

**Revenue Management for Airline Alliances :
Passenger Origin-Destination Simulation Analysis**

by

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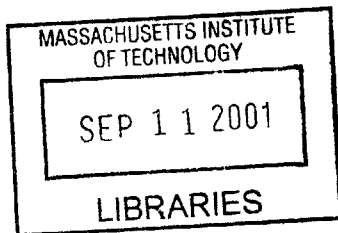
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ABSTRACT

The increasing importance of airline alliances and codesharing creates new challenges for the revenue management systems currently used by the airlines. In this thesis, these challenges were discussed quantitatively and proposed solutions were tested, using a computer tool called the Passenger-Origin Destination Simulator.

The performance of current revenue management methods was assessed in a hypothetical environment, which modeled the hub-and-spoke US domestic market. In this environment, an alliance of two airlines competed against another airline. The performance of origin-destination revenue management methods, especially those using bid-price control, was shown to be sensitive to the evaluation of codeshare passengers. The sole use of different evaluation or discount methods for these passengers, by taking into account either the fare of their whole itinerary or the corresponding local fare, did not give an accurate estimate of the value of those passengers for the alliance. This issue limits the revenue gains of the alliance partners using origin-destination methods.

Two innovative schemes, bid-price sharing and bid-price inference, were proposed to allow airlines to more accurately assess the value of connecting passengers for the alliance, by allowing each alliance partner to estimate the revenue displacement costs on the other partner's legs. The use of bid-price sharing with an origin-destination revenue management method produced an additional revenue gain on the order of one percent for the alliance. With bid-price sharing, the alliance performed almost as well as if it were a single airline using the same method. The bid-price inference scheme led to similar results, while being easier to implement technically and legally. However, it required preliminary tuning to ensure its revenue performance.

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INTRODUCTION

Motivation and Goals

The motivation for undertaking this research originates in the simultaneous development of sophisticated airline revenue management systems and large airline alliances worldwide.

Following research work initiated in the late 1980s in academia (Belobaba, 1987) and the Operations Research departments of large airlines, a growing number of airlines have been implementing increasingly sophisticated revenue management systems during the 1990s. These systems, which aim at maximizing the revenue generated by selling seats at different prices, have been shown to produce revenue gains comparable to the current profits of the airline industry (Smith et al., 1992). Meanwhile, alliances have been created between airlines seeking to enter new markets and strengthen their existing market positions. In January 2001, 19 of the 25 largest airlines in the world¹ were members of one of the five global airline alliances.

The context of airlines alliances creates new challenges for revenue management systems (De La Torre, 1999), which now have the added complexity of dealing with codeshare passengers. However, as this thesis will show, this context also represents an opportunity for further increasing the revenue of the alliance airlines.

The first goal of this thesis is to quantify the performance of current revenue management systems in an airline alliance and identify the challenges created by the alliance context. The second goal is to propose innovative but feasible solutions to address these issues. In order to achieve these goals, a computer tool is used, called the Passenger Origin-Destination Simulation (PODS).

¹ In terms of total revenue passenger-miles (RPKs), ICAO Data, 1999.

Structure of the Thesis

This thesis is structured in two parts.

Part I provides the reader with information on airline alliances, revenue management, and the implications of the alliance context for revenue management.

- Chapter 1 defines the concepts of airline alliances and codesharing, discusses the economic motivations and regulatory framework for airline alliances, proposes a typology of current airline alliances, and reviews the contractual implications of alliances for revenue management.
- Chapter 2 provides an introduction to the objectives and process of revenue management, describes current revenue management algorithms, and stresses the operational revenue management issues raised in the context of airline alliances.

Part II presents the simulation results of current and proposed alliance revenue management practices.

- Chapter 3 gives a brief description of the Passenger Origin-Destination Simulation, and discusses the results of a baseline simulation in the alliance environment.
- Chapter 4 assesses the performance of current revenue management methods in airline alliances, using different discount methods for the evaluation of codeshare paths, and the impact of a key alliance parameter in PODS, the joint image of the alliance partners.
- Chapter 5 proposes and tests two methods that aim at improving the performance of revenue management systems in the alliance context, by allowing the alliance airlines to evaluate the displacement costs of codeshare passengers on their partner's legs.

Finally, a concluding chapter summarizes the findings and contributions of this thesis, and proposes further research directions.

PART I

AIRLINE ALLIANCES AND REVENUE MANAGEMENT

CHAPTER 1. AIRLINE ALLIANCES

Introduction

The aim of this chapter is to present the reader with some notions of airlines alliances and codesharing, which will be useful for the understanding of the remaining chapters of this thesis. For a detailed discussion of these concepts, the reader is referred to the more comprehensive Chapters 1, 2 and 4 of De La Torre's thesis (De La Torre, 1999), from which much of the material of this chapter has been drawn.

Alliance Definition

De La Torre proposes to define an airline alliance as “any kind of agreement between independent carriers to mutually benefit from the coordination of certain activities in the provision of air transportation services.”

These activities may include, by increasing degree of commitment:

- Codesharing (this activity will be described in more detail below)
- Scheduling of flight arrival and departure times
- Location of arrival and departure gates
- Joint frequent flyer programs
- Share of airport lounges and other ground facilities
- Share of passenger services such as baggage handling, check-in and ticketing
- Share of support services including maintenance and catering
- Share of distribution and retailing functions
- Joint purchasing of such items as fuel, passenger-service goods and aircraft
- Joint advertising campaigns and creation of an alliance brand recognition
- Joint allocation of resources (fleet and crew planning)
- Equity investment in partner's stock

Codesharing

The US Department of Transportation (DOT) defines codesharing as “a common airline industry practice where, by mutual agreement between the cooperating carriers, at least one of the airline designator codes used on a flight is different from that of the airline operating that flight.”²

Practically, a flight from Paris to Boston operated by Air France under the flight number AF 332 can be marketed by Delta Airlines under the flight number DL* 8202, with the asterisk indicating that this flight is a codeshare flight operated by a different airline. In the following, we will refer respectively to the **operating carrier** and the **marketing carrier** of a codeshare flight.

To better understand the implications of codesharing, it is important to remind the reader of the different options that can be offered to a customer wanting to fly from A to B:

- On a **non-stop flight**, the passenger flies directly from A to B.
- On a **one-stop flight**, the passenger still flies on the same aircraft from A to B, but this aircraft stops temporarily in an intermediate city C before going to the final destination B.
- On a **connecting flight**, the passenger has to change airplanes in the intermediate city C before reaching his or her final destination B. In the following, we will refer to the different **flight legs** of a connecting flight. In our example, the connecting flight has two legs, from A to C and from C to B.

² Cited in Wynne, 1998.

Depending on the trip length and the importance of air service from A to B, an itinerary may involve several stops or connections in different intermediate cities. However, stops and connections increase the passenger's total travel time, and passengers tend to prefer a non-stop flight to a one-stop flight, and a one-stop to a connecting flight to avoid the hassle of changing airplanes.

Furthermore, connecting flights can be refined depending on how the different flight legs of the flight are operated and marketed:

- The different flight legs of an **on-line connecting flight** are operated by the same airline.
- The different flight legs of an **inter-line connecting flight** are operated by different airlines.
- The different flight legs of a **codeshare connecting flight** are operated by different airlines, but one of the operating airlines can market all the flight legs under its own designator code.

Inter-line connecting flights tend to be less attractive to passengers than on-line connecting flights, because they are usually less convenient in terms of the coordination of schedule between the flight legs, location of the terminal and gates, and do not offer a seamless service in general. However, a codeshare connecting flight operated by two different partner airlines is considered the same as a single airline on-line connecting flight by the **Computer Reservation System (CRS)** used by travel agents. Most CRS thus display the flights available for a certain market in the following order:

1. Non-stop flights
2. One-stop flights
3. On-line and codeshare connecting flights
4. Inter-line connecting flights

Codesharing thus enables what were formerly inter-line connections, which appeared for instance only on the third screen of the CRS, to now appear on the first or second screen, along with the on-line connections, and therefore to be much more likely to be proposed by the travel agent to a customer.

Codesharing is the most common activity involved in airline alliances. Historically, the first codesharing agreement was signed in 1967 between USAir (then Allegheny Airlines) and several regional carriers, which took over service from major cities to small communities formerly serviced by Allegheny Airlines (Oster and Pickrell, 1988). Allegheny Airlines could no longer operate economically on these routes with the jet aircraft it had just acquired, but was not allowed in the then regulated US airline industry to stop providing service on these routes, and solved the problem by signing a “replacement” codeshare agreement. However, since then the main motivation for codesharing agreements has been the strengthening of existing market positions and the access to new markets. The first international codesharing agreement was signed in 1985 by American Airlines and Qantas (GRA, 1994), and gave the American carrier access to the Australian market.

A variety of codesharing agreements can be found in the industry. Following the distinction made by Oum et al. (1996), it is useful to differentiate parallel codesharing from complementary codesharing. **Parallel codesharing** refers to codesharing between two partners operating on the same route, whereas with **complementary codesharing** the partners use each other’s flights to provide connecting service to markets where they did not operated before. These two types of codesharing agreements serve different goals, as it will be discussed in the next section.

Motivations for Airline Alliances

Air transportation is perhaps the paradigm of a global industry, and it should not be surprising to see a strong trend of consolidation in this particular sector in an era of globalization. Because air transportation is a truly global service, being a large player in this industry is more a necessity than a goal. As we will see later in this chapter, international

mergers and acquisitions are often constrained by law, so that the formation of global alliances has been the most prominent sign of this consolidation.

The main economic motivation for the formation of airline alliances is the competitive advantage associated with market power.

First, creating an alliance enables an airline to increase its market coverage, with several major advantages over serving new destinations on its own:

- The airline is able to enter new markets without the infrastructure, marketing and competitive costs of serving these new destinations on its own. Indeed, the airline does not need to assign aircraft and crew to this route, or rent airport terminal space. It also benefits from the market knowledge and customer base of its partner.
- Besides, codesharing allows a “progressive entry” into a market, and does not change the competition equilibrium as the plain entrance of a new competitor would. The current “hub-and-spoke” networks of major airlines act as a deterrent against competition on one airline’s hub to spoke markets. New entrants trying to break in these markets are likely to face predatory prices from the incumbent airline that will drive them out of business quickly, while majors expose themselves to retaliation on their own most profitable hub to spoke routes. Codesharing allows an airline to enter new markets while limiting these risks.
- It should finally be mentioned that codesharing is sometimes the only way to get into congested, slot-controlled airports like London Heathrow.

Second, creating an alliance enables an airline to strengthen its market position in the markets it already serves:

- The airline is able to increase its apparent frequency on these markets through parallel codesharing, which in turns tends to increase its market share non-linearly (Simpson, Belobaba, 1982).
- Competition between the alliance partners is also dampened on these markets, strengthening the alliance position against the other competitors. For instance, the alliance partners are able to rationalize capacity utilization by setting a common, not self-competing flight schedule, and to use bigger aircraft when the consolidation of the partners' passenger loads is important enough.

To sum up, entering an alliance enables an airline to increase its market share both by extending its market coverage and strengthening its existing market position, yielding economies of scope and economies of density.

On the other hand, costs are also associated with creating an alliance. The interaction between the cooperating carriers may involve important transactional costs. Apart from the costs related to overcoming cultural barriers and standardizing processes, the close coordination of certain activities, like revenue management, may require substantial investment. Finally, an airline also needs to weight the opportunity cost associated with entering one alliance instead of another.

Degree of Alliance Partners Involvement

Under the broad alliance definition given in the beginning of this chapter fall a variety of agreements that involve some of the activities mentioned above. A distinction can be made between **marketing** or **transactional alliances**, which usually focus on codesharing practices on a few specific routes, and **strategic alliances**, which involve a higher number of coordinated services, a higher level of commitment, and a long-term view for the alliance.

In spite of the high degree of cooperation the alliance partners may reach, a strategic alliance remains fundamentally different from a merger in that the founding entities remain independent. However, some alliance may involve an investment in the partner's equity to tighten the link between the partners. The investment can be unidirectional when one partner, generally the largest one, invests in the other partner, or bi-directional when both partners exchange equity.

It should be noticed that law usually sets an upper limit on foreign investment in an airline in a given country. In the United States, the maximum foreign equity in a domestic carrier is set to 25%. This is a major constraint for international mergers and the establishment of foreign-owned airlines in a country, even if more flexible agreement can be negotiated, and have lead to the creation of the foreign-owned *Virgin Blue* airline in the Australian domestic market, for instance. The legal constraints are usually less important for airline alliances, and it is one of the main reasons why carriers often form alliances instead of merging.

Alliance Typology: Current Alliances

The alliances can also be contrasted according to their scope and the importance of the carriers involved. Most alliances fall in one of the categories proposed by De La Torre, which are inspired by the categories used by the US General Accounting Office (GAO, 1995).

Global Alliances

The major **global alliances** have grown from the alliance of a few so-called **flag carriers** from different countries. These flag carriers have both a strong domestic and international presence, and many of them used to be government-owned in Europe and Asia. A global alliance is seen as a means to expand each partner's network and to create a global network, mostly through complementary codesharing. These alliances have reached various degrees of

integration, and all aim at creating brand name recognition for the alliance, and providing a seamless service to the customer. As of January 2001, there are three major global alliances.

- **Star Alliance**, launched in 1997, is now the largest airline alliance, formed by Air Canada, Air New Zealand, All Nippon Airways, Ansett Australia, Austrian Airlines, British Midland, Lauda Air, Lufthansa, Mexicana Airlines, SAS, Singapore Airlines, Thai, Tyrolean Airways, United and Varig. It currently serves 815 destinations around the world³.
- **Oneworld**, the launch of which was delayed until 1998 by antitrust concerns over a partnership between American Airlines and British Airways over the Atlantic, is now formed by Aer Lingus, American Airlines, British Airways, Cathay Pacific, Finnair, Iberia, LanChile and Qantas. It serves 550 destinations worldwide⁴.
- In response to those two major alliances, **Skyteam** has been launched in 2000 by AeroMexico, Air France, Delta Airlines and Korean Air, and already offers 450 destinations in its network⁵.

Two other alliances may be considered as global alliances, although they differ in size and scope from the previous ones.

- **KLM/Northwest** is the oldest global alliance. Although its scope is more limited than the larger alliances mentioned above, it was the first alliance to be granted antitrust immunity by the US DOT, in 1992, and it is now probably the most integrated one.
- **Qualiflyer** is the alliance formed around Swissair, with Sabena, Air Portugal, Turkish Airlines, AOM, Crossair, Air Littoral, Air Europe, Polish Airlines, Portugalia and

³ <http://www.star-alliance.com>, January 2001.

⁴ <http://www.oneworld.com>, January 2001.

⁵ <http://www.skyteam.com>, January 2001.

Volare Airlines. It differs from the previous ones in that one airline, Swissair is by far the largest airline in this alliance (many of the other partners are partially or completely owned by Swissair), and the scope of the alliance is mostly European.

Since 1997, global alliances have been growing relatively fast. Airlines worldwide keep discussing the possibility of joining an alliance or switching to another one. However, the number of “drop-outs” has been low: to date, only six airlines have quit an alliance, out of them five have joined another alliance⁶. The stability of global airline alliances is a debated topic, and might be affected by a change in the economic conjecture in the future.

US Domestic Alliances

Alliances have also been formed at the US domestic level. They typically involve two major domestic carriers (Northwest and Continental, for instance), who seek to complement each other’s networks through complementary codesharing. However, the overlap of their respective networks is generally greater than within international alliances, and the partners also practice parallel codesharing on the overlapping markets. As it has been discussed earlier, parallel codesharing strengthens the alliance position on overlapping markets, and concerns have sometimes been raised over a possible excessive domination of the alliance on these markets (cf. the section below on the regulation of airline alliances).

Regional Alliances

Another type of alliance emerged following the US Airline Deregulation Act of 1978, which drove major carriers out of the low-density markets where large jets could not be operated economically. They later formed **regional alliances** with smaller regional commuter carriers, which “feed” the major carrier’s hubs through complementary codesharing. Now these

⁶ Literature review, Anne Dunning, MIT, January 2001.

regional alliances have also developed outside the US, especially in the European Union (EU), and are often integrated into a major global alliance.

Transactional Alliances

Most large airlines, apart from their involvement in a global alliance, also participate in a number of **point-specific** or **transactional alliances**. Such alliances do not require a high degree of commitment from the partners, and are limited to a few routes where the partners deem an alliance more profitable than simple interlining. These alliances are not strategic, and are created and dismantled according to the evolving needs of the partners.

Regulation of Airline Alliances

An important concern about alliances is how they affect the vitality of competition in the codeshare markets. The economic impact of airline alliances for the partners, the competitors and the customers is a controversial topic that will not be discussed here. The reader is referred to De La Torre or Pels (Pels, 2001) for more detail on this subject. In any case, regulatory agencies in the US and, more recently, in the EU, have become interested in overseeing the creation of airline alliances. Below, a summary of Oum, Yu and Zhang (Oum et al., 2001) is provided.

Since December 1987, DOT approval is required for any codesharing agreement involving a US carrier. The DOT stated that an international alliance would not be approved unless it is covered by a bilateral agreement or otherwise brings benefits to the US, and unless the foreign country allowed US carriers codesharing rights in its markets. Although the DOT has the final authority to approve or disapprove codesharing agreements, the US Department of Justice (DOJ) reviews codesharing proposals for potential antitrust violations. International airline alliances cannot, by law, lead to a merger, but the DOJ approaches codesharing agreements and the associated alliances from the same perspective

as mergers. If it determines that a proposed alliance would cause anticompetitive effects, it may impose conditions on it or prohibit it altogether.

Beyond the right to challenge any approval by the DOJ in the airline sector, the DOT has also the power to grant antitrust immunity in international aviation agreements. In some cases, these immunities can be plain (Northwest/KLM alliance, 1992), and the partners are allowed to closely coordinate their activities and operate as if they had achieved a cross-border merger. In other cases, antitrust laws still apply to certain routes, and the ability to coordinate activities is restricted (United Airlines/Lufthansa alliance, 1996). Historically, antitrust immunities have been granted by the US in exchange for open skies agreements (with the Netherlands and Germany for the Northwest/KLM and United Airlines/Lufthansa alliances respectively), or access to critical airports (domestic US codesharing authority for British Airways has been granted in exchange for access privileges to London Heathrow for United Airlines and American Airlines).

The European Union has also recently started to review the antitrust implications of airline alliances, first driven by anticompetitive concerns over the proposal of the alliance between British Airways and American Airlines in 1996, and the growing perception that the US have used alliances and antitrust immunities to sign open skies agreements with its member states. The European Commission (EC) typically approves alliances, but requires that the carriers accept certain remedies designed to avoid excessive market domination. For the alliance between British Airways and American Airlines that gave birth to Oneworld, the partners had to agree on such conditions as reducing their combined frequencies on their interhub routes, and giving up slots and facilities in London Heathrow if a competing airline wanted to but could not obtain them through the standard bidding procedure.

The novelty of the airline alliances phenomenon, the heterogeneity of the competitive policies between regulated and deregulated countries, as well as some inconsistencies in the

regulatory authorities⁷ result in the absence of a unified framework for regulating international airline alliances today.

Impact of Codesharing on Revenue Management – Contractual Level

With alliances, three flight types instead of one have to be handled by the CRS and the Revenue Management (RM) systems of the airlines: normal flights, partner-operated codeshare flights, and airline-operated codeshare flights. In this chapter we have described how the CRS lists codeshare flights, which is rather straightforward, even if it is not always transparent to the customer. The critical problem that will be the focus of this thesis is the impact of alliances and codesharing on revenue management.

Following the analysis of De La Torre, the problem posed by alliances to revenue management lies at two different levels. First, at a contractual level, the partners have to reach an agreement on seat allocation and revenue sharing on codeshare flights. Then, at the operational level, the partners have to implement the agreement in their RM system so as to maximize the benefits for the alliance and the partners. The operational problem will be described in the next chapter on revenue management, we will review here the most common agreements for seat allocation and revenue sharing.

Seat Allocation Criterion

The alliance partners first have to agree on how they allocate the seats available on a codeshare flight, and how the seat inventory will be controlled during the booking process. There are two widely used types of agreement for seat allocation: block space codesharing and free sale codesharing.

⁷ For instance, the European Commission approves alliances at the EU level, but open skies agreements are reached with the individual member states.

In **block space codesharing**, the aircraft cabin is virtually partitioned in two between the operating partner and the marketing carrier. The operating carrier keeps control of its own part of the inventory, while the marketing partner creates a new “pseudo-flight” with a capacity equal to the block space specified in the agreement. Because using fixed block sizes carries the risk of leaving one partner with empty seats while the other cannot accommodate excessive requests, the agreement usually allows the size of the block to be changed during the booking process. The marketing carrier usually starts by asking for a small block space, and then requests additional space as the block sells out. Depending on the agreement, this request may be accepted automatically through a computerized inter-company communication link, or may require the marketing carrier to call its partner and ask for approval.

In an **automated or “free sale” codesharing** agreement, the operating carrier keeps control over the whole inventory, but allows the marketing partner to directly access the inventory by providing information about seat availability in each class. The operating partner then automatically treats booking requests by the marketing partner according to the availability and the details of the agreement, which may impose a quota on the number of seats to be booked by the marketing partner. This type of agreement aims at providing a more seamless inventory control between the partners, and has a greater potential for optimizing the combined revenue of the alliance than block space codesharing. However, it requires constant communication between the partners, and tends to be used only in strategic alliances, whereas simpler block space codesharing is used in the multiple transactional alliances that an airline is involved in. When the number of partners in a strategic alliance becomes important, investing in a common standardized communication link becomes critical to optimizing the alliance seat inventory control. As of this writing, the members of the Star Alliance are planning to create a standardized protocol called StarNet to link their heterogeneous seat inventory control systems. No alliance has yet committed to creating a centralized seat inventory control system, because of the important investment needed and the uncertainty over the real benefits of such a centralized system compared to a simple interface like StarNet. Besides, reaching this degree of operations integration would probably raise both fears of loss of independency from the partners and antitrust concerns from the regulatory agencies.

Revenue Sharing Criterion

The alliance partners also have to agree on how the combined revenue obtained from a codeshare flight should be split between them. The two most common ways to share the revenue are based either on operating costs or a proration method.

Some airline practicing parallel codesharing on a city pair choose to share the combined revenues generated by both airlines on this route based on their respective operating costs. Though aimed at maximizing the alliance revenue on this route, revenue sharing based on costs is complicated as estimating operating costs is a difficult task, and often leads to an inequitable distribution of revenue. Besides, it raises the problem of allocating the revenue generated by connecting passengers through this route, and often does not take into account the costs associated with displaced passengers in the rest of the partners' networks.

Most airlines choose to use a proration method to share revenue on complementary codeshare routes. This method logically evolved from the agreements on interlining routes, for which the International Air Transport Association (IATA) formed the Prorate Agency in 1950. In this type of agreement, the airlines split the codeshare connecting ticket fare according to set proration factors or base amounts. The type of proration may vary from market to market within a codeshare agreement, the most frequently used are:

- **Flat amount.** Each partner marketing the flight pays a specific dollar amount per passenger to each partner operating a leg of the codeshare flight. The amount is specified by fare class for each codeshare flight.
- **Fixed percentage of fare.** Each partner marketing the flight pays a fixed percentage of the ticket fare amount per passenger, specified by fare class.
- **Proration by miles flown.** Proration factors are not fixed as in the previous method, but are proportional to the mileage flown by the passenger on the legs operated by the partners.

- **Yield proration.** Proration factors aim at reflecting the cost of displacing local passengers supported by the operating partner on the codeshare legs. For instance, in the PODS simulator used in this thesis, the revenue is split according to the ratio of the local full coach (Y) fare.

Summary

This chapter has introduced the reader to the concepts of airline alliances and codesharing. An overview of the motivations for and regulations of alliances, and a typology of current airline alliances were provided. Finally, the contractual implications of alliances for revenue management were summarized. In the remaining of this thesis, we will focus on the operational implications of airline alliances in terms of revenue management, using a computer tool, the Passenger Origin-Destination Simulator.

CHAPTER 2. REVENUE MANAGEMENT

Introduction

This chapter will give the reader an overview of current revenue management practices, which is necessary to the understanding of the second part of the thesis. After introducing the concept and elements of revenue management, we will describe briefly the RM algorithms used in the Passenger Origin-Destination Simulator (PODS), which will be described in the next chapter. Apart from the references that will be given for each algorithm, additional explanations and examples of the implementation of these algorithms in simple networks can be found in Gorin (2000), Lee, A. (1998), Wei (1997) and Williamson (1992).

Concept and Elements of Revenue Management

After the 1978 deregulation of the US airline industry, the airlines were allowed to compete with each other by setting their own prices, instead of the distance-based standard fare set by the Civil Aeronautics Board (CAB). For the airlines, this fare had been a clear obstacle to competition, but it had the virtue of being set high enough to cover their operating costs. In the deregulated environment, prices are set according to demand and supply, and it can be the case that if only one fare were to be offered on a market, it might be too low to cover the flight operating costs. **Figure 2.1** is a simplified representation of the cost and demand curves for a particular flight. In this market, no matter what the single fare offered by the airline is (for this simple demand curve, the revenue-maximizing fare is \$250), the revenues represented by the hatched area are smaller than the costs, represented by the shaded area, of carrying the number of passengers willing to pay this fare, in this case 50 passengers.

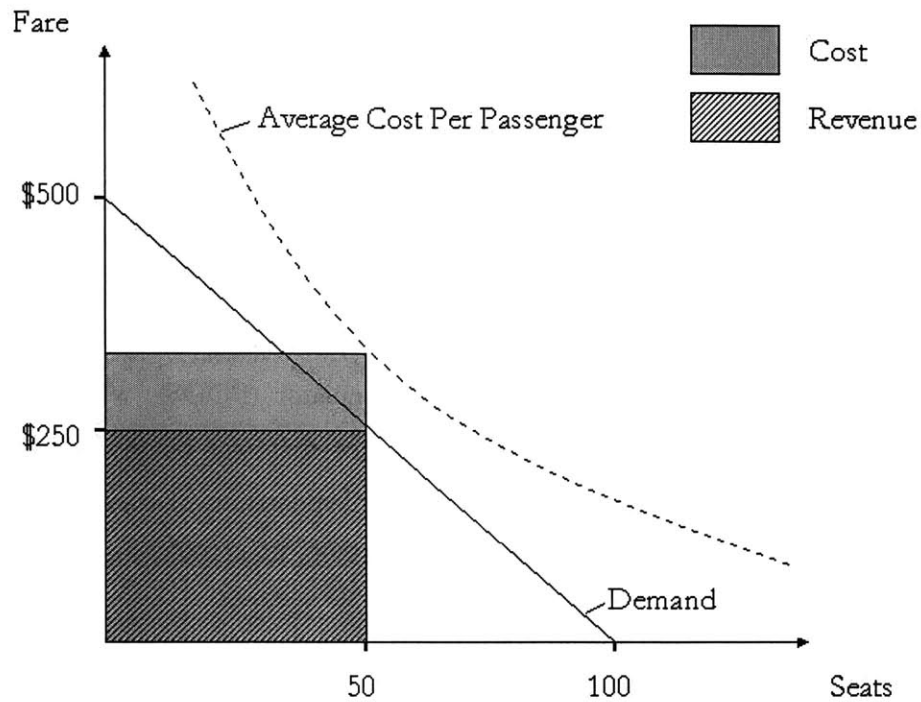


Figure 2.1. Airline offering a single fare.

Therefore, in order to be profitable on such a route, an airline has to offer several fares on this market. Ideally, the airlines would like to charge each passenger a different price that would be equal to his maximum **willingness-to-pay** (WTP). Practically, the airlines have segmented the demand into different categories, and offer several fares targeted at each of these categories. This practice is referred to as **differential pricing** (Belobaba, 1987). **Figure 2.2** represents an ideal situation where an airline segments the market in four categories, and each passenger buys the fare targeted at its category. In this case, we see that the revenue is greater than the operating costs. In reality, passengers will try to get the lowest fare that meet their needs, therefore appropriate **fences** between categories need to be designed by the airline's marketing and pricing departments to prevent passengers from spilling to a lower fare category. Those fences generally consist of several **restrictions** associated with each fare category.

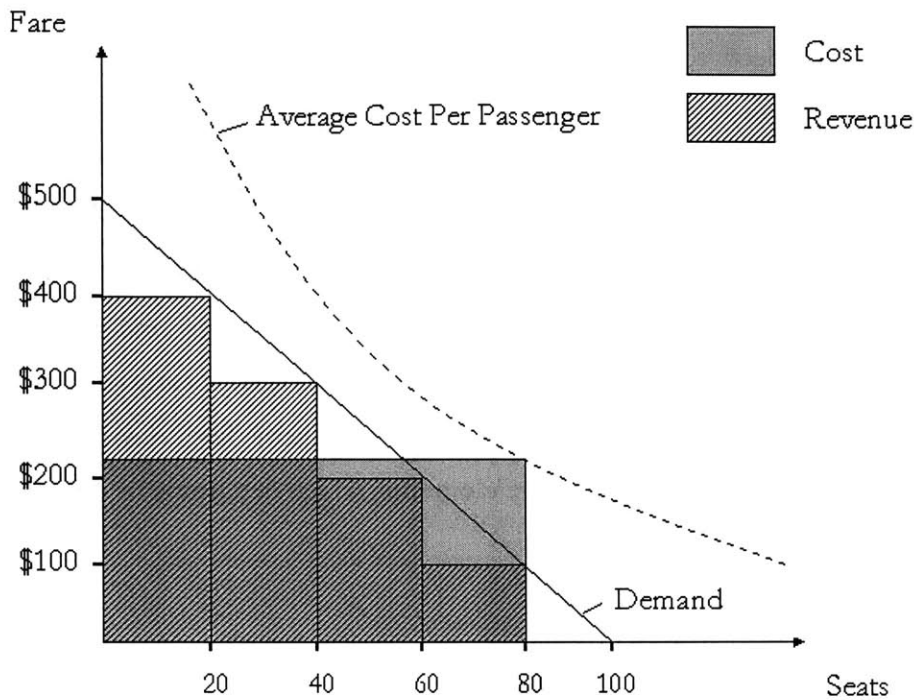


Figure 2.2. Differential pricing.

A common way of segmenting the market is to offer a higher fare for a higher level of in-flight services (such as wider seats, better food and fancy entertainment systems), that is, the first class, to those passengers with a higher WTP. In addition, the airlines have found another way to segment the market, essentially by discriminating between **business passengers** and **leisure passengers**, while they often both sit in the same economy class. Business travelers are not very price-sensitive, as their company usually pays for their air tickets. They are willing - but not always happy - to pay a premium for having the possibility of booking late, holding multiple reservations and canceling at the last moment, in order to get the schedule that best fit their needs. On the other hand, leisure travelers usually plan their trips in advance, do not change plans at the last minute, and are above all extremely price-sensitive. These categories obviously do not cover the variety of air travel demand, but discriminating between the two has proven very effective economically for the airlines. In this context, differential pricing consists of offering low fares to the leisure passengers, and preventing the business travelers from buying these fares by imposing restrictions on them, such as advance purchase, no-refundability, Saturday night stay requirement etc. This

practice has enabled the airlines both to increase their load factors by stimulating the demand for low fares, and to keep yield high by charging higher fares to business passengers. From the passenger perspective, fares for leisure trips have been decreasing steadily, and as a result of the induced air travel growth business passengers benefit from increased frequencies.

Of interest to us is the fact that because of the behavior of the business travelers and of the restrictions applied to leisure fares, the higher-yield business class seats tend to be booked later than the others. Therefore those seats need to be protected against early leisure booking requests, according to the forecasted demand of the different fare classes. This **seat inventory control** relies on **three consecutive elements**, which determine its effectiveness:

- **Demand Forecasting**
- **Determination of the network value of each passenger**
- **A Booking Control Mechanism**

The determination of the network value of a given passenger will be described last, as it will allow us to introduce the different revenue management algorithms used in PODS.

Forecasting

Forecasting is a complex subject that will not be described extensively in this thesis. For more details on this topic, the reader is referred to Swarek (1996) and Zickus (1998). For the purpose of this research, however, a few notions related to forecasting need to be introduced.

The development of hub-and-spoke networks has reinforced the inherent **dichotomy of air travel demand and supply**. The air travel demand is defined on an **Origin-Destination (O-D)** basis, as each passenger wants to travel from a particular point A to another point B.

The air travel supply, on the contrary, consists of many **flight legs**, materialized by airplanes flying from airport 1 to airport 2, often through another hub airport. In this chapter, we will make a distinction between the forecasts that are performed on an O-D market basis, and those made on a flight leg basis. From the airline perspective, these forecasts differ essentially on two points:

- First, most airlines have historically kept record of their past bookings on a flight leg basis only, which corresponds to the “operational reality” of the airline. As a result, forecasting on an O-D basis is a much more difficult exercise, because these airlines have not had the necessary O-D historic database available.
- Second, due to the multiplicity of O-D markets served by a flight leg in hub-and-spoke networks, the mean demand for a particular O-D market, specified by passenger fare class and itinerary, might be a very small number, often less than unity. As a result, the variability of this forecast will be very high compared to its mean value. This, as we will see in the next section, can pose a problem to RM algorithms.

Booking Control Mechanism

Once the passenger demand has been forecasted, and a network value has been attached to each passenger on a flight (cf. below), the final step of seat inventory control is, given this information, to manage the booking process in order to maximize revenue. Two different methods are used in the industry: booking limits and bid prices.

Booking Limits

The first, and still most commonly used technique to control the booking process is to impose booking limits on the different fare classes or booking classes⁸ offered on each leg. The total capacity of the aircraft being fixed, a certain number of seats are assigned to the different fare classes (partitioned approach) or group of fare classes (nesting), according to the forecasted demand and the network value of the passengers.

Partitioned approach

A first approach is to assign a certain number of seats to each class on a given leg. This approach has the drawback of not being robust to variability in the demand. For example, if more people want to book in the highest fare class than forecasted, these potential higher-yield passengers will be spilled because not enough seats have been protected for them. Besides, if the fare structure and forecast have been determined on an O-D basis, the numbers forecasted for each particular O-D and class are so small that it becomes impractical to use this approach.

Nesting

To overcome this problem, the widely implemented **Expected Marginal Seat Revenue (EMSR)** algorithm (Belobaba, 1987) uses the concept of nesting. A joint level of protection is determined for the set of nested upper classes against the lower classes (EMSRa algorithm). Thus, the seats assigned to a given fare class are always available for bookings in a higher fare class, so that the higher yield passengers in the example above are not spilled. In practice, it is effective and easier to protect the nested upper classes only against the next lower class (**EMSRb** algorithm).

⁸ The booking classes and the fare classes may not be the same, as it will be shown when introducing the virtual nesting concept.

The EMSRb algorithm developed by Belobaba (Belobaba, 1992) is the following:

On a particular flight leg, there are n classes. For each class c , we know:

- The class fare f_c
- The mean demand for that class \bar{d}_c
- The variability of the demand for that class σ_c

For each nest $[1..c]$ grouping the upper classes 1 to c , we determine as a linear combination of each class 1 to c :

- The nest average fare $f_{[1..c]}$
- The nest total mean demand $\bar{d}_{[1..c]}$
- The variability of the nest total demand $\sigma_{[1..c]}$

Then, the seat protection level for the nest $\pi_{[1..c]}$ is set to be the number of seats x for which the expected marginal seat revenue (EMSR) of the x^{th} seat in the nest is no longer greater than the EMSR of the 1st seat booked on the next lower class. The EMSR of the i^{th} seat in a fare class c is the product of the fare class fare by the probability that this seat will be booked.

Finally, the booking limit for each class β_c is set to be the number of seats available minus the protection of the joint upper classes 1 to $c-1$.

The algorithm can be written as follows:

For $c = 1..n$

Computation of the average fare and total demand for the nest [1..c] :

$$f_{[1..c]} = \sum_{k=1..c} f_k \bar{d}_k / \sum_{k=1..c} \bar{d}_k$$

$$\bar{d}_{[1..c]} = \sum_{k=1..c} \bar{d}_k$$

$$\sigma_{[1..c]} = \sqrt{\sum_{k=1..c} \sigma_k^2}$$

Computation of the joint protection level of classes 1 to c against class c+1 :

$$\begin{aligned} \pi_{[1..c]} &= \text{Max}_x x_{[1..c]} \mid \{ \text{EMSR}(x_{[1..c]}) > f_{c+1} \} \\ &= \text{Max}_x x_{[1..c]} \mid \{ \text{Probability}(x_{[1..c]} \text{ are booked}) * f_{[1..c]} > f_{c+1} \} \\ &= x_{[1..c]} \mid \{ \text{Probability}(x_{[1..c]} \text{ are booked}) = f_{c+1} / f_{[1..c]} \} \end{aligned}$$

End

Capacity = Leg capacity

For $c = n..1$

Computation of the booking limit for class c

$$\beta_c = \text{Capacity} - \pi_{[1..c-1]}$$

$$\text{Capacity} = \text{Capacity} - \beta_c$$

End

For a passenger itinerary or “path” traversing several legs, the booking control is then done on a **per leg basis**: a passenger will be allowed to book a seat in class c only if on all the legs traversed by the O-D path, there are seats available in this class. However, the bookings limits on each leg can be set to take into account the total network value of a given passenger, as we will see later in this chapter.

Bid-Price Approaches

Another approach to seat inventory control is to set, for each leg, a single “bid price” above which a request for a seat on that leg will be accepted.

The booking control is then truly **path based**: a passenger will be able to book a seat at a fare f if this fare is greater or equal to the sum of the bid prices on all legs traversed⁹.

The main advantage of this method is its simplicity compared to the booking limits method: there is a single bid price for each leg, instead of n booking limits for each fare class or booking class on each leg. However, this method has two drawbacks. First, it makes a “binary” (yes or no) decision when receiving a booking request without discriminating between fare values. The request will be accepted no matter if it is \$1 or \$500 above the bid price. Second, this method does not impose a maximum booking limit or number of seats to be sold at a given price, meaning that requests will be accepted as long as they exceed the bid price, so the bid prices need to be updated often as bookings are accepted.

Network Value Determination – Single Airline Case

Valuation as a Local Passenger

The simplest way of determining the value $f_{l,c}$ of a fare class c on a leg l is to group local and connecting passengers of this fare class in the same booking class or “**bucket**” (cf. **Figure 2.3**). In the PODS simulations performed for this thesis, the airlines will offer four fare classes Y, B, M and Q, Y being the unrestricted full coach fare, and the others increasingly restricted and cheaper fares.

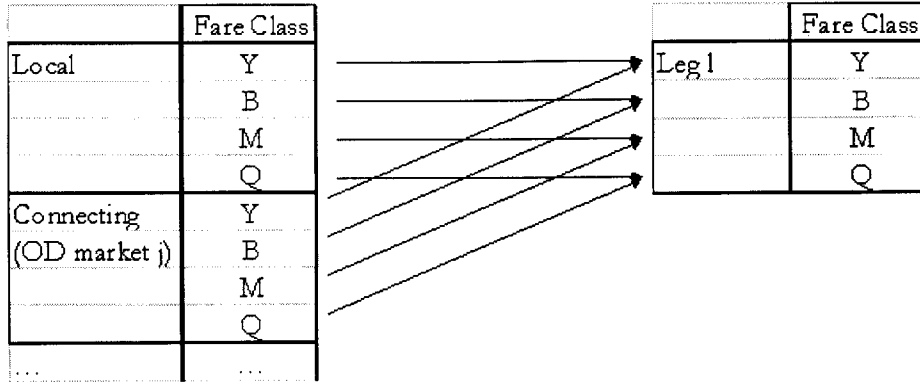


Figure 2.3. Fare class grouping.

