Matching of Lowest Fare Seat Availability in Airline Revenue Management Systems

By

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ABSTRACT

By enabling passengers to compare easily and book directly from airline inventories, Internet-based ticket distribution has forced airlines to compete for the lowest price level and more importantly, to ensure seat availability at that price. To retain market share, many airlines track and match the lowest fare of their competitors – both the price level and the associated seat availability through the use of revenue management seat inventory controls.

This thesis uses simulation to examine the impacts of an airline matching its competitor's lowest fare seat availability. In a single symmetric market, simulations demonstrate that the airline using a more sophisticated revenue management system generally obtains lower revenues the more it matches the seat availability of its competitor's lowest fares – losing as much as 9.2%. At the same time, the matched airline benefits consistently in terms of improved revenues.

These findings extend to a much larger mixed-fare simulation network with four airlines: when a legacy airline matches the lowest fare seat availability of a "low-cost carrier" (LCC), the legacy airline loses at least 3.4% and as much as 8.5% in revenue. At the same time, the LCC and the other two peripheral competitors gain as much as 5.3% in revenue. The legacy airline's revenue management system recovers from the damage done to a degree that depends on the sophistication of the revenue management methods it uses. In the absence of seat availability matching, the network revenue management system using hybrid forecasting and DAVN for inventory control outperforms the leg-based system using standard forecasting and EMSRb for inventory control by 3.0% in revenues. Moreover, using the network system, the matching airline loses 3.4% to 5.8% in revenue from seat availability matching, significantly less than the 6.2% to 7.0% of revenue it loses using the leg-based system. Unlike leg-based inventory control, network inventory control isolates the revenue loss to the LCC markets, where hybrid forecasting performs better than standard forecasting.

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I am grateful to Singapore Airlines for the financial support through the past four years at Penn and MIT. In addition, I would like to show my appreciation to my colleagues and superiors who mentored me during my summer internships and to the Human Resources department for their understanding and administrative support. I hope I have proved to be a worthwhile investment and look forward to working at SIA.

My thesis would not have been possible without the Passenger Origin-Destination (PODS) Consortium. I would like to thank Craig Hopperstad for programming the simulator. I appreciate the sponsoring airlines for their data and feedback and in particular, Thomas Fiig from SAS for his ideas on lowest fare seat availability matching.

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I am truly thankful for the support from my dad and my two wonderful sisters. I am lucky to have my mother whom I seek to emulate in her entrepreneurial and generous ways and my grandmother who has given me unconditional love and the love of good food.

Thank you Jen, for your love, support and accepting me for who I am. This thesis is dedicated to you.

Author's Biography

The author comes from Singapore. He originally aspired to be a geneticist through his years at Dunman High School and Victoria Junior College. Instead, he decided that traveling abroad will allow him to learn more and make greater contributions. Under the generous sponsorship of Singapore Airlines, he started at the University of Pennsylvania in 2003 intending to major in Biological Basis of Behavior. In 2006, he graduated *summa cum laude* with an Economics degree. In between, he participated actively as a Benjamin Franklin Scholar at Penn, studied abroad at the London School of Economics and the Katholieke Universiteit Leuven, took Professor Robert Rescorla's amazing course on learning, wrote a research paper on the decolonization of Sri Lanka under Professor Lynn Hollen Lees and topped Professor Jeremy Siegel's introductory course in Finance. He learned many valuable lessons as an intern at Singapore Airlines at the departments of Singapore Sales, Product Innovation and Network Revenue Management. He also cultivated an interest in Game Theory and Industrial Organization from courses taught by Professor Steven Matthews, Dr. Philipp Schmidt-Dengler and Professor Patrick Van Cayseele.

In September of 2006, he entered the Massachusetts Institute of Technology as a candidate for the Master of Science in Transportation. He learned from many inspiring teachers, including Dr. Peter Belobaba, Professor Amedeo Odoni, Professor Cynthia Barnhart, Professor Nigel Wilson and Professor Joseph Sussman. MIT was a wonderful place for his curious mind and he attended many incredible events like Media Lab's Human 2.0 Symposium, architecture talks by Rem Koolhaas, Olafur Eliasson, Nicholas Negroponte and Zaha Hadid, the MIT Communications Forum and the Sigma Xi speech by Associate Professor Amy Finkelstein.

He researched under MIT's Passenger Origin-Destination Simulator (PODS) Consortium led by Dr. Peter Belobaba, and presented findings in Houston (January 2007) and Minneapolis (May 2007). The fruitful year at MIT will conclude at the PODS meeting in Frankfurt in September 2007, a few days before he officially embarks on his career at Singapore Airlines.

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5 SIMULATION INPUTS AND ANALYSIS OF RESULTS (NETWORK 'S')

List of Abbreviations

AP	Advance Purchase
AT	Adaptive (Accordion) Threshold
DAVN	Displacement Adjusted Virtual Nesting
DFW	Dallas-Fort Worth International Airport
DWM	Decision Window Model
EMSR	Expected Marginal Seat Revenue
emult	Elasticity Multiplier
FA	Fare Adjustment
FCYM	Fare Class Yield Management
Frat5	Fare Ratio at which 50% of the passengers sell-up
FT	Fixed Threshold
GDS	Global Distribution System
HF	Hybrid Forecasting
KI	Karl Isler (Discrete) Fare Adjustment
LCC	Low Cost Carrier
Loco	Lowest Competitor Class Open
LP	Linear Programming
MCI	Kansas City International Airport
MR	Marginal Revenue (Continuous) Fare Adjustment
MSP	Minneapolis-St Paul International Airport
O-D	Origin-Destination
OR	Operations Research
ORD	Chicago O'Hare International Airport
PE	Price Elasticity
PODS	Passenger Origin-Destination Simulator
pp	Percentage point
QF	Q-forecasting
RM	Revenue Management
SF	Standard Forecasting
WTP	Willingness-to-pay

CHAPTER 1
INTRODUCTION

By the time Farecast launched as an airfare prediction website in June 2006, it was already renamed from Hamlet. The question it answers for consumers seeking the lowest fare available remains – "to buy or not to buy?"[1] For the past forty years, airline Revenue Management (RM) has been shaping, and shaped by, consumer behavior. Airlines maximize revenues through revenue management processes: segmenting their limited and perishable inventories of seats as fare products using restrictions and prices and then, depending on the demand forecasted, allocating seats to customers who arrive at different times and have dissimilar willingness-to-pay (WTP). Revenue management was the major airline success story after deregulation enabled pricing variations in 1978 – American Airlines reported in 1992 a "quantifiable benefit at $1.4 billion" over three years.[2]

The tide began turning against traditional revenue management methods when the steady climb of the Low Cost Carriers (LCCs) like JetBlue and AirTran ensued. These upstarts led in depressing airfares and abolishing ticket restrictions. In addition, LCCs pushed the Internet to prominence as a distribution channel and thereby slashed search costs for consumers – the costs of comparing prices of competing products. As passengers were exposed to unprecedented cheap choices and price transparency, their sensitivity to prices heightened. Their interest in paying for products eroded – business-travel managers started refusing the exceedingly high walk-up fares.[3] Farecast, a business model built on analyzing, predicting and insuring the cheapest fares for passengers, is a culmination of the trend of consumers demanding the lowest fare available. In 2007, Scott Nason, Vice-President – Revenue Management at American Airlines, regards "pricing transparency" and "understanding of consumer behavior [online]" as two primary factors that will determine the future of revenue management.[4]

The popularity of websites like Farecast and web-based fare availability "screen scraping" tools like FareChase and Cliqbook force airlines to compete solely on price. In fact, some airlines began using these powerful software tools themselves to find the lowest competitor fare. Prompted in part by the fear of losing market share and in part by the desire to deprive rivals of revenues, some airlines participate in ad-hoc fare class availability matching, overriding their revenue management systems. Such matching

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[1] University of Washington. (April 1, 2003). Airfare analyzer could save big bucks by advising when to buy tickets. *University of Washington Press Release.* Retrieved April 25, 2007, from the World Wide Web: http://www.washington.edu/newsroom/news/2003archive/04-03archive/k040103.html
[2] Smith, B.C., J.F. Leimkuhler, R.M. Darrow. (1992). Yield Management at American Airlines. *Interfaces*, 22(1), 8-31.
[3] The Economist. (April 20, 2002). Saturday Night Fever – US Airlines and Ticket Prices. *The Economist.* Retrieved June 15, 2007, from the World Wide Web: http://www.factiva.com
[4] Nason, S. D. (2007). Forecasting the Future of Airline Revenue Management. *Journal of Revenue and Pricing Management*, 6(1), 64-66.

threatens to undo the benefits brought by the more analytic revenue management process. In addition, it exposes the gap in revenue management systems – the systems do not take competitors' fares and availabilities directly into account in spite of their immense impacts on revenue outcomes.

Theoretically, revenue management systems should incorporate the real-time availability of rival fares, forecast the impact on passenger choices and optimize the inventory allocation accordingly. However, since the cost of such implementation is prohibitive but the benefit remains unclear, airlines should understand the effects of the lowest fare seat availability matching they already engage in, for a start.

The goal of this thesis is to investigate the impacts of matching the seat availability of the lowest competitor fare available, on metrics such as revenues, load factors, yields and market shares. In the remainder of Chapter 1, I will describe in greater detail the history of airline revenue management, from the beginnings and the traditional applications to the ascendance of LCCs and the responses from the legacy airlines. I will then discuss the goals and methods and lay out the structure of the thesis in further detail. In Chapter 2 I will review the literature and theory related to this thesis. Following that, in Chapter 3, I will describe the simulation environment used in this thesis. In Chapter 4, I will describe the simulation inputs and evaluate the results in a single symmetric market before moving on to simulating a network in Chapter 5. Finally, in Chapter 6, I will summarize of the main findings and propose future directions for research.

1.1 THE BEGINNINGS OF AIRLINE REVENUE MANAGEMENT

Before 1972, when fares for a cabin on a given route were typically uniform, airlines focused their research on controlling overbooking.[5] They maximized revenue through maximizing the number of passengers carried. As the name suggests, overbooking is the deliberate selling of seats beyond capacity on certain high demand flights. That happens when the expected number of cancellations, no-shows and go-shows maximize revenue, depending on the likelihood of offloading extra passengers or the airplane taking off with empty seats.

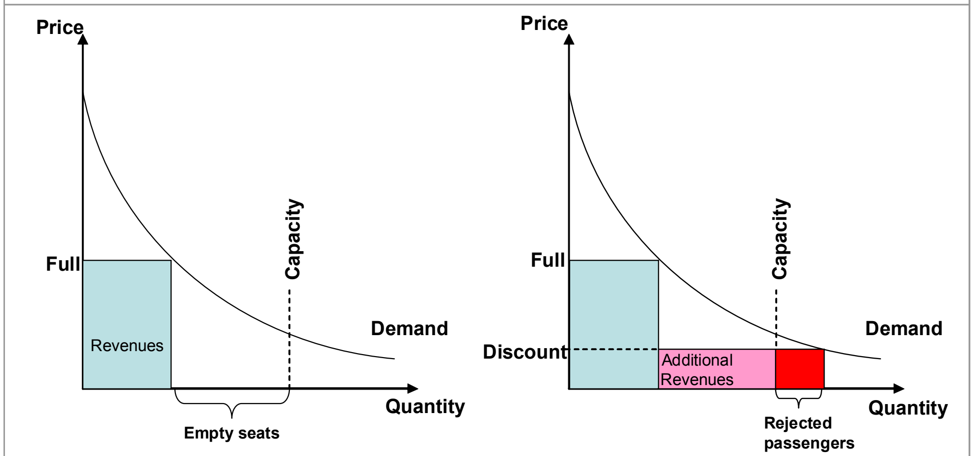
In the 1970s, in bid to attract new passengers to fill seats that still departed empty, BOAC (British Airways), American Airlines and other airlines introduced discounted fares.[6] To reduce diversion of full-fare passengers, these fares carried a requirement of an advance purchase (AP) of a specified number of days before flight departure and a restriction of a minimum stay of seven days. Revenue management became more complex with differential pricing. On top of maximizing passenger count, airlines had to optimize the mix of passengers – the allocation of seats between discount and full-fares that would maximize revenue. In situations where demand exceeded capacity (Figure 1-1), the

[5] McGill, J. I., G. J. van Ryzin. (1999). Revenue Management: Research Overview and Prospects. *Transportation Science*, 33(2), 233-256.
[6] Belobaba, P.P. (1998). Airline Differential Pricing for Effective Yield Management. In G.F. Butler & J. Peel (Eds.). *The Handbook of Airline Marketing* (pp. 349-361). New York: McGraw Hill.

airlines had to reject the early-booking discount passengers to protect seats for late-booking full-fare passengers. Conversely, airlines could not focus completely on yield when expected demand was low, since the number of seats was fixed in the short-run and the unsold product would expire upon departure.

FIGURE 1-1

Differential Pricing – Additional Revenues and Rejected Passengers



1.2 TRADITIONAL APPLICATIONS OF AIRLINE REVENUE MANAGEMENT

Deregulation of the US airline industry in 1978 brought about even greater flexibility and market influence in pricing.[7] Over the years, airlines introduced additional fare products in attempt to approach the absolute maximum revenue situation in theory, where each accepted passenger's fare reflects his maximum willingness-to-pay.

In order to extract revenues by making passengers reveal their true willingness-to-pay, airlines created numerous fare products, or fare classes, by bundling their fares with restrictions and AP requirements to fence passengers with higher willingness-to-pay out of lower fares. The restrictions included mandatory Saturday night stay, non-refundable tickets and round trip purchase requirement.

As alluded to earlier, a main complication is that low-yielding leisure travelers tend to book earlier than high-yielding business travelers, creating the need for inventory control based on forecasts of various passenger types. When their expected contributions are higher and demand exceeds supply, higher-fare passengers have seats saved for them by an inventory allocation system that rejects lower-fare passengers. That is achieved by adjusting fare class availability.

[7] General Accounting Office. (1999). Airline Deregulation: Changes in Airfares, Service Quality, and Barriers to Entry. Report to Congressional Requestors. GAO/RCED-99-92. Washington, D. C.

Over the years, seat allocation algorithms have progressed from leg-based control to Origin-Destination (O-D) control and allocation based on network contribution of the passenger.[8] Since the seat inventories are limited, concepts of displacement and opportunity costs became central to their allocation. At the same time, progressively sophisticated theory, computer systems and databases have enabled more accurate forecasting at a disaggregate level.

Conventional applications of revenue management were successful in limiting dilution from higher-fare passengers buying lower fares because the "fare fences" erected between different fare classes were effective, especially the compulsory Saturday night stay dreaded by businessmen.[9] The business and leisure consumers were clearly separated by those restrictions. Moreover, search costs were high and pricing was more opaque due to commission-based travel agents.

1.3 THE RISE OF THE LOW COST CARRIERS AND THE INTERNET

The proliferation and subsequent rise to prominence of LCCs coupled with the Internet as a dominant booking platform violated the foundations conventional revenue management systems were built upon.

Contrary to the existing legacy airlines, the low-fare airlines used much simplified fare structures. There are three major reasons why LCCs removed the fare restrictions and requirements used to segment demand. Firstly, LCCs removed the restrictions because they could afford to do so in terms of economics. With relatively low overhead costs from young fleets and workforces, they required less revenue to break even or turn profits. The second reason is that LCCs were technically less capable of capitalizing on the restrictions. Relative to the full-fledged revenue management systems owned by legacy carriers, LCCs' basic or non-existent revenue management processes could not fully utilize the independent demands created by fare restrictions. Thirdly, the entrant LCCs were eager to stimulate demand and capture market share from incumbents. The low-fare airlines pursued consumers who were ready to defect because they were weary of the legacy carriers' complicated fare restrictions and wide variations in fares.

The successful incursions by LCCs forced the incumbent legacy carriers to similarly streamline their fare products – major restrictions were eliminated or diluted, advance purchase was simplified and fares were capped.[10] Fare product simplification degraded

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[8] Belobaba, P.P. (2002). Airline Network Revenue Management: Recent Developments and State of the Practice. In D. Jenkins (Ed.). *The Handbook of Airline Marketing* (pp. 141-156). New York: McGraw Hill.

[9] Lee, S. (2000). Modeling Passenger Disutilities in Airline Revenue Management Simulation. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA.

[10] Delta Airlines. (Jan 5, 2005). Delta Slashes Everyday Fares up to 50 Percent as Airline Introduces SimpliFares™ Nationwide. *Delta Airlines Press Release*. Retrieved June 21, 2007, from the World Wide Web: http://news.delta.com/article_display.cfm?article_id=9584

assumptions like fare class demand independence that are crucial to the standard form of forecasting. In turn, the traditional revenue management systems that rely on standard forecasting were weakened.

Concurrently, the Internet came to the fore as a distribution channel and modified consumer behavior. To keep costs low, LCCs avoided the orthodox distribution channels like the costly Global Distribution System (GDS). Many LCCs sold tickets online exclusively, diverting booking traffic from travel agents to the Internet. Realizing the potential cost savings and revenue potential, major corporations including Sabre, Microsoft and several airlines also founded Internet booking sites like Expedia, Travelocity and Orbitz. These sites featured price comparisons prominently, fueling the trend of consumers seeking the lowest fare available. With price movements becoming more transparent and search costs significantly lowered, consumers became more price-sensitive. Legacy airlines were often forced to match LCCs' low-fares availability frequently to retain market share.

The increased transparency afforded by LCCs and the Internet awakened the passengers' awareness to fare variations. Sophisticated Internet-based fare tracking companies like Farecast and later Yapta emerged to capitalize on consumers' desire to secure the lowest fare in face of the wide fare fluctuations caused by airlines' revenue management systems. In turn, the popularity of these Internet tools among users and the media deepened consumers' familiarity with fare trends.

1.4 RESPONSES AND ENHANCEMENTS TO RM SYSTEMS

1.4.1 Integrated into Revenue Management Systems

The dismantling of fare restrictions disrupted the legacy airlines' revenue management systems. To stem their loss of revenue, research has been focused on new methods to enhance conventional revenue management systems to function effectively in the less-restricted fare environment and respond suitably to the altered consumer behavior. The core idea behind some of these enhancements is to close fare classes at optimal points to force sell-up. Sell-up refers to a passenger purchasing a higher fare class as a result of his first-choice fare class being unavailable. To determine where these ideal points of fare closure are, the airlines have to estimate the probability and willingness of passengers buying a higher fare class. The concept of sell-up and two related enhancements: Q-forecasting (QF) and Hybrid Forecasting (HF) are explained in further detail in Chapter 2.

1.4.2 Post-RM Adjustment of Inventory Availability

In order to curtail the market share growth by entrant low-fare airlines and in response to passengers' heightened sensitivity to prices, legacy airlines began to match seat availability of the lowest competitor fare on certain routes. That helped them show up on top of the list in Internet compare-then-buy searches. Such availability matching is not incorporated fully into revenue management systems. Instead, the availability matching overrides the fare class closures already calculated as optimal by the revenue management systems. Since the matching activity lies outside of the revenue management system, it may be redundant or even regressive, harking back to the days before formal revenue management systems were used, when designated route controllers relied on instincts to shut fare classes.

The post-RM adjustment of inventory availability is merely a Band-Aid for airlines before they fully incorporate competitor fare availably data and model the competitive effects in their revenue management systems. Existing revenue management systems rely heavily on their own historical booking trends although competitor fares and availability have a significant impact on bookings. Dennis Cary, Vice President, Revenue Management at United Airlines, calls for the integration into revenue management systems "more intelligence about the shifting competitive landscape."[11]

1.5 OBJECTIVES AND METHODS OF THE THESIS

The goal of this thesis is to use simulation to examine the impacts of seat availability matching on airlines. To cover the range of scenarios where availability matching is being done or could be of interest to airlines, different types of seat availability matching and various combinations of revenue management systems are simulated. Two market settings are used in this thesis: a single symmetric market and a network of 572 markets where four asymmetric airlines compete.

Specifically, three types of availability matching are investigated: firstly Open Matching, where an airline re-opens fare classes already made unavailable by the revenue management system, to be as available as the least restrictive rival; secondly Closure Matching, where an airline closes fare classes that the are still available from the revenue management system but are lower then the lowest fare among competitors, and thirdly Bi-directional Matching, where an airline does both of the above.

1.6 STRUCTURE OF THE THESIS

This thesis is organized into five further sections: a review of related literature and theory of revenue management, an explanation of the simulation environment of the Passenger Origin-Destination Simulator (PODS), a discussion of the simulation inputs, results and analyses in a single symmetric market and then in a network, and finally a conclusion summarizing the main findings and proposing directions for future research.

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[11] Cary, D. (2004). Future of Revenue Management: A View from the Inside. *Journal of Revenue and Pricing Management*, 3(2), 200-203.

Chapter 2 presents an overview of literature that is relevant to the thesis. It provides a historical framework, explaining the fundamental concepts of revenue management, highlighting the shifts in the field brought by LCCs and the future changes likely in the field. The goal of the chapter is to substantiate the need to simulate the effects of lowest fare seat availability matching on airline revenue management.

The first part of Chapter 3 introduces three aspects of how PODS works to simulate accurately the competitive booking process: of the general architecture, of the passenger choice model and of the implementation of RM systems and theories used by actual airlines. The focus of the second part is the implementation of lowest fare seat availability matching in PODS.

Having explained the underlying theory and construction of the simulator, in Chapter 4 I will describe the inputs and take an analytic look at the outcomes of the simulation runs. I will start investigating of the effects of lowest fare seat availability matching from the proof-of-concept stage by studying simulations of two airlines competing in a single symmetric market that has no fare restrictions. There are three main groups of scenarios. Firstly, I will study the hypothetical use of availability matching to make an airline with a rudimentary revenue management system more protective of higher fare classes. This is to reduce the extent of which their passengers pay less than their willingness-to-pay in an unrestricted fare environment. The second group examines whether it is lucrative or tactical for an airline with an advanced revenue management system to match an airline with a simple system in terms of the lowest fare seat available. Thirdly, I will examine the scenarios where two airlines with the same revenue management system match each other in lowest fare availability.

In Chapter 5, I will simulate scenarios where a legacy airline availability matches an LCC, in an asymmetric network with four airlines and 572 markets. Half of the markets are traditional and restrictive while the other half of the markets are less restrictive because of the presence of an LCC. I will compare the performance of the matching airline when it uses combinations of leg-based inventory control or O-D inventory control with standard forecasting or hybrid forecasting.

Finally, in Chapter 6, I will summarize the key findings of the thesis and suggest future directions for research.

CHAPTER 2
LITERATURE AND THEORY REVIEW

The primary goal of this chapter is to review the literature that precede and motivate this thesis – to show why this thesis is necessary. The secondary aim is to explain the concepts that will be used in the rest of this thesis.

The chapter is divided into two main sections: first, an overview of the development of airline revenue management so far and then a discussion focused on the relationship between airline revenue management and competition. The first section provides a historical overview of conventional revenue management methods used by airlines and how they were then adapted for the less restrictive fare environment brought by LCCs.

The second section on airline revenue management and competition covers three sub-topics: the future of airline revenue management, the literature on price matching and inventory control under competition. The future of airline revenue management is a discussion on the inadequacies of the current systems and possible future enhancements that incorporate competitors' fare availability. The section on price matching literature acknowledges that competitive effects on airlines have been studied, but only at a macro, fare pricing level. A micro, fare availability level is required for revenue management. The third sub-section discusses two papers that examined the specific issue of inventory control under competition. Although these two studies studied micro, availability level issues, they use analytical methods, whereas this thesis uses simulation.

2.1 AIRLINE REVENUE MANAGEMENT

This section starts with an overview of the conventional methods of airline revenue management, tracing the progress from leg-based algorithms to Network-based systems with Origin-Destination inventory control. Following that, I will explain the disruption to conventional revenue management systems caused by the rise of LCCs and the Internet, in particular, the effects when crucial fare restrictions were removed. I will then focus on the methods of Q-forecasting and hybrid forecasting that were developed to improve the performance of conventional revenue management systems in the undifferentiated fare environment.

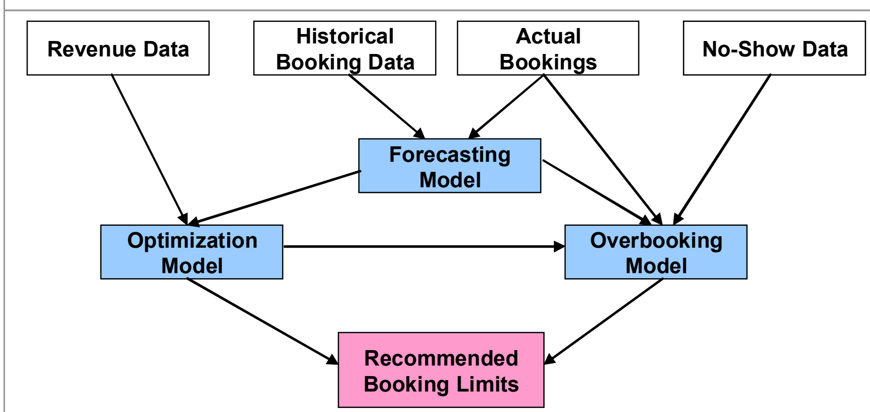
2.1.1 Conventional Airline Revenue Management

The goal of airline revenue management is to maximize revenue given limited, perishable inventories of seats that have predominantly fixed operating costs in the short run. There are various approaches to solving the revenue maximization problem. However, for historical reasons described in Chapter 1, conventional airline revenue management has relied on a central assumption – the demand for different fare classes are independent. Legacy airlines successfully segmented seats into fare classes that carry certain restrictions, requirements and fares, creating the traditional fare environments. Using fare classes, the airlines encouraged most passengers to purchase only products that fit their profile, depending on their sensitivity to time and price, and their propensity to cancel or change flights.

Barnhart, Belobaba and Odoni[12] identify the third generation of airline revenue management systems, already installed at major airlines of the world, as at least capable of generating forecasts and booking controls by fare class and have Operations Research (OR) models incorporated. The systems' three main components, as illustrated in Figure 2-1, are the models for forecasting, overbooking and inventory control. Airlines maximize their revenues through forecasting demand and allocating supply to that demand through pricing and controlling their seat inventories. Historical bookings are used in conjunction with actual bookings received in the demand forecasting model. The forecast produced is then combined with revenue data to generate booking limits in the optimization model, otherwise known as the inventory control model. Concurrently, the demand forecast is combined with no-show data, actual bookings and booking limits for use by the overbooking model to recommend an optimal overbooking level. Eventually, the overall recommended booking limits are obtained by combining outputs from the inventory control model and the overbooking model.

FIGURE 2-1

Third Generation Airline RM System



Reproduced from Barnhart, et al.

For the rest of this section, I will concentrate on the optimization component of inventory control, in particular the methods used in this thesis. There are two literature reviews that go into much more depth, especially for forecasting and overbooking. McGill and van Ryzin[5] describe the development of revenue management in the traditional fare

[12] Barnhart, C., P. P. Belobaba, A. R. Odoni. (2003). Applications of Operations Reseach in the Air Transport Industry. *Transportation Science*, 37(4), 368-391.

environments and provide a comprehensive survey of the literature. Boyd and Bilegan[13] present a more up-to-date and technical overview of revenue management, with an emphasis on the enabling electronic media like centralized reservation and revenue management systems.

The inventory control methods reviewed can be conceptualized alternatively as pricing methods. This is because pricing and inventory control intertwine to the extent that they are essentially two perspectives to solve the same revenue maximization problem. However, as Pak and Piersma[14] have argued, fare class closures can be more directly formulated as an inventory allocation issue rather than a pricing problem.

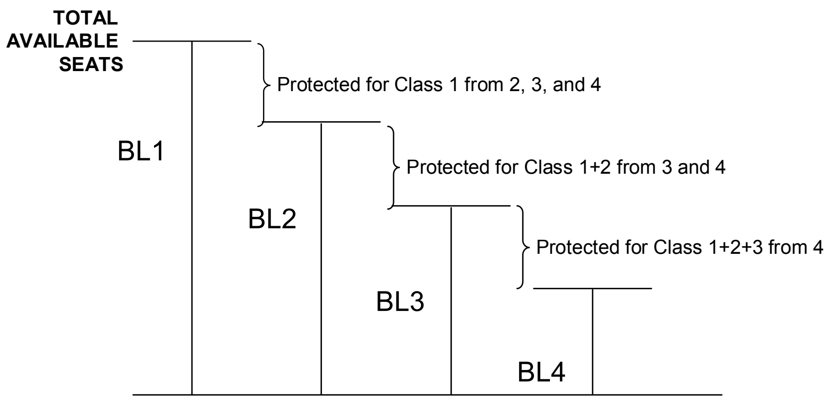
2.1.1.a Fare Class/Leg-based Control

At the start of revenue management, when airlines moved away from a simplistic first-come-first-served system, in order for them to decide "to sell or not to sell" as bookings arrived, Littlewood[15] introduced the concept of displacement costs. He created a rule for protecting full-fare seats conditional on the probability that a discount-fare passenger would displace a full-fare passenger. Belobaba[16] expanded on Littlewood's work by building quantitative decision rules that determine the revenue maximizing protection levels and therefore booking limits for multiple nested fare class inventories (Figure 2-2). The decision rules are based on the Expected Marginal Seat Revenue (EMSR) – the expected revenue obtained if there is an additional "marginal seat" on a flight, calculated based on the fare and forecasted demand.

[13] Boyd, E. A., I. C. Bilegan. (2003). "Revenue Management and E-Commerce." *Management Science,* 49(10), 1363-1386.
[14] Pak, K., N. Piersma. (2002). Airline Revenue Management. *ERIM Report Series Reference No. ERS-2002-12-LIS.*
[15] Littlewood, K. (1972). Forecasting and Control of Passenger Bookings. *12th AGIFORS Symposium Proceedings*.
[16] Belobaba, P. P. (1987). Air Travel Demand and Airline Seat Inventory Management, Ph.D. Thesis, Flight Transportation Laboratory, Massachusetts Institute of Technology, Cambridge, MA.

FIGURE 2-2

Nested Booking Limits and Class Protection Levels



Reproduced from Barnhart, et al.

EMSR was refined by BELOBABA[17] in 1992 to become the EMSRb probabilistic decision model that has since been extensively incorporated into many airlines' revenue management systems. EMSRb is a base algorithm used frequently in this thesis.

Assuming demand to be stochastic (Gaussian) and independent for each fare class, the EMSRb model determines the leg-based nested booking limits, based on the expected revenue from having an incremental, marginal seat protected for higher fare classes. In other words, a seat is saved for the higher fare classes so long as the revenue expected from protecting it exceeds the revenue from the fare class below them. It is a nested approach in that protection levels, and therefore booking limits, are figures jointly held by several higher or lower fare classes respectively. A more in-depth explanation of EMSRb is given by Belobaba and Weatherford.[18]

2.1.1.b Origin-Destination Control

With leg-based control, bottlenecks are likely – for itineraries connecting multiple legs, the same fare class must be available throughout for successful booking. Moreover, leg-based control only guarantees yield maximization but not revenue maximization in a network because it ignores network effects. For example, a passenger booking in a lower fare class and connecting from a relatively empty leg to an almost full leg could bring more revenues to the airline overall, but would be displaced by a high fare class local passenger on the second leg. Leg-based control is sub-optimal because it favors local passengers.

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[17] Belobaba, P. P. (1992). The Revenue Enhancement Potential of Airline Revenue Management Systems. *ASTAIR Proc. Adv. Software Tech. Air Transport,* London, U.K.
[18] Belobaba, P. P., L. R. Weatherford. (1996). Comparing Decision Rules that Incorporate Customer Diversion in Perishable Asset Revenue Management Situations, *Decision Sciences*, 27(2), 343-363.

To overcome the shortcoming, Origin-Destination (O-D) control was developed to allocate inventories based on the revenue contributions of the passengers' itineraries. O-D control is especially beneficial to airlines operating extensive hub-and-spoke networks.

"Virtual buckets" was developed at American Airlines by Smith and Penn[19] to replace fare classes for inventory control. Based solely on its revenue contribution, each combination of itinerary and fare type is assigned to a "virtual" booking class that is internal to the airline's reservation system. Seat availability is then determined by the booking limits set for that booking class. The downside to relying only on revenue contribution is that it is "greedy" and always prefers connecting passengers, even though if the flights are full, local passengers could contribute more overall.

The revenue contribution method was refined into Displacement Adjusted Virtual Nesting (DAVN) to take into displacement costs into account. DAVN controls inventories based on the Network Revenue value, which is the total itinerary fare adjusted by the costs of displacing local passengers. Detailed discussions of virtual classes and DAVN can be found in Williamson[20], Vinod,[21] Lee[22] and Wei[23]. DAVN is used for network simulations in this thesis.

An alternative method for O-D control is based on bid prices. A booking is accepted if its fare exceeds the bid price established for that itinerary. This competing approach was developed and discussed by Simpson[24], Wei[23], Talluri and van Ryzin[25].

In the late 1990s, most major airlines were busy upgrading their revenue management systems to handle virtual nesting and O-D control, not expecting the upcoming upheaval brought by the Low Cost Carriers and the Internet.[11]

2.1.2 Low Cost Carriers and Today's Fare Environments

Although LCCs carry one out of four U.S. domestic passengers today, there was no obvious tipping point that marked their success. Some LCCs have existed for decades,

[19] Smith, B. C., C. W., Penn. (1988). Analysis of Alternative Origin-Destination Control Strategies, *AGIFORS Symposium Proceedings*, 28, 123-144.
[20] Williamson, E. L. (1992). Airline Network Seat Inventory Control: Methodologies and Revenue Impacts. Ph.D. Thesis, Massachusetts Institute of Technology, Cambridge, MA.
[21] Vinod, B. (1995). Origin and Destination Yield Management. *The Handbook of Airline Economics*, D. Jenkins (ed.). The Aviation Weekly Group of the McGraw-Hill Companies, New York, NY, 459-468.
[22] Lee, A. Y. (1998). Investigations of Competitive Impacts of Origin-Destination Control using PODS. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA.
[23] Wei, Y. J. (1997). Airline O-D Control using Network Displacement Concepts. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA.
[24] Simpson, R. W. (1989). Using Network Flow Techniques to Find Shadow Prices for Market and Seat Inventory Control, Memorandum M89-1, MIT Flight Transportation Laboratory, Massachusetts Institute of Technology, Cambridge, MA.
[25] Talluri, K. T., G. J. van Ryzin. (1999). A Randomized Linear Programming Method for Computing Network Bid Prices, *Transportation Science* 33, 207-216.

and others have come and gone. Rather, a host of factors created the conducive environment for their ascendance, of which we will highlight two here.

First, in the 1990s, demand for air travel mirrored the vigorous growth of the U.S. economy. Buoyed by the robust demand for fully flexible, walk-up fares, legacy carriers priced those fares higher than before.[11] However, even as load factors remained healthy, the high fare ratio annoyed business travelers and left legacy carriers vulnerable to the no-frills, low-fares entrants, as Bender and Stephenson noted.[26] The high level of demand also meant that the airline operations were strained and passengers were more likely to receive poor service and willing to defect to a new airline.

Second, as the legacy airlines matured, their costs, especially unionized labor costs, became harder to contain. Once again, that meant they were susceptible to losing market share to low-cost, low-fare entrants.

For a comprehensive understanding of the growth of LCCs, refer to Gorin[27] for the impact of LCCs on revenue management and network flows and to Ito and Lee[28] for the conditions favoring market entry by LCCs.

By offering lower fares and removing ticket restrictions like mandatory Saturday Night Stay, LCCs quickly gained popularity among consumers. Not willing to cede market share, the legacy airlines matched these moves in the affected markets. Since the fare restrictions are crucial to the segmentation of demand in revenue management systems employed by the legacy carriers, the growth of the less restricted fare structure disrupted the functionality of traditional revenue management systems. Specifically, less restricted fare structures cause the "spiral down" phenomenon – the partial breakdown of traditional revenue management systems and the dilution of revenue as a result of passengers booking in a lower fare class than they are willing to pay for.

2.1.2.a The Spiral Down Effect

Facing the market share growth by entrant LCCs, the legacy carriers responded by matching the LCC pricing and less restrictive fare structures. While such reactions slowed the erosion of the legacy airlines' customer bases, the removal of fare restrictions were detrimental to conventional revenue management systems. Traditional revenue management is built on the foundation of restrictions that effectively segment demand into significantly independent fare classes. With the restrictions eliminated or weakened, the performance of traditional revenue management systems based on standard forecasting deteriorated –he problem was "spiral down."

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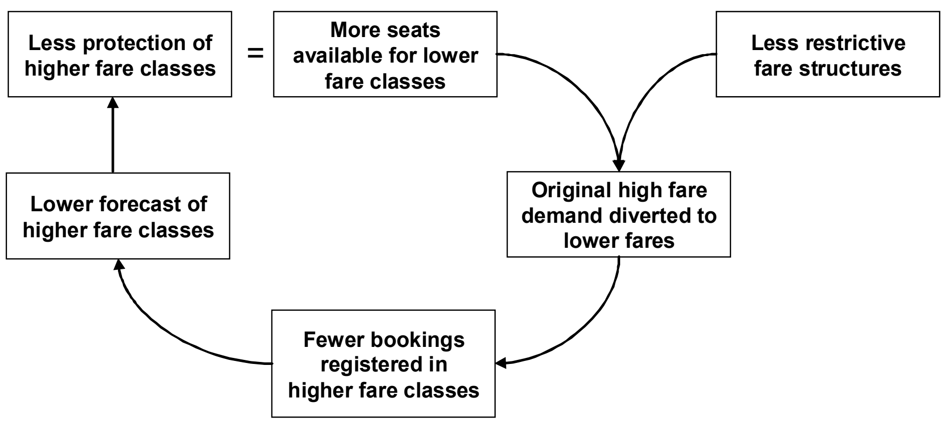
[26] Bender, A. R., F. J. Stephenson. (1998). Contemporary Issues Affecting the Demand for Business Air Travel in the United States, *Journal of Air Transport Management* 4(2), 99-109.
[27] Gorin, T. O. (2004). Assessing Low-fare Entry in Airline Markets : Impacts of Revenue Management and Network Flows. Doctoral Thesis, Massachusetts Institute of Technology, Cambridge, MA.
[28] Ito, H., D. Lee. (2003) Low Cost Carrier Growth in the U.S. Airline Industry: Past, Present and Future. Brown University Department of Economics Paper No. 2003-12.

Spiral down is the phenomenon that begins when the less restrictive fare structures result in "buy down" or passengers purchasing tickets of fare classes lower than they previously would, because they now can. Subsequently, the records of fewer higher fares purchased feed back into the revenue management system resulting in a lower forecast of high fare passengers – causing fewer seats to be protected for high-fare passengers. This then cycles as weaker protection once again allows passengers to purchase tickets of lower fare classes. The vicious cycle is illustrated in Figure 2-3.

FIGURE 2-3
Spiral Down



For a detailed, mathematical treatment of the spiral down phenomenon, refer to Cooper, Homem-de-Mello and Kleywegt.[29]

While many airlines were still adjusting to their new, sophisticated O-D revenue management systems, LCCs brought the new problem of spiral down. In response, academics have developed revenue management tools for the new, less restricted fare environment, although industry practice lags behind slightly. I will introduce the two methods used in this thesis, Q-forecasting and hybrid forecasting, in the next section.

2.1.3 Revenue Management Methods for the New Environment

Passengers who buy a fare lower than what they are willing to pay for initiate spiral down. Naturally, the revenue management methods developed to counteract spiral down prevent the "buy down" from happening. The cornerstone of these new methods is controlling inventory based on passengers' estimated willingness-to-pay instead of relying on fare class demand independence.

[29] Cooper, W.L., T. Homem-de-Mello, A. J. Kleywegt. (2006). Models of the Spiral-Down Effect in Revenue Management, *Operations Research*, 54(5), 968-987.

2.1.3.a Q-forecasting

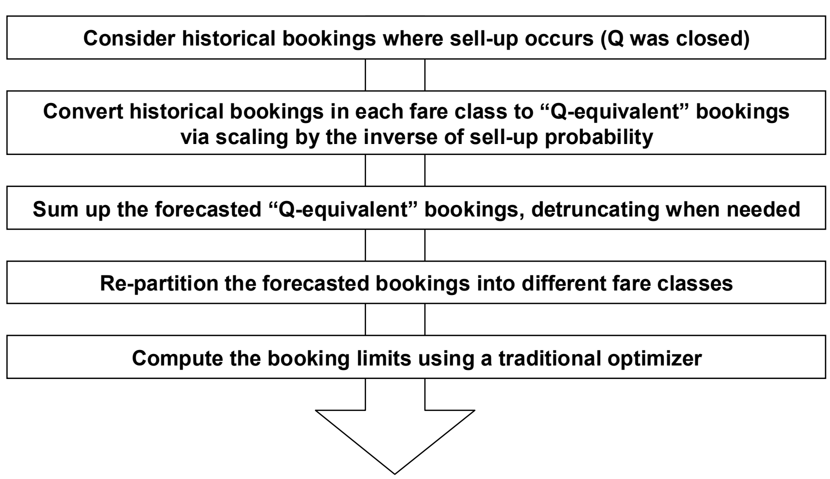
Belobaba and Hopperstad[30] developed Q-forecasting as a forecasting approach that does not require fare class demand independence. Instead, Q-forecasting assumes that fare classes are fully undifferentiated – there is no distinguishing restriction or requirement attached to a fare class except for its price.

The willingness-to-pay of a passenger is literally the maximum price a passenger is ready to spend on the itinerary. With the knowledge of passengers' willingness-to-pay, airlines are able to cause sell-up, where a passenger denied booking on their first choice of a particular path and fare class purchases the next higher fare class available. As suggested by Bohutinsky[31] in her Master's thesis, the airline can capitalize on sell-up by rendering the cheaper fare class unavailable and profiting the difference in fares. This is assuming the passenger stays with the airline, whether on the same flight or on another flight.

The Q-forecasting method starts by forecasting only the demand for the lowest class (known as the Q class), converting demand forecasts into the number of "Q-equivalent" passengers. It then re-partitions the demand strategically by forcing sell-up. It achieves sell-up through closing lower fare classes based on projected passenger willingness-to-pay. The concept of sell-up that was initially utilized under circumstances where fares carried restrictions was transplanted and adapted for the undifferentiated fare environment. An overview of the process is illustrated in Figure 2-4.

FIGURE 2-4

Overview of Q-forecasting Process



Reproduced from Cléaz-Savoyen

[30] Belobaba, P., C. Hopperstad. (2004). Algorithms for Revenue Management in Unrestricted Fare Markets. INFORMS Meeting on Revenue Management, Massachusetts of Technology, Cambridge, MA.
[31] Bohutinsky, C. H. (1990). The Sell Up Potential of Airline Demand. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA.

Cléaz-Savoyen concluded in his Master's thesis that based on simulations, airlines using Q-forecasting effectively recover part of the revenues lost due to the dismantling of fare restrictions.[32]

2.1.3.b Hybrid Forecasting

While Q-forecasting performs well in the completely unrestricted fare environment, such fare structures relying solely on price as the differentiator are not yet seen in reality. More frequently, fare restrictions are only partially removed. Boyd and Kallesen[33] argue that in the simplified, semi-restricted fare structure created, instead of breaking passengers down according to traditional lines of business versus leisure, the demand should be segregated into yieldable (product-oriented) demand and priceable (price-oriented) demand. A more in-depth discussion of these two forms of demand is given by Reyes[34] in his Master's thesis on hybrid forecasting. In short, yieldable demand cares about the product rather than the price and standard forecasting should be applied. On the other hand, priceable demand should be forecasted with a method like Q-forecasting to prevent revenue dilution and spiral down.

