travel, tourism or simply keeping proximity with relatives. It is thus important that the provided service quality meets high standards. In practice, however, air transportation is increasingly faced with the problem of congestion: aiming at service quality increase tends to increase frequency to meet each passenger's time requirements. Alas, airlines share a limited resource, whose bottleneck is the capacities at the airports, which have a limited extension potential at medium term.

For this reason, many airports are congested, which implies huge delay propagation throughout the whole air traffic network. The Joint Economic Committee (JEC) reports that the total amount of observed arrival delays for 2007 reaches a record of 4.3 million hours (*Your Flight Has Been Delayed Again*, 2008). These delays obviously have huge impacts: first of all, the airlines' operational cost increase is estimated by JEC to $19 billion. The value of the passengers' lost time, and thus unproductiveness due to these delays is estimated to $12 billion, and finally, the spill out to other industries is estimated to $10 billion. In addition to the economical aspect, JEC also reports the environmental impact of these delays: the total amount of additional fuel consumed because of delays is estimated at 740 million gallons of jet fuel, generating 7.1 million metric tons of carbon dioxide: this represents almost 1.2‰of the total US emission in 2007: the Energy Information Administration[1] estimates the total US emissions of carbon dioxide to be 6021.8 million metric tons.

As alarming as these numbers are, the forecasts are that congestion, and thus delays, get from bad to worse: the Federal Aviation Association (FAA) predicts a yearly increase of 2.5% for the number of flights until 2025 (*Annual Report 2008*, 2008). As pointed out by Schaefer et al., 2005, each 1% increase of the number of flights incurs a 5% increase in delays.

The National Airspace System, because of its tight network nature with interconnections between passengers, aircraft and crews, is subject to huge levels of propagations in the system. Due to this, delays at one congested airport can affect the entire network. For example, the New York Aviation Rulemaking Committee (NYARC) reports that three-quarters of nationwide flight delays in the US originated from the New York area in summer 2007 (NYARC, 2007). This illustrates the impact of delay propagation from a single airport to the nationwide network.

It is thus imperative that operations at congested airports are controlled in order to protect the

[1] `www.eia.doe.gov`

entire system. The multi-billion dollar question the regulatory authorities are thus faced with is what to do to improve the current situation and turn pessimistic delay forecasts into more optimistic ones. The underlying question is whether competition will force airlines to adapt their scheduling strategy by themselves due to the high delay costs or if competition-regulatory measures are required.

In this paper, we study the impact of a voluntary frequency reduction of an airline in a competitive environment using the Passenger Origin-Destination Simulator (PODS). The detail of PODS as a revenue management simulator tool is described in Cusano, 2003. We show that airlines cannot benefit from frequency reduction in a competitive environment. However, although we provide some ideas on possible regulations, we do not study the question of their effects in application.

This study is the first step of an extensive exploratory work merging as different aspects of the airline business as revenue management, operation scheduling and on-the-day operation management. Although we do not provide a solution to the congestion problem, we show that the current system of air traffic requires to be revised for the quality of service to be improved.

The contributions are mainly that we provide, to our knowledge, the first comprehensive study on the relationships between schedule, market share and revenue in the context of reducing airline operations, and hence congestion, at a given airport. Furthermore, we introduce a framework allowing a comprehensive study of the real problem airlines are faced with, namely congestion in a competitive environment. We are thus able to identify the tools lacking to address a real-size problem, and list possible FAA regulations to be tested. Finally, we show the application of the framework on a single-market scenario in which two airlines compete, and show that, from the airlines' point of view, a voluntary frequency reduction at an airport is not profitable.

The paper is structured as follows: in section 2, we briefly review the literature on air-traffic control and the existing measures that are currently used in the US. Section 3 describes the theoretical framework used for our simulations. In section 4, we present a case study on a single-market for which two airlines compete. In section 5, we give a detailed description of the extensions to be considered to be able to study a real-world case, and we conclude with section 6.

## 2 Literature Review

Due to its complexity and different publication deadlines, an airline schedule is usually elaborated in a succession of iterative sub-problems which starts around one year before the day of operations. We focus here on the revenue management, the operational scheduling and the daily operational part of the process; for more details, see Kohl et al., 2007 and Weide, 2009.

The first problem an airline is faced with is to decide which routes to fly and at which frequency. The choice is mainly based on market demand estimations and forecasts, but also depends on competitor airlines. The revenue management starts with determining markets and frequencies, and then manages the ticket prices on each market to maximize the revenue. The route choice is made with the objective of maximizing revenue; operational costs are, if at all, considered using rough cost estimations only, and recovery costs are not considered at all.

Once the legs are determined, the operational part of the schedule is constructed (fleet assignment, tail assignment, crew pairing and crew rostering). The objective of operational scheduling is to ensure that all flights are flown such that the total cost of operations is minimized.

Alas, on the day of operations, unexpected events such as bad weather, crew illness or technical failures disturb the schedule. Such events are called *disruptions*, and face the airline with the *recovery* problem, consisting in retrieving the original schedule as fast as possible while minimizing recovery costs (incurred by delays, compensation to passengers and crew…). As shown in section 1, recovery costs are huge and mitigate most of the revenue of an airline.

As a well known fact in Operations Research, the iterative process leads to sub-optimal solutions. Many studies on integrated approaches exist, see for example Cordeau et al., 2001, Mercier and Soumis, 2007, Weide et al., 2008 or Papadakos, 2009. However, all of them assume the route choice as given. Lately, secondary objectives such as robustness or recoverability (see for example Ageeva, 2000, Lan et al., 2006, Yen and Brige, 2006, Eggenberg and Salani, 2009 or Weide, 2009) are used at the operational scheduling phase in order to make schedules less sensitive to delay propagation and build schedules generating less recovery costs. All of these methods also assume the route choice as a provided input, allowing at most the retiming of flight departures within a limited time window.

Finally, the whole scheduling process is performed independently by each airline. The external constraints for the whole schedule design are maintenance constraints for aircraft and contract constraints for crew, but airlines are free to schedule flights and frequencies at most airports in the US. Exceptions are the JFK, EWR, LGA, ORD and DCA airports which have been slot controlled in various ways since 1968 (Harsha, 2009).

