Revenue Management Impacts of Multiple-Hub Codeshare Alliances

by

James D. Ferea

B.S. Civil Engineering
University of California, Berkeley, 1993

Submitted to the Department of Civil and Environmental Engineering
in Partial Fulfillment of the Requirements for the Degree of

MASTER OF SCIENCE
in Transportation

at the
Massachusetts Institute of Technology
June 1996

© 1996 Massachusetts Institute of Technology
All Rights Reserved

Signature of Author

Department of Civil and Environmental Engineering
May 24, 1996

Certified by

Professor Peter P. Belobaba
Department of Aeronautics and Astronautics
Thesis Advisor

Accepted by

Professor Joseph M. Sussman
Chairman, Departmental Committee on Graduate Studies

JUN 05 1996
ARCHIVES
Revenue Management Impacts of Multiple-Hub Codeshare Alliances

by

James D. Ferea

Submitted to the Department of Civil and Environmental Engineering on May 24, 1996 in Partial Fulfillment of the Requirements for the Degree of Master of Science in Transportation

ABSTRACT

Airlines are currently rapidly expanding their international route networks by forming alliances with other carriers. Through marketing programs such as codesharing, schedule coordination and frequent flyer mileage tie-ins, these "strategic" alliances generate additional traffic flows for the alliance carriers. However, without the coordination of their revenue management systems, these airlines may not be obtaining the full revenue benefits of these alliances. In fact, because the marketing programs generate traffic for the alliance network and the airlines' respective revenue management systems are competitive tools used to maximize each of their own revenues, some carriers may actually be losing revenues to their alliance "partners".

This thesis examines the interactions between revenue management systems of alliance airlines and their impacts on revenues and traffic flows. Previous research studied the impacts of different seat inventory control systems over single hub connecting complexes. In a multiple hub network, spilled traffic may be recaptured onto other paths that transit a different hub if seats are available for the passenger's request on those flight legs. This idea of passenger recapture is incorporated into the MIT optimization/booking simulation to model multiple hub networks. The effects of revenue management over a multiple hub network with varying levels of passenger recapture are explored for an actual transatlantic alliance network using current seat inventory control methodologies.

The interaction of seat inventory control systems is then examined by splitting apart the network into the subnetworks of the carriers in the alliance and applying different control methodologies to each carrier. The resulting revenues and traffic flows of each scenario indicate that significant interaction occurs between the revenue management systems as more advanced revenue management systems spill less desirable traffic to the other carrier, compromising the other carrier's ability to collect its own high revenue traffic. Under some circumstances this leads to a reduction in overall network revenues. This suggests that the selection of revenue management systems of carriers in strategic alliances might have as much an impact as the effect of increased marketing and schedule coordination.

Thesis Supervisor: Dr. Peter P. Belobaba
Title: Associate Professor of Aeronautics and Astronautics
Acknowledgments

There are a great number of people who have made my stay at MIT both rewarding and exciting. I would first like to thank my thesis and academic advisor, Peter Belobaba, without whom none of this would have been possible. Besides being an excellent teacher and counselor, he has given me the tools to succeed. I'm sure that he will miss the rest of us as much as we will miss him. I would also like to thank KLM Royal Dutch Airlines for providing not only the financial support necessary for my studies, but also an interesting and challenging problem to research.

The MIT experience would not have been the same if it had not been for the other two of the “Three Airmigos”. Daniel “AA” Skwarek, our intense “discussions” raised my level of thinking beyond that used for most of my classwork. You have become like a younger brother to me, sometimes pesky but usually welcome. It has been a pleasure to work with James “Human Palace” Nissenberg, whose humorous insights and observations on life often provided a needed and welcome escape from my studies. Don’t worry James, one day San Diego will get the attention that it deserves. Numba Foah! I wish you two the best of luck and am confident that you will succeed in all of your endeavors.

I could not have survived my graduate education without the ceaseless support and motivation from my friends. Thanks to Ed and Monica for their continual encouragement and to Joshua and Joey and the rest of the Berkeley crowd who reminded me that home is only a phone call away. I express my appreciation to Mathieu for being a true friend and to Peter for providing me with the real “Boston” experience. To the folks at CL, thanks for keeping me up to date with the strange and interesting facets of undergraduate life. I express my gratitude to my Uncle Al and Aunt Lenore, who created an East Coast family for me and who sustained with me emotional support.

And a special thanks to my grandmother, who taught me to believe in myself and inspired me to reach for the top.
# Table of Contents

1. **INTRODUCTION** .................................................................................................................. 9
   1.1 **Motivation** ....................................................................................................................... 13
   1.2 **Thesis Objective** ............................................................................................................. 15
   1.3 **Thesis Structure** ............................................................................................................ 17

2. **INTRODUCTION TO REVENUE MANAGEMENT** ............................................................ 19
   2.1 **The Need for Revenue Management** ............................................................................. 19
   2.2 **Leg Based Seat Inventory Control** ................................................................................. 21
   2.3 **Network Approach to Seat Inventory Control** ............................................................... 23
      2.3.1 **Stratified Bucketing** ................................................................................................. 26
      2.3.2 **Virtual Nesting** ......................................................................................................... 29
      2.3.3 **Local Displacement Cost Adjustments** .................................................................... 32

3. **SEAT INVENTORY CONTROL IN A MULTIPLE HUB NETWORK** ............................. 37
   3.1 **Simulating the Booking Process** .................................................................................... 37
   3.2 **Simulation Results of Current Control Methods with Only One Path Choice** ............... 42
      3.2.1 **Fare Class Control** .................................................................................................... 42
      3.2.2 **Virtual Nesting** ......................................................................................................... 43
      3.2.3 **Local Displacement Costs** ....................................................................................... 44
   3.3 **Simulation Results with Additional Available Paths** .................................................... 48
   3.4 **Summary** ........................................................................................................................ 52

4. **SEAT INVENTORY CONTROL IN A MULTIPLE HUB CODESHARE ALLIANCE** ...... 55
   4.1 **Strategic Codeshare Alliances** ....................................................................................... 55
      4.1.1 **Types of Alliances** .................................................................................................... 57
      4.1.2 **Implications for Revenue Management** ................................................................... 58
   4.2 **Simulation Results for Different Seat Inventory Control Combinations** ....................... 58
      4.2.1 **Fare Class Control and Virtual Nesting** ................................................................ 59
      4.2.2 **Virtual Nesting by Both Carriers** ............................................................................ 62
      4.2.3 **Fare Class Control and the Bid Price Approach** ....................................................... 65
      4.2.4 **The Bid Price Approach and Virtual Nesting** ......................................................... 66
      4.2.5 **The Bid Price Approach by Both Carriers** ............................................................... 68
      4.2.6 **Analysis of Carrier Revenues** ................................................................................ 71
   4.3 **Summary of Findings** ..................................................................................................... 72

5. **CONCLUSIONS** .................................................................................................................. 75
   5.1 **Summary** ....................................................................................................................... 75
   5.2 **Areas for Further Research** .......................................................................................... 77
List of Tables

TABLE 2.1 A THEORETICAL FARE CLASS HIERARCHY DEFINED BY RESTRICTIONS ........................................ 22
TABLE 2.2 STRATIFIED BUCKETS DEFINED BY SPECIFIC REVENUE RANGES ........................................ 27
TABLES 3.1 NETWORK SPILL RATES AS FUNCTIONS OF DEMAND AND RECAPTURE RATES .................... 52
TABLE 3.2 PERCENTAGE OF LOCAL TRAFFIC ON NETWORK AS FUNCTION OF DEMAND AND
                  CONTROL METHOD ........................................................................................................ 52
TABLE 4.1 DISTRIBUTION OF NETWORK TRAFFIC BY FARE CLASS WHEN EUROPEAN CARRIER
                  USES FARE CLASS CONTROL AND US CARRIER USES VIRTUAL NESTING. .................................. 62
TABLE 4.2 REVENUE DIFFERENCE WHEN ONE CARRIER USES THE BID PRICE APPROACH AND
                  THE OTHER CARRIER USES EITHER FARE CLASS CONTROL OR VIRTUAL NESTING AS COMPARED
                  TO WHEN BOTH CARRIERS USE FARE CLASS CONTROL ................................................................ 67
TABLE 4.3 REVENUE DIFFERENCE WHEN THE EUROPEAN CARRIER USES THE BID PRICE APPROACH
                  TO VIRTUAL NESTING AND THE US CARRIER MOVES FROM VIRTUAL NESTING TO THE BID PRICE
                  APPROACH AS COMPARED TO WHEN BOTH CARRIERS USE FARE CLASS CONTROL .............................. 69
TABLE 4.4 REVENUE DIFFERENCE OVER FARE CLASS CONTROL FOR THE REVENUE POOLS UNDER DIFFERENT
                  INVENTORY CONTROL COMBINATIONS ..................................................................................... 72
List of Figures

FIGURE 2.1 Introduction of New Fare Class Leads to Increased Revenues .................................................. 19
FIGURE 2.2 Introduction of New Fare Classes Can Lead to Flight Profitability ........................................ 20
FIGURE 2.3 Example of a Point-to-Point Network and a Hub and Spoke Network ..................................... 24
FIGURE 2.4 Nested and Partitioned Fare Class Structures ......................................................................... 26
FIGURE 3.1 Simulation Network Map ...................................................................................................... 38
FIGURE 3.2 Expected Revenue Gains from an ESRb Fare Class Control System over a First Come-First Served System with No Control ............................................................... 42
FIGURE 3.3 Revenue Comparison of Virtual Nesting over ESRb Fare Class Control ................................ 44
FIGURE 3.4 Revenue Comparison of Local Displacement Cost Adjustments to Virtual Nesting over ESRb Fare Class Control .............................................................. 45
FIGURE 3.5 Percent Load Difference Between Local Displacement Cost Adjustments and Virtual Nesting .................................................................................................................. 46
FIGURE 3.6 Revenue Performance for ESRb Fare Class Control with Three Available Paths Compared to One Available Path .................................................................................. 49
FIGURE 3.7 Revenue Performance for Leg Specific Virtual Nesting with Three Available Paths Compared to One Available Path .................................................................................. 50
FIGURE 3.8 Comparison of Different Seat Inventory Control Revenue Results for a Recapture Rate of 70% ...................................................................................................................................... 51
FIGURE 4.1 Revenue Difference When One Carrier Uses Virtual Nesting As Compared to When Both Carriers Use ESRb Fare Class Control ........................................................................ 59
FIGURE 4.2 Revenue Difference When Both Carriers Use Some Form of Virtual Nesting As Compared to When Both Carriers Jointly Use Fare Class Control ........................................... 63
FIGURE 4.3 Revenue Difference When One Carrier Uses the Bid Price Approach to Virtual Nesting As Compared to When Both Carriers Use ESRb Fare Class Control ........................................... 65
FIGURE 4.4 Revenue Difference When Both Carriers Use the Bid Price Approach to Virtual Nesting As Compared to When Both Carriers Use ESRb Fare Class Control ........................................... 70
1. Introduction

1.1 Motivation

In 1938, the Civil Aeronautics Authority (CAA) was created to regulate the budding airline industry. The purpose of airline regulation was to ensure a safe and financially secure airline industry. The CAA and eventually the Civil Aeronautics Board (CAB) determined the routes that airlines could fly and the fares which airlines could charge. By the mid-1970's it was widely accepted that the CAB's regulation of the airline industry was not successful as airlines rarely achieved the financial rates of return required to ensure long term viability. Also, airlines began to compete by offering high quality services such as free alcohol, more frequencies and even piano bars on larger aircraft since they were not able to compete on price. The increased operating costs of providing high service levels were often enough justification for the CAB to raise fares [1].

These fare increases fostered a growing discontent with the CAB. Many people felt that the CAB fostered an inefficient airline industry that was protected from competition. Enacted in 1978, the Airline Deregulation Act would lead to the eventual demise of the CAB, ending federal government control over domestic fares and routes [2]. The new, low cost airlines that began operations in the early 1980's forced the prederegulation carriers to match their low fares. At the same time, the prederegulation carriers discovered that offering low fares could stimulate traffic to fill seats that would have otherwise gone unsold. These new fare classes imposed various restrictions on travel to segment the market and keep passengers that were willing to pay high fares from paying low fares. In order to ensure that not too many discount seats were sold, airlines developed seat inventory control systems, also known as yield management systems, that determined the proper number of seats to set aside for high fare passengers who generally make their requests later than low fare passengers. Additionally, with the ability to determine their own routes, the airlines moved away from traditional point-to-point route networks and began to develop hub and spoke systems. This not only increased the number of markets served by each airline, but it also increased the number of markets
served by each flight leg. This led to an equivalent increase in the number of passenger
types on a particular flight and increased the complexity of managing the booking process.

With the passage of deregulation, a number of low cost carriers entered the
market. Using low wage nonunionized labor, they were able to pass their low costs on to
consumers in the form of lower fares and they quickly invaded many of the country’s
trunk routes. With innovative marketing practices such as frequent flyer programs,
regional code share agreements and the introduction of the previously described yield
management systems, the prederegulation carriers were often able to force these carriers
out of business. In other cases, they simply bought out the low cost carriers. After
surviving the onslaught of low cost competition, the airlines began to consolidate their
route networks and several of the prederegulation carriers merged with one another.
After this period of industry consolidation, airlines placed orders for record numbers of
aircraft and began to grow by building new hubs and expanding service into international
markets. The recession and Gulf War in the early 1990s coupled with the aircraft
deliveries which had been ordered a few years earlier caused the airline industry to lose
more in a few years than the industry had made in profits since it was founded. At one
point, over 30% of the industry’s capacity was operating under Chapter 11 protection.