The mean and standard deviation of the demand for each bucket are then determined as a linear combination of the local and connecting demand. The average fare of the bucket can be set to be the local fare, a mileage weighted fare, or a demand weighted fare between the local and connecting fares of class c . In the following, we will use the latter method:

$$f_{1c} = (f_{1c\text{Local}} * \bar{d}_{1c\text{Local}} + \sum_j f_{1c\text{Connecting } j} * \bar{d}_{1c\text{Connecting } j}) / (\bar{d}_{1c\text{Local}} + \sum_j \bar{d}_{1c\text{Connecting } j})$$

$$\bar{d}_{1c} = \bar{d}_{1c\text{Local}} + \sum_j \bar{d}_{1c\text{Connecting } j}$$

$$\sigma_{1c} = \sqrt{(\sigma_{1c\text{Local}}^2 + \sum_j \sigma_{1c\text{Connecting } j}^2)}$$

⁹ Except for the HBP algorithm, for which the fare f should not be greater than the sum, but greater than the maximum of the heuristic bid prices of the legs traversed by a connecting itinerary.

The simplest RM method, **Fare Class Yield Management (FCYM)**, uses such a network valuation method, based on a leg-based forecast, and uses the EMSRb algorithm with 4 booking (fare) classes as a booking control mechanism to compute the nested fare class protection levels $\pi_{[1..c]}$ and booking limits β_c on each leg l (cf. **Figure 2.4**). In this thesis, this method will be referred to as simply “**EMSRb**” or “**Eb.**”

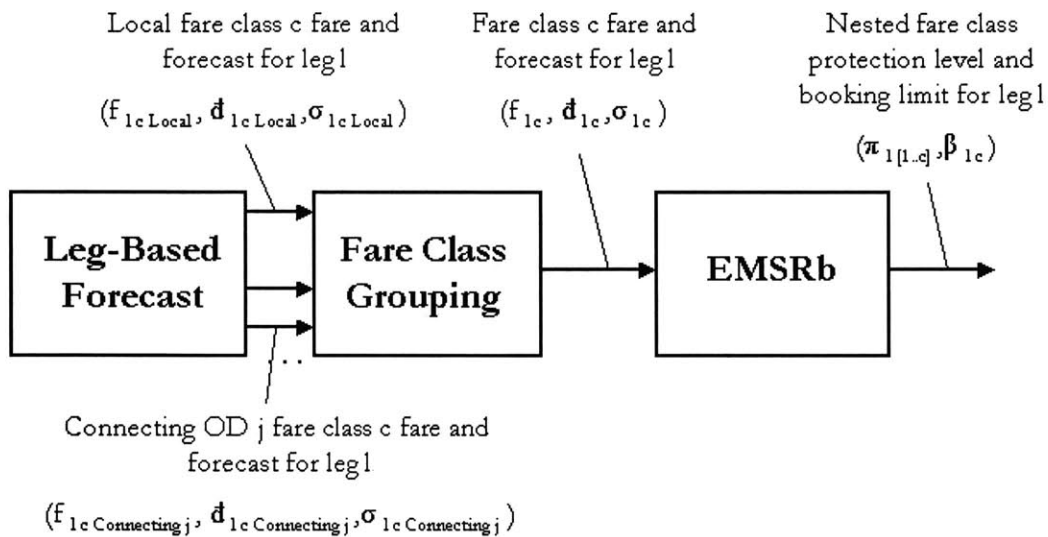


Figure 2.4. Eb - EMSRb Fare Class Yield Management.

Connecting Valuation

The valuation method presented above has the drawback of not discriminating between a local passenger and a connecting passenger of the same fare class, even if the latter brings more revenue to the airline. This can lead to a “bottleneck” effect for connecting passengers when one of the legs traversed is full due to local traffic, because FCYM does not specifically protect seats for connecting passengers.

The concept of **virtual nesting** enables an airline to take into account this issue, and give preference to a connecting passenger over a local passenger. Instead of grouping the local and connecting fares of a class c in the same bucket, the fares are grouped into a larger number of **virtual buckets** (8 buckets will be used in this thesis), according to their total dollar value (cf. **Figure 2.5**). For instance, the value of a connecting B fare might be equal or greater than a local Y fare, so these fares can be grouped in the same virtual bucket v1.

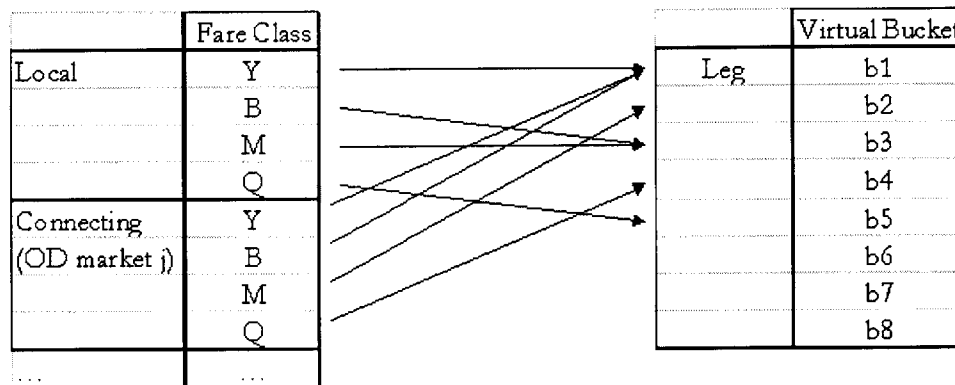


Figure 2.5. Virtual nesting.

The buckets boundaries in terms of revenue value are chosen to create buckets of roughly similar demand, in order to increase the method's robustness to variations in demand. The mean fare, total demand and standard deviation of demand of a virtual bucket are computed by a simple linear combination, as for the simple fare class grouping previously described:

$$f_{1v} = (f_{1v \text{ Local}} * \bar{d}_{1v \text{ Local}} + \sum_j f_{1v \text{ Connecting } j} * \bar{d}_{1v \text{ Connecting } j}) / (\bar{d}_{1v \text{ Local}} + \sum_j \bar{d}_{1v \text{ Connecting } j})$$

$$\bar{d}_{1v} = \bar{d}_{1v \text{ Local}} + \sum_j \bar{d}_{1v \text{ Connecting } j}$$

$$\sigma_{1v} = \sqrt{(\sigma_{1v \text{ Local}}^2 + \sum_j \sigma_{1v \text{ Connecting } j}^2)}$$

The number of virtual buckets used by various airlines in the industry is generally of the order of 10 to 40. When the number of virtual buckets is simply equal to the number of classes, and these virtual buckets are labeled like the FCYM buckets (Y, B, M, Q), the virtual nesting method is called fare stratification. It has the advantage of not requiring any modifications of the CRS compared to using simple FCYM. But the booking classes (buckets), even if labeled as Y, B, M and Q, are not the same as the fare classes Y, B, M and Q, as the fares classes are assigned to a bucket according to the total passenger revenue.

In our PODS simulations, the RM method called **Greedy Virtual Nesting (GVN)** uses this network valuation method with 8 **network-wide fixed buckets**. It is based on a forecast specified by leg and bucket, and uses EMSRb to calculate the booking limits for the 8 buckets on each leg (cf. **Figure 2.6**).

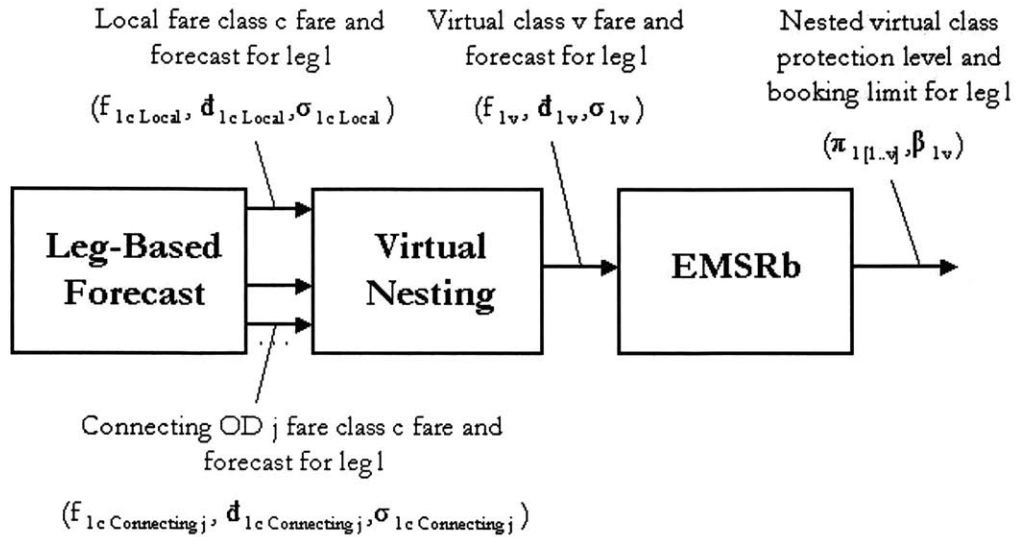


Figure 2.6. GVN - Greedy Virtual Nesting.

Displacement Valuation

The previous valuation method still has the drawback of not giving the preference, on a two-leg itinerary A-B-C for example, to two local passengers over a connecting passenger of the same fare class, while local passengers have generally a higher yield than connecting passengers. Indeed, when estimating the value of the connecting passenger A-B-C on leg B-C, the method does not take into account the cost of displacing a local passenger on leg A-B to accommodate that connecting passenger.

Evaluating displacement costs allows a network-wide, and not only leg-based optimization of seat inventory control. The methods that take into account displacement cost, and enable this network optimization will be called **Origin-Destination Revenue Management**

methods¹⁰ (O-D RM methods). However, some of them may use on a leg-based forecast (HBP¹¹), or a leg-based control mechanism such as EMSRb (HBP, DAVN¹²).

The displacement cost is a single value on a leg, independent of fare classes, like the bid-price concept introduced above. Two methods can be used to evaluate the displacement cost on a leg: solving a deterministic **Linear Program (LP)** or determining the **critical EMSR value (EMSRc)**.

Deterministic Linear Programming approach

One can solve the deterministic LP associated with the problem of finding the number of seats x_{lc} to be sold on each leg l ($l=1..m$) for each class c ($c=1..n$) in order to maximize the network total revenue, given the fare structure f_{lc} and the capacity on each leg. The primal problem can be written as:

$$\begin{aligned} \text{Max}_x (\text{Revenue}) &= \text{Max}_x \left(\sum_{l=1..m, c=1..n} f_{lc} x_{lc} \right) \\ \text{Subject to: } & \left\{ \sum_{c=1..n} x_{lc} = \text{Leg capacity}_l \right\}_{l=1..m} \\ & \left\{ x_{lc} < \bar{d}_{lc} \right\}_{l=1..m, c=1..n} \end{aligned}$$

While solving for the optimal solution x^*_{lc} of the primal problem, one can also obtain the optimal solution f^*_{lc} of the dual problem. On each leg, the dual solution can be interpreted as the additional revenue generated by relaxing the capacity constraint by one unit on that leg, and is called the **shadow price** of the leg, SP_l . It represents an estimate of the displacement cost on that leg. It should be noted that:

¹⁰ Although it could be argued that GVN is an O-D method, as it makes a difference between local passengers and connecting passengers.

¹¹ This method will be described later in this chapter.

¹² Idem.

- This estimate is purely deterministic and does not take into account the stochastic nature of the demand.
- In order to solve the deterministic LP over the network, one must have performed an O-D forecast, disaggregated by fares and paths.

A straightforward way of using the LP solution for seat inventory control is to use the shadow prices SP_1 of each leg directly as bid prices BP_1 . The deterministic **Network Bid Price (NetBP)** algorithm uses this approach, accepting a request for an itinerary only if the fare is greater than the sum of the shadow prices over the itinerary (cf. **Figure 2.7**).

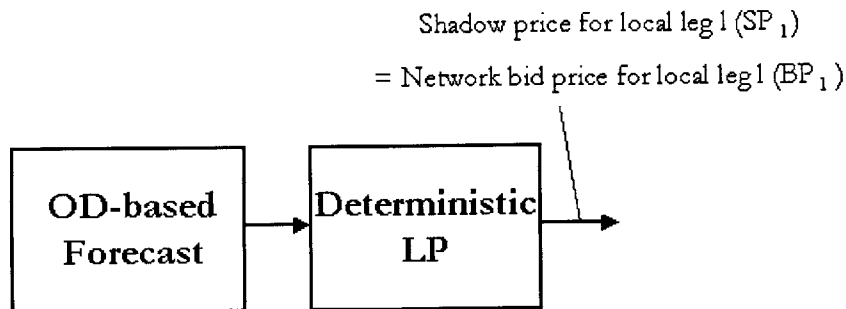


Figure 2.7. NetBP - Deterministic Network Bid Price algorithm.

The more complex **Displacement Adjusted Virtual Nesting (DAVN)** algorithm, based on GVN, uses the shadow prices as displacement costs. On each leg, the displacement costs of the other legs traversed by a connecting itinerary are subtracted from the total connecting itinerary fare $f_{1c \text{ Connecting}}$ to obtain the **pseudo-fare** $pf_{1c \text{ Connecting}}$ of the itinerary. The pseudo-

fare of a local passenger $pf_{1cLocal}$ is simply set to be the local fare $f_{1cLocal}$. The pseudo-fares are then nested into 8 **leg-specific virtual buckets**, and EMSRb is used as a control mechanism for the buckets limit (cf. **Figure 2.8**).

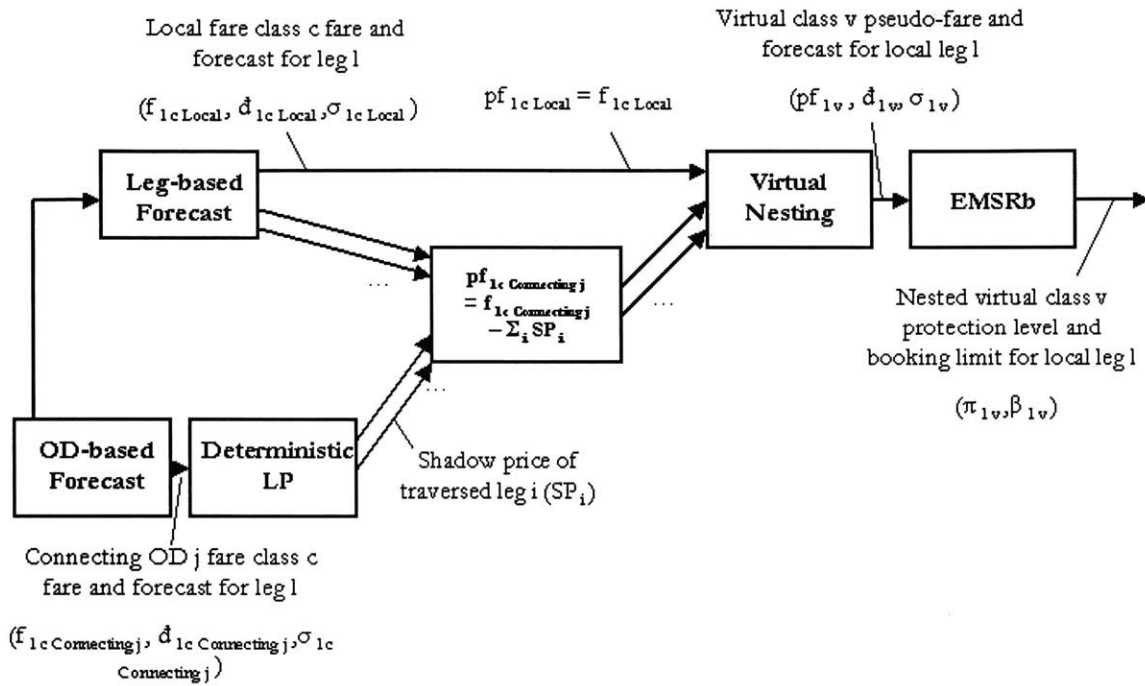


Figure 2.8. DAVN - Displacement Adjusted Virtual Nesting algorithm.

EMSRc approach

A second method to estimate the displacement cost on a given leg is to calculate the **critical EMSR value (EMSRc)** on that leg, defined as the EMSR value of the last seat available on that leg.

EMSRc	= EMSR (last seat available)
	= Min {EMSR ($x_{[1..n]} = \text{Leg Capacity}$), f_n }
	= Min {Probability ($x_{[1..n]} = \text{Leg capacity seats are booked}$) * $f_{[1..n]}$, f_n }

The EMSRc value on a leg can be interpreted as the expected revenue increase from adding a seat on this leg. It should be noted that, contrary to the shadow prices:

- The EMSRc values take into account the stochastic nature of the demand.
- The EMSRc values can be computed separately on each leg, so that this computation does not require an O-D forecast.

The **Heuristic Bid Price (HBP)** algorithm developed by Belobaba (Belobaba, 1998) uses the EMSRc values, computed using 8 **network-wide fixed buckets**, to calculate bid prices for each leg (cf. **Figure 2.9**):

- The bid price for a local passenger $BP_{i\text{Local}}$ on a leg is set to be the EMSRc value on this leg.
- The bid price for a connecting passenger $BP_{i\text{Connecting}}$ on a leg l is the EMSRc value on this leg plus the sum of the displacement costs of the local passengers on each traversed leg i .
- The displacement cost is heuristically estimated to be, for each leg traversed i , the EMSRc value of leg i times the product of the percent of local passengers on legs i and l .
- Then, the heuristic bid price for a connecting path is set to be the maximum of the bid prices $\text{Max}_i BP_{i\text{Connecting}}$ over the legs traversed by the itinerary, which means that the heuristic bid prices of the legs are not “additive”, like the shadow prices determined by a LP optimization in NetBP and DAVN, or the prorated fares of ProBP (cf. below). This poses a problem when we try to compare these different kinds of bid prices, as we will see in Chapter 5.

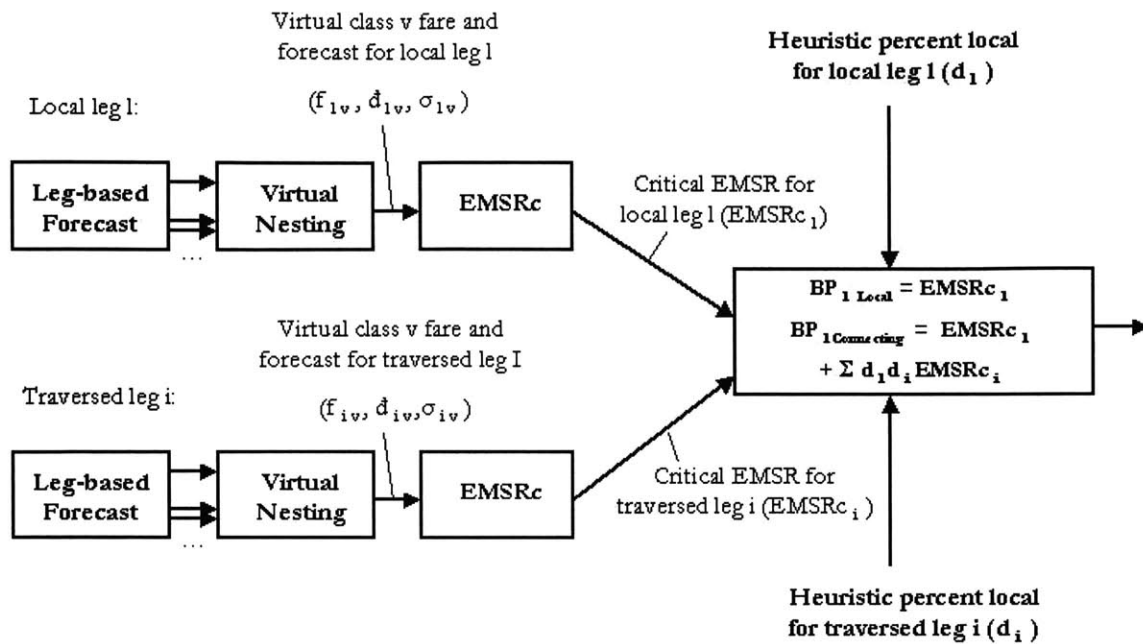


Figure 2.9. HBP - Heuristic Bid Price algorithm.

The HBP algorithm has two main drawbacks:

- It computes the EMSRc values separately on each leg using the total itinerary fares, which means that these values are overestimated.
- It then uses a heuristic to try to capture the network effects, which in turns requires estimating the percent of local passengers on each leg.

Bratu (1998) developed the iterative **Prorated Bid Price (ProBP)** algorithm, to obtain prorated bid prices on each leg which take into account the displacement costs more accurately. The idea behind the ProBP algorithm is to perform an iterative network-wise proration of the EMSRc values of each leg, until convergence is obtained (cf. **Figure 2.10**):

- The total fares of each O-D itinerary f_{1c_j} are used as inputs for the first EMSRc computation.
- The “raw” EMSRc values $EMSRc_l$ obtained on each leg l are then prorated over all the L_j legs traversed by the O-D itinerary j .
- The prorated fares of each O-D itinerary prf_{1c_j} on the different legs traversed by this itinerary are then used as inputs to recalculate the EMSRc values.
- The process is iterated until some convergence criterion on the prorated fares is met.
- The converged prorated fares are used as itinerary-additive bid prices BP_1 on each leg.

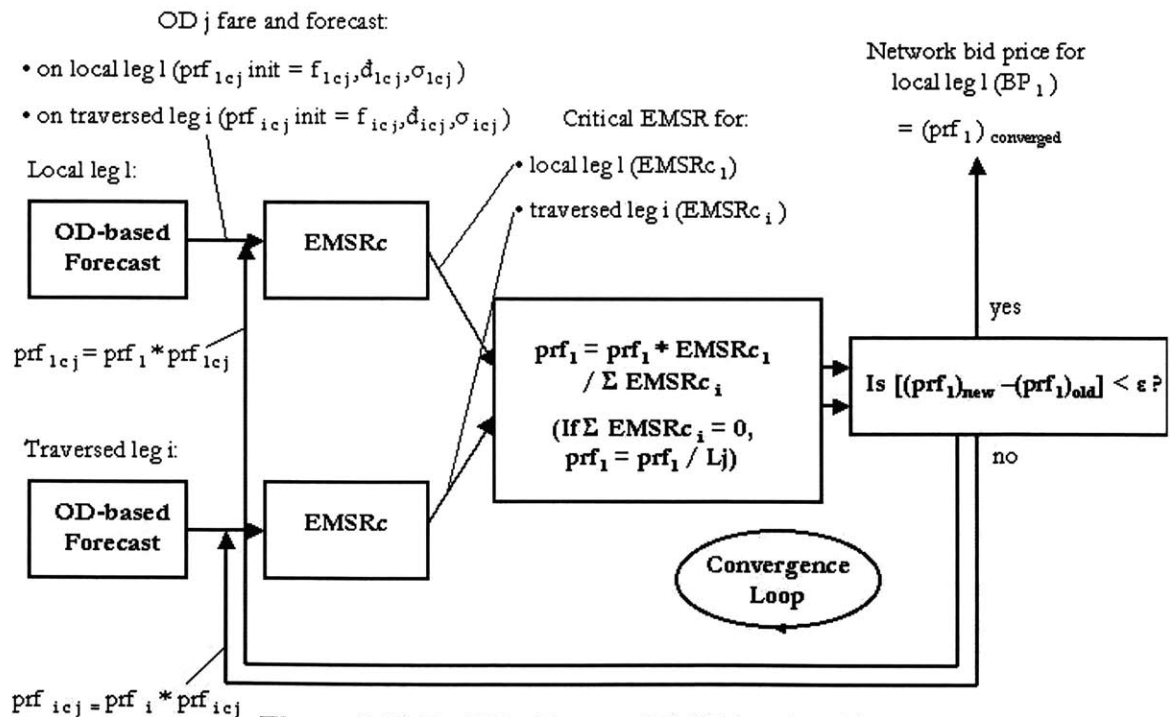


Figure 2.10. ProBP - Prorated Bid Price algorithm.

Network Value Determination – Alliance Issues

In the context of airline alliances, the determination of the network value of a passenger is further complicated in the case of codeshare flights. In the following, we will focus on the problem of codeshare connecting flights, which will interest us in the remainder of this thesis.

Even in the most tightly integrated alliances, each partner performs the determination of the network value of a passenger separately. Joint network optimization would require, in addition to a complete antitrust immunity, a potentially important investment in a common system. The question faced by the alliance partners is then, given these separate processes, how to determine the network value of the codeshare passengers so as to achieve a balance between:

- Optimizing one airline's revenue,
- Optimizing the total alliance revenue.

We will introduce here three means to achieving these objectives, which will be investigated in the second part of the thesis: the use of different **discount methods for codeshare passengers**, **bid-price sharing (BPS)** and **bid-price inference (BPI)**.

Discount Methods for Codeshare Passengers

Consider a codeshare connecting flight consisting of two legs, operated respectively by the partner airlines B and C. To evaluate the network value of a codeshare connecting passenger on this flight, an airline partner has several options:

- Considering only the local passenger fare on the flight leg it operates. This is a logical evolution from the method used on inter-line connecting flights, to which we will

refer as **“local discount.”** When it uses this method, the airline is mostly concerned with optimizing its own revenue.

- Considering the total itinerary fare. This method, to which we will refer as **“no discount,”** is more concerned with optimizing the total alliance revenue, as it would be the method used by the alliance if the alliance was a single airline.

Bid-Price Sharing and Bid-Price Inference

The use of discount methods alone does not allow an airline to take into account the displacement costs incurred on its leg by the other partner airline. Even when using no discount, an airline assumes that the capacity on its partner’s leg is not limited when it assigns a value to a codeshare connecting passenger.

When the partners use O-D RM methods which take into account displacement costs, the ideal way for an airline to take into account the displacement costs on the partner-operated legs, and thus to maximize the alliance revenue, would be to have access to its partner’s heuristic bid prices (HBP), shadow prices (DAVN) or prorated fares (ProBP). We will generally refer to this practice as **“bid-price sharing,”** including when the partners use DAVN, for which the use of this term is not proper.

However, this practice is probably a few years ahead from what alliances can achieve today, for both practical and legal reasons, as a complete antitrust immunity might be required. Therefore, we will also investigate in this thesis the possibility of sharing information between the partners at a lower level, for example by inferring the displacement cost of codeshare connecting passengers from the CRS fare class availability information on the partner’s leg. We will refer to this practice as **“bid-price inference,”** even when the alliance partners use DAVN.

Summary

This chapter has presented the reader with the objective and the three steps of the revenue management process. The algorithms that will be used in PODS were briefly described, and the revenue management issues raised in the context of airline alliances were stressed, which will be addressed in the second part of this thesis.

PART II

PODS INVESTIGATION OF AIRLINE ALLIANCES

CHAPTER 3. THE PASSENGER ORIGIN-DESTINATION SIMULATOR

Introduction

In this chapter, we present a brief description of the tool that will be used to investigate the issues of revenue management for airline alliances presented in Chapter 1 and Chapter 2, the Passenger Origin-Destination Simulator (PODS). Early versions of the simulator have been extensively described by Wilson (1995) and Swarek (1996), and updated and summarized explanations on the PODS architecture can be found in Lee, A. (1998) and Gorin (2000). Next, we will define the alliance simulation framework that we will use in this thesis. We will first review the PODS parameters that will remain set for the rest of the discussion, and those that will be investigated in the next chapters. Then, we will describe a reference simulation that will be used both to introduce the main characteristics of the alliance in PODS network D, and as a baseline case for further studies.

The PODS Simulator

The PODS simulator was originally developed at the Boeing Company by Hopperstad, Berge and Filipowski, as an evolution of the Boeing **Decision Window Model (DWM)**, Boeing 1993). The PODS research consortium was subsequently formed between MIT and several American and European airlines, which purpose is to use the simulator as an investigation tool for studying the impact of RM systems in competitive airline markets (cf. for example Belobaba et al, 1997).

Unlike some earlier RM simulators like MITSIM (Williamson, 1992 and Mak, 1992), PODS incorporates a full passenger decision model based on the Boeing DWM, so that the passengers are able to choose between competing airlines, paths and fares in a variety of origin-destination markets, according to parameters that will be summarized in this chapter. PODS also features various forecasting and RM algorithms, and is currently the most comprehensive RM simulator, to our knowledge.

The PODS Process and Architecture

PODS simulates a competitive air transportation network, currently set to look like a domestic US market between 42 major cities that would be served by two or three hubbing airlines¹³. More precisely, it simulates the actions and interactions of passengers and airlines during the booking period for a single day of departure. The booking period extends over 16 successive time frames, the first time frame beginning 63 days before departure and the last ending on the departure day. After the simulation is over, it is possible to analyze the results of the airlines, which can use various RM methods.

To this end, PODS runs an iterative process, performing multiple trials for the same departure day. This allows the airlines to progressively build the historical database they need to operate the forecasting component of their RM systems: manually initialized numbers in the database are progressively replaced by the “real” passenger demand generated by the simulator. To be more precise, each PODS **case** or **simulation** currently consists of 5 independent trials, each composed of 600 successive (and thus correlated) samples. The initial 200 samples of each trial are discarded to eliminate the initial conditions effects, and the results from the 5 trials are averaged to give stable and statistically significant results¹⁴.

The PODS architecture consists of five elements, which are linked as shown in **Figure 3.1**.

¹³ The network used in this thesis will be described more extensively later in this chapter.

¹⁴ On the determination of the number of samples necessary, the reader is referred to Lee, A. (1998).

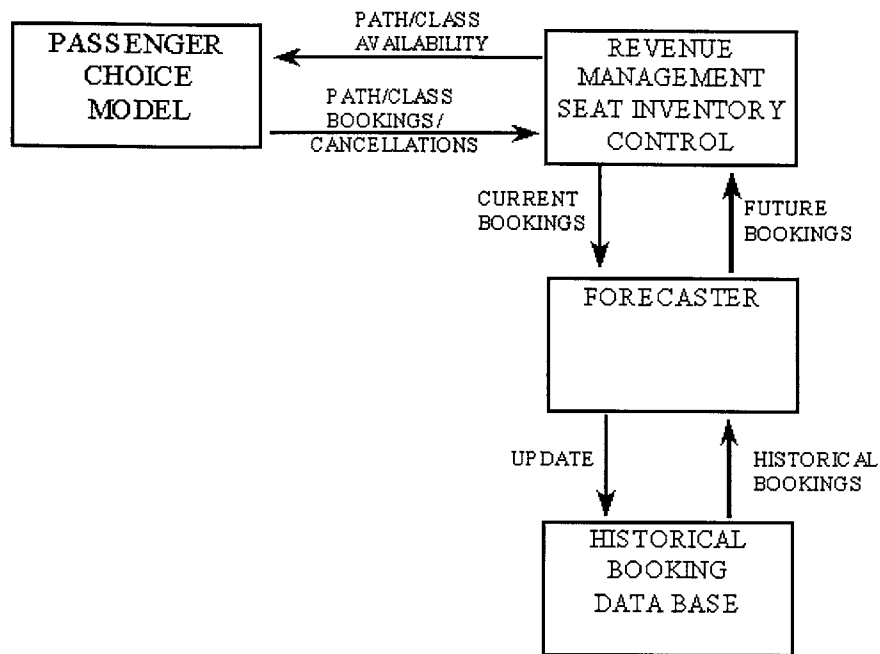


Figure 3.1. The PODS Architecture (courtesy of Hopperstad).

In the **passenger choice model**, a passenger population is generated by embedded stochastic processes aiming at capturing passenger group behavior. The passengers are evenly split between the business and leisure categories, and want to fly to different cities according to the heuristic input attractiveness of each city pair. The simulator then assigns specific characteristics to each individual passenger:

- The time before departure at which the various passengers will book and might decide to cancel their flight, as well as the probability of the passengers actually showing up at the airport are set according to heuristic curves that aim at reproducing the patterns observed in the industry.
- Each passenger is assigned a favorite airline, the airline which he/she will call first, and a **decision window**, consisting of the earliest departure time and latest arrival time that he/she is willing to accept for his/her trip. The decision window is set

according to time-of-the-day empirical demand curves, the duration of each flight and the schedule tolerance of each passenger type.

- The maximum “out-of-the-pocket” price a passenger is willing to pay (WTP) for his/her flight is determined according to empirical price elasticity curves.
- In addition, generalized costs are associated to such disutilities as having a Saturday night stay restriction, not flying on his/her favorite airline, having a connection instead of flying non-stop, replanning the flight etc. according to a study conducted by Lee, S¹⁵.

Then, given the airlines schedule and fares, which are fixed and have been set to reflect the current US hub-and-spoke network environment with input from actual airlines, each passenger tries to book a flight that:

- Has a fare value smaller than his/her WTP,
- Fits in his/her decision window (as mentioned above, generalized costs are associated with replanning),
- Minimizes the total cost, that is the flight fare plus the generalized disutility costs associated to the flight.

The airlines accept or reject the passengers’ booking requests, according to the **Revenue Management / Seat Inventory Control** system they use, and to the demand **Forecast**, which is performed using the **Historical Booking Database**. It should be noted that, in

¹⁵ Lee, S., *Standard Disutility Values*, PODS v. 8 Technical Specifications, Appendix II, September 2000.

addition to the various RM algorithms described in Chapter 2, PODS allows the testing of several forecasting and detruncation¹⁶ methods.

If a passenger does not obtain his/her **first choice** flight, the following can happen, taking airline A's point of view:

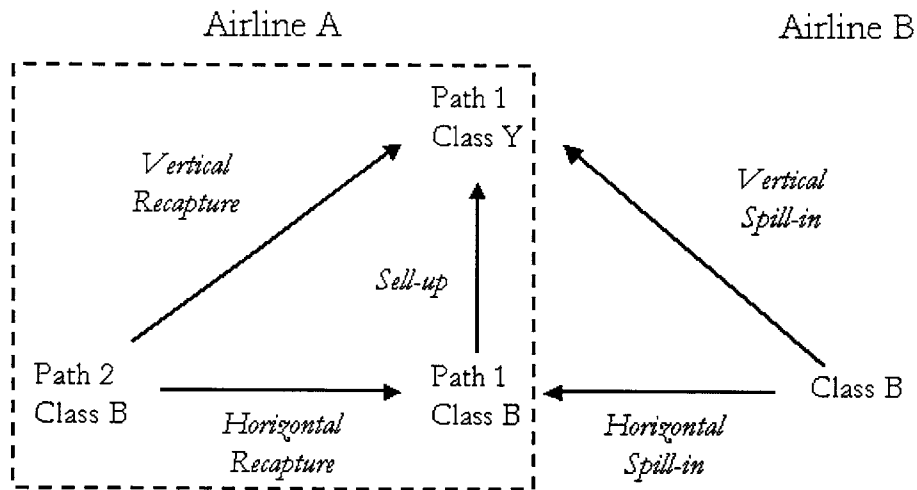


Figure 3.2. Passenger choice.

- **Sell-up** occurs when a passenger ends up flying in a higher class than he/she initially requested.
- **Recapture** occurs when a passenger flies on a path different from the path he/she initially requested, but stays on an alliance's flight. If recapture is combined with sell-

¹⁶ Detruncation consists of estimating the total demand for a historical flight that was full, had that flight not being full. This operation is essential to produce an accurate forecast of unconstrained demand for future flights.

up, we will speak of **vertical recapture**, if not, we will speak of **horizontal recapture**.

- **Spill-in** occurs when a passenger flies on an alliance flight, after having been denied a booking request on a competing airline, airline B in this case. If spill-in is combined with sell-up, we will speak of **vertical spill-in**, if not, we will speak of **horizontal spill-in**.
- If neither competitor offers him/her an acceptable alternative, a passenger might eventually decide not to fly (**no-go**).

Simulation Input Parameters

In order to run a PODS simulation, one must specify a value for a number of different parameters including those mentioned above. For the purpose of this thesis, we will essentially consider the following parameters:

- The **Demand Factor (DF)** is a parameter scaling linearly the level of demand generated by the simulator. It can be tuned to obtain different airline average load factors¹⁷, and should usually be in the range of 0.8 to 1.1 to reflect the load factors actually observed in the industry.
- The **Joint Image (JI)** of the partners in a two-partner alliance is a parameter reflecting the customers' perception of the flights offered by the alliance airlines on codeshare markets. In every codeshare market, the alliance operates three flights a day, but each of these flights is marketed as two separate itineraries by the two alliance partners¹⁸. If JI is set to 1, the customers will perceive these two itineraries as being the same flight, considering the alliance as a single airline. For instance, if the

¹⁷ The definition of the average load factor will be given later in this chapter.

¹⁸ The reader is referred to the section "Alliance in Network D" below for additional explanations.

alliance is competing against only one other airline, the probability of a passenger contacting either alliance airline first is 50%, the same as the probability of a passenger contacting the competing airline first. If JI is set to 2, the customers will perceive the two codeshare itineraries as two distinct flights, considering the alliance partners as two different carriers. The probability of a passenger contacting any of the three airlines first remains 33% in this case, yielding a 66% chance for the alliance to be contacted first. The implications of the alliance joint image will be discussed in a dedicated section of Chapter 4.

- Several parameters control the use of the different **RM methods** by the airlines. Here, the different airlines will use one of the “standard” RM methods described in Chapter 2: EMSRb, HBP, DAVN and ProBP. The results obtained by the airlines with these RM methods will be presented in Chapter 4.
- The **Discount Method** used by each of the two alliance partners to evaluate codeshare passengers can be set independently, but in the simulations presented in this thesis the discount method will be the same for both partners. Besides, the same discount method will be used for both the network optimization step and the decision fares of a partner. We will test the two discount methods introduced in Chapter 2: Local Discount, and No Discount.
- The use of **Bid-Price Sharing (BPS)** or **Bid-Price Inference (BPI)** between the alliance partners can be turned on or off. The actual implementation of BPS and BPI in PODS will be described in Chapter 5.
- In certain simulations, we will make a **passenger’s first choice his/her only choice**, meaning that a passenger will not fly if its first choice is not available. This setting contrasts with the standard full choice setting described above, where a passenger will consider the alternate fares/itinerary/airlines that can meet its needs, if his/her first choice is not available. This will enable us to separate the “pure” effects

of using advanced RM methods from the more complex phenomenon involved in the passenger choice process.

Simulation Outputs

The PODS simulator generates several output files, which contain both very detailed and summarized results of the simulation. In this study, we will essentially focus on the following outputs:

- The **number of passengers** carried by the different airlines, which can be detailed by type (local, connecting, codeshare etc.), by choice (first choice, sell-up etc.), by markets or by legs.
- The total number of **Revenue Passenger Miles (RPM)** flown by each airline, which is the most useful metric on which to base each airline's **market share**. The number of RPMs of a given flight is the number of passenger carried on the airplane times the distance flown in miles.
- The **Average Load Factor (ALF)** of each airline, which is the ratio of the total number of RPMs flown by the airline over the total number of Available Seat Miles (ASMs) it offers. The number of ASMs of a given flight is the seat capacity of the airplane times the distance flown in miles.
- The **percent of local passengers** (as opposed to connecting passengers) carried by each airline over its network.
- The **yield** of each airline, which is the average revenue per RPM, or the average fare paid by the passengers per mile flown (Total revenue = average yield * total number of RPMs).