On the day of operations, the recovering from disruptions was also addressed independently by airlines. As congestion grew, the FAA introduced a collaborative inter-airline regulation to make the recovery more efficient; the regulation is the *Ground Delay Program* (GDP), which determines all flights' departures within a geographical region using a greedy push-back strategy at airports operating at reduced landing capacity.

Airlines were first reluctant to comply with GDPs, mainly for fairness issues but as it turned out, all airlines complying with the regulation eventually realized that the compliance allowed for delay reduction on the whole network. Capacity allocation mechanisms used by the FAA during GDPs however provide benefits to all airlines. Indeed, Vossen and Ball, 2005 show that the current scheme in practice, ration-by-schedule (RBS), minimizes the maximum ground delays allotted to the different flights. However, Hanowsky, 2008 also shows that there might be inequities in the allocation of delay across airlines and types of planes, and points out the importance of equity and the several metrics of fairness. Barnhart. et al., 2009 studies alternative capacity allocation mechanisms based on airline-network fairness.

Ongoing research has involved studies on the different methods of FAA interventions, by explicitly allocating capacity and managing demand. These can be classified into two types: strategic and operational initiatives. The former are only applied to a limited extent. Traditionally used mechanisms for strategic initiatives are to allocate capacity using grandfathering of slots and a lottery system. More proactively, administrative controls place caps on the airport capacity, and limit the number of operations (*Code of Federal Regulations*, Title 14, Part 93). Alternatively, mechanisms such as congestion pricing and airport slot allocation have been proposed (Harsha, 2009). In 2007, US Transportation Secretary Mary Peters announced a goal of reducing the number of operations per hour from the New York airports, first by voluntary means, and also indicated a possible use of market-based mechanisms (Marks, 2003). However, the implementation of slot-auction mechanisms received severe criticism from the industry, and was finally not implemented (WilmerHale, 2009).

Operational strategies for capacity allocation have included slot allocation during Ground Delay Programs (GDP) and Airspace Flow Programs (AFP). Mechanisms such as RBS are being used by the FAA (Vossen and Ball, 2005). Alternatives to the RBS that address issues such as network-fairness based allocations (Barnhart. et al., 2009) or slot exchange mechanisms (Harsha, 2009) are being proposed and studied.

Most of these studies make assumptions about the airline and passenger response by considering average revenues instead of explicitly considering revenue management, which has not yet been considered when modeling capacity controls and the resulting schedule changes of airlines.

Airline Revenue management is an effort by the airlines to maximize revenues using differential pricing. Because the operating costs of the flight are fixed in the short run, revenue management aims to maximize the revenue per flight in order to maximize profit (Barnhart et al., 2003). This paper also indicates that the studies in the field of combining the effects of airline schedule planning and recovery with those in revenue management have been limited.

We thus see that, although controlling airline operations in a proactive way seems beneficial, only few studies address the problem of evaluating such control measures by considering the entire problem, namely including competition, operations, congestion and responses to irregularities.

# 3 Global Simulation Framework

The objective of the simulations is to get insight about the implications of schedule modifications (whether imposed or not) on revenue in a competitive environment. We sketch here a detailed framework, which is schematized in Figure 1.

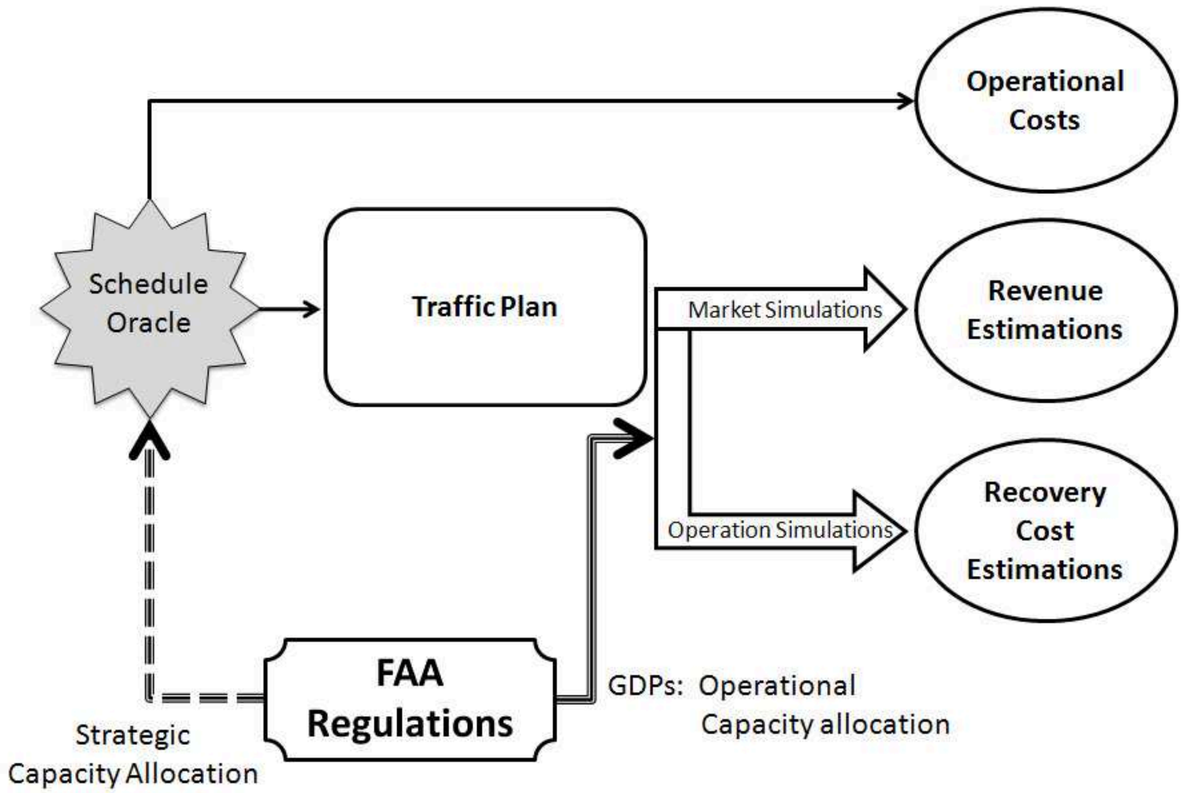


Figure 1: Simulation process to evaluate the global performance of a schedule. An oracle decides on the routes and frequencies including potential FAA regulations (dashed arrow).