Belobaba and Hopperstad[30] developed the hybrid forecasting method to categorize bookings into the two demand categories and then forecast the demand of product-oriented and price-oriented passengers in order to set the optimal level of protection for seat availability. Reyes found through simulation that with assumptions of higher willingness-to-pay, hybrid forecasting improves an airline's revenues by about 3% when used instead of standard, pick-up forecasting.[34]

The successful incursion of LCCs and the elimination of certain fare restrictions have encouraged legacy airlines to modify their revenue management systems away from relying on fare class demand independence. However, for a variety of reasons like high costs of implementation, these systems still do not incorporate competitive effects. In the next section, I will cover the literature discussing the future of airline revenue management. They argue that inventory control systems in the future should take competition into account.

[32] Cléaz-Savoyen, R. L. (2005). Airline Revenue Management Methods for Less Restricted Fare Structures. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA.
[33] Boyd, E.A., R. Kallesen. (2004). The Science of Revenue Management when Passengers Purchase the Lowest Available Fare. *Journal of Revenue and Pricing Management*, 3(2), 171-177.
[34] Reyes, M. H. (2006). Hybrid Forecasting for Airline Revenue Management in Semi-Restricted Fare Structures. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA.

2.2 AIRLINE REVENUE MANAGEMENT AND COMPETITION

2.2.1 The Future of Airline Revenue Management

A common criticism of existing revenue management methods is that they fail to take into account the effects of competition. Nason[4] argued that as a result of the transparency created by online fare comparison companies, in the near future, revenue management systems need to be aware of competitors' prices and integrate them into the demand forecasts and elasticity measures. Ratliff and Vinod[35] indicated "competitive awareness" as the primary driver of revenue management systems change in the coming years. In particular, they stress the need for "real-time" control of pricing and availability and describe some recent vendor systems that have begun to include competitor fare availability information.

These papers imply that although legacy airlines have addressed the simplified fare structure brought by LCCs, they have not properly tackled the other issue of price transparency and low consumer search costs brought by the Internet. For revenue management systems, competitors' prices and availabilities have become as important as historical databases of bookings. There is a need to account for the competition. As a result, in the short term, airlines have been matching the lowest fare seat availability of their competitors.

Consumer behavior has also shifted. Focusing on the "strategic consumer" who postpones purchase if he believes a low-fare class will re-open, Anderson and Wilson[36] showed that the growing passenger awareness of fare trends can significantly influence airlines' revenues. Airline revenue management systems need to understand such strategic consumer behavior in the future when controlling fare class closures or re-openings. This is especially true with seat availability matching, since it causes airlines to modify their fare class availability more often.

2.2.2 Price Matching

Competitive effects on airline fares have not been ignored in the literature. However, the studies so far have focused on the macro level of price matching and are too broad for understanding the effects of competition on the micro level – of seat availability matching.

Evidence of the effects of price matching or the influence competition holds over prices is extensive in economics literature. Borenstein and Rose[37] concluded in their empirical

[35] Ratliff, R., B. Vinod. (2005). Airline Pricing and Revenue Management: A Future Outlook. *Journal of Revenue and Pricing Management,* 4(3), 302-307.
[36] Anderson, C. K., J. G. Wilson. (2003). Wait or Buy? The Strategic Consumer: Pricing and Profit Implications, *Journal of the Operational Research Society*, 54, 299-306.
[37] Borenstein, S., N. Rose. (1994). Competition and Price Dispersion in the U.S. Airline Industry. *The Journal of Political Economy*, 102(41), 653-683.

study that price dispersion witnessed in airfares suggests that price discrimination variation over routes is based on passengers' readiness and ability to switch between competing airlines. Evans and Kessides[38] formed a statistical basis to substantiate the unstated industry "golden rule" – where airlines with multi-market contract do not provoke price wars in a route because they fear a backlash in other markets. Varian[39] highlighted the practice of "price signaling" between airlines to maintain steady prices and referred to Nomani's[40] account of the practice.

With LCCs, proof of competitive price matching and their impacts is similarly strong. Morrison[41] estimated passengers' savings as a result of Southwest Airlines entry into markets. The US Department of Transportation's report in 1996[42] also recorded legacy airlines price matching entrant LCCs.

Since pricing and inventory control remain separate at airlines, it is not sufficient to only examine the broad issue of pricing under competition. In the next section, I will compare two papers that analyze the specific problem of inventory control under competition.

2.2.3 Inventory Control Under Competition

Mahajan and van Ryzin[43] extended the newsvendor or inventory competition game and examined how competing symmetric firms selling limited substitutable goods affect each other with their inventory decisions when consumers can choose dynamically. Their analytic conclusion is that under competition, firms tend to overstock. In other words, at Nash equilibrium, firms are pressured by competition to make goods available to the detriment of their profits. In the context of airlines, the results should be interpreted as discount, lower-yield seats being overstocked at the expense of under-protecting seats for higher-yield passengers. In this thesis, I will use simulation to examine the revenue effects when airlines overstock lower fare classes by re-opening fare classes when availability matching the lowest competitor fare available.

Netessine and Shumsky[44] showed a contradictory finding with his analytic framework: at equilibrium, an airline would provide fewer low-fare seats when competing with another airline on the same flight leg than when it is a monopoly or monopolist. The caveat is

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[38] Evan, W. N., I. N. Kessides. (1994). Living by the "Golden Rule": Multimarket Contact in the U.S. Airline Industry. *The Quarterly Journal of Economics*, 109(2), 341-366.
[39] Varian, H. R. (1999). Market Structure in the Network Age. *Understanding the Digital Economy*, MIT Press, Cambridge, MA.
[40] Nomani, A. Q. (1990). Fare Warning: How Airlines Trade Price Plans. *The Wall Street Journal,* 9 October 1990, pp B1.
[41] Morrison, S. A., Actual, Adjacent and Potential Competition Estimating the Full Effect of Southwest Airlines. *Journal of Transport Economics and Policy,* 35(2), 239-256.
[42] US Department of Transportation. (1996). The Low Cost Airline Service Revolution. Report of the Office of the Secretary.
[43] Mahajan, S., G. van Ryzin. (2001). Inventory Competition under Dynamic Consumer Choice. *Operations Research*, 49(5), 646-657.
[44] Netessine, S., R. A. Shumsky. (2005). Revenue Management Games: Horizontal and Vertical Competition. *Management Science,* 51(5), 813-831.

that such an outcome is dependent on the assumption that high-fare passengers, but not low-fare passengers, overflow from one airline to another.

Since this thesis will use simulation instead of analysis, both types of overflow are possible. Although airline inventory control under competition has been studied using analytic and empirical frameworks, it has yet to be examined using simulation. Many airline situations get too complicated to be handled elegantly by direct analysis without simplifying assumptions. Simulation appears to be a good step next.

2.3 SUMMARY

This chapter has provided the historical perspective and theoretical motivations for simulating inventory availability matching under competition. As highlighted by the papers discussing the future of revenue management, the current generation of revenue management systems reviewed has been more focused on internal records of historical bookings rather than competitor seat availability. As airlines tackle the problem of "spiral down" due to less restricted fare structures, they have to concurrently face complications from the external forces of competitor seat availability. Consumers' awareness of fares and fare trends, made possible by the increasing price transparency with Internet-based fare tracking companies, means airlines have to respond to the certain segment of customers who demand the lowest fare available. Although the effects of competition on price matching have been explored, there is a need to examine the impacts of competition on fare class availability matching. So far, the studies on inventory availability under have been analytical. This thesis will instead investigate how availability matching of inventory affects airline revenue management systems using simulation.

CHAPTER 3
SIMULATION ENVIRONMENT – PODS

A simulation approach is used to investigate the revenue impacts of seat availability matching. Simulation captures the characteristics of a competitive airline network, especially two types of the dynamic interactions: first, between passenger choice and inventory control and second, between airlines. While analytical methods can be useful for obtaining results in some situations, like to find game theoretic equilibrium positions, they are usually static. As Netessine and Shumsky's analytical paper[44] noted, the complexities of network interactions mean that competitive airline models rapidly overwhelm direct analysis, as the number of fare classes and booking limits increase.

The first half of this chapter describes the Passenger Origin-Destination Simulator (PODS) used in this thesis and has three sections: an overview of the general architecture, a detailed look at the passenger choice model and a close examination of the revenue management system. The second half is focused on the PODS capabilities for simulating seat availability matching of the lowest competitor fare. The aim of this chapter is to describe how PODS is used to simulate real-life scenarios and verify theoretical knowledge.

3.1 GENERAL ARCHITECTURE

PODS is a simulation program that realistically integrates passenger decisions of airline, path and fare class over multiple observations of a single day of the week. A typical run is made up of five trials, with each trial consisting of 600 samples. Since the simulations begin with user defined inputs, the first 200 direct observations calculated are used to progressively initiate the historical bookings database, and are then discarded. In other words, a single run in PODS averages results from five trials of 400 departure dates, or 2000 iterations.

In PODS, the pre-departure process is modeled as 16 consecutive time frames and the airlines' revenue management systems modify the seat availability by paths and fare classes at the start of each time frame. The database is then updated at the end of each time frame.

The days to departure for the time frames are inputs that can be adjusted by users. For the purpose of this thesis, the 16 time frames start off from 63 days prior to departure and being a week long, but are compressed to just a few days as departure approaches.

Table 3-1: Time Frames

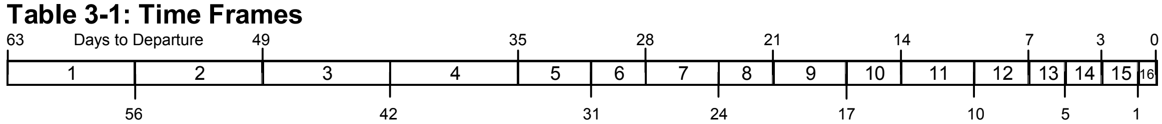
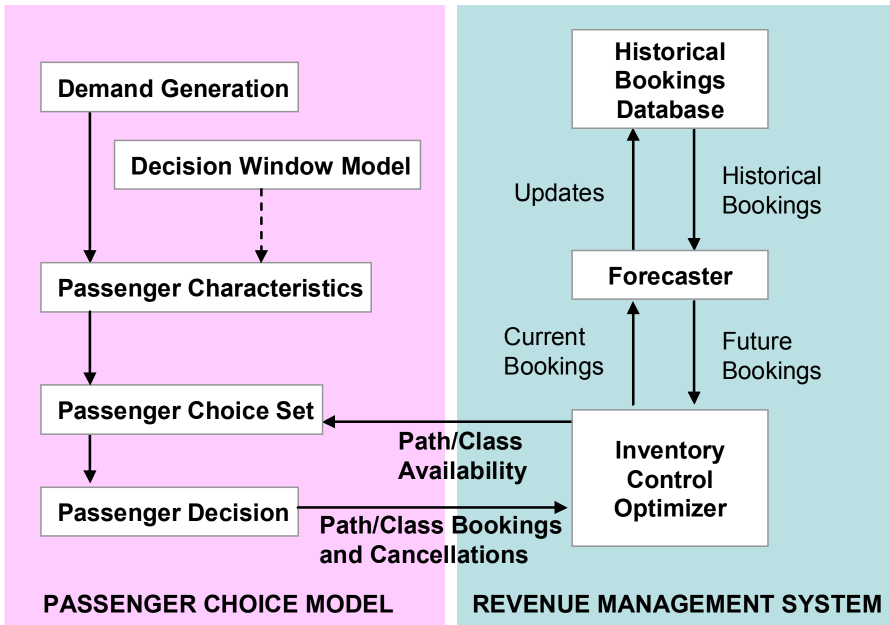


FIGURE 3-1

PODS Architecture



The architecture of PODS consists of two halves: the passenger side and the airline side (Figure 3-1). The passenger half, known as the passenger choice model, is an enhanced, evolved version of the Decision Window Model (DWM) developed originally at Boeing.[45] There are four successive steps. First, it generates demand in the simulation as total demand per Origin-Destination market for each passenger type (business or leisure) and each departure date. It then imbues these individual passengers with various characteristics like their decision windows (their tolerance for total time spent on flight), airline preference, maximum willingness-to-pay and disutility costs caused by ticket restrictions. The third step is determining the passenger choice set from the passenger characteristics and the path/class availability given by the inventory control optimizer. Finally, the passengers pick the fare and path option with the lowest total cost in terms of fares and disutilities.

The airline half is made up by the airline's revenue management system. The forecaster predicts future bookings based on current and historical bookings. Based on these predictions, the inventory control optimizer determines and supplies the path and fare class availability. The bookings or cancellations are continuously updated to the airlines databases. The revenue management systems employed by airlines in PODS are the third generation revenue management models described earlier in Chapter 2.1.1. A range of revenue management methods from the more basic like leg-based EMSRb, Adaptive Threshold to the more sophisticated involving DAVN can be simulated.

[45] The Boeing Company. (1997). Decision Window Path Preference Methodology Description, Seattle, WA.

3.2 PASSENGER CHOICE MODEL

The passenger choice model in PODS determines how passengers behave when faced with choices from different airlines. The four consecutive steps involved will be outlined in this section. For a more detailed and technical treatment of the PODS demand model, please refer to Carrier's[46] Master's thesis on modeling passenger choice.

3.2.1 Demand Generation

For this step, the Passenger Choice Model generates an average daily air travel demand for each of the O-D markets in the user-defined network. The demand is then divided between leisure and business travelers. The basis of this demand is data provided by the airlines forming the PODS Consortium. Variability is then created randomly, though neither seasonal nor day-of-week variability are modeled.

Two inputs in PODS influence the stochastic demand generation process: the base fares and the numbers of passengers that would travel at those base fares. There is a base fare and an associated number of passengers for each of the passenger types.

The mean demand resulting from the inputs of the base fares and the passenger numbers is designated as 1.00. If a specific multiple of that baseline demand is desired, lower or higher demands can then be obtained from scaling. For example, a demand level of 2.00 would generate twice the demand caused by that number of passengers willing to travel at those base fares.

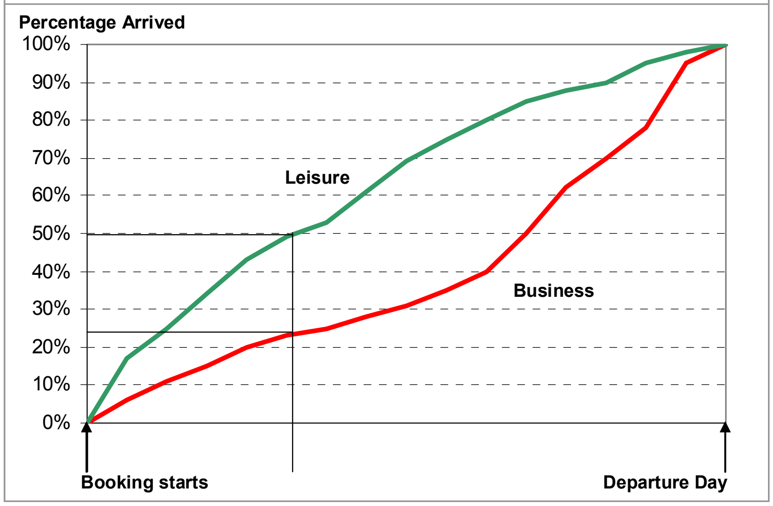
As for deciding when the demand arrives, in PODS, users can modify the arrival curves, or the percentage of bookings that arrive against days to departure, by passenger type – business or leisure. For this thesis, the booking curves used, adapted from actual airline data, are as shown below in Figure 3-2. They manifest the trend that business travelers tend to book later than leisure passengers.

Specifically, the figure illustrates that leisure passengers book much earlier – by the time half the leisure passenger have arrived to make their bookings, only about a quarter of business travelers have done so.

[46] Carrier, E. (2003) Modeling Airline Passenger Choice: Passenger Preference for Schedule in the Passenger Origin-Destination Simulator (PODS). Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA.

FIGURE 3-2

Arrival Curves by Passenger Type



3.2.2 Passenger Characteristics

In the second step, three sets of characteristics are endowed upon the passengers generated by the earlier step. Each passenger is first assigned a decision window – a period of time framed by the earliest acceptable departure time and the latest acceptable arrival time. Paths that fall completely within the decision window will be considered by the passenger. If no path qualifies, the passenger has to re-plan his/her trip at additional cost.

The passenger is also assigned a characteristic of maximum willingness-to-pay (WTP) – the maximum fare a passenger is prepared to pay to travel. The WTP is generated from price-demand curves for business and leisure passengers, based on user inputs. The formula for the curves is given as:

$$\mathrm{P}(\text{pay at least } f) = \min\left[1, e^{\frac{\ln(0.5)*(f - basefare)}{(emult-1)*basefare}}\right]$$

where: f is the fare

basefare is an input in PODS, at which an input specified number of passengers are willing to pay to travel

emult is the elasticity multiplier such that 50% of passengers are willing to pay emult*basefare to travel

Business passengers have higher emult, meaning their price-demand curve drops off more slowly since they are less price-sensitive. In contrast, once the fare is past a certain multiplier of the basefare, the probability of a leisure traveler willing to pay that fare falls quickly.

The third characteristic given to a passenger is the disutility costs randomly generated based on his/her passenger type. These costs indicate the passengers' sensitivity to a range of restrictions such as advance purchase, schedule preference, airline preference and path quality. For a more comprehensive description of disutility costs, refer to Lee.[47]

3.2.3 Passenger Choice Set

The third step involves ruling out certain path/fare class choices provided by the revenue management system because these choices have either advance purchase requirements that have lapsed or a fare higher than the passenger's WTP. If the airline has closed the fare class/path, those options are also absent from the passenger choice set. In addition, the choice of not booking is always included in the choice set.

As I will explain later in Chapter 3.4, the passenger choice set is where seat availability matching overrides the revenue management system, resulting in more or fewer choices available to the passengers.

3.2.4 Passenger Decision

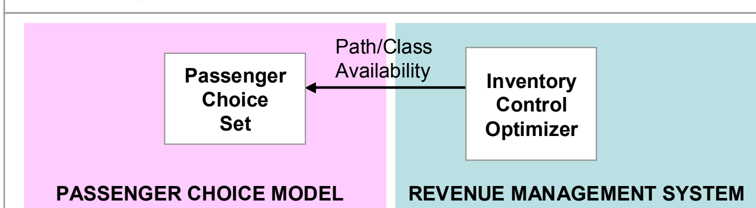
The passenger will then calculate the total costs of the fare and disutility costs and select the path/fare option with the lowest costs. This booking decision is then returned to the revenue management system.

3.3 IMPLEMENTING REVENUE MANAGEMENT SYSTEMS AND THEORIES

Three types of inventory control schemes, out of many more available in PODS, will be used in the simulations for this thesis: AT90, DAVN and variants of EMSRb. At the start of each time frame, the inventory control optimizers sends information of path and fare class availability to provide the passenger choice set (Figure 3-3).

FIGURE 3-3

Inventory Control Optimizer



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47 Lee, S. (2000). Modeling Passenger Disutilities in Airline Revenue Management Simulation. Master's Thesis, Massachusetts of Technology, Cambridge, MA.

3.3.1 Fare Class Yield Management (FCYM) – EMSRb with Standard Forecasting

The Fare Class Yield Management (FCYM) scheme performs all its processes on a flight leg basis: detruncating data, forecasting demand, optimizing using the EMSRb algorithm (discussed in Chapter 2.1.1.a) and determining nested fare classes booking limits. FCYM is the baseline scheme of inventory control in PODS.

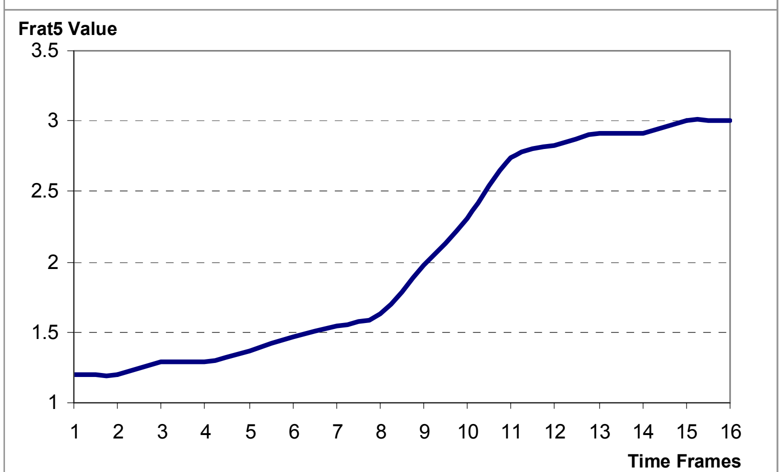
FCYM is a traditional revenue management scheme reliant on fare class restrictions. As previously discussed in Chapter 2.1.2.a, it spirals down in an unrestricted fare environment because standard forecasting fails. In response, enhancements like Q-forecasting, based on sell-up, were developed by researchers to reduce spiral down. In this section, I will first explain the parameter "Frat5" that is used to represent the probability of sell-up in PODS. Frat5s can either be inputs or estimated. Then, I will describe how sell-up behavior is incorporated in PODS using Frat5s. Finally, I will show how Q-forecasting and hybrid forecasting, based on sell-up, are implemented in PODS.

3.3.1.a Input Frat5s

Frat5 exists only as a parameter in PODS. It is used by a simulated airline as a proxy to determine passengers' willingness-to-pay. It is the acronym for Fare ratio (relative to the lowest fare) at which 50% of passengers are expected sell-up from the lowest fare class (Q) to a higher, more expensive fare class during a certain time frame. Therefore, a higher Frat5 represents a higher probability of sell-up and WTP among passengers.

FIGURE 3-4

Frat5 Curve: Input "C"



An input Frat5s curve is a set of Frat5s entered into PODS by the user. Frat5s typically increase progressively across time frames towards the date of departure, reflecting mainly the change in the mix of business and leisure travelers as shown earlier in Figure 3-2. Business travelers, who are willing to pay relatively more, book comparatively later. As such, an input Frat5s curve showing Frat5s across time frames obtains an S-shape, as seen in Figure 3-4. This implies that a business traveler who is willing to pay and therefore sell-up more has a higher probability of being informed that his/her first choice is not available and pushed to sell-up.

The input Frat5s curve shown in Figure 3-4 and used in this thesis is labeled as "C" in PODS, the middle of five S-shaped curves A to E arbitrarily created by Cléaz-Savoyen[32] to perform sensitivity analyses on input Frat5s.

3.3.1.b Estimating Frat5s – Average Conditional Forecast Prediction

Using input Frat5s is somewhat unrealistic because airlines would not directly know their passengers' willingness-to-pay. While input Frat5s can be used for "proof-of-concept," PODS also has the functionality for estimating Frat5s based on historical bookings, which is more in line with what airlines are able to do.

The method of estimating sell-up was introduced by Hopperstad and explained in detail by Cléaz-Savoyen.[32] For the purpose of this thesis, I will focus on the specific sell-up method used in this thesis. My explanation of the conditional forecast prediction (average) method is based on Hopperstad's detailed description.[48]

"Conditional"

The theory of conditional probability of sell-up is that sell-up is affected by, or conditional upon, the lowest open competitor class (Loco). Airlines are able to ascertain rival fare availability easily today – Loco can be found with methods like "screen scraping" or GDS information.

In PODS we have information for two observed types of demands: for a certain fare class i of our airline and for our lowest fare class (fare class Q) if the Loco is a certain Fare Class j. For the conditional probability of sell-up, we use these two observed types of demand that are conditional on the Loco to derive the ratio for the conditional probability of sell-up.

The ratio $\frac{\text{Demand for our fare class i if Loco is j}}{\text{Demand for our fare class Q if Loco is j}}$ gives us the probability that a passenger whose first choice is our fare class Q would sell-up to our fare class i given that during his/her booking, the Loco is j.

"Forecast Prediction"

The main idea of forecast prediction is that the number of actual bookings in a fare class relative to the earlier forecasted prediction provides a correction to the previously

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48 Hopperstad, C. (2007). Methods for Estimating Sell-up: Part II. *AGIFORS Joint Revenue Management and Cargo Study Group Meeting*.

estimated sell-up figure. As the sell-up figure is progressively corrected, a more accurate number emerges. Regressions are performed across time frames and Loco.

"Average"
The term "average" means that the conditional forecast prediction estimate is weighed by the historical distribution of Loco.

Implementation of Average Conditional Forecast Prediction in PODS
In PODS, the estimated Frat5s for the average conditional forecast prediction method are obtained with the formula:

$$frat5_{loco,\,tf} = \frac{-\ln(.5)}{b \cdot (1+(1+loco)c) \cdot tf^{d}} + 1$$

where: tf is the time frame
and the coefficients b, c and d are obtained from minimizing:

$$\sum_{loco} \sum_{lev} \left(obs_{loco,\,lev} - a \cdot e^{-b(fratl_{lev}-1)(1+(1+loco)c)\cdot tf^{d}} \right)^2$$

where: $obs_{loco,lev}$ is the ratio of the historical bookings to the Q forecast for a certain Loco and level
$fratl_{lev}$ is the fare ratio associated with the level

The fare ratios are not weighed by the number of observations because the revenue management system is a biased experimenter that produces observations at various levels for itself.

3.3.1.c Probability of Sell-up

PODS offers two choices for incorporating sell-up behavior. The user can choose to input an arbitrary figure as the probability of sell-up (*psup*). Alternatively, the probability of sell-up can be derived from the Frat5s curve. A comparison of the two ways can be found in Soo's Master's thesis.[49] In this thesis, only the Frat5 method is used.

[49] Soo, Y. S., Fare Adjustment Strategies for Airline Revenue Management and Reservation Systems. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA.

For the Frat5 method, the probability of sell-up is assumed to be a negative exponential distribution, as shown in the function below.

$$psup_{q \to f} = e^{-\left(\frac{fare_f}{fare_q} - 1\right) econ}$$

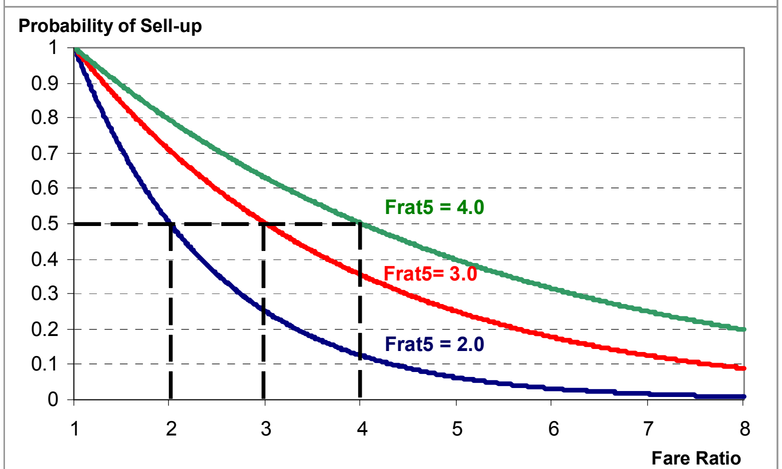
where: $fare_f$ = Fare of higher fare class, f
$fare_q$ = Fare of lowest fare class, q
$econ$ = Elasticity constant

The elasticity constant for a certain time frame ($econ_{tf}$) is calculated from the Frat5 for that time frame ($Frat5_{tf}$).

$$econ_{tf} = \frac{-\ln(.5)}{Frat5_{tf} - 1}$$

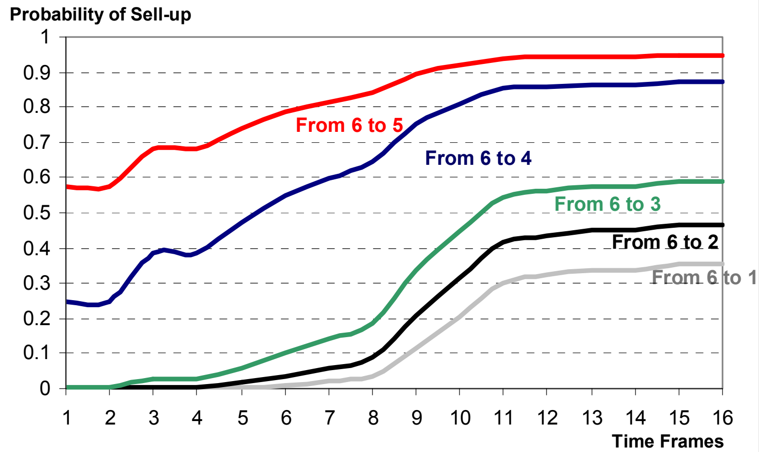
Figure 3-5 illustrates that for a given fare ratio, as Frat5s increases, the probability of sell-up increases. The figure also makes clear that each Frat5 corresponds to the fare ratio at which there is a 0.5 probability of sell-up.

FIGURE 3-5
Relationship between Probability of Sell-up and Frat5



Assuming fares of $125 to $500 from fare class 6 (lowest) to fare class 1 and input Frat5s curve "C," Figure 3-6 shows that the probability of sell-up curves across time frames retain the S-shape of the Frat5s. This is because passengers arriving later are more likely to sell-up. The largest increases in probabilities happen in the middle time frames of the booking process. It is also clear that passengers are much more likely to sell-up from the lowest fare class (6) to the next higher fare class (5) than subsequently higher fare classes (4 to 1).

FIGURE 3-6
Probability of Sell-up across Time Frames



3.3.1.d Q-forecasting Implementation in PODS

Building on the theory of Q-forecasting covered in Chapter 2.1.1.a, this section will explain how it is modeled in PODS, based on a presentation by Hopperstad.[48]

Historical bookings in higher classes are transformed into "Q-equivalent" bookings via scaling by the inverse of sell-up probability.

$$book_q = \frac{book_f}{psup_{q \to f}}$$

where: $book_q$ is "Q-equivalent" bookings
$book_f$ is historical bookings in higher-than-Q fare class f
psup is sell-up probability.

In PODS, the Q-forecasting forecast is produced by time frame. The Q-forecast is then partitioned into fare class forecasts using time frame sell-up probabilities.

$$fc_{f,tf} = Qfc\,(\,psup_{q \to f+1,tf} - psup_{q \to f,tf}\,)$$

where: *fc* is fare class forecast
f is fare class
tf is time frame
Qfc is Q-equivalent forecast
psup is sell-up probability.

The last of this multi-step process aggregates forecasts across time frames to generate forecasts for each fare class.

3.3.1.e Hybrid Forecasting Implementation in PODS

Hybrid forecasting is necessary for the optimal performance of an inventory control optimizer if the fare structures are mixed – a combination of traditional, restricted fare markets and simplified, less-restricted markets.

An important step is to classify the historical bookings into product-oriented or price-oriented demand. In PODS, there are three options. The first option, called the "path rule," is used in this thesis. Under that rule, a passenger is considered product-oriented if the next lower class available is on the same path. The other two options, the "airline rule" and the "market rule," involve a passenger buying a product when the next lowest fare class available is with the same airline and in the market respectively. The two types of demands, product-oriented demand and price-oriented demand, are then forecasted using standard pick-up forecasting and Q-forecasting respectively.

3.3.2 Load Factor Threshold Algorithm

The Load Factor Threshold methods are used in PODS to reflect the simpler processes used by LCCs that generally eschew complex revenue management systems.

3.3.2.a Fixed Threshold

For the Fixed Load Factor Threshold Algorithm, a cumulative load over capacity threshold between 0% and 100% is determined for each fare class from the lowest fare class up. The threshold for the highest fare class is therefore the overall load factor target. A fare class is closed when its corresponding load threshold has been reached. It is a rather rigid and basic way of managing bookings.

3.3.2.b Adaptive Threshold (AT)

The Adaptive Threshold method is a refined form of the Fixed Load Factor Threshold method. It has a target load factor but initial fare class load thresholds that are allowed to fluctuate. At every time frame, its fare class load values are calculated and fare class thresholds are re-optimized in response to the number of bookings so far, in order to achieve the target load factor. The type of AT currently implemented in PODS is the "Accordion" threshold, where the user can control the amount of fluctuation allowed by changing the minimum and maximum level of the accordion parameter convergence constant.

The re-optimization process is achieved by changing the accordion parameter (apv') using this equation:

$$apv' = \max\left\langle apvn, \min\left\{ apvx, hapv_l\left[1+\left(\frac{tgtlf}{hlf_l^{-1} * cnvgcon}\right)\right]\right\}\right\rangle$$

where: *apvn* is the minimum accordion parameter value allowed
apvx is the maximum accordion parameter value allowed
$hapv_l$ is the average historical accordion parameter value for leg l
tgtlf is the target load factor
hlf_l is the average historical load factor, leg l
cnvgcon is the convergence constant

AT90, with the "90" referring to a 90% load factor target, is used in PODS to replicate the simpler inventory control system a LCC competitor employs in the absence of more formal revenue management systems.

3.3.3 Displacement Adjusted Virtual Nesting (DAVN)

Displacement Adjusted Virtual Nesting, is the O-D inventory control method, based on O-D forecasts, outlined earlier in Chapter 2.1.1.b. The central issue with O-D control is that a connecting passenger may bring higher revenues overall to an airline if the legs are generally not full, but could displace higher-yield local passengers if the legs are full. DAVN presents a passenger's contribution to the airline suitable for comparison by deducting the displacement costs of the other flight legs from the connecting passenger's fare. These passenger values are then placed in "virtual buckets" or "virtual" booking classes that are "nested," or jointly protected from lower classes.

$$Bucketed\ Fare_{Leg\ k} = OD\ Fare - \sum_{\substack{m \in itinerary \\ m \neq k}} d_m$$

To compute the displacement costs, a linear programming (LP) problem is solved where total revenue is maximized subject to constraints of capacity and demand forecasted. Displacement costs and details of the LP can be found in Williamson's doctoral thesis.[20]

The LP is formulated like this:

$$\mathrm{MAX}\left(\sum_{OD_i}\sum_{Class_j} p_i{}^j x_i{}^j\right)$$

Subject to constraints:

$x_i{}^j < f_i{}^j$	$\forall OD_i, class_j$	Fare class demand constraint
$\sum_{OD_i}\sum_{Class_j} x_i{}^j \delta_i{}^k < C_k$	$\forall legs\ k$	Capacity constraint

where: *i* represents an O-D market
j represents a fare class
k represents a leg
p represents the fare
x represents the actual number of passengers
f represents the forecasted number of passengers
C represents the capacity of an aircraft
δ_i^k is 1 if leg *k* is part of path *i* and is otherwise 0

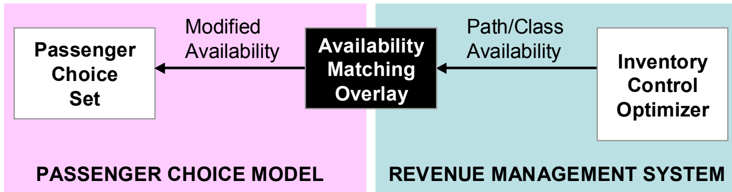
The "dual solution" of the LP provides, for each leg *k*, the optimal number of passengers for each O-D market and fare class. More importantly, it provides the marginal revenue obtained by expanding the capacity by one seat. The marginal revenue is used to calculate displacement costs.

Finally, for each leg, all fares are sorted by their "bucketed fares" and the EMSRb optimizer is used to determine the booking limits for each of these "nested virtual buckets."

3.4 AVAILABILITY MATCHING CAPABILITIES IN PODS

The treatment of Lowest competitor class open (Loco) availability matching in PODS is similar to what is done at airlines in that it is not directly integrated into the revenue management system. It is implemented as an overlay that overrides the path/class availability information sent from the inventory control optimizer to the passenger model (Figure 3-7). It could make unavailable fares classes originally left open or re-open classes shut down by the revenue management system.

FIGURE 3-7
Availability Matching Overlay



The availability matching overlay follows evaluates the Loco at the end of each time frame and modifies seat availability at the beginning of the next time frame. As the name of Lowest Competitor Class Open implies, the emphasis on the Loco is to find the lowest fare class available, and it can be a different competitor airline each round. Airlines simulated in PODS are capable of three types of matching: closure, open and bi-directional.

3.4.1 Closure Matching

Closure Matching enables an airline to be at least as restrictive as the least restrictive rival. The implementing airline scans competitors' fare class availability and shuts down fare classes that are lower than the Loco, even if the revenue management system kept it open. An airline performing Closure Matching does not wish to keep a cheaper fare class available for longer than the most available rival.

An example illustrated in Figure 3-8 shows Airline 1 having fare classes 1 to 4 left open and available by the revenue management system. As it implements Closure Matching, it cannot be more open than its rivals and therefore shuts down fare class 4.

FIGURE 3-8
Closure Matching

Increasing Price

	Airline 1	Rival 1	Rival 2
Fare class 1	available	available	available
Fare class 2	available	available	available
Fare class 3	available	**Loco**	closed
Fare class 4	available	closed	closed
Fare class 5	closed	closed	closed
Fare class 6	closed	closed	closed

Airline 1's Inventory Control Optimizer shuts down fare classes 5 and 6 but not fare class 4. Airline 1 has fare class higher than Loco available.

Increasing Price

	Airline 1	Rival 1	Rival 2
Fare class 1	available	available	available
Fare class 2	available	available	available
Fare class 3	available	**Loco**	closed
Fare class 4	**closed**	closed	closed
Fare class 5	closed	closed	closed
Fare class 6	closed	closed	closed

Closure matching overlay shuts down fare class 4 of Airline 1 to match Loco.

Availability matching does not change seat availability if the implementing airline is already at least as restrictive as the Loco. For example, if it has fare classes 1 to 3 open and Loco is one of fare classes 3 to 6 (i.e. equally or more open), the availability matching mechanism takes no action – the airline is comfortable with being equally or more restrictive

The basic equation in PODS for Loco Closure Matching is:

$$hiclose_p = \max[1, loco_p + match_p] + 1$$

where: $hiclose_p$ is the highest closed class for path p
$loco_p$ is the lowest competitor class open for path p
$match_p$ is the matching parameter chosen by the airline implementing Closure Matching

Through $match_p$ (discrete values -2 to 2), PODS offers the additional option of offsetting the matching by one or two fare classes. In other words, instead of Closure Matching with Loco as a target, an airline can perform Closure Matching with the target being one or two fare classes higher or lower than the Loco. This thesis will focus on exact matches, where the $match_p$ is always set to 0. This means that the implementing airline targets the Loco exactly.

3.4.2 Open Matching

On the other hand, Open Matching enables an airline to keep a fare class open for as long as any rival does. After ascertaining competitors' fare class availability, the airline re-opens any fare class that is higher than the Loco but was already shut down by the revenue management system. This imitates the real world phenomenon of an airline wishing to always appear as the lowest fare available in fare searches. To retain market share, airlines are known to have employees who override revenue management decisions to match availability based on screen-scraping rival availability information.

The implication is that fare classes that were initially shut down by the revenue management system in anticipation of higher revenue passengers are now re-opened, suggesting fewer than revenue-optimal seats are saved for higher-fare passengers. Airlines that open match do not override their revenue management systems if they are already equally or more open than their rivals – they aim to be at least as open as the most open competitor.

An example of a situation where an implementing airline takes action, as shown in Figure 3-9, is when it has only fare classes 1 to 2 open but a rival airline still has a cheaper fare class 3 open. The Open Matching mechanism will re-open class 3 for booking because the airline does not wish to be more restrictive.

FIGURE 3-9

Open Matching

Increasing Price

	Airline 1	Rival 1	Rival 2
Fare class 1	available	available	available
Fare class 2	available	available	available
Fare class 3	closed	**Loco**	closed
Fare class 4	closed	closed	closed
Fare class 5	closed	closed	closed
Fare class 6	closed	closed	closed

Airline 1's Inventory Control Optimizer shuts down fare classes including Loco fare class 3.

Increasing Price

	Airline 1	Rival 1	Rival 2
Fare class 1	available	available	available
Fare class 2	available	available	available
Fare class 3	**Re-opened**	**Loco**	closed
Fare class 4	closed	closed	closed
Fare class 5	closed	closed	closed
Fare class 6	closed	closed	closed

Open matching overlay re-opens fare class 3 of Airline 1 to match Loco

The basic equation in PODS for Loco Open Matching is:

$$lopen_p^* = \max[lopen_p, loco_p + match_p]$$

where: $lopen_p$ is the lowest open class for path p
$loco_p$ is the lowest competitor class open for path p
$match_p$ is the matching parameter chosen by the airline implementing Open Matching

3.4.3 Bi-directional Matching

Bi-directional Matching combines Closure and Open Matching. It is a tactic used by an airline trying to be as restrictive and open as the competing airline with the Loco.

Based on competitor fare class availability, the airline now shuts down the fare class that has a lower fare (fare class 4) than the Loco (fare class 3) but have not been shut down by its own revenue management system yet (Figure 3-10). It also reopens the fare class (fare class 2 in Figure 3-10) that has a higher or equal fare as the Loco but has already been shut down by the revenue management system.

FIGURE 3-10

Bi-directional Matching (Both Open *and* Closure Matching)

Increasing Price

	Airline 1	Rival 1	Rival 2
Fare class 1	available	available	available
Fare class 2	available	available	available
Fare class 3	available	**Loco**	closed
Fare class 4	available	closed	closed
Fare class 5	closed	closed	closed
Fare class 6	closed	closed	closed

Increasing Price

	Airline 1	Rival 1	Rival 2
Fare class 1	available	available	available
Fare class 2	available	available	available
Fare class 3	closed	**Loco**	closed
Fare class 4	closed	closed	closed
Fare class 5	closed	closed	closed
Fare class 6	closed	closed	closed

Increasing Price

	Airline 1	Rival 1	Rival 2
Fare class 1	available	available	available
Fare class 2	available	available	available
Fare class 3	available	**Loco**	closed
Fare class 4	closed	closed	closed
Fare class 5	closed	closed	closed
Fare class 6	closed	closed	closed

Bi-directional matching overlay re-opens or shuts down fare class to match Loco

3.5 SUMMARY

In this chapter, I described the Passenger Origin-Destination Simulator used in this thesis to test the impacts of lowest fare seat availability matching. The first half of the chapter explains how the characteristics of a competitive airline network are simulated, specifically the two components: the passenger choice model and the airline revenue management system. The passenger choice model describes how demand is generated, given specific characteristics, choice sets and then fare/path decisions. The airline revenue management system section explains how two methods that were created to suit a less-restricted fare environment – Q-forecasting and hybrid forecasting – are implemented and the difference between simulating leg-based and O-D based inventory control systems. The second half of the chapter introduces the availability matching capabilities in PODS used for this thesis.

Having established the background literature and PODS simulation environment, the next two chapters will be used to describe and analyze simulations of lowest fare seat availability matching in airline revenue management systems. In Chapter 4, the scenarios are simulated in a single symmetric market with unrestricted fares, while in Chapter 5, the scenarios are expanded to a much bigger network with 572 markets, four airlines and a mixed fare structure.

