A CONGESTION PRICING MODEL TO HANDLE "DAY OF OPERATIONS" AIRPORT CAPACITY REDUCTIONS

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Dedication

I dedicate this dissertation to my parents, Mohammad Iqbal Kara and Zohra Hajiani.

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Abstract

A CONGESTION PRICING MODEL TO HANDLE “DAY OF OPERATIONS” AIRPORT CAPACITY REDUCTIONS

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The airline industry in the United States provides one of the major modes of transportation. It is a highly connected network used by over 712.6 million people in 2010 [FAA, 2011] and is the most common means of travel for origin-destination pairs of greater than 250 miles. In 2007, due to a high volume of flights and an inefficient allocation of resources, congestion was generated in the system that was estimated to cost $32 billion to the overall economy [Ball et al., 2010]. This has forced the U.S. Department of Transportation (DOT) to provide alternate solutions to allocate system resources more efficiently, thus relieving congestion.

Researchers have proposed alternate “day of operations” schemes to allocate runway access including, ration-by-schedule (RBS), permits, auctions, credit points, and congestion pricing. In “congestion pricing system,” prices are announced for runway access for each time window and the users respond by either paying the announced price for using it, or not paying it and competing for runway access for later time windows. By charging airlines to use the scarce runway access, the aim is to provide service to those who value it the most. Congestion pricing has been successfully used for regulating access to ground transportation (e.g. highways, downtown areas).

Previous approaches developed the congestion pricing model for air transportation by using theoretical models such as econometric, queuing-based, or simulations. Most of these models operate for an individual time period, using average revenue and operating costs across several flights for all airlines.

This research proposes a system that implements the basic econometric model of congestion pricing embedded within an optimization model that uses actual recorded revenue and operating costs of airlines. For each time period, this system determines an airline's individual flight decisions: (i) paying the price announced and operating the flight, (ii) delaying the flight to a less congested time period, or (iii) cancelling the flight, thereby optimizing the allocation across multiple time periods. The research provides a new mechanism for calculating the airline costs of delay as well as a mechanism for setting the congestion prices.

The results of imposing congestion prices are compared to other suggested rationing schemes to see the impact on airline costs, passenger throughput and passenger delay: ration-by-schedule (currently used by Air Traffic Management) and ration-by-distance. The analysis demonstrates that the proposed congestion pricing method shows improved performance with respect to passenger statistics (both throughput and delay), however it is more costly to airlines since they have to pay for the runway access during congested periods.

Chapter 1: Introduction

The airline industry in the United States serves as one of the major transportation networks for travel of greater than 250 miles and therefore has a major impact on the country's economy. It is the fastest and most connected network (compared to other means of transportation) transporting both people and cargo. *FAA Aerospace Forecasts Fiscal Years 2011-2031* [FAA, 2011] reported that in the year 2010, the industry operated 51.2 million flights on 7,096 aircrafts; transporting 712.6 million passengers, 35.9 billion Revenue Ton Miles[1] (RTM) of cargo between both domestic and international airports. It further predicted that by the year 2031, the number of passengers per year in the U.S. may grow to 1.3 billion. This suggests the importance of air transportation to the U.S. economy.

The demand for additional routes, new airports and increased capacity in terms of runways, gates and baggage facilities at existing airports, is increasing far faster than the resources to satisfy this growth. Several studies have identified that it is airport flight capacity rather than airspace capacity that is the choke point.

According to the Operational Evolution Plan (OEP) [FAA, 2005b], there are 35 major airports that account for about 73% of commercial passengers enplanements in this country. In 2005, 23 of these airports exceeded their flight capacity and others will by the end of 2020. These congested airports cause delays in the system, and incur costs to the airlines, airports, and the overall economy. For instance, according to [Ball et al., 2010], in 2007, delays cost $32 billion to lost economic productivity.

Since airports have been identified as the choke point, all flights using these airports (as an origin, a destination, or a stopover point) result in delays that propagate throughout the nationwide network. As there is little air traffic at night, the delays are absorbed during the lightly scheduled nighttime hours, only to begin again the following morning.

[1] Revenue Ton Mile = One ton of revenue cargo transported one mile.

Although the ideal solution to the congestion problems at the airports would be to expand the airport capacity, this solution is often not viable. There is little room to expand at many of these airports. For example, at airports like LaGuardia, which has averaged over 70 minute delays on most afternoons in Summer 2007 [Wang et al., 2008], runway capacity is limited by the geographical location of the airport. Even if capacity expansion is feasible, the time to build a runway averages between fifteen and thirty years from the time of the first feasibility study to the completion of a runway. Thus, the DOT is forced to consider solutions other than capacity increases.

The DOT would like to be presented with alternative solutions that accomplish a number of goals simultaneously:

- assure that the valuable runway access is used efficiently.
- assure that all airlines, including new entrants, have the opportunity to enter the market. New entrants are likely to ensure adequate competition within airlines and thereby reasonable airfares and quality of service.
- ensure that any congestion management plan is perceived as fair to all stakeholders.

Even for a few airports, LGA, EWR, JFK, DCA and ORD, where DOT announced the use of "slot controls" to limit the number of flights that can be scheduled to land or depart, the capacity was determined by assuming "perfect weather" day. Thus, the allocation does not take into account the likelihood of any weather-related incidents that would reduce the overall flight capacity, nor does the current allocation consider that stochastic perturbations in the landing and takeoff of aircrafts may result in inefficient use of runway capacity. Robert Sturgell in 2008, acting as FAA administrator at that time, stated that "airlines have to be more realistic about scheduled operations at U.S. airports. Schedules predicated on a bright sunny day every day are just flat out impractical ... and they create havoc anytime when weather hits." He notes that the amount of operations an airport can handle has to be the starting point of any conversation about congestion. "The flight cap at LaGuardia is currently too high," Sturgell stated[Field, 2008].

1.1 Research Objective

Currently, on "day of operations" whenever there is imbalance, due to either overscheduling or reduced capacity, between runway capacity and arriving flights', a Ground Delay Program (GDP) is imposed. When a GDP is imposed, flights arrival times are rationed according to their schedule (Ration-by-Schedule) and airlines are given the opportunity to swap flights within their allocation. In this scheme, some more valuable flights may be delayed longer than other less valued flights when an airline has fewer flights to use as swaps. These delayed flights might result in a serious disruption of the airline's network, hence, it might be economically efficient for the airline to avoid delays by gaining access at a cost (i.e., a fee) to slots closer to the scheduled arrival time. Similarly, low-cost carriers might incur undue hardships due to the fact that they have tighter turnaround times and therefore, are more likely to see network-wide disruption for relatively short delays. Additionally, regional carriers also might be penalized since they have little control over their own schedules, as they generally work as a subsidiary airline for one or more mainline carriers that have the authority to determine which of these flights are cancelled, delayed or allowed to depart on time.

A better approach would be to base the allocation on "economic efficiency", i.e., resources are allocated to those who value them the most [Varian, 2003]. Two major market-based allocation methods for scarce resources based on economic efficiency are "auctions" and "congestion pricing". In auctions, the quantity of goods (runway capacity, in this case) is set and users determine the price. In contrast, in a congestion-pricing setting, the price is set *a priori* and the quantity is determined based on how many are willing to pay the announced price. Ideally, both will lead to the same equilibrium point. However, in the situation of day of operations congestion, where decisions are to be made in as little as fifteen minutes prior to the departure time of the flight, the auction mechanism needs to be simple enough to determine the price and the winners in a very short period of time. Given the fact that the airline has to make many decisions within this fifteen-minute period, it may be difficult to design a mechanism that is appropriate for this allocation problem.

This research is concerned with the question of how one could set a congestion price for a process that is as complicated and dynamic as runway access. The literature has provided a general framework for setting congestion prices, but no such mechanism has taken into account the likely actions of an airline as it relates to each flight and the multiple decisions that can be made about each flight: namely, should an airline pay the toll immediately and be sure of an on-time departure, postpone the decision and take a short delay in order to pay a lower toll or possibly no toll in a future period, or cancel the flight altogether? The airline must be given sufficient information to make such decisions for each flight in its schedule and the algorithm must be capable of adjusting future prices based on the responses made in a given period. Thus, congestion pricing for airlines is similar to the dynamic pricing used on roadways, with one important difference: roadways have a very large number of independent decision makers whereas, for runway access to a given airport, there may be only a handful of decision makers (the airlines) who must make multiple interrelated decisions.

The objective of this research is to develop a methodology for the setting of congestion prices that could be used by Air Traffic Flow Management (ATFM). One wishes to find prices such that the airlines will limit the number of flights that pay the toll in the period to be approximately equal to the capacity of the runway at that period. Thus, one wants to set the price such that the airlines' response to the congestion price is to have demand and supply approximately equal. The algorithms employed must be both fast and responsive enough in the setting of these prices such that when new weather conditions are announced or when airlines do not respond as expected, one can set the next period's prices to force better compliance between supply and demand. The congestion prices must consider, (i) the overall profitability of given flights, (ii) the impact that given flights have on the overall schedule at the airport, and (iii) the competition of a given flight among all flights of all airlines.

1.2 Contribution

This research contributes to the current literature in the following ways:

- This research provides an automated system to calculate congestion prices based on the basic economic theory described in the literature. This research extends prior attempts at setting congestion pricing by considering: i) the profitability of each flight rather than using average ticket prices for all flights of a given aircraft size, ii) uses detailed cost-of-delay models to evaluate the differences in delay based on length of delay, size of aircraft and where the delay might be taken (gate, taxi-way or airborne), iii) considers end-of-day conditions, iv) considers the cost of cancellation when evaluating whether it is better to delay a flight or cancel that flight, and v) considers whether a delay in the given flight is likely to propagate delays in the system because of the inability of that flight to make a connection to a follow-on flight.

  This research is unique in its incorporation of each of these activities in the pricing considerations. It is also unique in that it allows the decisions to be based on whether it might be cheaper for an airline to incur a delay in order to reduce its overall costs by waiting and paying a lower congestion price for some subsequent time period. Thus, this research considers a multi-period decision-making process by each airline for each flight.

- This research presents a new methodology for calculating the costs of delay for any individual flight. The model is based on a EuroControl model of delay, but has been expanded to be useful for any aircraft type and also usable when the underlying components of the EuroControl model (e.g., fuel, crew, maintenance, or other operational costs) have been changed. The original model did not allow such modifications and therefore, could not be used when an underlying component (such as fuel costs) changed dramatically.

- The research performs a comparative analysis of congestion pricing to two alternative non-economic approaches to rationing runway capacity: Ration-by-Schedule (RBS) and Ration-by-Distance (RBD). The first of these (RBS) is currently being used by Air Traffic Flow Management (ATFM) for allocating runway capacity while the second (RBD) is one being promoted as being better for both the airlines and for passengers as it reduces the total expected flight delay [Hoffman et al., 2007] and correspondingly, the total passenger delay.

With respect to RBS, the new methodology results in reducing delays for both flights and passengers, increasing passenger throughput and improving ontime statistics. Compared to RBD, the congestion pricing method is better in terms of flight and passenger throughput (in most cases), worse in terms of total flight delay but still better in terms of passenger delay. However, in terms of profit, the new approach might cost up to 15% of total airline profit compared to other approaches during extreme congestion periods. However, even in July 2007, when the highest congestion ever recorded occurred, the number of such extreme congestion periods was relatively few. Therefore, this new approach has the potential to improve systems performance by forcing airlines to pay for the congestion they impose on the system.

Questions that this research attempts to answer include:

- Can a congestion pricing approach be derived which is consistent with economic theory and with airline practice and is therefore likely to result in economically efficient outcomes? Are there issues unique to the airline network that require consideration when designing a congestion pricing model? Can such characteristics be included in the pricing mechanism?

- Given a congestion pricing mechanism, is the methodology computationally capable of obtaining the pricing in the short time available?

- How much would congestion pricing cost the airlines? Would congestion pricing cost the airlines less than the current weight-based landing fees? Would congestion prices vary significantly among airports?

- Is the congestion pricing approach equitable across all airlines and all aircrafts, or is there a certain subgroup to which it is more favorable?
- In what regard does the congestion pricing approach work better than the other allocation approaches of Ration-by-Schedule (RBS) and Ration-by-Distance (RBD)? What stakeholders would benefit from using the congestion pricing methodology?

1.3 Organization

This dissertation is organized as follows: Chapter 2 provides a literature search on the economics of congestion pricing, the alternative approaches for calculating such pricing and the application of congestion pricing to the airline runway allocation problem. It also provides a discussion related to the current system's allocation approach and its issues. It provides a discussion of other alternative approaches for allocating resources in air transportation that have been proposed in the recent literature. An illustrative example is also provided which is later used to illustrate how the proposed methodology works. Chapter 3 discusses in detail the proposed cost of delay model together with a sensitivity analysis of the cost of delay model. Chapter 4 describes the congestion pricing model (CPM), its components, the theoretical justification and an illustration of how it works. Chapter 5 provides a comparison of the congestion pricing model relative to the Ration-by-Schedule (RBS) approach and the Ration-by-Distance (RBD) approach, and also provides details about the dataset used to perform the comparison. Chapter 6 provides the results of these experiments. Chapter 7 provides general conclusions and suggestions for future work in this area.

Chapter 2: Literature Review

This dissertation describes a mechanism to calculate congestion prices that would apply during an announced Ground Delay Program (GDP). This chapter begins with a discussion of economic principles that relate to handling congestion in general. It highlights the economic literature that addresses how to design pricing mechanisms to ensure that scarce resources are put to their best uses. It continues the discussion with a brief introduction to the general economic theory of congestion pricing and then provides historical proposals for its use in handling airspace congestion (Section 2.1). Next, in Section 2.2 the FAA's current approach to handling congestion when it occurs either on runways or en-route is described. This approach is known as "Cooperative Decision Making" (CDM). Section 2.3 then describes some of the suggested improvements to CDM as well as a few alternatives that would replace CDM completely. Section 2.4 describes in detail one of the simulators built recently that analyzes the impact of different rationing rules during a GDP. The last section (2.5) provides a short discussion of the chapter and identifies the reasons for reexamining the current ground delay process methodology.

The chapter begins with a discussion of the economic principles that relate to handling congestion in general. Since the economic efficiency goal is to put scarce resources to their best use, a discussion of general market mechanisms that aim to accomplish that goal is provided. Next the chapter proceeds to discuss how such designs might be used in designing a day of flight market that allocates scarce airspace and runway capacity. Some of the insights from the literature on market design are highlighted that may have application in designing a day of flight market to allocate scarce airspace capacity.

[Roth, 2007] has outlined the key features of design that result in efficient and stable markets. The term "efficient" means that the goods are allocated to those that value them the most. The term "stable" means that no coalition of buyers could renege on the outcome of the mechanism and negotiate privately with the seller in a way that would make the coalition of buyers and the seller better off. In the present assignment, an important question to address is whether a good final allocation of air space capacity can be developed using a day of flight market when both demand and capacity are subject to stochastic weather.

There are two main mechanisms for market-based allocation methods for scarce resources. One is to use auctions and the other is congestion pricing. Auctions have been successfully used for the allocation of goods and services in an efficient manner whenever:

- One can assure that the market is sufficiently "thick," i.e., it can attach a sufficient number of participants so that there is competition for the goods being offered.
- There is sufficient time to make considered decisions. In the air congestion context, this means that the mechanisms allows the users sufficient time to be able to evaluate the value of any alternative decision.
- Straightforward responses are encouraged, i.e., when users bid their true values rather than attempting to bid based on what they perceive the asset's value is to someone else.
- Strategic behavior is discouraged (gaming and collusion).

In the situation of day of operation congestion, the issues of participation are not a concern since access to the airspace is controlled by the federal government and all must participate to gain access. However, if a market is to operate on the day of flight, there may be little time to create an auction mechanism that allows the market to close in a timely fashion. Predicting the value of the entity may be difficult given the stochastic nature of weather, and it may be hard to define the actual item being auctioned in terms of an exact departure and/or arrival time. Similarly, since a single airline will need to be bidding on multiple access rights with both substitutable and complementary characteristics (some flight delays can be substituted for others at equivalent costs, while others produce network effects that magnify delays), it may be difficult to provide good valuations to the auction without the process being very complicated or difficult to close quickly.

Thus, it is not clear that an auction mechanism can be defined that satisfies Roth's criteria for an economically efficient result. Therefore, the alternative market-based mechanism is considered, i.e., congestion pricing.

One can consider an auction to be a quantity-based market mechanism. That is, the regulator sets the quantity available at any given time period and the airlines would set the price through an auction. An alternative to a quantity-based system is a price-based system whereby the regulator sets the price for access and the airlines would respond by indicating if they are willing to pay that price. Thus, it would be incumbent upon the regulator to appropriately set the price so that the airlines response would closely match the capacity of the system. This dissertation will discuss a mechanism for setting such prices. Following are the theoretical issues with setting such prices.

The idea of how to price transportation is not new. French civil engineer, Jules Dupuit in an article published in 1844 [Dupuit, 1844], argued that one should determine the optimum toll for a bridge based on marginal utility. [Pigou, 1920] furthered this concept by making the distinction between private and social marginal products and costs. He originated the idea of externalities, i.e., costs imposed or benefits conferred on others that are not taken into account by the person taking the action. He argued that the existence of externalities is sufficient justification for government intervention. He proposed that the government should impose taxes on negative externalities (e.g., overuse of public services) and should reward positive externalities (e.g., the government should provide support to education because individuals do not necessarily see the societal benefits of such investments). [Knight, 1924] argued that privately owned, competitive roads would result in their optimal use and optimal investment, since market forces would provide the pricing signals necessary for optimal use.

William Vickrey, winner of the Nobel Prize for Economics in 1996, proposed in 1951 that subway systems and road networks should impose fares that increase in peak times and in high-traffic areas. He argued that time-of-day pricing could better balance supply and demand. Such pricing would encourage the use of alternative modes of transportation, such as car pools and public transportation and would actually increase the throughput on the tolled highways since congestion reduces the overall throughput. Vickrey argued that congestion pricing allocates the scarce resource based on an efficiency principal —the goods are allocated to those that value them the most. In addition, pricing plays two other important purposes: it provides information about the areas that most require capacity expansion and it provides resources for such expansion.

In a seminal work, [Vickrey, 1969] created a bottleneck congestion model. He defined a bottleneck as, “one where a relatively short route segment has a fixed capacity substantially smaller relative to traffic demand than that of preceding or succeeding segments.” Due to such short segments in higher demand periods, congestion accumulates and delays increase. Based on evaluating the cost of time waiting in queues versus the cost of waiting at the origin, he describes an equilibrium point. Applying tolls equal to this equilibrium point, some users will shift to alternative periods and will arrive either earlier or later to the congested location within the network. Thus, the amount of toll charged can be approximated to the value of one’s time relative to the queue. In addition to the toll amount, he also estimates the revenue generated by applying tolls and compares it with cost of capacity expansion and concludes that congestion pricing can be efficient and can also help generate revenues for capacity expansion.

2.1 Congestion Pricing

2.1.1 A General Congestion Pricing Concept

Congestion pricing is one approach that the government can use to alleviate some types of congestion. The idea is to charge a toll to users for the use of scarce resource (i.e., road segment, airspace, energy) such that, as a result, resources are assigned to (used by) users that value it the most and (if priced correctly) social welfare is maximized. An additional advantage is that it allows opportunities to generate revenue in order to increase the scarce

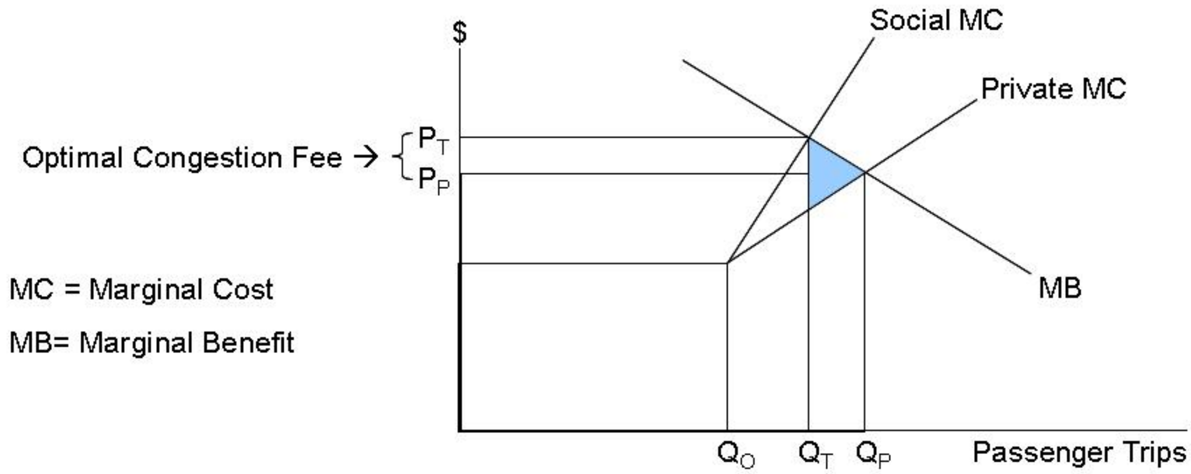

Figure 2.1: Theory for Congestion Pricing

resource where capacity is most needed. The fundamental principle behind the theory of congestion pricing is that, one must impose a congestion toll on each user which is equal to the external cost that the user imposes on the system as a whole, [de Neufville and Odoni, 2003]. Economists refer to this as forcing users to "internalize external costs." The rationale is simple: users who are willing to pay the congestion price (compensate for the external cost they impose on the society) must be achieving revenue that exceeds the toll, thereby increasing total economic welfare. Those who cannot pay the congestion price, should not gain access since they do not obtain sufficient economic revenue to overcome the external cost they impose on the society by using the facility.

Congestion pricing therefore forces the optimal use of the facility by employing the toll equal to the external cost associated with an additional (marginal) user. Figure 2.1 describes this congestion price in the context of supply and demand. P_P and Q_P define the price and quantity respectively when no external delay cost is assigned. P_T and Q_T define the price and quantity when external delay cost has been added (price including the congestion toll). The line segment *MB* defines the marginal benefit. Curve "Private MC" (Marginal Cost) defines the additional user cost incurred by an individual user ("internal delay cost"). Curve "Social MC" (Marginal Cost) is the expected marginal cost incurred by an individual user provided they also take into account their respective external costs. The difference between these curves ("Private MC" and "Social MC") at each level of marginal benefit (MB) is equal to the external delay cost generated by an additional user. The blue area identifies the cumulative congestion toll that needs to be charged across all the users in order to optimally use the facility at that quantity level.

In practice, however, it may be difficult to apply this theoretical congestion pricing theory to the airspace congestion problem. Mainly, it may be difficult to:

- accurately estimate the marginal external costs at any given level of demand. This may be especially true in an oligopolistic setting where there are only a few players determining much of the demand.
- observe congestion pricing effects on elasticity since the public cannot observe how the fees impact the prices charged.
- determine the amount of the congestion fee that will lead to an equilibrium point given the current approach of airlines to take short-term losses in the hope of obtaining greater market share and future market gains.
- accomplish politically, since the impact of congestion pricing is likely to be higher costs for certain segments of the airline industry, specifically general aviation and the regional carriers.

2.1.2 General Congestion Pricing Idea

In addition, some economists maintain that congestion reflects an efficient distribution of resources. [Mayer and Sinai, 2003] argue that the network benefits of an airline's hub-and-spoke network exceed the self-imposed delay costs resulting from flight bank-related congestion, and that if the airlines are willing to incur these costs, then they should not be eliminated.

[Czerny, 2006] argues that there is demand complementarity for airport capacity because of the network character of the airline industry. Since the regulator does not have perfect information of the social costs and benefits of airline operations, it will not be able to efficiently set congestion prices and the outcome will be lower social welfare than a direct slot allocation system. However, as Mayer and Sinai state, congestion pricing could be an appropriate solution at non-hub airports with constant levels of delay throughout the day [Mayer and Sinai, 2003].

Daniel is the economist leading the argument that congestion pricing would be more effective than auctions (see [Daniel, 1995, Daniel and Pahwa, 2000, Daniel and Harback, 2008]). He argues that it is impossible to set the quantity of slots to be auctioned at an optimal level because both demand and capacity are stochastic. In other words, they are subject to random variation primarily due to weather. Therefore, setting a fixed quantity of slots to be auctioned is ineffective because some aircrafts will arrive later and some slots will go unused; when the delayed aircrafts arrive, demand for slots will exceed supply. The quantity of slots could be set lower, but that would result in unused capacity at certain times. On the other hand, congestion prices can be set dynamically and the airlines can respond on an as-needed basis. That is, they do not need to decide whether or not to accept the price until the time of takeoff.

A major debate in the congestion pricing literature is whether users internalize self-imposed delay. Brueckner and others believe that users internalize self-imposed delay and thus congestion prices should be adjusted to reflect this internalized delay (see [Brueckner, 2002a, Brueckner, 2002b, Brueckner and Van Dender, 2008]). He uses both symmetric and asymmetric models of carrier airport flight shares to demonstrate that congestion pricing systems based on internalization are optimal. Atomistic congestion charges are not efficient because airlines are overcharged for delay that they have already internalized.

Daniel and others believe that users do not internalize self-imposed delay and thus congestion prices should be set equal to all delay costs. [Daniel and Harback, 2008, Daniel and Harback, 2009] evaluated published papers that claimed that users internalize delays. They conclude that the models used in these papers do not produce evidence of internalization when evaluated using better quality data and more precise definitions of delays. They believe that users behave “atomistically” because they anticipate the behavior of competitors; i.e., they assume that if they reduce flights during peak periods, then competitors will replace those flights with their own. Therefore, a congestion pricing system must assume that users behave atomistically to achieve economic efficiency. [Rupp, 2009] also proved with empirical evidence, using data from 1995 to 2004, that airlines do not internalize cost.

Morrison and Winston empirically address the internalization debate [Morrison et al., 1989]. They agree with the fundamental theoretical insight concerning internalization, but question how important it is in the real world. They estimate the net benefits (welfare effects) of optimal tolls taking into account, internalization of their own congestion costs and then recalculating the welfare effects assuming tolls are set in an atomistic setting. They find that 91% of the net benefits of optimal tolls can be realized with atomistic tolls. They therefore suggest that internalization be ignored for policy purposes.

Despite the debate over whether users internalize self-imposed delay, most economists generally agree that a congestion pricing system could improve economic efficiency by forcing users to internalize delay imposed on other users. However, some economists note that congestion pricing systems could be ineffective because users could manipulate the posted congestion charges. [Brueckner and Verhoef, 2010].

[Johnson and Savage, 2006] calculate a congestion price based on data from Chicago O’Hare Airport. They conclude that the current airport departure weight-based fees are inefficient because airlines do not consider the costs imposed on other flights and because the charges imposed favor smaller aircrafts even though they use the same amount of runway capacity. Their approach computed congestion fees based on departure queue and the airline’s market share. A companion paper [Ashley and Savage, 2010] computes congestion prices for Chicago O’Hare airport using the same data, but based on arrival queues instead of departures. They find that prices based on arrival queues are about a fifth of the prices based on departure queues computed earlier [Johnson and Savage, 2006].

Similarly, [Daniel and Pahwa, 2000] compared three different congestion pricing schemes and concluded that the current weight-based fee system is inefficient compared to any of the congestion pricing schemes. The paper examines approaches based on an econometric model [Morrison, 1983, Morrison et al., 1989], deterministic queue bottleneck congestion [Vickrey, 1969, Arnott et al., 1990] and stochastic queuing model embedding a bottleneck congestion model within the queue [Daniel, 1995] (see below for more on these approaches).

Another question debated in the literature is what mechanism to use to set the congestion prices. Although the theory of congestion pricing is mainly developed and applied for the management of road use,[1] researchers have applied such road pricing models to airspace congestion (see [Levine, 1969, Carlin and Park, 1970, Morrison, 1983, Morrison et al., 1989, Oum and Zhang, 1990]). There is a fundamental difference between road pricing and airspace pricing, however: while road users can be considered atomistic, with each user accounting for a tiny share of the total traffic, airlines must be viewed as nonatomistic given that one or two carriers dominate most major congested airports [Brueckner, 2002b].

2.1.3 Theoretical Congestion Pricing Models

Congestion pricing has not been implemented at any U.S. airport to date although proposals for its use and mechanisms for calculating the appropriate prices exist. [Schank, 2005] describes airport cases where so-called "congestion pricing" was implemented. However, he argues that neither of these cases had effective theory to begin with and had potential flaws in practice.

This section presents a short overview of this literature. Models that simulate congested transportation are divided into three different categories, namely: econometric models like [Carlin and Park, 1970, Morrison et al., 1989, Brueckner, 2002a, Verhoef, 2008], bottleneck models with simple deterministic queues like [Vickrey, 1969, Arnott et al., 1990] and queuing-theoretic models like [Koopman, 1972]. Much of the original queuing work on airport congestion [Koopman, 1972] was used to determine the amount of delay, waiting times, etc., but not concerned with issues of cost of delays or pricing models to reduce these

[1] For a brief report, see [GAO, 2003].

delays.

[Daniel, 1995] presented a stochastic queuing model embedded within the bottleneck congestion that describes a theoretical methodology for determining congestion prices.

Basic Econometric Model

All the approaches that use econometric models (for e.g. [Morrison et al., 1989, Brueckner, 2002b]) have similar basic structure:

For any single time period of the day, for any single carrier:

$$Profit = \sum_{\text{for all flights}} ((Price - OperatingCost) * Flight - CongestionCost * Flight)$$

In this model, *CongestionCost* is a function of the number of flights, and can be divided into Congestion Cost incurred by the same carrier's other flights and the congestion cost incurred by other carriers' flights in that time period.

Marginal Profit with respect to an extra flight, i.e. the cost associated with adding another flight to the airlines schedule is:

$$MarginalProfit = Price - OperatingCost - CongestionCost(ownflights)$$

The congestion price should be set so that the cost of adding one more flight to an existing schedule that is at the capacity of the system is exactly equal to the marginal profit of the added flight.

Given available capacity of a runway at a particular time period is k, then setting the congestion price equal to the marginal profit of the $k + 1^{st}$ flight will assure that the flights of highest value are allowed to fly. Thus the congestion price is set such that the $k + 1^{st}$ flight has zero profit, i.e.

$$CongestionPrice(CP) = Price - OperatingCost - CongestionCost(ownflights)$$

For atomistic behavior, $CongestionCost(ownflights)$ is dropped, i.e., carriers behaving atomistically do not internalize the congestion cost generated by their own flights. Therefore, the Congestion Price (CP) for any single time period is equal to the marginal cost of the $k+1^{st}$ flight which is equal to its marginal profit.

The first authors to use this model are Winston and Morrison.[2] They differentiate between arrival(A) and departure(D) flights while calculating revenue, cost and congestion cost; the flights were divided into six different classes denoted by "i"(international, cargo, majors and nationals, commuter, other commercial [primarily regional] and general aviation). The profit was calculated for an entire day, with 24 unique one-hour period denoted by "t." Airport maintenance cost (M) and runway costs are separate from operating cost and are only functions of the number of flights in the system. The resulting toll becomes,

$$\begin{aligned} Toll^i_{A/Dt} &= MarginalCongestionCost_A \\ &+ MarginalCongestionCost_D \\ &+ MarginalCongestionCost_M \end{aligned}$$

Brueckner (along with other authors) has also used a similar econometric model in several of his papers, both technical and published [Brueckner, 2002a, Brueckner, 2002b, Brueckner and Van Dender, 2008]. His basic model assumes two airlines at any airport with different cases of elasticity (perfect and imperfect)[3] and substitutability (perfect, independent and dependent).[4] He computed the social optimum for each of these cases and then, based on different airline behaviors and airline shares, calculated different tolls.

[2] [Morrison et al., 1989]

[3] Perfect elasticity refers to the case where no airlines have market power.

[4] Perfect substitutability means that the service provided by different airlines are perfect substitutes from a passenger's standpoint, independent substitutability refers to the case where one airline's schedule has no effect on another airline's schedule, while dependent means that one airline's schedule impacts a competitor's schedule.

For perfect elasticity and substitutability, with an equal flight share with Cournot behavior[5] of airlines, the toll is:

$$Toll = \frac{1}{2} MarginalCongestionDamage(MCD)$$

MarginalCongestionDamage(MCD) is the Marginal Congestion Cost for adding another flight. MCD is equal to the atomistic tolls paid by airlines, if none of the airlines internalize the cost generated by their own flights. In this case, both the airlines internalize half of the congestion cost caused by the total flight share (i.e., 2 times the optimal flight share due to symmetrical flight share) and with the toll equal to remaining congestion cost, the social optimum is achieved. With Cournot behavior and different flight shares, the toll becomes,

$$Toll = (1 - \alpha)MCD \text{ where } \alpha = \text{larger airline's market share } (> \frac{1}{2})$$

Another behavior among airlines is a Stackelberg Leader[6] with Cournot follower. The toll for such a combination is:

$$Toll(leader) = \frac{1}{2}(1 + \lambda)MCD \text{ where } (\frac{1}{2} < \lambda < 1)$$

$$Toll(follower) = \frac{1}{2}MCD$$

With this combination, the tolls assessed to different airlines are different when attempting to attain the social optimum. In such cases, the Stackelberg leader has to pay a higher toll than its Cournot follower, since it does not internalize the entire cost of its other flights. Another case studied occurs when, instead of a Cournot follower, there is a competitive fringe that does not internalize any of its cost (probably since there are very few flights or

[5]Cournot behavior: The player considers other players' quantities (flight share in this case) fixed while making the strategy

[6]Stackelberg leader: The leader behaves with respect to its follower's action (market leader).

they are all operated by different airlines). The toll then becomes,

$$Toll = MCD$$

In this case, the Stackelberg leader doesn't internalize any cost at all, while the fringe is behaving atomistically, therefore, they all pay atomistic tolls.

For imperfect elasticity, Brueckner uses, instead of a constant price, a functional form for passenger demand relative to price. Therefore, the social optimum changes with the inclusion of market power. There cannot be any Cournot-behaving airlines and so, with imperfect demand and perfect substitutability, the only case is of the Stackelberg leader with a competitive fringe, thus the toll for such case is,

$$Toll = MCD$$

For imperfect substitutability, two cases are mentioned, the completely independent case, where flights offered by different airlines are independent of each other. Again, for the Stackelberg leader and the competitive fringe, the toll is,

$$Toll(leader) = \frac{1}{2}(1+\mu)MCD \text{ where } (0 < \mu < 1)$$

$$Toll(fringe) = MCD$$

For imperfect substitutability with some dependence between airlines flights, the toll for the fringe remains the same, but the toll for the Stackelberg leader becomes,

$$Toll = \frac{1}{2}(1+\eta)MCD\text{where } (0 < \eta < 1) \text{ and } (\eta > \mu)$$

The summary of these different cases based on different behaviors of airlines and different economic conditions is that:

- a uniform toll for all airlines is not optimal in most of the cases.

- internalization of congestion costs is advantageous to dominant carriers at hub airports.

- different tolls for different airlines will have strong political opposition.

The above models do not consider network effects. [Brueckner, 2002b] also looks at network effects and determines different tolls based on an airline's share of total flights at an airport. In [Verhoef, 2008], results are similar when considering a slightly different model that allowed the imperfect elasticity of the airlines and considered the market power impact on the equilibrium. Also, [Brueckner and Verhoef, 2010] identify the problem where atomistic tolls are susceptible to manipulation once the airline knows the flight share of its competitor, thereby presenting the idea of manipulable congestion tolls.

Betancor, Rus and Nombela also use similar models to compute tolls for airlines [Betancor et al., 2003]. The additional constraint in their model is that an airport is also a profit maximizing agent. Efforts made by airlines to increase punctuality and to reduce congestion are incorporated. This model allows both slot price and slot quantity to be varied in order to improve social welfare. They also looked at the cascading effects of congestion between two connecting periods. They provide results of simulation using data from Madrid Airport, along with the intuitive result that the capacity expansion at the airport decreased the marginal cost of using the facility.

Bottleneck Models

Vickrey's bottleneck congestion model [Vickrey, 1969] is described earlier. This section describes one of the extensions of his model as reported by [Arnott et al., 1990]. N individuals (aircrafts, in this case) travel between two endpoints while passing through a bottleneck (runway) capable of serving s aircraft per time unit. Queues develop at the bottleneck whenever traffic exceeds the service rate. Total travel time is $T(t) = T^f + T^v(t)$, where T^f is the fixed component of the travel time, assumed to be zero. $T^v(t)$ is the variable time waiting in queue, for an aircraft enqueued at time t. Waiting time in queue for an aircraft is the ratio of the length of the queue at time t and the service rate s; or $T^v(t) = \frac{D(t)}{s}$, where $D(t)$ is the length of queue at time t. If t^* is the most preferred time and $\tilde{t}$ is the time an aircraft joined the queue to achieve the preferred time, then $\tilde{t} = t^* - T^v(\tilde{t})$. From [Vickrey, 1969], the cost of the trip, C, is linear in travel time, specifically it is:

$$C = \alpha(Queuetime) + \beta(TimeEarly) + \gamma(TimeLate)$$

where α, β and γ are the values of queuing-time cost, early-time cost and late-time cost respectively. Let t_q and $t_{q'}$ be times when the queue begins and ends respectively. The times are given by:

$$t_q = t^* - (\frac{\gamma}{\beta + \gamma})(\frac{N}{s})$$

$$t_{q'} = t^* - (\frac{\beta}{\beta + \gamma})(\frac{N}{s})$$

$$\tilde{t} = t^* - (\frac{\beta\gamma}{\alpha(\beta + \gamma)})(\frac{N}{s})$$

The departure rate from queue $r(t)$ is:

$$r(t) = \begin{cases} s + \frac{\beta s}{\alpha - \beta} & \text{for } t \in [t_q, \tilde{t}), \\ s - \frac{\gamma s}{\alpha + \gamma} & \text{for } t \in (\tilde{t}, t_{q'}] \end{cases}$$

At the equilibrium point, since each aircraft has the same trip cost, total cost, TC, no-toll equilibrium is:

$$TC^e = (\frac{\beta\gamma}{\beta + \gamma})(\frac{N^2}{s})$$

and total travel cost, TTC, equals total delay cost, and SDC, equals TC/2. Letting $a = (\frac{\beta\gamma}{(\beta+\gamma)})(\frac{N}{s})$, the socially optimal toll τ for an aircraft at t is :

$$\tau = \begin{cases} 0 & \text{for } t < t_q, \\ a - (t^* - t)\beta & \text{for } t_q < t < t^*, \\ a - (t - t^*)\beta & \text{for } t^* < t < t_{q'}, \\ 0 & \text{for } t > t_{q'}, \end{cases}$$

A coarser toll of one step function is computed based on this socially optimal toll with the premise that, most tolls are uniform over the day or are step functions. Coarser toll ρ^c applied over the time interval $[t^+, t^-]$ (also defined by the paper) is defined as:

$$\rho^c = \frac{\beta\gamma}{2(\beta+\gamma)}(\frac{N}{s})$$

Some of the interesting results include:

- efficiency gains from computing the optimal congestion toll using bottle neck model can be substantially greater than the efficiency gains achieved from a naive flow model of congestion.
- a significant fraction of the gains can be achieved by using a single step coarse toll which is easy to implement.
- total delay costs are of the same magnitude as total variable travel time costs, and are important to include in the cost-benefit analysis.

Queuing Theory Models

[Daniel, 1995] uses two stochastic queues, one for arrival and one for departure, embedded within a bottleneck model. Days are broken into banks of arriving/departing flights and a hub-and-spoke network is assumed at the airport. Each flight has a most preferred arrival time τ^A and most preferred departure time τ^D with some layover and interchange-encroachment costs; the former is the cost incurred if the flight is on the ground for longer than scheduled time $\tau^D - \tau^A$(i.e., either arrived earlier than τ^A or departs later than τ^D) while the latter is the cost incurred if the flight has less than scheduled time between its arrival and departure preferred time $\tau^D - \tau^A$. Arrival of flights follows a Poisson distribution with time dependent rates and the service time of the queue is deterministic. At the bottleneck equilibrium, identical aircrafts have the same total expected cost of queuing, layover and interchange-encroachment cost. Data from the first week of May 1990 at Minneapolis-St.Paul Airport (MSP) was used for simulation purposes. Using this simulation data and different statistical testing techniques, among different airline behavior models (such as Atomistic, Stackelberg Dominant with Atomistic Fringe and Nash Dominant with Atomistic Fringe,), the simulation results conclude that Atomistic/Stackelberg Dominant behavior was observed at MSP airport.

Daniel further extended his model to include "elastic demand" as a result of congestion fee as well as different aircraft operating time preferences and layover and queuing time values [Daniel, 2001]. Elastic demand allows the change in composition of aircraft type in traffic while different costs cause the sorting of aircrafts such that more costly (with respect to layover and queuing time values) aircrafts will schedule closer to preferred times. For the same data as used above, he showed that the dominant carrier (NorthWest in this case) will still schedule close to the most preferred time while paying the daily average congestion fee of around \$295. Other major airlines will be willing to incur some delay and pay congestion costs ranging around \$206-\$212, while the regional airlines incur more delays and thereby pay lower congestion fees ranging from \$64-\$71, on average. General Aviation (GA) will pay the least of all, around \$28-\$43 depending on demand elasticity. The heterogeneous costs will force the GA to be farthest from the preferred time but paying the smallest amount of congestion fee.

In [Daniel and Harback, 2009], using the original model (as described in [Daniel, 1995]), the authors present for each of 27 U.S. airports, the number of arrivals; the average weight-based fee, average congestion fee, average delay with weight-based fee, average delay with congestion-based fee, change in daily cost per operator, change in daily revenue and net gain to airport. The estimates of the congestion fee are provided for the dominant carrier(s) at their hub airport as well as for the other carriers at that airport. Congestion fees can be as high as $2753 for other carriers and $2323 for Delta (dominant carrier) at Atlanta (ATL) airport, to as low as $226-$201 at LaGuardia (LGA) airport.

[Janic and Stough, 2005] use a queuing-based using a diffusion approximation model to illustrate the airport. In their approach, the airport is treated as a queue with congestion only defined when the demand-capacity ratio is greater than one (in other words, there are more flights than the current airport capacity can handle). They argue that the flights should be charged for the entire congested period and the delays should be computed for the whole congested period. A revenue model is used to calculate the additional flights' revenue while the congestion cost is only considered effective if it compromises the expected profitability of a new flight.[7] They applied this approach to LGA using data from July 2001 and concluded that this type of model is more applicable to non-hub airports with many airlines having a fairly equal share of flights. At such airports, two observations were more prominent, namely: small regional flights affecting larger flights are eliminated and that up-gauging will be stimulated. In the case of a hub airport, this model favors the dominant carrier and compromises competition.

2.1.4 Simulations involving Congestion Pricing

Apart from the above mentioned theoretical approaches to congestion pricing, some recent work has been done that supports the application of congestion pricing at U.S. airports. Two such approaches follow:

[7]This is similar to the econometric model where the toll is effective only when it can keep the extra flight out of the congested period.

Congestion Pricing for New York airports

[Poole and Dachis, 2007] discussed some of the airlines' concerns and their issues with congestion pricing, namely:

- Airlines argue that pricing will be ineffective since congested airports are the busiest airports in the U.S. Thus, there is no off-peak time nor are there alternative airports. Therefore, the airlines will simply incur the prices. Up-gauging is also not a likely outcome. Rather, the connections to smaller markets will disappear when congestion costs are imposed. If the congestion price does not apply to all, i.e., there are special carve-outs and exemptions, then there will be a greater distortion.

  Poole and Dachis refute this argument by presenting the results of a simulation at the three New York airports. They show that the current congestion was reduced to acceptable levels. The results also show that no significant connections to smaller markets were lost. There are no Essential Air Service(EAS) flights and a very small General Aviation (GA) population at these New York airports that might be exempted from the congestion pricing. However, they argue that GA should not be carved out in any case.

- JFK and EWR are special cases since these airports are departure hubs for many transatlantic flights and thereby have many connecting flights to smaller markets that rely on these airports for international flights. Also, foreign carriers that are exempted by bilateral agreements might gain advantage over national carriers.

  Poole and Dachis argue that the congestion cost would be more favorable to foreign carriers as opposed to the current weight-based fee. They also discussed ICAO policy and bilateral agreements and concluded that congestion pricing can be legally applied to these airports. So, potential exemption to international flights is also non-optimal.

- Congestion pricing would undercut needed capacity expansions and the revenue generated by the congestion cost will be invested in other projects rather than in capacity expansion.

Poole and Dachis suggested a "Plavin Lockbox," whereby all the revenue generated can only be used for capacity expansion.

- Congestion does not take place exclusively at airports, but also within the airspace. This argues that the airports are not the only reason for the congestion, but that airspace near New York airports is also part of the bottleneck generating congestion. Poole and Dachis showed that at least at New York airports, airspace is only 1/3 of the delay problem.

- The Levine Challenge [Levine, 2007] as described by Michael E. Levine, discusses the preconditions for an effective pricing system for these airports, i.e., no exemptions to congestion pricing, proper control of generated revenue and creation of congestion-charge fund for capacity expansion. Without satisfying these conditions,he feels the pricing will both fail and do economic damage.

  Poole and Dachis showed a simulation based on the system that meets the Levine Challenge. As Levine himself pointed out there is a need for "transparent and equitable pricing and efficient use of the funds generated" [Levine, 2007].

For La Guardia airport (LGA), Poole and Dachis used the NEXTOR simulation data (described in the next section). For Kennedy (JFK) and Newark (EWR) airport, they provided a simple model to calculate congestion cost based on departure queues.

To estimate the congestion price, Poole and Dachis used a simple Pigovian framework of using the difference between individual aircraft cost. They compared the cost of taxiing out for that aircraft relative to the external marginal cost, that is, the cost of delays imposed on other aircraft in the departing queue. The external congestion cost can be divided into two types. The first external congestion cost is due to an aircraft in a queue increasing the number of aircrafts in front of other aircrafts wishing to depart afterwards. Another is the knock-on effect, that a longer queue implies larger number of planes affected by delays. An optimal congestion price will be the one that will force the airline to pay for these external costs and thereby reduce the demand for the departure.

The average variable cost (AVC) of an aircraft in a departure queue is the combination of both the operating cost of an aircraft and the time cost of passengers. For the simulation discussed, an average departing aircraft at JFK was estimated to have a per minute queue cost of $50. The load factor was found to be around 85% and the resulting per passenger cost was estimated to be $0.52 per minute. This gives the delay cost per minute in case an aircraft is delayed in the departing queue. What remains to be found is the relationship between the number of aircrafts in the queue and the expected delay. A simple linear regression method was used to estimate delay by time of day using historical data. The minimum time an aircraft takes from gate to runway is defined to be 10^{th} percentile of taxi-out time for that day. Anything on top of that is considered to be delay. Based on the simulation, throughout the day the congestion prices ranged from approximately $2000 during peak hours to $100 for night hours at JFK. The authors show that these prices were sufficient to reduce the current congestion to acceptable levels [Dachis, 2007].

NEXTOR (National Center of Excellence for Aviation Operations Research) Simulations

In November 2004, a human-in-the-loop simulation was conducted by the NEXTOR (National Center of Excellence for Aviation Operations Research) at George Mason University. This human-in-the-loop simulation studied alternative approaches to congestion management. The simulation examines the effects of different congestion management methods on a given (existing) schedule at LaGuardia Airport (LGA). This simulation was supported by FAA and DOT, and had several research teams from different universities and the airline industry involved.

[Donohue and Hoffman, 2007, Ball et al., 2007] discuss the simulation where the participants were provided with policy decisions that related to alternative demand management approaches. The participants were then asked to respond by changing their existing schedules in response to the new policies. Representatives from the FAA, airlines and airport

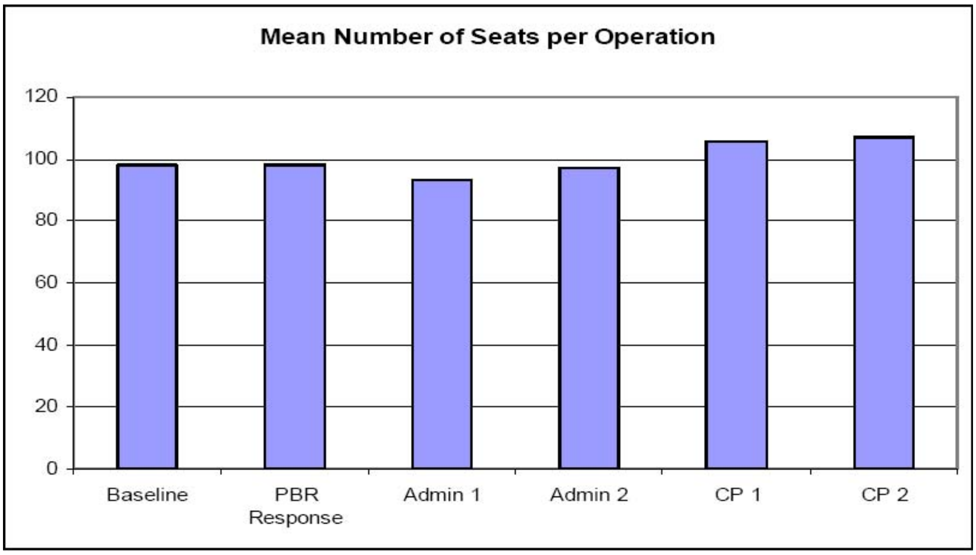

Figure 2.2: Mean average gauge of aircraft results from the simulation

operators were invited to participate in these simulations.

During the simulation, there were three sequences, for a total of five moves. The first scenario used a baseline schedule of operations at LGA and placed into effect a "Passenger Bill of Rights" rule that would force airlines to compensate passengers for flight delays. The second scenario again started with the baseline schedule, but had the FAA provide two rounds of administrative actions that tried to both reduce congestion and increase competition. The third scenario again started with the baseline schedule, but imposed two rounds of congestion pricing. The second round of the congestion pricing simulation adjusted the congestion pricing used in the first round.

Figure 2.2 shows the result of the first simulation. As seen, congestion pricing rounds resulted in a larger average gauge of aircrafts at LGA airport. Since in this scenario, any airline could use the airport if willing to incur the congestion price, there was no need for larger airlines to hold onto slots. Therefore, some inefficient flight legs were replaced by a new airline's more efficient flight legs. It is evident that these changes led to a more efficient use of slot resources.

Another simulation was held in May 2005 at the University of Maryland. This simulation dealt with a general auction design and participants were given first hand experience of a mock auction. The objective was not to obtain definitive data on specific outcomes, but rather to teach the participants the rules of the auction and how the auction mechanism would work. The details of this design are described in [Ball et al., 2007] and [Donohue and Hoffman, 2007].

2.1.5 Congestion Prices

The following table, Table 2.1, provides a summary of some of the congestion prices (in dollars) that are reported in the literature.

2.2 Current System

Currently, Air Traffic Flow Management (ATFM) deals with the case where there is an imbalance between demand and capacity. It is an important instrument to keep the delays on the ground rather than in the air to minimize disruption, thereby having the least economic impact on the users and better utilizing the resources (airport and other air traffic management resources). All of ATFM strategies employ three principal interventions:

- ground holding: delaying a flight's takeoff at the departure airport for some specified amount of time
- rerouting: changing some of the route of the flight from its departure to arrival airport to manage the traffic flow
- metering: controlling the rate of flights at some spatial boundary (e.g. arriving at a given air traffic control sector or airport) by adjusting space between aircrafts.

Some of the ATFM strategies include Ground Stops (GS), Airspace Flow Program (AFP), Ground Delay Programs (GDP) and Miles-in-Trials (MIT).

- Ground Stop (GS) is a ground holding of an aircraft to avoid traffic at or around the

Table 2.1: Congestion Prices (in $)

Author(s)	Approach	Airport	Duration	Fee Structure	Congestion Price($)
[Daniel, 1995]	Bottleneck congestion with stochastic queue	Minneapolis (MSP)	1^{st} week May 1990	atomistic	\$275-\$550
[Daniel, 2001]	Bottleneck congestion with stochastic queue Heterogeneous cost and elastic demand	Minneapolis (MSP)	1^{st} week May 1990	non-atomistic	\$28 (GA) -\$295 (Northwest)
[Daniel and Harback, 2009]	Bottleneck congestion with stochastic queue	Atlanta (ATL) Boston (BOS) Newark (EWR) LaGuardia (LGA) Minneapolis (MSP) Philadelphia (PHL) San Francisco (SFO)	28^{th} July- August 3^{rd} 2003	non-atomistic	\$2,323-\$2,753 \$541-\$564 \$860-\$994 \$201-\$226 \$1303-\$1,503 \$1,161-\$1,364 \$568-\$580
[Janic and Stough, 2005]	Queuing using diffusion approximation	LaGuardia (LGA)	July 2001	non-atomistic	\$6,000- \$58,000
[Johnson and Savage, 2006]	Departure queue bottleneck congestion	Chicago (ORD)	22^{nd} Sept. 2004 15^{th} Sept. 2004	non-atomistic	\$343-\$17,000 \$14,000- \$1,300,000
[Ashley and Savage, 2010]	Simulated Arrival queue bottleneck congestion	Chicago (ORD)	22^{nd} Sept. 2004 15^{th} Sept. 2004	non-atomistic	<\$100-\$6000 <\$100-\$44,000
[Poole and Dachis, 2007]	Departure queue	Kennedy (JFK) Newark (EWR)	August 2007	atomistic	\$2,000
[Ball et al., 2007]	Human-in-the-loop simulation	LaGuardia (LGA)	August 2007	atomistic	\$275-\$1,200

departure airport. It is also to be invoked when there are severe weather conditions (e.g., heavy storms) or high security threats.

