Airline Revenue Management under Alternative Fare Structures

by

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ABSTRACT

Airline revenue maximization consists of two main components: pricing and revenue management. Revenue management systems are used to control seat inventory given a forecasted demand to maximize revenues. Fare structures have been constructed by major network airlines to segment demand with multiple fare products and numerous restrictions, a practice known as differential pricing.

The increasing presence of low-cost carriers with simplified fare structures (compressed fare levels and fewer booking restrictions) combined with recent market demand shifts have led some major network carriers to explore the use of simplified fare structures. This research examines the performance of revenue management systems under these alternative fare structures as compared to the performance of these systems with the traditional fare structure. The objective is to measure the impacts on overall revenue and revenue management under alternative fare structures.

The Passenger Origin-Destination Simulator (PODS) is used in this research to test the impact on revenue management of alternative fare structures. Results show that alternative fare structures lead to overall revenue reductions. The magnitude of reduction is as high as 20 percent when all fare restrictions are removed compared to the traditional base case fare structure. However, leg-based fare-class revenue management still produces a large revenue gain, up to 17 percent, over a first-come-first-serve regime regardless of the fare structure used. Furthermore, incremental revenue gains from origin-destination control as opposed to fare-class revenue management are still present with alternative fare structures. The incremental revenue gains are greater than 1 percent in all cases and greater than 3 percent when advance purchase requirements are removed. In the case when all restrictions are removed, origin-destination control actually performs better at a given network average load factor than with a traditional fare structure.

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Chapter 1 Introduction

1.1 Airline Revenue Management under Alternative Fare Structures

Revenue maximization encompasses two main functions: pricing and revenue management. Pricing, namely differential pricing, entails the development of a multi-tiered fare structure with different restrictions and requirements placed on each fare product. The goal of differential pricing is to get passengers to buy tickets that are close to their maximum willingness to pay for transport. Furthermore, revenue management is the practice of controlling seat inventory to protect seats for last-minute passengers who are willing to pay more for travel by limiting the amount of seats that can be booked in low fare classes. A revenue management system includes a detailed forecaster to project future bookings for all flights in all markets using a historical database and an optimizer that sets inventory control limits on the number of seats to make available in each fare class either on a leg or in a market.

A fare structure with different fare levels attempts to segment passengers into distinct groups by adding restrictions and requirements to the low-fare ticket classes. This allows price-sensitive but schedule flexible passengers, typically thought of as leisure passengers, to book lower-priced tickets, assuming revenue management inventory control allows them to be available. At the same time, less flexible passengers, typically business passengers, usually have only higher-fare options because the restrictions and requirements placed on low fare-class tickets are unattractive to this segment of passengers. Some common restrictions put in place by airlines include non-refundability, Saturday night stay requirements, maximum stay requirements, advance purchase requirements, and a fee charged if any changes are made to a reservation (typically known as a "change fee"). The ultimate goal is to sell different fare products to these different segments of demand by using the aforementioned restrictions and revenue management to limit the number of seat that are available at low fares. A more complete explanation of these principles can be found in Belobaba (1987).

The restrictions serve a distinct purpose in segmenting demand. A leisure traveler typically has travel plans well thought out in advance and is elastic with respect to price. Leisure travelers typically can meet all of the restrictions. Business travelers, on the other hand, are more affected by the use of restrictions. One reason why the non-refundability restriction exists is to deter business travelers, willing to pay a high fare, from buying a low fare product. A business traveler may not know travel plans until the last minute and is inelastic with respect to price because this traveler has to travel. The restrictions essentially corral the business travelers into the higher fare classes because many business travelers cannot purchase their tickets in advance (rationale for advance purchase requirement), need to be able to change tickets if plans change or refund tickets if a travel plans are cancelled (rationale for change fee and non-refundability), and want to fly during weekdays because business does not typically occur on weekends (rationale for Saturday night stay restriction). Finally, inventory control uses demand forecasts to ensure that it protects enough seat inventory for those passengers that will be booking last minute, high-yield tickets.

Airline revenue management, defined as seat inventory control, is responsible for large revenue gains by airlines. Smith et al. (1992) estimate that leg-based revenue management has generated approximately $500 million per year in extra revenue for American Airlines. The network airlines have invested a large amount of money into these revenue management systems because they know they are getting a return on their investment. This leads to a major concern that revenue management systems may not perform as well, that is provide significant incremental benefits, if a relaxation of the fare restrictions is implemented, in response to growing price competition.

1.2 Motivation

A current issue in the airline industry is the increasing presence of low-cost carriers. These carriers typically have fare structures that include a compressed set of fares, meaning that the dispersion of fares between fare classes is less than in a traditional fare structure, and a relaxation of some or all of the ticket restrictions that have become commonplace among network air carriers. In the face of this new competition, the network carriers must rethink their own pricing and fare structures. Some network carriers have implemented alternative fare structures in markets where they compete with low-cost carriers. This leads to questions regarding the overall revenue performance of the network carrier. A very pertinent question is the performance of their revenue management systems given compressed fares and relaxed restrictions.

The motivation of this thesis stems from two main sources. First, revenue management has been studied extensively in the past twenty years. Previous works have repeatedly shown the revenue benefits of implementing a revenue management system to control the allocation of seat availability by fare class (protect inventory for segments of the demand that are willing to pay more) based on demand forecasts. Furthermore, incremental revenue gains have been reported when implementing a more sophisticated origin-destination (OD) control revenue management system versus traditional fare-class yield management. See Lee (1998) for a detailed analysis of incremental benefits of OD control. However, most of these prior studies have focused on experiments where the network carriers keep all of the traditional restrictions in place and have a single set fare structure.

Airline fare structures and passenger disutilities have been examined (Lee (2000) presents the modeling of passenger disutilities), but these studies did not address the impacts on revenue management of changing the relative fare values, or removing ticket restrictions. Examining parametrically the performance of revenue management methods when the fare structure changes and/or ticket restrictions have been removed has not been examined before in detail and would address the current changes in the airline industry as traditional network carriers have been questioning these traditional restrictions and fare structures given the emergence of profitable low-cost carriers. The results and conclusions can be used to determine if revenue management is still as effective when the traditional assumptions of airline pricing are broken down and alternative fare structures with fewer restrictions are used. An alternative fare structure can incorporate a compressed fare structure (fare classes are closer together in terms of fare value) or relaxed restrictions (removing some or all of the aforementioned restrictions), or a combination of both.

Second, traditional network carriers are currently being threatened by low-cost carriers (LCC). LCCs typically have somewhat different fare structures and fewer ticket restrictions than the network carriers. In this environment, they have been thriving while network carriers have been taking drastic measures to recover revenue and cut costs. The LCCs are expanding into more of the network carriers' markets. Network carriers, such as America West Airlines, have relaxed some of their ticket restrictions and altered their fare structure in an attempt to boost revenue and compete more effectively with the LCCs. Other network carriers, witnessing America West's success with this move, have gradually attempted the same changes in select markets. This study's main objective is not focused on pricing and market entry. However, the motivation for this line of inquiry stems from the fact that airlines have recently been faced with the prospect of simplifying fare structures and restrictions to remain competitive. This thesis will examine specifically the effect that these changes might have on the performance of a revenue management system.

1.3 Thesis Objective

This thesis examines the impact on revenue management methods with alternative fare structures. An alternative fare structure refers to a fare structure where fare values have been compressed and/or some or all of the ticket restrictions relaxed. Beginning with the traditional differentiated fare structure laden with ticket restrictions, the study examines parametrically the performance of revenue management algorithms when some or all of these restrictions are removed. This is combined with changing the fare values in all markets to test revenue management performance when fares change, primarily when fare differentials are compressed.

The goal of this thesis is to examine the performance of revenue management methods under different fare and restriction regimes. It attempts to answer the question if an airline simplifies its fare structure, then will the fundamental benefits of revenue management still be realized and will the incremental benefits of a more sophisticated OD control system still exist. Not only does this study examine if revenue management benefits still occur under different fare structures, but also to what magnitude revenue management benefits the airlines given alternative fare structures.

1.4 Thesis Structure

The first chapter of this thesis gives a brief description of airline revenue management methods and possible variations in performance given changes in the fare structure such as removing advance purchase requirements and/or ticket restrictions. The motivation for this thesis is also presented as well as the main objectives of the research. Finally, an overview of the thesis structure is given.

Chapter Two examines the basic premise of revenue management and gives some detail into the specific "vanilla" revenue management used by most airlines. Also, the chapter introduces the Passenger Origin-Destination Simulator (PODS), the tool that is used in this thesis to test hypotheses, including the specific network to be used, Network D. The discussion includes an overview of PODS, its passenger choice model, its uniqueness as an airline simulator, and presents some of the baseline fare structure parameters used in this study.

The third chapter examines fare structures assumed to be representative of traditional network carriers. This chapter includes a general overview of disutilities and fare structures in theory and how they are represented in the PODS simulator. It begins with an examination of the economic theory of price differentiation. Then, a discussion of passenger disutilities and willingness to pay ensues. The focus is on restriction disutilities and some examples, both hypothetical and from the PODS simulator, are used. Advance purchase requirements are also discussed. There is a brief description of market-based fare structures and structured fare structures. Finally, some examples of different fares structures from real world airlines help to illustrate the theory and some common differences among the traditional network air carriers and low cost carriers are discussed.

The fourth chapter examines parametric tests of fare-class yield management (FCYM) and OD revenue management control in PODS. The experiments in this chapter focus on changing fare ratios and values, such as compressing and expanding fare differentials as well as initiating business fare reductions while keeping the traditional fare restrictions.

Chapter Five presents PODS simulation results pertaining to the performance of revenue management methods given changes in the fare product restrictions. The experiments in this chapter include removing some or all of the fare product restrictions and reducing and/or removing advance purchase requirements. The results presented focus on the impact of revenue management methods on the airlines' performance given that a fundamental change in the fare structure has occurred.

Chapter Six, the final chapter, reviews the findings of the thesis, its objective and methodology, and provides some future research directions. The findings are synthesized with the initial hypotheses, namely to determine whether there are still revenue management benefits when the fare structure is radically changed and simplified. Finally, unanswered questions of the thesis are discussed and this discussion leads to a description of new directions for further research.

Chapter 2 PODS and Revenue Management Methods

The Passenger Origin-Destination Simulator (PODS) is a competitive computer simulation that is used to test airline revenue management methods. It was developed by Craig Hopperstad and The Boeing Company and is used extensively in a series of studies and theses produced by the MIT Flight Transportation Laboratory, now The International Center for Air Transportation. PODS simulates a competitive origin-destination network, which can have from one to five airlines. Using choice models, simulated passengers make a decision regarding carrier and product choice. Furthermore, one can input different revenue management methods for the airlines to use in the simulation. The simulation produces output that can be used to analyze the performance of these different revenue management methods given sets of input parameters.

This chapter is intended to provide a brief overview of PODS and the revenue management methods available for use in the simulation. Wilson (1995) provides a more detailed introduction to the PODS simulator. The first section of this chapter briefly examines the motivation for PODS as a revenue management research tool and a competitive simulation. Then, there is a short explanation of the PODS system architecture and the underlying passenger choice model. Finally, the chapter concludes with an outline of the revenue management methods used in PODS and their basic premise.

2.1 Motivation for the PODS simulator

PODS research has focused on its use as a revenue management tool. The development of airline revenue management, discussed in more detail later in this chapter, has caused profound change in the industry. Many fare products are offered to different market demand segments. Furthermore, recent developments in computing power have led to the feasible implementation of larger and more complex revenue management algorithms. This makes PODS a very useful simulation to test these algorithms under different conditions to examine how they perform in the simulated network.

While some studies have focused on the overall benefit of revenue management versus no revenue management, also known as first-come-first-serve (FCFS), more recent studies have shifted attention to the incremental benefit of network OD control versus the leg-based EMSR heuristic developed by Belobaba (1987 and 1992). This incremental benefit will also be explored in this thesis. Furthermore, the numerous parameters in PODS allow for the examination of the performance of revenue management methods under different circumstances, including changes in demand, fare structures, or passengers' disutilities.

There are a number of significant differences between PODS and other airline revenue management simulations. First, PODS allows for passenger choice among airlines/paths/fares using a sophisticated passenger choice model, described in the next section of this chapter, that allows for simulated passengers to define a decision window based on the Decision Window Model developed by The Boeing Company and to exhaust a complete choice set given parameters before simulated passengers become choose not to fly. This is in stark contrast to earlier simulators that operated on a "first-choice-only-choice" (FCOC) principle. Essentially, if the simulated passenger's first choice was not available, then the passenger would not travel. In PODS that passenger may have a second or third choice that is available and books it.

Second, as stated above, PODS simulates a competitive airline network. This means that passengers who may prefer Airline 1 might instead fly Airline 2 because of the passenger choice model allowing a choice set and the fact that up to five airlines can be programmed into the simulation. This is a very important part of the simulation because researchers can examine the competitive effects of different RM methods, fare structures, forecasting techniques, scheduling, and numerous other topics. Also, each airline can have a different revenue management method. Thus, not only can PODS output report the incremental benefits of revenue management, but it can also report the incremental loss from not having revenue management when one or more competitors do.

The choice model applied to simulated passengers in PODS and the competitive nature of the simulation set it apart from previous simulators. It is both the choice model and the competitive nature of the simulator together that makes PODS such a powerful simulator. This is partially due to the fact that, other than scheduling choice, competition creates a large number of choices for the simulated passengers. On top of all of this is the revenue management system that allocates available seat inventory in every simulated leg or market.

2.2 PODS System Structure

PODS simulates a competitive airline network environment with many origin-destination markets. The main focus of PODS research has been on the incremental performance of airlines when some or all of them implement different forms of revenue management. See, for example, Lee (1998), Zickus (1998), Gorin (2000), and Carrier (2003). Many different parameters can be changed to test different hypotheses within the simulation. This section describes the PODS simulator by giving a brief description of its architecture, the simulation mechanism, and simulation environment.

There are essentially four models within the PODS system architecture: the passenger choice model, revenue management, forecaster, and historical booking database. All four of these components are linked in the simulator. Figure 2-1 graphically displays the four models and the linkages between the models.

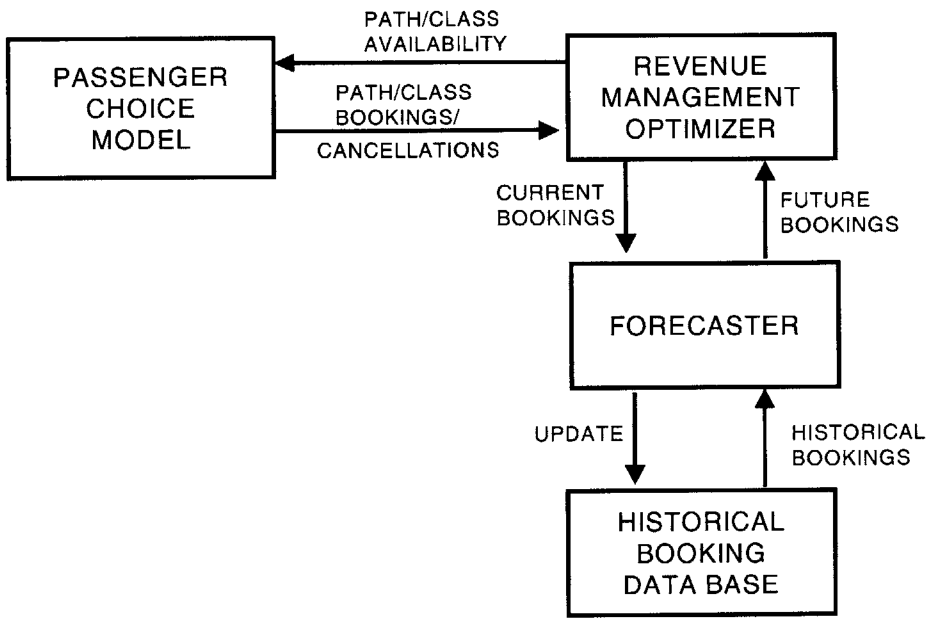

Figure 2-1: Basic PODS System Structure (Courtesy of Hopperstad)

PODS begins at the passenger choice model. Passengers are generated stochastically based on input parameters, such as mean demand by origin-destination. These generated passengers can be of two types: business or leisure. PODS generates path preferences for passengers based on passenger type and the input parameters. Each passenger has a choice set with a descending preference of itinerary.

Again, the passenger choice model is of paramount importance to PODS and in making it much more sophisticated than other airline simulations. The following is a brief description of the model, however Lee (1998) provides a nice detailed description of the passenger choice model. The passenger choice model uses input parameters, such as disutilities and willingness-to-pay to formulate the choice set of a simulated passenger. The first step is to generate disutility costs, favorite airline choice and the decision window of a specific passenger. Then, a maximum willingness-to-pay (WTP) is generated. Next, a total perceived cost is calculated for each option accounting for the disutility costs and fare. Finally, the model attempts to assign passengers to available seats on itineraries within the choice set of the simulated passenger, starting with the most preferred itinerary.

The revenue management model is used next. While simulated passengers are using their choice set to inquire about specific itineraries, the revenue management model, which may use a different algorithm for each airline, determines whether or not to accept the itinerary and book it or not. The decision to accept or reject the itinerary request is based on the booking limits that are formulated and set by the revenue management algorithm. This topic is examined further in the next section. The forecaster and historical database are used so that booking limits are calculated by incorporating some forecasting method, which is influenced by historical bookings. If the RM system deems the itinerary unavailable, then the passenger may try his or her next choice, but if the RM system accepts the request then it is booked and the availability is adjusted to reflect the booking.

This process is repeated for every simulated passenger in PODS. After a certain interval of time, known in PODS as a "timeframe", the current bookings in the revenue management model are reported to the forecaster. The forecaster then adds that data to the historical database and a new forecast is generated from the updated historical data. The new forecast is used to reset booking limits and bid prices.

The above process, called a "sample" is repeated many times to generate a large enough sample to obtain statistical significance. The standard number of samples in a "trial" is 600. Furthermore, one "run" consists of five trials. Among the 600 samples per trial, the first 200 are known as "burns". These samples are only used to develop the historical database to develop a forecast. Therefore, a single "run" normally consists of 2000 samples, but this is a variable parameter.

2.3 *Revenue Management*

Airline revenue management is essentially a form of inventory control used by airlines to manage and control the sale of airline seats in a market so that seats are protected for travelers that are willing to pay for them. Fare class yield management (FCYM) is a rather widely used revenue management approach. Seats are controlled on a leg basis, which is in contrast to newer OD control algorithms that manage inventory by market/path. For example, let us say an airline offers fares in the SFO-BOS market, but all flights connect through MSP. Using FCYM seats on SFO-MSP flights and seats on MSP-BOS flights would be controlled and demand forecasted independently. However, using OD control, demand would be forecasted and/or inventory would be controlled on the SFO-BOS market level. These newly developed algorithms are complex and require substantially more computing power and data, hence only a handful of the world's largest airlines currently use these systems. Many airlines still use FCYM as their primary method of inventory control. However, the advances in computing power and the relative limitations of FCYM have led an increasing number of airlines to explore the possibility of implementing OD control systems.

As stated above, FCYM is a leg-based approach. It does not differentiate between local passengers and connecting passengers on a flight leg in an airline network. The availability of a certain fare class is calculated independently over every leg. This is a limitation of the leg-based model because the specific booking class must be available on all legs to book a multi-leg itinerary. This can result in a sub-optimal solution for maximizing revenues over a hub and spoke network. See Belobaba (1998) for a more detailed explanation.

In this study PODS will use four different revenue management algorithms. Expected marginal seat revenue method (EMSRb) is used as the aforementioned FCYM method. Heuristic bid price (HBP), displacement adjusted virtual nesting (DAVN), and probabilistic bid price (ProBP) are the three OD control methods. This section briefly discusses each of the four methods. A more detailed description of the first three methods with examples can be found in Lee (1998). The formulation of ProBP can be found in Bratu (1998).

2.3.1 Fare Class Yield Management (FCYM) Using an Expected Marginal Seat Revenue (EMSRb) Algorithm

Belobaba (1987) developed the EMSR model and EMSRb followed in 1992. This is considered to be the base case for most of the simulations run for this study. It is a leg-based inventory control revenue management algorithm that uses EMSRb to optimize the seat inventory and availability of fare classes. It is a nested, top-down approach, meaning that a protection level (booking limit) is set for Y, the highest fare class, then B, the next highest, and so on until all inventory has been allocated to a fare class. Specifically, the expected marginal revenue of a seat is the expected revenue from selling that seat given the probability density function of the flight leg demand forecast. Given the forecast, EMSRb sets a booking limit for each fare class in a top-down fashion as mentioned above so that the expected marginal value of the last seat of the higher protecting fare class is less than the next lower class's fare. Wei (1997) provides a more detailed explanation and calculation of the EMSR curve.

EMSRb is a very common RM algorithm in the industry. Since it is a leg-based revenue management algorithm, forecasting, optimization and control are all calculated on each leg independently. This implies that in order to book a multi-leg itinerary in Q class, each leg must have availability in Q to book the itinerary. This may not be revenue maximizing if, for example, there is only 1 seat left on leg 1, but leg 2 has plenty of availability. If the Y fare for leg 1 only is $300 but the Y fare for the connection is $500, then the last seat on leg 1 should be held for a connecting passenger who will pay $500. However, if the first passenger to request an itinerary is the local passenger for leg 1 only, the revenue management control will allow the booking to take place because it does not differentiate between the local and connecting passenger. An OD control algorithm can recognize this difference.

FCYM based on the EMSRb algorithm is significant because of its wide usage. It also provides a departure point, as it is easy to differentiate between its implementation as the optimizer for FCYM and the OD control methods. Thus, EMSRb provides a base case for this study, so that the incremental benefit of OD control can be examined.

2.3.2 Heuristic Bid Price (HBP)

Heuristic bid price is also known as Greedy Virtual Nesting (GVN) with EMSR Heuristic Bid Price. It is very similar to GVN, which is described in Lee (1998). Belobaba (1998) outlines the HBP method. There are two main differences between EMSRb and HBP. First, the evolution from EMSRb to GVN encompasses the change in booking class definition. In EMSRb the booking classes are the actual published fare classes. In GVN the booking classes are "virtual" classes, so bookings are mapped into virtual classes. The advantage of this is that GVN always favors the highest fare passengers, hence the name "greedy". Forecasting and seat inventory control are still performed on a leg basis. These virtual classes are present in the HBP algorithm as well. They are a constant set as an input parameter in PODS. Currently, the upper bounds of each virtual bucket are set so as to have demand-equalized buckets. Second, HBP uses a different optimization and availability control methods. Again, HBP uses the virtual class concept and its forecasting is also done on a leg basis. Furthermore, for local paths HBP uses EMSRb booking limits. However, for connecting paths, HBP uses a bid price method instead of using EMSR booking limits, although the EMSR value of the last seat available on a leg is used as part of the method's calculation. The bidprices for a connecting path are calculated as follows:

$BP_{C,\, leg1} = EMSR_1 + \text{d-factor} * EMSR_2$

$BP_{C,\, leg2} = EMSR_2 + \text{d-factor} * EMSR_1$

where $EMSR_1$ is the critical expected marginal seat revenue on leg 1
$EMSR_2$ is the critical expected marginal seat revenue on leg 2
d-factor is the displacement factor coefficient

Each of these decision rules is a weighted sum of the EMSR values of the two legs in question of the connecting itinerary. One of the legs is weighted with a d-factor, which is a displacement coefficient used to add a penalty on to connecting itineraries essentially swaying the algorithm to accept more local bookings instead of low-fare connecting paths. To summarize, an incremental booking is accepted if:

$FARE > MAX[BP_{C,\,leg1}\ ,\ BP_{C,\,leg2}]$

where: $BP_{C,\,leg1}$ is the bidprice for leg 1

$BP_{C,\,leg2}$ is the bidprice for leg 2

The EMSR values, which calculate the bid price, are re-optimized every 200 bookings in PODS.

The main benefit of HBP is that an airline can still use its leg-based forecaster and database. HBP is easier to implement than complete OD control methods given that an airline already uses FCYM.

2.3.3 Displacement Adjusted Virtual Nesting (DAVN)

Displacement Adjusted Virtual Nesting uses a deterministic network linear program (LP). A discussion network displacement concepts can be found in Wei (1997). The LP generates shadow prices for each leg and each departure using an Origin-Destination Fare class (ODF) forecast. The actual fare and the shadow price are used to calculate a "pseudo-fare". This calculation implies that DAVN will not unconditionally favor connecting passengers, but instead considers the displacement of a passenger on the second leg before accepting a connecting passenger. The calculation for a connecting itinerary follows:

$PF_{leg1} = Fare_{leg1} - \text{shadow price}_{leg2}$

$PF_{leg2} = Fare_{leg2} - \text{shadow price for}_{leg1}$

where: PF_{legi} is the pseudo-fare for leg i

The shadow price can be interpreted as the displacement cost, potential revenue lost by accepting a connecting passenger, of the connecting itinerary. Finally, the pseudo-fares are mapped into virtual classes and leg-based EMSRb is used for seat inventory control. Unlike HBP, the virtual buckets in DAVN are not constant, but the virtual bucket bounds are initially set and then redefined at every timeframe. Re-optimization of the LP occurs at the start of every timeframe, which produces new shadow prices and pseudo-fares that are optimized on a leg basis.

To recap, DAVN uses a LP that generates shadow prices for each leg, which are then used to calculate pseudo-fares for each ODF. A connecting itinerary is calculated by subtracting the shadow price of leg 2 from the leg 1 fare. The pseudo-fare is mapped to a virtual class, and the booking limits of the virtual classes are calculated using EMSRb. An airline using DAVN controls its seat inventory by leg, but uses OD path data for forecasting and database.

2.3.4 Probabilistic Bid Price (ProBP)

Probabilistic Bid Price is the final method examined in this study. It is a recently developed revenue management method having been formulated and initially tested in PODS by Bratu (1998). It uses a bid price method to perform inventory control. The main difference between it and HBP is that ProBP calculates the bid price for each leg in an OD path in the following way. The fare of the ODF multiplied by the critical EMSR value of the leg is divided by the sum of the critical EMSR values of all legs in the ODF space. In essence, the bid price is a pro-ration of the critical EMSR value, defined as the EMSR value of the last seat sold on a leg. From Lee (2000), mathematically it is defined as:

$$\Sigma_{m\in L(j)}EMSR_c(m) \neq 0 \rightarrow PRF(j,k) = (EMSRc(k) * F_j) / (\Sigma_{m\in L(j)}EMSRc(m))$$

where L_j is the set of all legs that traverse the ODF

F_j is the actual fare of ODFj

PRF(j,k) is the prorated fare of ODFj on leg k

EMSRc(m) is the critical EMSR value of leg m.

ProBP also uses a convergence model to correct for the overestimation of the critical EMSR value. It is an iterative model that is used because the EMSRb model uses the actual ODF fare when calculating the critical EMSR value, which overestimates it. ProBP re-optimizes every 200 bookings and repeats until the critical EMSR value converges within a $10 range, given a maximum number of iterations.

ProBP is a bid price method like that of HBP, but with some key differences. Its main difference is that the forecaster and database are leg-based in HBP, but they are calculated at the ODF level in ProBP. However, they are also both bid price methods as opposed to strict booking limits. While they both use path-based seat inventory control, the calculation of the inventory control is quite different. HBP uses a path-based control method that was described in the preceding pages. The formulation of ProBP presented directly above shows that the seat inventory control method for it is distinctly path-based using prorated critical EMSR values.

2.3.5 Summary

This section has presented the four main revenue management methods that will be used in the PODS simulation runs done for the purpose of this study. The main focus is on the incremental benefit of introducing OD control algorithms to replace FCYM. Thus EMSRb is a base case and sets the standard for the other algorithms' performance.

Each revenue management algorithm has three major specifications, namely the type of database and forecaster (leg or path-based), the type of inventory control (leg or path-based), and the method of calculating inventory control (booking limit or bid price). Table 2-1 below summarizes these specifications for each revenue management algorithm.

Revenue Management Algorithm	Database and Forecaster	Type of Control	Method of Control
EMSRb	Leg-based	Leg-based	Booking limit
HBP	Leg-based	Path-based	Bid price
DAVN	Path-based	Leg-based	Booking Limit
ProBP	Path-based	Path-based	Bid Price

Table 2-1: Summary of revenue management methods

2.4 Simulation Environment

The PODS simulator has been developed extensively and many new features have been added. Currently, there are three main networks in use for experimentation. These are known as Networks D, E, and R. This thesis only uses Network D because the focus of this study can be analyzed clearly using it alone.

2.4.1 Network D

Network D is comprised of 252 legs and 482 markets. There are two airlines that fly from a hub (each airline has a different hub) to 40 spoke cities; 20 to the east of the hub and 20 to the west. This network most likely compares to the domestic United States market. A representative map of Network D appears below in Figure 2-2.

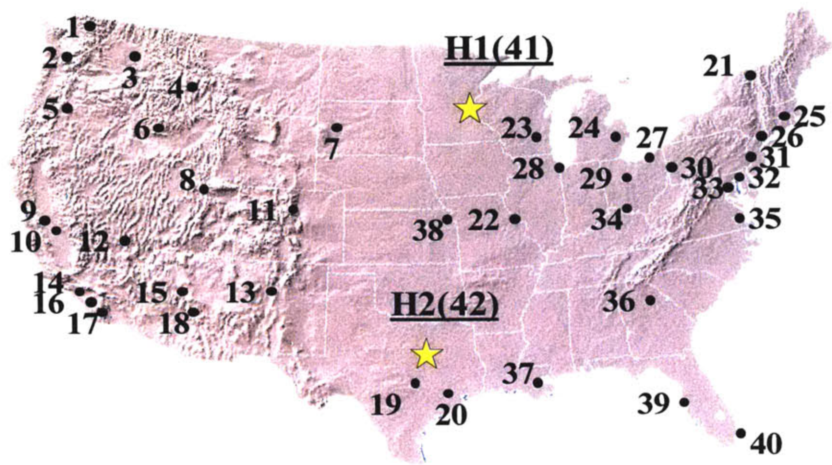

Figure 2-2: Representative Network D map

Network D introduced a competitive network of connecting flights on a large scale. The large scale leads to many more path options for simulated passengers, which is more representative of the real world. Each airline offers flights to all spokes from its hub thrice daily and all airplanes for both airlines have a capacity of 100. These facts, while having led to a number of interesting experiments and results, are also a limitation of the network because it is rather symmetric with respect to the two competing airlines. However, Network D has been well calibrated and provides very robust results for this study.