Now, airlines are more cautious about rapid expansion. Instead of trying to serve
as many markets as possible with their own aircraft, they have realized that it is often more
cost effective to form alliances with other carriers that are better equipped to serve certain
passenger flows. For example, instead of flying to many small destinations in Europe
which could not support nonstop service from the US, some carriers have formed code-
share alliances with European carriers whereby they deliver passengers to the European
carrier at its home base and the European carrier carries the passengers on to their final
destination. The carriers may also cooperate in other areas such as marketing, ground
operations and purchasing. One alliance currently has antitrust immunity that allows the
two airlines to jointly determine fares and capacity in their markets and effectively market
the alliance as one airline.
While these agreements have expanded the networks which carriers are able to market to their passengers and stimulated certain passenger flows, most carriers are not able to quantify the revenue contributions of these agreements [3]. Also, some of these alliances create large multiple hub networks giving passengers the option of completing most of their journey on the carrier of their choice. However, without a jointly controlled yield management system, these carriers are not able to have full control over their passenger flows if some of the flight legs on the routes that they are marketing are controlled by the other airline in the alliance or the other airline in the alliance is able to sell seats from its own inventory at will. Since the optimization heuristics in each yield management system differentiate between different types of passenger flows and traffic is likely to be spilled from one airline to the other because of frequent flyer promotions and other marketing products, it is likely that some airlines are being harmed by these agreements.

1.2 Thesis Objective

The primary purpose of this thesis is to examine how differing revenue management systems affect the revenue performance of multiple hub code share alliances. Marketing ploys such as joint product offerings and frequent flyer mileage reciprocity stimulate demand for the alliance and not for individual carriers. At the same time, the respective revenue management systems of the carriers competitively vie for this traffic. For example with expectations of higher revenue traffic, sophisticated revenue management systems may spill low fare traffic to the other carrier which will eventually deny that carrier's ability to capture its own high fare traffic. This has serious implications on the long term stability of these agreements if carriers end up competing with their partners. On the other hand, airlines may realize that some partners have significantly more to gain by some partnerships and they may decide to jointly maximize revenues and determine a revenue sharing agreement which fairly rewards the carriers according to their inputs. Regardless of which strategy partnering airlines decide to pursue, the resulting changes to traffic flows from the interaction of the revenue management systems deserves attention.
In order to study the revenue management impacts of a large scale, multiple hub airline code share alliance, it is important to have an understanding how current revenue management techniques perform in a multiple hub environment. Virtually all of the previously published research on network revenue management relies on data from traffic flows over a single hub network or single connecting banks. While conclusions from this research may be applied to single hub carriers and provide valuable insight into the revenue performance of multiple hub networks, virtually every major US carrier operates more than one hub and has traffic flows which can traverse any one of those hubs to complete their journey. The traffic flows over different hubs are not independent. In most cases, demand exists for travel between two geographical points at various time intervals throughout the day. Demand does not exist for a specific routing, particularly when more than one routing is available. A passenger spilled from her first request for travel may be recaptured if another routing in her desired time window is offered by the same carrier. To accurately incorporate the effects of route choice, spill and recapture into current simulations would require extensive modeling of passenger choice behavior. This is beyond the scope of this research. Instead, some assumptions regarding this behavior will be made and the sensitivity of these assumptions will be tested.

Previous research has studied different seat inventory control methods and the ease with which they can be implemented. This has involved moving from methodologies which attempt to optimize revenues on each flight leg individually to methodologies which realize that ignoring multiple leg traffic flows may have adverse revenue impacts and should be treated differently than single leg flows. While a network based seat inventory control algorithm might provide optimal revenues, current forecasting techniques are not able to supply these models with accurate and realistic data. Airlines must therefore rely on control methodologies which incorporate network structure into a leg based optimization algorithm. The algorithms which will be explored in this thesis have all been implemented in some form by major domestic carriers.

Once the seat inventory control methods have been examined for multiple hub networks, the multiple hub code share alliance can be examined. This involves splitting a
multiple hub network into two sets of flights and applying different control algorithms to each subnetwork. Testing different combinations of algorithms applied to the subnetworks not only examines the revenue benefits to be gained by integrating the partner's revenue management systems, but the resulting revenue performance and traffic flows of each combination provide valuable information about where the benefits and the burdens of the alliance are produced. This analysis enables the alliance carriers to determine how to jointly maximize their revenues and gives them insight on how to share the revenues created by the alliance.

It is important to note that the purpose of this thesis is not to determine the precise revenue improvements that different seat inventory control mechanisms will generate. Instead the results are used to explain how the different methods used by each airline in such an alliance interact both with the method used by the other airline and with the network and traffic flows of that airline. In this way, a trend can be developed for airlines to gauge how their own particular revenue management system, route structure and traffic flows would interact with those of prospective partners.

1.3 Thesis Structure

The remainder of thesis is divided into four chapters. The next chapter provides an introduction to the inventory seat control problem. The importance of seat inventory control is examined, as are the problems associated with balancing solutions to the problem with the effectiveness that the solutions can be implemented. Current leg based fare class models are examined and explained. The shortcomings of leg based models lead to a discussion on network approaches to the seat inventory control problem. Namely, the ability to control flows on a network level is mixed with the restrictions of setting booking limits on flights at the fare class level. The heuristics which will be discussed are “Stratified Bucketing”, “Virtual Nesting” and “Local Displacement Cost Adjustments”.

Chapter 3 discusses the modeling of seat inventory control in a multiple hub network. The simulator which is used to model the network of flights is introduced, and the method of path choice in a multiple hub network and how it was modeled in this thesis
is discussed. The network is simulated with fare class nesting, virtual nesting and local displacement cost adjustments to virtual nesting for only one path choice to compare the performance of inventory control methods used in this research when simulated using only one available path choice for the modeled network with the results of these methods from previous research. Next, the multiple path choice concept is incorporated into the simulation and its effects on network traffic and revenues are studied.

Multiple hub codeshare alliances will be discussed in Chapter 4. The different types of agreements will be introduced and their relevance to revenue management will be explained. The modeling aspects of the multiple hub codeshare alliance will be touched upon before discussing the simulation of different combinations of seat inventory control between the alliance carriers and drawing conclusions from their results. The findings here not only indicate how revenues and traffic are affected by the revenue management systems of the alliance carriers; they also begin to describe the effects of yield management systems in a competitive environment.

Finally, in Chapter 5 the thesis is concluded by discussing the overall findings and suggesting directions for further research. This research shows that the interactions between revenue management systems of airlines in strategic codeshare alliances are significant and can lead to measurable revenue differences.
2. Introduction to Revenue Management

Like any private business, an airline's main objective is to maximize profits. However, once an airline is committed to flying a fixed schedule approximately 90% of its costs have already been set [4]. The marginal cost of carrying each passenger includes items such as a small amount of incremental fuel, meals, and commission. The problem of maximizing profits is therefore largely a problem of maximizing revenues. Airlines attempt to accomplish this through marketing promotions such as frequent flyer programs, offering many flights in each market to increase market share and by offering discount fares. Airlines also maximize revenues by managing passenger demand through the number of seats available to different fare types. This is known as revenue management.

2.1 The Need for Revenue Management

The excursion fare was introduced to the domestic US market in 1975 [5]. Offering the same seats at different fares, this was the first case of differential pricing by

![Figure 2.1 With this demand curve at a single fare, revenues are maximized when the fare is set at $200. Fifty seats are sold and $10,000 is generated. However, if another fare is offered at $100, then 25 additional seats are booked, increasing revenues to $12,500 or by 25%.](image)
airlines in the US. Differential pricing can be described as charging different segments of the market prices which those markets segments are willing to pay. Imagine a demand curve for a flight as shown in Figure 2.1. When only one fare is charged, maximum revenues are generated at a fare of $200. Fifty seats are booked, however some of these people are willing to pay up to $400 while some people do not fly at all because they do not value the trip by even $200. By introducing a second lower fare of $100 and ensuring that passengers pay the maximum fare which they are willing to pay, the flight carries 25 more people and generates revenues of $12,500, an increase of 25%.

Differential pricing becomes important when one fare cannot produce enough revenue to cover the costs of a flight. This occurs when the average cost curve for the flight lies entirely above the demand curve, as shown in Figure 2.2. At the revenue maximizing fare, 50 passengers demand to fly, however 63 passengers are needed to cover the cost of the flight. The flight will become profitable if new fares are introduced which can generate enough revenue to cover the difference between the flight's costs and the revenues from one fare class. In this case, introducing new fares of $300 and $100 will

![Diagram showing differential pricing](image)

*Figure 2.2 When additional fare classes are added, the flight can become profitable if the revenues from the added fare classes are greater than the difference between the flight's costs and revenues from one fare class.*
increase revenues by $5000 and the flight becomes profitable.

It is extremely important that the airline ensures that passengers are not able to book a request in a lower fare class than the highest one that they would be willing to buy. A passenger from the previous example might be willing to pay the $300 fare but would probably prefer to pay $200 since that increases the passenger's welfare. In order to prevent this "diversion", restrictions are attached to the different fares. Business travelers tend to be time sensitive and price insensitive while leisure passengers tend to be the exact opposite. This means that business passengers are more willing to pay higher fares in order to fly when they need to travel. This is often with very short notice. The less time sensitive leisure passengers will fly whenever there is an affordable fare. The restrictions placed on lower fares often involve advance purchase, purchase of a round trip itinerary instead of a one way itinerary, minimum length of stay or stay over a Saturday night and non-refundability. The restrictions become more strict as the fare decreases.

While most people do not argue that leisure travelers benefit from differential pricing, many people complain that offering many different fares for each flight is price discrimination against passengers who must travel with short notice, especially when the highest fare can be up to six times greater than the lowest fare. Because each fare has a different set of restrictions attached to it, airlines are actually offering a different product for each fare. Transportation between two points is not the only product being sold. The flexibility with which travel can occur is being sold as well. Often, other amenities such as preferred seating, frequent flyer mile bonuses and better positioning on a waiting list are included with the higher fares. As shown previously, differential pricing allows otherwise unprofitable flights to be profitable. This allows more flights to be operated and improves the travel flexibility which is so highly valued by the business traveler.

2.2 Leg Based Seat Inventory Control

Generally, seat inventory control occurs at the flight leg level, since it is at this level that the basic tasks of revenue management can be readily undertaken. These tasks include historical data collection, forecasting, optimization and control. Because
differential pricing resulted in many different fares for each market, airlines developed seat inventory control systems that attempted to maximize the number of passengers in the highest fare classes on each flight. Since higher fares were subject to fewer restrictions, the fare classes were defined by the types of restrictions associated with the different fare levels, as shown in Table 2.1. Managing this fare class structure would lead to higher yields and also to higher revenues for a fixed output. Control takes place at the fare class level. For each flight, forecasts for each fare class are generated according to the airline’s data collection and forecasting processes. Next, seat protections for fare classes are set according to the optimization process employed by the airline. These seat protections are then used to determine booking limits, or the number of seats available to each fare class. Booking requests are accepted as long as there are seats available in the fare class on all requested legs.

The choice of optimization technique is inherent to revenue maximization performance. Optimal seat protections are required to open enough seats for low yield traffic without spilling high yield traffic. For a discussion of recent work in this area, please see Tan [6] and Williamson [7]. The optimization technique employed by many airlines today is the Expected Marginal Seat Revenue (EMSR) method developed by Belobaba [8]. Historical data is used to determine an average revenue value for each fare class. Seats are protected for each fare class from lower fare classes so that the expected revenue from the last passenger in that fare class is equal to the expected revenue from the first passenger in the lower fare class. The expected revenue of each passenger is derived from the forecast distribution of demand for each fare class and the average revenue

<table>
<thead>
<tr>
<th>Fare Class</th>
<th>Fare Product</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y</td>
<td>Full Fare</td>
</tr>
<tr>
<td>B</td>
<td>3 Day AP One-Way Discount</td>
</tr>
<tr>
<td>M</td>
<td>7 Day AP One-Way Discount</td>
</tr>
<tr>
<td>H</td>
<td>14 Day AP Sat. Night Stay Non Refundable</td>
</tr>
<tr>
<td>Q</td>
<td>21 Day AP Sat. Night Stay Non Refundable</td>
</tr>
<tr>
<td>K</td>
<td>“Sale” Fares</td>
</tr>
<tr>
<td>V</td>
<td>Special Promotions</td>
</tr>
</tbody>
</table>

Table 2.1 A theoretical fare class hierarchy defined by restrictions.
values of each fare class. The booking limit for a particular fare class is the difference between the capacity of the aircraft and the sum of the seat protections for the higher fare classes.

While this formulation produced optimal seat allocations between any two fare classes taken into isolation, it ignores the interrelation of fare classes due to their nested architecture. In 1992, Belobaba altered the method to produce joint protection levels for fare classes. In the modified "EMSRb" model, the seat protection for the highest fare class $\pi_1$ is determined such that the expected revenue of the $\pi_1$th passenger is equal to the marginal revenue of the first passenger in the second fare class and the booking limit on the second fare class is the aircraft's capacity minus $\pi_1$. The seat protection level for the first and second highest fare classes $\pi_2$ is determined by combining the demand probability distributions for the first and second fare classes and choosing $\pi_2$ such that the expected marginal revenue from the $\pi_2$th passenger is equal to the expected revenue of the first passenger in the third fare class. The booking limit on the third fare class is the difference between the aircraft's capacity and $\pi_2$. The protection levels and booking limits for all remaining fare classes are set in this fashion by combining the demand distribution probabilities to determine the optimal joint protection of all seats in the higher fare classes. While the EMSRb approach does not produce the optimal booking limits, it's overall revenue performance has been shown to come within 1% of the provably optimal solutions of Curry [9] and Wollmer [10].