- Miles (Minutes)-in-Trails (MIT) are used to control miles (minutes) required between two aircrafts. The change in separation distance is used to control the flow rate of aircrafts. MIT might propagate to flights hundreds of miles away from the airport.
- Airspace Flow Program (AFP) is a relatively new program to reroute flights away from a constrained airspace caused by inclement weather.
- Ground Delay Program (GDP) is used to manage traffic flow at an arrival airport by delaying flights at departure airports.

In the current system, when demand exceeds supply, a GDP is imposed. A description of how GDP currently works is therefore presented.

2.2.1 Ground Delay Program (GDP)

The Ground Delay Program (GDP) is a short-term strategy to reduce air traffic congestion at an airport by decreasing the rate of arriving flights according to the foreseen imbalance between demand and capacity. GDPs have been implemented since 1981 and have been deemed successful (along with some improvements such as Collaborative Decision Making [CDM]) to date. The motivation behind GDPs is to convert the foreseen airborne delays into safer and cheaper ground delays [Ball and Lulli, 2004].

While a GDP is in effect, airlines flying into the airport are assigned a delay computed by a Ration-by-Schedule (RBS) approach. That is, each flight is ordered based on its published arrival, thereby receiving a proportional delay based on their Official Airline Guide (OAG) published, scheduled arrival time. Using this approach, flights at the beginning of the GDP are assigned shorter delays compared to the ones towards the end of an announced delay period. Alternative approaches of allocation other than RBS are discussed in [Manley, 2008].

Once the RBS allocation is made, the airlines now "own" these slots for a given GDP announced time period. Each airline impacted may choose to reorder their own flights in this GDP ordering; they may also cancel flights. When a flight is cancelled, it results in a schedule with holes in the ordering. A "Compression" algorithm is invoked to fill these holes by moving flights up along the schedule with the added provision that the airline has the right to insert some other flight into the schedule as needed (see Slot Credit Substitution below for details). This incentivizes airlines to provide up-to-date information on their flights' status, since an early announcement of a cancellation allows an airline to obtain a slot later in the day.

2.2.2 Collaborative Decision Making (CDM)

Since 1998, GDPs have been implemented under Collaborative Decision Making (CDM). The idea of CDM is to increase information exchange between all the parties involved, such as airlines, airports, the FAA and the air traffic controllers. This is done using a common situational awareness system that allows operational problems to be solved in a timely and coordinated manner [FAA, 2005a]. This, in turn, increases the efficiency and equity of GDPs while ensuring that available perishable resources (arrival time slots) are utilized. The basic premise is that "shared information and collaboration in planning and executing ATFM initiatives benefits all ATM users as well as the ATM service provider" [Metron, 2000]. Following are some of the advantages of CDM based GDPs:

- CDM provides the overall picture to all the parties involved. Thus, an airline can see the overall situation at the airport(s) and can plan its schedule accordingly.
- under CDM, information is shared instantly, e.g., any announced cancellation provides a revised picture of the situation, thereby improving the GDP parameters.
- this coordination may allow a GDP to be cancelled before planned, due to the reduction in demand (removal of cancelled flights).

- Under CDM, the airlines have a right to swap their slots among, not just their own, but also with competitor's flights. This way, fewer slots are wasted and airlines can plan ahead to perform their operations efficiently.

Further details about CDM and its implementation can be found in [Manley, 2008,de Neufville and Odoni, 2003].

2.2.3 Slot Credit Substitutions (SCS)

Slot Credit Substitutions (SCS) are a natural extension of the current system and were implemented in May 2003. Under CDM, the airlines cancel and substitute their own flights to better facilitate their overall schedule. However, only when an airline cancels a flight can it make substitutions and the airlines would not see the consequences of this action until executed. With the SCS paradigm, an airline gets a "conditional cancellation" opportunity. That is, it announces that it is willing to give up a certain slot (by cancelling a flight) in return for a later, desirable slot. The CDM paradigm takes care of these requests and then matches the pairs of flights for potential substitution. This pairing is termed as "bridging" in the SCS environment. An analysis by Metron Aviation [Wright, 2004] regarding SCS benefits suggested that SCS requests produced around 3000 bridging opportunities with an average savings of 20 minutes per bridging flight, resulting in a total of 120,000 minutes of delay savings.

2.2.4 An Illustrative Example

Consider the example illustrated in Figure 2.3(a) that shows the original schedule at an airport. Each cell represents a flight, defined by airline code (for example, *UAL* denotes United Airlines[8]), aircraft code,[9] along with its revenue. The X-axis indicates the scheduling order (ascending) in which the flight plan was filed within the same time window. Y-axis indicates different time windows. Flights are ordered from top to bottom and left to right.

[8]List of airlines code is provided in Appendix A.
[9]Full list provided in Appendix B.

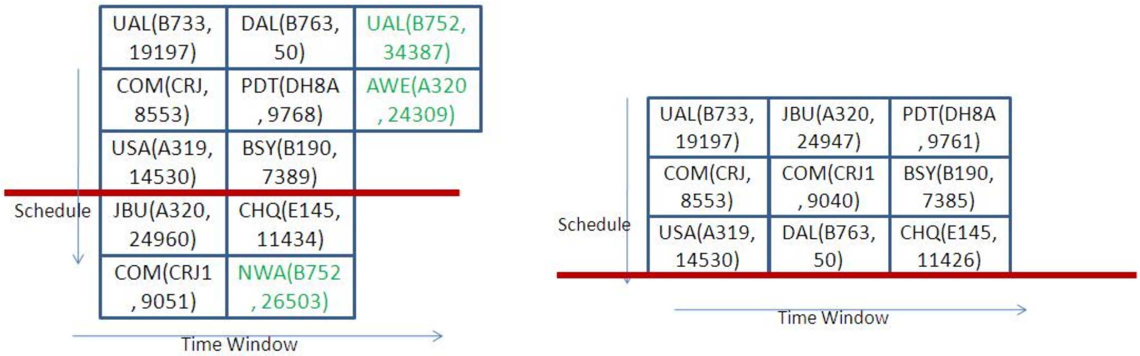

Figure 2.3: (a) Original schedule, (b) Ration by Ration-by-Schedule (RBS) allocation

The red line indicates the announced capacity for the time window. In this example, the capacity is reduced to 3 per time window and a total of 3 time windows.[10] Therefore, two out of the first five flights will be rescheduled. Figure 2.3(b) shows what happens when RBS is applied to the original schedule. All extra flights were cascaded to the later time windows. Given the ordering, an airline might substitute one of its flights with another to better accommodate its schedule, e.g., assuming that Delta (DAL) and Northwest (NWA) are now a single airline, Delta might cancel its flight (DAL[B763,$50]) to use the slot for Northwest flight (NWA[B752, $26,503]) since it is more profitable. In the current schedule, three larger (and more profitable) flights are cancelled due to unavailability of slots. In the later chapters, the same example will be discussed to illustrate how congestion pricing might alter the allocation.

2.2.5 Issues with Current System

The idea of GDP was based on a concept of equity and fairness with RBS allocation being the most fair among others. However, due to an imbalance in the share of flights at given airports among different airlines, the current system favors a smaller group of larger airlines since they have far more flexibility in the swapping of flights. Given the fact that flights

[10] In reality however, one can always reschedule a flight in the subsequent period.

are not single entities, but rather part of a larger network and delays propagate into later delays, the current system works well for an airline having many flights at a given airport, but not as well for a carrier having only a few valuable flights at an airport dominated by another carrier. In fact, due to different proportions of airlines' shares in most cases, an airline with a smaller share at any congested airport suffers the most compared to an airline with a larger share of flights.

Another problem associated with the current system is that, because airlines care about published online performance and because their associated regional carriers may be charged with the delay statistics (rather than the major carrier that determined the delays), smaller regional airlines may be susceptible to gaming from the larger airlines who transfer the large carriers' delays to the smaller carriers.

The RBS approach is considered fair and equitable only if there are no exemptions to a group of flights. However, in the current system there are several exceptions to the rule. Often when a GDP is invoked, it is tiered according to distance and only cities within a given radius around the GDP airport are affected by it. All airborne flights are already exempted as are many international flights. This results in favoring carriers with long hauls and penalizes regional flights.

2.3 Alternative Approaches

Many alternative ideas have been considered in the literature to overcome the issues with the current system. This section discusses a few of the newer approaches that either further expand on the current system or replace it completely with alternative systems.

2.3.1 Slot Trading [Vossen and Ball, 2006]

[Vossen and Ball, 2006] further developed the concept of trading slots among airlines when the Ground Delay Program (GDP) is in effect. Instead of simple rounds of substitutions and cancellations after the initial allocation of slots using the Ration-by-Schedule (RBS), their research studied the consequences of allowing the airlines to trade slots among themselves unconditionally (unlike Slot Credit Substitution or SCS). They interpret the Compression algorithm as a way of slot trading between two airlines where an airline trades its earlier but useable slot for a later slot with another airline that can use the earlier slot. Currently, this algorithm only allows "one-for-one" trades. Vossen suggests a general model to perform "k-for-n" trades initially while providing a practical implementation of a "two-for-two" trades model. Airlines periodically submit a list of trade offers based on their preference while a mediator decides (based on some decision rule) to accept some of these offers. The role of mediator is modeled as an optimization model, while the decision rule can be considered as the objective function of that optimization model. Different decision rules can be used. The paper proposes a straightforward rule: i.e., the number of accepted offers. The airline's list of trade offers can be used to represent the airline decision-making model. Two models used in the experiments are:

- maximizing the on-time performance for each airline by maximizing the number of flights that are delayed at most by 15 minutes.
- minimizing the passenger delay costs (total or average) for each individual airline.

The experimental analysis was done using historical data from a set of GDPs at Boston Logan Airport from January to April of 2001. Vossen concludes that using either airline decision-making model, the slot trading method proposed shows promising results. In the case of maximizing on-time performance, it reached theoretical bounds while in the case of minimizing passenger delay cost model the results were significant, especially when a step-wise function was used for delay costs.

2.3.2 Proportional Random Allocation (PRA)

Another idea proposed by both [Vossen, 2002] and [Pourtaklo and Ball, 2009, Pourtaklo and Ball, 2010, Pourtaklo, 2010] is that of Proportional Random Allocation (PRA). The idea for this allocation is simply that each flight has a share in all the slots that it can use (that is, all the slots after the scheduled time of the flight until the end of congested period), therefore at each time slot, a flight is chosen with some probability (equal to 1/all flights competing for that slot). A PRA share for that flight would be the summation of its probabilities across all potential slots. A fair share FS of an airline would then be the summation of the PRA share of all its flights. The PRA mechanism takes into account the limited number of slots available and at the same time, also considers the larger share of earlier flights as opposed to later flights. However, this approach is not used to allot slots to flights; rather, it is used to compute "fair share" of airline (collection of flights). The intuition for this allocation mechanism is that it meets the fundamental principles of equity.

2.3.3 Preference-Based Proportional Random Allocation (PBPRA)

As the title suggests, this approach [Pourtaklo and Ball, 2009, Pourtaklo, 2010] is based on the PRA allocation described earlier. In addition to considering the fair share of an airline's slots, it also considers the airline's preference regarding what slots it wants for what flights. An ordered preference list of pairs of flights and slots is also provided for each airline. The approach breaks the whole process into two steps:

- Step 1: Determine a fair share (FS) for each airline.
- Step 2: Allocate flights to slots in a manner consistent with the fair share determined in Step 1.

For Step 1, the approach uses the PRA mechanism that give fair shares for all the airlines. Step 2 is again divided into phases. For the first phase, Phase I, airlines are randomly chosen in proportion to their fair share (more accurately, in proportion to a fractional part of their fair share; this gives an airline with a fair share of less than 1 a chance to compete). Once an airline is chosen, it is assigned the highest flight-to-slot assignment on its preference list and its fractional share is set to 0. Phase I ends when there are no more fractional shares for any airline. Phase II is ordered with respect to time, that is, for each earliest unassigned slot, an airline proportional to its fair share is chosen and assigned the highest flight-to-slot assignment from its list of preference slots. The fair share of the airline is decreased by 1. Continue assigning slots in the same manner until no airlines have anymore preferences.

Some experimental results were done with the self-generated preference list with the underlying principle of reducing the marginal cost of delay. Again, these experiments were done at a Flow Constrained Area (FCA) either an airspace or a ground airport. Different capacity reductions were studied and the approach was compared along with the standard RBS (Ration-by-Schedule) procedure currently used.

2.3.4 Dual Price Proportional Random Allocation (DB-PRA)

This approach [Pourtaklo and Ball, 2010,Pourtaklo, 2010] is a further extension to the previously described approach [Pourtaklo and Ball, 2009] and adds to the previously described algorithms to allocate flights to slots. In the previous approach, all the slots were implicitly assumed to be of equal value to the airlines. However, in reality, an airline may be willing to lose more than a single slot at any other time in order to get a preferred slot. This approach allows airlines to "pay more" for slots that they prefer. The approach identifies two sets of airlines, one set that maintains on-time performance and hence is willing to pay more for the preferred slots and receive fewer but more valuable slots, while the other set of airlines can tolerate more delay than cancellations. Instead of using fair share proportions, an additional parameter, P_H, is used to determine the higher price an airline (or set of airlines) is willing to pay in order to receive the preferred slot. The corresponding price P_L for the other set of airlines (that wish to tolerate delay over cancellation) is computed using the Fair Share (FS) of airlines and P_H. Similar to the previous approach, two steps are defined and the DB-PRA algorithm is also divided into two phases; however, in this case, Phase I deals with a set of airlines that value the slot by at least P_H and all those airlines are provided with their respective preferred slots. For rest of the remaining slots, the PBPRA approach can be used for allocation with the value of all the slots being P_L and the fair share of all the airlines being $1/P_L$. The same data set as used in the previous approach is being used with the same design of experiments. Due to the difference in slot values for different airlines, the approach concludes that this new approach helps airlines better optimize their internal costs.

2.3.5 Credit Points

A similar approach to slot trading is credit points (similar to artificial currency), as suggested in [Sheth and Gutierrez-Nolasco, 2008,Sheth and Gutierrez-Nolasco, 2009]. Although this approach is mainly suggested for airspace congestion, it can be applied to ground delays straightforwardly. The basic idea is to allow airlines to associate preferences to their flight priorities and even route preferences during the filing process of the flight plan. Each day, each airline is allocated a fixed number of credit points that they can use as they wish. The flights with a higher number of credit points are given priority when assigning a route (or in case of runway congestion, slots). Although there can be many different variations regarding how many credit points to assign, when they would expire, etc., for the experimental design purposes, the number of credit points provided to an airline is five times the number of their flights for that day, with the credits expiring at the end of the day. An airline typically assigns 0-10 credit points to each of its flight (and all of its routes) based on its importance in the airline schedule. In case the preferred route (or slot) is not allotted to the flight, the number of credit points associated to that route is given back to the airline. In the experimental design, flights scheduled on August 24, 2005 between the hours of 3:00 pm and 7:00 pm EDT are used. FACET[11] was used for simulation purposes, using the FAA's ETMS data. The credit points assigned by the airlines to their flights was done based on the distance a flight covers, so a flight that travels the greatest distance gets more credit points with the presumption that longer distanced flights are more importance to airlines. However, other factors to determine credit point distribution among flights and routes, as well as experts' knowledge can be used. A "swapping" mechanism to swap routes between flights of different airlines is also used termed as "Negotiation." The result showed great improvement from historical scenarios and at the least, because of the credit points,

[11] For details on FACET, see [Bilimoria et al., 2001].

the number of congested sectors during the studied time frame was zero (as opposed to having an average of 2 congested sectors in the historical case). This approach concludes that adding the user's preference to the flight schedule can reduce delays and congestion significantly; given a better strategy to assign credit points to flights (and routes), it might further improve the overall performance of the air transportation system.

2.3.6 Permit Trading

A recent project funded by NASA dealt with the study of "Market Based Approaches to Slot Auction and Enroute Airspace Management." The goal was to study and analyze different market mechanisms, their technical issues and hurdles to overcome in case a system is selected for implementation. The project studied many market-based mechanisms in detail and the combinations thereof and identified over 3000 various combinations. The "Free-Pass Permit Concept" was finally chosen to be implemented and a human-in-the-loop simulation was performed. Details are described by [Berardino et al., 2010e, Berardino et al., 2010a, Berardino et al., 2010b, Berardino et al., 2010c, Berardino et al., 2010d]. Here, only the concept of the free-pass permit is introduced. Again, although this approach deals with air space congestion, it can be used for runway congestion.

The approach selected deals with the day of operations market, that is, how to deal with the congestion at the airport that is generated on the day of operations. In this concept, all the airlines are issued a number of free-pass permits which give an airline, "a right to land at a given airport within a fifteen-minute time window without any GDP or AFP[12] delays imposed." Permits are time-of-day based and can be only used in that specific time window for that given day at a given airport. The number of permits issued and how they are distributed is decided by the service provider (such as FAA, ATFM, etc.). For the simulation purposes, the total number of permits was set to 20% of the scheduled operations in any given hour; the distribution was proportional to each airline's share of flights in the schedule. The participant is provided with basic flight information including the scheduled

[12] Air Space Flow Program.

departure and arrival times, the aircraft type, the turnaround time and the future itinerary of the aircraft, as well as the expected delay if the flight does not use a permit and the cost of that delay. This is to ensure that a participant is fully aware of the outcome of any and all of its potential decisions. Two different scenarios were used for the simulation, specifically:

- Free Permits without Sales: All airline representatives (participants of the simulation) are allowed to apply their free-pass permits to any of their capable flights. "Capable" refers to the ability of the flight to reach the arriving airport safely within the time frame of the permit.

- Free Permits with Sales: In this scenario, in addition to applying free-pass permits to their own flights, an airline representative is allowed to sell its permits to other airlines for money, thereby introducing permit/slot trading. The airlines were therefore provided with some cash at the start of the simulation.

Results of the simulations suggested that introducing the permits concept could further improve the current system. It would be relatively easy to implement with the current CDM paradigm.

2.4 GDP Rationing Rule Simulator(GDP-RRS)

[Manley, 2008], in her dissertation, designed a simulator GDP Rationing Rule Simulator (GDP-RRS) to analyze the impact of different rationing rules available in the literature. She then gathered performance metrics based on flight, passengers and fuel and perform comparative analysis. For the Design of Experiments in this research, her simulator is used to run alternative approaches like Ration-by-Schedule (RBS) and Ration-by-Distance (RBD). Here, a list of different rationing schemes she implemented along with the overall design of her simulator are described.

2.4.1 Different Strategies

For Manley's simulator, she analyzes the following different strategies:

- Ration-by-Schedule (RBS): As mentioned earlier, this assigns slots among flights based on the order of their scheduled arrival times as published in Official Airline Guide (OAG). It is a first-scheduled, first-served approach to assigning slots. Ties are broken randomly in case of same scheduled arrival time. This approach is currently used by the Air Transportation Flow Management (ATFM) system when GDP is implemented.

- Ration-by-Passengers (RBPax): This strategy prioritizes flights by the number of passengers on board. A flight with a larger number of passengers is preferred over flight with a lesser number. In case of a tie, the RBS approach is used.

- Ration-by-Aircraft Size (RBAcSize): This strategy takes into account the categories based on aircraft size, i.e. heavy, large and small. Priority is given to the heavy aircraft first, then the large and finally the small category. In the case that two flights belong to same class, RBS is used to order those.

- Ration-by-Distance (RBD): This strategy assigns slots to flights based on the distance between the airports. Priority is given to long-haul flights over short-haul flights. Manley uses Greater Circle Distance (GCD) to sort flights,[13] unlike [Hoffman et al., 2007] who use estimated enroute time for each of flights[14]. Ties are broken using RBS approach.

- Ration-by-Fuel-Flow high precedence (RBFFhigh): This strategy uses the taxi fuel burn rate to order the flights. Flights with higher taxi burn rates are given precedence. The rationale is to avoid excess fuel burn. Ties are broken using RBS.

- Ration-by-Fuel-Flow low precedence (RBFFlow): This strategy again uses the taxi fuel burn rate to order the flights, however, the preference is now given to flights with

[13]For the experiments in this research, the same distance parameter is used.

[14]A rationale might be to avoid the uncertainty due to route information, since an airline might report a longer route in its flight plan but change it once airborne.

low taxi fuel burn rates. The rationale behind this strategy is to incentivize airlines to use fuel efficient aircrafts. Ties are again broken using the RBS approach.

2.4.2 Design of GDP-RRS

Here, a brief description of the design of Manley's simulator is provided. Figure 2.4 discusses the main steps of her simulator. The simulator starts with an initialization step that gathers and calculates the basic information of the flight (e.g., PAX, Load Factor, scheduled time, aircraft type, taxi fuel burn rate, etc.) and the GDP (the time of GDP as well as what tiers are impacted). Next, it classifies the flights as ones impacted by the GDP and as those that are exempted from the GDP. Exempted flights include international flights, already airborne flights and pop-up flights, etc. A priority queue is generated based on this classification in the next step. Based on the available capacity, slots are generated and times are assigned to these slots in the next step. Finally, all flights are assigned initial slots, with exempted flights first and then the rest of the flights are sorted with respect to the strategy used. The substitution step allows airlines with cancelled flights to assign those empty slots to their other flights. Preference can be given to either the earliest scheduled next flight or the flight with more passengers. The next step, compression then tries to reallocate any slots that were emptied due to cancellation and the substitution. Finally, the last step gathers all the performance metrics. In case there are no cancelled flights,[15] the simulator goes directly to the last step of gathering statistics and skips the substitution and compression steps.

2.5 Summary

Starting with the brief introduction on the theory of congestion pricing, this chapter highlights some of the theoretical work done regarding the application of congestion pricing to reduce congestion in transportation infrastructure. It also describes some of the recent work done when applying congestion prices to airports. Human-in-the loop simulations suggest that congestion pricing might work provided it is computed accurately and implemented

[15]Potential cancelled flights are predetermined in the data.

PROCEDURE: GDP-RRS

```
Initialize
Classify Flights
Create Priority Queues
Create Slots
Assign slots to flights
Substitution
Compression
Gather statistics
```

Figure 2.4: Procedure for GDP-RRS simulator

efficiently. The latter part of the chapter describes the current implemented system that deals with congestion at airports and its limitations. It also covers some of the more recent and alternative approaches that are suggested in the literature. Some of these approaches are extensions to the current system while others suggest replacing the current system with a new mechanism for ordering flights during the GDP. A brief description and intuition is provided for each of these approaches and references are provided therein. Finally, a descriptive summary of recent work done is provided that includes a simulator for a few of the rationing approaches studied currently in the GDP literature.

Chapter 3: Cost of Delay

This chapter starts with a brief introduction (Section 3.1) of what is meant by delay costs and the reasons for needing such calculations. Section 3.2 describes some of the earlier approaches to computing the costs of delay, one of which is also the basis of the new model[1] described in Section 3.3 of this chapter. Section 3.4 describes the results and observations that were made when using this new model to compute the cost of delay. Section 3.5 discusses the sensitivity analysis done in order to further understand the model. The chapter ends with summary section (section 3.6).

3.1 Introduction

The airline industry moves millions of passengers and tons of cargo annually. The Schumer report estimated that in 2007, airport delays cost the economy about 40.7 billion dollars [Schumer, 2008]. Disruptions in one part of the airspace impact the entire network as delays propagate. It is estimated that almost 50% of the entire airspace delays are caused by delays that originate at the New York/New Jersey/ Pennsylvania airports. This implies that delays and their true costs are vital to airport and airspace management decision making.

Similarly, researchers are applying more holistic approaches to the feedback control of the air transportation system [Donohue et al., 2008, Donohue and Hoffman, 2007, Ball et al., 2007]. Many of these approaches rely on economic feedback [NextGen, 2008, Xiong, 2010, Rupp, 2005], including the cost of delays to the airlines. Therefore, understanding the true cost of a delay is not only of interest to the airlines that incur these costs, but is essential for air transportation management, policy and control.

[1] This research was done with other colleagues [Kara et al., 2010a, Ferguson et al., 2011] for the purpose of evaluating the true cost of delay to airlines use in this congestion pricing model, as well in other studies of airline behavior [Ferguson, 2011].

In general a flight can be delayed due to several reasons. These are issues internal to the airlines operations, mainly:

- mechanical problems with the aircraft.
- schedule disruption due to bad weather or air traffic management initiatives (Ground Delay Programs [GDPs] or Air Flow Programs [AFPs]).
- misaligned crew/aircraft due to a previously delayed flight.
- scheduling multiple flights during a time period in excess of runway capacity at normal weather day.

The two most significant causes of delay are (i) weather which can reduce the capacity of both the airspace and the runways, and (ii) overscheduling that creates queues that further reduce capacity on runways, taxiways and gates.

Based on weather forecasts and schedules, air traffic management estimates the resulting reduction in capacity within various segments of the airspace and at a variety of airports. It announces Ground Delay Programs (GDPs) that hold aircrafts at the departing airport, in order to have the amount of flying aircrafts better match the capacity of the system. For capacity reduction in air, Air Flow Programs (AFPs) are employed to suggest/announce alternative routes for the flights. Holding an aircraft at a gate is both cheaper and safer than an airborne hold, and allows the system to be better managed.

Finally, the delays previously described induce future delays in the system, because the aircraft or crews may not arrive at their next assignment on time. Even when the crew does arrive, they may not be able to work another flight because they have exceeded their allowable working hours.

3.2 Background

Although much has been written on the impact of delay on both passengers and airline costs, such costs are difficult to estimate because airlines consider their operating costs proprietary. Currently, there are two major approaches in the literature for computing airline operating costs. The first is one often labelled as the "cost factor approach." Here, a linear combination of the costs associated with each segment of the flight is considered[2] [JEC, 2008, Cook et al., 2004]. One can further segment delay costs into those directly attributed to the flight and those attributed to propagated delay [ITA, 2008, Cook et al., 2004]. Cook et. al [Cook et al., 2004] further differentiated the propagated delay between primary delay caused by same airframe (i.e. rotational) or different airframe (i.e. non-rotational).

The other option is that of the "aggregate cost approach" which is based upon the relationship between operational costs and delays incurred. A simple version would be to estimate the delay cost by taking the total operating cost and multiplying by the percent of the flight time attributed to delay [Zou and Hansen, 2010].

The cost factor approach requires more detailed information about each phase of a flight and its associated costs, while the aggregate cost approach, although not detailed, is easier to calculate since the total operating cost is published for most flights.[3]

3.2.1 Aggregate Cost of Delay Model

[Zou and Hansen, 2010] introduced an aggregate cost approach where a direct empirical basis is established by adding operational performance variables into airline cost models and observing their effects on airline expenses. The BTS Ontime database is used to construct operational performance metrics. Data is collected on a quarter-year basis for aircraft type. Regression is applied to understand the relationship between the cost to airlines and Revenue-Ton-Miles (RTM).

For operational performance, two sets of metrics have been developed. "Delay-buffer" metrics consider two types of delays, delay against schedule and delay against schedule buffer time of a flight. Thus, the first delay is against the scheduled time as announced in

[2]The EuroControl model, described later, and the proposed model both use cost factor approach.
[3]A more detailed comparison of these approaches is provided in [Zou and Hansen, 2010].

the OAG[4] schedule, and the other is the delay against the average of observed travel time recorded historically. In order to characterize the delay against schedule, average positive arrival delay per airline quarter has been chosen. A buffer for each flight is defined as the "difference between the scheduled flight time and the 5^{th}, 10^{th} and 20^{th} percentiles of all observed travel time, for a given segment (directional), airline, and quarter." The average buffer is the average of the calculated buffer time over all the flights for each airline and quarter. So, delay-buffer metrics consists of a total of six performance metrics, three for each delay against the schedule and the delay against the schedule buffer.

The other set of metrics is "time-based" metrics. These metrics are based on three time intervals, "Total Absorbed Time (TAT)", "Scheduled Time" (S) and "Actual Time" (A). TAT (denoted by T_{tot}) can then be divided into the following subsets, scheduled-active time (S $\cap$ A), scheduled-non-active time (S $\cap \sim$ A) and active-non-scheduled time ($\sim$S $\cap$ A). Normalizing these intervals by the total absorbed time gives the probabilities $P_{S\cap A}$, $P_{S\cap\sim A}$ and $P_{\sim S\cap A}$ respectively. The authors use T_{tot}, $P_{S\cap\sim A}$ and $P_{\sim S\cap A}$ as three operational performance metrics.

The authors used regression to analyze the behavior between airline model inputs and outputs. Due to its flexibility, they have used the translog functional form as a base model. Revenue-ton-mile (RTM) is the only measure used to represent the aggregate output. Following are the inputs of the model:

- Cost input:
  - Fuel price (fuel expenses per gallon)
  - Labor price (per employee per quarter)
  - Materials price (producer price index (PPI))
  - Capital input (multiplying capital stock with the utilization rate, load factor is used as a proxy)
- Performance input

[4]Official Airline Guide.

Table 3.1: Airline delay cost estimates ($ billions), for 2007 [Zou and Hansen, 2010]

	Cost category		Buffer5**	Buffer10	Buffer20
7 major airlines*	Delay-based model	Delay against schedule	4.1	3.3	3.1
		Buffer	3.2	2.6	1.9
		Total	7.3	5.9	5.0
	Time-based model	Delay against schedule	6.7	6.7	6.7
		Buffer	2.8	2.4	1.8
		Total	9.5	9.1	8.5
Industry wide	Delay-based model	Delay against schedule	5.7	4.6	4.4
		Buffer	4.6	3.7	2.7
		Total	10.3	8.3	7.1
	Time-based model	Delay against schedule	9.4	9.4	9.4
		Buffer	4.1	3.4	2.7
		Total	13.5	12.8	12.1

– Stage length (total distance flown/total number of departures flown)

– Points served by airline (extracted from BTS Ontime)

– Average positive delay by airline (available in BTS Ontime)

The data used was from BTS Ontime [BTS, 2007]. For accurate analysis, nine major airlines were studied from the beginning of 1995 through the end of 2007.

Several different estimation results are provided in the paper [Zou and Hansen, 2010] based on all the different parameters and performance metrics mentioned. The main results are shown below.

Table 3.1 shows airline cost estimates in $ billions for 2007 using this approach with different parameters. The first three rows refer to delay-based model. Among these three rows, the first row shows the reduction in costs if the delay against schedule is eliminated to zero (referred as "Delay against Schedule") . The second row indicates the delay based on the buffered schedule, i.e., the amount of padding that the airline inserted to have an on time arrival. The third row shows the reduction when both the delay against schedule and the schedule buffer are eliminated (referred as "Total").

Similarly, the next three rows refer to the time-based model. The fourth row (referred to as *Delay against Schedule*) shows the reduction in cost if both $P_{S \cap \sim A}$ and $P_{\sim S \cap A}$ are reduced to zero. The sixth row (referred as Total) further adds the effect of removing schedule buffer as in delay-based model case, the fifth row (referred as "Buffer") is then computed based on the difference of the other two rows indicating reductions when only schedule buffer is eliminated. The first half of the table report results for seven major airlines while US Airways and American West were excluded due to the confounding of a merger. However, the remaining table takes these airlines into account by extrapolating their costs based on Available Seat Miles (ASM) as reported in BTS [BTS, 2007]. Buffer5 (Buffer10, Buffer20) means that the schedule buffer is measured for the 5^{th}(10^{th}, 20^{th}) percentile of the reported time.

They concluded that:

- Delay and buffer impact airline costs significantly. One minute of increased delay incurs approximately 0.6% increase in variable costs to an airline.
- A flight's activity outside of the scheduled time interval impacts airline cost more significantly as compared to changes within the scheduled time interval.

3.2.2 EuroControl (EC) Model

A report that evaluated the cost of flight delays at European airports was prepared by the Performance Review Unit, EuroControl in 2004 [Cook et al., 2004]. This EC report describes a methodology based on the cost factor approach and presents results detailing the cost to airlines of delays during various segments of a trip. The costs are divided into short delays (less than 15 minutes) and long delays (greater than 65 minutes). The report provides the resultant multiplier (euros per minute) for any such segment. The types of delays considered include gate delay, access to runway delay (both taxi in and out delays), enroutes delays, and landing delays (circling or longer flight paths to overcome congestion while approaching the airport). The data used in the study consisted of data collected from European airlines, air traffic management as well as interviews and surveys conducted by the research team with airlines.

The EC report specifies that delays incurred can be of two types: "tactical delay" and "strategic delay". The report makes the distinction between tactical delays (delays encountered that are greater than the announced schedule, i.e., delays above the anticipated padding of the schedule) and strategic delays (i.e., the delay relative to an unpadded schedule). Both U.S. and European airlines increase the arrival time over unimpeded time so that they can report on time performance even when the system is over-capacitated. Another distinction that the report makes is between "gate-to-gate" (or single flight) delays and "network-level delays". The gate-to-gate delay is the delay that an individual flight incurs based on the environment it encounters, while the network delays are the effects that the flight causes to the rest of the network. The EC report discusses all of the above mentioned types of delays. However, considering the congestion pricing model relevant to this dissertation, the main interest is tactical primary delay since the main concern is the delay incurred by an individual flight and how valuable that flight is relative to other flights scheduled to arrive/depart within the same time interval. In the report, two types of delays have been chosen for demonstration: delays of short duration (15 minutes or less) and delays of long duration (65 minutes or more). Similarly, three cost scenarios have been used to "allow more realistic ranges of values."

The EC report describes the model as an additive model, where each component describes some proportion of the total cost. Table 3.2 shows what costs factors are included as input in these cost scenarios under different delay characteristics. For details, see [Cook et al., 2004]. Figure 3.1 details the inputs and outputs of their model.

Further exploration of their cost factors revealed the following costs involved:

- Fuel Cost: The report provides different fuel burn rates for each aircraft type studied and for all segments of the flights. The prices for all cost scenarios and the conversion

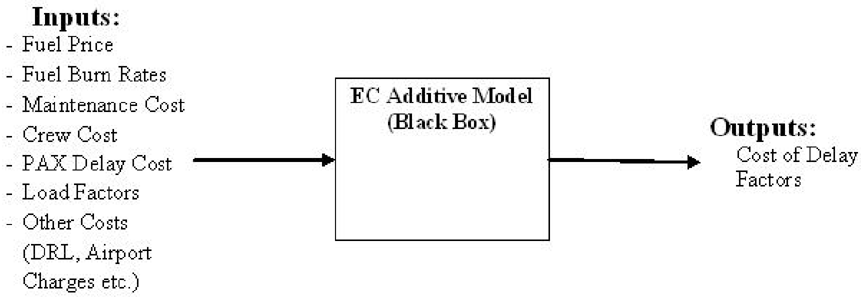

Figure 3.1: EuroControl Model

Table 3.2: Low, base and high cost scenarios

Factor	short delay type: **15 minutes basis**			long delay type: **65 minutes basis**		
	low	**base**	**high**	**low**	**base**	**high**
load factor	50%	70%	90%	50%	70%	90%
transfer passengers	15%	25%	35%	15%	25%	35%
arrival/departure	domestic	EU	non-EU	domestic	EU	non-EU
turnaround time	60 mins	60 mins	60 mins	60 mins	60 mins	60 mins
parking	remote	pier	pier	remote	pier	pier
fuel price	low	base	high	low	base	high
weight payload factor	50%	65%	80%	50%	65%	80%
airborne fuel penalty	none	none	applied	none	none	applied
handling agent penalty	none	none	none	none	none	charged
extra crew costs	none	none	low	none	medium	high
airport charges	averaged	averaged	max/2	averaged	averaged	max/2
pax cost of delay to AO, EUR/min	0	0	0.05	0.32	0.40	0.48
aircraft depreciation, rentals & leases	Strategic cost model used			Strategic cost model used		
BHDOC scenario	low	base	high	low	base	high
maintenance	15%	15%	15%	15%	15%	15%

rate from euros to dollars are also provided. (See Table 2-12 and Annex C in [Cook et al., 2004]).

- Extra Crew Cost: The report defines extra crew cost as extra costs paid in addition to the usual flight and cabin crew salaries and expenses. It may include employing additional crew (both flight and cabin crew) or incurring additional pay for regular crews due to unexpected increases in working hours. The report does not specify the exact methodologies used to obtain the crew cost component of the multiplier in order to preserve confidentiality of airline data. However, the report describes under what circumstances the cost factors will be increased (refer to Table 3.2).

- Maintenance Cost: The maintenance cost is defined to be the cost of maintaining both the airframe and power plant of the aircraft. The additional maintenance cost incurred for a one-minute delay is stated in the report as approximately 15% of the "Block Hour Direct Operating Cost" (BHDOC). The proportions of how maintenance costs are divided into different segments of the flights are given in Annex J of [Cook et al., 2004]. BHDOCs are given in the report for low, base and high cost scenarios for the 12 different aircraft systems studied (see Table 2-11 in [Cook et al., 2004]).

- Depreciation Cost: The report assumes that there is no additional depreciation cost caused by delays. Thus, the depreciation component of total delay is taken to be zero for all segments and cost scenarios.

- Passenger Delay Cost: Passenger Delay Cost (or PAX delay cost) is defined as the compensation paid by the airlines to passengers who have experienced delayed flights. Passenger Delay (in cost per passenger per minute) is given as: none for low and base cost scenarios, 0.05 for the high cost scenario for 15 minutes of delay, and 0.32, 0.40 and 0.48 for low, base and high cost scenarios, respectively, for 65 minutes delay. The load factors assumed are: 50% for low, 70% for base and 90% for high cost scenarios.

- Other Costs: This factor is a catch-all component that attempts to include any other cost factors mentioned in Table 3.2 (such as parking, airport charges, handling agent penalty, weight payload factor, etc.). No specific cost factors were given in the report, except details of different airport charges at different EU airports (see Annex L in [Cook et al., 2004]).

Table 3.3: Tactical Ground Delay Costs (euro/min.): At-gate only (without network effects)

Aircraft and number of seats		based on 15 minutes' delay			based on 65 minutes' delay		
		cost scenario			cost scenario		
		low	base	high	low	base	high
B737-300	125	0.6	0.9	14.5	20.4	44.6	82.8
B737-400	143	0.6	0.9	15.8	23.7	50.3	92.3
B737-500	100	0.6	0.8	13.8	16.6	38.2	73.5
B737-800	174	0.5	0.8	17.1	28.4	58.6	105.2
B757-200	218	0.6	1.0	20.2	35.6	71.7	126.0
B767-300ER	240	0.6	1.2	27.8	39.2	84.9	155.1
B747-400	406	1.8	2.2	49.0	67.1	142.2	258.7
A319	126	0.6	0.9	14.7	20.8	45.0	83.8
A320	155	0.6	0.9	16.3	25.3	53.5	96.5
A321	166	0.7	1.0	16.6	27.3	56.3	100.7
ATR42	46	0.4	0.6	8.6	7.8	19.7	40.6
ATR72	64	0.5	0.6	9.6	10.7	25.0	48.6

Table 3.4: Tactical Ground Delay Costs (euro/min.): taxi only (without network effects)

Aircraft and number of seats		based on 15 minutes' delay			based on 65 minutes' delay		
		cost scenario			cost scenario		
		low	base	high	low	base	high
B737-300	125	3.0	4.6	19.0	22.9	48.4	87.1
B737-400	143	3.0	4.7	20.3	26.1	54.1	96.6
B737-500	100	3.0	4.6	18.2	19.0	42.0	77.8
B737-800	174	2.9	4.5	21.6	30.8	62.3	109.5
B757-200	218	3.4	5.3	24.9	38.4	76.0	131.0
B767-300ER	240	4.5	7.2	34.0	43.2	91.0	162.1
B747-400	406	10.6	15.9	61.7	76.4	156.3	276.2
A319	126	2.6	4.1	18.4	22.8	48.2	87.4
A320	155	2.6	4.0	20.1	27.3	56.7	100.1
A321	166	3.0	4.7	20.9	29.7	60.1	105.0
ATR42	46	0.6	0.9	8.2	7.9	20.0	40.0
ATR72	64	1.1	1.8	10.3	11.4	26.1	49.2

Based on the analysis done, the EC report provides cost of delay factors (in euros). The delay is divided into three segments of the flight: delay on the ground at the gate (Table 3.3), delay while taxiing at either airport (Table 3.4) or delay while airborne (enroute and holding, Table 3.5). These segments were chosen for discussion because they reflect the fidelity of publicly available data.

3.3 Cost of Delay Model

Although the Eurocontrol model is detailed enough and covers almost all the factors involved in the cost of delay, there is no way to update the cost factors since not all of the individual cost factors are provided due to the proprietary nature of the embedded information. Also, the model is based on data from European Union airlines for 12 aircraft types. In the absence of this transparency, the factors provided prohibit the separation of fuel cost changes from crew or maintenance costs and also prohibit an update of summary factors when any of

Table 3.5: Tactical Airborne Delay Costs and Holding (euro/min.): (without network effects)

Aircraft and number of seats		based on 15 minutes' delay			based on 65 minutes' delay		
		cost scenario			cost scenario		
		low	base	high	low	base	high
B737-300	125	9.5	14.8	34.1	28.9	57.8	102.3
B737-400	143	9.2	14.3	34.6	32.0	63.3	111.4
B737-500	100	8.9	13.7	31.6	24.5	50.3	91.1
B737-800	174	7.8	12.5	33.1	36.5	71.3	122.6
B757-200	218	10.3	16.1	40.7	46.2	88.2	149.7
B767-300ER	240	14.2	22.5	57.1	54.2	108.4	189.5
B747-400	406	27.6	42.2	102.4	97.5	188.8	332.7
A319	126	7.1	11.1	29.1	28.1	56.4	101.3
A320	155	7.7	12.0	32.3	32.9	65.3	115.0
A321	166	9.5	14.9	36.2	36.5	70.7	122.2
ATR42	46	1.6	2.6	10.8	9.1	21.9	42.8
ATR72	64	2.2	3.4	12.8	12.7	28.1	52.6

these cost change or an alternative aircraft is considered. Therefore, in order to develop a more transparent and reusable cost of delay model, regression analysis is performed to learn the relationship between the provided costs (fuel, crew, maintenance, etc.) and the computed factors.[5] The idea is therefore to:

- identify coefficients for the cost factors
- model each of the individual coefficients and cost factors
- update the model with the publicly available costs of U.S. airlines
- extend the fleet mix to over 100 aircraft types
- update the model for changes in fuel cost

[5]This research is reported in [Kara et al., 2010a, Ferguson et al., 2011].

- structure the model to enable the updating of the data over various time periods

3.3.1 Methodology

The methodology is divided into three major steps: starting with regenerating the Euro-Control (EC) Model and then fitting the EC model in order to find the unknown coefficients. Once the coefficients are known, it is demonstrated how the model can be used on U.S. data for any carrier, aircraft type and load factor.

Regenerating the EC Model

This analysis starts with a similar additive general model for each of the different segments paired with the different cost scenarios that include all the different cost factors. Due to the fidelity of the available U.S. data, the flights are divided into three segments: gate, taxi and enroute (which includes both airborne and holding). For each of these segments, three cost scenarios and two range delays are provided, hence, for each of these 18 different cases (segments $\times$ cost scenarios $\times$ delay ranges) are modeled:

$$\begin{aligned} C_{delay} = c_{fuel} &\times \text{fuel burn rate} \times \text{fuel price} \\ &+ c_{crew} \times \text{crew cost} \\ &+ c_{maintenance} \times \text{maintenance cost} \\ &+ c_{other} \times \text{other cost} \\ &+ c_{pax} \times \text{PAX delay cost} \times (\#\text{ seats}) \times \text{load factor} \end{aligned} \tag{3.1}$$

Table 3.6 shows the elements of the EC cost of delay model. The elements highlighted in green were provided for all 18 scenarios and 12 aircraft in the report. The elements highlighted in yellow were assumptions made for this analysis or derived inputs from 2003 BTS data. Lastly, the elements highlighted in red were derived from fitting this model to

Table 3.6: Elements of EuroControl Cost of Delay Model

	Data	Source	Gate Delay Cost	Taxi Delay Cost	Airborne Delay Cost
Fuel	Fuel Burn Coefficient	Assumed	0	1	1
	Taxi Burn Rate	EC Report	N/A	given	N/A
	Burn Rate	EC Report	N/A	N/A	given
	Fuel Cost per Gallon	EC Report	N/A	given	given
Crew	Crew Coefficient	Not provided	Identified in this analysis		
	% of BHDOC	[BTS, 2003]	28%	28%	28%
	BHDOC	EC Report	given	given	given
Maint.	Maint Coefficient	Not provided	Identified in this analysis		
	% of BHDOC	EC Report	15%	15%	15%
	BHDOC	EC Report	given	given	given
PAX	PAX Coefficient	Assumed	1	1	1
	Load Factor	EC Report	given	given	given
	Seats per aircraft	EC Report	given	given	given
	PAX Cost per minute	EC Report	given	given	given
Other	Other Cost per minute	Assumed	$1	$1	$1

Table 3.7: Elements of EuroControl Cost of Delay Model

		Fuel %	crew %	maint %	dep %
BTS BHDOC for 12 aircraft	2003 data	41%	25%	22%	11%
	normalized for 15% maint.	45%	28%	15%	12%

the 216 data points (18 scenarios × 12 aircraft).

While the percentage of the Block Hour Direct Operating Costs (BHDOC) in euros was provided for maintenance in the EC report, the percentage of the BHDOC for crew was not provided. Therefore, the same percentage of crew costs for both European and U.S. BHDOCs is assumed. Table 3.7 shows the 2003 BTS percentages for BHDOC for fuel, crew, maintenance, and depreciation. These percentages were normalized for the given 15% of BHDOC for maintenance, given in the EC report. Thus, 28% of BHDOC for crew costs is assumed for this analysis.

Fitting the EC Model to find unknown coefficients

Microsoft Solver was used to find the crew, maintenance and the other cost factors' coefficients for each segment, each cost scenario and each delay range (3×3×2). The sum of the squared difference between the EC report delay cost factors for the 12 aircraft versus the fitted model's cost factors were minimized to find the best fit for each segment. The coefficients were constrained to be positive, larger than or equal to coefficients for each lower cost scenario and larger or equal to coefficients for each lower delay range. The results of these fits are shown in Table 3.8, the newly derived non-dimensional coefficients are shown in blue.

Table 3.9 shows the goodness of fit of the newly derived model compared to the EC Delay cost factors by aircraft type, segment, cost scenario and delay range using the 12 aircraft types used in the EC study. It is noted that these aircrafts represent 28% of the U.S. domestic operations from 2005 to 2009. Values highlighted in green were overestimated

Table 3.8: Fitted non-dimensional coefficients for crew, maintenance and other costs

Gate: Cost Factor Coefficients	Based on 15 min. delay cost scenario			Based on 65 min. delay cost scenario		
	low	base	high	low	base	high
Fuel	-	-	-	-	-	-
Crew	0.03	0.03	0.33	0.03	0.46	1.07
Maint	0.00	0.00	0.00	0.00	0.00	0.00
Pax	1.00	1.00	1.00	1.00	1.00	1.00
Other	0.21	0.21	0.21	0.21	0.21	0.21

Taxi: Cost Factor Coefficients	Based on 15 min. delay cost scenario			Based on 65 min. delay cost scenario		
	low	base	high	low	base	high
Fuel	1.00	1.00	1.00	1.00	1.00	1.00
Crew	-	0.00	0.26	-	0.43	1.01
Maint	0.00	0.00	0.00	-	0.00	0.00
Pax	1.00	1.00	1.00	1.00	1.00	1.00
Other	0.12	0.12	0.12	0.12	0.12	0.12

Airborne: Cost Factor Coefficients	Based on 15 min. delay cost scenario			Based on 65 min. delay cost scenario		
	low	base	high	low	base	high
Fuel	1.00	1.00	1.00	1.00	1.00	1.00
Crew	-	0.01	0.29	-	0.46	1.09
Maint	0.00	0.00	0.00	0.00	0.00	-
Pax	1.00	1.00	1.00	1.00	1.00	1.00
Other	0.10	0.10	0.10	0.10	0.10	0.10

by the new model by more than 10% and values highlighted in red were underestimated by more than 10%.

Examination of this data shows that the model fits the data especially well for all long delays (over 65 minutes). It also fits well for taxiing out and at-gate delays. For both the baseline and high cost scenarios, the taxiing out delays fit all but the very largest and smallest aircraft which compose only 1% of the flights in the U.S. These estimates do show a significant discrepancy for the low scenario for large aircraft while airborne. However, for all other segments and scenarios, the derived factors are appropriate to use. For the congestion pricing model, all delays are assumed to be gate delays and therefore the low cost scenario can be used for the model.

Chi square goodness of fit tests were done to examine how statistically well these derived coefficients fit the EC report factors, as shown in Table 3.10. All cost scenarios were examined for airborne, taxi and gate delay cost factors. The chi square results showed 99.8% or better confidence that the model fit the original EC report factors for all cost scenario and segments.

Modify Model for U.S. Data

To apply this model to the U.S. data, the following changes were made that are more consistent to the U.S. airlines:

- Cost factors derived from the BTS P52 database (fuel price, crew and maintenance cost) [BTS, 2007] are used.
- The fuel burn rate while en route from the BTS P52 database is used. Taxi burn rates used are derived from the ICAO engine emissions databank. (See [ICAO, 2009]).
- The PAX delay cost coefficient is set to 0, since in the U.S., it is not incurred by the airlines.
- For other delay ranges, the following formulas are used:
  - For any delay less than or equal to 15 minutes, the 15 minutes cost factor is used.