2.5 The Fare Structure in PODS

A main portion of this study has to do with alternative fare structures. Fare structures will be discussed extensively in Chapter 3. However, upon describing PODS in this chapter, it would provide clarity to introduce the base fare structure used in PODS at this point.

The fare structure encompasses a set of fare classes. In our study, there are four fare classes: Y, B, M, and Q. Y represents the highest fare in a market and Q the lowest fare.

In the real world, some airlines may have 10 or more fare classes, but only four are used in this thesis because it still provides realism in revenue management. Since there are four fare classes in each market, each market will have four fares of which some or all of them may be available to prospective passengers depending on inventory control and advance purchase requirements.

2.5.1 Ticket Restrictions in The Base Case

Airlines differentiate their product by adding restrictions and advance purchase requirements to certain fare classes. This may restrict some passengers from buying the lowest fare and instead purchasing a higher-fare ticket. This is one of the goals of revenue management, to get passengers to pay as close to their maximum willingness-to-pay as possible. Likewise, PODS uses disutilities, discussed in Chapter 3, to formulate a generalized cost function so that tickets with restrictions will have an added "perceived" cost that may affect the choice set of a simulated passenger. The restrictions are placed on certain fare classes. Table 2-2 lists the restrictions and their real world counterpart.

PODS Disutility	Real-World Equivalent
Disutility 1	Saturday night stay requirement
Disutility 2	Non-refundability
Disutility 3	Change fee

Table 2-2: PODS disutilities and equivalent restrictions

In addition to ticket restrictions there is an advance purchase requirement. However, before discussing advance purchase restrictions in PODS, a brief discussion of the cumulative booking curves in PODS is necessary as this defines the process as to how passengers approach the booking process over simulated time.

2.5.2 Booking Curves in PODS

The passenger booking process in PODS has 16 timeframes. The booking process commences at the equivalent of 9 weeks before departure. Each timeframe corresponds to a specific number of days before departure. Table 2-3 displays the mapping of timeframes into the number of days before departure.

Timeframe	1	2	3	4	5	6	7	8
Days from Dep.	56	49	42	35	31	28	24	21
Timeframe	9	10	11	12	13	14	15	16
Days from Dep.	17	14	10	7	5	3	1	0

Table 2-3: Timeframe mapping to days before departure

Bookings occur during each timeframe and revenue management forecasts are updated either at the beginning of every timeframe or after a specific number of bookings. Passengers are distributed to arrive at certain timeframes by the formulation of a cumulative booking curve. Two of these curves are parameters in PODS, one for business passengers and the other for leisure passengers. A graphical representation of the cumulative booking curves appears below in Figure 2-3.

As can be seen in the in Figure 2-3. Leisure passengers cumulatively book tickets much earlier than business passengers: 75 percent of leisure travelers book tickets at least 21 days in advance of departure, while only 35 percent of business travelers have booked tickets by that same time before departure. Furthermore, 30 percent of business travelers attempt to book travel within 7 days of departure.

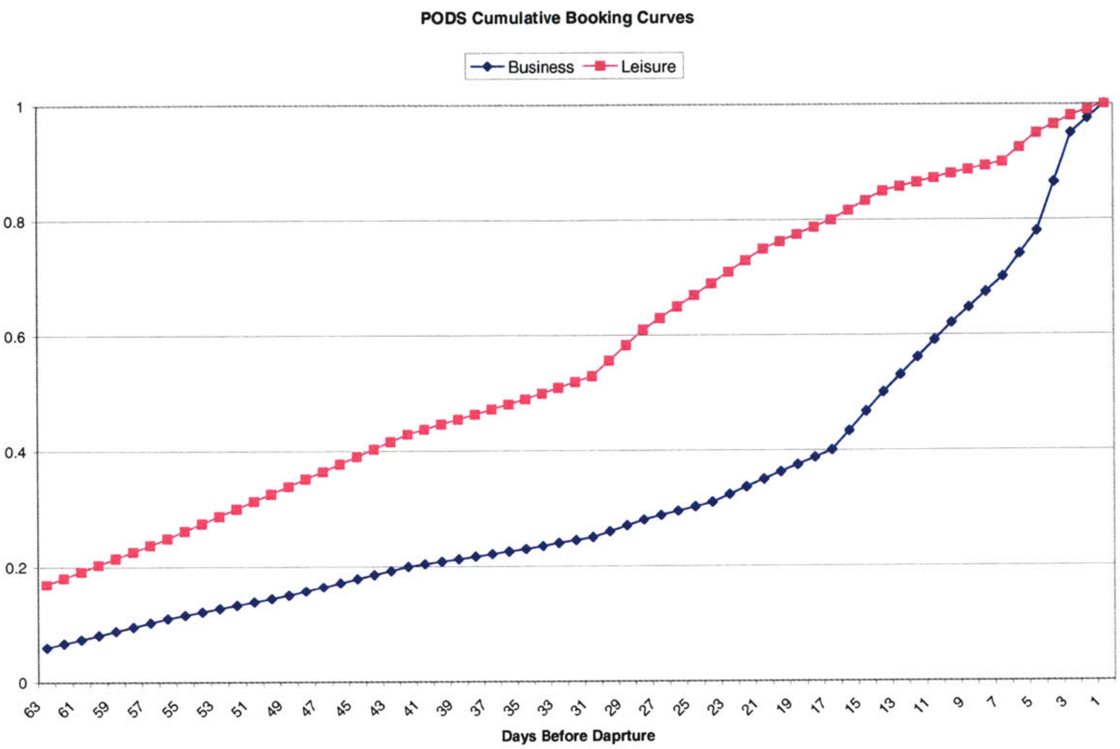

Figure 2-3: PODS Cumulative Booking Curves

2.5.3 Advance Purchase Requirements in PODS

PODS also incorporates an advance purchase requirement in its fare structure. An advance purchase requirement forces the closure of a booking class at a specific time even if the RM system has seat availability in that class. Thus, last-minute passengers are forced into a choice set that only consists of high fare booking classes. Again, in PODS there are timeframes that can be translated into a specific number of days before departure. The advance purchase requirements typically used in our base case are shown in Table 2-4.

Fare Class	Timeframe when Class Closes	Days before Departure
Y	16	0
B	12	7
M	10	14
Q	8	21

Table 2-4: Advance Purchase Requirements in Base Case

2.5.4 PODS Base Fare Structure

The fare structure incorporates the ticket restrictions and advance purchase requirements to differentiate the product of each booking class. The main focus of this thesis is to examine revenue management performance when the traditional fare structure, sometimes called the base fare structure, presented above is abandoned for an alternative fare structure that is characterized by a relaxation of some of these parameters that differentiate the booking classes. This base fare structure is presented in Table 2-5.

Fare Class	Advance Purchase (timeframe)	Restriction 1 (Sat. night stay req.)	Restriction 2 (Non-refundable)	Restriction 3 (Change fee)
Y	16 (0 days)	NO	NO	NO
B	12 (7 days)	YES	NO	NO
M	10 (14 days)	YES	YES	NO
Q	8 (21 days)	YES	YES	YES

Table 2-5: PODS base fare structure

2.6 Summary

This chapter briefly gave an introduction to PODS and revenue management. It began with a general synopsis of PODS as well as the importance of it as a simulator and its improvements against previous simulators. Then, a brief description of the PODS system structure was presented. The next section introduced the four revenue management algorithms that are used in this study. Next, the simulation environment, Network D, was introduced and an explanation of its components was given. Finally, the base fare structure in PODS was explained

The next chapter will focus on disutilities and fare structures. It will provide a description of passenger disutilities, how some of these disutilities are used in fare structures, and a general economic overview of price differentiation. Also, the fare class restrictions and advance purchase requirements will be explained. Examples of fare structures will be provided and it will also give the disutility levels in PODS and how these disutility parameters affect passenger choice in PODS.

Chapter 3 Airline Fare Structures and Passenger Disutilities

Airline passengers are faced with many decisions when making a choice of flying in a specific market. There is a wide range of options available to them, which could include airline, routing, and time of departure. The final decision made by a passenger is not based solely on the monetary cost of the ticket, but also on the perceived costs from the unattractiveness of some of the features of that ticket. This level of unattractiveness of certain features of a ticket can be thought of as a disutility. While some of these disutility factors are not directly controlled by the airline, fare structures, set by airlines, and disutilities are related in that the structures of fares include, in many cases, the use of restrictions to increase the disutility of passengers, so that a passenger may buy a higher fare rather than face the restriction(s) of the lower fare. Along with examining the concepts of disutilities in this chapter, we will also discuss airline fare structures.

An overview of the economic theory of price differentiation is given in section 3.1. Section 3.2 introduces the concept of passenger disutilities. This introduction leads to an examination of the use of passenger disutilities in the development of airline fare structures in Section 3.3. Section 3.4 further develops the description of airline fare structures by looking at the role of advance purchase requirements. Section 3.5 briefly introduces structured fare ratios and market-based fares, and outlines the differences between the two. Finally, some real world examples of different fare structures of competing airlines in specific markets are described in Section 3.6. Section 3.7 provides a chapter summary.

3.1 An Economic Overview of Differential Pricing

The principles of airline revenue management and the fare structures used by most network air carriers today are based on the economic theory of differential pricing. This is very closely related to price discrimination. As stated above, one of the main goals of differential pricing is to get passengers to pay a fare that is closer to their maximum willingness-to-pay and to stimulate more demand that otherwise wouldn't fly if only one uniform fare existed in a market. In pursuing this goal the airlines earn more revenue, and the formal goal is to maximize profit using revenue management. The first part of this section discusses price discrimination, as it is the precursor to differential pricing and revenue management. Then, an economic overview of differential pricing is given with an example of how charging more than one price to different market segments will increase revenues.

3.1.1 Price Discrimination

According to Tirole (1988) price discrimination can be divided into three separate categories known as the three degrees of price discrimination. They represent three cases where firms attempt to charge different prices of an identical good to different people or groups. This subsection briefly examines all three degrees for background to airline price differentiation. A much more thorough theoretical discussion of price discrimination appears in Tirole (1988). Also, see Phlips (1983) for a very detailed book pertaining solely to the economics of price discrimination.

The first degree of price discrimination is also known as perfect price discrimination. It occurs in rare instances and usually when consumers are facing a monopolist. In this case, suppose that each consumer has some maximum willingness to pay w. Then, the firm lets price p = w and the firm captures the entire consumer surplus. Each consumer pays his or her maximum willingness to pay.

The second degree of price discrimination is a little bit more common than the first, but is more complex theoretically. In this case, there are heterogeneous consumers, which can be offered specific bundles of goods that meet their needs and tastes individually. Some most common examples of this type of price discrimination are two-part tariffs, where there is some fixed premium and then a variable usage cost. For example, most consumers of mobile telephones are charged a fixed monthly fee for service and then are charged a variable per minute rate for phone usage over that month. Another example is a tie-in sale where one buys a product that requires some complementary product and that complementary product must be purchased from the same company that produced the original product. For example, if a consumer buys a computer printer from a company, then the consumer must also buy printer ink cartridges that are produced only by the same company that produced the printer.

Finally, the third degree of price discrimination deals with the segmentation of demand. This concept drives price differentiation in the airline industry. A company produces a single product and knows that its aggregate demand can be divided into groups or segments of demand. In the case of the airline industry the most common market segmentation is that of business and leisure travelers. The company will offer different prices to the different market groups it identified in an effort to maximize profit. According to Tirole (1988), "Optimal pricing implies that the [firm] should charge more in market [segments] with the lower elasticity of demand." This is also essentially what airlines attempt to do. However, the third degree of price discrimination differs slightly from airline differential pricing. The theory of price discrimination implies that the firm cannot discriminate within a market group. Airlines, on the other hand, will charge different prices to those in the same market segment of demand if the opportunity to do so arises.

3.1.2 Differential Pricing

As stated above, differential pricing is, or is very similar to, third degree price discrimination. Demand is segmented into specific groups. Each of these groups has different price sensitivities. The easiest way to describe differential pricing is with an example. A more comprehensive treatment of differential pricing, as well as the source of the following example, can be found in Daudel and Vialle (1994).

There is a linear, continuous, and decreasing demand function. A firm sets a single price P_1, and a corresponding quantity Q_1. Then, revenue $R_1 = P_1*Q_1$. This is shown graphically below in Figure 3-1.

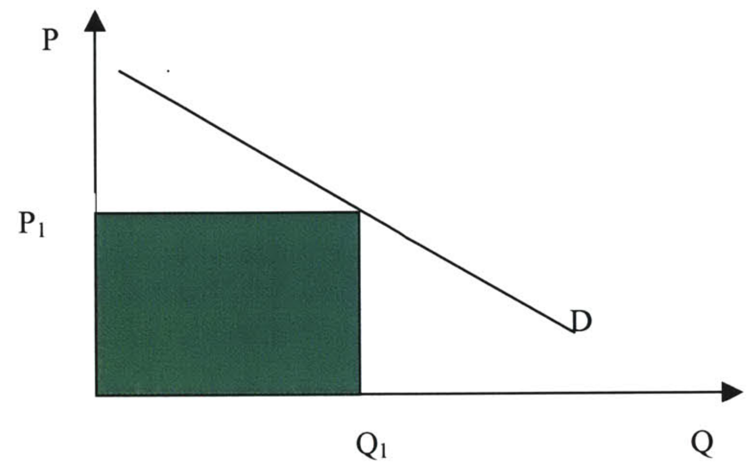

Figure 3-1: A firm offering a single price

Now suppose that the firm has identified two distinct market segments within the aggregated demand. The firm then introduces a second price P_2, which is less than P_1. There will be quantity Q_2 produced at a price of P_2. For this theoretical example it is essential to assume that these two market segments are completely distinct. This means that customers who are willing to pay P_1 will not shift to the new lower price P_2. Therefore, if P_2 were the only price offered, then revenue $R_2 = P_2*Q_2$. Finally, if both prices are offered simultaneously to the two distinct market segments, which is graphically depicted below in Figure 3-2, then

$$R_{12} = P_1*Q_1 + P_2(Q_2-Q_1)$$

which is equivalent to:

$$R_{12} = P_2*Q_2 + Q_1(P_1-P_2)$$

Since $(Q_2-Q_1) > 0$ and $(P_1-P_2) > 0$, then it follows from the above results that $R_{12} > R_1$ and $R_{12} > R_2$. The revenue from offering two different prices is greater than offering only one of the two prices. This same process could continue for a firm offering infinitely many prices.

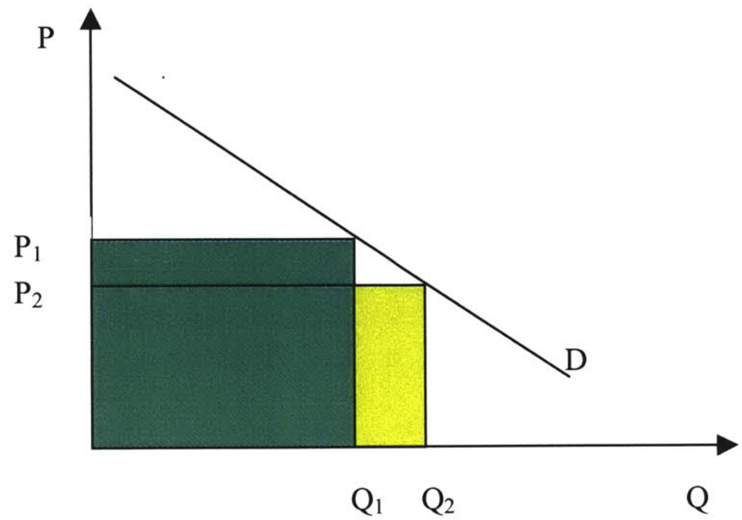

Figure 3-2: A firm offering two prices

The example above confirms the positive benefits of differential pricing. However, the example utilized some theoretical economic assumptions that may not be so distinct in real world airline pricing. The demand segments may be more numerous, not completely distinct, and difficult to identify.

3.2 Passenger Disutilities

Each airline passenger has a willingness-to-pay for travel in a specific market. While a passenger's choice greatly depends on price, there are several other factors as well. For example, a passenger may need to depart in the evening only, or may need to be at his or her destination on Wednesday and be back at the origin by Friday. Furthermore, a frequent traveler may have a preferred carrier because of a loyalty program or a perceived higher level of service. Finally, a passenger wants to travel for the least amount of time possible and would find it rather inconvenient, for example, to fly from Boston to Seattle with a connection in Orlando. All of these examples become part of the choice set of a passenger when trying to choose among travel options in a market. Departure time, loyalty, and travel time affect the total choice set and the choice made among the feasible remaining choices left in the choice set. Thus, these factors have a "perceived" cost and formulating them as passenger disutilities allows for integration of economic utility theory and airline passenger choice. There are four major types of disutilities that arise frequently in air travel and are represented in PODS. The next paragraphs briefly explain each. Lee (2000) provides a more detailed discussion of disutilities.

3.2.1 Replanning Disutility

The replanning disutility is based on the passenger's time decision window. A passenger knows when he or she would want to depart from the origin and arrive at the destination, but realizes that there may not be a flight at those exact times. Thus, the passenger builds a time window that includes, at the bounds of the window, the earliest time at which he or she is willing to depart and the latest time at which he or she is willing to arrive. This can be extended to include specific days of departure. A disutility occurs if there is no available itinerary within the decision window. At this point, a passenger either does not go or must replan using options that are partially or totally outside of the decision window. The disutility would be higher as the proposed replanned itinerary is further outside of the window.

3.2.2 Unfavorite Airline Disutility

The unfavorite airline disutility is rather straightforward. In most cases, consumers have more than one choice of airline for travel in a specific OD market. Some passengers may simply choose the carrier that offers the lowest available fare in the market given a time window. However, a large proportion of travelers have a preference for a specific airline in a market. This can be for numerous reasons. The employer of a business traveler may have a corporate agreement with a specific carrier. A carrier may have an extremely attractive frequent flyer loyalty program or may offer an extra amenity, such as personal video screens in every seat back or a few extra inches of legroom in the main cabin. This is the case for most passengers when deciding on a path in an OD market. Thus, the airline that is their first choice for any or all of the aforementioned reasons is preferred and any path that uses an airline other than their first choice has a disutility associated with those paths. This added disutility increases the perceived cost of an itinerary that does not use a path with the passenger's favorite airline.

3.2.3 Path Quality Disutility

The path quality disutility is based on time, but is not dependent on the decision window of passengers. Among path choices in an OD market, some of them may be non-stop flights, while others may be one-stop or connecting flights. The connecting flights are longer, require one to traverse an intermediate airport and wait for the next leg of the journey. Passengers, in general, want to fly on the most direct path that is possible given that the fare is the same. Thus, any itinerary that includes a stop or a connection is considered inferior to a non-stop path. A fixed, stochastic disutility is used to quantify in monetary terms the inconvenience that a passenger endures when his or her path includes a stop or connection.

3.2.4 Restriction Disutilities

Finally, airlines create differentiated fare structures by introducing restrictions on certain tickets. In general, the more restrictions a ticket has in a particular market, the cheaper the ticket is. The rationale for this is to stimulate segments of market demand that are not willing to pay high prices while ensuring that those who can afford the high prices do not have the opportunity to purchase a lower fare because the added restrictions are too "costly" for them. Restriction disutilities are presented in more detail in the next section.

3.3 Restriction Disutilities

There are four main restrictions used by traditional network airlines to differentiate fare products. First, certain fare products in a market may be restricted to certain times of the day and/or certain days of the week. For instance, a certain fare may only be valid for travel on Tuesdays, Wednesdays, and Saturdays, which are traditionally off-peak days for air travel, or a ticket may be restricted to departures before 8 a.m. or after 7 p.m. Second, there may be minimum and/or maximum stays placed on a certain fare product. The most common restriction known to the frequent traveler is the Saturday night stay restriction. This restriction simply means that the minimum stay on the fare product is until the first Sunday after departure from the origin. This restriction is extremely common and is used chiefly to segment leisure travelers who do not mind staying at a destination over the weekend and business travelers that wish to return to their origin before the weekend. The minimum/maximum stay requirement can also be used to force a length of stay at a destination or to limit the length of stay at a destination. Third, many airlines charge a fee for changes made to a ticket before departure. This is known as a "change fee". A nominal fee of $25 to $200 is charged if one wants to change the path of the itinerary or the day of travel. Again, the focus here is to differentiate between customers that are willing to pay for flexibility and those that will not. Finally, many low-fare products are non-refundable. This condition is designed to ensure that a passenger does not use up inventory only to cancel it at the last minute without any penalty to him or her. Typically, only the highest unrestricted fares are fully refundable. This captures additional revenue for those passengers that need to be extremely flexible and are willing to pay for it because they will buy a high fare product while making sure that low fare speculative bookings do not occur that will be cancelled. Some airlines, such as JetBlue, have gone so far as to make all fares non-refundable.

All four types of restrictions discussed above have an associated disutility that can be used to formulate a perceived cost for each restriction. Different fare classes have associated combinations of restrictions and when all the disutility costs are calculated, the path with the lowest "perceived" cost is chosen by each individual passenger. The precise disutility coefficients used in PODS were presented in Section 2.5. The restrictions are a central issue to this study. There is also an advance purchase requirement placed on certain fare classes, which also plays a significant role in this thesis. However, an advance purchase requirement does not affect the generalized cost function of passengers because it is a function of a passenger's arrival in the booking process rather than a function of fare classes. An example of restrictions placed on fare classes in a hypothetical market appears below in Table 3-1.

Fare Class	Day of Week	Stay Req.	Change Fee	Refundable
Y	All	None	$0	Yes
B	All	1 night	$50	No
M	All	Saturday night	$100	No
Q	Mon., Thur., Fri., Sun.	Saturday night	$100	No
L	Tues., Wed., Sat.	Saturday night	$100	No

Table 3-1: An example of fare class restrictions

In PODS, there are disutility coefficients placed on each one of the three restrictions that can be used in the simulation. The coefficients are different for business and leisure travelers and are not constant over passengers, but are instead stochastically distributed Gaussian. This attempts to place a total "perceived" cost on a ticket in specific markets by multiplying the disutility coefficient with the base fare (Q-fare) and a base fare coefficient (BFC) that is 1 for leisure passengers and 2.5 for business travelers. Table 3-2 presents the Gaussian mean disutility coefficients used in PODS.

Passenger Type	Disutility 1 Sat. night Stay	Disutility 2 Non-refund.	Disutility 3 Change Fee
Business (Mult. By BFC)	0.9 (2.25)	0.3 (0.75)	0.3 (0.75)
Leisure (Mult. By BFC)	1.75 (1.75)	0.25 (0.25)	0.25 (0.25)

Table 3-2: Disutility coefficients in PODS

Table 3-2 presents some interesting information about passengers in the simulation. The first set of numbers gives the raw mean disutility coefficient. However, the table is easier to interpret when the mean disutility coefficients have been multiplied by the base fare coefficients. This calculation appears in parentheses in each cell of the table. Tickets with a Saturday night stay restriction incur a high perceived cost from both business and leisure travelers. However, business passengers incur a higher perceived cost from this restriction as well as the non-refundability and change fee restrictions. The latter two restrictions add a significant perceived cost to a ticket for business travelers, but not nearly as much for leisure travelers.

From these disutilities and the base fare structure presented in section 2.5, it is possible to determine, on average, the rank choices of fare products for business and leisure travelers in a specific market given the fares in that market. A graphical example appears below, which further explains the concept of perceived cost.

Let us assume that there is a market that has the following fare classes, values, and restrictions shown in Table 3-3.

Fare Class	Y	B	M	Q
Fare	400	200	150	100
Restriction 1	NO	YES	YES	YES
Restriction 2	NO	NO	YES	YES
Restriction 3	NO	NO	NO	YES

Table 3-3: Example of fares in a market

From Tables 3-2 and 3-3, we can calculate the total perceived cost for both a business and leisure traveler on average for all fare classes. This appears below graphically in Figures 3-3 and 3-4.

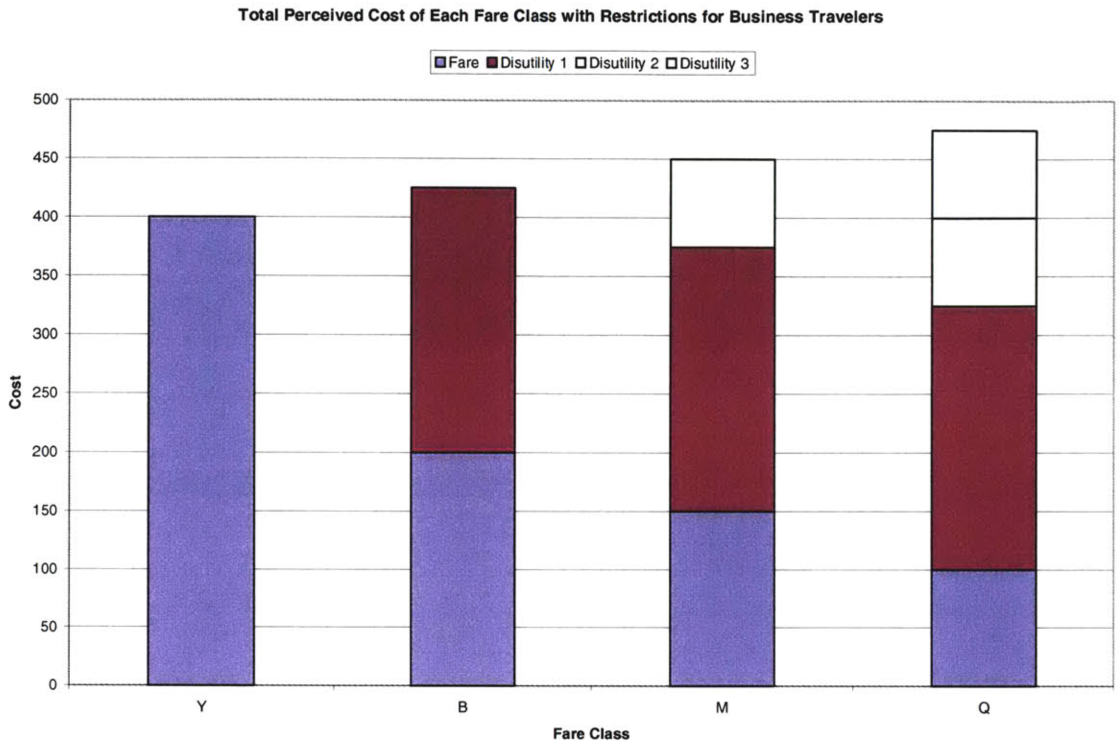

Figure 3-3: Total Perceived Cost for Business Travelers

Figure 3-3 helps to show why the ticket restrictions are so important for getting business travelers to buy high fare class tickets. On average, the unrestricted Y fare has the least perceived cost to a business traveler. This means that, on average, the Y-fare is the business travelers' first choice, followed by B, M, and then Q.

Likewise, Figure 3-4, shown below, gives the opposite impression about leisure travelers. The restrictions do not add as much perceived cost. Thus, the fare is more important since the change fee and non-refundability restrictions do not place a large extra cost on the ticket. Leisure travelers are flexible and plan their trips ahead of time without much need to cancel or change plans. On average, the Q fare has the least perceived cost to the leisure passenger, which makes it a leisure traveler's first choice, followed by M, B, and then Y. In fact, the willingness to pay of most leisure travelers is such that they would not be willing to buy a Y ticket.

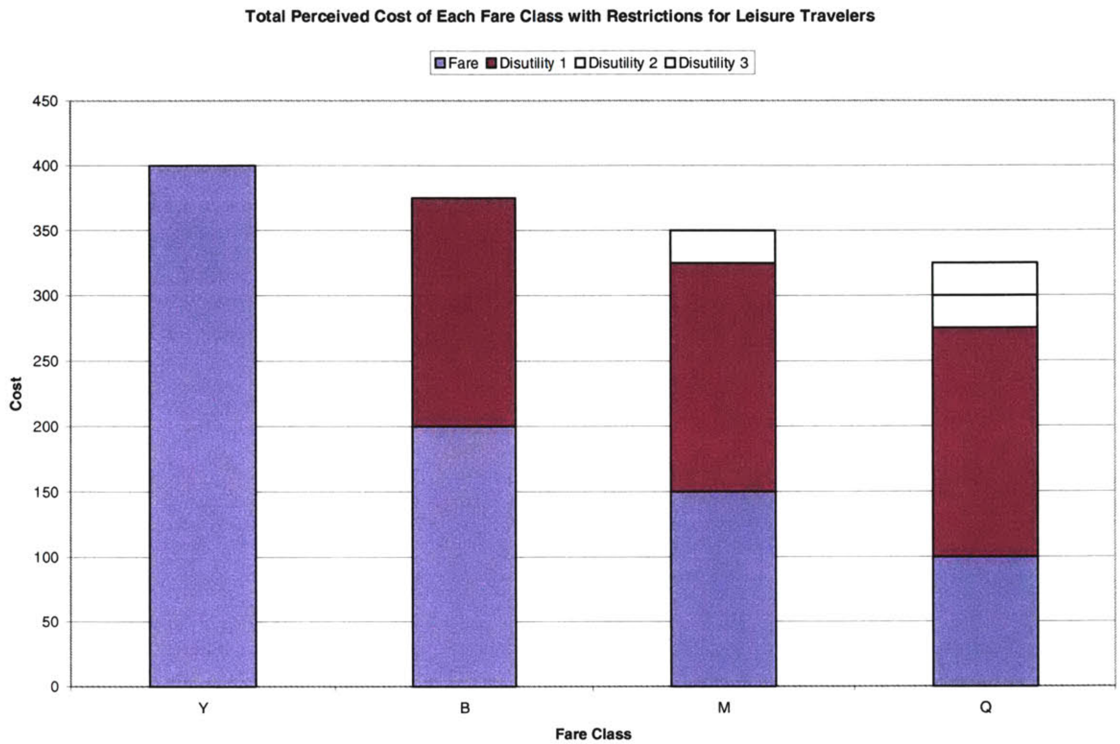

Figure 3-4: Total Perceived Cost for Leisure Travelers

This section examined the major types of disutilities that occur in the path choice passengers must make and presented the representation of perceived cost in PODS. Disutilities can be used to calculate a "perceived" cost of a particular path option given the fare and the associated cost of the inconveniences of the particular option. Furthermore, disutility theory becomes relevant when airlines add restrictions to tickets in an effort to segment demand and develop differentiated fare structures that push people to pay a fare that is much closer to their willingness to pay.