2.3 Network Approach to Seat Inventory Control

While the leg based fare class control method provides a means of increasing revenues, it clearly does not approach the maximum achievable level. Mathematically, the leg based approach will always produce inferior results to an integer network program solution, however it is not practical to control inventory on that level at this time. Instead, airlines have adjusted the leg based model to incorporate some of the network effects while maintaining most of the leg based model structure.
With differential pricing, revenue maximization appears to be relatively simple. Demands for each origin to destination traffic flow by fare class (ODF) are forecast and an integer network program is solved to determine the flows which would maximize network revenues. Booking limits would then be set for each flight to protect seats on each flight leg for each of the ODF flows in the optimal solution. Unfortunately, it is not that easy. Problems arise with this formulation because the hub network structure leads to thousands of ODF demands which need to be forecast for even a small network and it is currently not possible to produce accurate forecasts for these flows. Also, demands are not deterministic nor are they independent of fare class, as is assumed with this formulation which leads to a degradation of the solution when applied to the network.

Prior to deregulation, the route structures of most airlines were point-to-point networks. In a point-to-point network, most markets are served with nonstop or one stop service. A passenger would often have to change airlines at an intermediate point with a long connecting time if a direct routing was not available. The ability of airlines to enter routes at will led to the development of hub and spoke systems. Instead of serving each market with direct service, airlines funnel their flights into an intermediate city (the hub).
where quick connections are made before the flights leave for their final destinations. Consider a small airline that wishes to fly from two cities on the west coast to two cities on the east coast (Figure 2.3). The point-to-point network requires four aircraft and serves four markets. The hub network (with a mid-continent hub, for example) only requires two aircraft but it serves eight markets. With half of the aircraft, the hub and spoke network serves twice as many markets as the point-to-point route structure. The hub network is efficient because it allows carriers to market service in hundreds of markets with a limited number of aircraft. Many of these markets are not large enough to sustain nonstop service. In fact, the number of markets served grows exponentially as the number of cities on each side of the hub grows. On any particular flight, passengers are likely to be traveling between a number of origin to destination (OD) city pairs. Similarly, they will also be in different fare classes. For a hub network with 40 cities served on each side of the hub, there are 1680 possible OD itineraries and 11,760 possible OD fares assuming that the airline uses seven fare classes. On any particular flight there are 287 possible ODF combinations. It is doubtful that any realistic forecast could be made for this many demands on a flight which is likely to have less than 200 seats available. The real power of the hub network is its ability to generate incremental connecting traffic flows over the “local” component of all flight legs. Small amounts of connecting traffic from many OD city pairs can lead to a significant increase in overall traffic and revenue. The traffic on each OD flow, however, is usually very small and highly variable. The resulting “small numbers problem” makes it almost impossible to forecast ODF traffic flows with any accuracy.

Even if it were possible to forecast the ODF flows of the network correctly, the resulting solution to the program would still not lead to the revenue maximizing solution. Since demand is variable, it is unlikely that the exact demands in the solution would actually “show up”, resulting in a less than optimal objective. This is because the solution requires a partitioned assignment of booking limits. Partitioned booking limits are protections that are only available to the particular flows which are protected by the booking limits. It would be possible to deny a traffic flow because the booking limits for
that flow had been reached even though lower booking classes still had seats available. This is clearly an inferior solution since it results in revenue loss, denying a definite high fare passenger for a possible low fare passenger. In order to avoid this loss, nested booking limits have been implemented. In a nested environment, seats in a particular booking class are protected for sale from seats in lower booking classes. However, the seats in that booking class are available for sale to higher booking classes (Figure 2.4). If more passengers in a fare class arrive than originally forecast, they can be accommodated at the expense of lower class traffic. Similarly, if fewer passengers arrive for a lower fare class than originally forecast, additional space is available for higher fare class passengers. Nested fare classes reduce the revenue impacts of forecast errors and lead to positive gains over partitioned classes.

2.3.1 Stratified Bucketing

Under fare class control, fares are assigned to each class according to the restrictions attached to that fare. While yields and revenues increase with each fare class for each market, there is usually no correlation between yields and revenue values within the same fare class for different markets. For example, both having the same advance
purchase and length of stay restrictions, a K class LAX-PHX fare may cost $39 while a K class LAX-JFK fare may cost $200. While the LAX-PHX fare represents a higher yield, the LAX-JFK fare represents a higher overall contribution to the network. Since the purpose of revenue management is to maximize revenues, it does not clear that these two fares should be controlled equally. If there is a choice between choosing a passenger from either itinerary, generally the latter should receive more availability. Depending on the nature of demand on some flight legs, it is likely that some fare classes will have higher revenue values than higher fare classes on the affected leg. From the previous example of a fare class structure on a flight leg, if few of the K class passengers are local passengers but many of the higher Q class passengers are local, it is possible that the average Q fare will be lower than the average K fare. The control structure will first determine the booking limits for the higher Q class. Because its average fare is lower than the next class, Q class will not have seats protected for sale from the higher value K class and the booking limits for Q and K class will be the same. This makes the optimization process virtually ineffective, since it does not give more protection to the higher value fare class and it leaves the higher value fare class open to bookings from the lower value fare classes.

With “stratified bucketing”, the booking class separations are not based on the fare product restrictions but rather on distinct value ranges. For example, instead of representing a trip that must be purchased 21 days in advance with a Saturday night stay a Q class booking may represent any one way fare with a revenue range of $249-150 (Table 2.2). This strategy is based on the notion that the overall value to each flight leg is the

<table>
<thead>
<tr>
<th>Fare Bucket Classification</th>
<th>Stratified Bucket Revenue Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y</td>
<td>$700 +</td>
</tr>
<tr>
<td>B</td>
<td>$500 - $699</td>
</tr>
<tr>
<td>M</td>
<td>$350 - $499</td>
</tr>
<tr>
<td>H</td>
<td>$250 - $349</td>
</tr>
<tr>
<td>Q</td>
<td>$150 - $249</td>
</tr>
<tr>
<td>K</td>
<td>$75 - $149</td>
</tr>
<tr>
<td>V</td>
<td>$0 - $74</td>
</tr>
</tbody>
</table>

*Table 2.2 Stratified buckets defined by specific revenue ranges.*
revenue value of the booking request and not its yield. Using this methodology, all passengers with similar total revenue values on a flight leg are given equal seat availability on that leg since they are valued equally by the leg. From an operational standpoint, the average revenue value for each bucket is guaranteed to lie in the same cardinal order as the fare classes themselves, ensuring that the optimization process is not corrupted.

While stratified bucketing can provide substantial revenue gains over leg based fare class control, it does not come without costs. First, all fares must be refiled with the Air Tariff Publishing Company into the new buckets which represent their revenue value instead of the traditional fare class definitions. The highest unrestricted fare in some markets may not fall into the Y range, but airlines may be required to offer a Y fare in all markets. This dilutes the average revenue value of Y class for the optimization and leads to a loss of control as these ODFs cannot be closed out even though more valuable traffic may be forecast. Also, depending on the number of fare classes available and the pricing in markets served by the airline, it will be likely that some markets will have more than one fare assigned to the same bucket. This leads to a loss of differential control for these ODFs since they must now be controlled jointly. If they are not put into the same fare class then the overall benefits of stratified bucketing are reduced since the fare class structure is violated. Similarly, corporate rates and special agreements which guarantee fares into certain classes can also dilute the full stratification of fares.

Even though seat inventory control still occurs at the leg level, stratified bucketing introduces a limited form of network control. Because fares generally increase with distance, seat availability for any ODF is determined only by the fare value, and booking classes are ordered by revenue value, stratified bucketing gives more availability to long haul passengers. This can be seen in Example 2.1, where fares are mapped into stratified buckets for a flight that goes from Boston to Pittsburgh and then on to Los Angeles. While the full fare from Boston to Los Angeles is mapped into the highest bucket, the full fare from Boston to Pittsburgh is only mapped into the third highest bucket and receives less availability than the 3 day advance purchase from Boston to Los Angeles. Also, within each OD market there are at least two fares which are mapped into the same bucket.
and must be controlled jointly. On any flight leg within a given fare type, connecting passengers are likely to have more seats available than local passengers. Load factors are likely to increase over fare class control as multiple leg connecting passengers displace single leg local passengers. Network yields are expected to decrease since fares do not increase linearly with output (i.e., at the same rate as the distance involved). Nevertheless, undertaking a leg based optimization of stratified value buckets with protections for the high revenue buckets will usually produce a significant revenue increase over fare class control.

2.3.2 Virtual Nesting

While stratified bucketing provides gains over fare class control, its amount of control is limited by the number of booking classes employed by the airline in its CRS. With only a limited number of fare classes, it is likely that the revenue ranges of some fare classes may be large and that more than one fare will be mapped to the same value class in some markets. Large revenue ranges also lead to a poor differentiation among traffic

<table>
<thead>
<tr>
<th></th>
<th>Class Definition</th>
<th>Short Haul</th>
<th>Long Haul</th>
<th>Connection</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>BOS-PIT</td>
<td>PIT-LAX</td>
<td>BOS-LAX</td>
</tr>
<tr>
<td>Y</td>
<td>Full Fare</td>
<td>$359</td>
<td>$689</td>
<td>$734</td>
</tr>
<tr>
<td>B</td>
<td>3 Day One-Way Discount</td>
<td>$274</td>
<td>$529</td>
<td>$659</td>
</tr>
<tr>
<td>M</td>
<td>7 Day One-Way Discount</td>
<td>$224</td>
<td>$379</td>
<td>$449</td>
</tr>
<tr>
<td>H</td>
<td>14 Day Sat. Night Non Refund.</td>
<td>$189</td>
<td>$349</td>
<td>$405</td>
</tr>
<tr>
<td>Q</td>
<td>21 Day Sat. Night Non Refund.</td>
<td>$139</td>
<td>$284</td>
<td>$309</td>
</tr>
<tr>
<td>K</td>
<td>&quot;Sale&quot; Fares</td>
<td>$105</td>
<td>$239</td>
<td>$249</td>
</tr>
<tr>
<td>V</td>
<td>Special Promotions</td>
<td>$74</td>
<td>$189</td>
<td>$219</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Class Definition</th>
<th>Short Haul</th>
<th>Long Haul</th>
<th>Connection</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>BOS-PIT</td>
<td>PIT-LAX</td>
<td>BOS-LAX</td>
</tr>
<tr>
<td>Y</td>
<td>$700 +</td>
<td></td>
<td>Full</td>
<td>Full</td>
</tr>
<tr>
<td>B</td>
<td>$500 - $699</td>
<td></td>
<td>3 Day/7 Day</td>
<td>3 Day</td>
</tr>
<tr>
<td>M</td>
<td>$350 - $499</td>
<td>Full</td>
<td>14 Day/21 Day</td>
<td>7 Day/14 Day</td>
</tr>
<tr>
<td>H</td>
<td>$250 - $349</td>
<td>3 Day</td>
<td>Sale/Special</td>
<td>21 Day</td>
</tr>
<tr>
<td>Q</td>
<td>$150 - $249</td>
<td>7 Day/14 Day</td>
<td>Special</td>
<td>Sale/Special</td>
</tr>
<tr>
<td>K</td>
<td>$75 - $149</td>
<td>Sale</td>
<td></td>
<td></td>
</tr>
<tr>
<td>V</td>
<td>$0 - $74</td>
<td>Special</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Example 2.1 Mapping of restriction ordered fares to a revenue stratified hierarchy.
flows, especially when the demands within specific fare classes are grouped together at both the top and bottom of the bucket. For example, the revenue range of B class in Table 2.2 is $699-500. If the traffic flows in B class are evenly divided between two ranges of $425-450 and $550-575 then it would seem logical to protect the higher revenue demands separately from the lower revenue demands.

As an other alternative approach to fare class control, American Airlines developed the concept of virtual classes. Instead of being limited to the number of available booking classes within the computer reservation system, ODFs are mapped into revenue valued buckets, and the forecasting and optimization occurs on these buckets in the same manner as in regular fare class control. This methodology allows the airline to offer as much control as desired by using many smaller revenue range buckets than under stratified bucketing and allows it to be more selective in the passenger flows which it accepts. The bucketing does not take place within the actual booking class structure and it is hidden from the CRS display, allowing the continued use of the fare product booking class definitions for identification of the restrictions attached to the ODF. For example, a Y fare would still represent a full fare itinerary, but may not be mapped into the highest bucket available to a flight. It therefore may not have any availability even though seats are still open on the flight. Stratified bucketing may be thought of as a limited type of virtual nesting because of the revenue value ordering of its buckets.

The virtual nesting technique is illustrated by Example 2.2. Using the same markets and with ten virtual classes, each ODF fare is mapped into a virtual class according to its value. Due to the specific value of the virtual classes, the highest short haul fare receives less availability than the fourth largest connecting fare. Historical demands are recorded by virtual class and it is at this level that forecasts are generated. One of the available leg optimization heuristics such as EMRSr is used to generate seat protections and booking limits for the virtual classes. When an ODF is requested, its virtual class is determined from the revenue value of the ODF and the revenue ranges in the virtual class table. The request is accepted if seats are available on each of the requested flight legs in the proper virtual class.
Because the virtual classes are hidden, they do not need to represent the same revenue ranges for every flight leg. On short haul flights, there are likely to be many ODF demands with a small revenue value if most of the passengers are local to that flight leg only. Similarly, a long haul international flight will not have many low revenue ODF demands since the fares for the local market are likely to be higher than those on the rest of the network. When the virtual classes are defined over the network for these types of flight legs, some classes will have little demand while others will have large amounts of demand and little differentiation will be made between the flows in these classes. It would seem beneficial therefore to set the revenue ranges of the virtual classes independently of each other to reflect the particular ODF demands of each leg. While this would possibly map some ODFs into a different virtual class on each leg, these ODFs will receive seat availability as long each of those virtual classes has not reached its booking limit. Due to its ability to better distinguish passenger flows on impacted flight legs, leg based virtual
nesting has been shown in previous studies to produce a small but significant revenue improvement over network based virtual nesting [6].