CHAPTER 4
SIMULATION INPUTS AND ANALYSIS OF RESULTS (SINGLE SYMMETRIC MARKET)

The purposes of this chapter are to explain the various scenarios simulated and to analyze the outcomes. All the simulations in this chapter involve two airlines competing in a single symmetric market that has a completely unrestricted fare structure. Section 4.1 provides an overview of this single symmetric market. The scenario results are then analyzed as three groups. The first group, examined in sections 4.2 and 4.3, tests the hypothesis that Closure Matching the seat availability of better-performing revenue management systems reduces the spiral down of a system based on EMSRb and standard forecasting. The second group of scenarios, discussed in sections 4.4 to 4.6, has an airline using a revenue management system based on EMSRb with Q-forecasting match, in terms of lowest fare seat availability, an airline using the Adaptive Threshold method. The motivation of this second group of scenarios is to find out how a sophisticated revenue management system reacts to availability matching a simple, threshold-based method. Symmetric simulations where both airlines use the advanced revenue management system of EMSRb with Q-forecasting form the third group that is covered in sections 4.7 to 4.9.

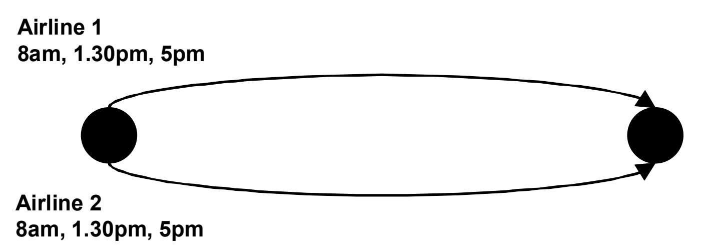
For each scenario, I will describe the inputs, such as the revenue management system settings chosen for the modeled airlines, and explain their significance. Following that, I will highlight the main features of the base cases – the situations where neither airline matches seat availability. I will then analyze the simulation outputs when availability matching of the lowest priced seat is used, first the effects on Airline 1, the matching airline, then the impacts on Airline 2, the matched airline. The focus will be on the changes in metrics such as revenue, load factor, yield, fare class mix and fare class closure curves. Where Q-forecasting is used, I will first examine the outputs resulting from the use of input Frat5s as “proof-of-concept” before verifying them with the results obtained when Frat5s are estimated.

4.1 OVERVIEW OF THE SINGLE SYMMETRIC MARKET

Simulations are set up for a single Origin-Destination market where two airlines compete. The total supply of seats for the market is 600. Airline 1 has three daily flights, each with 100 seats, paired to depart at the same time as the Airline 2’s three daily flights, as shown in Figure 4-1.

FIGURE 4-1

Supply in the Single Symmetric Market



None of their six fare classes carry restrictions (illustrated in Table 4-1), making them undifferentiated, implying that traditional revenue management methods using standard forecasting will not perform well.

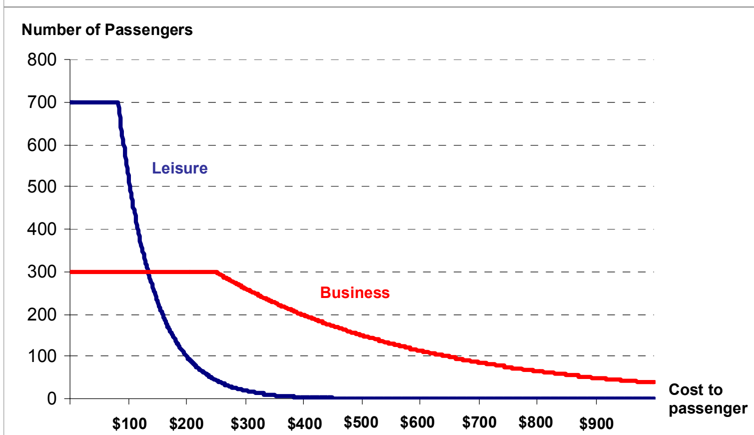
Table 4-1: Fully Unrestricted Fare Structure – Six Fares without Restrictions

Fare Class	Fare		Advance Purchase	Restriction 1	Restriction 2	Restriction 3
1	$500	Highest fare class	None	None	None	None
2	$400		None	None	None	None
3	$315		None	None	None	None
4	$175		None	None	None	None
5	$145		None	None	None	None
6	$125	Lowest fare class	None	None	None	None

To see if the impacts of availability matching change with demand, three demand levels are simulated: low (0.80), medium (1.00) and high (1.20). Both the low and high demand levels are scaled to the medium, baseline demand level. Demand generation is explained in detail in Chapter 3.2.1. The demand for the single symmetric market is shown graphically in Figure 4-2.

FIGURE 4-2

Demand in the Single Symmetric Market



4.2 EMSRB WITH STANDARD FORECASTING CLOSURE MATCHING AT90

It is unlikely that an airline today would use standard forecasting as the part of its revenue management system when it faces a completely or partially restriction-free fare structure. Such a system would spiral down because the assumption standard forecasting relies on – the demand independence of fare classes – is no longer true. As a result, passengers will book only in the cheapest fare class. However, it remains theoretically interesting to investigate the effects of availability matching through the hypothetical use of Closure Matching to reduce spiral down. If an airline's revenue management system spirals down, it would naturally be interested in Closure Matching a more restrictive system that resists spiral down.

I first established a situation where Airline 1 uses the inventory control algorithm EMSRb incorrectly with standard forecasting in a completely unrestricted fare structure – the revenue management system spirals down. I then set up Airline 1 to closure match Airline 2 that uses the Adaptive Threshold system, which spirals down less.

4.2.1 Inputs

Airline 2's Adaptive Threshold (AT) system is set to target a load factor of 90% in order to represent a typical high load achieved or desired by a LCC today. The system is given the acronym of "AT90." The minimum level of the accordion parameter convergence constant, an input explained in Chapter 3.3.2.b, is 0.50 and the maximum is 1.50. Within the AT90 system, we input three levels of initial Fare Class Load Threshold – restrictive, medium and loose, as indicated in Table 4-2.

Table 4-2: Three Types of Initial Fare Class Load Thresholds for AT90

LOOSE		MEDIUM		RESTRICTIVE	
Fare Class	Load Threshold	Fare Class	Load Threshold	Fare Class	Load Threshold
1	100%	1	100%	1	100%
2	90%	2	90%	2	90%
3	80%	3	80%	3	80%
4	70%	4	65%	4	60%
5	60%	5	50%	5	40%
6	50%	6	35%	6	20%

The fare class load threshold levels are initial parameters that could be changed by the system as bookings come in. For example, if an airline uses the "Restrictive" set of thresholds, it would initially target to have only 20% of the plane filled by the cheapest Fare Class 6 before shutting it down. However, if demand for the airline's seats is weak, it may loosen its Fare Class 6 threshold at later time frames to allow more bookings in order to achieve the target load factor.

For the base case scenario, neither airline uses Closure Matching. We then have Airline 1 use Closure Matching. Each run is repeated for the three demand levels of low, medium and high and the three threshold levels restrictive, medium and low.

4.2.2 Base cases

In the baseline situations where no matching takes place, because of standard forecasting, Airline 1's revenue management system spirals down in the unrestricted fare environment much more than Airline 2 does. To demonstrate the spiral down phenomenon, the revenues obtained by the airlines in the semi-restricted fare environment (seen in Table 4-3) are compared to those achieved in the unrestricted fare environment (shown earlier in Table 4-1).

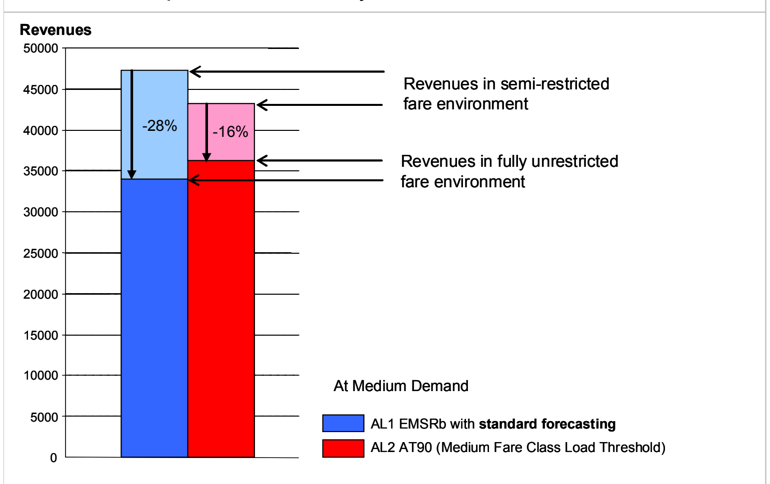
Table 4-3: Semi-restricted Fare Structure

Fare Class	Advance Purchase	Restriction 1	Restriction 2	Restriction 3
1	None	No	No	No
2	**3 days**	No	**Yes**	No
3	**7 days**	No	**Yes**	**Yes**
4	**14 days**	No	**Yes**	**Yes**
5	**14 days**	No	**Yes**	**Yes**
6	**21 days**	No	**Yes**	**Yes**

The example where demand is set to the medium level and Airline 2 uses medium fare class load thresholds is illustrated in Figure 4-3. Compared to the semi-restricted fare environment, Airline 1 loses 28% of revenue in an unrestricted fare environment and underperforms Airline 2. Airline 2 loses 16% of its revenues.

FIGURE 4-3

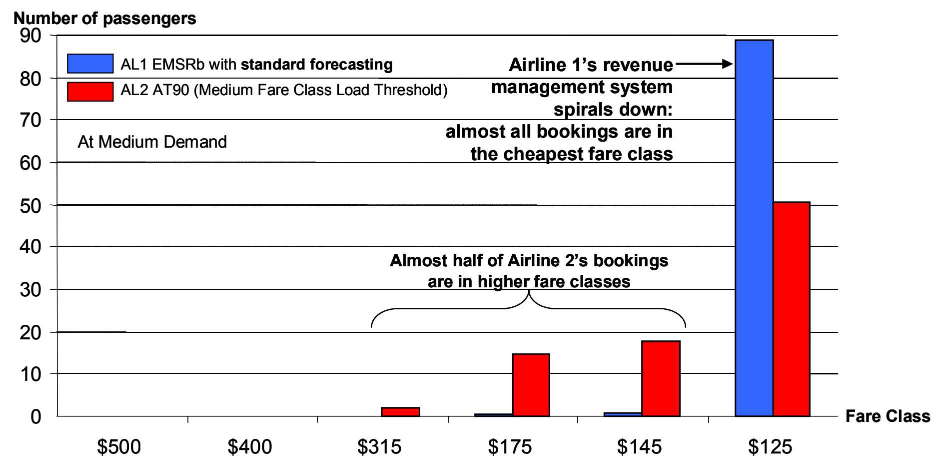
Revenues: Spiral Down in Fully Undifferentiated Fare Environment



The revenue management method using standard forecasting relies on fare class independence and effective fare restrictions that are no longer true in this situation. As seen in Figure 4-4, almost all of Airline 1 is filled with passengers who successfully make their bookings in the cheapest fare class – a clear indication of a meltdown of the RM system.

FIGURE 4-4

Fare Class Mix: Fully Undifferentiated Fare Environment, Without Matching

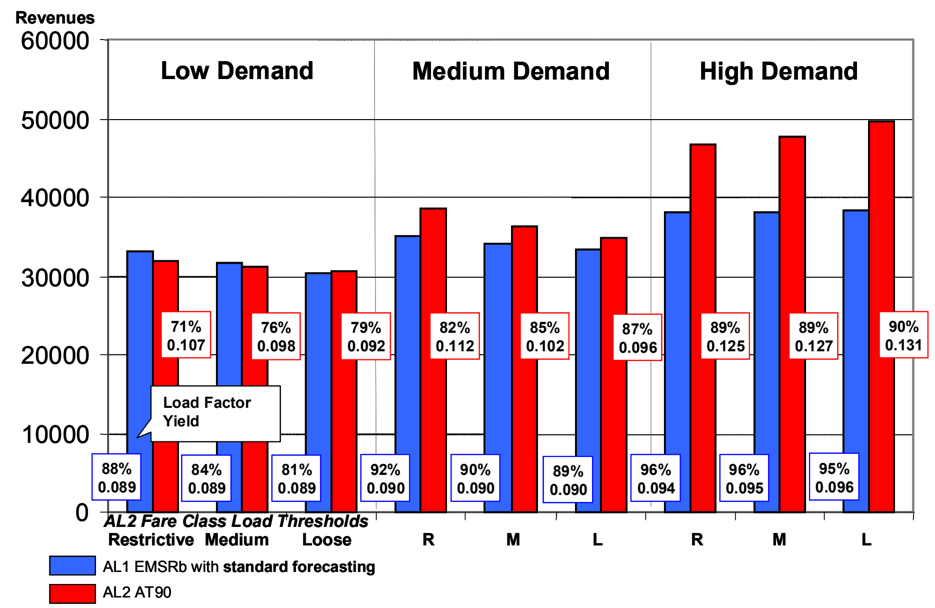


In contrast, it can be seen from that same figure that for Airline 2, due to its load thresholds for each fare class and its load factor target, about 40% of its bookings are not made in the cheapest fare class. In the example shown in Figure 4-4, Airline 2 has an initial load threshold of 35% for fare class 6 but adapts to the low demand and tolerates 50% of the plane being filled with fare class 6 passengers instead. In other words, although Airline 2's fare class loads are adaptive, they are relatively rigid compared to Airline 1's – the AT90 system with medium thresholds, targeting 35% of seats for fare class 6, would allow 50% but not 90% of the plane to be filled with fare class 6. Airline 1 could reduce spiral down by emulating and achieving Airline 2's fare class mix.

Airline 2's better fare class mix is reflected in the revenues – without Closure Matching, Airline 2 obtains higher revenues than Airline 1, except at low demand where their revenues are similar (Figure 4-5).

FIGURE 4-5

Base Cases Without Matching

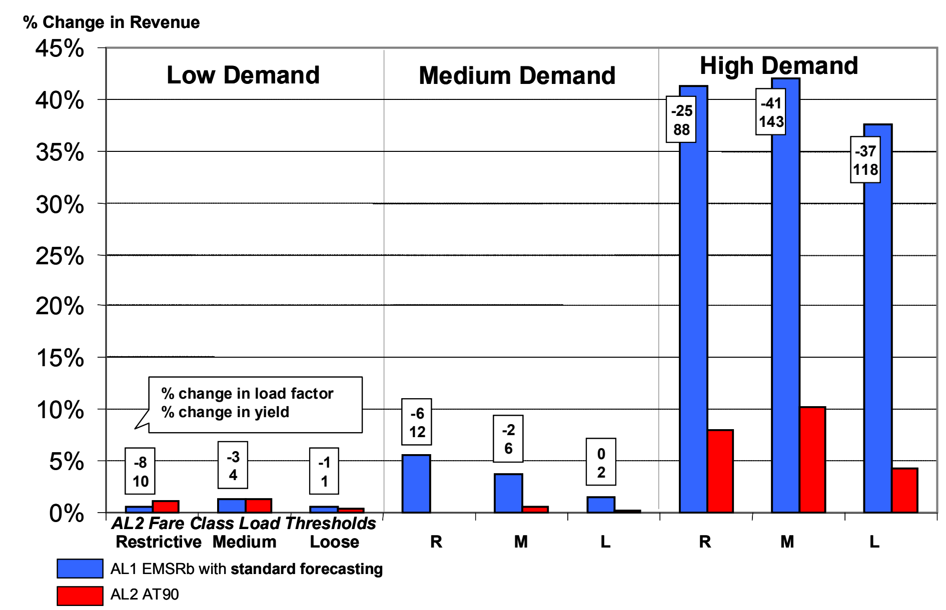


4.2.3 Impacts on Airline 1

In general, by Closure Matching Airline 2, Airline 1's yields rise more than load factors fall, leading to revenue improvements – these effects become more pronounced as demand rises and fare class load threshold targets tighten (Figure 4-6). The increase in demand impacts revenue improvements much more than the tightening of fare class load threshold targets.

FIGURE 4-6

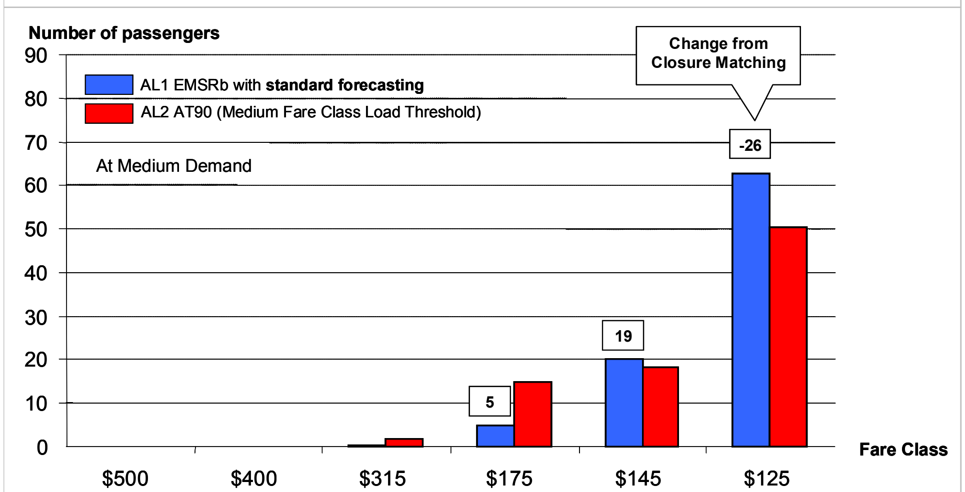
Changes in Revenues, Load Factors and Yields as AL1 Closure Matches



Looking at the specific situation of medium demand when Airline 2 has medium fare class load thresholds, as Airline 1 closure matches Airline 2, its fare class mix improves. Airline 1 sheds passengers from the cheapest fare class 6 to gain passengers in higher fare classes 4 and 5 (Figure 4-7, compare with Figure 4-4).

FIGURE 4-7

Fare Class Mix: With Closure Matching

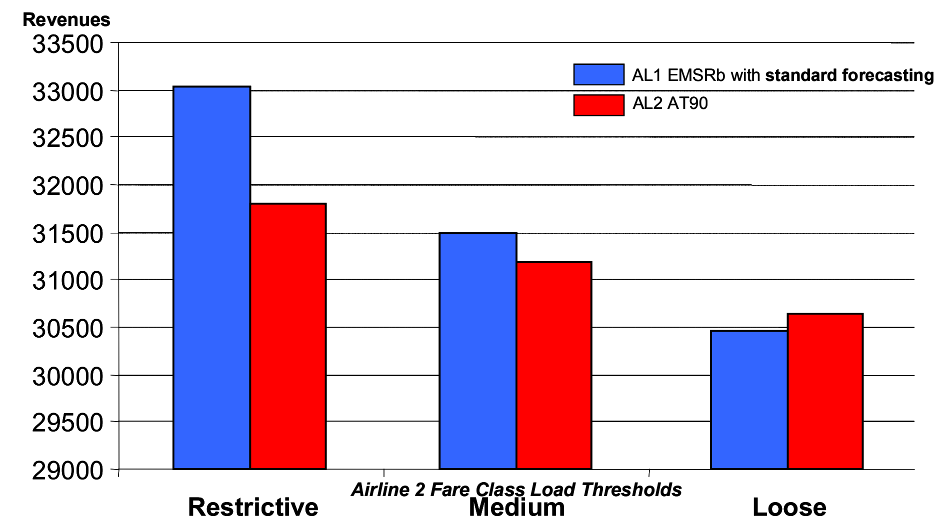


4.2.3.a Less Revenue-Effective at Low Demand

Closure Matching is less revenue-effective for Airline 1 at a low demand. This is because even before Closure Matching, Airline 2 already underperforms Airline 1 in terms of revenues when it has medium or restrictive fare class load thresholds (Figure 4-8). At this low demand, Airline 2 does poorly – it has load factors that range from 71% to 79%, even though its target is 90%. Airline 1, being less restrictive, took all the low-fare demand.

FIGURE 4-8

At Low Demand, AL2 Underperforms before Closure Matching

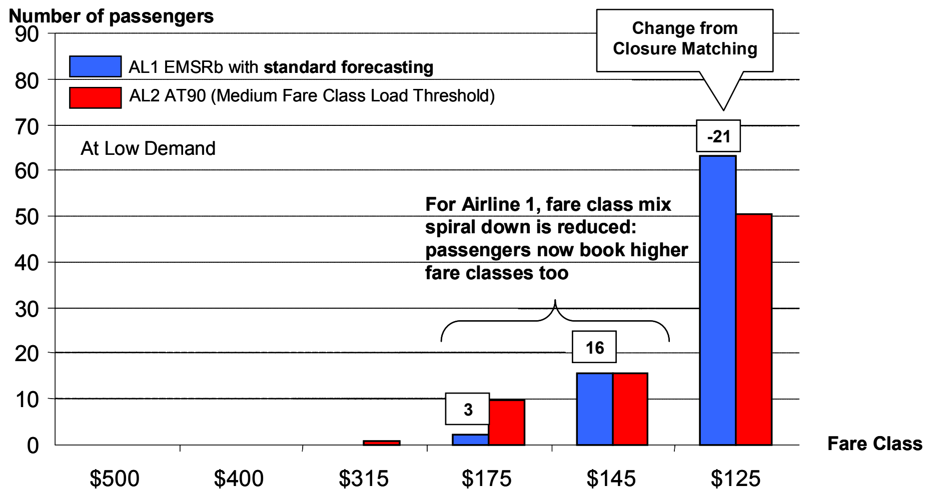


	Restrictive		Medium		Loose	
Load Factor	88.1	71.0	84.0	75.9	81.3	78.9
Yield	0.0893	0.098	0.0893	0.0978	0.0893	0.0924

When Airline 1 closure matches Airline 2's revenue management system, its yields still rise and its load factors fall as they should, and spiral down is reduced as demonstrated by the improved fare class mix (Figure 4-9). However, the improvement in yield is not much larger relative to the drop in load factor, so Airline 1 revenues increase by only between 0.51% and 1.23% with Closure Matching.

FIGURE 4-9

Fare Class Mix: with Closure Matching

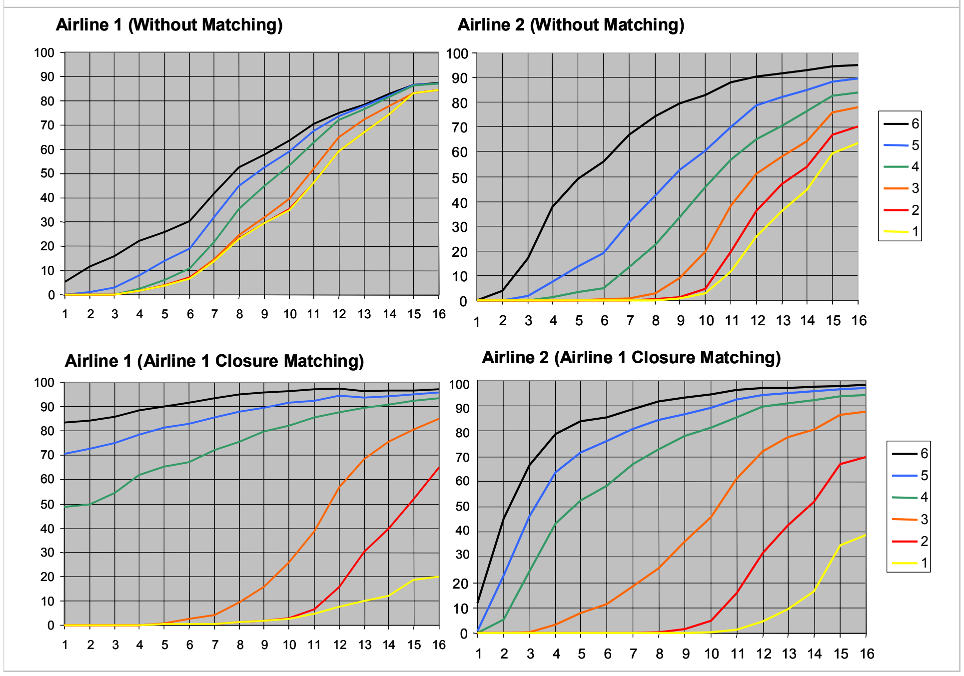


4.2.3.b Very Revenue-Effective at High Demand

At high demand, the benefits of Closure Matching are enormous for Airline 1, with revenues increasing by an average of about 40%, more than it had spiraled down from a semi-restricted fare environment. Airline 1's revenues also surpass those of Airline 2. Closure Matching by itself would not explain the dramatic improvements – from the fare class closure curves in Figure 4-10, we see that Airline 1 starts closing down fare classes 4 to 6 *more* aggressively than Airline 2. We also see that Airline 1 correspondingly closes fare classes 1 to 3 less aggressively. Closure Matching would only make Airline 1 *as* aggressive. As it turns out, Airline 1's standard forecasting builds on the effects of Closure Matching. By latching onto Airline 2's relatively rigid and more ideal fare class mix, Airline 1 moves into a reverse-of-spiral-down, or "spiral up" phenomenon at high demand: the better fare class mix leads to improved forecasts of bookings-to-come and more protection for higher fare classes, subsequently encouraging sell-up and eventually generating a better fare class mix again. Airline 1 is able to take advantage of the sell-up opportunities available at high demand that Airline 2's AT90 are not as capable of exploiting.

FIGURE 4-10

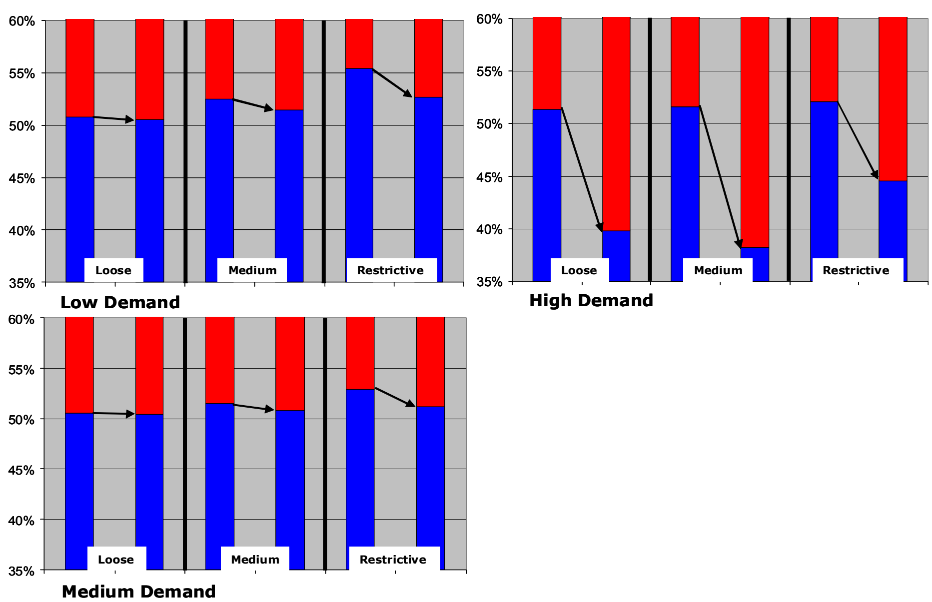
Fare Class Closure by Time Frames (At High Demand)



4.2.3.c Market Share

Although Airline 1's market share falls as it closure matches (Figure 4-11), it maintains approximately 50% market share at lower and medium demand levels. It is only at high demand that Airline 1's market share loss should be a worry, since market share falls by about 10% to about 40% with Closure Matching, compared to the spiral down base cases.

FIGURE 4-11



4.2.4 Impacts on Airline 2

Airline 2 benefits in terms of revenues as Airline 1 closure matches, especially at high demand (Table 4-4). In other words, Airline 1's revenue gains from Closure Matching Airline 2 are not at the expense of Airline 2. Airline 2's stable revenues can be attributed to its AT system, which is hardly affected by Closure Matching. In particular, its fare class thresholds ensure that it would not take many more low-fare passengers just because Airline 1 rejected them. At low and medium demand, Airline 2's revenues, yields, loads and fare class mixes are not significantly changed by Airline 1's matching, as shown in Table 4-4.

Table 4-4: Changes in Airline 2's Revenue, Yield, Load Factor and Fare Class Mix as Airline 1 Matches

Demand Level	Fare Class Load Thresholds	Revenue Change	Yield Change	Load Factor Change	Change in Number of Passengers in Fare Class					
					1 ($500)	2	3	4	5	6 ($125)
Low (0.80)	Restrictive	1.2%	-1.0%	2.2%	0.0	0.0	-0.7	0.2	2.0	0.0
	Medium	1.3%	0.1%	1.3%	0.0	0.0	-0.1	0.3	0.7	0.0
	Loose	0.4%	0.1%	0.4%	0.0	0.0	0.2	0.2	0.0	0.0
Medium (1.00)	Restrictive	0.0%	-0.8%	0.9%	0.0	0.0	-0.6	0.2	1.1	0.0
	Medium	0.6%	0.0%	0.6%	0.0	0.0	0.0	0.2	0.4	0.0
	Loose	0.2%	0.1%	0.2%	0.0	0.0	0.0	0.2	0.1	-0.1
High (1.20)	Restrictive	**8.0%**	**6.5%**	1.5%	0.0	1.4	3.7	0.2	-1.3	-2.7
	Medium	**10.2%**	**9.2%**	0.8%	1.1	2.6	2.2	0.2	-0.9	-4.4
	Loose	**4.3%**	**3.5%**	0.7%	0.4	1.2	0.5	0.6	0.1	-2.2

At high demand, Airline 2 load increases with Airline 1 Closure Matching are modest (rising by 0.7% to 1.5%), since it already reaches its target of 90% load factor before matching. Instead, its large yield increases (3.5% to 9.2%) drive the improvements in revenues (4.3% to 10.2%). Airline 2, the matched airline, benefits even as its rival Airline 1 performs better with Closure Matching – Table 4-4 illustrates that Airline 2's fare class mix leans towards a heavier percentage of higher fare class passengers.

By analyzing the changes in sources of revenues for Airline 2 as Airline 1 matches (shown in Table 4-5), we see that the revenue improvements come primarily from an increase in sell-up. With Airline 1 becoming more restrictive, Airline 2 also starts to close its lower fare classes earlier. This leads to more passengers being forced to buy a fare class higher than they wanted as a first choice.

Table 4-5: Sources of Changes in Revenue

Demand Level	Fare Class Load Thresholds	Change in Revenues (Summed across fare classes)				
		Total	First Choice	Sell-up	Recapture (Horizontal and Vertical)	Spill-in from Airline 1 (Horizontal and Vertical)
High (1.2)	Restrictive	3711	867	8132	-56	-5232
	Medium	4862	-4632	9453	-283	327
	Loose	2112	-4794	7451	-500	-46

4.2.5 Conclusions

The simulation results show that the effects of Availability Matching are not trivial. Closure Matching an AT90 system successfully decreases spiral down in the revenue management system based on standard forecasting and EMSRb. In general, Closure Matching allows the matching airline to experience an increase in yield that outweighs its loss in load factor. By shadowing a more restrictive system, the matching airline's system rejects more low-fare passengers in favor of fewer passengers that pay higher fares.

In this scenario, Closure Matching is not as effective at low demand because both the matching and matched airlines have almost equal revenues prior to matching. The nature of Closure Matching requires a well-performing revenue management system to latch onto.

The reduction in spiral down from Closure Matching is especially pronounced at high demand in this scenario. With Closure Matching, EMSRb with standard forecasting sets in motion a positive cycle of more sales, better forecasts and greater protection of higher fare classes, taking advantage of the fact that the AT90 system used by the competitor is less capable of exploiting high demand.

Except at high demand, Airline 1's loss of market share from Closure Matching is minor and not a cause of concern. At high demand, even though Airline 1's market share typically falls by 10%, these drops appear acceptable against the revenue gains from Closure Matching, which average 40%.

When Airline 2, the matched airline, uses AT90, it remains stable in face of Closure Matching. It does not lose revenue when Airline 1 gains revenues. In fact, at high demand, it obtains sizeable revenue increases of up to 10.2% because its yields rise significantly. The high demand combined with Airline 1 becoming more restrictive allows Airline 2 to force more sell-up.

4.3 EMSRB WITH STANDARD FORECASTING CLOSURE MATCHING EMSRB WITH Q-FORECASTING

In the second scenario that tests the hypothetical use of Closure Matching to reduce spiral down, Airline 2 uses EMSRb with Q-forecasting. EMSRb with Q-forecasting's key difference with AT90 is that it is more sophisticated and responsive to changes in demand. Q-forecasting is designed to encourage sell-up and counteract spiral down. Therefore, Airline 2 is expected to outperform Airline 1 by even more in the base scenarios without matching.

4.3.1 Inputs

For Airline 2's Q-forecasting capability, we first use the input Frat5s "C" that is an arbitrarily generated set of Frat5s. It demonstrates a medium willingness-to-pay. The willingness-to-pay increases monotonically as the date of departure approaches. Its details were explained earlier in Chapter 3.3.1.a and illustrated in Figure 3-4.

Since an airline would not have a ready set of Frat5s to use in real life, the runs are repeated with the Frat5s estimation method known as Average Conditional Forecast Prediction (**ACFP**). Airlines are able to estimate Frat5s with a method like ACFP, which approximates passengers' willingness-to-pay based on the lowest available fare in the market. This method was clarified in detail in Chapter 3.3.1.b. In short, ACFP is preferred over the other estimation methods because its estimates are conditional on the lowest competitor class open and therefore in line with rest of the simulation.

All the runs are duplicated in demand settings of low, medium and high.

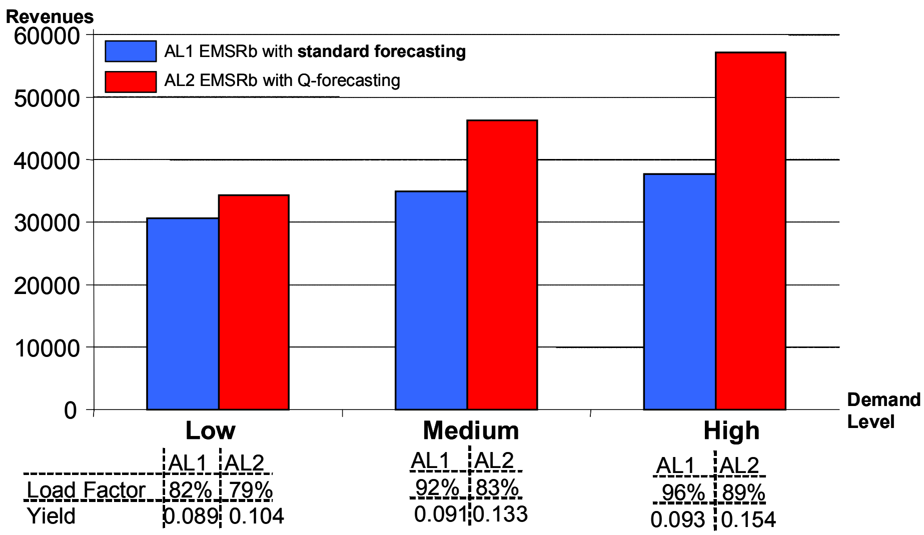
4.3.2 Base cases

For the outcomes resulting from the use of input Frat5s, Airline 1 underperforms Airline 2 because it has a less adept revenue management system. The difference becomes more pronounced as demand strengthens, as evident in Figure 4-12. At low demand, Airline 2 obtains 12% more revenue than Airline 1, but at high demand, Airline 2 achieves revenue that is one and a half times that of Airline 1's.

For each level of demand, Airline 1 has similar revenues to the previous scenario when Airline 2 uses AT90. As expected, using EMSRb with Q-forecasting, Airline 2 outperforms Airline 1 by more than when it uses AT90 (Figure 4-12, compare with Figure 4-5).

FIGURE 4-12

Base Cases Without Matching (Input Frat5 “C”)



The fare class mix (Table 4-6) shows that Airline 1’s revenue management system using standard forecasting spirals down to the lowest fare class consistently whereas Airline 2 successfully resists the degeneration of fare class mix. As such, Airline 1 has an incentive to closure match Airline 2, in order to approach the more ideal fare class mix Airline 2 gets.

Table 4-6: Fare Class Mix before Airline 1 Closure Matches Airline 2

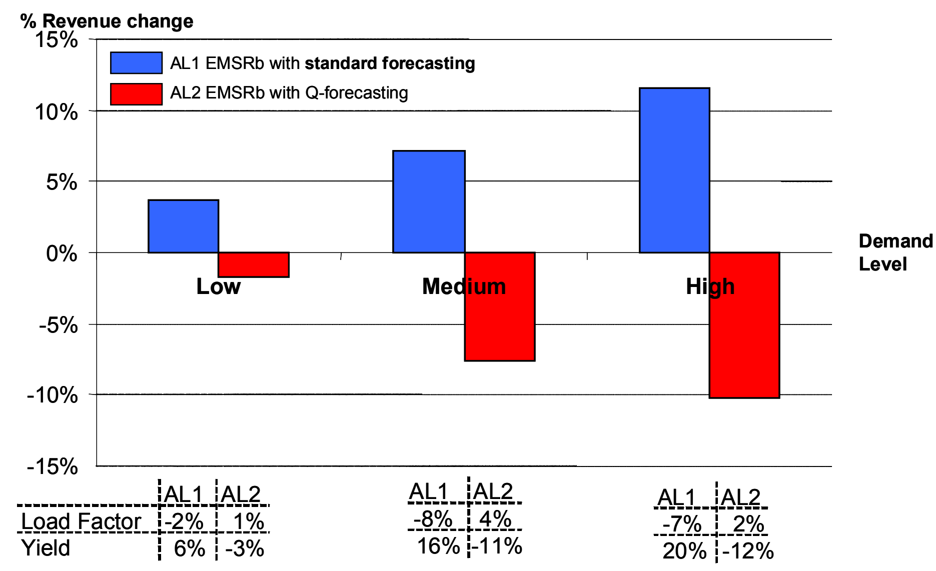
Demand Level	Airline	Number of Passengers in Fare Class					
		1 ($500)	2	3	4	5	6 ($125)
Low (0.80)	Airline 1	0.0	0.0	0.0	0.0	0.0	81.7
	Airline 2	0.7	0.6	3.9	5.3	7.2	60.8
Medium (1.00)	Airline 1	0.0	0.0	0.5	1.1	1.2	88.9
	Airline 2	1.0	3.5	13.0	19.3	17.7	28.4
High (1.20)	Airline 1	0.0	0.1	1.2	3.8	2.3	88.9
	Airline 2	1.9	6.1	20.1	29.2	17.2	14.2

4.3.3 Impacts on Airline 1

As Airline 1 closure matches Airline 2, it experiences positive revenue effects across the range of demands. These revenue increases become larger as demand increases (Figure 4-13), chiefly because the two airlines had a bigger revenue difference prior to Closure Matching (Figure 4-12).

FIGURE 4-13

Revenue Changes as Airline 1 Closure Matches (Input Frat5)



The Closure Matching manifests clearly as Airline 1's revenues rise, load factors fall and yields rise while the exact reverse happens to Airline 2 – Airline 1's figures converge towards Airline 2's figures, as shown in Table 4-7. Spiral down is reduced in Airline 1 and the fare class mixes of both airlines are now much more similar. That is especially true in fare classes 4 to 6, where the numbers for both airlines are very close. Spiral down in the matching airline is reduced at the expense of the matched airline.

Table 4-7: Metrics after Airline 1 Closure Matches Airline 2

Demand Level	Airline	Revenues	Load Factor	Yield	Number of Passengers in Fare Class					
					1 ($500)	2	3	4	5	6 ($125)
Low (0.80)	Airline 1	**335253**	79.8%	0.095	0.0	0.1	0.9	**5.0**	**7.3**	**66.5**
	Airline 2	**333134**	79.3%	0.101	0.4	0.6	2.7	**6.4**	**7.8**	**61.5**
Medium (1.00)	Airline 1	354639	84.4%	0.101	0.0	0.1	2.0	**18.3**	**29.0**	**35.0**
	Airline 2	360302	85.8%	0.119	0.7	2.1	6.5	**19.0**	**26.2**	**31.2**
High (1.20)	Airline 1	41987	89.6%	0.112	0.0	0.1	3.7	**26.6**	**35.7**	**23.5**
	Airline 2	51400	90.4%	0.135	1.5	3.8	11.3	**29.2**	**30.8**	**13.9**

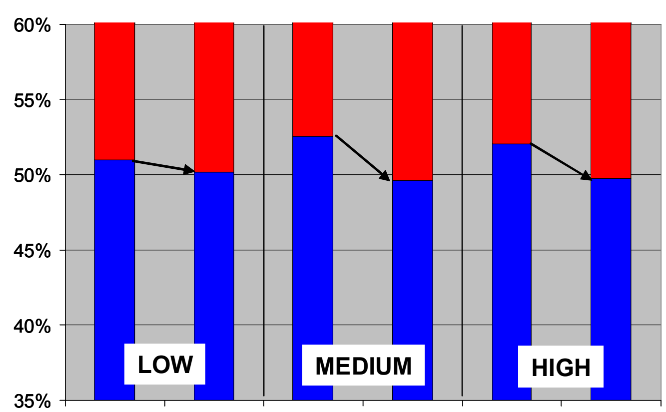
4.3.3.a Revenues Increase at High Demand

There is a large revenue increase of almost 12% when demand is high. However, the increase is still not as dramatic as those seen when Airline 1 was using EMSRb with standard forecasting and Closure Matching Airline 2's AT90 at high demand. It appears that the revenue management system of Airline 1 cannot build on Closure Matching Airline 2's EMSRb with Q-forecasting the same way it could with Airline 2 using AT90. For this scenario, post-matching, Airline 1's revenues remain below Airline 2's. The difference is probably because the EMSRb with Q-forecasting system adapts more to the competitor and demand, and would not let Airline 1 monopolize the high fare classes like AT90 allowed.

4.3.3.b Market Share

Airline 1's market share falls as it closure matches and becomes more restrictive (Figure 4-14), but it should not be a major concern as Airline 1 maintains approximately 50% market share.

FIGURE 4-14
Market Share Changes as Airline 1 Closure Matches



4.3.4 Impacts on Airline 2

Earlier, when Airline 2 used AT90, its revenues did not suffer from Airline 1's improved performance with Closure Matching. However, in this case, when Airline 2 uses a system based on EMSRb with Q-forecasting, its revenues are hurt by Airline 1 Closure Matching (Figure 4-13). At low demand, Airline 2's revenues even go below Airline 1's after Closure Matching.

Before Closure Matching, Airline 2 has a strong RM dominating Airline 1's weak RM, especially at high demand levels (Figure 4-12). With Closure Matching, Airline 1's system converges upon Airline 2's. Airline 2 loses revenues because it is flexible (more so than AT90) and therefore susceptible to competitive effects. It faces losses because its yields drop more than its load factors rise.

Table 4-8 demonstrates the greater flexibility of EMSRb with Q-forecasting and the associated vulnerability to competitive effects caused by availability matching. The fluctuations in the number of passengers in Airline 2's fare classes caused by Closure

Matching are much greater compared to the mild changes experienced when Airline 2 used AT90 at the corresponding level of demand (Table 4-4).

