Ancillary Revenues in the Airline Industry: Impacts on Revenue Management and Distribution Systems

by

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Abstract

Airlines have increasingly depended on ancillary revenue in response to rising fuel costs, decreased yields, and an increasingly competitive environment. Estimates indicate that U.S. airlines collected over $8 billion in ancillary revenue in 2012. Ancillary revenue poses challenges for airlines, including revenue management (RM) and distribution since total revenue maximization requires consideration of ancillary revenue and ticket revenue. In this thesis, we: (1) describe trends contributing to the movement towards ancillary revenue; (2) present three methods for incorporating ancillary revenue into revenue management and distribution; (3) evaluate the revenue performance of these methods using the Passenger Origin Destination Simulator (PODS), a competitive airline simulator.

One method of including ancillary revenue into RM is **RM Input Adjustment with Class Level Estimates**, which involves modifying input fares to the optimizer. Because fare values to the optimizer are aggregated by market and class, the airline uses class level estimates of ancillary revenue potential to augment fares. Another method involves modifying the fare value at the time of availability control, or Availability Fare Adjustment. In network optimization, the availability fare refers to the fare used to compare an itinerary-class to the control mechanism, like displacement adjusted virtual nesting (DAVN) or additive bid price (ProBP). **Availability Fare Adjustment with Class Level Estimates** also involves using class level estimates of ancillary revenue. Alternatively, we test scenarios where the airline estimates ancillary revenue for individual passengers in **Customized Availability Fare Adjustment with Passenger Specific Estimates**. Although this type of estimation is not feasible yet, results from Customized Availability Adjustment give a theoretical bound to revenue gain.

We find that incorporating ancillary revenue opens availability for lower yield passengers. Revenue increases occur from extra bookings in these classes because more bookings are taken. Revenue losses occur from higher class passengers buying down to cheaper seats. Without willingness to pay (WTP) forecasting, net revenue losses of up to –2.6% are observed. In advanced RM systems with WTP forecasting, revenue gains of +0.6% are observed for **Class Level RM Input Adjustment**, +0.9% for **Class Level Availability Fare Adjustment**, and +2.6% for **Passenger Specific Customized Availability Adjustment**.

Thesis Supervisor: Peter P. Belobaba
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1 Introduction

1.1 Overview of the Challenges in the U.S. Airline Industry

The airline industry is a major force in any economy with a developed transportation system. In the United States, as of 2012, the industry generates around $200 billion in annual revenues, enplaning 565 million passengers per year [11]. The aviation sector affects as much as 8% of US GDP [5], impacting a variety of other industries as well, ranging from aircraft manufacturing to couriers and delivery services to airport infrastructure.

Since deregulation in 1978, the airline industry has experienced periods of boom and bust through alternating patterns in positive and negative net profit. For example, the U.S. industry posted record losses in the period from 2001 through 2005 with an average operating margin of -9% [1], partly in response to the effects of September 11th on both passenger travel behavior and the rise of low-cost-carriers. The industry then returned to record profitability in 2006, posting an 11% operating margin. The profits were short-lived, however, as the industry tumbled into losses again in 2008 with a -13% margin as the industry was subjected to record-high jet fuel prices [12].

This brief snapshot highlights a few of the many challenges experienced by the airline industry. Its highly competitive nature, large fixed and volatile variable costs, as well as its transparency in the public eye makes airline management both unique and difficult. However, even with the plethora of challenges and setbacks, there exist just as many opportunities for strategy and innovation. Airlines have responded in various ways in an attempt to recover their losses and maintain consistent profitability. These strategies have ranged widely, from the founding of yield management to recent filings for bankruptcies by the major legacy carriers in order to restructure their labor costs to key mergers that consolidated redundant networks.

1.2 Defining Ancillary Revenue in the Airline Industry

One recent strategy that airlines have increasingly depended on is revenue from ancillary sources. Strictly speaking by dictionary definition [18], these are revenues derived from sources providing something additional to a main part or function – in the case of the airline industry, these are revenues that are not derived from the service of transporting a passenger from origin to destination. Because airlines can derive revenues from a large variety of sources, the arena of possible ancillary revenues is complex and not easily defined; but we will attempt to outline the major portions of operating revenue for a major airline, highlighting different sources of ancillary revenue.

1. **Passenger Ticket Revenues**

   These are revenues derived from the sale of tickets for air travel. Traditional airlines derive most of their operating revenues from passenger ticket revenues. Passenger ticket revenues, as reported to the U.S. Department of Transportation, refers to revenue derived from the sale of tickets on flights that are **solely** operated by the airline. For example, revenue from a booking on United Airlines from Newark (EWR) to Denver (DEN) is considered passenger ticket revenue, because United operates direct flights between these two airports. Passenger ticket revenues are typically the airline's main source of business.

2. **Ticket Revenue Derived from Codesharing**

   Codesharing is an agreement between two independent airlines to market a connecting itinerary across a shared route. For example, consider revenue from a passenger booking for Boston (BOS) to Frankfurt (FRA) through Newark (EWR). The passenger booked through Lufthansa, which only operates the EWR-FRA flight. Since Lufthansa codeshares with United, the passenger is able to fly the BOS-EWR leg on a United operated flight. Lufthansa then gives United an agreed upon portion of the revenue obtained. Technically, this is considered "ancillary revenue" – and it is even reported to the DOT as "transport-related revenues" – and whether these revenues are considered ancillary revenues or ticket revenues is up to debate. However, compared to other sources of ancillary revenue, we argue that codeshare revenue is more related to the main source of business.