2.3.3 Local Displacement Cost Adjustments

Both stratified bucketing and virtual nesting improve revenue performance because they place importance on flows which contribute higher revenues to the network. Namely, if given the choice between carrying a high fare passenger or a low fare passenger on a flight leg then the high fare passenger is always chosen. Because of this, these methods are “greedy” and do not always result in passenger flows that maximize network revenues. Since connecting passengers usually pay a higher fare than local passengers, the greedy methods promote connecting traffic flows at the expense of local flows. This can have negative revenue benefits if a connecting passenger causes a local passenger to be spilled on each leg of his itinerary since it is likely that the sum of the local fares that are spilled is greater than the connecting passenger’s fare. For example a BOS-LAX passenger in M class from the previous example would contribute $449, however a local passenger in the same class on each flight would contribute $603, or 34% more than the connecting passenger. As demand across the network begins to rise, the local revenue loss increases since a higher percentage of local passengers are spilled from the network. To make matters worse, multiple leg ODFs are likely to book before single leg ODFs, resulting in further local spill. For example on the BOS-PIT leg, a BOS-LAX H fare which must be purchased 14 days prior to departure is in a higher virtual class than the local Y fare which has no advance purchase restrictions. These passengers will be spilled if long haul demand is high and virtual class V6, which contains the BOS-PIT Y fare, has little seat availability.

Under the circumstances in which revenue is lost due to local passenger spill it should be clear that the network revenue value of a connecting passenger to each flight leg is not the full fare of the ODF request [11]. Rather, the network value, NV_{ikl}, to each leg of a multiple leg request should be the fare, F_{ik}, discounted by some estimate of local passenger revenue loss, RLOC_{ij}, on the other flight legs of the request.

\[ NV_{ikl} = F_{ik} - RLOC_{ij} \] (2.1)
For a two leg request, RLOC$_j$ can be approximated as the expected marginal revenue of the last passenger, EMR$_i$(A), on the leg multiplied by the probability, P$_j$, that the next passenger on each leg in the request will be a local passenger. This is because revenue displacement only occurs when local passengers are spilled from each of the requested flight legs. The request should be accepted if the discounted fare on each leg of the request is larger than the expected revenue from the last passenger on that leg.

\[
NV_{ikl} \geq EMR_i(A)
\]  

(2.2)

Substituting in for the network revenue value and rearranging terms gives the result that a request should be accepted if its OD fare is greater than the expected revenue of the last passenger on each leg and the expected revenue spilled from the other leg when two local passengers are displaced by this request. This is also known as a "bid price" for the ODF request.

\[
F_{ik} \geq EMR_i(A) + RLOC_j
\]  

(2.3)

\[
F_{ik} \geq EMR_i(A_i) + P_iP_jEMR_j(A_j)
\]  

(2.4)

This leg based bid price heuristic provides a framework by which to evaluate requests for multiple leg itineraries. When flight legs carry low percentages of local traffic, RLOC$_j$ will be small and the bid price is not much higher than the fare required to receive availability on the single flight leg $l$. As local traffic increases, RLOC$_j$ increases and multiple flight leg requests become less desirable and require higher fares to have seat availability.

In practice, local displacement cost adjustments can be applied to fare class control, stratified bucketing or virtual nesting. Under a static updating system, when a multiple leg request is made, the CRS determines the bid price from the relevant EMR$_i$(A) computed at the last revision point in the booking process and the P$_i$ values based on historical traffic loads and demands for each leg. In other cases, a system wide local probability factor is applied. This reduces the need to distinguish between local demand and actual local traffic carried. Once the bid price has been established, it is compared with the fare value of the booking request. If the fare value is greater than the bid price,
the request is accepted subject to the availability of the request's booking/virtual classes on each of the requested flight legs. The request is automatically denied if the fare value does not meet the bid price. As an example, suppose that a passenger from the previous Boston to Los Angeles market requests a Q class itinerary with a fare of $309. At the time of the request, the following conditions apply:

\[ EMR_{BOS\rightarrow PIT}(A) = 175 \quad P_{BOS\rightarrow PIT} = 60\% \]
\[ EMR_{PIT\rightarrow LAX}(A) = 275 \quad P_{PIT\rightarrow LAX} = 50\% \]

The minimum acceptable fare on the BOS-PIT leg would be $258 (175 + 0.6*0.5*275) and it would be $328 (275 + 0.6*0.5*175) on the PIT-LAX leg. Since the Q class fare is not acceptable on the PIT-LAX leg, the request would be denied, however, an H class fare of $405 would be acceptable subject to the booking limits defined by the optimization. Even if Q class seats are still available on the PIT-LAX leg, the expected displacement costs of spilling local revenue make accepting this request unattractive since it is likely that a higher revenue combination of passengers will request space on these flight legs.

Bid price heuristics are the result of continuing adjustments to the control structure to manage network flows while maintaining control at the leg level. While not possessing the full ability to determine the optimal flows over the network, bid price heuristics advance network control by approximating the overall attractiveness of connecting ODFs and rejecting those which have potentially negative revenue impacts. This has resulted in a control structure which determines seat availability according to revenue contribution with an adjustment for the realization that the highest revenue bookings will not always result in maximum revenues.

This chapter has discussed the need for advanced revenue management control methodologies due to the complex nature of network traffic flows. The discussion of fare class control, virtual nesting and local displacement cost adjustments provide the tools to examine revenue management in both a multiple hub network and in a code share alliance. In the next chapters, these techniques will be simulated in a multiple hub network to gain a better understanding of their actual performance in this environment. This provides a
basis for understanding the resulting traffic patterns and revenues when the codesharing airlines' seat inventory control methods interact with each other.
3. Seat Inventory Control In a Multiple Hub Network

Before an examination of multiple hub code share alliances is undertaken, a framework must be developed which allows an effective method of determining how different seat inventory control systems interact with the airline booking process. It must then be verified that the framework produces an effective and realistic representation of the booking process.

3.1 Simulating the Booking Process

This thesis attempts to examine how revenue management systems of cooperating airlines interact with each other and affect revenues and traffic. Simulation provides an effective way to measure these interactions by modeling the booking process using a mathematical representation of it. Since all of the input measures can be controlled, simulation provides the means to fully explore the performance of seat inventory control heuristics by altering the inputs and determining each heuristic’s sensitivity to each input. For example, since traffic flows can be held constant, simulation allows for traffic and revenue changes which are solely due to different optimization techniques to be determined. Similarly, the reactions of the techniques to changes in overall demand allow the methods to be tested under a variety of demand conditions.

The ultimate purpose of simulation is to gauge the revenue benefits that can be achieved by using different revenue management strategies. While it is possible to model its various components such as forecasting, booking limit optimization and passenger generation and assignment, the airline booking process cannot be replicated exactly. For example, while data can be gathered to explain the behavior of passenger demand, assumptions regarding its behavior must be made which can be incorporated into the mathematical framework of the model. Even though the simulation does not perfectly model the booking process, it does provide a platform from which to judge the strategies and to justify their implementation costs.
The actual simulation used in this thesis research is an extension of that used by Williamson in her doctoral dissertation [7]. To gauge the performance of different seat inventory control methods, an optimization and booking routine simulate the airline booking process for a network of flights according to assumed booking control and reservations practices. An actual multiple hub and spoke network for a major transatlantic airline alliance was modeled to gauge the impacts of varying control methods. This network represents the European eastbound flows of the alliance airlines. All of the traffic flows involving the incorporated flights have been included in the simulation, resulting in 46 flight legs which traverse four hub cities (Figure 3.1). Both long-haul international routes and short-haul domestic routes are represented, providing 237 different OD routings using 7 different fare classes. Ten dummy legs are also included to consolidate

![Transatlantic Multiple Hub Network](image)

*Figure 3.1 Simulation network map.*
traffic flows which are not represented by an actual flight leg. In the simulation, the demand factors on the flight legs range from 0.61 to 1.89, however most flights have a demand factor close to or greater than 1.0, creating a heavily loaded network. These flows simulate a peak-demand environment to examine the effects of seat inventory control.

In addition to the previously described network, other inputs needed by this simulation include the aircraft capacities on each of the flight legs, the fare products and routings for each OD market as well as the number of booking periods and the incremental demands between each revision point. The dynamic nature of the booking process is incorporated by using revision points at which the reoptimization is performed to update the booking limits and seat protections. These updates are used to take into account the difference between forecast and actual demand during the previous booking period. The number of revision points is determined by the airline and reflects the airline’s importance on “optimal” seat protections and its ability to forecast incremental fare class demands. This simulation uses 16 revision points, resulting in 16 booking periods prior to each flight. Other concerns of revenue management such as overbooking and passenger sell up are not included in this simulation. While their exclusions lead to a less precise modeling of the entire booking process, the ability to measure the effects of seat inventory control methodology is not altered.

Once all of the input data has been gathered, the simulation runs according to the process described earlier. Based on forecast demands until flight departure, booking limits are generated for each flight using a specific optimization technique. The flight legs of the two airlines may be controlled separately. For example, one carrier might use EMSRb fare class control while the other carrier might use greedy virtual nesting or both carriers might use greedy virtual nesting with separate value classes calculated solely from their own leg demands. Demand is generated for each ODF in a Poisson process using the expected mean and standard deviation of bookings for the incremental booking period. Fare class and market based booking curves ensure that actual passenger booking behavior is replicated. For example, demand for higher classes is not significant until the

39
end of the booking process while demand for leisure classes is higher at the beginning of the booking process. Once generated, each demand is accepted if seats are available for its fare class on all of the requested flight legs and the affected booking limits are decremented. This process repeats until the last booking period before flight departure has been simulated.

Previous work by Belobaba [8,11], Tan [6] and Williamson [7] on seat inventory control systems has focused on their impacts for single-hub networks. While this previous research provides a measure for how the control techniques perform comparatively, it makes unrealistic assumptions about the nature of demand in multiple hub networks. In the actual booking process, a passenger requests travel in a specific OD market in a specific time window. The agent finds the available flight routing and then prices out the routing which maximizes the passenger's utility. Some of the factors which determine the utility are the overall travel time, the departure and arrival times and the availability of nonstop or one stop flights. The booking is made if the passenger is willing to pay this fare. If not, the passenger is “spilled” from the flight segments involved and the agent prices the passenger's next best itinerary. The next itinerary may be on a different carrier if the agent is an independent agent and the passenger does not have preferences for a specific carrier. The process continues until an acceptable itinerary is found or the passenger decides to forgo travel.

The single hub model simulated previously assumes that traffic in a specific OD market is associated only with a particular hub connecting complex. A passenger who is denied her request is spilled out of the network. A multiple hub network, which most airlines in the US operate, usually offers another choice with similar departure and arrival times as the original request for multiple leg itineraries. This option for travel should be considered when a passenger is spilled from the original travel request. However, as stated earlier, the passenger usually does not make a request for travel on a specific routing. This choice is determined from the routings which are still available at the time the request is made and the utility not related to fare that each routing offers.
Modeling specific consumer decision process accurately would require an extensive modeling of passenger choice behavior and goes beyond the scope of this research. Actual traffic flows, however, are a result of this decision process. Passengers have already made their choices according to their preferences and the available travel options at the time of their requests. For this simulation, these flows are then considered to represent each passenger's first path choice. To simulate passenger choice behavior, a probability is incorporated into the simulation booking process that determines the percentage of the time a passenger denied her request will request travel on her next preferred path. This path is chosen from a list of available paths from the passenger's OD which are ranked according to the number of stops en route and the total travel time. If the next request is also denied, then the next best path is chosen from the list, again with a certain probability. This is defined as the recapture probability and represents the likelihood that the airline is able to retain passengers when they are spilled from their travel requests. By allowing passengers the opportunity to use different routings for ODs that have multiple routings in the network, the recapture probability incorporates the multiple hub structure of the network into the simulation.

Realistically, this probability is different for all passengers. A travel agent making a request is likely to look at the next itinerary on the CRS screen regardless of the airline while an agent of the airline would hardly be expected to generate bookings for his competitors. Some travelers may call another airline if they are denied access to nonstop flights while others may be tied to the airline through frequent flyer loyalty. In the simulation, the recapture probability rate is held constant for all passengers in an attempt to equilibrate these effects. For example, if the recapture rate is set at 70% and all of the flight legs on a passenger's list of acceptable flights are full, then there is a 70% likelihood that a passenger will request a second path and a 49% (70% of 70%) likelihood that a third path will be requested. Only three path choices are available in the simulation as the computation time becomes increasingly prohibitive as the number of available path choices are increased. The effects of different recapture rates are examined in the following section.
3.2 Simulation Results of Current Control Methods With Only One Path Choice

For this simulation, the EMSRb optimization heuristic previously described was used with a variety of control structures to model the airline booking process. To gauge the relative reactions of the methods to different levels of demand, each control method was tested for five different demand levels: 80%, 90%, 100%, 110% and 120% of the demand data supplied by the alliance carriers. Also, each control method-demand level combination was tested at one of the three recapture probabilities to determine the sensitivity of this relatively untested input. Before discussing these effects, the control methods will be compared against each other using only one available path choice. This forms a basis for how to compare the control methods under the previously explored single hub network environments and the multiple hub network under examination.