Table 4-8: Changes to Airline 2's Revenue, Yield, Load Factor and Fare Class Mix as Airline 1 Closure Matches

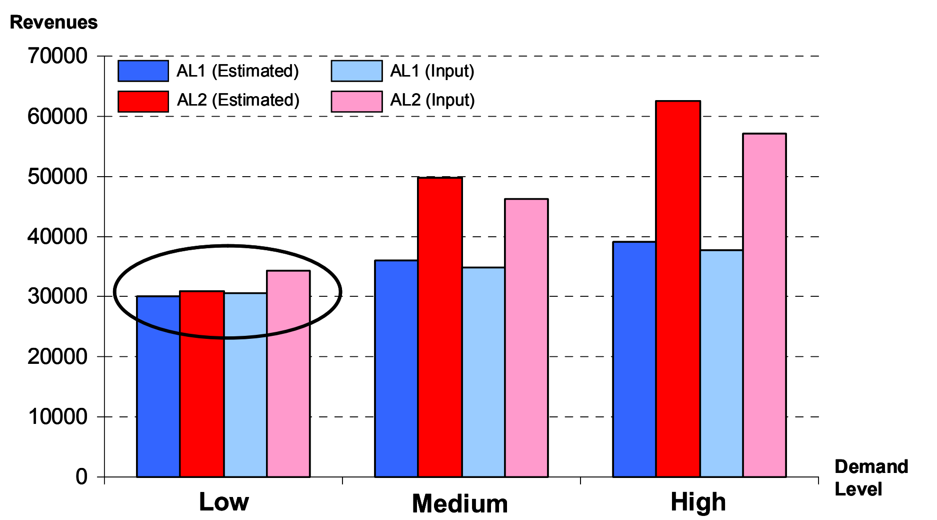
Demand Level	Revenue Change	Yield Change	Load Factor Change	Change in Number of Passengers in Fare Class					
				1 ($500)	2	3	4	5	6 ($125)
Low (0.80)	-1.7%	-2.6%	1.0%	-0.3	0.0	-1.2	1.1	0.6	0.7
Medium (1.00)	-7.6%	-10.8%	3.5%	-0.3	-1.4	-6.5	-0.3	8.5	2.8
High (1.20)	-10.3%	-12.0%	2.0%	-0.4	-2.3	-8.8	0.0	13.6	-0.3

4.3.5 Results Obtained using Estimated Frat5s

Overall, the base cases obtained using estimated Frat5s are similar to the input Frat5s base cases, as shown in Figure 4-15. The only exception occurs at low demand when Frat5s are estimated – Airline 2 achieves revenue similar to Airline 1 even though Airline 2 has Q-forecasting. It is likely that the Frat5s are underestimated. Like standard forecasting, Q-forecasting fails to prevent spiral down at low demand when Frat5s are underestimated, since the protection of seats are still from the top fare class down.

FIGURE 4-15

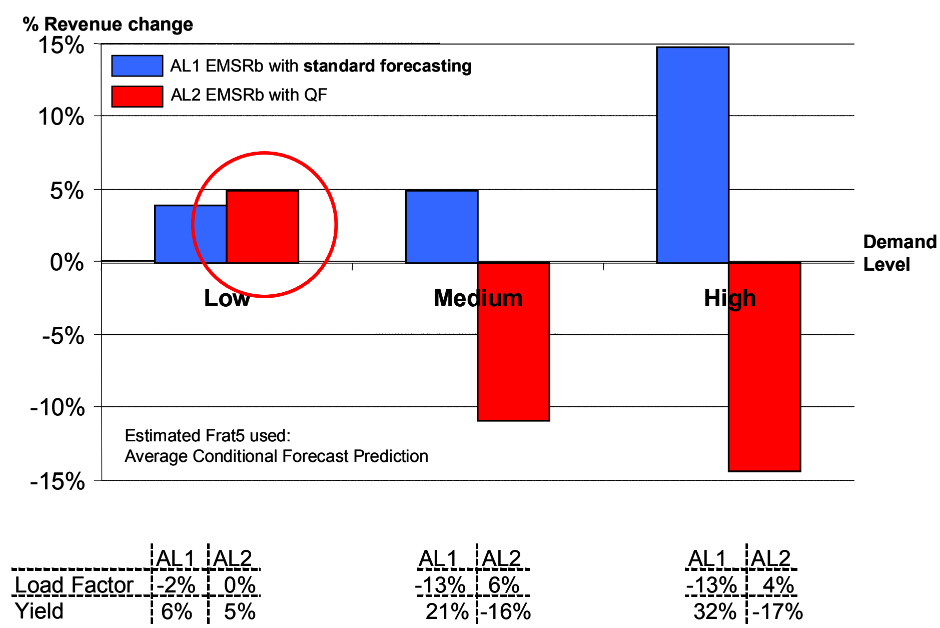
Base Cases without Matching (Estimated cf. Input)



Similarly, for the revenue changes, there is one significantly different result when Frats5s are estimated (circled in Figure 4-16). It is also at low demand, for Airline 2. Airline 2 gains 4.6% in revenues because its load factor drops by 0.4% while its yield rises by 4.9%, even though the reverse should happen.

FIGURE 4-16

Revenue Changes as Airline1 Closure Matches (Estimated Frat5)



When Frat5s are estimated, after being closure matched by Airline 1, unlike when input Frat5s are used, Airline 2 goes through unusual changes: it loses passengers in the lowest fare class but gains passengers in the higher fare classes (Table 4-9).

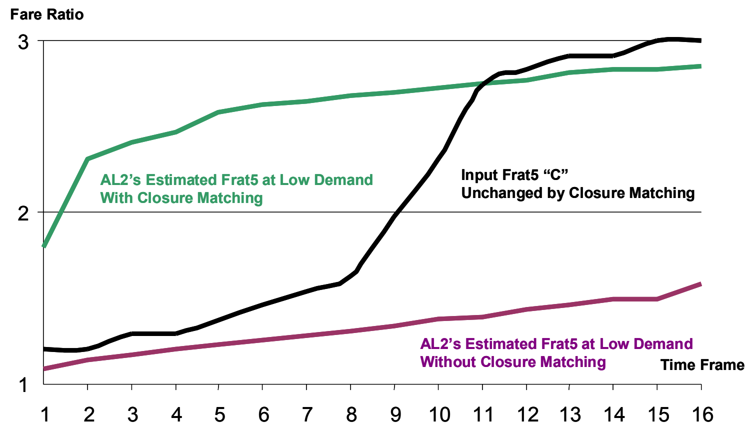
Table 4-9: Changes to Airline 2's Revenue, Yield, Load Factor and Fare Class Mix as Airline 1 Closure Matches (Estimated Frat5s)

Demand Level	Revenue Change	Yield Change	Load Factor Change	Change in Number of Passengers in Fare Class					
				1 ($500)	2	3	4	5	6 ($125)
Low (0.80)	**4.6%**	4.9%	-0.4%	0.2	0.1	1.0	3.0	4.0	-8.5
Medium (1.00)	-10.9%	-16%	6%	-0.6	-2.0	-11.4	5.7	11.9	1.2
High (1.20)	-14.4%	-17%	4%	-1.7	-3.8	-14.5	18.0	5.1	-0.2

At low demand, without matching, Airline 2 is not sufficiently protective because it underestimates the Frat5s. Estimated Frat5s change according to the demand and supply, unlike the input Frat5s that remain the same. As Airline 1 Closure Matches and becomes more restrictive, Airline 2 estimates a higher set of Frat5s (Figure 4-17). Consequently, Airline 2 gains revenue with Closure Matching instead of being hurt by it. This exception illustrates the problems of estimating willingness-to-pay and Frat5s.

FIGURE 4-17

Frat5 Changes as Airline1 Closure Matches



Frat5 estimation is more accurate at medium and high demand and less affected by Closure Matching. At those demand levels, the outcomes are similar regardless of whether Frat5s are input or estimated (Figure 4-16).

4.3.6 Conclusions

Closure Matching is also effective in reducing spiral down and increasing revenues of Airline 1 when the matching target, Airline 2, uses EMSRb with Q-forecasting. There are three other similarities with the earlier scenario (when Airline 2 used AT90): Closure Matching allows Airline 1 to improve its yield by a factor that more than offsets the fall in loads, Closure Matching becomes more effective as demand increases and Airline 1's market share losses are negligible.

The two major differences with the earlier scenario can be attributed to the responsiveness of Airline 2's revenue management system of EMSRb with Q-forecasting. Firstly, Airline 1 is unable to reap incredible 35% to 45% gains in revenues at high demand because Airline 2 is no longer the relatively passive AT90. Secondly, compared to the earlier AT90, the EMSRb with Q-forecasting system gets hurt much more by Closure Matching because its forecasts and allocation are more affected by the matching.

Overall, the results obtained using estimated Frat5s are similar to those from input Frat5s, with an exception at low demand, where estimating Frat5 is problematic.

4.4 EMSRB WITH Q-FORECASTING OPEN MATCHING AT90

Moving away from the hypothetical scenarios, I will now examine the more realistic applications of availability matching – where an airline with a more advanced revenue management system matches the low fare seat availability of an airline with a simple system. In response to the bargain-hunting consumer behavior brought by the growth of the LCC and the Internet distributors, legacy airlines, with their advanced revenue management systems, match low fare availability to be displayed earlier in fare searches. They are wary of ceding market share that would encourage further LCC growth, although the outcomes of such matching are unclear.

To represent an advanced revenue management system used by a legacy airline, Airline 1 is assigned a system of EMSRb with Q-forecasting. Airline 2 uses the simple AT90 system, representing a more basic LCC system.

There are three possible forms of lowest fare seat availability matching. This section examines the first – Open Matching. A legacy airline may open match a LCC when it wants to ensure that it shows up as the lowest fare on airfare searches. Open Matching causes the legacy airline to be at least as open and available as the LCC and retain market share among low-fare passengers, against low-priced competitors. The downside of Open Matching is that fewer seats are protected for higher-fare passengers. The two other forms – Closure Matching and Bi-directional Matching – will be covered in the sections 4.5 and 4.6 respectively.

4.4.1 Inputs

Airline 1 first uses input Frat5s "C" and then uses estimated Frat5 method ACFP. For Airline 2's AT90, I will vary the fare class load thresholds between loose, medium and restrictive. Runs are performed across low, medium and high demand levels.

Specifically for the Open Matching, I will simulate an even lower demand (0.60 scaling). The reason is to test the hypothesis that an airline Open Matching at such low demand would deny passengers from the competitor while hurting its own revenues. The airline trusts its more capable revenue management system and knows that certain competitors have either a basic revenue management system or lack a formal one.

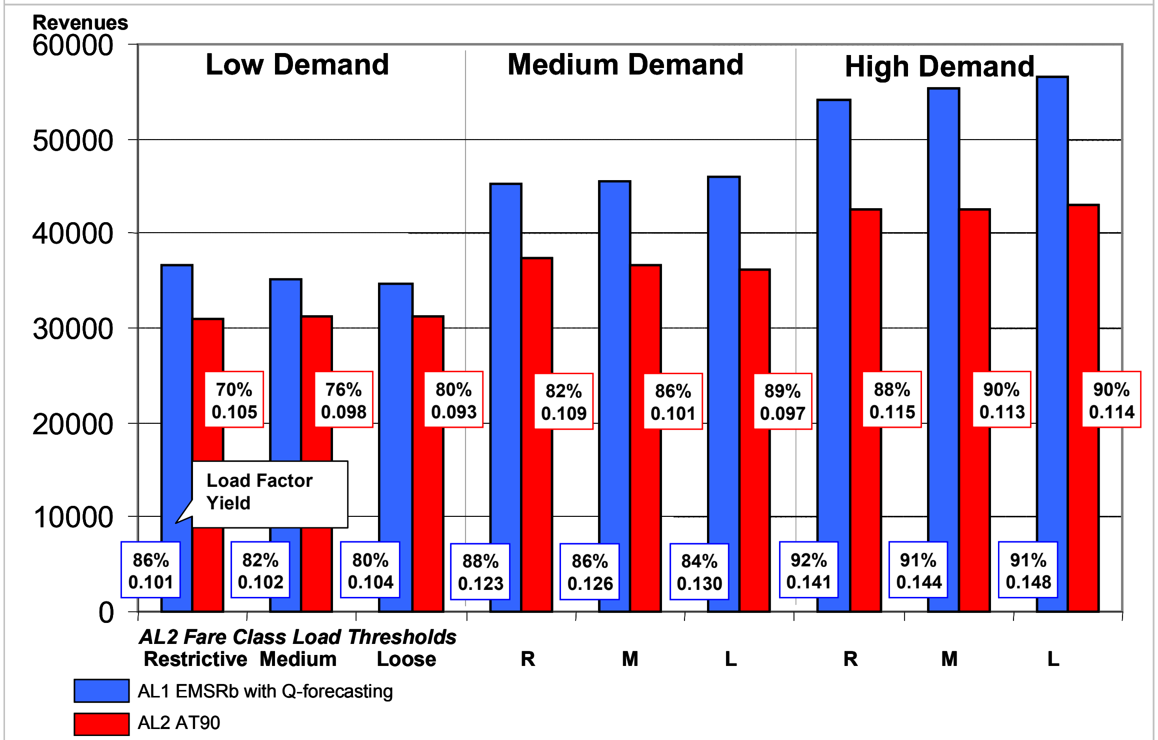
4.4.2 Base Cases

The base cases are where there is no seat availability matching – they are the same for Open Matching, Closure Matching and Bi-directional Matching. In other words, the base cases described here are valid for chapters 4.4, 4.5 and 4.6.

As expected, Airline 1's EMSRb with Q-forecasting outperforms Airline 2's AT90 consistently in terms of revenue (Figure 4-18). Airline 1 achieves superior yields with the singular exception when demand is low and Airline 2 is using restrictive fare class load thresholds. Airline 1 always has an equal or higher load factor than Airline 2.

FIGURE 4-18

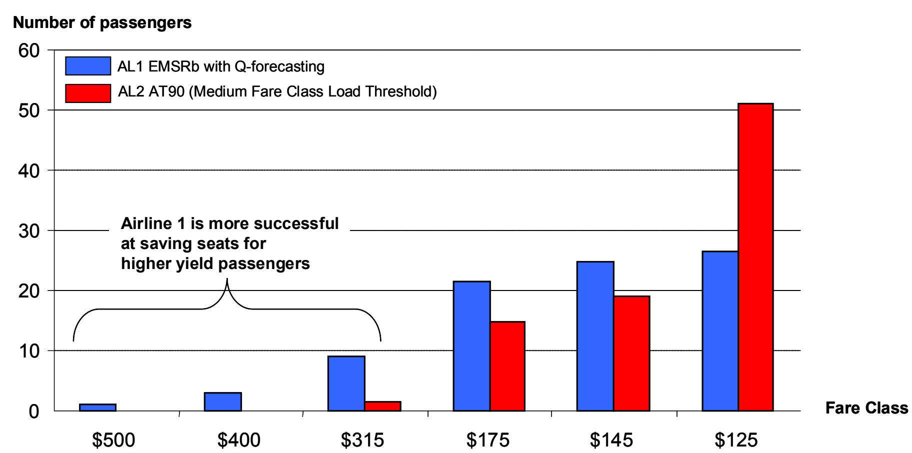
Base Cases Without Matching (Input Frat5)



Airline 1's intelligent RM system is more successful in saving seats for higher-yield passengers, as seen in the fare class mix example shown in Figure 4-19.

FIGURE 4-19

Fare Class Mix: at Medium Demand without Open Matching



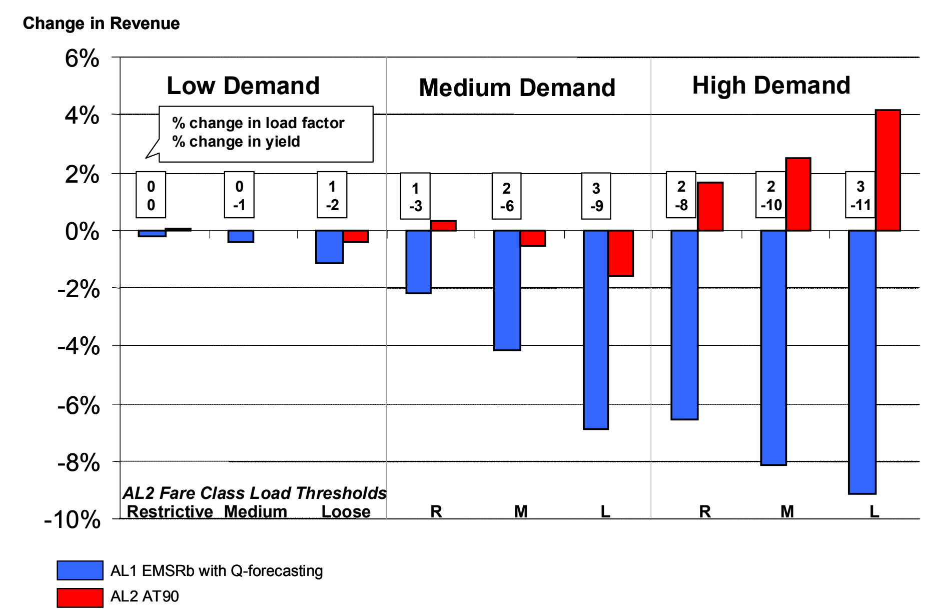
4.4.3 Impacts on Airline 1

In this scenario, Open Matching – the selective overriding of an advanced revenue management system by re-opening closed fare classes to match the competitor's lowest available fare – causes Airline 1's revenues to fall consistently. The falls become greater as demand levels rise and fare class threshold tighten, by as much as 9.2% (Left to right on Figure 4-20). Although Airline 1's load factor is boosted by additional low-fare passengers, its yield suffers because the high-fare passengers buy down to cheaper fare classes or fail to book as a result of fewer seats protected for them. In other words, even when Airline 1 sees an increase in the number of passengers in lowest fare class, these passengers are either customers who used to buy higher fares but are now able to book at a lower fare class or travelers with low willingness-to-pay who displace the higher-fare passengers arriving later.

Airline 1's revenues fall from Open Matching by a greater percentage as demand increases. At a high demand, without Open Matching, Airline 1's revenue management system acts effectively to close down cheaper fare classes faster while Airline 2's relatively inflexible system is less able to take advantage of the situation. This means that as Airline 1 open matches Airline 2, more overriding and sub-optimal adjustment occurs. More closed fare classes are re-opened than compared to the low demand level, resulting in the steeper drops in revenues.

FIGURE 4-20

Changes as Airline 1 Open Matches

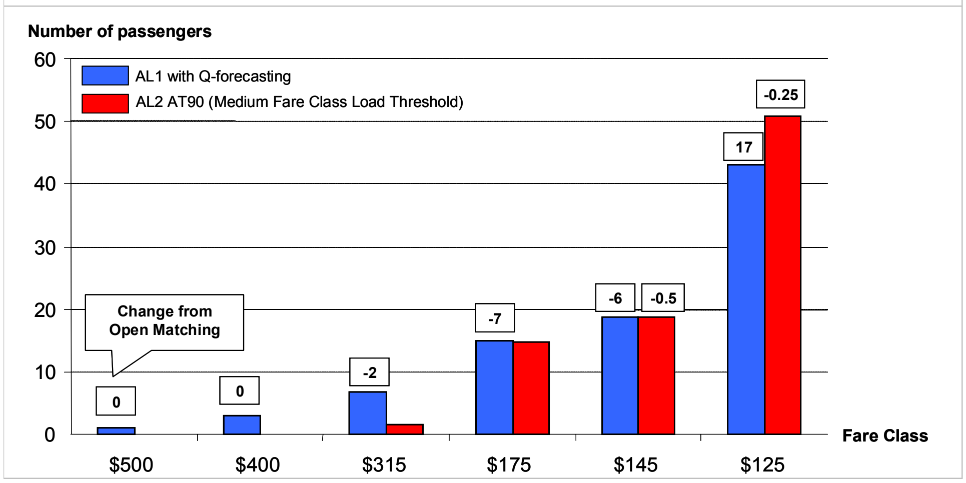


As Airline 2's fare class load thresholds become looser, Airline 1 is Open Matching an increasingly less restrictive Airline 2, causing Airline 1's revenues to decrease by larger amounts as the intervening Open Matching prevails more over the optimizing revenue management system. The drops in yield outpace the rises in load factors. Figure 4-20 shows that the impact of demand is stronger than that caused by the differences in fare class load thresholds.

For example, where demand level and fare class threshold levels are both medium, the fare class mix shifts towards lower fare classes. The higher fare classes 3, 4 and 5 decrease in number of passengers while the lowest fare class 6 sees a big increase (Figure 4-21).

FIGURE 4-21

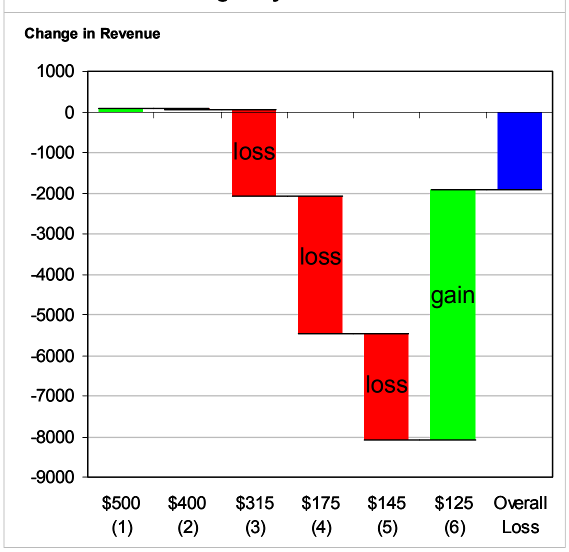
Fare Class Mix: at Medium Demand with Open Matching



Airline 1's load factor improves by 2%, but is unable to offset the erosion of yield (-6%). Although revenue gains from the cheapest fare class 6 are impressive, the cumulative losses from the next four higher fare classes are even greater (Figure 4-22) – leading to an overall loss.

FIGURE 4-22

AL1 Revenue Changes by Fare Class

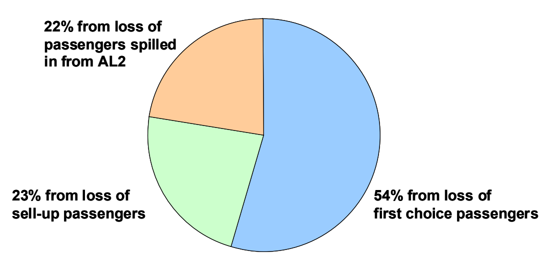


In order to be as available as Airline 2, with Open Matching Airline 1 keeps fare class 6 open for much longer than without matching, allowing it to get extra passengers and revenues in that fare class.

For Airline 1's fare classes (2, 3, 4 and 5) that decreased in revenues after Open Matching, the dominant reason, accounting for 54% of lost revenues, is the loss of first choice passengers (Figure 4-23). These passengers who used to select one of fare classes 2 to 5 as their first choice now either buy from a lower fare class that has become available or are spilled to Airline 2. Similarly, Airline 1 sees a drop in revenue because there is now less sell-up for higher fares, since availability of low fares mean passengers are no longer forced to sell-up. Sell-up refers to passengers buying a higher fare class when denied a lower fare class booking. There is also less spill-in from Airline 2 for these higher fare classes.

FIGURE 4-23

Sources of Losses



4.4.3.a Market Share

With increased load factors brought by Open Matching, Airline 1 improves its market share across demand levels and fare class load thresholds, though the improvements are slight. In other words, Airline 1 does not capture much market share from Airline 2 through Open Matching. The greatest increase is only 0.88%, which happens when demand is medium and fare class load thresholds are loose (Table 4-10).

Table 4-10: Market Share with Open Matching (and without Open Matching)

	Low Demand (0.80)			Medium Demand (1.00)			High Demand (1.20)		
	Restrictive	Medium	Loose	Restrictive	Medium	Loose	Restrictive	Medium	Loose
Market Share	55.14% (55.12%)	51.98% (51.94%)	50.05% (49.83%)	52.10% (51.82%)	50.51% (49.81%)	49.61% (48.73%)	51.35% (50.94%)	51.03% (50.42%)	50.95% (50.30%)
Change	0.02%	0.04%	0.22%	0.28%	0.70%	0.88%	0.41%	0.61%	0.65%

4.4.4 Impacts on Airline 2

Although Airline 2 is hurt, ironically it loses less revenue than Airline 1 in all of the simulated settings (Figure 4-20). At medium and low demand, when Airline 2 has medium or loose fare class load thresholds, its revenues decrease slightly when open matched. In these situations, Airline 2 loses passengers in the lower fare classes 5 and 6 as Airline 1 intended, since Airline 1 no longer spills passengers in these classes over to Airline 2 because of Open Matching. Moreover, Airline 2 does not fill the additional empty seats with higher-yield passengers because its fare class load threshold is not sufficiently restrictive – incoming passengers are still booked in lower fare classes that remain open. Regardless, the magnitude of revenue decreases is slight, with the greatest loss capped at -1.6%.

Airline 2 even improves its revenues in some situations, when it becomes sufficiently restrictive. With Open Matching, Airline 1 sells out its inventory faster than before, so more late booking, higher yield passengers are spilled to Airline 2. With stricter thresholds, Airline 2 gains revenues by channeling these passengers to higher fare classes. In addition, at high demand, Airline 2's system adapts to the increased demand and performs even better by rejecting low-fare passengers for higher-fare ones.

4.4.5 Even Lower (0.60) Demand

Perhaps where there is insufficient demand to satisfy both Airline 1 and Airline 2, Airline 1 would consider Open Matching a tactic – fighting for low-fare passengers with Airline 2 by Open Matching so that Airline 2 cannot fill its seats. Airline 1's revenues would still be boosted by high-fare bookings as a result of its advanced revenue management system, while Airline 2 would only have insufficient low-fare bookings.

The simulation results suggest that at a lower demand level (0.60), there is little opportunity for Open Matching (Table 4-11). The legacy carrier's sophisticated revenue management system will keep low fare class open anyway when demand is low.

Table 4-11: At Lower (0.60) Demand, Figures Hardly Change with Open Matching (Input Frat5s)

Fare Class Load Thresholds of Airline 2	Airline	Revenue Change	Yield Change	Load Factor Change	Change in Number of Passengers in Fare Class					
					1 ($500)	2	3	4	5	6 ($125)
Loose	Airline 1	-0.09%	-0.11%	0.00%	0.00	0.00	-0.01	-0.09	-0.08	0.16
	Airline 2	0.01%	0.00%	0.02%	0.00	0.00	0.00	0.00	0.00	0.00
Medium	Airline 1	-0.13%	-0.11%	0.01%	-0.01	0.00	-0.02	-0.2	0.12	0.11
	Airline 2	0.01%	0.00%	0.00%	0.00	0.00	0.00	0.01	0.00	0.00
Restrictive	Airline 1	-0.07%	-0.11%	0.01%	0.00	0.00	-0.01	-0.24	0.23	0.04
	Airline 2	0.05%	0.10%	0.02%	0.00	0.00	0.01	0.01	-0.01	0.00

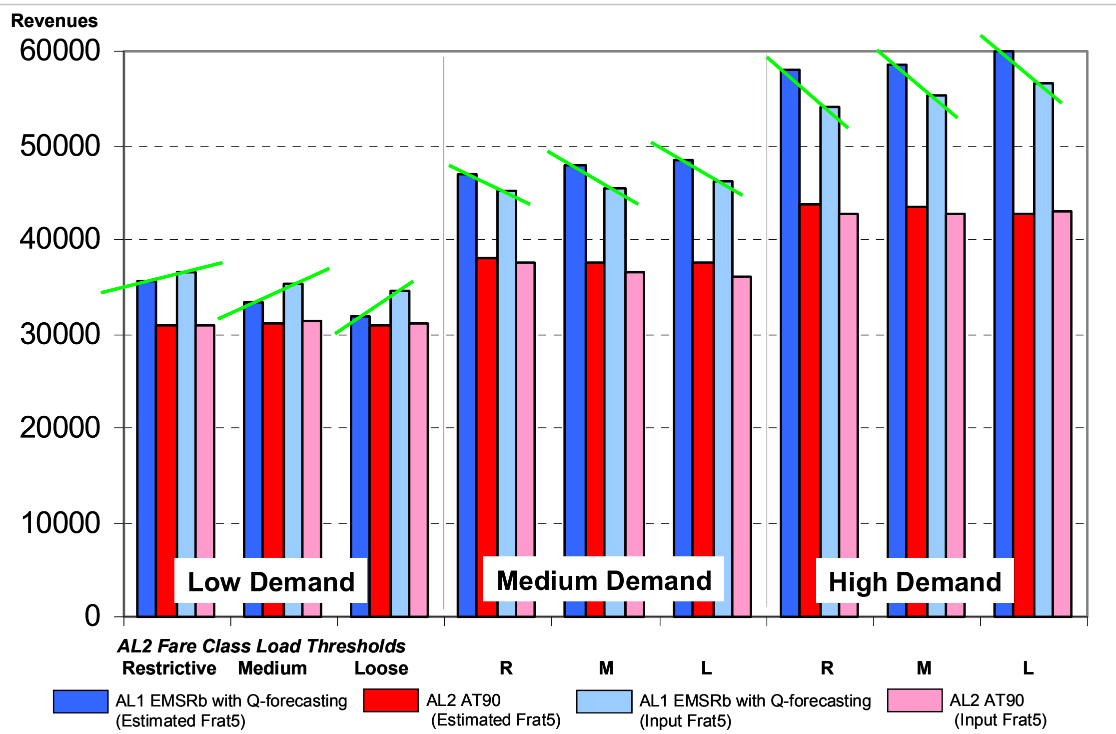
4.4.6 Results Obtained using Estimated Frat5s

Compared to the base cases obtained when Airline 1 used input Frat5s, the base cases generated when Airline 1 uses estimated Frat5s are similar in a qualitative sense – Airline 1 does better than Airline 2 (Figure 4-24).

Quantitatively, Airline 2's revenues achieved with AT90 are consistent whether Airline 1 used input or estimated Frat5s. At low demand, Airline 1's revenues are lower when using estimated Frat5s instead of inputting them. As explained earlier, the lower revenues reflect the difficulty of estimating Frat5s. The reverse happens at medium and high demand – Airline 1 does better with estimated Frat5s than input Frat5s.

FIGURE 4-24

Base Cases without Matching (Estimated cf. Input)

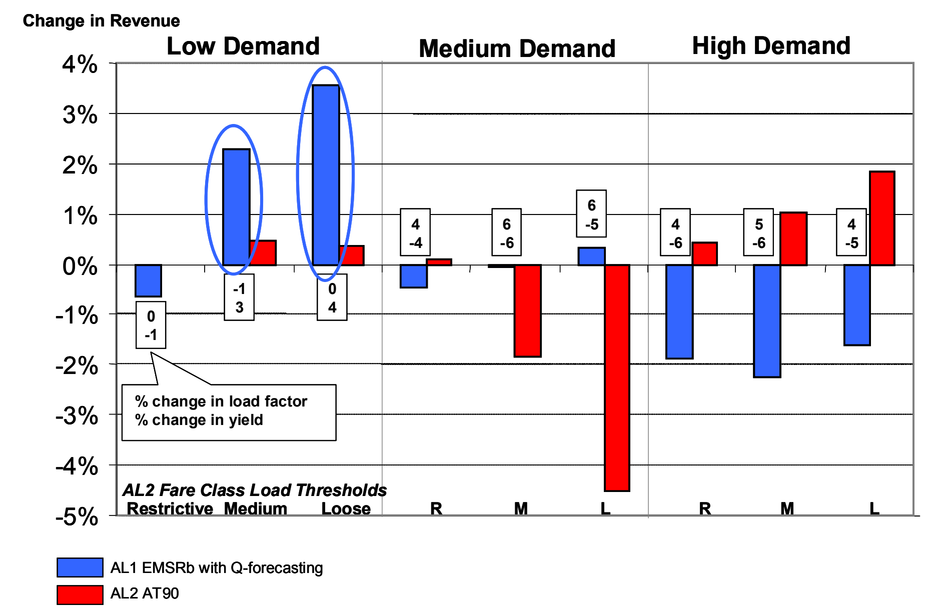


From these differences in base case revenues, Open Matching is expected to hurt Airline 1 less (with estimated Frat5s instead of input Frat5s) at low demand levels since Airline 1 starts off with figures that are closer to Airline 2's. Conversely, we expect Open Matching to hurt Airline 1 more at medium and high demand.

With estimated Frat5s, the changes caused by the legacy airline Open Matching the LCC exhibit less stability (Figure 4-25, compare with Figure 4-20). The legacy airline only does consistently worse with Open Matching at high demand.

FIGURE 4-25

Changes as Airline 1 Open Matches (Estimated Frat5)



At low demand, Airline 1 gains surprising improvements in revenues and yields. These counter-intuitive improvements are derived from the fare class mix improvements, as shown in Table 4-12. Airline 1 becomes more restrictive with Open Matching at low demand and medium/loose thresholds. These anomalies indicate the complications of estimating Frat5s at low demand.

Table 4-12: Fare Class Mix Improvements for Airline 1 at Low Demand (Estimated Frat5s)

Demand Level	Threshold Levels	Airline	1 ($500)	2	3	4	5	6 ($125)
Low Demand	Medium Thresholds	Airline 1	0.13	0.3	0.66	1.23	0.79	-3.75
		Airline 2	0	0	-0.01	0.1	0.16	0.07
	Loose Thresholds	Airline 1	0.15	0.33	1.05	1.18	0.55	-3.58
		Airline 2	0	0	0	0.04	0.13	0.07

4.4.7 Conclusions

Open Matching hurts the matching Airline 1 more than the matched Airline 2. The more Open Matching occurs, the greater the damage to Airline 1, so Open Matching causes the greatest revenue loss at high demand and when Airline 2 uses loose fare class load thresholds. The least damage occurs at the lowest (0.60) demand simulated, since almost no Open Matching takes place then.

Even though Open Matching allows the Airline 1 to gain passengers in lower fare classes, those increases in revenues are insufficient to compensate for the loss of revenues from higher fare classes. Airline 1's revenue management system, though sophisticated, is unable to repair the disruption caused by Open Matching. The increases in market share are insignificant, especially in light of the costs incurred to obtain them.

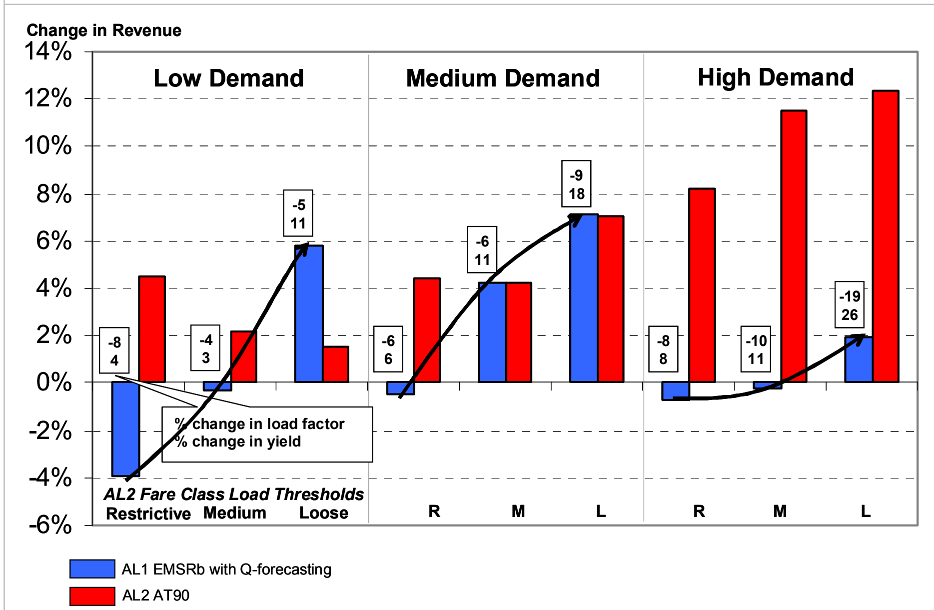
4.5 EMSRB WITH Q-FORECASTING CLOSURE MATCHING AT90

Closure Matching allows Airline 1 to shut down the lowest fare class as soon as that fare is no longer available Airline 2. Such availability matching represents an Airline 1 that only wants a low fare seat to be available when it is also available at Airline 2.

4.5.1 Impacts on Airline 1

Figure 4-26 illustrates that the changes caused by Closure Matching display an obvious positive trend moving from restrictive to loose thresholds but no definite trend moving from low to high demand.

FIGURE 4-26
Changes as Airline 1 Closure Matches



4.5.1.a Revenue Losses at Restrictive Thresholds

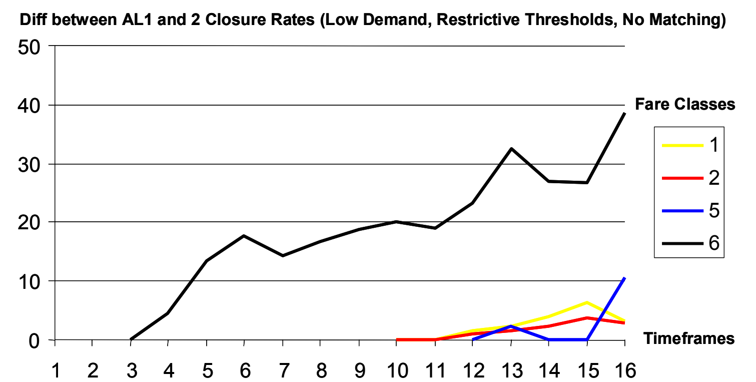
When Airline 2 uses restrictive thresholds, Airline 1 overrides the optimal closure levels determined by its revenue management system and becomes overly restrictive with Closure Matching. Although it gains 4% to 8% in yield, it loses 6% to 8% in load factor, resulting in overall losses in revenues.

Example: At Low Demand

An approximation of the Closure Matching rates is obtained by subtracting Airline 1's base case closure rates from Airline 2's base case closure rates. For example, at low demand and restrictive thresholds, since Airline 2 is closing down fare classes 1, 2, 5 and 6 faster than Airline 1 (Figure 4-27), Closure Matching is expected to cause Airline 1 to increase closure rates in those fare classes by about the differences shown. The differences are very large, going up to as much as 40%, because Airline 2 has restrictive fare class load thresholds.

FIGURE 4-27

Difference between Airline 1 and 2 Closure Rates in Base Case



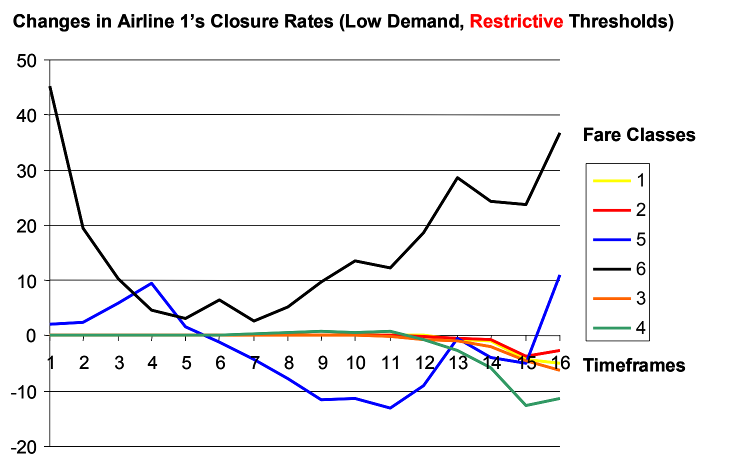
The change in Airline 1's fare class mix from Closure Matching (Table 4-13) suggests that it probably becomes more restrictive in fare classes 2 and 6, as expected. The loss of revenue from fare class 6 is crucial in causing the overall loss in revenues. At the same time, Airline 1 becomes less restrictive in fare classes 1 and 5.

Table 4-13: Airline 1's Change in Fare Class Mix from Closure Matching (Restrictive Thresholds)

Demand Level	Threshold Levels	Airline	Change in:	1 ($500)	2	3	4	5	6 ($125)
Low Demand	Restrictive Thresholds	Airline 1	Average number of Pax	0.1	-0.2	0.4	1.4	10.4	-18.8
			Average Revenues	$57	-$84	$136	$240	$1512	-$2342

FIGURE 4-28

Changes in Airline 1's Closure Rates as it Closure Matches



Airline 1's changes in closure rates (Figure 4-28) exhibit very similar trends to the expected Closure Matching rates (Figure 4-27) for fare classes 5 and 6 in the later time frames. However, Airline 1's revenue management system incorporates these later external increases in closures and compensates for them by opening up fare class 5 more before the Closure Matching takes place. Although the revenue management system increases Airline 1's number of passengers and revenues in fare class 5 (Table 4-13), it is insufficient to offset the loss of revenues from fare class 6. Airline 1's revenues decrease overall – Closure Matching a restrictive Airline 2 causes too much overriding that Airline 1's revenue management system cannot bring back to balance.

4.5.1.b Revenue Gains at Loose Thresholds

On the other hand, when Airline 2 uses loose thresholds, Airline 1 gains revenues through Closure Matching. Although its load factors fall by 5% to 19%, its yields rise by more – by 11% to 28%.

Example: At Low Demand

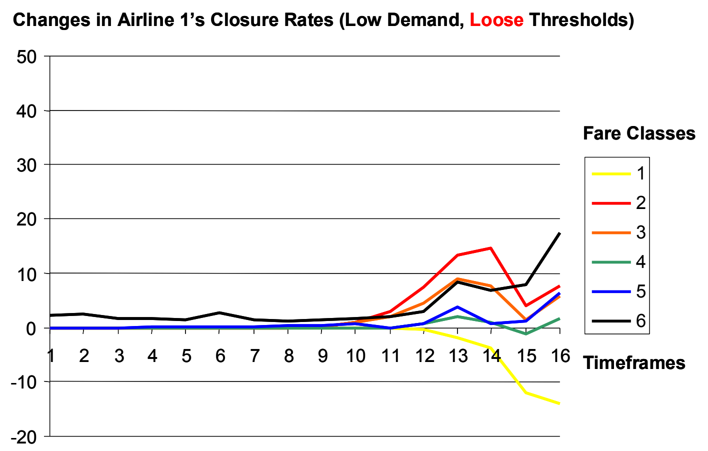
When Airline 2 is relatively less restrictive, Airline 1 closure matches relatively less. Table 4-14 shows that the changes in Airline 1's fare class mix from Closure Matching an Airline 2 with loose thresholds happen on a smaller scale. The increases and decreases are limited to fewer than 10 passengers, in contrast to the much larger shifts of almost 19 passengers experienced when the thresholds were restrictive (Table 4-13).

Table 4-14: Airline 1's Change in Fare Class Mix from Closure Matching (Loose Thresholds)

Demand Level	Threshold Levels	Airline	1 ($500)	2	3	4	5	6 ($125)
Low Demand	Loose Thresholds	Airline 1	**5.1**	-1.1	-2.9	0.8	2.0	**-7.5**

Figure 4-29 illustrates that the changes in closure rates of Airline 1 when Airline 2's thresholds are loose are limited to 20%, as opposed to the changes that exceed 40% in the case of restrictive thresholds. Moreover, the Closure Matching tends to occur much later, from time frame 10 onwards. Since more bookings have already been made by then, Closure Matching is less disruptive of Airline 1's optimized revenue management system.

FIGURE 4-29
Changes in Airline 1's Closure Rates as it Closure Matches



4.5.1.c Market Share

Airline 1's market shares fall when it closure matches. The changes in market share as the legacy airline closure matches is of much greater magnitude (Table 4-15) than when it open matches (Table 4-10). For example, at high demand and loose thresholds, Airline 1 loses 6% in market share.