The simulation starts from a schedule obtained from an oracle: this schedule corresponds to the output of the route choice problem, i.e. the set of flights to be flown. We then estimate the quality of the schedule according to three aspects:

1. the estimated revenue
2. the operational costs
3. the estimated recovery costs

The operational costs can be evaluated using optimization tools or using cost approximations. The revenue is estimated using market simulations; the main difficulty in the simulation is the passenger demand estimation, especially as changes in the schedule might affect the demand itself. In this paper, we use PODS as revenue estimator.

PODS is a computer simulation tool used to test airline revenue management methods. It has been developed by Craig Hopperstad at the Boeing Company, see for example Hopperstad, 1997, Carrier, 2003. For a selection of different pricing schemes and airlines, PODS models passenger decisions using choice models; it simulates an airline network with several O-D markets and price structures and is composed of four different modules: passenger choice model, revenue management, forecaster, and historical booking database, which are linked in a simulator. A schematic of PODS and details of the framework are available in Cusano, 2003.

The estimation of recovery costs is also critical, as they depend on the severity of a given disruption. Currently, recovery costs are not explicitly considered and only non-monetary metrics such as total delay, total passenger delay, 15 minute on-time performance or number of canceled flights are used. However, in order to get a correct estimation of a schedule, monetary estimations are required.

As shown in Figure 1, the only FAA regulation is the GDP on the day of operations. However, if explicit FAA regulations were to be introduced at the scheduling phase, they would have to be considered by the oracle (dashed arrow in Figure 1). A plausible regulation is, for example, a limited number of departing and/or landing flights at a given airport within a time window.

The global performance of a schedule is then obtained by subtracting the estimated operational and recovery costs from the estimated revenue. Using the oracle for different airlines at the same time (or using one specific oracle for each airline) allows to simulate a real-world situation of competing airlines and to determine the profit (or the deficit) of each individual airline with respect to changes in the system.

The proposed framework thus allows us to compare the global benefit of airlines with respect to explicit FAA regulations such as airport capacity constraints, but it also allows us to evaluate the potential benefit of incentives such as rewards for frequency-reduction or a first-priority rule during GDPs for airlines that reduced their number of operations at a given airport.

# 4 Case study

The framework introduced in section 3 is theoretical, as most of the tools required are either missing or not able to solve large scale problems, as required to address real problems. In this section, we focus on a single market for which two airlines compete. We assume that

| Flight | F1 | F2 | F3 | F4 | F5 |
|---|---|---|---|---|---|
| Departure | 8.11 | 11.00 | 14.61 | 17.11 | 19.00 |
| Arrival | 11.50 | 14.39 | 18.00 | 20.50 | 22.39 |

Table 1: Arrival and departure times of the 5 daily flights the base scenario BASE.

the passenger demand is independent of schedule changes (and thus constant throughout the simulations) and we do not consider disruptions. We thus focus on the analysis of the effects of airline schedule management on the revenue management. The single origin-destination (OD) market with the following specifications:

| | |
|---|---|
| Distance | 1440 miles |
| Block hours: | 3.39 hours |
| Nbr airlines: | 2 (A1 and A2) |
| Flights per airline per day | 5 |
| Nbr seats per flight | 100 |
| 0 Nbr of fare classes | 6 (class 1 being the highest, 6 the lowest) |

In the BASE scenario, both airlines share the market equally with identical departure times and capacities. We denote the two airlines by A1 and A2. Table 1 details the departure and arrival times for the 5 daily flights.

Starting from this even market, we derive two distinct sets of scenarios. The former is a set of 4 scenarios (I0 to I3) for which airline A1 modifies its schedule and A2 remains with its original one. The latter is a set of 3 scenarios (R1 to R3) for which A2 responds to the schedule changes made by A1 in a competitive way.

The revenues are estimated using PODS, which takes as input a passenger demand profile, the airlines' pricing strategy (that we assume is the same), the airline schedule (frequency, departure and arrival times and aircraft capacities). It then simulates the booking process of the passengers and the adaptive airlines' pricing strategies and outputs revenue management statistics such as total revenue, load factors, number of passengers per fare class. . .

## 4.1 Scenario set without competitive response

In this instance set, airline A1 voluntarily modifies its schedule as reported in Table 2, while A2's schedule remains unchanged as in BASE.

In I0, A1 retimes all flights, postponing each of them by 1 hour. In scenario I1, A1 decides to cut its schedule by one flight, namely F3; the other flights remain as originally scheduled. In

| Instance | BASE | I0 | I1 | I2 | I3 |
|---|---|---|---|---|---|
| Departure F1 | 8.11 | 9.11 | 8.11 | 8.11 | 8.11 |
| Capacity F1 | 100 | 100 | 100 | 100 | 100 |
| Departure F2 | 11.00 | 12.00 | 11.00 | 11.00 | 11.00 |
| Capacity F2 | 100 | 100 | 100 | 100 | 100 |
| Departure F3 | 14.61 | 15.61 | # | # | # |
| Capacity F3 | 100 | 100 | # | # | # |
| Departure F4 | 17.11 | 18.11 | 17.11 | 15.50 | 15.50 |
| Capacity F4 | 100 | 100 | 100 | 100 | 125 |
| Departure F5 | 19.00 | 20.00 | 19.00 | 18.00 | 18.00 |
| Capacity F5 | 100 | 100 | 100 | 100 | 125 |

Table 2: Scenarios for initiatives by A1, A2 having the same schedule than BASE for all instances.