3.4 Advance Purchase Requirements

Advance purchase requirements have become an integral part of the fare structure of network air carriers. The advance purchase requirement complements inventory control by automatically stopping sale of low fare tickets at certain thresholds before departure. This restriction forces last-minute passengers to either buy a ticket from a higher fare class or not fly. By doing this, airlines can once again segment market demand and increase revenues.

Airlines typically set advance purchase requirements to stop the sale of low-fare tickets at about 21 to 14 days before departure in most markets. However, in some leisure markets, such as Hawai'i, some of the lowest fare products have 60-day advance purchase requirements. In a typical market, the advance purchase requirement was set because it was believed that almost all leisure travelers, who normally plan their travel well in advance, book their itinerary at least two to three weeks before their trip. Hence, virtually all of the passengers booking trips within two weeks of departure are business travelers. Even if inventory control sets booking limits such that a low fare class were to remain open on a flight due to low bookings, the advance purchase requirement stops the sale of low fare tickets at the threshold since it is assumed that a high percentage of remaining bookings to come are from business travelers who are willing to buy the higher fare class if necessary. However, the above rationale seems to be waning. The evolution of the internet has spawned "web specials" and last minute deals that appeal to leisure travelers. A higher proportion of leisure travelers are booking travel closer to departure through these new channels. Table 3-4, shown below, includes advance purchase requirements examples on fare classes as well as the restrictions given in Table 3-1.

Fare Class	Day of Week	Stay Req.	Change Fee	Non-Refund	Advance Purchase
Y	All	None	$0	Yes	0 days
B	All	1 night	$50	No	3 days
M	All	Saturday night	$100	No	7 days
Q	Mon., Thur., Fri., Sun.	Saturday night	$100	No	14 days
L	Tues., Wed., Sat.	Saturday night	$100	No	14 days

Table 3-4: An example of fare classes with restrictions and advance purchase requirements

This section briefly presented advance purchase requirements and their justification. The exact advance purchase requirements and the cumulative booking curve of passengers in PODS can be found in Section 2.5. Advance purchase requirements stop the sale of low fare tickets at specific time thresholds before departure to prevent more bookings in that class from occurring even if inventory control wanted to leave availability in that class. This action segments passengers into those who plan trips well in advance, typically leisure passengers, and those who book last-minute itineraries, usually business passengers, with the latter group having to purchase from higher fare classes. The above discussion has provided a base as to how and why airlines offer multiple fare products in the same market. However, the next section will briefly examine the actual determination of the fare levels and the difference in fares between fare classes.

3.5 Market-based Fares Versus Structured Fares

Airlines make decisions regarding fare levels in every market they serve. The decision is compounded by the fact that there are multiple fares in each market. Not only is there a decision as to the fare level in the market, but also the dispersion of fares in the same market. The level of dispersion can have a great impact on revenue management performance. This section introduces the concepts of market-based fares and structured fares.

Airline fares are loosely based on the distance between the origin and destination in order to cover costs, but an even greater driver of airline fares is market forces. Furthermore, the dispersion of airline fares in a single market is based on the mix of passengers in a market and the demand for the different fare products. This implies that an airline will price according to market conditions and not based upon some formula. In this thesis this type of pricing is called market-based pricing. The dispersion of fares in each OD market is based on market conditions. For example, the Boston-San Francisco market, which has significant business traffic, may have an unrestricted fare that is six times the lowest discounted fare. On the other hand, a traditional leisure market, such as Boston-Las Vegas, may have an unrestricted fare that is only four times the lowest restricted fare. Structured fares have a constant fare ratio over all markets.

3.5.1 Structured Fares

Structured fares were used in early versions of the PODS simulator. Each fare class value is a ratio of the lowest fare class, also known as the base fare. These fares are easy to calculate and depend only on the base fare set in each market. One significant limitation of this is that the ratios are constant over all markets and thus do not account for possible differences in demand for higher fare classes in specific markets or competitive forces. An example appears below in Table 3-5.

Fare Class	Boston-Las Vegas	Boston-San Francisco
Y	4.0*Q fare BOSLAS	4.0*Q fare BOSSFO
B	2.0*Q fare BOSLAS	2.0*Q fare BOSSFO
M	1.5*Q fare BOSLAS	1.5*Q fare BOSSFO
Q	Q fare BOSLAS	Q fare BOSSFO

Table 3-5: An example of structured fares across markets

3.5.2 Market-Based Fares

Examining the characteristics of each individual market and making a judgment as to what set of fare values to place on the different fare products in that market in order to maximize revenue determine market-based fares. Each fare class value is a ratio of the lowest fare class. However, the ratio values vary from market to market to better capitalize in differences in passenger type mix and market conditions in different markets. It is presumed, and examined in this study, that OD control revenue management provides a greater incremental benefit because not only does it control inventory for each market, but it can differentiate between a market whose unrestricted fare is three times the base fare and a market whose unrestricted fare is seven times the base fare and control inventory accordingly to maximize network revenues. Table 3-6 gives an example of this.

Fare Class	Boston-Las Vegas	Boston-San Francisco
Y	3.0*Q fare BOSLAS	5.4* Q fare BOSSFO
B	1.9*Q fare BOSLAS	2.4*Q fare BOSSFO
M	1.5*Q fare BOSLAS	1.7*Q fare BOSSFO
Q	Q fare BOSLAS	Q fare BOSSFO

Table 3-6: An example of real fares across markets

The base case of Network D in PODS uses market-based fares as inputs. The fare ratios are not uniform, but based on the specific market and actual fare data. Overall, fares follow some distribution with a mean and standard deviation. These figures for each fare class have been given in Table 3-7.

Fare Class	Y	B	M	Q
Mean Ratio	3.74	1.93	1.37	1
Standard Deviation Ratio	1.14	0.58	0.23	1
Minimum	1	1	1	1
Maximum	8.99	5.34	3.11	1

Table 3-7: Mean, standard deviation, min, and max of real fares in PODS (N=482)

This section examined the differences between market-based and structured fares. It included some examples of market-based fares and the descriptive statistics of market-based fare data used in the PODS simulator. The main benefit associated with market-based fares is that OD control revenue management can differentiate between markets with differing fare ratios. Furthermore, it can capitalize on the fare ratio differences by market in order to better optimize revenue.

After discussing disutilities, restrictions, fare structures, and economic theory, the next section examines the airline industry today by displaying some actual fare structures that are currently in place in certain markets by airlines. The examples shown in the next section will clearly demonstrate the wide range of demand segmentation and price differentiation that occurs in practice. They will also introduce the subtle differences among major network carriers and the stark differences between the fare structures of network carriers and new low-cost carriers that employ what has been termed "alternative fare structures".

3.6 Examples of Airline Fare Structures

This section is meant to give some examples of fare structures that are currently in use today by U.S. airlines in U.S. domestic markets. The examples will show how airlines use the principles mentioned above to develop a fare structure that effectively segments demand and coincides with the inventory control of their RM system.

Four markets will be examined in these examples. They are San Francisco to Phoenix, New York (JFK) to Long Beach, Denver to Albuquerque, and Boston to Los Angeles. There are more airlines serving these markets than will be shown. The main point of these examples is twofold. First, it is to show an array of airlines, some of which have different fare structures than others, so that both the traditional network carriers and some low cost carriers are represented in these examples. Second, the markets chosen are ones in which the interaction between the network and low-cost carriers is present except for Boston-Los Angeles, which is a traditional carrier market. This makes the examples more interesting because it provides a glimpse of how network carriers compete with the low-cost carriers as compared to a market with relatively little low-cost competition.

All fares shown are regular, published round-trip fares that are not promotional web specials. The fares were gathered from www.travelocity.com on April 6, 2003 except those of JetBlue Airways, which were taken from their own website www.jetblue.com.

3.6.1 Denver to Albuquerque (DEN-ABQ)

Two airlines offer non-stop service in this market, United Airlines (UA) and Frontier Airlines (F9). UA is a network carrier while Frontier is a new low-cost carrier. Below in Table 3-8 is Frontier's fare structure in this market.

Fare Code	Fare	Refund-able	Change Fee	Adv. Purch.	Min Stay	Max Stay	Misc.
L14NRX	$178	NO	$100	14 days	NO	NO	
LNR	$218	NO	$100	NO	NO	NO	
VNR	$298	NO	$100	NO	NO	NO	
HNR	$418	NO	$100	NO	NO	NO	
BNR	$498	NO	$100	NO	NO	NO	
KNR	$618	NO	$100	NO	NO	NO	
YF9	$818	YES	NO	NO	NO	NO	

Table 3-8: Frontier's Fares DEN-ABQ

This fare structure is straightforward. There are only seven fares. None of them has a minimum or maximum stay restriction. Only the lowest fare has an advanced purchase requirement. However, all except the Y fare have a $100 change fee and are non-refundable. This structure should be compared to UA's fare structure in this market, which is given below in Table 3-9.

Fare Code	Fare	Refund-Able	Change Fee	Adv. Purch.	Min Stay	Max Stay	Misc.
TRA14NRS	$178	NO	$100	14 days	NO	30 days	
TA7QN	$218	NO	$100	7 days	NO	NO	
SA3QN	$298	NO	$100	3 days	NO	NO	
WLE30M7N	$332	NO	$100	30 days	Sat. Night	7 days	Mon.-Thur., Sat.
WHE30M7N	$338	NO	$100	30 days	Sat. Night	7 days	Mon-Thur., Sat.
VA7BIZN	$398	NO	$100	7 days	NO	NO	
VLE14NR	$416	NO	$100	14 days	Sat. Night	30 days	Mon-Thur., Sat.
WA0QN	$418	NO	$100	NO	NO	NO	
VHE14NR	$436	NO	$100	14 days	Sat. Night	30 days	
VA0QN	$498	NO	$100	NO	NO	NO	
QA0QN	$618	NO	$100	NO	NO	NO	
HOE21NQ	$718	NO	$100	21 days	Sat. Night	30 days	
HE21NQ	$758	NO	$100	21 days	Sat. Night	30 days	
MBIZN	$818	NO	$100	NO	NO	NO	
BA3S	$1074	YES	NO	3 days	NO	NO	
BUAS	$1164	YES	NO	NO	NO	NO	
AFS4BUAS	$1164	YES	NO	NO	NO	NO	First Upgrade
YUAS	$1364	YES	NO	NO	NO	NO	

Table 3-9: UA's fares DEN-ABQ

UA, a large network carrier has more fare offerings than Frontier. The fares also have more restrictions. Almost all are non-refundable and have a $100 change fee. A number of the fares have advance purchase requirements and Saturday night stay restrictions. However, UA has nearly matched Frontier on all of its fares. The only difference is that UA places an advance purchase requirement on some of the lowest fares. This is a competitive response. This is where UA relies on its inventory control. The fares that are published to compete with Frontier are in low fare classes that quite possibly are closed rather quickly by the RM system to prevent many of UA's passengers from getting these cheap fares.

The DEN-ABQ market consists of one network carrier and one low-cost carrier. Their fare structures are quite different, but the network carrier attempts to somewhat mirror the low-cost carrier. However, the network carrier does keep an advance purchase requirement on some of the lowest fares that it offers whereas the low-cost carrier does not. In this case, UA partially matches Frontier's fares.

3.6.2 New York (JFK) to Long Beach (JFK-LGB)

American Airlines (AA) and JetBlue Airways (B6) serve JFK-LGB non-stop. Several other airlines compete in this market with connecting service. This is a long-haul, coast-to-coast market. AA and JetBlue have been in fierce competition in this market. Table 3-10 lists the fares of JetBlue in this market. It is a rather simple structure with only six fares. However, it differs significantly from Frontier in the DEN-ABQ market. While Frontier had a $100 change fee and no advance purchase on most of its fares, JetBlue has instead kept somewhat the advance purchase requirement on most of its fares but only charges a $25 change fee. Another major difference is that JetBlue's highest fare still has a change fee and is non-refundable.

Fare Code	Fare	Refund-Able	Change Fee	Adv. Purch.	Min Stay	Max Stay	Misc.
L	$248	NO	$25	14 days	NO	NO	
B	$278	NO	$25	14 days	NO	NO	
B	$318	NO	$25	7 days	NO	NO	
Q	$358	NO	$25	3 days	NO	NO	
H	$398	NO	$25	3 days	NO	NO	
K	$498	NO	$25	NO	NO	NO	
Y	$598	NO	$25	NO	NO	NO	

Table 3-10: JetBlue's fares for the JFK-LGB market

AA is a traditional network carrier with a sophisticated RM system. Its fares for the JFK-LGB market appear below in Table 3-11. AA offers many fare products and, like UA in the DEN-ABQ market, have fares that mirror those of JetBlue. In fact, AA has a set of fares that exactly match those of JetBlue. The matched fares given by AA are in low fare classes, so the RM system still has the ability to release only small amounts of availability to these fares. The system can effectively protect seats for AA's high revenue passengers that are willing to pay AA's B or Y fare. They further protect their network seats by restricting passengers that book one of the matched fares to fly on the non-stop JFK-LGB legs. This keeps low fare traffic from taking seats on other flights that can be filled with higher yield, higher paying passengers.

Fare Code	Fare	Refund-Able	Change Fee	Adv. Purch.	Min Stay	Max Stay	Misc.
LR14C25N	$278	NO	$25	14 days	NO	NO	N/S only
LR7JC25N	$318	NO	$25	7 days	NO	NO	N/S only
NR3JC25N	$358	NO	$25	3 days	NO	NO	N/S only
VR3JC25N	$398	NO	$25	3 days	NO	NO	N/S only
VS30X7MN	$452	NO	$100	30 days	Sat. night	7 days	
QRJC25N	$498	NO	$25	NO	NO	NO	N/S only
VB30X7MN	$512	NO	$100	30 days	Sat. night	7 days	
Q14XENR	$589	NO	$100	14 days	Sat. night	30 days	Mon-Thurs., Sat.
KRJC25N	$598	NO	$25	NO	NO	NO	N/S only
Q14WENR	$649	NO	$100	14 days	Sat. night	30 days	Mon.-Thurs., Sat.
KRGNR	$838	NO	$100	NO	NO	NO	
MRJC25N	$878	NO	$25	NO	NO	NO	N/S only
HE14NR	$1042	NO	$100	14 days	Sat. night	NO	
HRJC25N	$1178	NO	$25	NO	NO	NO	N/S only
HR26G	$1532	YES	NO	NO	NO	NO	
M10E2BZN	$1870	NO	$100	10 days	2 days	30 days	
BAP3S	$2266	YES	NO	NO	NO	NO	
Y26	$2324	YES	NO	NO	NO	NO	

Table 3-11: AA's fares in the JFK-LGB market

3.6.3 San Francisco to Phoenix (SFO-PHX)

The SFO-PHX market has a number of competitors, but this example focuses on America West Airlines (HP). America West is a major U.S. airline that has straddled the line between being a traditional carrier and a low-cost carrier. While they have a traditional hub and spoke network, the airline has recently changed its fare structure in an attempt to capture more demand, especially business demand. America West's fare structure is a hybrid of the very traditional network carriers and that of a low-cost carrier. There are numerous fare products, a $100 change fee and non-refundability. Most fares also have an advance purchase requirement, but America West has shed the Saturday night stay restriction to make these fares feasible to a greater number of business travelers. Following America West's lead, other network carriers have begun experimenting with this as well. America West's fare structure in this market is given below in Table 3-12.

Fare Code	Fare	Refund-Able	Change Fee	Adv. Purch.	Min Stay	Max Stay	Misc.
KR14N3	$206	NO	$100	14 days	1 day	NO	
LR7N3W	$222	NO	$100	7 days	1 day	NO	
QA14NSU	$284	NO	$100	14 days	1 day	NO	
BR7N2W	$340	NO	$100	7 days	NO	NO	
BA7N2	$360	NO	$100	7 days	1 day	NO	
WA3N1	$448	NO	$100	3 days	NO	NO	
H6	$494	YES	NO	NO	NO	NO	
Y6Q	$650	YES	NO	NO	NO	NO	
YUP6	$888	YES	NO	NO	NO	NO	First Upgrade

Table 3-12: America West's Fare Structure SFO-PHX

3.6.4 Boston to Los Angeles (BOS-LAX)

The final example in this section is the BOS-LAX market. In contrast to the markets shown above, this market has only a few low-cost carriers providing connecting service. AA and UA, both of which have non-stop and connecting service, are the market share leaders in this market. AA's fare listings are shown below in Table 3-13. UA's fare listings have been omitted, as they are extremely similar in value and structure.

AA fare Code	Fare Range	Adv. Purch.	Refund-able	Change Fee	Stay Req.	Comments
L	$203-283	21 days	NO	$100	Sat. night	Not valid on N/S
N	$308-520	7-21 days	NO	$100	Sat. night	Only $520 fare valid on N/S
V	$469-529	21-30 days	NO	$100	Sat. night	
Q	$579-673	21 days	NO	$100	Sat. night	
H	$1106	14 days	NO	$100	Sat. night	
B	$2414	3 days	YES	NO	None	
Y	$2467-2600	None	YES	NO	None	

Table 3-13: AA's Fare Structure BOS-LAX

In this market there is a much wider dispersion of fare values. The lowest fare is barely over $200, but the unrestricted Y fare is $2400. Also, unlike other markets with direct LCC competition, a $100 change fee, non-refundability and a Saturday night minimum stay are enforced for every fare class other than Y and B. This implies that if a passenger cannot meet the Saturday night stay requirement, then he or she must buy the B fare, which is $2400. One other interesting restriction is that even though AA offers non-stop service, passengers are restricted from flying non-stop if they buy one of the lowest fares. A passenger must pay at least $520 to have the convenience of the non-stop flight.

The four examples above are meant to give a representative example of the types of fare structures that are currently being used by U.S. airlines. The aforementioned fare structures are quite different. AA and UA follow a very traditional network structure with a number of restrictions on all but the highest fare classes. On the other hand, America West, Frontier, and JetBlue have fewer restrictions on their fare classes and have what would be described as an alternative fare structure for the purpose of this thesis. These fare structures are the focus of this thesis, more specifically RM performance with these alternative fare structures in place. The above examples show that these fare structures are used by a number of airlines and affect many U.S. OD markets.

3.7 Summary

Airline passengers usually have many choices when contemplating flying between two markets. Each passenger has a willingness-to-pay in his or her mind when making a decision as to which flight to take in a market or to fly at all. However, airlines have managed to develop a set of restrictions and requirements to further differentiate pricing. This typically makes lower fares more restrictive. The passenger's choice is more difficult because now they also have to value the set of restrictions and determine the trade-off between a cheaper ticket with more restrictions and a more expensive ticket with fewer restrictions, assuming that both of these options fit into the passenger's decision window and the airline has availability in both fare classes.

Airlines use these restrictions to develop a fare structure that effectively segments demand into groups. The overall goal is to minimize the economic consumer surplus by getting passengers to pay a price that is extremely close to their total willingness-to-pay, which is the same thing as the maximization of revenues. The most straightforward demand segmentation is to split demand into business and leisure categories. Most business travelers have to be at a destination at a specific time, want flexible tickets in case plans change, and want to fly during the week. Knowing that most business travelers follow this generalization, airlines want to implement restrictions on low fare classes to ensure that business travelers cannot purchase these lower fares. At the same time, these restrictive low fares are ideal for price-sensitive leisure passengers. This creates revenue for the airline because leisure passengers that are willing to adhere to the restrictions so that they are eligible for the low fare will fly, whereas they would not be willing to pay the fare if one single fare existed. The low fare classes are controlled by airline revenue management systems as forecasts are used to protect a certain number of seats for higher fare classes and low fare class seats are released only when there is enough capacity that the low-fare passenger would not be displacing a high-fare paying passenger based on projected forecasts.

At the beginning of this chapter, economic theory was introduced to provide some background into the development of price discrimination and differential pricing. Next, we looked at disutility theory, ticket restrictions and requirements, and how these factors influence the airline's fare structure. This included the disutility values used in PODS and how this shapes the choice set of business and leisure passengers. This chapter then examined the fare structure itself by comparing briefly market-based and structured fares. Finally, the chapter closed with some examples of current fare structures in the industry.

The next chapter will begin giving more insight into airline revenue management performance as the first set of results regarding changes in the distribution and level of fares are presented.

Chapter 4 Changes in Fares and Fare Ratios

This chapter, along with Chapter 5, presents results from the PODS simulator. The results have been split into two chapters because this thesis examines two distinct changes to the traditional fare structure. Chapter 4 examines revenue management performance when the fare values are varied either by fare reductions or changes in the fare ratios between fare classes. The latter concept draws upon the structured fare concept developed in Chapter 3. Chapter 5 will consider the cases where the restrictions are actually altered such that the airlines offer a simplified fare structure.

Two cases are presented in this chapter. The first case is to use structured fare ratios. Recall that structured fares use the same fare ratios over different fare classes for all markets. An example is that if we set the Y fare to be four times the Q fare, then this will be true for all markets. The contrast to this is market-based fares, where these fare ratios can vary by market, based on market characteristics. This case looks at results when the fare ratios are compressed and expanded. The second case examines the effect on revenue management performance when a business fare reduction is implemented. This corresponds to a reduction in the Y and B fares in PODS.

Section 4.1 introduces the comparisons of simulations for each case and why these sets of simulations were chosen. A brief overview of the base case traditional fare structure results is given in Section 4.2. The structured fare case is presented in Section 4.3. Section 4.4 discusses the fare reduction results. Finally, Section 4.5 provides a synthesis and conclusion of the Chapter 4 cases.

4.1 PODS Simulation Runs and Relevance of Results

This chapter and the next set out to compare several sets of results. An overview of the relevance of the different results that will be shown is given in this section. These sets of results for each experiment correspond to the different types of revenue management systems available to airlines as well as results of general interest.

- The loss in revenue from implementing an alternative fare structure when using leg-based RM.
- The gain of leg-based RM versus simple FCFS under alternative fare structures.
- The incremental gain incurred from using OD Control (network-based RM) versus leg-based RM, especially after correcting for differences in average load factor.

The first result, the loss in revenue from implementing an alternative fare structure, shows the impact of the alternative fare structure on the airline's total revenue performance. While this result assumes leg-based RM, it gives an idea as to the overall impact from implementing the alternative fare structure.

The next result is the magnitude of gain that leg-based control has over FCFS. This is a simple result, yet very important. We want to determine whether leg-based RM still provides significant gains over no RM.

Finally, we want to know if OD control still garners an incremental benefit when an alternative fare structure is used, as well as the magnitude of the benefit. These results are then compared to results under a traditional fare structure. There is a natural connection between OD control performance and the ALF. At higher ALFs, the OD control system should perform better and provide higher revenue gains because the OD control system has more passengers in the network and can be more selective in accepting bookings. This greater selectivity implies that the OD control system will be able to achieve greater revenue gains because it now has more leverage in choosing the "right" passengers that will generate more revenue over the network. Thus, we can conclude that OD control performance can be separated into a load factor effect and an RM effect. The goal of Chapters 4 and 5 is to isolate the OD control effect and measure it under alternative fare structures. We introduce OD control performance curves to normalize over a range of ALFs. Running several simulations at different ALFs allows for the construction of curves by comparing ALF and relative revenue gain and fitting a curve to those data points.

4.2 Base Case Results

This section briefly describes the base case results of the PODS Network D simulation that is used as a benchmark against all future cases with alternative fare structures. The base case performance measures are the basis of some of the figures presented in future sections, but this section will present them explicitly and with some explanation.

4.2.1 Base Case Fares and Passenger Mix

As mentioned in Chapter 2, the fares used in the baseline scenario are market-based. This means that each fare value and the resultant fare ratios in each market are different because the fares are dependent on the conditions and characteristics of each market. Fare statistics for the network are expressed as a mean and standard deviation fare ratio where the ratio is the fare class value divided by the Q-fare value. The statistics for the PODS Network D base case appear below in Table 4-1.

Fare Class	Y	B	M	Q
Mean Ratio	3.74	1.93	1.37	1
Standard Deviation Ratio	1.14	0.58	0.23	1
Minimum	1	1	1	1
Maximum	8.99	5.34	3.11	1

Table 4-1: PODS Base Case Fare Statistics

For example, the statistics in Table 4-1 imply that, on average, a Y fare in any given market will be 3.74 times more expensive than the Q fare in that same market. However, this statistic has a standard deviation of 1.14 and it is possible that the Y fare may actually be the same as the Q fare or as much as 8.99 times the Q fare depending on the market.

These fares, combined with leg-based RM and a specified base case demand, yield a fare class mix in the base case as shown in Figure 4-1. The fare class mix appears "boat-shaped". A significant portion of passengers book Y and Q with fewer passengers booking the middle classes B and M. In this base case there is a greater proportion in Q than in Y. The boat-shape occurs because of the sharp contrast between the willingness to pay of the average leisure passenger and the average business passenger. Using the mean fare ratios given in Table 4-1, on average over 90 percent of business passengers are willing to pay the mean Y fare, while less than 50 percent of leisure passengers are willing to pay the mean M fare. Overall, approximately 45 percent of passengers carried are in Q, 26 percent in Y, 13 percent in B and 14 percent in M.

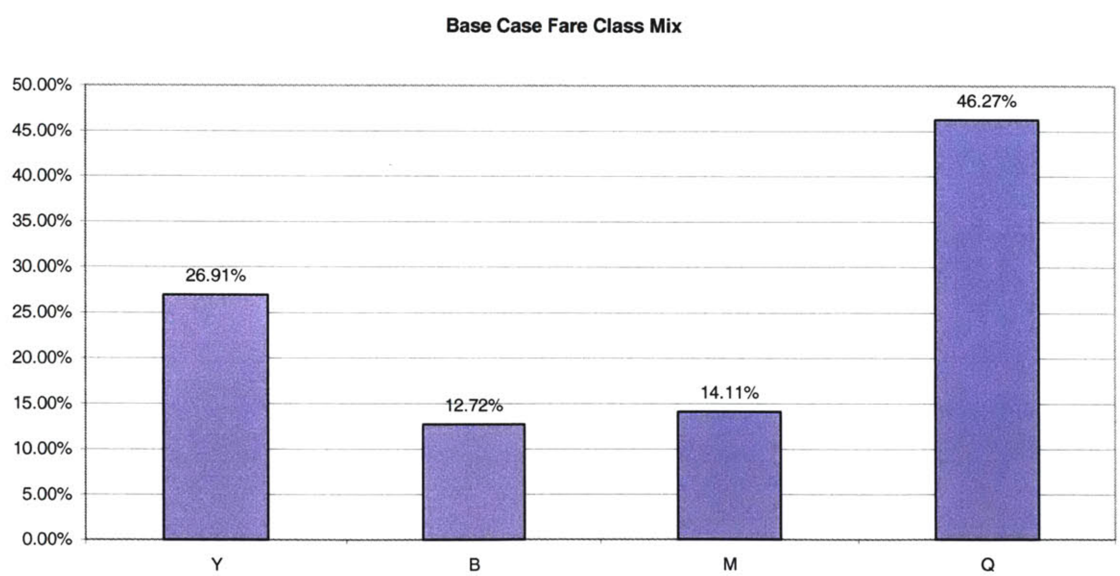

Figure 4-1: Base Case Fare Class Mix

4.2.2 OD Control Performance in the Base Case

In order to present the alternative fare structure cases in future sections this section will provide the base case results for OD control performance. Just to recap, the three OD control methods examined are DAVN, HBP, and ProBP. The base case performance will be represented in the alternative fare structure cases as a curve mapping relative revenue gains against a range of average load factors.

Figure 4-2 reports the incremental benefit of OD control for each of the three OD control methods over FCYM leg-based RM for Airline 1. Airline 2 uses leg-based RM. There is approximately an 1.5 percent increase in revenues when using DAVN and ProBP and just less than 1 percent when using HBP. The revenue decrease for Airline 2 is less than the revenue gain for Airline 1. This supports the hypothesis that overall network revenue management increases total system revenues.

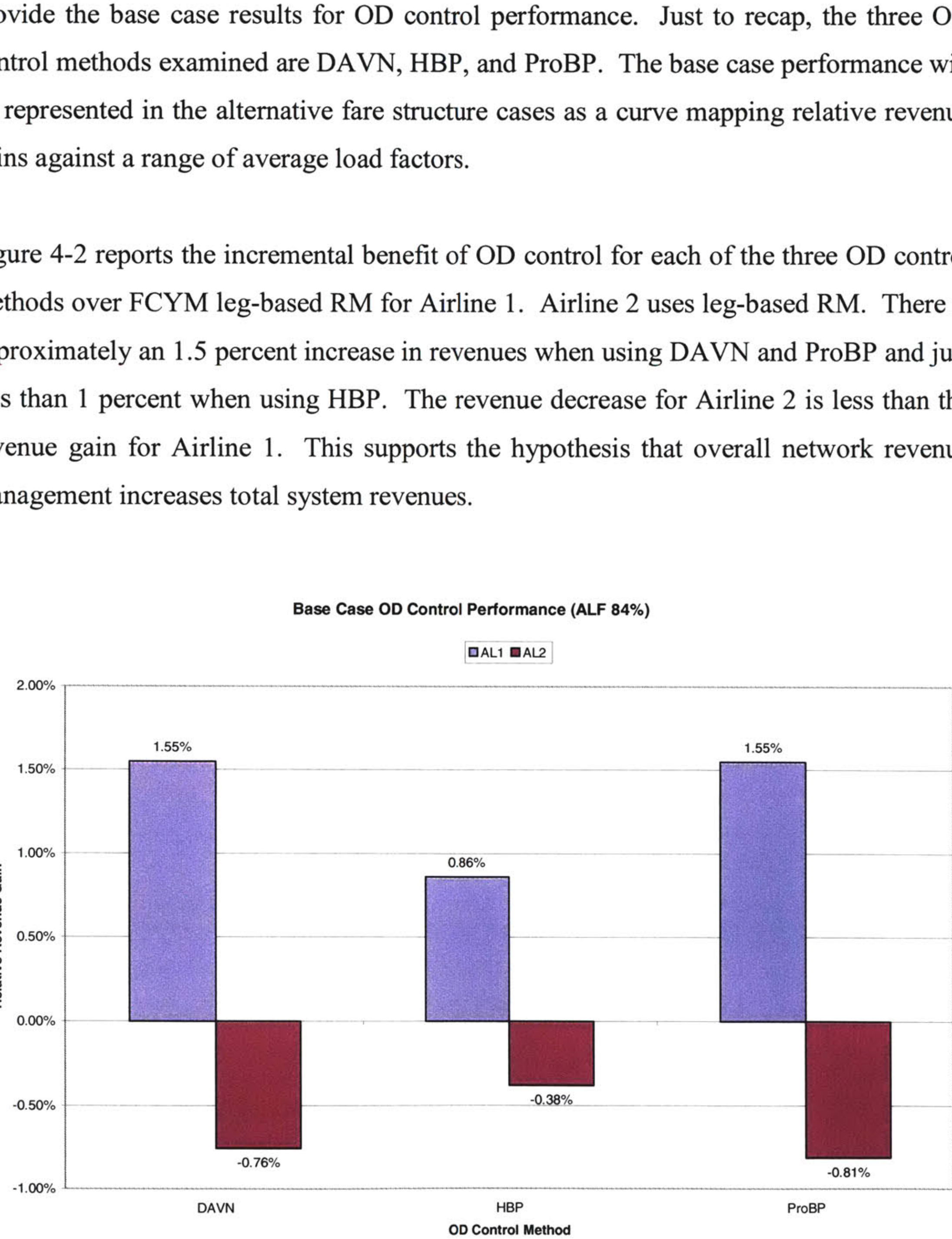

Figure 4-2: Base Case OD Control Performance

In this section, we briefly examined the base case results for two reasons. First, it gave an introduction as to the types of statistics that will be used in the alternative fare structure cases. Second, this section reviewed the base case RM performance. The next sections of Chapter 4 and Chapter 5 will compare this base case to alternative fare structures to examine overall revenue performance as well as the performance of leg-based and OD control RM.