Although Airline 1 maintains approximately 45% to 50% market share, in many of these situations it loses both market share and revenues (highlighted in Table 4-15)

Table 4-15: Market Share with Closure Matching (and without Closure Matching)

	Low Demand (0.8)			Medium Demand (1.0)			High Demand (1.2)		
	Restrictive	Medium	Loose	Restrictive	Medium	Loose	Restrictive	Medium	Loose
Airline 1	52.10% (55.14%)	50.55% (51.98%)	48.34% (50.05%)	49.42% (52.10%)	47.74% (50.51%)	46.27% (49.61%)	48.62% (51.35%)	47.59% (51.03%)	44.95% (50.95%)
Change	-3.04%	-1.43%	-1.71%	-2.68%	-2.77%	-3.34%	-2.73%	-3.44%	-6.00%

4.5.2 Impacts on Airline 2

Airline 2's revenues improve in all scenarios from Closure Matching (Figure 4-26). Specifically, revenues rise more as demand increases. At low demand, Airline 2's revenues increase by about 2% to 4%, at medium demand, the increases are from around 4% to 6% and at high demand the increases are approximately 8% to 12%.

Table 4-16 indicates that at low demand, revenue improvements are driven mainly by increases in load factors rather than changes in yields. However, at medium and high demand, the yield increases take over as the primary reasons revenues rise.

Table 4-16: Airline 2's Improvements in Load Factors and Yields from Closure Matching

		Low Demand (0.8)			Medium Demand (1.0)			High Demand (1.2)		
		Restrictive	Medium	Loose	Restrictive	Medium	Loose	Restrictive	Medium	Loose
AL2	Load Factor	4%	2%	1%	3%	2%	0%	1%	0%	0%
	Yield	0%	0%	0%	1%	2%	7%	7%	11%	12%

With Closure Matching, Airline 1 becomes more restrictive, and the rejected passengers turn to Airline 2. At low demand, the increased number of passengers improve Airline 2's load factor because Airline 2 does not hit its target load factor of 90% with those extra passengers (Table 4-17). As demand increases, Airline 2 achieves the target load factor without matching. Then, as Airline 1 closure matches, Airline 2 starts rejecting lower-fare passengers and saves seats for higher-fare passengers instead, while maintaining the 90% load factor.

Table 4-17: Airline 2's Load Factors

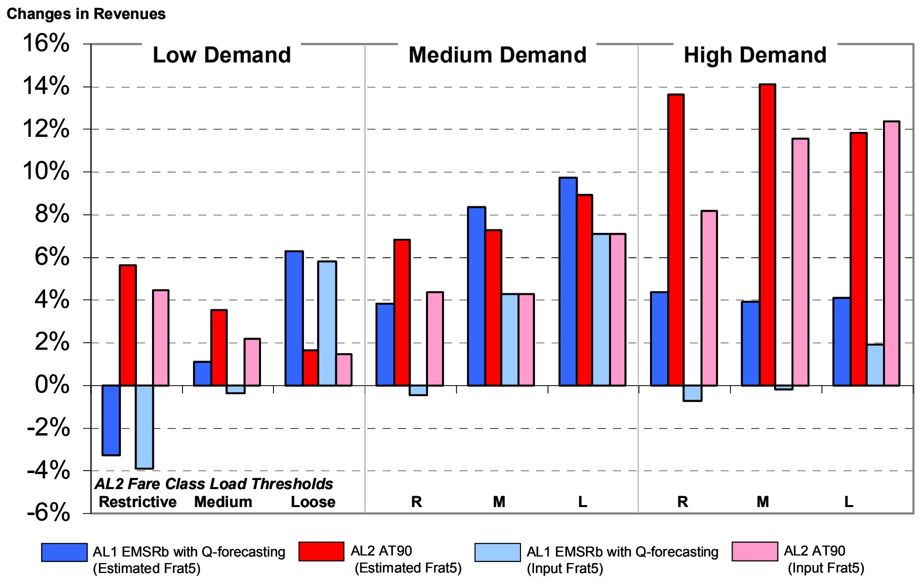
		Low Demand (0.8)			Medium Demand (1.0)			High Demand (1.2)		
		Restrictive	Medium	Loose	Restrictive	Medium	Loose	Restrictive	Medium	Loose
AL2	Load Factor (Without matching)	70%	76%	80%	82%	86%	89%	88%	90%	90%
	Load Factor (With matching)	73%	78%	81%	84%	88%	89%	89%	90%	90%

4.5.3 Results Obtained using Estimated Frat5s

In general, outputs using estimated Frat5s confirm the results found using input Frat5s (Figure 4-30). With Closure Matching, Airline 1 tends to do better with estimated Frat5s than with input Frat5s. This is because the revenue management systems of the airlines become more restrictive with Closure Matching, improving the Frat5s estimated. Input Frat5s do not change with matching. These estimated Frat5 results suggest that actual results achieved by an airline are more positive than the input Frat5 results show.

FIGURE 4-30

Changes as Airline 1 Closure Matches



4.5.4 Conclusions

In contrast to Open Matching, Closure Matching sometimes benefits the matching airline (using EMSRb with Q-forecasting) as much as or more than the matched airline (AT90). Like the Open Matching scenarios, Airline 2 benefits from all Closure Matching scenarios simulated.

Closure Matching is still a process that disrupts the revenue management system, so the more Closure Matching occurs, the more it causes Airline 1 to be overly restrictive and lose revenues. Airline 1's revenue management system responds to Closure Matching and maximizes revenue while taking into account the changes Closure Matching brings. At more extreme cases, for example when Airline 2 uses restrictive fare thresholds, the revenue management system is unable to completely recoup the revenues lost through being unnecessarily restrictive.

Airline 1's losses in market share are significant, especially when considering it loses both market share and revenues in some cases. The input Frat5 results may be overly pessimistic, since input Frat5s do not change with Closure Matching. When Frat5s are allowed to change through estimation, Closure Matching performs significantly better. Overall, Closure Matching is more beneficial to Airline 1 (using EMSRb with Q-forecasting) than Open Matching is.

4.6 EMSRB WITH Q-FORECASTING BI-DIRECTIONAL MATCHING AT90

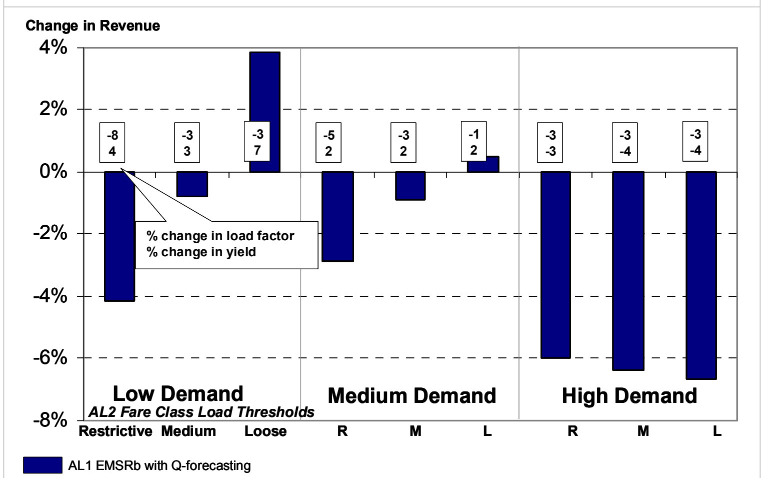
Bi-directional Matching allows Airline 1 (using EMSRb with Q-forecasting) to match in both directions. Airline 1 manually re-opens the lowest fare class as long as that fare class remains available at Airline 2. At the same time, it shuts down the lowest fare class as soon as that fare class is closed at Airline 2. Bi-directional Matching shadows the competitor more closely than either of Open Matching and Closure Matching.

4.6.1 Impacts on Airline 1

Overall, Bi-directional Matching tends to hurt Airline 1 – its revenues fall except in the two scenarios (Figure 4-31). Load factors fall throughout the scenarios simulated and is accompanied by falls in yield at high demand.

FIGURE 4-31

Changes as Airline 1 Matches in Both Directions

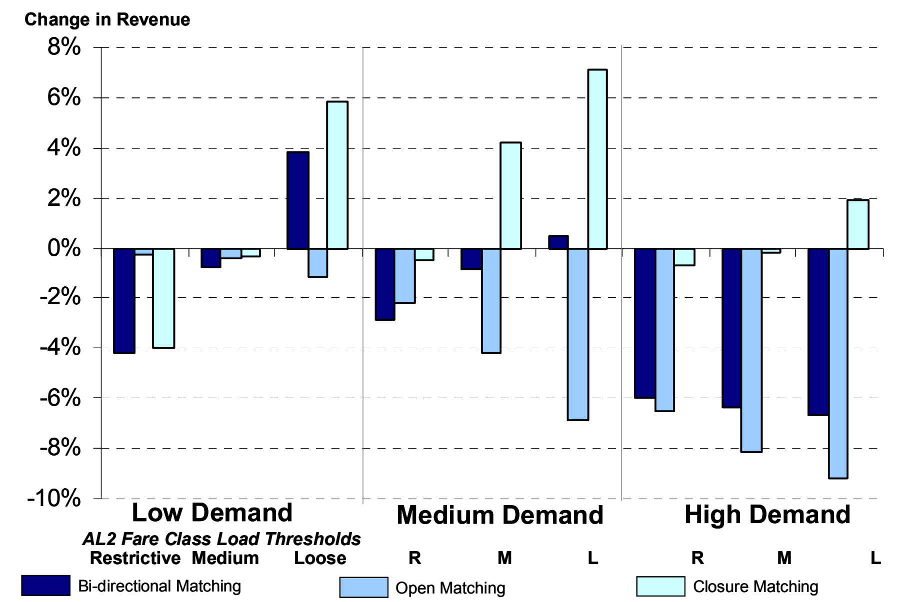


At low and medium demand, Bi-directional Matching makes Airline 1 more restrictive, since loads fall consistently while yields rise – Closure Matching dominates. At low demand, little Open Matching takes place. At low demand, where Airline 2 has loose thresholds, Bi-directional Matching increases revenues Airline 1, echoing the results of Closure Matching (Figure 4-32).

At high demand, Open Matching dominates. As described earlier, it is very costly to open match at high demand because yields fall greatly while load factors hardly improve. Adding Closure Matching to Open Matching softens the damage to yields – they fall by only 4%. Unfortunately, load factors also fall from Closure Matching, making Bi-directional Matching a revenue-losing strategy at high demand.

FIGURE 4-32

Changes to Airline 1's Revenues as It Matches



4.6.1.a Market Share

Table 4-18 shows that the drops in market share that come with Bi-directional Matching follow the Closure Matching changes closely, while moderated by the slight improvements in market share with Open Matching.

Table 4-18: Market Share Change with Bi-directional Matching

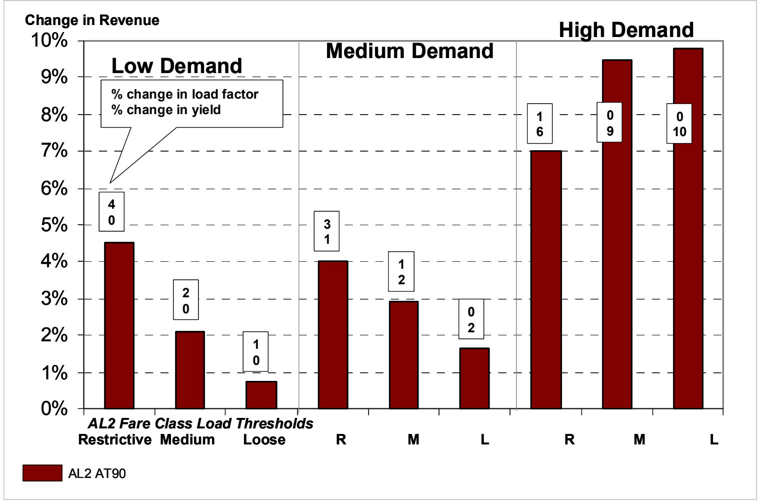
	Low Demand (0.8)			**Medium Demand (1.0)**			**High Demand (1.2)**		
	Restrict -ive	**Medium**	**Loose**	**Restrict -ive**	**Medium**	**Loose**	**Restrict -ive**	**Medium**	**Loose**
Base cases	55.14%	51.98%	50.05%	52.10%	50.51%	49.61%	51.35%	51.03%	50.95%
With Bi-directional Matching	52.11%	50.63%	49.04%	49.89%	48.85%	48.51%	49.86%	49.62%	49.41%
Change with Bi-directional Matching	-3.03%	-1.35%	-1.01%	-2.21%	-2.77%	-1.10%	-1.49%	-1.41%	-1.54%
Change with Open Matching	0.02%	0.04%	0.22%	0.28%	0.70%	0.88%	0.41%	0.61%	0.65%
Change with Closure Matching	-3.04%	-1.43%	-1.71%	-2.68%	-2.77%	-3.34%	-2.73%	-3.44%	-6.00%

4.6.2 Impacts on Airline 2

In every scenario simulated, Airline 2's revenues increase after it is matched in both directions (Figure 4-33). At low and medium demand, the increases average around 2 to 3%, while at high demand, the increases run as high as 10%.

FIGURE 4-33

Changes to AL2's Revenue as AL1 Matches in Both Directions



Moving from left to right of Figure 4-33, the driver of revenue improvements shift from load factor gain to yield increase. At low demand, Closure Matching is dominant. Airline 2 picks up more passengers as they are rejected by Airline 1. As demand becomes higher and as restrictions become looser, Airline 2 begins before matching with a load factor close to 90%. Having already achieved its load factor target, Airline 2 then benefits from Bi-directional Matching by improving its yield – allowing high-fare passengers to displace low-fare passengers.

FIGURE 4-34

Changes to AL2's Revenues as AL1 Matches

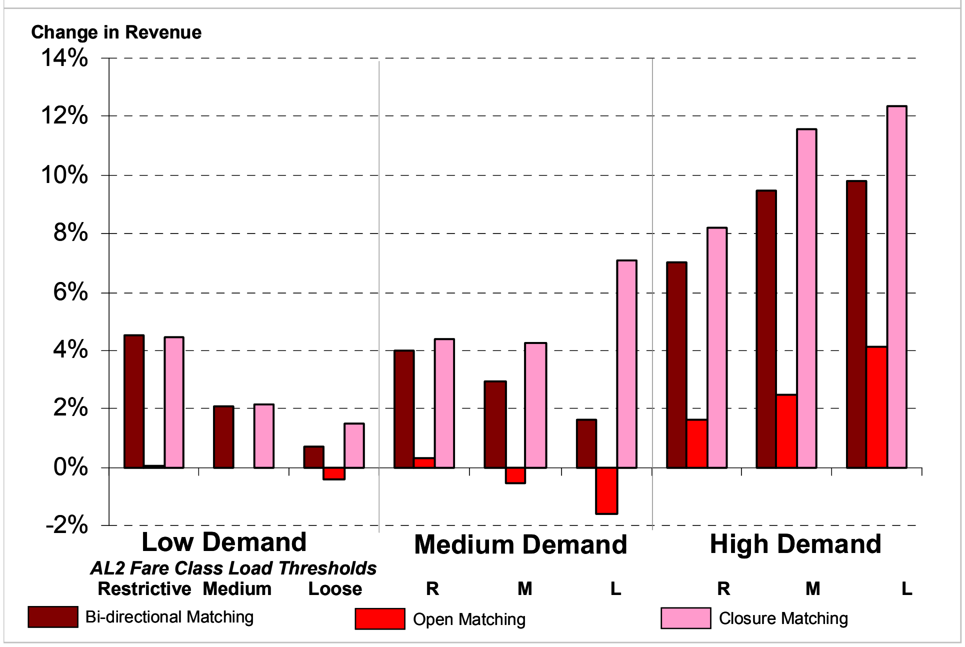


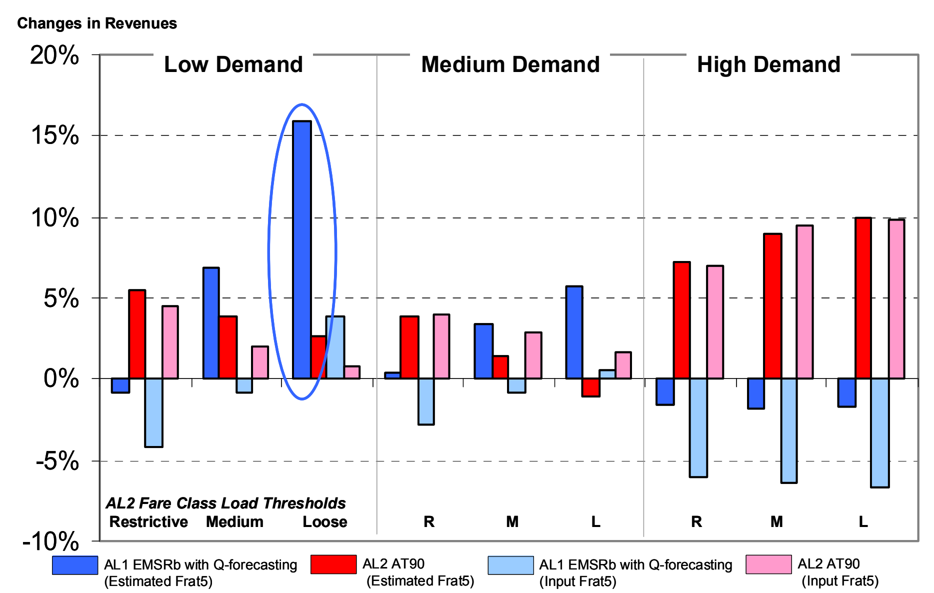
Figure 4-34 verifies that the revenue effects of Closure Matching dominate at low and medium demand. At high demand, the two forms of matching moderate each other, resulting in revenue changes higher than when Open Matching is used but lower than when Closure Matching is carried out.

4.6.3 Results Obtained using Estimated Frat5s

In comparisons of results of input and estimated Frat5s in earlier scenarios, two phenomena surfaced: firstly, without matching, estimated Frat5s tend to be underestimated at low demand. Secondly, with Closure Matching, results using estimated Frat5s tend to be better those using input Frat5s, since Closure Matching improves the Frat5s estimated.

Looking at the results using estimated Frat5s with those two concepts in mind, we look at a deviation of estimated Frat5 results from input Frat5s results (circled in Figure 4-35).

FIGURE 4-35
Changes as Airline 1 Matches in Both Directions



The deviation can be explained by the two concepts, since it occurs with Bi-directional Matching. In part, at low demand without matching, estimated Frat5s are too low. Open Matching leads to improvements about 5% higher than input Frat5 results (explained earlier in Chapter 4.4.6 and Figure 4-25). In addition, the Closure Matching component also causes a further improvement of about 5% with improvements in willingness-to-pay estimates (discussed in Chapter 4.5.3 and Figure 4-30).

4.6.4 Conclusions

Bi-directional Matching occasionally benefits the matching Airline 1 as much as or more than Airline 2, but because of the Open Matching component, it is damaging at high demand.

If the goal of an airline is to match exactly the availability of a competitor, Bi-directional Matching is more appealing than either Open Matching or Closure Matching alone. However, the goal of an airline is to maximize revenues. The simulated results suggest that matching in both directions helps sometimes in hedging against losses, although that also means that the gains are more restrained. Moreover, since there are no gains from Closure Matching at high demand, the Open Matching causes large losses. Comparing the three forms of matching, Closure Matching remains the most sensible form for an airline using EMSRb with Q-forecasting.

The market share losses follow largely the trends seen in Closure Matching, but are moderated by the slight market share improvements that come with Open Matching.

4.7 EMSRB WITH Q-FORECASTING OPEN MATCHING EMSRB WITH Q-FORECASTING

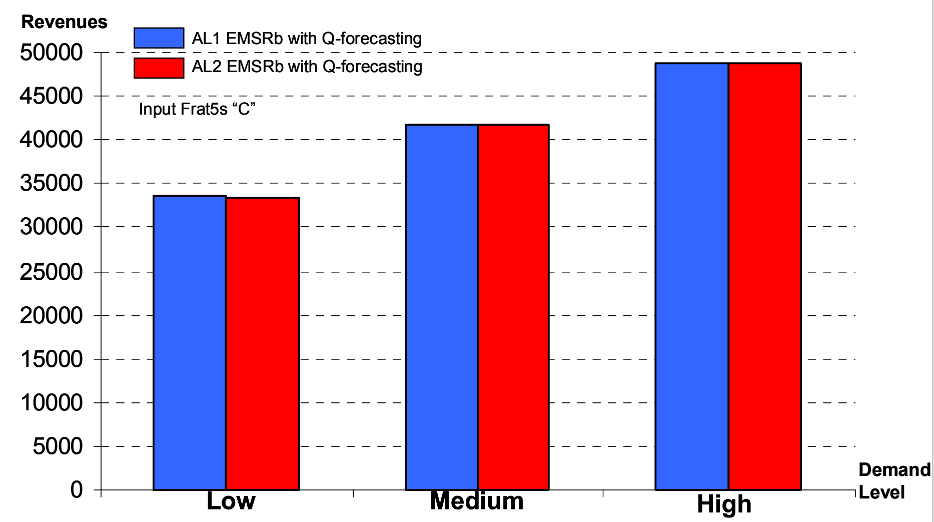
In the following scenarios of Chapters 4.7, 4.8 and 4.9, both Airline 1 and Airline 2 use the same revenue management system so that the only difference is availability matching. Both airlines use EMSRb with Q-forecasting, representing an advanced revenue management system capable of avoiding spiral down significantly. As before, the Frat5s used are input "C" or Frat5s estimated using the average conditional forecast prediction method. Two scenarios are simulated: first, Airline 1 matches Airline 2. The second scenario has both airlines matching each other.

4.7.1 Base cases

Since neither airline matches, these are the base cases for all three groups of matching scenarios. Open Matching is discussed in Chapter 4.7, Closure Matching in Chapter 4.8 and Bi-directional Matching in Chapter 4.9. When both airlines use EMSRb with Q-forecasting, they mirror each other in terms of revenues, load factors, yields and fare class mixes (Figure 4-36).

FIGURE 4-36

EMSRb with QF vs EMSRb with QF Base Cases (Input Frat5s)



	Low AL1	Low AL2	Medium AL1	Medium AL2	High AL1	High AL2
Load Factor	80%	80%	86%	86%	91%	91%
Yield	0.100	0.100	0.115	0.115	0.128	0.127

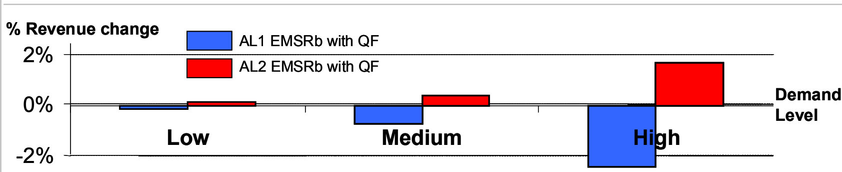
4.7.2 Airline 1 Open Matching: Impacts on Airline 1

When the revenue management systems are symmetric, Open Matching has minimal impact on either airline, as shown in Figure 4-37. Even at high demand, the changes barely exceed 2%. This is different from the larger scale of changes when the airlines use asymmetric revenue management systems.

Open Matching lowers the revenues of the matching airline insignificantly at low demand and by greater amounts as demand increases. Airline 1, the matching airline, turns less protective compared to its baseline, non-matching RM system. The loosening in inventory control is seen the simulation results – Airline 1 maintains or improves slightly its load factor but dilutes its yield with Open Matching. Its revenues decrease because the falls in yields cause more losses than the rises in loads bring gains.

FIGURE 4-37

Changes as Airline 1 Open Matches (Input Frat5)

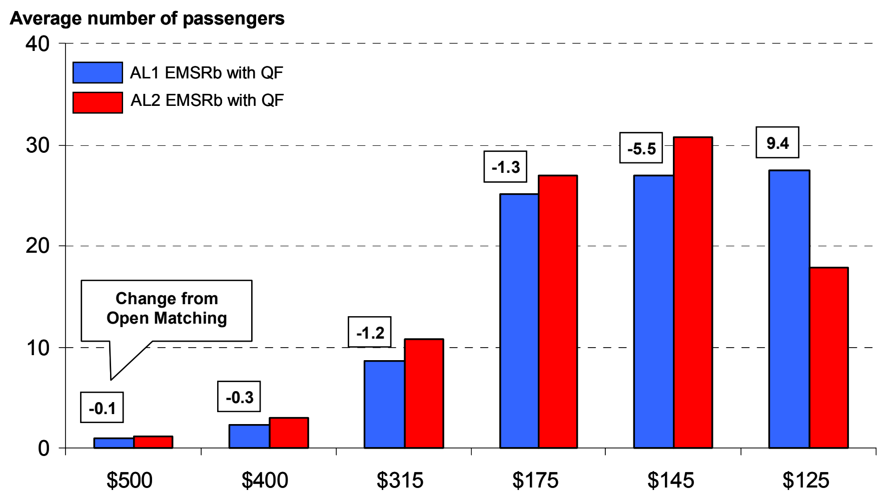


	Low AL1	Low AL2	Medium AL1	Medium AL2	High AL1	High AL2
Load Factor	0%	0%	0%	0%	1%	0%
Yield	0%	0%	-1%	1%	-4%	2%

For example, at high demand, the Open Matching airline loses 2.5% of its revenues because its yield falls by 4% while its load factor increases by only 1%. It gains passengers in the cheapest fare class but loses passengers from all the remaining five higher fare classes (Figure 4-38).

FIGURE 4-38

Fare Class Mix: at High Demand when Airline 1 Open Matches



4.7.3 Impacts on Airline 2

When revenue management systems are symmetric, Airline 2 gains less than 2% in revenues when Airline 1 open matches it (Figure 4-37). The airline does not benefit much from a more open competitor. This is especially true in that Airline 2's loads do not improve, since Open Matching reduces the spill of passengers from Airline 1 to 2 – Airline 1's fare class would be open for as long as Airline 2's is open. Previously, Airline 2 could have been available exclusively and pick up passengers shut out by Airline 1 fare class closures. When Airline 1 open matches Airline 2, Airline 2's revenue gains tend to be derived from increased yields, especially when demand is high. As Airline 2 loses some lowest-fare passengers to Airline 1, it fills these seats with higher-fare passengers instead, as shown in Table 4-19. These results echo the findings when revenue management systems of the two airlines are asymmetric.

Table 4-19: Airline 2's Change in Fare Class Mix from Open Matching

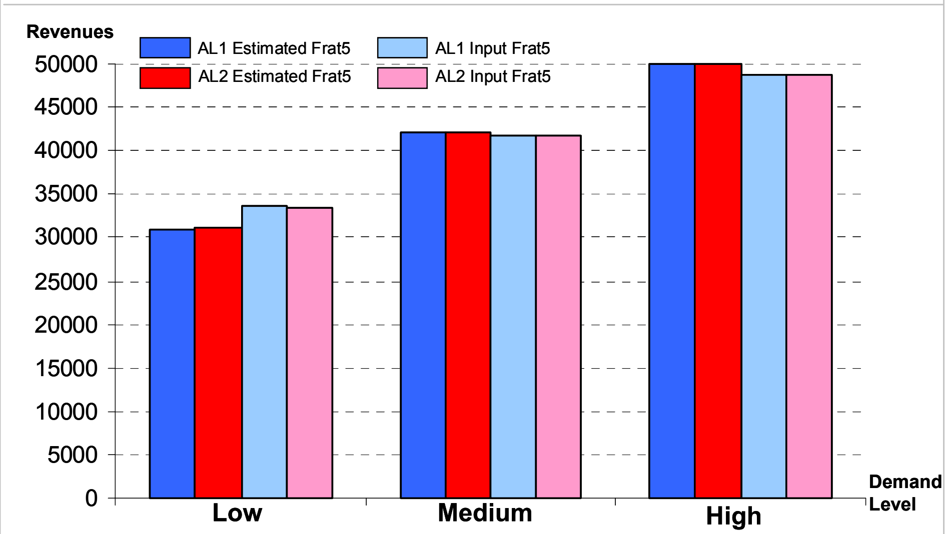
Demand Level	Change in Yield	Change in Number of Passengers in Fare Class					
		1 ($500)	2	3	4	5	6 ($125)
Low	0.1%	0.01	0.00	0.06	-0.01	0.03	-0.11
Medium	0.5%	0.03	0.10	0.17	0.09	0.03	-0.61
High	2.0%	0.12	0.35	0.91	0.68	-1.62	-0.82

4.7.4 Results Obtained using Estimated Frat5s

The simulation outcomes for the base cases using estimated Frat5s are similar to those for the base cases using input Frat5s (Figure 4-39). The exception happens at low demand, where estimated Frat5s for EMSRb with Q-forecasting underestimate passengers' willingness-to-pay.

FIGURE 4-39

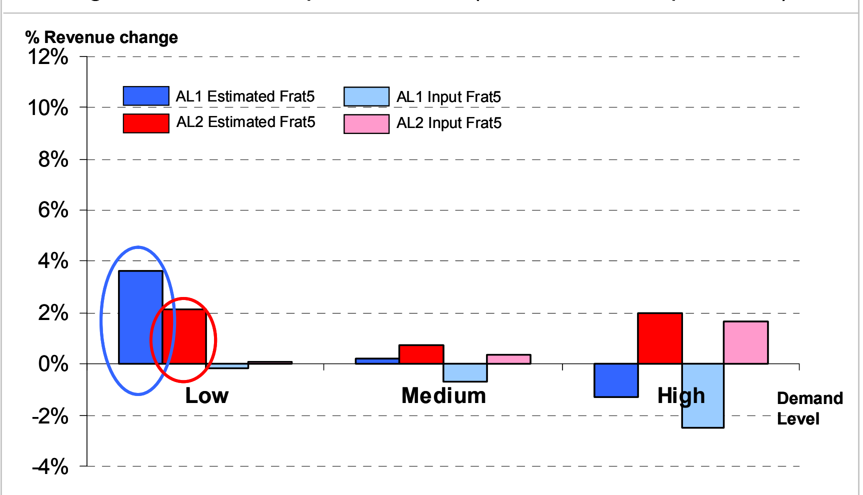
EMSRb with QF vs. EMSRb with QF (Estimated cf. Input Frat5)



At low demand, both airlines 1 and 2 improve their revenues with Airline 1 Open Matching Airline 2 when estimated Frat5s are used (circled in Figure 4-40), unlike when input Frat5s are used. As explained earlier, this unusual result can be attributed to the underestimation of Frat5s before matching.

FIGURE 4-40

Changes as Airline 1 Open Matches (Estimated cf. Input Frat5)



We witness the increased estimate of willingness-to-pay indirectly by comparing the Figures 4-41 and 4-42. Figure 4-41 illustrates the difference between the two airlines' closure rates. The difference curves of the higher fare classes fall below the horizontal axis at later timeframes. That means Airline 2 is more open in those fare classes then and Airline 1 will open match accordingly. From Figure 4-42 we see that on top of Open Matching those higher fare classes, Airline 1 closes its lower fare classes much more aggressively to force more sell-up, motivated by a higher estimate of willingness-to-pay.

FIGURE 4-41
Differences between AL1 and 2 Closure Rates

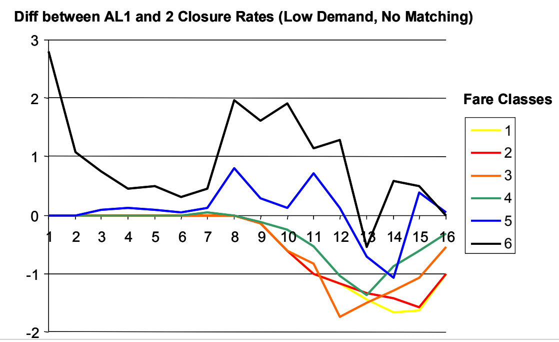
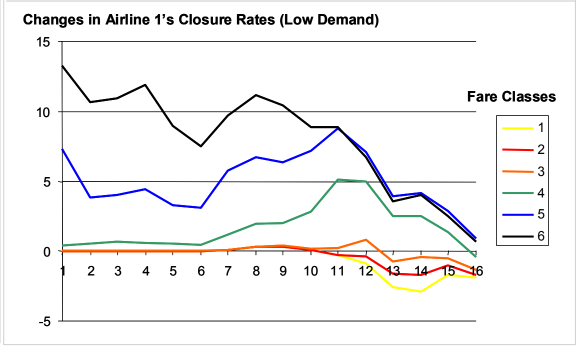


FIGURE 4-42
Changes in AL1's Closure Rates as it Open Matches



4.7.5 Both Airlines Open Match

With input Frat5s, both airlines lose revenues when they open match each other, as shown in Table 4-20. Their losses deepen as demand strengthens. The magnitude of change is small – less than 2%.

Their revenues decrease from the less restrictive availability produced by their mutual Open Matching. Both airlines gain more passengers, at the expense of lowering yields. With Open Matching, they keep their lower fare classes open for longer than their revenue management systems deem optimal. Since fare classes are undifferentiated, by failing to close lower fare classes in time, they discourage sell-up but encourage buy-down.

Table 4-20: Changes in Revenues, Load Factors and Yields when Both Airline Open Match

	% Change in	Low Demand (0.8)		Medium Demand (1.0)		High Demand (1.2)	
		AL1	AL2	AL1	AL2	AL1	AL2
Input	Revenues	-0.13%	-0.11%	-0.52%	-0.52%	-1.59%	-1.26%
	Load Factors	0.0%	0.1%	0.1%	0.1%	0.8%	0.5%
	Yields	-0.1%	-0.2%	-0.7%	-0.6%	-2.3%	-1.7%
Estimated	Revenues	3.98%	3.44%	0.50%	0.33%	0.71%	0.88%
	Load Factors	-0.05%	-0.46%	0.9%	0.4%	1.54%	1.71%
	Yields	4.07%	3.93%	-0.4%	-0.1%	-0.82%	-0.82%

Results from using estimated Frat5s show slight increases in revenues, but at less than 1%, the increases are negligible at medium and high demand. At low demand, the increases are atypically high because without matching, the Frat5s are underestimated.

4.7.6 Conclusions

When two airlines use the same advanced revenue management system like EMSRb with Q-forecasting in a single symmetric market, Open Matching is often counterproductive for the airline that open matches. When one airline open matches, the matching airline loses revenues but the matched airline gains. The difference with earlier asymmetric cases is that the losses for the matching airline are capped at a much lower percentage.

Both airlines' revenues are lowered when they open match each other. It is not lucrative for the airlines to be both more open than the optimal level determined by their revenue management systems, especially as demand becomes higher. Open Matching extends the period of time a low fare class is available, encouraging bookings in lower fare classes instead of higher fare classes.

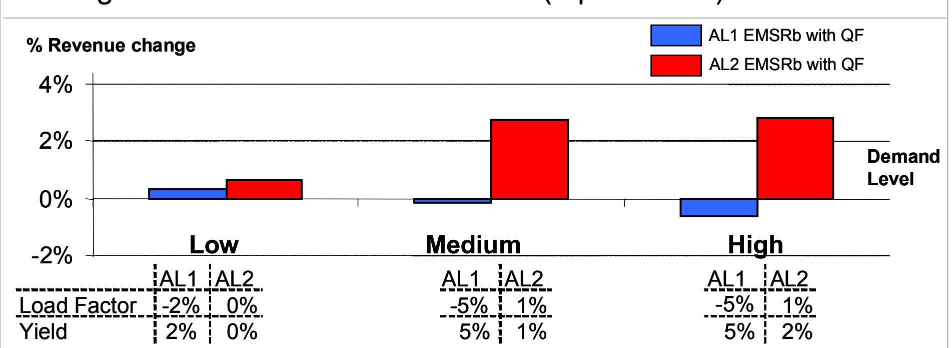
4.8 EMSRB WITH Q-FORECASTING CLOSURE MATCHING EMSRB WITH Q-FORECASTING

4.8.1 Airline 1 Closure Matching: Impacts on Airline 1

As Airline 1 closure matches Airline 2, its revenues stay constant – changing by less than 1% (Figure 4-43). Airline 1 becomes slightly more restrictive with Closure Matching. It protects more seats for higher fare passengers than when its fare class closures relied solely on its revenue management system. Consistently, Airline 1's load factor falls but yield rises. Its falling load factor is offset by its rise in yield. For Airline 1, Closure Matching Airline 2 is marginally worse for its revenues as demand increases because more availability matching and overriding of the revenue management system takes place.

When compared to the earlier scenario when Airline 2 uses a different revenue management system, with symmetric revenue management systems, the revenue changes are very limited, because Airline 1 is availability matching an airline that uses the same revenue management system as itself.

FIGURE 4-43
Changes as Airline1 Closure Matches (Input Frat5s)



4.8.2 Airline 1 Closure Matching: Impacts on Airline 2

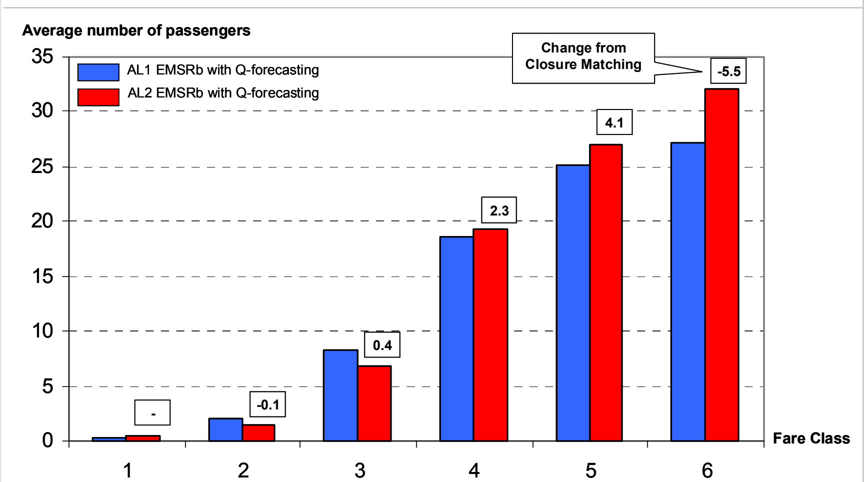
Airline 2, the matched airline, gains revenues for two reasons: it absorbs the passengers spilled by Airline 1 and it carries more higher-fare passengers. Its revenue improvements are also of a smaller scale (not exceeding 4%) than in the asymmetric revenue management systems scenario.

Closure Matching is one-directional. Airline 1 closes fare classes, but does not re-open fare classes, to match the lowest available class of Airline 2. As a result of Closure Matching, Airline 2 is always as open or more open, but never less open, when compared to Airline 1. The spill of passengers from Airline 1 to 2 increases, and that is reflected in Airline 2's load factors improvements by 1% (Figure 4-43).

The second way that Airline 2 benefits from Airline 1's Closure Matching is that its yields improve in the more restrictive environment. For example, at high demand, Airline 2 drops passengers from its lowest fare class but picks up more passengers from its next three higher fare classes (Figure 4-44). This is because of two phenomena in the more restrictive environment: first, Airline 2 saves more seats for, and therefore has more successful bookings from, passengers whose first choice is a higher fare. Secondly, there is more sell-up. For example, passengers who wanted to buy fare class 4 are pushed by fare class closures to purchase the more expensive fare class 3 instead.

FIGURE 4-44

Fare Class Mix: at Medium Demand with AL1 Closure Matching

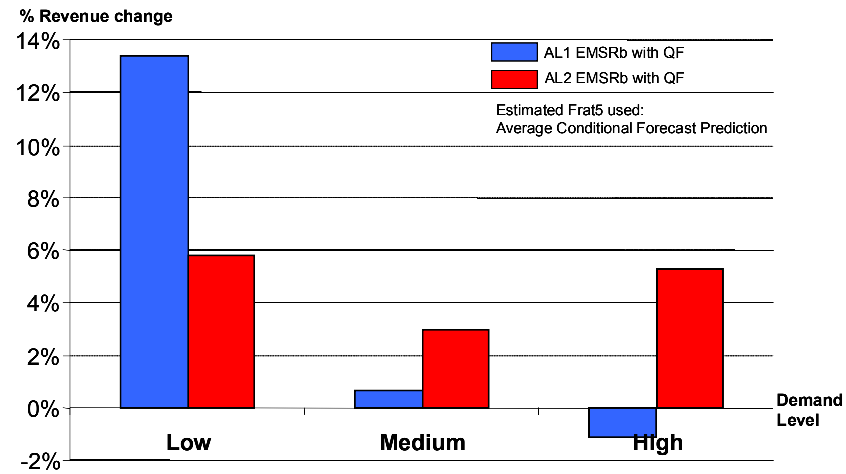


4.8.3 Results Obtained using Estimated Frat5s

When Airline 1 uses the average-conditional Frat5s estimator and closure matches, its revenues improve significantly when demand is low (Figure 4-45). That is significantly different from the input Frat5 outcomes.

FIGURE 4-45

Changes as Airline1 Closure Matches (Estimated Frat5)

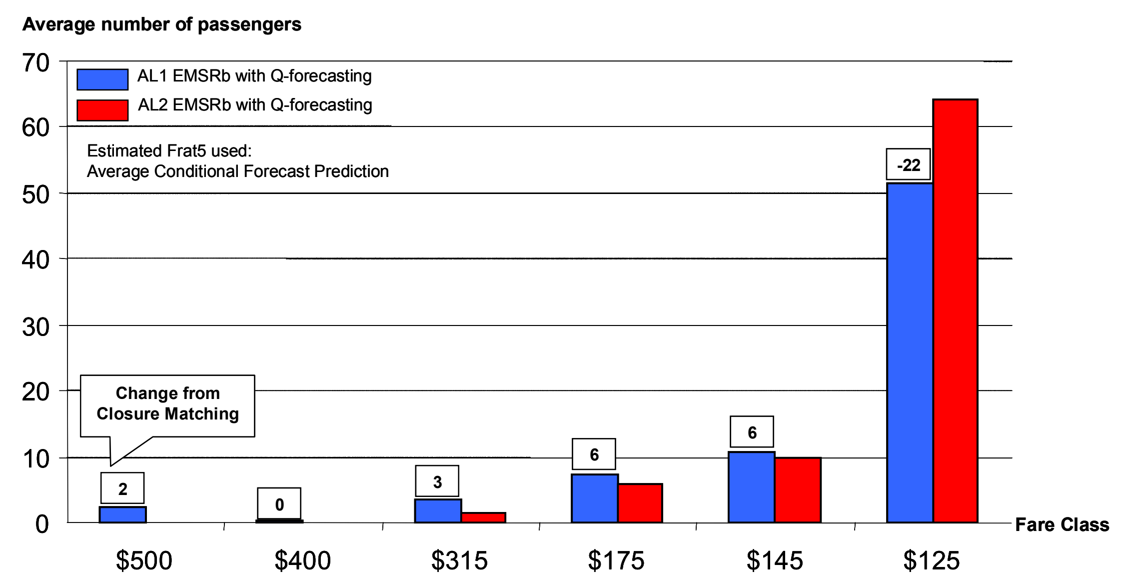


	Low AL1	Low AL2	Medium AL1	Medium AL2	High AL1	High AL2
Load Factor	-6%	2%	-11%	3%	-12%	3%
Yield	20%	4%	13%	0%	13%	3%

Once again, estimating Frat5s at low demand is problematic. When estimated Frat5s are used, willingness-to-pay is estimated based on demand. At low demand, without matching, Airline 1 starts with more than 60% of passengers buying the lowest fare class, suggesting that it underestimated the passengers' willingness-to-pay. With Closure Matching, the loss of 22 low-yielding passengers in the lowest fare class is more than offset by the gain of passengers in higher-yielding fare classes (Figure 4-46). Revenues increase as the yield gain (20%) outpaces the load loss (-6%). The Frat5s estimated improve dramatically.