Table 3.9: Percentage Difference of model vs. EC Report factors

Aircraft and Number of seats		Based on 15 min. delay cost scenario low	base	high	Based on 65 min. delay cost scenario low	base	high	Domestic operations (2005-2009)
ATR42	46	-2%	-7%	-12%	0%	-6%	-9%	0%
ATR72	64	4%	1%	-1%	0%	-1%	-2%	0%
B737-500	100	-14%	-14%	-10%	-2%	-2%	-3%	3%
B737-300	125	-12%	-13%	-6%	-1%	1%	1%	2%
A319	126	12%	9%	8%	1%	4%	4%	1%
B737-400	143	-10%	-11%	-4%	-1%	1%	1%	7%
A320	155	5%	3%	4%	1%	1%	3%	5%
A321	166	0%	-2%	4%	0%	3%	5%	1%
B737-800	174	13%	8%	5%	1%	-1%	1%	5%
B757-200	218	10%	8%	8%	1%	3%	4%	4%
B767-300E	240	12%	10%	7%	1%	0%	3%	0%
B747-400	406	21%	21%	4%	2%	-1%	-7%	0%

Tactical Airborne Delay Costs enroute and holding (% Diff from EU Report)

Aircraft and Number of seats		Based on 15 min. delay cost scenario low	base	high	Based on 65 min. delay cost scenario low	base	high	Domestic operations (2005-2009)
ATR42	46	-10%	-11%	-16%	0%	-7%	-12%	0%
ATR72	64	6%	-3%	-4%	0%	-1%	-3%	0%
B737-500	100	9%	6%	-1%	1%	0%	-2%	3%
B737-300	125	9%	6%	5%	2%	3%	3%	2%
A319	126	1%	-3%	4%	0%	3%	4%	1%
B737-400	143	9%	4%	4%	0%	2%	2%	7%
A320	155	1%	-1%	3%	1%	0%	4%	5%
A321	166	2%	-2%	7%	0%	4%	5%	1%
B737-800	174	13%	8%	1%	1%	-1%	0%	5%
B757-200	218	6%	3%	5%	0%	3%	4%	4%
B767-300E	240	11%	5%	2%	1%	-1%	2%	0%
B747-400	406	13%	13%	-7%	1%	-2%	-7%	0%

Tactical ground delay costs: taxi only (% Diff from EU Report)

Aircraft and Number of seats		Based on 15 min. delay cost scenario low	base	high	Based on 65 min. delay cost scenario low	base	high	Domestic operations (2005-2009)
ATR42	46	1%	-7%	-19%	0%	-7%	-13%	0%
ATR72	64	-10%	7%	-7%	0%	-1%	-4%	0%
B737-500	100	-7%	5%	-4%	0%	-1%	-3%	3%
B737-300	125	-7%	0%	6%	1%	2%	3%	2%
A319	126	-4%	4%	8%	0%	4%	4%	1%
B737-400	143	2%	5%	5%	-1%	2%	2%	7%
A320	155	-3%	-3%	8%	0%	0%	5%	5%
A321	166	-8%	0%	11%	0%	4%	6%	1%
B737-800	174	1%	-4%	0%	0%	-2%	0%	5%
B757-200	218	11%	4%	5%	0%	3%	4%	4%
B767-300E	240	28%	5%	0%	0%	-2%	2%	0%
B747-400	406	-24%	-23%	-25%	-1%	-4%	-9%	0%

Tactical ground delay costs: at-gate only (% Diff from EU Report)

Table 3.10: Chi square Fit of Cost of Delay model vs. EC Report factors

Chi Square Goodness of Fit		Cost Scenario All	Low	Base	High
Degrees of Freedom		71	23	23	23
Statistic for 99.8% confidence that model fits data		**41.51**	**8.21**	**8.21**	**8.21**
Gate	Statistic	0.84	0.19	0.77	8.16
Taxi	Statistic	5.18	0.41	0.84	3.94
Airborne	Statistic	10.81	2.19	3.52	5.10

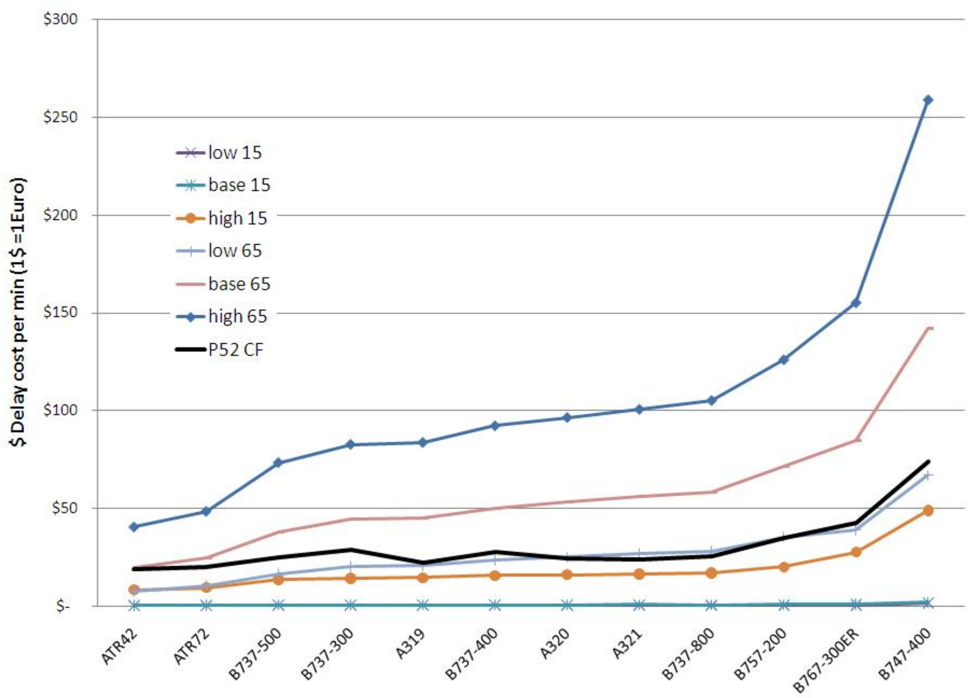

Figure 3.2: Tactical Ground Delay Costs: Gate only vs. Operational Costs

– For any delay above 65 minutes, the cost factor for 65 minutes and above delay is used.

– For delays between 15 and 65 minutes, a cost factor is interpolated using the two data points above.

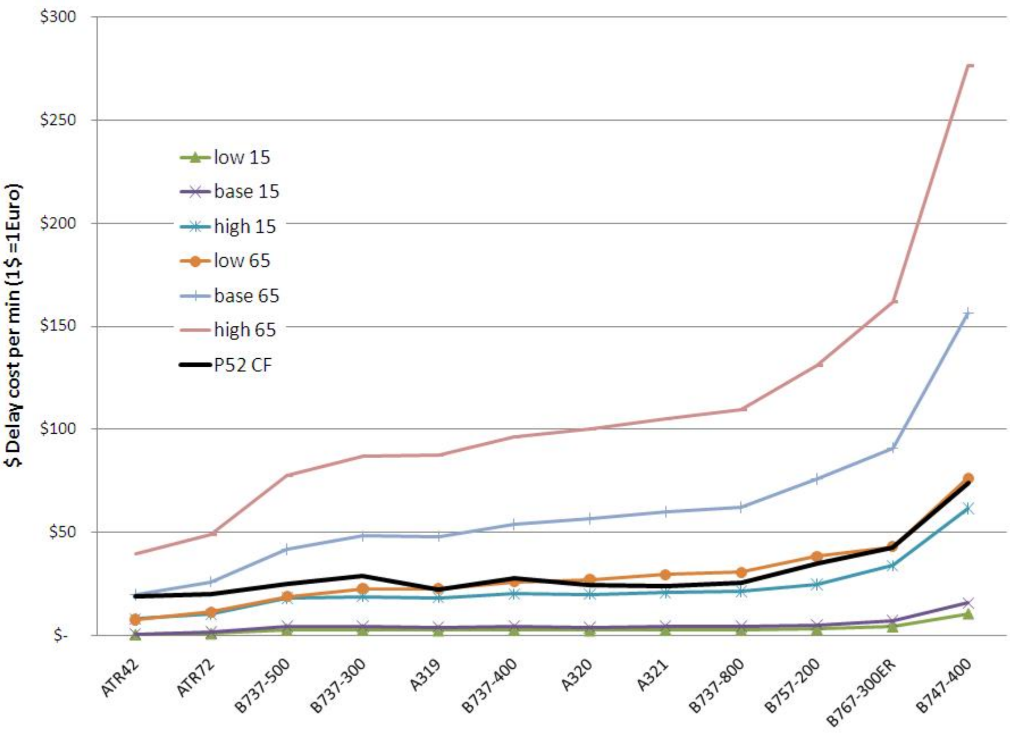

Figure 3.3: Tactical Ground Delay Costs: Taxi only vs. Operational Costs

Before beginning the work to determine the cost coefficients for the new model, an examination of overall cost factors in the U.S. compared to those incurred in Europe was observed. The delay cost factors were computed, based on the EC factors, for the different types of segments (gate, taxi and airborne-and-holding) and for the given 12 aircrafts. These delay cost factors were compared with the average operational cost per minute using P52 [BTS, 2007] data from the BTS database for U.S. airlines.

Figures 3.2-3.4 show that in each of these flight segments the shape of the curves are similar, affirming that these cost factors are consistent with the operational costs in the U.S. These results support the assumption of that it is appropriate to use BTS crew cost percentages of Block Hour Operating Costs (BHDOC) when calculating total costs.

When using the same model but using fuel burn rates as reported in U.S. databases, the analysis shows that fuel burn rates reported in the U.S. are lower than those reported in the

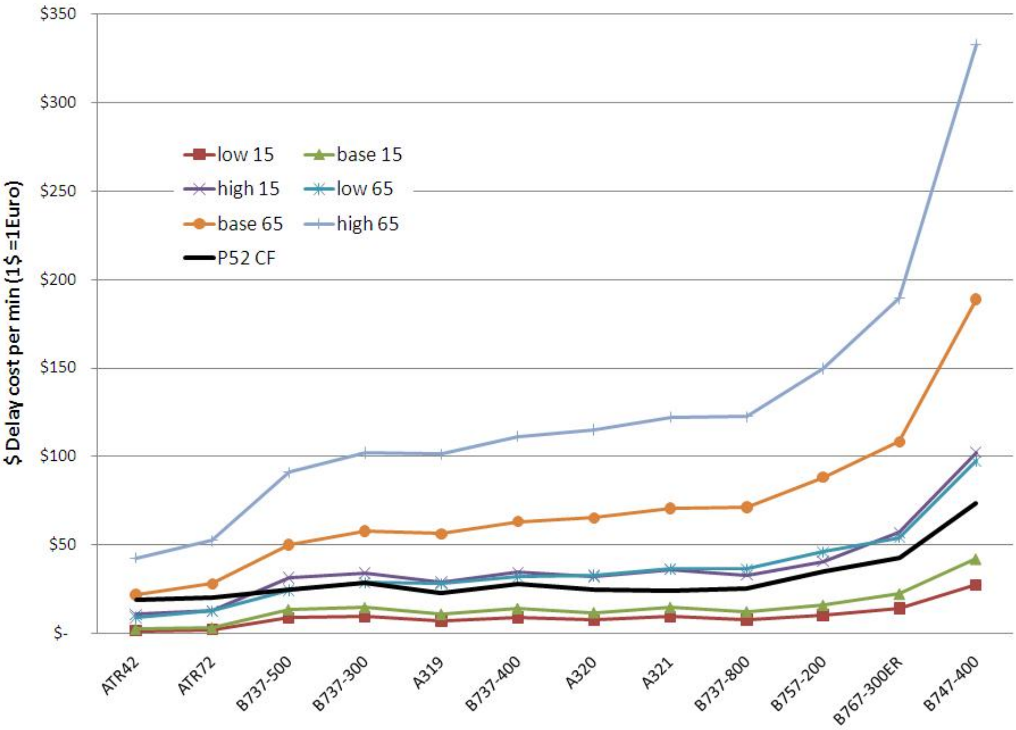

Figure 3.4: Tactical Airborne Delay Costs: Enroute and Holding vs. Operational Costs

EC report. This means that even using the model postulated in the EC report, U.S. airlines show slightly lower costs for equivalent delays than that of the EC report. Coefficients for the base cost scenario from Table 3.8 is used for developing U.S. delay cost factors.

The next section (Section 3.4) shows results of a case study where the costs of delays derived are applied for computing the operational delay costs for aircraft not described in the EuroControl study. Such aircraft represents 72% of aircraft operations in the U.S. These factors can be derived for any time period for which historical BTS cost data is available.

For the network effect of these delays, the delay multipliers based on American Airlines case study (see [Beatty et al., 1998] or Table 2-20 in [Cook et al., 2004]) can be used.

Table 3.11: July 2007 Departure delays by segment of flight for selected airports

	Gate Delay	Taxi out Delay	Airborne Delay	Taxi in Delay	Total Delay
July 2007 Delay costs	$ 8,492,145	$ 10,754,556	$ 41,441,667	$ 3,110,810	$ 63,799,178
Delay cost per flight	$ 30.26	$ 38.33	$ 147.69	$ 11.09	$ 227.37
Delay minutes	4,022,321	2,276,214	1,052,131	728,188	$ 8,078,854
Delay cost per minute	$ 2.11	$ 4.72	$ 39.39	$ 4.27	$ 7.90

Table 3.12: July 2007 Departure delays for airlines exceeding $1M in delay costs

Airline	Gate Delay	Taxi out Delay	Airborne Delay	Taxi in Delay	Total Delay	# Flights	$ per flight
American	$ 1,272,838	$ 1,828,159	$ 5,859,727	$ 873,476	$ 9,834,200	38,399	$ 256.11
Southwest	$ 581,768	$ 581,715	$ 6,201,624	$ 229,303	$ 7,594,410	28,722	$ 264.41
Delta	$ 727,080	$ 1,215,887	$ 3,079,572	$ 290,221	$ 5,312,760	13,233	$ 401.48
US Airlines	$ 416,258	$ 892,844	$ 3,764,669	$ 196,096	$ 5,269,868	15,129	$ 348.33
United	$ 550,133	$ 1,030,883	$ 2,945,020	$ 254,389	$ 4,780,425	19,015	$ 251.40
Continental	$ 885,487	$ 1,111,575	$ 2,341,061	$ 218,211	$ 4,556,335	14,387	$ 316.70
Jet Blue	$ 626,087	$ 1,001,468	$ 2,048,026	$ 183,966	$ 3,859,548	14,752	$ 261.63
Northwest	$ 184,893	$ 364,349	$ 1,536,632	$ 99,053	$ 2,184,927	7,048	$ 310.01
American Eagle	$ 423,625	$ 376,629	$ 851,741	$ 142,279	$ 1,794,274	24,508	$ 73.21
Air Trans	$ 393,055	$ 287,737	$ 927,879	$ 103,138	$ 1,711,810	7,670	$ 223.18
Air Winsconsin	$ 204,604	$ 133,906	$ 1,204,321	$ 28,433	$ 1,571,264	12,259	$ 128.17
Com Air	$ 223,066	$ 337,824	$ 939,059	$ 69,319	$ 1,569,268	8,556	$ 183.41
ExpressJet	$ 321,204	$ 348,175	$ 586,765	$ 51,283	$ 1,307,427	11,211	$ 116.62
Republic Airlines	$ 131,820	$ 75,043	$ 886,370	$ 16,935	$ 1,110,167	5,147	$ 215.69

3.4 Results of Case Study

This study examines delay costs for U.S. airlines departures from 12 major airports (EWR, JFK, LGA, DCA, BWI, IAD, SFO, OAK, SJC, BOS, PHL, DFW) for one of the busiest months in U.S. aviation history (July, 2007). Delays by segment of flight, by aircraft type, by airline and by hour of day are examined in this case study. ASPM [ASPM, 2007] Flight Data is used to obtain the duration of these delays. Tables 3.11-3.16 show the results of this case study.

Table 3.11 indicates that even though the majority of delays occur on the ground (87%), the airlines incur the greatest delay costs while their flights are airborne (65%). Since a flight delayed in the air is twenty times the cost of an aircraft delayed at the gate, there is an economic advantage for airlines to hold flights at the origin airport rather than delayed in the air.

Table 3.13: July 2007 Departure delays for aircrafts exceeding $1M in delay costs

Aircraft	Gate Delay	Taxi out Delay	Airborne Delay	Taxi in Delay	Total Delay	# Flights	$ per flight
B752	$ 794,859	$ 1,435,696	$ 3,691,511	$ 444,658	$ 6,366,725	18,662	$ 341.16
B737	$ 602,399	$ 582,814	$ 4,649,791	$ 204,566	$ 6,039,570	22,570	$ 267.59
MD82	$ 619,102	$ 895,085	$ 3,230,645	$ 455,587	$ 5,200,419	20,840	$ 249.54
A320	$ 666,428	$ 1,315,475	$ 2,594,288	$ 294,020	$ 4,870,211	20,241	$ 240.61
B733	$ 574,161	$ 618,854	$ 3,464,556	$ 181,687	$ 4,839,259	19,561	$ 247.39
A319	$ 308,906	$ 603,246	$ 2,826,820	$ 145,379	$ 3,884,352	14,650	$ 265.14
CRJ2	$ 333,964	$ 333,642	$ 2,528,964	$ 78,126	$ 3,274,695	22,824	$ 143.48
B738	$ 523,472	$ 683,996	$ 1,764,857	$ 190,269	$ 3,162,595	12,479	$ 253.43
E145	$ 542,696	$ 422,478	$ 1,808,727	$ 109,635	$ 2,883,536	23,464	$ 122.89
MD88	$ 295,444	$ 503,327	$ 1,659,392	$ 98,798	$ 2,556,961	6,142	$ 416.31
E170	$ 189,513	$ 119,199	$ 1,321,926	$ 29,081	$ 1,659,718	7,637	$ 217.33
B735	$ 355,881	$ 430,128	$ 741,454	$ 79,724	$ 1,607,188	6,102	$ 263.39
MD83	$ 187,480	$ 233,817	$ 1,015,068	$ 119,692	$ 1,556,057	5,900	$ 263.74
E190	$ 211,808	$ 228,699	$ 1,021,585	$ 31,092	$ 1,493,185	4,694	$ 318.11
E135	$ 256,153	$ 276,426	$ 711,110	$ 63,297	$ 1,306,986	13,355	$ 97.86
B712	$ 262,947	$ 197,903	$ 700,814	$ 71,115	$ 1,232,779	6,894	$ 178.82
CRJ1	$ 177,892	$ 252,791	$ 732,486	$ 54,852	$ 1,218,021	6,498	$ 187.45
B734	$ 120,198	$ 213,059	$ 819,107	$ 54,217	$ 1,206,580	4,268	$ 282.70

Table 3.12 shows the airlines that exceeded one million dollars in delay costs for July 2007 from the selected airports in this study. American Eagle realized the lowest delay costs per flight, largely due to their more fuel efficient fleet of CRJ-700s, Embraer ERJ-135/145s, and SAAB 340 turboprops. Delta Airlines, on the other hand, showed the greatest delay costs per flight, mostly due to their less fuel efficient fleet.

Table 3.13 shows the aircraft that exceeded one million dollars in delay costs for July 2007 from the selected airports for this study. As expected, the fuel efficient Embraer ERJ-135/145s showed the lowest delay costs per flight. However, the older less fuel efficient MD88s and B757-200s show the greatest delay costs per flight.

Analysis of the airline delay costs by time of day (Table 3.14) shows that average cost of delay per flight ramp up from lows in the early morning (5-6 am) to a peak between 5-6 pm and then begin to subside with relatively small costs by 10 pm. The gate delay costs are highest in late afternoon (5-7pm), whereas taxi out delays are highest between (4-6 pm) and airborne delays are highest in the early mornings (6-9 am). Overnight flights can also have significant delay costs, but these reflect the few large aircraft flights that, when

Table 3.14: July 2007 Departure delay costs by time of day

Time of Day	Gate Delay	Taxi out Delay	Airborne Delay	Taxi in Delay	Total Delay	# Flights	$ per flight
12-1am	$ 22,765	$ 14,804	$ 120,664	$ 5,632	$ 163,865	500	$ 327.73
1-2am	$ 12,931	$ 6,853	$ 64,375	$ 3,217	$ 87,376	201	$ 434.71
2-3am	$ 5,270	$ 5,212	$ 52,553	$ 3,717	$ 66,751	118	$ 565.69
3-4am	$ 9,587	$ 13,905	$ 97,884	$ 1,881	$ 123,258	127	$ 970.53
4-5am	$ 11,819	$ 4,340	$ 52,281	$ 1,176	$ 69,616	109	$ 638.68
5-6am	$ 43,822	$ 26,166	$ 304,460	$ 16,053	$ 390,500	2,254	$ 173.25
6-7am	$ 120,525	$ 361,186	$ 2,990,143	$ 194,745	$ 3,666,599	20,175	$ 181.74
7-8am	$ 217,893	$ 493,522	$ 3,373,441	$ 231,127	$ 4,315,984	19,756	$ 218.46
8-9am	$ 289,591	$ 784,156	$ 3,124,226	$ 215,999	$ 4,413,972	20,182	$ 218.71
9-10am	$ 259,797	$ 650,089	$ 2,511,443	$ 180,034	$ 3,601,363	17,617	$ 204.43
10-11am	$ 264,222	$ 491,762	$ 2,638,476	$ 165,847	$ 3,560,307	17,238	$ 206.54
11-12pm	$ 335,033	$ 493,040	$ 2,771,531	$ 208,298	$ 3,807,903	17,859	$ 213.22
12-1pm	$ 431,748	$ 506,069	$ 2,937,395	$ 211,522	$ 4,086,734	18,161	$ 225.03
1-2pm	$ 565,399	$ 625,994	$ 2,876,425	$ 223,525	$ 4,291,344	17,660	$ 243.00
2-3pm	$ 644,341	$ 721,229	$ 2,540,171	$ 213,641	$ 4,119,382	16,385	$ 251.41
3-4pm	$ 778,806	$ 783,087	$ 2,689,679	$ 230,410	$ 4,481,982	16,913	$ 265.00
4-5pm	$ 802,846	$ 1,047,412	$ 2,617,860	$ 212,301	$ 4,680,419	18,232	$ 256.71
5-6pm	$ 975,523	$ 1,093,879	$ 2,637,803	$ 238,021	$ 4,945,226	18,302	$ 270.20
6-7pm	$ 813,213	$ 891,570	$ 2,105,195	$ 186,777	$ 3,996,754	15,983	$ 250.06
7-8pm	$ 754,016	$ 749,206	$ 1,773,709	$ 145,386	$ 3,422,317	15,585	$ 219.59
8-9pm	$ 584,859	$ 561,539	$ 1,317,165	$ 103,529	$ 2,567,092	12,381	$ 207.34
9-10pm	$ 343,817	$ 253,808	$ 982,618	$ 59,593	$ 1,639,837	8,867	$ 184.94
10-11pm	$ 111,404	$ 117,220	$ 504,545	$ 31,724	$ 764,893	3,793	$ 201.66
11-12am	$ 92,917	$ 58,507	$ 357,626	$ 26,655	$ 535,705	2,203	$ 243.17
Grand Total	$ 8,492,145	$ 10,754,556	$ 41,441,667	$ 3,110,810	$ 63,799,178	280,601	$ 227.37

delayed, exhibit these as costly airborne delays.

Table 3.15 shows that parity rarely exists between opposite markets. An extreme case of opposite markets is highlighted in red (JFK-ANC and ANC-JFK); these markets' average varies by $754. Another opposite markets pair is highlighted in green (SFO-LAX and LAX-SFO), because these markets' average delay costs per flight are within $28 of each other.

Table 3.16 evaluates the differences in delay costs among the 12 selected airports. It is observed that average delay costs for departures out of JFK are twice the average delay costs of departures from DFW.

From the above analysis, the following conclusions are made:

- The cost factors from the EC report and costs as reported by U.S. carriers in BTS P52 database follow similar trends. Thus, the general approach taken by EuroControl can be applied, with minor modifications, to compute the cost of delays of U.S. flights.

Table 3.15: July 2007 Departure delay costs for top 12 market pair delay costs

Market	Gate Delay	Taxi out Delay	Airborne Delay	Taxi in Delay	Total Delay	# Flights	$ per flight	difference
DCA-LGA	$ 14,499	$ 71,972	$ 342,688	$ 4,114	$ 433,273	919	$ 471.46	
LGA-DCA	$ 16,547	$ 62,979	$ 169,572	$ 6,584	$ 255,682	920	$ 277.92	$ 193.55
JFK-LAX	$ 43,668	$ 167,542	$ 156,062	$ 26,318	$ 393,590	709	$ 555.13	
LAX-JFK	$ 29,592	$ 34,487	$ 273,140	$ 28,438	$ 365,657	715	$ 511.41	$ 43.73
BOS-LGA	$ 22,719	$ 46,799	$ 313,541	$ 5,794	$ 388,854	961	$ 404.63	
LGA-BOS	$ 17,641	$ 68,828	$ 241,567	$ 7,473	$ 335,509	950	$ 353.17	$ 51.47
ATL-LGA	$ 50,207	$ 70,232	$ 205,080	$ 27,704	$ 353,222	835	$ 423.02	
LGA-ATL	$ 51,346	$ 106,689	$ 151,247	$ 17,844	$ 327,126	845	$ 387.13	$ 35.89
LGA-ORD	$ 30,354	$ 111,835	$ 187,679	$ 13,913	$ 343,781	892	$ 385.41	
ORD-LGA	$ 24,352	$ 59,329	$ 148,979	$ 13,082	$ 245,741	890	$ 276.11	$ 109.29
JFK-ANC	$ 23,588	$ 45,255	$ 265,200	$ 970	$ 335,013	223	$ 1,502.30	
ANC-JFK	$ 6,733	$ 6,783	$ 147,021	$ 14,380	$ 174,917	234	$ 747.51	$ 754.79
JFK-SFO	$ 27,699	$ 125,408	$ 156,253	$ 10,428	$ 319,788	562	$ 569.02	
SFO-JFK	$ 21,095	$ 29,069	$ 201,833	$ 20,438	$ 272,435	589	$ 462.54	$ 106.48
ATL-EWR	$ 55,128	$ 51,721	$ 145,523	$ 6,169	$ 258,541	676	$ 382.46	
EWR-ATL	$ 40,611	$ 56,130	$ 84,972	$ 11,654	$ 193,366	682	$ 283.53	$ 98.93
SFO-LAX	$ 27,771	$ 29,325	$ 175,898	$ 25,051	$ 258,045	1049	$ 245.99	
LAX-SFO	$ 47,983	$ 41,140	$ 133,639	$ 10,419	$ 233,182	1067	$ 218.54	$ 27.45
ATL-PHL	$ 35,457	$ 35,830	$ 174,688	$ 6,140	$ 252,115	635	$ 397.03	
PHL-ATL	$ 29,554	$ 55,115	$ 75,821	$ 11,129	$ 171,619	632	$ 271.55	$ 125.48
LAX-OAK	$ 11,536	$ 11,823	$ 216,957	$ 7,632	$ 247,948	883	$ 280.80	
OAK-LAX	$ 11,007	$ 14,764	$ 181,690	$ 8,932	$ 216,394	885	$ 244.51	$ 36.29
MCO-PHL	$ 23,899	$ 24,717	$ 189,311	$ 9,549	$ 247,476	598	$ 413.84	
PHL-MCO	$ 28,373	$ 44,707	$ 91,317	$ 6,824	$ 171,220	597	$ 286.80	$ 127.04

- The appropriate multipliers for crew and maintenance costs are determined that, when combined with the other factors, produce multipliers close to those reported in the EC report.

- Airborne delays, when incurred, dominate ground delay costs, so airlines are economically encouraged to maximize ground delay costs.

- Newer, more fuel efficient aircraft provide airlines with the least delay costs.

- The cost of delay is not proportional to the flights flown. One reason for this non-intuitive result is that when a flight is cancelled, it is recorded as having zero delay.

The calculations of the cost of delayed flights (ignoring all cancelled flights) total $63.8M for July 2007. Many economic modeling and analysis efforts require a good understanding of the costs that an airline will incur when it experiences delays at the gate, while taxiing or while enroute. This model provides a relatively straightforward mechanism for calculating

Table 3.16: July 2007 Departure and delays and delay costs for 12 selected airports

Airport	Gate Delay	Taxi out Delay	Airborne Delay	Taxi in Delay	Total Delay	# Flights	$ per flight	Total Delay	$ per min	delay per flight
DFW	$ 959,984	$ 881,398	$ 2,674,620	$ 213,078	$ 4,729,080	26,013	$ 181.80	715,435	$ 6.61	27.50
JFK	$ 701,569	$ 1,819,817	$ 1,929,810	$ 132,221	$ 4,583,418	12,594	$ 363.94	675,469	$ 6.79	53.63
PHL	$ 505,110	$ 1,006,537	$ 2,147,482	$ 127,386	$ 3,786,516	17,089	$ 221.58	585,909	$ 6.46	34.29
LGA	$ 409,444	$ 1,035,883	$ 1,895,051	$ 119,169	$ 3,459,548	14,760	$ 234.39	533,884	$ 6.48	36.17
EWR	$ 594,332	$ 1,093,532	$ 1,296,275	$ 115,202	$ 3,099,341	13,075	$ 237.04	535,720	$ 5.79	40.97
BOS	$ 416,529	$ 475,273	$ 2,035,500	$ 147,260	$ 3,074,561	11,680	$ 263.23	367,926	$ 8.36	31.50
SFO	$ 262,320	$ 328,623	$ 1,933,248	$ 151,861	$ 2,676,051	12,782	$ 209.36	280,038	$ 9.56	21.91
DCA	$ 214,479	$ 322,695	$ 1,838,970	$ 90,158	$ 2,466,301	11,087	$ 222.45	266,938	$ 9.24	24.08
IAD	$ 244,891	$ 356,161	$ 1,575,527	$ 87,773	$ 2,264,352	11,246	$ 201.35	292,379	$ 7.74	26.00
BWI	$ 264,315	$ 264,049	$ 1,585,187	$ 99,819	$ 2,213,370	10,248	$ 215.98	242,499	$ 9.13	23.66
OAK	$ 96,497	$ 95,769	$ 1,227,613	$ 64,249	$ 1,484,127	6,875	$ 215.87	125,457	$ 11.83	18.25
SJC	$ 66,585	$ 44,986	$ 1,049,198	$ 55,618	$ 1,216,387	5,843	$ 208.18	89,718	$ 13.56	15.35

such costs and for predicting how such costs are likely to increase when there is a change in fuel costs, aircraft type, or when some other cost might be added to the overall cost structure. It is informative explaining why airlines are currently down-gauging the aircraft size: the newer regional jets are more fuel efficient and airborne fuel costs dominate the overall cost. Fuel costs, coupled with the fact that the airlines can offer increased frequency and observe higher load factors, encourage airlines to down-gauge. Although such policies are favored by the industry, they result in less efficient use of both the airspace and airport runways.

3.5 Sensitivity Analysis

In order to further understand the model, a sensitivity analysis was performed on the cost of the delay model and initial results were reported in [Kara et al., 2010b]. This section briefly describes the approach therein.

Fuel and crew costs influence delays since they have the highest impact on operational costs. Therefore, these costs were varied and observations were made on how the delay costs incurred by airlines are impacted by variations in these costs. In previous work [Ferguson et al., 2009], it was observed that airlines have incurred far wider swings in fuel costs between 2005-2009 than any variation seen in crew costs, maintenance costs or other operations costs. Fuel costs have been as low as $2.50 per gallon and as high as $3.50 per gallon during this time period. In contrast, crew, maintenance and depreciation costs have remained relatively flat. On further examination, significant changes in crew costs during the period 2000-2005 were also observed, therefore sensitivity analysis is also performed on these costs.

3.5.1 Methodology

For fuel price changes, the variation was per gallon fuel charges from $1.50 to $4.50 with the base price being $2.04 (the average fuel price incurred by the airlines during the Summer 2007). Since no fuel is burned while at the gate, only the taxi and airborne segments of delayed flights are examined. These changes were computed for 30 minutes of delay, since the trends are similar across all delay ranges greater than 15 minutes (due to interpolating the delay cost for ranges between 15 and 65 minutes). The BTS P52 database [BTS, 2007] is used to determine aircraft type for each flight and taxi burn rates are used from ICAO engine emissions databank [ICAO, 2009].

For crew costs, BTS P52 [BTS, 2007] is used to determine crew costs per hour by aircraft type for Summer 2007 (as a base cost) and these costs are then varied by decreasing and increasing such costs by as much as 50%. Crew cost changes for longer delays (above 65 minutes) are shown only since such costs become significant to total delay costs when delays increase significantly. For shorter delay ranges, the shape of the graph remains constant (i.e., a straight line), although the absolute costs will be proportionately less.

All the aircraft types that were flown during Summer 2007 and reported in ASPM [ASPM, 2007] were used.

3.5.2 Results

Sensitivity of Total Delay Costs to Fuel Price Changes

Figure 3.5 compares the percentage change in total cost of delay for airborne and taxi delays. High fuel prices (e.g., $4.50 per gallon) result in the total cost of delay increasing by almost 53% when airborne as compared to a 42% increase for taxiing delays.

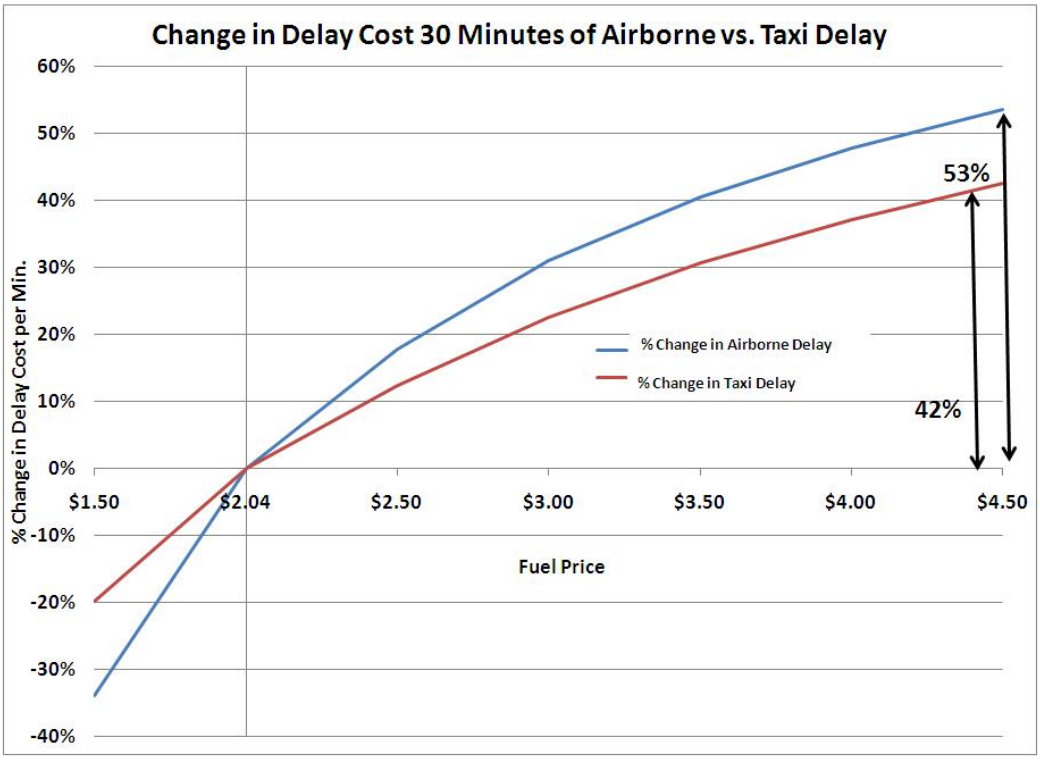

Figure 3.5: Change in Cost of Delay (30 minutes of delay) airborne vs. taxi delay

Figure 3.6 examines how the cost of delay varies with aircraft type during the airborne segment of the trip. All aircrafts have the same general relationship to fuel price when graphing the percent change in delay against the change in fuel cost curve. Of course, the absolute change in delay cost as fuel cost increases is dependent on the aircraft type. For a 30-minute airborne delay, with a fuel price of \$4.50 (more than 200% increase), the delay cost can vary from less than \$13.00 per minute (for aircraft type E120) to as large as \$300.00 per minute (for aircraft type B74S, a variant of the B747).

The greatest change in the delay cost is incurred by the aircraft type B74S (a variant of B747), with an increase of about 200% from \$101 to \$300, when comparing current prices of approximately \$2.00 per gallon to a high price of \$4.50 per gallon.

Similarly, when averaging the delay costs of aircraft from a given manufacturer and looking at the delay costs by manufacturer, Figure 3.7 shows the change in cost of delays

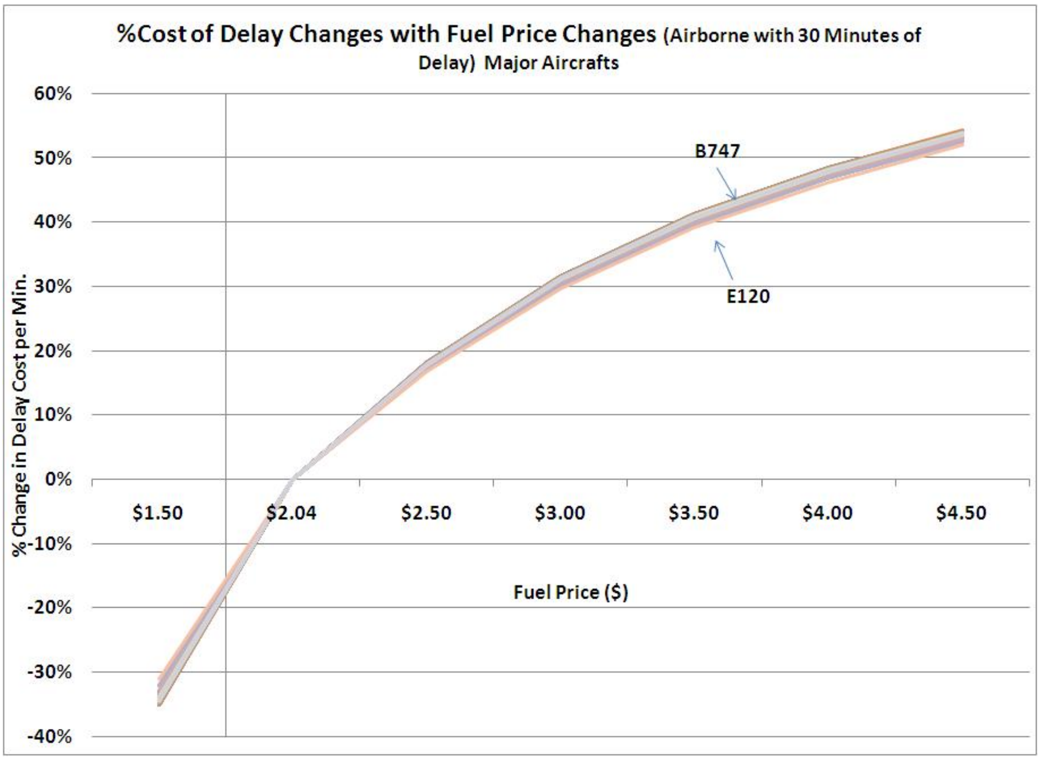

Figure 3.6: % Change in Cost of Delay with fuel price change (30 minutes of airborne delay) major aircrafts

when fuel price changes from $1.50 to $4.50. The delay cost, when the fuel price is $4.50, ranges from a low of $20 per minute for Dash's aircraft type, to a high of approximately $220 per minute for Lockheed aircraft type. Exact delay costs computed for both 30 minutes of airborne delays and taxi delays for each aircraft is provided in the Appendix D.

In the U.S., the approach to handling over-capacity is to try to have as much of the delay take place on the ground rather than in the air. This is accomplished through the Ground Delay Program (GDP) whereby planes are precluded from taking off until there is sufficient airspace and runway availability to ensure that the airborne delay is small. Therefore, for any typical delayed flight, long airborne delays are rare. According to the Schumer report [Schumer, 2008], in 2007, airborne delays accounted for about 15% of total delays.

Thus, it is the taxiing segment of the flight that incurs the majority of the fuel delay cost. For the taxi segment, taxi burn rates are used. These burn rates are approximately

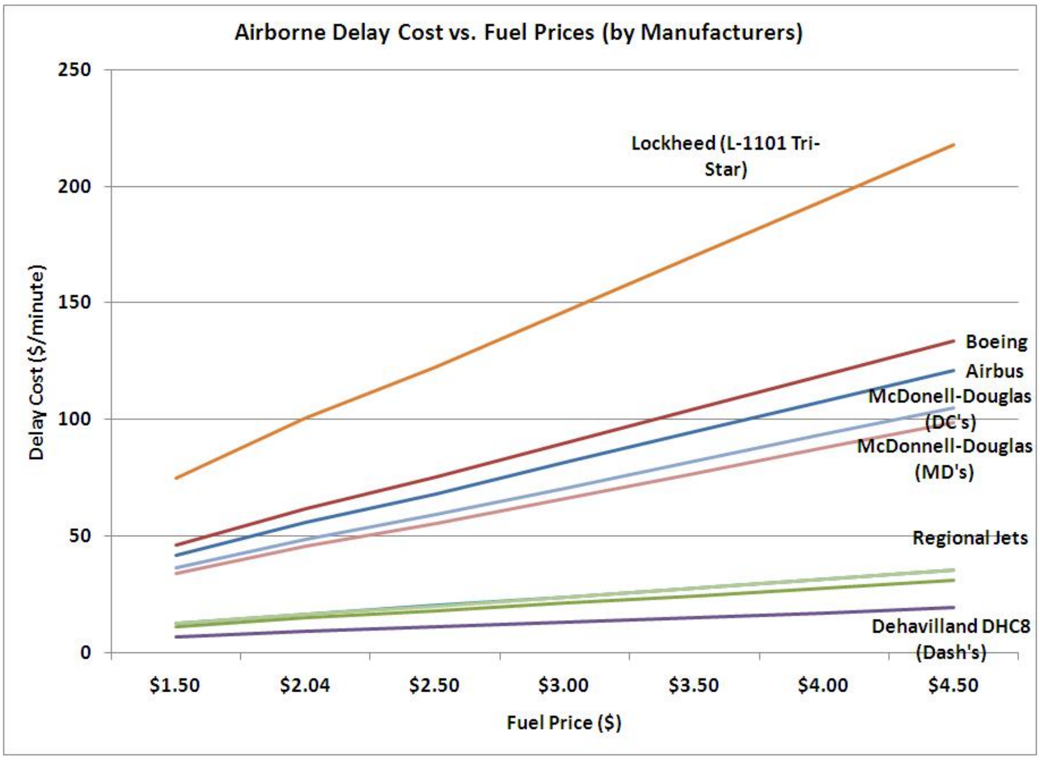

Figure 3.7: Airborne delay cost vs. fuel prices (average by manufacturers)

7%[6] of the airborne fuel burn rate. This means, that more than fuel price, different fuel burn rates impact the changes in cost of delay.

During taxiing it is observed that aircraft types have more varied effects on delay costs due to significantly different taxi burn rates. Figure 3.8 shows the percent change in cost of delay with changes in fuel prices for aircraft types grouped by manufacturer. Airbus and Boeing aircrafts are most sensitive to fuel price changes due to their higher fuel consumption. Embraer jets are the most efficient with Dash's and Regional Jets (CRJ's) following them. Table 3.17 shows the mean and range of percent change in delay cost for 30 minutes of taxi delay for different aircrafts grouped by manufacturer. Range is defined here as the difference between the maximum and the minimum value.

In the case of the Airbus, the A310 is the most efficient (34% change in cost of delay)

[6]Fuel burn rates are derived from BTS P52 [BTS, 2007] and Taxi burn rates are derived from ICAO Engine Emissions [ICAO, 2009]. The percentage is the difference observed between them.

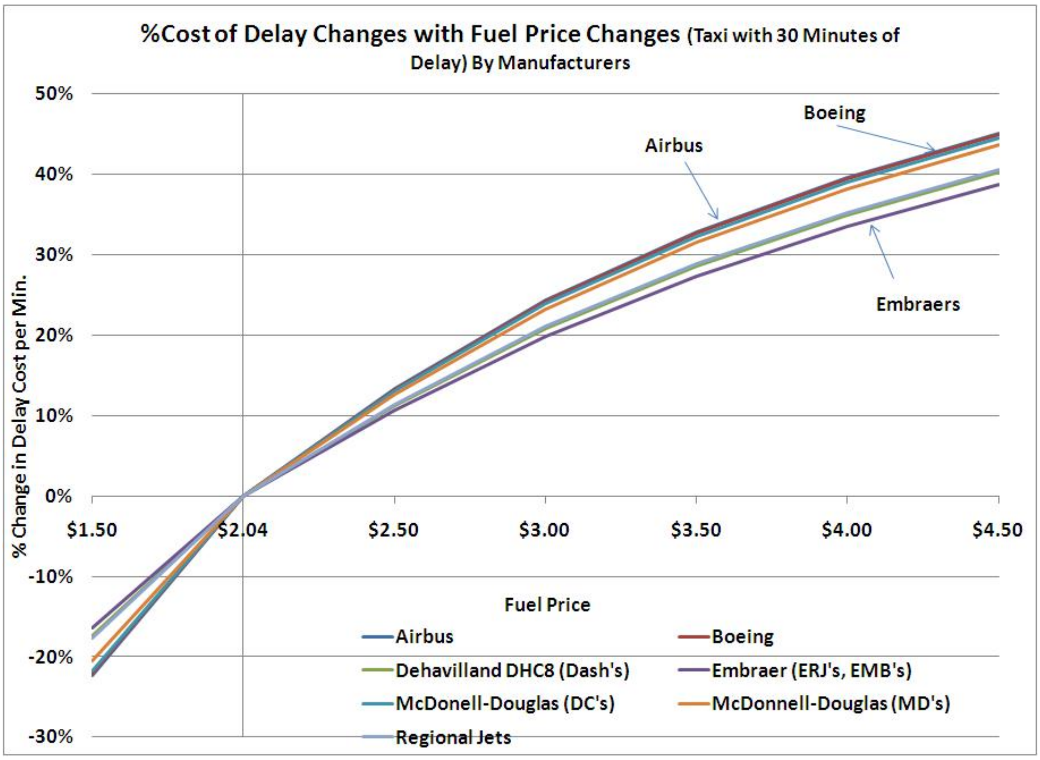

Figure 3.8: Change in Cost of Delay with fuel price change (30 minutes taxi delay) average by manufacturers

while A346 is least efficient (50% change in cost of delay at fuel price $4.50). For Boeing, the range is between 31% and 49% change in cost of delay with B727-100 being most efficient and B747 being the least. In the case of Dash's, the DC8 is the most sensitive to fuel price changes: 51% change in cost of delays with a fuel price of $4.50 while most of the aircraft lie between 38% and 47% range of percentage change. For regional jets, apart from E110, which is a business jet and out performs all of the others, most lie in the 39%-44% range.

Sensitivity of Total Delay Costs to Crew Cost Changes

For crew cost changes, the aircrafts were grouped by seat size, varying the size by 25 seat increments. Figures 3.9, 3.10 and 3.11 and Tables 3.18, 3.19 and 3.20 show the percentage change in cost of delay for gate, taxiing and airborne delays, respectively, of a 65 minute duration.

Table 3.17: Mean and range of %Change in delay cost by manufacturers for different fuel prices for 30 minute delay at taxi

	Fuel Price							
Manufacturer	$1.50		$3.00		$4.00		$4.50	
	Mean	Range	Mean	Range	Mean	Range	Mean	Range
Airbus	-22.3%	15.7%	24.3.6%	11.6%	39.6%	15.7%	45.1%	16.5%
Boeing	-20.9%	15.5%	23.4%	12.2%	38.3%	16.8%	43.7%	17.8%
Dash, MD's and DC's	-20.0%	14.9%	22.7%	10.2%	37.5%	13.3%	42.9%	13.8%
Regional Jets	-17.0%	12.6%	20.5%	11.6%	34.4%	17.0%	39.7%	18.4%

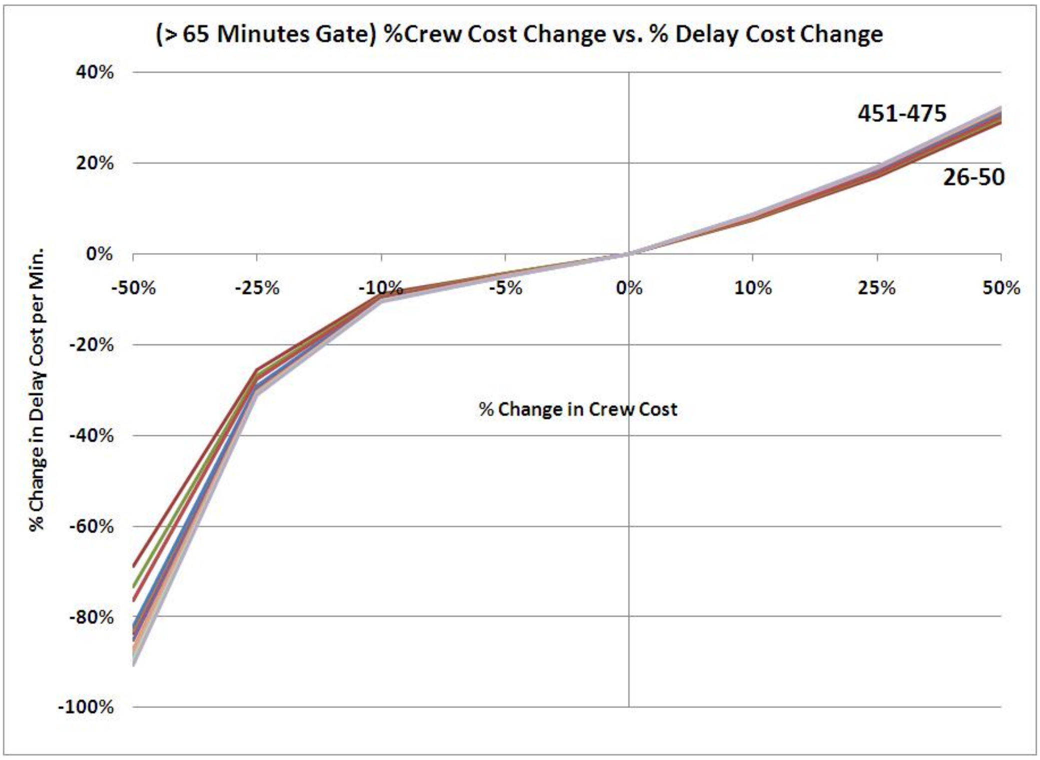

Figure 3.9: % Change in Cost of Delay vs. % Crew Cost Change (> 65 minutes gate delay)

For the ground delay segment, since there is no fuel factor involved and crew costs are the major portion of the delay costs, the changes in crew cost incur proportional changes in cost of delay. At a 50% increase in crew costs, the percentage increase in delay costs is around 30% for all seat sizes. The larger seat size group of aircrafts tend to be affected

Table 3.18: %Change in Cost of Delay vs. %Change in Crew Costs (> 65 minutes gate delay)

	%Change in Crew Cost					
Seat Size	-50%	-25%	-10%	10%	25%	50%
0-25	-76%	-28%	-9%	8%	18%	30%
26-50	-69%	-26%	-9%	8%	17%	29%
51-75	-73%	-27%	-9%	8%	17%	30%
76-100	-84%	-29%	-10%	8%	18%	31%
101-125	-83%	-29%	-10%	8%	18%	31%
126-150	-83%	-29%	-10%	8%	18%	31%
151-175	-82%	-29%	-10%	8%	18%	31%
176-200	-76%	-28%	-9%	8%	18%	30%
201-225	-88%	-31%	-10%	9%	19%	32%
226-250	-85%	-30%	-10%	8%	19%	31%
251-275	-88%	-31%	-10%	9%	19%	32%
276-300	-87%	-30%	-10%	9%	19%	32%
301-325	-90%	-31%	-10%	9%	19%	32%
376-400	-88%	-31%	-10%	9%	19%	32%
401-425	-89%	-31%	-10%	9%	19%	32%
451-475	-91%	-31%	-11%	9%	19%	32%

more than the smaller seat size group, due to their larger crews. For the taxiing segment, the percentage change in delay costs are less affected by a percentage in crew costs. This is due to the fact that during this segment fuel costs dominate the total cost. At a 50% increase in crew costs, the percentage increase in delay cost is less than 30%.

In the taxi component of delay costs, the larger seat size groups are less affected by crew costs as compared to the smaller seat size group. This is due to the fact that for larger aircrafts taxi burn rates are higher, making the total delay cost more sensitive to fuel burn and making the change in delay costs due to changes in crew costs relatively smaller.

For the airborne segment of the trip, the fuel costs become the major component of delay costs. The difference in the percentage change of delay costs for different seat size groups is more visible; larger aircraft are less affected due to their higher fuel burn rates. A 50% increase in crew costs results in percentage change in delay costs between 2% and 8%.