- The total **revenue** of each airline, which can be detailed by passenger choice (first choice, sell-up etc.).

Alliance in Network D

The network that we will use to is a derivative of PODS network D, which had been designed to investigate the competition between two comparably sized carriers in a hypothetical US domestic market. In network D, airline A was operating from a northern hub, similar to Minneapolis/Saint Paul (MSP), while airline B was operating from a southern hub, similar to Dallas/Fort Worth (DFW). Both airlines served the same markets, linking each one of twenty cities in the West of the US to each one of twenty cities in the East through their respective hubs. Both airlines offered three unidirectional trips on the departure day, and thus organized three connecting banks (or “waves”) at their respective hubs in the morning, at noon and in the evening. As a result, network D consisted of 482 markets, 252 flight legs, and 2892 possible paths.

A third airline is introduced in this network by splitting one of the two existing airlines. The identity of the airline to be split is the first alliance parameter that has to be set in PODS. In this study, the former airline B has been split into two alliance partners, airline B and airline C, which operate from the same DFW hub. The second parameter to be set is the geographical layout of the alliance, which can be either East/West or North/South. For the remaining of this thesis, the latter option has been chosen: the new airline B serves twenty cities in the North of the US, on both West and East coasts from the southern hub, while airline C serves the remaining twenty southern cities. This choice allows the alliance partners to offer on-line connects, from northwestern cities to northeastern cities for airline B, from southwestern cities to southeastern cities for airline C, and thus allows us to test the impact of O-D RM algorithms for B and C. In addition, the alliance partners can serve the remaining markets (Northwest to Southeast, Southwest to Northeast) only by offering codeshare flights. For instance, a passenger wishing to fly from Seattle (SEA) to Miami (MIA) has the choice between flying on three “paths”:

- A from SEA to MSP, then A from MSP to MIA
- B from SEA to DFW, then B*(operated by C) from DFW to MIA
- C* (operated by B) from SEA to DFW, then C from DFW to MIA

As a result, even if the number of flight legs operated by the airlines is unchanged, the total number of paths offered to customers increases to 3552.

At this point, it should be noted that the alliance is not symmetrical. Because airline B serves northern cities from a southern hub, its flights are longer-haul on average than those of airline C, which serves southern cities from the same hub.

The last parameter to be set is the identity of the airline operating the interhub flights for the alliance, between DFW and MSP. In order to increase the aforementioned asymmetry between the alliance partners, airline B has been chosen to operate these extra flights. The resulting network is depicted in **Figure 3.3**.

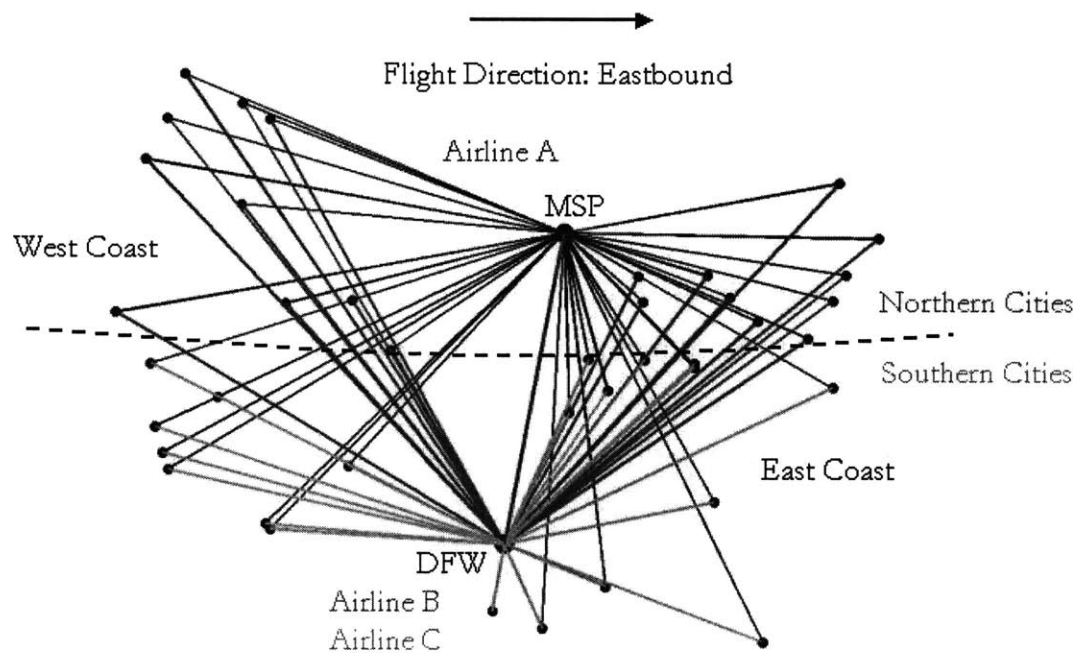


Figure 3.3. Alliance in network D.

As a result of these settings, the alliance partners are not “equal”, and have distinct characteristics, a situation often found in current airline alliances.

Characteristics of the Alliance - Baseline Case, $JI=1$

Parameters

We will use the following set of parameters to define the baseline case:

- The demand factor is set to 1.0.
- The joint image of the alliance partners is set to 1, which means that, in codeshare markets, customers perceive the two codeshare flights offered by the alliance as only one flight, and have a 50% chance of contacting either alliance partner first (and a 50% chance of contacting the other competitor).
- The alliance partners use the local discount method to value their codeshare paths and their partner’s codeshare paths.

As mentioned in Chapter 1, for all simulations the alliance revenue split agreement is based on the ratio of the local full coach (Y) fares between the two legs of a codeshare flight. Therefore each alliance partner will pay for the codeshare flights it marketed a certain amount per passenger to the other partner, according to this ratio.

It should be noted that this simulation differs from previous alliance investigations using PODS (Lee, S., 2000), which did not take into account disutility costs, used a fixed fare structure¹⁹, and performed a 20-trial simulation.

¹⁹ The fares of the different classes on a given market were simply multiples of a base fare (Y: 4, B: 2, M: 1.5, Q: 1), as opposed to the “realistic,” industry-based fares used here.

We will now describe the asymmetry between the two alliance partners, and then contrast the characteristics of the alliance to those of Airline A. The airlines' characteristics are summarized in **Figure 3.4**²⁰.

2 airlines:

Parameter	A	B	C	Alliance
Market Share (points)	49.22	50.78	0	50.78
RPM (pax.mi)	10248762	10573023	0	10573023
ALF (points)	83.54	82.99	0	82.99
Network Local (%)	52.44	55.07	0	55.07
Yield (cents)	13.68	12.95	0	12.95
Net Revenue (\$)	1401737	1369643	0	1369643
Total Pax	7118	7251	0	7251

↓ ↘

Alliance:

Parameter	A	B	C	Alliance
ASM (seat.mi)	12267966	7956273	4783257	12739530
ASM (%)	49.06	31.82	19.13	50.94
Market Share (points)	49.20	30.89	19.91	50.80
RPM (pax.mi)	10252623	6436486	4149366	10585852
ALF (points)	83.57	80.9	86.75	83.09
Network Local (%)	52.48	57.89	51.74	54.93
Yield (cents)	13.67	11.52	15.17	12.95
Net Revenue (\$)	1401932	754295	616683	1370978
Total pax	7122	3767	3488	7255
Codeshare pax	0	816	815	1631
Codeshare pax (%)	0.00	21.65	23.38	22.48

Figure 3.4. Airlines results, $DF=1.0$, E_b vs. E_b/E_b , $JI=1$, Local Discount.

The reader will notice that the characteristics of airline A and of the alliance as a whole are not exactly identical whether there are two or three airlines in the network. Indeed, with a joint image equal to 1, the alliance partners treat the same number of passenger requests as if they were a single airline, but they treat those requests according to separate optimization processes. As a result, the alliance as a whole carries a slightly different number of passengers, and the characteristics of the different airlines are affected. However, these

²⁰ In this thesis, we will refer to the RM systems used by the different airlines with the following convention: E_b vs. ProBP/DAVN means that airline A uses EMSRb, airline B uses ProBP, and airline C uses DAVN.

differences are smaller than 0.1%, which is close to the limit of statistical significance allowed by performing a simulation with 5 trials.

Airline B vs. Airline C

From **Figure 3.4**, we see that, compared to airline C, **airline B**:

- Offers **more ASMs**, because as mentioned above it operates **longer-haul flights**, and the interhub flights.
- Carries a **higher percent of local passengers**. Indeed, airline B own-connecting flights are less attractive compared to those of airline A for the northern cities, and airline C for the southern cities, because of their more circuitous routing from/to northern cities through the southern hub.
- Has a **lower average load factor**. This is the result of airline B carrying relatively fewer connecting passengers, who occupy a seat on two legs, and more local passengers, who occupy a seat only on one leg.
- Carries **more passengers**, because it operates the interhub flights. Other simulations have been performed which show that conversely, if airline C operates these interhub flights, it carries more passengers than airline B²¹.
- Flies **more RPMs**, because of the longer-haul flights it operates, and the higher number of passengers it carries.
- Has a **lower yield**. The fact that it carries more local passengers than airline C (57.9% vs. 51.7%) would suggest that airline B should have a higher yield, because local passengers tend to pay a higher fare per mile flown than connecting passengers

²¹ Cf. Appendix.

of the same fare class. However, this difference is offset by the much longer-haul flights operated by airline B: it offers 31.8% of the total network ASMs compared to 19.1% for airline C, while they both operate airplanes with the same capacity on an equal number of routes (except for the inter-hub flights, but other simulations show that the number of ASMs associated with these flights is small²²). Those flights yield less revenue per passenger mile than the shorter-haul flights, as fares increase less than linearly with distance. As a result, the average yield of airline B is lower.

- Gets **higher revenue**. Indeed, the higher number of RPMs flown by airline B offsets its lower average yield.

Conversely, compared to airline B, **airline C**:

- Offers fewer ASMs, as it operates **shorter-haul flights**.
- Carries a **lower percent of local passengers**. Indeed, airline C own-connecting flights are more attractive compared to those of airline B because of the short routing from/to southern cities through the southern hub.
- Has a **higher average load factor**, because of its lower network percent of local passengers.
- Carries **fewer passengers**, as it does not operate the interhub flights.
- Flies **fewer RPMs**, due to its shorter-haul flights, and the lower number of passengers it carries.
- Has a **higher yield**, as its shorter-haul flights offset its lower network percent of local passengers.

²² Cf. Appendix.

- Gets **lower revenue**, because its lower number of RPMs offsets its higher yield.

Implications for Codeshare Passengers

Because of its lower ALF, airline B has more room to accommodate codeshare passengers without displacing its own-connecting and local passengers. Besides, the proportion of distance flown on codeshare routes is higher for airline B than airline C, and so is the revenue allocated on these routes. Indeed, the revenue split is based on the ratio of local Y fares, which are higher for airline B because it operates the longer-haul leg of the codeshare flights. Overall, airline C always pays more to airline B on the codeshare flights marketed by C (\$88,561 in this case), than airline B pays to airline C on the codeshare flights marketed by B (\$75,650 in this case). Therefore, **codeshare passengers are much more desirable for airline B than for airline C.**

However, because the alliance partners use the same discount method for their own codeshare and their partner's codeshare paths, the availability is the same for two codeshare paths on the same market. Therefore, **the two partners statistically carry the same number of codeshare passengers**, as the decision made by a partner airline on whether accepting or not a codeshare booking request is the same for its own codeshare path and the partner's codeshare path.

Alliance vs. Airline A

The differences between airline A and the alliance are relatively less important than those between the alliance partners, and tend to evolve depending on the use of different RM methods. The characteristics of airline A compared to the alliance that usually remain true beyond this baseline case are:

- Its slightly **lower number of ASMs**, and **shorter-haul flights**.

- Its usually **lower RPM** market share, due to the lower number of ASMs it offers.
- Its **higher yield**, as it operates shorter-haul flights.

More important to us is the fact that **the codeshare routes of the alliance are competitive compared to those of airline A in terms of distance and schedule**. A computation shows that the alliance codeshare flights are only 79 miles (4.0%) and 9 minutes (2.4%) longer on average than the equivalent connecting flights on airline A. As a result, the market share on these markets is 51.1% for airline A, and 49.9% for the alliance with $JI=1$. The balanced competitive situation on these markets provides us with a good baseline case to investigate the impact of RM and discount methods on codeshare traffic.

Summary

This section has briefly introduced the reader to the structure and simulation process of PODS. The main input parameters that will be tested, and the outputs on which we will base our analysis were described. The PODS framework for airline alliances was presented, and the results from a baseline simulation were discussed. In the next chapters, we will build on these results to investigate current and potential future RM practices in airline alliances.

CHAPTER 4. REVENUE MANAGEMENT IN AIRLINE ALLIANCES: CURRENT PRACTICE

Introduction

In this chapter, we will use PODS to study several current industry practices in revenue management in airline alliances. We will focus primarily on two topics: the customer perception of codeshare flights as it is modeled in PODS, and the performance of O-D RM methods in the alliance context.

The widespread industry practice of codesharing raises the issue of the customer perception of codeshare flights. In PODS, this perception is modeled by a parameter called the alliance joint image. In this chapter, we will first assess the sensitivity of the alliance results overall and in codeshare markets to this parameter, when the alliance partners use EMSRb. Later in the chapter, we will also determine whether the joint image parameter has an impact on the relative performance of the O-D RM methods used by the alliance partners.

Next, we will investigate the interaction between the RM systems used by the alliance partners. The relative performance of various combinations of O-D RM methods will be assessed when local discount is used for codeshare passengers. The impact of the discount method will then be discussed by contrasting those results with those obtained using total fares as decision fares on codeshare paths.

The Impact of the Joint Image Parameter in PODS

As mentioned in Chapter 3, the alliance joint image parameter in PODS reflects the customers' perception of the codeshare flights offered by the alliance. In the PODS model, the passengers will have either a 50% chance ($JI=1$) or a 66% chance ($JI=2$) to contact either

alliance airline first in codeshare markets. The other markets are not affected by the joint image parameter, as they are served by airline A and only one of the alliance partners.

It is clear that, with the very simple joint image model used in PODS, the alliance benefits from each of its codeshare flights being perceived as two distinct itineraries, which is the case when the joint image parameter is set to $JI=2$. In the “real world” however, passengers’ first choice is influenced by many other parameters:

- One major factor in passengers’ preference – especially business passengers - is the frequency of service offered by an airline on a market. In many markets, one competitor’s market share tends to increase non-linearly with its frequency share, typically following an S-curve (Simpson, Belobaba, 1982). This reflects the importance for time-sensitive travelers of finding a flight that fit their schedule, as well as having the possibility of taking another flight if they miss their initial flight. It is one of the main reasons why it is extremely difficult for an airline to enter a market where a competitor already offers a large number of flights per day, such as the spoke markets served from a major carrier’s hub.
- Another increasingly important factor is the passenger’s membership in a frequent flyer program. These programs are designed to retain the frequent-flying, and therefore most valuable customers of an airline, by allowing passengers to earn “miles” on their flights, which can be redeemed later in various ways, from seat class upgrades to free flights on the same airline. The rewards increase non-linearly with the number of miles owned by the passenger, and have proven extremely effective in making “captive” the “elite” (i.e. with a large stock of miles) members of these programs, who bring the most revenue to the airline. The concept has grown beyond the airline’s boundaries, with the creation of joint frequent flyers programs between different carriers, especially in the context of alliances, and the involvement of other stakeholders of the tourism industry, credit card companies, car rental companies, hotels etc.

- Finally, the overall airline image clearly influences one passenger's first choice. The image is built on the brand name recognition created by advertisement, the passenger's previous experiences of flying with that airline, his/her possible knowledge of the airline's quality of service, safety record etc.

In PODS, these complex aspects cannot be currently investigated, as the competitors offer the same frequency on all markets (three flights a day), and are equally likely to be one passenger's favorite airline.

However, the simple PODS joint image parameter allows us to quantify the impact of a strategy common to most alliances, which consists of promoting an alliance brand name, while keeping the individual partners' separate identities and brands. In this context, it is unclear whether the passengers perceive the different codeshare flights offered by an alliance, which are usually advertised separately and appear as distinct flights on the CRS screen of a travel agent, as different alternatives or not.

In the two-partner alliance simulated in PODS, this suggests that the joint image parameter of the partners in codeshare markets should be set between $JI=1$ and $JI=2$. In this section, we will test the sensitivity of the alliance results to the joint image parameter, overall and in codeshare market, by comparing the $JI=1$ and $JI=2$ cases, everything else staying the same.

Baseline Case, $JI=2$

In order to have a first point of comparison, we introduce a new baseline case, with the same parameter settings as the baseline case presented in Chapter 3, except for joint image, now set to $JI=2$. The results from this simulation are summarized in **Figure 4.1**.

Airlines results, DF=1.0, Eb vs. Eb/Eb, JI=2, Local Discount:

Parameter	A	B	C	Alliance
Market Share (points)	48.07	31.59	20.34	51.93
RPM (pax.mi)	10022623	6586832	4240729	10827561
ALF (points)	81.7	82.79	88.66	84.99
Network Local (%)	53.57	56.94	49.87	53.55
Yield (cents)	13.48	11.63	15.43	13.12
Net Revenue (\$)	1351287	781268	638943	1420211
Total pax	7015	3825	3524	7348
Codeshare pax	0	956	956	1912
Codeshare pax (%)	0.00	25.00	27.13	26.02

Difference, JI=2 vs. JI=1:

Parameter	A	B	C	Alliance
Market Share (change in points)	-1.13	0.70	0.43	1.13
ALF (change in points)	-1.87	1.89	1.91	1.90
Network Local (change in %)	1.09	-0.95	-1.87	-1.38
Yield (change in cents)	-0.19	0.11	0.26	0.17
Net Revenue (change in %)	-3.61	3.58	3.61	3.59
Total pax (change in %)	-1.50	1.53	1.02	1.28
Codeshare pax (change in %)	0	17.21	17.25	17.23

Figure 4.1. Airlines results, DF=1.0, Eb vs. Eb/Eb, JI=2, Local Discount. Comparison with JI=1.

Comparing these results with those of the baseline case with JI=1, we notice that, when the alliance joint image is switched to JI=2:

- **The number of codeshare passengers carried by the alliance increases.** As expected, setting JI=2 gives the alliance a marketing advantage over airline A. The probability of one passenger contacting the alliance first on these markets increases relatively by 32% (from 0.5 to 0.66), and the number of codeshare passenger carried by the alliance by 17%. The difference between these two numbers can be explained by the fact that, as the capacity of the alliance flights legs stays the same, the high average load factor prevents the alliance from accommodating all the new codeshare passengers.
- **The total number of passengers carried by the alliance increases,** but we notice that this number increases far less than the number of codeshare passengers. This

means that many non-codeshare passengers have been spilled by the alliance, to accommodate codeshare passengers.

- **The decrease in the percent of local passengers carried by the alliance** corroborates the former statement: some local passengers have been spilled to accommodate codeshare passengers, who bring more total revenue to the airline.
- **The alliance average load factor increases**, because of the greater number of passengers it accommodates with the same flight capacities.
- **The RPM market share of the alliance increases**, because it now carries a greater number of passengers on a longer average stage length, as the percent of local passenger it carries has decreased.
- **The alliance yield increases**, which means that the decrease in the percent of shorter-haul, higher-yield local passengers carried by the alliance is somehow offset by a change in the fare class mix. **Figure 4.2** represents the change in the alliance passenger mix between $JJ=1$ and $JJ=2$, by class and type. It shows that the new codeshare passengers carried by the alliance are mainly Y class, while many own-connecting and local passengers displaced are Q class. Overall, we see that the alliance carries less Q class, and more M, B and especially Y class passengers. At this demand factor, this change in passenger mix tends to increase the alliance average yield.

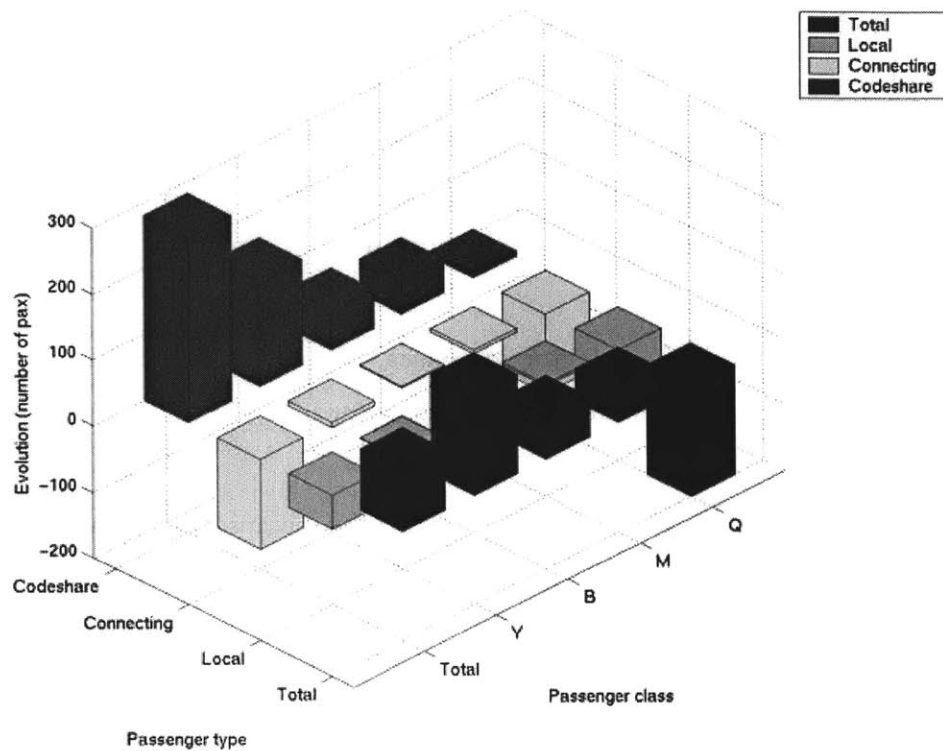


Figure 4.2. Changes in alliance passenger mix, $Jl=2$ compared to $Jl=1$.

- As a result of its greater RPM market share and higher yield, **the alliance revenue increases**. At this level of demand ($DF=1.0$), the increase is 3.6%.

Overall Impact at Different Demand Factors

We are now going to see if the trends presented above are robust to a variation in the level of demand. **Figures 4.3 to 4.8** represent the difference in the airlines results with $Jl=2$ compared to $Jl=1$, when the demand factor ranges from $DF=0.8$ to $DF=1.1$, and the network load factors range accordingly from 70.7% to 86.9%.

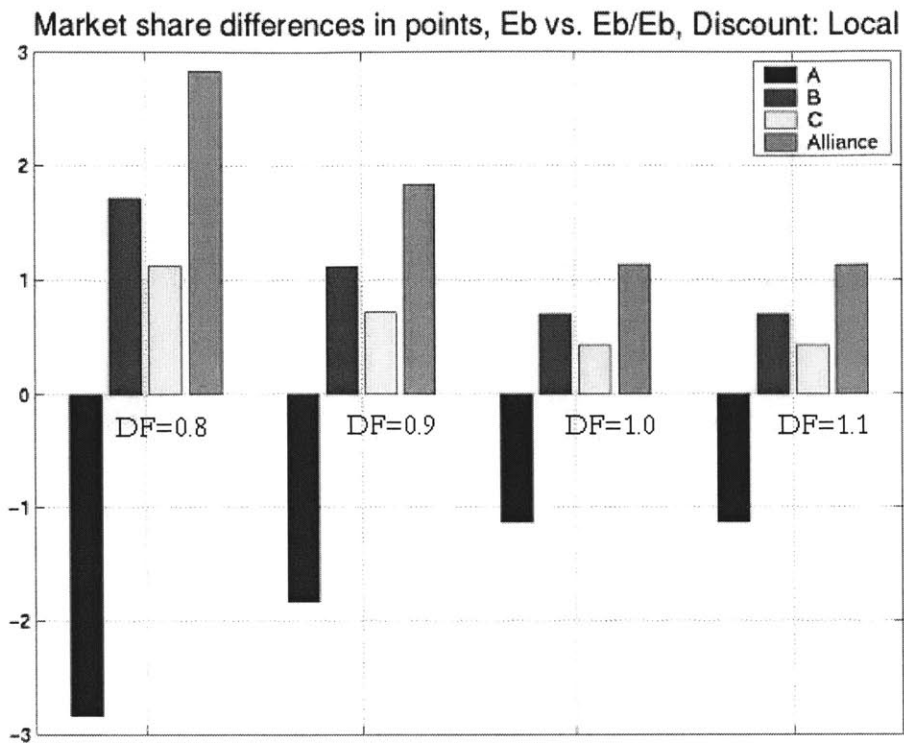


Figure 4.3. Changes in alliance results, JI=2 compared to JI=1.

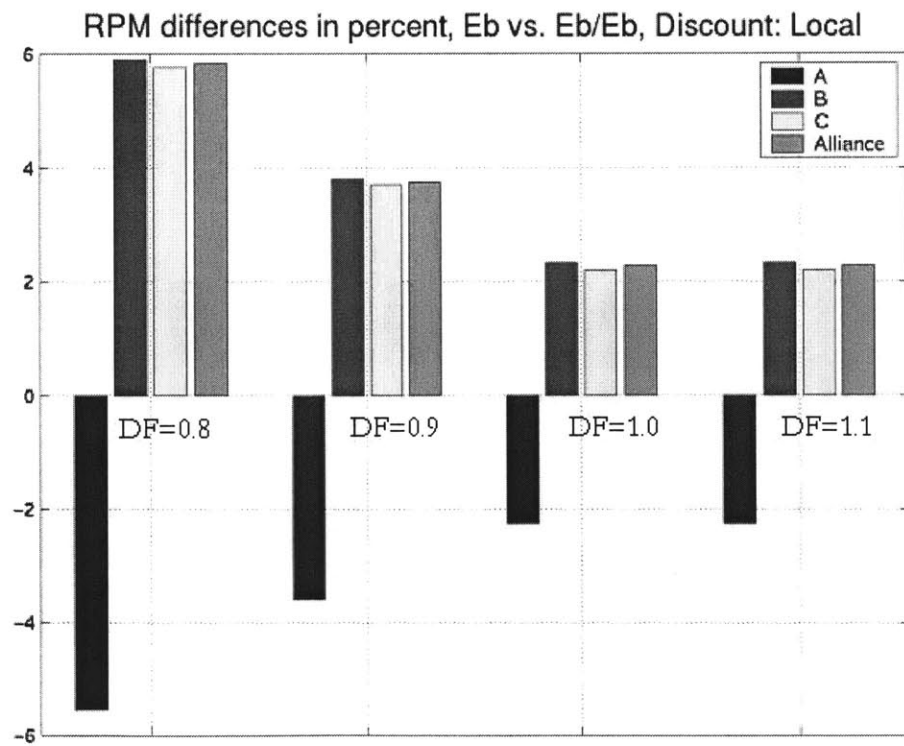


Figure 4.4. Changes in alliance results, JI=2 compared to JI=1.

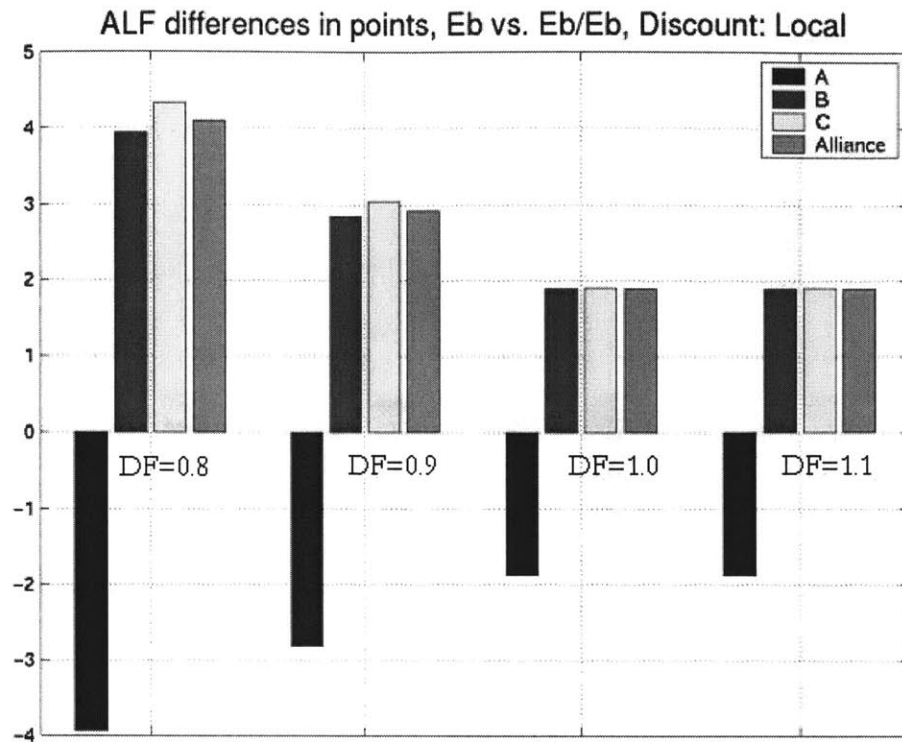


Figure 4.5. Changes in alliance results, JI=2 compared to JI=1.

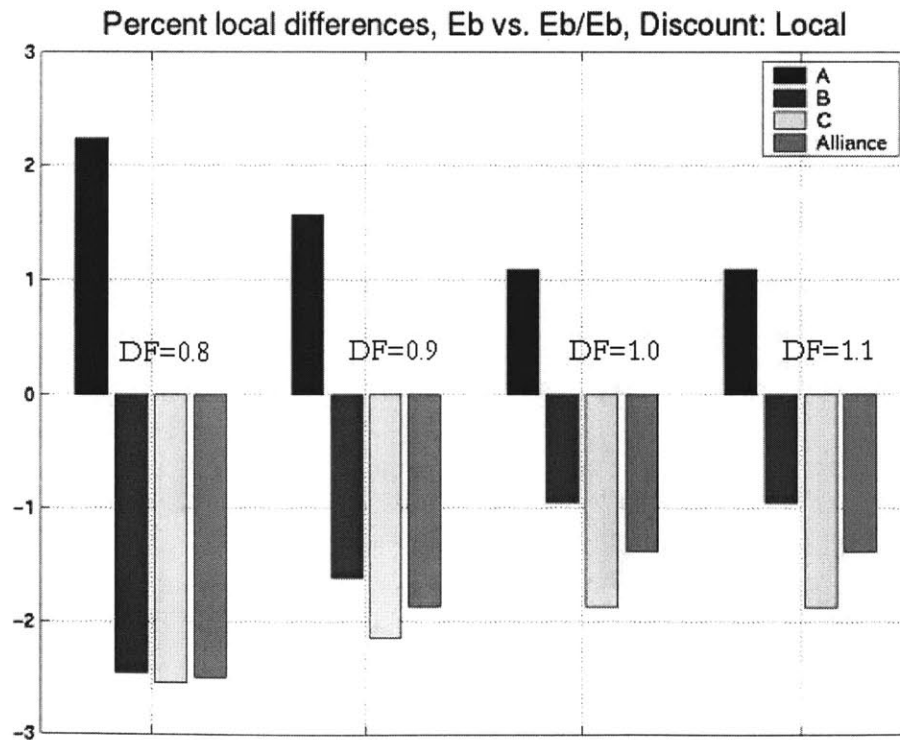


Figure 4.6. Changes in alliance results, JI=2 compared to JI=1.

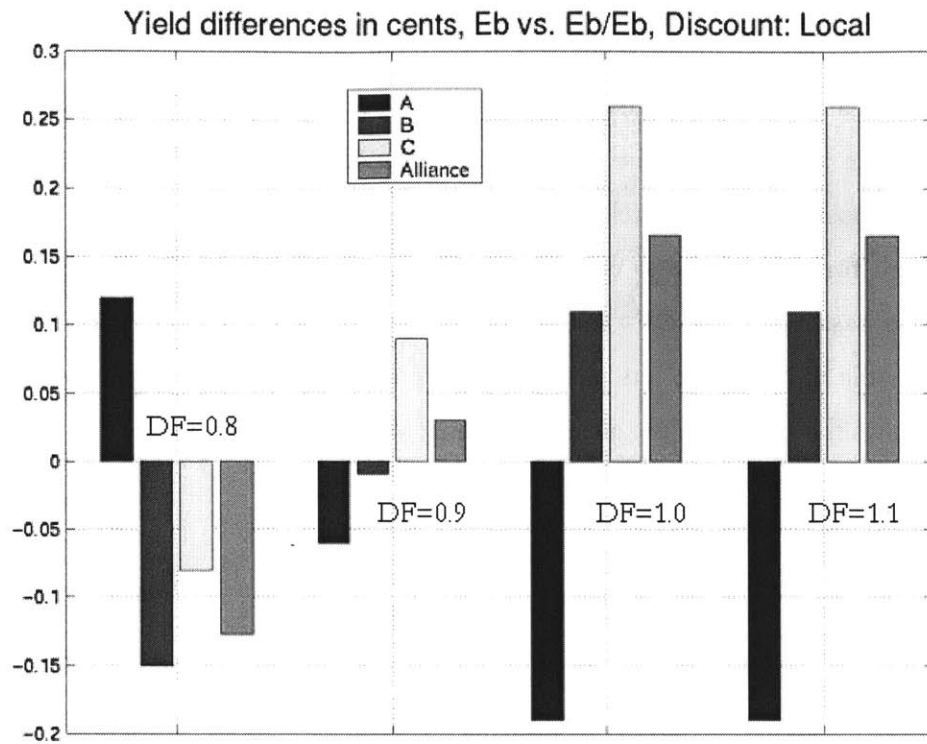


Figure 4.7. Changes in alliance results, JI=2 compared to JI=1.

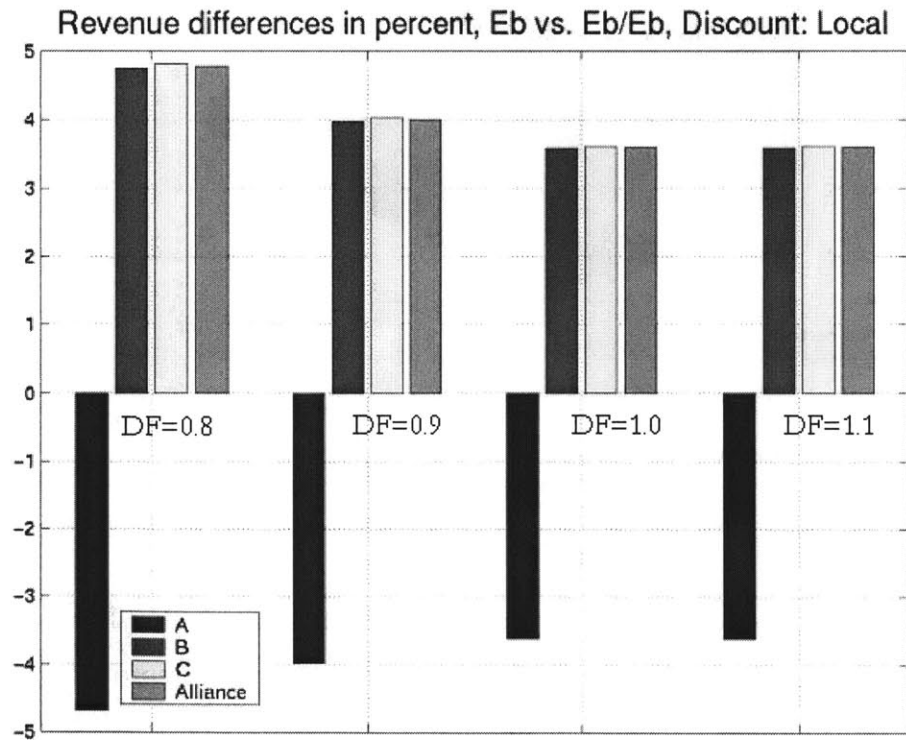


Figure 4.8. Changes in alliance results, JI=2 compared to JI=1.

At low demand factors, the alliance ALF is lower, so that the alliance has more room to accommodate extra codeshare passengers. Therefore, at lower demand factors, the alliance ALF and RPM market share increase more, while the percent of local passengers decreases more. But for the same reason, the difference in alliance average yield between $Jl=2$ and $Jl=1$ becomes positive only at relatively high demand factors. Only then, demand is sufficiently high for the alliance to compensate the loss of higher-yield local passengers by spilling Q class passengers (cf. $DF=1.0$, above). On the contrary, when demand is low, the alliance is not able to “improve” its passenger mix enough, and its average yield decreases. **Figure 4.9** shows the change in the alliance passenger mix at $DF=0.8$:

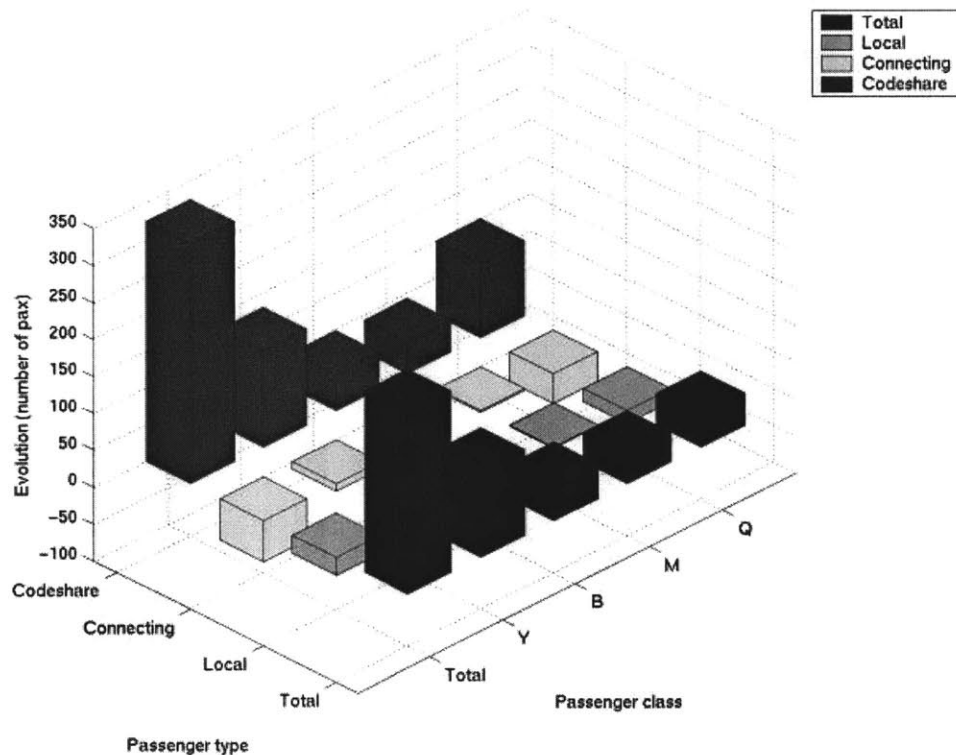


Figure 4.9. Changes in alliance passenger mix, $Jl=2$ compared to $Jl=1$, $DF=0.8$.