FIGURE 4-46

Fare Class Mix: at Low Demand with Airline 1 Closure Matching



4.8.4 Both Airlines Closure Match

In theory, both airlines should see increases in revenues when they closure match each other, regardless of demand, since they would act as two airlines colluding monopolistically.

The simulated revenues verify the theory, as shown in Table 4-21. Both airlines' revenues improve by 1% to 2% when they closure match each other.

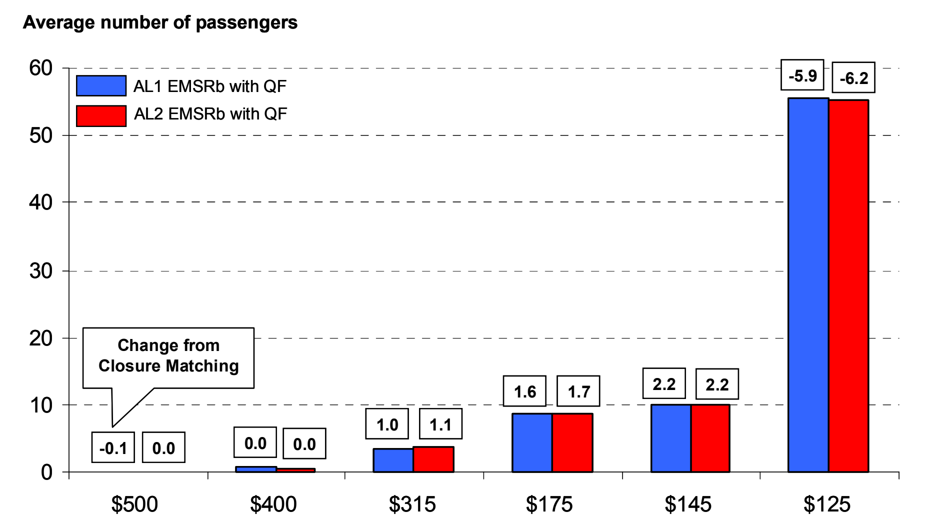
Table 4-21: Changes in Revenues, Load Factors and Yields when Both Airlines Closure Match (Input Frat5s)

% Change in	Low Demand (0.8)		Medium Demand (1.0)		High Demand (1.2)	
	AL1	AL2	AL1	AL2	AL1	AL2
Revenues	1.2%	1.4%	1.3%	1.5%	1.5%	1.6%
Load Factors	-1.5%	-1.6%	-3.3%	-3.4%	-3.8%	-4.0%
Yields	2.8%	3.1%	4.8%	5.0%	5.5%	5.8%

The revenue improvements come from increased yields that overcome the decline in load factors. For example, looking at the fare class mix at low demand when both airlines Closure Match (Figure 4-47), both airlines reject passengers from the lowest fare class to accept in their place fewer passengers from the higher fare classes.

FIGURE 4-47

Fare Class Mix: at Low Demand when Both Airlines Closure Match



The results obtained using estimated Frat5s are similar, as seen in Table 4-22 – both airlines still gain from Closure Matching.

Table 4-22: Changes in Revenues, Load Factor s and Yields when Both Airlines Closure Match (Estimated Frat5s)

% Change in	Low Demand (0.8)		Medium Demand (1.0)		High Demand (1.2)	
	AL1	AL2	AL1	AL2	AL1	AL2
Revenues	7.9%	7.3%	1.1%	0.7%	2.0%	1.9%
Load Factors	-5.3%	-5.2%	-7.4%	-7.7%	-9.2%	-9.5%
Yields	14.0%	13.3%	9.1%	9.1%	12.3%	12.6%

4.8.5 Conclusions

Typically, when an airline with a sophisticated revenue management system like EMSRb with Q-forecasting closure matches unilaterally, it overrides its optimal revenue management system to be overly restrictive. It loses revenue – protecting too many seats for higher-fare passengers by rejecting lower-fare passengers. The same happens when an airline closure matches another that has the same revenue management system. However, the losses and improvements are very limited in this symmetric scenario compared to the earlier asymmetric scenario where Airline 2 uses a different revenue management system.

Airline 2 benefits from being closure matched because Airline 1 becomes more restrictive. Airline 2 improves its yield from increased sell-up and gains passengers from the greater amount of spill from Airline 1. In this symmetric scenario, the benefits are less than in the earlier asymmetric scenario, since the symmetry implies less closure matching takes place.

When Airline 1 and its competitor Airline 2 both decide to match each other in terms of closing fare classes, they both benefit. Together, they create a more restrictive fare environment and increase their yields by forcing more sell-up.

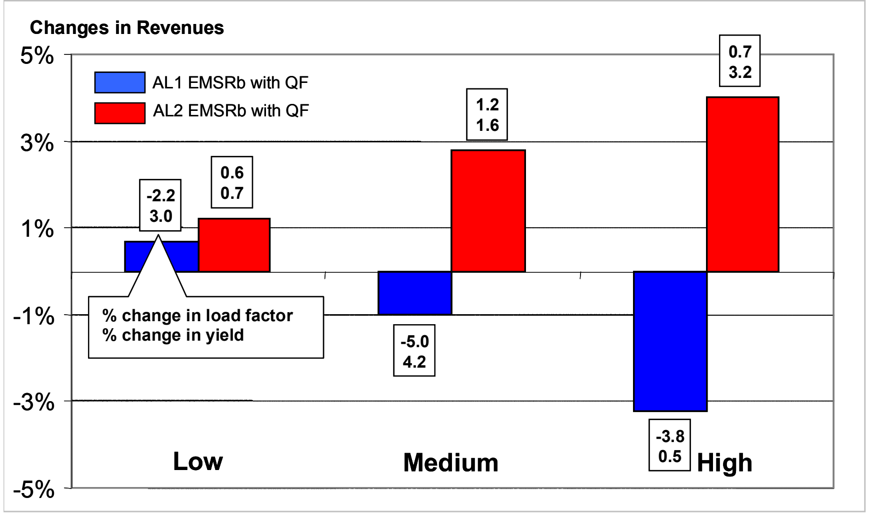
4.9 EMSRB WITH Q-FORECASTING BI-DIRECTIONAL MATCHING EMSRB WITH Q-FORECASTING

4.9.1 Impacts on Airline 1

Airline 1 Bi-directional Matching Airline 2 increases Airline 1's revenues by about 1% at low demand. However, as demand increases, it causes revenue drops from 1% to around 3% (Figure 4-48).

FIGURE 4-48

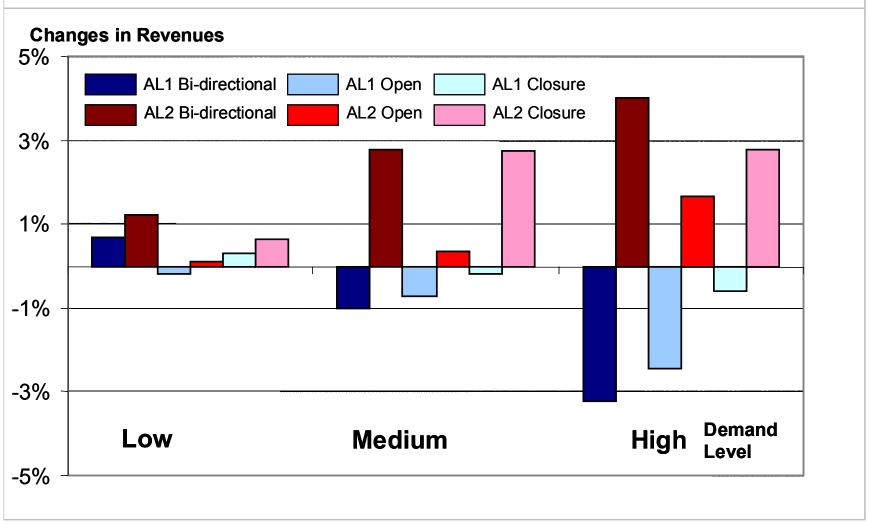
Changes as AL1 Matches in Both Directions



The worsening performance as demand increases and the limited scale of change are similar to the results from Open and Closure Matching (Figure 4-49). Bi-directional Matching seems to simply sum up the changes caused by both forms of matching. However, the two forms of matching do not cause the same magnitude of change – Airline 1's lower load factors and higher yields after Bi-directional Matching indicate that it becomes more restrictive and suggests that the impacts of Closure Matching is more dominant.

FIGURE 4-49

Changes as AL1 Matches in Both Directions



4.9.2 Impacts on Airline 2

The revenues of the matched airline, Airline 2, increase as a result of Bi-directional Matching for all the demand levels simulated. Both its yield and load factor rise from the matching, suggesting the airline benefits through increased spill from Airline 1 and a more restrictive fare availability environment. The increase is greater as demand rises. Once again, the changes for Bi-directional Matching seem to be accumulated changes from Open and Closure Matching (Figure 4-49).

Compared to the asymmetric scenario where Airline 2 uses AT90, in this symmetric scenario, Airline 2's gains and losses are on a smaller scale because less seat availability matching takes place.

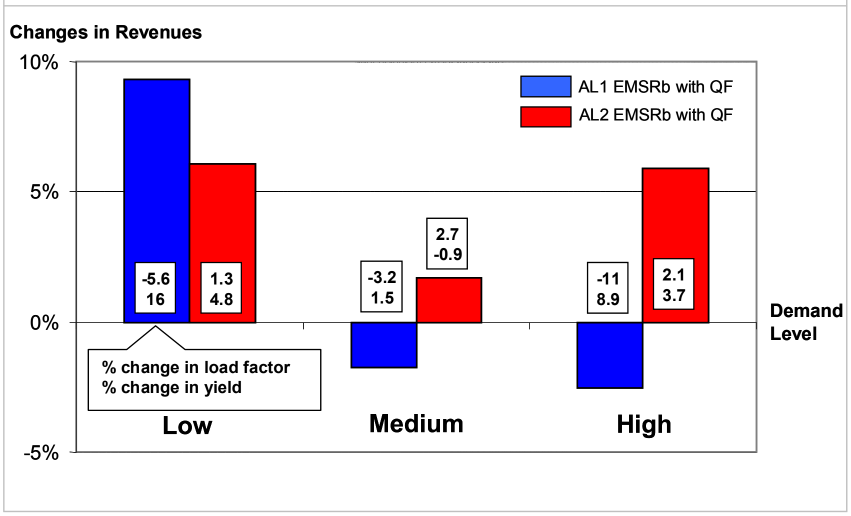
4.9.3 Results Obtained using Estimated Frat5s

With estimated Frat5s, the changes are larger than but similar in general to when input Frat5s are used (Figure 4-50, compare to Figure 4-48). For Airline 1, its loads fall and yields rise from Bi-directional Matching with estimated Frat5s as with input Frat5s.

The main differences occur at low demand. As explained earlier, the improvements with matching at low demand for Airline 1 comes mainly from it underestimating passengers' willingness-to-pay at low demand without matching.

FIGURE 4-50

Changes as AL1 Matches in Both Directions (Estimated)



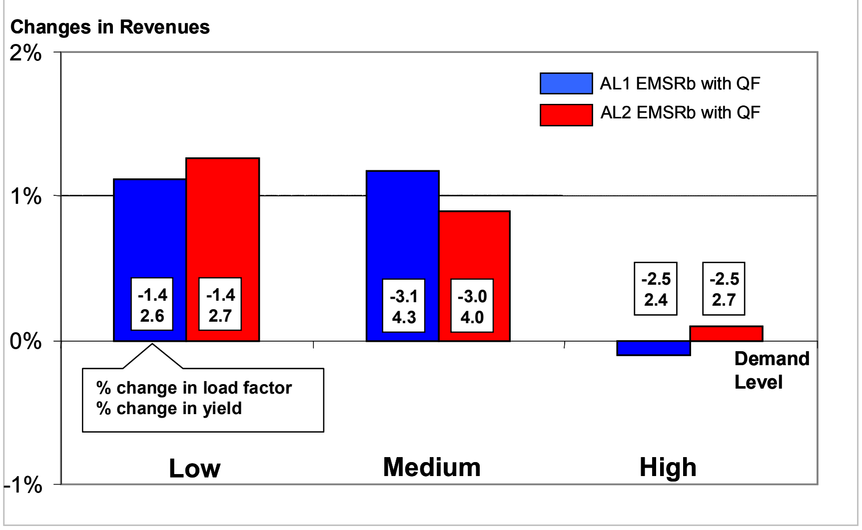
4.9.4 Both Airlines Match

When the two airlines match each other in both directions, the general outcome is revenue gains for both airlines, except at high demand when revenues stay constant

(Figure 4-51). For all demand levels, the load factor falls while the yield rises, indicating that Closure Matching is prevalently more dominant than Open Matching. That helps to explain the increases in revenues – both airlines force more sell-up among their passengers. At high demand, the negative impacts of both airlines Open Matching negate the positive impacts of Closure Matching.

FIGURE 4-51

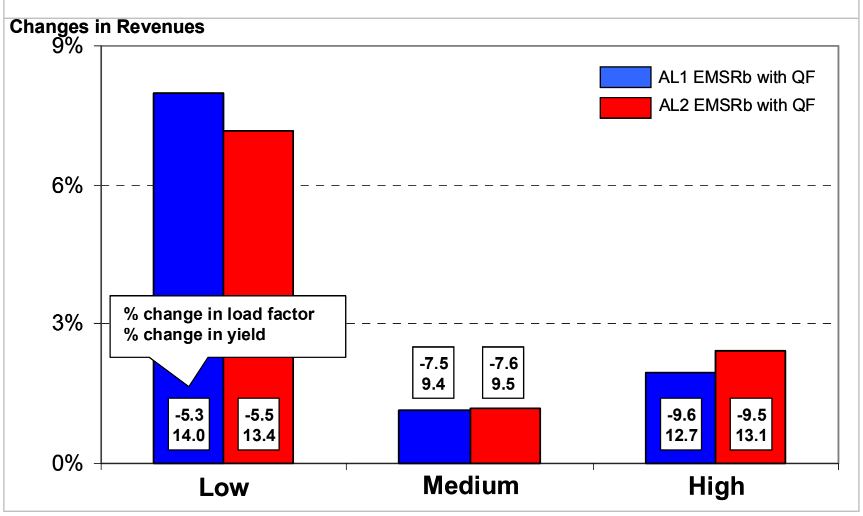
Changes as Both Airlines Match in Both Directions (Input)



With estimated Frat5s, the same results of improvements are seen at low and medium demand (Figure 4-52). Improvements in revenues are seen even at high demand, and that can be attributed to the fact that with estimated Frat5s, Open Matching causes revenues increases when both airlines open match (Chapter 4.7.5).

FIGURE 4-52

Changes as Both Airlines Match in Both Directions (Estimated)



4.9.5 Conclusions

When Airline 1 uses EMSRb with Q-forecasting and matches in both directions Airline 2 that also uses EMSRb with Q-forecasting, Airline 1 loses revenues because it overrides what its revenue management system decided as optimal. As demand increases, more Open Matching and Closure Matching occur, leading to greater adjustments to the revenue management system and worse revenue performances. In contrast, Airline 2 gains revenues, improving both its load factor and yield with Bi-directional Matching.

As with Closure Matching, if instead both airlines bi-directional match each other, they both increase their revenues, at low and medium demand where Closure Matching dominates. At high demand, the results are more mixed because Open Matching causes large losses, negating the gains from Closure Matching.

4.10 SUMMARY

Table 4-23: Summary

No.	Scenario Type	AL1 RM System	AL2 RM System	Type of Low Fare Seat Availability Matching	Impacts on Airline 1's Revenues	Impacts on Airline 2's Revenues
1	Hypothetical use of Closure Matching to reduce spiral down	EMSRb with Standard Forecasting	AT90	Closure	Always positive (especially at high demand, up to 42%)	Always positive (especially at high demand, up to 10.2%)
2		EMSRb with Standard Forecasting	EMSRb with Q-forecasting	Closure	Always positive (up to 11.6% with input Frat5s)	Always negative (down to -10.3% with input Frat5s)
3	Advanced revenue management system matching simple system	EMSRb with Q-forecasting	AT90	Open	Always negative (especially at high demand, down to -9.2%)	Positive at restrictive thresholds and high demand (up to 4.2%)
4				Closure	Positive (Loose thresholds) Negative (Restrictive thresholds) Between -3.9% and 7.1%.	Positive (especially at high demand, up to 12.3%)
5				Bi-directional	Mostly negative. Between -6.7% and 3.9%.	Always positive (up to 9.8%)

6	Symmetric: Advanced revenue management system matching the same system	EMSRb with Q-forecasting	EMSRb with Q-forecasting	Open (AL1)	Slightly negative (down to -2.5%)	Slightly positive (up to 1.7%)
7				Open (Both)	Slightly negative (down to -1.6%)	Slightly negative (down to -1.3%)
8				Closure (AL1)	Slightly negative (down to -0.6%)	Slightly negative (up to 2.8%)
9				Closure (Both)	Slightly positive (up to 1.4%)	Slightly positive (up to 1.6%)
10				Bi-directional (AL1)	Mostly negative (down to -3.2%)	Always positive (up to 4.0%)
11				Bi-directional (Both)	Mostly positive (up to 1.2%)	Mostly positive (up to 1.3%)

Availability matching constitutes an adjustment to the revenue management system that is not integrated into the process. It affects the revenue management system and although the system adjusts to account for this external force, it often results in losses for the matching airline. Scenarios three to five suggest that when an airline's revenue management system is already doing well, the less availability matching is done by an airline with an advanced revenue management system on an airline with a simple system, the better for its revenues.

Out of the three forms of matching, Closure Matching appears to be the best-performing for Airline 1. This is probably an artifact of the direct feedback and spilling between the two airlines as one becomes more restrictive with Closure Matching. Although Bi-directional Matching has the benefits of hedging losses and gains, it is also causes the most availability matching, and therefore does not perform as well. The matched airline gains revenues, especially at high demand.

In the symmetric scenarios where both airlines use the same revenue management system, the losses and gains are more restrained, because the matching airline is following the actions of an airline that is very much like itself. This finding concurs with the concept that less availability matching is better. The most gains are derived when the two airlines closure match each other, forcing a more restrictive fare availability environment.

In the first two scenarios where Closure Matching is used to reduce the spiral down of Airline 1's revenue management system, there are visible improvements to Airline 1's revenues and fare class mixes. The impacts of availability matching depend on the revenue management systems the airlines use. In the first scenario, Airline 1's gains are not at the expense of Airline 2 that uses AT90, in the second scenario where Airline 2 uses a more responsive revenue management system of EMSRb with Q-forecasting, they are.

CHAPTER 5
SIMULATION INPUTS AND ANALYSIS OF RESULTS (NETWORK 'S')

The scenarios in the previous chapter were simulated in a single symmetric market were useful for isolated, theoretical studies of the effects of lowest fare seat availability matching. To add more realism to my analysis, in this chapter, I will proceed to simulate scenarios in a network of markets.

The network used, known as Network 'S' in PODS, is a simplified representation of the U.S. airline network. Two main features make it much more realistic than the single symmetric market. First, there are more airlines, and these airlines are asymmetric – four airlines with different revenue management systems and varying network coverage are simulated in this network. As a result, less direct feedback occurs between any two airlines. Second, two fare structures exist: around half of the markets, 276 markets, have a more restricted, traditional fare structure while the other half, 296 markets, have a less restricted fare structure, representing markets where LCCs have entered.

I will first provide an overview of Network 'S,' then describe and analyze the four scenarios simulated. In the first and second scenarios, Airline 1 uses revenue management systems that control inventories on a leg-basis. Airline 1 uses EMSRb with standard forecasting in the first scenario and EMSRb with hybrid forecasting in the second scenario. For the third and fourth scenarios, Airline 1 uses revenue management systems that control inventory by itineraries – specifically those based on the DAVN method of Origin-Destination control, which was introduced in Chapter 2.1.1.b and explained technically in Chapter 3.3.3. Airline 1 bases its system on DAVN with standard forecasting in the third scenario and DAVN with hybrid forecasting in the fourth scenario.

5.1 OVERVIEW OF NETWORK 'S'

5.1.1 Route Networks and Revenue Management Systems

The four airlines have route networks that vary in size, location of hub and markets served. They all provide services that connect through their hubs, as well as point-to-point services that bypass their hubs. They compete in two ways: first, they overlap in many O-D markets served through their respective hubs. In addition, each airline serves the hubs of all three competitors. Figures 5-1 to 5-4 illustrate their route networks.

FIGURE 5-1
Route Network of Airline 1 (MSP/Legacy)

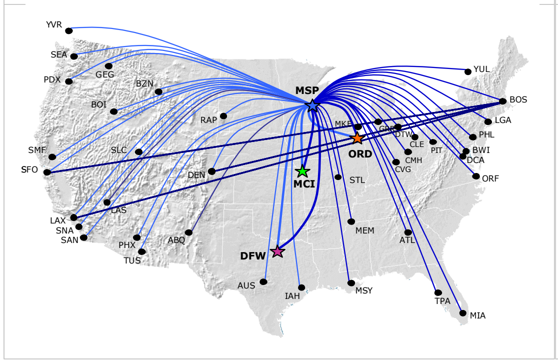
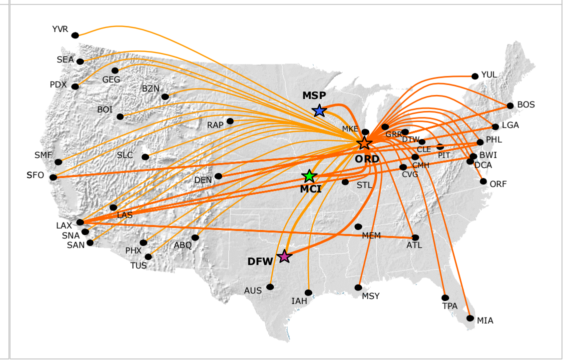


FIGURE 5-2
Route Network of Airline 2 (ORD/Legacy)



Airline 1 is a legacy airline based in Minneapolis-Saint Paul. As a default, it uses the basic leg-based EMSRb inventory control algorithm with standard forecasting for revenue management. It serves every O-D market in Network 'S.' To represent a traditional hub-and-spoke carrier, it has only three point-to-point services that bypass its hub.

With its hub in Chicago, Airline 2 is another legacy airline. Its revenue management system is based on O-D inventory control method DAVN with standard forecasting. It has a network that is comparable to Airline 1's, covering most, but not all, the O-D markets.

FIGURE 5-3
Route Network of Airline 3 (MCI/LCC)

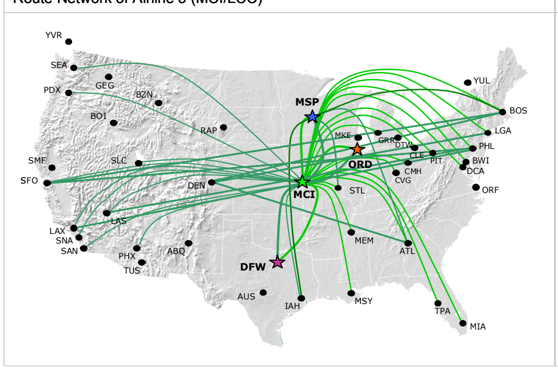
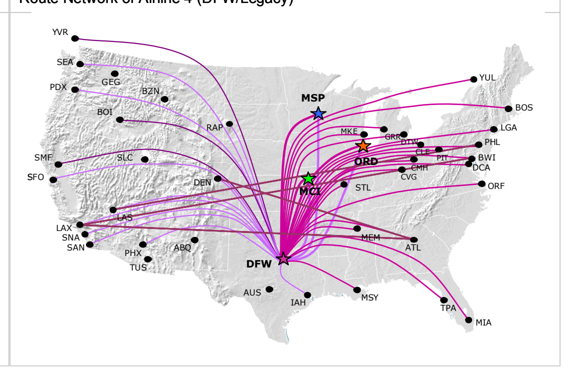


FIGURE 5-4
Route Network of Airline 4 (DFW/Legacy)



Airline 3 is the only LCC of the four airlines. Its hub is located in Kansas City. For revenue management, it controls its inventories using the adaptive load factor threshold method, described earlier in Chapter 3.3.2.b. It is present in slightly more than half of Airline 1's markets and characteristic of LCCs, it has significantly more point-to-point services.

Airline 4, the third network carrier, has its hub at Dallas-Fort Worth. Like Airline 2, it uses DAVN network inventory control with standard forecasting as part of its revenue management system. Its network is smaller than those of airlines 1 and 2.

The route networks are summarized in Table 5-1.

Table 5-1: Summary of Network 'S' Route Networks

Airline	Number of Origin Cities (Includes Competitor Hubs)	Number of Destination Cities (Includes Competitor Hubs)	Number of Services that Bypass Hub	O-D Markets (Local/Connect)
Airline 1 (MSP)	24	24	3	572 (49/523)
Airline 2 (ORD)	24	23	6	548 (51/497)
Airline 3 (MCI)	15	20	19	296 (44/252)
Airline 4 (DFW)	18	24	4	428 (44/384)

5.1.2 Mixed Fare Structures

Network 'S' has a mixed fare structure. In the 296 markets where the LCC (Airline 3) has entered, fares are lower and many restrictions have been removed (Table 5-2).

Table 5-2: Fare Structure for Markets with LCC

Fare Class	Average Fares	Requirements and Restrictions			
		Advance Purchase	Minimum Stay	Cancellation Fee	Non-refundable
1	$324.14	None	None	None	No
2	$250.95	None	None	Yes	No
3	$188.21	7 days	None	None	Yes
4	$146.38	7 days	None	Yes	Yes
5	$125.47	14 days	None	Yes	Yes
6	$104.56	14 days	None	Yes	Yes

On the other hand, without the LCC present, higher fares persist (Table 5-3). There are slightly stricter advance purchase and cancellation fee restrictions. However, as with the LCC markets, fares in these non-LCC markets no longer carry a minimum stay requirement. There are 276 non-LCC markets.

Table 5-3: Fare Structure for Markets without LCC

Fare Class	Average Fares	Requirements and Restrictions			
		Advance Purchase	Minimum Stay	Cancellation Fee	Non-refundable
1	$674.96	None	None	None	No
2	$530.33	3 days	None	Yes	No
3	$385.69	7 days	None	Yes	Yes
4	$257.13	10 days	None	Yes	Yes
5	$208.92	14 days	None	Yes	Yes
6	$160.71	14 days	None	Yes	Yes

5.2 AIRLINE 1 (EMSRB WITH STANDARD FORECASTING) MATCHING AIRLINE 3 (AT90)

5.2.1 Inputs

The revenue management combinations for the first scenario are the defaults of Network 'S' as described in the previous section. Airline 1 uses EMSRb with standard forecasting. In most of the markets without the LCC, it faces competition from Airline 2 and Airline 4 using the more advanced network revenue management system – DAVN with standard forecasting. At the same time, it competes with the LCC Airline 3 in the less restricted markets. Airline 3 uses AT90 with initial fare class load thresholds that are loose (Table 5-4).

Table 5-4: Loose Initial Fare Class Load Thresholds for AT90

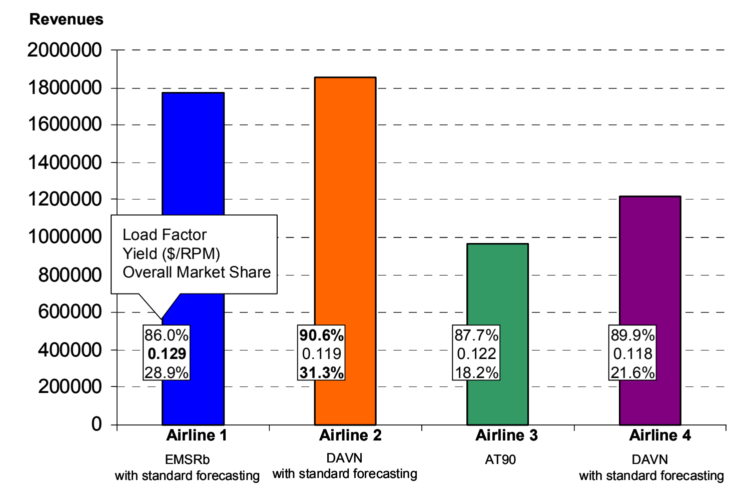
LOOSE	
Fare Class	**Load Threshold**
1	100%
2	90%
3	80%
4	70%
5	60%
6	50%

I will first simulate the base case where there is no matching. Then, I will have Airline 1 availability match Airline 3's (the LCC) lowest fare seat availability in three ways: Closure Matching, Open Matching and Bi-directional Matching.

5.2.2 Base Case

Airline 1, the main airline under investigation, has the highest yield, but slightly less revenue and market share than Airline 2 because it has the lowest load factor (Figure 5-5). Airline 2 has the highest revenue, load factor and market share because of its O-D revenue management system (DAVN) and wide network. Since Airline 4 uses the same revenue management system as Airline 2, but has a smaller route network, it has very similar load factor and yield, but lower revenue and market share. Airline 3 has the lowest revenues and market share because it operates in the fewest markets that also have lower fares.

FIGURE 5-5
Baseline Metrics in Network 'S' (AL1: EMSRb with Standard Forecasting)



The breakdown of revenues between the LCC and non-LCC markets (Figure 5-6, Figure 5-7) indicate that 80% of Airline 4's revenues are exposed to the LCC , the highest of all three legacy airlines. Both Airline 1 and Airline 2 derive about 60% of their revenues from LCC markets, since the LCC has entered the markets with denser traffic.

FIGURE 5-6
Baseline Metrics in LCC Markets (AL1: EMSRb with Standard Forecasting)

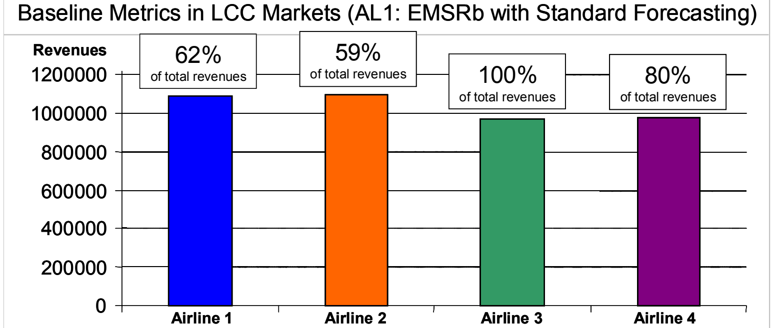
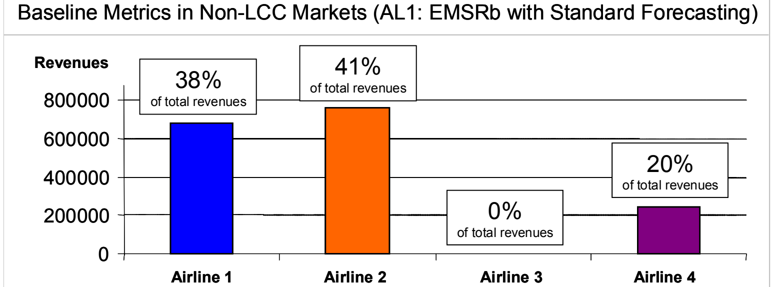


FIGURE 5-7
Baseline Metrics in Non-LCC Markets (AL1: EMSRb with Standard Forecasting)



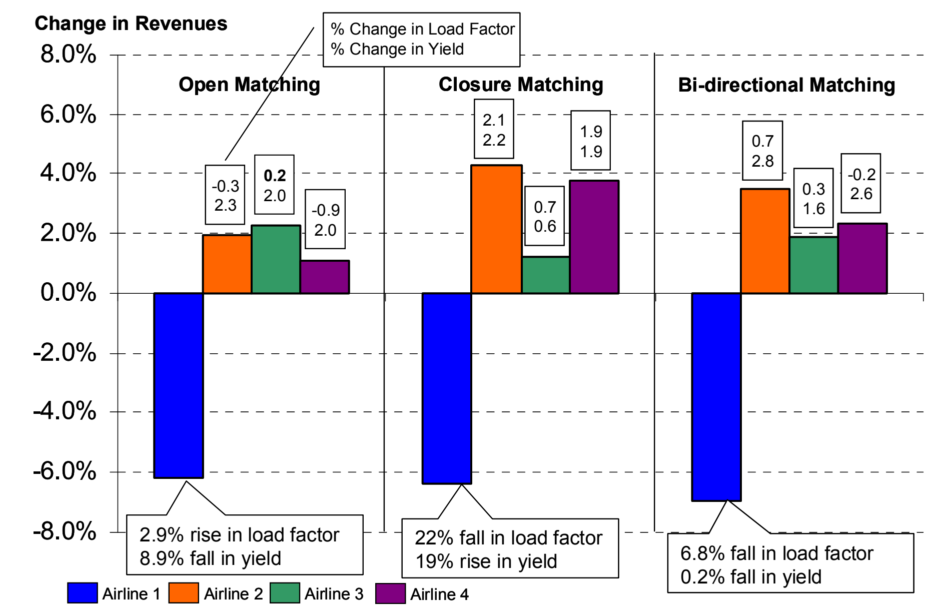
5.2.3 Overview of Changes with Seat Availability Matching

First, all three types of availability matching cause Airline 1 to lose approximately 6% to 7% of its revenues (Figure 5-8). However, the underlying reasons are different: for Open

Matching, Airline 1 gains extra passengers but dilutes its yield, for Closure Matching, the reverse happens. For Bi-directional Matching, both load factor and yield drop, with a magnitude of change between those of Open and Closure Matching. The revenue losses are especially unfavorable because for all three types of seat availability matching, all the other airlines gain revenues.

FIGURE 5-8

Overview of Changes as AL1(EMSRb with SF) Matches AL3



Having initially the second highest revenue of $1,771,185, lowest load factor of 86% and highest yield of 0.129, as Airline 1 open matches Airline 3, its load factor overtakes Airline 3's but its yield falls to the lowest among all four airlines (Table 5-5). As Airline 1 closure matches, its load factor drops to a relatively low 67.5%, although it yield is boosted proportionally. With Bi-directional Matching, Airline 1's load factor falls and remains the lowest, while its yield falls slightly but remains the highest. With each type of seat availability matching, Airline 1's revenue falls but remains second highest among the four airlines.

Table 5-5: Metrics after Matching (AL1: EMSRb with SF)

Type of Matching	Metric	Airline 1	Airline 2	Airline 3	Airline 4
Open	**Revenue**	1661261	**1887109**	992096	1236038
	Load Factor	88.5%	**90.3%**	87.9%	89.1%
	Yield	0.117	0.122	**0.125**	0.120
Closure	**Revenue**	1658085	**1931304**	981896	1268841
	Load Factor	67.5%	**92.5%**	88.3%	91.6%
	Yield	**0.153**	0.122	0.123	0.120
Bi-directional	**Revenue**	1648071	**1916495**	988662	1251647
	Load Factor	80.2%	**91.3%**	87.9%	89.7%
	Yield	**0.129**	0.123	0.124	0.121

5.2.3.a Direct, Collateral or Indirect Changes in Revenues

The impacts of seat availability matching on the revenues are direct if the changes result immediately from the LCC markets, where the matching takes place. However, if the impacts are collateral or indirect, the revenue changes are derived from the non-LCC markets, where availability matching does not take place. For example, all four airlines serve SFO (San Francisco) and DCA (Washington, DC) through their hubs, but only Airline 3 does not serve ORF (Norfolk Airport). When Airline 1 matches the seat availability of Airline 3 in the LCC market SFO-DCA, direct revenue impacts to all four airlines come from that market. Collateral or indirect impacts to airlines 1, 2 and 4 come from a non-LCC market like SFO-ORF.

If the impacts of seat availability matching come evenly from the two types of markets, the proportion of revenue changes from the LCC markets should correspond to the proportion of revenue derived from that the LCC markets prior to matching. In other words, if the revenue losses from availability matching come equally from both types of markets, 62% of Airline 1's losses should come from LCC markets, where it used to obtain 62% of its revenues from.

As illustrated in Figure 5-9, when Airline 1 matches the seat availability of Airline 3, most of its losses stem directly from the LCC markets (73%/90%/85% respectively for Open/Closure/Bi-directional).

FIGURE 5-9
Changes in LCC Markets as AL1(EMSRb with SF) Matches AL3

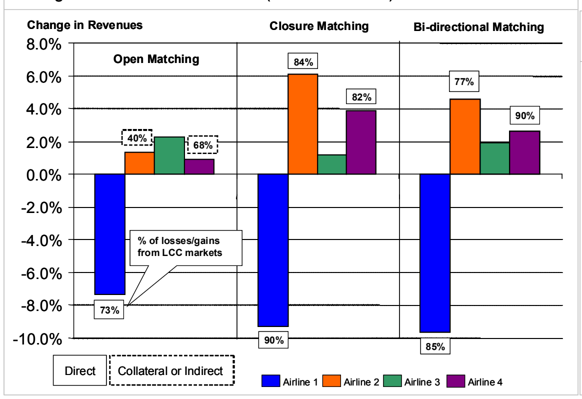
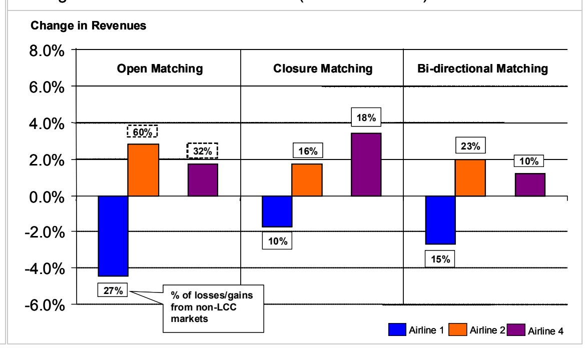


FIGURE 5-10
Changes in Non-LCC Markets as AL1(EMSRb with SF) Matches AL3



Similarly, Airline 2 and Airline 4 gain directly from LCC markets when Airline 1 closure matches or bi-directional matches Airline 3's seat availability. The exceptions happen when Open Matching takes place. Respectively, Airline 2 and 4 gain 60% and 32% of their revenue improvements from the non-LCC markets, where they only used to obtain 41% and 20% of their total revenues. Furthermore, seat availability matching does not take place in these markets and the matching target is neither of these two airlines.

These collateral gains by Airline 2 and Airline 4's revenues are drive by two causes. The first cause is that Airline 1 uses leg-based inventory control on itineraries that may involve more than one leg. For example, when Airline 1 makes the legs SFO-MSP and MSP-DCA more available as it open matches Airline 3 in the LCC market SFO-DCA, it cannot ensure that the seats on the two legs are offered to SFO-DCA passengers as intended. The seats may be taken by passengers on non-LCC itineraries. By taking excessive low-fare passengers, Airline 1 then spills higher-fare passengers to airlines 2 and 4. The second reason explains why the indirect changes only happen with Open Matching. Airline 1 was more restrictive than Airline 2 and Airline 4 in the non-LCC markets before seat availability matching, so Open Matching, rather than Closure Matching, makes a bigger difference in these markets.

5.2.3.b Market Share

The changes to Airline 1's market share are mostly at the expense of, or to the benefit of, Airline 2 and Airline 4, even though Airline 1 matches Airline 3's seat availability (Table 5-6). Like in the single symmetric market, this can be attributed to the relative rigidity of AT90, the revenue management system assumed for Airline 3. Moreover, unlike the single market scenario, where passengers spilled from the matching airline tend to book on the matched airline or vice versa, passengers now have more airlines to choose from.

In addition, since Airline 1 controls inventory by legs but matches lowest fare seat availability by path, there is a significant proportion of collateral market share changes in the non-LCC markets. With Open Matching, Airline 1's gain of market share from competitors is much more significant in the non-LCC markets (1.5 pp) than the LCC markets (0.1pp). With Closure Matching, Airline 1 not only loses market share in the LCC markets (5.1pp, mostly to airlines 2 and 4) but also in the non-LCC markets (1.7pp, to airlines 2 and 4).

Table 5-6: Market Share by Market Type (AL1: EMSRb with SF)

LCC Markets								
	Airline 1		Airline 2		Airline 3		Airline 4	
	Market Share %	% point change	Market Share	% point change	Market Share	% point change	Market Share	% point change
Without	25.8	-	27.0	-	23.4	-	23.8	-
Open	25.9	0.1	26.9	-0.1	23.5	0.1	23.7	-0.1
Closure	20.7	-5.1	29.3	2.3	24.4	1.0	25.6	1.8
Bi-directional	23.8	-2.0	27.9	0.9	23.9	0.5	24.4	0.6
Non-LCC Markets								
	Airline 1		Airline 2		Airline 3		Airline 4	
	Market Share %	% point change	Market Share	% point change	Market Share	% point change	Market Share	% point change
Without	39.6	-	46.3	-	-	-	14.1	-
Open	41.1	1.5	45.3	-1.0	-	-	13.6	-0.5
Closure	37.9	-1.7	47.3	1.0	-	-	14.8	0.7
Bi-directional	40.3	0.7	45.9	-0.4	-	-	13.8	-0.3

5.2.4 Impacts on Airline 1

The other three airlines will be discussed in later sections; for this section, I will focus on analyzing Airline 1's losses. Airline 1's revenues decline 6% to 7% with all three types of seat availability matching and the greatest drop in revenues happens with Bi-directional Matching.

The fare class mix of Airline 1 as it matches Airline 3 in seat availability (Figure 5-11) and the changes in fare class mix (Figure 5-12) show that as Airline 1 becomes less restrictive with Open Matching, its load factor rises. There is a pronounced increase in of 17 passengers from fare class 6 that outweighs the loss of fewer passengers from fare classes 1 to 5. Since fare class 6 passengers pay the lowest fares, Airline 1's yield falls, and by more than its load factor rises, leading to the revenue loss. The changes to Airline 1's fare class mix from Open Matching occur mainly in the LCC markets.

FIGURE 5-11
Fare Class Mix of AL1(EMSRb with SF) as AL1 Matches AL3

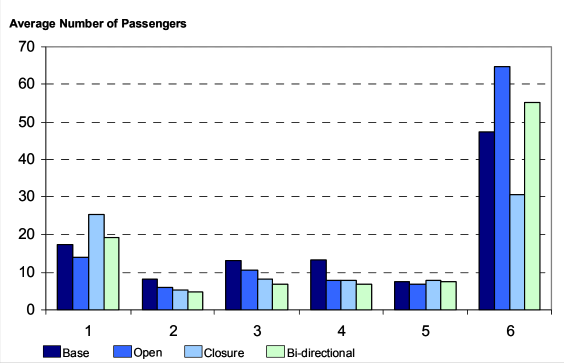
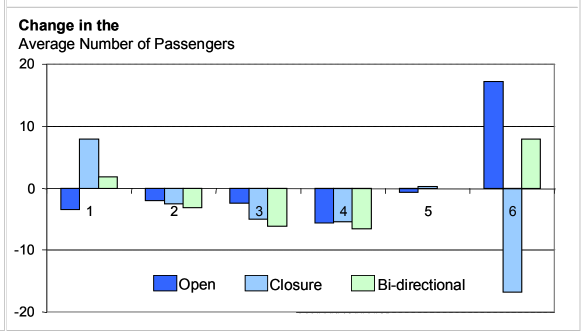


FIGURE 5-12
Changes in Fare Class Mix of AL1(EMSRb with SF)



When Airline 1 closure matches Airline 3, its increase in the average number of fare class 1 passengers causes a significant rise in yield of 19%. Unfortunately, it becomes overly restrictive and loses passengers in all the other fare classes, especially fare class 6 where it loses an average of about 17 passengers. This translates to a 22% drop in load factor and an overall revenue loss.