Table 3.19: %Change in Cost of Delay vs. %Change in Crew Costs (> 65 minutes taxi delay)

	%Change in Crew Cost					
Seat Size	-50%	-25%	-10%	10%	25%	50%
0-25	-54%	-21%	-8%	7%	15%	26%
26-50	-43%	-18%	-6%	6%	13%	23%
51-75	-45%	-18%	-7%	6%	13%	24%
76-100	-52%	-20%	-7%	6%	14%	25%
101-125	-43%	-18%	-6%	6%	13%	23%
126-150	-41%	-17%	-6%	5%	12%	22%
151-175	-41%	-17%	-6%	5%	13%	22%
176-200	-35%	-15%	-5%	5%	11%	20%
201-225	-45%	-18%	-7%	6%	13%	23%
226-250	-38%	-16%	-6%	5%	12%	21%
251-275	-38%	-16%	-6%	5%	12%	21%
276-300	-34%	-15%	-5%	5%	11%	20%
301-325	-41%	-17%	-6%	6%	13%	23%
376-400	-26%	-12%	-4%	4%	9%	17%
401-425	-28%	-12%	-5%	4%	10%	18%
451-475	-32%	-14%	-5%	5%	11%	19%

Table 3.20: %Change in Cost of Delay vs. %Change in Crew Costs (> 65 minutes airborne delay)

	%Change in Crew Cost					
Seat Size	-50%	-25%	-10%	10%	25%	50%
0-25	-7%	-4%	-1%	1%	3%	6%
26-50	-7%	-3%	-1%	1%	3%	6%
51-75	-8%	-4%	-2%	2%	4%	7%
76-100	-9%	-4%	-2%	2%	4%	8%
101-125	-6%	-3%	-1%	1%	3%	5%
126-150	-6%	-3%	-1%	1%	3%	6%
151-175	-5%	-2%	-1%	1%	2%	5%
176-200	-4%	-2%	-1%	1%	2%	4%
201-225	-5%	-3%	-1%	1%	2%	5%
226-250	-5%	-2%	-1%	1%	2%	4%
251-275	-4%	-2%	-1%	1%	2%	4%
276-300	-4%	-2%	-1%	1%	2%	3%
301-325	-4%	-2%	-1%	1%	2%	4%
376-400	-4%	-2%	-1%	1%	2%	3%
401-425	-3%	-1%	-1%	0%	1%	2%
451-475	-3%	-1%	-1%	1%	1%	3%

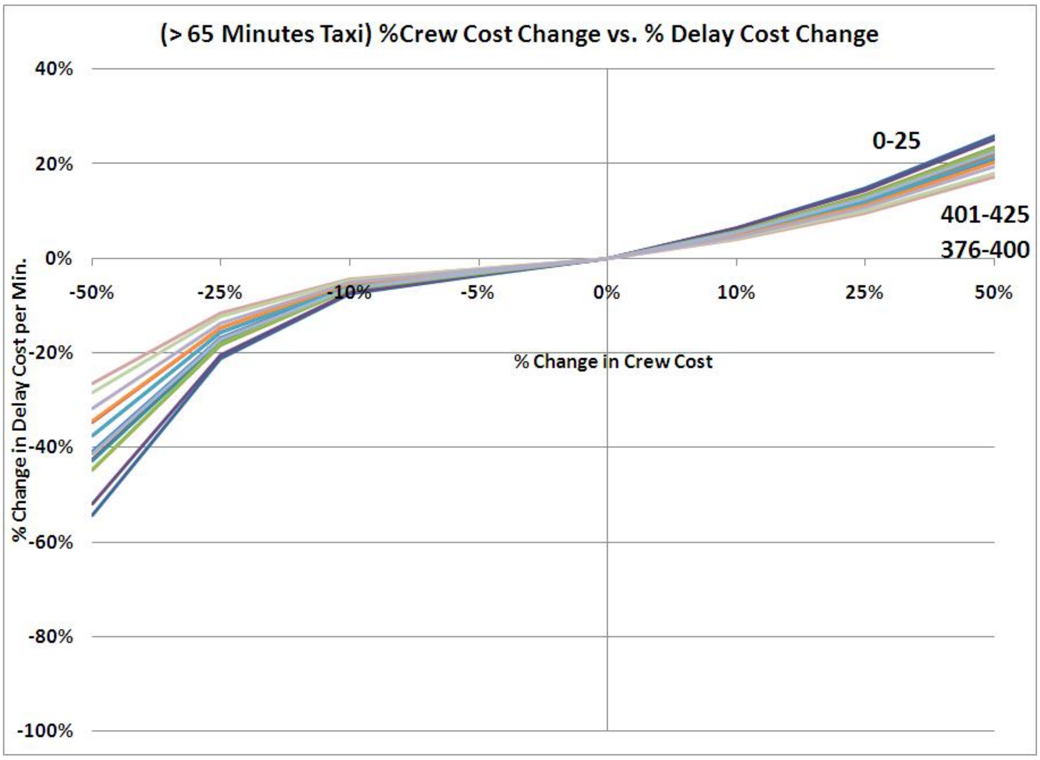

Figure 3.10: %Change in Cost of Delay vs. %Crew Cost Change (> 65 minutes taxi delay)

3.5.3 Conclusion

From the results regarding the sensitivity analysis, the following observations were made:

- Fuel costs have the greatest impact on delay costs. An increase in fuel price of about 200% (from \$2.04 to \$4.50) increases the cost of delay by up to 50% for airborne delays.
- This result is consistent with the current process for handling delays. Namely, the Ground Delay Program (GDP) is designed to have aircrafts incur the delays, when possible, at the gate or while in line for takeoff rather than while airborne.
- Since airborne delays are relatively infrequent (about 15% of the whole delay incurred by flights in Summer 2007), taxi segments of the flight are the ones that create the greatest operational cost to the airline with respect to fuel price changes.

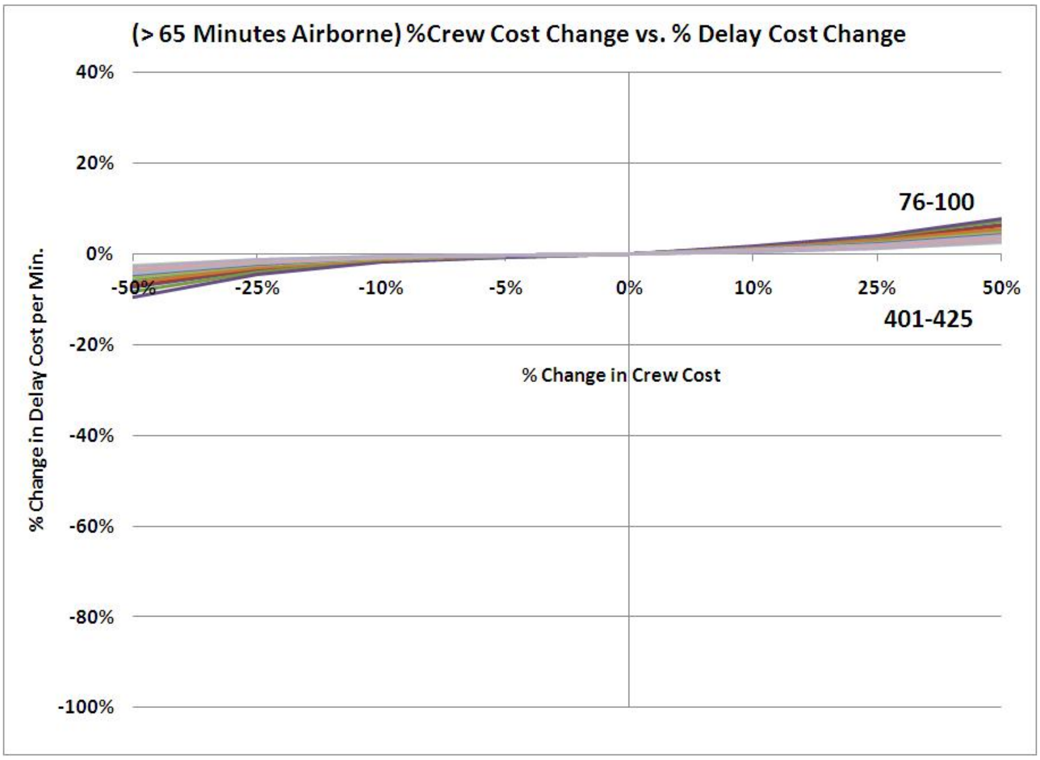

Figure 3.11: %Change in Cost of Delay vs. %Crew Cost Change (> 65 minutes airborne delay)

- Fuel burn rates are as important as fuel prices; the same amount of taxi delay in an efficient aircraft can save delay costs by as much as 10%.
- This analysis has also shown that fuel burn rates for regional jets are better than those for larger aircraft. Thus, by choosing to use smaller regional jets, the airlines save on total operational costs while providing the opportunity to have greater frequency and higher load factors.
- As fuel costs increase, crew costs become far less important to the overall delay and flying costs, since fuel costs are the major component. For ground delays, however, crew costs are a larger component of total delay costs, and larger aircraft are most impacted since they have larger crews.
- This analysis of delay costs is consistent with current airline behavior. Namely:

- Smaller aircrafts in the current fleet have better fuel burn rates than larger aircraft and can be flown with higher load factors (since it is easier to fill a smaller plane), so the airlines are likely to continue to use these aircrafts.
- When airlines use smaller aircrafts, besides saving on fuel costs, they may also have greater flexibility in repositioning passengers since there are fewer passengers per aircraft.
- By using smaller aircrafts, an airline can increase frequency to a given market.

This analysis therefore concludes that, as the economy recovers from the current recession, it is expected that the airlines are more likely to increase frequency rather than up-gauging to larger aircraft. Although this practice might not be efficient from an airspace-use perspective, it makes good economic sense for an airline.

3.6 Summary

This chapter starts with the discussion of why it is important to determine the cost of delays to not just airlines, but to the whole U.S. economy. An introduction was provided about other approaches that compute the cost of delay to airlines and where these approaches have been used. Section 3.3 discusses in detail the approach introduced in this dissertation, along with the conclusions that were drawn based on the new model. Lastly, a sensitivity analysis was reported on this model that supported airlines current behavior of using more frequent, smaller aircrafts despite the fact that they increase the congestion at both airports and in the airspace.

This research considered only delay costs. Work by [Rupp, 2005] performed regression models to determine the relationships between delay costs and both congestion prices and cancellations. A key conclusion drawn in Rupp's analysis is that airlines' cancellation and delay decisions are interdependent and therefore need to be treated as a single decision process. Several factors, such as hub vs. non-hub airlines, larger vs. smaller aircraft, etc., are identified as deciding variables that determine the final status of flights. Similarly

[Xiong, 2010] also found that airlines behave significantly differently regarding cancellations; larger legacy carriers have a tendency to cancel less important shorter flights in order to reduce delays for larger aircrafts.

This chapter introduced a major component of the congestion pricing model that is described in the next chapter.

Chapter 4: The Congestion Pricing Model

This chapter describes the model used for generating congestion prices. Section 4.1 introduces the proposed model and compares it to some of the approaches discussed in the literature review. Section 4.2 illustrates the idea using the example presented in Chapter 2. Section 4.3 discusses the sources of data in detail. Section 4.4 discusses the preprocessing of the data required for the model. Section 4.5 describes the Revenue/Cost model. Section 4.6 provides a brief summary of the Cost of Delay model. Section 4.7 describes the Optimization model which is the core component of the Congestion Pricing Model. Section 4.8 describes the use of the model. Section 4.9 mentions other details about the model. Finally, the last section describes some possible extensions to the model.

4.1 Introduction

The proposed congestion pricing model is an extension of the econometric model described earlier. Similar to [Morrison et al., 1989], the day is divided into time periods. However, a fifteen minute time window is chosen to be the time period, rather than the time window of one hour chosen by [Morrison et al., 1989]. Also, in contrast to their model, the proposed model computes the unique revenue for each individual flight and its associated costs (both normal operating costs and delay costs). The model only looks at arriving flights with the presumption that applying congestion pricing to the arrivals will also control the departing flights. This is consistent with the current GDP approach. A more structured model is used to compute the cost of delays incurred by airlines unlike other econometric models which use only the average cost per minute multiplied by the number of minutes of delay. Instead, a cost of delay model is used which is dependent upon where the delay occurs and is nonlinear in the amount of delay. An equilibrium price is determined such that “given price and capacity, no flight operator has incentive to change its flight status." A flight status can be flown on time, delayed or cancelled.

Unlike [Morrison et al., 1989], a spill-over is considered from one period to the next. That is, a flight can opt to arrive at either its preferred (scheduled) time period or in any subsequent time period.[1] This is similar to the model described in [Betancor et al., 2003], although their model only studied spill-over to one additional time period (for a total of two time periods). The price in most general econometric models is independent of prices in subsequent time periods, however, in the proposed model a flight might be allotted a slot later in the day due to the spill-over effect. This results in a greater economic efficiency as there are more choices available to each participant, leading to reduction of congestion prices at different time periods.

The proposed congestion pricing model is different from a bottleneck congestion model which captures the stochastic nature of traffic and weather. In contrast, the new model is deterministic and therefore does not consider the capacity changes that may occur later in the day. It assumes full knowledge of the day of operations before hand, i.e., it has to be given the capacity for the whole day in advance. However, in order to compute new congestion prices based on an updated scenario, the model may be run again by updating the data, (e.g., updating the capacity, fixing the flights that are already airborne, etc).

In addition, the model assumes that all the stakeholders involved are compliant. That is, all parties will choose to pay the toll if the flight remains profitable and will choose the most profitable time period based on maximizing profit. The experiments will assess the sensitivity of prices to this assumption. Since the model is profit maximizing, it assumes that all airlines will have a profit maximizing objective. It is noted that there may be other factors that would alter this objective and have added both costs and constraints to accommodate some identified exceptions. These additional considerations are discussed later in this chapter. In addition, whenever the user of the model finds that demand and supply are not in equilibrium, the input data be can updated, the already assigned slots

[1]The number of subsequent time periods is explored further in the design of experiments.

fixed and the model run again.

4.2 Illustrative Example Revisited

Consider the example shown in Figure 4.1(a) from Chapter 2. The same schedule is used; however, now the congestion pricing might change the allocation made. Figure 4.1(b) shows the reduced schedule along with the congestion price (the numbers below the bold red line).

The rationale is quite simple: for each time window, the proposed approach assigns the slot to the most profitable flights, but does not schedule any flight prior to its scheduled arrival time. Once capacity is reached for a given time period, flights are cascaded to the next time window and the procedure continues. However, if that was the only case, Piedmont flight (PDT[DH8A,$9,768]) should have been in the second time window instead of the third time window, as appears in Figure 4.1(b). This is because it is marginally more profitable for the Piedmont flight to be delayed than the Com Air flight (COM[CRJ1,$9,051]). The total profitability of the schedule increases by allowing the PDT flight to be delayed one time window in order to allow the Com Air flight to use this slot.

Note that this system will automatically swap the flights among airlines when a given flight of one airline is more profitable than a given flight of another (or same) airline.

The end result is a new, reduced schedule with the most profitable flights flying as close to their scheduled time as possible. The model will also have an airline delay a flight (even if it is profitable in a given time period) if delaying that flight will yield it more profit. Thus, if it is more profitable to delay a flight 15 minutes (and thereby pay a 15-minute delay cost plus the congestion price of the next time period), the flight will be delayed.

From the literature review and the discussion in the previous section, it is known that the congestion price should be exactly equal to the marginal benefit of adding one additional resource to the current system. Simply put, the congestion price for any time window should be equal to the "dual price" of the capacity constraint for the time window. In this example, for the first time window, Com Air flight COM(CRJ,$8,553) is the extra flight that will be

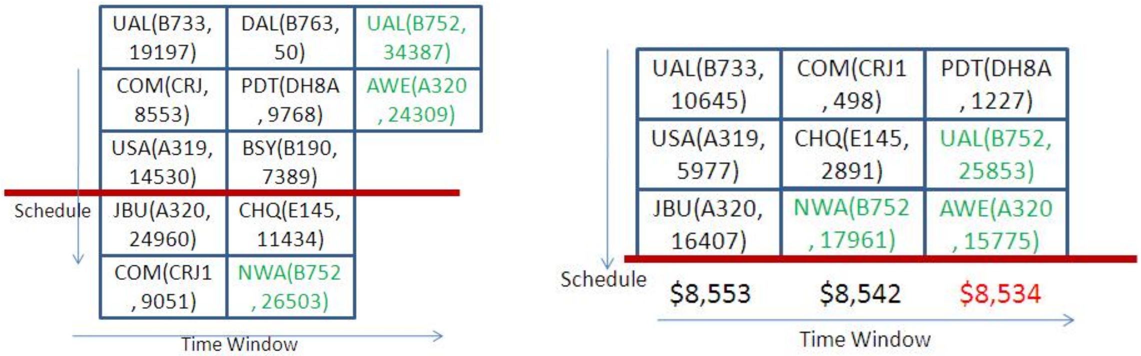

Figure 4.1: (a) Original Schedule, (b) Ration by Congestion Pricing (CP) Allocation

added given increased capacity; therefore, the congestion price for the first time window is \$8,553. At this congestion price, rationally, this flight is not generating additional revenue to the system and therefore, the model will delay it to the next time window. For any flight delayed in the first period, the profit of that flight in the next period is equal to its original profit minus its cost of delay for one time period. All flights scheduled in this time period plus those delayed and still waiting for a slot all compete for the capacity of this time period. For example, Chautauqua's flight CHQ(E145,\$11,434) departs in the second time window as scheduled whereas Big Sky's flight BSY(B190,\$7,389) is delayed two time periods and the first of two Com Air flights is delayed more than two time periods.

4.3 Data Sources

The data comes from the following sources:

Aviation System Performance Metrics (ASPM) [ASPM, 2007]

- ASPM Flight Data Dictionary provides all the flown flights with both the scheduled and actual time in terms of fifteen minute time bins. It also provides, aircraft type, air carrier, origin and destination for each flight, and tail numbers and flight numbers for most of the flights. A fifteen minute time bin is referred to as time period (or time window). Thus, there are ninety-six time periods in a day. The “ideal” departure time is estimated to be the scheduled departure time for the flight.

The Airline Origin and Destination Survey (DB1B) [DB1B, 2007]

The Airline Origin and Destination Survey (DB1B) is a 10% sample of airline tickets from reporting carriers collected by the Office of Airline Information of the Bureau of Transportation Statistics. Data includes origin, destination and other itinerary details of passengers transported. This database is used to determine air traffic patterns, air carrier market shares, and passenger flows. DB1B Market table contains directional market characteristics of each domestic itinerary of the Origin and Destination Survey, such as the reporting carrier, origin and destination airport, prorated market fare, number of market coupons, market miles flown, and carrier change indicators. This database provides the airfares between markets.

Bureau of Transportation Statistics (BTS) [BTS, 2007]

- BTS P52 provides the operational cost for the flight. Operational cost includes direct cost (both “total flying cost” and “total fuel cost”), hours of flight and gallons of fuel issued. The direct cost along with hours of flight is used to compute fixed cost per hour, while the latter two are used to compute fuel used in gallons per hour or fuel burn rate per hour (variable cost). It also provides the maintenance cost and crew costs for the cost of delay model.

- BTS T100 provides both the total number of passengers and total seats flown which are used to calculate load factors. These load factors combined with airfare from DB1B give the revenue per flight.

- BTS ONTIME also provides the scheduled and the actual departure and arrival times for all scheduled flights. In addition to ASPM, BTS OnTime also has canceled flights. However, the number of flights in the BTS database is considerably smaller than those in ASPM. This is due to the fact that not all carriers report to BTS, while ASPM is the extended version of the ETMS.[2] The preprocessing section (Section 4.4) discusses how both these databases are used in order to generate a single compact schedule of the flights per day at the studied airports.

International Civil Aviation Organization (ICAO) Engine Emissions Databank [ICAO, 2009]

ICAO emissions database provides the taxi fuel burn rate per aircraft type used to compute the cost of delay of a fuel usage costs.

Airport Capacity Benchmark Report 2004 [FAA, 2004]

This report provides three different rates for hourly number of operations (including both arrival and departure) based on different weather scenarios:

- Optimum: represents good weather with visual separation.
- Marginal: describes weather not good enough for visual approaches, but still better than instrument conditions.
- IFR: Instrument Flight Rules, defined as instrument conditions (ceiling less than 1000 feet or visibility less than 3 miles) when radar is required to separate aircraft.

For a given hourly capacity, it is assumed that there are equal number of arrivals and departures, although the model is flexible in handling whatever capacities are provided by air traffic control (ATC).

4.4 Preprocessing

During the preprocessing step, two different schedules (one from ASPM and one from BTS) are merged into a single, more complete schedule. Since there is no obvious way to pair

[2]Enhanced Traffic Management System.

flights from one schedule to the other, a variety of heuristics are used to generate the final schedule. The preprocessing is as follows:

- All flights flown by international flights (whether between two domestic airports or one domestic and one international airport) are fixed to be flown.
- All flights that are flown by domestic airlines to or from international destinations are fixed to be flown.
- All cargo flights, humanitarian and military flights (that appear in ASPM) are fixed to be flown.
- All General Aviation (GA) flights are removed from the system under the premise that the commercial flights have a higher priority than these flights. Any unused capacity can be assigned to GA flights.
- From the BTS Ontime schedule, flights that are reported canceled are considered by the model as potential flights. These flights are not used for pairing of flights since ASPM schedule only contains flown flights.
- From BTS Ontime schedule, flights that are reported diverted are removed from the system. Since, by definition[3] a diverted flight "is [a] non-stop flight that lands at a destination other than the original scheduled destination." These flights are never reported into ASPM as it only records flown flights.

For all the fixed flown flights, the time slots (at their actual flown time) are pre-assigned to these flights and capacity limits are reduced accordingly. These fixed flights can be termed as "exempted" flights in GDP scenarios.

Once all these flights are separated, the remaining flights are paired. The goal is to remove duplicate copies of flights so that all flights are considered only once. Also, since both schedules provide extra information about the flights, pairing these flights will help

[3]As mentioned in [DOT, 2008].

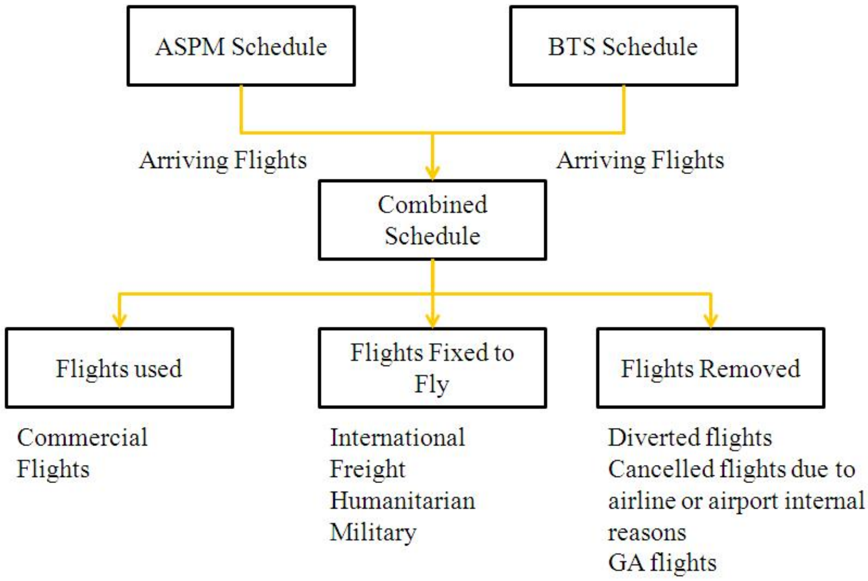

Figure 4.2: Preprocessing step

explain the final status of these flights both historically and from the model output. Figure 4.2 shows the division graphically.

4.4.1 Pairing Flights: Algorithm

In order to pair the flights, queries are used to join the different tables (i.e., ASPM and BTS OnTime) in an attempt to find the perfect match between flights from different schedules. These queries start with the most constrained cases and remove constraints at each step. A manual check is performed after each query to ensure that no flight from either schedule is paired to multiple flights. The queries in which the flights are paired are listed below in sequential order:

1. *Query1* Join by date, airport, origin, destination, carrier where time windows are equal, flight numbers are equal, aircraft type are equal and tail numbers are equal.

2. *Query2* Join by date, airport, origin, destination, carrier where time windows are equal, flight numbers are equal and tail numbers are equal.

3. *Query3* Join by date, airport, origin, destination, carrier where time windows are equal, flight numbers are equal and aircraft type are equal.

4. *Query4* Join by date, airport, origin, destination, carrier where time windows are equal, aircraft type are equal and tail numbers are equal.

5. *Query5* Join by date, airport, origin, destination, carrier where time windows differ by one, flight numbers are equal, aircraft type are equal and tail numbers are equal.

6. *Query6* Join by date, airport, origin, destination, carrier where time windows are equal and tail numbers are equal.

7. *Query7* Join by date, airport, origin, destination, carrier where time windows are equal and aircraft type are equal.

8. *Query8* Join by date, airport, origin, destination, carrier where time windows are equal and flight numbers are equal.

9. *Query9* Join by date, airport, origin, destination, carrier where time windows differ be one, flight numbers are equal and aircraft type are equal.

10. *Query10* Join by date, airport, origin, destination, carrier where time windows are equal.

11. *Query11* Join by date, airport, origin, destination, carrier where time windows differ by one and aircraft type are equal.

12. *Query12* Join by date, airport, origin, destination, parent carrier (wherever possible) where time windows are equal, flight numbers are equal, aircraft type are equal and tail numbers are equal.

13. *Query13* Join by date, airport, origin, destination, parent carrier (wherever possible) where time windows are equal, flight numbers are equal, and either aircraft type are equal or tail numbers are equal.

14. *Query14* Join by date, airport, origin, destination, parent carrier (wherever possible) where time windows are equal, and either flight numbers are equal or aircraft type are equal or tail numbers are equal.

15. *Query15* Join by date, airport, origin, destination, parent carrier (wherever possible) where time windows differ by one.

16. *Query16* Join by date, airport, origin, destination, parent carrier (wherever possible) where time windows differ by at most 4 and flight numbers are equal

From *Query12*, the ASPM schedule is joined by parent carriers since most of the regional carriers use the parent carriers' designation and the BTS schedule might report flights as mainline carriers' flights. A manual check is performed at the end to see if any further flights can be paired. Remaining unpaired flights from either schedule are added to the final schedule. As a result, a single schedule is generated for each day at each airport.

The canceled flights from BTS are then added to the final schedules. Each final schedule contains for each flight: a scheduled time in terms of time period, air carrier,[4] aircraft type[5] (priority is given to ASPM, in case of conflict), origin, destination and whether it is an arriving or departing flight at the airport under study. Lastly, if available, the status of the flight historically (whether it was flown/canceled) is also added for analysis purposes.

After a single schedule is generated using these two different tables, the next step is to compute the revenue and cost factors for each flight along with any other fees imposed on the flight.

[4]ASPM and BTS OnTime use different code schemes for air carriers. In BTS OnTime, flights operated by regional carriers are often reported as operated by mainline carriers. All the flights in ASPM schedule are also changed accordingly. The link between mainline and regional carriers is generated manually by looking at which regional carriers fly under which carriers at different airports.

[5]Similar to air carriers, BTS and ASPM use different code schemes for aircraft types, using historical data; a complete database table is generated to link these code schemes.

4.5 Revenue/Cost Model

In order to compute congestion prices, it is important to understand the economics of the airline industry and thereby, the price that will result in agreement between supply and demand. Thus, there is a need to know the value that an airline places on a given flight. An important point worth mentioning is that these models will not be able to include the exact costs incurred by any given airline. However, reported costs of running aircraft of various sizes and the average costs incurred by a given airline for fuel, crew, maintenance and depreciation are collected and used to obtain reasonably accurate comparative values for a given set of flights.

To calculate a congestion fee, for each flight segment, the following data is collected:

- Revenue (R) of a flight is the total amount generated by the flight. It is a multiple of average airfare between the airports (both direct and connecting flight's ticket prices are used) and the average load factor (from BTS T100). The revenue also discounts the other fees collected with the ticket price by airlines, but are not part of the airlines revenue (more specifically, 94.9% of airfare is used[6]). In addition to these discounts, additional revenue generated by belly cargo and other miscellaneous fees (e.g., baggage fee, booking cancellation fee, etc.) are also added ($0.44 per ticket). The final airfare is thus,

$$\text{New Airfare} = 0.949 \times \text{Airfare } + \$0.44.$$

- Operating Cost (O) of a flight is the dollar amount it costs an airline to operate the flight. Only direct costs are considered which include: maintenance, labor and other costs. No lease, depreciation or other indirect costs are included in this operating cost. These direct costs[7] per hour are reported by the airlines in BTS P52 Database [BTS, 2007]. Fuel costs are computed separately by multiplying the fuel burn rate of

[6] See [Ferguson, 2011] for a detailed description on how the average fare is computed.

[7] Direct costs are the total operations cost minus the fuel operations cost divided by total flight time (in hours) as reported in BTS P52.

the aircraft,[8] fuel prices per gallon and total airtime of the flight.

- Weight based landing fee (W) is the fee charged by airport per landing. Different airports have different landing fee rates per 1000 lbs., therefore, this cost is computed by multiplying the aircraft weight (more specifically Maximum Landing Weight or MLW rounded up to 1000 lbs.) to these landing fee rates.

- Congestion Fee (λ) of a flight is the amount the airline is charged if it chooses to fly in a congested time period. This is the cost calculated by the optimization model. For any time period where there is no congestion, the congestion fee is zero.

4.6 Cost of Delay Model

This section summarizes the model from the previous chapter that is used to compute the cost incurred by airlines in case a flight is delayed. The model evaluates costs of delay for each of the different segments of flight (gate delays, taxi-out/taxi-in delays, and airborne delays). The model is an additive model that considers fuel burn rates, crew costs, maintenance and other costs (including baggage, ticketing and gating). The cost factors varied based on the length of the delays, where short delays were considered to be those less than fifteen minutes, while long delays were those over sixty-five minutes.

The additive model has the following parameter values:

$$\begin{aligned} C_{delay} = c_{fuel} \times & \text{ fuel burn rate} \times \text{ fuel price} \\ & + c_{crew} \times \text{ crew cost} \\ & + c_{maintenance} \times \text{ maintenance cost} \\ & + c_{other} \times \text{ other cost} \end{aligned} \tag{4.1}$$

[8]Fuel burn rate is the ratio between total fuel issued (in gallons) and hours of flight time, both reported in BTS P52.

Table 4.1: Coefficients for Airline Cost of Delay Model

Cost Factor	Gate		Taxi		Airborne	
	15 min	65 min	15 min	65 min	15 min	65 min
Fuel	0	0	1	1	1	1
Crew	0	0.46	0	0.43	0.01	0.46
Maintenance	0	0	0	0	0	0
Other	0.21	0.21	0.12	0.12	0.1	0.1

All cost data is in dollars/minute. Table 4.1 contains the coefficients for each cost component and segment of flight. Note that the coefficients are independent of aircraft type. However, each of these coefficients is multiplied by a corresponding cost that is aircraft dependent. Thus, the model computes delay costs that are aircraft-type specific and will vary with changes in fuel, crew and maintenance or other costs (as reported by the airline in the BTS database).

For delays of less than 15 minutes, 15 minutes cost factor is used; for delays greater than 65 minutes, 65 minutes cost factors are used; for delays between 15 and 65 minutes, an interpolation is done using two data points. The basis of this modeling effort uses the short and long delays because those are the two categories found in the Euro Control Report upon which this model is based [Cook et al., 2004]. Figure 4.3 shows the functional diagram of this model.

Note that for the congestion pricing model in this study, all the delays are taken at the gate of departure airport; therefore the model only uses the cost of delays at gate segment. A more detailed description of how this model was created is provided in the Chapter 3

4.7 Optimization Model

The optimization model is the core of the congestion pricing model, which maximizes cumulative profit for all flights subject to capacity constraints. Profit is computed using the revenue/cost model defined above, while the capacity constraints are for each time window,

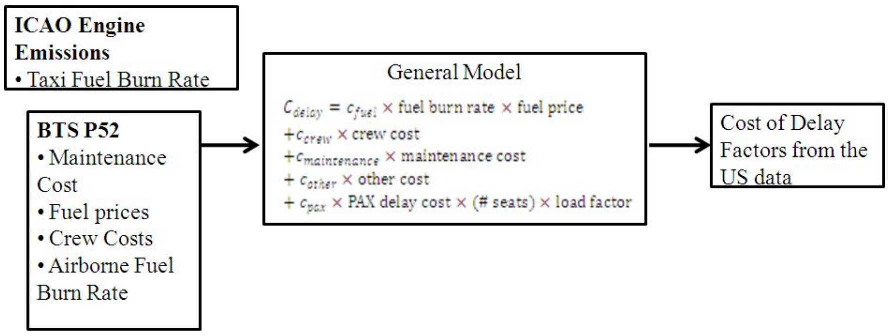

Figure 4.3: Functional diagram for Cost of Delay Model

the number of flights that are flown is not greater than the capacity of that time period. In the case of a non-congested period, the congestion price will be zero and all flights will opt to fly. In cases where there is an insufficient capacity, some of the flights will choose to delay or cancel the flights because the congestion price announced will make the flight unprofitable to be flown in this time period. These flights will be then be rescheduled at the next available time window, with the delay cost added to their operating costs. These delayed flights compete in these future time windows with the flights scheduled to depart in that time window. The optimization model considers the entire day and takes a global view of all flights during all time periods, choosing the time period to fly each flight so that the flight incurs its maximum profit. If no such time period provides a profitable option, the flight is cancelled. An additional constraint regarding the flight cancellation is added, i.e., how long a flight is allowed to be delayed before it is cancelled by the model despite still being profitable. This stopping criterion reflects the preferences of airlines to cancel a flight early in order for other, more important flights to experience less delay. At the end, the model outputs the new schedule for all of the flights as well the computed congestion prices for each time window.

4.7.1 Mathematical Formulation

Using following sets,

- **Sets:**

$\mathcal{T}$: Time Windows (Periods/Bins)

$\mathcal{F}$: Flight segments, indexed by k where $1 \leq k \leq |\mathcal{F}|$

$\mathcal{Y}^k$: copies of k^{th} flight with scheduled time window $t(k) \in \mathcal{T}$ and multiple actual time windows $j \in \mathcal{T}$ where $t(k) \leq j \leq t(k) + l^k$

$\mathcal{Y}$: $\bigcup_k \mathcal{Y}^k$ Union of copies of all flights

- **Indices:**

j : Time periods $j \in \{1, \dots, |\mathcal{T}|\}$

k : Flights $k \in \{1, \dots, |\mathcal{F}|\}$

- **Parameters**

R^k : Revenue of k^{th} flight

O^k : Operating cost of k^{th} flight

W^k : Weight-based landing fee of k^{th} flight

$t(k)$: scheduled arrival time of k^{th}flight $t : \mathcal{F} \to \mathcal{T}$

d_j^k : delay cost per minute of k^{th} flight with delay of "$15 \times (j - t(k))$" minutes (From delay model)

l^k : number of time windows the k^{th} flight can be delayed. $t(k) + l^k \leq |\mathcal{T}|$

- **Variables**

$$x^k := \begin{cases} 1 \; k^{th} \text{ flight flown} \\ 0 \text{ otherwise} \end{cases} \tag{4.2}$$

$$y_j^k := \begin{cases} 1 \; k^{th} \text{ flight is flown in time window } j \in \mathcal{T} \text{ with delay of } (j - t(k)) \times 15 \text{ minutes} \\ 0 \text{ otherwise} \end{cases} \tag{4.3}$$

$$\lambda_j : \text{Congestion fee at time window } j \in \mathcal{T} \tag{4.4}$$

- **Formulation of Problem P**

$$\max \sum_{k \in \mathcal{F}} \left[R^k - O^k - W^k \right] \times x^k - \sum_k \sum_{j=t(k)}^{t(k)+l^k} \left[15(j - t(k)) d_j^k + \lambda_j \right] \times y_j^k \tag{4.5}$$

s.t.

$$\sum_{j=t(k)}^{t(k)+l^k} y_j^k = x^k \qquad \forall_{k \in \mathcal{F}} \tag{4.6}$$

$$\sum_k y_j^k \leq C_j \qquad \forall_{j \in \mathcal{T}} \tag{4.7}$$

$$x^k \leq 1 \qquad \forall_k \tag{4.8}$$

$$y_j^k \leq 1 \qquad \forall_k \forall_j \tag{4.9}$$

For each k^{th} flight (defined by variable x^k), there is some original scheduled time window $t(k) \in \mathcal{T}$, and some actual time window $j \in \mathcal{T}$ when it is flown. Therefore there are l^k copies per flight (defined by variable y_j^k) and the model selects the variable with a $j \in \mathcal{T}$

that indicates the time window when it is most profitable to fly.

The objective function maximizes total profit over all time periods and flight segments. It has both fixed costs (operating cost per flight and landing fees) defined in terms of x^k and variable costs (delay cost that is based on $j - t(k)$ per flight and congestion cost based on $j \in \mathcal{T}$ determined by the solution) defined in terms of y_j^k.

The first constraint (4.6) indicates that for each flight $x^k \in \mathcal{F}$, at most, one copy of the flight variable ($y_j^k \in \mathcal{Y}^k$) can be non-zero in the final schedule indicating that the flight was assigned a slot $j \in \mathcal{T}$ and was delayed for $15 \times (j - t(k))$ minutes. The case where all copies of the flight variables are zero indicates that the flight is cancelled for the day and $x^k = 0$.

The second constraint (4.7) is the capacity constraint per time window $j \in \mathcal{T}$. It assures no more than c_j flights will arrive at the airport (based on their departure time at originating airport).

The third (4.8) and fourth (4.9) constraints indicate that x^k and y_j^k can take a value of at most 1.

In reality, both the x and y variables are binary variables. It is later shown that the lp solution will yield integer solutions.

4.7.2 Running the Optimization Model

Note that the optimization model described is non-linear, because the objective function has a quadratic term ($\lambda_j \times y_j^k$) in it. A technique similar to Bender's decomposition is used in order to solve the problem. At each iteration, λ_j is fixed and the model is solved. Then values of λ_j are updated and the model is solved again for optimality. This is repeated until the value of the objective function cannot be further improved. Adding a superscript to the λ_j, i.e. λ_j^v, where v indicates the number of iterations, the model is initially solved by setting $\lambda_j^0 = \underline{0} \;\; \forall j$.

Thus, the problem P is solved with $\lambda_j^{=}\underline{0}$ and the dual prices associated with each capacity constraint 4.6 are obtained. The dual prices measure the value to the objective function

Initialize $\lambda_j^0 := \underline{0}$
$v := -1$
repeat
  $v := v + 1$
  Run the Optimization Model with λ_j^v
  $\lambda_j^{v+1} :=$ get new dual prices
until $\lambda_j^{v+1} \neq \lambda_j^v$

Figure 4.4: Procedure to compute Congestion Prices

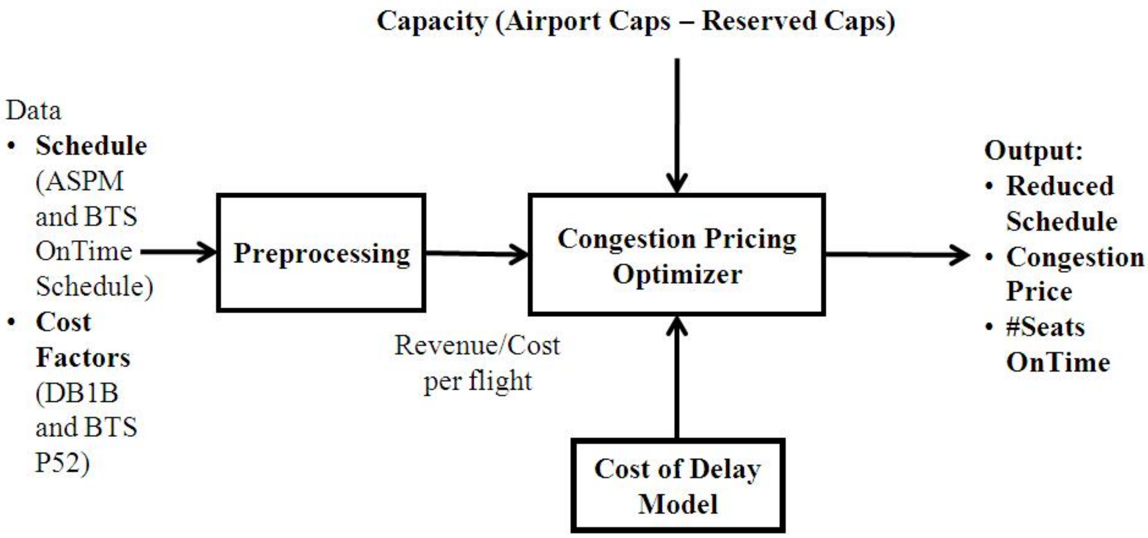

Figure 4.5: Functional diagram of the Congestion Pricing Model

of adding an extra unit (an additional slot in this case). Note that it is also the profit generated by the next flight that can be added to this time window, hence by fixing this dual price as the congestion fee, the next flight becomes non-profitable and is delayed by one time window. Figure 4.4 shows the pseudocode for the computation and convergence of the congestion prices.

4.8 Working of the Model

The Congestion Pricing Model (CPM) is the combination of all the components defined in the previous sections. Figure 4.5 shows the functional diagram of the model. The inputs to this model are: original schedules (both from ASPM and BTS OnTime) where each flight belongs to some scheduled arrival bin (in terms of 15 minutes time bin), the capacity limits for each time period at a given airport, and revenue and costs for each flight.

The preprocessing stage combines the two different schedules (from ASPM and BTS OnTime) into a single schedule and then determines the revenue and costs associated with each flight.

Once each flight is assigned a revenue and cost, the optimization model is invoked. Embedded in the model are the associated delay costs (based on the cost of delay calculations). The model determines the choice for each flight that maximizes overall profit. The model outputs a schedule that satisfies the capacity limits in each 15 minute time bin. Hence, for each flight, a specified delay and a congestion cost is determined. If the flight is cancelled, then the model also determines the cancellation cost which is equal to the flight's profit. It also provides the equilibrium congestion price for each 15 minute time bin. The congestion price is zero in cases where there are fewer flights than the capacity of that time window. In the case of two flights competing for a single time window with same profit, a further step is considered in the optimization process.

When two competing flights have equal profit, this implies that the linear programming problem is degenerate. Thus, there are more than m variables having a reduced cost equal to zero. In this case, any m of these variables can be chosen to be in the solution (i.e., flown in this time period). It is noted that such degenerate solutions might result in either too many or too few flights actually choosing to fly (since the economic response to such a congestion price for the airline is indifferent). Thus, one must learn over time whether the congestion price should be slightly increased or decreased when such degeneracy occurs.

4.9 Assumptions of the Model

Apart from the flights that are fixed to be either flown or cancelled as mentioned in Section 4.4, some other assumptions of the model are:

- The airlines behave rationally, i.e., when delays and cancellations must occur, the airline will prioritize flights based on profitability.
- The only network effects considered in the model are: (i) assuring flights overnight where scheduled, and (ii) adding extra costs associated with missing a turnaround time for the follow-on flight.
- The model examines airports separately and delays flight at the departing airport based on the capacity at the arriving airport. This is in accordance with the current system where the Ground Delay Program (GDP) only deals with the arriving flights at an airport.
- Delays only occur at the gate of the departure airport. This means that whenever a flight is rescheduled, it is allowed to stay at the gate at the departure airport and no extra cost is imposed on the flights. In reality, an airline may incur additional costs because of gating congestion issues.

4.10 Variations to the Basic Model

The two variations added to modify the model that consider, issues with overnight flights and the addition of the cancellation cost model are discussed below.

4.10.1 Network Effects due to Overnight and Departure Segments

In general, the model assigns arrival slots to flights based on their profitability. However, for some airlines the need to begin the next day with all aircrafts positioned as planned may have more value than the profitability of a single flight. Therefore, for flights that were scheduled to remain overnight at an airport, the airlines may be willing to incur additional delay and/or congestion costs even if these costs result in negative revenue. Since such decisions will impact the overall congestion of the system, the model must consider these decisions when determining the congestion costs of each time period.

Similarly, there are certain flights for which, if the arrival time is after a specific time period, there will be a significant impact on another (possibly highly profitable) flight or flights. Therefore, the delay cost of the flight is not the only penalty incurred by the airline; there may be additional costs because its next departure segment may be delayed due to the unavailability of an aircraft or its crew.

Adding these extensions in the model is fairly straightforward. For the overnight flights, x^k is fixed to be one. This means that the flight will arrive at the airport regardless of the delay costs (i.e., one of the y_j^k to be equal to 1). In the worst case, it will get the slot with greatest delay possible (largest value of j).[9]

A second mechanism for allowing these flights to overnight at the appropriate airport is to extend arrivals into the early morning hours of the next day (at airports allowing late arrivals). It is termed as the "sink time window"; at the end of the day, the model can allow any overnight flights to choose this time window when all other time windows have more profitable flights that use up the available capacity. The cost of using this sink time window is set high in order to encourage flights to choose alternatives over the extreme case.

In order to add a sink time window for each of the overnight flights, calculate the delay cost from its scheduled time $t(k)$ to the time window after the end of day 97 (or 105). Introduce a new variable o^k for overnight flights. This variable is also added into constraint 4.6 for all overnight flights k; this implies that if none of the y_j^k variables are one, since x^k is one, o^k will be one. For the congestion price, profit of the overnight flight k and a penalty of \$50 is chosen. This will prevent the flight from choosing the sink if any other slot is available.

For simplicity, it is assumed that any flight that cannot be linked to a departure segment and arrives after 5 pm that day is considered to be an "overnight flight."

[9]Depends on l^k determined by the design of experiments.

Specifically for flights with departure segments later in the day, search for the time window when the next departure segment for that aircraft is scheduled to depart. If the arrival flight arrives on or fifteen minutes before its scheduled departure time, no penalty is charged. Otherwise, an additional delay cost for each fifteen minutes of delay on the ground is added to the delay cost of the flight. It is noted that the delay cost calculations are the same since the aircraft type is identical. However, the magnitude of the delay may increase nonlinearly depending on the delay.

Adding this constraint into the optimization model requires adding a few more parameters to the optimization model. First, extra information regarding the k^{th} flight is added, i.e., if there exists a departure segment flight, its scheduled departure time, this is termed as $dep(k)$: departure time of k^{th} flight $dep : \mathcal{F} \to \mathcal{T}$. If this is 0, the flight does not have a departure segment. Second, an extra variable $depdelay(j,k)$ is introduced that captures the delay cost only if the departure segment is delayed, if j^{th} time window is assigned to k^{th} flight. Mathematically,

$$depdelay(j,k) := \begin{cases} 1 \text{ if } j \geq dep(k) \\ 0 \text{ otherwise} \end{cases} \tag{4.10}$$

Finally, with these two parameters, an additional term is subtracted from the objective function to account for the departure delay cost incurred by flight operators in case the corresponding y_j^k variable is selected. A minimum turn around time of 2 time windows of delay is also added when computing the delay cost of the departure segment; this is based on the assumption the next flight cannot depart until 30 minutes after it arrives.

$$-\sum_{k} \sum_{j=t(k)}^{t(k)+l^k} \Big[15 \times depdelay(j,k)(j - dep(k) + 2) d_{j+2}^k\Big] \times y_j^k \tag{4.11}$$

Matching Tail Numbers

All that remains is to find a departure segment later in the day (if it exists) for each arriving flight k. If there is one, set that to be the $dep(k)$ of flight k. If not, if the flight is scheduled to arrive after 5 pm, then fix its corresponding x^k variable to be one in the model, or else do nothing.

The only way to match such a pair of arrival and departure flights is by using tail numbers, that is, for each arrival flight, find a departing flight that belongs to the same airline, is the same aircraft (using tail numbers), is scheduled later than the scheduled arriving time of the arrival flight with some turn around time. However, using the publicly available databases, this is not an easy task, since for most of the flights, tail numbers are either null or equal to the flight numbers. Heuristics have been applied to match these seemingly different sets of flights with multiple iterations by relaxing constraints. For the turn around time, a greater than 30 minutes of turnaround time (> two time windows) is assumed between the arrival and departure segment. Following are the queries (in the mentioned order) used to match the flights between arrival and departure flights.

1. *Query1* Join by date, airport, carrier, where turnaround time is > 1, aircraft type are equal, tail numbers are equal and both are domestic flights.

2. *Query2* Join by date, airport, carrier, where turnaround time is > 1, aircraft type are equal, tail numbers are equal and both are domestic flights.

3. *Query3* Join by date, airport, carrier, where turnaround time is > 1, aircraft type are equal, tail numbers are equal and one of them is domestic while other is international.

4. *Query4* Join by date, airport, carrier, where turnaround time is > 1, aircraft type are similar.[10] and both are domestic flights.

After invoking each query, a manual check is performed to remove the duplicates or one-to-many matchings. Turnaround time is the difference between scheduled arrival time of

[10]Similar indicates the cases where there are multiple codes used for the same aircraft type.

arriving flight and scheduled departure time of departing flight in time periods of 15 minutes, so "> 1" condition means at least 30 minutes of turnaround time between these flights is scheduled.

4.10.2 Cancellation Costs

The original optimization model did not have any cost associated with the cancellation of the flight except for the lost profit of the flight. Flights are forced to be cancelled within l units of time periods, in case they are not assigned a slot. The rationale behind this concept is that no airline is willing to keep its flights delayed at the gate for very long periods of time. This is because the airline needs to reschedule the passengers and because it needs the use of the aircraft. Therefore, if a flight continues to incur delay costs, it will eventually be cancelled.

An alternative method for determining whether to cancel a flight is to consider a cancellation cost (and keep all revenue associated with the flight). The idea is that an airline will need to pay for reconnecting passengers to their final destination, but the revenue obtained from each passenger is kept by the airline. Since there is currently no concrete model available to compute cancellation costs, a rule-based working model for cancellation costs is created.

For each flight k, if it is cancelled, the carrier will incur some cost because it must reschedule passengers onto other flights. It was estimated to be \$100 per passenger. The number of passengers $PAX(k)$ is computed by multiplying load factors with the seating capacity of the aircraft flight k is assigned. It will save all the fuel costs associated with that flight, since this flight will not be flown. In order to accomplish this, another parameter is added, $fuel(k)$, which is equal to the total fuel cost per flight k. This is the fuel burn rate of the aircraft multiplied by the total airborne time multiplied by the fuel price.[11] The cancellation cost therefore becomes:

[11] \$2.04 per gallon for Summer 2007.

$$-\sum_{k\in\mathcal{F}}\Big[(100PAX(k)-fuel(k))(1-x^k)\Big] \tag{4.12}$$

By adding this extra cancellation cost to the objective function, the optimization model takes into consideration the penalty of cancellation in the same fashion that it treats delay costs. l^k can now be set such that $t(k)+l^k \leq 96$ (or 104). This way, the model can take into account the cancellation costs.

It is acknowledged that this may be a rather crude model to compute cancellation costs and in reality, cancellation costs often depend on a number of different parameters with several propagating effects. This approximation of a cancellation cost model is used in order to test the sensitivity of the results to such costs.

4.11 Application in Ground Delay Program (GDP)

In order to use this model in a real GDP scenario, the following occurs. Whenever a GDP is announced at any airport, the reduced capacities are provided to the CPM model. The model will then produce the congestion prices for the entire day starting at whatever time Air Traffic Flow Management (ATFM) indicates. The congestion prices will be announced to airlines who will then decide whether to pay the congestion price or delay the flight until the next time window. In the case where the congestion prices did not produce desirable results, the model can be rerun to reflect the change in capacity that has occurred due to the responses provided. The process will be run again with the updated information about the airline's decision (changed schedule) as well as any changes in weather conditions and resulting capacity changes. When there is more capacity than anticipated, future period congestion prices could be reduced through a "learning model." When capacity is further limited because more flights chose to accept the congestion price or because weather conditions worsened, then capacity is reduced to reflect the reduced capacity.

4.12 Summary

This chapter describes the complete congestion pricing model. The first section compares the model with approaches mentioned in the literature review. The second section describes the idea using the illustrative example. Next, all the data sources along with how the data is processed in order to facilitate the model is described. Later, all the components of the model are described in detail, and finally, how they all are combined in order to compute the congestion prices and the new reduced schedule per day per airport. Assumptions/limitations of the model are then mentioned, some of which can be relaxed in future study to analyze different behaviors. Finally, some of the extensions to the model are discussed along with the procedure to embed them.

Chapter 5: Design of Experiments

This chapter discusses the design of experiments that have been performed to illustrate how the congestion pricing model could work. In the first part of this chapter, details of the data sample are provided used to perform the experiments. Section 5.2.2 describes in detail the design of experiments, the alternative approaches used for comparison with the new model, the performance criteria measured, and the input parameters varied for sensitivity analysis.

5.1 Data

To test this model, the data chosen is from one of the most congested periods in recent times, i.e., Summer 2007. The analysis examined every day in July 2007 in which a Ground Delay Program (GDP) was implemented. A variety of airports with varying characteristics were chosen, for e.g., an East coast versus West Coast airport, a slot controlled airport versus a non-slot controlled airport, a non-hub airport vs. a dominant carrier airport, etc. The following five airports were chosen:

- Boston Logan Airport (BOS): BOS is the only airport where the airport authority has the right to implement a Congestion-Pricing-based allocation scheme. No single airline has a major share at the airport and so, it is a non-dominated airport.

- Newark Liberty International Airport (EWR): EWR is another slot-controlled airport with the limit set to 81 operations per hour. However, this limit did not exist in 2007. It is one of the hub airports for Continental Airlines (COA) which runs its international flights across the Atlantic Ocean from this airport.

Table 5.1: Statistics for the data

Airport	Number of Days	Total Flights	Exempted Flights	Removed Flights	Flown Flights	Cancelled Flights
BOS	7	3599	285	235	3012	67
EWR	13	6722	645	372	5310	395
LGA	10	5555	185	357	4788	225
PHL	5	3017	145	150	2695	27
SFO	16	7680	743	444	6465	28
Total	**51**	**26573**	**2003**	**1558**	**22270**	**742**

- LaGuardia Airport (LGA): LGA is one of the slot-controlled airports, i.e., there is a limit as to how many flights can be scheduled at any given time period. Currently (since 2009), it is 71 operations (including both arrival and departure) per hour. In 2007, it was set to 75 operations per hour. It has several different airlines competing for the resources with similar proportions of flights at this airport. LGA has almost no international traffic and most of its flights connect New York City to other domestic cities.

- Philadelphia International Airport (PHL): PHL is a non-slot controlled airport and an international hub for U.S. Airways (USA). However, there is also a significant presence of a low-cost carrier, i.e., Southwest Airlines (SWA), at this airport.

- San Francisco International Airport (SFO): SFO is the only west coast airport in this study. It is also a non-slot controlled airport with a proportionally large amount of international flights, most of which connect the United States to the Far East. This airport is also a hub for United Airlines.