4.3 Structured Fares, Compression and Expansion of Fare Ratios

Most PODS simulations have assumed a market-based fare structure where the ratios of fare values between fare classes depend on each individual market, its demand characteristics, and competition. However, in this section we describe an experiment using structured fares to look at the effect of compressing or expanding the fare ratios. This experiment also attempts to show that OD control performs better under market-based fares than structured fares with similar mean fare ratios.

The hypothesis in this case is that network RM performance under structured fares will be worse than under market-based fares with mean fare ratios similar to the structured ratio values. The reasoning for this stems from the fact that OD control can take advantage of market-based pricing because it will protect more for high-fare ratio markets than low-fare ratio markets. With structured fares, OD control does not have this advantage since the fare ratios are the same in all markets. Also, network RM performance will be better as the fare ratios are expanded when normalizing for ALF. This occurs because higher fare ratios make those passengers who are willing to buy high fare class tickets even more valuable. Network RM can recognize and capitalize on this by protecting more aggressively for these passengers when the fare ratios are higher.

This case will examine four sets of structured fare ratios. These ratios along with the mean average real fare ratios appear below in Table 4-2.

Fare Ratios.	Y	B	M	Q
Market-based	3.74	1.93	1.37	1.00
Y=3str	3.00	1.50	1.125	1.00
Y=4str	4.00	2.00	1.50	1.00
Y=5str	5.00	2.50	1.875	1.00
Y=6str	6.00	3.00	2.25	1.00

Table 4-2: Fare Ratios Used in This Case

4.3.1 Fare Ratios: Revenue Change from Alternative Fare Structure

Table 4-3 gives the relative revenue change from compressing or expanding the fare structure as compared to the market-based fare base case. All of the structured fare cases except Y=6 have higher revenues than the market-based fare base case. At Y=3, the compressed fare structure gets more passengers to book in higher fare classes causing the small gain over the base case. At Y=4 and Y=5, the fare ratios are expanded beyond the mean ratios of the market-based fare base case. The gains are more substantial because the fares paid are higher on average, but the fare ratios are not so large that they discourage business passengers with a high willingness to pay to purchase B and Y fares. However, this does occur at Y=6. Fewer business passengers are buying from the high fare classes, which results in an overall decrease in revenue as compared to the market-based fare base case.

	Y=3	Y=4	Y=5	Y=6
Airline 1	0.92%	6.25%	3.98%	-5.16%
Airline 2	2.36%	7.44%	5.04%	-4.09%

Table 4-3: Revenue Comparison of Structured Fares to the Base Case

Figure 4-3, displayed below, shows the fare class mix, that is the percentage of passengers booked in each fare class, at different fare ratios. The market-based fare base case is also shown for comparison.

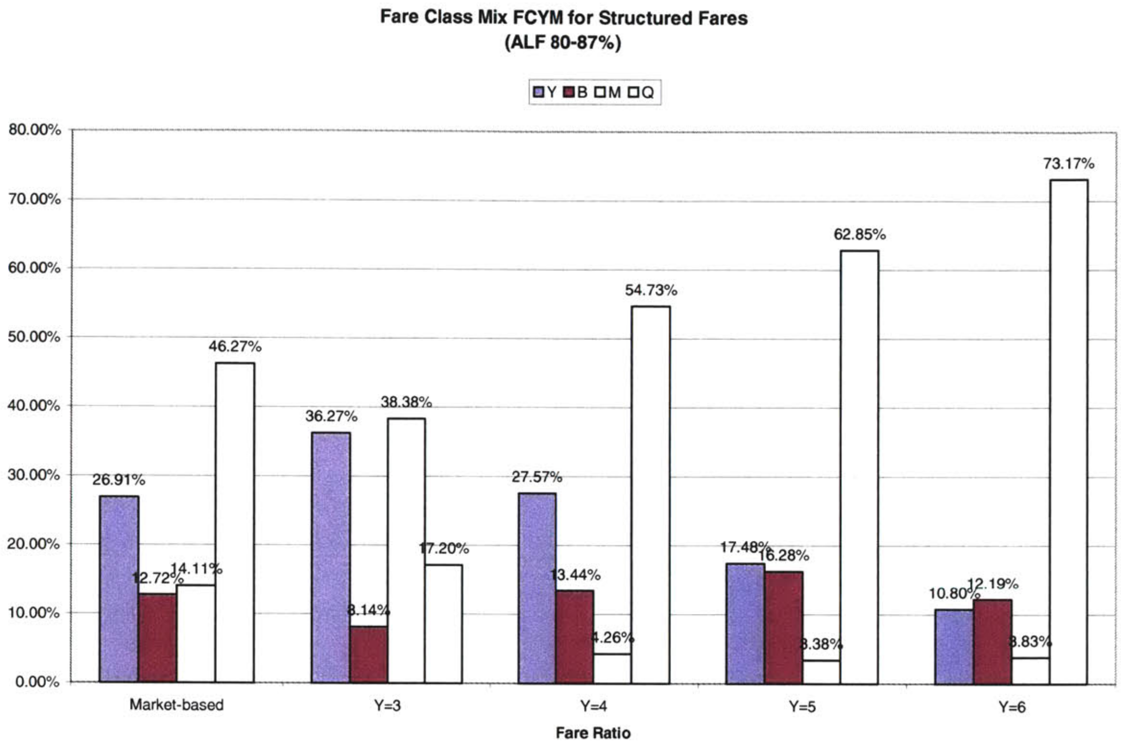

Figure 4-3: Fare class mix at different fare ratios using leg-based RM

The results in Figure 4-3 show a dramatic trend in fare class mix as the fare ratios increase. At Y=3, more business passengers book in Y and many leisure travelers book in M rather than Q. At these fare ratios most leisure passengers are willing to pay for an M fare, so even if Q is closed, a leisure passenger arriving before the advance purchase cutoff will more than likely still pay for an M. As the fare ratios expand, there is a large increase in the proportion of travelers who buy Q. This is due to the fact that at Y=5 and Y=6, the lower fare classes become more attractive to business travelers. Even with the "perceived" cost of the restrictions, the Q fare is perceived to be more attractive than the Y fare for business travelers.

4.3.2 Fare Ratios: Revenue Gains from Leg-Based RM (FCYM)

Figure 4-4 shows the revenue gain of leg-based RM at the different compressed and expanded structured fares.

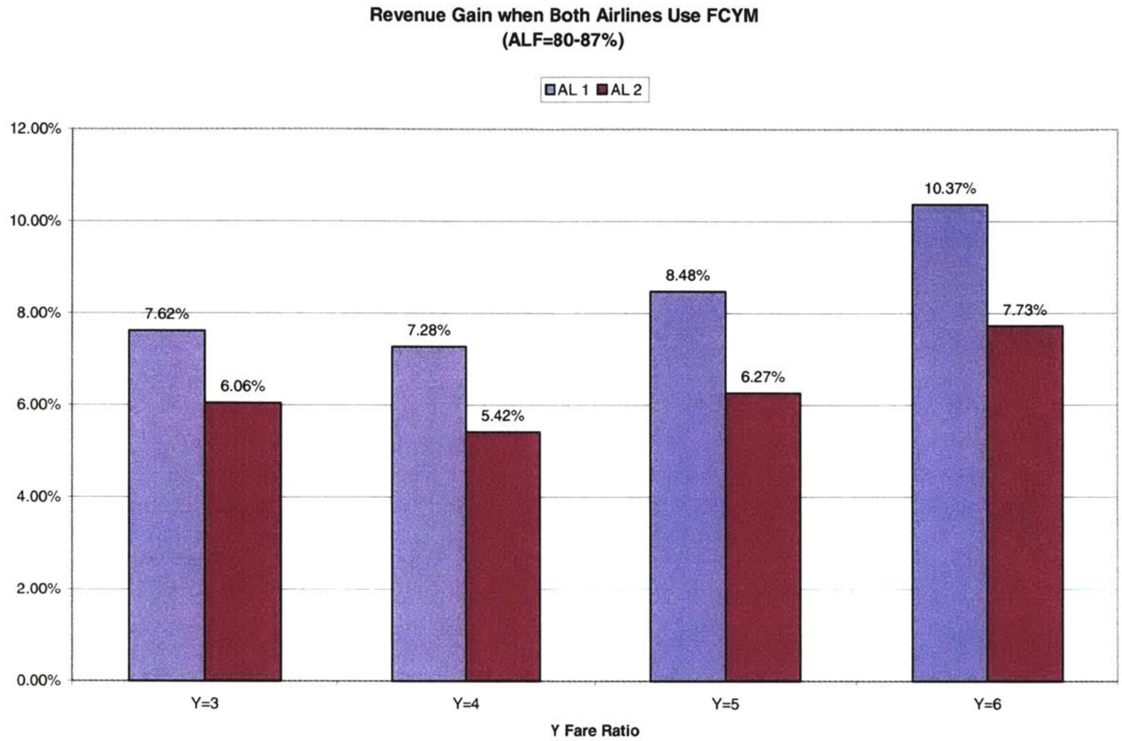

Figure 4-4: Both airlines move from FCFS to leg-based RM at different structured fare ratios

Both airlines have a noticeable gain in all the structured fare cases presented. Airline 1 has revenue gains on the order of 7 to 10 percent while airline 2 has gains of 6 to 8 percent. Leg-based revenue management provides a benefit to revenues whether fares are relatively compressed or expanded. Another expected result is that leg-based RM performs better as the fare ratios are expanded. This occurs because higher fare ratios create more leverage for the RM system. High fare class passengers become even more important as the fare value of those higher fare classes increases and the RM system takes advantage of this fact. With higher fare ratios protection of high fare class inventory becomes even more important because the value added to the network of passengers who book from the high fare classes is even greater. Leg-based RM protects seats for these passengers willing to pay for a high fare class and will protect even more so if the value of those who book from the high value fare classes is higher.

The results in Figure 4-4 have an average load factor range of 80 to 87 percent. Compressing or expanding the fare ratios affects the ALF because more passengers will travel when fares are compressed and fewer passengers will travel when fares are expanded. The ALFs for each case are given in Table 4-4.

Airline	Market-based	Y=3	Y=4	Y=5	Y=6
Airline 1	84.54%	86.80%	83.42%	81.89%	80.25%
Airline 2	84.01%	86.36%	82.86%	81.27%	79.63%

Table 4-4: ALF at Different Structured Fare Ratios

4.3.3 Fare Ratios: Incremental Benefit of OD Control

Finally, we want to examine the performance of OD control under alternative fare structures. Figure 4-5 displays the incremental benefit of OD control when Airline 1 moves from leg-based RM to OD control. Airline 2 uses leg-based control.

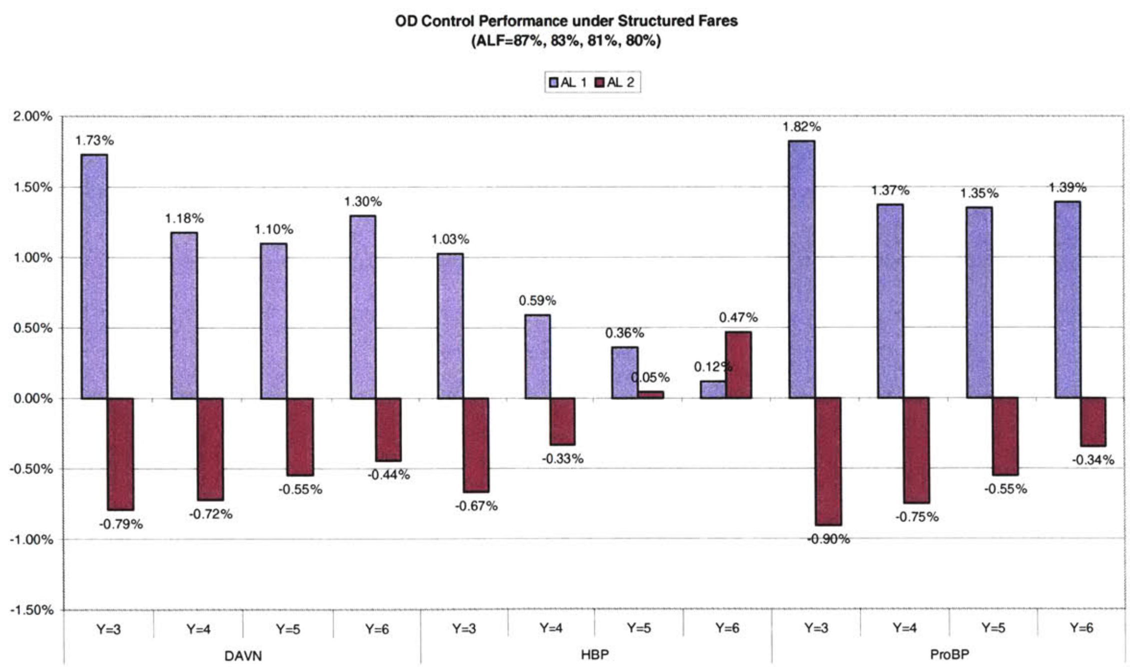

Figure 4-5: OD Control performance with different structured fare ratios

The gains from OD control are 1 to 2 percent for DAVN and ProBP and up to 1 percent for HBP. OD control is not a zero-sum game as Figure 4-5 shows. In each case, the revenue loss suffered by Airline 2 is less than the gain attained by Airline 1. The gains are greatest at Y=3 because the compressed fare structure induces more travel and an increase in average load factor, which increases the leverage of OD control. The revenue gains are lower at Y=4 and Y=5 as load factors drop due to decreased ALFs. Finally, revenue gains are somewhat higher at Y=6 despite the lower ALF because expanded fare ratios increase the leverage of the OD control system. There are fewer Y passengers, but those Y passengers are worth quite a bit more. The important concept here is that OD control still provides a substantial incremental benefit under structured fares of varying ratios.

The above analysis alluded to the fact that alternative fare structures lead to changes in the ALF. As mentioned earlier, there is a natural connection between OD control performance and the ALF. There are greater incremental revenue gains from OD control at a higher network ALF. Figure 4-6, 4-7, and 4-8 correct for this by looking at an "OD control performance curve" over a range of ALFs.

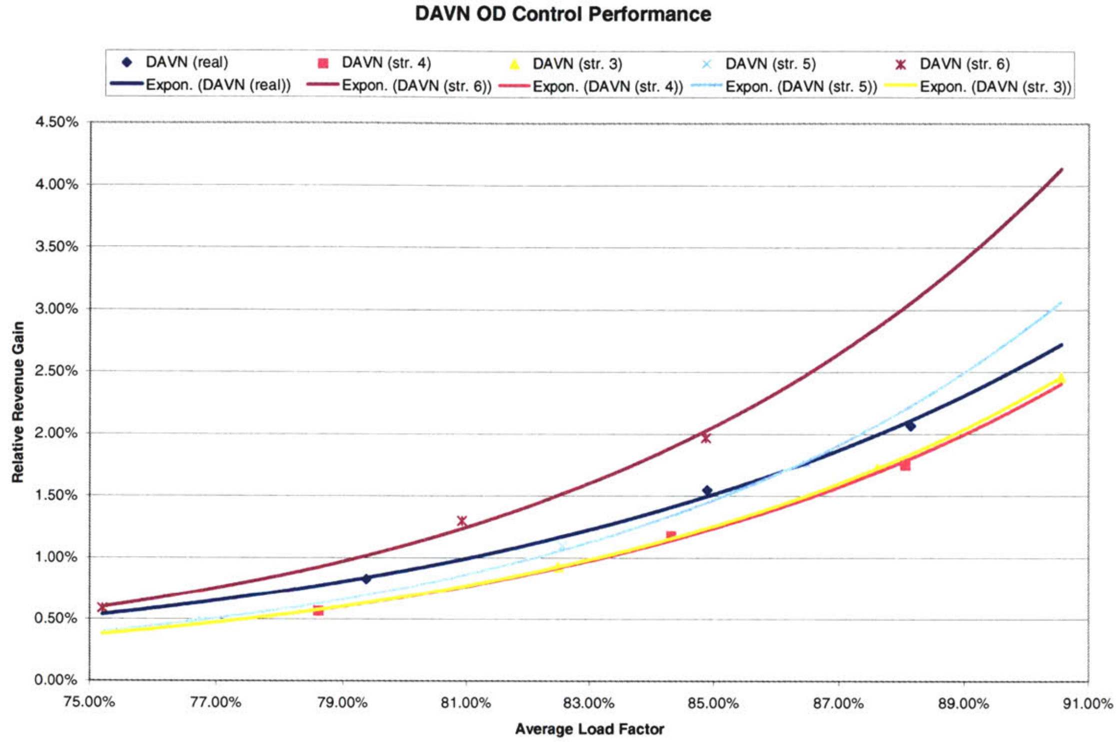

Figure 4-6: Fare Ratio DAVN OD Control Curve

The Y=4 case is most closely associated with the real fare base case because the Y=4 ratios are close to the means of the market-based fare base case ratios. Figure 4-6 shows that DAVN performs better under market-based fares than with Y=4 fares. This makes sense as the market-based fare base case still has some markets in which the fare ratio is greater than that of the structured Y=4 case. OD control can differentiate between the high and low fare ratio markets. Thus, OD control should and does perform better with market-based fares. However, structured fares with Y=6 performs better than even the market-based fare base case.

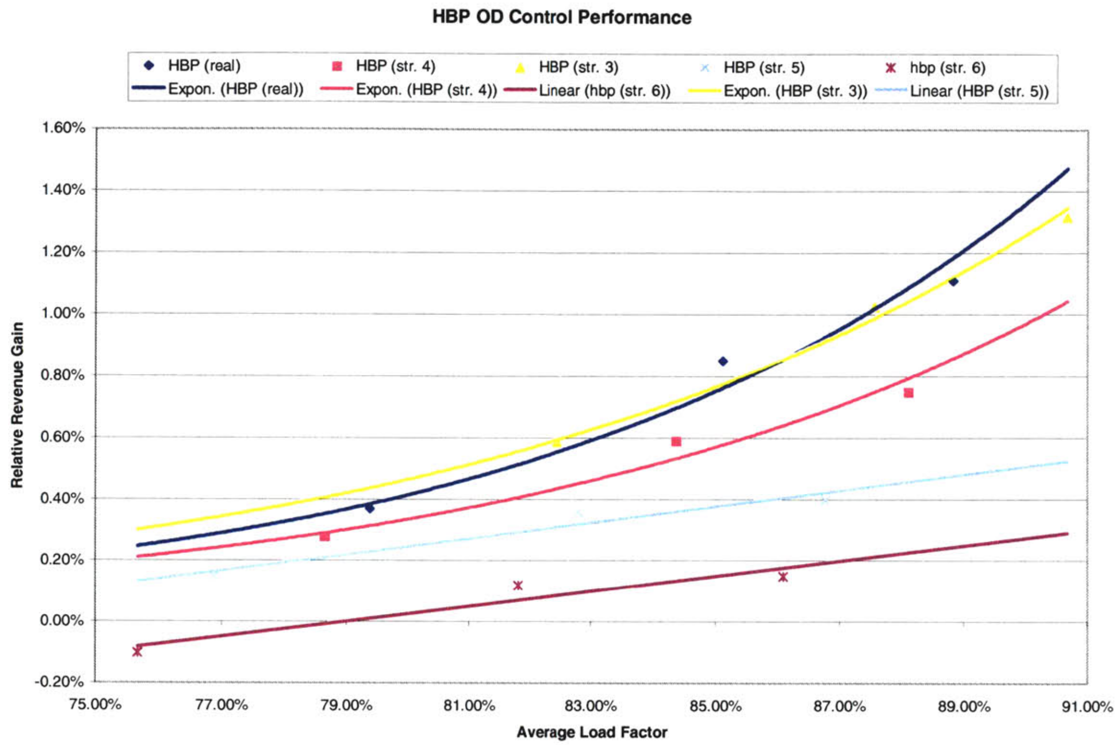

Figure 4-7: Fare Ratio HBP OD Control Curve

Figure 4-7 shows OD control curves for HBP with structured fares. HBP has less of a gain than DAVN and ProBP, and the curves are somewhat different. HBP with market-based fares performs better than with Y=4 fares for the same reasons as mentioned above for DAVN. However, contrary to DAVN and ProBP, HBP with Y=6 fares performs much worse than with Y=4 fares and the market-based fare base case. Part of this has to do with the inundation of Q passengers that cannot be completely controlled by HBP. HBP has a harder time handling large variations in fares because these fare values are condensed into 8 buckets. As the fares are expanded, buckets are forced to have wider ranges, which reduces the effectiveness of HBP in our simulations.

Finally, Figure 4-8 displays the OD control curves for ProBP when different structured fare ratios are used. The results in Figure 4-8 are very similar to those reported in Figure 4-6 for DAVN. The market-based fare base case performs better than Y=4 fares, but the Y=6 case performs better than the market-based fares used in the base case. An expansion in the fare structure again leads to more leverage for the OD control system because the passengers in the higher fare classes are worth even more.

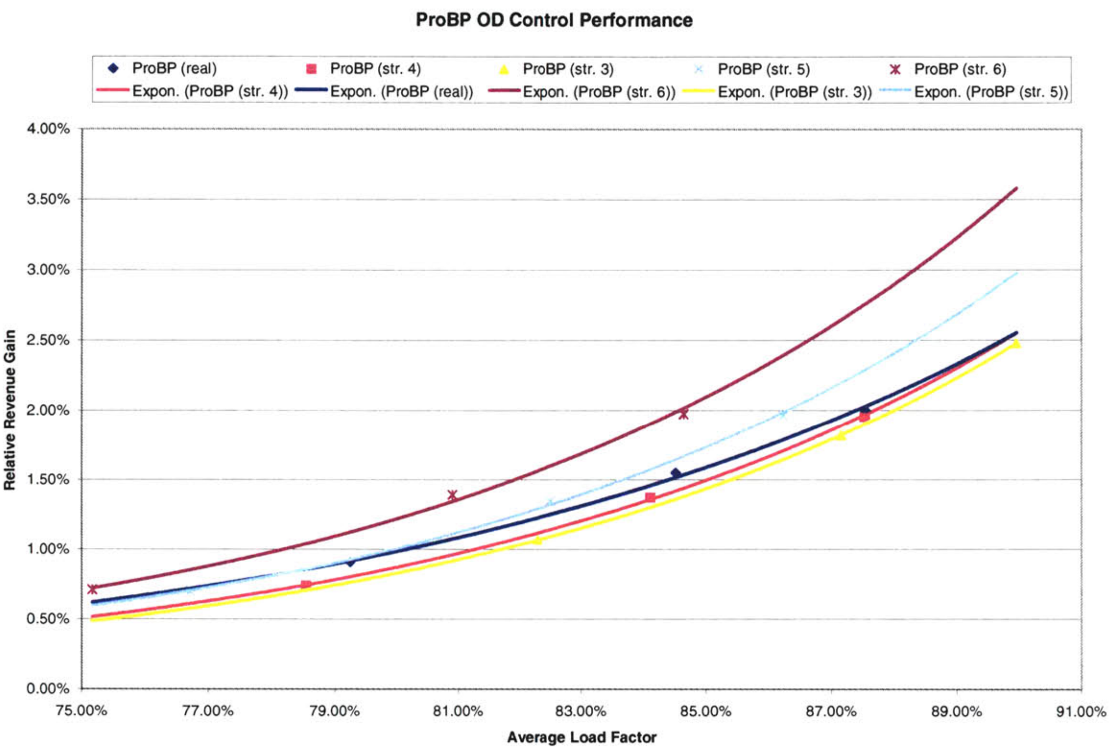

Figure 4-8: Fare Ratio ProBP OD Control Curve

4.3.4 Fare Ratios: Case Summary

This case presented RM performance when different structured fare ratios were used. The different fare ratios created a situation in which fares were being compressed and expanded. In terms of revenue, the Y=3, Y=4, and Y=5 cases had revenues that exceeded the market-based fare base case. However, at Y=6, the fare ratios have been expanded too much and cause revenue dilution because not all business travelers are willing to pay for Y fares that are six times the Q fare. Results showed that leg-based RM was still very effective in yielding revenue gains over FCFS. Furthermore, an incremental gain from OD control was still observed. However, the incremental benefit of OD control was less when Y=4 fare ratios were used as compared to the market-based fare base case for all three OD control methods. For DAVN and ProBP, a Y=6 fare ratio actually performed better than the market-based fare base case, which suggests that expanded fare structures lead to larger revenue gains from the implementation of OD control. However, Y=6 fares performed poorly for HBP due the wider range of fare values that must be mapped into the 8 buckets. Again, the main conclusion reached is that, regardless if fares are compressed and expanded, leg-based RM still provides significant revenue gains over FCFS and OD control still garners an incremental revenue benefit for all structured fare ratios tested.

4.4 Business Fare Reductions

This section examines a case involving changes to fare values, namely reductions in fare values of the higher booking classes. The fact that fare values are only reduced in higher booking classes implies that this action will mainly affect business travelers. Reducing business fares was part of a fare structure revamp carried out by America West Airlines in early 2002, and was replicated in a simulation.

The business fare reduction is represented in PODS by inducing a 20 percent fare cut in all markets for both the Y and the B fare. Reducing the Y and B fares so that they will still be slightly above the value of the M fare will avert any possible fare inversions. Note that this experiment and all subsequent experiments will be using market-based fares rather than the structured fares. The new mean fare ratios are presented below in Table 4-5.

Fare Class	Y	B	M	Q
Mean Ratio	3.00	1.57	1.37	1
Standard Deviation Ratio	0.92	0.45	0.23	1
Minimum	1	1	1	1
Maximum	7.19	4.27	3.11	1

Table 4-5: Fare Ratio Statistics with Business Fare Reduction

It is expected that proportionally more passengers will fly in the classes with a fare reduction. However, the resultant change in fare class mix does not guarantee an overall increase in revenues as leisure travelers will more than likely not be willing to pay for even the reduced business fare. Furthermore, this action acts very similarly to a compression of fares as can be seen in Table 4-5. Not only are the mean Y and B ratios lower, but also their standard deviations are lower. It has already been shown above in the last case that fare compression leads to reduced OD control performance.

4.4.1 Fare Reduction: Revenue Change from Alternative Fare Structure

Figure 4-9 displays the revenue change from implementing the business fare reduction when both airlines make the fare structure change and both airlines are using leg-based RM. Recall that the fare reduction is on the order of 20 percent in all markets for Y and B fares only.

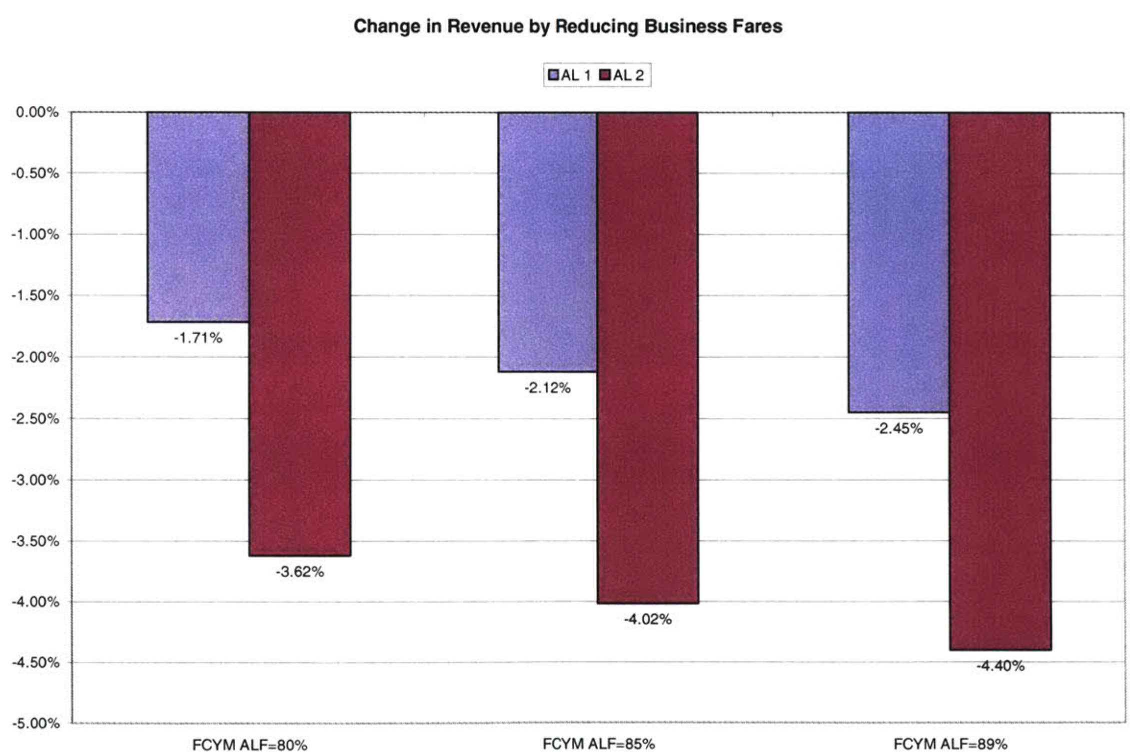

Figure 4-9: Revenue Change from implementing Alternative Fare Structure using leg-based RM

Depending on the demand and ALF, the revenue reduction from reducing business fares by 20 percent in all markets is 2 percent to 4 percent. This is a rather small change in revenue considering that all markets see this fare reduction. The increased ALF implies that more business travelers are flying because of the fare reduction. It might also be the case that a few leisure travelers are now willing to buy the B-fare where before they might have chosen not to fly.