3. **Ticket Revenue Derived from Outsourcing to Regional Airlines**

   Major legacy airlines outsource the operation of some of its flights to regional carriers, while still marketing seats on these regional flights as their own product. For example, a booking from Sioux Falls (FSD) to Chicago (ORD) is sold by United but is operated by Skywest Airlines (which is branded as United Express). Like codeshare revenue, regional affliate revenue can be technically considered as an ancillary source, but it is also strongly related to passenger ticket revenue, and a case could be made to include them within that tabulation.

4. **Cargo and Mail Revenue**

   Many passenger-based airlines also carry cargo and mail revenue in the hull of their aircraft along with their passengers in the cabin (however, some airlines are *all-cargo* airlines like Federal Express or United Postal Service, who optimize their networks to solely carry cargo). The argument for considering these revenues as part of the main source of business becomes weaker, because they do not involve transporting passengers; however, they still require the operation of the aircraft. Like many of these sources, defining them as ancillary sources or main sources of revenue is a grey area and can be debated.

5. **Add-Ons - Revenue Derived From Selling Products and Services Directly to Passengers**

   We define *add-ons* as products and services that are sold or utilized by passengers at any point before, during, and after the actual flight (an example of a service utilized by the passenger after a flight is a car rental package). The type of add-ons that could be offered to passengers and the emphasis on these sources depend on the business model of the airline. To give a small number of examples of ancillary sources in this particular category, it is helpful to imagine the decision process of a hypothetical passenger who is travelling in the air transportation sector.

   - First, before even booking a ticket, the passenger has a trip purpose - the demand for air travel is derived from demand for trips: people do not fly on aircrafts for the sake of flying! For example, the passenger might be taking a vacation trip, so he has a willingness to pay for certain types of vacation packages or deals that might include a hotel booking, tour, or car rental.
   - Then, during the actual booking process, he might decide to buy a pass for priority boarding or lounge access before the flight. It is more beneficial for the airline at this point if the passenger is booking on the airline's own website, because a cleaner and more streamlined interface with multiple options for add-ons can be presented in the most effective manner.
   - At the airport during check-in, he might decide to check a bag or decide to upgrade to an alternate version of an economy seat (e.g.: United's Economy Plus product).
   - On the aircraft, he might purchase a drink, eat lunch, or shop virtually using an onboard magazine on onboard the aircraft's wireless LAN.

   In combination with the airline's target of brand perception, the offer of add-ons within the booking process can truly be a sophisticated shopping experience. Comparable business models in other industries include the Las Vegas tourism industry, for example, where revenue is made not only from hotel bookings but also the casino floor, restaurants, shows, etc. There is an integration of the base product - such as hotel rooms - and add-ons, posing interesting challenges when the company decides to allocate its hotel inventory, particularly for lower prices. In a typical Las Vegas hotel, the room is not sold to try to maximize revenue from hotel bookings; rather, the room is sold to guests who are *expected* to spend extra amounts for add-ons to make up for a lower base room rate.

6. **Revenue Derived from Other Sources that Do Not Involve Transporting Passengers**

   These are sources of revenues that do not directly affect the individual passenger on a trip. Sources of these ancillaries may vary from selling frequent flyer miles to credit card companies to purchasing an oil refinery to advertising onboard an aircraft. These sources of revenue can represent a significant portion of operating revenue: for example, in 2011, United Airlines received $1.8 billion from the sale of miles in its Frequent Flyer program (MileagePlus) to credit card companies [21], who in turn reward customers based on spending.

An overall summary with common and/or interesting examples in each category is listed in Figure 1.1.

MAIN SOURCE	DEBATABLE		ANCILLARY REVENUE			
			Add-Ons - Directly Purchased by Passengers			Indirectly Related to Passengers
Passenger Tickets	Code-sharing	Cargo	Before Flight	During Flight	After Flight	Advertising Onboard Aircraft
			Carry On Bags	Extra Seat Pitch	Car Rentals	Oil Refinery (Delta Air Lines)
	Outsourcing to Regional Airlines	Mail	Checked Baggage	Priority Boarding		Rental of Flight Equipment
			Itinerary Changes	Food and Drink	Hotel Packages	Rental of Ground Equipment
			Trip Protection	Seat Selection		Sale of Miles to Companies

Figure 1.1: Examples of Ancillary Revenue Sources

One of the common themes across each of these different categories is the ambiguity of different activities. What exactly should an airline consider to be ancillary revenue? As indicated in Figure 1.1, there are grey sources of revenue that can be debated as either part of the main source of revenue or as ancillary revenue.

For the purposes of this thesis, we chose to define the distinction between ancillary revenue sources that are purchased directly by the passenger – add-ons – versus those that are not related to the passenger. We are primarily concerned with activities that fall in the former category, because that affects our assumptions about passenger willingness to pay, which directly affect RM optimization models, availability quotes, and bottom line. That is not to say that other sources of ancillary revenue cannot be important as well to maximizing revenue for an airline. Frequent Flyer programs, for example, are of great importance to marketing as it fosters customer loyalty, albeit in a less quantitatve sense. The management of an oil refinery by Delta is instrumental to corporate strategy, by seeking to cover part of its operating costs. However, in this thesis, we are only concerned with add-ons.