We still notice an “improvement” in the passenger fare class mix, as the alliance gains more Y passengers than B, M or Q. But it is far less dramatic than the improvement shown in **Figure 4.2**, and **Figure 4.7** shows that the alliance yield actually decreases at this demand factor.

However, **Figure 4.8** shows that the decrease of alliance yield at low demand factors is offset by the increase in the number of RPMs, so that the revenue gains of the alliance with $JI=2$ compared to $JI=1$ are actually higher at a low demand factor. Overall, because of this balancing effect, the alliance revenue increase under $JI=2$ is quite stable through the demand factor range investigated, around 4%.

Impact on Selected Codeshare Markets

The results presented above describe the effect of the joint image parameter on the alliance's overall results, over the whole network. However, we know that joint image affects only codeshare markets, so we will now focus on these markets. As the previous results show that the level of demand influences the effect of joint image, we will study two different codeshare markets in the PODS network:

- A relatively low demand market, from Helena, MT to New Orleans, LA (8.8 passengers carried per day by all airlines),
- A relatively high demand market, from Los Angeles, CA to New York, NY (20.4 passengers carried per day by all airlines).

Figures 4.10 to 4.12 show the effect of joint image on the alliance results on the low demand market.

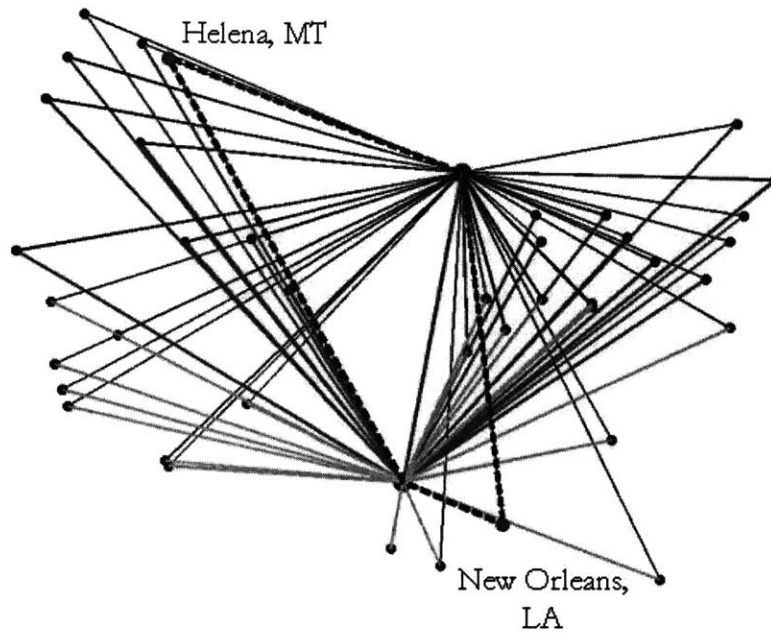


Figure 4.10. A low demand market (Helena, MT – New Orleans, LA).

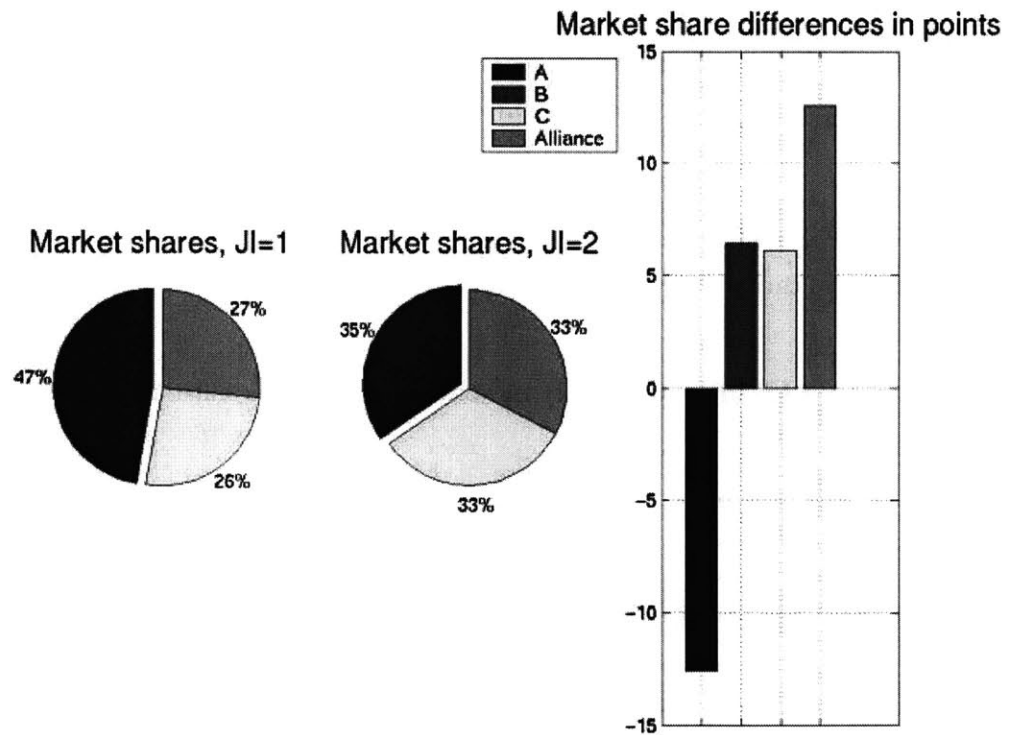


Figure 4.11. Changes in market share, JI=2 compared to JI=1.

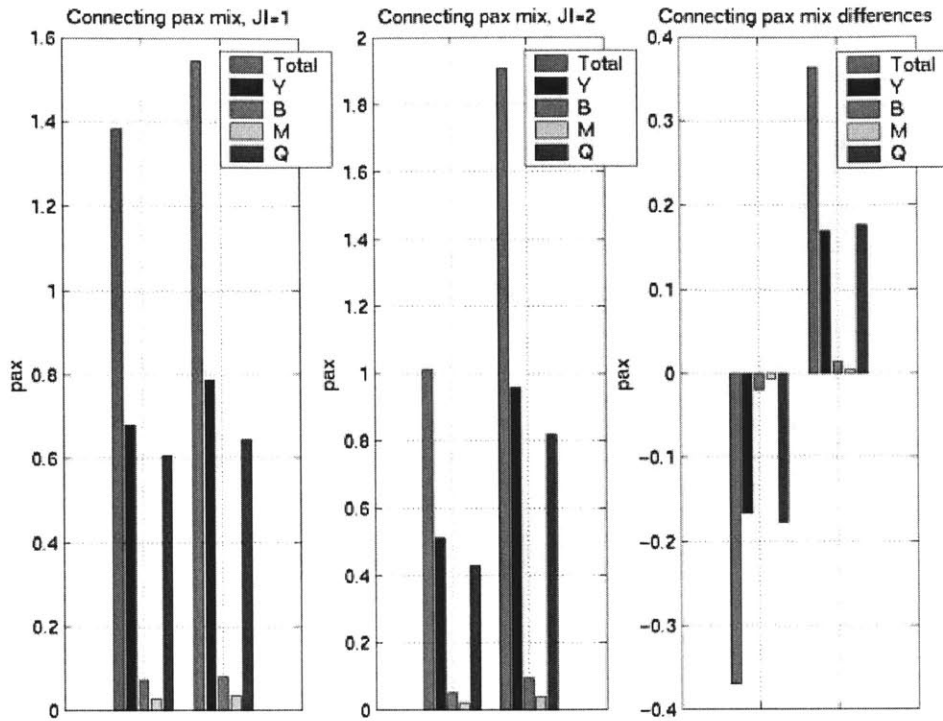


Figure 4.12. Changes in passenger mix, JI=2 compared to JI=1.

Because the alliance offers a shorter itinerary than airline A (cf. **Figure 4.10**), its market share with JI=1 is greater than the market share of airline A in the Helena-New Orleans market. Indeed, the shorter an itinerary is, the greater the chances are that it fits in one passenger's decision window²³. When JI=2, the market is close to an even split between the three airlines (cf. **Figure 4.11**): as the demand on this market is low, the alliance is able to accommodate most of the new passengers who choose to call them first. **Figure 4.12** shows that the alliance accepts these new passengers in all fare classes, more in Q class than in Y class.

In a higher demand market, the situation is different (**Figures 4.13 to 4.15**):

²³ Cf. Chapter 3, on the PODS passenger's decision window model.

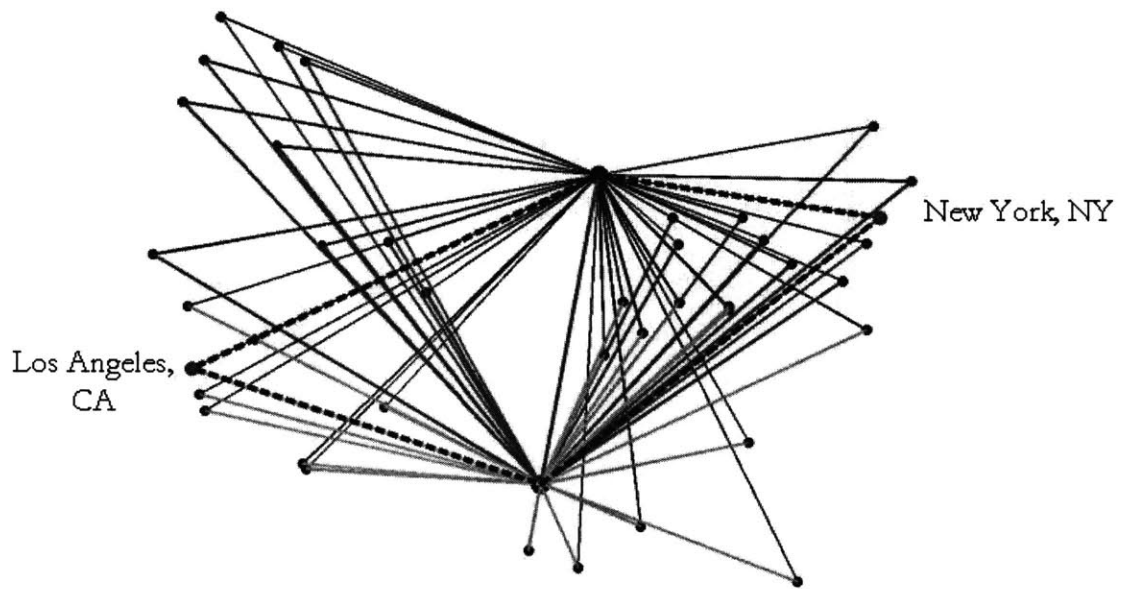


Figure 4.13. A high demand market (Los Angeles, CA – New York, NY).

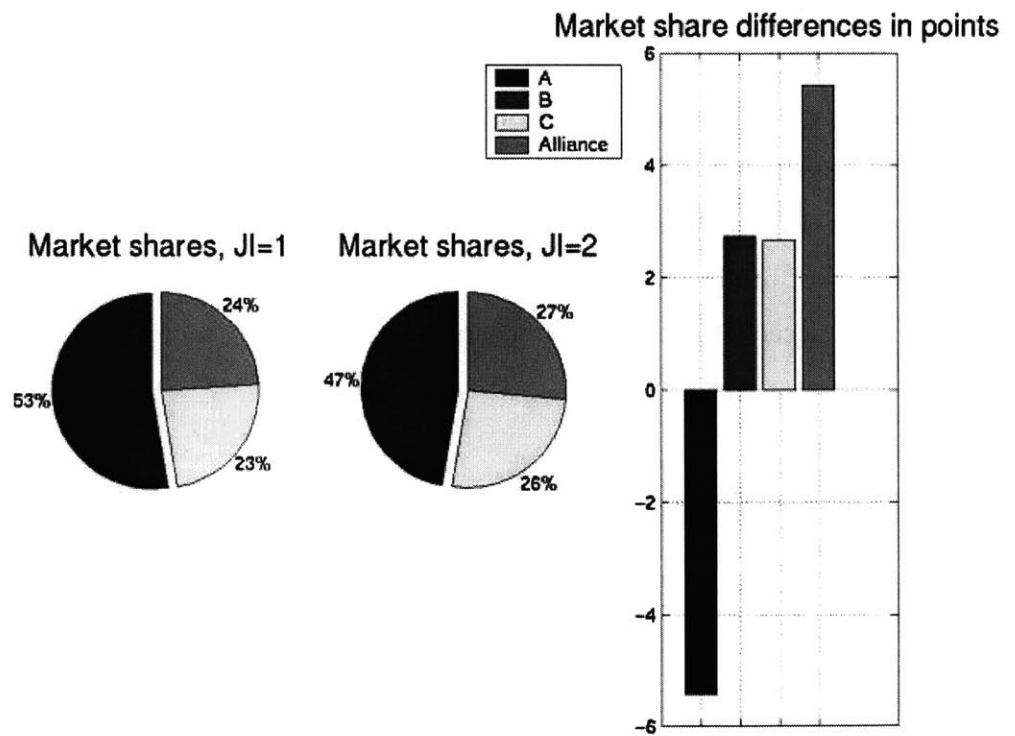


Figure 4.14. Changes in market share, JI=2 compared to JI=1.

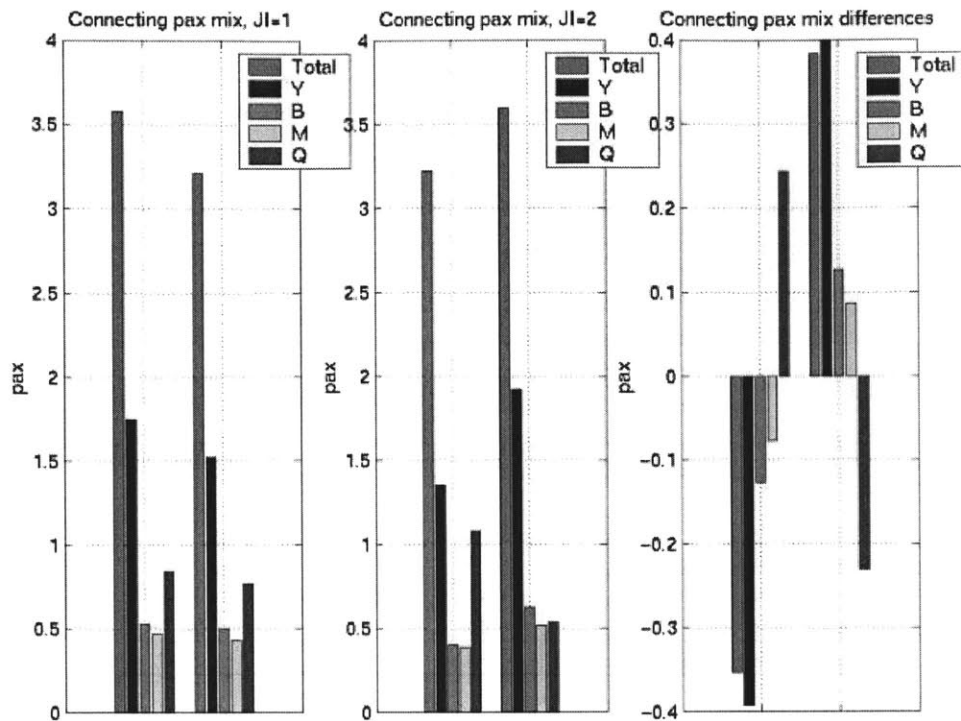


Figure 4.15. Changes in passenger mix, JI=2 compared to JI=1.

When JI=1, airline A has a market share edge over the alliance (cf. **Figure 4.14**), as it offers a slightly shorter itinerary (cf. **Figure 4.13**), even if the difference is not as obvious as in the Helena-New Orleans market. When JI=2, the market is still close to a 50/50 split between airline A and the alliance. As the level of demand is high in this market, the load factors are high on the two flight legs, and the alliance cannot accommodate all the new potential codeshare passengers. However, **Figure 4.15** shows that the alliance accepts new high-class passengers, overwhelmingly from Y class, who previously flew on airline A, and dumps its previous Q class codeshare passengers on its competitor.

Figure 4.16 summarizes the results in terms of passengers carried and market share in these two markets:

Market	Helena, MT - New Orleans, LA			
Market Size (pax)	8.8			
Airline	A	B	C	Alliance
Passengers, JI=1	4.15	2.3	2.33	4.63
Passengers, JI=2	3.04	2.86	2.86	5.72
Passengers difference	-1.11	0.56	0.53	1.09
Market Share, JI=1 (%)	47.27	26.20	26.54	52.73
Market Share, JI=2 (%)	34.70	32.65	32.65	65.30
Market Share difference (points)	-12.56	6.45	6.11	12.56
Market	Los Angeles, CA - New York, NY			
Market Size (pax)	20.4			
Airline	A	B	C	Alliance
Passengers, JI=1	10.73	4.76	4.88	9.64
Passengers, JI=2	9.67	5.34	5.45	10.79
Passengers difference	-1.06	0.58	0.57	1.15
Market Share, JI=1 (%)	52.68	23.37	23.96	47.32
Market Share, JI=2 (%)	47.26	26.10	26.64	52.74
Market Share difference (points)	-5.41	2.73	2.68	5.41

Figure 4.16. Summary, JI=2 compared to JI=1.

From these investigations, it appears that:

- The joint image parameter in PODS has a significant impact on the alliance results. Over the whole network, the alliance can expect a revenue gain in the order of 4% with JI=2 compared to JI=1, for a demand factor ranging from DF=0.8 to DF=1.1.
- The gains are higher when the overall level of demand is low, and in low-demand codeshare markets. When demand is high, the alliance cannot accommodate all new codeshare passengers, but is able to increase yield by improving its passenger fare mix. In network D, the market share gains in a codeshare market can vary from 5 to 13%, depending on the level of demand of that market.

Setting the alliance joint image to JI=2 increases the alliance market share, and thus the alliance leverage when the alliance partners implement O-D RM methods. Therefore, we will

primarily use this setting, assuming that the passengers perceive codeshare itineraries as distinct alternatives, when investigating the impact of O-D RM methods, as their effect will be “magnified.” However, when we need to compare the alliance results with the results of the alliance as a single airline B (cf. Chapter 3), especially in Chapter 5, we will have to use a $JI=1$ setting.

Interaction of the RM Systems of the Alliance Partners

Airline alliances often involve airline partners with different RM systems. Some airlines have large Operations Research departments, which develop in-house advanced RM systems. Others airlines buy off-the-shelf RM systems from companies like Pros[®] or Sabre[®]. Finally, many smaller airlines do not use RM at all. It is important to understand how the RM systems of the different partners interact to determine the relative revenue gains of the partners in the alliance, and of the alliance as a whole. In this section, we will try to answer the following questions:

- What is the impact of one or both alliance partners investing in an O-D RM system on the revenue of its partner and on the alliance as a whole?
- How do the individual characteristics of each partner (ALF, short-haul vs. long-haul etc.) condition the performance of different RM systems?
- What is the effect of using different discount methods for inter-partner codeshare passengers on the performance of the different RM systems?
- Does our assumption concerning the alliance joint image in PODS ($JI=1$ or $JI=2$) impact the performance of different RM systems?

We will first study in detail different combinations of RM methods used by the alliance at $JI=2$, with local discount of the codeshare passengers. Then, we will compare these results to those obtained using no discount, and with an alliance joint image of $JI=1$.

Study with Local Discount of Codeshare Paths, $JI=2$

For this study, we will use as a baseline case the simulation with $DF=1.0$, all airlines using EMSRb, $JI=2$, and local discount for decision fares on codeshare paths. We will compare to this case the results of simulations where one or both alliance partners use HBP, DAVN, or ProBP, while airline A still uses EMSRb.

HBP Study, Local Discount

The HBP algorithm uses 8 network-wide virtual buckets,²⁴ where fare classes are grouped according to their total itinerary value, to calculate bid prices on each leg. The bid prices for connecting itineraries take into account the displacement costs on the legs traversed using a heuristic described in Chapter 3. Therefore, compared to local paths:

- At low ALF, own-connecting paths are given preference, according to their total itinerary value,
- At high ALF, own-connecting paths are given a lower preference, because of the displacement cost incurred.

However, because of the use of local discount, the codeshare paths are treated as local paths, and are nested without taking into account the total itinerary fare. Therefore, in the bucket structure used by HBP, codeshare passengers are nested lower than own-connecting passengers, and the EMSRc bid prices on each leg are reduced. Own-connecting paths are then controlled by HBP bid prices, which include displacement cost, whereas codeshare paths are effectively controlled only by the reduced EMSRc value on each leg. As a result, with local discount, the bid prices for codeshare paths tend to be low compared to own-connecting paths

²⁴ Cf. Chapter 2.

The airlines' total revenue and average yield when one or both alliance partners use HBP are presented in **Figure 4.17 and 4.18**. On the top of each figure, the different combinations of RM methods used by the alliance partners are represented using the convention defined in Chapter 3, omitting the method used by airline A, which is EMSRb in all cases.

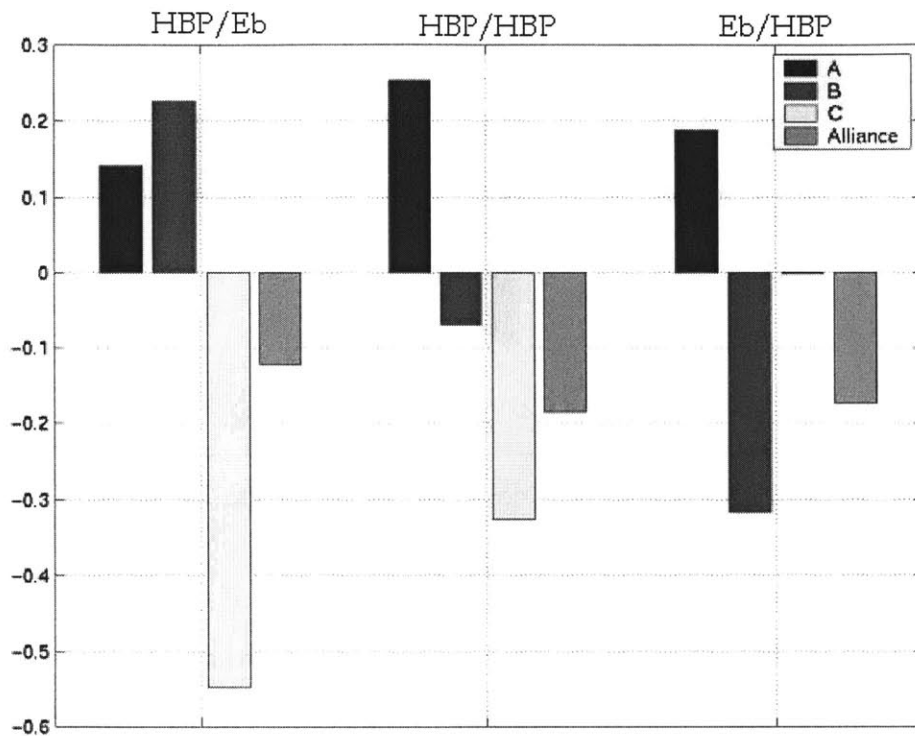


Figure 4.17. Revenue differences in percent, HBP compared to EMSRb, DF=1.0, JI=2, Local Discount.

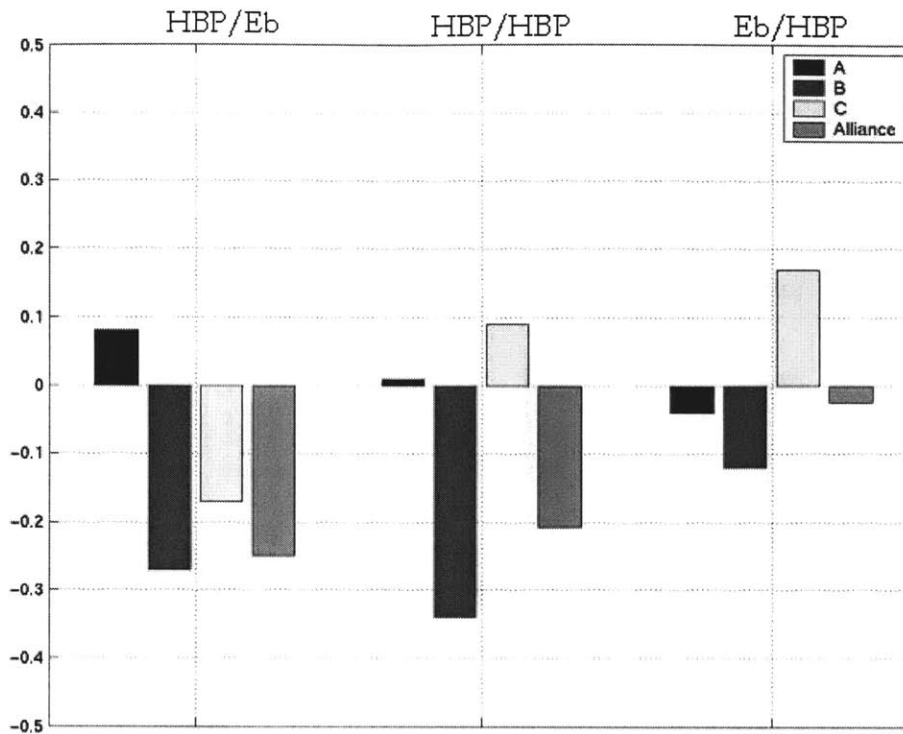


Figure 4.18. Yield differences in cents, HBP compared to EMSRb, DF=1.0, JI=2, Local Discount.

We see that the use of HBP by any alliance partner translates into a net revenue loss for the alliance compared to using EMSRb. This result is unexpected, as previous PODS studies show that HBP performs consistently better than EMSRb²⁵. The analysis of the changes in passenger mix and passenger choice will help us to explain these results.

Case 1: Eb vs. HBP/Eb (Figures 4.19 and 4.20)

²⁵ Cf. for instance Belobaba, 1998.

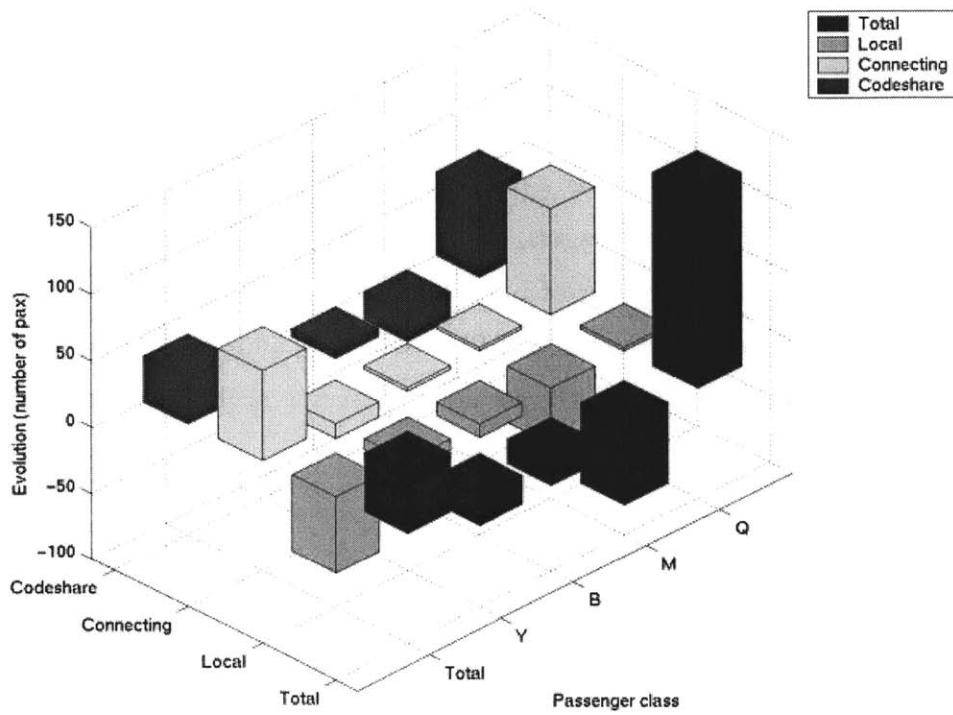


Figure 4.19. Change in airline B passenger mix, HBP/Eb vs. Eb.

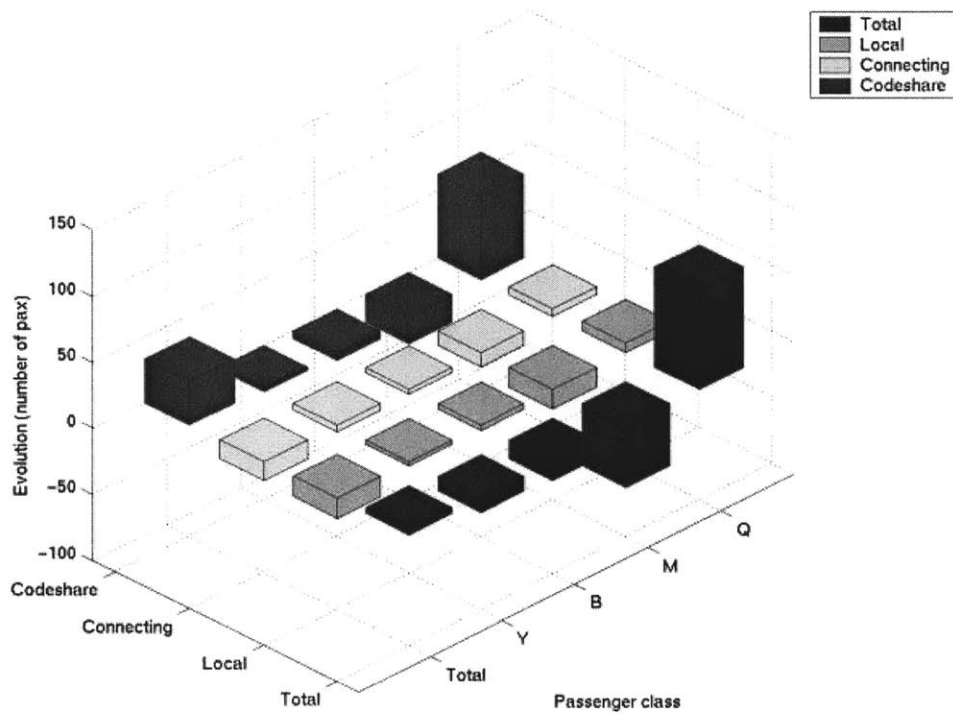


Figure 4.20. Change in airline C passenger mix, HBP/Eb vs. Eb.

Figure 4.19 shows that, as expected when using HBP, airline B carries more own-connecting passengers, because of its relatively low ALF, but it also carries more codeshare passengers, because of the use of local discount. The increase in own-connecting and codeshare passengers, who are mostly Q class, displaces a significant number of local passengers, essentially in the M class. As a result of this change in fare class mix, and the decrease in the number of local passengers, airline B average yield goes down. However, with the overall increase in the number of passengers airline B carries, who moreover are mostly connecting passengers, its number of RPMs is way up, and the revenue sharing on codeshare paths is favorable to airline B, so airline B sees a slight increase in revenue (0.23%).

On the other hand, airline C does not discriminate between local, connecting and codeshare passengers as it uses Eb. Therefore, airline C spills both local and own-connecting passengers, mostly M class, to accommodate the extra codeshare passengers, who are mostly Q class. As a result, airline C's yield goes down, while the number of passengers it carries barely increases. Besides, the revenue split agreement on codeshare passengers is unfavorable to airline C, so airline C loses revenue (-0.55%). Overall, the alliance loses revenue (-0.12%).

Case 2: Eb vs. Eb-HBP (Figures 4.21 and 4.22)

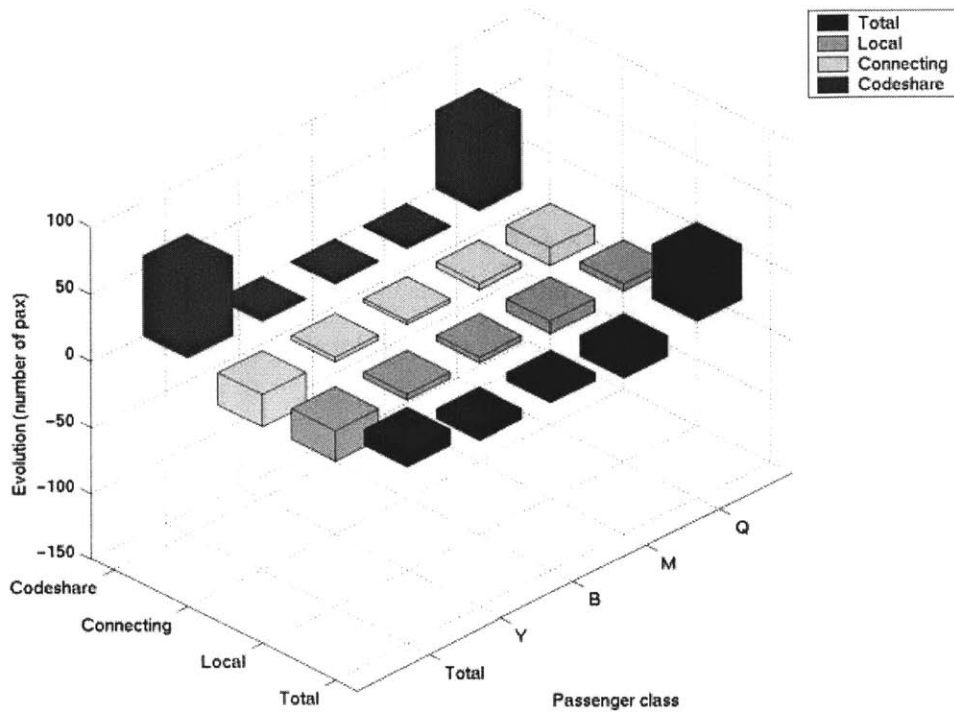


Figure 4.21. Change in airline B passenger mix, E_b/HBP vs. E_b .

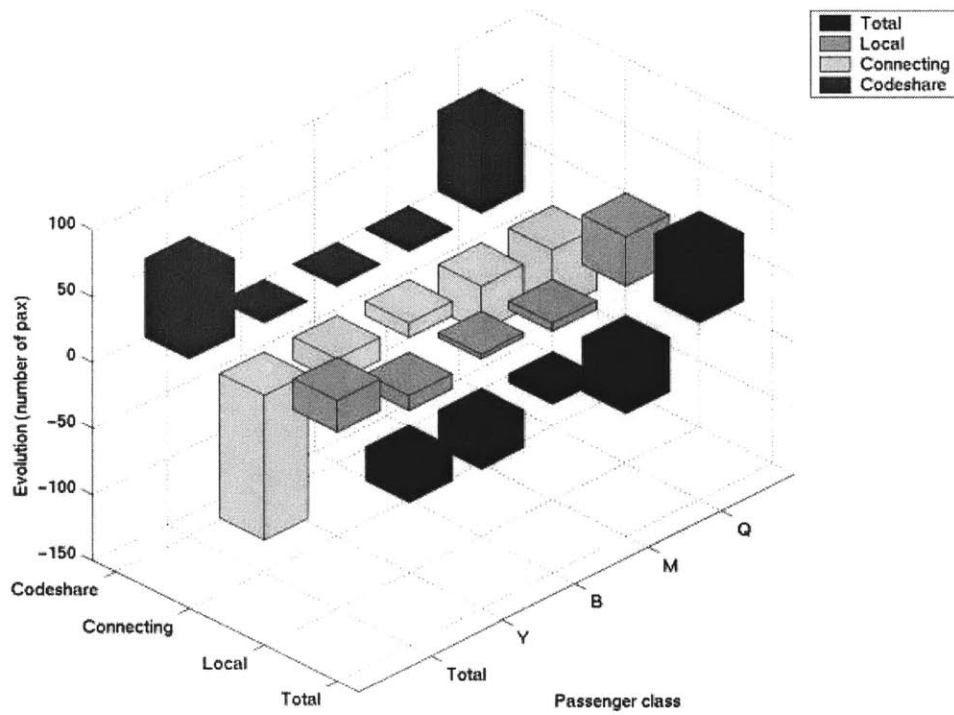


Figure 4.22. Change in airline C passenger mix, E_b/HBP vs. E_b .

Because of its higher ALF, airline C with HBP chokes off its own-connecting passengers, mostly in Q and M class, in favor of codeshare and local Q class passengers, who do not incur displacement costs. Overall, airline C carries fewer passengers, and the revenue split agreement for the additional codeshare passengers it carries is not favorable, but airline C yield goes up because of the increased percentage of local passengers. The two effects balance quite exactly, and airline C revenue stays the same.

The situation of airline B is very similar to the situation of airline C in the previous case (Eb vs. HBP/Eb). However, its revenue losses (-0.32%) are somehow limited by the favorable revenue split agreement on the new codeshare passengers. As a whole, the alliance loses revenue (-0.17%).

Case 3: Eb vs. HBP/HBP (Figures 4.23 and 4.24)

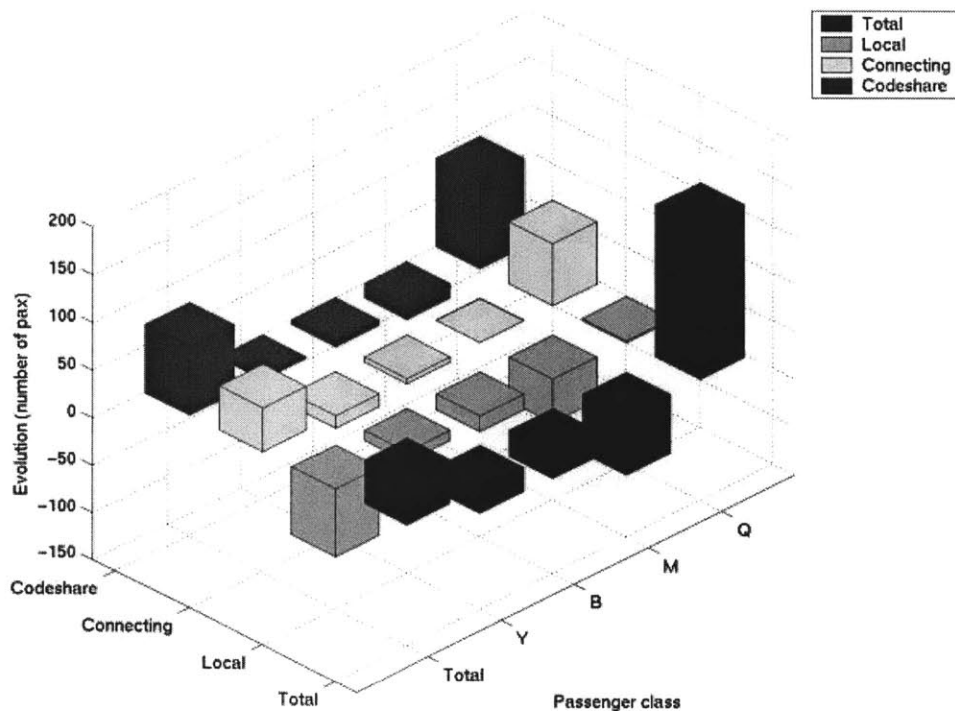


Figure 4.23. Change in airline B passenger mix, HBP/HBP vs. Eb.