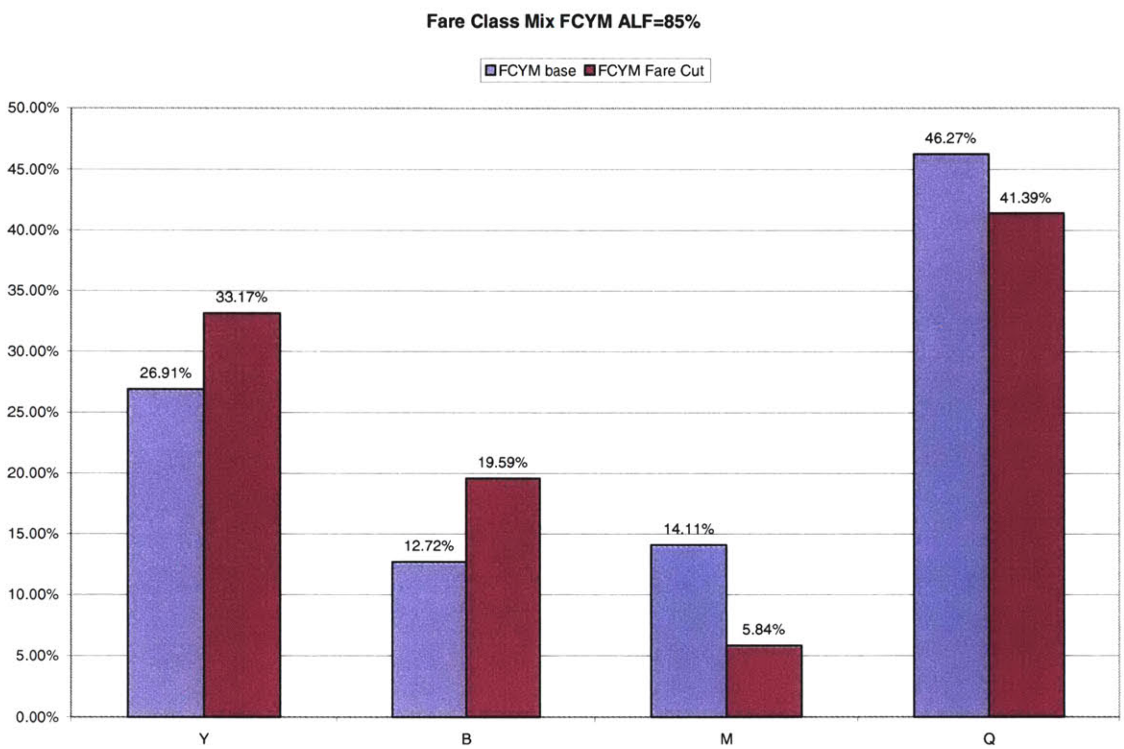

Figure 4-10: Fare Class Mix with fare reduction using leg-based RM

Figure 4-10 shows the proportion of travelers in each fare class, for Airline 1 using leg-based RM, in the base case and after the business fare reductions have occurred. There is an increase in the proportion of Y and B traffic as expected, which helps to preserve yield and revenue. There is also a resultant drop in the proportion of both M and Q, which suggests, especially the drop in Q, that some leisure travelers do also sell-up if the business fares are reduced. This fact also leads to the preservation of revenue and supports the rather small revenue drop from executing a business fare reduction.

4.4.2 Fare Reduction: Revenue Gains from Leg-Based RM (FCYM)

Figure 4-11 displays the revenue gain when both airlines move from FCFS to FCYM leg-based control. Three different demands are shown with the resultant average load factors given along the X-axis. The gain from initiating FCYM is greater when overall demand is greater.

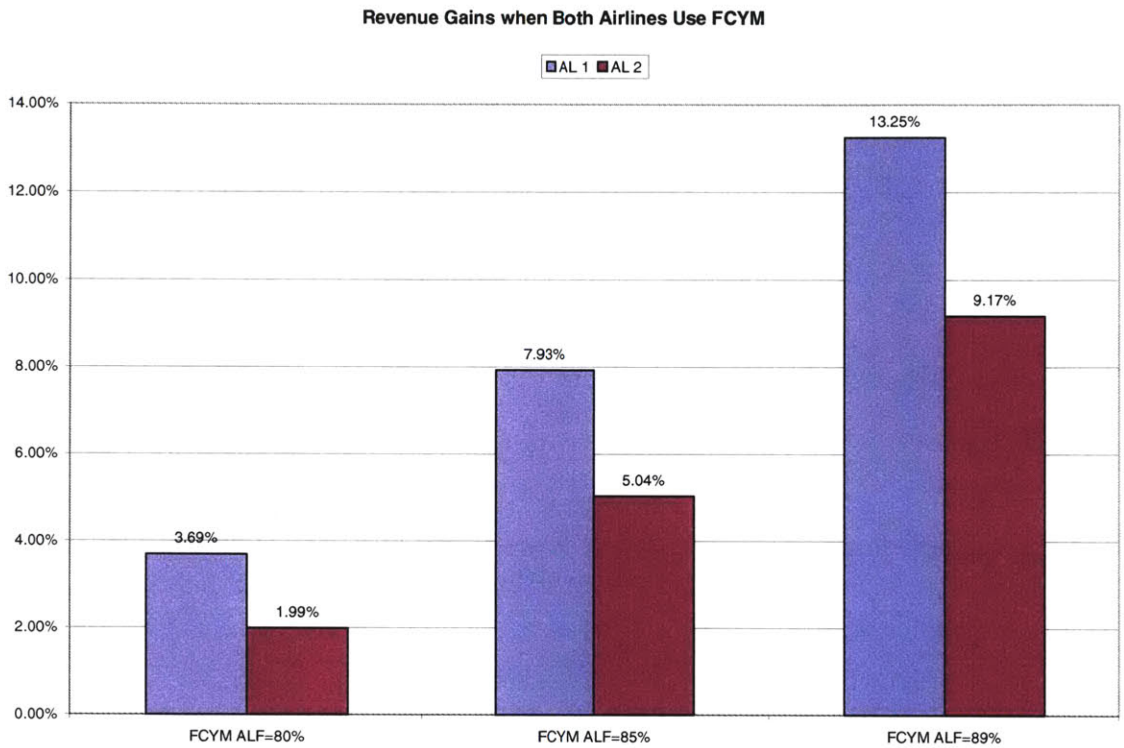

Figure 4-11: Both airlines move from FCFS to leg-based RM with business fare reduction

Leg-based RM provides a 2 percent to 13 percent increase in revenue depending on the ALF. Airline 1 has slightly larger gains due to the slight asymmetries that exist in Network D. The hub of Airline 1 is better positioned geographically such that a greater number of destinations are closer to it. Specifically, there are a number of large markets in which Airline 1 has a slight advantage because it has a better path quality than Airline 2. This explains the greater gains for Airline 1. The important concept here is that even with a significant reduction in business fares leg-based RM still provides a large benefit over FCFS for both airlines. This benefit can be as high as 13 percent at the highest demand level tested. Furthermore, the business fare reduction has increased the ALFs by about 1 percentage point.

4.4.3 Fare Reduction: Incremental Benefit of OD Control

Figure 4-12 shows the incremental relative revenue gain of OD control methods over FCYM. Only Airline 1 implements OD control. Airline 2 still uses FCYM.

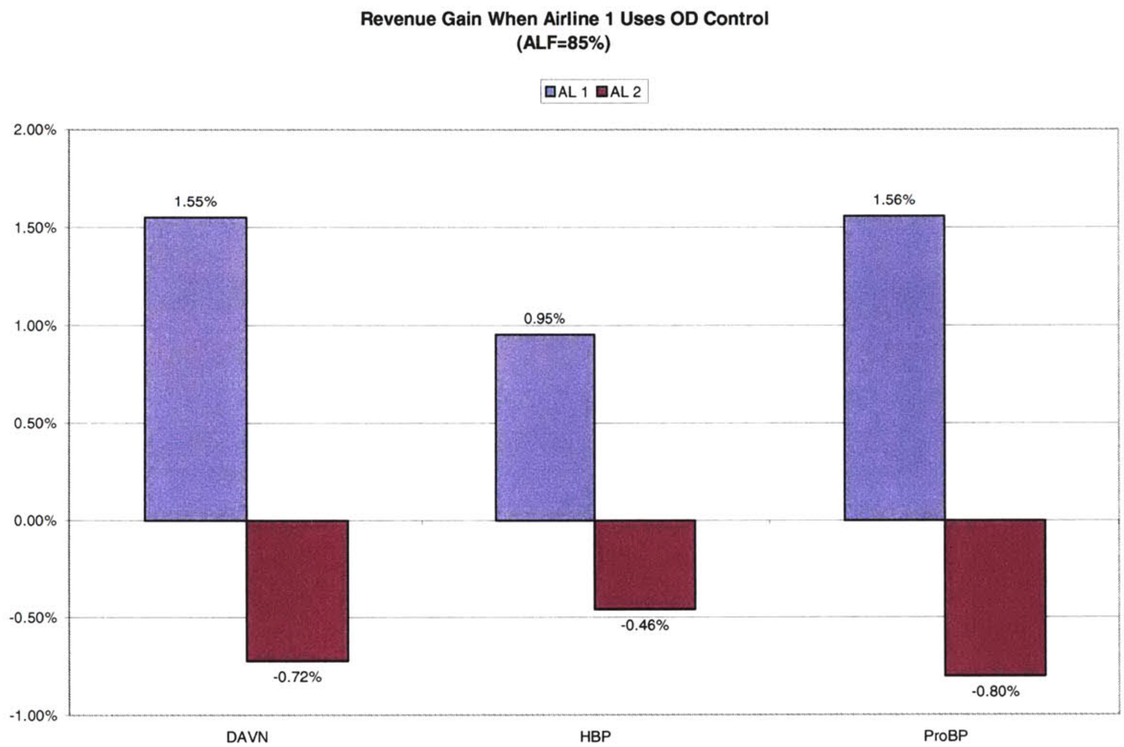

Figure 4-12: OD Control performance with a business fare reduction

Both DAVN and ProBP yield approximately a 1.5 percent gain at an 85 percent ALF. HBP garners an almost 1 percent gain. Airline 2 loses less than one percent when its competitors uses OD control. These results are very similar to the revenue gains reported in the base case. However, as mentioned above, the ALF is approximately 1 percent higher with reduced business fares than in the base case. Figures 4-13, 4-14, and 4-15 show the OD Control curves for DAVN, HBP, and ProBP respectively.

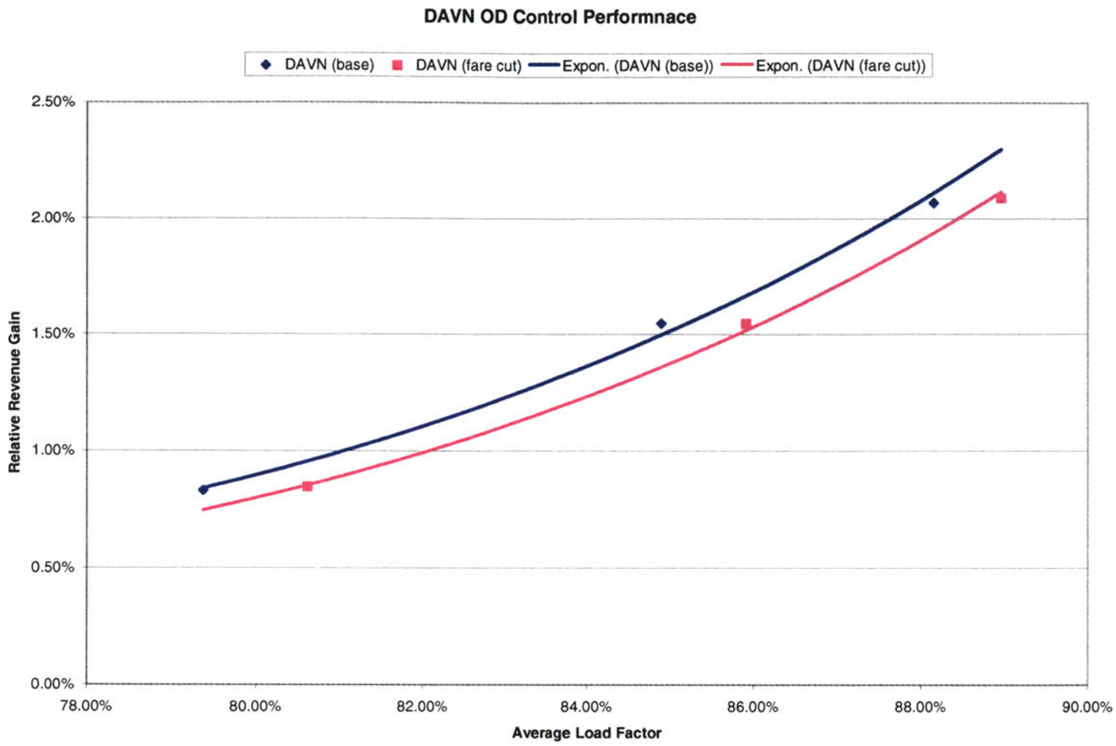

Figure 4-13: Fare Reduction DAVN OD Control Curve

Figure 4-13 shows a very clear result. DAVN performs slightly better with the higher business fares given a fixed ALF. The fare reduction causes a downward shift of the OD Control curve. While the actual relative revenue increase from Airline 1 implementing DAVN in the base case and in the reduced business fare case are the same at 1.55 percent, part of that 1.55 percent increase in the reduced business fare case is due to an increase in ALF. Adjusted for network ALF, DAVN performance is slightly lower with the reduced business fares.

The above result makes intuitive sense given the results in Section 4.3.3. A reduction in business fares acts the same as compressing the fare structure because the Y and B ratios will be lowered from the business fare reduction. Fare compression leads to lower OD control performance, though this may be made up by the increased ALF.

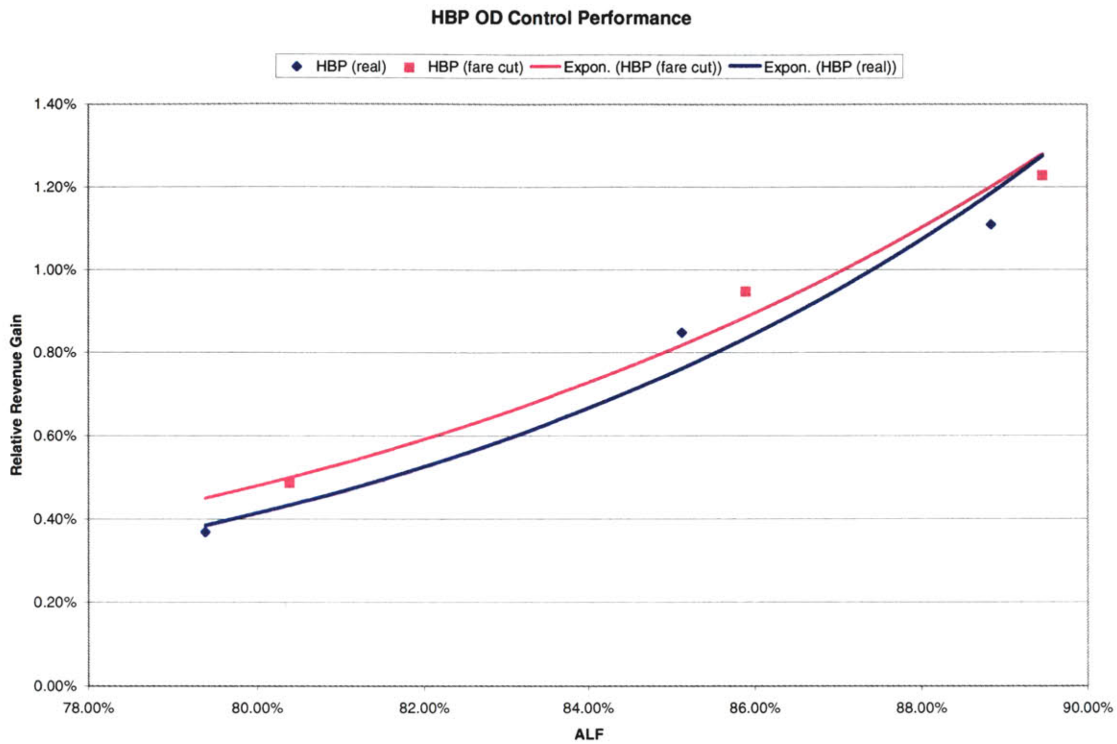

Figure 4-14: Fare Reduction HBP OD Control Curve

Figure 4-14, displays the fare reduction HBP OD control curve in contrast to the base case HBP OD control curve. The shifting of the HBP OD Control curve with reduced business fares is opposite of the DAVN result. The fare reduction actually increases the HBP performance given an ALF, albeit the difference in the two curves is negligible. It can be explained by the fact that HBP performs better with a compressed fare structure because the virtual buckets have tighter bounds. This allows HBP to better distinguish the fare values of bookings.

Figure 4-15 displays the business fare reduction ProBP OD Control curve and compares it with the base case. There is a downward shift of the curve when the business fare reduction is ismplemented. Thus, similar to DAVN, ProBP also sees a reduction in performance when reducing the business fares. Again, we have a situation where the actual relative revenue gain for ProBP at a certain demand is approximately the same whether or not business fares have been reduced. However, the increase in ALF from the business fare reduction accounts for some of that gain, so the actual ProBP OD control performance gain is less for the reduced business fare case than the base case.

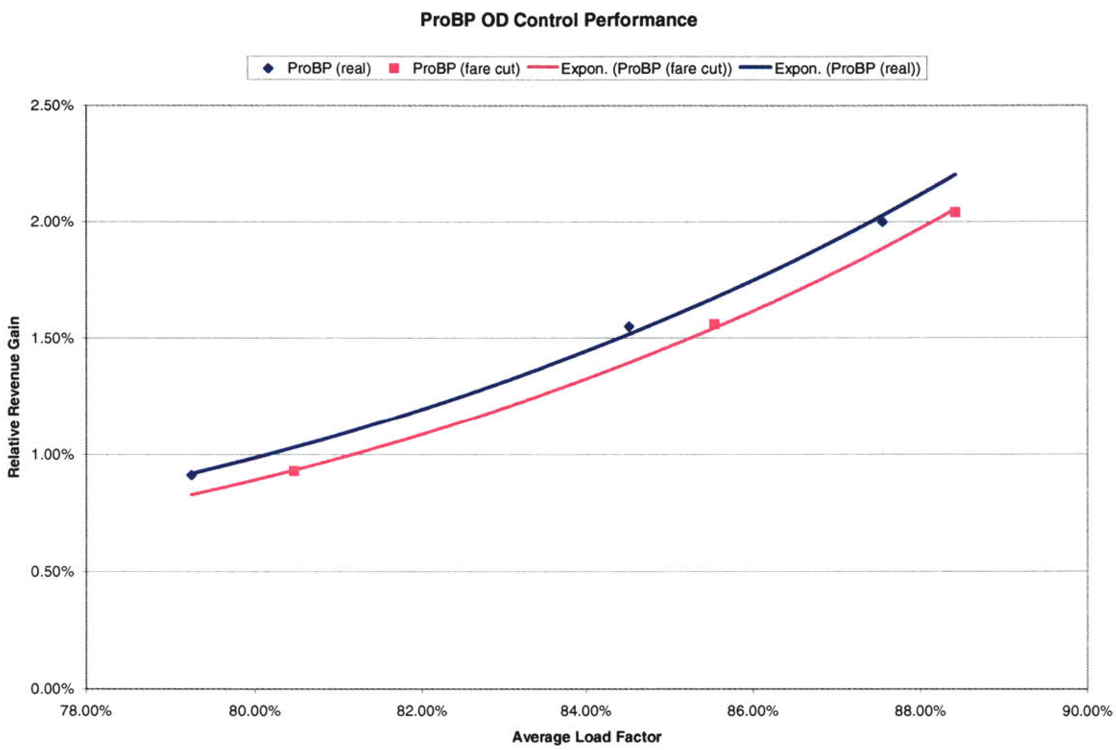

Figure 4-15: Fare Reduction ProBP OD Control Curve

4.4.4 Fare Reduction: Case Summary

Section 4.4 presented a case where business fares, Y and B fares, were reduced by 20 percent in all markets. This acted as a fare compression. The change in fare structure does not result in severe revenue degradation. The revenue loss from reducing business fares is only on the order of 2 percent to 4 percent. The results clearly showed that leg-based RM provided an increase in revenue compared to FCFS. Finally, OD control performance was presented. The incremental benefit of OD control with reduced fares is almost identical to the base case. However, a reduction in business fares increases ALF by about 1 percentage point. Thus, holding ALF constant to isolate the OD control performance, DAVN and ProBP perform better without the fare reduction. On the other hand, HBP performs nearly the same with the business fare reduction as it does without the business fare reduction. As explained above, HBP shows a slight increase in performance when the fare values are compressed because the virtual buckets have tighter bounds. This makes passengers more distinct to the HBP OD control system. Finally, while reducing business fares leads to slight revenue losses, leg-based control garners more revenue than FCFS and OD control still performs almost as well as in the base case for DAVN and ProBP and actually performs slightly better for HBP when there is a business fare reduction.

4.5 Summary

This chapter is the first of two to present PODS simulation results. Chapter 4 first provided a brief overview of the base case results with the traditional fare structure. Then, it presented two experiments dealing with changes in the actual fare values in all markets. The results included examining the loss of revenue from implementation of the alternative fare structure, the benefit of leg-based RM, as well as the incremental benefit of OD control.

The first experiment used structured fare ratios, as opposed to market-based fare ratios, to look at what happens when the fare values in the different fare classes are compressed or expanded. A compressed fare structure reduced the performance of both leg-based and OD control RM compared to the base case traditional fare structure while an expanded fare structure showed an increase in performance of both leg-based RM over FCFS and of the incremental benefit of OD control over leg-based control. However, in all cases leg-based control provided higher revenues than FCFS and the incremental benefit of OD control over leg-based control was positive and on the order of 1 percent or more.

The other experiment presented in this chapter returned to the market-based fare structure. In this case, the fare values of the two high value fare classes, Y and B, were reduced by 20 percent. This acted as a compression of the fare structure, as the mean and standard deviation of the Y and B fare ratios decreased. The revenue change from the business fare reduction was on the order of 2 percent to 4 percent. For this case, leg-based control generated a 2 percent to 13 percent gain in revenue over FCFS, and the incremental benefit of OD control was nearly as much as in the base case. However, the increase in load factor from the fare reduction partially accounts for the equivalent revenue gain from OD control. After correcting for the change in ALF, there is a slight decrease in OD control performance with a business fare reduction as compared to the base case. Finally, even with a business fare reduction FCYM leg-based control still provides revenue benefits and OD control offers an incremental benefit nearly equivalent to results with the traditional fare structure.

While this chapter examined changes in the fare ratios, the next chapter will focus on removing fare class restrictions and advance purchase requirements without changing fare values or ratios.

Chapter 5 Removal of Fare Restrictions

This chapter will proceed similarly to Chapter 4. More experiments, also called cases, will be presented that examine the performance of both leg-based and network RM under alternative fare structures. The main difference lies in the fact that in Chapter 4 experiments were performed where the actual fare values and ratios were changed but the structure of the fare restrictions remained the same, whereas this chapter retains the base case market-based fare structure and holds fare values constant but removes fare restrictions and/or advance purchase requirements. The main goal is to simulate an airline that is offering a simplified fare structure similar to that offered by LCCs in the airline industry and to determine the impacts on revenue management.

The results of this chapter encompass three cases. First, both airlines remove the Saturday night stay restriction from their fare structure in all markets. The other two restrictions and advance purchase (AP) requirements remain in the fare structure as described in Chapter 2. As was shown in the examples given in Chapter 3, LCCs typically use a fare structure that does not include a Saturday night stay restriction. Second, all three of the restrictions used in PODS are removed, but the advance purchase requirements still apply. Recall that the three restrictions represent the Saturday night stay requirement, non-refundability, and change fee. Finally, the three restrictions remain in the fare structure but AP requirements are gradually reduced until they are completely removed. Note that the first two directly affect the generalized cost function and will change the preference ranking of some or all of the simulated passengers while the third case, the removal of AP requirements does not. The same base case that was presented in Section 4.2 is also used as the benchmark in this chapter.

Section 5.1 begins this chapter by discussing consequences of removing restrictions from the traditional fare structure. RM performance under alternative fare structures, specifically removal of Saturday night stay, removal of three restrictions, and reduction/removal of AP, is presented in Sections 5.2, 5.3, and 5.4 respectively. A summary of results is given in Section 5.5.

5.1 Consequences of Removing Restrictions

The alternative fare structures presented in this chapter depend on the generalized cost function of passengers and how far before departure a passenger attempts to make a booking. Changing the restrictions on fare classes will change the generalized cost function perceived by passengers, which may change their choice set. For example, there may be a passenger that attempts to book a seat more than seven days in advance but he or she prefers a completely flexible ticket with no restrictions. In the traditional fare structure, a Y-fare would be the only product that would satisfy this person's request. However, if there is no longer a Saturday night stay restriction, then a B-fare would also be in this person's choice set, and since both B and Y are unrestricted, then a the B-fare would always be perceived cheaper than a Y-fare to all passengers. Likewise, removing all three restrictions from the fare structure implies that the generalized cost function comprises only the actual fare values of the different fare products. In this case, all passengers will prefer the Q-fare assuming that the passenger meets the advance purchase requirements and the RM system has Q availability on the relevant paths at the time of booking. Tables 5-1 (business passengers) and 5-2 (leisure passengers), shown below, give the change in total perceived cost of each fare class in an example where the fare values of the market are Y=400, B=200, M=150, and Q=100 and the disutility parameters of the passengers are the mean values as given in Table 3-2.

	Traditional Fare Structure	No Saturday night Stay	Three Restrictions Removed
Y	\$400	\$400	\$400
B	\$425	\$200	\$200
M	\$450	\$225	\$150
Q	\$475	\$250	\$100

Table 5-1: Total Perceived Cost of Fare Products for a Business Passenger

	Traditional Fare Structure	No Saturday night Stay	Three Restrictions Removed
Y	$400	$400	$400
B	$375	$200	$200
M	$350	$175	$150
Q	$325	$150	$100

Table 5-2: Total Perceived Cost of Fare Products for a Leisure Passenger

In Table 5-1, it is evident that in the base case a business passenger, on average, will prefer the Y-fare because of the high "perceived" cost of the restrictions. However, removing the Saturday night stay changes this completely. In this case, on average B will be most preferred, and then M, Q, and Y is the least preferred fare class. If all three restrictions are removed, the Q-fare is the most preferred on average.

Table 5-2 illustrates that the restrictions have less of an effect on leisure travelers. Most leisure travelers are not willing to pay for a Y or B fare. Thus, Q is always the most preferred fare class product for leisure travelers regardless of the restriction regime used, but some leisure travelers purchase from higher fare classes due to lack of availability in Q or because they do not meet the advance purchase requirement of the Q-fare.

Keeping all restrictions in place but reducing AP requirements has a different effect because it does not change the generalized cost function of passengers. If the RM system does not close availability due to high demand, then reducing AP keeps the lower fare value classes open longer. Thus, passengers booking closer to the day of departure have a greater chance of still being able to book from a low fare class. There are two consequences to this. First, late-arriving leisure passengers that have a low willingness to pay and would not have traveled might now be able to book a ticket. Second, late-arriving business passengers with a higher WTP and the ability to meet the restrictions placed on a low fare class ticket may now buy a Q or M fare when they would have bought a Y fare if AP was in place. From the airlines' perspective, the former consequence is a positive one that results in higher system ALFs, but the latter consequence is a negative one because it promotes sell-down and revenue dilution.

5.2 Removal of The Saturday Night Stay Restriction

The Saturday night stay restriction is considered to be one of the most powerful restrictions used in airline pricing to effectively segment business passengers from leisure passengers. Most business passengers have meetings during the week and do not want to be away from home on the weekend. On the other hand, leisure passengers usually go on vacation or go to visit friends and family during a weekend period.

In this experiment, only the Saturday night stay restriction is removed. The other two restrictions, non-refundability and a change fee, remain in place as well as the AP requirements. This ensures that some product differentiation occurs and that the lower-value fare classes are still artificially closed close to departure to discourage diversion of last minute passengers.

Because this restriction plays an important role in the segmentation of demand, the removal of it system-wide should have a significant impact on revenues. Most of this effect should be concentrated on business travelers since, without the restriction, Y will no longer be a business traveler's first choice on average. Instead, B will be the average business traveler's first choice. Hence, in the experiment there should be a large shift in traffic from Y to B.

5.2.1 No Saturday Night Stay Restriction: Revenue Change from Alternative Fare Structure

Figure 5-1 looks at the revenue change when both airlines are using leg-based RM control and both airlines remove the Saturday night stay restriction.