| Instance | BASE | | I0 | | I1 | | I2 | | I3 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Airline | A1 | A2 | A1 | A2 | A1 | A2 | A1 | A2 | A1 | A2 |
| Revenue [$] | 87376 | 87613 | 85137 | 89901 | 74823 | 94916 | 76973 | 92667 | 80908 | 91475 |
| Total Pax | 399.24 | 399.8 | 396.97 | 401.75 | 333.06 | 412.8 | 334.65 | 411.32 | 368.36 | 405.67 |
| % Business pax | 46.39 | 46.42 | 45.81 | 47.18 | 47.51 | 49.95 | 50.19 | 47.86 | 46.09 | 48.80 |
| ALF [%] | 79.85 | 79.96 | 79.39 | 80.35 | 83.27 | 82.56 | 83.66 | 82.26 | 81.86 | 81.13 |
| Yield | 0.1563 | 0.1565 | 0.1558 | 0.1578 | 0.1643 | 0.1609 | 0.1605 | 0.1642 | 0.1569 | 0.1611 |

Table 3: Results of simulation using PODS for the scenarios without competitive response.

I2, A1 reschedules the last two flights of the day with a better time coverage of the afternoon. Finally, in I3, additionally to the rescheduling of the afternoon flights as in I2, A1 increases the capacity of F4 and F5 by 50 seats to compensate the capacity lost because of the canceled flight.

The objective of these scenarios is to highlight the impact on the revenue management (simulated by PODS) of A1's scheduling decisions. We summarize the results of the simulations in Table 3, showing, for each airline in each scenario, the total revenue, the total number of transported passengers, the percentage of business passengers, the average load factor (ALF) and the yield. Table 4 reports the average load factors for each of the 6 fare classes (fare class 1 being the highest and 6 the lowest).

| Instance | BASE | | I0 | | I1 | | I2 | | I3 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Airline | A1 | A2 | A1 | A2 | A1 | A2 | A1 | A2 | A1 | A2 |
| Fare Class 1 [%] | 5.00 | 5.07 | 4.94 | 5.17 | 5.16 | 5.54 | 5.43 | 5.29 | 5.59 | 5.35 |
| Fare Class 2 [%] | 8.17 | 8.21 | 8.07 | 8.33 | 8.92 | 9.36 | 9.46 | 8.84 | 9.46 | 8.80 |
| Fare Class 3 [%] | 13.63 | 13.71 | 13.33 | 14.01 | 15.19 | 15.88 | 16.09 | 14.96 | 15.89 | 14.80 |
| Fare Class 4 [%] | 13.32 | 13.18 | 13.09 | 13.65 | 15.66 | 15.48 | 16.41 | 15.04 | 15.83 | 14.53 |
| Fare Class 5 [%] | 5.86 | 5.29 | 5.92 | 7.01 | 12.16 | 11.15 | 13.58 | 11.96 | 10.25 | 9.26 |
| Fare Class 6 [%] | 33.87 | 34.50 | 33.92 | 32.26 | 26.19 | 25.16 | 22.70 | 26.16 | 35.06 | 28.38 |
| Empty [%] | 20.15 | 20.04 | 20.73 | 19.57 | 16.72 | 17.43 | 16.33 | 17.75 | 7.92 | 18.88 |

Table 4: Load factors for each of the 6 fare classes for scenarios without competitive response. Fare class 1 is the highest and fare class 6 the lowest.

As expected, in `BASE`, both airlines equally share the single market, with a similar average load factor of around 80% and around 46.5% business passengers. The situation however changes significantly when A1 takes retiming initiatives (`I0`): around $2\%$ of the revenue is directly transferred from A1 to A2. Looking at the number of transported passengers, we again observe a direct transfer of around 0.5% from A1 to A2, most of them being business passengers; the average load factor changes by the same amount. Retiming thus does affect revenue management of both airlines, and interestingly, A2 directly benefits from A1's (poor) retiming decision.

When simply canceling one flight (`I1`), the loss of revenue for A1 is of 14.37%, although 20% of the frequency (and total capacity) is cut; 16.57% of passengers are lost compared to `BASE`. This means that A1 is able to mitigate the frequency/capacity reduction thanks to revenue management. Furthermore, we observe that, unlike scenario `I0`, the loss of A1 is not equivalent to the gain of A2. Indeed, A2 increases its revenue by 8.43% and carries only 3.25% more passengers with respect to `BASE`. This means that A2 makes its additional profit by selling more high-fare tickets: indeed, as shown in Table 4, the average load factors for the 3 highest fare classes (classes 1, 2 and 3) are increased by 0.47, 1.15 and 2.17 respectively, whereas the lowest fare class (class 6) decreases by 9.34 compared to `BASE`. This comes because A2 has the monopole on flight F3, whose revenue jumps from $18,996 to almost $23,770, i.e. an increase of 25.13%. The most interesting part is the increase of load factor for both airlines, although the total number of transported passengers decreases by 6.76%. The reason is that the capacity of A1 is reduced due to the flight cancellation, implying a total capacity reduction in the system of 10%.

When compensating the canceled flight by retiming the remaining two afternoon flights (F4 and F5), A1 actually loses some passengers compared to `I1` (0.48%), but increases its revenue by 2.87%. The revenue gain is made by additional business passengers, who move from 47.51% in `I1` to 50.19% in `I2`. The gain of A1 is comparable to the loss of A2, which loses about as many business passengers as A1 recaptures; interestingly, the number of transported passengers and the average load factors for both airlines are similar for `I1` and `I2`. However, compared to `BASE`, A1 still loses 11.90% of its revenue.