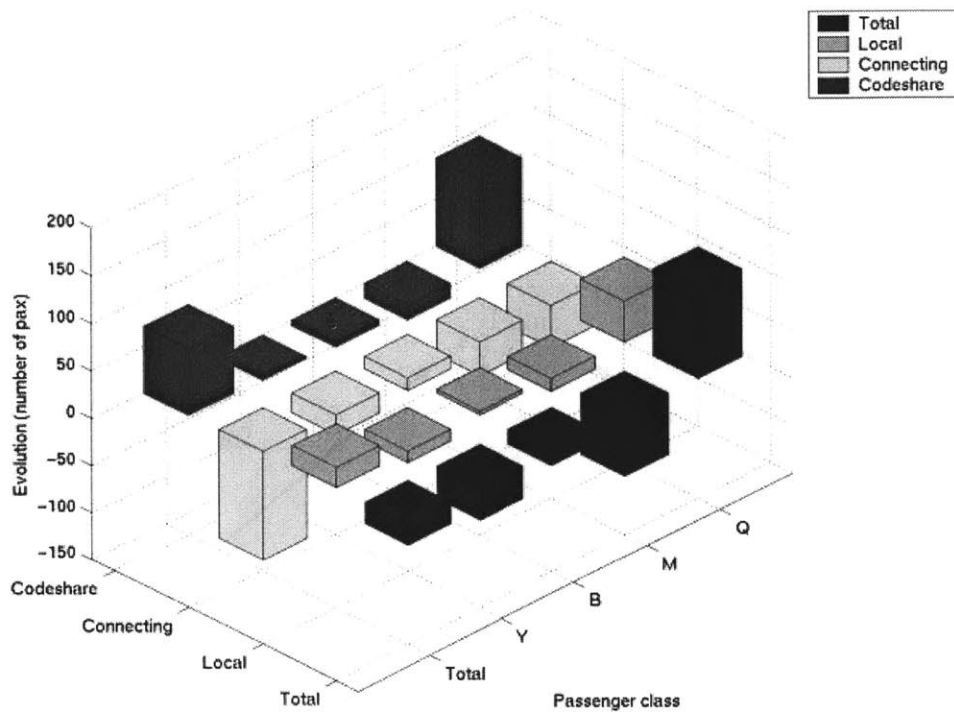


Figure 4.24. Change in airline C passenger mix, HBP/HBP vs. Eb.

In this case, we see a combination of the worst effects of the two previous cases, with the largest increase in the number of codeshare passengers. Airline B still carries more own-connecting passengers, but they are mostly Q class, as the new codeshare passengers are, and both displace a large number of local M passengers. Therefore, airline B's RPMs go up but its yield goes down, and overall B loses revenue (-0.07%). Airline C is in the same situation as when it was the only partner using HBP, except that its results are worsened by the higher number of codeshare passengers it carries, so that airline C loses revenue (-0.33%). Overall the alliance loses more revenue than in the previous cases (-0.19%).

Another way to analyze the situation is to look at the changes in the number of passengers carried by the alliance, categorized according to their first choice. Indeed, a passenger flying in a given class on a given path on one of the alliance's partners' flights might have initially requested a different fare class, on a different path, on a different airline. Studying the evolution of the number of passengers carried by first choice allows us to see the impact of the RM methods on the decision made by the airline of accepting or not accepting a booking

request. **Figure 4.25** recalls the different passenger choice categories that we will use in the alliance context:

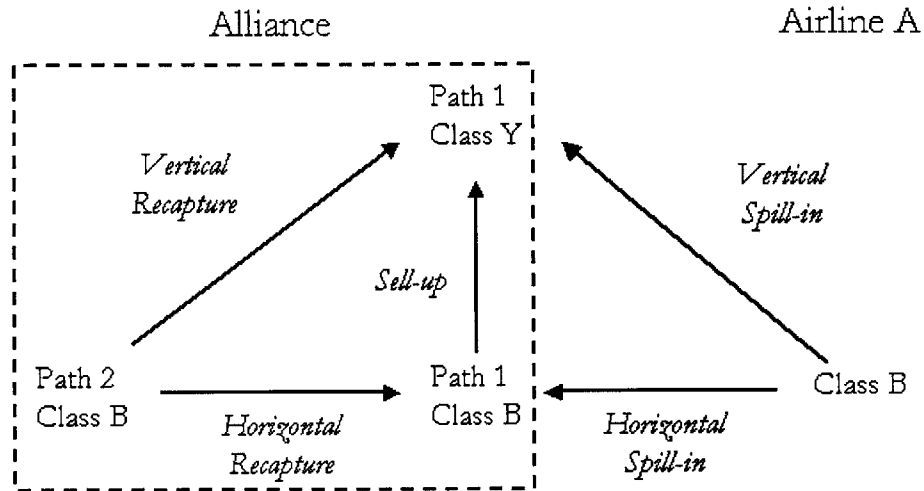


Figure 4.25. Passenger choice in the alliance context.

The remaining possibility for a passenger is simply to get his/her **first choice**. We will not look at the passengers deciding not to fly (**no-go**) here.

Figure 4.26 shows the differences in the passengers carried by the alliance by class and choice, when both alliance partners use HBP, compared to the case where all airlines use EMSRb.

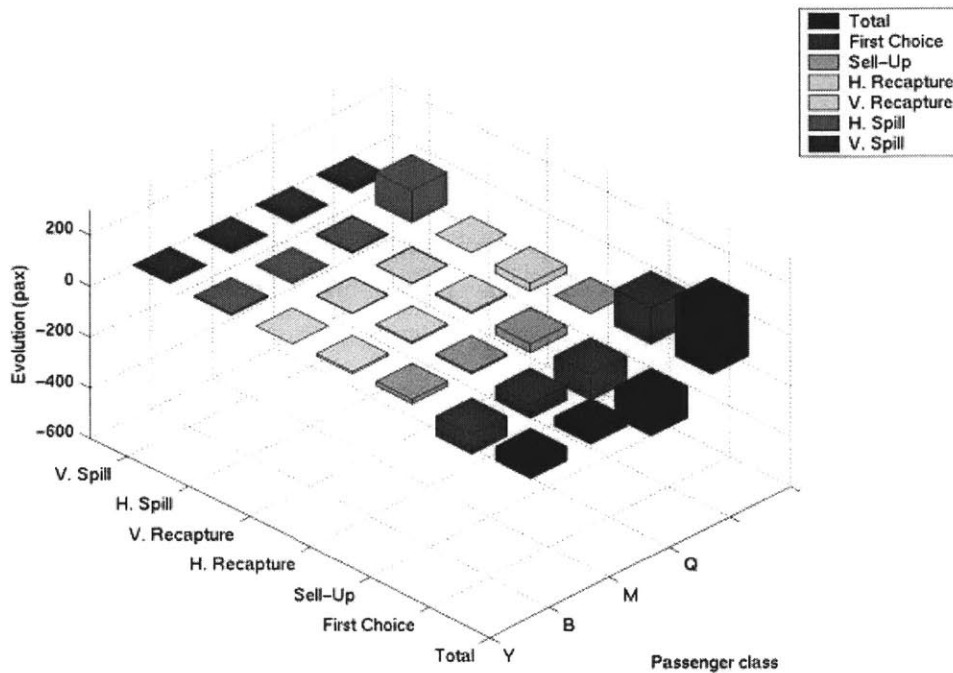


Figure 4.26. Change in alliance passenger choice, HBP/HBP vs. Eb.

We see that when the alliance uses HBP, it refuses first choice requests from passengers in Y, B and M classes, which correspond to the local and connecting passengers displaced to accommodate the new codeshare passengers, who are mostly Q class. The increase in Q codeshare passengers comes both from an increase in first choice requests accepted by the alliance and horizontal spill-in from the competing airline A.

DAVN Study, Local Discount

The DAVN algorithm uses 8 leg-specific virtual buckets,²⁶ where fare classes are grouped according to the total itinerary values, taking into account the displacement costs for own-connecting passengers. Therefore, as it was the case with HBP, compared to local paths,

²⁶ Cf. Chapter 2.

own-connecting paths are given a higher preference at low ALF, and a lower preference at higher ALF.

Because of the use of local discount, the codeshare paths are treated as local paths, and are nested without taking into account the total itinerary fare. However, because own-connecting paths are nested according to their pseudo-fares (taking into account the displacement costs), they are not systematically nested higher than codeshare paths. In DAVN, the booking limits for both codeshare and own-connecting paths are then set directly according to this nesting²⁷, so that the codeshare paths are probably only slightly under-protected on average. Therefore, compared to HBP, one would expect to see a reduced flow of codeshare passengers with DAVN, which is likely to be closer to the revenue-maximizing number for the alliance partners.

The airlines' total revenue and average yield when one or both alliance partners use DAVN are presented in **Figure 4.27 and 4.28**:

²⁷ In HBP the bid prices for connecting paths are differentiated from the bid prices for local (and codeshare) paths using a heuristic, *after* the leg bid prices have been computed using fixed virtual buckets. In DAVN, the total itinerary fares and displacement costs are taken into account *before* the nesting into leg-specific buckets (cf. Chapter 2).

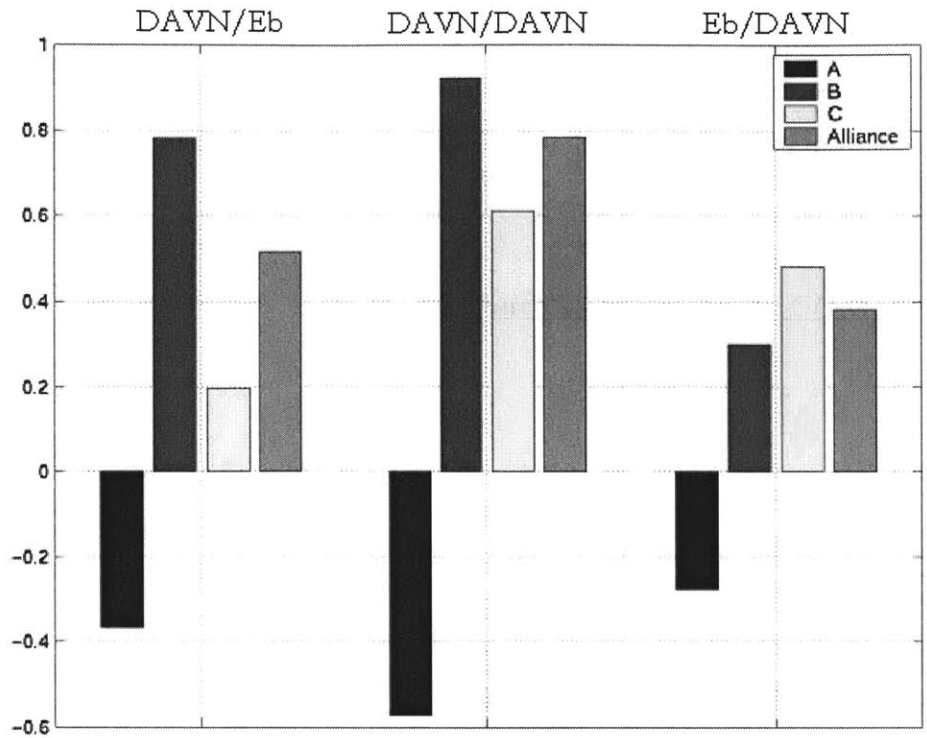


Figure 4.27. Revenue differences in percent, DAVN compared to EMSRb, DF=1.0, JI=2, Local Discount.

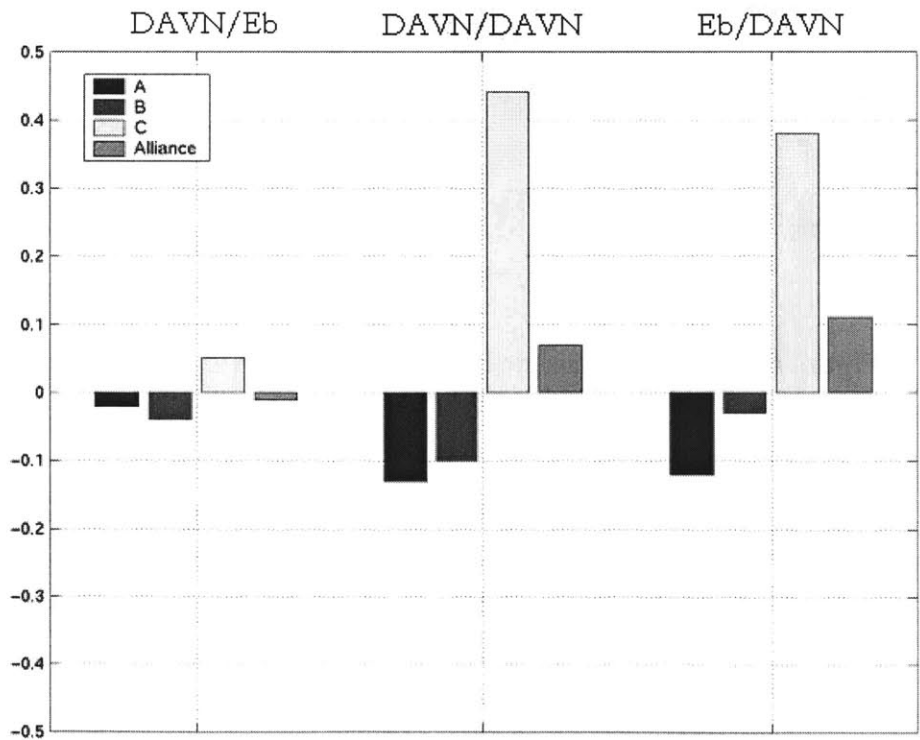


Figure 4.28. Yield differences in cents, DAVN compared to EMSRb, DF=1.0, JI=2, Local Discount.

We see that, with the use of DAVN by one or both alliance partners, the alliance as a whole and the alliance partners see an increase in revenue. However, the two partners do not benefit equally from using DAVN: airline B sees the greatest increase in revenue whenever it uses DAVN.

Case 1: Eb vs. DAVN/Eb (Figures 4.29 and 4.30)

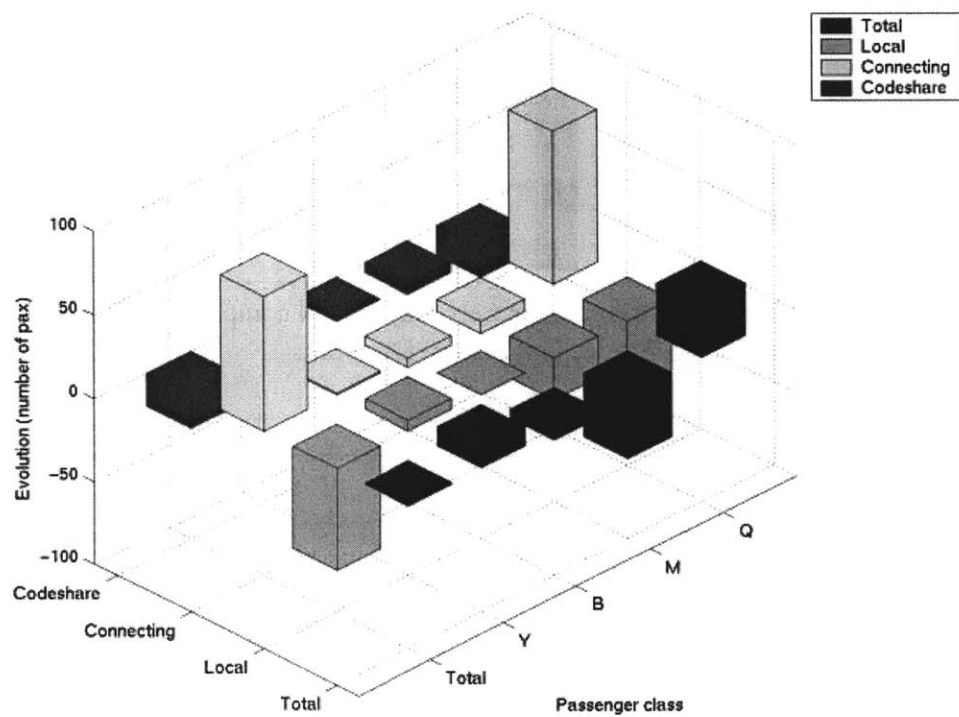


Figure 4.29. Change in airline B passenger mix, DAVN/Eb vs. Eb.

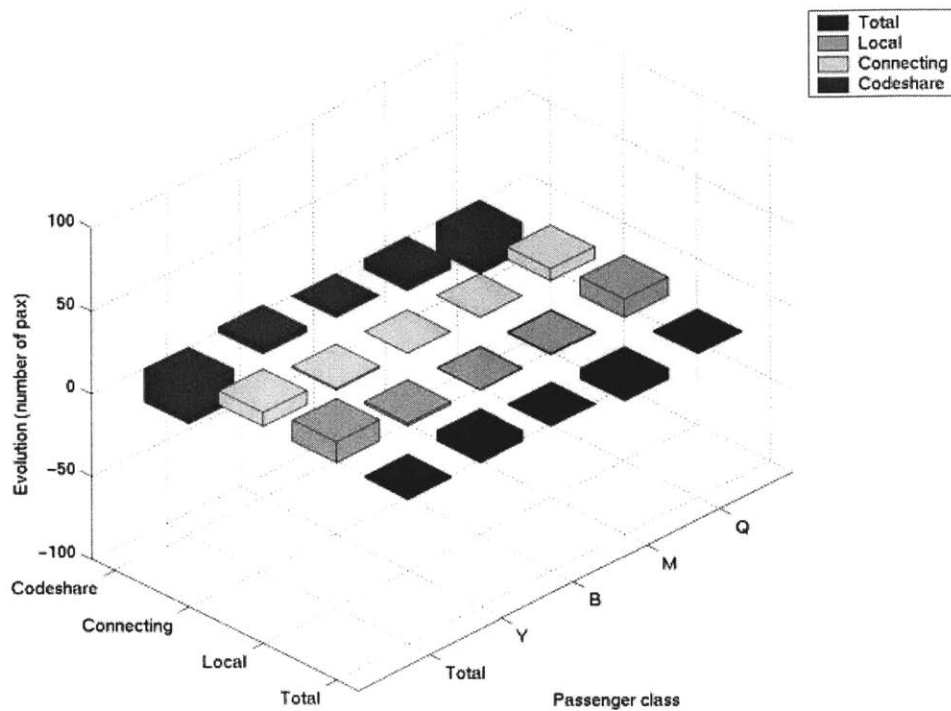


Figure 4.30. Change in airline C passenger mix, DAVN/Eb vs. Eb.

Using DAVN allows airline B to increase the number of its own-connecting passengers (essentially in Q class), while decreasing the number of local M and Q class and codeshare Q class passengers, because of the particular nesting of own-connecting passengers mentioned above. Overall, the revenue of airline B increases by 0.78%. The reduced number of codeshare passengers in turn benefits airline C, which revenue increases by 0.20%. Overall, the total alliance revenue increases by 0.52%.

Case 2: Eb vs. Eb/DAVN (Figures 4.31 and 4.32)

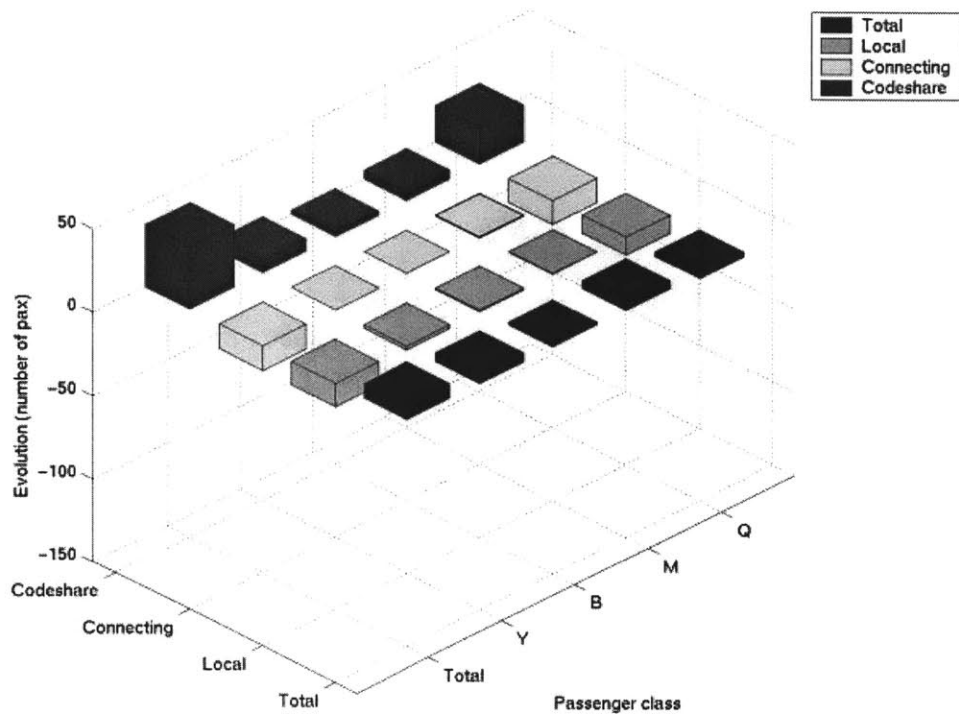


Figure 4.31. Change in airline B passenger mix, Eb/DAVN vs. Eb.

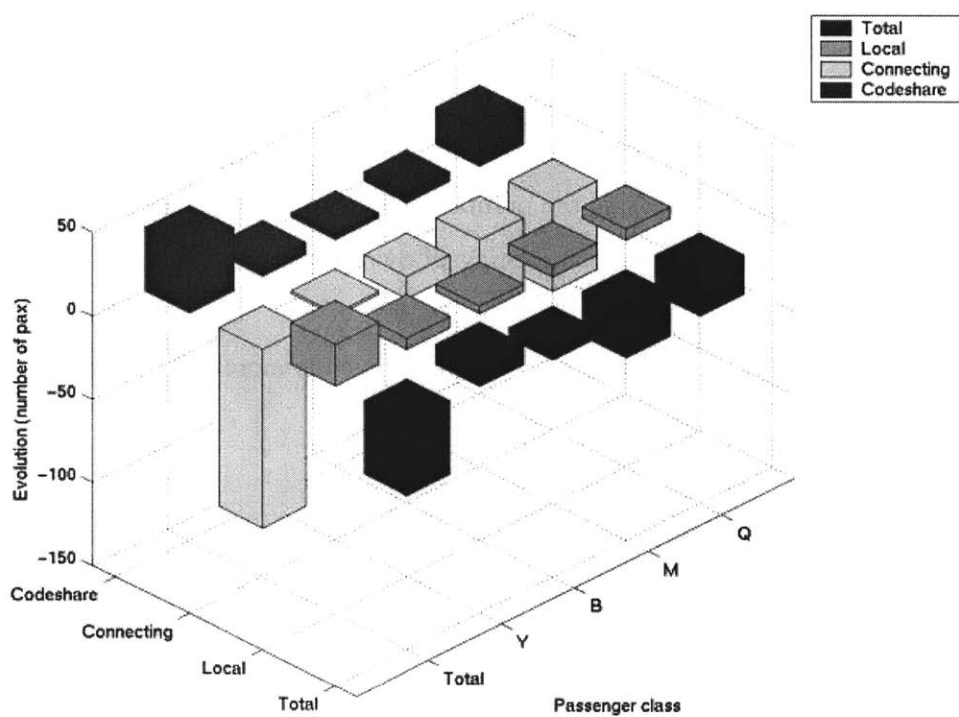


Figure 4.32. Change in airline C passenger mix, Eb/DAVN vs. Eb.

As when it was using HBP, airline C reduces the number of its own-connecting passengers (mostly Q and M class) when it uses DAVN, due to its high ALF. But the number of codeshare passengers does not increase as much as with HBP, because of the aforementioned specificities of DAVN nesting. The increase in airline C's yield offsets the decrease in the number of passengers it carries, and airline C's revenue increases by 0.48%. Because of its lower ALF and the revenue sharing agreement, airline B benefits of the increase in the number of codeshare passengers, and sees a revenue increase of 0.30%. As a whole, the alliance revenue increases by 0.38%.

Case 3: Eb vs. DAVN/DAVN (Figures 4.33 and 4.34)

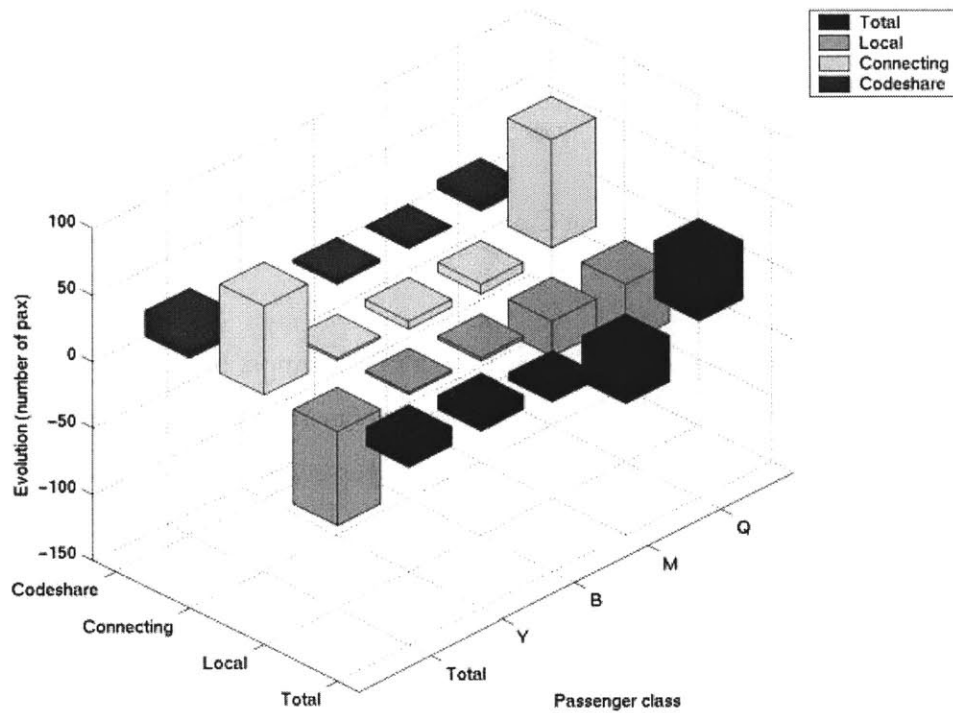


Figure 4.33. Change in airline B passenger mix, DAVN/DAVN vs. Eb.

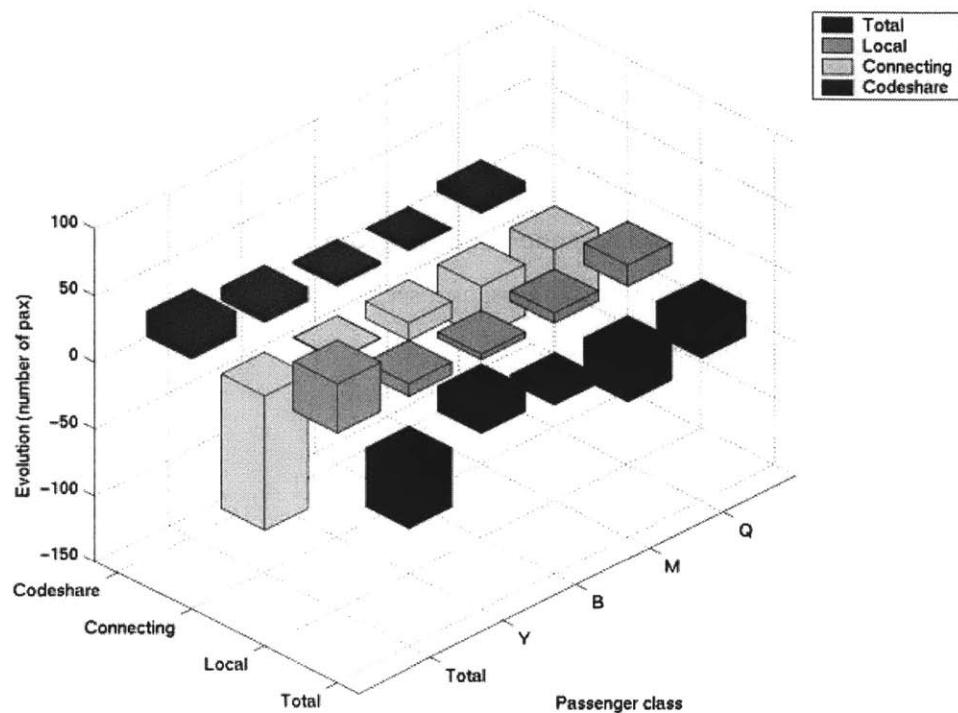


Figure 4.34. Change in airline C passenger mix, DAVN/DAVN vs. Eb.

When both alliance partners use DAVN, there is a combination of the good impacts of DAVN seen in the previous two cases. Airline B benefits from an increased number of connecting passengers as well as a few extra codeshare passengers. Airline C limits its own-connecting passengers, while the increase in codeshare passengers is small enough to allow airline C to carry more local passengers. Overall, the revenue increases by 0.92% for airline B, 0.61% for airline C and 0.78% for the alliance.

Looking at the changes in the number of passengers by choice (**Figure 4.35**), we see that the alliance denies some first-choice Q and M booking requests, and accepts more B and Y first-choice requests, showing that DAVN performs as expected in this alliance situation. The loss of first-choice Q bookings is offset by an increase in spill-in from airline A in the same class, which mostly consists of connecting passengers.

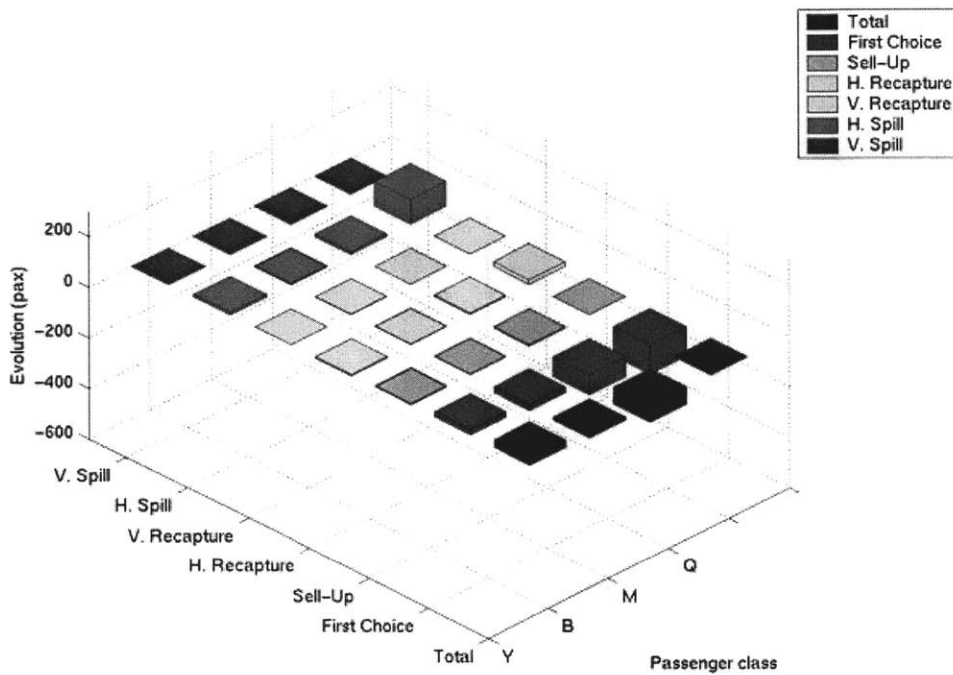


Figure 4.35. Change in alliance passenger choice, DAVN/DAVN vs. Eb.

ProBP Study, Local Discount

With ProBP, as it was the case with HBP and DAVN, own-connecting paths are given a higher preference at low ALF compared to local paths, and a lower preference at higher ALF. Because of the use of local discount, the codeshare paths are treated as local paths, and are nested without taking into account the total itinerary fare. Therefore, in the bucket structure used to compute the initial EMSRc values on each leg, codeshare passengers are nested lower than own-connecting passengers, and the initial EMSRc bid prices on each leg are reduced. However, because the fares of own connecting paths are then prorated while the fares of codeshare paths are not, the converged bid prices are finally over-valuated, making the bid prices for own-connecting paths particularly high.

The airlines' total revenue and average yield when one or both alliance partners use ProBP are presented in **Figure 4.36** and **4.37**:

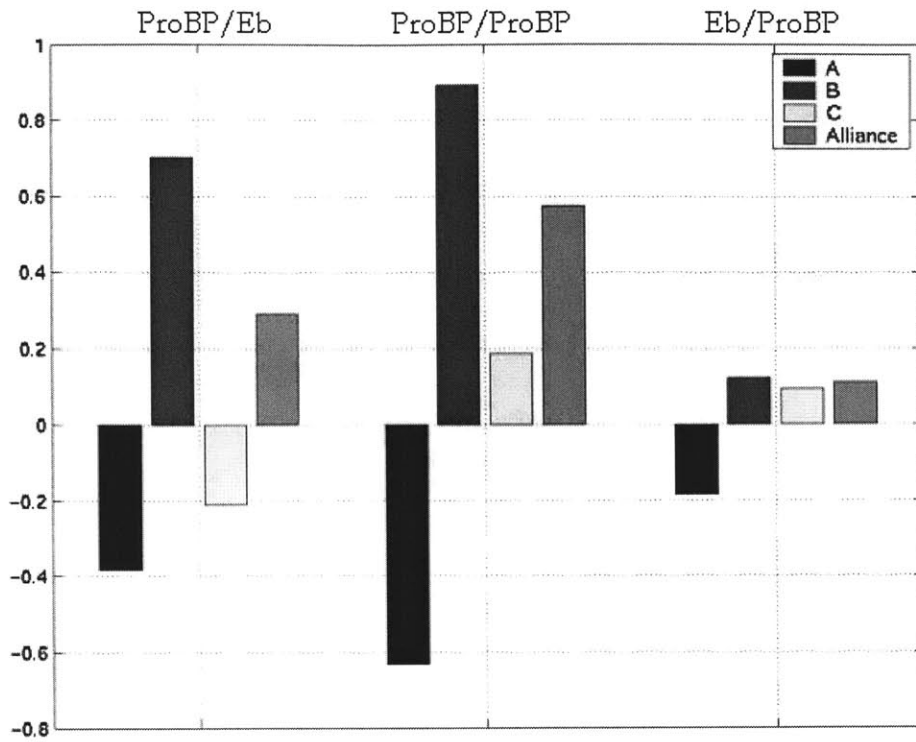


Figure 4.36. Revenue differences in percent, ProBP compared to EMSRb, DF=1.0, JI=2, Local Discount.

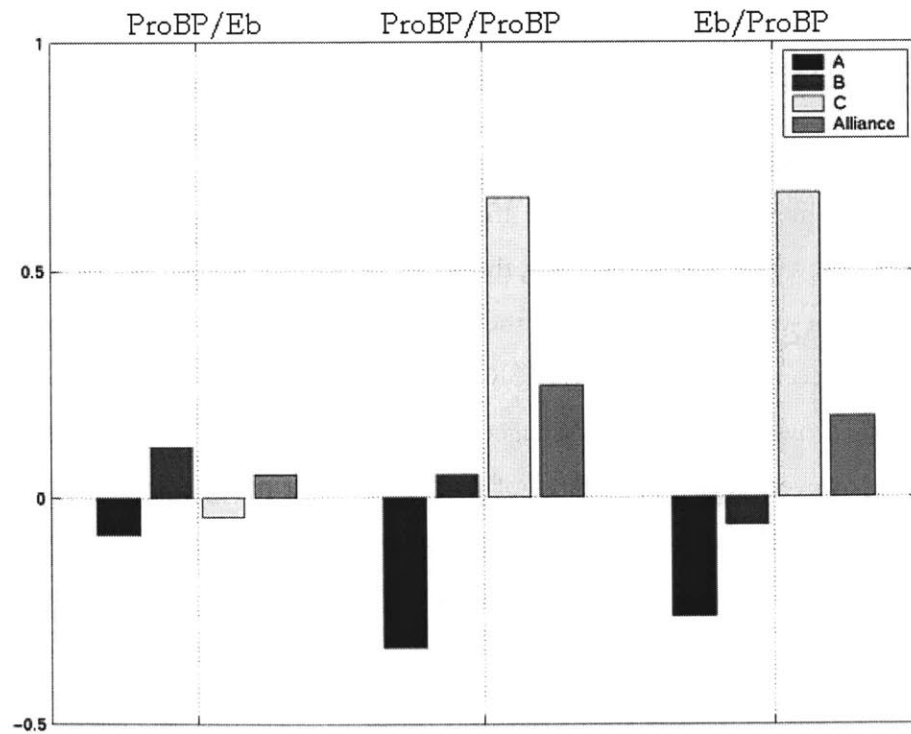


Figure 4.37. Yield differences in cents, ProBP compared to EMSRb, DF=1.0, JI=2, Local Discount.

We see that ProBP with local discount does not perform as well as DAVN for the alliance. The maximum revenue gains achieved by the partners and the alliance as a whole are smaller than those observed when one or both alliance partners use DAVN. Besides, the use of ProBP by airline B alone has a negative revenue impact on airline C.

Case 1: Eb vs. ProBP/Eb (Figure 4.38 and 4.39)

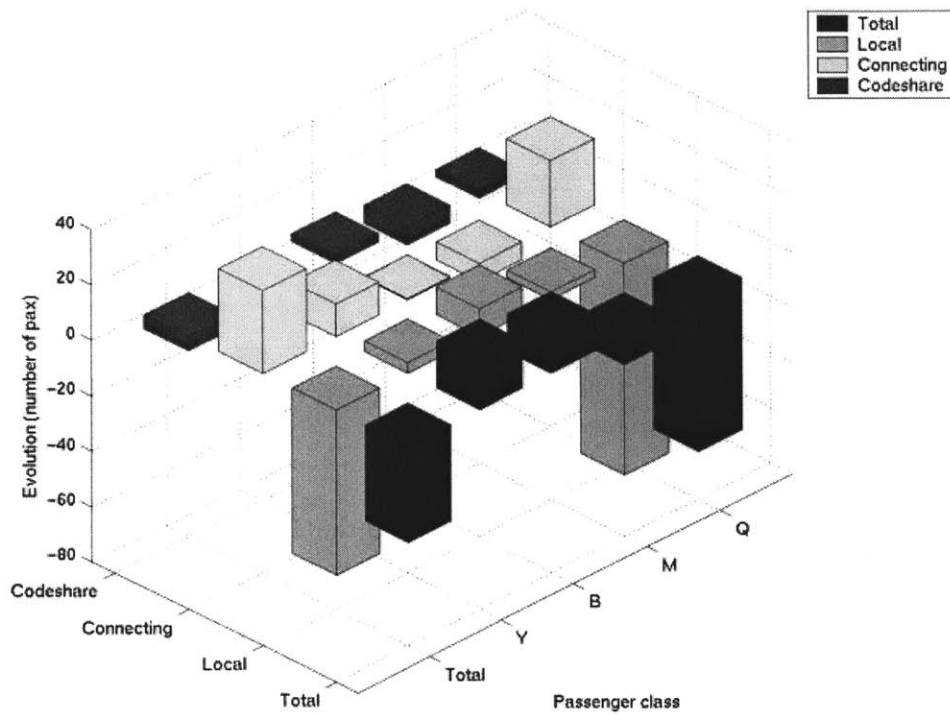


Figure 4.38. Change in airline B passenger mix, ProBP/Eb vs. Eb.