3.2.1 Fare Class Control

The importance of seat inventory control is shown in Figure 3.2 which shows the revenue gains of EMSRb fare class control over no seat inventory control with only one

Figure 3.2 Expected Revenue Gains from an EMSRb fare class control system over a First Come-First Served system with no control. Average leg load factors for EMSRb fare class control are indicated for each demand level.
path available for each booking request. Without seat inventory control passengers are served on a first come-first served (FCFS) basis. A booking request is accepted as long as seats are available on all requested flight legs. Since low fare leisure traffic tends to book before business traffic, high demand flights will sell out with low revenue passengers. Fare class control however will save seats for expected higher fare passengers and spill low fare passengers. As demand increases, the percentage of low revenue passengers accepted under FCFS increases while fare class control rejects these passengers in favor of taking the larger numbers of high fare passengers. This explains why seat inventory control is so important; when demand exceeds supply, seat inventory control provides additional revenues for relatively little cost. With low profit margins in the airline industry, effective seat inventory control often means the difference between profit or loss. Because most airlines use at least some form of fare class control, it will form the base against which other control methods will be measured.

3.2.2 Virtual Nesting

As explained earlier, virtual nesting differentiates passengers according to their revenue contribution to the network, giving priority to those passengers who contribute higher fares to the network. It also results in a more pure optimization of booking limits. Ten virtual classes are utilized for this simulation and they are optimized from both network-wide and leg specific perspectives. The actual class ranges are determined by separating the fare ordered forecast demand into ten equal segments and taking the fare value at each cutoff point. Network-wide virtual bucketing considers the demand across the entire network while the leg specific optimization only considers the demands specific to each flight leg.

Figure 3.3 shows the revenue comparison between virtual nesting and fare class control. By differentiating among passengers by fare value, virtual nesting is able to produce a small but significant increase in network revenues. However, leg virtual nesting in this simulation network only outperforms network virtual nesting at high levels of demand, contrary to results found by Tan[6]. While the results for demand adjustments of 90% and 100% are not statistically different from each other, there is still a clear trend. At
low demand levels, leg specific virtual nesting spills more passengers from the network than network-wide virtual nesting resulting in slightly lower revenues, however the leg specific formulation segregates additional demands better and produces less spill from these demands than the network formulation. Leg specific virtual nesting produces higher revenue gains than network virtual nesting when demand increases and eventually outperforms network-wide virtual nesting, however the overall difference between the two formulations does not vary by more than 0.2%.

3.2.3 Local Displacement Costs

While virtual nesting produces significant revenue gains over EMSRb fare class control, local passenger spill often represents over one half of the total passengers spilled on this network. This implies that local passengers are being spilled in favor of connecting passengers and the acceptance of connecting traffic is resulting in local revenue loss. In order to correct for these effects, the leg specific bid price heuristic described previously for determining minimum acceptable multiple leg fares was employed.

![Bar chart showing revenue comparison of virtual nesting over EMSRb fare class control. The average leg load factor for the simulation is included shown at each point and is relatively the same, regardless of virtual class determination.](image-url)
Because the local displacement cost logic described earlier was developed for single hub network complexes, bid prices have only been defined for two leg itinerary requests. For this thesis, a bid price was developed for more than two legs by extending the previous definition. When three flight leg itineraries are requested, the expected local revenue diversion from each possible outcome is added into the bid price. Local passengers can be spilled from either one of the downline legs or from both of the downline legs. This results in the following formulation for a three leg request.

\[
BP = EMR_i(A_i) + P_iP_{j1}(1-P_{j2})EMR_{j1}(A_{j1}) + P_iP_{j2}(1-P_{j1})EMR_{j2}(A_{j2}) + P_iP_{j1}P_{j2}(EMR_{j1}+EMR_{j2}) \tag{3.1}
\]

and by simplifying

\[
BP = EMR_i(A_i) + P_iP_{j1}EMR_{j1}(A_{j1}) + P_iP_{j2}EMR_{j2}(A_{j2}) \tag{3.2}
\]

![Figure 3.4 Revenue comparison of local displacement cost adjustments to virtual nesting over EMRSb fare class control. Results from both network and leg specific virtual classes are shown. Average leg load factors are shown for each demand factor and do not vary much by virtual class determination.](image)
The bid price heuristic for a three flight leg request reduces to a simple extension of the two leg case. The same extension also occurs for four legs. Previous research by Belobaba [11] showed this formulation to produce revenue gains over virtual nesting in a single hub (two leg) environment. For this network, however, local displacement cost adjustments to virtual nesting reduced overall revenues from virtual nesting. At lower demand levels, this formulation even underperformed EMSRb fare class control, as shown in Figure 3.4. As with virtual nesting, the use of network-wide virtual classes as the basis for the bid price heuristic outperform leg specific virtual classes at lower demand levels, but the leg specific system is better able to segment increasing demands, resulting in higher increases over a network-wide system.

The primary reason for the underperformance of the bid price method is that it results in much greater spill than virtual nesting. If a multiple leg passenger request is denied to leave space for two or three local passengers, then more passengers are carried on the network and the amount of overall spill decreases. While the bid price technique did increase the number of one leg passengers over virtual nesting slightly, the number of
two and three leg passengers carried decreased dramatically, causing the overall spill rate of the bid price method to increase over virtual nesting (Figure 3.5). Most of the spilled traffic came from the lowest fare class on flights inbound to the US hubs.

The increase in overall spill suggests that the bid prices under this formulation are too high. Multiple leg passengers are spilled out of the network and are not replaced by single leg passengers. One problem with this control structure is that the leg forecasting and optimization is done prior to the bid price determination. Booking limits on flight legs are optimized using the entire forecast demand. Some of this demand is eliminated when the bid prices are calculated, however, and will not be allowed to book seats. This means that the protection levels in the fare classes of the denied demands will be too high and will likely block passengers in lower classes. For example, imagine that on a particular flight ten seats are allotted to V2 based on forecast demands. However due to the nature of traffic on the network, five multiple leg passengers will have requests whose fares will not meet the bid price of their requests. On average, these five seats in V2 will remain unsold. Passenger fares in the local market are likely to be placed in lower virtual classes and it is these passengers which the bid price method is supposed to capture. However, these passengers do not receive extra availability and they are likely to remain uncaptured.

It would seem that the solution to this problem would be to calculate the bid price for each forecast demand and then reoptimize the booking limits once all of the demands which do not meet their bid price have been removed. This can only be accomplished if demands are forecast at the ODF level. It is not known how much demand to exclude from each class due to local displacement costs because demands are forecast at the fare class or virtual class level. Instead the problem can be approached in another way. The purpose of a local displacement cost adjustment is to ensure that local passengers are not displaced by connecting passengers. The leg specific bid price heuristic will remove multiple leg connecting flows, but the local passenger flows displaced by the multiple leg flows do not receive additional availability, as explained earlier. In a resimulation of the bid price heuristic, additional availability is given to local ODFs over connecting ODFs in the same virtual classes to compensate for the connecting ODFs which are removed due to
their unsatisfactory revenue contributions. This approach was successful at increasing local traffic and overall loads however revenues decreased as additional availability was given to local traffic flows. A close examination of the data reveals that the traffic increase occurs almost entirely in the lowest fare class implying that this method gives too much availability to low revenue local ODFs which then displace high revenue connecting passengers. This method could be further tested by restricting increased seat availability to higher fare class or virtual class ODFs. Because of time restrictions, this research area is left open for further study.

3.3 Simulation Results with Additional Available Paths

The previous sections discuss how the simulated network performs under previously tested seat inventory control methods. However, the previous sections ignore the multiple hub aspect of the network and does not allow for recapture to other available paths. This was alleviated by incorporating the passenger recapture probability into the simulation as described earlier. The first part of this section will examine how multiple path availability and differing recapture rates affect the revenue performance of the different control structures as compared to the one path availability case. The second part of this section will compare the various control methods against each other in a realistic multiple hub environment.

With the introduction of multiple path choices into a route network, it could be postulated that overall spill on the network would decline. Passengers which are denied their original request for travel are likely to find space available on other routing options and not be spilled completely out of the network. As passengers are spilled to less desired flights, network revenues increase as seats which would have gone unsold are now filled. Revenues would increase even further with an increasing recapture probability since it would be more likely that denied passengers could be reaccommodated. It appears that this reasoning is likely true under EMSRb fare class control. Figure 3.6, which provides the revenue difference of different recapture rates for three available paths against one path (or a zero recapture rate) for fare class control, shows that increasing recapture rates result in higher revenues for any level of demand. For each demand level, network spill
decreased as recapture probability increased, as additional traffic was carried on the network.

This also holds true for the other control methods at low demand levels. However, as demand increases the relative revenue performance for high recapture probabilities begins to deteriorate and eventually the higher recapture rates underperform the lower recapture rates, as illustrated for leg specific virtual nesting in Figure 3.7. As the recapture probability increases, passengers that are denied their original request are likely to find space on other routings. Multiple leg passengers that are recaptured attempt to drive up load factors, however, because virtual nesting already gives preference to long haul traffic, load factors are higher than under EMSRb fare class control and flights reach capacity faster, increasing spill. These multiple leg passengers constitute a higher percentage of the network load and are displacing local passengers, which leads to an increase in local revenue displacement and lower network revenues. This problem is exacerbated by the fact that multiple leg passengers often have many paths to choose from.

![Figure 3.6 Revenue performance for EMSRb fare class control with three available paths compared to one available path.](image-url)
while short haul local passengers have no other path choices once spilled from their original path. While the revenue differences of changing recapture rates are significant, the absolute difference between full recapture and no recapture is never more than one percent for any control method. This implies that the gains from recapturing spilled traffic onto additional paths is largely offset by the spill resulting from this recapture traffic.

The overall revenue performance of the different control methods as compared to EMSKb fare class control is shown in Figure 3.8. These results show the same trends as under the single hub case and the trends apply to all recapture probabilities. The gains from virtual nesting result almost entirely from its selection of higher revenue passengers. Under all scenarios, EMSRb fare class control produces the smallest amount of spill and the highest percentage of local traffic on the network. However, high revenue traffic is not guaranteed seat protection since high yield local traffic is given priority over the lower yield but higher revenue connecting traffic. The revenue differences between these traffic flows can be extremely large on short haul flight legs. For example, on one short haul leg

![Figure 3.7 Revenue performance for leg specific virtual nesting with three available paths compared to one available path.](image)
in the simulation, the highest fare in the local market was $249 while a long haul international ODF in a lower fare class was $429, a 72% difference.

EMSRb fare class control shows a declining spill rate as the recapture rate increases across all levels of demand, while the virtual nesting scenarios exhibit decreasing spill with increasing recapture rates at lower levels of demand and increasing spill with higher recapture rates at higher levels of demand (Tables 3.1). Virtual nesting produces higher load factors than EMSRb since it concentrates on accepting higher revenue connecting traffic and recaptured multiple leg traffic results in local passenger spill. This is verified by the fact that the percentage of local traffic on the network decreases with increasing recapture rates. However, the decrease for virtual nesting and the bid price heuristic is much larger than that for fare class control. Also, as demand increases, the percentage of local traffic on the network decreases for the virtual nesting approaches while it increases for fare class control (Table 3.2). Local or connecting passenger flows are not distinguished under fare class control and a local passenger may block a connecting passenger from booking an itinerary and thus leave open seats on other flights.

![Comparison of different seat inventory control revenue results for a recapture rate of 70%](image)

*Figure 3.8 Comparison of different seat inventory control revenue results for a recapture rate of 70%.*
Because local and connecting passenger flows are not distinguished for these open seats and some of the connecting flows have already been spilled, the probability for taking more local traffic increases.

<table>
<thead>
<tr>
<th>Recapture Rate</th>
<th>Control Method (Demand Adjustment = 80%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>EMSRb</td>
</tr>
<tr>
<td>None</td>
<td>6.76</td>
</tr>
<tr>
<td>50%</td>
<td>6.23</td>
</tr>
<tr>
<td>70%</td>
<td>6.14</td>
</tr>
<tr>
<td>100%</td>
<td>6.02</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Recapture Rate</th>
<th>Control Method (Demand Adjustment = 120%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>EMSRb</td>
</tr>
<tr>
<td>None</td>
<td>25.40</td>
</tr>
<tr>
<td>50%</td>
<td>24.81</td>
</tr>
<tr>
<td>70%</td>
<td>24.78</td>
</tr>
<tr>
<td>100%</td>
<td>24.78</td>
</tr>
</tbody>
</table>

Tables 3.1 Network spill rates as functions of demand and recapture rate.

<table>
<thead>
<tr>
<th>Demand Level</th>
<th>Control Method (Recapture = 70%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>EMSRb</td>
</tr>
<tr>
<td>80%</td>
<td>43.87</td>
</tr>
<tr>
<td>90%</td>
<td>44.42</td>
</tr>
<tr>
<td>100%</td>
<td>44.72</td>
</tr>
<tr>
<td>110%</td>
<td>45.25</td>
</tr>
<tr>
<td>120%</td>
<td>45.86</td>
</tr>
</tbody>
</table>

Table 3.2 Percentage of local traffic on network as a function of demand adjustment and control method.