Finally, when compensating the flight cancellation by both retiming and additional capacity on flights F4 and F5 (scenario `I3`), A1 is able to limit the loss of revenue compared to `BASE`: the loss is of 7.4%, i.e. almost half of the revenue lost due to the flight cancellation is recaptured. Remarkably, unlike scenario `I2`, the revenue comes from a significant passenger recapturing (10% more than for `I2` for 12.5% additional capacity). The load factor however decreases from `I2` to `I3`, meaning that not all the additional capacity is exploited by A1. Looking at the class load factors in Table 6, we see that they are similar for the highest two fares classes; in `I2` however, classes 3 to 5 have slightly higher load factors. Thus, A1 makes its additional revenue

| Flight | F1 | F2 | F3 | FAdd | F4 | F5 |
|---|---|---|---|---|---|---|
| Departure | 8.11 | 11.00 | 14.33 | 16.50 | 18.00 | 19.50 |
| Arrival | 11.50 | 14.39 | 17.72 | 19.89 | 21.39 | 22.89 |

Table 5: Updated schedule of A2 in response to the removal of flight F3 by A1 used in scenarios `R1-R3`.

by allocating the additional capacity to low fare passengers (average load in class 6 increases from 22.7% in `I2` to 35.06% in `I3`). Looking at A2, we observe similar results: load factors of classes 1 to 3 are similar, classes 4 and 5 decrease and class 6 increases; the magnitude of the changes is, however, smaller than for A1. Interestingly, compared to `BASE`, A2 make 5.87% more revenue for only 1.8% more passengers; compared to `I2`, the revenue decreases by 6.9% while the number of carried passengers diminues by 11.26%.

We conclude from these preliminary results that, as expected in a competitive environment, A2 benefits from the frequency/capacity reduction of A1 even without modifying its schedule. We see two main phenomena: retiming mainly changes the fare class distribution of both airlines, with a direct transfer between airlines, i.e. the gain of one airline is almost equal to the loss of the other. Changing capacity and/or frequency has a consequence on both load factors and fare class distribution, and the changes are no longer symmetric: A1 loses more than A2 gains. This clearly highlights the efficiency of revenue management, showing that airlines with higher capacity/frequency are able to manage it better in order to attract more high fare passengers.

## 4.2 Scenario set with competitive response

In this set of scenarios, we allow airline A2 to respond competitively to the frequency reduction of A1: in scenario `R1`, A2 adds a flight FAdd in response to A1 canceling flight F3. A2 also slightly retimes its afternoon flights (F3-F5), as shown in table 5.

In scenario `R1`, A1 simply cancels flight F3 (no retiming nor capacity change), while A2 uses the schedule shown in Table 5 with 100 seats for each flight (i.e. 600 seats in total). In `R2`, A1 retimes and increases the capacity of its afternoon flights as in `I3`, while A2's schedule remains as in `R1`. Finally, in `R3`, A1 has same schedule than in `I3`, and A2 reduces the capacity by 25 seats on flights F3, FAdd, F4 and F5; A2 thus has 500 seats as in `BASE`, but with higher frequency. `R1` is thus the extension of `I1` with A2's competitive response, and `R2` and `R3` are two different extensions of `I3`.

Table 6 shows the revenue, passenger, average load factor (ALF) and yield statistics and Table 7 summarizes the average load factor for the 6 fare classes for scenarios `R1-R3`.

Looking at the revenues of A2, it is clear that the competitive response benefits to A2: in all scenarios, the revenue is higher than in the corresponding scenario without competitive

| Instance | BASE | | R1 | | R2 | | R3 | |
|---|---|---|---|---|---|---|---|---|
| Airline | A1 | A2 | A1 | A2 | A1 | A2 | A1 | A2 |
| Revenue [$] | 87376 | 87613 | 74166 | 100975 | 78035 | 99633 | 79485 | 92752 |
| Total Pax | 399.24 | 399.8 | 329.61 | 468.84 | 360.39 | 458.63 | 367.53 | 407.01 |
| % Business pax | 46.39 | 46.42 | 49.35 | 44.45 | 45.73 | 45.84 | 44.46 | 50.05 |
| ALF [%] | 79.85 | 79.96 | 82.40 | 78.14 | 80.09 | 76.44 | 81.67 | 81.40 |
| Yield | 0.1563 | 0.1565 | 0.1607 | 0.1538 | 0.1547 | 0.1552 | 0.1545 | 0.1628 |

Table 6: Results of simulation using PODS for the scenarios with competitive response.

| Instance | R1 | | R2 | | R3 | |
|---|---|---|---|---|---|---|
| Airline | A1 | A2 | A1 | A2 | A1 | A2 |
| Fare Class 1 [%] | 5.33 | 4.84 | 5.57 | 5.00 | 5.41 | 4.54 |
| Fare Class 2 [%] | 8.94 | 7.62 | 9.01 | 7.63 | 9.08 | 7.57 |
| Fare Class 3 [%] | 15.09 | 12.67 | 14.99 | 12.59 | 15.30 | 12.82 |
| Fare Class 4 [%] | 14.92 | 12.33 | 14.61 | 12.13 | 15.35 | 12.33 |
| Fare Class 5 [%] | 8.51 | 6.29 | 5.21 | 3.87 | 9.30 | 7.20 |
| Fare Class 6 [%] | 29.61 | 34.39 | 40.71 | 35.22 | 37.45 | 23.38 |
| Empty [%] | 17.60 | 21.86 | 9.90 | 23.56 | 8.11 | 32.16 |

Table 7: Load factors for each of the 6 fare classes for scenarios with competitive response. Fare class 1 is the highest and fare class 6 the lowest.

response. In R1, the introduction of an additional flight (increasing frequency and capacity by 20%) generates 6.38% more revenue for A2 compared to I1. The number of transported passengers is increased by 13.53%, but the average load factor is decreased from 82.56% to 78.14%. Comparing the average fare class loads shows that A2 sells proportionally few high fare seats in R1 than in I1. In absolute, this also holds except for the highest fare class, for which A2 sells 4.98% more tickets in average. A1 is also affected by the competitive response: the revenue is decreased by 0.89% compared to I1 and 1.04% fewer passengers are transported. The fare class loads are similar for the high fare classes; loads for fare classes 4 and 5 are decreased and increased for class 6. For both airlines, the loads of high fare classes are almost unchanged after A2's competitive response. However, for both airlines, fare classes 4 and 5 have significantly lower loads (in particular class 5), but more seats are sold at lowest fare (class 6). We see that the additional flight barely affects the high fare passengers, but allows more passengers to obtain tickets at the lowest fare; as A2 has more capacity, it is able to balance the loss of revenue per passenger by selling more tickets, which explains the differences in revenue between I1 and R1.