Finalizing the time period and the airports, a total of 51 airport days were chosen when the GDP was in effect in at least one of these airports during the month of July 2007.

Table 5.2: Flight statistics for airports studied

Airport	Total Flights	Profit ($)	OnTime Flights (%)	Delayed Flights(%)	Cancelled Flights (%)
BOS	3599	31,931,538	49%	49%	2%
EWR	6722	61,570,344	46%	47%	7%
LGA	5555	36,565,098	49%	47%	4%
PHL	3017	20,479,061	52%	47%	1%
SFO	7680	95,865,652	35%	65%	0.4%

Table 5.1 provides further detail on the data regarding the number of domestic flights, exempted (fixed to be flown) flights and removed flights. The last two columns show the historical status of the remaining flights. These are the total number of flights (i.e., 23,012) that are provided as input to the new system. The exempted flights are either the flights belonging to international carriers, have international origins, or are non-commercial flights (e.g., military, freight, etc). Slots for these flights are removed from the capacity (as reserved caps). In addition, there is a collection of "removed flights." They are one of three types: (i) either flights cancelled due to mechanical reasons or other airline issues, or (ii) the diverted flights, or (iii) General Aviation (GA) flights.

Table 5.2 provides the detail of the flights used for the experiments. As shown, around 50% of the flights were on time (including ones that were delayed by no more than 15 minutes), except at SFO where the ontime percentage is lower. Less than 10% of the flights were cancelled at any airport and the total percentage of cancelled flights is 3.22% or 742 flights out of 23,012 total flights. However, there were many delayed flights.

Figure 5.1 shows the flights by airlines (only airlines with > 100 flights are shown). During the days studied, most of the airlines have around 50% of their flights on time; Frontier (FFT) has only 30% while United (UAL) has approximately 35%.

Table 5.3 shows the landing fee ($ per 1000 lbs.) for the airports chosen for the study.

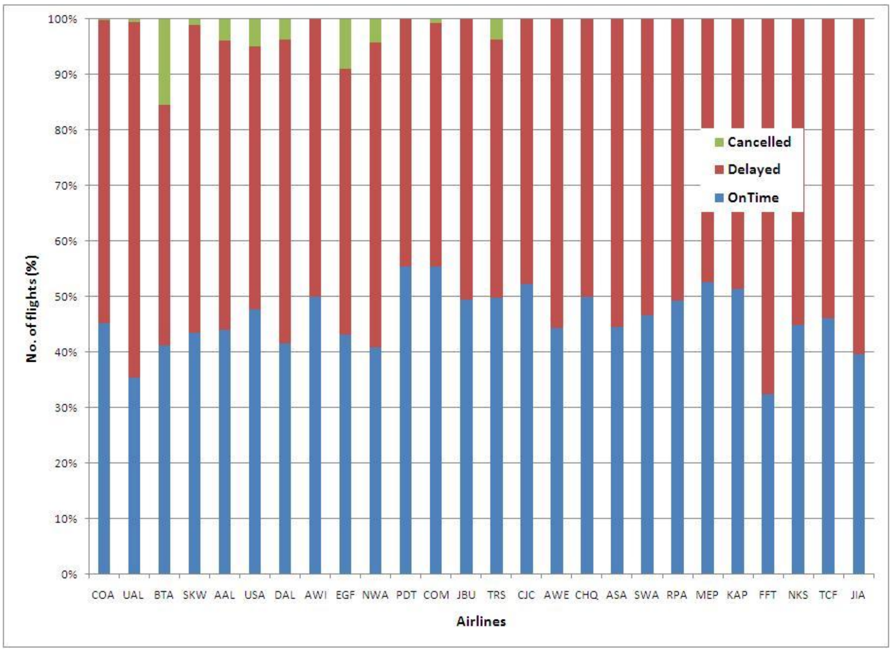

Figure 5.1: Historical status of flights by airline at 5 airports

Table 5.3: Weight based landing fee per 1000 lbs, Summer 2007

Airport	BOS	EWR	LGA	PHL	SFO
$ per 1000lbs.	$3.77	$5.83	$6	$1.63	$3

5.2 Design of Experiments

This section describes the input parameters (later used as variables for the analysis) of the new system, the alternative approaches against which the new system will be compared and the performance metrics used for the comparison.

5.2.1 Input Parameters

For the designs, three different input parameters are chosen that will be varied while running the model for a single airport day.

- Capacity: As discussed before, capacity is defined to be a limit at each airport, on the number of flights allowed to arrive in 15 minute time bins. Generally at airports it is announced as the airport arrival rate (on an hourly basis). It is provided by the ASPM Airport Data Dictionary [ASPM, 2007]. However, as observed for the current data, it is deemed too high at times even when a Ground Delay Program (GDP) been implemented at an airport. Since the new model is mainly based on capacity constraints, a slight change in the capacity beyond a certain limit is likely to propagate to a proportionally larger change in the congestion prices as well as the total amount of delays incurred. Therefore, four different scales of capacity, based on published airport capacity benchmarks [FAA, 2004] are chosen for all the airports. This report provides three different rates for the hourly number of operations (both arrival and departure) based on three different weather scenarios, i.e., "optimum", "marginal" and "IFR". Since, the fidelity of the model is 15 minute time windows and the data is given in hourly time windows and includes both arrival and departure slots (4 fifteen-minute periods $\times$ 2 types of operations [arrivals and departures] = 8), the data is rounded to the closest multiple of 8 and then divided by 8 to get a benchmark on 15 minutes of arrival capacity. In the case of PHL, however, these benchmarks were found to be higher than the actual schedule from ASPM [ASPM, 2007], therefore all the capacity scenarios were reduced accordingly.

Another value for capacity is also added, *MarginalLow (ML)*, based on the Marginal values and IFR values; between 2 pm to 7 pm, the capacity is set to the IFR limit, since most of the GDP's in the data take place later in the afternoon. For the rest of the time period, marginal capacity limit is used.

- Cancellation Policy (l^k): l^k defines the number of time periods a flight is allowed to be delayed before the model cancels the flight. In the experiment, the impact of allowing (i) up to a 3 hour delay (or 12 time windows),[1] (ii) up to a 5 hour delay (or 20 time windows), or (iii) allowing an unlimited amount of delay but including a cancellation cost (as described in Chapter 4) were tested.

[1]Similar to tarmac delay rule.

Table 5.4: Different capacity parameters at airports (per 15 minutes)

Airport	Capacity Scenarios			
	IFR (L)	MarginalLow(ML)	Marginal (M)	Optimal (H)
BOS	6	8/6	8	11
EWR	8	10/8	10	11
LGA	9	10/9	10	11
PHL	9	10/9	10	12
SFO	9	10/9	10	12

- End of Day (EOD): For all of the days, the model starts at 12:00AM and runs until 11:59pm. Thus, there are having a total of 96 time windows (each of 15 minutes) in a day. To handle late arrivals, the flights are allowed to spill over for 2 more hours (2:00AM next day) into the following day (104 time windows). Capacity for the additional time windows is the same as for the last time window of the actual day, and as there are no new flights scheduled at this time (since the model is set to work for only one day), the current day flights are allowed to spill over to the next day.

5.2.2 Alternative Approaches

To test the model, two alternative approaches, Ration-by-Schedule (RBS) and Ration-by Distance (RBD), that are well studied in the current literature are chosen so that the results of the new model can be compared against their results.

- Ration-by-Schedule(RBS): Ration-by-schedule is fully-described in Chapter 2. Basically, it assigns the flights based on a first-scheduled, first-served basis, i.e. priority is given to the ones that were scheduled earlier. Flights at the beginning of the GDP period (or more accurately, congested period) experience lesser delays compared to ones at the end.

- Ration-by-Distance(RBD): Similar to Ration-by-Schedule (RBS), this approach also assigns slots based on some ordering of the flights, however, in this case, priority is given to long-haul flights over short-haul flights. A greater circle distance (GCD) is used to sort flights. Similar to the RBS approach, substitution and compression can be performed after the RBD approach if cancelled flights exist in the system.

For either of these approaches, the modified version of the code developed by [Manley, 2008] is used. The modifications relate to exempted flights. For each GDP event, her code determines what flights are exempted from the GDP. In the case of RBS, it looks at the sector information and determines whether any flight belongs to the exempt sector and if so, that flight is assigned the earliest available slot. International flights are also handled in a similar fashion. For current experiments, since only commercial domestic flights are used, all the international flights and military flights are exempted beforehand by removing those slots ("Reserved Caps") from the overall capacity. Similarly for RBD, it is assumed that no long haul flights are exempted.

5.2.3 Performance Metrics

Finally, to determine performance metrics the major stakeholders and their interests are considered:

- Airlines: Airlines are one of the major stakeholders, and are the only stakeholder that in any GDP, make the decision of how to re-order flights during a GDP. For this analysis, the following metrics are chosen with respect to an airline's performance:
  - Final Profit: For each flight, the final profit is recorded after all of the fixed costs (e.g., operating costs) as well as the variable costs (e.g., delay cost and congestion price) are removed from the revenue of the flight. There are no equivalent costs for alternative rationing schemes except for the delay costs incurred by a flight and the cancellation cost (based on the cancellation model introduced in the previous chapter), in the case of cancellation. It is noted that a congestion pricing scheme, if implemented, would likely remove padding from the schedule. The

resulting profitability of a congestion pricing scheme is therefore underestimated.

For a noncancelled flight:

$$\text{Final Profit} = \text{Revenue - Fixed Cost - Delay Cost - Congestion Cost}$$

For a cancelled flight:

$$\text{Final Profit} = \text{Revenue - Fixed Cost - Cancellation Cost}$$

  - Congestion Pricing: A congestion price is recorded for each congested time period.
  - Seats OnTime: Seats OnTime is an important criteria for airlines that care about their ontime statistics. The number of seats (which is a surrogate for passengers) able to reach their destination without any scheduled delay is recorded.

- Air Traffic Flow Management (ATFM): Any policy to be implemented requires that the ATFM policy makers agree to use the allocation scheme. The following are the performance metrics ATFM is more interested in:
  - Number of Flights: Flight throughput is recorded since, from an airport or the Air Transportation Management(ATM) perspective, throughput is as important as the revenue generated.
  - Flight Delay: Flight delay is recorded for each flight in the new approach (in terms of difference between j and $t(k)$ for k^{th} flight). In the alternative approaches, it is computed from its scheduled time to its assigned controlled time of arrival (CTA).

- Passengers (PAX): The major performance metrics of concern to passengers are:
  - Number of PAX Flown: PAX throughput is most important criteria for passengers. Therefore PAX throughput is recorded, and if the flight gets cancelled, an

algorithm is used to relocate PAX from that flight to other flights of the same airline.[2]

– PAX Delay: PAX delay for a delayed flight is a multiple of its flight delay, however, the PAX Delay for a cancelled flight is a function of how early in the day the flight was scheduled. Earlier flight operators have greater opportunities to relocate passengers to other flights that day. If a passenger is not relocated, then a delay until 6 am next morning is assumed and accounted for.[3]

– PAX OnTime: PAX OnTime is another important criteria for passengers. Similar to Seats OnTime, the number of passengers who were able to reach their destination without any scheduled delay is recorded.

– Cancellations: The number of cancelled flights is recorded.

In addition to the aforementioned performance metrics, proportional equity with respect to airline and aircraft delays has been computed for the congestion pricing approach. In terms of runway access, equity measures whether costs or benefits are distributed fairly among the users when the arrival demand exceeds the capacity at an airport [Hoffman and Davidson, 2003].

Proportional Equity with respect to airline delay[4] is defined as:

$$\text{Proportional Equity for airline delay} = -\log_{10}\left(\frac{\text{airline delay}}{\text{total delay}} \Big/ \frac{\text{airline flights}}{\text{total flights}}\right) \tag{5.1}$$

Similarly, for aircraft delay:

$$\text{Proportional Equity for aircraft delay} = -\log_{10}\left(\frac{\text{aircraft delay}}{\text{total delay}} \Big/ \frac{\text{aircraft flights}}{\text{total flights}}\right) \tag{5.2}$$

[2] See [Manley, 2008] for details.

[3] As shown in [Manley, 2008].

[4] Logarithm is used to reduce the range and the negative sign is to convert the graph showing preferable airlines on the top.

Table 5.5: Design of Experiments per capacity level

Appr-oach	Caps	End of Day	l	Profit ($)	Average CP ($)	Max. CP ($)	Flight		PAX		Cancelled Flights	Seats OnTime	PAX OnTime
							Throughput	Delay (Mins.)	Throughput	Delay (Mins.)			
CP	(H,M,ML,L)	96	3hr										
RBD	(H,M,ML,L)	96	3hr										
RBS	(H,M,ML,L)	96	3hr										
CP	(H,M,ML,L)	96	5hr										
RBD	(H,M,ML,L)	96	5hr										
RBS	(H,M,ML,L)	96	5hr										
CP	(H,M,ML,L)	96	C										
RBD	(H,M,ML,L)	96	C										
RBS	(H,M,ML,L)	96	C										
CP	(H,M,ML,L)	104	3hr										
RBD	(H,M,ML,L)	104	3hr										
RBS	(H,M,ML,L)	104	3hr										
CP	(H,M,ML,L)	104	5hr										
RBD	(H,M,ML,L)	104	5hr										
RBS	(H,M,ML,L)	104	5hr										
CP	(H,M,ML,L)	104	C										
RBD	(H,M,ML,L)	104	C										
RBS	(H,M,ML,L)	104	C										

Table 5.5 shows the overall picture of the statistics gathered for each airport and approach.

5.3 Summary

This chapter described the design of experiments used to observe the performance of the proposed model. The input parameters are identified and the metrics of performance are defined. The next chapter discusses the results produced using the design of experiments explained in this chapter.

Chapter 6: Results

This chapter provides the results of the comparative analysis, and details the design of experiments described in the previous chapter. Section 6.1 shows the results when comparing the congestion pricing approach with the alternative approaches mentioned. Further statistics are then provided in Section 6.3 regarding the congestion prices as well as analysis of airline equity issues. Finally, Section 6.4 summarizes the results.

6.1 Design of Experiments: Results

In the previous chapter, three different input parameters are mentioned that can be used to perform sensitivity analysis to the congestion pricing approaches as well as other approaches.

The first of the variables types is the End of Day (EOD) parameter which increases capacity at the end of the day for all three approaches. Flights that go beyond the last time window will be considered cancelled by all the approaches. The second variable is the capacity. For this variable, the capacity is set at four different levels. Finally, the third variable to consider is the cancellation policy. Cancellation policy (l) defines how long a flight is allowed to be delayed before it gets cancelled.

Tables 6.1, 6.2, 6.3 and 6.4 show the final results of the design of experiments across all airports. Analysis of individual airports is discussed in Section 6.2.

Looking at the overall results, it is observed that the results are intuitive and support the theory that congestion pricing can allocate the limited capacity to those that value it the most. The following discussion looks at each of the performance metric separately.

Table 6.1: Summary of results for Optimum capacity (H)

Appr-oach	Caps	End of Day	l	Profit ($)	Average CP ($)	Max. CP ($)	Flight Throughput	Flight Delay (Mins.)	PAX Throughput	PAX Delay (Mins.)	Cancelled Flights	Seats OnTime	PAX OnTime
CP	H	96	3hr	373634821	59	8662	23012	26760	2067408	1550460	0	2402223	1967846
RBD	H	96	3hr	373260934	0	0	22966	79650	2063334	6728417	46	2223088	1833494
RBS	H	96	3hr	373082852	0	0	22980	83235	2063662	8378490	32	1995589	1637250
CP	H	96	5hr	373634821	59	8662	23012	26760	2067408	1548660	0	2402191	1967950
RBD	H	96	5hr	373333395	0	0	22980	82995	2064084	6342887	32	2223038	1833454
RBS	H	96	5hr	373082852	0	0	22980	83235	2063662	8378490	32	1995589	1637250
CP	H	96	C	373685140	60	8662	22985	26760	2065473	2572839	27	2399216	1965656
RBD	H	96	C	373333395	0	0	22980	82995	2064084	6342887	32	2223038	1833454
RBS	H	96	C	373082852	0	0	22980	83235	2063662	8378490	32	1995589	1637250
CP	H	104	3hr	373712708	41	294	23012	26760	2067408	1551165	0	2402191	1967812
RBD	H	104	3hr	373540126	0	0	22998	80370	2066658	5601257	14	2223088	1833494
RBS	H	104	3hr	373785165	0	0	23012	83715	2067408	7127130	0	1995589	1637250
CP	H	104	5hr	373712708	41	294	23012	26760	2067408	371235	0	2402191	1967986
RBD	H	104	5hr	373612588	0	0	23012	83715	2067408	5215727	0	2223038	1833454
RBS	H	104	5hr	373785165	0	0	23012	83715	2067408	7127130	0	1995589	1637250
CP	H	104	C	373763027	41	294	22985	26760	2065473	2573724	27	2399216	1965617
RBD	H	104	C	373612588	0	0	23012	83715	2067408	5215727	0	2223038	1833454
RBS	H	104	C	373785165	0	0	23012	83715	2067408	7127130	0	1995589	1637250

Table 6.2: Summary of results for Marginal capacity (M)

Appr-oach	Caps	End of Day	l	Profit ($)	Average CP ($)	Max. CP ($)	Flight Throughput	Flight Delay (Mins.)	PAX Throughput	PAX Delay (Mins.)	Cancelled Flights	Seats OnTime	PAX OnTime
CP	M	96	3hr	369370269	468	15020	23012	129075	2067408	7903725	0	2049394	1681618
RBD	M	96	3hr	371151747	0	0	22762	146205	2055698	14330387	250	2116662	1759461
RBS	M	96	3hr	372225502	0	0	22968	220695	2062142	21002295	44	1531358	1260254
CP	M	96	5hr	369779541	424	15020	23012	129435	2067408	7738695	0	2055638	1686818
RBD	M	96	5hr	371940940	0	0	22878	181095	2059924	12862487	134	2115801	1758922
RBS	M	96	5hr	372225502	0	0	22968	220695	2062142	21002295	44	1531358	1260254
CP	M	96	C	370361869	376	15020	22944	113100	2064487	8613659	68	2079060	1706415
RBD	M	96	C	372445030	0	0	22968	220305	2062354	12185942	44	2115706	1758864
RBS	M	96	C	372225502	0	0	22968	220695	2062142	21002295	44	1531358	1260254
CP	M	104	3hr	369572151	449	3772	23012	129075	2067408	7905090	0	2049376	1681418
RBD	M	104	3hr	371554689	0	0	22806	147255	2060752	12613547	206	2116662	1759461
RBS	M	104	3hr	373141360	0	0	23012	221355	2067408	19250175	0	1531358	1260254
CP	M	104	5hr	369987235	404	3263	23012	129435	2067408	7743375	0	2055620	1686661
RBD	M	104	5hr	372343882	0	0	22922	182145	2064978	11145647	90	2115801	1758922
RBS	M	104	5hr	373141360	0	0	23012	221355	2067408	19250175	0	1531358	1260254
CP	M	104	C	370565105	357	2956	22944	113160	2064487	8613104	68	2079400	1706591
RBD	M	104	C	372847973	0	0	23012	221355	2067408	10469102	0	2115706	1758864
RBS	M	104	C	373141360	0	0	23012	221355	2067408	19250175	0	1531358	1260254

Table 6.3: Summary of results for MarginalLow capacity (ML)

Appr-oach	Caps	End of Day	l	Profit ($)	Average CP ($)	Max. CP ($)	Flight Throughput	Flight Delay (Mins.)	PAX Throughput	PAX Delay (Mins.)	Cancelled Flights	Seats OnTime	PAX OnTime
CP	ML	96	3hr	338844291	2967	15020	22883	392010	2064670	23795066	129	1754175	1435281
RBD	ML	96	3hr	364792160	0	0	22206	197430	2030374	34630167	806	2031242	1694730
RBS	ML	96	3hr	366529090	0	0	22797	517470	2040064	56321805	215	1304414	1072761
CP	ML	96	5hr	338933900	2965	15020	22893	398310	2064920	21350109	119	1762190	1442019
RBD	ML	96	5hr	367580666	0	0	22535	315855	2046439	30529362	477	2024810	1690065
RBS	ML	96	5hr	366529090	0	0	22797	517470	2040064	56321805	215	1304414	1072761
CP	ML	96	C	364105853	835	15020	22571	264120	2054008	18546936	441	1824910	1495325
RBD	ML	96	C	369064159	0	0	22797	458130	2058817	27542082	215	2023992	1689444
RBS	ML	96	C	366529090	0	0	22797	517470	2040064	56321805	215	1304414	1072761
CP	ML	104	3hr	355975090	1394	6557	23012	461145	2067408	28173165	0	1729962	1414410
RBD	ML	104	3hr	365196602	0	0	22250	198480	2035428	32912247	762	2031242	1694730
RBS	ML	104	3hr	370103115	0	0	23012	530205	2067408	47908110	0	1304414	1072761
CP	ML	104	5hr	359534285	1105	5120	23012	461790	2067408	23393025	0	1741530	1424151
RBD	ML	104	5hr	368034492	0	0	22587	318480	2051669	28757442	425	2024810	1690065
RBS	ML	104	5hr	370103115	0	0	23012	530205	2067408	47908110	0	1304414	1072761
CP	ML	104	C	365087119	745	3343	22606	278850	2055869	18694391	406	1820161	1490986
RBD	ML	104	C	370686072	0	0	23012	530205	2067408	25390932	0	2023992	1689444
RBS	ML	104	C	370103115	0	0	23012	530205	2067408	47908110	0	1304414	1072761

Table 6.4: Summary of results for IFR capacity (L)

Appr-oach	Caps	End of Day	l	Profit ($)	Average CP ($)	Max. CP ($)	Flight Throughput	Flight Delay (Mins.)	PAX Throughput	PAX Delay (Mins.)	Cancelled Flights	Seats OnTime	PAX OnTime
CP	L	96	3hr	301259337	4927	23585	22232	366675	2043474	28256533	780	1608389	1323598
RBD	L	96	3hr	358145086	0	0	21591	227850	2001727	54340696	1421	1932005	1623994
RBS	L	96	3hr	349982926	0	0	21859	737130	1938670	115489680	1153	996742	825165
CP	L	96	5hr	301266422	4921	23585	22245	375180	2043882	27356309	767	1620725	1333849
RBD	L	96	5hr	359409475	0	0	21785	316155	2011229	52571926	1227	1928004	1620998
RBS	L	96	5hr	350195185	0	0	21859	761280	1940157	114745065	1153	996742	825165
CP	L	96	C	348956012	1681	23585	21831	207750	2017711	28582106	1181	1705355	1405166
RBD	L	96	C	359789164	0	0	21859	399705	2013415	52773226	1153	1927313	1620463
RBS	L	96	C	350195185	0	0	21859	761280	1940157	114745065	1153	996742	825165
CP	L	104	3hr	329642019	2756	11275	22795	683190	2063090	46722116	217	1502881	1233280
RBD	L	104	3hr	359022371	0	0	21681	231585	2011273	51174946	1331	1932005	1623994
RBS	L	104	3hr	363384779	0	0	22769	849540	2042390	88689375	243	996742	825165
CP	L	104	5hr	334208655	2487	11275	22795	685155	2062995	37079996	217	1522308	1249432
RBD	L	104	5hr	361611495	0	0	22017	352950	2028526	47657761	995	1928004	1620998
RBS	L	104	5hr	362697079	0	0	22769	897630	2037147	91192815	243	996742	825165
CP	L	104	C	358712476	978	3726	22230	387255	2044708	26466574	782	1632514	1341411
RBD	L	104	C	366434522	0	0	22769	788745	2064038	42144406	243	1927313	1620463
RBS	L	104	C	362697079	0	0	22769	897630	2037147	91192815	243	996742	825165

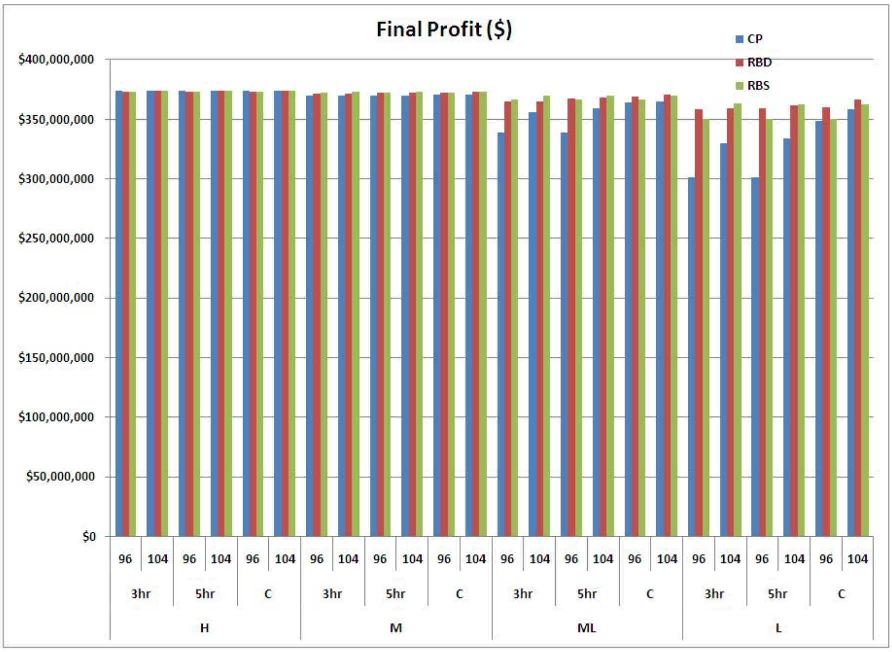

Figure 6.1: Final profit (all airports)

Figure 6.1 shows the final profit gained by all three different approaches. For optimal capacity (H), congestion was at a minimum and therefore there were few time periods where a congestion cost was imposed. Similarly, very few flights were delayed or cancelled; congestion pricing delayed 7% of the total flights and 0.1% flights were cancelled. RBS and RBD approaches delayed 22% and 14% flights respectively and 0.1% and 0.2% flights were cancelled respectively. Hence, the variable costs were low at such capacity levels resulting in a small amount of lost profit with any of the three approaches. At marginal levels (M), again most of the profits are maintained, however compared to optimal capacity level, the loss in profit is marginally higher, since the variable costs of congestion and delays have gone up. Particularly, the congestion price is costing more than the other two approaches; this is due to the extra congestion cost incurred by the carriers that is now charged by the governing authority. Other input parameters do not vary the results much at these capacity levels. However, for the Marginal Low (ML) and IFR levels (L) of capacity, all three approaches lose profit, with the congestion pricing approach losing the most (15% in cases where End of

Day (EOD) is set to midnight as compared to the alternative approaches). This is because, due to highly congested time periods, the congestion cost at those time periods have gone up resulting in a larger increase in variable costs. In RBS and RBD approaches, flight costs as well as cancellation costs are the reasons for the drop in profit. Changes in cancellation policy do not seem to have much effect except when a flight is allowed to be delayed more than 5 hours with a cancellation cost (case C). In this case, for RBS and RBD, the delay costs increase but in the cancellation case, the congestion pricing chose to cancel more flights since it is cheaper to do so compared to operating them (recovering profit levels similar to alternative approaches). Allowing flights to be delayed for 2 more hours at the end of day (case 104) allows the congestion pricing approach to recover some of the profit. The other two approaches do not vary much by other input parameters, except when there are lesser resources, RBD performs better because in RBD, when short haul flights run out of a resource, they get cancelled as opposed to all flights having equal access in RBS. However, since short haul flights are less profitable than long haul flights, RBD recovers more profit comparatively.

Figures 6.2 and 6.3 show flight throughput and passenger (PAX) throughput respectively. Again, as anticipated, except in the cancellation model cases, the CP approach performs better or within 2%-4% of RBS and RBD figures by these measures. This is because it maximizes profit by operating more flights and therefore, flight throughput is better than other approaches. However, in the cancellation cost models, operating a flight becomes more expensive than incurring a cancellation cost. This results in an increased number of cancelled flights and loss in passenger throughput. The impact is especially significant during IFR capacity level (L). Adding two more hours of capacity (case 104) increases flight throughput. PAX throughput has a similar behavior for the congestion pricing approach. However, for the other two approaches, RBS is better (or similar) in flight delay statistics, but performs badly with respect to passenger throughput. This is because generally long haul flights are larger fleets with higher load factor, and in RBD more passengers fly even though RBS operates more flights.

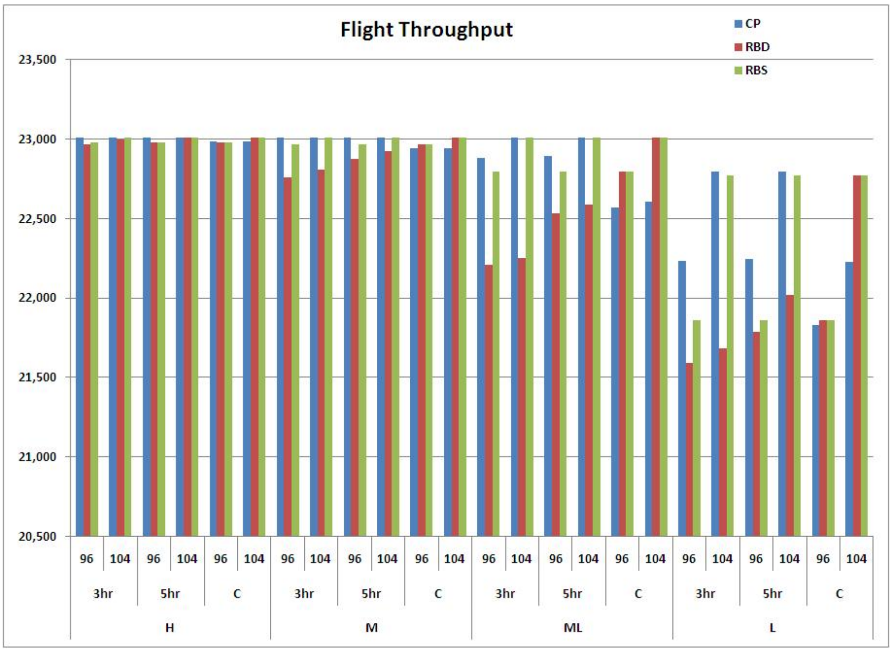

Figure 6.2: Flight throughput(all airports)

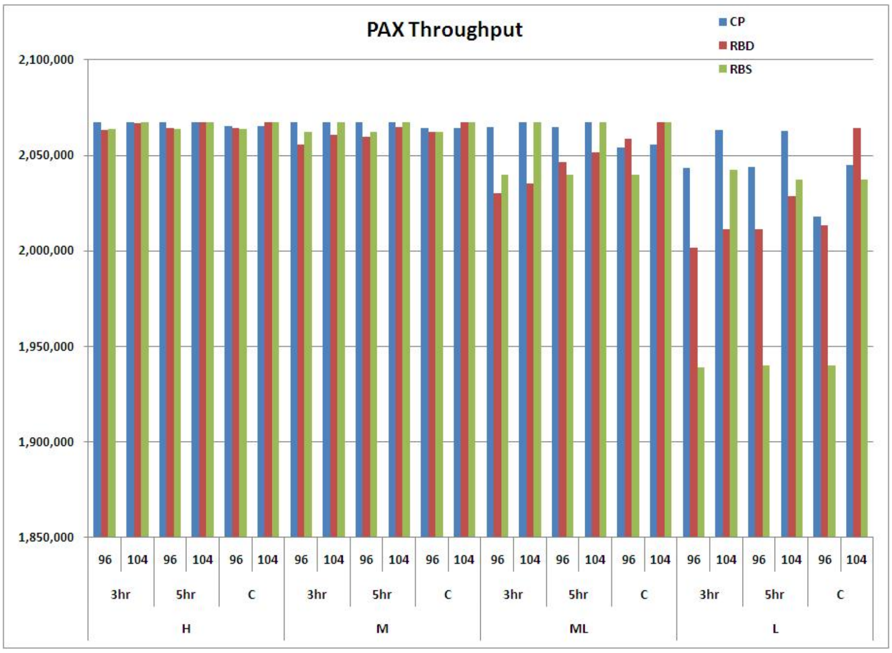

Figure 6.3: Passenger throughput (all airports)

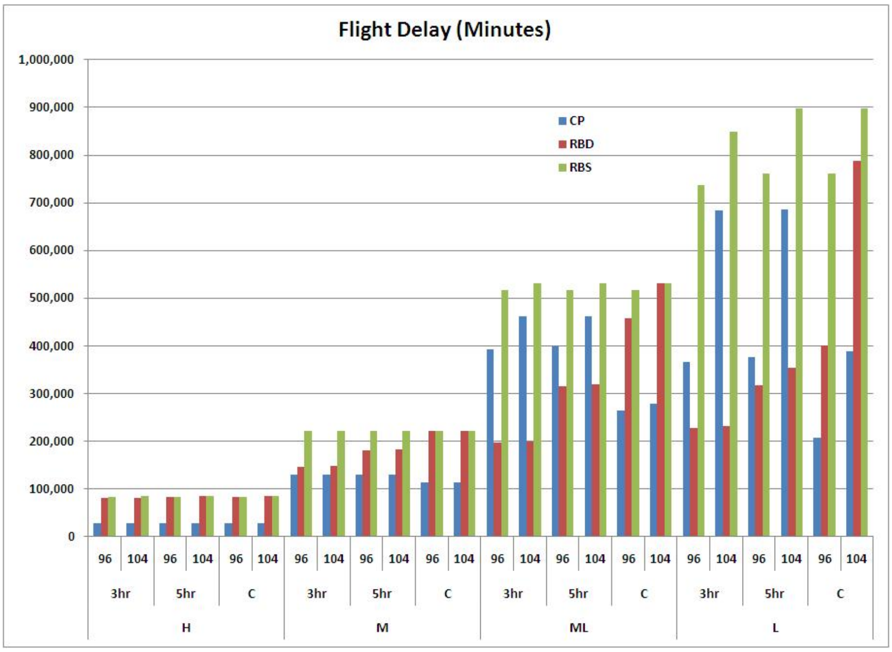

Figure 6.4: Flight delay in minutes (all airports)

Figures 6.4 and 6.5 show flight delay and passenger (PAX) delay respectively. For flight delays, CP performs better when the capacity levels are high (greater than 50% better than other approaches) or when the cancellation cost model is used. For the lower capacity levels (i.e., ML and L), RBD performs better than others (in some cases, RBD performs three times better than the CP approach). However, for PAX delay the CP approach is better. This is because there is a large number of cancellations by the RBD approach, having better performance for flight delays, but also large a number of stranded or relocating passengers, thereby increasing passenger delay. RBS performs worse in both performance metrics. The RBS approach tries to distribute delay evenly to all flights, hence all flights are equally delayed, irrespective of their profitability or route. CP performs very well when looking at the passenger delay. Passengers delays were reduced on average from 50% in case of RBD to approximately 80% with respect to RBS in worst scenarios.

Figure 6.6 shows the number of cancelled flights. Intuitively, reduction in capacity will increase cancellations due to lack of resources. Therefore, at IFR levels the cancellations

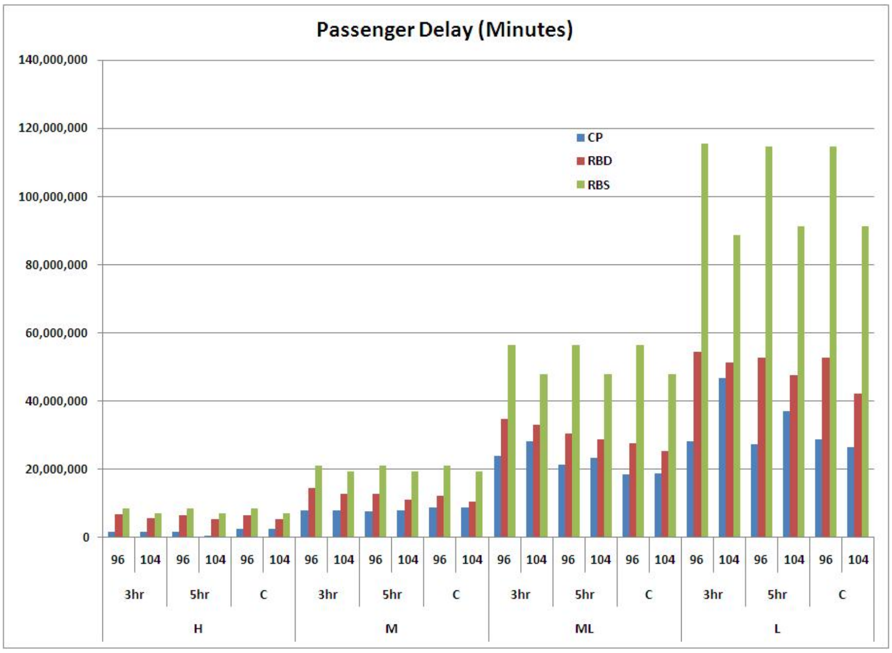

Figure 6.5: Passenger delay in minutes (all airports)

are highest. In the case of the restrictive cancellation policy, RBD cancels more flights because it delays regional flights which after 3 hour or 5 hour delays are cancelled by this approach. In the third case, RBS and RBD incur the same number of cancellations. CP has the least number of cancellations in the restrictive cases, greater than 50% less than the RBS approach and within 20%-40% with respect to the RBD approach. This is because it optimizes the slot allocation by maximizing profit. Cancelled flights mean lost profit. However, when compared to incurring a cancellation cost in the cancellation model case, it becomes more profitable to cancel a few flights while reducing the overall congestion. In one of the IFR capacity scenario, 2% cancellations recovered almost all of the profit. The restrictive cases of cancellation policy do not differ much by allowing two more hours of delay.

Figures 6.7 and 6.8 show the number of seats on time and number of passengers on time respectively. In the optimal capacity scenario (H), the CP approach performs 20% better than the RBS approach and 10% better than the RBD approach, however, in all other

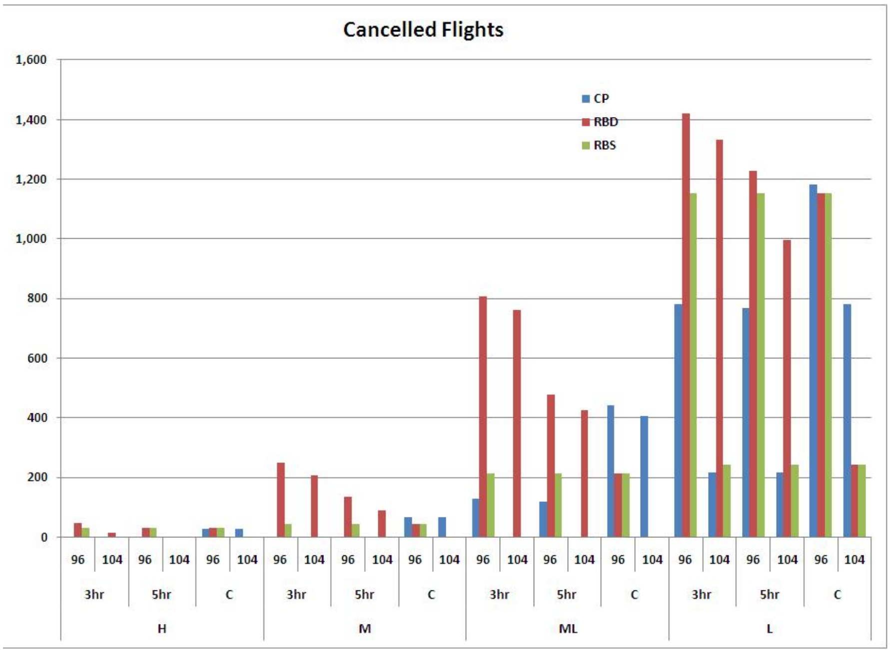

Figure 6.6: Cancelled flights(all airports)

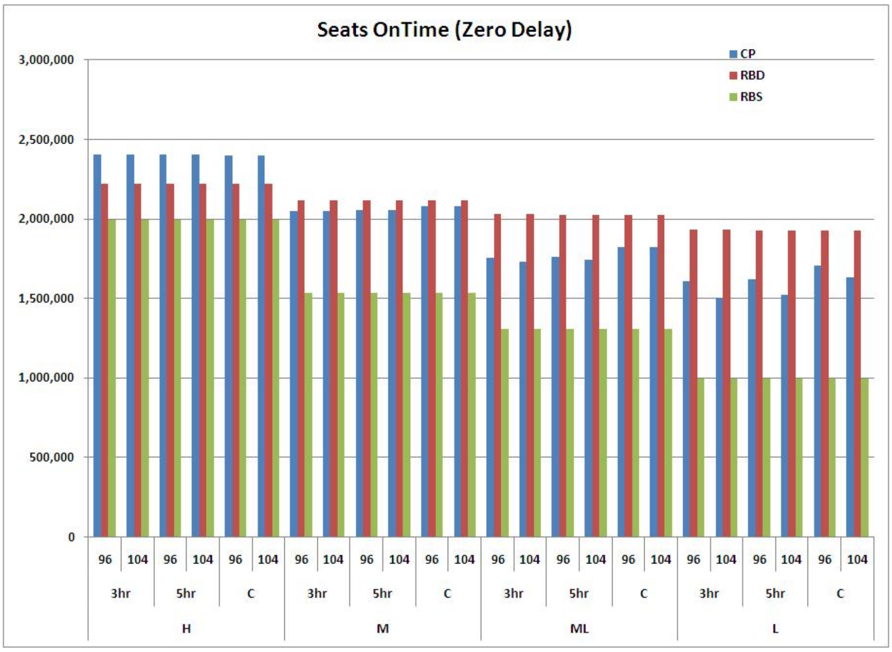

Figure 6.7: Seats ontime (all airports)

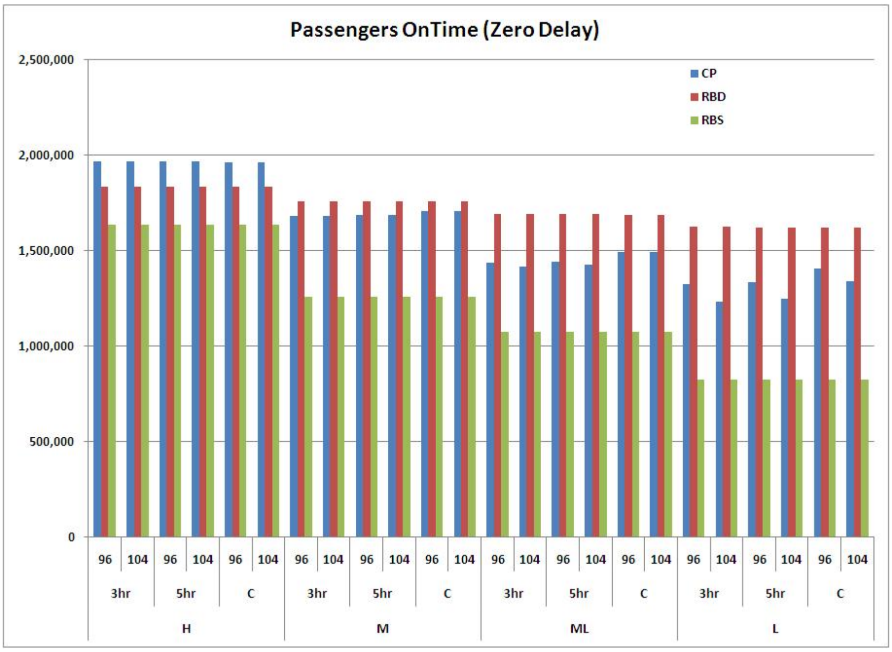

Figure 6.8: Passengers ontime (all airports)

capacity scenarios, the RBD approach performs 10%-20% better than the CP approach. However, the CP approach gives better PAX throughput, indicating that even if not many passengers are ontime, most passengers eventually reach their destination when the resources are allocated based on the CP approach. RBS performs uniformly worse than either RBD or CP in both of these performance metrics, implying that, at least for passengers, RBS performs poorly. PAX delay is evenly distributed with CP approach.

6.2 Airport Analysis

The following shows the results of the comparative analysis for each individual airport. Similar charts as the one discussed above are presented for each airport separately. In addition to these charts, a comparison between the revenue generated using a congestion pricing approach versus revenue generated by weight-based landing fee is also shown.

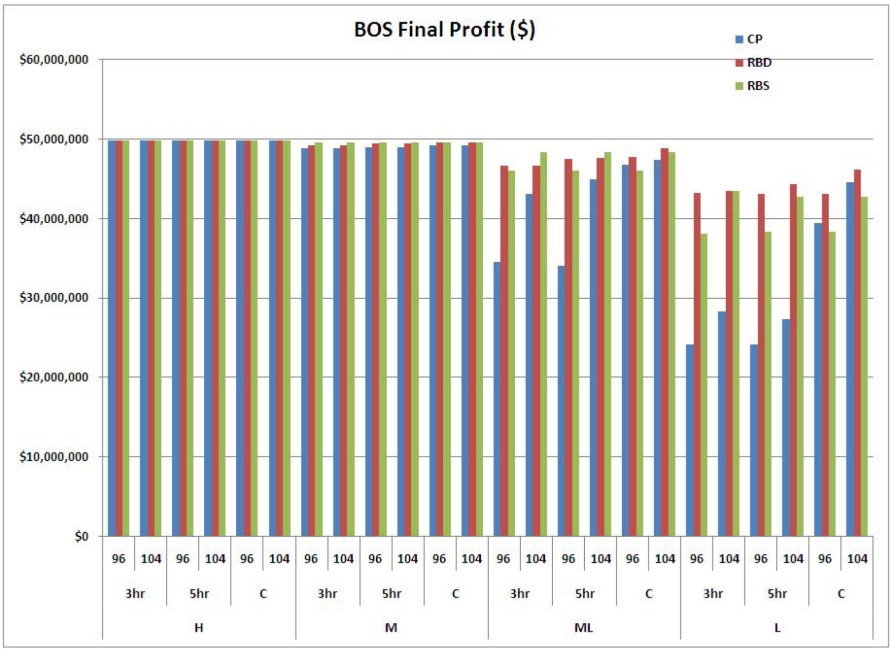

Figure 6.9: Final profit (BOS)

6.2.1 Boston Logan Airport (BOS)

Figures 6.9 through 6.16 show the performance measures for Boston airport (BOS). The profit trend (Figure 6.9) is similar to the aggregate behavior observed for all flights across all airports.. With the lower two capacity cases, the total profit for all flights is lower for congestion pricing than in the RBS and RBD approaches due to congestion prices. In the cancellation model cases (C), the profit goes up, since it is cheaper to cancel flights rather than flying them.

Figure 6.10 shows the flight throughput at BOS for the selected days in July 2007. Here, too, the behavior is similar to the aggregate behavior with the CP approach performing slightly worse in the case of the cancellation model. Figure 6.11 shows the passenger throughput. At BOS, the CP approach is better in PAX throughput except for the cancellation model cases where RBD performs slightly better. RBS, however, gives the worst performance for passenger throughput despite having better flight throughput.

Figure 6.12 shows flight delays in minutes at BOS. There are no delays in the optimal

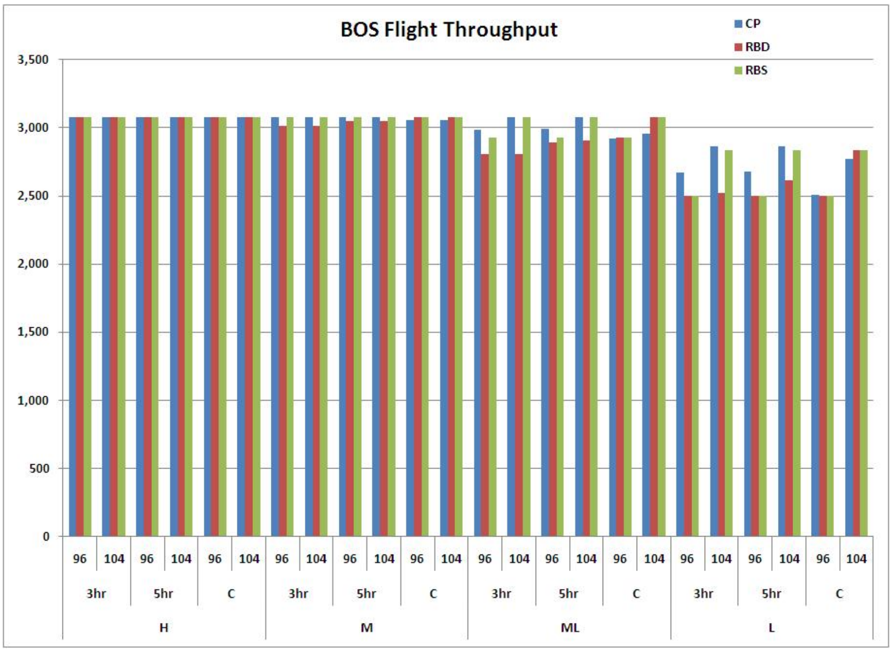

Figure 6.10: Flight throughput (BOS)

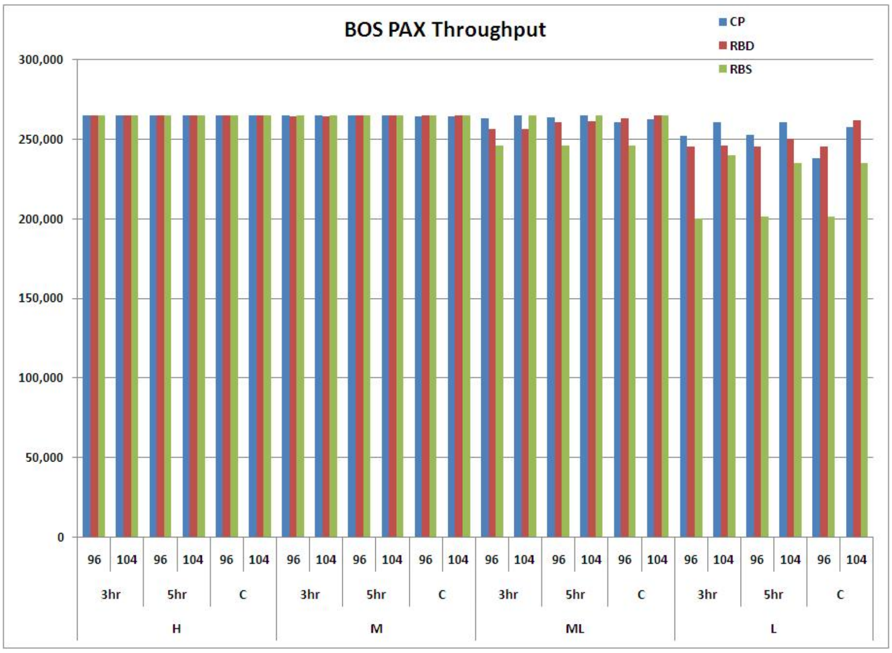

Figure 6.11: Passenger throughput (BOS)

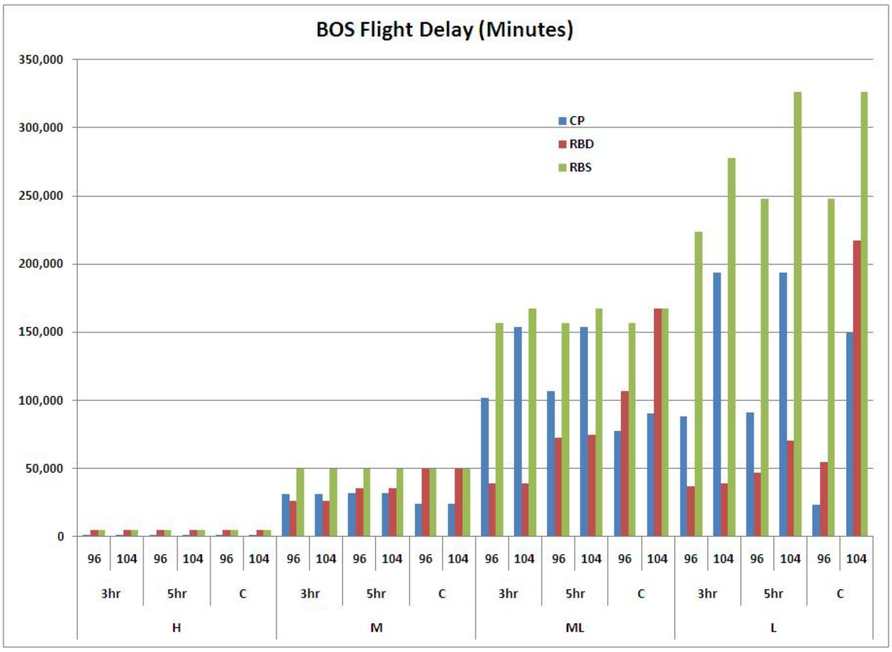

Figure 6.12: Flight delay (BOS)

capacity (H)[1]. Except for the cancellation model cases, where CP performs better (since cancelled flights incur zero delay), RBD leads both in Marginal Low (ML) and IFR (L) capacity scenarios.