3.4 Summary

The simulation of seat inventory control heuristics to a multiple path network results in small but significant revenue differences from the single path network simulation. The importance of accurately modeling a network is shown by the fact that spill and recapture to other available paths results in additional revenues at realistic demand levels. The increased revenues at these demand levels also suggest that codeshare alliances generate additional revenues merely from their ability to recapture additional flows onto their combined network.
Now that these methods have been discussed and examined in a multiple hub network, it is possible to focus on their interaction with each other when the network is split apart into two subnetworks that have differing seat inventory control systems. In this way, the revenue performance of strategic codeshare networks under varying combinations of inventory control can be addressed.
4. Seat Inventory Control In a Multiple Hub Codeshare Alliance

As airlines strive to cut costs and improve profitability, they have increasingly formed alliances with other carriers. These alliances involve a wide variety of cooperative and marketing agreements. The cooperative agreements include joint purchasing, performing ground handling at each other's stations, and sharing gate and terminal space. Marketing agreements include listing other carrier's flights in its schedule, allowing frequent flyer mileage to be accrued or redeemed on the other carrier, coordinating schedules and codesharing. Of all of these arrangements, codesharing is estimated to be one of the most successful instruments of generating traffic and increasing revenues for alliance carriers [3]. However, codesharing has not been studied thoroughly from a revenue management perspective. Increases in traffic do not necessarily lead to increases in revenue if a partner's revenue management system is more advanced. This chapter examines the effects of different revenue management systems by codesharing partners on revenues and traffic.

4.1 Strategic Codeshare Alliances

Codesharing is the process by which an airline places its two digit airline designator code onto the flights of other carriers. To designate that the flight is actually operated by a different carrier, the two digit code is followed by an asterisk on the CRS and on the airline ticket. For example, NW* would be a flight marketed by Northwest Airlines but operated by another carrier. Codesharing allows carriers to market the flights of other carriers and to provide a larger variety of OD market combinations to their passengers for less cost than would otherwise be possible if the carriers operated the services on their own. The benefit of codesharing results from the higher position which the codeshared itineraries receive on the CRS display and the increased likelihood that a travel agent will book the carrier's particular itinerary over another carrier's competing itinerary or other interline connections. Often, the codesharing carriers coordinate their schedules and share terminal space to facilitate efficient passenger connections.
While European carriers have historically codeshared flights with one another on less dense markets, the use of codesharing agreements escalated when major US airlines began codesharing with commuter airlines that flew into their major hub cities. This allowed the major airlines to withdraw unprofitable jet service from many sparse markets but still enjoy the feed from these cities to the rest of their network. Often, the commuter carrier painted their aircraft in the same livery as their partner, moved their operations into the major carrier’s terminal, developed its schedules around that of its “big brother” and even began operating under names which reflected the identity of the major carrier instead of their own to give passengers the idea that were indeed flying the same airline for their entire journey. Soon, every major network US carrier codeshared with regional carriers, relying on them for feed at their hubs and other major cities in their networks.

On the international level, codesharing was largely restricted to the single route level until United Airlines and British Airways began a broad arrangement in 1987, linking cities served by United to British Airways flights in Chicago [12]. Similar arrangements were introduced whereby a carrier operates to a foreign gateway and then feeds its passengers to a domestic (of the other country) carrier’s flights using its own codes. For example, American Airlines delivers passengers to London and then British Midland carries them on to Glasgow, Belfast, and Edinburgh under the AA code.

The concept of a “strategic alliance” was first introduced in 1992 when Northwest Airlines and KLM Royal Dutch Airlines were given antitrust immunity to coordinate scheduling and pricing. This allowed the two carriers to integrate their networks and they began codesharing on all transatlantic flights operated by the carriers as well as flights operated beyond their respective gateways of Amsterdam, Boston, Detroit and Minneapolis. Currently, KLM markets flights to 88 points in the United States served by Northwest while Northwest markets flights to over 30 cities throughout Europe, Africa and the Middle East served by KLM. While individually serving these markets would be prohibitively expensive and unprofitable, the two airlines were able to increase their transatlantic market share by carrying traffic in over 1000 markets between a beyond Northwest gateway city to a beyond KLM gateway city [3]. This trend is likely to
continue as American, United and Delta Airlines all have antitrust immunity applications on file at this time for strategic alliances of their own.

4.1.1 Types of Alliances

There are two types of alliances from a revenue management perspective: the blocked space arrangement and the open inventory arrangement. In a blocked space agreement, one airline buys a fixed number of seats from the operating carrier and then sells the seats as their own. This creates two distinct passenger cabins within the aircraft. It is possible that a request for seats on the operating carrier’s flight will be denied because its share of the seats has been sold even though the codesharing carrier still has seats available from its own inventory. In some of these alliances, the codesharing carrier provides its own representatives on board the aircraft to handle their passengers’ needs. Due to their restrictive nature, blocked space arrangements are normally applied only to codeshare alliances which cover a few limited routes and do not involve service beyond the gateway cities of the involved flights. The blocked space agreement will not be modeled since this is normally not the way that flights are operated in a large scale alliance and because the codeshared flights may be controlled individually by each airline.

Under the open inventory arrangement, the codesharing airline is able to book seats on the operating carriers flights as long as space is still available for the particular booking request. If the operating carrier uses a fare class control inventory system, it will accept requests from the codeshare carrier as long as the requests are in fare classes which still have availability. With a virtually nested system, requests will be accepted as long as the revenue paid to the operating carrier falls within an open virtual class. Many agreements involve prescribed prorates, whereby the revenues paid to the operating carrier are predetermined. In other instances, the carriers determine how the revenues will be divided from the resulting traffic and revenues generated by the alliance. In this type of arrangement, each request is treated according to the operating carrier’s control structure for each leg of the request. For example, if a request involves one flight leg on each carrier and one carrier uses fare class control while the other carrier uses virtual nesting, the request would be judged by its fare class type for the first carrier and by its overall
revenue value for the second type. This method of controlling booking requests allows the carriers to treat the traffic of each carrier equally, subject to the limitations of their respective inventory control systems and is the method that will be modeled in this thesis.

4.1.2 Implications for Revenue Management

Integrating their networks and generating additional traffic flows should provide beneficial revenue impacts to both of the alliance carriers. However, if airlines in these alliances do not coordinate their revenue management practices, they may not be obtaining the entire achievable revenue benefit from the generated traffic increase. For any optimization problem, maximizing each subproblem does not necessarily maximize the overall solution. So while each airline may use the revenue management system best suited for its own needs, revenues over the entire network may not be optimized. On the contrary, because revenue management systems are a competitive weapon used to increase revenues at the expense of other carriers and the alliance carriers often offer competitive service with each other in some of the same markets, it is possible that uncoordinated revenue management in a strategic codeshare alliance may actually be harmful to one of the carriers.

4.2 Simulation Results for Different Seat Inventory Control Combinations

Modeling a multiple hub codeshare alliance under which the codeshare carrier can book seats on the operating carrier’s flights subject to the booking limits assigned by the operating carrier involved altering the simulation described previously. Each carrier was given the ability to set the booking limits on its flights independently of the other carrier, using any of the three seat inventory control techniques previously used. When using network based virtual nesting, the revenue ranges of the virtual classes are determined solely from the demands for a carrier’s own network of flights since it would not have information about its partner’s flights. Once each airline sets the booking limits on its flights, booking requests are handled as before with each request needing availability on each flight leg in order to be accepted. The only difference is that one leg may require a high fare class request if controlled by an airline using fare class control while the other leg
may require a high revenue value request if controlled by an airline using virtual nesting. Fares are not prorated between multiple leg requests that involve travel on both carriers, so that each carrier treats a "joint" request as if it receives the whole fare. This is consistent with a situation where the carriers have decided to jointly maximize revenues and will therefore not discount the value of this interline traffic to the revenue received by each carrier only. A recapture rate of 70% is used and assumes that passengers are flexible to some extent with the routing of a particular request, particularly for multiple leg itineraries with similar departure and arrival times at the origin and destination. Passengers preferences for the two carriers due to inflight service differentiation or frequent flyer mile age also raises the recapture rate.

4.2.1 Fare Class Control and Virtual Nesting

This section will examine the impacts when one of the alliance carriers moves from fare class control to virtual nesting. When virtual nesting is introduced by either carrier, revenues increase over joint EMSRb fare class control for most levels of demand (Figure 4.1). In the network modeled in this simulation, the revenue is affected more when the US carrier institutes virtual nesting largely because its flights make up a larger percentage of the network. Only 17 of the 46 flight legs represented on the network and three of the eleven transatlantic flight legs are flown by the European carrier. Traffic carried solely by

![Figure 4.1: Revenue difference when one carrier uses virtual nesting as compared to when both carriers use EMSRb fare class control.](image-url)
the US carrier accounts for approximately 54% of the network's revenues while traffic only on the European carrier accounts for approximately 32% of the network's revenues. The US carrier makes up a larger percentage of the network and it would be expected that changes made by the US carrier would have more of an impact on the overall network performance than changes made by the European carrier. Rather than looking solely at the revenue performance of each combination of inventory control methods, the resulting traffic patterns provide an indication of how these same method combinations would perform under any network structure offered by the carriers.

These scenarios exhibit many of the same changes found when both carriers use virtual nesting from the previous chapter, but to a lesser extent. For example, the average leg load factors increase over joint fare class control largely due to the increase in connecting traffic. This connecting traffic displaces local traffic, causing network spill to rise. The average revenue per passenger rises as higher revenue traffic is given priority and lower fare class passengers constitute a greater percentage of the overall fare class mix as lower fare class but higher revenue long haul traffic is given priority over short haul high fare class traffic.

The percentage of jointly carried traffic increases at the expense of traffic carried solely by each carrier as one carrier places priority on longer haul flows. While joint passenger traffic increases and the traffic of the carrier making the advance to leg specific virtual nesting decreases due to local passenger displacement, the other carrier's traffic decreases only slightly. This decrease comes from traffic displaced by the additional joint flows. Even though the overall traffic carried by the other carrier decreases by less than 1%, the distribution of passenger loads by fare class changes dramatically as passengers which would have only used the carrier which made the change in seat inventory control now use both carriers or only the other carrier. This implies that the booking limits on one carrier's flights, and thus its revenue management decisions, have a significant impact on the other carrier. For example, when the US carrier implements leg specific virtual nesting, the European carrier sees its own revenues fall by approximately 1%. In contrast, when the European carrier implements leg specific virtual nesting, the US carrier sees its
revenues rise by 0.30% even though the European carrier’s own revenues fall by 2%. These changes are offset by the large increases in joint revenues generated by the inventory control method change that can be as high as 30% depending on who implements leg specific virtual nesting and the level of demand on the network.

When leg specific virtual nesting is implemented by one of the carriers, network revenues increase for all levels of demand. As stated earlier, the gains are larger when the US carrier institutes the change because it constitutes a larger percentage of the network. Also, when the European carrier implements the virtual nesting on its own, it saves space for long haul transatlantic flows, some of which originates behind a US gateway. Many of these flows, however, reside in lower fare classes and may not have space on the US carrier’s fare class controlled flights and will be spilled from the network. Because the European carrier’s flights beyond its gateway tends to have lower load factors, this issue is not a factor when the US carrier uses virtual nesting and the European carrier uses fare class control. The percentage revenue increase of leg specific virtual nesting over fare class control rises as the level of demand increases as long as flights do not reach capacity and space is available to carry the higher revenue traffic. As flights reach capacity at higher demand levels, multiple leg passengers begin to displace local passengers from the higher fare classes and the gains from taking higher revenue passengers are somewhat offset by local displacement costs.

When network-wide virtual nesting is implemented by one of the carriers, the revenue gain tends to be greater when the advance is used by the European carrier. In fact, when the US carrier implements network virtual nesting, the resulting revenues show a decrease from joint fare class control at some levels of demand. Network spill increases with virtual nesting, but when the virtual classes are defined over the US carrier’s subnetwork, the virtual class ranges do not do a good job of segmenting passenger flows on each leg and lower revenue traffic is accepted than that which would be accepted with virtual classes defined over the individual flight legs. This is shown by the fact that the overall network loads between leg specific virtual nesting and network virtual nesting by the US carrier are practically equal and yet the leg specific virtual classes result in a
passenger fare class distribution which is weighted more towards the higher fare classes than the passenger fare class mix distribution from network based classes, as shown in Table 4.1.

<table>
<thead>
<tr>
<th>Method</th>
<th>C</th>
<th>Y</th>
<th>B</th>
<th>M</th>
<th>H</th>
<th>Q</th>
<th>V</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leg</td>
<td>11.04%</td>
<td>6.87%</td>
<td>12.85%</td>
<td>21.32%</td>
<td>12.64%</td>
<td>18.99%</td>
<td>16.29%</td>
</tr>
<tr>
<td>Network</td>
<td>10.94%</td>
<td>6.78%</td>
<td>12.81%</td>
<td>21.24%</td>
<td>12.51%</td>
<td>19.48%</td>
<td>16.23%</td>
</tr>
</tbody>
</table>

Table 4.1 Distribution of network traffic by fare class when European carrier uses fare class control and US carrier uses virtual nesting.

When the European carrier implements network-wide virtual nesting on its own, at low demand levels it carries increased transatlantic traffic beyond its gateway at the expense of local traffic. This additional traffic is carried by both carriers on the transatlantic legs. The local revenues displaced on the European carrier’s domestic flights are more than offset by the higher revenues of the European carrier’s beyond flows and the additional traffic carried on the US carrier’s subnetwork. In fact, because the European carrier’s beyond gateway flights have lower load factors at low demand levels, local passenger spill is not a significant factor and setting booking limits according to network wide traffic demands gives segments higher revenue flows better than leg specific virtual classes. This lets the European carrier better differentiate high revenue multiple leg traffic flows to increase revenues. As demand increases, the increase in multiple leg traffic causes an increasing amount of local passengers to be spilled, compromising network revenues.