When retiming its afternoon flights (R2), A1 is able to recapture some of the lost revenue: A1 gains 5.22% more than in scenario R1. All observations made for I3 (lower load factors but more transported passengers, similar load factors for high fare classes, decrease in load factors for fare class 5 and increase in fare class 6) hold for R2 as well, but the magnitude is reduced, mainly for A2.

Scenario R3 is the case in which A1 has low frequency with higher capacity and A2 has high frequency and low capacity. Clearly, A2 is dominant on the market compared to BASE: it has

| Aircraft Size | 75 seats | 100 seats | 125 seats |
|---|---|---|---|
| Block hour cost | 2000 | 2500 | 3000 |
| Cost/departure | 700 | 800 | 900 |

Table 8: Cost structure used to compute operating costs. All costs are in US$.

increased its revenue by 5.87%. Although total capacity of A2 is unchanged between BASE and R3, the number of passengers transported by A2 is increased by 1.8%; the additional revenue is generated by low fare passengers who buy the second cheapest ticket instead of the cheapest one. A1 actually loses more than A1 gains, as the revenue is reduced by more than 9%. Although the average load factor and the average load factors by fare class increase relatively, this is only due to the capacity reduction (450 seats in total for R3 for 500 in BASE): in absolute, all fare classes but fare class 5 have lower number of passengers. Although it is not reflected by the relative numbers in Table 7, A2 sells more tickets in high fare classes than A1.

Finally, looking at the evolution of the average revenue per flight, per passenger and per seat (see Figure 3), we see that A1 has a higher revenue per flight in scenario R3, but a clear lower revenue per passenger and per seat. This is enhanced by the yield, which is clearly higher for A2 than A1 (the yield in R3 is 0.1545 and 0.1628 for A1 and A2 respectively).

We thus see that in a system with over-capacity, airlines tend to sell more tickets at lowest fare to fill up the aircraft, whereas in the case the capacity is limited, more tickets in fare class 5 are sold. Additionally, we remark that the low-frequency-high-capacity schedule of A1 cannot compete with the high-frequency-low-capacity of A2: the better time coverage of the flights allows A2 to attract passengers with higher willingness to pay. The conclusion is that an airline cannot benefit from voluntarily reducing frequency, whether the competing airlines respond or not. This conclusion has, however, to be contrasted: it holds when considering revenue indeed, but we do not consider operational costs. The following section addresses this issue, including approximate operating costs and comparing the airlines' profits instead of the raw revenue.

## 4.3 Including operational costs

As shown previously, an airline has no interest of reducing frequency in terms of revenue. In this section, we consider approximate operational costs to compare the airlines' profits for scenarios BASE and R3. We use the cost structure shown in Table 8:

Additionally, we assume a constant cost of $37 per passenger for catering, an overhead of 15% and a distribution of 9%. The operating cost of a single flight is given by the following formula:

$$\text{Cost} = (1 + \text{Overhead}) \times ([\text{BlockTime} \times \text{CostPerBlockHour}] + [\text{NbrPax} \times \text{CostPerPax}] + \text{DepCost}) \,,$$

| Flight | F1 | | F2 | | F3 | | F4 | | F5 | | FAdd | | TOTAL | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Airline | A1 | A2 | A1 | A2 | A1 | A2 | A1 | A2 | A1 | A2 | A1 | A2 | A1 | A2 |
| BASE | 2595 | 2691 | 3779 | 3816 | 3079 | 3087 | 1291 | 1427 | -1551 | -1638 | # | # | 9192 | 9383 |
| R3 | 2405 | 2350 | 3953 | 3124 | # | 4813 | 3147 | -99 | 395 | -942 | # | 2099 | 9900 | 11345 |

Table 9: Profits for all flights for instances BASE and R3. All values are in US$, non exiting flights are marked by #.

and the profit of a single flight is given by

$$\text{profit} = (1 - \text{Distribution}) \times (\text{Revenue} - \text{Cost}).$$

Table 9 shows the profit for each flight of instances BASE and R3.

Remarkably, A1 is actually *increasing* its profit when removing one flight and adding capacity. However, its profit increases by only 2.1%, whereas A2 increases it by 14.6%. We also see that the late afternoon flights have negative values, meaning that the flight costs more than it generates revenue. Actually, with the high-frequency-low-capacity schedule of A2 in R3, two flights are in deficit. However, both airlines reduce the deficit with respect to BASE and increase the profit on the remaining flights.

We thus see that even when considering operating costs, the high-frequency-low-capacity schedule performs better than the low-frequency-high-capacity one, although both airlines increase their profit.

# 5 Further requirements and research directions

The content of this exploratory study is to introduce a methodology to evaluate incentives or regulations in a realistic model of the current air traffic industry. In order to achieve a full evaluation of the problem; tools that are able to evaluate real-sized problems are thus required. Each module represented in Figure 1 has to be adapted in an appropriate way an implemented within a global simulator. We hereafter briefly describe the limitations and requirements for each module independently.

**Schedule Oracle** The oracle is certainly one of the most sensitive modules, as it must model the competitive responses of airlines with respect to external incentives or regulations. Ideally, schedules should be optimized according to different objectives modeling the airlines' business intentions. The additional difficulty is due to the number of different objectives, as the oracle might consider not only expected revenue, but also the operational and/or recovery costs. The methods used for the oracle thus range from expected revenue optimization to robustness or recoverability approaches, which all differ depending on external regulations or incentives.

**Revenue Simulator** Currently, PODS, the revenue management simulator, is not yet able to simulate a nation-wide network. But, before even considering tackling the simulation of the whole problem, there are several preliminary issues to be solved with respect to revenue management. First of all, as revenue management is market based (as opposed to leg-based), it is non-trivial to evaluate revenue on a leg-based basis. The usual technique is to use a *pro-rated* revenue, i.e. the revenue of a multi-leg ticket is distributed to each flight according to its duration.

**Operational Costs** Evaluating the operational costs is not trivial, but it is a widely studied field in literature. The difficulty is that it is hard to define a suitable cost-structure for operational costs, especially with the continuously fluctuating fuel prices.