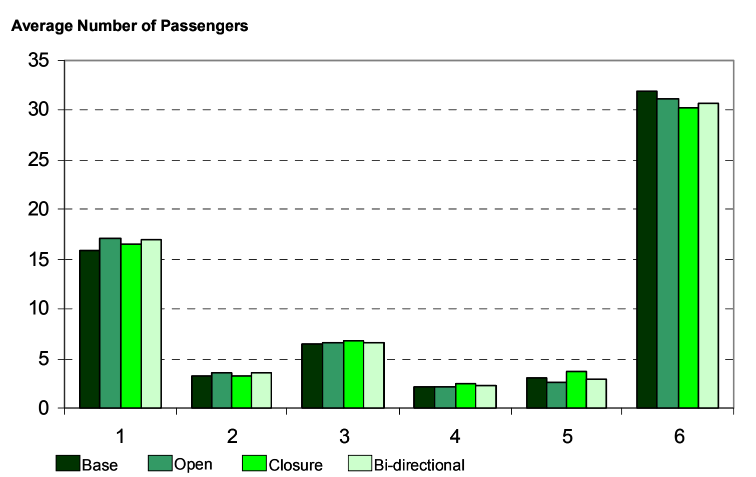
When Airline 1 matches Airline 3's seat availability in both directions, the passenger number for fare class 6 rises because of Open Matching. At the same time, the average number of passengers rises for fare class 1 because of Closure Matching. The downside to matching in both directions is that the decreases in passenger numbers for the fare classes in between – fare classes 2 to 4 – are compounded. As a result, Airline 1's load factor and yield both fall, causing an overall greatest loss in revenue across the three types of lowest fare seat availability matching.

5.2.5 Impacts on Airline 3

The changes to Airline 3 when it is matched in the lowest fare seat availability are on a relatively smaller scale, because it uses AT90 – a revenue management system that does not respond directly to seat availability matching. The revenues increase, but are capped at 2%. The changes in load factor or yield are also limited to about 2%. The fare class mix, shown in Figure 5-13, experiences only relatively small fluctuations. The middle fare classes 3 and 4 are almost constant throughout the absence or presence of different types of seat availability matching.

These findings of slightly improved revenues and small changes in yields and loads concur with the earlier single symmetric market scenario where an airline using AT90 was the subject of seat availability matching by an airline using EMSRb with standard forecasting (Chapter 4.2.4).

FIGURE 5-13
Fare Class Mix of AL3 as AL1(EMSRb with SF) Matches AL3



5.2.6 Impacts on Airlines 2 and 4

Airlines 2 and 4 have very similar fare class mixes before seat availability matching, and they tend to change in the same way after matching (Figure 5-14 and Figure 5-15). However, Airline 2 has more passengers in fare classes 4 to 6. Both airlines have similar load factors and these extra passengers are from Airline 2's with larger average aircraft capacity.

FIGURE 5-14

Fare Class Mix of AL2 as AL1(EMSRb with SF) Matches AL3

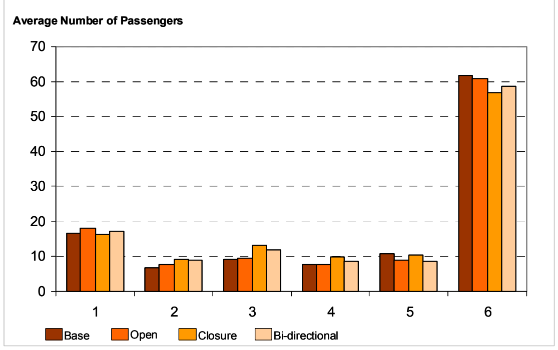
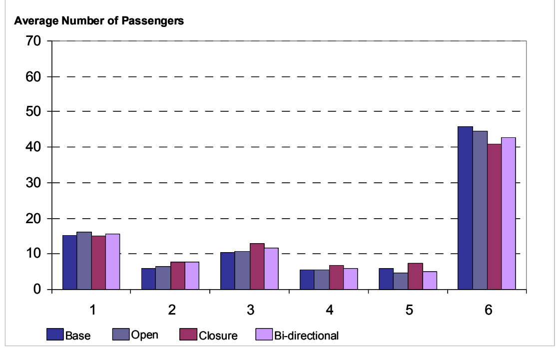


FIGURE 5-15

Fare Class Mix of AL4 as AL1(EMSRb with SF) Matches AL3



With Open Matching, the number of passengers rise in fare classes 1, 2 and 3 but fall in fare classes 5 and 6 for both airlines. Their revenue gains are driven by their yields rise. With Closure Matching, load factors improvements build on the increases in yields, caused mainly by the increase in passengers in fare classes 2 to 4.

5.2.7 Conclusions

When Airline 1 performs seat availability matching against Airline 3's lowest fares, regardless of the type of matching (Open, Closure or both), the revenue effects are consistently negative for itself (loss of 6% to 7%) but positive for the other three airlines. Most of the impacts are direct – revenues increase or decrease in the LCC markets.

However, particular to Open Matching, a significant portion of the revenue changes of Airline 2 and Airline 4 are collateral or indirect, from the non-LCC markets. There are two reasons for these indirect changes: first, LCC and non-LCC markets share the same legs but Airline 1's leg-based inventory control loosens or tightens control by leg, and is unable to isolate seat availability matching to the specific O-D pair. The second reason, which makes the phenomenon unique to Open Matching, is that Airline 1 was more restrictive than Airline 2 and Airline 4 in the non-LCC markets before seat availability matching. The influence Open Matching exerts indirectly on non-LCC markets rather than directly on LCC markets is also reflected in Airline 1's 1.5pp gain in market share in the former and 0.1pp gain in the latter.

Changes in Airline 1's market share are most pronounced with Closure Matching – Airline 1 loses 5.1pp market share in LCC markets and 1.7pp in non-LCC markets. In general, Airline 1 gains or loses market share to Airline 2 and Airline 4, rather than Airline 3 that it is matching. This exchange of market share is more realistic than the single market scenario, where passengers spilled from the matching airline book on the matched airline or do not travel at all. Airline 3 undergoes limited changes in load factor and therefore market share when the airline is matched in terms of lowest fare seat availability because its AT90 revenue management system is relatively inflexible.

In this scenario, standard forecasting is used by Airline 1 even though the fare structures have becomes less-restricted. As a result, standard forecasting leads to overly loose inventory control. In the next scenario, I will examine Airline 1's performance when it uses hybrid forecasting instead. For product-oriented demand, Airline 1 would still control inventory based on standard forecasting, but towards price-oriented demand, it would use Q-forecasting.

5.3 AIRLINE 1 (EMSRB WITH HYBRID FORECASTING) MATCHING AIRLINE 3 (AT90)

5.3.1 Inputs

Airline 1 uses EMSRb with hybrid forecasting, meaning it continues to forecast demand using standard pick-up forecasting for product-oriented passengers but now uses Q-forecasting for price-oriented passengers. Although demand forecasting is now done on a O-D basis, inventory control remains leg-based. For the categorization of historical bookings necessary for hybrid forecasting, the "path rule" is used, meaning a passenger is considered "product-oriented" if he/she booked a fare class when the next lower class is still available on the same path. The other airlines use the same revenue management systems as they have before – airlines 2 and 4 use DAVN with standard forecasting while Airline 3 uses AT90.

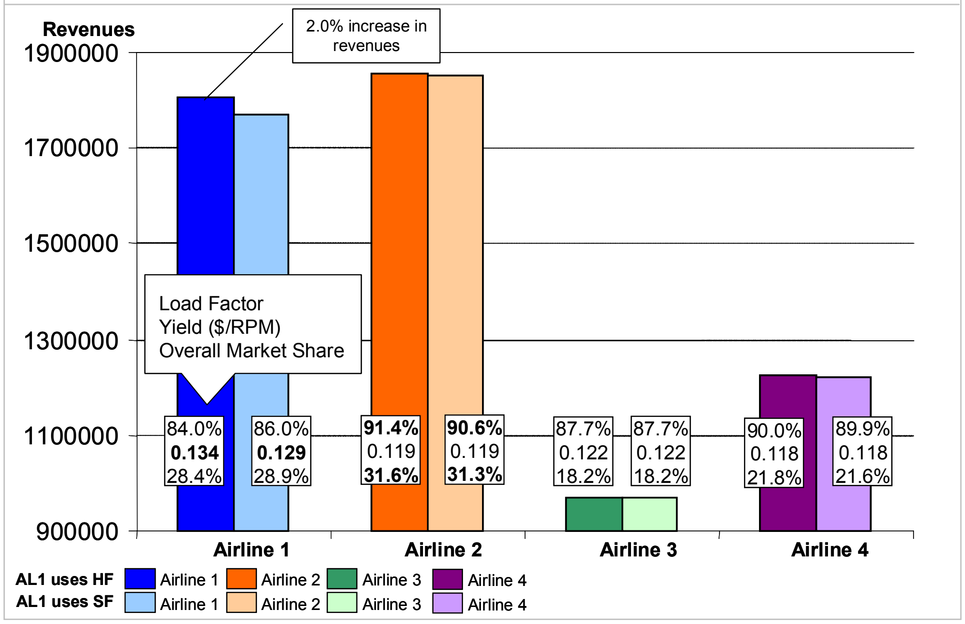
The base case will be presented first, followed by the changes when Airline 1 matches the seat availability of Airline 3 in the three ways of Open Matching, Closure Matching and Bi-directional Matching.

5.3.2 Base Case

With hybrid forecasting, Airline 1 performs better than with standard forecasting – its revenues increase by 2%. The revenue improvements come mainly from an increase in yield rather than load factor (Figure 5-16). The other three airlines have revenues and yields that are generally the same as when Airline 1 used standard forecasting. Airline 2 increased its load factor slightly, as Airline 1's load factor drops by 2%.

FIGURE 5-16

Baseline Metrics in Network 'S' (AL1: EMSRb, HF cf. SF)



The breakdown of revenue by market type indicates that the revenue gains by Airline 1 with hybrid forecasting come from both the LCC and non-LCC markets (Figure 5-17 and Figure 5-18). This is expected since the more suitable method of Q-forecasting is now used for price-oriented demand whereas standard forecasting continues to be used for product-oriented demand. The use of Q-forecasting that tightens inventory control towards price-oriented demand also explains yield – rather than load factor – as the driver of revenue improvements.

FIGURE 5-17

Baseline Metrics in LCC Markets (AL1: EMSRb, HF cf. SF)

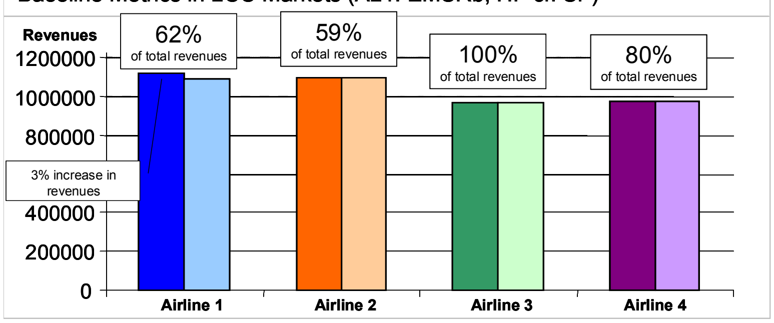
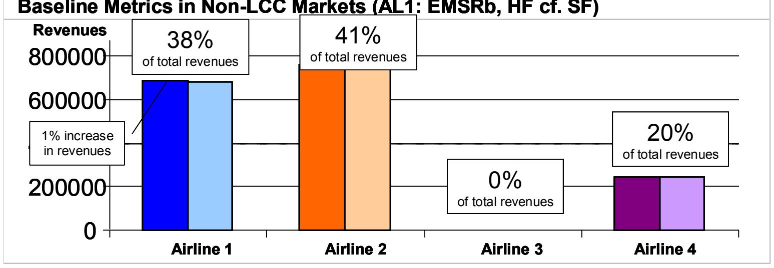


FIGURE 5-18

Baseline Metrics in Non-LCC Markets (AL1: EMSRb, HF cf. SF)

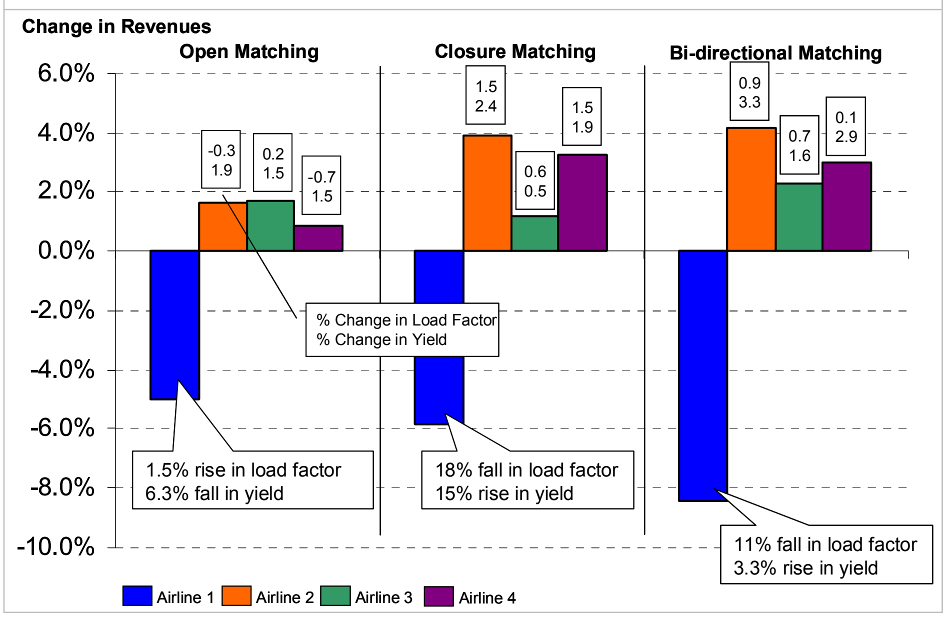


5.3.3 Overview of Changes with Seat Availability Matching

Similar to when Airline 1 used standard forecasting, when Airline 1 uses hybrid forecasting, it does worse in revenues with all three ways of matching (Figure 5-19). Once again, the other airlines gain from the seat availability matching. However, in this scenario, with Open Matching and Closure Matching, the drops in Airline 1's revenue are less negative in both absolute and percentage terms. The magnitude of the changes in Airline 1's load factors and yields is also smaller. In other words, not only does the revenue management system using hybrid forecasting do better than the system using standard forecasting without lowest fare seat availability matching, it is less negatively affected by either Open Matching or Closure Matching. At the same time, the three other airlines gain less revenue from Airline 1 Open or Closure Matching than before.

FIGURE 5-19

Overview of Changes as AL1(EMSRb with HF) Matches AL3



Starting from the initial second highest revenue of $1,805,799, the lowest load factor of 84% and the highest yield of 0.134, as Airline 1 open matches Airline 3, Airline 1's load factor increases but remains the lowest. Its yield falls but remains the highest (Table 5-7). Clearly, the negative impacts of Open Matching are less pronounced in this scenario where Airline 1 uses hybrid forecasting than previously when it used standard forecasting.

Table 5-7: Metrics after Matching (AL1: EMSRb with HF)

Type of Matching	Metric	Airline 1	Airline 2	Airline 3	Airline 4
Open	**Revenue**	1715348	**1887325**	9840389	1233847
	Load Factor	85.2%	**91.1%**	87.9%	89.4%
	Yield	**0.126**	0.121	0.124	0.119
Closure	**Revenue**	1700107	**1929533**	979162	1263758
	Load Factor	68.9%	**92.8%**	88.3%	91.4%
	Yield	**0.154**	0.122	0.122	0.120
Bi-directional	**Revenue**	1652863	**1934462**	989792	1260200
	Load Factor	75.5%	**92.2%**	88.3%	90.2%
	Yield	**0.139**	0.123	0.124	0.121

As Airline 1 closure matches, its load factor drops to 68.9%, which is not as low as when it did the same while using standard forecasting (67.5%). It is only with Bi-directional Matching that the negative impacts are stronger when Airline 1 uses hybrid forecasting instead of standard forecasting. Airline 1's load falls to 74.5% from 84% – a much bigger drop than when it used standard forecasting and matched in both directions (80.2% from 86.0%).

5.3.3.a Direct, Collateral or Indirect Changes in Revenues

Like the earlier scenario, most of the revenue changes happen directly in the LCC markets (Figure 5-20) while Airline 2 and 4 benefit indirectly from Open Matching in non-LCC markets (Figure 5-21). The difference with the previous scenario is that with hybrid forecasting, Airline 1 does less badly in the LCC markets when Open or Closure Matching is implemented. The source of the overall improvements in revenues is the performance in the LCC markets rather than the non-LCC markets. In the LCC markets, with Open Matching, Airline 1 now loses only 5.5% of revenues (hybrid forecasting) instead of losing 7.3% of revenues (standard forecasting). With Closure Matching, Airline 1 loses only 8.6% of revenues (hybrid forecasting) rather than losing 9.3% of revenues (standard forecasting).

FIGURE 5-20

Changes in LCC Markets as AL1(EMSRb with HF) Matches AL3

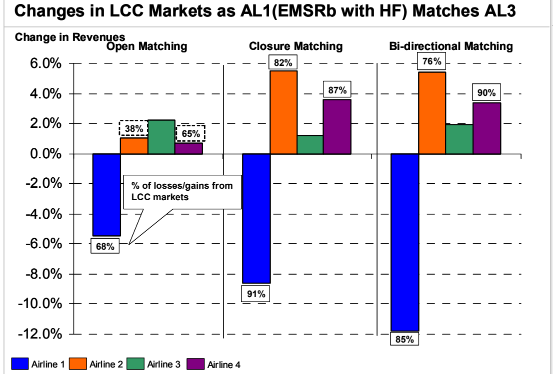
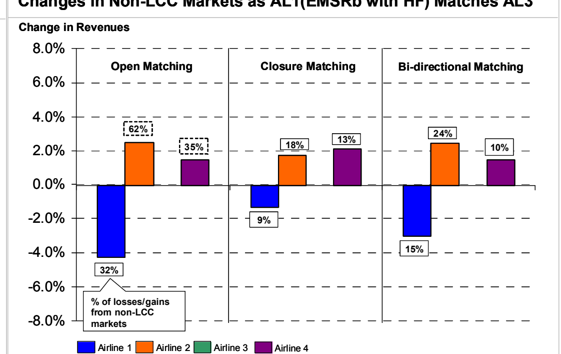


FIGURE 5-21

Changes in Non-LCC Markets as AL1(EMSRb with HF) Matches AL3



5.3.3.b Market Share

As before when Airline 1 uses standard forecasting, the changes to Airline 1's market share when it uses hybrid forecasting are tied to changes at airlines 2 and 4 (Table 5-8). In addition, since inventory control remains leg-based, there is still pronounced collateral impacts from seat availability matching. For Open Matching, Airline 1 loses 0.6pp market share in the non-LCC markets but maintains the same market share in LCC markets. As for Closure Matching, it loses 4.2pp market share in the LCC markets but also 1.2pp in the non-LCC markets.

The main difference from the previous scenario is that as a result of stricter inventory control from using Q-forecasting towards price-oriented demand, Airline 1 starts with a lower overall load factor. The changes in load factor for Airline 1 are also slightly smaller in scale with hybrid forecasting (up to 4.2pp) compared to standard forecasting (up to 5.1pp).

Table 5-8: Market Share by Market Type (AL1: EMSRb with HF)

LCC Markets								
	Airline 1		Airline 2		Airline 3		Airline 4	
	Market Share %	% point change	Market Share	% point change	Market Share	% point change	Market Share	% point change
Without	25.6	-	27.1	-	23.4	-	23.9	-
Open	25.6	0.0	27.2	0.1	23.4	0.0	23.8	-0.1
Closure	21.4	-4.2	28.9	1.8	24.3	0.9	25.4	1.5
Bi-directional	22.6	-3.0	28.5	1.4	24.1	0.7	24.9	0.9
Non-LCC Markets								
	Airline 1		Airline 2		Airline 3		Airline 4	
	Market Share %	% point change	Market Share	% point change	Market Share	% point change	Market Share	% point change
Without	38.4	-	47.3	-	-	-	14.3	-
Open	39.0	0.6	47.0	-0.3	-	-	14.0	-0.3
Closure	37.2	-1.2	48.1	0.8	-	-	14.7	0.4
Bi-directional	38.5	0.1	47.3	0.0	-	-	14.2	-0.1

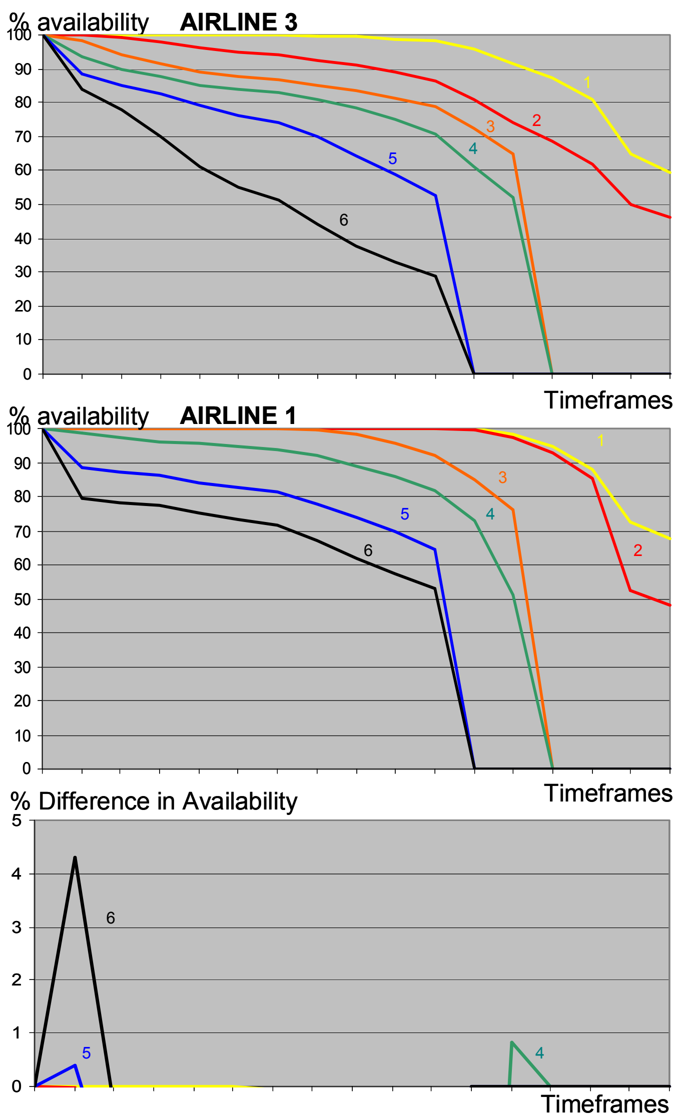
5.3.4 Impacts on Airline 1

One of two possible reasons explain why Airline 1 using EMSRb with hybrid forecasting is less negatively affected by Open or Closure Matching in the LCC markets when compared to when it uses EMSRb with standard forecasting. First, the explanation could be straightforward – less seat availability matching takes place in the LCC markets when Airline 1 uses EMSRb with hybrid forecasting. This would be true should hybrid forecasting make Airline 1's inventories more open than Airline 3's before Open Matching, or more closed than Airline 3's before Closure Matching. Second, it could be that the revenue management system based on EMSRb with hybrid forecasting recovers more quickly and strongly from the disruption caused by the non-RM seat availability matching.

For Open Matching, Figure 5-22 and Figure 5-23 illustrate that the first hypothesis is probably untrue. We compare the average availabilities of the fare classes across all flights of Airline 1 and Airline 3. Where Airline 3 is more available than Airline 1, the positive difference in availability gives an idea of the scale and the timeframe when Airline 1 may open match Airline 3. When Airline 1 uses EMSRb with standard forecasting, it is only less open than Airline 3 in the first time frame for fare classes 5 and 6 and at a later time frame for fare class 4. The differences in percentage availability do not exceed 5%.

FIGURE 5-22

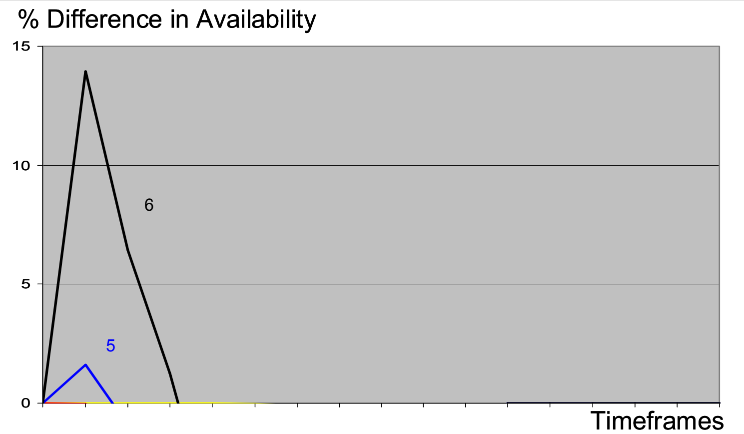
Difference in Availability of AL3 and AL1
(EMSRb with Standard Forecasting)



On the other hand, when Airline 1 uses hybrid forecasting, the gap it needs to bridge with Open Matching appears to be greater than 10% for fare class 6 – more Open Matching is needed.

FIGURE 5-23

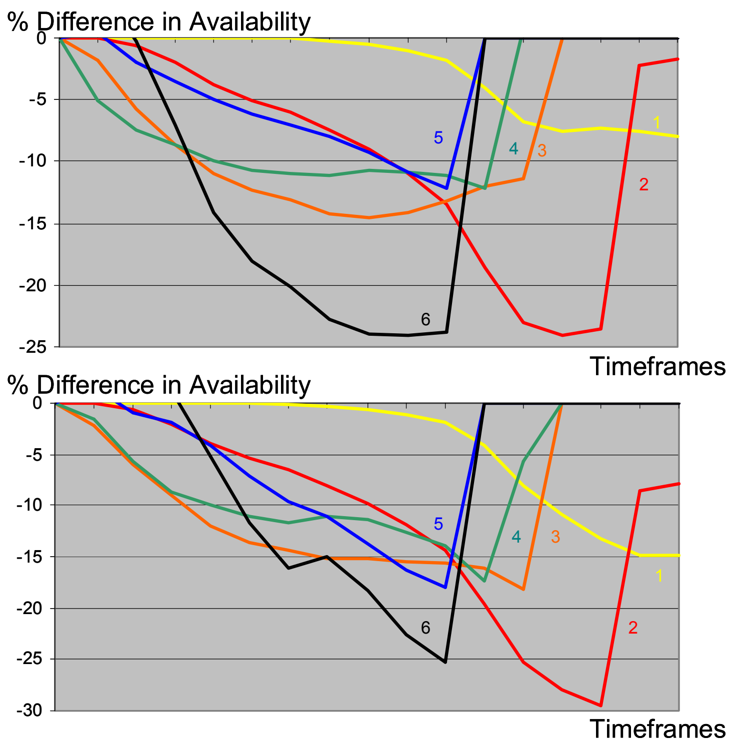
Difference in Availability of AL3 and AL1 (EMSRb with Hybrid Forecasting)



For Closure Matching, Figure 5-24 shows that it is probably true that less availability matching takes place with hybrid forecasting. Closure Matching happens where Airline 3 is less available than Airline 1, as illustrated in Figure 5-24. When Airline 1 uses hybrid forecasting, there is a smaller difference in the availability than when it uses standard forecasting, especially in fare class 6 – less Closure Matching is needed.

Hybrid forecasting, relative to standard forecasting, reduces spiral down and makes the inventory control system more restrictive towards price-oriented demand in LCC markets. As a result, there is more Open Matching and less Closure Matching in the LCC markets.

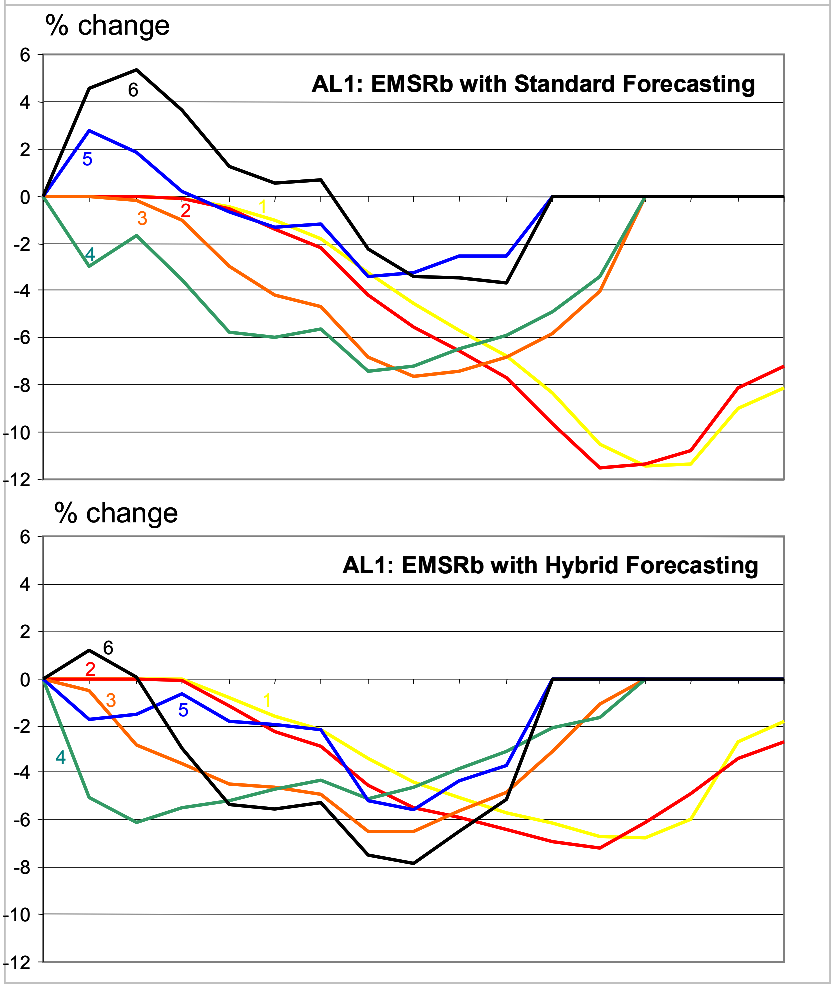
FIGURE 5-24
Difference in Availability of AL3 and AL1 (EMSRb with SF cf. HF)



However, the data on the differences in the seat availability of Airline 1 and Airline 3 before matching is static. It suggests what may happen, but the actual process would be dynamic. The change in availability results from a combination of the matching of seat availability and the reaction by the revenue management system to the availability matching. The revenue management system reacts to the seat availability matching by generating new forecasts of demand and booking limits for inventory control.

Figure 5-25 illustrates the changes in fare class availabilities as Airline 1 open matches Airline 3. Surprisingly, when Airline 1 uses hybrid forecasting, even though it should perform more Open Matching, it ends up being less open and available in fare classes 5 and 6 than when it uses standard forecasting. The change in fare class availability also reveals that the initial Open Matching in lower fare classes sets off further changes in higher fare classes. It appears that the revenue management system based on EMSRb with hybrid forecasting is more robust and reacts quickly against seat availability matching to limit the revenue damage, when compared to the system based on EMSRb with standard forecasting.

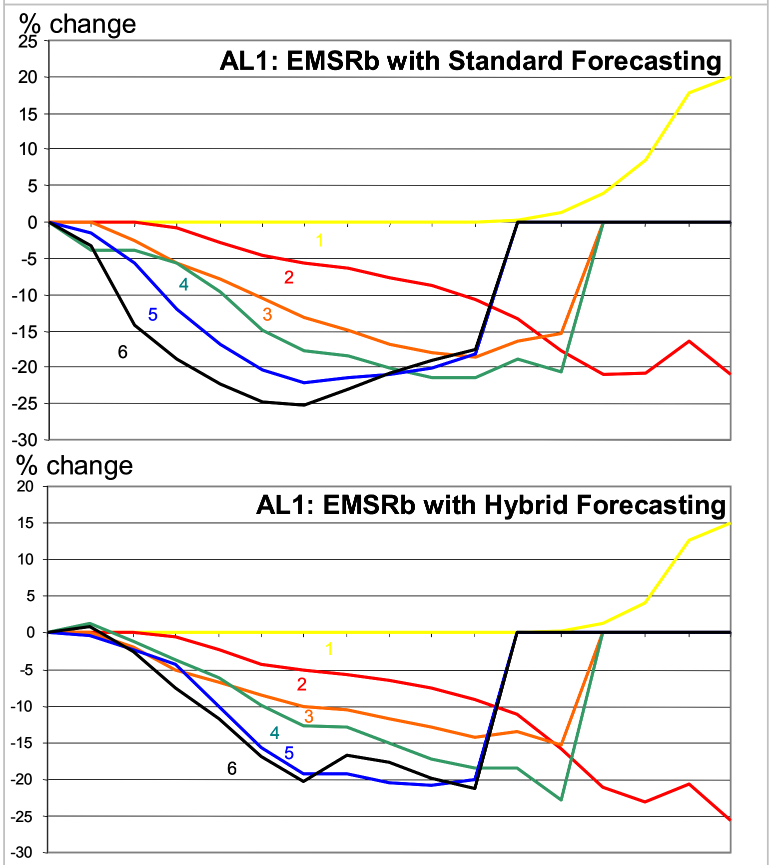
FIGURE 5-25
Change in Fare Class Availability when AL1 Open Matches AL3



At the same time, when Airline 1 uses hybrid forecasting, less Closure Matching is needed and correspondingly the changes to the fare class availabilities are on a smaller scale than when it uses standard forecasting (Figure 5-26).

FIGURE 5-26

Change in Fare Class Availability when AL1 Closure Matches AL3



As a result, the changes in fare class mix for Airline 1 when it uses hybrid forecasting are smaller than when standard forecasting is used, as shown in Figure 5-27 and Figure 5-28.

FIGURE 5-27

Fare Class Mix of AL1(EMSRb with HF) as AL1 Matches AL3

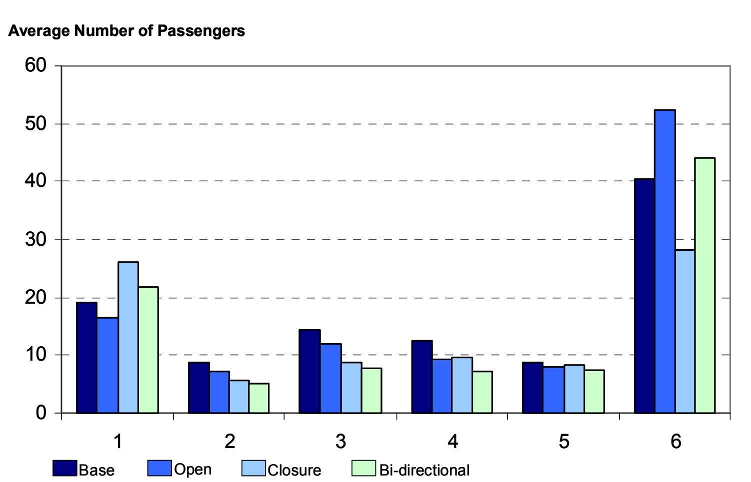
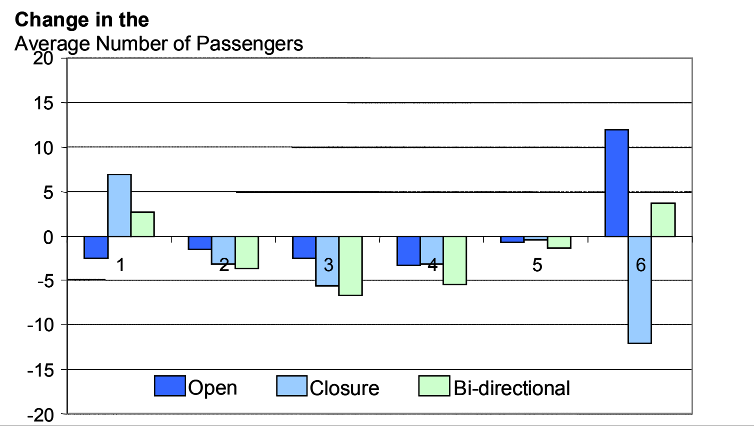


FIGURE 5-28

Changes in Fare Class Mix of AL1(EMSRb with SF)



5.3.5 Conclusions

With Airline 1's revenue management system based on hybrid forecasting instead of standard forecasting, before seat availability matching, Airline 1 now has 2.0% more revenues. Most of the revenue improvements come from the LCC markets as a result of hybrid forecasting.

As Airline 1 matches the seat availability of Airline 3's lowest fares, the revenue effects are still negative for each type of matching. However, the losses in revenue are lower for Open Matching (-5.0%) and Closure Matching (-5.9%) than before (-6.2%/-6.4% respectively). The improved performance comes from the switch in the revenue management system to hybrid forecasting, and are derived mainly from the LCC markets. In these markets, less Closure Matching is needed with Q-forecasting since Airline 1 is more restrictive towards price-oriented demand than before. For Open Matching, looking at the change in the fare class availabilities, it appears that the revenue management system based on hybrid forecasting reacts more quickly and capably to Open Matching and limits the revenue loss more effectively.

Airline 1 performs better with or without seat availability matching when it uses a revenue management system that incorporates hybrid forecasting instead of standard forecasting, while controlling inventory based on EMSRb. However, the control of seats is still being done leg-by-leg. As explained earlier in an example, with leg-based inventory control, seats made available for a passenger flying SFO-DCA on the legs SFO-MSP and MSP-DCA may not be taken by a connecting passenger on that itinerary. With O-D control, a seat made available for the path SFO-DCA cannot be taken by passengers on other paths. In the next section, I will investigate if a more specific form of network-based inventory control, namely DAVN, performs better with lowest fare seat availability matching.

5.4 AIRLINE 1 (DAVN WITH STANDARD FORECASTING) MATCHING AIRLINE 3 (AT90)

5.4.1 Inputs

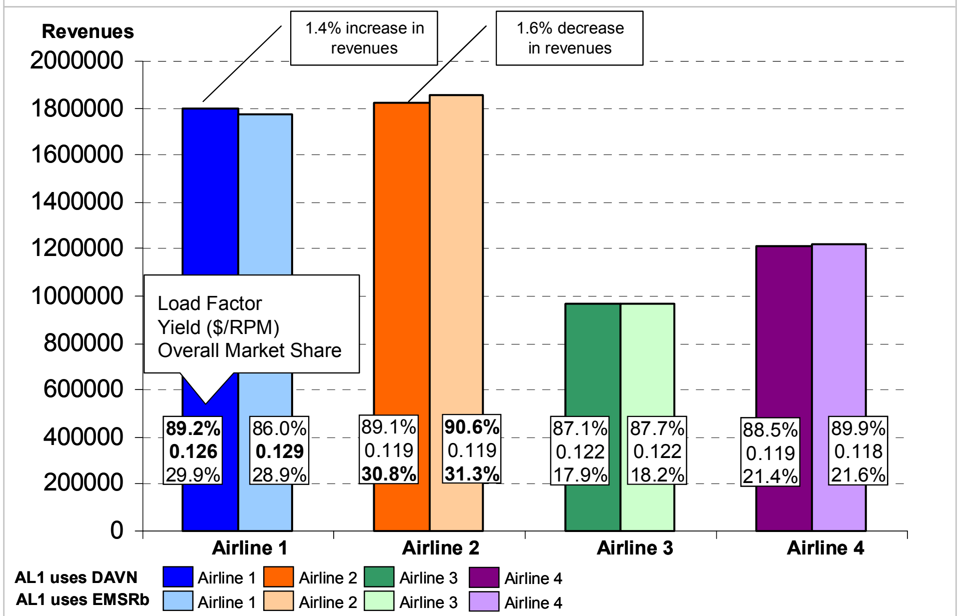
Like Airline 2 and Airline 4, Airline 1 now uses DAVN with standard forecasting. DAVN is an O-D form of inventory control, in contrast to earlier scenarios that used leg-based methods for inventory control. Airline 3 retains its AT90 revenue management system.

Firstly, I will present the base case where no seat availability matching is done. Then, I will discuss the changes when Airline 1 matches the seat availability of Airline 3 in the three ways of Open Matching, Closure Matching and Bi-directional Matching. I will highlight the differences between using DAVN with O-D inventory control and EMSRb with leg-based inventory control.

5.4.2 Base Case

Using O-D inventory control instead of only leg-based inventory control, Airline 1's revenues improve by 1.4%, led by a 3.2% rise in its load factor (Figure 5-29). Unlike leg-based inventory control, DAVN does not erroneously favor high-yielding local passengers over lower-yielding – but overall more lucrative – connecting passengers. Airline 2 is hurt the most by Airline 1's change of revenue management system since its network overlaps most with Airline 1. Its revenues decrease by 1.6% as its load factor falls, causing Airline 1's and Airline 2's revenues, load factors and market shares to be about the same. Airline 1's yield drops, but remains the highest. The changes at Airline 3 and Airline 4 are minor – slight drops in load factor and market share.

FIGURE 5-29
Baseline Metrics (AL1: With Standard Forecasting, DAVN cf. EMSRb)



There is a 6% increase in revenue in LCC markets when O-D inventory control is used instead of leg-based control. At the same time, there is a 2% decrease in revenues in the non-LCC markets. However, the percentage of revenue each airline derives from the LCC and non-LCC markets remain similar to the two earlier scenarios (Figure 5-30 and Figure 5-31).