4.2.2 Virtual Nesting by Both Carriers

When both carriers use some form of virtual nesting, there are five different possible combinations of inventory control: both carriers use leg specific virtual nesting, both carriers use network-wide virtual nesting with virtual classes defined over the entire network, each carrier uses network-wide virtual nesting defined only over its subnetwork, and one carrier uses leg specific virtual nesting while the other carrier uses network-wide virtual nesting with classes defined over its own network. The revenue gains over fare class control for these different scenarios are shown in Figure 4.2.
When the carriers control inventory with either network-wide or leg specific virtual classes, the scenario is the same as the virtual nesting scenarios from the previous chapter. Over the entire network, the increase in multiple leg traffic results in higher load factors and increased spill from that of fare class control used by both airlines. Since booking requests are prioritized by revenue value instead of by fare class type and a lower fare class multiple leg request will have the same revenue value as a higher fare class local request on a particular flight shifts the spill of passengers to the higher fare classes from the lower fare classes for both carriers. This situation is exacerbated because the multiple leg passengers will often book before the local leg passengers. The average revenue collected per passenger rises faster than the amount of spilled traffic, allowing for incremental revenue gains over fare class control. While the US carrier spills more traffic due to local passenger displacement, the European carrier's overall load on the network
actually increases as the number of jointly carried passengers increases faster than the spill of local European traffic, even at high demand levels.

When both carriers use network-wide virtual nesting independently of each other, the overall revenues tend not to be statistically different than when network virtual nesting is used jointly. Independent control spills fewer local passengers than joint control, and it also results in slightly lower overall spill. Traffic shifts to the lower fare classes for the European carrier’s flows as compared to joint network virtual nesting while the US carrier’s flows and jointly carried flows remain somewhat constant with respect to fare class. The traffic shift can be attributed to the changed virtual class values which are more heavily weighted to the US carrier’s demands under joint control.

From the previous section when discussing inventory control changes for only one carrier, revenues are maximized when the European carrier chooses network-wide virtual nesting and when the US carrier chooses leg specific virtual nesting. It is not surprising, therefore, that when the European carrier uses network virtual nesting and the US carrier uses leg virtual nesting, that revenues are maximized for this combination of control methods, at least at lower demand levels. At higher demand levels of 110% and 120%, the difference between this combination of inventory control is not significant from joint leg specific virtual nesting, which produced slightly higher revenues. Across all levels of demand, the European carrier’s traffic flows increase over joint leg specific virtual nesting, but not at the expense of the US carrier. Joint traffic flows decrease slightly. At low demand levels traffic for the European carrier shifts to the higher fare classes while at high demand levels it shifts from the higher classes to the lower classes. Revenues on the European carrier’s subnetwork increase over those on joint leg specific virtual nesting regardless of demand level. Traffic flows by fare class and revenues on the US carrier’s subnetwork remain virtually unchanged suggesting that changes made by the European carrier have little effect on the US carrier.

When the European carrier uses leg specific virtual nesting and the US carrier uses network-wide virtual nesting, revenues are higher than joint fare class control, but this combination does not perform as well as the previous combinations. Traffic flows on the
European carrier remain fairly constant as compared to joint leg specific virtual nesting, but traffic on the US carrier shifts from the higher fare classes to the lower fare classes. At lower demand levels, this combination spills more traffic than joint leg specific virtual nesting, however at higher demand levels both local traffic and jointly carried traffic increase and the traffic loads between the two scenarios become more even. The jointly carried traffic increases at the expense of the US carrier.

4.2.3 Fare Class Control and the Bid Price Approach

When the bid price heuristic applied to virtual nesting is implemented by only one of the alliance carriers and the other carrier uses EMSRb, the deficiency of the bid price approach applied to the entire network in the previous chapter becomes clear (Figure 4.3). When the bid price approach is applied only to the European carrier, network revenues are able to increase slightly over that of fare class control. However, when implemented only by the US carrier, the bid price approach causes an overall decrease in revenues.

There is no difference in traffic or revenues when the European carrier uses the bid price approach as compared to using virtual nesting except at the highest demand rate.
This result holds for both leg specific and network-wide virtual nesting. At a demand level of 120%, the difference of loads by carrier, loads by fare class and percentage of local traffic between virtual nesting and the bid price approach is minimal and there is no statistical difference between the revenue outcomes for these two cases for either leg defined or network defined virtual classes. Because the European carrier operates only one hub, the flows defined over its subnetwork can have at most two flight legs. The bid prices generated for the carrier’s multiple leg flows are therefore the same bid prices which would have been generated using the previous, two leg formulation of the bid price. However, because traffic flows change only under conditions of high demand, the bid price calculation is either too low and too many multiple leg requests are being accepted at the expense of local traffic or that local passenger displacement is not a problem on the European subnetwork. The fact that only three of the flights on the European carrier’s subnetwork approach capacity supports the latter argument.

The bid price approach decreases network revenues by up to one percent from the virtual nesting approach when used by the US carrier for either virtual class structure. The introduction of local displacement costs by the US carrier reduces multiple leg traffic by 5% while local traffic increases by less than 2%, resulting in significant increases in spill over virtual nesting. The majority of the net increased spill occurs in the lowest fare class for the US carrier. The additional local traffic carried offsets spill in the other fare classes. The European carrier’s traffic flows and jointly carried traffic flows remain virtually unchanged. Jointly carried traffic flows do not vary because they are likely to have a high revenue value, receiving high availability, but this revenue value is only discounted against the US carrier’s flight legs. Since the European carrier’s flights tend not to reach capacity, even lower fare class joint carrier requests are accepted. The European carrier’s flows are not affected since the joint flows with which they interact do not vary much.

4.2.4 The Bid Price Approach and Virtual Nesting

When one carrier uses a local displacement cost adjustment and the other carrier moves from fare class control to virtual nesting, there are significant revenue gains on the network as the changing carrier realizes the gains of virtual nesting. These gains can be
seen in Table 4.2, which shows the revenue gains over fare class control for the combinations of the bid price approach and virtual nesting and for the bid price approach and fare class control.

When the US carrier uses the bid price approach to virtual nesting and the European carrier moves from fare class control to virtual nesting, unexpected traffic patterns emerge. Traffic on the network increases. Local traffic on the European carrier’s subnetwork is displaced by connecting traffic only the long haul transatlantic flights, however the local displacement on these legs can be up to 20%. Its domestic flights carry no noticeable difference in local traffic, however the flows on the European carrier’s outbound “dummy” leg, which represents destinations not covered by the simulation and are used to only represent multiple leg flows transiting the carrier’s gateway, increase by up to 10%. Traffic which was previously carried jointly is now carried only by the US carrier, raising the amount of traffic on its network. Concentrating on high revenue value requests, the European carrier spills a greater percentage of its traffic from the higher fare classes due to local traffic spill while the percentage of spill for the US carrier’s flows and jointly carried flows increase in the lower fare classes as the bid price mechanism further

<table>
<thead>
<tr>
<th>Demand Adjustment</th>
<th>Control Method</th>
<th>80%</th>
<th>90%</th>
<th>100%</th>
<th>110%</th>
<th>120%</th>
</tr>
</thead>
<tbody>
<tr>
<td>EU</td>
<td><strong>Leg Bid Price</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>US Fare Class Control</td>
<td>0.04</td>
<td>0.19</td>
<td>0.25</td>
<td>0.23</td>
<td>0.23</td>
<td></td>
</tr>
<tr>
<td>US Network Virtual Nesting</td>
<td>0.31</td>
<td>0.65</td>
<td>0.71</td>
<td>1.10</td>
<td>1.18</td>
<td></td>
</tr>
<tr>
<td>US Leg Virtual Nesting</td>
<td>0.35</td>
<td>0.77</td>
<td>1.13</td>
<td>1.52</td>
<td>1.65</td>
<td></td>
</tr>
<tr>
<td>EU</td>
<td><strong>Network Bid Price</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>US Fare Class Control</td>
<td>0.25</td>
<td>0.31</td>
<td>0.35</td>
<td>0.28</td>
<td>0.18</td>
<td></td>
</tr>
<tr>
<td>US Network Virtual Nesting</td>
<td>0.53</td>
<td>0.79</td>
<td>0.82</td>
<td>1.08</td>
<td>1.07</td>
<td></td>
</tr>
<tr>
<td>US Leg Virtual Nesting</td>
<td>0.58</td>
<td>0.93</td>
<td>1.26</td>
<td>1.53</td>
<td>1.61</td>
<td></td>
</tr>
<tr>
<td>US</td>
<td><strong>Leg Bid Price</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EU Fare Class Control</td>
<td>-0.19</td>
<td>-0.29</td>
<td>-0.18</td>
<td>-0.17</td>
<td>-0.09</td>
<td></td>
</tr>
<tr>
<td>EU Network Virtual Nesting</td>
<td>0.01</td>
<td>0.24</td>
<td>0.42</td>
<td>0.61</td>
<td>0.72</td>
<td></td>
</tr>
<tr>
<td>EU Leg Virtual Nesting</td>
<td>-0.22</td>
<td>-0.06</td>
<td>0.10</td>
<td>0.53</td>
<td>0.77</td>
<td></td>
</tr>
<tr>
<td>US</td>
<td><strong>Network Bid Price</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EU Fare Class Control</td>
<td>-0.42</td>
<td>-0.76</td>
<td>-0.95</td>
<td>-0.83</td>
<td>-0.95</td>
<td></td>
</tr>
<tr>
<td>EU Network Virtual Nesting</td>
<td>-0.18</td>
<td>-0.06</td>
<td>-0.09</td>
<td>0.06</td>
<td>0.07</td>
<td></td>
</tr>
<tr>
<td>EU Leg Virtual Nesting</td>
<td>0.01</td>
<td>0.24</td>
<td>-0.28</td>
<td>0.61</td>
<td>0.72</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.2 Revenue difference when one carrier uses the bid price approach and the other carrier uses either fare class control or virtual nesting as compared to when both carriers use fare class control. Revenues increase whenever a carrier moves from fare class control to virtual nesting.
removes lower value requests. Revenues increase over the network because the European carrier is higher revenue value traffic while the US carrier is carrying more traffic in higher fare classes.

The scenario under which the European carrier uses the bid price approach and the US carrier moves from fare class control to virtual nesting produces expected traffic patterns for virtual nesting. While the European picks up a small amount of additional flows, the US carrier’s traffic declines by up to 8% as multiple leg passengers displace local passengers, which decline by up to 15% over the whole network at high demand levels. Passenger flows which are displaced from the US carrier’s full flights find space on the European carrier’s transatlantic flights and jointly carried flows increase by up to 46%. The fare class mix of the European carrier does not vary much from when the US carrier used fare class control, however, the distribution of US carried traffic and jointly carried traffic shifts to the lower fare classes. The introduction of virtual nesting decreases network revenues for the US carrier. However, revenues increase slightly for the European carrier and they increase by 15-25% for jointly carried traffic, which more than offsets the local revenue loss on the US carrier’s network allowing revenues to rise slightly.

4.2.5 The Bid Price Approach by Both Carriers

As was the case for when the US carrier used virtual nesting, there are no changes to the resulting network traffic patterns and revenues when the US carrier uses the bid price approach and the European carrier moves from virtual nesting to the bid price approach, except at the highest level of demand. Even at this demand level, the traffic and revenue differences are statistically insignificant. As described earlier, the local displacement cost adjustment only has an effect for high levels of demand suggesting that local passenger displacement is not a great issue on the European carrier’s network.

Reiterating the importance of local traffic to the US carrier’s network, there is a significant drop in revenues and traffic when the European carrier uses the bid price approach and the US carrier moves from virtual nesting to the bid price approach. Network traffic declines by up to three percent, however, the entire decline is attributable
<table>
<thead>
<tr>
<th>Control Method</th>
<th>80%</th>
<th>90%</th>
<th>100%</th>
<th>110%</th>
<th>120%</th>
</tr>
</thead>
<tbody>
<tr>
<td>EU Network Bid Price</td>
<td>0.53</td>
<td>0.79</td>
<td>0.82</td>
<td>1.08</td>
<td>1.07</td>
</tr>
<tr>
<td>US Network Virtual Nesting</td>
<td>-0.18</td>
<td>-0.06</td>
<td>-0.09</td>
<td>0.02</td>
<td>0.07</td>
</tr>
<tr>
<td>EU Network Bid Price</td>
<td>0.58</td>
<td>0.93</td>
<td>1.26</td>
<td>1.53</td>
<td>1.61</td>
</tr>
<tr>
<td>US Leg Bid Price</td>
<td>0.01</td>
<td>0.24</td>
<td>0.42</td>
<td>0.61</td>
<td>0.75</td>
</tr>
<tr>
<td>EU Network Virtual Nesting</td>
<td>0.31</td>
<td>0.65</td>
<td>0.71</td>
<td>1.10</td>
<td>1.18</td>
</tr>
<tr>
<td>US Network Bid Price</td>
<td>-0.39</td>
<td>-0.21</td>
<td>-0.28</td>
<td>0.15</td>
<td>0.31</td>
</tr>
<tr>
<td>EU Leg Bid Price</td>
<td>0.35</td>
<td>0.77</td>
<td>1.13</td>
<td>1.52</td>
<td>1.65</td>
</tr>
<tr>
<td>US Leg Bid Price</td>
<td>-0.22</td>
<td>-0.06</td>
<td>0.10</td>
<td>0.53</td>
<td>0.77</td>
</tr>
</tbody>
</table>

Table 4.3: Revenue difference when the European carrier uses the bid price approach to virtual nesting and the US carrier moves from virtual nesting to the bid price approach as compared to when both carriers use fare class control. The US carrier’s introduction of using a local displacement cost adjustment results in a significant decrease of network revenues.