1.3 Effects of Ticket Unbundling

Responses to add-ons have been mixed. On one hand, passengers who were previously accustomed to services that were traditionally packaged within the structure of a ticket – complimentary meal service or checked baggage, for example – complain that the airlines take every opportunity to *nickel-and-dime* their customers. Spirit Airlines, for example, frustrates many consumers who complain about not knowing why they were charged certain fees (Spirit is the only airline in the United States that charges passengers for their carry-on bags that must ride in the overhead bins).

On the other hand, marketing executives promote the opportunities for extra variability in options and consumer choice. In the case of enhanced legroom and seat width, passengers have the option of upgrading their economy ticket for a price below the cost of upgrading to first class. In an *a la carte* fashion, each passenger is able to pick and choose exactly which products and services he would like as part of his travel experience.

An additional implication is the effect of lowering the base ticket fare. By unbundling the extra services from the base product of the transportation service, airlines can theoretically sell a lower base ticket fare, making up the difference by selling the add-ons. This, particularly in an era with transparency in online search engines and the price sensitivity of some passengers, is instrumental in allowing an airline to remain competitive on the base ticket fare. While some airlines such as Spirit Airlines or RyanAir primarily target these price-sensitive passengers by lowering their base ticket fare, other airlines are forced to follow suit in order to remain competitive in the market.

Finally, we comment on the effect of unbundling on distribution systems and online travel agencies. Whereas previously these systems aggregated and standardized fare quotes across most airlines to present to the consumer, the effect of unbundling begins to make this process more opaque. Because each airline may offer differentiated products, it becomes tougher for these agencies to normalize fare quotes to present to the consumer. For example, a base $60 Spirit fare may not be comparable to a base $80 United fare, because Spirit Airlines charges for carry-on bags.

1.4 Challenges in Quantifying Ancillary Revenue Impacts

The airline industry is one of the most transparent industries in the United States. Every quarter, airlines are required to report a number of metrics to the Bureau of Transportation Statistics, including data on revenue, expenses, employees, aircraft, traffic, capacity, etc. Unfortunately, the manner in which the revenue data is reported veils the tabulation of ancillary revenue, particularly given our previous discussion of the ambiguity of these activities.

Specifically for revenue, the Bureau of Transportation Statistics collects data on the following categories:

- **Transport Revenue** is reported with 5 subcategories that is considered main sources of revenue: revenue from **passenger tickets, freight/cargo, public service, charters, and mail**. Additionally, within transport revenue, three subcategories are considered by the Department of Transportation (DOT) as ancillary revenue: revenue from **baggage fees, reservation cancellation fees, and miscellaneous fees**. Miscellaneous fees implicitly include revenue from Frequent Flyer partner programs, non-revenue passengers, pet transportation, and standby fees.
- **Transport-Related Revenue** is reported as a single lump sum. This category includes revenue from in-flight sales (liquor, food, movies), hotel/restaurant/food service, rents, and include regional affiliate outsourcing, etc. These revenues are **not** included in the official definition of ancillary revenue.

There are two implications from this categorization of data. First, given the plethora of marketing options that were discussed earlier, it is unclear where these add-ons fall within the 8 categories reported to the DOT. Because of this, there may be inconsistencies in reporting ancillary revenue by airline, as there is no clear, standard guidance for modern activities in this outdated tabulation. Second, the DOT itself has a definition of ancillary revenue – the sum of *baggage fees, reservation change fees, and miscellaneous fees.* This tabulation is incomplete because it clearly disregards add-on revenue from in-flight sales, which are located within *transport-related revenue* and lumped together with other irrelevant sources of revenue. Lastly, ancillary revenue from both direct-passenger and indirect-passenger sources are also lumped together within *miscellaneous fees.*

However, information about ancillary activities can be gleaned from other sources, such as Form 10K (the annual shareholders' report) filed to the SEC, for example. IdeaWorks Company, sponsored by Amadeus, utilizes these additional data sources to report on the state of ancillary revenue globally and within the U.S. [19]. Figure 1.3 compares estimates of ancillary revenue by carrier for 2011 from the Department of Transportation as well as from IdeaWorks. Since IdeaWorks does not consider reservation cancellation fees as ancillary revenue, we have subtracted the corresponding numbers from DOT's estimates in order to have a slightly more consistent comparison of the two.