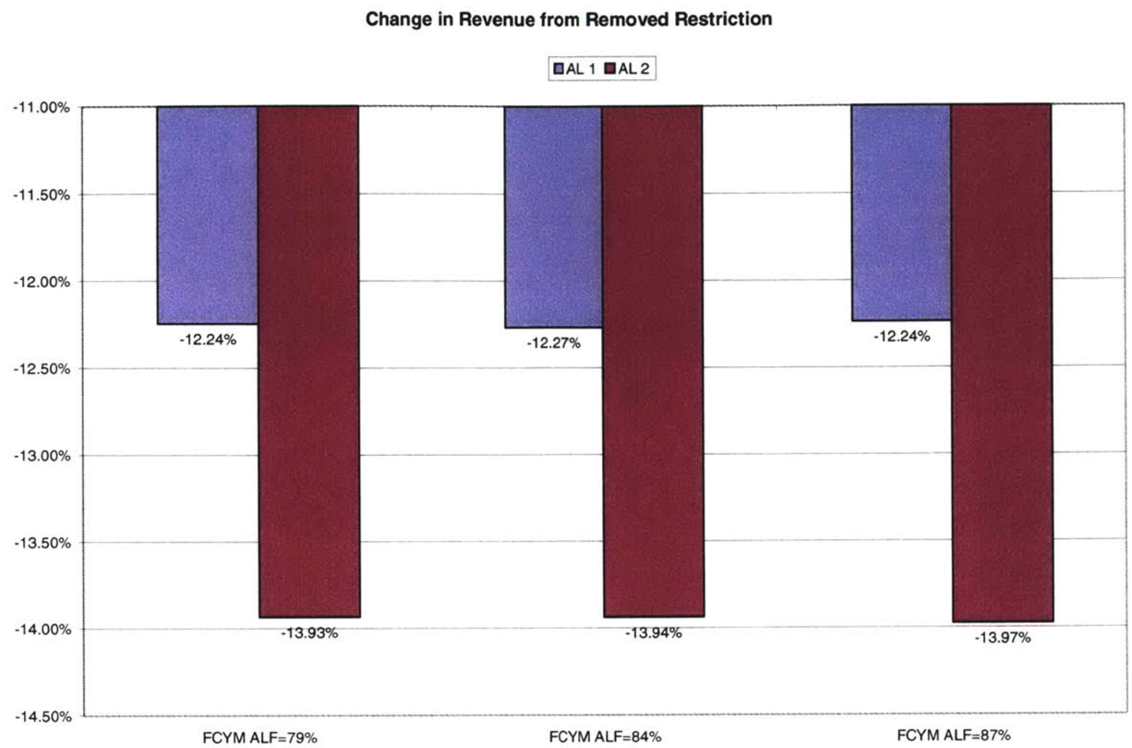

Figure 5-1: Revenue Change from Implementing Alternative Fare Structure using Leg-Based RM

Airline 1 sees a revenue reduction of about 12 percent while Airline 2 realizes a revenue reduction of almost 14 percent. This is a very large revenue change considering only one restriction was removed from the fare structure. The airlines with leg-based RM are performing well below that of the traditional fare structure base case in terms of absolute revenue.

The fare class mix is graphically given below in Figure 5-2 to examine the cause of this large revenue reduction. The hypothesis stated at the beginning of this section is confirmed, namely that there is a large shift in traffic from Y to B. The proportion of Q passengers is nearly the same as in the base case, which suggests that leisure travelers are largely unaffected by the change in fare structure. There is a large decrease in the proportion of Y passengers and an increase in the proportion of B passengers. There is also a significant increase in the proportion of M passengers. The increase in M passengers stems from the fact that on average M is the business traveler's second choice. However, for some business passengers M is their first choice now.

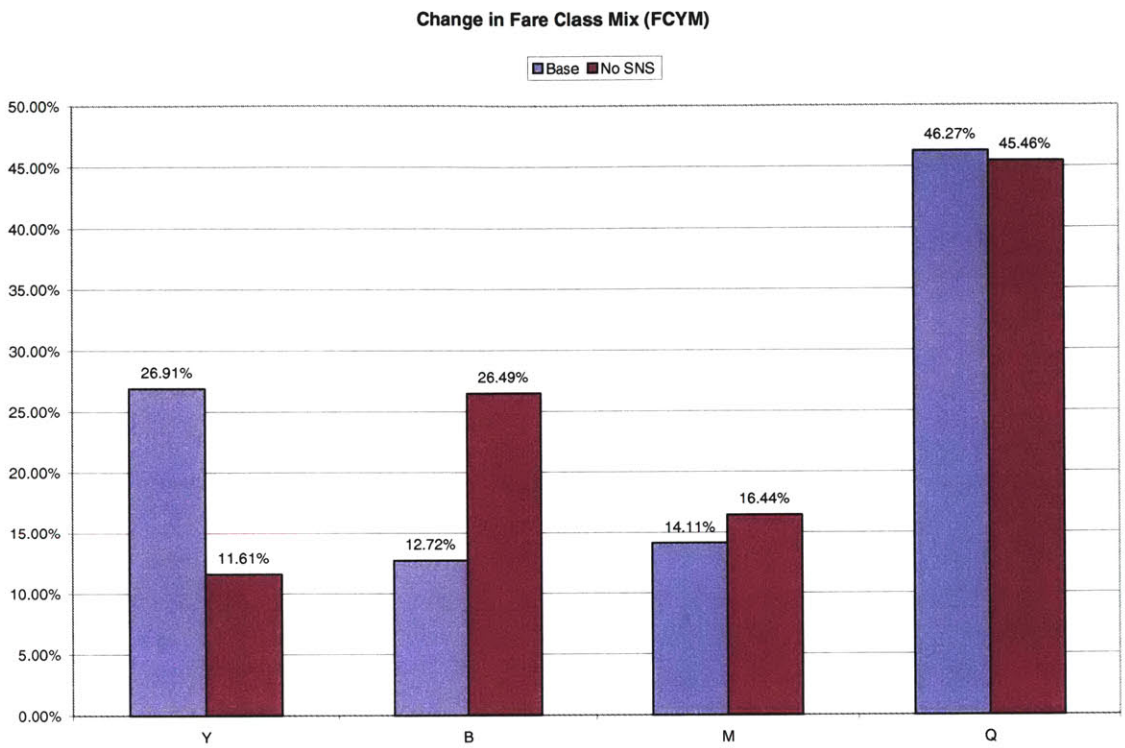

Figure 5-2: Fare Class Mix with No Saturday Night Stay Restriction

5.2.2 No Saturday Night Stay Restriction: Revenue Gains from Leg-Based RM (FCYM)

The first step in this case is to examine the revenue effects of the alternative fare structure with leg-based RM. This result is shown below in Figure 5-3. Three different demand levels were tested to compare results at different ALFs. Moving from no control to leg-based control still provides a revenue gain for both airlines. This gain ranges from 3 percent to 16 percent depending on the airline and demand. The benefit of implementing RM matches or exceeds the benefit achieved with a traditional fare structure, which were on the order of 3 percent to 14 percent.

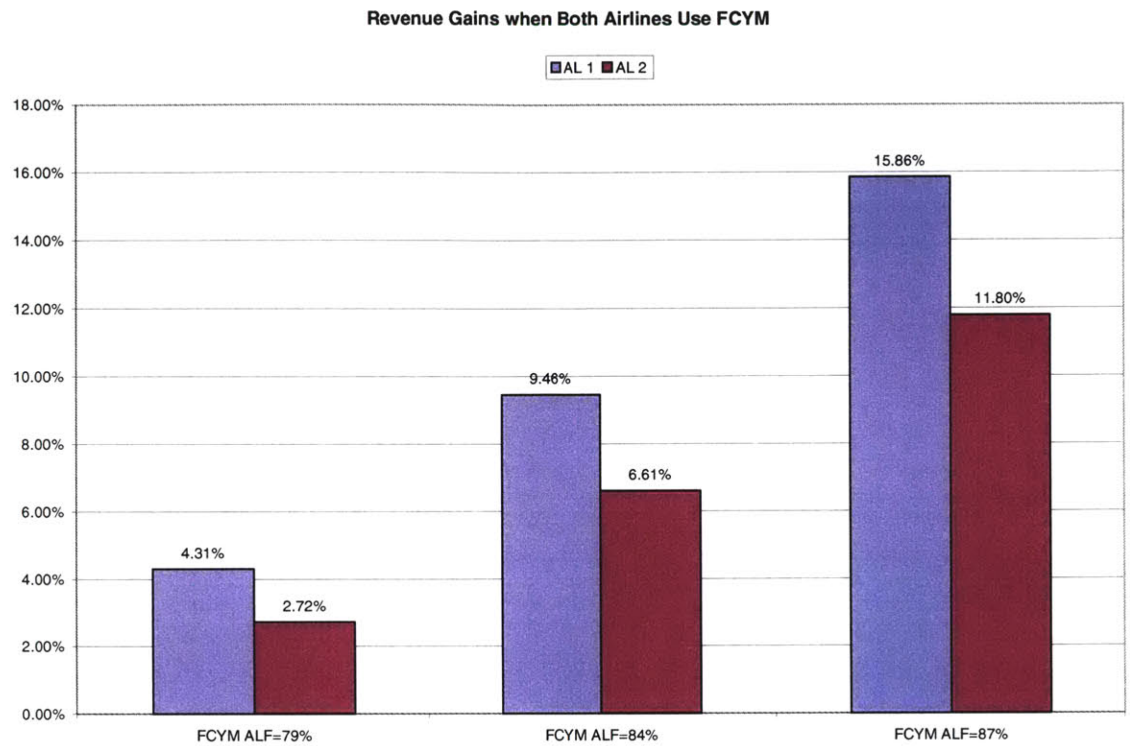

Figure 5-3: Both Airlines Move from FCFS to leg-based RM with No Saturday Night Stay

It is very clear that leg-based control is important to increase revenue. In this case, AP requirements are still intact and two of three restrictions are still in place to provide some product differentiation. However, leg-based control allows for the protection of the higher fare classes because there are still many business passengers willing to pay for a Y-fare. This fact makes leg-based control under an alternative fare structure even more important than in the traditional fare structure base case. Without the Saturday night stay restriction, a Y-fare will only be bought if a passenger books a seat less than 7 days before departure or if inventory control has closed the B fare class.

5.2.3 No Saturday Night Stay Restriction: Incremental Benefit of OD Control

This section will look at the incremental benefit of implementing OD control when the Saturday night stay restriction has been removed. OD control may not perform as well with this type of fare structure because the Y fare class will only receive bookings if inventory control has closed the B fare class or for passengers booking seats within 7 days of departure. Figure 5-2 confirms that less than 12 percent of passengers are booking in Y. With a very large proportion of passengers in B, M, and Q it is almost as if the fare structure has been compressed as was presented in Section 4.4, and with a compressed fare structure OD control does not perform as well as in the traditional fare structure.

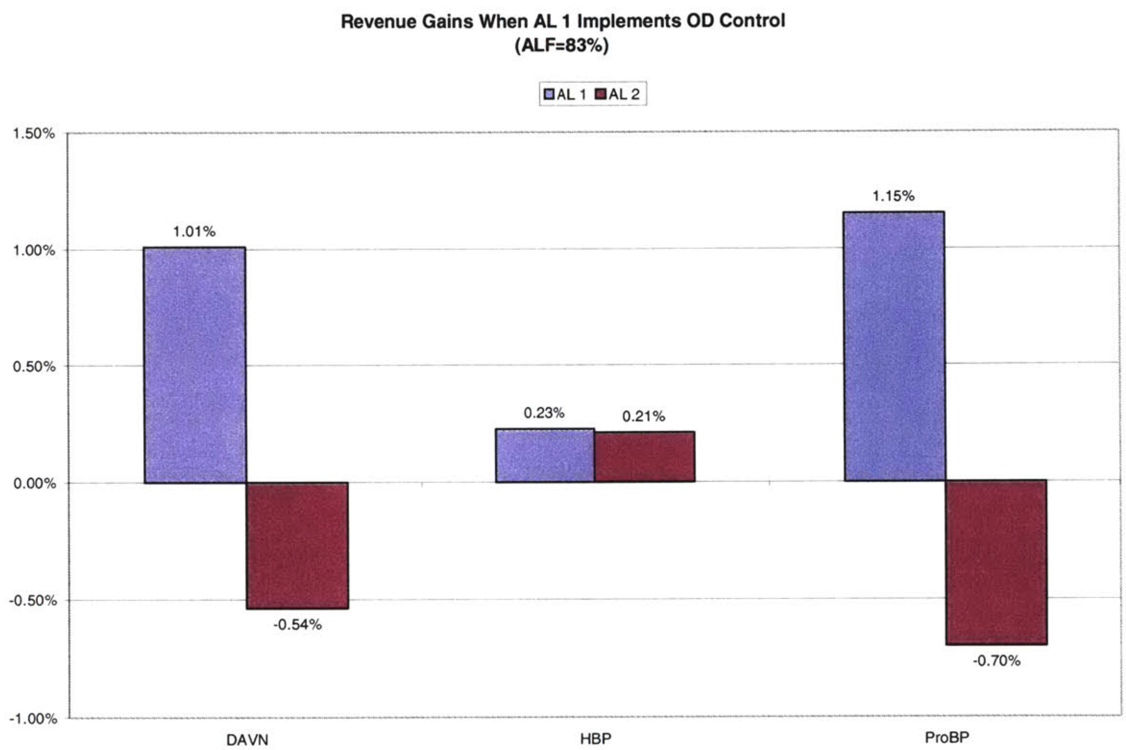

Figure 5-4: OD Control Performance with No Saturday Night Stay Restriction

Figure 5-4 shows the incremental benefit of the three typical OD control methods when the Saturday night stay has been removed by both airlines but only Airline 1 uses OD control. DAVN and ProBP yield slightly more than a 1 percent gain, while HBP does not perform as well, garnering only 0.2 percent. Again, there is a change in load factor as this case sees a 1-percentage point drop in ALF as compared to the traditional fare structure base case. It would seem that OD control in the base case performs better. However, all three OD control methods still provide a positive benefit even after removing the restriction.

Figures 5-5, 5-6, and 5-7 show DAVN, HBP, and ProBP, respectively, OD Control curves for the base case and for the case when the Saturday night stay restriction is removed.

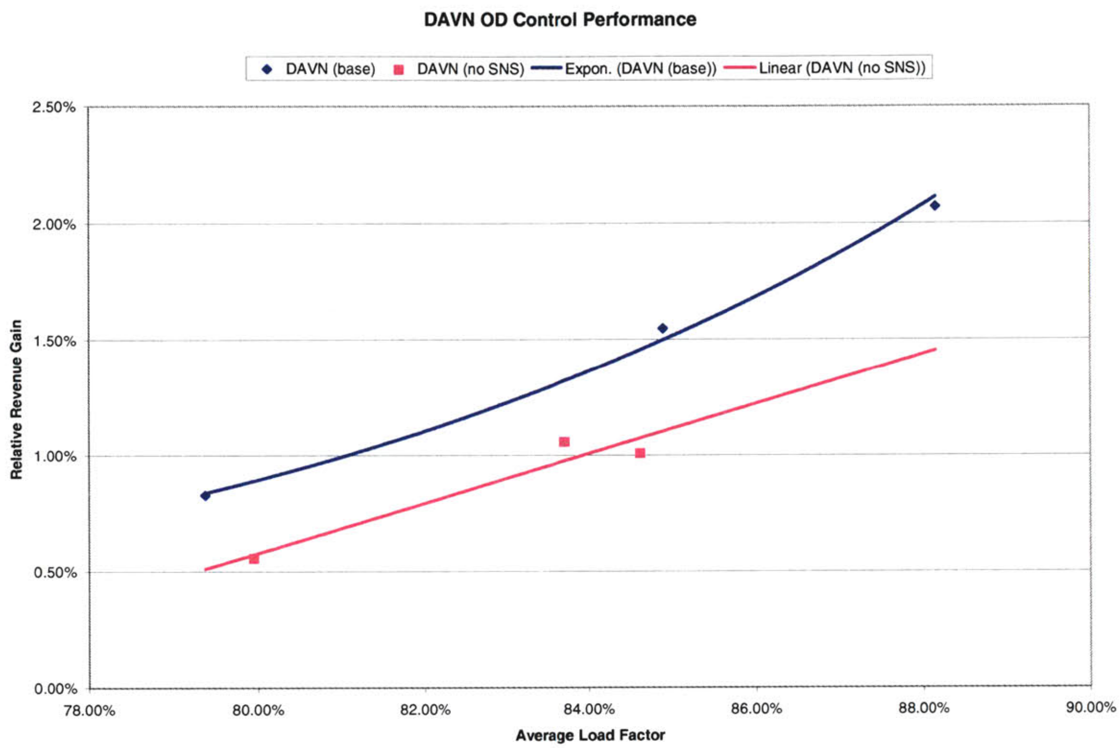

Figure 5-5: No Saturday Night Stay DAVN OD Control Curve

Figure 5-5, above, examines the OD Control curve for DAVN with and without the Saturday night stay restriction. It is very clear after normalizing over a range of ALFs that OD control performs better in the traditional fare structure base case. Not only is there a large downward shift in the curve when removing the restriction, but also the curve, which is non-linear in the base case, becomes much more linear. This implies not only that RM performance is not as good when the restriction is removed, but also that the gap in performance grows larger as the ALF is higher.

The reason for the decrease in performance is that OD control has less leverage without the restriction. The differentiation between business and leisure passengers is somewhat blurred and the absence of a restriction to differentiate between Y and B classes reduces the effectiveness of OD control. Only RM controls and AP requirements can force a passenger into the Y fare class. With so few Y passengers, it is almost as if the RM system is working with only three classes instead of four, much like the case of a compressed fare structure.

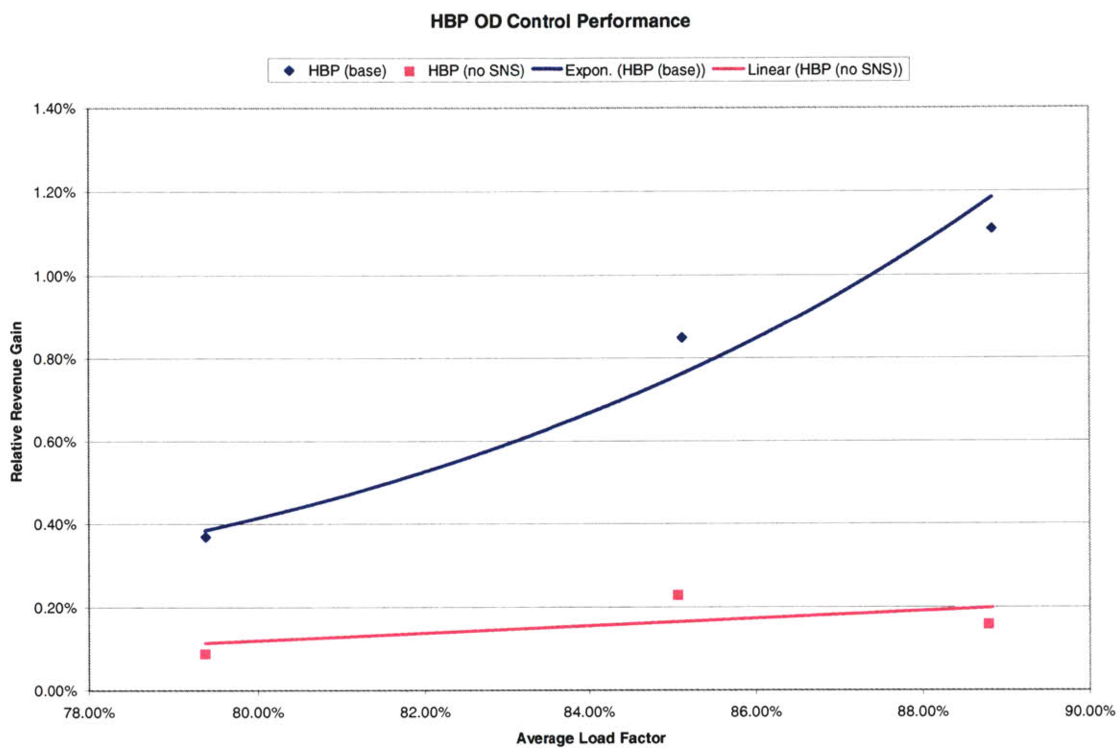

Figure 5-6: No Saturday Night Stay HBP OD Control Curve

Figure 5-6, shown above, gives the traditional and alternative fare structure RM curves for HBP. HBP without the Saturday night stay is even worse off than DAVN. Not only is the curve rather flat, as in the DAVN case, but also the incremental benefit of HBP is extremely low. There is an extremely large performance gap.

The poor performance of HBP has to do with the virtual bucket scheme that it uses and was explained in Chapter 2. The problem is that even though the Y fare values exist, very few passengers actually book them. Thus, most of the passengers are booking from the B, M, and Q fare classes. However, the Y fares cause the need for the virtual bucket ranges to incorporate these high Y fares, though few people book them. This causes many B, M, and Q fares to get mapped into the same bucket. Though there are 8 virtual buckets, only 4 or 5 of them are being used effectively. The buckets are too widely defined for this case causing weaker performance. If the buckets are open too long, then too many low-fare bookings are accepted, including spill-in because the other airline will close its low fare classes to protect inventory leaving low fare passengers to flock to the airline using HBP, but if the buckets are not open long enough, then even B passengers are spilled to the other airline.

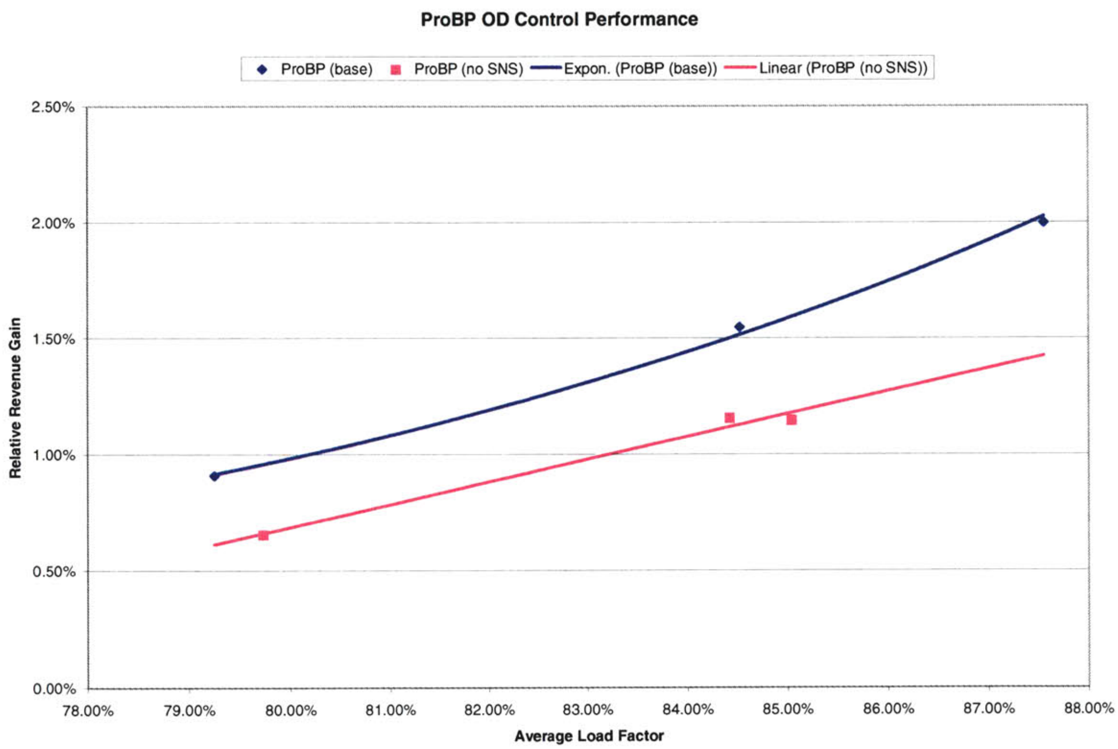

Figure 5-7: No Saturday Night Stay ProBP OD Control Curve

Finally, the OD Control curve for ProBP without a Saturday night stay restriction is given in Figure 5-7. The result for ProBP is very similar to that of DAVN. First, there is a large downward shift of the curve when the restriction is removed implying a decrease in the incremental performance of the OD method. Second, the OD Control curve is much flatter and more linear when the restriction is removed, which means that the performance gap is even greater at higher ALFs. The same explanation for the performance of DAVN applies to ProBP as well. The lack of Y passengers means that there is less leverage for OD control to achieve revenue gains.

5.2.4 No Saturday Night Stay Restriction: Case Summary

The removal of the Saturday night stay restriction had profound effects on revenues and on the RM systems tested. Removing the restriction led to a 12 to 14 percent decrease in revenues using leg-based RM. This revenue decrease was mainly the result of business passengers switching from Y to B and M, where the B fare is on average 50 percent less than the Y fare. However, leg-based control does provide up to double-digit percentage gains over FCFS without the restriction. Furthermore, the incremental benefit of OD control RM was less when the restriction was removed. DAVN and ProBP gained slightly over 1 percent while HBP gained less than one-fourth of a percent. This compares to 1.5+ percent for DAVN and ProBP and just less than 1 percent for HBP in the base case. There was a sharp downward shift of the OD Control curves for all three methods and the curves were also flatter. This is due to the large proportion of passengers in B, M and Q, which restricts the leverage of OD control since Y is never the first choice of a traveler when the Saturday night stay restriction is removed. However, leg-based RM provided large revenue gains and the incremental benefit of OD control still garnered extra gains, though less than in the base case.

5.3 Removal of The Saturday Night Stay, Non-Refundability, and Change Fee Restrictions

This section presents the case where all three of the restrictions represented in PODS are removed across the system for both airlines. Unlike the last case where there was still some product differentiation, removing all three restrictions reduces the differentiation to almost nil. There are still AP requirements and RM controls, but the removal of all three restrictions means that the total "perceived" cost of each fare product is simply its fare value for both types of passengers. This means that all simulated passengers will always have Q as their first choice. It is left to the AP requirements and RM system to ensure that some passengers that are willing to pay a higher fare sell-up into a higher fare class.

In this case, revenue is expected to be degraded even further than in the case presented in Section 5.2. There should be a mass transfer of passengers into the Q fare class. Since a majority of leisure travelers were already in Q class in the base case, the removal of all three restrictions should change the behavior of business passengers more dramatically than leisure passengers. The main concern is that business passengers who book early enough may find an available Q fare when they were willing to buy a Y fare. This diversion risk is further exacerbated by the fact that the business travelers that do find Q inventory may displace leisure passengers who are not willing to sell-up and find that the Q fare class is closed when they arrive.

5.3.1 Removal of Three Restrictions: Revenue Change from Alternative Fare Structure

The change in revenue from removing all three restrictions for both airlines using FCYM is shown below in Figure 5-8. There is a profound loss of revenue on the order of 19 percent to 21 percent. This compares to a loss of 12 percent when only the Saturday night stay restriction was removed. The results are very clear in that restrictions used to differentiate the product and segment demand are very important to increase revenue. Only the AP requirements remain, which only segment demand based on how close to departure a passenger attempts to book a ticket. In this situation, every passenger is going to choose the lowest fare that is available at the time of booking because to all passengers all fare classes are equal except for the actual fare charged.

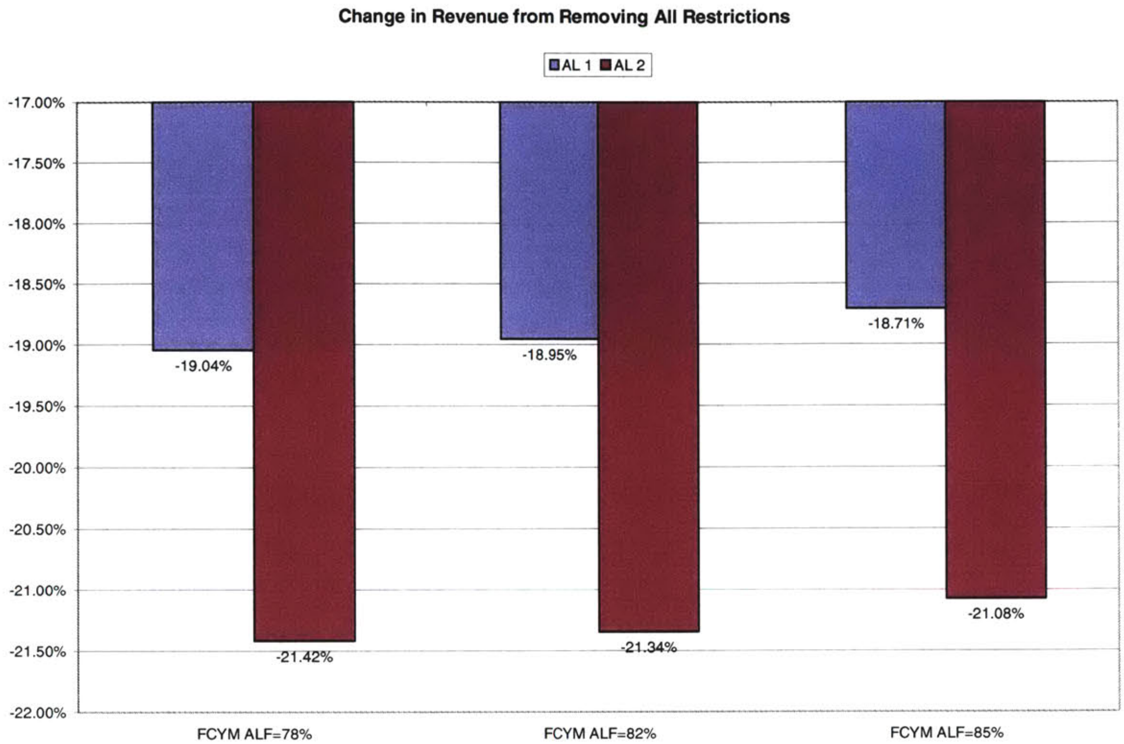

Figure 5-8: Revenue Change from Implementing Alternative Fare Structure

The source of this revenue degradation can be further investigated by looking at the fare class mix of Airline 1 using leg-based RM with all three restrictions removed. This appears below in Figure 5-9 and is compared to the traditional fare structure base case. As was hypothesized at the beginning of this section, there is a large transfer of passengers from the higher fare classes to the lower fare classes. In particular, there is a large move from the Y fare class and a large influx into the Q fare class. With this alternative fare structure over 60 percent of passengers are booked in Q. In contrast barely 10 percent are now booked in Y with only another 10 percent booked in B. This fare structure allows for early-arriving business passengers to book M or Q fares if they are made available by the RM system because all fare classes are unrestricted. This explains the huge shift from Y to Q. There is also a slight shift of traffic from B to M.