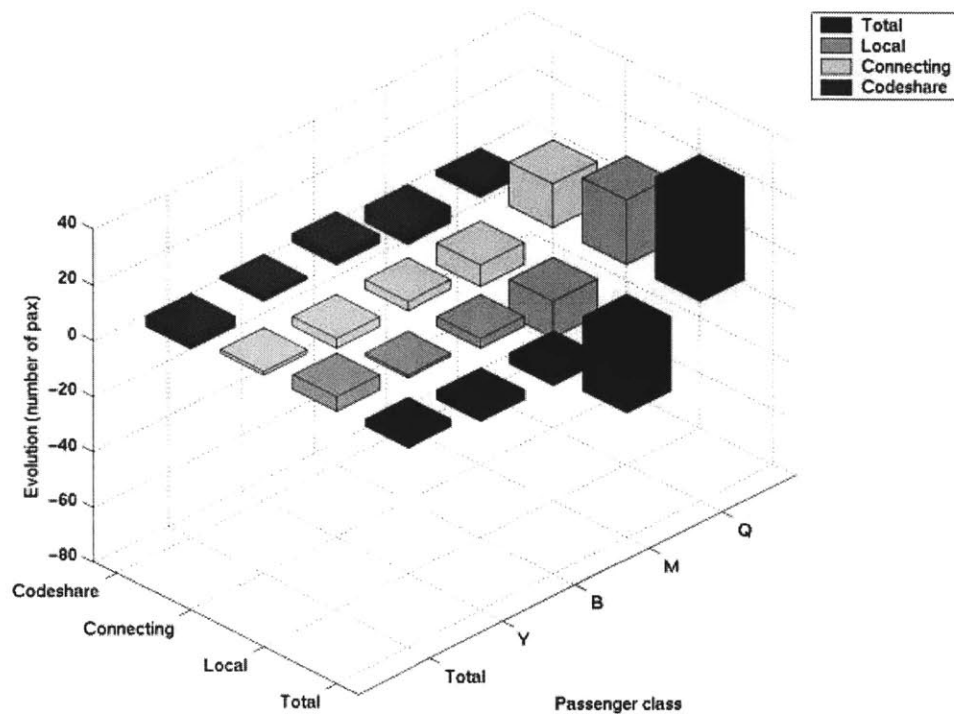


Figure 4.39. Change in airline C passenger mix, ProBP/Eb vs. Eb.

For airline B, the main difference between this case and the Eb vs. DAVN/Eb case is the much smaller increase in the number of own-connecting passengers, while the number of codeshare and local passengers still decreases. As a result, airline B carries fewer passengers without increasing significantly its yield, and its revenue gain is smaller (0.70%). This seems to confirm that treating codeshare passengers as local passengers distorts the ProBP bid prices, making the bid prices for own-connecting passengers artificially high. The slight decrease in airline C's revenue (-0.21%) is due to a degradation of its passenger fare class mix, as local and own-connecting Q class passengers replace M class passengers. As a whole, the alliance revenue increases only by 0.29%.

Case 2: Eb vs. Eb/ProBP (Figures 4.40 and 4.41)\

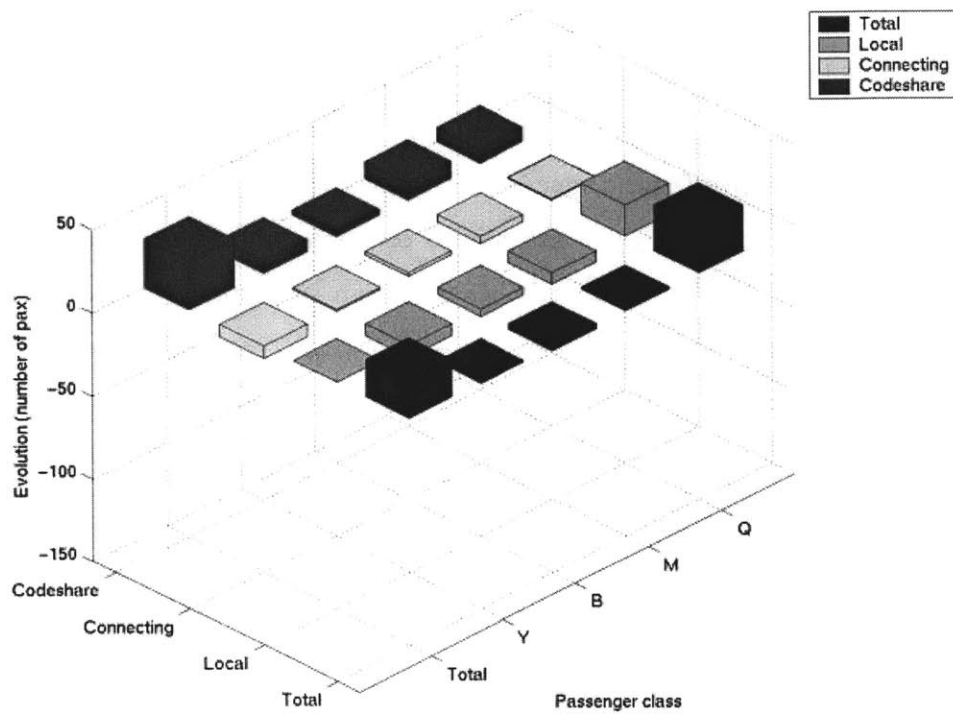


Figure 4.40. Change in airline B passenger mix, Eb/ProBP vs. Eb.

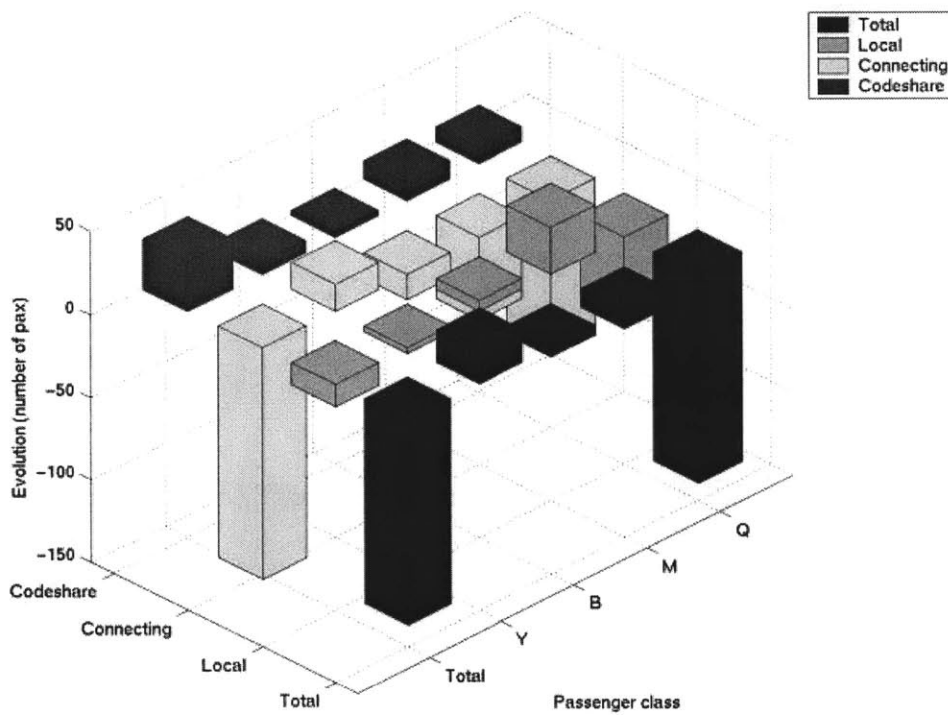


Figure 4.41. Change in airline C passenger mix, Eb/ProBP vs. Eb.

The use of ProBP by airline C leads to a large decrease in airline C's number of own-connecting passengers, again confirming a distortion of the own-connecting bid prices. The important increase in airline's C yield, due to the many Q class connecting passengers it spills, barely offsets the large decrease in the number of passengers it carries, and airline C's revenue increases by only 0.09%. Airline B benefits from an increase in the number of codeshare passengers carried by the alliance, and sees a 0.12% revenue gain. Overall, the alliance revenue increases by only 0.11%.

Case 3: Eb vs. ProBP/ProBP (Figures 4.42 and 4.43)

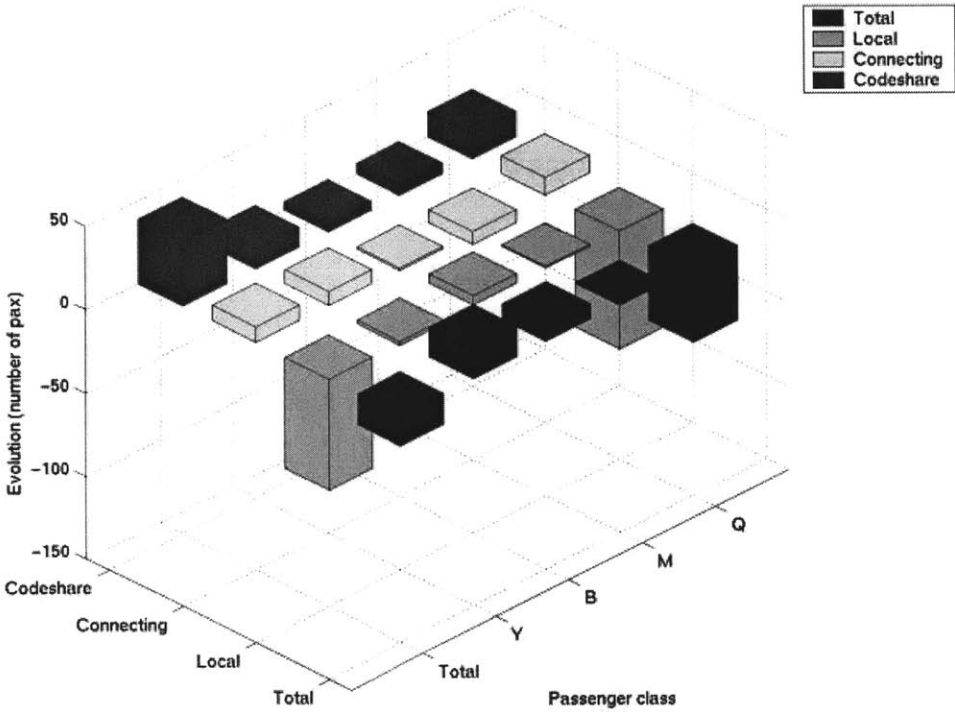


Figure 4.42. Change in airline B passenger mix, ProBP/ProBP vs. Eb.

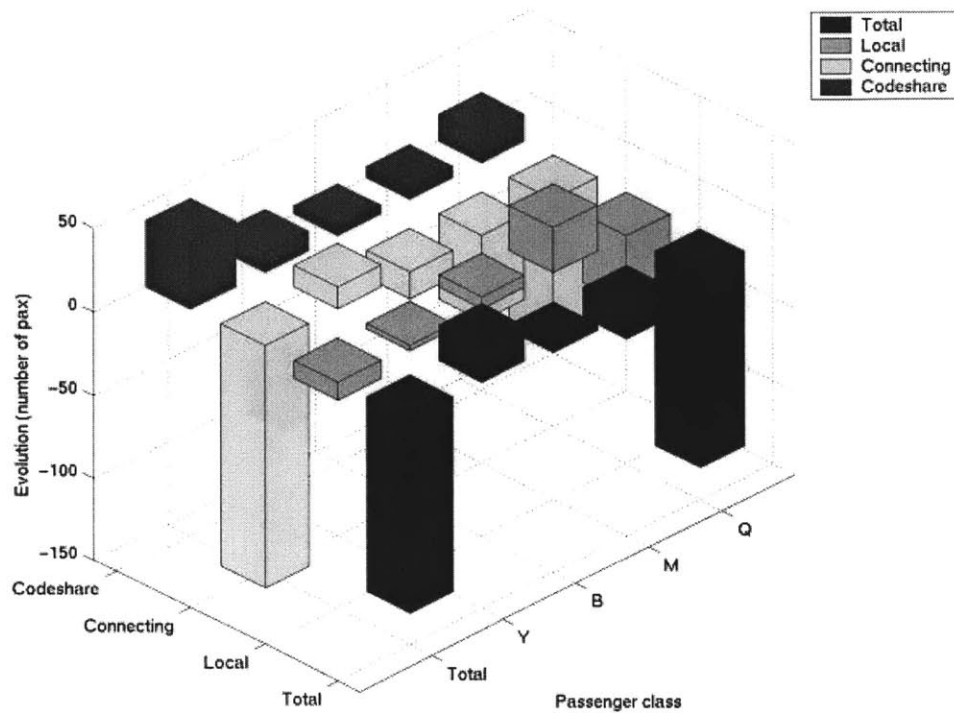


Figure 4.43. Change in airline C passenger mix, ProBP/ProBP vs. Eb.

In this case, the total number of passengers carried by each alliance partner decreases. Airline B sees only a very small increase in the number of its own-connecting passengers, but a significant increase in the number of codeshare passengers, so that overall its revenue gains (0.90%) are higher than in the Eb vs. ProBP/Eb case. Airline C's situation is very similar to the Eb vs. Eb/ProBP case, and its revenue increases by 0.19%. Overall, the alliance revenue increase is 0.58%.

Figure 4.44 shows that the loss of many first-choice Q class connecting passengers is not offset by the horizontal recapture between the partners, and the increase in Q class codeshare spill-in from airline A.

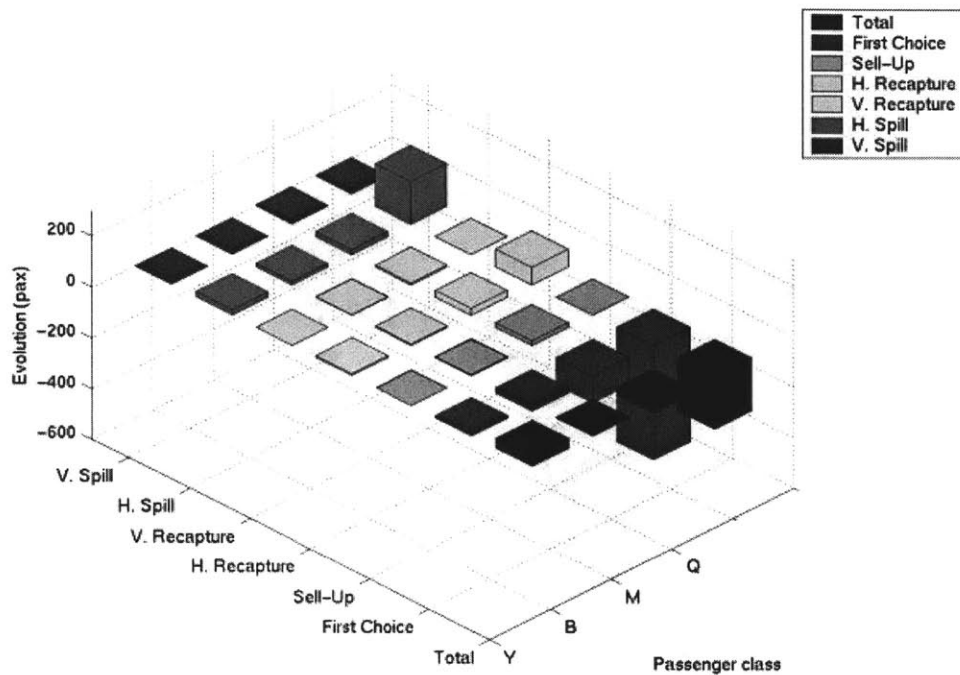


Figure 4.44. Change in alliance passenger choice, ProBP/ProBP vs. Eb.

Impact of the Discount Method on the Performance of RM Systems in the Alliance

Local Discount - Summary

Figure 4.45 summarizes the performance of the different combinations of RM systems tested, with local discount of codeshare passengers:

YM	A	B	C	Alliance
Eb vs. HBP/Eb	0.14	0.23	-0.55	-0.12
Eb vs. HBP/HBP	0.25	-0.07	-0.33	-0.19
Eb vs. Eb/HBP	0.19	-0.32	0	-0.17
Eb vs. DAVN/Eb	-0.37	0.78	0.2	0.52
Eb vs. DAVN/DAVN	-0.57	0.92	0.61	0.78
Eb vs. Eb/DAVN	-0.28	0.3	0.48	0.38
Eb vs. ProBP/Eb	-0.38	0.7	-0.21	0.29
Eb vs. ProBP/ProBP	-0.63	0.9	0.19	0.58
Eb vs. Eb/ProBP	-0.18	0.12	0.09	0.11

Figure 4.45. Interaction of the RM methods used by the alliance partners. Revenue gains in percent over the baseline case (Eb vs. Eb/Eb), DF=1.0, JI=2, Local Discount.

- The use of local discount for codeshare paths with HBP makes the bid prices for these paths excessively low. As a result, the alliance partners carry many codeshare passengers, who displace higher-revenue passengers, and the alliance revenue decreases compared to the EMSRb case.
- The use of local discount for codeshare paths with ProBP makes bid prices excessively high, especially for own-connecting passengers, and leads to a deteriorated performance for ProBP.
- DAVN is more robust to the use of local discount for codeshare paths, as it nests own-connecting paths according to their pseudo fares.

No Discount

Using the total itinerary fare as the decision fare for codeshare paths gives these paths a higher value compared to using the local discount method. As a result, both alliance partners carry more codeshare passengers when they use total fares as decision fares, as shown in **Figure 4.46**:

Discount	Parameter	HBP	DAVN	ProBP
Local	Total pax	7373	7319	7212
	Codeshare pax	2055	1951	1991
	Codeshare pax (%)	27.87	26.65	27.61
None	Total pax	7368	7316	7263
	Codeshare pax	2107	2060	2130
	Codeshare pax (%)	28.59	28.17	29.33

Figure 4.46. Effect of the discount method on the number of codeshare passengers carried by the alliance, DF=1.0, JI=2.

Figures 4.47 to 4.50 show the alliance revenue gains when both alliance partners use HBP, DAVN and ProBP, with and without local discount:

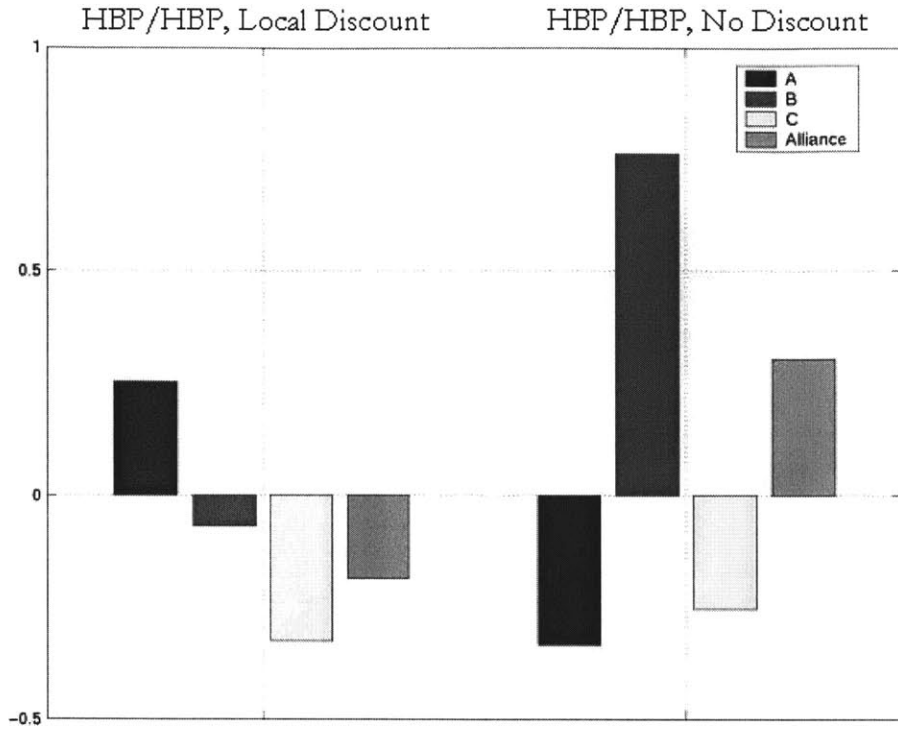


Figure 4.47. Revenue differences in percent, HBP compared to EMSRb, DF=1.0, JI=2, Local Discount vs. No Discount.

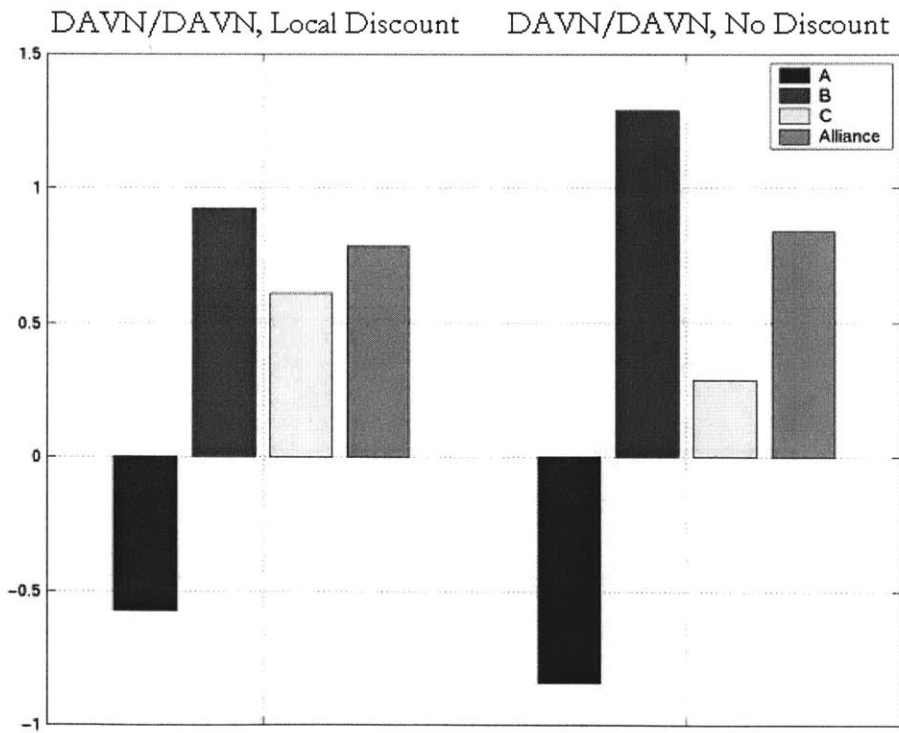


Figure 4.48. Revenue differences in percent, DAVN compared to EMSRb, DF=1.0, JI=2, Local Discount vs. No Discount.

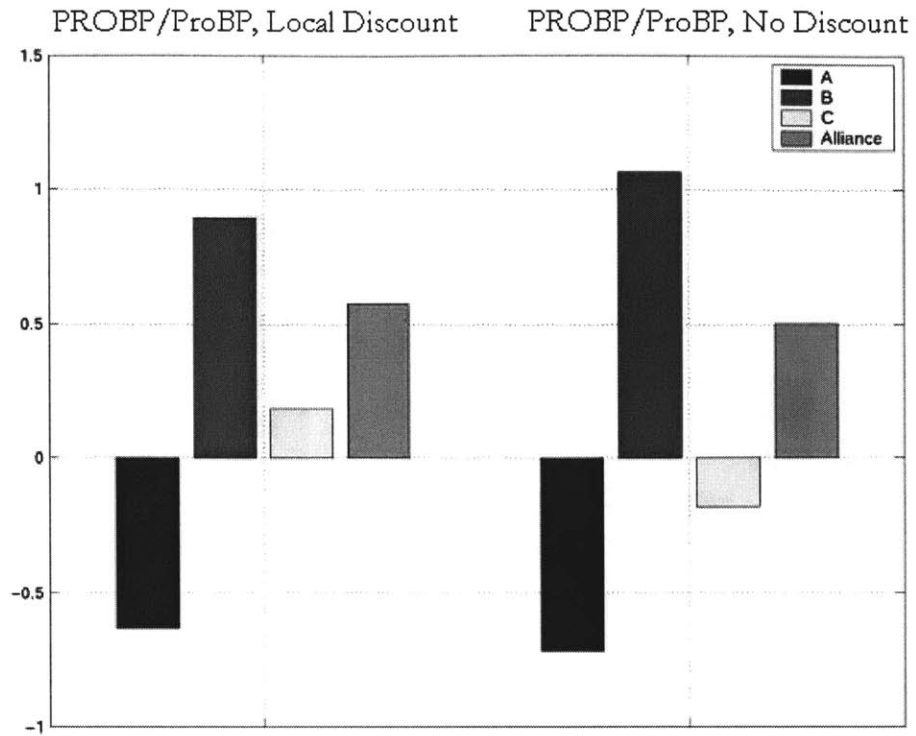


Figure 4.49. Revenue differences in percent, ProBP compared to EMSRb, DF=1.0, JI=2, Local Discount vs. No Discount.

YM	A	B	C	Alliance
Eb vs. HBP/Eb	0.03	0.35	-0.68	-0.11
Eb vs. HBP/HBP	-0.33	0.76	-0.25	0.30
Eb vs. Eb/HBP	-0.17	0.25	0.10	0.18
Eb vs. DAVN/Eb	-0.47	0.79	0.27	0.56
Eb vs. DAVN/DAVN	-0.84	1.29	0.29	0.84
Eb vs. Eb/DAVN	-0.46	0.74	0.27	0.53
Eb vs. ProBP/Eb	-0.19	0.39	-0.59	-0.05
Eb vs. ProBP/ProBP	-0.72	1.06	-0.18	0.50
Eb vs. Eb/ProBP	-0.38	0.53	-0.02	0.28

Figure 4.50. Interaction of the RM methods used by the alliance partners. Revenue gains in percent over the baseline case (Eb vs. Eb/Eb), DF=1.0, JI=2, No Discount.

- The use of total fares for decision fares on codeshare paths improves the results of HBP, as it increases the bid prices of codeshare paths, which were excessively low with local discount.
- DAVN is less sensitive to the discount method used, because of the specificities of its nesting. With total fares, the codeshare paths are slightly over-protected, and the alliance carries more codeshare passengers. Therefore airline B, for which codeshare passengers are desirable, benefits from the use of total fares, whereas airline C suffers. Overall, using total fares instead of local fares with DAVN merely increases the asymmetry between the alliance partners, and is close to a zero-sum game, as the revenue gains of the alliance as a whole are not significantly different from those obtained when using local discount.
- With total fares for decision fares on codeshare paths, ProBP performs worse than with local discount, because the bid prices are further distorted. Indeed, the codeshare paths, which are not prorated, are now nested according to their total fares, thus further increasing the converged prorated bid prices.

It appears that none of the two discount methods proposed for codeshare paths gives satisfactory results, especially for bid-price methods.

Impact of Alliance Joint Image on the Performance of RM Systems in the Alliance

The performances of the different combinations of alliance RM systems at $JI=1$ are presented in **Figure 4.51**:

YM	A	B	C	Alliance
Eb vs. HBP/Eb	0.14	0.2	-0.5	-0.12
Eb vs. HBP/HBP	0.2	-0.08	-0.25	-0.16
Eb vs. Eb/HBP	0.11	-0.25	0.05	-0.12
Eb vs. DAVN/Eb	-0.28	0.7	0.11	0.43
Eb vs. DAVN/DAVN	-0.48	0.78	0.57	0.69
Eb vs. Eb/DAVN	-0.26	0.25	0.51	0.37
Eb vs. ProBP/Eb	-0.29	0.69	-0.32	0.23
Eb vs. ProBP/ProBP	-0.61	0.83	0.35	0.61
Eb vs. Eb/ProBP	-0.28	0.1	0.35	0.21

Figure 4.51. Interaction of the RM methods used by the alliance partners. Revenue gains in percent over the baseline case (Eb vs. Eb/Eb), DF=1.0, JI=1, Local Discount.

If we compare this table with the results obtained at JI=2 (**Figure 4.45**), we do not see great differences in the **relative** performance of the O-D RM methods compared to EMSRb (the baseline case in **Figure 4.51** is also at JI=1). A closer look reveals that in most cases, airline B performs usually slightly worse, and airline C slightly better with JI=1. This trend is consistent with the fact that at JI=1, the alliance leverage on codeshare passengers is smaller, thus limiting the asymmetry between the revenue gains of airline B and airline C. But the difference is barely significant.

Interactions of the RM Systems of the Alliance Partners - Summary

From the study of the interaction of alliance RM systems, we can draw the following conclusions:

- The use of DAVN or ProBP by one or both alliance partners results in revenue gains for the alliance. At $DF=1.0$, the revenue gains are higher with DAVN (order of 0.7% to 0.9% with both partners using DAVN) than with ProBP (order of 0.6% with both partners using ProBP), which bid prices are distorted by the use of a discount method for codeshare paths. On the contrary, HBP performs worse than EMSRb in most of the cases studied (order of -0.1% to -0.6% with both partners using HBP), due mostly to its ineffective control of discounted codeshare passengers.
- The revenue gains are not evenly shared between the alliance partners. Airline B typically gains more revenue than airline C, in both absolute and relative terms. In some cases, airline B is the main benefactor of airline C investing in an O-D RM method (Eb vs. Eb/ProBP, $DF=1.0$, $JI=2$, No Discount). In other cases, airline B's switching to an O-D RM system results in a revenue loss for airline C, because of the increased number of codeshare passengers carried by the alliance (Eb vs. HBP/Eb, $DF=1.0$, $JI=2$, Local Discount) or changes in airline C passenger fare class mix (Eb vs. ProBP/Eb, $DF=1.0$, $JI=2$, Local Discount).
- The individual characteristics of the alliance airlines condition the effect of using an O-D RM method:
 - Airline B, which has a relatively low ALF, tends to increase the number of own-connecting passengers it carries. Airline C, which has a relatively high ALF, tends to decrease the number of own-connecting passengers it carries.
 - Because of the differences in the partner's ALF and the revenue sharing agreement, codeshare passengers are much more beneficial to airline B than to airline C.

- Our assumption concerning joint image has been shown to affect the alliance market shares in codeshare markets, but it does not affect significantly the relative performance of O-D RM systems compared to EMSRb.
- Using total fares for decision fares instead of local discount on codeshare paths leads to an increase in the number of codeshare passengers carried by the alliance, and reinforces the asymmetry between airline B and airline C results. However, it does not lead to a significant improvement of the alliance total revenue compared to using local discount, as the losses of airline C compensate the gains of airline B. Indeed, codeshare paths are still misevaluated as the alliance airlines do not have information on the displacement costs incurred by a codeshare passenger on their partner's leg.

Summary

In this chapter, current alliance RM practices were investigated. The impact of the joint image parameter in PODS was quantified. The importance of the interactions between different RM systems in the alliance was shown. The evaluation of codeshare paths was identified as a critical issue with current RM practices, whether the alliance partners use local fares or total fares as decision fares. In the next chapter, we will test two methods that estimate the displacement costs on the partner's legs, so as to correctly evaluate codeshare paths.

CHAPTER 5. BID-PRICE SHARING AND BID-PRICE INFERENCE

Introduction

In Chapter 4, the evaluation of codeshare paths was shown to be a major issue in alliance revenue management. Depending on the load factor and the RM method used by the alliance partners, the local fare and total fare discount methods can lead to either an underestimation or an overestimation of the value of codeshare paths on a leg, compared to local and on-line connecting paths. This incorrect evaluation results in deteriorated performance of O-D revenue management methods, especially bid-price algorithms (ProBP, HBP), which appear to be more sensitive to the accuracy of codeshare path value than DAVN.

In order to evaluate accurately the codeshare paths and optimize total alliance revenue, each alliance airline needs to estimate the displacement costs caused by codeshare passengers on the other partner's leg. In this chapter, we assess two methods for achieving this objective. The first one, bid-price sharing, assumes that the alliance airlines have direct access to their partner's displacement costs. In the second, bid-price inference, the alliance airlines use their partner's fare class availability information to estimate their displacement costs.

Bid-Price Sharing

Bid-Price Sharing in PODS

When the alliance uses Bid-Price Sharing (BPS, defined in Chapter 2) in PODS, each alliance airline makes available to its partner information about the network displacement cost on its own legs, depending on the RM system it uses:

- For DAVN, the displacement cost is the shadow price of each leg, which results from solving the deterministic LP over the airline's network²⁸.
- For ProBP, the displacement cost is the converged value of the bid price on each leg, which results from the iterative proration of the critical EMSR value of each leg over the airline network.
- For HBP, the displacement cost is related to the critical EMSR value on each leg.

Each airline then incorporates this information into its bid prices/pseudo-fares for controlling codeshare itineraries. This assumes that each airline uses an **O-D RM method**, and uses the **total fare values**, which now include the displacement costs on the partner's leg, for codeshare paths.

However, the optimization processes of the alliance partners (LP solving for DAVN, EMSRc computation for HBP and ProBP) remain **separate**. Therefore, the combined RM systems of the partners are not equivalent to a single airline's RM system. In this section, we will compare the alliance results with BPS to those the alliance would obtain if it were a single airline using the same O-D RM method.

So as to reduce the information flow between the alliance airlines²⁹, and avoid potentially unstable feedback effects³⁰, the information is exchanged only at the beginning of **each time frame**, i.e. 16 times during the booking process. Therefore, the alliance partners do not have perfectly up to date information on each other's displacement costs, resulting in potential lag effects.

²⁸ The reader is referred to Chapter 2 of this thesis for a description of the RM methods mentioned in this chapter.

²⁹ A real-time exchange of bid prices would be difficult to implement. Also, for some RM methods such as DAVN in PODS, the displacement costs are re-calculated only at each time frame.

³⁰ With bid-price sharing, each airline using an O-D method modifies its bid-prices/pseudo fares depending on its partner's displacement costs. The partner in turn modifies its own bid-prices/pseudo fares, and this process could lead to instability if a positive feedback loop were created.

The bid-price sharing scheme in PODS is outlined in **Figure 5.1**:

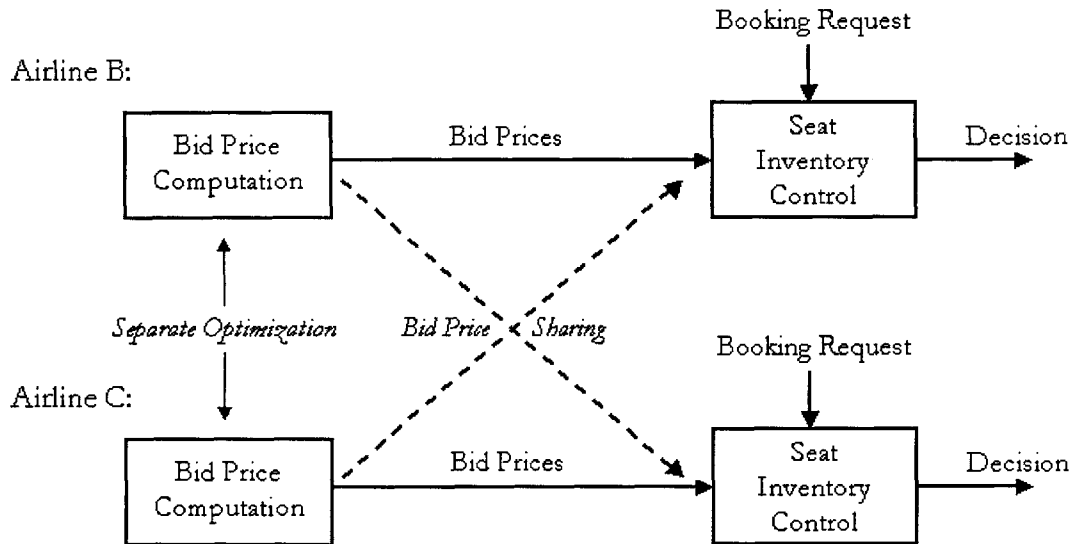


Figure 5.1. Bid Price Sharing in PODS.

HBP and Bid-Price Scaling

Because HBP bid prices are computed using a heuristic constant (cf. Chapter 2), they are not directly comparable with ProBP prorated fares and DAVN shadow prices, which are based on a genuine network optimization. Therefore, when one partner uses HBP and the other DAVN or ProBP, the HBP bid prices need to be processed before being used by the network optimizing partner, and vice-versa.

The simplest solution to this problem, conceived by Hopperstad as part of this research, consists of scaling all HBP bid prices by a constant, in order to make them commensurable to network-optimized bid prices. The partner using HBP computes this constant, *HBPSCL*,

as the average ratio of its own path's HBP bid prices HBP_p over the sum of the local EMSRc bid prices of each leg BP_l traversed by the path p :

$$HBPSCL = \frac{\sum_{p=1}^{npaths} \frac{HBP_p}{\sum_{l=1}^{nlegs} A_{p,l} \cdot BP_l}}{npaths}$$

Where $A_{p,l} = 1$ if leg l is traversed by path p , $= 0$ otherwise.

The partner using HBP can then scale down the bid prices he passes to his network-optimizing partner (by multiplying them by $HBPSCL$) and scale up the bid prices he receives (by dividing them by $HBPSCL$).

Figure 5.2 gives an example of the procedure, for a two-path, four-leg network:

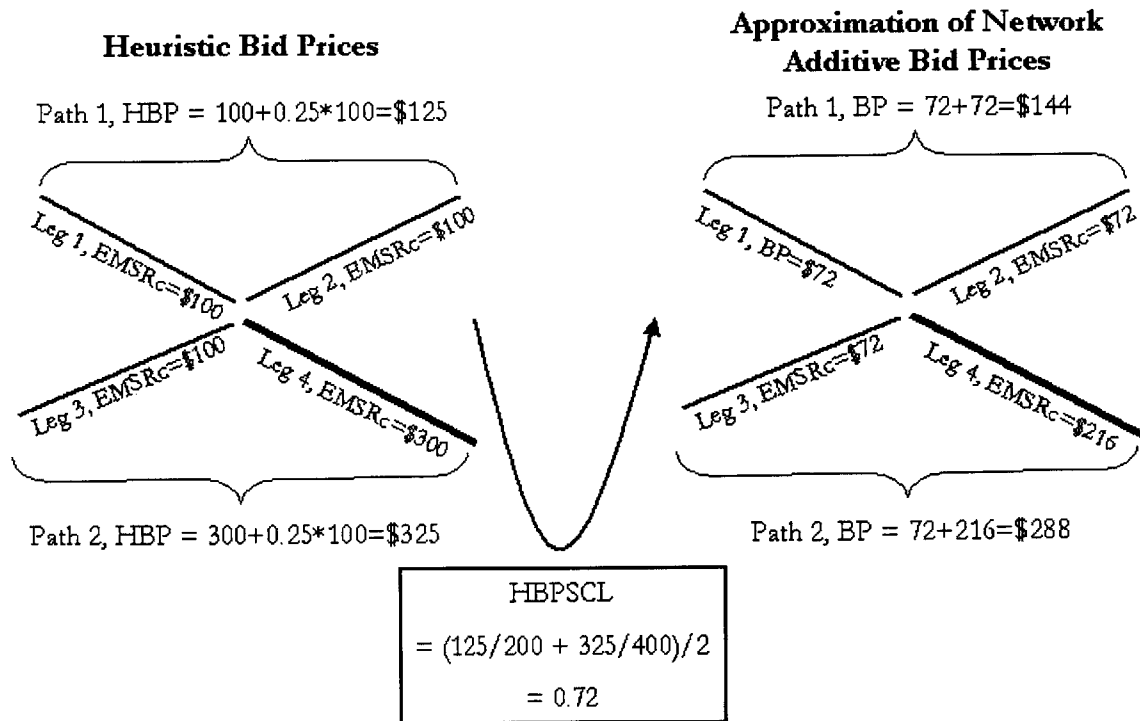


Figure 5.2. Bid Price Scaling.