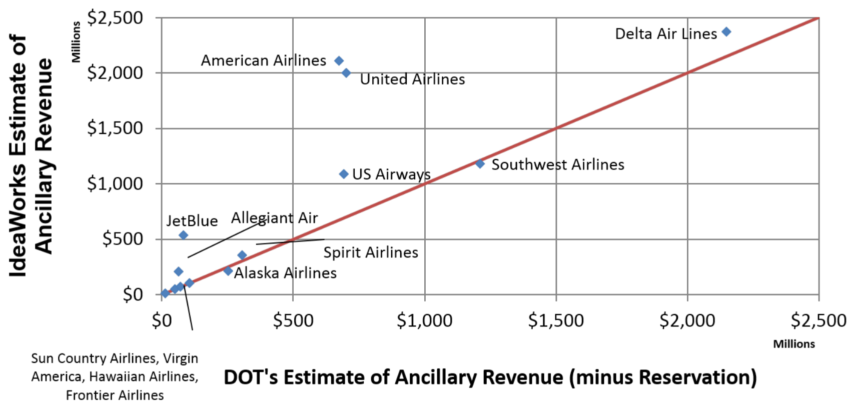


Figure 1.2: IdeaWorks and DOT Estimates of Ancillary Revenue in 2011 by U.S. Carrier

We see from the figure that there are large variations between estimates of ancillary revenue, depending on who is tabulating the data and what categories and definitions are assumed. Estimates can vary by as much as +200%, as in the case of American Airlines. Industry-wide, summed estimates range from \$6 – \$10 billion per year in 2011. To summarize, currently, there is no industry-wide standard or agreement on the definition or reporting of ancillary revenue. There is no distinction between ancillary revenue from sources that are directly related to passengers and sources that are not, which are of interest to different departments within an airline.

1.5 The Growing Importance of Ancillary Revenue in the U.S. Airline Industry

Nonetheless, it is interesting to examine the recent trends in ancillary revenue, particularly if we keep the reference data and definitions constant by year. In Figure 1.3, industry level ancillary revenue from DOT data is tabulated by year, with absolute numbers in red bars and as a percent of operating revenue in blue lines.

From this chart, we see that especially around 2007, airlines began aggressively pursuing ancillary revenue. In part because of increased competition from low cost carriers, most airlines found it necessary to unbundle their product at this time. The rationale for unbundling is to

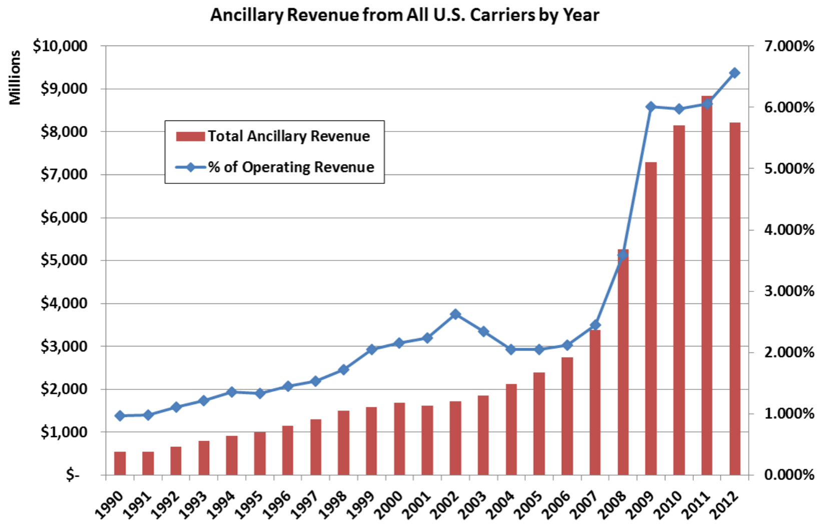


Figure 1.3: DOT Estimate of U.S. Ancillary Revenue (1990 – 2012)

simply keep up with competition in lowering the advertised base ticket fare. If one airline in a market unbundles and lowers its base ticket fare, the other airlines would be at a marketing disadvantage if they didn't follow suit. Additionally, in an environment where even the slimmest of positive margins needs to be earned, ancillary revenue representing around 7% of their total operating revenue indicates that add-ons are solidified as a significant part of the business model.

However, there are also differences among the airlines in the extent of their emphasis on add-ons as it relates to their business models. Some airlines, like Spirit Airlines and RyanAir, target the extreme price-sensitive passengers by dramatically lowering their base ticket fare to draw market share. Indeed, between the period from 2007 to 2012, the average ticket price for Spirit Airlines dropped by 22% [20]. Other airlines, like Allegiant Air, model themselves as travel companies that aim to transport leisure travelers to warm destinations. Allegiant emphasizes the complete travel experience, focusing on selling hotel and vacation packages under the brand name Allegiant Travel. Additionally, Southwest Airlines decided to differentiate itself in the marketplace by not charging for checked bags and not charging for ticket changes, surrendering potential for millions of dollars in ancillary revenue to put itself at a marketing advantage.

In Figure 1.4, the ancillary revenue gained as a proportion of operating revenue in 2011 is shown for each U.S. carrier. Some low-cost-carriers like Spirit, Allegiant, AirTran, and Frontier clearly center their business model on ancillaries for reasons such as those listed above. Major network legacy carriers maintain ancillary shares of 3 – 8%, presumably because more of their