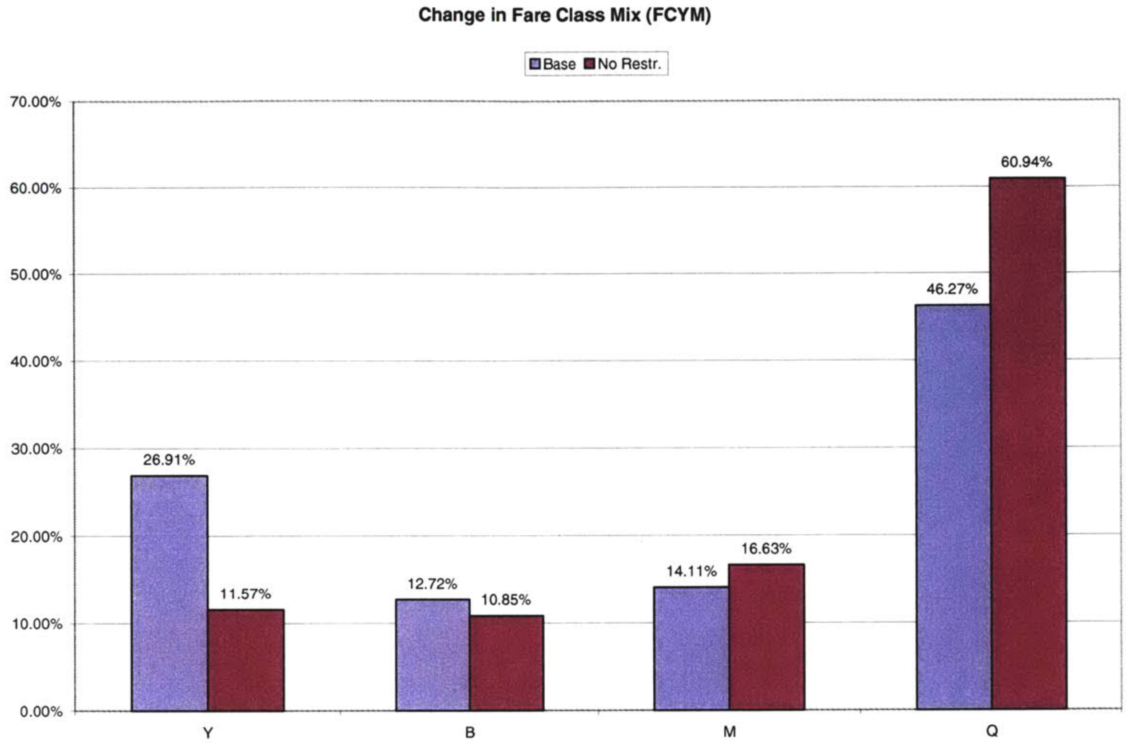

Figure 5-9: Fare Class Mix with Three Restrictions Removed Using Leg-Based RM

5.3.2 Removal of Three Restrictions: Revenue Gains from Leg-Based RM (FCYM)

Figure 5-10, displayed below, shows the revenue gain for both airlines from implementing leg-based RM. It is very clear from this figure that leg-based RM increases revenues as compared to FCFS. Airline 1 gains from 4 percent to 17 percent depending on demand and Airline 2 gains between 3 percent and 13 percent. These statistics are greater than the case when only one restriction was removed as well as the traditional fare structure base case. This can be explained by the fact that other than the AP requirements we are seeing the full leverage of an RM system. RM and AP requirements are the only mechanisms available in this situation to get those passengers willing to pay for a high fare class product to do so. FCYM manages to protect high fare class inventory because from history and forecasts it knows that some passengers are willing to buy-up into these fare classes.

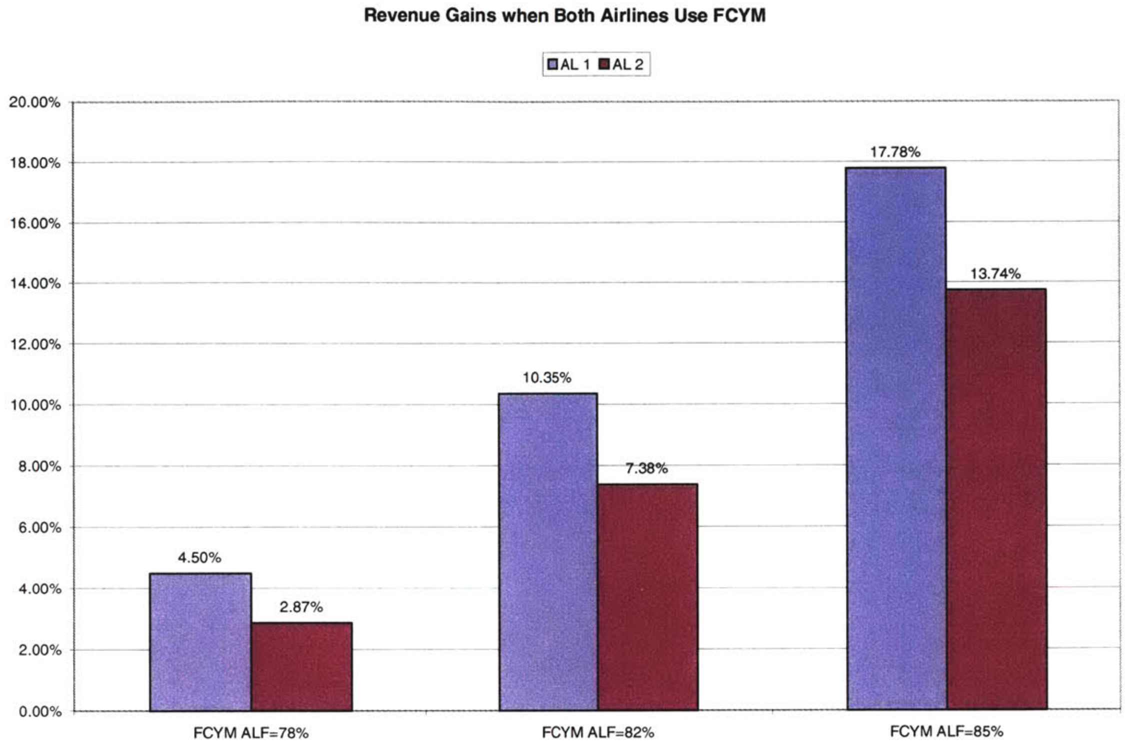

Figure 5-10: Both Airlines Move from FCFS to leg-based RM with Three Restrictions Removed

5.3.3 Removal of Three Restrictions: Incremental Benefit of OD Control

This section will look at the incremental gain of OD control over leg-based RM. Again, we are dealing with a situation where RM and AP requirements are the only two factors for getting people to buy-up into higher fare classes. Thus, the revenue gain is highly dependent on the leverage that OD control will have in this situation.

The incremental gains from the three standard OD control methods tested appear in Figure 5-11. This figure displays the benefit at an ALF of 82 percent, nearly 2 percentage points lower than the traditional fare structure base case. DAVN and ProBP each gain between 1 percent and 1.5 percent, a little lower than the base case, but HBP gains nearly 1 percent in this case. HBP gains more at a lower ALF when all three restrictions are removed than in the base case.

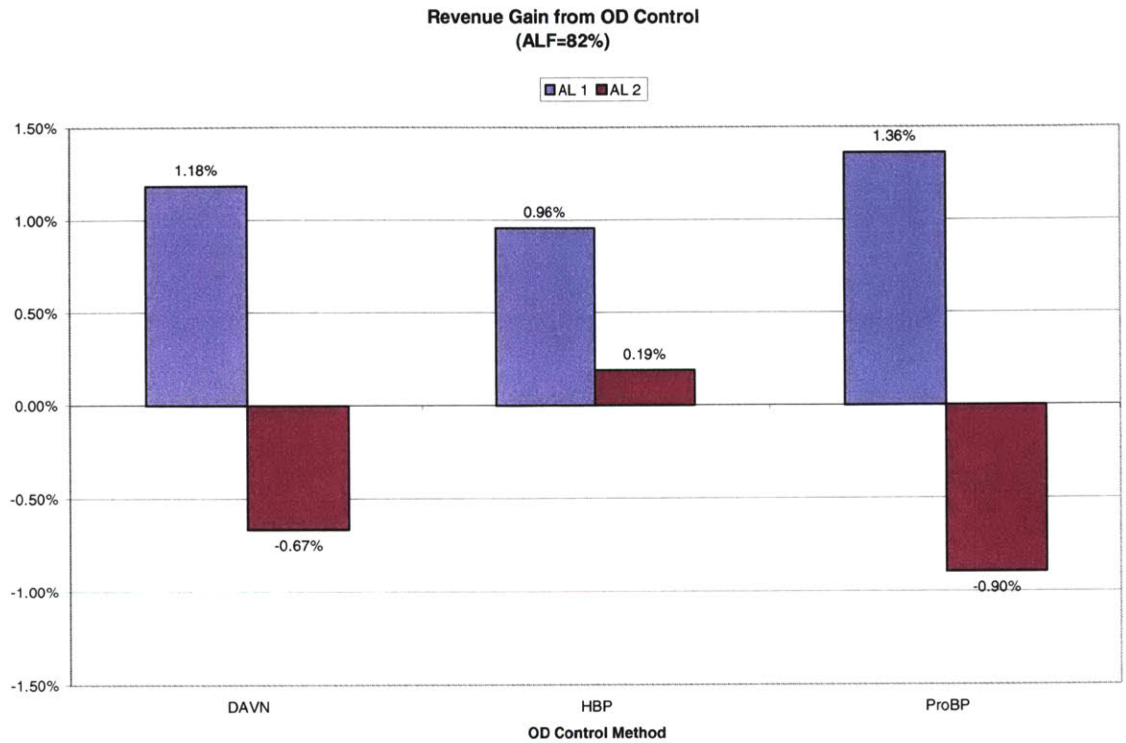

Figure 5-11: OD Control Performance with Three Restrictions Removed

Although results for DAVN and ProBP are slightly lower when all restrictions have been removed versus the base case, the ALF is 2 percentage points lower with the alternative fare structure. The OD control performance curves for DAVN, HBP, and ProBP with the removal of three restrictions appear below in Figures 5-12, 5-13, and 5-14, respectively. The traditional fare structure base case RM curves also appear in the figures.

The comparative DAVN OD Control curves appear below in Figure 5-12. At lower ALFs, OD control with the traditional fare structure outperforms RM without all three restrictions. However, at all higher load factors, above 81 percent, DAVN without all three restrictions performs better than DAVN with the traditional fare structure. DAVN is using its full capabilities as a network RM tool to find the right passenger mix at the ODF level. The reason that DAVN performs better is that leg-based control cannot differentiate between differently valued Q passengers. Leg-based RM cannot tell the difference between a $50 Q passenger and a $200 Q passenger. On the other hand, DAVN has the ability to differentiate between these low-value and high-value Q passengers because fares are mapped into different buckets. It is not necessarily the result that DAVN performs extremely well, but more so that leg-based control performs quite poorly relative to OD control.

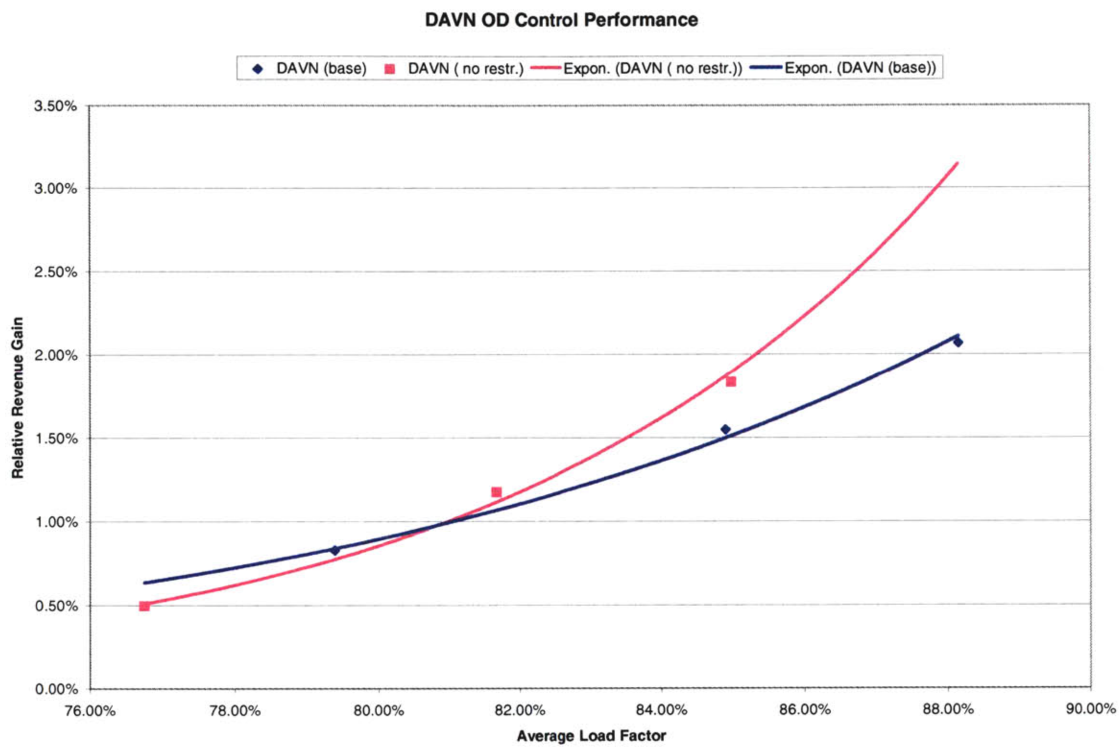

Figure 5-12: Three Restrictions Removed DAVN OD Control Curve

We have already seen in Figure 5-11 that HBP without the three restrictions performs better at a lower ALF. This already suggests that this alternative fare structure is a good match for the HBP OD control method. The HBP OD Control curve for both the alternative fare structure and the base case appear below in Figure 5-13. The good performance of HBP without restrictions is apparent, but the RM curve, after normalizing for ALF, also shows that the RM performance curve under the alternative fare structure is very flat. This means that below an 87 percent ALF HBP performs better with the alternative fare structure, but at high ALFs HBP with the traditional fare structure performs better. This is a good example of why graphing the OD Control curves are important instead of relying on one point estimate as given Figure 5-11.

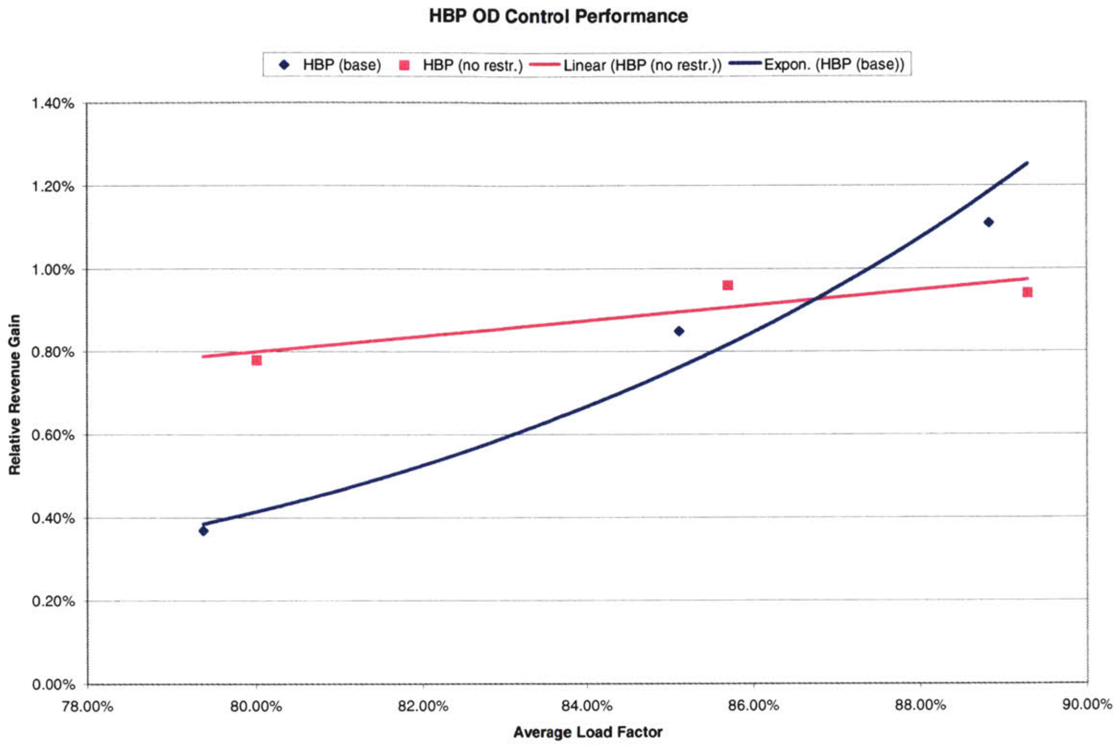

Figure 5-13: Three Restrictions Removed HBP OD Control Curve

The solid performance of HBP without restrictions at lower ALFs can be explained in much the same way as was the case for DAVN. Leg-based control cannot differentiate between different passengers in the same booking class, which is important in this case since over 60 percent of passengers are booked in Q. HBP maps the fares into buckets, which allows for passenger differentiation within the same booking class. However, the HBP OD Control curve is rather flat under the alternative fare structure. It does not perform as well as HBP in the base case at high ALFs. The reason for this is that at higher ALFs, there are more passengers attempting to book, which leads to greater selectivity. For HBP, this means that the low fare value buckets are closed sooner. With so many trying to book Q fares, the buckets with most of the Q fares get closed too early causing passengers to spill to the other airline.

The alternative and traditional fare structure OD Control curves for ProBP appear below in Figure 5-14. The results and explanation essentially mirror that of DAVN. However, in this case the ProBP OD Control curve without restrictions remains above that of the traditional fare structure over the complete range of average load factors. This suggests that ProBP performs better than DAVN with this alternative fare structure at lower ALFs. Furthermore, ProBP performs better without the three restrictions than ProBP in the base case overall ALFs between 77 percent and 88 percent. Finally, as stated earlier, the increased performance can be attributed to the fact that OD control can differentiate between low value Q passengers and high value Q passengers whereas leg-based RM cannot.

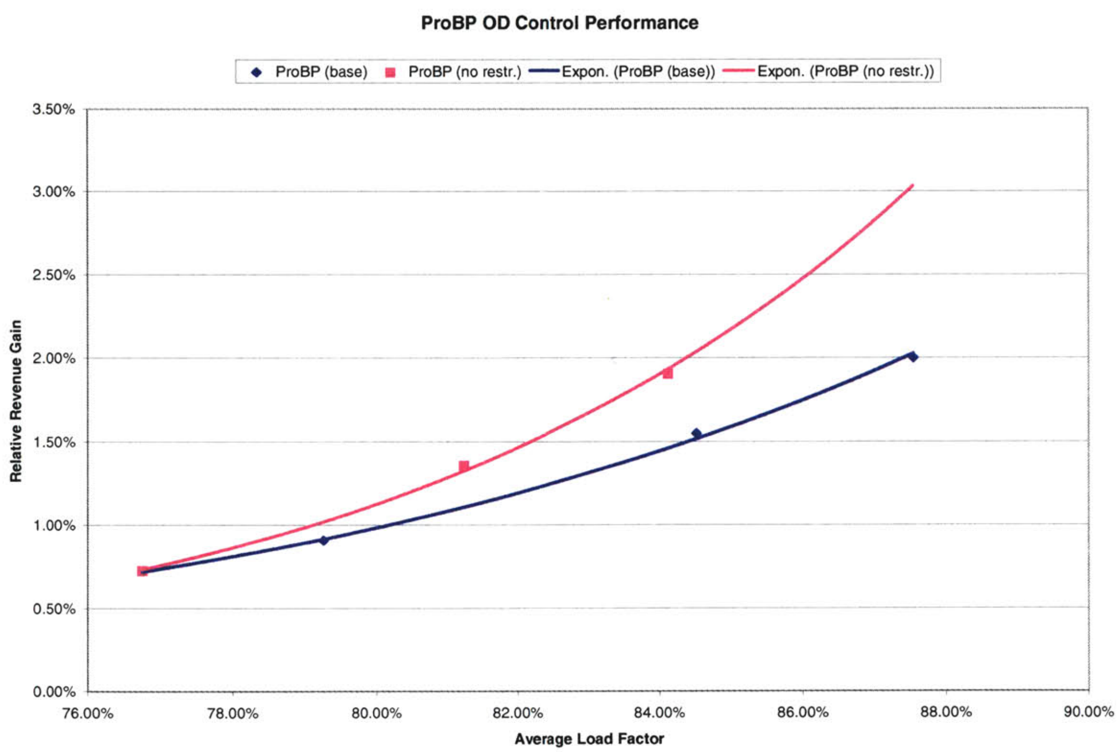

Figure 5-14: Three Restrictions Removed ProBP OD Control Curve

5.3.4 Removal of Three Restrictions: Case Summary

Removal of all three fare class restrictions leads to even further revenue degradation. Airline 1 sees a drop in revenue of about 19 percent while Airline 2 suffers a negative revenue change of 21 percent as compared to the traditional fare structure base case. There is a large shift in traffic from Y class to Q class as now all passengers' first choice is Q. However, without restrictions, the implementation of leg-based RM provides for greater gains, on the order of 3 percent to 17 percent, as compared to the base case and the case where only the Saturday night stay restriction was removed. Furthermore, OD control, after correcting for load factor effects, performs better without the three restrictions than in the traditional fare structure base case. The increased performance is due to the fact that with so many passengers in Q class, it is crucial to be able to differentiate between high and low value passengers within a fare class. OD control can do this, but leg-based control cannot make this distinction.

The end result is that removal of the three restrictions causes a large decrease in revenues. There is a very pertinent function of these restrictions, namely to better differentiate the product and segment demand. Leg-based RM and OD control still provide worthwhile revenue benefits even when all three restrictions have been removed from the fare structure. In this case, the benefits are even greater than the incremental benefits seen in the traditional fare structure base case.

5.4 Reduction and Removal of Advance Purchase Requirements

The final case of this chapter will look at the reduction and removal of advance purchase requirements. For this case the fare class restrictions are reinstated. With the restrictions in place, there is still significant product differentiation and the perceived cost of each fare product for business and leisure travelers reverts to what it was in the base case. However, the removal of AP requirements places the burden of closing fare classes solely on the RM system. This implies that on legs with fewer bookings, passengers booking close to departure may still have the opportunity to book in a lower fare class.

There will be three alternative cases in this experiment. This allows for the gradual reduction of AP requirements until the final case where all AP requirements are removed. The parameters (advance purchase requirements) of the three cases, as well as the base case, appear below in Table 5-3.

	Y	B	M	Q
Base Case	0 days	7 days	14 days	21 days
AP14	0 days	3 days	7 days	14 days
AP7	0 days	1 day	3 days	7 days
AP0	0 days	0 days	0 days	0 days

Table 5-3: AP requirements for the Different Cases in the Experiment

From Figure 2-3, 25 percent of leisure passengers book within 21 days of departure and 65% of business passengers book within 21 days. Thus, removing AP requirements may cause several things to happen. First, some business travelers may sell-down to a lower fare class even though they were willing to buy a Y fare because now the lower fare classes stay open longer unless the RM system closes them. This is a rather minor consequence because with all of the fare class restrictions in place, the average business passenger will place Y as his or her first choice, although this still has the potential to reduce revenues. Second, some leisure passengers that arrive close to departure may also sell-down because they were willing to buy an M or B fare, but Q is still open since the AP requirement has been removed. Again, this is not a major consequence because very few leisure passengers are willing to pay for anything more than a Q fare. Third, late arriving passengers that would not have booked a seat because they were only willing to pay for the Q fare may now be able to book a Q fare if the RM system has not closed Q class on the relevant legs or in the relevant OD market. This final consequence will probably have a bigger impact because 25 percent of leisure passengers potentially fall into this category. The ALF should increase dramatically, but the revenue change is uncertain because carrying more people may increase revenue, but this action may also dilute revenues in that more Q-class passengers are being taken that may quite possibly displace higher value Y or B passengers.

5.4.1 Removal of Advance Purchase: Revenue Change from Alternative Fare Structure

Figure 5-15, shown below, graphically displays the change in revenue when both airlines, using leg-based RM, reduce/remove AP requirements. The revenue change for Airline 1 is a loss of 1 percent for the AP14 case, but nearly 7 percent for the AP0 case (removing AP requirements completely). Airline 2 fares a little better as it loses less than 1 percent in the AP14 case and not more than 2 percent if AP requirements are completely removed.

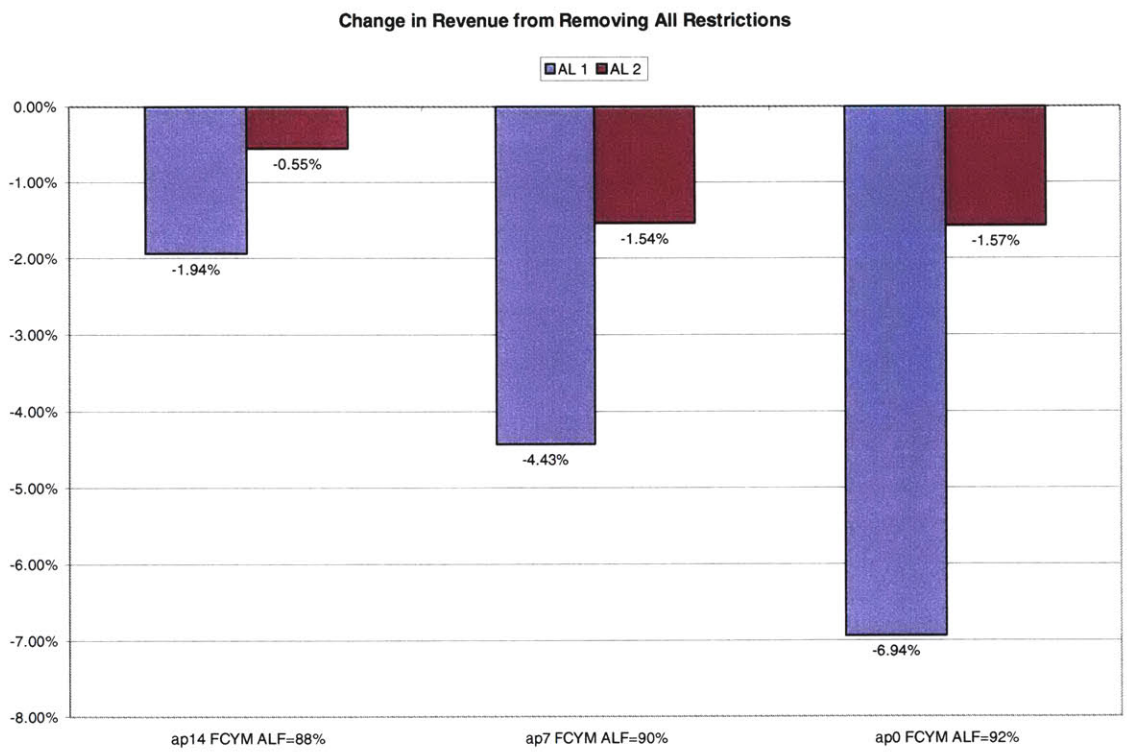

Figure 5-15: Revenue Change from Implementing Alternative Fare Structure

The loss in revenue from reducing AP requirements is significantly less than removing some or all fare class restrictions. This enforces the fact that restrictions are a very powerful tool in segmenting demand. The smaller loses seen in this case have mainly to do with the revenue dilution that occurs because last minute leisure travelers may have the opportunity to book low fare classes that the AP requirement normally closes and also sell-down of last minute business passengers willing to pay for a higher fare class is encouraged. This, in turn, may displace some higher revenue passengers.

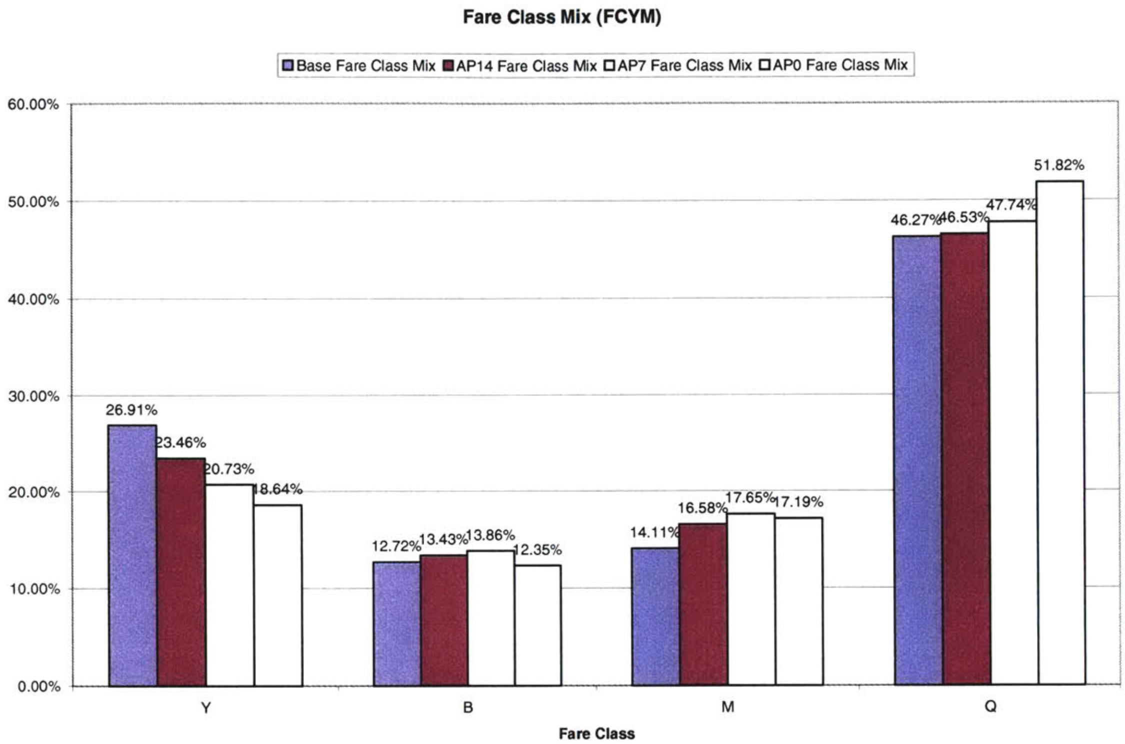

Figure 5-16: Fare Class Mix with reduced AP Requirements Using Leg-Based RM

The revenue change from removing/reducing AP requirements is explained further with the presentation of the evolution of the fare class mix as AP is reduced and eventually removed in Figure 5-16. Starting with the traditional fare structure base case and moving to AP14, AP7, and then AP 0, there is a definite decrease in the proportion of Y passengers from about 27 percent in the base case to 18 percent in the AP0 case. The proportion of B passengers remains almost constant, while the proportion of M passengers increases slightly from 14 percent to 17 percent. Finally, the proportion of Q passengers increases from 46 percent in the base case to nearly 52 percent without any AP requirements. Although this change occurs, note that it is not nearly of the same magnitude as the shift from Y to Q that was shown in Figure 5-9 for the case where all three fare class restrictions were removed. This supports the aforementioned hypothesis that some revenue dilution does occur when AP is reduced/removed, but the revenue change is not nearly as great as when restrictions are removed.