**Recovery Costs** The difficulty of estimating recovery costs is twofold: first, recovery costs are hard to evaluate a priori as they depend on the severity of a disruption and the used recovery strategy; second, they involve non-monetary costs such as customer and/or crew dissatisfaction which may impact the revenue in addition to the directly generated costs. For the monetary cost evaluation, it is most likely that simulation would lead to the best results, which raises the question of choosing a set of disruptions. Furthermore, each disruption scenario has to be adapted with respect to other airlines, different regulations, etc.

**Global Simulator** Once the issues of the individual modules are resolved, we are faced with the problem of integrating them. Indeed, the different modules interact among themselves as, for example, passenger dissatisfaction may influence the passenger demand.

**FAA Regulations** Testing different regulations or incentives is the primary purpose of the simulator, but it does not answer the question of what these regulations should be. Clearly, using airport capacity caps, slot auctioning or a reward rule for complying airlines are possible measures, but if one expects regulations to be approved by airlines, on certainly has to elaborate them by taking into account their compliance.

# 6 Conclusion

In this exploratory work, we introduce a theoretical framework to estimate the effects of congestion, competition and external regulations within a simulator. We discuss the requirements of each of the modules contained in the simulator.

We illustrate part of the simulator on a single market case study. We show that in a competitive environment, an airline does not benefit from reducing its flight frequency with respect to revenue. Additionally, considering approximations on operational costs, we show that this also holds in terms of profits.

This study is intended to set milestones for future research for making air traffic a mode reliable and profitable business for both customers and carriers.

# References


Ageeva, Y. (2000). *Approaches to incorporating robustness into airline scheduling*, Master's thesis, Massachusetts Institute of Technology.

*Annual Report 2008* (2008). International Air Transport Association.
**URL:** *http://www.iata.org*

Barnhart, C., Belobaba, P. and Odoni, A. R. (2003). Applications of operations research in the air transport industry, *Tranportation Science* **37**(4): 368Ű391.

Barnhart., C., Bertsimas, D., Caramanis, C. and Fearing, D. (2009). Equitable and efficient coordination of traffic flow management programs, *Technical report*, Working Paper.

Carrier, E. (2003). *Airline passenger choice: Passenger preference for schedule in the passenger origin-destination simulator*, Master's thesis, Massachusetts Institute of Technology.

*Code of Federal Regulations* (Title 14, Part 93).

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

Cusano, A. (2003). *Airline revenue management under alternative fare structures*, Master's thesis, Massachusetts Institute of Technology.

Eggenberg, N. and Salani, M. (2009). Uncertainty feature optimization for the airline scheduling problem, *Technical report*, Ecole Polytechnique Fédérale de Lausanne, Switzerland.

Hanowsky (2008). *A Model to design a stochastic and dynamic ground delay program subject to non-linear cost functions*, PhD thesis, Massachusetts Institute of Technology.

Harsha, P. (2009). *Mitigating Airport Congestion: Market Mechanisms and Airline Response Models*, PhD thesis, Massachusetts Institute of Technology.

Hopperstad, C. (1997). Pods modeling update, *Technical report*, AGIFORS Yield Management Study Group Meeting, Montreal, Canada.

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

Lan, S., Clarke, J.-P. and Barnhart, C. (2006). Planning for robust airline operations: Optimizing aircraft routings and flight departure times to minimize passenger disruptions, *Transportation Science* **40**: 15–28.

Marks, A. (2003). Clogged airports: A plan to cut n.y.c. air traffic, The Christian Science Monitor.
**URL:** *http://www.csmonitor.com/2007/1023/p01s08-usgn.html*

Mercier, A. and Soumis, F. (2007). An integrated aircraft routing, crew scheduling and flight retiming model, *Computer & Operations Research* **34**: 2251–2265.

NYARC (2007). New york arc report, *Technical report*, New York Aviation Rulemaking Committee.
**URL:** *http://www.faa.gov/library/reports/media/NY%20ARC%20Report.pdf*

Papadakos, N. (2009). Integrated airline scheduling: Decomposition and acceleration techniques, *Computer & Operations Research* **36**(1): 176–195.

Schaefer, A., Johnson, E., Kleywegt, A. and Nemhauser, G. (2005). Airline crew scheduling under uncertainty, *Transportation Science* **39**(3): 340–348.

Vossen, T. W. and Ball, M. O. (2005). Optimization and mediated bartering models for ground delay programs, *Naval Research Logistics* **53**: 75–90.

Weide, O. (2009). *Robust and Integrated Airline Scheduling*, PhD thesis, The University of Auckland, New Zealand.

Weide, O., Ryan, D. and Ehrgott, M. (2008). Solving the robust and integrated aircraft routing and crew pairing problem in practice - a discussion of heuristic and optimization methods, *Technical report*, Department of Engineering Science, University of Auckland.

WilmerHale (2009). Airline slot auction rules and related litigation head toward termination.
**URL:** *http://www.wilmerhale.com/about/news/newsDetail.aspx?news=1596*

Yen, J. W. and Brige, J. R. (2006). A stochastic programming approach to the airline crew scheduling problem, *Transportation Science* **40**: 3–14.

*Your Flight Has Been Delayed Again* (2008). Joint Economic Committee.
**URL:** *http://jec.senate.gov*

# A Graphs

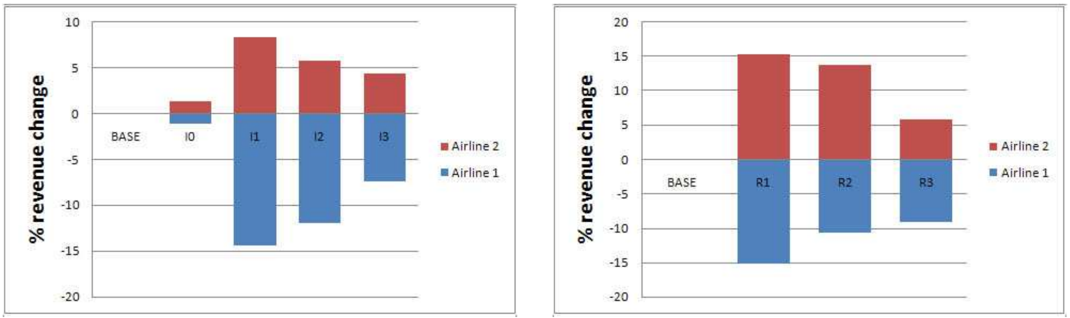


Figure 2: Relative revenue changes for both instance sets with respect to BASE.