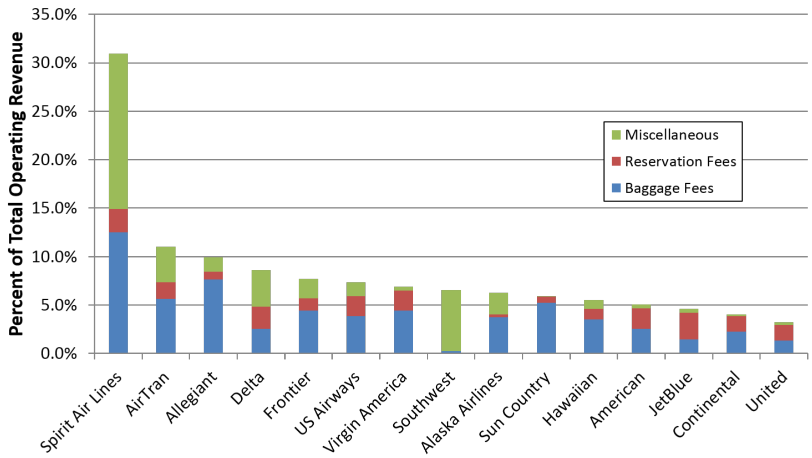


Figure 1.4: DOT Estimate of Ancillary Revenue in 2011 by Carrier

operating revenue is derived from international traffic. As of 2013, most carriers still offer a bundled product (checked bag, food, drink) on long-haul international flights.

Nonetheless, even 3% of operating revenue represents over a billion dollars in ancillary revenue for United. While the sales of air tickets and management of seat inventory have improved continuously with revenue management over the last 30 years, passenger-related ancillary revenue remains an uncertain frontier with much room for improvement. Currently, although passenger willingness to pay for tickets has been extensively studied, there has been little work on willingness to pay for add-ons. With more airlines unbundling their product and lowering their base ticket fare to remain competitive, it becomes increasingly important to account for add-ons in the airline revenue optimization process.

1.6 Research Motivation

The basic premise behind revenue maximization in revenue management is simple: given a flight or set of flights in a network, allocate seats to reserve for passengers who are willing to pay the most. Optimally, each seat would be filled with the passenger who is willing to pay the highest dollar value for that particular seat. The airline depends on the forecast of the expected revenue contribution of passengers in order to decide who to prioritize availability to.

Traditionally, the expected revenue contribution is based on posted ticket fare. For example, a connecting passenger flying internationally would be worth more than a connecting passenger flying domestically if an airline were considering who to sell the seat to on a domestic leg. The availability the airline decides to offer to the passenger is based on his network value, which scales based on ticket price.

However, given the recent trends in unbundling and the derivation of additional revenues from add-ons sold to passengers, it is logical that the airline should consider the expected value of a passenger from not only his ticket value, but also his overall potential for any additional add-on ancillary revenue. Intuitively, if a particular passenger buys a $100 ticket but is willing to pay $50 in add-ons, then his availability should be calculated as if he is a $150 value passenger.

Therefore, in this thesis, we present four methods for incorporating ancillary revenue into the RM optimizer and/or the availability distribution process. In order to test revenue impacts, we utilize our competitive airline market simulator, the Passenger Origin Destination Simulator (PODS). The four methods, which are explained fully in Chapter 3, have varying levels of difficulty and feasibility based on their required data, data accuracy, and successful integration with distribution systems.

1.7 Outline of Thesis

The thesis is organized into six chapters:

- **Chapter 1** (current) presents an overview of the airline industry and the recent shift towards ancillary revenue. It also details the motivation behind the research: the logical next step to leveraging ancillary revenue data into revenue management.
- **Chapter 2** gives an outline of differential pricing and revenue management, including a brief overview, and some common optimizer schemes and forecasting techniques.
- **Chapter 3** discusses the goal of revenue maximization, given the intersection of revenue management and ancillary revenue. It also presents a few methods for incorporating ancillary revenue into revenue management and distribution.
- **Chapter 4** presents the Passenger Origin Destination Simulator (PODS), a simulator that models the passenger process in order to test airline revenue management strategies, as well as presents the experimental methods used in the thesis.
- **Chapter 5** reports the results of the research and delivers key insights on RM strategies to incorporate ancillary revenue and maximize revenues. It explores theoretical possibilities given more detailed understanding of individual passenger behavior.
- **Chapter 6** summarizes the findings and implications in the context of the overall airline business and outlines possibilities for the future of the airline industry.

2 Background and Literature Review

2.1 Introduction

The purpose of this chapter is to introduce many of the pricing schemes and revenue management strategies commonly seen throughout the industry that will be referenced and utilized in our experiments and results, exploring the evolution of major strategies over the last 30 years. It is important to understand the underlying logic and models, as they will relate to our experiments as we alter them to account for ancillary revenue potential.

We briefly touch on airline pricing in the context of economics, beginning with the theory of differential pricing and the development of fare structures. We explore the roles of restrictions and the industry movement towards simplified, semi-restricted fare structures with the rise of low-cost-carriers.

We then explore the basics of revenue management, which calculates protection limits given set fare structures and capacity constraints. An overview of forecasters and optimizers is presented, first in the context of a leg-based RM system and then in the context of a network-based RM system.

2.2 Pricing

2.2.1 Theory of Price Discrimination

For airlines, differential pricing consists of both price discrimination – the practice of charging different prices for the same product – as well as product differentiation. Using differential pricing, airlines are able to construct fare structures that segment demand and generate higher revenues.