FIGURE 5-30
LCC Markets (AL1: Standard Forecasting with DAVN)

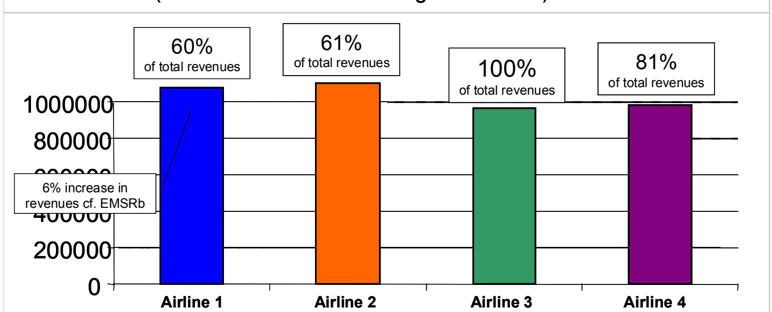
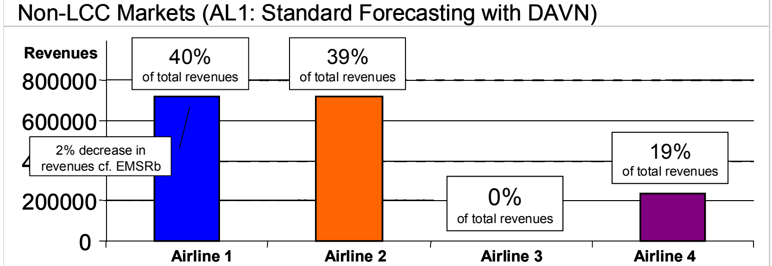


FIGURE 5-31
Non-LCC Markets (AL1: Standard Forecasting with DAVN)



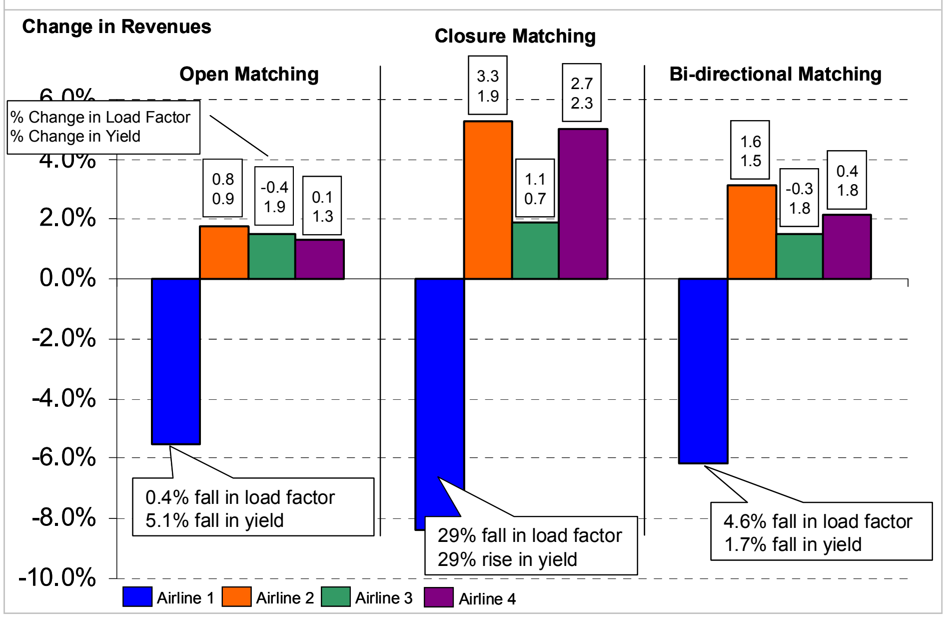
5.4.3 Overview of Changes with Seat Availability Matching

Overall, the changes as Airline 1 matches Airline 3 in terms of the lowest fare seat availability are the similar to the two earlier scenarios – Airline 1's revenues fall while the other three airlines gain (Figure 5-32).

Specifically, when Airline 1 bases its revenue management system on O-D inventory control DAVN and standard forecasting, as it open matches Airline 3's lowest fare seat availability, it loses only 5.5% of its revenues, less than the 6.2% it loses when its method of inventory control is leg-based EMSRb. Its yield falls by less than before, and more interestingly, its load rises slightly instead of falling, even as it open matches to make its lower-fare seats more available. This finding reveals that while the EMSRb form of leg-based inventory control allowed overly large increases in loads because availability matching could not be specific to the path, the DAVN form of O-D inventory control corrected the problem. As a result, less displacement of high-yield passengers by lower-yield passengers takes place and less revenue is lost.

FIGURE 5-32

Overview of Changes as AL1(DAVN with SF) Matches AL3



As Airline 1 bi-directional matches Airline 3, it also does better with O-D inventory control DAVN than leg-based inventory control EMSRb, losing 6.2% of its revenues instead of 7.0%. However, as Airline 1 closure matches Airline 3, it loses 8.3% in revenues instead of 6.4%. The reasons for this inferior performance will be discussed in the next section.

Initially, Airline 1 has the second highest revenue of $1,795,958, the highest load factor of 89.2% and the highest yield of 0.126. After it open matches Airline 3, Airline 1's yield becomes the lowest (Table 5-9). After Closure Matching Airline 3, Airline 1 has a yield that is significantly higher than the other airlines, but also a load factor that is smaller by a wide margin.

Table 5-9: Metrics after Matching (AL1: DAVN with SF)

Type of Matching	Metric	Airline 1	Airline 2	Airline 3	Airline 4
Open	**Revenue**	1697468	**1852770**	979581	1228979
	Load Factor	88.8%	**89.7**	86.8	88.6
	Yield	0.119	0.121	**0.125**	0.120
Closure	**Revenue**	1646013	**1916808**	983107	1274061
	Load Factor	63.3%	**92.0%**	88.1%	90.9%
	Yield	**0.163**	0.122	0.123	0.121
Bi-directional	**Revenue**	1685011	**1877660**	979470	1239394
	Load Factor	85.1%	**90.5%**	86.8%	88.9%
	Yield	**0.124**	0.121	**0.124**	0.121

5.4.3.a Direct, Collateral or Indirect Changes in Revenues

In general, the revenue change to each airline still comes directly from the LCC markets (Figure 5-33 and Figure 5-34). The exceptions remain that Airline 2 and Airline 4's revenue changes with Open Matching are still derived indirectly from the non-LCC markets.

FIGURE 5-33
Changes in LCC Markets as AL1(DAVN with SF) Matches AL3

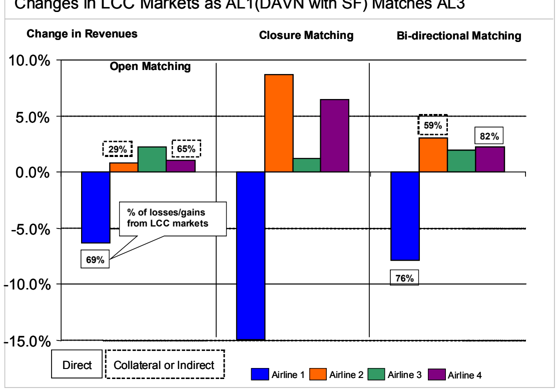
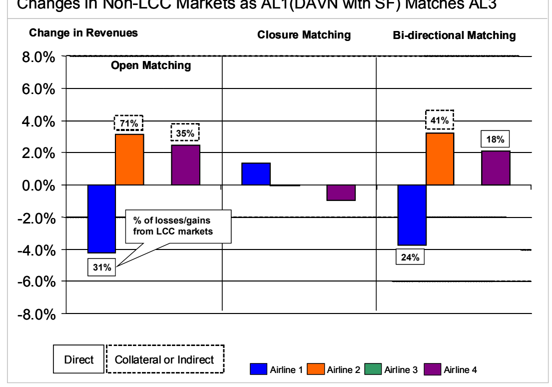


FIGURE 5-34
Changes in Non-LCC Markets as AL1(DAVN with SF) Matches AL3



With Closure Matching, Airline 1 gains revenues in the non-LCC markets. This is a deviation from the earlier two scenarios. The improvement in the non-LCC markets is the result the O-D inventory control method DAVN. When Airline 1 uses leg-based inventory control method EMSRb, to closure match the lower seat availability of Airline 3 in a LCC market, it makes both legs of the market less available to all passengers, without regard for their itineraries. For example, Airline 3 has lower seat availability than Airline 1 in fare class 6 for the market SFO-PHL. With Closure Matching, Airline 1 adjusts its inventory to make fare class 6 less available on the legs SFO-MSP and MSP-PHL. Airline 1 inadvertently rejects many fare class 6 passengers from the non-LCC markets that involve either of the two legs. When Airline 1 uses leg-based EMSRb inventory control, it loses $11,210 on non-LCC markets involving either the SFO-MSP or

MSP-PHL leg (Table 5-10). In contrast, when Airline 1 uses O-D DAVN inventory control, it only loses $733 on those non-LCC markets. The collateral damage on the non-LCC markets – where seat availability matching does not occur – is sharply reduced with O-D inventory control. Overall, Closure Matching brings an improvement in revenues in non-LCC markets when Airline 1 uses O-D inventory control with DAVN.

Table 5-10: Revenues of LCC Market SFO-PHL and Associated Non-LCC Markets (Standard Forecasting, EMSRb cf. DAVN)

Market		Leg-based Inventory Control (EMSRb with SF)			O-D Inventory Control (DAVN with SF)		
		Without Matching	With Matching	Difference	Without Matching	With Matching	Difference
LCC	**SFO-PHL**	**$2,597**	**$3,190**	**$593**	**$3,707**	**$3,657**	**-$50**
Non-LCC involving SFO-MSP	**SFO-YUL**	$2,084	$890	-$1,194	$2,058	$2,148	$90
	SFO-ORF	$1,012	$549	-$463	$972	$882	-$90
	SFO-DTW	$2,517	$1,863	-$654	$2,390	$2,579	$189
	SFO-MKE	$1,703	$1,268	-$435	$1,615	$1,717	$102
	Total	**$7,316**	**$4,570**	**-$2,746**	**$7,035**	**$7,326**	**$291**
Non-LCC involving MSP-PHL	**YVR-PHL**	$4,627	$3,015	-$1,612	$4,496	$4,598	$102
	SMF-PHL	$2,852	$1,922	-$930	$3,645	$3,171	-$474
	BOI-PHL	$2,635	$1,792	-$843	$3,451	$3,470	$19
	GEG-PHL	$2,600	$1,951	-$649	$3,735	$3,847	$112
	TUS-PHL	$818	$433	-$385	$1,146	$972	-$174
	BZN-PHL	$1,927	$1,021	-$906	$2,316	$2,378	$62
	ABQ-PHL	$5,488	$4,061	-$1,427	$3,567	$3,677	$110
	RAP-PHL	$793	$458	-$335	$1,405	$1,311	-$94
	AUS-PHL	$3,738	$2,361	-$1,377	$2,733	$2,046	-$687
	Total	**$25,478**	**$17,014**	**-$8,464**	**$26,494**	**$25,470**	**-$1,024**
Non-LCC	***Total***	**$32,794**	**$21,584**	**-$11,210**	**$33,529**	**$32,796**	**-$733**

In the LCC markets, when Airline 1 closure matches Airline 3, the decrease in revenues is much larger when Airline 1 uses the O-D inventory control method DAVN than when it uses the leg-based method EMSRb. The reason for the larger drop with DAVN is twofold: Airline 1 starts with better performance in the LCC markets and the specificity of O-D inventory control means that these better-performing markets lose revenues from Closure Matching. The losses that used to be accounted for in the non-LCC markets now show up rightfully in the LCC markets. Table 5-10 shows the example of the SFO-PHL market. Compared to leg-based inventory control, Airline 1 has higher revenue with O-D inventory before matching, but loses, instead of gains, revenue from Closure Matching.

Another example is the LCC market SAN-ATL. When Airline 1 uses the EMSRb leg-based inventory control method, it derives $2,689 from that market before Closure Matching Airline 3 and $3,639 after Closure Matching. Although Airline 1 closure matches Airline 3 in this market to reduce seat availability on SAN-MSP and MSP-ATL, the bookings rejected are not from SAN-ATL, but from other itineraries. The number of passengers with the SAN-ATL itinerary increases from around 12 to 19. With O-D inventory control method DAVN, Airline 1 obtains $4,217 from this market because it allows more connecting passengers to book. The number of passengers is around 26. However, when Airline 1 implements Closure Matching, the effective and specific O-D inventory control rejects passengers from the itinerary SAN-ATL. As a result, Airline 1 earns only $1,608 from the SAN-ATL market after Closure Matching. Aggregated over all the LCC markets, the overall result is a much greater loss from Closure Matching when Airline 1 uses DAVN.

5.4.3.b Market Share

When Airline 1 uses leg-based inventory control, as it open matches and becomes less restrictive, it gains loads and market share in the non-LCC markets instead of the LCC markets. As it closure matches and turns more restrictive, it sheds passengers and market share in both the non-LCC and LCC markets.

With O-D inventory control, Airline 1 now isolates the direct effect of seat availability matching to the LCC markets (Table 5-11). With Open Matching, Airline 1 becomes less restrictive and gains market share by 0.5pp in the LCC markets. In the non-LCC markets, it loses 1.7pp of market share. O-D inventory control only allows passengers with the matched itinerary to book, unlike leg-based inventory control that allows passengers with any itinerary involving the re-opened legs to book. With Closure Matching, Airline 1 loses market share by 8.2pp in the LCC markets – leading to Airline 1's lowest market share in LCC markets (17.8%) in the scenarios so far. At the same time, its market share in the non-LCC markets is unaffected by Closure Matching.

Table 5-11: Market Share by Market Type (AL1: DAVN with SF)

LCC Markets								
	Airline 1		Airline 2		Airline 3		Airline 4	
	Market Share %	% point change	Market Share	% point change	Market Share	% point change	Market Share	% point change
Without	26.0	-	27.1	-	23.1	-	23.8	-
Open	26.5	0.5	26.8	-0.3	23.1	0.0	23.6	-0.2
Closure	17.8	-8.2	30.9	3.8	24.7	1.6	26.6	2.8
Bi-directional	25.3	-0.7	27.4	0.3	23.3	0.2	24.0	0.2
Non-LCC Markets								
	Airline 1		Airline 2		Airline 3		Airline 4	
	Market Share %	% point change	Market Share	% point change	Market Share	% point change	Market Share	% point change
Without	43.3	-	43.7	-	-	-	13.0	-
Open	41.6	-1.7	45.0	1.3	-	-	13.4	0.4
Closure	43.3	0.0	43.7	0.0	-	-	13.0	0.0
Bi-directional	41.5	-1.8	45.1	1.4	-	-	13.4	0.4

5.4.4 Impacts on Airline 1

The fare class mix of Airline 1, as shown in Figure 5-35 and Figure 5-36, show that with Open Matching, Airline 1 gains fare class 6 passengers but loses passengers from all higher fare classes, as with previous scenarios.

FIGURE 5-35
Fare Class Mix of AL1(DAVN with SF) as AL1 Matches AL3

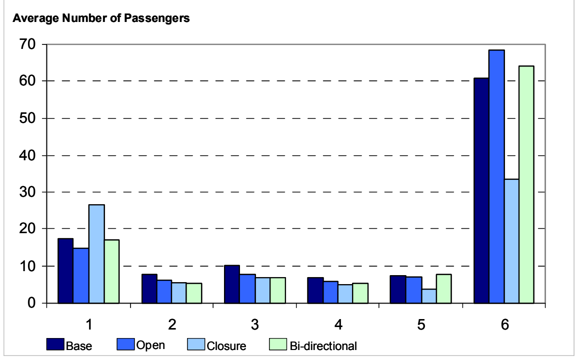
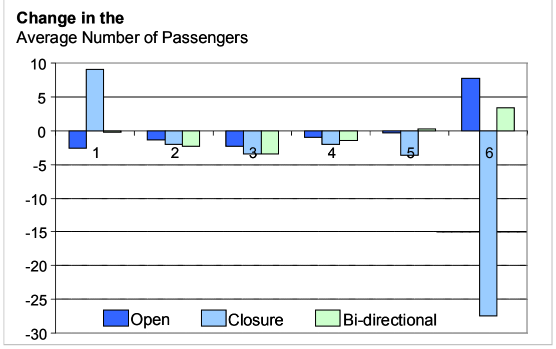


FIGURE 5-36
Changes in Fare Class Mix of AL1(DAVN with SF)



With Closure Matching, Airline 1 gains fare class 1 passengers but loses passengers from all lower fare classes. Although this is the same as previous scenarios, the loss in fare class 6 is much higher than when Airline 1 uses leg-based inventory control.

5.4.5 Conclusions

With O-D inventory control, Airline 1 gets more revenue in the base case as it allows more connecting passengers to book, correcting the local-bias of leg-based inventory control. As it matches the seat availability of Airline 3, Airline 1 loses revenue, to the benefit of the other three airlines, which gain revenue.

With Open Matching, Airline 1 loses less revenue using O-D inventory control than leg-based inventory control. O-D inventory control allows Airline 1 to restrict bookings to only the passengers booking the specific itinerary as open matched, limiting the number of low-yield passengers displacing higher-yield passengers At the same time, the path-specific inventory control causes more losses with Closure Matching. In the LCC markets, the losses become much greater than before as the negative effects of Closure Matching are now fully accounted for there. In the non-LCC markets, Airline 1 benefits slightly from Closure Matching as collateral damage is minimized.

In general, with and without lowest fare seat availability matching, Airline 1's performance is enhanced by O-D DAVN. However, Airline 1 results in LCC markets remains weak, because it still uses standard forecasting, which makes it not sufficiently restrictive in the base case and subsequently to reject too many low-fare passengers with Closure Matching. In the next scenario, I will investigate if pairing O-D inventory control with hybrid forecasting improves Airline 1's outcomes.

5.5 AIRLINE 1 (DAVN WITH HYBRID FORECASTING) MATCHING AIRLINE 3 (AT90)

5.5.1 Inputs

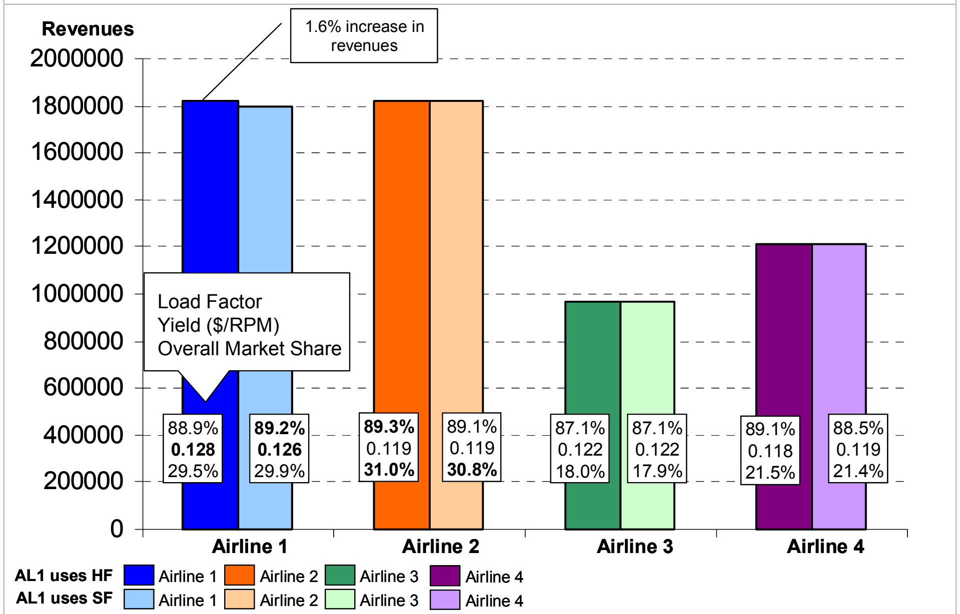
In this scenario, Airline 1 combines the DAVN form of O-D inventory control that is more suited to networks with hybrid forecasting that is more suited to mixed fare structures. Airline 2 and Airline 4 continue to use the DAVN system with standard forecasting, while Airline 3 still uses AT90.

I will first discuss the base case where there is no seat availability matching. Following that, I will examine the outcomes as Airline 1 matches the seat availability of Airline 3 with Open Matching, Closure Matching and Bi-directional Matching. Since O-D control and hybrid forecasting are more suited to the mixed fare structure network, this system is expected to generate the best performance for Airline 1 with and without seat availability matching.

5.5.2 Base Case

Before seat availability matching is done, Airline 1 achieves the highest revenue and yield among the four airlines using the system based on DAVN and hybrid forecasting (Figure 5-37). Its revenues are also the highest so far in the four scenarios simulated. The revenues represent a 1.6% increase over those obtained using the earlier system of DAVN with standard forecasting and a 1.1% improvement compared to the results from the system based on EMSRb with hybrid forecasting. Airline 2 has slightly lower revenues than Airline 1, but has the highest load factor and market share. Airline 3 and Airline 4 remain largely unchanged compared to when Airline 1 uses standard forecasting.

FIGURE 5-37
Baseline Metrics (AL1: DAVN, Hybrid cf. Standard Forecasting)



The split of revenues between the LCC and non-LCC markets remain similar to the three earlier scenarios (Figure 5-38 and Figure 5-39). Airline 1 improves in both the LCC markets and the non-LCC markets.

FIGURE 5-38
LCC Markets (AL1: DAVN with Hybrid Forecasting)

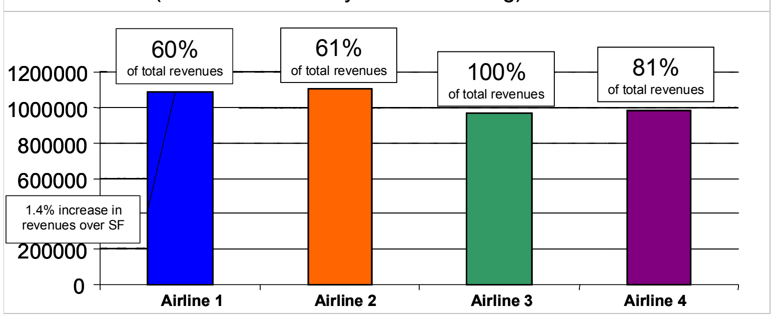
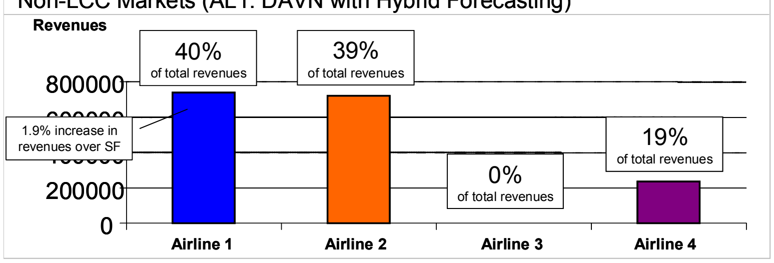


FIGURE 5-39
Non-LCC Markets (AL1: DAVN with Hybrid Forecasting)

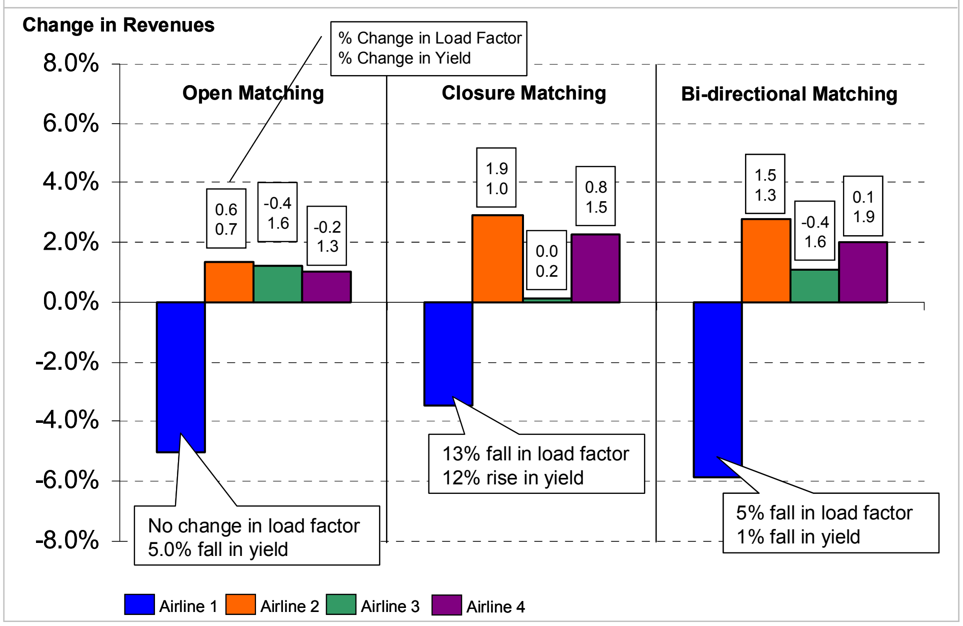


5.5.3 Overview of Changes with Seat Availability Matching

Airline 1's revenues decrease while the other three airlines' revenues increase with each of the three types of seat availability matching (Figure 5-40). This general finding agrees with the outcomes of the three earlier scenarios. The difference is that Airline 1's decreases and the other airlines' increases for each type of availability matching are the lowest so far. With Closure Matching especially, Airline 1's drop in revenue is 3.4%, in contrast to the drops of in revenue of 6.4%, 5.9% and 8.3% for the previous three scenarios. Another difference in this scenario is that when Airline 1 closure matches it, Airline 3 barely benefits, unlike the earlier three scenarios where it gains at least 1% in revenues.

FIGURE 5-40

Overview of Changes as AL1(DAVN with HF) Matches AL3



Like the previous scenario when Airline 1 uses DAVN with standard forecasting, with DAVN and hybrid forecasting, for Open Matching, the load factor for Airline 1 experiences no change. This indicates that the O-D method of DAVN is able to limit the influx of passengers as it becomes less restrictive with Open Matching.

5.5.3.a Direct, Collateral or Indirect Changes in Revenues

The causes of revenue changes are largely the same as the scenario when Airline 1 uses DAVN with standard forecasting, but hybrid forecasting causes significant improvements in the LCC markets, especially for Closure Matching (Figure 5-41 and Figure 5-42).

FIGURE 5-41
Changes in LCC Markets as AL1(DAVN with HF) Matches AL3

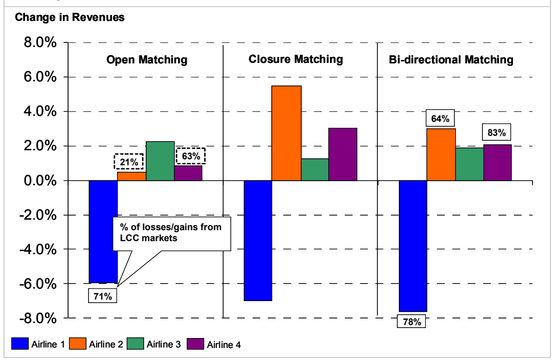
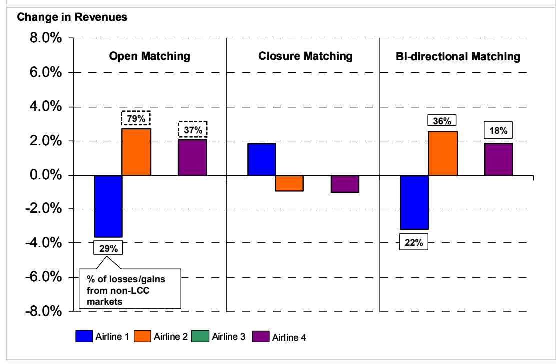


FIGURE 5-42
Changes in Non-LCC Markets as AL1(DAVN with HF) Matches AL3



In the non-LCC markets, Airline 1's improvement with Closure Matching is slightly higher with hybrid forecasting (1.8%) than with standard forecasting (1.3%). At the same time, in LCC markets, with hybrid forecasting Airline 1's decline in revenue of 7.0% is greatly improved from the 15% decline when it uses standard forecasting. This improvement is generated by two phenomena: first, less Closure Matching is required in LCC markets with Q-forecasting as Airline 1 becomes more restrictive compared to with standard forecasting. Second, as explained in Chapter 5.3.4, revenue management systems based on hybrid forecasting appear to recover better from seat availability matching than systems based on standard forecasting.

As a result, the fare class mix of Airline 1 using DAVN with hybrid forecasting shows more restrained changes (Figure 5-43 and Figure 5-44). This is especially true for the change in passenger numbers in fare class 1 and fare class 6 with Closure Matching, compared to when Airline 1 uses DAVN with standard forecasting.

FIGURE 5-43
Fare Class Mix of AL1(DAVN with HF) as AL1 Matches AL3

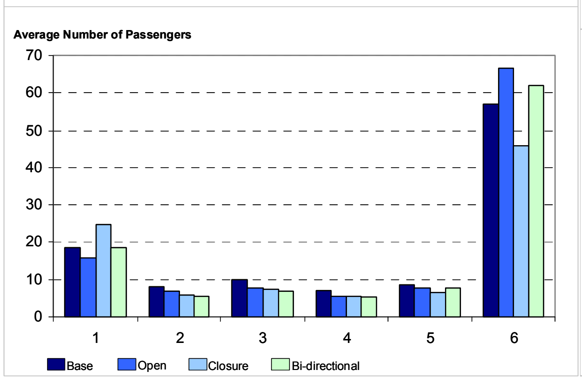
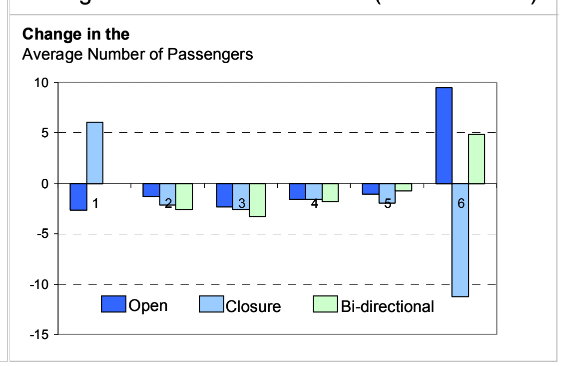


FIGURE 5-44
Changes in Fare Class Mix of AL1(DAVN with HF)



5.5.3.b Market Share

Similar to the earlier scenario when Airline 1 uses DAVN and standard forecasting, in this scenario when it uses DAVN and hybrid forecasting, the O-D method of inventory control restricts the direct impacts of seat availability matching to the LCC markets. With Open Matching, Airline 1 becomes more open and gains market share only in the LCC markets and with Closure Matching, it becomes more restrictive and loses market share only in the LCC markets (Table 5-12). In the non-LCC markets, Airline 1 loses market share with Open Matching and gains market share with Closure Matching instead.

Unlike the earlier scenario when the forecasting method is standard forecasting, the changes in market share when hybrid forecasting is used are smaller – the largest fall is 3.9pp as Airline 1 closure matches (much lower than the earlier 8.2pp).

Table 5-12: Market Share by Market Type (AL1: DAVN with HF)

LCC Markets								
	Airline 1		Airline 2		Airline 3		Airline 4	
	Market Share %	% point change	Market Share	% point change	Market Share	% point change	Market Share	% point change
Without	25.6	-	27.3	-	23.2	-	23.9	-
Open	26.3	0.7	26.9	-0.4	23.1	-0.1	23.7	-0.2
Closure	21.7	-3.9	29.1	1.8	24.1	0.9	25.1	1.2
Bi-directional	25.2	-0.4	27.5	0.2	23.3	0.1	24.0	0.1
Non-LCC Markets								
	Airline 1		Airline 2		Airline 3		Airline 4	
	Market Share %	% point change	Market Share	% point change	Market Share	% point change	Market Share	% point change
Without	43.0	-	43.7	-	-	-	13.3	-
Open	41.6	-1.4	44.9	1.2	-	-	13.5	0.2
Closure	43.5	0.5	43.4	-0.3	-	-	13.1	-0.2
Bi-directional	41.6	-1.4	44.9	1.2	-	-	13.5	0.2

5.5.4 Conclusions

The combination of O-D inventory control and hybrid forecasting is more suited to the mixed fare structure of this network, resulting in the stronger performance of Airline 1. Airline 1 achieves the highest revenue among all four airlines, which is also its highest revenue for all four scenarios. With lowest fare seat availability matching, Airline 1 loses revenue, but the least compared to the previous three scenarios. DAVN with hybrid forecasting does better than both DAVN with standard forecasting and EMSRb with hybrid forecasting. The improvement is the most pronounced in Closure Matching, where O-D inventory control isolates the negative effects to the LCC markets and hybrid forecasting enhances Airline 1's performance against availability matching in LCC markets.

However, in spite of Airline 1's best performance in this scenario when compared to other combinations of revenue management systems simulated, seat availability matching still produces negative outcomes for the matching airline and positive outcomes for the matched airline and the other airlines.

5.6 SUMMARY

Table 5-13: Summary

Scenario	Inventory Control	Forecasting Method	Base Case Revenues	With Availability Matching	
				On Airline 1	On Other Airlines
1	EMSRb (Leg-based)	Standard	-	Loss of 6% to 7%, mostly direct from the LCC markets.	Gains, up to 4%. Collateral gains for Open Matching.
2		Hybrid	Improvements mostly from the LCC markets.	Loss of 5% to 8%, mostly direct.	Gains, up to 4%. Collateral gains for Open Matching.
3	DAVN (O-D)	Standard	DAVN (SF) improves 1.4% cf. EMSRb (SF)	Loss of 5.5% to 8.3%. Closure Matching damaging in the LCC markets but positive in the non-LCC markets.	Collateral gains of up to 5.3% with Closure Matching.
4		Hybrid	Further improvement of 1.6% with HF cf. SF.	Loss of 3.4% to 5.8%, lowest of four scenarios.	Gains, less than 3%, lowest of all scenarios. Airline 3 does not gain with Closure Matching.

Seat availability matching of Airline 3's lowest fare when Airline 1 has a more advanced revenue management system hurts the matching Airline 1 while benefiting the matched Airline 3, across the four scenarios simulated (Table 5-13). This is true regardless of the type of matching. The overarching finding is that lowest fare seat availability matching causes Airline 1 to lose at least 3.4% and up till 8.5% of its pre-matching revenue. In this network setting, the two airlines that neither match nor are matched, Airline 2 and Airline 4, gain collateral benefits consistently.

In general, the degree of revenue loss with seat availability matching for Airline 1 is lower with O-D inventory control (DAVN) than leg-based inventory control (EMSRb). It is also lower when hybrid forecasting is used instead of standard forecasting. The more advanced the revenue management system, the better Airline 1 performs both before and after lowest fare seat availability matching.

O-D inventory control isolates the negative effects to the LCC markets where the lowest fare seat availability matching takes place. At the same time, hybrid forecasting improves the performance in the LCC markets, with or without availability matching. Therefore, when the O-D form of inventory control DAVN is used together with hybrid forecasting, the performance of Airline 1 is the strongest. Without seat availability matching, it starts with the highest revenues. Moreover, with seat availability matching, it loses the least revenues of all four scenarios. In fact, it gains collateral revenue benefits in non-LCC markets when it closure matches Airline 3 in the LCC markets. In addition, with Airline 1 using DAVN with hybrid forecasting, Airline 3 does not benefit from Closure Matching, unlike the other three scenarios.

CHAPTER 6
CONCLUSIONS

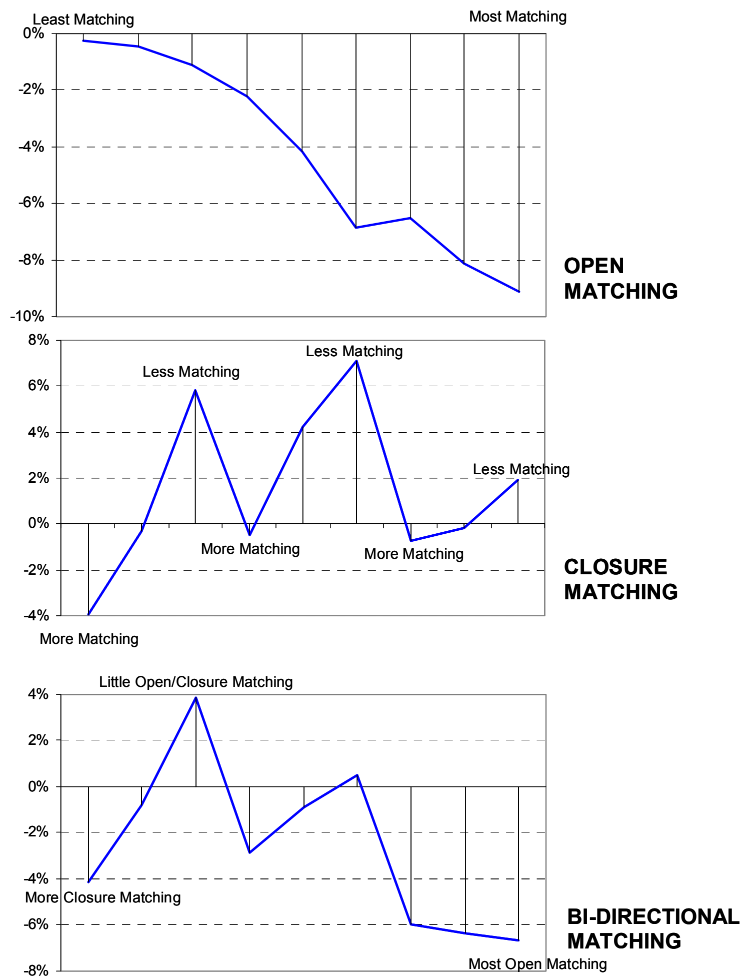
6.1 SUMMARY OF OBJECTIVES AND METHODS

At the start of this thesis, I explained how the growth of Internet-based applications for airline ticket distribution coupled with the wide fare fluctuations caused by airline differential pricing practices and revenue management systems have encouraged passengers to intensify their searches for the lowest fares available. Subsequently, I noted that airlines have not effectively incorporated competitors' low-fare seat availabilities into their revenue management systems. As an intermediary measure for retaining market share, airlines match the price level and seat availability of their competitors' lowest fares. The objective of this thesis is to investigate how seat availability matching affects the airlines implementing it or subject to it, using the Passenger Origin-Destination Simulator. I varied the revenue management systems examined between the earlier methods designed for traditional fare structures (like leg-based inventory control with standard forecasting) and the more complex methods optimized for simplified fare structures (like O-D inventory control with hybrid forecasting). Three levels of demand were simulated. Simulations were carried out in either a single symmetric market of two airlines or a much larger mixed-fare network of 572 asymmetric markets involving four airlines. Three types of matching were tested: Open Matching to ensure the matching airline is at least as available as its lowest fare competitor, Closure Matching to cause the airline to be at least as unavailable as its lowest fare competitor and Bi-directional Matching that performs both of the above.

6.2 SUMMARY OF FINDINGS AND IMPLICATIONS FOR AIRLINES

In general, seat availability matching of the lowest competitor fare has significant impacts on the revenues of the matching and matched airlines. Often, these impacts are negative for the airline implementing seat availability matching but positive for the other airlines. For example, in the single unrestricted fare and symmetric market, where an airline using a relatively sophisticated revenue management system (EMSRb with Q-forecasting) matches the lowest fare seat availability of an airline using a simple system (AT90), the lesser the degree of matching, the better the performance of the matching airline. This finding holds regardless of the type of matching (Figure 6-1).

FIGURE 6-1
Airline 1's Revenue Changes (Single Symmetric Market)



Although the airline revenue management system responds to and recovers from the external adjustment of seat availability matching, the matching airline loses as much as 9.2% of its revenue. That worst performance happens with Open Matching when the matching airline's revenue management system is most asymmetric with its competitor and the demand is at the highest. The best performance of the Open Matching airline happens when demand is lowest and when revenue management systems are the least asymmetric, precisely when the least seat availability matching takes place. In the single symmetric market, Closure Matching tends to be more beneficial than Open Matching. This is probably an artifact resulting from the single symmetric market – where there is more direct feedback and spilling between the two airlines as one becomes more restrictive with Closure Matching.

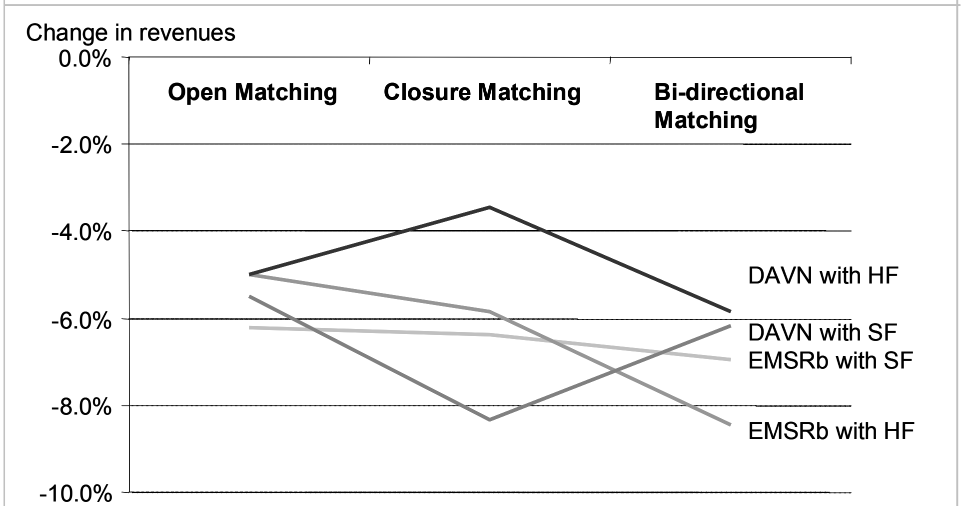
As for market share, often, the improvements with Open Matching are not impressive for the matching airline. Unfortunately, the losses are significant with Closure Matching, especially in light of the concurrent revenue losses incurred.

When two airlines use the same revenue management methods in the single symmetric market, due to the similarity of their systems, there is less matching activity when one airline shadows the lowest fare seat availability of the other. Consequently, the revenue changes are more limited than in the scenarios where the two airlines have asymmetric revenue management systems. The matching airline loses at most 3.2% in revenues. However, both airlines gain slightly if they match each other in lowest fare seat availability.

When extended to a much larger network of four airlines operating in 572 markets, the finding remains that a legacy airline with a mores sophisticated revenue management system loses revenue by at least 3.4% and as much as 8.5% when it matches the lowest fare seat availability of its LCC competitor. Across the four scenarios simulated, the matching airline's revenue falls consistently, while the matched airline and the other two peripheral airlines benefit. In addition, Origin-Destination revenue management – DAVN inventory control with hybrid forecasting – performs better than leg-based EMSRb inventory control with standard forecasting in the mixed fare structure network. This is true not just before seat availability matching, but also with matching – fewer losses result, especially for Closure Matching (Figure 6-2). Unlike leg-based inventory control, O-D control isolates the revenue loss to the LCC markets, where hybrid forecasting performs better than standard forecasting.

FIGURE 6-2

Airline 1's Revenues Changes (Network 'S')



Airline 1 only consistently benefits from seat availability matching in the hypothetical scenarios of the single symmetric market: when its revenue management system spirals down using standard forecasting and matches an Airline 2 using a better performing system. Airline 2's revenue does not fall from being matched when it uses a less responsive AT90 revenue management method but falls significantly when it uses a responsive EMSRb with Q-forecasting system.

The implications for airlines are that lowest fare seat availability matching may be more detrimental to revenues and less effective in retaining or attaining market share than they believe. The less seat availability matching is implemented by an airline, the better it performs. However, if such matching has to be done, the network simulations show that the use of a revenue management system that is better adapted to the fare environment is still preferable. For example, in a mixed-fare network, O-D revenue management that makes use of path-based DAVN with hybrid forecasting outperforms the simple system of leg-based EMSRb with standard forecasting – regardless of the absence or presence of lowest fare seat availability matching.

6.3 FUTURE RESEARCH DIRECTIONS

Since simulations seek to be as realistic as possible in order to be meaningful and applicable, future work done on lowest fare seat availability matching can be improved by taking three further factors into account. Although this thesis has isolated seat availability matching to LCC markets, an airline is unlikely to match all the paths where LCCs have entered. Future studies may wish to take path quality into consideration – where an airline only matches its competitor if they have comparable non-stop or connecting products. I have also focused on one airline matching another or two airlines matching each other. An interesting extension would be to investigate scenarios where more airlines match the seat availability of their competitors. Thirdly, it may be useful to model strategic consumers who wait for fare classes to re-open, or Internet companies representing these strategic consumers, when forecasting demand, controlling inventory and deciding whether to match the lowest fare availability of competitors.

Stepping back from tactical lowest fare seat availability matching, broader studies of how an airline performs if its revenue management system strategically takes into account competitors' seat availabilities would be meaningful to the development of airline revenue management.

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