To the US carrier as the European carrier’s flows and jointly carried flows remain almost constant for all demand levels. The distribution of passengers by fare class for the European carrier and for jointly carrier also remains almost unchanged, suggesting that the US carrier’s introduction of the bid price approach does not impact jointly carried flows to a great extent, which in turn do not impact the European carrier’s flows. In further support, the revenues for these two traffic flows are also similar between the two cases. While local traffic increases by up to two percent, multiple leg traffic decreases by up to six percent depending on network demand. This spilled traffic comes primarily from the lowest fare class in the US carrier’s network. With the bid price approach, the average fare per passenger increases by two to three percent. This suggests that the local displacement cost adjustment is successful at screening out low revenue multiple leg passengers, however it denies too many booking requests and too many passengers are lost, causing network revenues to fall. The revenue differences for each scenario are shown in Table 4.3.

Under joint bid price control, the airlines determine the virtual class ranges for demands across the entire network and the local displacement cost adjustment is applied.
to all legs of itineraries that involve flights by both carriers. Joint bid price control using either leg specific or network based virtual classes is the same scenario for bid price control modeled in the previous chapter. When using leg specific virtual classes there is almost no difference in traffic patterns when the carriers move from disparate networks that are both controlled with the bid price approach to a jointly controlled network and the minor revenue differences between these two cases are statistically insignificant (Figure 4.4). Since the virtual classes for each leg have the same revenue ranges for both joint or separate inventory control, the booking limits for each flight are the same. The only difference between these two combinations is that the bid price of joint carrier requests is determined by requests flights operated by both carriers and is higher than under separate control. But because the overall traffic flows remain virtually unaffected by these higher bid prices, we can assume that the bid prices generated by separate network control are not that much greater than the bid prices generated by joint control. This is highly likely, since the demands on most of the European carrier’s flights are less than or slightly over the flight’s capacity, resulting in very low expected marginal revenues for the last passenger.

With network-wide virtual buckets, joint seat inventory control with the bid price

![Figure 4.4 Revenue difference when both carriers use the bid price approach to virtual nesting as compared to when both carriers use ESMRb fare class control.](image-url)
approach produces significant gains over separate bid price control. Joint inventory control by both carriers results in up to one percent additional spill for each carrier. Local traffic declines by up to one percent while connecting traffic increases slightly. While the European carrier accepts more traffic in higher fare classes at the expense of traffic in lower fare classes, its revenues still decline. This decline, however, is more than offset by the revenues generated by the US carrier, which also accepts more traffic in higher fare classes at the expense of lower fare class traffic. Even though the new virtual class ranges created by combining the demand on the two carriers’ networks results in additional spill, the increase in average fare per passenger more than compensates for this loss. As with leg specific virtual classes, a jointly controlled network results in higher bid prices for jointly carried traffic. But the amount of jointly carried traffic does not decrease under joint control, suggesting that the actual bid prices are not rising by much, as a result of the low demand levels on the European carrier’s network.

4.2.6 Analysis of Carrier Revenues

For each of the scenarios studied, there are three different revenue pools which are collected. Revenues are collected by the European carrier and by the US carrier for traffic which is carried solely on their own networks. Revenues are also collected for jointly carried traffic flows and the alliance carriers must decide how these revenues are divided between them. As has been shown previously, traffic carried solely by one carrier is affected by the seat inventory control system used by the other carrier and therefore its revenues are also determined by the other carrier. In effect, the revenue management strategy that maximizes network revenues may result in lower revenues collected by one airline so that the other carrier may increase revenues by a larger amount.

The revenue comparisons to joint fare class control for the three revenue pools are shown in Table 4.4 for some of the seat inventory control strategies. For all combinations of control techniques, the European carrier’s own revenues decline slightly when compared to joint fare class control. The US carrier’s own revenues decline for all control combinations, except for those in which it uses fare class control and the European carrier moves beyond fare class control to virtual nesting or the bid price approach. Revenues for
traffic carried jointly by both carriers increases by 18-40% depending on the level of demand for the scenarios in which the US carrier’s revenues decline. This gain allows network revenues to increase beyond those of joint fare class control for most of the inventory control combinations. In these inventory control combinations, there is a negative spill of joint traffic. In other words, more traffic is carried jointly by the two airlines, than originally demanded. This implies that jointly carried traffic is largely traffic that originally demanded to travel on only one airline and has been recaptured by using both airlines. This factor alone points out one of the major benefits of strategic codesharing alliances.

<table>
<thead>
<tr>
<th>KLM Method</th>
<th>NW Method</th>
<th>% Revenue Improvement Over Fare Class Control</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Overall</td>
<td>KLM</td>
</tr>
<tr>
<td>VL</td>
<td>1.13%</td>
<td>-1.06%</td>
</tr>
<tr>
<td>VN</td>
<td>0.92%</td>
<td>-0.89%</td>
</tr>
<tr>
<td>BPL</td>
<td>0.10%</td>
<td>-0.91%</td>
</tr>
<tr>
<td>EMSRb</td>
<td>0.58%</td>
<td>-0.95%</td>
</tr>
<tr>
<td>VL</td>
<td>0.25%</td>
<td>-1.98%</td>
</tr>
<tr>
<td>VN</td>
<td>1.26%</td>
<td>-0.56%</td>
</tr>
</tbody>
</table>

Table 4.4 Revenue difference over fare class control for the revenue pools under different inventory control combinations.

4.3 Summary of Findings

The purpose of this research has not been to determine the optimal seat inventory control strategies that will maximize revenues for a strategic codeshare alliance. Instead, the focus has been to study how the interaction of the revenue management systems with the traffic flows over the network affects passenger selection and the resulting revenues. In this chapter, the interaction of different combinations of seat inventory control systems by each carrier was studied by simulating a representative strategic codeshare alliance network.

Through the discussion of the various inventory control combinations, it has been shown that the revenue management systems of the alliance carriers can interact with each other, affecting revenues and traffic. The carrier whose seat inventory control system is more selective in the passengers that it accepts will spill passengers to the other carrier.
These recaptured passengers, while providing revenues to the alliance which would have otherwise been lost, disrupt the passenger flows of the other carrier and may possibly lead to the spill of higher revenue traffic than that which was recaptured.

Also, the inventory combination which maximized revenues was not an integrated combination of any method. Instead the methods which individually maximized revenues for each carrier when the other carrier used fare class control, network wide virtual nesting for the European carrier and leg specific virtual nesting for the US carrier, consistently outperformed the other combinations of inventory control for realistic demand levels. This combination of control structures allows each carrier to take advantage of its own network characteristics. Namely, the European carrier operates a network with less demand on its feeder flights and thus benefits from a structure which differentiates passengers on a network wide level and segments demands between long haul fares while the US carrier operates a network with very high demands on its feeder flights and differentiates its passengers into local and long haul segments.

Finally, as each carrier chooses seat inventory control methods that become more discriminatory in the passengers that they accept, these carriers may see their own revenues decline. However, the decline in own carrier revenues is usually offset by gains in revenues of jointly carried traffic as these passengers are recaptured onto jointly carried paths. Depending on the combination of methods chosen by the alliance carriers, the increase in jointly carried revenues can be viewed as either an increase in revenues to be shared by the carriers according to some predetermined formula or more specifically, a combination of revenues lost by each carrier with the implementation of more advanced control techniques and incremental revenues generated by the actual existence of the alliance.
5. Conclusions

5.1 Summary

This thesis has focused on the revenue management impacts of multiple hub strategic codeshare alliances. Because the marketing impacts of these codeshare alliances generate traffic for the alliance carriers and seat inventory control systems are competitive weapons designed to maximize revenues for an individual carrier, it is possible that some airlines are experiencing negative revenue benefits from codesharing alliances. By examining a multiple hub codeshare alliance, the interactions of the airlines’ revenue management systems can be studied to determine patterns that may be expected to apply to other carrier’s with similar route networks and traffic flows. The network of an actual multiple hub codeshare alliance was modeled to simulate the expected impacts on traffic and revenues resulting from differing revenue management strategies consisting of fare class nesting control, virtual nesting and a heuristic bid price approach to virtual nesting.

Previous research has focused primarily on single hub networks and thus it was only necessary to model one path choice available to any particular OD request. However, in a multiple hub network, there is often more than one path available to an OD request with similar departure and arrival times. This alternative path choice availability was incorporated into the simulation by introducing a recapture rate, or probability that a passenger denied their ODF request will ask for travel on their next preferred path. The recapture rate removed the need to extensively model consumer path choice behavior. It was shown that higher recapture rates resulted in incremental revenue gains at realistic load factors, however for virtual nesting approaches at very high demand levels, higher recapture rates displace too many local passengers and simulated revenues are lower than that under lower recapture rates. This shows the importance of modeling the network correctly, since the revenue comparisons among the various control combinations can change at different recapture rates.

Modeling a multiple hub network also introduced passenger itineraries that consist of three and four flight legs for traffic that must traverse two hubs. While this did not
change the modeling aspects for fare class control and virtual nesting since seat availability is not determined by the number of paths in an itinerary for these methods, the bid price approach heuristic was extended to three and four leg itineraries. Based on the same logic as that for two path itineraries, the bid price heuristic when applied to this network increased multiple leg spill without a corresponding increase in local traffic. Network revenues declined from virtual nesting under this approach because the heuristically approximated bid prices are too high, resulting in the rejection of excessive multiple leg demands.

Examining the differing combinations of seat inventory control methods revealed that there are significant interactions between the airlines’ revenue management systems. A carrier’s decision not to accept certain traffic flows could have adverse impacts on the other carrier and on the overall alliance if these flows were recaptured by the other carrier and interfered with that carrier’s ability to carry higher revenue traffic. There were even a couple of scenarios when these impacts resulted in an overall deterioration of network revenues from the base case of fare class control, even though more advanced control techniques had been implemented. In fact, this is a result of the competitive nature of the revenue management systems. The more advanced system spills undesirable traffic from its own network and this traffic is likely to be recaptured by the other carrier if the other carrier’s revenue management system is not advanced. This traffic, however, is likely undesirable to the network as a whole and thus the strength of one carrier’s system can turn into a hindrance if the other carrier’s system cannot defend its part of the alliance network. For this reason, the a coordinated revenue management strategy is necessary to ensure that revenues are maximized, or at least safeguarded. This does not mean that both carriers should jointly optimize their networks with any particular revenue management strategy. As shown in the previous chapter, those scenarios did not lead to optimal revenues. Instead each carrier should likely choose the strategy that takes advantage of its own network characteristics. Choosing the optimal revenue management strategy not only results in the acceptance of the optimal traffic flows that originally request travel on a carrier’s network but also prevents undesirable recapture of traffic from the other case.
5.2 Areas for Further Research

While this thesis makes important conclusions regarding how revenue management systems interact with each other in a codeshare alliance, it also raises some interesting questions that deserve further attention. Modeling multiple hub networks introduces the idea of path selection over a list of available path routings. Assigning passenger flows to these routings by modeling passenger choice behavior with respect to factors such as total travel time, departure and arrival time, and number of stops en route will provide a more realistic representation of the passenger booking process. Similarly, the process by which the recapture rate is chosen should be further examined. Questions to be answered include the effects of a recapture that varies with the passenger type, or booking class, of the request or other factors such as whether the passenger is a frequent flyer member of the airline, the request is for a nonstop flight or connecting itinerary or the request is made early or late in the booking process.

The local displacement cost adjustment definition of a bid price for three flight leg itineraries should also be examined further. The heuristic bid prices used in this thesis produced bid prices which were too high and rejected too many multiple leg requests. Without applying this bid price heuristic to other networks that have three flight leg itineraries, it is not known whether the bid price formulation used in this thesis is flawed or the network characteristics are such that it causes the bid price approach to fail. Also, the booking limit optimization process when using a bid price approach should be reconsidered to take into consideration that the demand profile changes after the booking limits are set because certain multiple leg requests are denied due to their revenue value and not due to the seat availability of the request.

In the simulation, each carrier treated jointly carried passenger flows as if they received the entire revenue from those flows for seat availability consideration. This clearly increases the priority of these flows, since it gives them a higher revenue value than the airline actually receives for them. The obvious benefit of this is that these flows are
high revenue flows for the network and should therefore be protected, particularly when one carrier may deny a prorated request because it expects to get more revenue than the prorated fare but the other carrier cannot replace the lost request and so the overall network revenue is less than if the fare had not been prorated. However, as in virtual nesting, when demand levels on the network are high, protecting these higher revenue flows may not always result in maximum revenues, particularly if it results in increased spill. These losses must be compared against each other to determine an optimal way of determining seat availability for joint airline requests.

It would be of further interest to explore alliance networks with other characteristics than the one modeled for this simulation. The network in this simulation involves a US carrier with a multiple hub domestic network that operates at high load factors and a European carrier with a single hub domestic network that operates at lower load factors. There are other alliance networks possible which may cause the interactions to react differently. For example, one current airline alliance involves a US domestic carrier with a multiple hub domestic network that traditionally operates at low load factors and a European carrier that operates a single hub network with very high load factors. Another alliance involves a combination of European carriers that together operate four European hubs and a European carrier that operates hub complexes in both the US and Europe, creating a network with countless path choices. It is unlikely that the seat inventory control systems would have interacted in the same manner for these networks as for the network used in this simulation.

The previous suggestions would help to better approximate the revenue gains and traffic patterns of differing revenue management strategies in a multiple hub codeshare alliance. Because each alliance will have different network characteristics that shape the performance of the methods to their individual airlines and to the overall network, the selection of revenue management systems by airlines in a strategic alliance might have as much an impact as the effect of increased marketing and schedule coordination. And as carriers begin to align themselves with many other carriers to form route networks that
span the globe, the issue of revenue management system coordination will only become more important.
Bibliography