Price discrimination practiced by airlines stems from the fundamentals of willingness to pay (WTP) for the same product. For a specific flight and a specific product on that flight, there are people who are willing to pay various amounts. An example of a specific product is a fully unrestricted fare product, or a ticket without any restrictions such as a round trip requirement, a Saturday night stay requirement, or a nonrefundability clause. A typical business traveler, for example, might be willing to pay at most $600 for this particular product versus a typical leisure traveler who might only pay at most $200, holding all else equal. Business travelers, in general, tend to be less price sensitive (and willing to pay high amounts) because they are able to expense funds to their company in order to travel for business. Leisure travelers, in general, spend from discretionary budgets and therefore tend to be more price sensitive because they are not as willing to pay a higher out-of-pocket cost from their personal funds.

We can draw a price-quantity relationship curve that illustrates the concept of willingness to pay. In Figure 2.1, there are two products: A and B with prices P_A and P_B. The demand quantity for A, Q_A is less than the demand for B, Q_B because the price is higher for the same product. Another way to illustrate this point is that only the business traveler from above is able and willing to pay for Product A. However, both the business traveler and the leisure traveler are willing and able to pay for Product B, if available. This illustrates one of the key effects that revenue management and fare structures seek to minimize: buy-down. If both products are available, a rational business passenger will always choose the lower-priced product, given that the two products are exactly or almost the same.

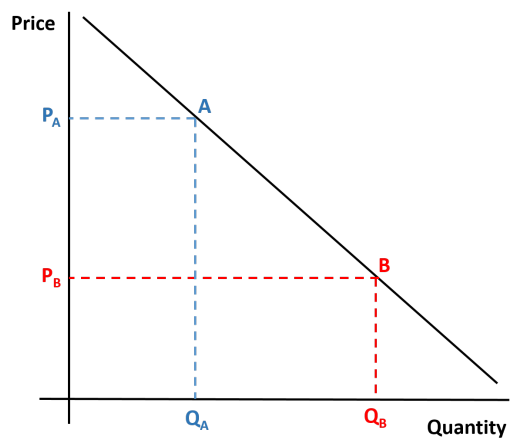


Figure 2.1: Two Products with Different Prices and Demanded Quantities

If an airline offers one single product priced at one point Figure 2.2 [Left], then the revenue for that flight can be calculated as the rectangular area underneath that point (if the quantity demanded is less than that of capacity). In this case, the total revenue obtained by offering one product X is $REV_X = P_X * Q_X$.

Alternatively, if the airline offers two additional products, A and B in Figure 2.2 [Right], then the total revenue is the sum of the three rectangles formed by $P_A, P_X, P_B, Q_A, Q_X, Q_B$. It is easy to see that as the number of price points increases, the theoretical amount of revenue obtained increases as well, capped by the area underneath the curve.

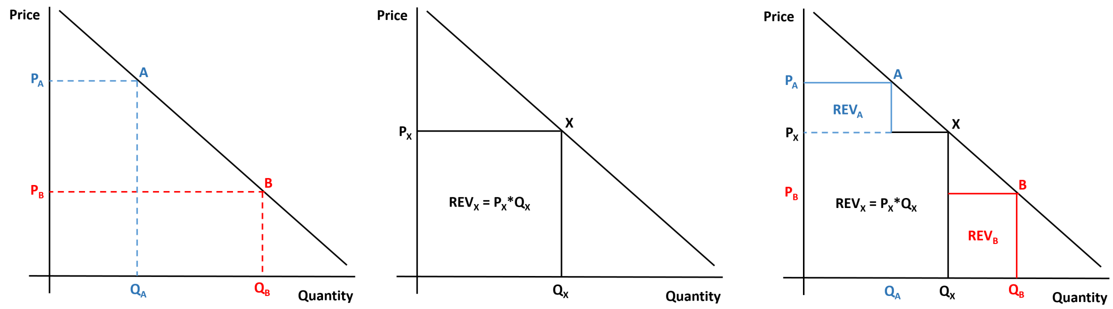


Figure 2.2: [Left] Revenue from One Price Point. [Right] Revenue from Three Price Points.

We draw attention to the blue rectangle formed by A and the red rectangle formed by B, as they represent common trends experienced by booked passengers in revenue management. The passengers that fall into the blue rectangle are those with an inherently higher willingness to pay, and were *sold up* to a higher price point with the introduction of product A. If A were not present, as in the case of Figure 2.2 [Left], then we say that there was consumer surplus not captured from these passengers, who would have paid the higher price point.

Additionally, the passengers that fall into the red rectangle formed by B have a lower willingness to pay. With the introduction of a lower fare product B, those passengers who would otherwise have not bought the product were *stimulated* into booking on this flight. If B were not there, then if there was a surplus of capacity, those aircraft seats would have spoiled and flown empty.

This illustrates one of the central themes of pricing and revenue management: the optimal balance of passengers can be obtained only through a revenue-focused strategy, which balances the number of high paying passengers with low paying passengers, as opposed to a yield-focused – target the few, valuable high WTP passengers – or a load factor-focused – target large numbers of low WTP passengers – strategy. A more comprehensive overview of the topic can be found in [6] by Belobaba.

2.2.2 Product Differentiation

One of the key challenges is "buy-down". Given two identical fare products, any rational customer would choose the one that costs less. For that reason, there are two main strategies that can be used to combat buy-down: product differentiation and revenue management.

Product differentiation is the art of adjusting the attributes of a product to appeal to different audiences. An airline fare structure is a collection of these different products. A good fare structure is one that effectively segments demand across different classes, discouraging customers from higher classes from buying down to lower classes, because utility-wise it would be less desirable for them to do so.