5.4.2 Removal of Advance Purchase: Revenue Gains from Leg-Based RM (FCYM)

The revenue gain from leg-based RM appears below in Figure 5-17. The revenue gain appears rather stable regardless of the degree of reduction in AP requirements. For Airline 1 the benefit of implementing leg-based RM with reduced AP requirements is approximately just under 7 percent to about 7.5 percent. For Airline 2, this gain is on the order of 4 percent to 5 percent. This is slightly less than the gains reported in the other fare structure cases. The reason for this is that the full set of restrictions is still in place. Therefore, significant product differentiation still exists unlike in the former two cases where demand segmentation was compromised with the removal of restrictions. Leg-based RM is more fully exploited without restrictions in place.

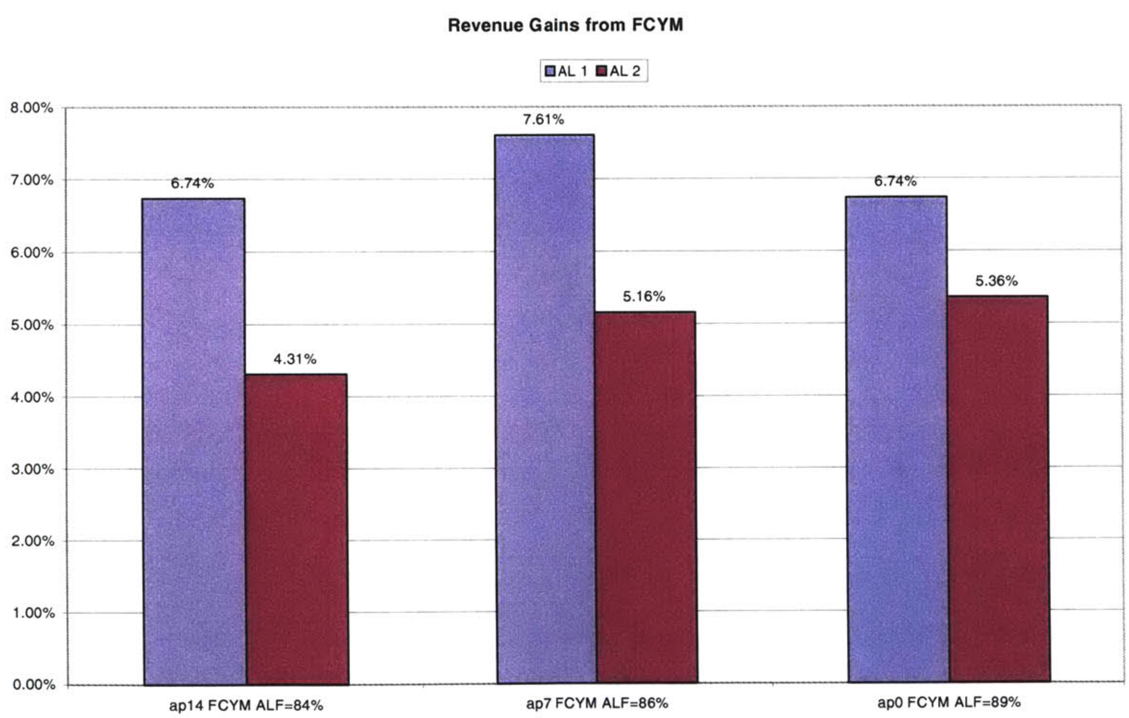

Figure 5-17: Both Airline Move from FCFS to leg-based RM with Reduced AP Requirements

5.4.3 Removal of Advance Purchase: Incremental Benefit of OD Control

There is a significant benefit of OD control when AP requirements are reduced, as shown in Figure 5-18. Even a slight reduction of AP requirements as in the AP14 case leads to over 2 percent revenue gains fro DAVN. However, at AP0, the gains for all three OD methods are in the 3 percent to 4 percent range.

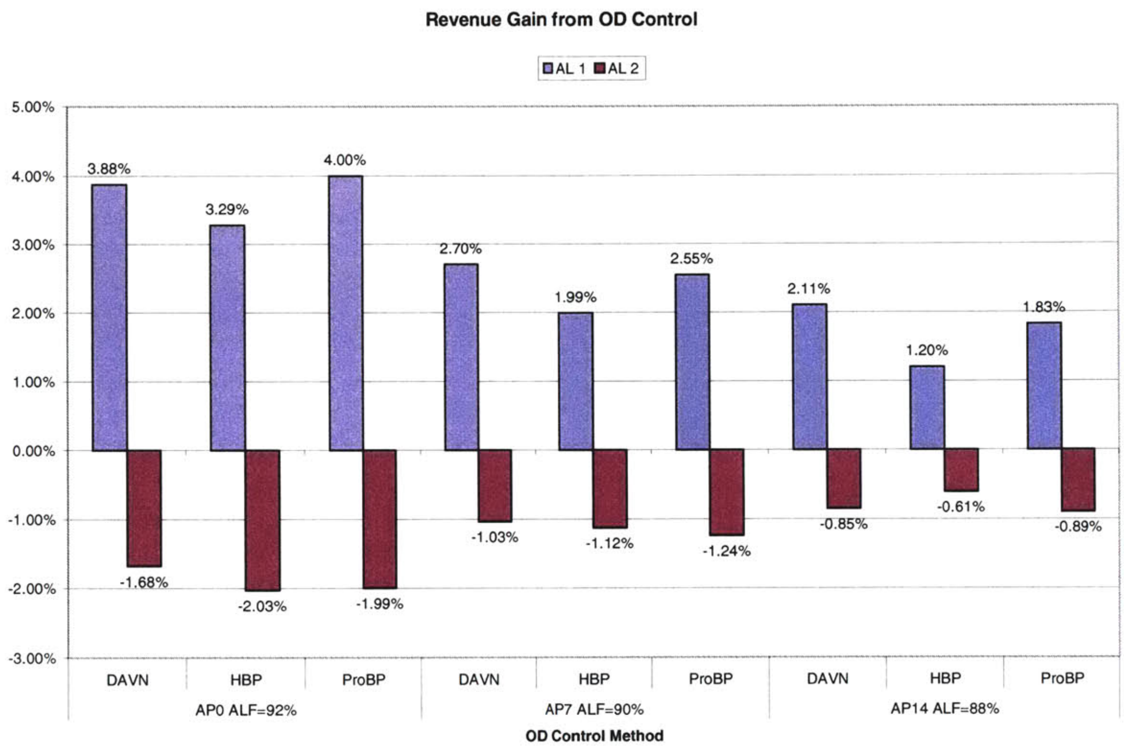

Figure 5-18: OD Control Performance with Reduced AP Requirements

The revenue gains from OD control are quite large in this case. The reason is that the average load factor increases dramatically when AP requirements are reduced. The main hypothesis for this case is that without AP requirements low load factor legs would be able to take on more passengers as Q class does not artificially close shutting out some last-minute leisure travelers. Indeed, this is what occurs as the ALF jumps to 88 percent to 92 percent, which is an extremely high network average load factor. A higher load factor partially accounts for the gains seen in Figure 5-18. OD Control curves with reduced AP requirements, as well as the base case, appear in Figures 5-19, 5-20, and 5-21 for DAVN, HBP, and ProBP, respectively. All AP cases for each OD control method appear in the same figure.

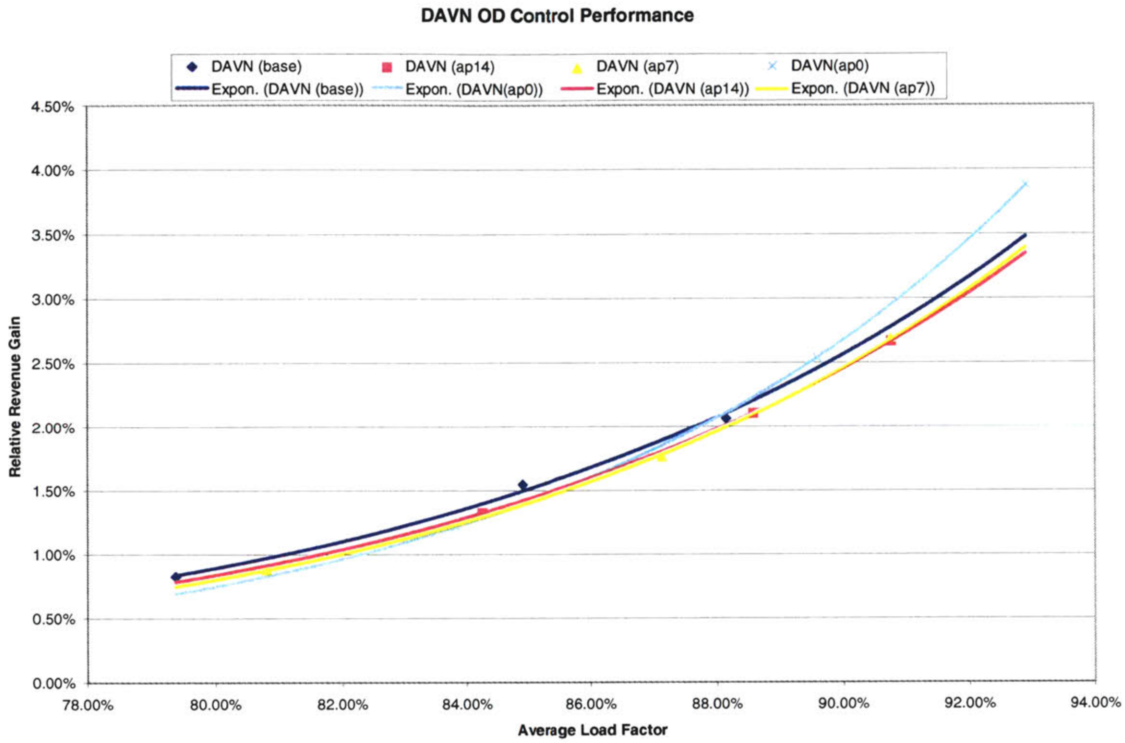

Figure 5-19: Reduced AP DAVN OD Control Curves

Figure 5-19 shows the DAVN OD Control curves when AP requirements are reduced, but all fare class restrictions remain in place. All of the curves are almost on top of each other and, for the most part, they all have the same slope. This suggests that, although the actual incremental benefit of OD control may be as high as 4 percent as shown in Figure 5-18, a good portion of that 4 percent gain is associated with the increase in ALF that occurs when reducing/removing AP. After correcting for this, DAVN with reduced/removed AP requirements performs very similarly to DAVN in the base case.

After correcting for ALF, DAVN with reduced AP performs about the same as DAVN with the traditional fare structure. The AP requirements are put in place to artificially close low fare classes to prevent dilution of last minute passengers. Most late-arriving business passengers are willing to pay a fare from the higher fare classes. The AP requirements protect against the dilution risk of these business passengers. However, business passengers are also very averse to the other fare class restrictions, so not all business passengers will want to book from a low fare class if given the opportunity because of the extra perceived cost of added restrictions that are bundled with low fare class bookings. Essentially, the restrictions keep demand fairly segmented. Furthermore, OD control will close down the fare class if it believes it needs to protect for higher fare class bookings. If it leaves open a low fare class up until very close to departure, then it is doing so because it believes that closing the fare class will result in spoilage. Thus, overall OD control performance should not be affected very much because OD control with reduced AP will only leave open OD markets where the associated legs do not have a high level of demand.

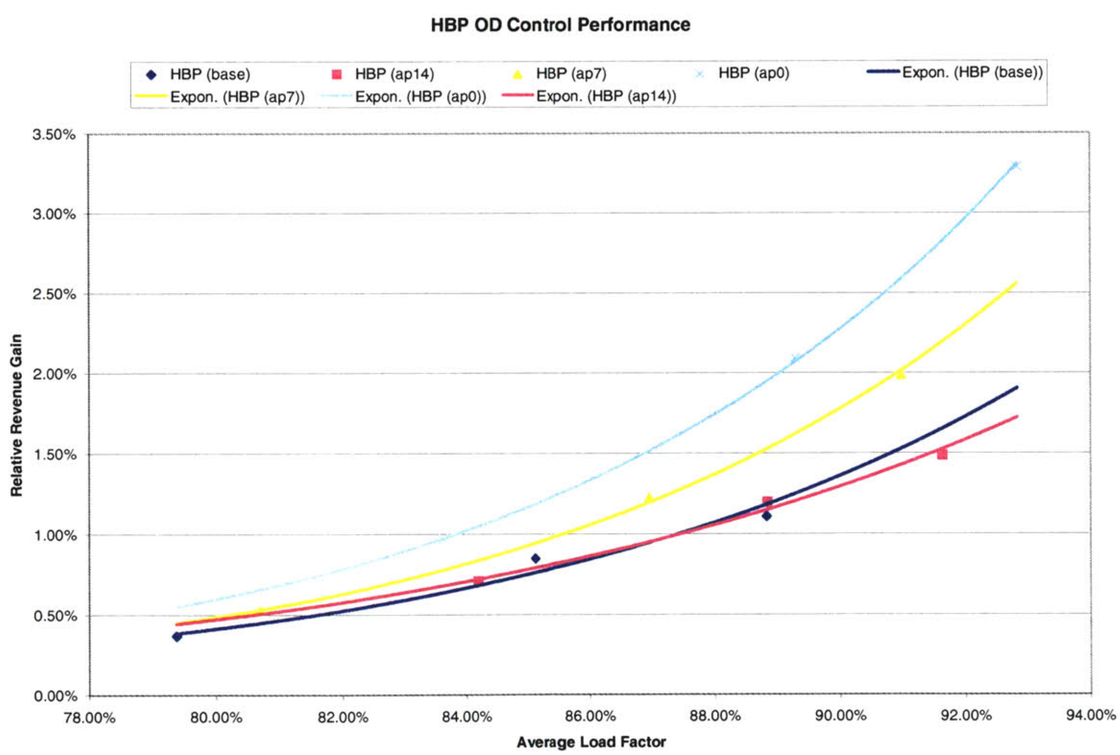

Figure 5-20: Reduced AP HBP OD Control Curves

The HBP OD Control curves for reduced AP requirements are shown above in Figure 5-20. The results for HBP are slightly different than for DAVN. For the AP14 case, the RM curve is essentially the same as in the base case, suggesting that a partial reduction of

AP requirements does not increase nor decrease HBP performance. However, the AP0 curve for HBP is shifted upward in relation to the base case implying that, incrementally, HBP performs better without AP than with AP after correcting for ALF differences. Again, the increased performance has to do with HBP's virtual bucket scheme. With no AP, low load factor legs can remain open until departure. Closure of a bucket only occurs if the bidprice is high enough. These factors allow HBP to control legs more effectively by ensuring that the last-minute leisure travelers that can find low fare classes open are higher value leisure travelers since closure occurs by bucket.

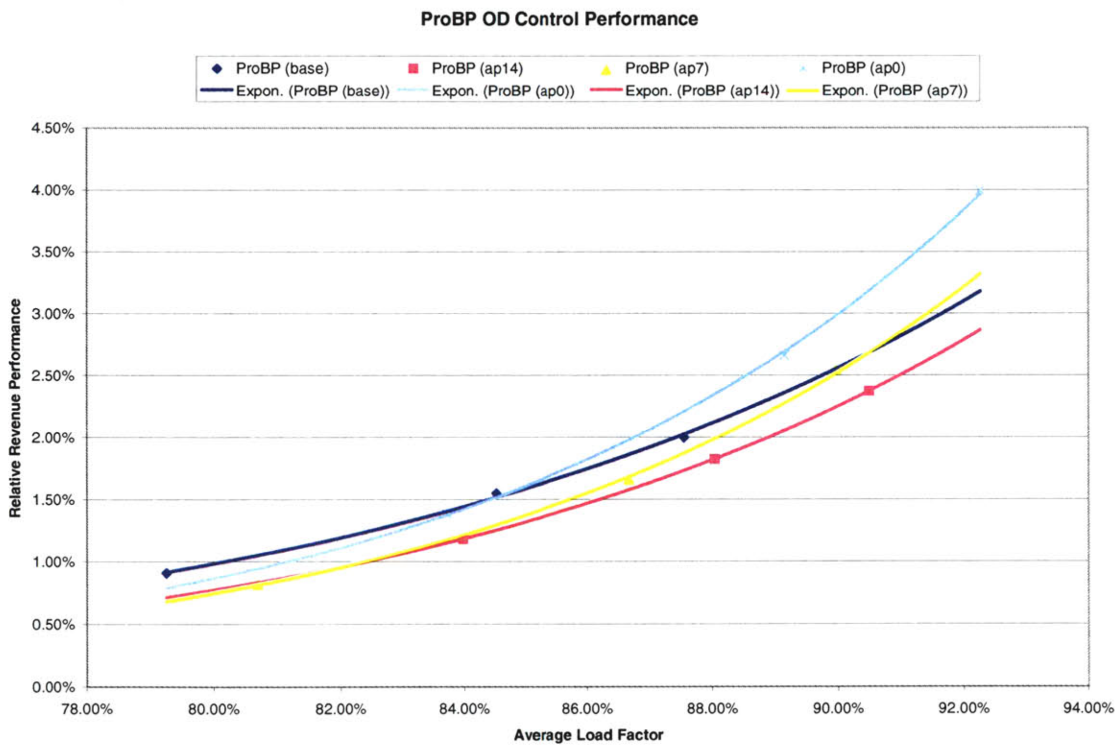

Figure 5-21: Reduced AP ProBP OD Control Curves

Finally, Figure 5-21 gives the ProBP OD Control curves with a reduction in AP requirements. These curves appear very similar to the DAVN OD Control curves for this experiment. The only difference is that they are a bit more spread out. ProBP OD control performance in the AP14 case is slightly less than that of the base case as indicated by the slight downward shift of the curve. However, removing AP requirements completely, case AP0, seems to increase ProBP's OD control performance at higher ALFs. The slope of the ProBP AP0 OD Control curve is slightly greater than in the base case. The bidprice mechanism should be the cause of this. Similar to HBP, the bidprice mechanism in ProBP can allow for more effective control of OD markets because the mechanism ensures that only high value low fare class ODFs remain open.

5.4.4 Removal of Advance Purchase: Case Summary

Reduction or complete removal of AP requirements leads to a revenue reduction of 1 percent to 7 percent. This is significantly less than the other cases in this chapter where restrictions were removed. This fact affirms the hypothesis that restrictions are crucial in differentiating the product and segmenting demand. Leg-based RM still provides approximately a 6 percent to 7 percent revenue gain over FCFS and the incremental benefit of OD control over leg-based RM is on the order of 2 percent to 4 percent. However, most of the incremental gain from OD control has to do with a sharp increase in network ALF. Completely removing AP requirements allows more last-minute passengers to find seats for which they are willing to pay. The end result is an ALF that encroaches and surpasses 90 percent. After normalizing the OD control gain over a range of load factors using curves for each OD method, the pure OD control effect is approximately equivalent to the traditional fare structure base case. Finally, it is very important to note that the removal of AP requirements seems to have less of a negative effect on revenues because the restrictions are still in place to segment demand. Also, in this case implementing leg-based RM and furthermore moving from leg-based RM to OD control yield a decent increase in revenue.

5.5 Summary

Chapter 5 presented additional results using alternative fare structures in the PODS simulation setting. While Chapter 4 looked at changes in fare values, Chapter 5 examined results when fare class restrictions and AP requirements were reduced and/or removed. This chapter used simplified fare structures with fewer restrictions, which fundamentally altered the hierarchy of the fare structure and changed passengers' preferences in the process. The results were presented in three cases; removal of Saturday night stay restriction, removal of all three fare class restrictions, and reduction/removal of AP requirements.

The first case looked at the results of removing the Saturday night stay restriction for both airlines. This had a rather profound effect on revenues as they dropped about 12 percent to 13 percent. There was a large shift in business traffic from Y to B, which caused the drop in revenue. Also, the network ALF remained about the same as that in the base case. However, leg-based RM yielded double-digit percentage revenue gains over FCFS and the incremental benefit of OD control over leg-based RM was still greater than 1 percent. After correcting for load factor differences OD control performance was slightly worse in this case than in the traditional fare structure base case.

The next case presented stripped away all of the fare class restrictions but full AP requirements remained in effect. Overall revenue results were even worse in this case as revenues dropped by 19 percent to 21 percent. The reason for this is that in this case there is no product differentiation. All passengers will have the lowest fare as their first choice. There was a shift in traffic from Y to Q and network average load factor was about 2 percentage points lower without restrictions than in the base case. The fact that there is virtually no product differentiation means that the full capabilities of RM are used to garner revenue gains. Thus, the revenue gains of leg-based RM for both airlines were quite large, greater than the base case and the case above with only one restriction removed. Furthermore, OD control not only provided a 1+ percent incremental benefit, but after correcting for the reduced ALF in this case the conclusion was reached that OD control actually performs better in this case than in the base case. This is due to the fact that leg-based RM cannot differentiate between Q passengers, which make up a majority of the traffic. On the other hand, OD control can differentiate between low-value Q passengers and high-value Q passengers. This fact causes the larger gains given an ALF, namely that we are seeing the full leverage of OD control being used to generate higher revenue.

The final experiment in this chapter reinstated all of the restrictions, but the AP requirements were reduced in increments until they were finally removed. Since the restrictions were reinstated, this case did not have as much of a drastic effect on revenue, which decreased by only 1 percent to 7 percent. There was some revenue dilution because more last-minute leisure passengers could book a low-fare, which displaced some higher fare business travelers, as well as business travelers having the opportunity to sell-down if the lower fare classes remained open. This caused a slight shift from Y to Q. The main effect of this change was that ALF increased dramatically. ALF was 4 percentage points to 8 percent points higher in this case than in the base case. Revenue gains from leg-based RM were approximately 6 percent to 7 percent, which is not as large as in the cases where restrictions had been removed. However, the incremental benefit of OD control was quite high, nearly 4 percent when all AP requirements were removed. This occurred because of the huge increase in network ALF. After correcting for load factor effects, it was found that OD control performed similarly with reduced/removed AP and in the base case. There may have been a slight increase in performance with no AP requirements.

The fundamental result of all three of these cases is that, while revenues do decrease from implementing the alternative fare structure, leg-based RM and OD control both provide meaningful, positive gains in revenue. There is no question that RM still has a major revenue impact even in an environment where very few if any restrictions exist. The next chapter will provide a brief conclusion and synthesis of the findings and provide some details as to some avenues of future research stemming from this thesis.

Chapter 6 Conclusions and Future Directions

6.1 Contribution and Synthesis of Thesis

The main objective of this thesis was to examine alternative fare structures in a simulation setting to report the overall revenue effects and revenue management performance. Historically, research using the Passenger Origin-Destination Simulator (PODS) assumed a fare structure with the traditional restrictions placed on fare classes to differentiate the product. These restrictions are a Saturday night stay, non-refundability and a change fee. The goal of placing these restrictions on specific fares is to force passengers willing to pay a higher fare to do so by making the low fares unattractive to them. Specifically, the restrictions' foremost function is to segment business travelers, usually with a high willingness to pay, from leisure travelers.

Recent changes in the industry, have caused some airlines to modify, and simplify, their fare structures, and provide the motivation for this study. Furthermore, new entrant low cost carriers (LCCs) typically employ an even more simplified fare structure with fewer fare class restrictions and a more compressed set of fare values. This thesis has parametrically examined the effect of airlines removing restrictions from the base case traditional fare structure in PODS to simulate the impacts on revenue and revenue management. The revenue impacts measured included both overall revenue levels and, more important, the performance of revenue management under these alternative fare structures.

The first part of this thesis examined the revenue management methods and provided a brief explanation of the PODS model focusing on the parameters used in this thesis. This was followed by a review of the general economic principles of revenue management and the notions of price differentiation and demand segmentation. Also, at the end of Chapter 3, some real world examples of fare structures in use today by major network airlines as well as LCCs in the United States were given to compare theory with what is done in practice.

The second part of this thesis focused on parametrically examining results of implementing alternative fare structures in a simulation setting to examine the impacts on revenue management. The alternative fare structures were modeled in PODS to evaluate the impacts on both leg-based and origin-destination (OD) control revenue management. Chapter 4 focused on changing fare ratios and values while keeping the traditional set of restrictions. These experiments involved compressing and expanding the fare structure and reducing business fares in all markets by 20 percent. Chapter 5 tested experiments with the base case fare ratios and values but instead removed some or all restrictions and AP requirements. Three experiments were presented in this chapter. First, the Saturday night stay restriction was removed. Then, all restrictions were removed, but advance purchase requirements were still utilized. Finally, the advance purchase requirements were removed, but all three restrictions were reinstated.

The crux of measuring OD control performance with different fare structures was to divide the incremental revenue gains of OD control into two "effects"; a load factor effect and a pure OD control effect. This was done because changing the fare structure while holding demand constant resulted in network average load factor (ALF) changes. These changes in ALF naturally affect the performance of OD control. A higher ALF results in greater RM gains. However, it was the OD control effect that we were interested in measuring. Thus, we simulated each alternative fare structure experiment at several demands, so OD Control curves could be constructed, which would allow for easy interpretation of the pure OD control effect. The curves allowed us to measure OD control revenue gains with different fare structures *given* a specific network ALF.

The PODS simulator was used to evaluate the impacts of alternative fare structures on revenue management performance. The results of the parametric simulation experiments lead to several interesting conclusions.

First, in all experiments, the alternative fare structure reduced revenues. This was expected because the restrictions were in place to segment demand. Removal of these restrictions should be expected to cause dilution. The magnitude of the decrease in revenues varied by experiment. The 20 percent reduction in business fares and the removal of advance purchase experiments had the lowest decrease in revenue while removing restrictions had the greatest negative impact on revenues, as high as a 20 percent revenue reduction when all three restrictions were removed.

Second, leg-based revenue management always generated substantial revenue gains over no revenue management for all alternative fare structures. In many cases, the gain of leg-based RM over first-come-first-serve was greater under an alternative fare structure than in the traditional fare structure base case, especially when restrictions were removed from the fare structure. The reason for this was that without restrictions to segment demand, leg-based RM contributes more to getting passengers to buy from higher fare classes since the restrictions, which normally aid in doing this, are no longer being used. The revenue increase from leg-based RM varied from 2 percent to 17 percent with the restriction removal cases and high demand cases yielding the higher end of the stated range.

Third, there is an incremental benefit of OD control over FCYM in all alternative fare structures. In all cases, DAVN and ProBP incrementally gain 1 percent or more over FCYM and HBP gains at least 0.25 percent. As compared to the traditional fare structure base case, the benefit of OD control is less in most alternative fare structure cases after correcting for load factor. This part of the analysis utilized the OD Control curves described above. However, OD control performs slightly better when all three restrictions are removed after correcting for ALF differences. This is due to that fact that without any restrictions OD control is very powerful compared to FCYM because it becomes more vital to distinguish between high value passengers and low value passengers in the same booking class since a majority of passengers in this case booked in Q class.

Although total airline revenues decreased in all cases, both leg-based RM and OD control garnered gains in revenue. While fare class restrictions and a traditional fare structure sufficiently differentiate a product and yield higher revenues, RM still improves revenues even in the simplest of alternative fare structures. In fact, RM performs better in relative terms in some of these environments because without sufficient product differentiation, as in the case when all three restrictions are removed which yielded the greatest overall revenue decline, RM contributes more by protecting inventory even more aggressively for those passengers willing to pay for it because the restrictions that were removed normally helps by segmenting demand. The bottom line is that both leg-based RM and OD control increase revenues regardless of the fare structure used. RM does not overcome revenue losses due to alternative fare structures, but without RM, the revenue losses would be substantially worse.

6.2 Future Research Directions

The approach used in this thesis was a first step in attempting to better understand alternative fare structures, both in terms of the total revenue effect of implementing such a fare structure and in determining the impacts on leg-based RM performance and network OD control RM performance. There are three main directions in which the research could be extended in the near future, as outlined in the following paragraphs.

First, this thesis assumed that both airlines implemented the alternative fare structure. This was done because under all circumstances an alternative fare structure created a prisoner's dilemma whereby if one airline implemented an alternative fare structure, then it is in the other airline's best interest to follow suit. However, in the short run there may be a situation where only one of two airlines has the alternative fare structure.

Second, it would be interesting to make one airline much smaller in the simulated network and call it a LCC with one of the alternative fare structures. The other airline, which would be a large network carrier would match the LCC's fare structure but only in the markets in which they compete. Market results could be examined as well as the network change in revenue and RM performance.

Third, the purpose of testing the performance of RM methods under alternative fare structures was to see if they would still perform well when some of the underlying assumptions, namely a traditional fare structure, upon which the algorithms were built were removed. Even though the current RM methods still showed solid revenue gains, there may be other algorithms that could be used that do not assume the traditional fare structure. These RM methods might be able to perform better than the current ones in use in an alternative fare structure environment. One possibility includes a new heuristic that would be based on the principles of a simpler fare structure. For example, a heuristic could be used that will close a fare class only when some load factor threshold on a particular leg has been reached. The load factor threshold would be a parameter that could be controlled by leg. A specific example of this would be that Q class would close on a leg when 50 percent of the seats have been booked, M class when 65 percent of the seats have been booked, and B class when 85 percent of the seats have been booked. This heuristic does not rely on restrictions or advance purchase requirements.

In conclusion, this thesis provided a first look at revenue management performance under alternative fare structures. While there are a number of future directions for this research, including the development of new RM algorithms that may perform better under alternative fare structures, the overwhelming conclusion of this thesis is that, although alternative fare structures do cause a reduction in revenues, current leg-based RM and OD control methods still provide revenue gains under alternative fare structures.

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