Figure 6.13 shows the passenger (PAX) delay metric at BOS. At Marginal (M) capacity level, RBD outperforms the CP approach slightly, however in worst capacity scenarios, the CP approach performs better in PAX delay even when using the cancellation model and reducing the number of flight throughput. RBS performs worse in PAX delay statistic when capacity levels go beyond Marginal (M) and towards IFR (L).

Figure 6.14 shows the number of cancelled flights at BOS. The CP approach cancels flights at all cancellation model cases (even in optimal capacity scenario [H]), however, it cancels the least number of flights when there is a restriction on how long can a flight be delayed at an airport, implying that it tries to reduce stranded flights compared to other approaches.

[1]In the case of the congestion pricing approach, no flight delays are observed, however, for the other two approaches, a small amount of delay is observed due to a difference in allocation.

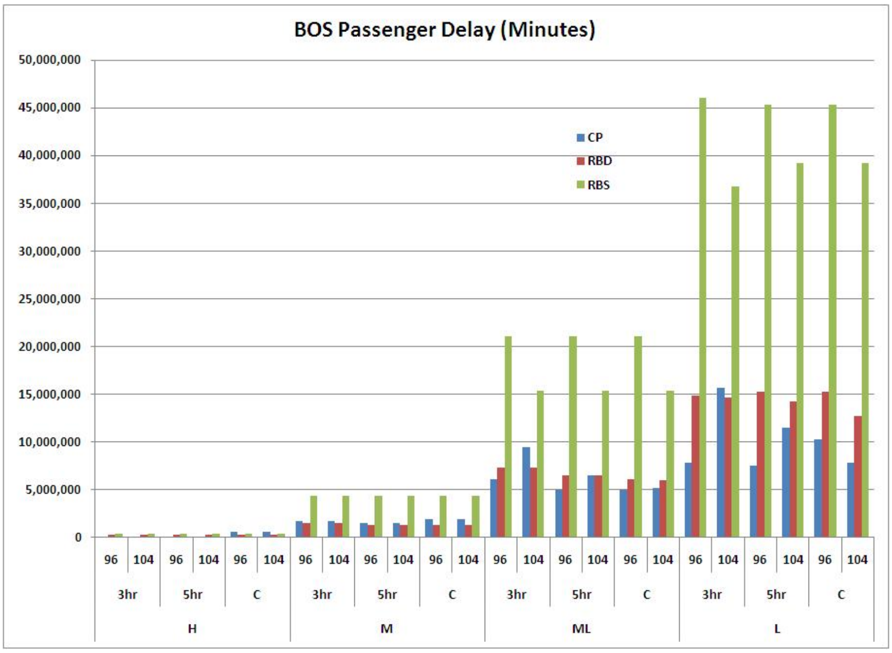

Figure 6.13: Passenger delay (BOS)

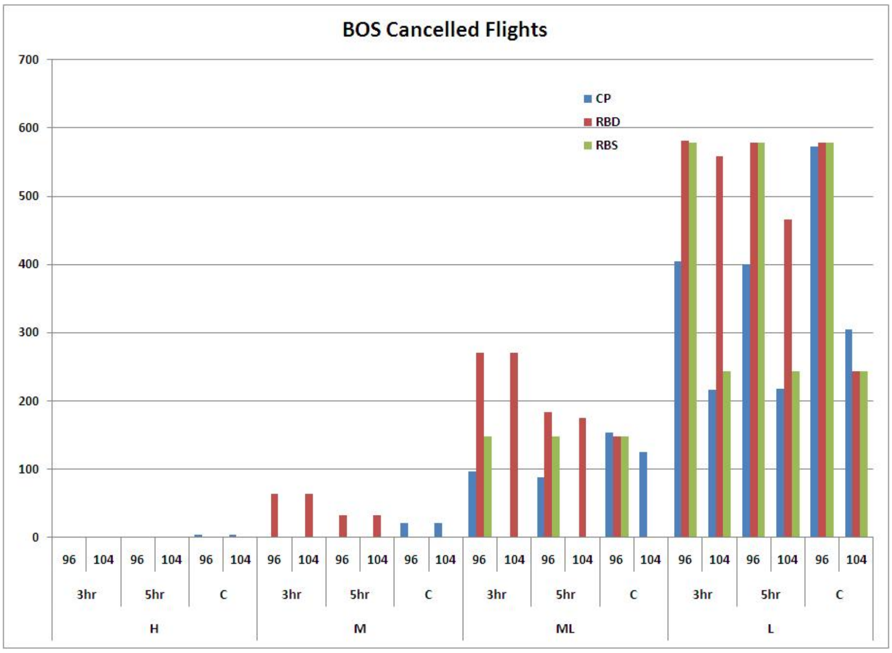

Figure 6.14: Cancelled flights (BOS)

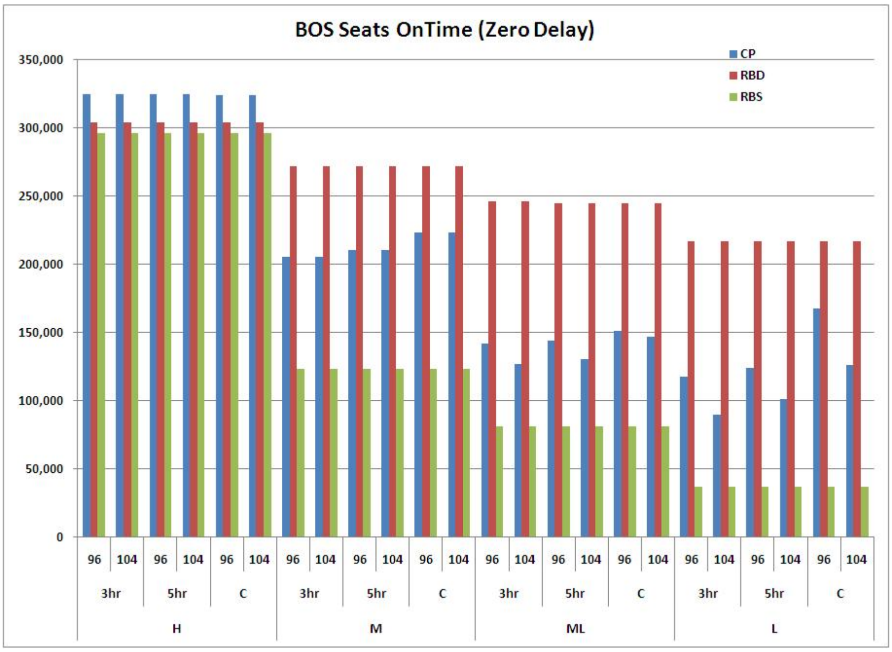

Figure 6.15: Seats ontime (BOS)

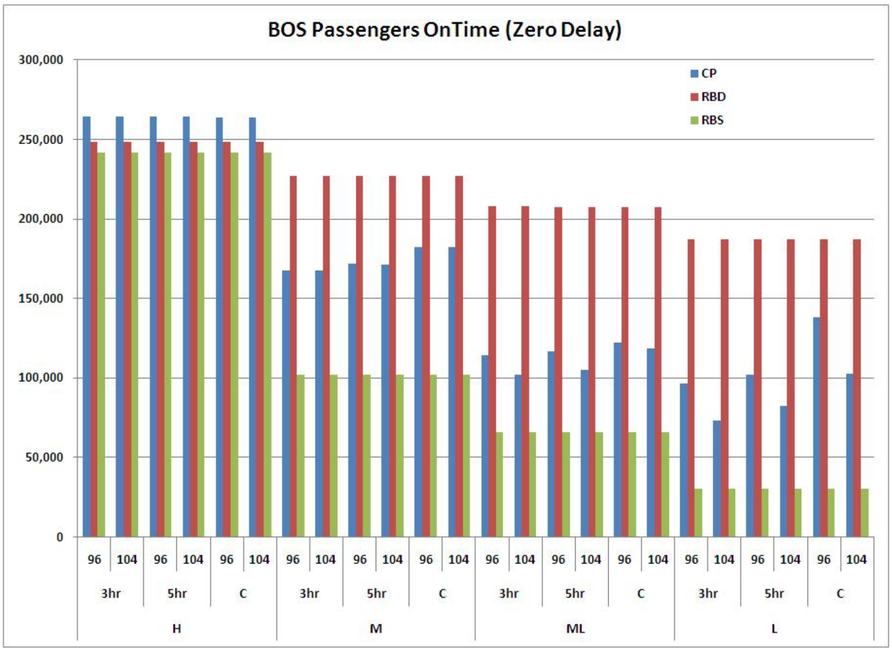

Figure 6.16: Passengers ontime (BOS)

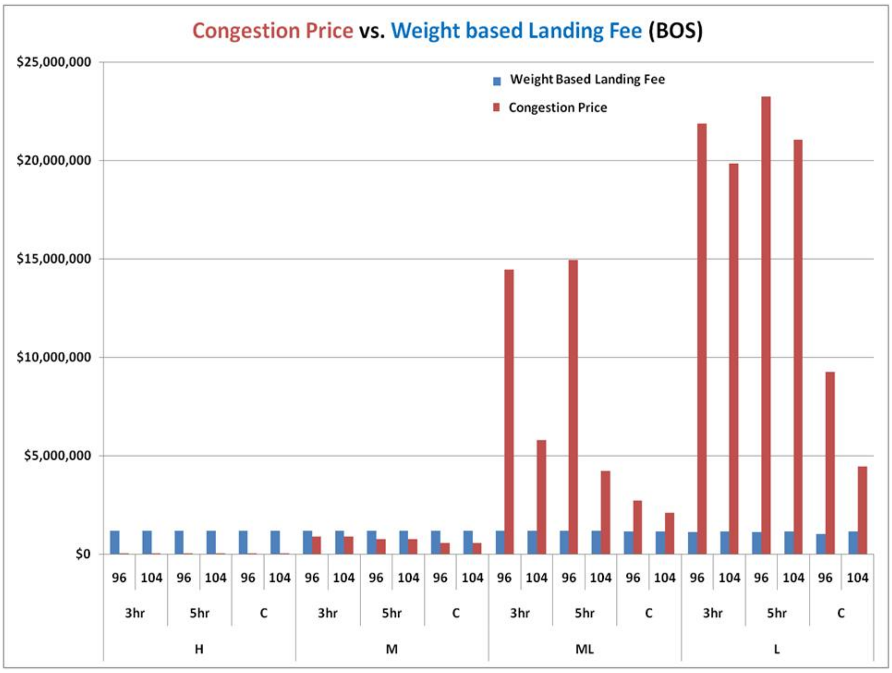

Figure 6.17: Revenue generated by Weight-Based Landing Fee vs. Congestion Price (BOS)

Figures 6.15 and 6.16 show the number of seats on time and passengers on time statistics. Similar to aggregate behavior, the RBD performs better with both most number of seats and passengers on time, however the PAX throughput is poor, arguing that CP is more fair with respect to passengers, at least at BOS airport.

Figure 6.17 shows the revenue generated by the congestion price versus the revenue generated by the current weight-based landing fee. At BOS, during the lower capacity levels (i.e., Marginal Low and IFR levels), the revenue generated by the new approach will be much higher than the current revenue generated. This means that at BOS the CP approach would not be revenue neutral if the airport experiences IFR conditions much of the time. However, if similar to July 2007 actual GDP occurrences, then by removing weight-based fees (or lowering them to a marginal amount), a CP-based pricing system can be created that is revenue-neutral.[2]

[2]Further analysis on average revenue per day is provided in Appendix E.

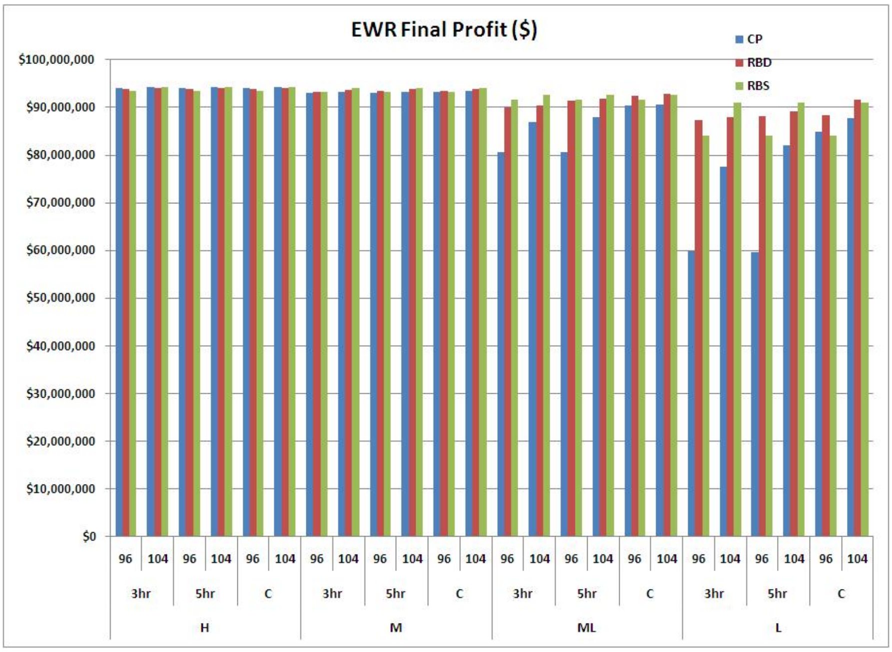

Figure 6.18: Final profit (EWR)

6.2.2 Newark Liberty International Airport (EWR)

Figures 6.18 through 6.25 show the performance metric at EWR airport. Figure 6.18 shows the total profit of flights at EWR. Except for the restrictive cases with the deadline set at midnight (EOD = 96) at the IFR capacity level (L), more than 86% of the total profit is recovered by the CP approach (even with the congestion price). The two anomalies indicate that a larger number of flights are scheduled later in the day at EWR, therefore, cancelling all flights after midnight has a greater impact at EWR than any other airport.

Figure 6.19 shows the flight throughput at EWR. The CP approach performs better except when the cancellation cost model is used. RBD performs worst when flights are not allowed to be delayed for more than 3 or 5 hours. All three approaches cancelled flights when there is a midnight (EOD = 96) deadline as compared to 2 am deadline (EOD = 104), referring again to flights scheduled to arrive later in the day at EWR.

Figure 6.20 shows the passenger throughput at EWR. For CP approach, the cancellation model case chooses to cancel more flights, however, with the midnight deadline at IFR

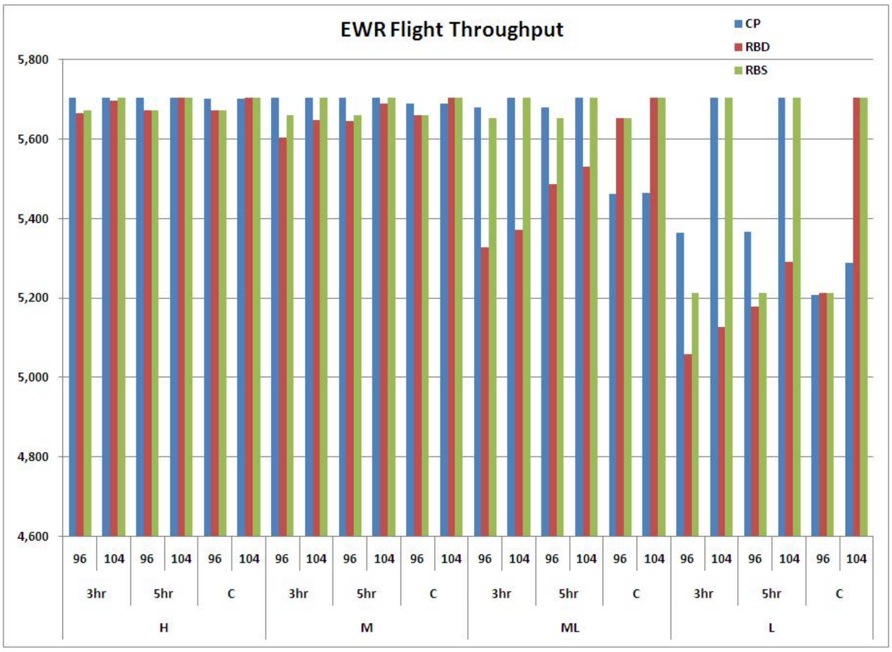

Figure 6.19: Flight throughput (EWR)

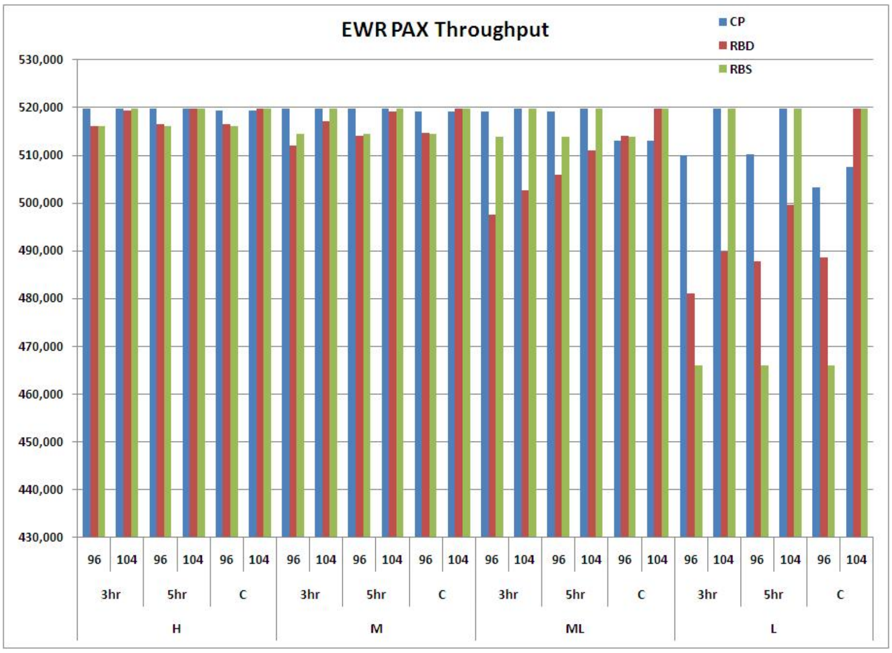

Figure 6.20: Passenger throughput(EWR)

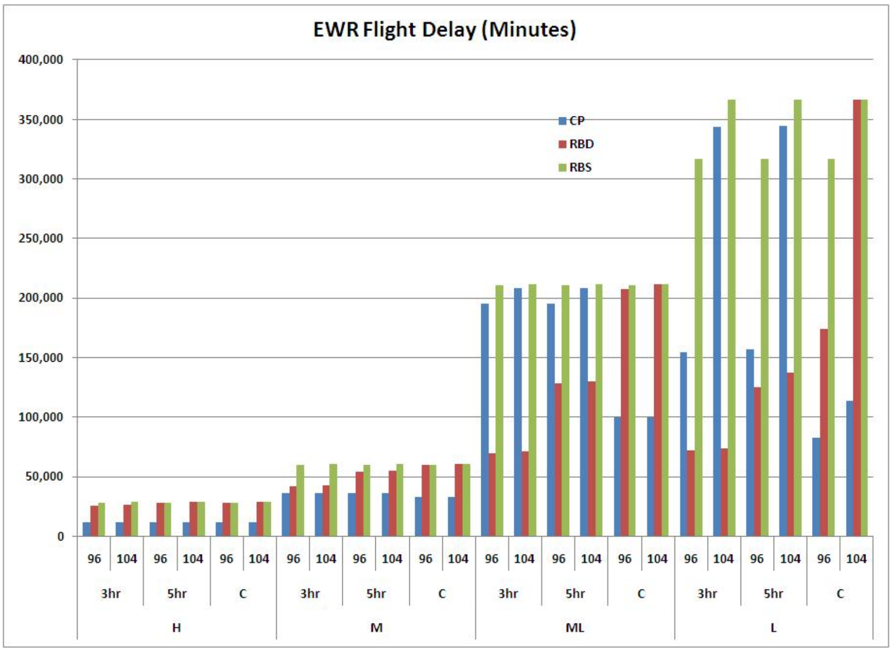

Figure 6.21: Flight delay (EWR)

capacity scenario, RBS performs poorly indicating that RBS allocation is bad for PAX throughput at airports like EWR (with later-in-the-day arrivals). By adding the two hours at the end of the day (till 2 am), the performance of both CP and RBS improves relative to passenger throughput, however RBD does not change much.

Figure 6.21 reports flight delays in minutes at EWR. RBD performs better in a flight delay metric than the congestion pricing approach, except for the cancellation model case, where more flights are cancelled by the model to reduce overall flight delays.

Figure 6.22 shows the passenger delays at EWR. Here, PAX delay is least in the cancellation model case, implying that even though more flights are cancelled, passengers are able to get to their destinations using alternate flights. The CP approach performs better than both RBS and RBD in all cases.

Figure 6.23 shows the number of cancelled flight at EWR. RBD cancels more flights in most of the cases, however, with cancellation model, the CP approach cancels more flights because it is more profitable to cancel a flight in those cases instead of paying a higher

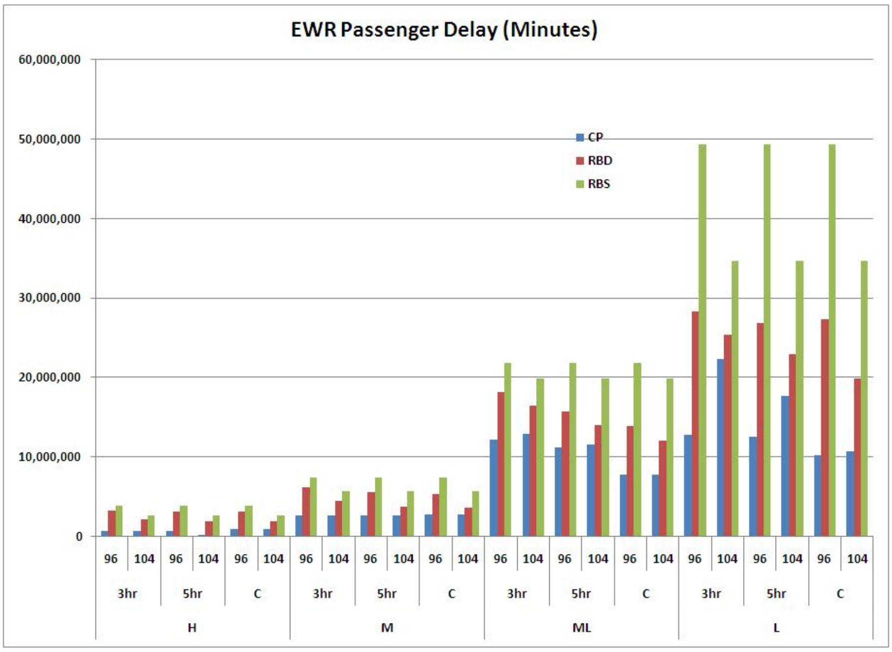

Figure 6.22: Passenger delay (EWR)

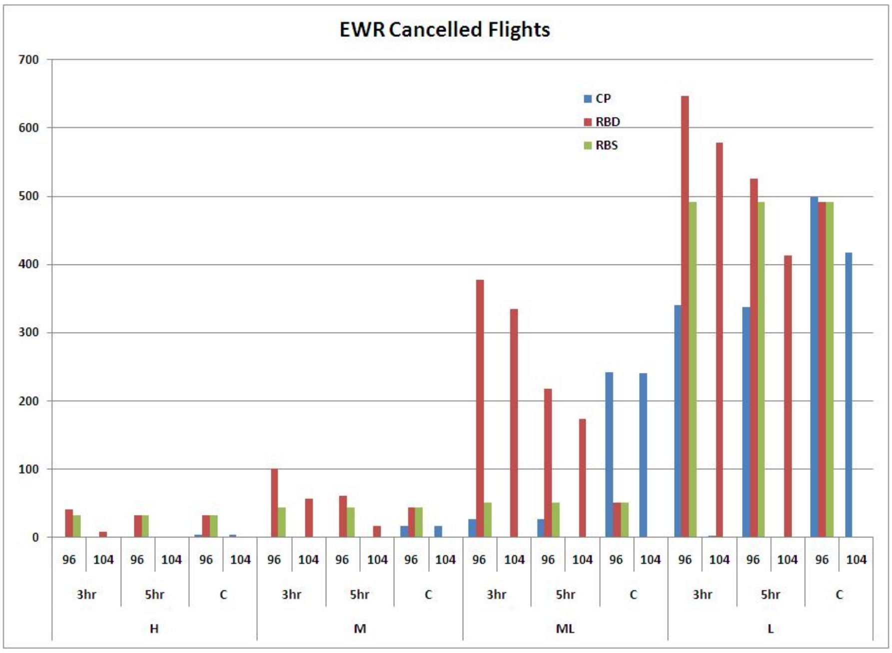

Figure 6.23: Cancelled flights (EWR)

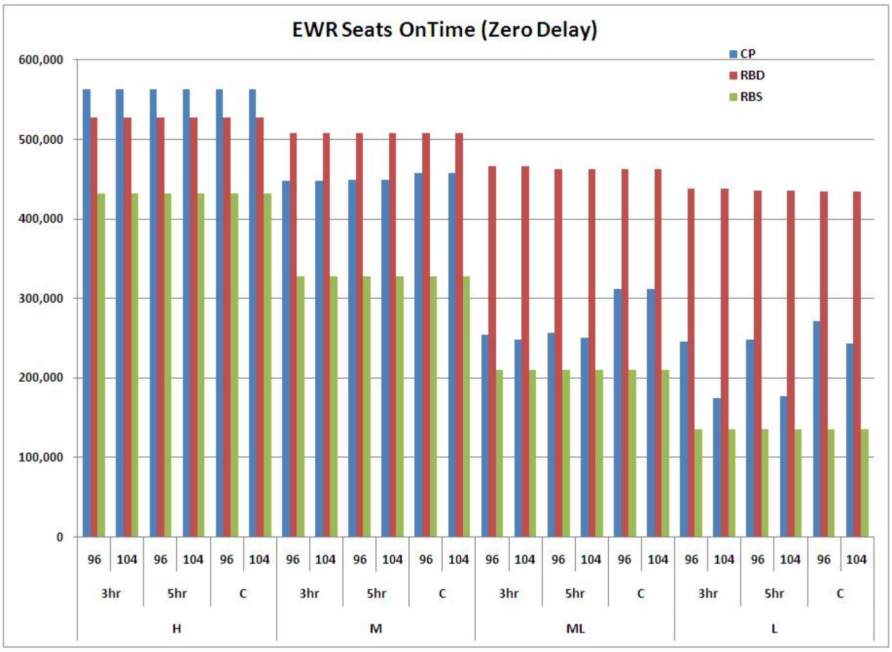

Figure 6.24: Seats ontime (EWR)

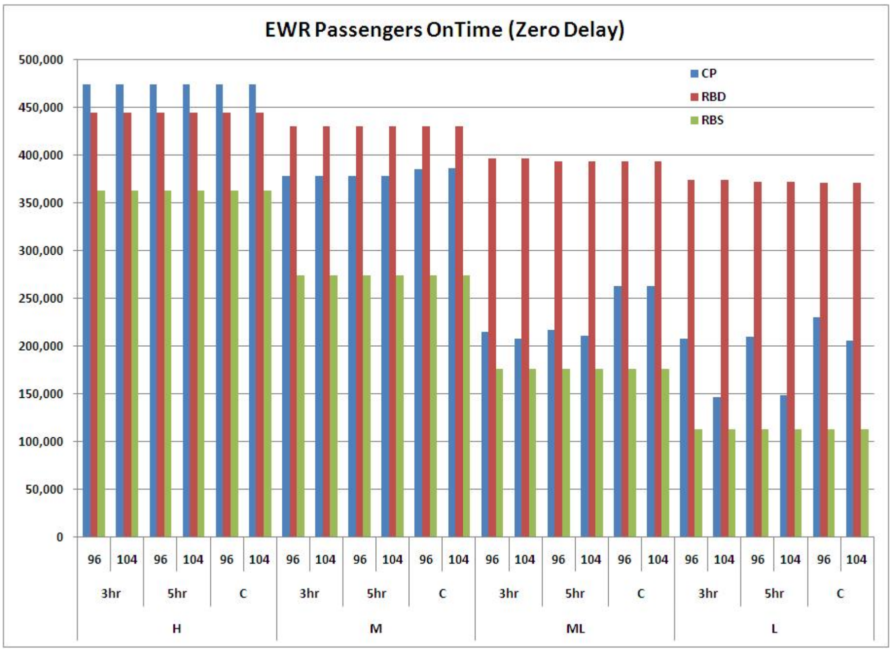

Figure 6.25: Passengers ontime (EWR)

price.

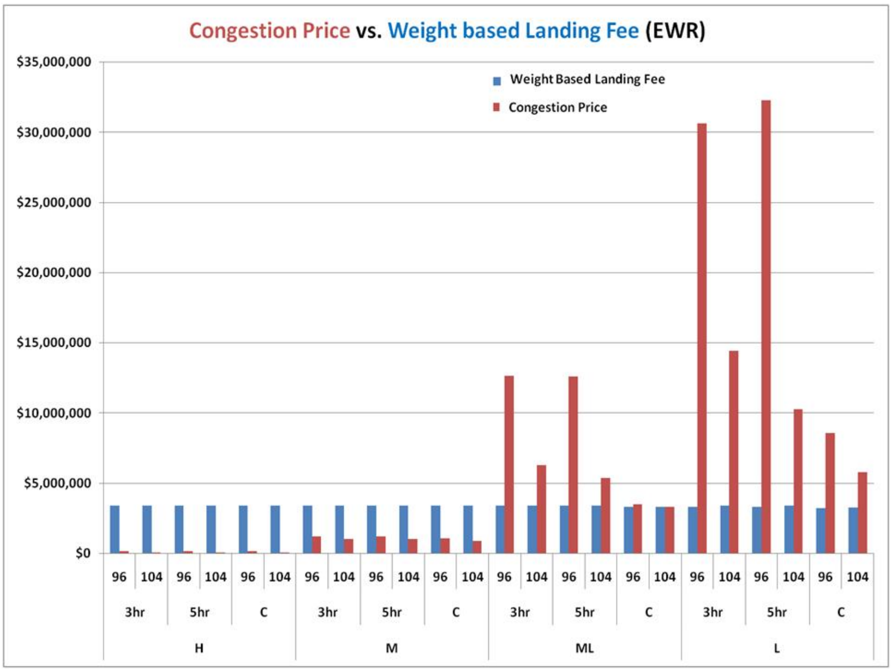

Figure 6.26: Revenue generated by Weight-Based Landing Fee vs. Congestion Price (EWR)

Figures 6.24 and 6.25 show seats ontime and passengers ontime for EWR. The behavior is similar to the aggregate level; RBD performing better than CP and RBS approach. However, as reported, the number of flights cancelled by RBD is also higher and PAX throughput lower, implying that using RBD approach few people were provided services while a larger percent of people were stranded or delayed.

Figure 6.26 shows the revenue generated by the congestion price versus the revenue generated by the current weight based landing fee. At EWR, similar to BOS during the lower capacity levels (i.e., Marginal Low and IFR levels), the revenue generated by the congestion pricing approach will be much higher than the current revenue generated.[3] However, in the case of the cancellation model, the differences in revenue is lower than in other restrictive cases. Similar to BOS, EWR will not provide a revenue neutral scenario to apply congestion prices if IFR conditions occur much of the time. but compared to BOS, at EWR adding

[3]Further analysis on average revenue per day is provided in Appendix E.

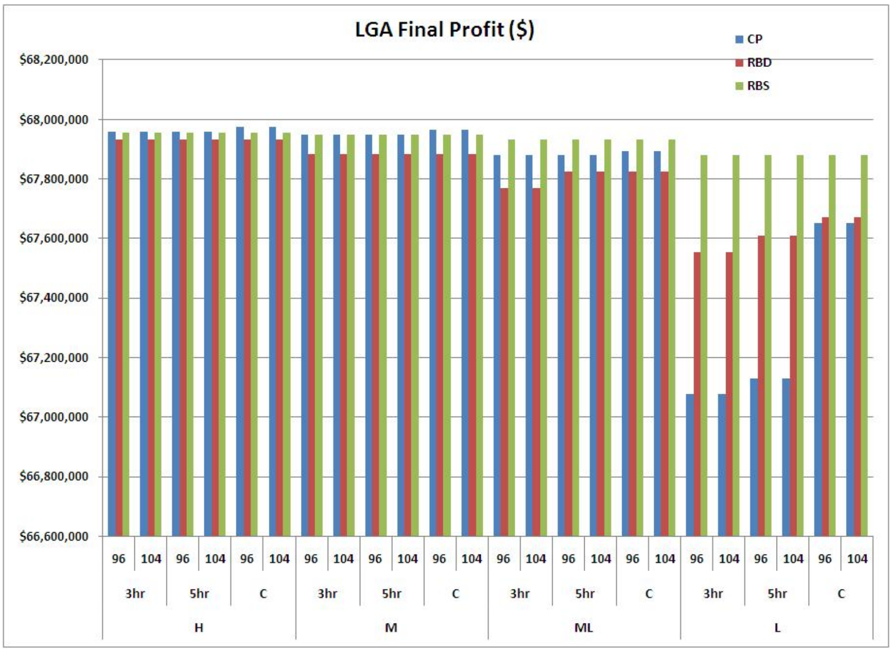

Figure 6.27: Final profit (LGA)

two more hours at the end of the day has a larger effect in reducing the congestion prices.

6.2.3 LaGuardia Airport (LGA)

Figures 6.27 through 6.34 show the statistics for flights arriving at LGA.

Figure 6.27 shows the total profit at LGA. At the IFR capacity level (L), the CP approach performs worst. This is due to many profitable flights competing for the resources, hence larger congestion prices and lower profits. Allowing the flights to be delayed longer than 3 hours (i.e., for 5 hours) slightly increases the profit. The cancellation model, however, generates better profit by cancelling more flights and reducing the competition.

Figure 6.28 shows the flight throughput at LGA. Flight throughput is 100% except for the cancellation model case. RBD cancels flights in the restrictive cases since there are short-haul flights that it keeps cascading until they cancel due to the deadline. The two hour extension at the end of the day has no effect in any of these approaches indicating that most of the congestion is reduced before midnight and therefore, none of the extra resources

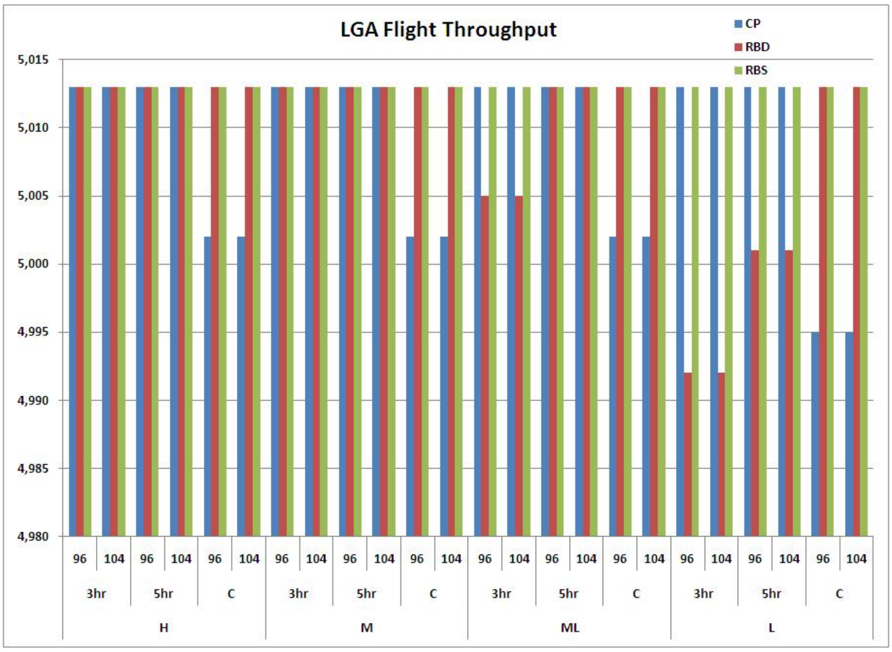

Figure 6.28: Flight throughput (LGA)

are used. This also indicates that there is sufficient capacity at the airport to handle these flights, however, the timing of flights results in poor performance.

Figure 6.29 shows passenger throughput for flights arriving at LGA. This is similar to flight throughput; passenger throughput is 100% except in the cancellation cost model case, where it is cheaper to cancel a flight rather than flying it.

Figure 6.30 reports the flight delay at LGA. The CP approach reports the least flight delays, almost a 50% better performance than either of the other two approaches.

Figure 6.31 shows the passenger delay at LGA. Again, this is similar to flight delay; the CP approach allocates resources such that both flight delays and passenger delays are reduced. RBS performs worst with respect to passenger delay, indicating that the current allocation scheme is worst for passengers (among the currently studied approaches).

Figure 6.32 shows the cancelled flights at LGA. The CP approach cancels flights only in the cancellation model to avoid larger congestion prices. RBD cancelled flights when short haul flights ran out of their limits to be further delayed.

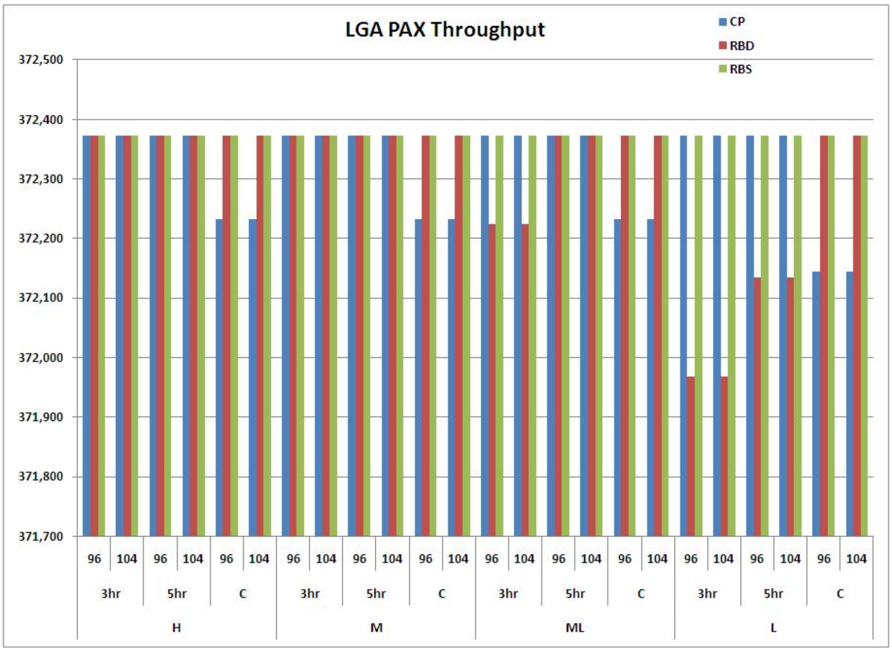

Figure 6.29: Passenger throughput(LGA)

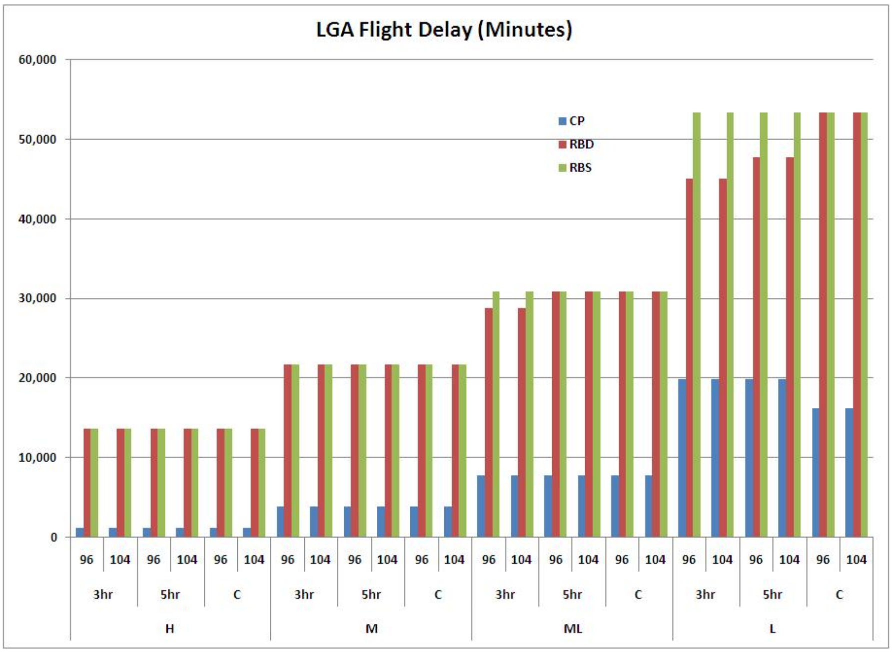

Figure 6.30: Flight delay (LGA)

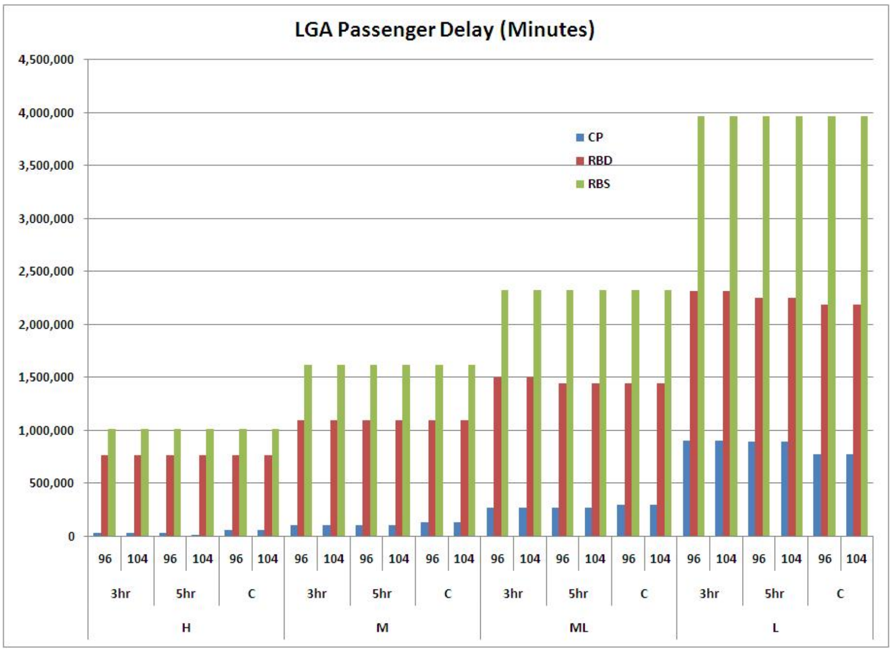

Figure 6.31: Passenger delay (LGA)

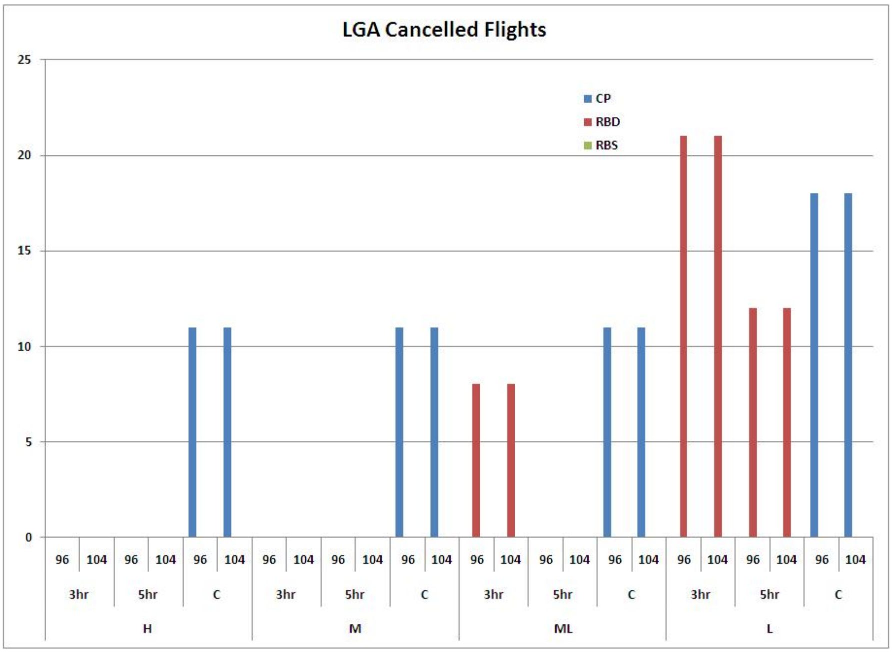

Figure 6.32: Cancelled flights (LGA)

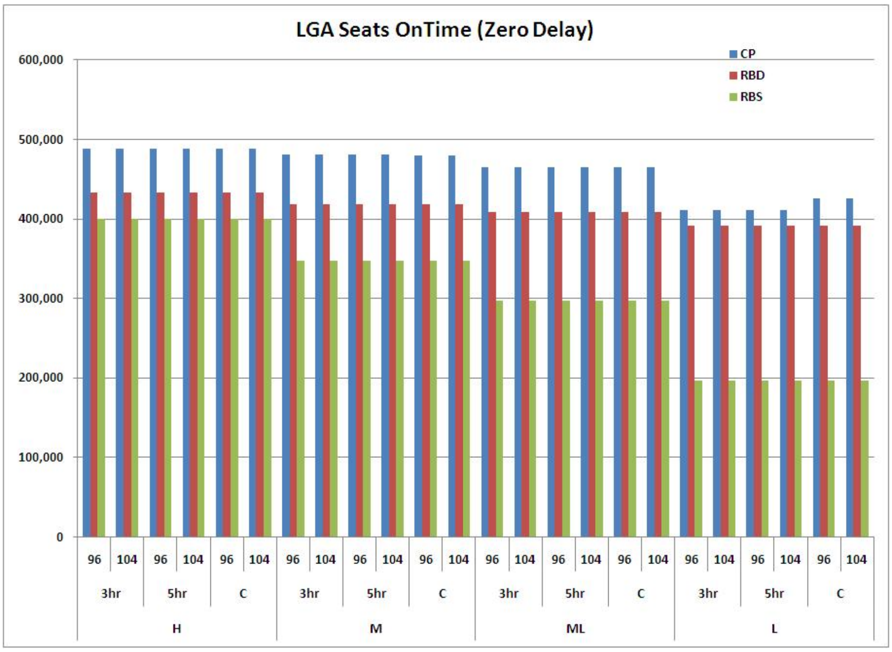

Figure 6.33: Seats ontime (LGA)

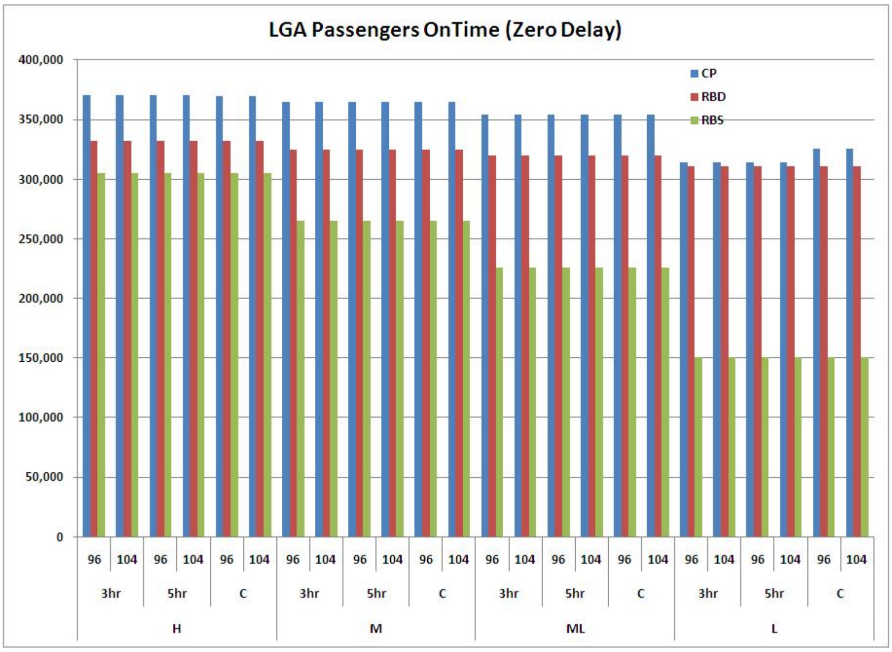

Figure 6.34: Passengers ontime (LGA)

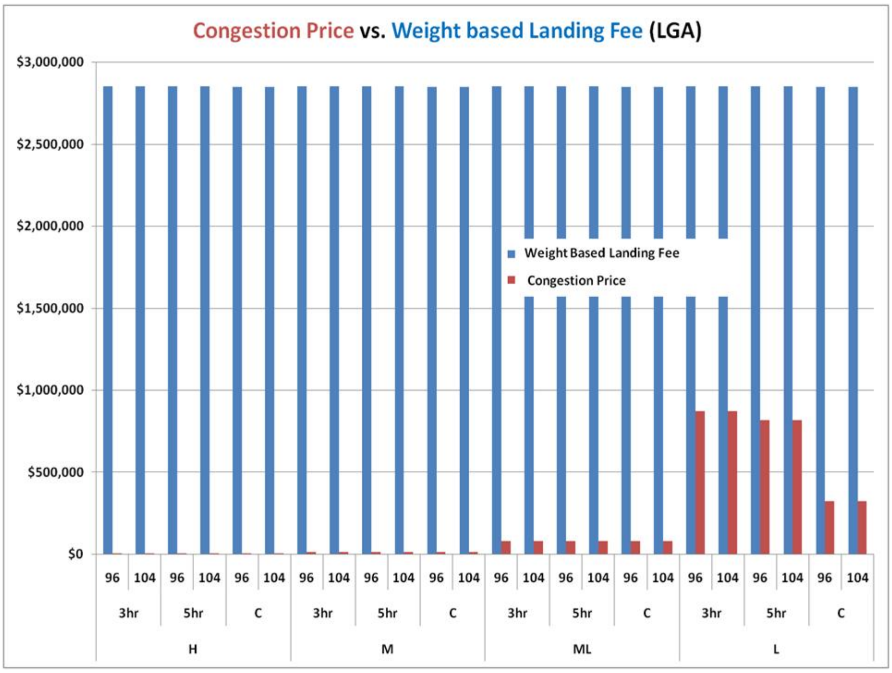

Figure 6.35: Revenue generated by Weight-Based Landing Fee vs. Congestion Price (LGA)

Figures 6.33 and 6.34 show seats and passengers ontime respectively at LGA. This is one of the airports where the CP performs better than RBD. RBS remains the worst performer. The better performance of the congestion pricing approach indicates that, given sufficient resources to accommodate all flights, the CP approach will also maximize ontime performance ratings.

Figure 6.35 shows the revenue generated by the congestion pricing approach versus the revenue generated by the current weight-based landing fee. In the case of LGA, the congestion reported was lower as all the flights were able to get runway access, therefore, for the days under study, the revenue generated by congestion prices is negligible compared to the revenue generated by the current weight-based landing fee.[4] A point to note is that at LGA, the charges are $6 per 1000 lbs. making it one of the expensive airports with respect to landing fees. Using the cancellation cost model reduces the number of flights, hence, lowering the total profit of the airlines with a congestion pricing approach.

[4]Further analysis on average revenue per day is provided in Appendix E.

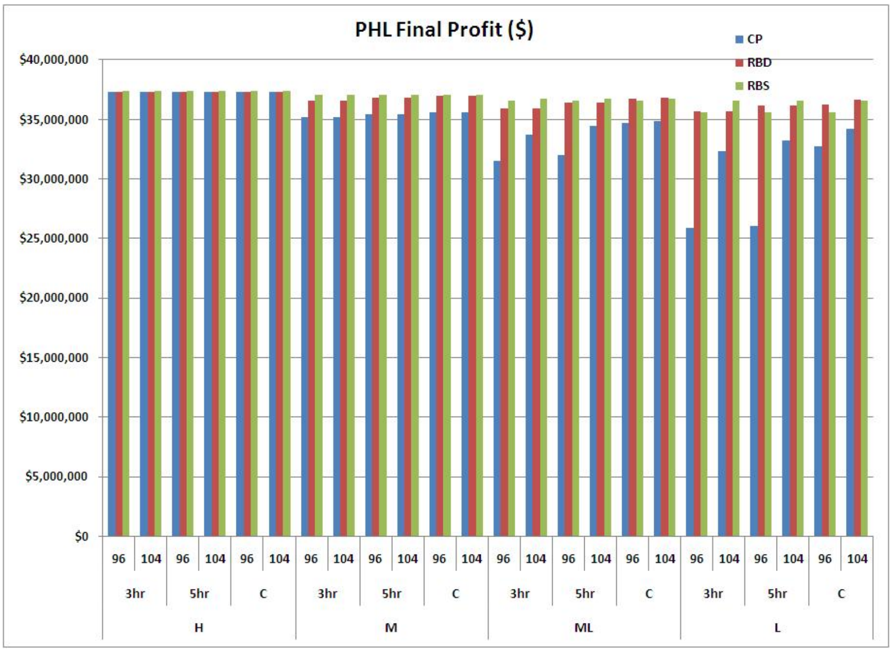

Figure 6.36: Final profit (PHL)

6.2.4 Philadelphia International Airport (PHL)

Figures 6.36 through 6.43 show the statistics for flights arriving at PHL. Figure 6.36 shows the profit at PHL. Except at the optimal capacity level (H), higher congestion prices have reduced overall profitability relative to RBS and RBD at PHL. Using the cancellation model increases the profitability by cancelling the least profitable flights. Allowing extra resources at the end of the day adds more to the profit than allowing flights to delay for longer duration (i.e., for 5 hours).