For example, assume that demand can be split into business customers and leisure customers. There are certain restrictions that can be imposed on different fare products that would make them appeal to these two segments unevenly. A business customer might perceive a higher *disutility* from being required to stay for Saturday night on a round-trip ticket. A leisure customer might be more flexible in his travel plans and be able to book the ticket earlier. For these reasons, we can take one flight and split its seats into two fare classes with different restrictions, as in Figure 2.3.

Class	Fare	Adv. Purchase	Sat. Night
Y	$ 500	0	No
Q	$ 200	21	Yes

Figure 2.3: Simple Two-Class Fare Structure

In this fare structure, a business-oriented passenger would be enticed to book in Y class, because he feels a disutility cost associated with a Saturday night stay. Additionally, since he might book close to departure, he might have no choice because the advanced purchase requirement sets in. A leisure-oriented passenger would be able to book the $200 Q fare, which served to stimulate this demand.

Alternatively, higher classes could have extra amenities associated with it, which would increase the utility from booking in that class. Essentially, whether restrictions or amenities are imposed is irrelevant - only the relative differences in disutility or utility across different classes matters to customers. This combination of price discrimination and product differentiation is termed as *differential pricing* by Belobaba [6], and is the basis for fare structures.

We introduce two types of fare structures that we will be using in our experiments:

- Fully Restricted Fare Structure
- Semi-Restricted Fare Structure

2.2.3 Fully Restricted Fare Structures

In practice, airlines can have up to dozens of classes, with restrictions and amenities and advanced purchase requirements which split the fare structure hundreds of different ways. We define an example of a *fully restricted* fare structure with 6 classes that we will use in our experiments below in Figure 2.4. AP refers to *advance purchase* requirements. R1, R2, and R3 are arbitrary restrictions that have different associated disutility costs.

Class	Fare	AP	R1	R2	R3
1	$ 414	0	-	-	-
2	$ 293	3	-	Yes	-
3	$ 179	7	Yes	Yes	-
4	$ 153	14	Yes	Yes	-
5	$ 127	14	Yes	Yes	Yes
6	$ 101	21	Yes	Yes	Yes

Figure 2.4: Example of a Fully Restricted Fare Structure

Ideally, all airlines would like to use fully restricted fare structures because by effectively segmenting demand into different fare classes, buy-down can be prevented as higher class passengers are discouraged from buying the lower fare. Forecasting becomes more straightforward as well, since the assumption that demand is independent for each class is reasonably valid.

2.2.4 Semi-Restricted Fare Structures

Understandably, however, customers can quickly become frustrated at the number of restrictions, which can be confusing and irritating. To the customer, restrictions such as requiring to stay Saturday night may seem unreasonable and illogical.

For these reasons, certain low cost carriers (LCCs) in the early 2000s introduced the idea of a *less-restricted*, or more simplified fare structure, according to [13]. Although for these individual airlines there are benefits associated with consumer brand value, there are negative buy-down repercussions of lost revenue for both that airline and other airlines within competing markets. Without certain restrictions, some higher class passengers might be able to buy down into a lower fare class. When a low cost carrier is in a market with a network legacy carrier, the NLC typically has little choice but to match the less restricted fare structure, as not doing so would cause the NLC to lose substantial traffic to the LCC.

Figure 2.5 shows an example of a semi-restricted fare structure. The first restriction – Saturday night stay requirement – is removed from all fare classes, which lowers the disutility fence that prevents higher classes from buying down to lower classes. Unfortunately, the effects last for more than one specific flight or day of bookings. The forecaster uses historical booking data on the number of bookings by each fare class - therefore, when higher class passengers buy lower class tickets, the forecaster is tricked into thinking there is large demand for these lower classes. Because there is more "demand" for the lower classes, the optimizer is enticed to protect fewer seats for higher class passengers, and the cycle continues. This is called the *spiral down* effect (more detail found in [14]), and its mitigation techniques will be described in Section 2.4.

Class	Fare		AP	R1	R2	R3
1	$	414	0		-	-
2	$	293	3		Yes	-
3	$	179	7		Yes	Yes
4	$	153	14		Yes	Yes
5	$	127	14		Yes	Yes
6	$	101	21		Yes	Yes

Figure 2.5: Example of a Semi Restricted Fare Structure

2.3 Revenue Management Systems Overview

After the airline determines its pricing schemes and fare structures, it needs to dynamically manage its inventory, from the start of the booking process (usually up to a year before departure) up until the day of departure. Depending the booking patterns at each checkpoint – reference points along the booking process that the airline can use to reevaluation its optimization – it may be ideal to have certain classes closed or open. For example, if there were a unusually large number of booking early, then it would be beneficial to close down classes and protect more seats for higher classes to generate more revenue. A computerized system that manages this process is called a *revenue management* system. According to Belobaba [4], it is widely accepted that the proper use of an RM system can lead to revenue increases of 4 to 6%.

The role of a revenue management system is to calculate booking limits for each fare class at every reference point along the booking process. Instead of allocating seats to each fare class, the typical RM system calculates serially nested booking limits via a top-down approach, as shown in Figure 2.5. More detail on this calculation is in Section 2.5.1.