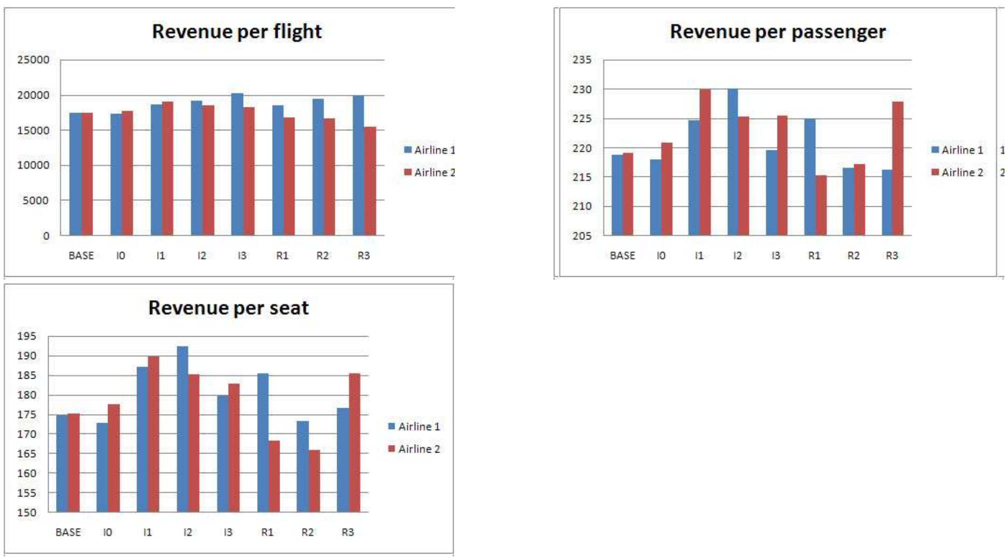


Figure 3: Average revenue per flight, per passenger and per seat for both airlines in all scenarios.


Figure 4: Revenue for each flight of airline A1 in the different scenarios. F3 is suppressed in scenarios `I1`-`I3` and `R1`-`R3`

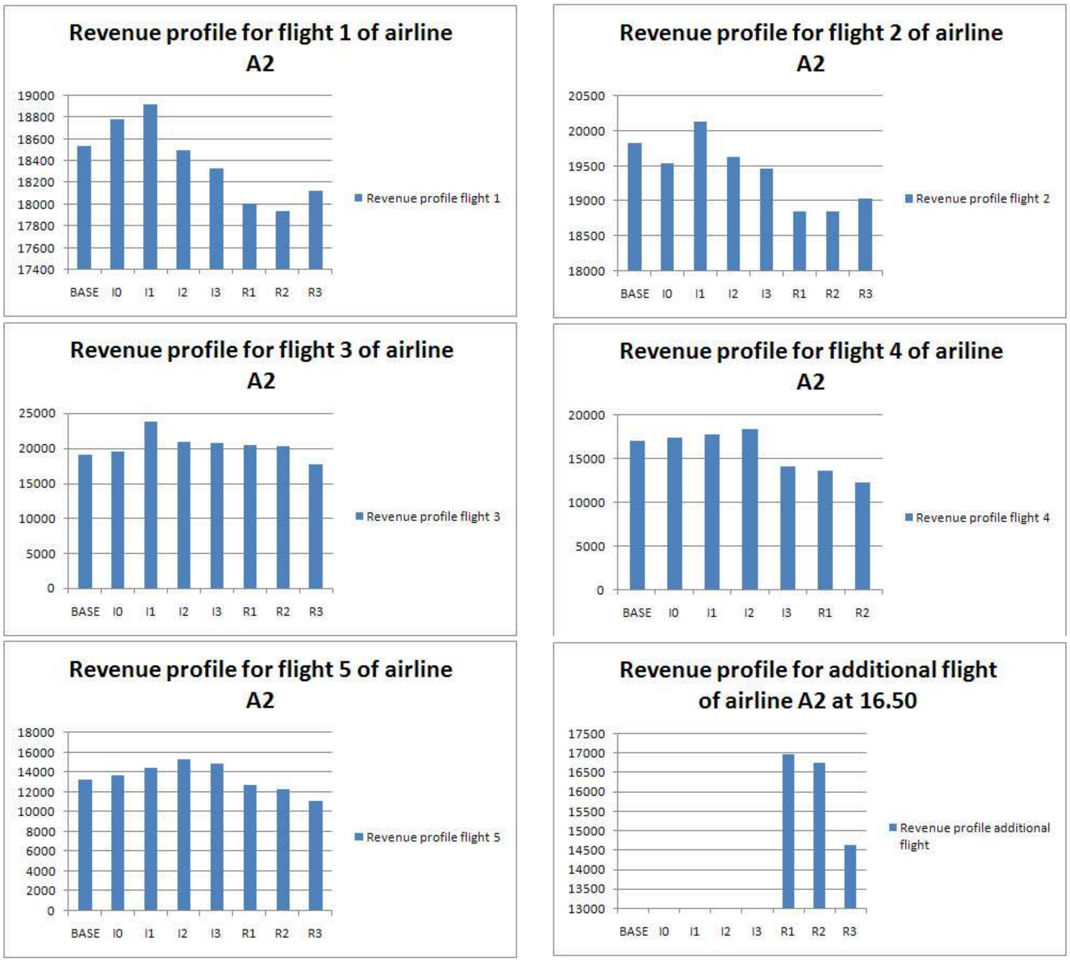


Figure 5: Revenue for each flight of airline A2 in the different scenarios. Flight Fadd is added in scenarios R1-R3.