Figure 6.37 shows the flight throughput statistic at PHL. Except for the cancellation model cases, the CP approach is better than RBD and better or similar to RBS in performance.

Figure 6.38 shows the passenger throughput for flights arriving at PHL. Similar to flight delay statistics, the CP approach performs better than or similar to other approaches except in the cancellation model cases.

Figure 6.39 reports flight delays at PHL. With the exception of optimal capacity (H)

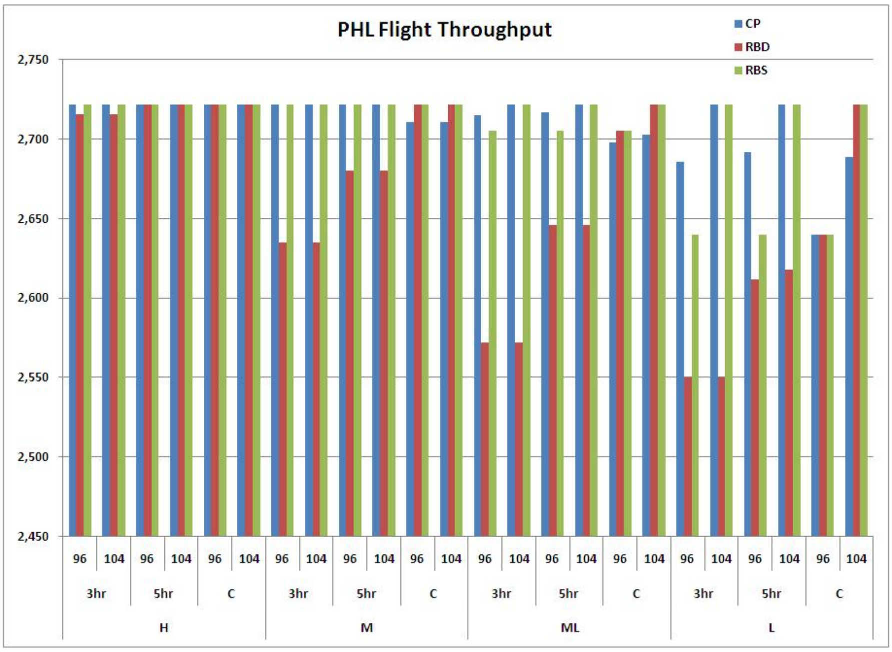

Figure 6.37: Flight throughput (PHL)

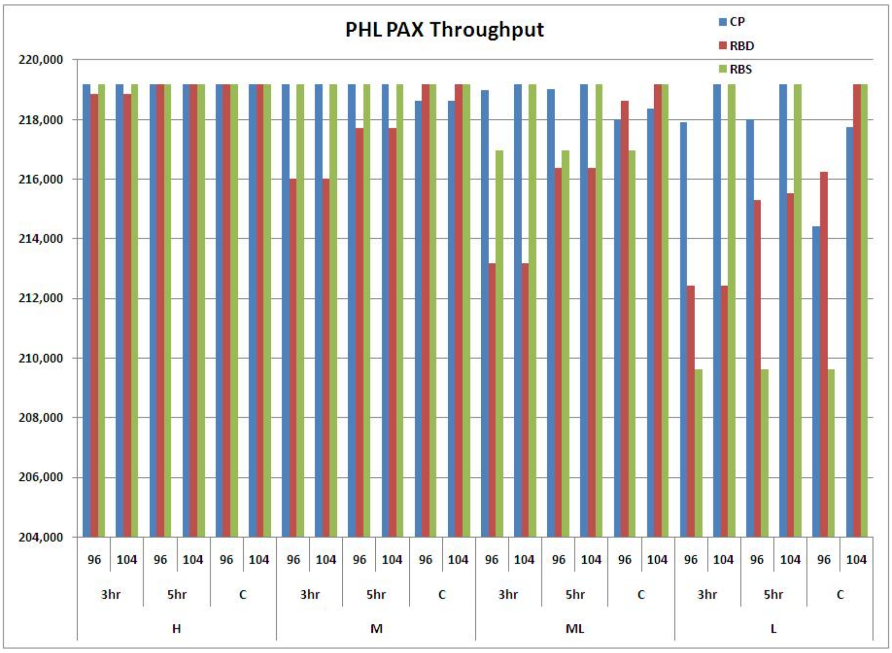

Figure 6.38: Passenger throughput (PHL)

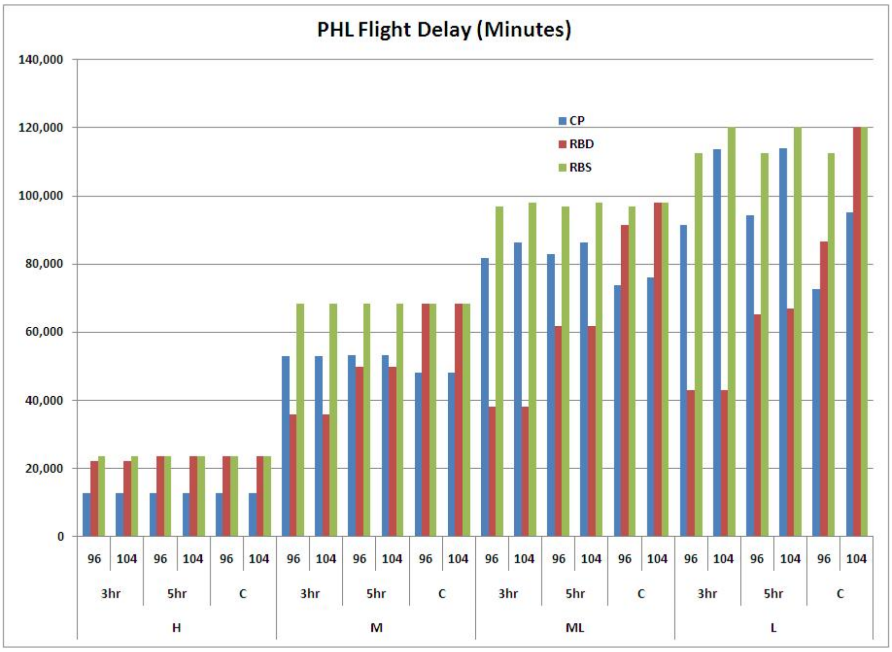

Figure 6.39: Flight delay (PHL)

scenarios and cancellation model scenarios, the CP performs worse than RBD. RBS also has poor performance with respect to flight delays.

Figure 6.40 shows passenger delay at PHL. The CP approach has better performance than both RBS and RBD, except for the cancellation model cases. RBS has passenger delays that are almost twice as large as either RBD or CP.

Figure 6.41 shows cancellations at PHL. RBD has a larger number of cancelled flights. The CP approach cancels most of its flights in the cancellation model scenario indicating that for these flights, it was cheaper to cancel rather than pay higher congestion prices.

Figures 6.42 and 6.43 show the ontime statistics for both seats and passengers at PHL. Similar to the aggregate level, RBD has better performance than other two approaches.

Figure 6.44 shows the revenue generated by the congestion price versus the revenue generated by the current weight based landing fee. Similar to BOS and EWR, at PHL, the revenue generated by congestion prices is higher than the revenue generated by weight

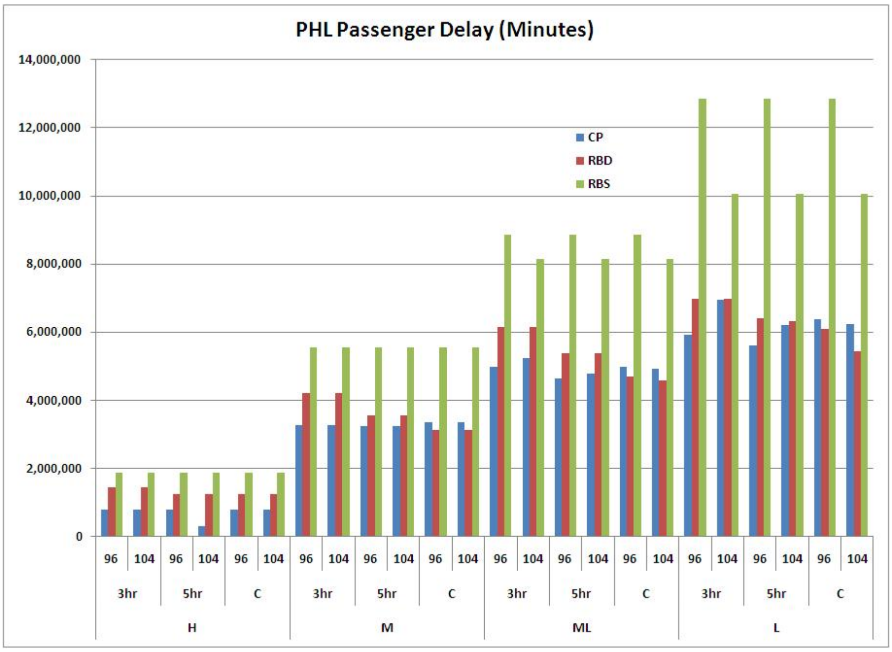

Figure 6.40: Passenger delay (PHL)

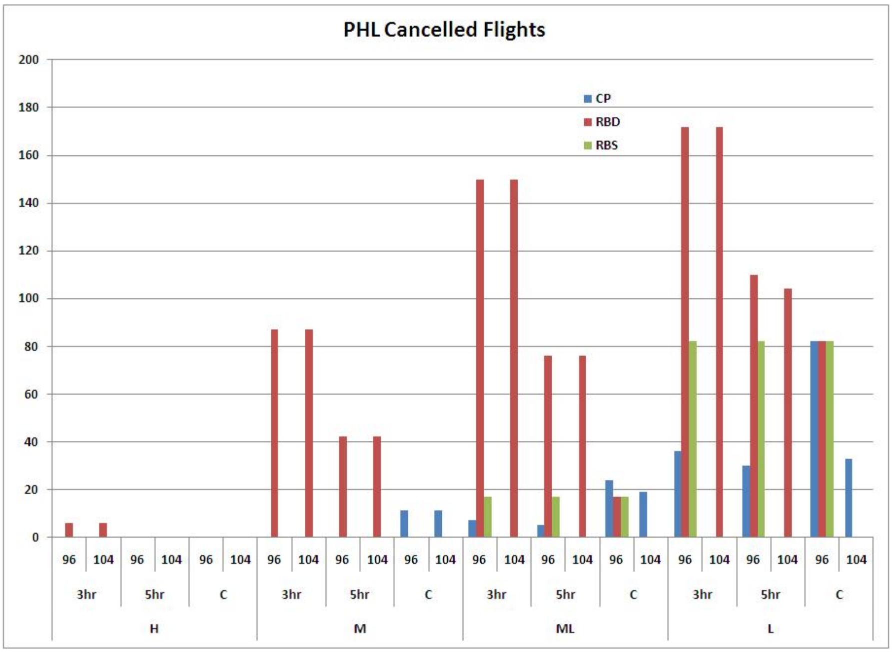

Figure 6.41: Cancelled flights (PHL)

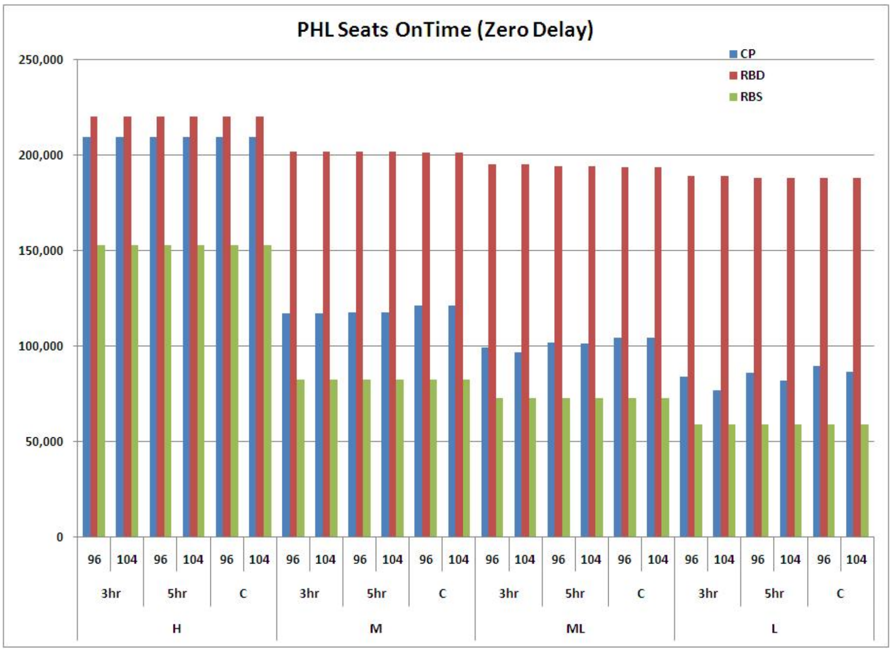

Figure 6.42: Seats ontime (PHL)

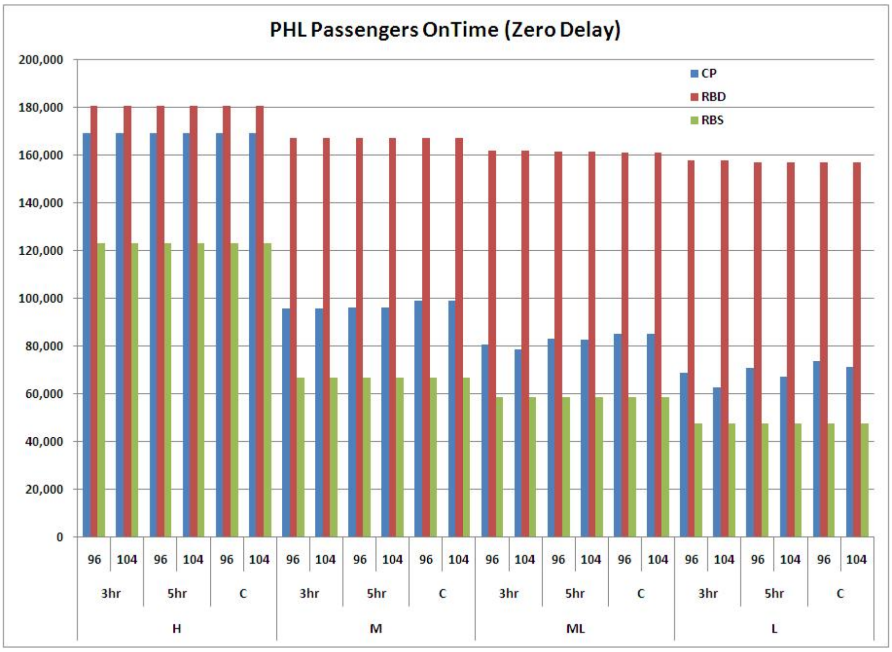

Figure 6.43: Passenger ontime (PHL)

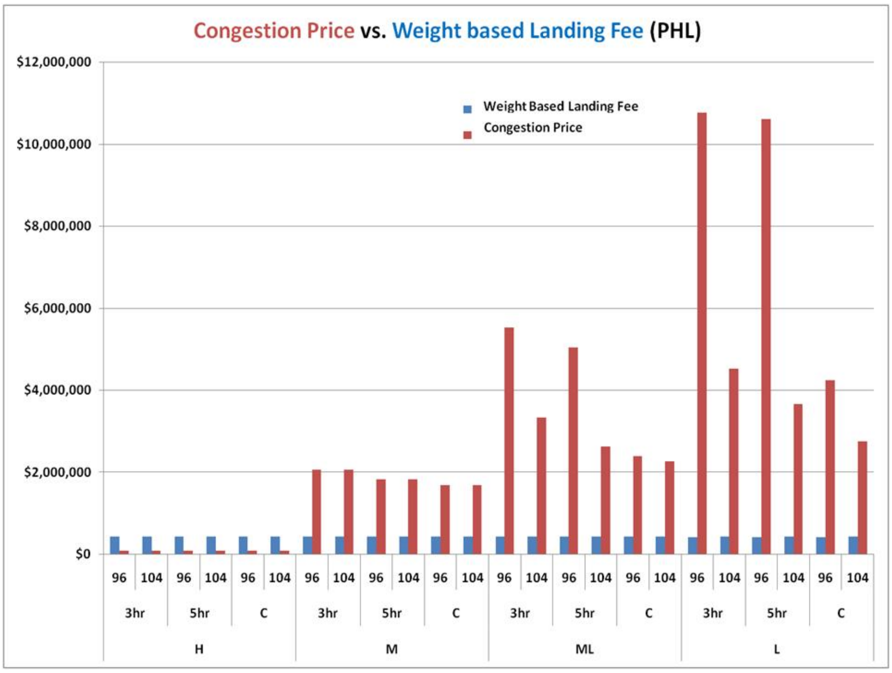

Figure 6.44: Revenue generated by Weight-Based Landing Fee vs. Congestion Price (PHL)

based fees during a congested day.[5] In fact, PHL has the lowest rate per 1000 lbs. for the fee, i.e. \$1.63. Even at the Marginal capacity level (M), the revenue generated is 4-5 times higher. Adding two extra hours at the end of the day decreases the revenue but allowing flights to delay longer has no effect. The use of the cancellation model seems to effect the revenue by cancelling more flights.

6.2.5 SanFrancisco International Airport (SFO)

Figures 6.45 through 6.52 show the statistics for SFO airport.

Figure 6.45 shows the profit at SFO airport. Except for the IFR (L) capacity level, CP outperforms the RBS and RBD approaches. No change is noticed by adding extra resources at the end of the day. The cancellation model case generates slightly higher profit.

Figure 6.46 shows the flight throughput at SFO. Except for the cancellation model case, flight throughput was 100%, indicating lower congestion at this airport.

[5]Further analysis on average revenue per day is provided in Appendix E.

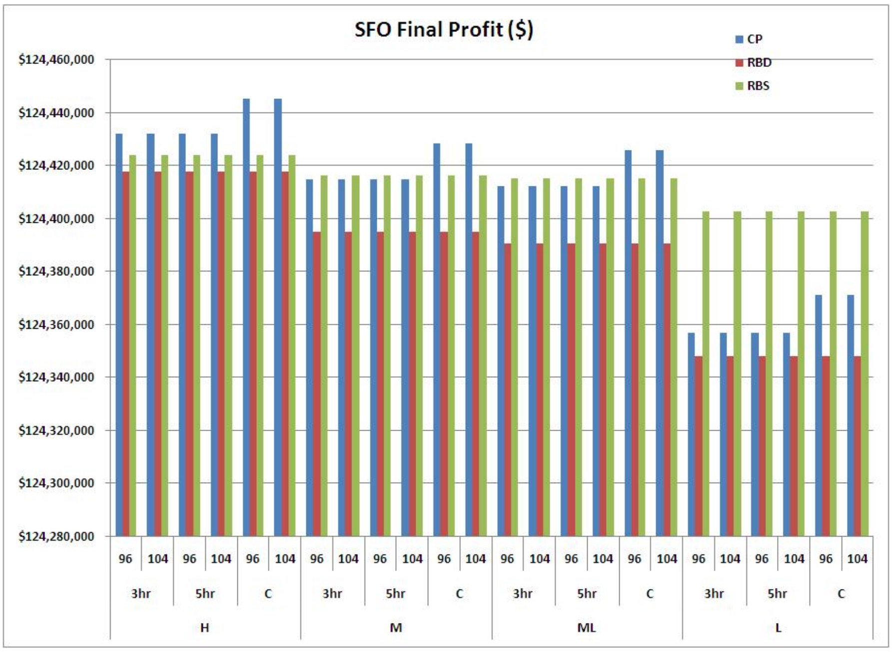

Figure 6.45: Final profit (SFO)

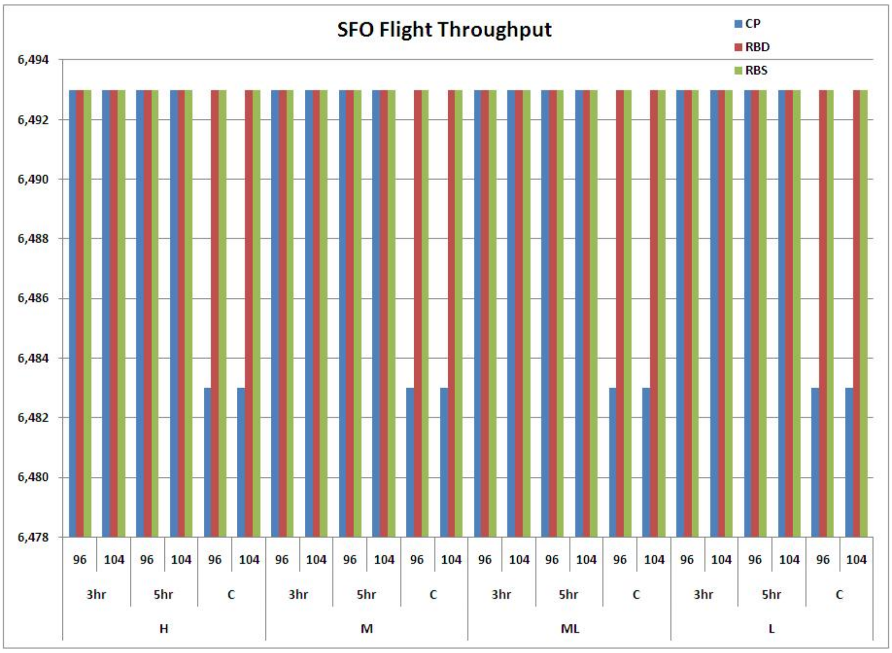

Figure 6.46: Flight throughput (SFO)

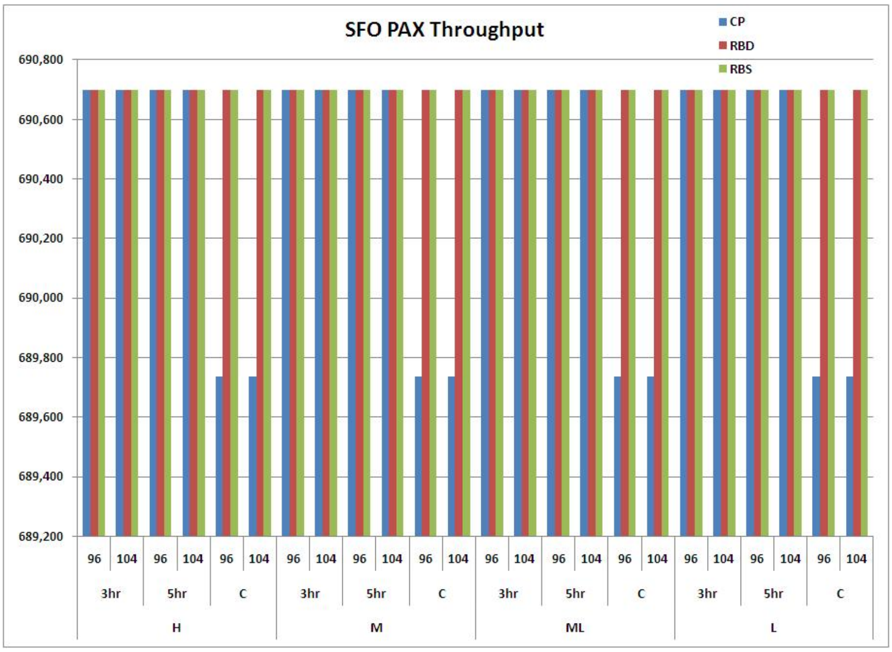

Figure 6.47: Passenger throughput (SFO)

Figure 6.47 shows passenger throughput at SFO. Similar to flight throughput, all the passengers reached their destination in all cases except in the cancellation model case, where the CP approach cancelled fewer flights.

Figure 6.48 shows the flight delays at SFO. The CP has performed well in all the cases, and the only factor that has a small effect on the flight delay statistics is the capacity level.

Figure 6.49 show the passenger delays. In IFR capacity level (L), CP approach reduces passenger delay by 50% relative to RBD and by 25% relative to RBS.

Figure 6.50 shows the cancelled flights at SFO airport. The CP approach cancelled a total of 10 flights for all scenarios which use the cancellation model, while none of the other two approaches cancelled any flights. Figures 6.51 and 6.52 show the ontime statistics of both seats and passengers at SFO. Similar to LGA, CP performs better when there are sufficient resources to allocate to all flights.

Figure 6.53 shows the revenue generated by the congestion price versus the revenue

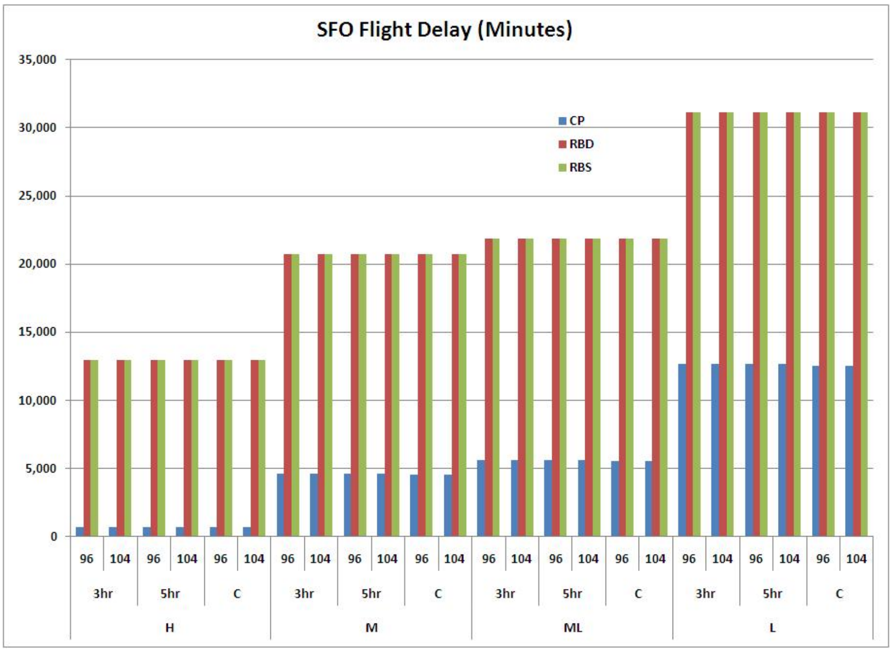

Figure 6.48: Flight delay (SFO)

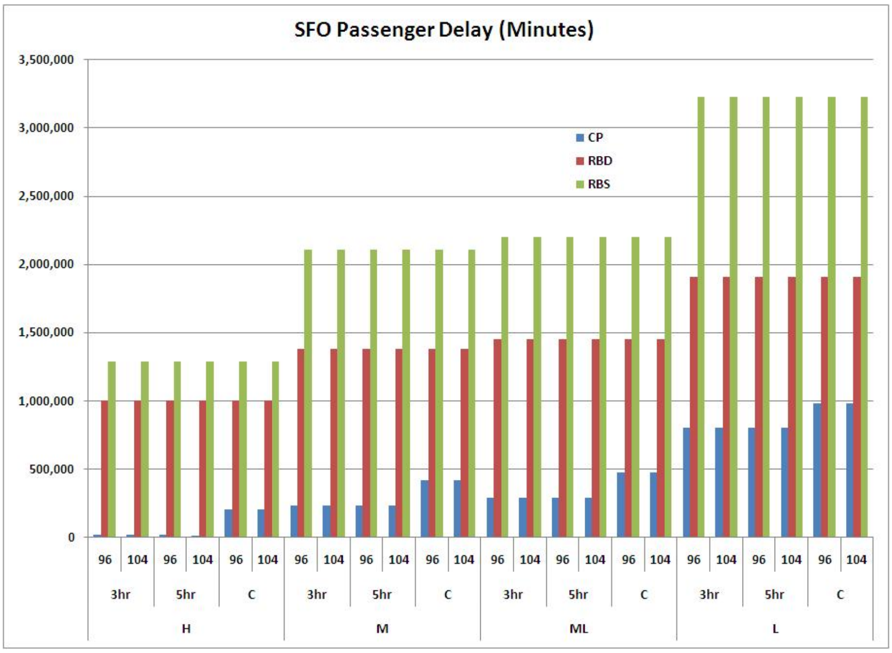

Figure 6.49: Passenger delay (SFO)

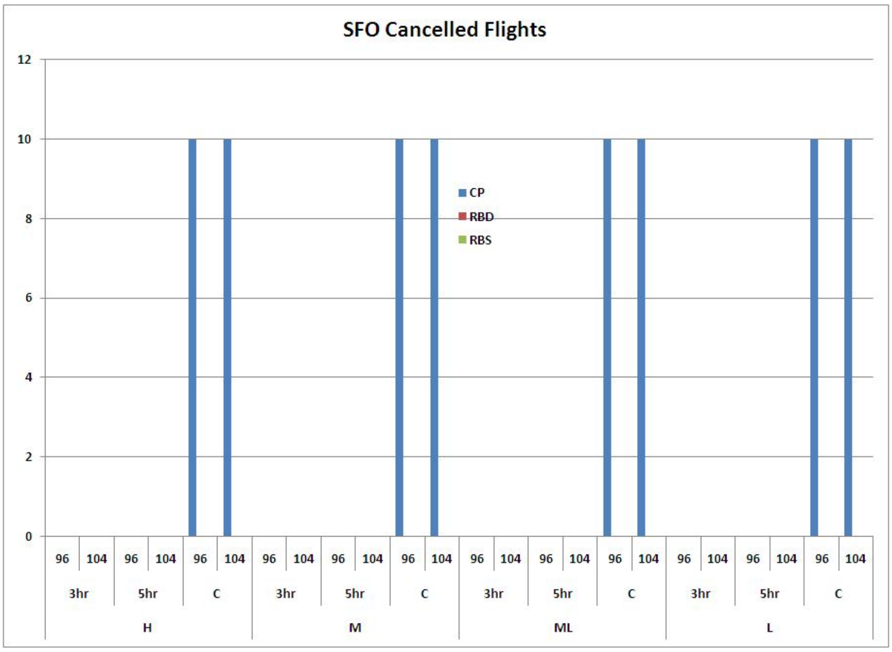

Figure 6.50: Cancelled flights (SFO)

generated by the current weight based landing fee at SFO. Again, similar to LGA, the revenue generated by congestion pricing is negligible compared to revenue by the weight-based landing fee.[6] At SFO, all the flights were able to obtain runway access. At least for the days and conditions studied at SFO, congestion was minimum, resulting in relatively low congestion prices.

[6]Further analysis on average revenue per day is provided in Appendix E.

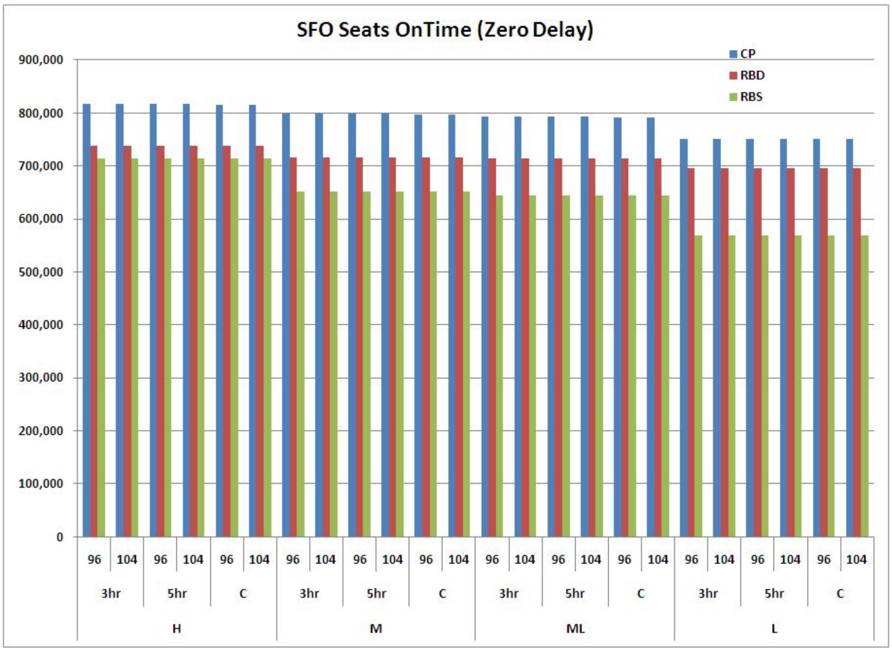

Figure 6.51: Seats ontime (SFO)

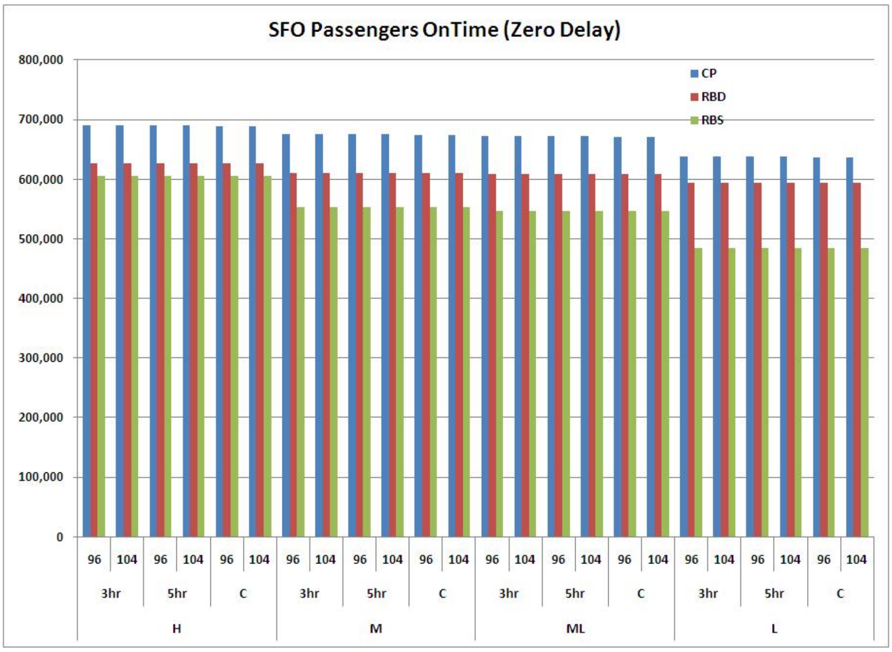

Figure 6.52: Passengers ontime (SFO)

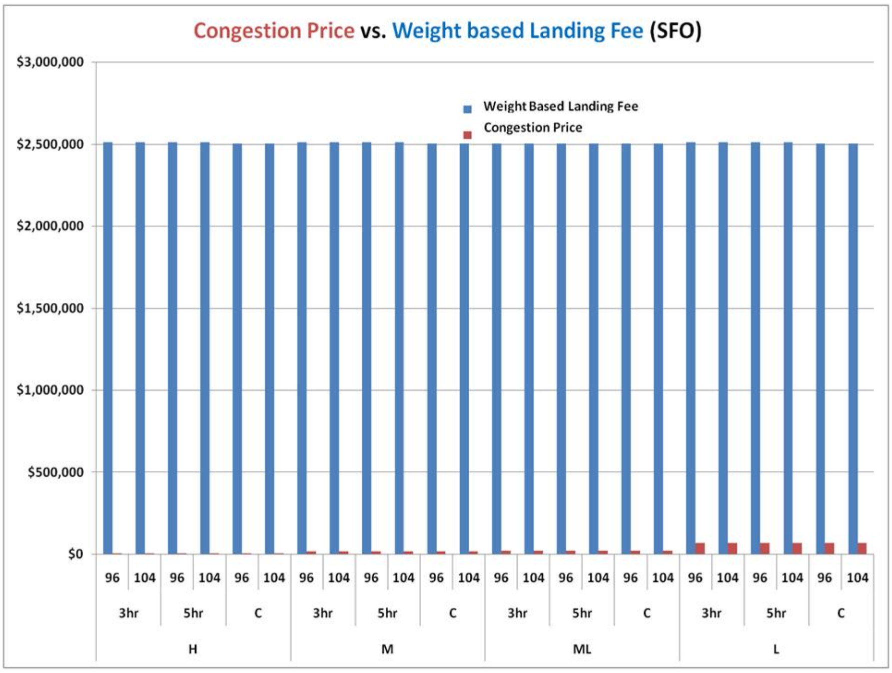

Figure 6.53: Revenue generated by Weight-Based Landing Fee vs. Congestion Price (SFO)

6.3 Further Statistics

This section provides further statistics regarding the new congestion pricing approach, mainly the magnitude of congestion prices for different scenarios. Figure 6.54 shows both the average as well as the maximum congestion prices for each of the scenarios. Intuitively, with higher capacity ranges (i.e., optimum [H] and marginal [M]), the congestion prices on average are relatively low with only few peak congestion periods having relatively high prices. At Marginal Low (ML) and IFR (L), however, the average congestion prices are higher than the maximum price in other capacity scenarios. End of day statistics also behave intuitively: with more capacity at the end of the day, the flights can obtain a later slot which results in lower congestion prices. The cancellation policy of a 3 and 5 hour delay allowance does not seem to have much effect at the prices. However, in the case of the cancellation cost model, since flights have more chances to obtain a slot, lower congestion prices are observed.

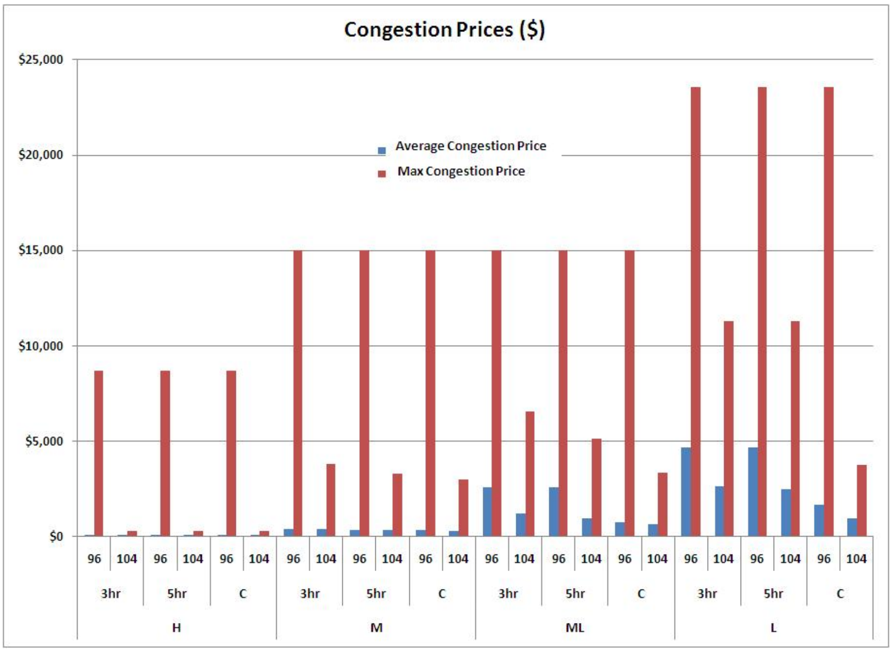

Figure 6.54: Average and maximum Congestion Price ($)

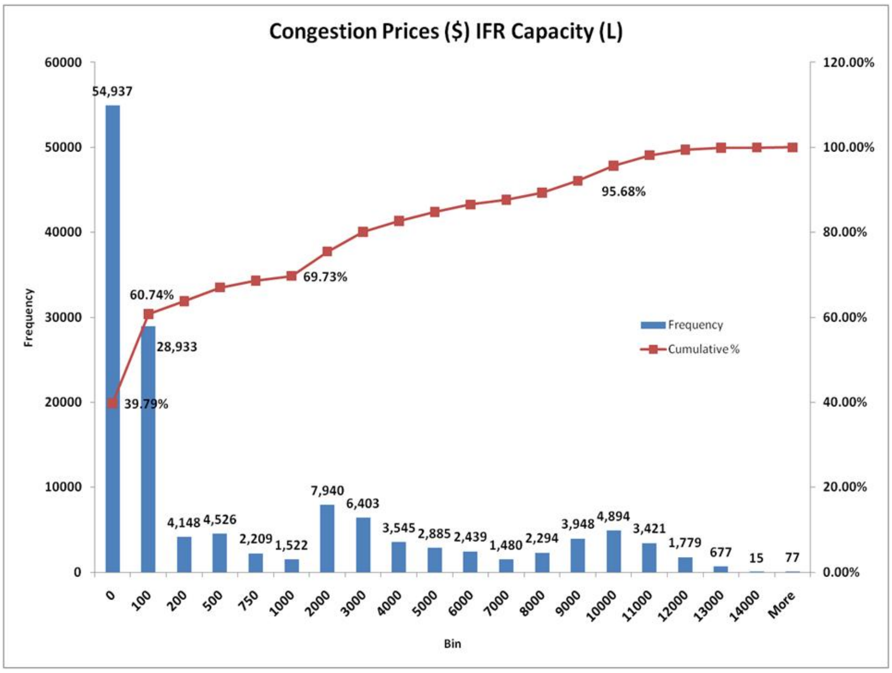

Figure 6.55: Histogram for Congestion Prices at IFR capacity level (L)

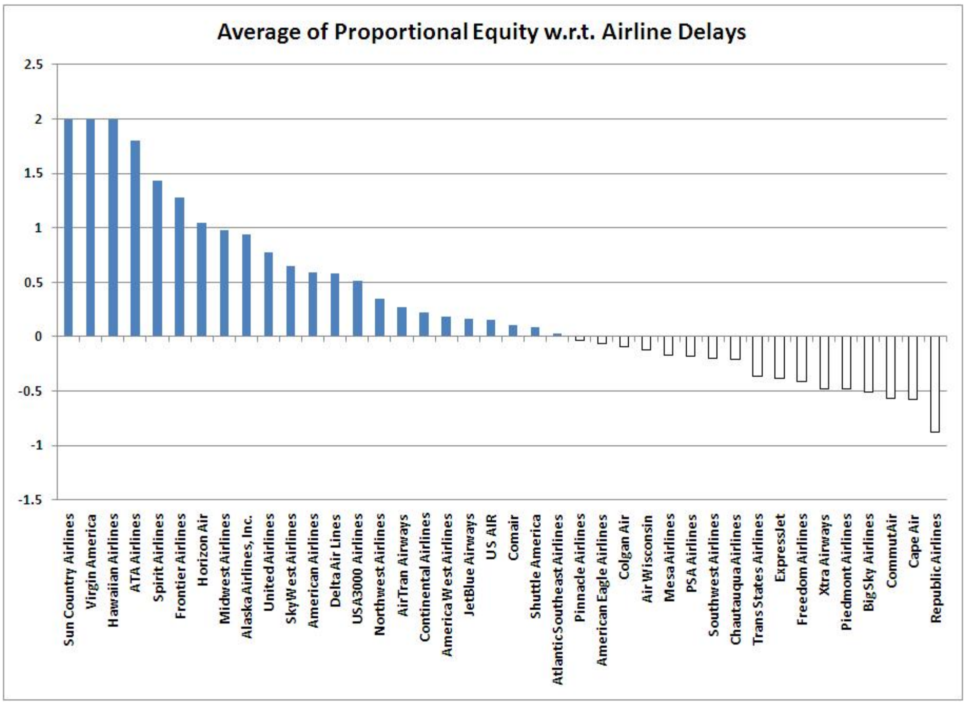

Figure 6.56: Average Proportional Equity with respect to airline delays across all scenarios

Figure 6.55 shows the histogram for the congestion prices in all cases with capacity set to IFR (L) level. Since, most of the higher congestion prices were recorded in this capacity scenario, it is interesting to see how these prices are distributed. There are total of 138,072 instances (6 runs each with 23,012 flights). Even with the worst capacity levels, 40% of the flights paid no congestion price, almost 70% of the flights paid less than \$1000, and 96% of the flights paid less than \$10,000 as a congestion price. This shows that even with the worst capacity scenarios, the congestion prices are high at very few time periods. Most of the time the congestion prices are low and would likely be at the aggregate less than weight-based prices.

Figure 6.56 shows the average airline proportional equity[7] across all 24 scenarios for the CP approach. The ones above the zero are favored by the system while the ones below zero are penalized more than their fair share. A value of zero indicates perfect equity. It

[7]Proportional Equity is defined as the airline's share of delay with respect to its proportion of flights. Formal definition is provided in the previous chapter.

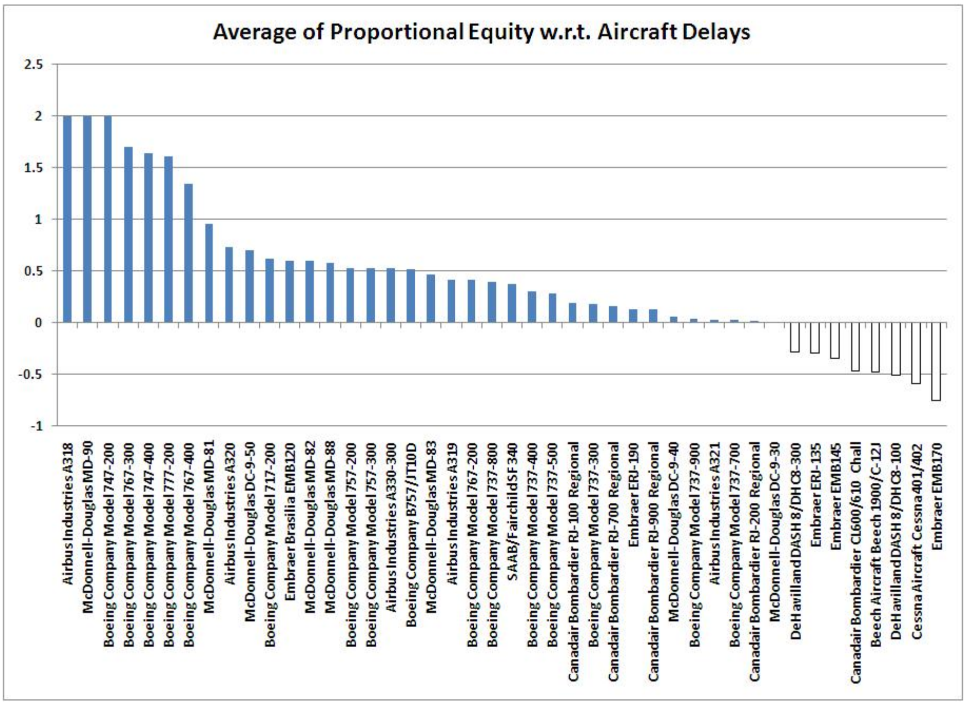

Figure 6.57: Average Proportional Equity with respect to aircraft delays across all scenarios

is observed that with respect to airlines, the congestion pricing approach favors the larger airlines as compared to regional ones, however, this is due to the fact that mainline carriers generally have larger fleets with higher load factors resulting in more profitable flights. SouthWest Airlines is, however, an outlier in this case. But Southwest has a better score when looking at proportional equity with respect to cancellations. Even though this might be similar to what happens currently, but when using the new approach, the discriminatory behavior is due to profitability and an airline's willingness to pay for the services it requires. This also explains one of the reasons as to why mainline carriers with subsidiary or regional carriers prefer their own flights over subsidiary/regional carriers in case of reduced capacity.

Figure 6.57 shows the average aircraft proportional equity across all 24 scenarios for the CP approach. Zero line indicates perfect equity, positive index indicates favorable by the system, while negative index indicates the opposite. In this case, the CP approach favors again larger aircrafts over smaller ones. Out of the eight aircrafts that have been penalized, 3 of them are under 20 seaters, two of them are 37 and 44 seaters respectively, two of them are 50 seaters and one of them is a 70 seater. This indicates, that the CP approach discriminates against the smaller aircrafts. This is again intuitive since, in general smaller aircraft mean a smaller number of passengers, and therefore less revenue. Again this discrimination is due to profitability of flights.

6.4 Summary

This chapter summarizes all the results and substantiates the theory that congestion pricing can be an efficient way to allocate runway access to competing flights when capacity is reduced. The chapter starts by showing statistics of the design of experiments aggregated over all airports and then individually by airport. Further statistics provide insight regarding the magnitude of congestion prices at different capacity levels and their frequency. At the end, some basic statistics for equity, namely proportional equity among airlines as well as among aircrafts, are discussed. Some of the conclusions derived from the comparative analysis are:

- Adding the variation to add two hours worth of capacity at the end of day had effected total profit at airports with lesser number of slots than flights (i.e., BOS, EWR and PHL). At EWR these effects were large since there were many scheduled arrivals at the end of the day which were able to get a runway access.
- Adding two hours of delay before cancelling a flight showed the incremental effect on the total profit at LGA and PHL, implying that at these airports there were larger numbers of flights that were still profitable after 3 hours of delay.
- For the days under study, both LGA and SFO, had sufficient capacity to allocate to all flights for all the days, however, with different approaches allocation schemes changed and the performance metrics show that difference: mainly, that the congestion price approach works better in terms of all passenger statistics at these airports. It prioritizes itself in order of increasing throughput, reducing delays and finally improving

ontime statistics.

- In scenarios where airlines are allowed to cancel a flight by paying a cancellation cost, more flights are cancelled. This suggests that at times, cancelling a flight is more profitable for airlines than to operate it and by doing so, an airline can recover the total profit lost by delay costs of not only the cancelled flight but other flights that are affected.

- At optimal capacity level (H), the congestion pricing approach performed similar to alternative approaches in terms of total profit, flight and passenger throughput. It performed better than these approaches in terms of both flight and passenger delays, as well as seats ontime and passenger ontime statistics. However, when the capacity level was very low, losses in profit with respect to the congestion pricing approach increased due to the additional cost (namely, the congestion price) charged. Thus, the airlines were required to pay for the congestion created, but more passenger and flight throughput was achieved with this economic incentive to fly larger and more profitable flights.

- With respect to the magnitude of congestion prices, even at IFR levels of capacity, 40% paid no congestion price 70% of the time; airlines paid at most $1000 as a congestion price while only 7% paid more than $10,000.

- Proportional equity with respect to both airline and aircraft delay indicate that most of the larger aircrafts of mainline carriers are favored. This is because, in general, they are more profitable than smaller aircrafts that belong to regional carriers.

Chapter 7: Conclusions and Future Work

This chapter starts with the summary of results achieved and describes next steps in this general research area. It also indicates how this work can be extended and applied to other aspects of the airline allocation problem.

7.1 Conclusions

This research has extended the literature on airport runway capacity allocation problem in the following ways:

7.1.1 Cost of Delay Model

This research provides a new methodology for calculating the costs of delay for any individual flight. The model is based on a EuroControl model of delay [Cook et al., 2004], but has been expanded to now be useful for any aircraft type and also usable when the underlying components of the EuroControl model (e.g., fuel, crew, maintenance, or other operational costs) have been changed. The original model did not allow such modifications and could therefore not be used when an underlying component (such as fuel costs) changed dramatically. A case study is reported that calculates the cost of delay for flights at 12 major U.S. airports for July 2007. A sensitivity analysis is also performed for this model by varying fuel and crew costs[1] along the baseline historical fuel prices and crew costs of Summer 2007.

Some of the conclusions drawn from the case study and the sensitivity analysis are:

- Airborne delays are expensive as compared to ground delays. Therefore, it is economical for airlines to prefer ground delays over delays in airborne or taxi segments.

[1] As these are the major components of the cost of delays compared to maintenance and other miscellaneous costs.

- Newer fuel-efficient aircrafts incur significantly less airborne delay costs than their older counterparts.
- For July 2007, the total delay cost of all the flights, excluding cancelled flights, at 12 major U.S. airports totalled \$63.8M.
- The analysis also provides insight into why airlines down-gauge; the newer, smaller aircraft are more fuel efficient, thereby reducing delay costs significantly for the airline. Additionally, higher load factors and increased frequency make down-gauging an attractive option.
- Fuel costs have the greatest impact on delay costs. An increase in fuel price of about 200% (from \$2.04[2] to \$4.50) increases the cost of delay by up to 50% for airborne delays.
- Fuel burn rates are as important as fuel prices; the same amount of taxi delay in an efficient aircraft can save delay costs by as much as 10%.
- As fuel costs increase, crew costs become far less important to the overall delay and flying costs. For ground delays, however, crew costs are a larger component of total delay costs, and larger aircraft are most impacted since they have larger crews.