As we see, scaling has the drawback of reducing the variability of the bid prices: after scaling, the difference between the bid prices of path 1 and path 2 is smaller (\$144) than before (\$200). This can lead to inconsistencies in estimating the availability of each fare class before and after scaling. For instance, for path 1, a fare class with a fare of \$130 would be labeled available by HBP but labeled unavailable using the sum of the scaled bid prices. On path 2, a fare of \$300 would be labeled unavailable by HBP and labeled available with the sum of the scaled bid prices.

To limit availability labeling errors, one could choose to use more sophisticated methods than scaling all bid prices by the same constant, like solving a linear least squares problem over the network. However, these methods would be computationally intensive, especially in large airline networks. Besides, preliminary testing proved that the total mislabeling rates obtained with simple bid-price scaling stayed in reasonable ranges, from 4% to 6% in network D at DF=1.0. In this chapter, we will use the simple bid-price scaling method for HBP when needed, and evaluate its performance.

Bid-Price Sharing, Alliance Partners Using the Same RM Method

We will first assess the performance of bid-price sharing when both partners use the same RM method. In order to compare the results obtained with and without BPS to those the alliance would obtain if it were a single airline, this study will be conducted at JI=1.

HBP

Figure 5.3 compares the revenue gains of the alliance partners using HBP, with and without BPS, to the results of the alliance as a single airline using HBP.

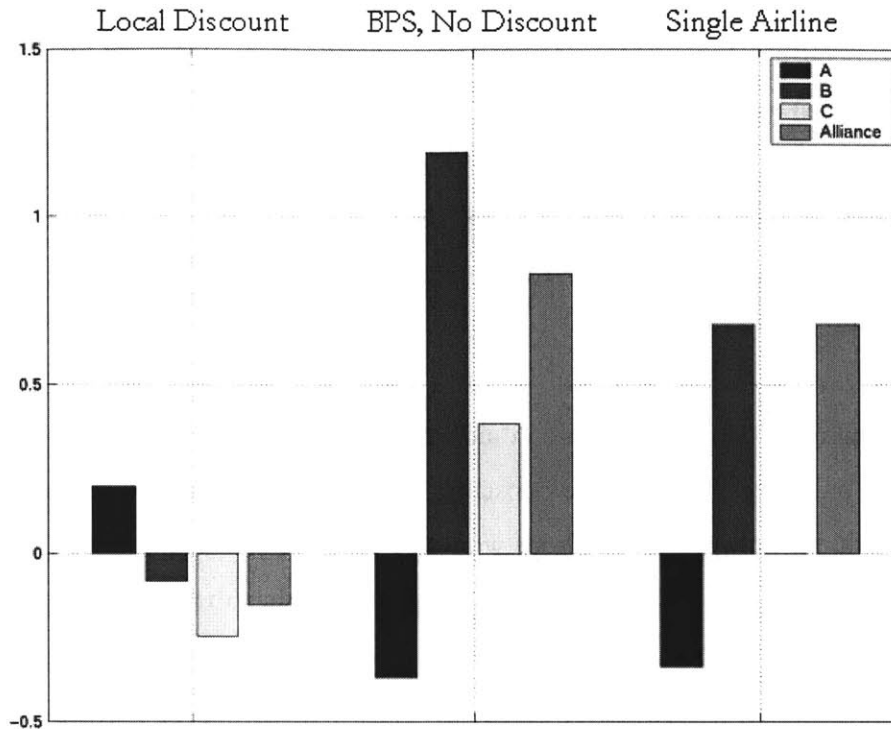


Figure 5.3. Revenue differences in percent, alliance using HBP compared to EMSRb, DF=1.0, JI=1.

We see that the use of BPS leads to a significant improvement of the alliance results. From a 0.16% revenue loss when the alliance used HBP with local discount, compared to using EMSRb, the alliance revenue increases by 0.83% when the alliance uses HBP with BPS. The revenue improvement is actually greater than if the alliance were a single airline using HBP (0.68%), which is an unexpected result as the alliance partners still optimize their networks separately.

To separate the effects of passenger choice from the impact of network optimization, similar simulations were performed, making a passenger's choice his/her only choice (cf. Chapter 3). With this particular simulation setting, a passenger will not consider alternative fares, itineraries or airlines if his/her first choice is not available. As a result, fewer passengers decide to fly than when full passenger choice is enabled, for a same level of demand. Because the average load factor influences the performance of RM methods, the simulations with first choice as the only choice were performed at a demand factor of DF=1.2, to obtain load factors comparable to those observed at DF=1.0 with full passenger choice. The baseline

cases at DF=1.2, with first choice as the only choice, are presented in **Figure 5.4** for the two-airline and the alliance environments:

2 airlines:	Parameter	A	B	C	Alliance
	Market Share (points)	49.27	50.73	0	50.73
	RPM (pax.m)	10309308	10615946	0	10615946
	ALF (points)	84.03	83.33	0	83.33
	Network Local (%)	54.67	57.85	0	57.85
	Yield (cents)	14.54	13.83	0	13.83
	Net Revenue (\$)	1499405	1468600	0	1468600

Alliance:	Parameter	A	B	C	Alliance
	Market Share (points)	49.3	30.56	20.14	50.7
	RPM (pax.m)	10318490	6397279	4214578	10611857
	ALF (points)	84.11	80.41	88.11	83.3
	Network Local (%)	54.61	61.7	53.56	57.76
	Yield (cents)	14.53	12.38	16.14	13.87
	Net Revenue (\$)	1499088	805092	666729	1471821

Figure 5.4. Airlines results, First choice only choice, DF=1.2, Eb vs. Eb/Eb, JI=1, Local Discount.

It should be noted that, even if the ALFs in these simulations are comparable to those observed with full choice at DF=1.0 (cf. **Figure 3.4**), other important airline metrics are significantly different. For instance, the average yield is substantially higher at this higher demand factor. Therefore, the results of these simulations, which reflect the “pure” effects of the network optimization process independently from passenger choice effects such as spill-in, sell-up and recapture (cf. Chapter 3), cannot be directly compared to the full choice results at DF=1.0. However, we can compare the performance of BPS *relatively* to the local discount and single airline cases, with full choice or first choice. The revenue gains of the alliance over the baseline Eb vs. Eb/Eb case are shown in **Figure 5.5**:

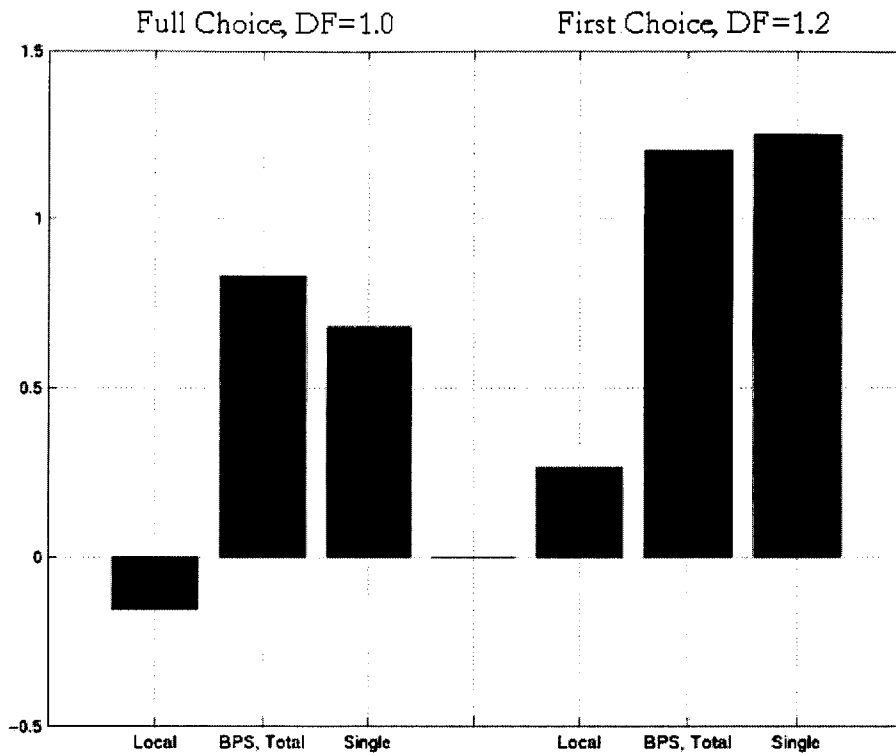


Figure 5.5. Alliance revenue differences in percent, full choice compared to first choice, alliance using HBP compared to EMSRb, $Jl=1$.

From **Figure 5.5**, it appears that the alliance revenue edge in the BPS case compared to the single airline case with full choice is due to passenger choice effects, as it disappears when first choice is the only choice. Then, as one would expect, the optimization of the whole alliance network results in greater revenue gains (1.25%) than two separate optimizations of the partners' respective networks (1.2%).

Figure 5.6 shows the changes in the alliance revenue by passenger choice, compared to the baseline Eb vs. Eb/Eb case:

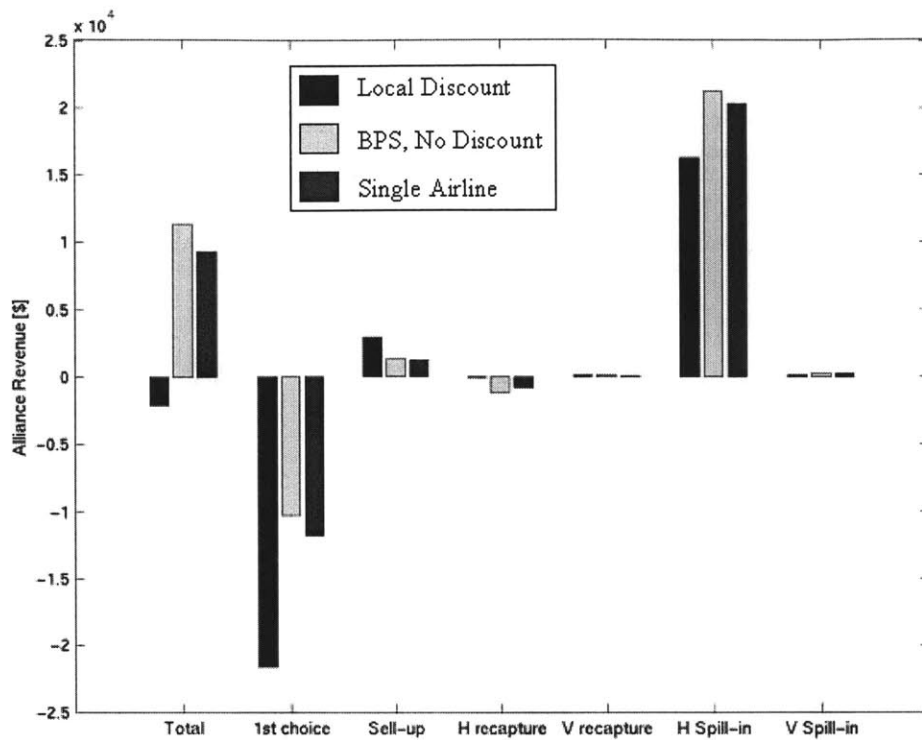


Figure 5.6. Alliance revenue differences in dollars, by passenger choice, alliance using HBP compared to EMSRb, DF=1.0, JI=1.

We see that the main part of the revenue increase obtained with BPS compared to the simple local discount case is due to reduced first choice revenue losses. As it was stressed in Chapter 4 (**Figures 4.24** and **4.25**), the use of HBP with local discount leads to an important flow of codeshare passengers in the alliance, mostly Q class, who displace higher total revenue passengers. First choice booking requests in Y, B and M classes are then denied in favor of those Q class passengers (**Figure 4.26**), and the alliance first choice revenue decreases. With BPS, the alliance is able to take only the “good” codeshare passengers, taking into account their displacement costs. As a result, excessive Q codeshare passengers are no longer accepted (the total number of codeshare passengers carried by the alliance drops by 127, from 1,775 to 1,648 passengers), and the loss of first choice revenue is halved. Furthermore, the alliance is able to better accommodate the passengers spilled by its competitor, hence increasing its revenue from spill-in. With BPS, the breakdown of revenue gains by passenger choice is very similar to the breakdown observed when the alliance is a single airline.

Figure 5.7 compares the revenue gains of the alliance partners using DAVN, with and without BPS, to the results of the alliance as a single airline using DAVN:

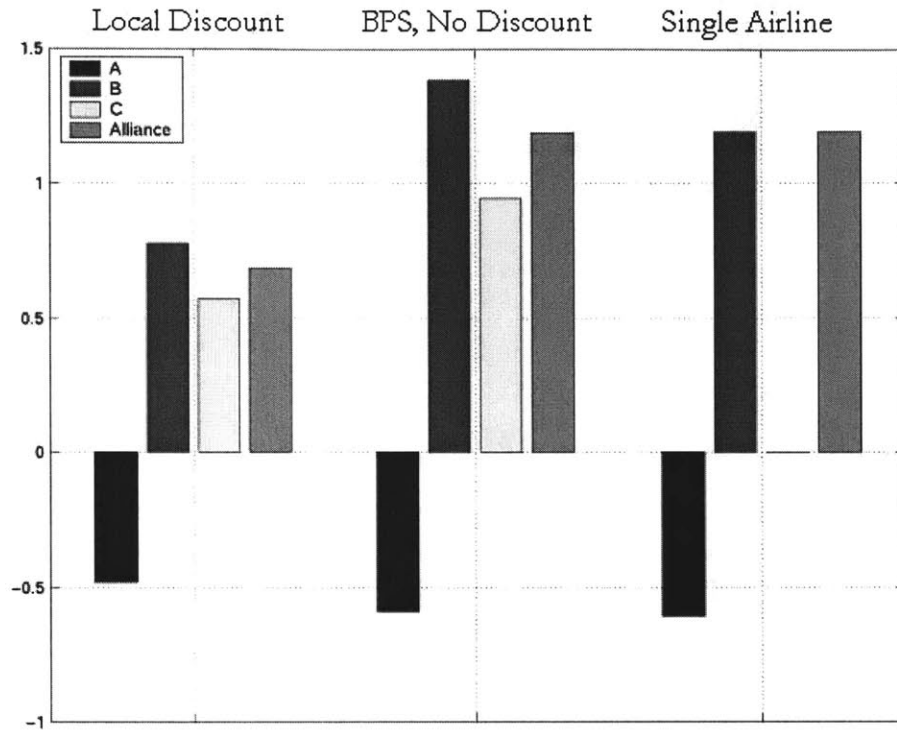


Figure 5.7. Revenue differences in percent, alliance using DAVN compared to EMSRb, DF=1.0, JI=1.

With DAVN, the alliance revenue gain when the alliance uses BPS is the same as if the alliance were a single airline (1.19%), significantly greater than the revenue gain obtained using local discount (0.69%). **Figure 5.8** shows that from a pure optimization standpoint, DAVN with BPS actually falls short of the single airline performance (1.1% vs. 1.73%). Compared to HBP, the incremental revenue gain of using BPS is smaller for DAVN (0.5% compared to 0.99%). This can be explained by the fact that even with local discount, the nesting method of the DAVN algorithm allowed the airline to limit the number of codeshare passengers it carries³¹. As a result, the performance of DAVN with local discount was

³¹ Cf. Chapter 4.

already significantly better than the performance of EMSRb (0.69%), while the use of local discount with HBP lead to a revenue loss compared to EMSRb (-0.16%). In **Figure 5.9**, we see that the use of BPS does not lead to a significant reduction of DAVN first choice revenue loss, which was already small compared to the first choice revenue loss of HBP with local discount. The decrease in the number of codeshare passengers is only of 70 passengers, from 1,669 to 1,599, confirming that with local discount, DAVN already controls fairly well the number of codeshare passenger the alliance carries. The alliance revenue increment of using BPS comes mainly from increased revenue spill-in from airline A.

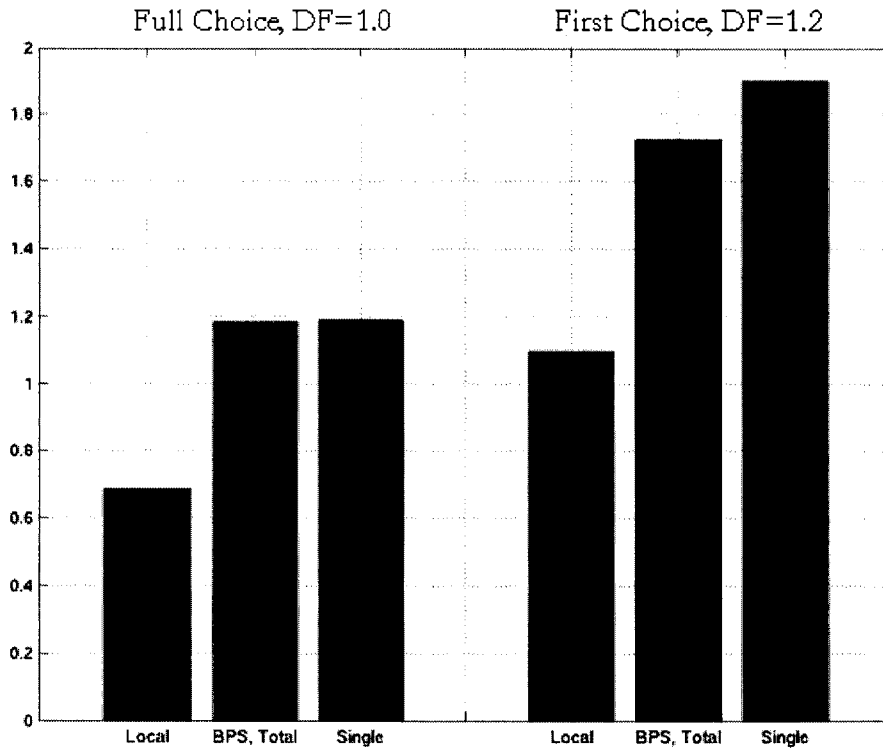


Figure 5.8. Alliance revenue differences in percent, full choice compared to first choice, alliance using DAVN compared to EMSRb, JI=1.

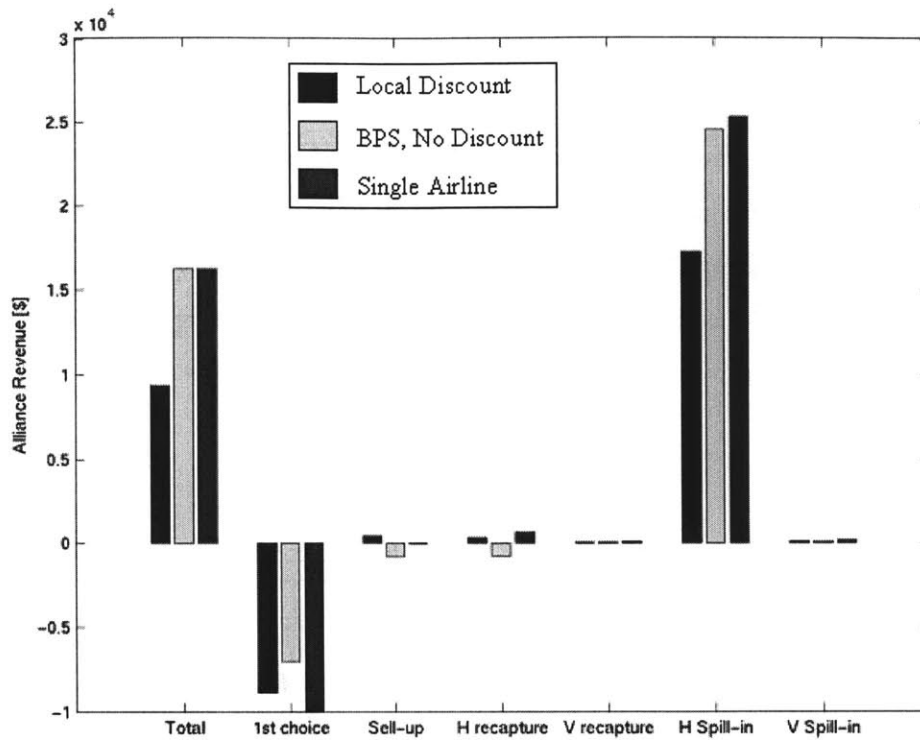


Figure 5.9. Alliance revenue differences in dollars, by passenger choice, alliance using DAVN compared to EMSRb, DF=1.0, JI=1.

ProBP

Figure 5.10 compares the revenue gains of the alliance partners using ProBP, with and without BPS, to the results of the alliance as a single airline using ProBP.

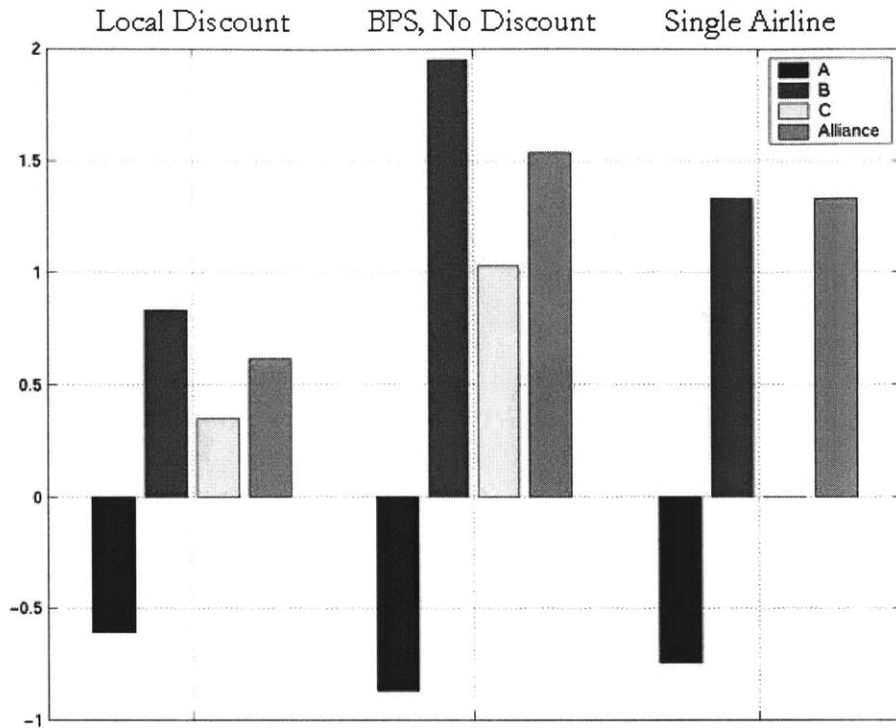


Figure 5.10. Revenue differences in percent, alliance using ProBP compared to EMSRb, DF=1.0, JI=1.

With ProBP, the use of BPS leads to revenue gains (1.53%) which are greater than those obtained if the alliance were a single airline (1.33%), and significantly greater than those obtained using local discount (0.61%). **Figure 5.11** shows that the optimization performance of ProBP with BPS (1.33%) is actually much lower than the performance of a single optimization (2.09%). The revenue gains of using BPS with ProBP, which are detailed in **Figure 5.12**, are mostly due to a reduction in first choice revenue losses. As it was the case with HBP, the use of BPS limits the number of codeshare passengers carried by the alliance (by 191 passengers, from 1,749 to 1,558).

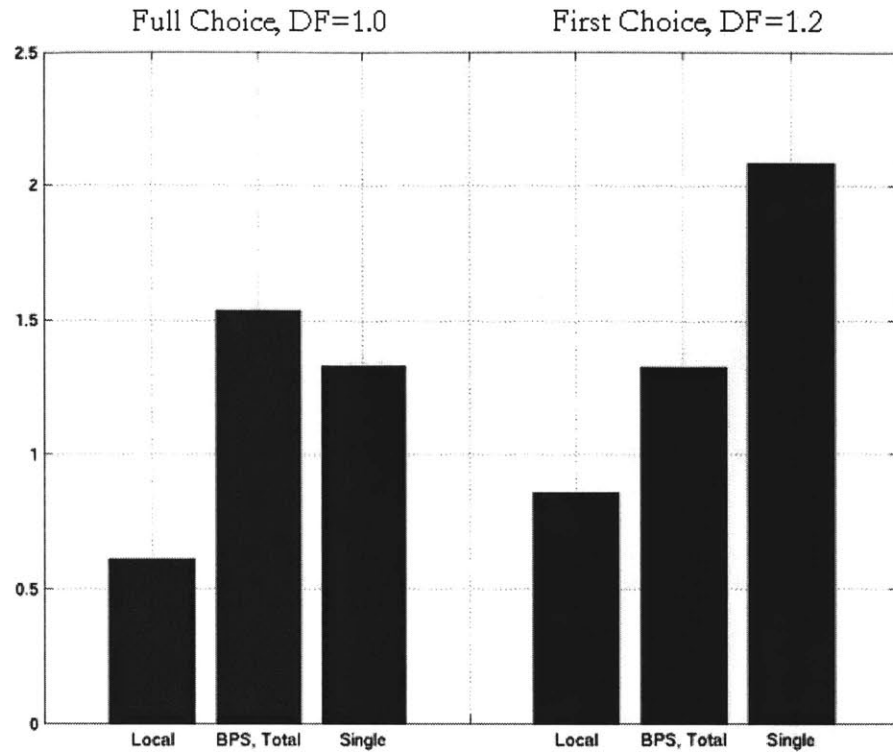


Figure 5.11. Alliance revenue differences in percent, full choice compared to first choice, alliance using ProBP compared to EMSRb, JI=1.

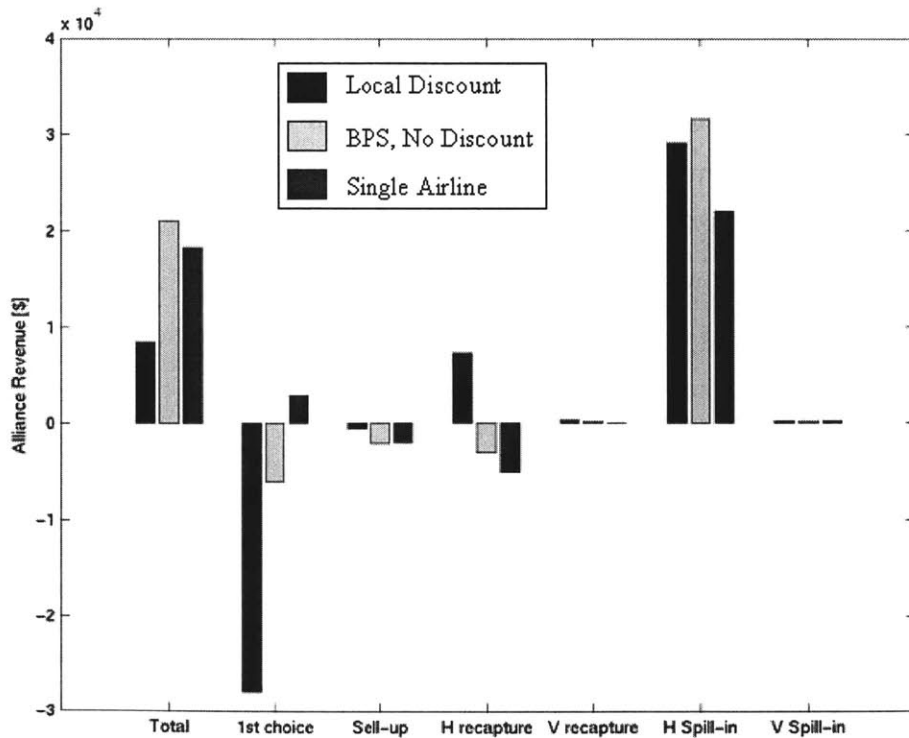


Figure 5.12. Alliance revenue differences in dollars, by passenger choice, alliance using ProBP compared to EMSRb, DF=1.0, JI=1.

Bid-Price Sharing, Alliance Partners Using the Same RM Method - Summary

Figure 5.13 summarizes the performance of HBP, DAVN and ProBP with and without BPS, with full passenger choice or first choice only:

		Full Choice, DF=1.0				First Choice, DF=1.2			
		A	B	C	Alliance	A	B	C	Alliance
HBP	Local Discount	0.2	-0.08	-0.25	-0.16	0	0.09	0.48	0.26
	BPS, No Discount	-0.37	1.19	0.38	0.83	0	1.23	1.16	1.2
	Single Airline	-0.34	0.68	0	0.68	0	1.25	0	1.25
DAVN	Local Discount	-0.48	0.78	0.57	0.69	0	0.92	1.32	1.1
	BPS, No Discount	-0.59	1.38	0.95	1.19	0	1.67	1.8	1.73
	Single Airline	-0.61	1.19	0	1.19	0	1.9	0	1.9
ProBP	Local Discount	-0.61	0.83	0.35	0.61	0	0.78	0.95	0.86
	BPS, No Discount	-0.87	1.95	1.03	1.53	0	1.48	1.15	1.33
	Single Airline	-0.75	1.33	0	1.33	0	2.09	0	2.09

Figure 5.13. Performance of OD RM methods used by the alliance partners.
Revenue gains in percent over the baseline case (E_b vs. E_b/E_b), $JI=1$.

To summarize, when the alliance partners use the same O-D RM method, the use of bid-price sharing leads to significant incremental revenue gains for the alliance, ranging from 0.5% to 1% compared to the use of local discount with the same RM method. The revenue increase is greater for bid-price methods, especially HBP, which are more sensitive to the correct evaluation of codeshare passengers than DAVN. For these methods, the revenue gains come mainly from a reduction of first choice revenue losses, whereas for DAVN it comes essentially from an increase in spill-in revenue.

Bid-Price Sharing, Alliance Partners Using Different RM Methods

In the previous section, the revenue impact of BPS when the alliance partners use the same RM method has been shown. In this section, we will determine if BPS is effective when the alliance partners use different RM methods. As the comparison with the single airline case is not possible, we will carry this study with the standard alliance joint image $JI=2$.

Without Bid-Price Scaling: DAVN & ProBP

In this case, the alliance partners exchange the LP shadow prices obtained in DAVN and the prorated EMSR critical values obtained with ProBP. These displacement costs are comparable, as they both come from network optimization processes, and are additive along an itinerary³². The revenue differences between the baseline case Eb vs. Eb/Eb and the two cases Eb vs. ProBP/DAVN and Eb vs. DAVN/ProBP are shown in **Figure 5.14**, when the alliance partners use local discount or BPS:

³² However, the reader should keep in mind that the LP optimization in DAVN is **deterministic** whereas ProBP takes into account the **probabilistic** nature of passenger demand.

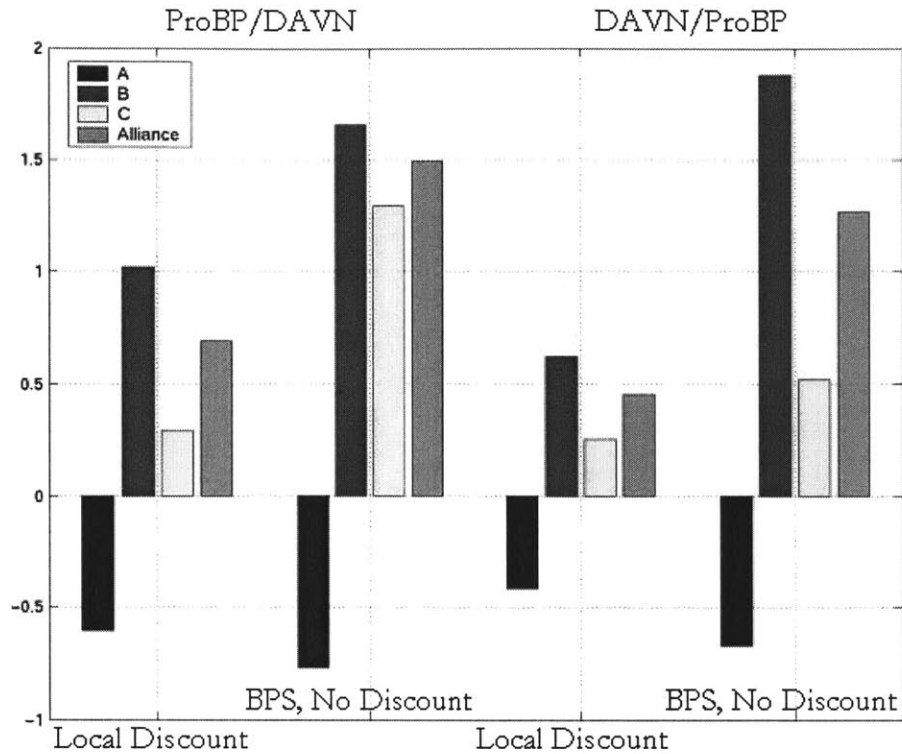


Figure 5.14. Revenue differences in percent, compared to EMSRb, $DF=1.0$, $JI=2$.

We observe significant revenue gains due to BPS. In both cases, with BPS, the alliance revenue is 0.80% greater than with local discount.

With Bid-Price Scaling: HBP with DAVN or ProBP

In these cases, the HBP heuristic bid prices need to be scaled in order to be compared with the DAVN shadow prices and the ProBP prorated fares (cf. *infra*). The revenue differences between the baseline case E_b vs. E_b/E_b and the four cases E_b vs. HBP/DAVN, E_b vs. DAVN/HBP, E_b vs. HBP/ProBP and E_b vs. ProBP/HBP are shown in **Figures 5.15** and **5.16**, when the alliance partners use local discount or BPS:

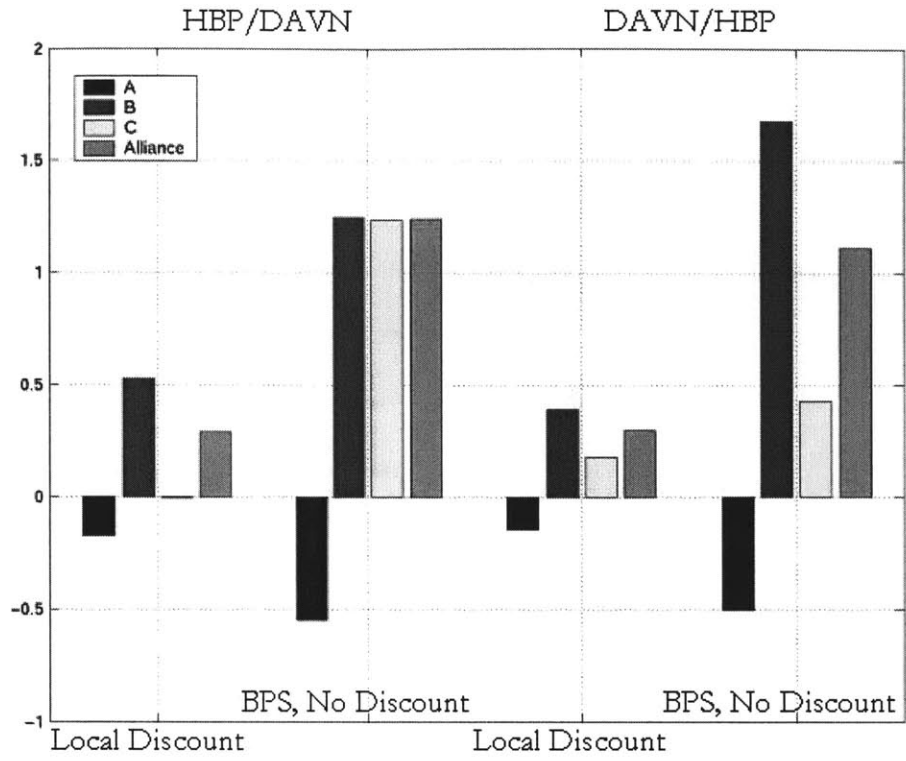


Figure 5.15. Revenue differences in percent, compared to EMSRb, DF=1.0, JI=2.

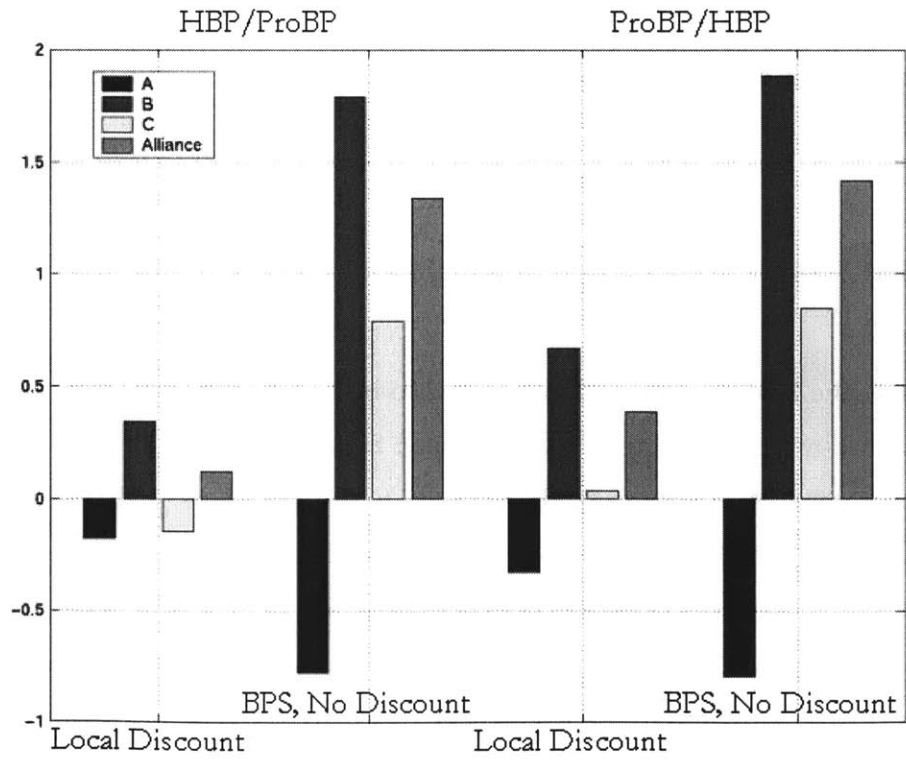


Figure 5.16. Revenue differences in percent, compared to EMSRb, DF=1.0, JI=2.

Once again, we observe significant revenue gains when the alliance partners use BPS instead of local discount. These incremental gains, which range from 0.81% (Eb vs. DAVN/HBP) to 1.21% (Eb vs. HBP/ProBP), are in general greater than those obtained above with DAVN/ProBP combinations that do not require bid-price scaling. Indeed, with local discount, the combination of HBP with DAVN or ProBP performs worse than a combination of ProBP and DAVN, and has thus a higher potential for revenue improvements. These results also prove that the simple bid-price scaling scheme proposed by Hopperstad enables effective BPS between the alliance partners when they use a combination of HBP and ProBP or DAVN.