The cost of delay analysis thus concludes that, as the economy recovers from the current recession (starting from 2009), it is expected that the airlines are more likely to increase frequency rather than up-gauging to larger aircraft. Although this practice might not be efficient from an airspace-use perspective, it makes good economic sense for an airline.

7.1.2 Congestion Pricing Model (CPM)

This research develops a Congestion Pricing Model or CPM, that takes into account, revenue and cost for each individual flight for any given time duration and considers all domestic flights at an airport. It takes into consideration the variable costs of delaying or cancelling

[2] Average fuel price in Summer 2007.

a flight as incurred by the airlines, as well as some network effects on the airline's overall schedule caused by such delays.

The core of this model is the optimization model that maximizes the total profit of all the flights for all fifteen-minute periods in a congested period from the time when a GDP is imposed until the end of the day. Thus, it considers any queues that might result from the GDP and imposes congestion costs until demand is again in alignment with supply. At each period, it determines a congestion price such that (based on the relative profit[3] of the flights capable of arriving at the airport in that time period) the number of flights choosing to pay the congestion price and depart is exactly equal to the arrival capacity available for that period.

The rest of the flights are delayed and cascaded to subsequent time periods to compete for the capacity in those time periods. A flight may be cancelled if it satisfies the cancellation criteria. That is, an airline might choose to cancel a flight if (i) the cancellation cost is less than any of the congestion fees plus delay costs, or, (ii) if a rule that a flight will not be delayed more than three or five hours is imposed.

The dual price of the capacity constraint for a specific time period can be used as the congestion price since this price is the value that one extra unit of capacity at that time period is worth. In this case, it is the price that the next flight would be willing to pay to obtain access to the runway. The model has included in the objective function costs incurred by the airline if the flight is delayed for a period that will force the follow-on flight of that aircraft to also be delayed. Similarly, to better model an airline's operational issues, the model forces flights that were scheduled to overnight at the airport to incur extremely long delays, but eventually land at that airport. Thus, the model assumes that a major priority of the airline is to have its next-day schedule begin without a need for the repositioning of aircraft. The model can be refined further if other rules are discovered that are more important than profitability to a given airline or flight.

When a Ground Delay Program (GDP) is announced and congestion pricing is imposed,

[3]The assumption is that airlines value their flights based on profitability.

Air Traffic Management may find that the airlines have responded in a manner inconsistent with the profit-maximizing assumptions. In this case, or when weather conditions change, the future prices must be adjusted to reflect the imbalance between supply and demand.

At the start of the Ground Delay Program (GDP), the model is run with the announced capacity. The congestion prices will be announced to the airlines, who will decide whether to accept the price or delay the flight. In the case where more airlines chose to fly than the congestion pricing model anticipated, the capacity limits for the next time period are reduced to accommodate the extra flights that will arrive at the airport during that fifteen-minute time period. The model is again run with these new capacity limits and the congestion prices for future time periods are reset (probably higher, since the demand is greater). Alternatively, the airlines might react to very high congestion prices by choosing to delay flights rather than accept this congestion price even though it would be profitable to fly them on time. In this case, fewer flights will accept the congestion price than anticipated. The users of the model can choose to either reduce the congestion price in the next period and observe the demand at this price. Thus, over time the users of the system can learn how to adjust the prices. An alternative, is to have the model re-adjust the prices by rerunning the model with a slight increase in capacity limits. Either method will allow a dynamic resetting of the prices.

Similarly when weather conditions change, the model can be re-run with the new capacity limits and depending on the increase or decrease of capacity, the model will adjust both the schedule and the prices accordingly.

The proposed system is unique with respect to other approaches in several respects, namely:

- It uses more realistic data for flight costs and revenues. In previous models, authors assumed average ticket prices and cost factors and did not consider the differences among airlines or aircraft sizes.

- This model considers all possible alternative decisions that can be made for a given flight: paying the congestion cost immediately, choosing to delay the flight one or more 15-minute periods in order reduce its overall delay and congestion pricing costs, or to cancel the flight. The model reflects the fact that when a flight is cancelled the airline keeps the revenue, but incurs the additional costs of re-ticketing passenger as well as any passenger hotel and food costs. Only [Betancor et al., 2003] considered allowing flights to spill over to future periods but they allowed spill-over only to one additional time period.

- Rather than considering the queueing effect of capacity imbalances, this model explicitly inputs the capacity as it is known at the time. Whenever new information is provided, the model can be re-run and corrections made to reflect the dynamic nature of ground delays.

7.1.3 Comparative Analysis of CPM

A comparative analysis of this new methodology is performed with other known and implemented approaches that are used to provide congestion management solutions and it is shown that the system based on congestion pricing methodology has advantages over these other approaches. Looking at the results of experiments, the following observations were made:

- With respect to the cost to airlines, congestion prices cost more than the current weight-based landing fee, however, even with the capacity limit set to IFR levels, with respect to the sampling data, 70% of the flights paid at most $1000, only 7% paid more than $10,000 and in the worst scenario, with IFR level capacity, 3 hour cancellation policy and no flights after midnight, the (non-zero) average was $5000. However, these congestion prices would only be used on days when GDPs were announced. During the summer of 2007, there were only a few such days. Thus, one can conceivably reduce weight-based fees such that together with congestion pricing fees, the entire pricing approach is revenue-neutral. In addition to that, the airlines are likely to save additional money because they would no longer need to "pad" their schedules in an attempt to predict delays and still maintain on-time performance.

- One important observation is that, allowing flights to be delayed longer than 3 hours (tarmac delay rule) is beneficial for both airlines and passengers since, it increases both flight and passenger throughput regardless of whether congestion pricing, Ration-by-Schedule or Ration-by-Distance is used. However, this modeling has not considered gate capacity issues and, if too many flights are delayed at the gate, there may be other capacity problems not considered in this research.[4]

- Revenue generated by the congestion pricing varied with respect to airports. When there was sufficient capacity at the airport (i.e., even at IFR limits), then the weight-based landing fee produced more revenue than did congestion pricing. For lower capacity levels, the congestion pricing method generated more revenue during times of severe congestion. However, the data sample used showed that out of 31 days at 5 airports (a total of a possible 155 days a GDP could have been announced) there were only 31 times when a GDP occurred. Thus, congestion prices would be non-zero only a fraction of the entire time. This suggests that a revenue-neutral approach to airport pricing is possible with a relatively low weight-based landing fee coupled with a congestion pricing scheme whenever GDPs occur.

- With respect to proportional equity in airline delay, regional airlines received a disproportionate amount of the delay. In RBS, this occurs because the major carrier chooses to fly their larger aircraft to maintain operational efficiency. In the congestion pricing approach, the same result occurs because larger aircrafts are more profitable. Interestingly, under a congestion pricing scheme, Southwest was found to delay their flights more than other airlines, but also to cancel them less frequently. Thus, the model indicates that Southwest could delay a flight for a few time periods and incur less cost than by either cancelling the flight or by incurring peak period congestion prices.

- Similarly when looking at proportional equity with respect to aircraft delay, flights assigned smaller aircrafts incurred a larger share of delays.

[4] See [Wang, 2011] for an analysis on gate delays.

- Looking from the stakeholder's perspective:
  - For airlines, not surprisingly, the congestion pricing approach added additional costs to the airlines and their associated profit went down (when only looking at the congested time periods). However, had the airlines known what the congestion price would be and were willing to pay such a cost, they might have chosen to remove padding and save operational costs that are included in the model. More interestingly, when a $100 per passenger cancellation cost is used, the total costs incurred were actually about the same as incurred by Ration-by-Schedule. Thus, having long delays but not being allowed to cancel a flight, costs the airlines more than simply incurring cancellation costs on some flights. For OnTime statistics (i.e., Seats OnTime), it is observed that Ration-by-Distance(RBD) performs better in almost all cases. This is true when there is significant congestion at an airport. However, in less-congested times, congestion pricing performed better with respect to OnTime statistics.
  - From the perspective of Air Traffic Flow Management (ATFM), flight throughput for the congestion pricing approach was similar to the Ration-by-Schedule (RBS) approach currently implemented at the airports. However, when capacity was severely reduced and one used a cost of cancellation as the determination of whether or not to cancel a flight, the congestion pricing approach cancelled more than 1000 flights (across all 51 days and 23,012 flights) resulting in total profits that were close to those of the RBS approach. With respect to flight delays, the congestion pricing approach performed better than the Ration-by-Schedule (RBS) approach in each of the scenarios. The Ration-by-Distance (RBD) approach outperforms all other approaches in terms of total flight delays. A point worth mentioning is that the total flight delay is constant in the absence of cancelled flights, and as observed in cases where there are no cancellations (specific

to a single airport), the congestion pricing approach performs better than Ration-by-Distance (RBD) approach. This implies that congestion pricing distributes flight delays evenly, compared to the RBD approach, which favors a smaller set of flights and severely penalizes others.

- From the perspective of passengers, with respect to PAX throughput, the congestion pricing approach performs better in all scenarios except when cancellation costs are part of the decision process and there is severe capacity limitations. In this case, cancelling a flight is better for the airlines than delaying some flights and such cancellations may not be best for the passengers impacted. With respect to total and average PAX delay, the congestion pricing approach performs better than either alternative approach in all scenarios. Average PAX delay per passenger is also lowest with the congestion pricing approach as compared to other approaches. Finally with respect to PAX OnTime, similar to "Seats OnTime," the Ration-by-Distance (RBD)approach performs better in all cases, except when looking at the airport level; the congestion pricing approach performs better when there is sufficient capacity with respect to all competing flights.

7.2 Future Work

Following are the directions for future research:

- Network Effects: In order to more closely simulate the behavior of the airlines and how congestion prices will effect the overall network of airlines, it would be beneficial to have more information about how a given flight's delay will propagate throughout the network of a given airline. With such information, additional costs can be included that better reflect network effects. Currently, the model prioritizes flights based on their profitability and only considers the follow-on flight. However, additional parameters and costs could be added that would change priority where appropriate by including the costs that may be incurred by an airline due to the disruption in their schedule. One may also include other priorities of the airline, where appropriate (e.g., international flights must depart within a certain time frame based on treaty agreements and may be given priority over more profitable flights.)

- Cancellation Model: Another step is to derive better cancellation models since cancellation costs have different characteristics than flight delays. Certain flights may incur significantly different per passenger cancellation costs because of the type of flight (e.g., high-valued customers, few alternative connections, etc). There are currently no models that take into account the various considerations made by airlines when making cancellation decisions. The only references found assign either a per flight cost (e.g., half the revenue of the flight, or a flat cost per flight) or, alternatively a per-passenger cost(e.g., $100 per passenger) as shown in this research This extension will require discussions with airline dispatching and operations personnel to determine the characteristics inherent in cancellation decisions.

- Airspace Congestion Pricing: An obvious extension is to use the congestion pricing model to allocate congested airspace. Portions of the airspace can be divided into segments and each such segment would have a capacity and thereby a specific number of slots associated with that segment at a given time period. The congestion price model can then be used to assign these slots among competing flights.

- Combinatorial Slots: Instead of treating each congested airspace and airport slots separately, the entire route can be combined into a single resource and assigned to flights using the model.

- Airline Decision Making Policy: Different airlines may have different policies regarding the value of delays and cancellations. Airlines may consider (i) throughput, (ii) average ontime performance, (iii) connectivity of flight to the overall network, and (iv) profitability. If it is determined that airlines have different policies, then the mechanism can incorporate such policies into the algorithm, thereby revising the prices to assure that demand and supply are in equilibrium.

- Agent Based Simulation: Another direction for extension is to study the overall effect on the National Airspace System (NAS) when all the airlines follow the congestion pricing methodology using an agent-based simulation environment. Such modeling can include a study of what happens when airlines choose alternative strategies for accepting announced prices.

- Airline Substitution Model: A slightly modified derivative of this model can be used to optimize the current airline schedule in case of capacity reductions. Thus, instead of considering the entire collection of flights that are scheduled to arrive at that airport at a given period of time, the model could be used to determine how to allocate the slots provided to the airline in a Ration-by-Schedule approach. Thus, the airline is given a specific number of slots in each time period by Air Traffic Flow Management (ATFM) and it uses a model very similar to the congestion pricing model to allocate the slots to given flights based on the profitability of such flights. Additional airline-specific rules regarding individual flights can also be added into the model to prioritize specific kind of flights.

Appendix A: List of Airlines

AIRLINE NAME	**FAACARRIER**	**IATACODE**
Alaska Airlines, Inc.	ASH	AS
Air Wisconsin	AWI	ZW
AirTran Airways	TRS	FL
American Airlines	AAL	AA
American Eagle Airlines	EGF	MQ
America West Airlines	AWE	HP
ATA Airlines	AMT	TZ
Atlantic Southeast Airlines	ASQ	EV
Big Sky Airlines	BSY	GQ
Cape Air	KAP	9K
Chautauqua Airlines	CHQ	RP
Colgan Air	CJC	9L
Comair	COM	OH
CommutAir	UCA	C5
Continental Airlines	COA	CO
Delta Air Lines	DAL	DL
ExpressJet	BTA	XE
Freedom Airlines	FRL	F8
Frontier Airlines	FFT	F9
Hawaiian Airlines	HAL	HA
Horizon Air	QXE	QX
JetBlue Airways	JBU	B6
Midwest Airlines	MEP	YX
Mesa Airlines	ASH	YV
Northwest Airlines	NWA	NW
Pinnacle Airlines	FLG	9E
Piedmont Airlines	PDT	US
PSA Airlines	JIA	US
Republic Airlines	RPA	RW
Shuttle America	TCF	S5
SkyWest Airlines	SKW	OO
Southwest Airlines	SWA	WN
Spirit Airlines	NKS	NK
Sun Country Airlines	SCX	SY
Trans States Airlines	LOF	AX
United Airlines	UAL	UA
USA3000 Airlines	GWY	U5
USAir	USA	US
Virgin America	VRD	VX
Western	CXP	XP

Appendix B: List of Aircraft

DESCRIPTION	AIRCRAFT NAME	ETMS CODE	SEATS
Airbus Industries A318	A318	A318	107
Airbus Industries A319	A319	A319	124
Airbus Industries A320	A320	A320	164
Airbus Industries A320	A320-200	A32023	150
Airbus Industries A321	A321	A321	199
Airbus Industries A330-300	A330-300	A333	295
Beech Aircraft Beech 1900/C-12J	BH-1900	B190	19
Boeing Company B757/JT10D	B757-200	B757	208
Boeing Company Model 717-200	B717-200	B712-B717	106
Boeing Company Model 737-300	B737-300	B733	128
Boeing Company Model 737-400	B737-400	B734	146
Boeing Company Model 737-500	B737-500	B735	108
Boeing Company Model 737-700	B737-700	B737	126
Boeing Company Model 737-800	B737-800	B738	162
Boeing Company Model 737-900	B737-900	B739	177
Boeing Company Model 747-200	B747-200	B742	452
Boeing Company Model 747-400	B747-400	B744	416
Boeing Company Model 757-200	B757-200	B752	208
Boeing Company Model 757-300	B757-300	B753	240
Boeing Company Model 767-200	B767-200	B762	216
Boeing Company Model 767-300	B767-300	B763	210
Boeing Company Model 767-400	B767-400ER	B764	245
Boeing Company Model 777-200	B777-200	B772	305
Canadair Bombardier CL600/610	CL600	CL600	18
Canadair Bombardier RJ-100 Regional	Canadair Reg-100	CRJ1-CRJ2	50
Canadair Bombardier RJ-700 Regional	Canadair Reg-700	CRJ7-CRJ9	50
Cessna Aircraft Cessna 401/402	Aztec	C402	8
DeHavilland DASH 8/DHC8-100	DHC-8-100	DH8A	37
DeHavilland DASH 8/DHC8-300	DHC-8-300	DH8C	50
Embraer Brasilia EMB120	EMB120	E120	30
Embraer EMB145/EP/EU/LU	Embraer ERJ 145	E145-E45X	50
Embraer EMB170	Embraer ERJ 170	E170	70
Embraer ERJ-135	Embraer ERJ 135/140	E135	44
Embraer ERJ-190	Embraer ERJ 190	E190	98
McDonnell-Douglas DC-9-30	DC9-30	DC93	105
McDonnell-Douglas DC-9-40	DC9-40	DC94	125
McDonnell-Douglas DC-9-50	DC9-50	DC95	139
McDonnell-Douglas MD-81	MD-80-81	MD81	142
McDonnell-Douglas MD-82	MD-80-82	MD82	142
McDonnell-Douglas MD-83	MD-80-83	MD83	142
McDonnell-Douglas MD-88	MD-80-88	MD88	142
McDonnell-Douglas MD-90	MD-90-30	MD90	162
SAAB/Fairchild SF 340	SF-340-B PLUS	SF34	35

Appendix C: Problem Formulation for a Single Day XX in MPL

```
TITLE
        congestion_price_model_w_overnight_w_cancel
OPTIONS
        DatabaseType=Access;
        DatabaseAccess="input_data.mdb";
INDEX
        node := 1..96;
        ind:= DATABASE("all_flights","ID");
        i := node;
        j := node;
        m := node;
        k:=ind;
        !pick all scheduled flights
        flight_arc[k,i] := DATABASE("all_flights",k="ID",i="TimeWindow"
    where DayIndex =XX);
        flight_copy_arc[k,i,j]:=DATABASE("y_values",k="ID",i="TimeWindow",
    j="alt_TimeWindow" where DayIndex =XX);
        overnight_flights[i,k]:=DATABASE("overnight_flights",k="ID",i="TimeWindow"
    where DayIndex=XX); !new index for overnight_flights if they use sink
DATA
        !pick caps
        cap[m]:=DATABASE("final_caps","Rem_Cap",m="TimeWindow" where Day_Index =XX);
        R[i,k] := DATABASE("all_flights","Revenue",k="ID",i="TimeWindow" where
    DayIndex =XX);
        C[i,k] := DATABASE("all_flights","FlightCost",k="ID",i="TimeWindow" where
    DayIndex =XX);
        W[i,k] := DATABASE("all_flights","Landing_Fee",k="ID",i="TimeWindow" where
```

```
    DayIndex =XX);
        FuelCost[i,k]:=DATABASE("all_flights","FuelCost",k="ID",i="TimeWindow" where
    DayIndex =XX);
        PAXCost[i,k]:=DATABASE("all_flights","PAX_Cost",k="ID",i="TimeWindow" where
    DayIndex =XX);
        DelayCost[i,k,j] := DATABASE("delaycost_copy","cost",k="ID",i="TimeWindow",
    j="alt_TimeWindow" where DayIndex =XX);
        DelayMin[i,j]:= DATABASE("delaycost_mins","DelayMinutes",i="TimeWindow",
    j="alt_TimeWindow");
        CongCost[m]:=DATABASE("CongestionCost","CongestionPrice",m="TimeWindow"
    where Day_Index =XX);
        DepDelayCost_Tot[i,k,j] :=DATABASE("delaycost_copy","dep_delay",k="ID",
    i="TimeWindow",j="alt_TimeWindow" where DayIndex =XX);
    ! DepFlight is zero for overnight_flights
        DepFlight[i,k]:=DATABASE("all_flights","NEXTTW",k="ID",i="TimeWindow" where
    DayIndex =XX);
    ! Congestion Cost for overnight flights (if they use the sink)
        CongCost_over[k,i]:=DATABASE("overnight_flights","CongestionCost",k = "ID",
    i="TimeWindow" where DayIndex =XX);
    ! Delay Cost for overnight flights (if they use the sink)
        DelayCost_over[k,i]:=DATABASE("overnight_flights","DelayCost",k = "ID",
    i="TimeWindow" where DayIndex =XX);



VARIABLES
        x[i,k in flight_arc];! WHERE cap[i]< scheduled_ops[i,d];
        y[i,k,j in flight_copy_arc];
        o[i,k in overnight_flights];
VARIABLES
```

```
        CongestionCost;
        DelCost;
MACRO
        CANCEL = sum(i,k in flight_arc: (PAXCost - FuelCost-W) - x(PAXCost-FuelCost-W));
        SINKCOST = sum(i,k in overnight_flights: (CongCost_over* o + DelayCost_over*o));
        TOTAL_PROFIT = sum(i,k in flight_arc: (R*x-C*x-W*x)) - DelCost  -CongestionCost
    -SINKCOST -CANCEL;
        TOTAL_PROFIT_CANCEL = sum(i,k in flight_arc: (R-C-W)) - DelCost  -CongestionCost
    -SINKCOST -CANCEL;

MODEL
        MAX TOTAL_PROFIT_CANCEL;
SUBJECT TO

        CongestionCost = Sum (j: CongCost[m=j]*Sum(i,k: y[i,k,j]));

        !Cost of Delay at Gate for Delayed Flights l>0 , at l=0, cost = 0 and
    !departure leg delay
        DelCost = sum(k,i,j in flight_copy_arc: y*DelayCost[i,j,k]*DelayMin[i,j])
            + sum(k,i,j in flight_copy_arc: y*DepDelayCost_Tot[i,j,k]);



        !each_flight is flown once, either at its original time l=0 or later times l>0
        single_flight[i,k in flight_arc] ->sing: x[i,k] = sum(j: y[k,i,j])+ o[k,i];

        !Lower bound on x variable (whether the flight has overnightstay or not)
        var_x[i,k in flight_arc] when DepFlight[i,k]<=0: x[i,k]=1;

        !Limited flight per arrival per time window per day,
        !either flight of this timewindow l=0 or flights from previous windows
        in_flight[j] -> infl when cap[m=j]>=0 : Sum(i,k: y[i,k,j])<=cap[m=j];
```

```
        in_flight[j] -> infl when cap[m=j]<0 : Sum(i,k: y[i,k,j])<=0;
BOUNDS
x[i,k in flight_arc]<=1;
y[i,k,j]<=1;
END
```

Appendix D: Sensitivity Analysis of Cost of Delay Model

		Fuel Price			
Manufacturer	Aircraft type	$1.50	$3.00	$4.00	$4.50
Airbus	A318	$21.47	$41.35	$54.61	$61.24
	A319	$21.75	$41.89	$55.32	$62.04
	A320	$23.24	$44.92	$59.37	$66.59
	A321-322	$25.68	$50.17	$66.49	$74.65
	A310	$50.95	$95.39	$125.02	$139.83
	A300-306	$52.19	$99.42	$130.91	$146.66
	A340-342-343-345-346	$52.23	$101.63	$134.57	$151.04
	A330-332-333	$52.23	$101.63	$134.57	$151.04
ATR's	AT43-AT72	$7.93	$14.49	$18.86	$21.04
Boeing	B737	$22.3	$42.51	$55.98	$62.71
	B712-717	$22.38	$43.05	$56.83	$63.72
	B735-736	$23.15	$44.42	$58.59	$65.68
	B733	$23.36	$44.74	$59	$66.12
	B734	$23.52	$45.29	$59.8	$67.05
	B738	$25.09	$47.98	$63.24	$70.87
	B739	$26.26	$50.32	$66.36	$74.38
	B732	$26.75	$50.47	$66.28	$74.19
	B73C-73Q	$27.28	$52.47	$69.27	$77.66
	B752-757	$31.56	$60.98	$80.6	$90.41
	B753	$36.56	$71.13	$94.18	$105.71
	B762	$41.3	$79.74	$105.37	$118.19
	B722	$43.7	$81.02	$105.89	$118.33
	B763-767	$44.59	$86.33	$114.15	$128.07
	B721-727	$44.59	$78.67	$101.39	$112.75
	B764	$48.54	$94.25	$124.72	$139.95
	B772-773-777-77L-77W	$59.64	$116.17	$153.86	$172.7
	B744-747	$88.58	$173.83	$230.67	$259.09
	B742-743	$98.26	$192.67	$255.61	$287.07
	B741	$102.28	$200.56	$266.08	$298.84

Table D.1: Cost of delay per minute for 30 minutes delay at airborne (by aircrafts)

		Fuel Price			
Manufacturer	Aircraft type	$1.50	$3.00	$4.00	$4.50
Dash's	DH8A	$6.49	$12.01	$15.69	$17.53
	DHC8	$6.49	$12.01	$15.69	$17.53
	DH8B	$6.84	$12.65	$16.52	$18.45
	DH8C	$6.84	$12.65	$16.52	$18.45
	DH8D	$11.13	$20.83	$27.3	$30.54
Embraer	E120	$5.04	$9.15	$11.89	$13.26
	E110	$12.19	$23.39	$30.86	$34.59
	E45X-145	$12.19	$23.39	$30.86	$34.59
	E140	$13.1	$25.08	$33.07	$37.06
	E170-175	$13.1	$25.08	$33.07	$37.06
	E135	$13.77	$26.44	$34.88	$39.1
	E190	$19.64	$37.85	$49.98	$56.05
Lockheed	L101	$76.94	$148.49	$196.2	$220.05
DC's	DC8	$6.49	$12.01	$15.69	$17.53
	DC91	$21.65	$40.89	$53.72	$60.13
	DC93	$28.68	$54.8	$72.21	$80.92
	DC9	$30.22	$58.39	$77.17	$86.57
	DC94	$31.84	$59.87	$78.56	$87.91
	DC95	$32.66	$63.27	$83.67	$93.87
	DC87	$40.83	$79.02	$104.48	$117.21
	DC86	$50.82	$99.1	$131.28	$147.37
	DC10	$64.19	$125.95	$167.12	$187.7
	DC8Q	$65.07	$122.95	$161.54	$180.83
MD's	MD90	$26.23	$50.45	$66.6	$74.67
	MD80-81-82-83-87	$30.22	$58.39	$77.17	$86.57
	MD88	$30.22	$58.39	$77.17	$86.57
	MD11	$71.23	$135.91	$179.03	$200.59
	MD10	$71.23	$135.91	$179.03	$200.59
RJ's	CL60	$11.67	$22.33	$29.43	$32.98
	CRJ2	$11.67	$22.33	$29.43	$32.98
	CRJ1	$12.53	$23.98	$31.62	$35.44
	CL30	$12.9	$24.65	$32.48	$36.39
	CRJ7	$12.9	$24.65	$32.48	$36.39
	CRJ9	$15.41	$29.82	$39.43	$44.23

Table D.2: Cost of delay per minute for 30 minutes delay at airborne (by aircrafts)-cont'd.

		Fuel Price			
Manufacturer	Aircraft type	$1.50	$3.00	$4.00	$4.50
Airbus	A318	$2.76	$4.02	$4.86	$5.28
	A319	$2.78	$4.04	$4.88	$5.3
	A320	$3.15	$4.81	$5.92	$6.47
	A30B	$4.15	$6.81	$8.59	$9.47
	A321-322	$2.64	$4.13	$5.13	$5.63
	A310	$7.95	$9.9	$11.2	$11.84
	A306	$7.25	$9.91	$11.69	$12.57
	A300	$7.44	$10.3	$12.2	$13.16
	A340-342-343-345	$5.75	$8.87	$10.94	$11.98
	A330-332-333	$5.88	$9.13	$11.29	$12.37
	A346	$8.61	$14.58	$18.56	$20.56
ATR's	AT43	$1.87	$2.42	$2.78	$2.97
	AT72	$1.97	$2.63	$3.06	$3.28
Boeing	B737	$3.33	$4.7	$5.6	$6.06
	B712-717	$2.93	$4.24	$5.11	$5.55
	B735-736	$3.39	$5	$6.07	$6.61
	B733	$3.34	$4.82	$5.81	$6.3
	B73S	$3.47	$5.08	$6.15	$6.69
	B734	$3.2	$4.75	$5.78	$6.29
	B738	$3.53	$4.99	$5.97	$6.46
	B739	$3.53	$4.99	$5.97	$6.46
	B732	$4.61	$6.39	$7.58	$8.17
	B73C	$3.43	$4.89	$5.87	$6.36
	B73Q	$3.74	$5.52	$6.71	$7.3
	B752-757	$3.99	$5.96	$7.28	$7.94
	B753	$3.93	$6	$7.37	$8.06
	B762	$4.61	$6.56	$7.86	$8.51
	B722	$8.77	$11.65	$13.57	$14.53
	B763-767	$4.61	$6.56	$7.86	$8.51
	B721	$12.25	$14.83	$16.55	$17.41
	B727	$12.55	$15.43	$17.35	$18.31
	B764	$5.31	$7.97	$9.75	$10.63
	B772-777-77L	$5.9	$8.92	$10.93	$11.93
	B773-77W	$7.7	$12.5	$15.7	$17.31
	B744-747	$8.5	$13.9	$17.5	$19.3
	B743	$7.81	$12.04	$14.86	$16.28
	B742	$9.73	$15.89	$19.99	$22.04
	B741	$9.19	$14.67	$18.33	$20.15
	B74S	$8.95	$14.43	$18.09	$19.91

Table D.3: Cost of delay per minute for 30 minutes delay at taxi (by aircrafts)

		Fuel Price			
Manufacturer	Aircraft type	$1.50	$3.00	$4.00	$4.50
Dash's	DH8A	$1.49	$2.04	$2.4	$2.59
	DHC8	$1.6	$2.26	$2.7	$2.92
	DH8B	$1.65	$2.3	$2.73	$2.94
	DH8C	$1.65	$2.3	$2.73	$2.94
	DH8D	$2.02	$2.68	$3.12	$3.34
Embraer	E120	$1.45	$2	$2.36	$2.55
	E110	$1.15	$1.34	$1.47	$1.53
	E45X-145	$1.57	$2.18	$2.59	$2.79
	E140	$1.69	$2.3	$2.71	$2.91
	E170-175	$1.89	$2.69	$3.23	$3.5
	E135	$1.67	$2.28	$2.69	$2.89
	E190	$2.18	$2.98	$3.52	$3.79
Lockheed	L101	$9.36	$13.74	$16.66	$18.12
DC's	DC8	$4.31	$7.69	$9.94	$11.07
	DC91	$3.94	$5.61	$6.73	$7.29
	DC93	$4.06	$5.74	$6.86	$7.42
	DC9	$3.6	$5.28	$6.39	$6.95
	DC94	$5.42	$7.31	$8.57	$9.2
	DC95	$3.85	$5.77	$7.04	$7.68
	DC87	$5.78	$9.11	$11.33	$12.43
	DC86	$5.71	$9.03	$11.25	$12.36
	DC10	$5.45	$8.63	$10.75	$11.8
	DC8Q	$9.96	$13.28	$15.5	$16.6
MD's	MD90	$3.55	$5.21	$6.32	$6.88
	MD80-81-82-83-87	$3.61	$5.31	$6.43	$7
	MD88	$3.67	$5.41	$6.58	$7.16
	MD11	$10.04	$14.03	$16.7	$18.03
	MD10	$10.2	$14.35	$17.11	$18.49
RJ's	CL60	$1.62	$2.25	$2.68	$2.89
	CRJ2	$1.62	$2.25	$2.68	$2.89
	CRJ1	$1.67	$2.3	$2.73	$2.94
	CL30	$1.74	$2.38	$2.8	$3.01
	CRJ7	$2	$2.9	$3.5	$3.79
	CRJ9	$1.87	$2.76	$3.36	$3.66

Table D.4: Cost of delay per minute for 30 minutes delay at taxi (by aircrafts) cont'd.

Appendix E: Revenue generated per day at understudy airports- Weight based fee vs. congestion pricing revenue

Following charts show the average revenue generated by flights paying weight-based landing fee at these airports as well as the revenue generated by congestion pricing approach presented in this research. Table E.1 shows the weight-based landing fee at studied airports for July 2007 as announced by the corresponding airport authorities.

Table E.1: Weight based landing fee per 1000 lbs, Summer 2007

Airport	BOS	EWR	LGA	PHL	SFO
$ per 1000lbs.	$3.77	$5.83	$6	$1.63	$3

The research only looks at the GDP days that occurred in the month of July 2007 at these airports and assumes that, since there was no GDP implemented on the rest of the days, there was no congestion and therefore no pricing mechanism would be implemented. However, weight-based landing fee would be collected based on each flight's landing and is independent of whether it is a GDP or a non-GDP day. Keeping this in mind, for these charts, the congestion pricing for all time periods on non-GDP days is assumed to be zero, while the weight-based fee is still applied. Hence, there is no revenue generated on a non-GDP day using the congestion pricing approach and the only revenue collected is from the GDP days.

These charts indicate that at different airports, revenue generated by congestion pricing varies to the extent that at some airports, for e.g., LGA and SFO, the revenue generated by weight-based fee is higher than the revenue generated congestion pricing, however, at other airports, BOS, EWR and PHL, the revenue generated by congestion prices, specifically at lower capacity levels, for only GDP days, is higher than the revenue generated by weight-based landing fees for the whole month of July 2007. At PHL, this is true for all capacity levels.

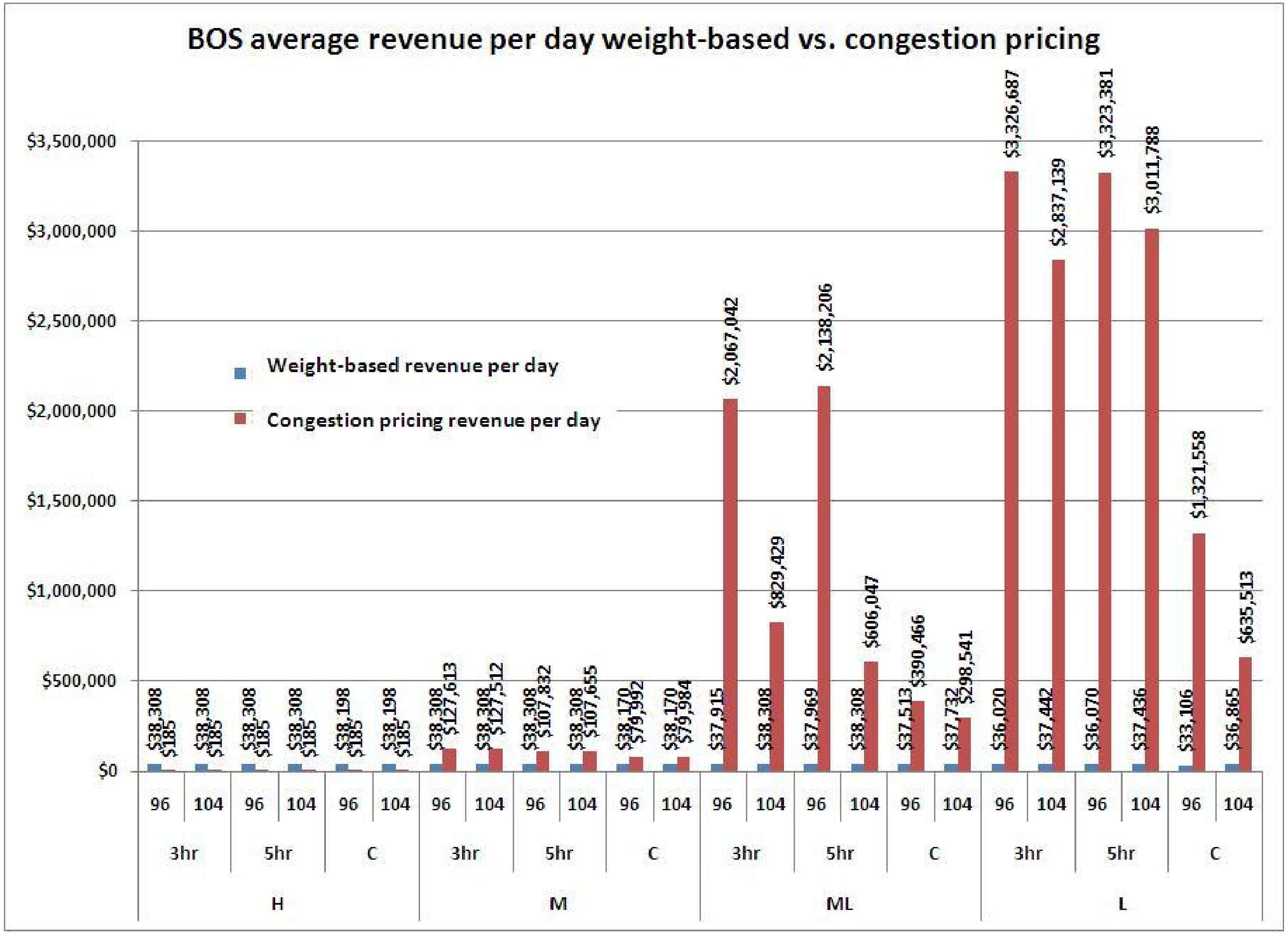

Figure E.1: BOS Average revenue per day - weight-based vs. congestion pricing

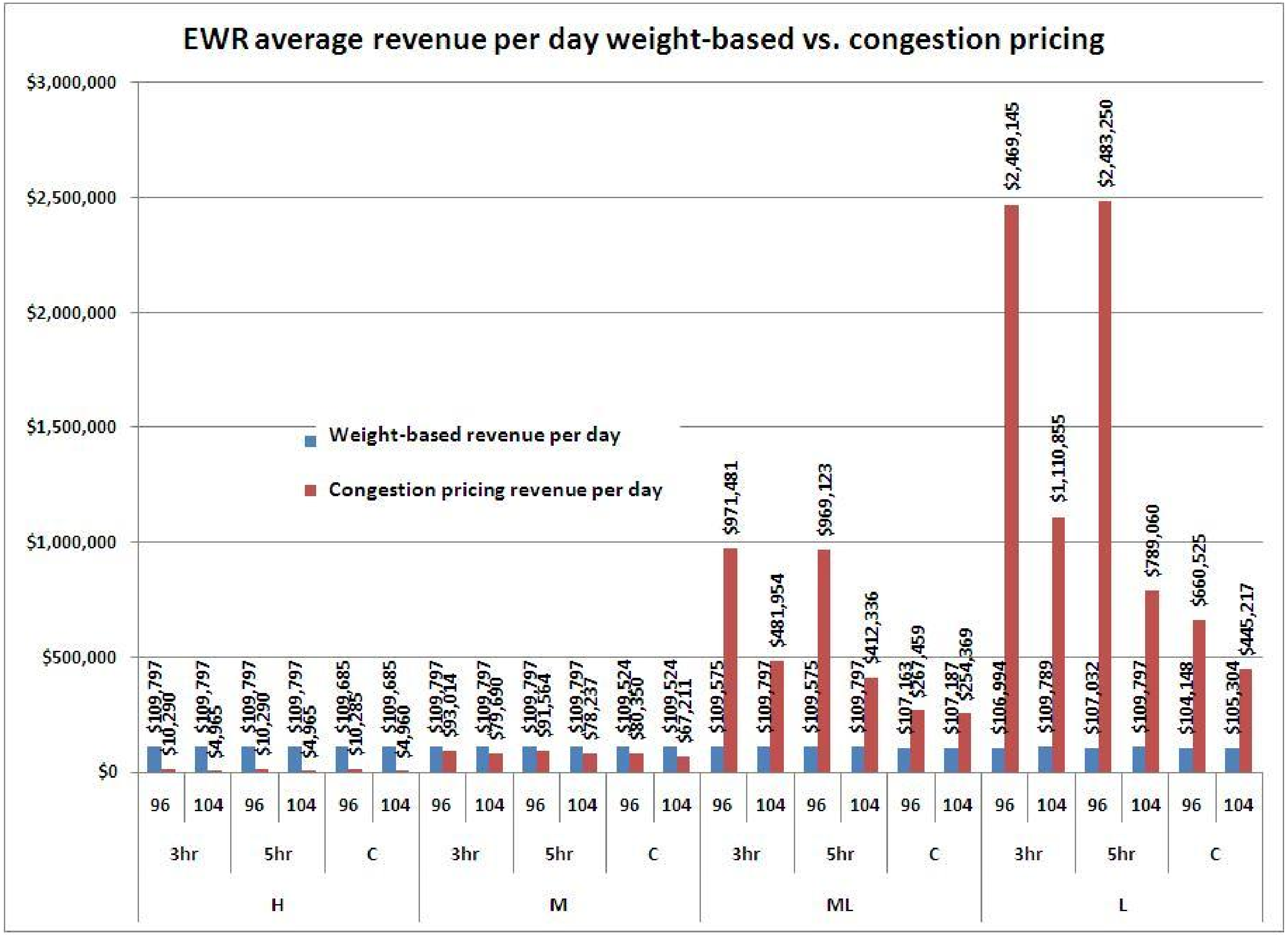

Figure E.2: EWR Average revenue per day - weight-based vs. congestion pricing

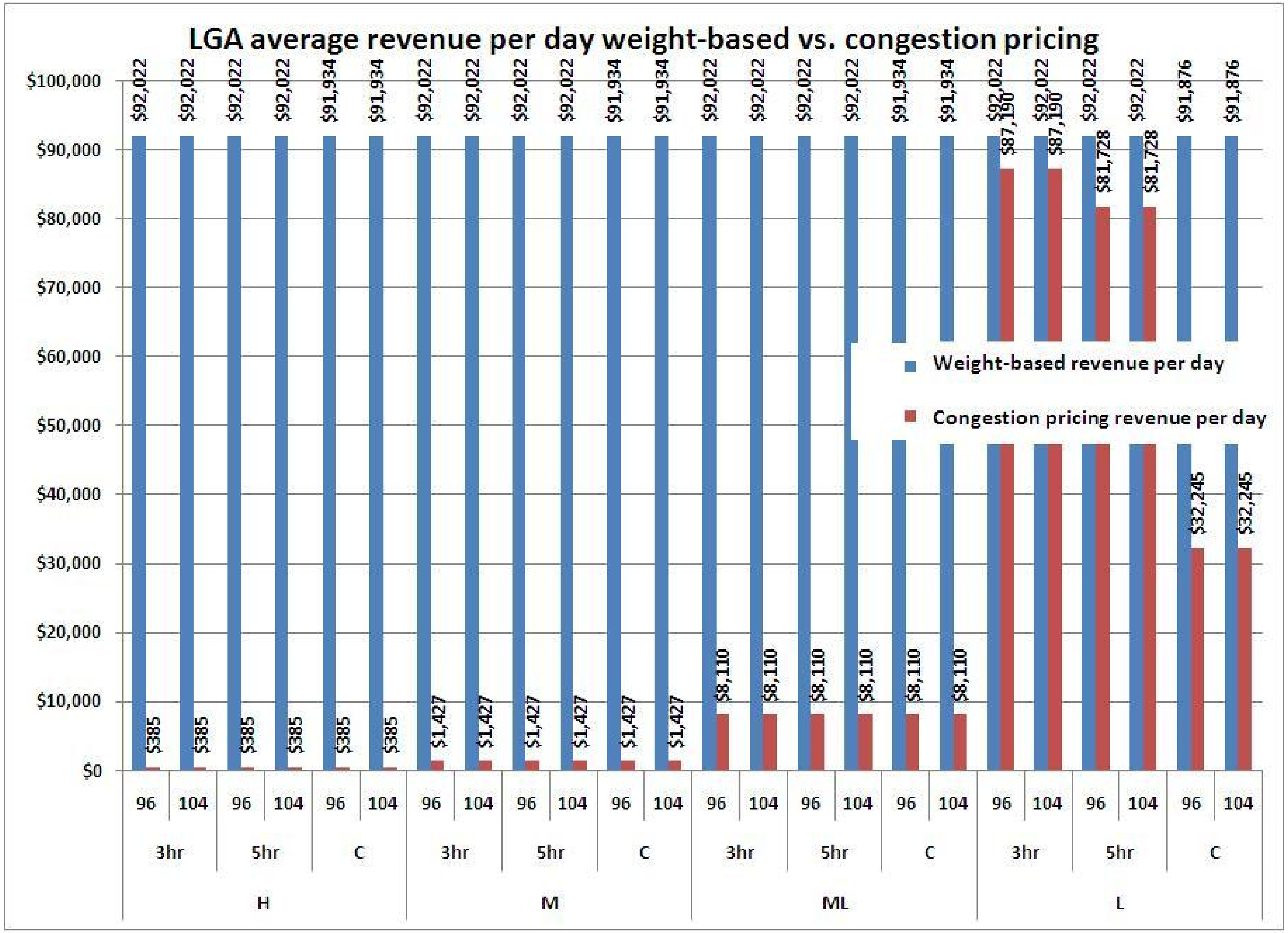

Figure E.3: LGA Average revenue per day - weight-based vs. congestion pricing

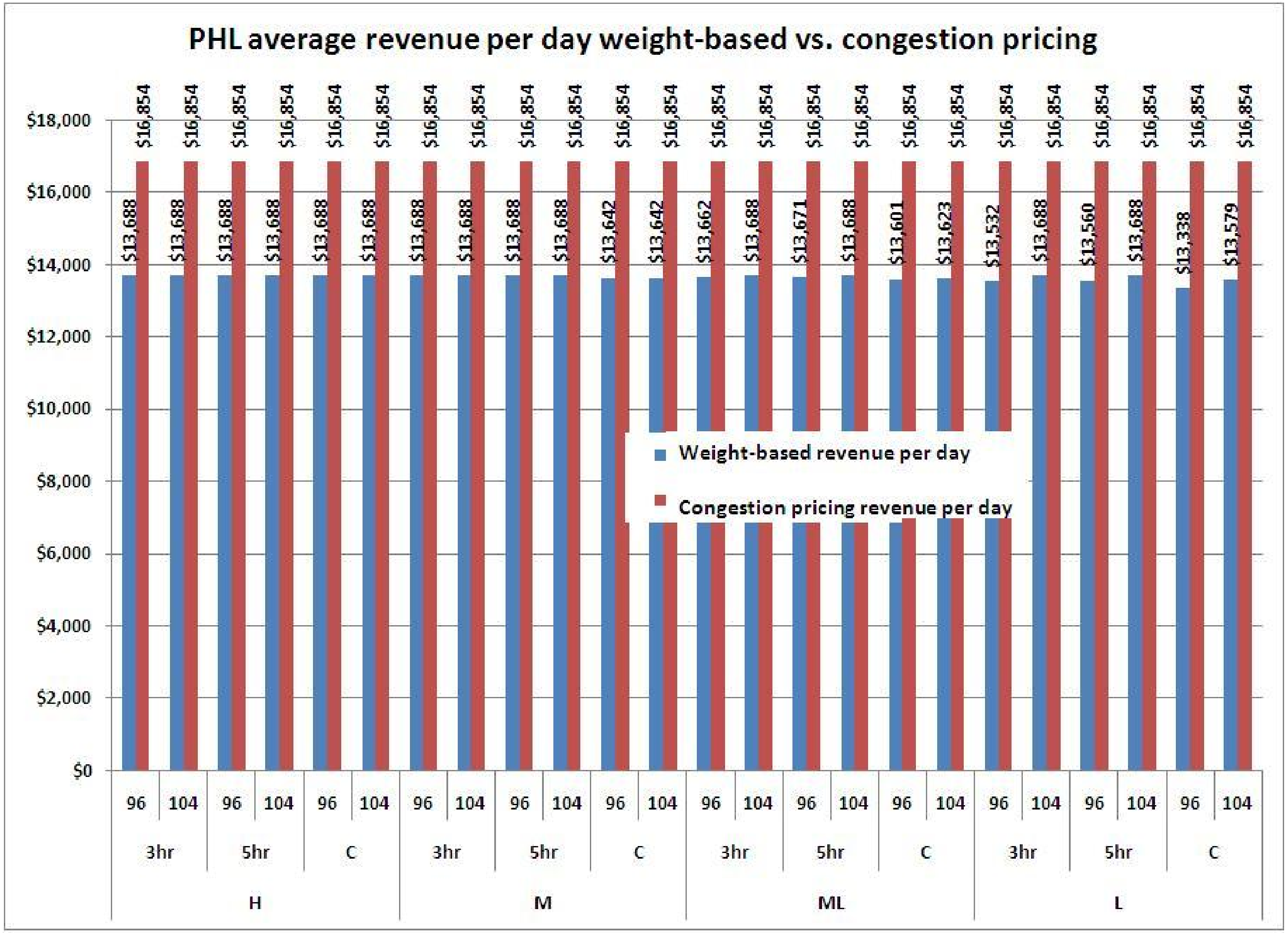

Figure E.4: PHL Average revenue per day - weight-based vs. congestion pricing

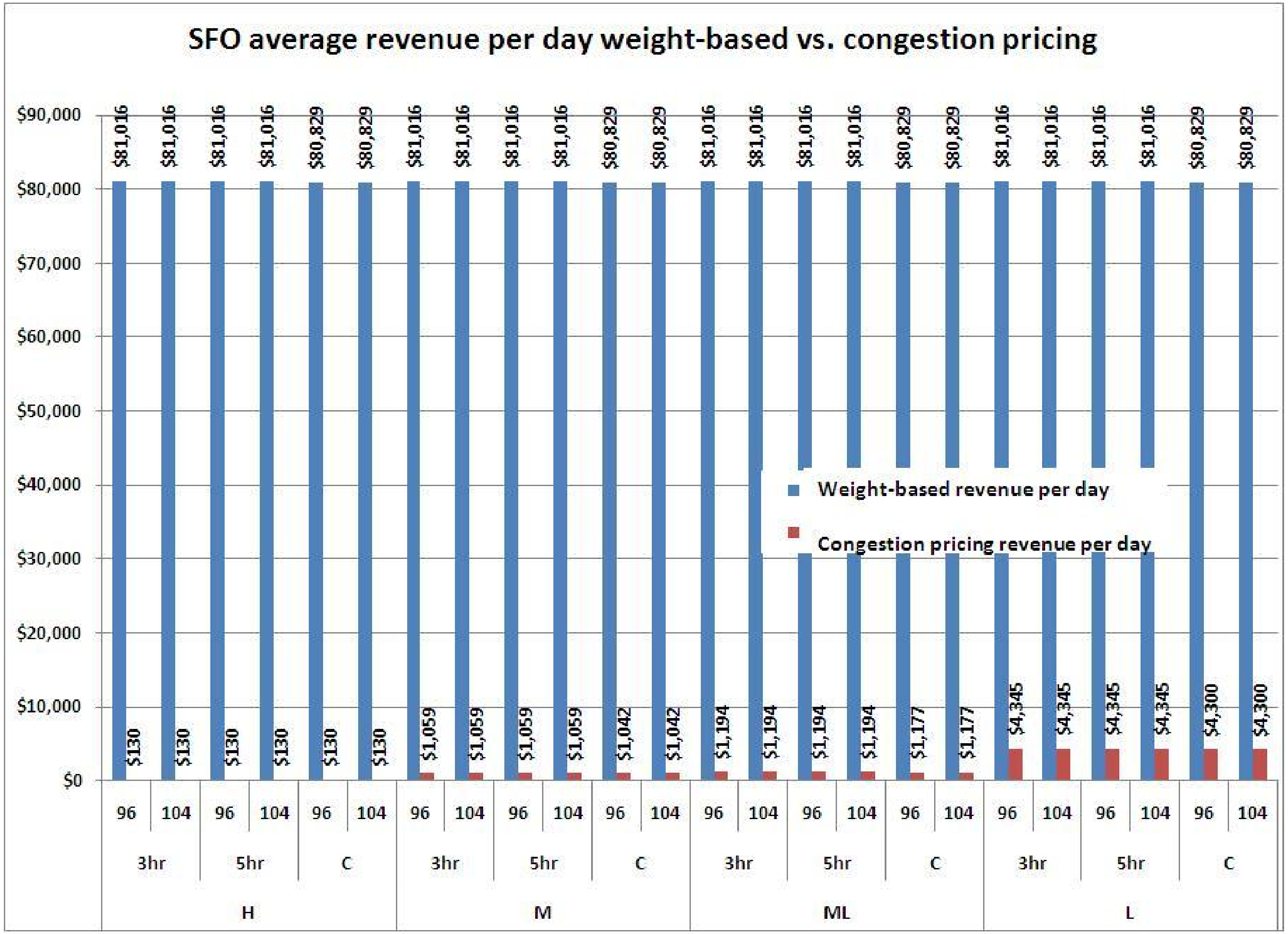

Figure E.5: SFO Average revenue per day - weight-based vs. congestion pricing

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Curriculum Vitae

Abdul Qadar Kara received his Bachelor's degree in Computer Science from Mohammad Ali Jinnah University, Karachi, Pakistan in 2002 and his Master's degree in Computer Science from Universität des Saarlandes, Saarbrücken, Germany in 2004. He has worked under various projects related to SAT-solvers, Natural Language Generation (NLG) and Verification during his academic career. Currently, he is working at Center for Air Transportation Systems Research (CATSR), George Mason University, as a Research assistant, where has worked on projects including the airline scheduling optimization model (ASOM) that develops an optimized schedule for a single benevolent airline. More recently, he worked on applying optimization techniques to develop a system that evaluates the effects of congestion pricing at airports in cases of inclement weather. He has over 10 years experience in programming and problem solving. His research interests include optimization, artificial intelligence, algorithms and mathematical logic. He has published over 6 papers, and briefed his work at national and international conferences.