Bid-Price Sharing, Alliance Partners Using Different RM Methods - Summary

Figure 5.17 summarizes the results discussed above, and gives for reference the revenue gains of the alliance partners using the same RM method when $JI=2$:

	Bid Price Scaling	BPS/Discount	A	B	C	Alliance
HBP	No	Local Discount	0.25	-0.07	-0.33	-0.19
	No	BPS, No Discount	-0.47	1.37	0.48	0.97
DAVN	No	Local Discount	-0.57	0.92	0.61	0.78
	No	BPS, No Discount	-0.65	1.55	1.04	1.32
ProBP	No	Local Discount	-0.63	0.9	0.19	0.58
	No	BPS, No Discount	-0.93	2.20	0.88	1.61
DAVN/ProBP	No	Local Discount	-0.41	0.62	0.25	0.46
	No	BPS, No Discount	-0.67	1.88	0.52	1.27
ProBP/DAVN	No	Local Discount	-0.6	1.02	0.29	0.69
	No	BPS, No Discount	-0.77	1.66	1.29	1.49
DAVN/HBP	Yes	Local Discount	-0.14	0.39	0.18	0.3
	Yes	BPS, No Discount	-0.5	1.68	0.43	1.11
HBP/DAVN	Yes	Local Discount	-0.17	0.53	0	0.29
	Yes	BPS, No Discount	-0.55	1.25	1.24	1.24
HBP/ProBP	Yes	Local Discount	-0.18	0.35	-0.14	0.13
	Yes	BPS, No Discount	-0.78	1.79	0.79	1.34
ProBP/HBP	Yes	Local Discount	-0.33	0.67	0.04	0.39
	Yes	BPS, No Discount	-0.79	1.88	0.84	1.42

Figure 5.17. Performance of OD RM methods used by the alliance partners. Revenue gains in percent over the baseline case (Eb vs. Eb/Eb), $DF=1.0$, $JI=2$.

When the alliance partners use different O-D RM methods, the use of bid-price sharing leads to significant incremental revenue gains for the alliance, ranging from 0.80% to 1.21% compared to the use of local discount with the same combination of RM method. The bid-price scaling scheme enables effective BPS between the alliance partners when one of them uses HBP.

Bid-Price Inference

The bid-price sharing scheme tested above assumes that the frequent exchange of displacement cost information between the alliance partners is technically feasible and legally possible. But exchanging displacement costs on the hundreds or thousands of legs a large airline operates daily between different computer systems might require significant IT investment. Besides, it might require the alliance partners to have received antitrust immunity to coordinate revenue management decisions.

For these reasons, it is interesting to see if the alliance partners could significantly enhance the performance of their distinct RM systems by making use of already available, less sensitive information. The **Bid-Price Inference** (BPI) method introduced here consists of inferring the partner's bid prices from the fare class availabilities on the partner's legs. Compared to BPS, BPI is an **approximate** method, but it is simpler to implement and less problematic technically and legally, because the information needed is already available publicly on the CRSs.

Bid-Price Inference: Local Path Method

The simplest method to estimate the bid price on a partner's leg, also proposed by Hopperstad as part of this research effort, is to use the partner's **local path** fare class availability information on that leg, simply based on CRS Availability Status (AVS). Without having any additional information on the partner's bid prices, a first guess would be to set the estimated bid price BP_{est} to:

- $BP_{est} = 0.5 (f_{hi} + f_{lo})$, where f_{lo} is the fare of the lowest class open, and f_{hi} is the fare of the highest class closed,
- $BP_{est} = 0.5 f_{lo}$, when all classes are open,
- $BP_{est} = f_{hi}$, when all classes are closed.

The interpolation constants above assume that the partner's bid prices are evenly distributed between the fare of the lowest class open and the fare of the highest class closed. If all classes are open, then the bid price should be halfway between zero and the fare of the lowest class in the local O-D market served by that leg. If all classes are closed, the bid price should be greater than or equal to the fare of the highest class, but we do not know by how much, so that the safest bet is to set the bid price equal to the fare of the highest class.

However, this interpolation can be improved if we know the distribution of the partner's bid prices between the fare of the lowest class open and the fare of the highest class closed. After parametric studies using ProBP in the network D used for our PODS simulations, Hopperstad found that the optimal interpolation coefficients are closer to:

- $BP_{cst} = 0.75 f_{hi} + 0.25 f_{lo}$, where f_{hi} is the fare of the highest class closed, and f_{lo} is the fare of the lowest class open,
- $BP_{cst} = 0.25 f_{lo}$, when all classes are open,
- $BP_{cst} = 1.1 f_{hi}$, when all classes are closed.

This suggests that in network D, the ProBP bid prices are in fact distributed closer to the fare of the highest class closed than to the fare of the lowest class open (respectively closer to zero if all classes are open), and typically do not exceed by much the fare of the highest class when all classes are closed.

For the alliance partners, the ideal way to interpolate accurately their partner's bid prices would be to calculate the interpolation constants of their respective networks, and exchange this information with their partner. The amount of data that needs to be exchanged (four coefficients) compare favorably with the real-time seamless access to all the partner's bid prices necessary to bid-price sharing. If this option was not possible, an alliance partner could also study the distribution of its own bid prices, and use the resulting interpolation constants to estimate the bid prices of a partner who is using a similar O-D RM method.

Bid-Price Inference: O-D Methods

With or without tuning of the interpolation constants, the method presented above only takes into account the **local** path fare class availability. A more accurate estimate of the bid price on a given leg could be obtained by using the information on the fare class availability of **all itineraries traversing that leg**.

An optimal solution could be found by solving a **linear least squares problem** over the partner's network, using the bid price obtained with the local path method as a target BP_{tgt} for each path p , with the objective of solving for the leg bid prices BP_l such that:

$$\sum_p \left(\sum_l BP_l \cdot A_{p,l} - BP_{tgt_p} \right)^2 \text{ is minimized}$$

Where $A_{p,l} = 1$ if leg l is traversed by path p , $= 0$ otherwise.

A heuristic solution could be more easily obtained by using an **iterative proration process** similar to ProBP, where the leg bid prices are first initialized using the local path method, and are then prorated over the different itineraries until a convergence criterion is met.

Preliminary tests performed were by Hopperstad to estimate the mislabeling rates of the three methods, and show that:

- Without tuning of the interpolation coefficients, the computationally intensive linear least squares method does not produce significantly lower error rates than the heuristic proration method, and therefore has not received further attention.
- Without tuning of the interpolation coefficients, the local path method produces high beta error rates³³, i.e. using the inferred bid prices it often mislabels as unavailable a path that was marked available by ProBP. It is consistent with the fact that bid prices are in fact distributed with a lower average than the average of the fare of the lowest class open and the fare of the highest class closed.
- With tuning of the interpolation coefficients, the heuristic proration and local path methods both produce reasonably low error rates ($\alpha = 0.09$ and $\beta = 0.13$ for the local path method, $\alpha = 0.07$ and $\beta = 0.02$ for the heuristic proration method).

Because of its simplicity, and because as we will see it performs quite well *a posteriori*, we will focus on the local path method.

Bid-Price Inference vs. Bid-Price Sharing

In this section, we will compare the performance of BPI, with and without tuning, to the respective performances of the local discount method and of BPS, for HBP, DAVN and ProBP. We will conduct this study at $J=1$, to compare the results with those found with BPS in the first section of this chapter.

³³ The alpha error rate (α) is the probability of a false positive, i.e. of marking a path/class available using the inferred bid prices which was marked unavailable by ProBP. Conversely, the beta error rate (β) is the probability of a false negative, i.e. of marking a path/class unavailable using the inferred bid prices which was marked available by ProBP.

Figure 5.18 and **5.19** present the difference in airline revenue when the alliance partners use HBP, respectively with local discount, BPI, tuned BPI and BPS, compared to the baseline case Eb vs. Eb/Eb:

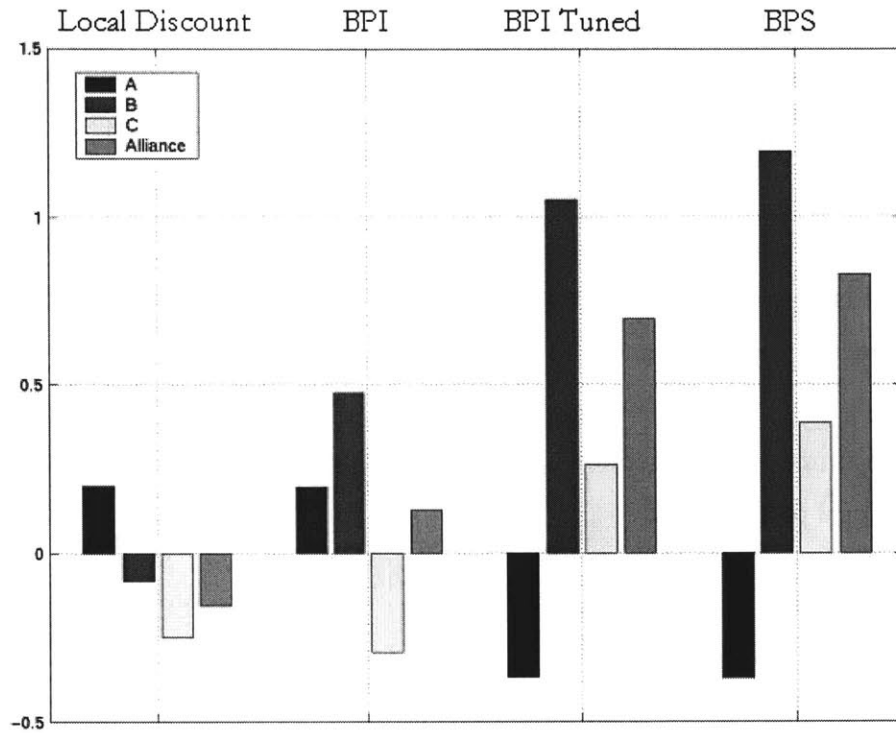


Figure 5.18. Revenue differences in percent, alliance using HBP compared to EMSRb, DF=1.0, JI=1.

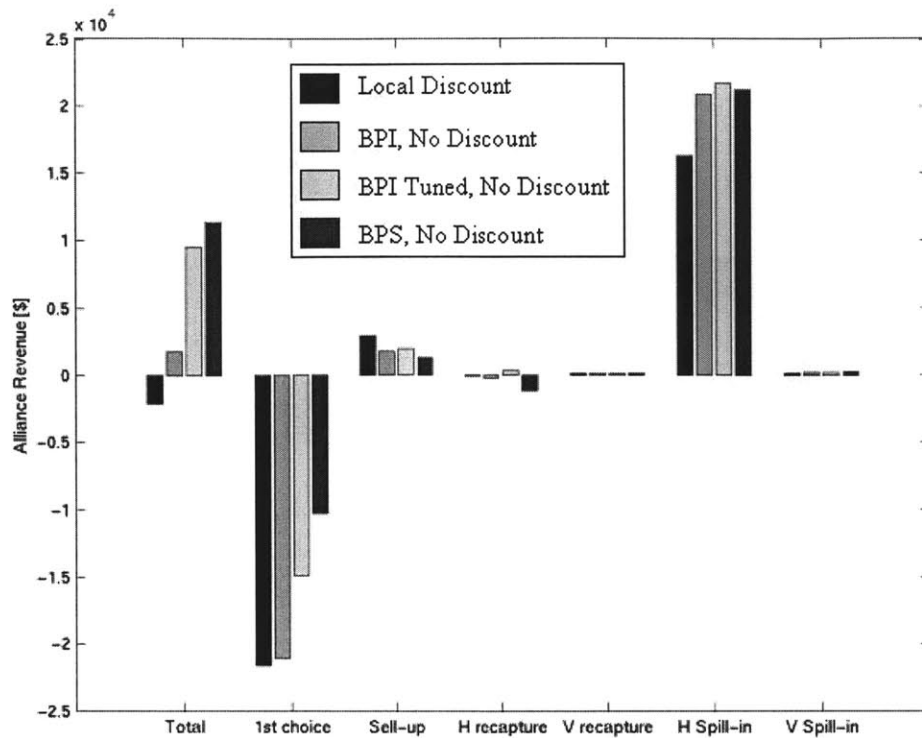


Figure 5.19. Alliance revenue differences in dollars, by passenger choice, alliance using HBP compared to EMSRb, DF=1.0, JI=1.

From **Figure 5.18**, we see that with tuning, BPI leads to alliance revenue gains that approach those obtained with BPS (0.7% vs. 0.83%). However, the revenue impact of BPI with HBP is quite sensitive to the tuning of the interpolation coefficients, as the performance of BPI without tuning (0.13%) falls short of these results. **Figure 5.19** shows that the ability to recover the first choice revenue losses strongly depends on the accuracy of the evaluation of codeshare paths, therefore on the accuracy of the interpolation constants.

DAVN

Figure 5.20 and **5.21** present the difference in airline revenue when the alliance partners use DAVN, respectively with local discount, BPI, tuned BPI and BPS, compared to the baseline case Eb vs. Eb/Eb:

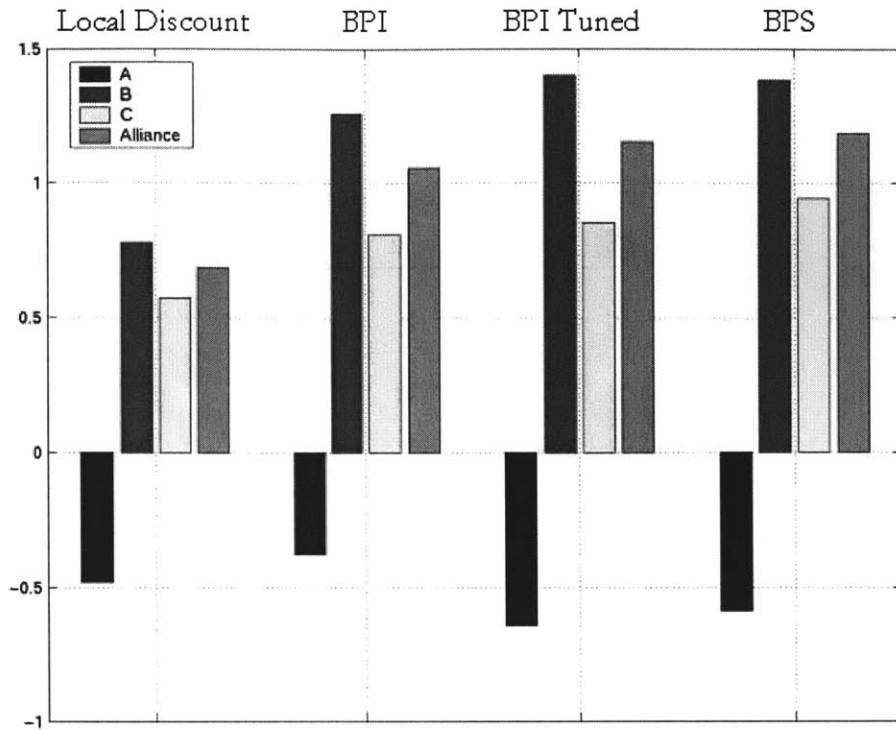


Figure 5.20. Revenue differences in percent, alliance using DAVN compared to EMSRb, DF=1.0, JI=1.

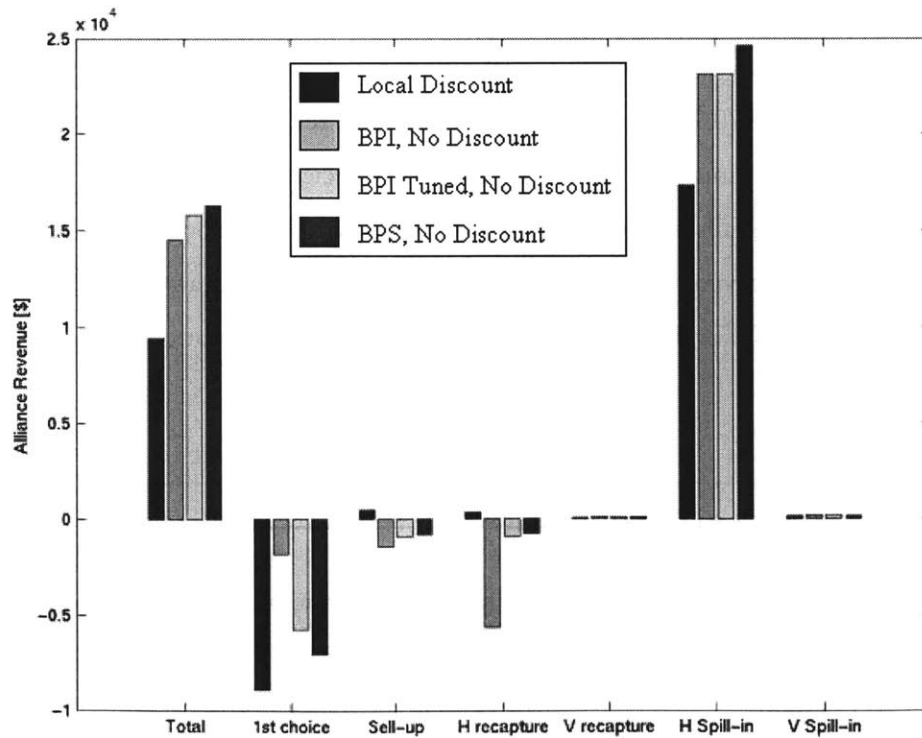


Figure 5.21. Alliance revenue differences in dollars, by passenger choice, alliance using DAVN compared to EMSRb, DF=1.0, JI=1.

The results above confirm the greater robustness of DAVN to the accuracy of the evaluation of codeshare passengers. Indeed, if we compare these results with the results of HBP, we notice that:

- The performance of BPI with tuning is much closer to the performance of BPS (1.15% vs. 1.19%),
- The performance of BPI is less sensitive to the tuning of the interpolation coefficients, as the performance of BPI without tuning is close to the performance of BPI with tuning (1.06% vs. 1.15%).

Figure 5.21 also confirms that, as we have seen in the first section of this chapter, the use of BPI or BPS with DAVN does not lead to a great decrease of first choice losses³⁴, but that the incremental revenue gains come mostly from increased spill-in.

ProBP

Figure 5.22 and **5.23** present the difference in airline revenue when the alliance partners use ProBP, respectively with local discount, BPI, tuned BPI and BPS, compared to the baseline case Eb vs. Eb/Eb:

³⁴ When the alliance uses BPI without tuning, we observe a decrease in first choice losses, but it is offset by an equivalent recapture revenue loss.

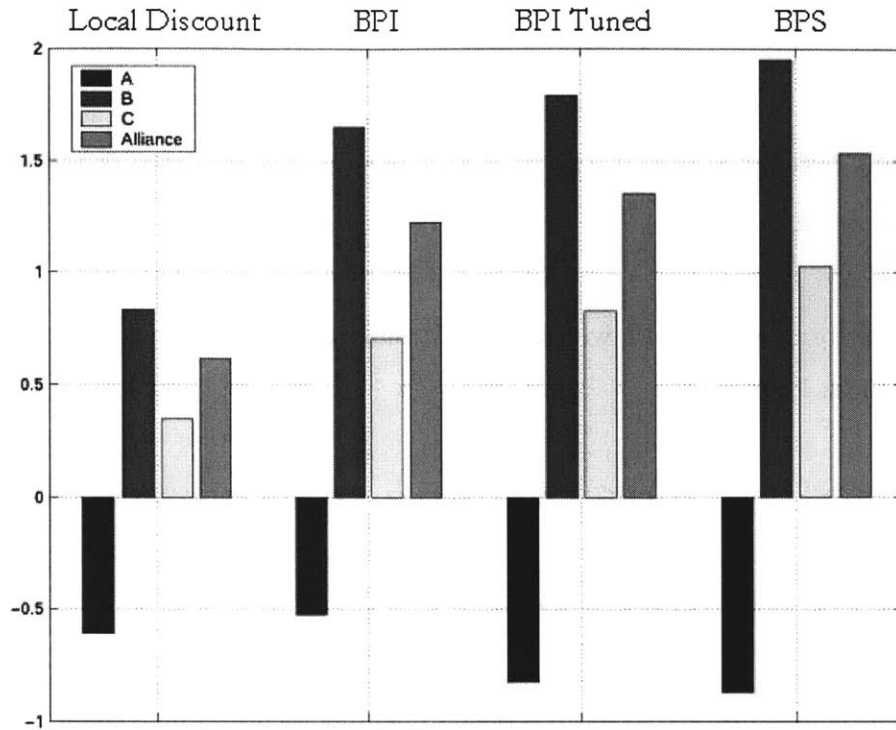


Figure 5.22. Revenue differences in percent, alliance using ProBP compared to EMSRb, DF=1.0, JI=1.

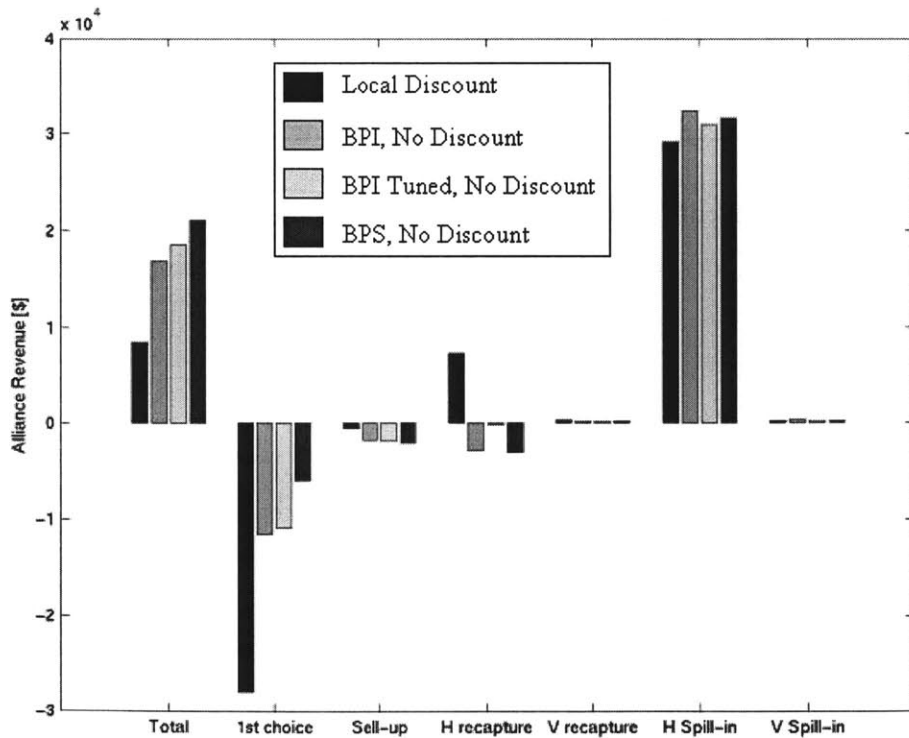


Figure 5.23. Alliance revenue differences in dollars, by passenger choice, alliance using ProBP compared to EMSRb, DF=1.0, JI=1.

With ProBP, the sensitivity of BPI to the accuracy of the interpolation coefficients appears greater than with DAVN, but lower than with HBP. With tuning, BPI does not perform as well as BPS (1.36% vs. 1.53%), but the performance of BPI without tuning is still good (1.23%, compared to 0.61% for local discount). In **Figure 5.23**, we see that the recovery of first choice revenue losses is about the same with or without tuning.

BPI vs. BPS – Summary

Figure 5.24 summarizes the performance of BPI with and without tuning of the interpolation coefficients and the performance of BPS, for HBP, DAVN and ProBP:

		A	B	C	Alliance
HBP	Local Discount	0.2	-0.08	-0.25	-0.16
	BPI, No Discount	0.2	0.47	-0.29	0.13
	BPI Tuned, No Discount	-0.37	1.05	0.26	0.7
	BPS, No Discount	-0.37	1.19	0.38	0.83
DAVN	Local Discount	-0.48	0.78	0.57	0.69
	BPI, No Discount	-0.38	1.26	0.81	1.06
	BPI Tuned, No Discount	-0.64	1.4	0.86	1.15
	BPS, No Discount	-0.59	1.38	0.95	1.19
ProBP	Local Discount	-0.61	0.83	0.35	0.61
	BPI, No Discount	-0.53	1.65	0.7	1.23
	BPI Tuned, No Discount	-0.83	1.79	0.83	1.36
	BPS, No Discount	-0.87	1.95	1.03	1.53

Figure 5.24. Performance of OD RM methods used by the alliance partners. Revenue gains in percent over the baseline case (E_b vs. E_b/E_b), $DF=1.0$, $JI=1$.

Overall, the use of BPI with tuning of the interpolation coefficients by the alliance partners leads to revenue gains approaching those obtained with BPS. Without tuning, the use of BPI

leads to smaller revenue gains, which are still significantly greater than those obtained with the local discount method. Bid-prices methods, especially HBP, are more sensitive to the accuracy of the interpolation coefficients than DAVN, and tend to perform worse using BPI without tuning.

Summary

In this chapter, two methods to improve the evaluation of codeshare passengers were tested. Bid-price sharing produces the greatest improvement of the alliance revenue over local discount, enabling the alliance to perform essentially as well as if it were a single airline. However, this method is difficult to implement and may require antitrust immunity. Bid-price inference is much easier to implement, but requires tuning in order to obtain performances similar to BPS.

CONCLUSION

Summary of Findings

The reader will recall that the first objective of this thesis was to quantify the performance of current revenue management systems in an airline alliance, and identify the critical issues created by the alliance context. Accordingly, the second objective was to propose and test new techniques to address these issues.

Performance of Current Revenue Management Systems in an Airline Alliance

The performance of current revenue management methods has been assessed in a virtual environment modeling the hub-and-spoke US domestic market, in which an alliance of two airlines competed against another airline. Multiple simulations were performed in this environment, varying the alliance joint image, the revenue management algorithms used by the airlines and the discount methods for codeshare passengers.

The alliance joint image parameter has been shown to have a significant impact on the magnitude of the alliance results in PODS network D. Over the whole network, the alliance revenue is typically 4% greater at $Jl=2$ than at $Jl=1$, for a demand factor ranging from $DF=0.8$ to $DF=1.1$, when all airlines use EMSRb. The difference is greater when the overall level of demand is low, and on low-demand codeshare markets. When demand is high, the alliance cannot accommodate all the extra codeshare passengers attracted by a higher joint image, but is able to increase yield by improving its passenger fare class mix. In network D, the alliance market share gains due to a higher joint image on a specific codeshare market can vary from 5 to 13%, depending on the level of demand of that market. However, joint image does not affect significantly the relative performance of origin-destination revenue management systems compared to EMSRb.

The use of DAVN or ProBP by one or both alliance partners results in revenue gains for the alliance compared to using EMSRb. At $DF=1.0$, the revenue gains are higher with DAVN (order of 0.7% to 0.9% with both partners using DAVN) than with ProBP (order of 0.6% with both partners using ProBP), which bid prices are distorted by the use of a discount method for codeshare paths. On the contrary, HBP performs worse than EMSRb in most of the cases studied (order of -0.1% to -0.6% with both partners using HBP), due mostly to its ineffective control of discounted codeshare passengers.

The individual characteristics of the alliance airlines condition the effect of using origin-destination revenue management methods. Airline B, which has a relatively low ALF, tends to increase the number of own-connecting passengers it carries, while airline C, which has a relatively high ALF, tends to decrease the number of own-connecting passengers it carries. Because of the differences in the partner's ALF and the revenue sharing agreement, codeshare passengers are much more beneficial to airline B than to airline C.

As a result, the revenue gains of using an origin-destination revenue management method are not evenly shared between the alliance partners. In the simulations, the longer-haul, lower ALF airline B typically gains more revenue than airline C, in both absolute and relative terms. In some cases, airline B is the main benefactor of airline C's investing in an origin-destination revenue management. In other cases, airline B's switching to an origin-destination revenue management system results in a revenue loss for airline C, because of the increased number of codeshare passengers carried by the alliance or changes in airline C passenger fare class mix.

Using total fares for decision fares instead of local discount on codeshare paths leads to an increase in the number of codeshare passengers carried by the alliance, hence reinforcing the asymmetry between airline B and airline C results. However, it does not lead to a significant improvement of the alliance overall results compared to using local discount, as the losses of airline C compensate the gains of airline B. Indeed, codeshare paths are still misevaluated as the alliance airlines do not have information on the displacement costs incurred by a codeshare passenger on their partner's leg.

Evaluation of Possible Improvements: Bid-Price Sharing and Bid-Price Inference

Two innovative schemes, bid-price sharing and bid-price inference, have been proposed to accurately evaluate the value of connecting passengers to the alliance, by allowing each alliance partner to estimate the displacement costs on the other partner's leg.

When the alliance partners use the same origin-destination revenue management method, the use of bid-price sharing leads to significant incremental revenue gains for the alliance, ranging from 0.5% to 1% at $JI=1$ compared to the use of local discount with the same RM method. The revenue increase is greater for bid-price methods, especially HBP, which are more sensitive to the correct evaluation of codeshare passengers than DAVN. For these methods, the revenue gains come mainly from a reduction of first choice revenue losses, whereas for DAVN it comes essentially from an increase in spill-in revenue. When the alliance partners use different origin-destination revenue management methods, the use of bid-price sharing leads to significant incremental revenue gains for the alliance, ranging from 0.80% to 1.21% at $JI=2$ compared to the use of local discount with the same combination of revenue management method. A simple bid-price scaling scheme enables effective bid-price sharing between the alliance partners when one of them uses HBP.

The use of bid-price inference with tuning of the interpolation coefficients by the alliance partners leads to revenue gains approaching those obtained with bid-price sharing. Without tuning, the use of bid-price inference leads to smaller revenue gains, which are still significantly greater than those obtained with the local discount method. Bid-price methods, especially HBP, are more sensitive to the accuracy of the interpolation coefficients than DAVN, and tend to perform worse using bid-price inference without tuning.

Contributions

From the findings summarized above, several conclusions can be drawn concerning airline alliances, and the use of revenue management tools by alliance partners in particular.

First, the customer perception of codeshare flights offered by an alliance in a market has a significant impact on the alliance market share in this market. Alliances considering replacing multiply listed codeshare flights with a single alliance flight in the future should weight the potential marketing benefits of such a strategy against the market share losses likely to be caused by not being listed multiple times in the CRSs.

Second, differences in the characteristics of the individual airlines in an alliance, notably their average load factor, as well as the interaction of the different revenue management methods they use, can lead to mixed results for the alliance as a whole, and to large disparities between the revenues of the alliance partners. It is thus important for the alliance airlines to understand the interaction of their revenue management systems in order to maximize the total alliance revenue, and accordingly to reach a revenue sharing agreement for codeshare passengers that is fair for all partners.

Third, the performance of origin-destination revenue management methods, especially those using bid-price control, has been shown to be particularly sensitive to the evaluation of codeshare passengers. The misevaluation of these passengers in current revenue management systems, whether the alliance partners use local fares or total fares to value these passengers, limits the revenue gains of the alliance partners using origin-destination methods, and represents an opportunity for future RM and reservations system development.

Finally, bid-price sharing seems promising for the improvement of alliance revenue over local discounting of codeshare passengers, enabling the alliance to perform almost as well as if it were a single airline, in revenue terms. However, this method is difficult to implement and may require antitrust immunity. Bid-price inference would be significantly easier to implement, but appears to require tuning in order to obtain performances similar to bid-price sharing.

Future Research Directions

From this first numerical investigation of revenue management for airline alliances, the following research directions could be explored:

- In the airline network investigated in this thesis, the alliance partners share a common hub. This is not the case in most alliances worldwide, which usually involve partners with distinct hubs. It would be interesting to see if the conclusions of this thesis could be generalized to a network with several alliance hubs.
- Similarly, alliances involving a greater number of partners, and partners of very different sizes, are the norm in the airline industry. By further dividing the network optimization process, these characteristics may affect the impact of the two solutions proposed in this thesis to improve the performance of origin-destination revenue management methods, bid-price sharing and bid-price inference.
- The technical implementation of bid-price sharing and bid-price inference, as well as their legal status, also deserve further investigation.
- In the longer term, one could develop revenue management systems for airline alliances that make use of the partner's information at the network optimization step of the seat control inventory process, and not only at the booking control step, like the bid-price sharing and bid-price inference schemes proposed in this thesis. Such systems could result in additional revenue gains for the alliance.

REFERENCES

- Belobaba, P. P. (1987), *Air Travel Demand and Airline Seat Inventory Management*, Ph. D. Thesis, Massachusetts Institute of Technology, Cambridge, MA, 1987.
- Belobaba, P. P. (1992), "Optimal vs. Heuristic Methods for Nested Seat Allocation," Presentation to AGIFORS Reservations Control Study Group Meeting, Brussels, Belgium, May 1992.
- Belobaba, P. P. and Wilson, J. L. (1996), "Impact of Yield Management in Competitive Airline Markets," *Journal of Air Transport Management*, Vol. 3, No. 1, pp. 3-9, 1996.
- Belobaba, P. P. (1998), "The Evolution of Airline Yield Management: Fare Class to Origin-Destination Seat Inventory Control," *Handbook of Airline Marketing*, 1st Ed., Chapter 23, pp. 285-302, 1998.
- Boeing Commercial Airplane Group (1993), "Decision Window Path Preference Methodology Time Mode," November 1993.
- Bratu, S. J-c. (1998), *Network Value Concept in Airline Revenue Management*, S. M. Thesis, Massachusetts Institute of Technology, Cambridge, MA, June 1998.
- De La Torre, P. E. F. (1999), *Airline Alliances: the Airline Perspective*, S. M. Thesis, Massachusetts Institute of Technology, Cambridge, MA, June 1999.
- Gellman Research Associates, Inc. (GRA 1993), "Airline Strategic Alliances: Definition and a Case for Caution," *Transportation Advisor*, Vol. 3 (1), January 1993.
- Gellman Research Associates, Inc. (GRA 1994), *A Study of International Code Sharing* Report submitted to the Office of Aviation and International Economics, DOT, Washington, DC, December 1994.
- General Accounting Office (GAO, 1995), *Airline Alliances Produce Benefits, but Effect on Competition is Uncertain*, GAO/RCED-95-99, Washington, DC, April 1995.
- Gorin, T. O. (2000), *Airline Revenue Management: Sell-up and Forecasting Algorithms*, S. M. Thesis, Massachusetts Institute of Technology, Cambridge, MA, June 2000.
- Lee, A. Y. (1998), *Investigation of Competitive Impacts of Origin-Destination Control Using PODS*, S. M. Thesis, Massachusetts Institute of Technology, Cambridge, MA, June 1998.
- Lee, S. (2000), "Alliance in Network D," PODS Summit XII, Cambridge, MA, September 2000.

- Mak, C. Y. (1992), *Revenue Impacts of Airline Yield Management*, S. M. Thesis, Massachusetts Institute of Technology, Cambridge, MA, January 1992.
- Oum, T. H., Park, J. H. and Zhang, A. (1996), "The Effects of Airline Codesharing Agreements on Firm Conduct and International Air Fares," *Journal of Transport Economics and Policy*, Vol. 30 (2), pp. 187-202, May 1996.
- Oum, T. H., Yu, C. and Zhang, A. (2001), "Global Airline Alliances: International Regulatory Issues," *Journal of Air Transportation Management*, Vol. 7, pp. 57-62, January 2001.
- Oster, C. V. and Pickrell, D. H. (1988), "Codesharing, Joint Fares, and Competition in the Regional Airline Industry," *Transportation Research*, Vol. 22A (6), pp 405-417, 1988.
- Pels, E. (2001), "A Note on Airline Alliances," *Journal of Air Transportation Management*, Vol. 7, pp. 3-7, January 2001.
- Simpson, R. W. and Belobaba, P. P. (1982), "The Demand for Air Transportation Services," Notes for Air Transportation Economics, Chapter 3, Massachusetts Institute of Technology, June 1982, updated August 1992.
- Smith, B. C., Leimkuhler, J. F. and Darrow, R. M. (1992), "Yield Management at American Airlines," *Interfaces*, 22:1, pp. 8-31, January 1992.
- Swarek, D. K. (1996), *Competitive Impacts of Yield Management Systems Components: Forecasting and Sell-Up Models*, S. M. Thesis, Massachusetts Institute of Technology, Cambridge, MA, June 1996.
- Wei, Y. (1997), *Airline O-D Control Using Network Displacement Concepts*, S. M. Thesis, Massachusetts Institute of Technology, Cambridge, MA, June 1997.
- Williamson, E. L. (1988), *Comparison of Optimization Techniques for Origin-Destination Seat Inventory Control*, S. M. Thesis, Massachusetts Institute of Technology, Cambridge, MA, May 1998.
- Williamson, E. L. (1992), *Airline Network Seat Inventory Control: Methodologies and Revenue Impacts* Ph. D. Thesis, Massachusetts Institute of Technology, Cambridge, MA, June 1992.
- Wilson, J. L. (1995), *The Value of Revenue Management Innovation in a Competitive Airline Industry* S. M. Thesis, Massachusetts Institute of Technology, Cambridge, MA, May 1995.
- Wynne, R. (1998), "From Queen Airs to RJs: Evolution in Major-Regional Airline Alliances and Code Sharing," *The Handbook of Airline Economics*, Mc Graw Hill, NY, 1998.
- Zickus, Jeffrey S. (1998), *Forecasting for Airline Network Revenue Management; Revenue and Competitive Impacts*, S. M. Thesis, Massachusetts Institute of Technology, Cambridge, MA, May 1998.

APPENDIX: BASELINE CASE WITH AIRLINE C OPERATING THE INTER-HUB FLIGHTS

In this appendix, we briefly describe the results of a baseline simulation with:

- DF=1,
- Eb vs. Eb/Eb,
- JI=1,
- Local Discount,

Where **airline C operates the interhub flights** between DFW and MSP (as opposed to airline B in all other simulations). The results are summarized in **Figure A.1**:

Parameter	A	B	C	Alliance
Market Share (p oints)	49.22	28.79	22	50.78
RPM (pax.mi)	10269013	6005681	4589011	10594692
ALF (p oints)	83.71	80.67	86.67	83.16
Network Local (%)	52.53	54.83	55.13	54.99
Yield (cents)	13.69	11.34	15.09	12.96
Net Revenue (\$)	1405750	692867	680227	1373094
Total pax	7136	3338	3925	7263
Codeshare pax	0	821	819	1640
Codeshare pax (%)	0.00	24.58	20.88	22.58

Figure A.1. Airlines results, DF=1.0, Eb vs. Eb/Eb, JI=1, Local Discount, airline C operates interhub flights.

We notice that, even if airline C operates interhub flights, the number of ASMs it offers and RPMs it flies are still significantly smaller than those of airline B. The changes in ASMs from the standard simulations is shown in **Figure A.2**:

Interhub carrier	Parameter	A	B	C	Alliance	Total
B	ASM (seat.mi)	12267966	7958273	4783257	12739530	25007496
	% of Total ASM	49.06	31.82	19.13	50.94	100.00
C	ASM (seat.mi)	12267966	7444575.00	5294955.00	12739530	25007496
	% of Total ASM	49.06	29.77	21.17	50.94	100.00

Figure A.2. Changes in ASMs, depending on the carrier operating interhub flights.

However, in spite of their small weight in terms of ASMs, the interhub flights determine³⁵ which alliance partner carries more passengers: when airline C operates these flights, it carries more passengers than airline B, contrary to what happens in the standard simulations.

³⁵ Apart from the variations in the number of passengers due to the use of different RM and discount methods.

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