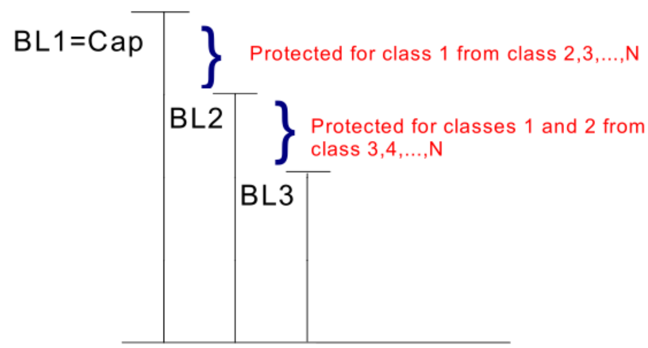


Figure 2.6: Serially Nested Class Buckets [2]

Modern revenue management systems consists of three main components [7]: a forecaster, a booking limit optimizer, and an overbooking model. These systems work in conjunction to calculate booking limits at each reference point in order to upload to the reservations/inventory system. At the next checkpoint, the airline gathers data on incremental bookings and cancellations, which it feeds into its database, which then feed into the forecasting model. A complete overview of a typical RM system is shown in Figure 2.7.

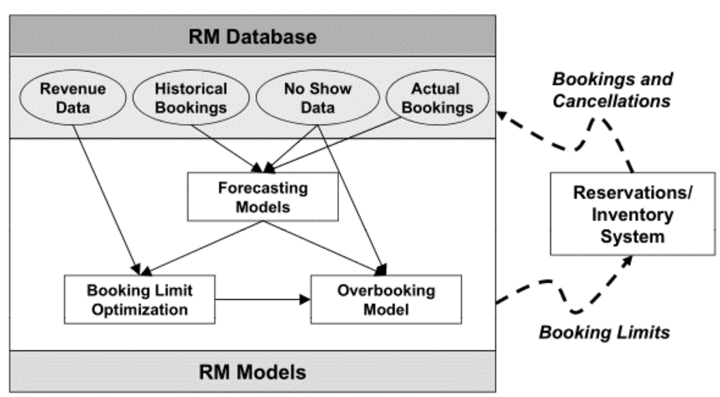


Figure 2.7: Airline Revenue Management System [7]

The objective of flight overbooking is to determine the maximum number of bookings to accept, given a (usually) fixed capacity. Overbooking models account for the no-show behavior of passengers to balance the potential revenue gains from accepting more passengers against the costs of voluntary or involuntary denied boarding. Although overbooking is an instrumental part of an RM system, we will not be employing overbooking models in our experiments.

Finally, we will briefly touch on two broad categories of RM systems: those that control seat inventory on a flight leg level and those that control inventory on a network level. These two categories of RM systems use different forecasting data - traditional leg level RM uses class-level passenger demand forecasts for each leg while a network level RM system uses origin-destination path forecasts. Network RM also needs to consider: (1) “mapping” classes from different OD itineraries onto flight legs, since itineraries overlap and (2) adjusting for the displacement cost of a connecting itinerary that occupies multiple legs. Further discussion will be presented in Section 2.5.3.

2.4 The RM Forecaster

The role of the forecaster is to estimate demand for each fare class in order to feed the booking limit optimizer and the overbooking model. The forecaster derives its demand based on both historical bookings as well as current, actual bookings observed between reference points. There are four main types of forecasters that are commonly used and that we use in our experiments.

Firstly, an airline may choose to forecast demand for a given flight leg or forecast demand for each origin-destination. The latter type of forecasting is instrumental when the optimizer is geared towards controlling inventory on a network level, as opposed to a leg level. A key difference between the two types of forecasts is the volume of data in path forecasting since the number of possible itineraries are orders of magnitude greater more than the number of flight legs. Essentially, if the RM system is leg-based, it will use leg-based forecasts; if network-based RM, use path forecasting. As we will see later, there are some adjustments and assumptions that can be made on the network level to simplify the amount of data needed. Implications for network vs. leg RM are discussed in Section 2.5.3.

Secondly, the forecaster may choose between the assumption of class independence or not. Assuming class independence implies that passengers from Class X have no desire to book in any other class. In fully restricted fare structures, this is a reasonable assumption, since passengers are enticed into specific fare classes based on their sensitivity levels to disutility costs and price. In semi-restricted fare structures, as alluded to previously, this assumption crumbles: since fewer restrictions are in place, higher class passengers have the opportunity and ability to buy-down to lower classes. Conversely to the airline’s benefit, lower class passengers may *sell up* to higher fare classes if their requested class is closed. A discussion of so-called *pickup or standard* forecasting versus *hybrid forecasting and fare adjustment* follows this section.

We summarize the models of forecasting that we will be using in our experiments. They are:

- Standard Forecasting, which can be used for both leg based and network based RM optimizers.
- Hybrid Forecasting, which is used solely for network based RM optimizers.

2.4.1 Standard Forecasting (Pickup)

Pick-up forecasting involves an airline forecasting *bookings-to-come (BTC)* for the remaining booking period on a flight at each reference point or *data collection point (DCP)* on the booking curve. In order to forecast bookings-to-come, pick-up forecasting averages with historically recorded bookings-to-come of previous departures. An example is given below in Figure 2.8.

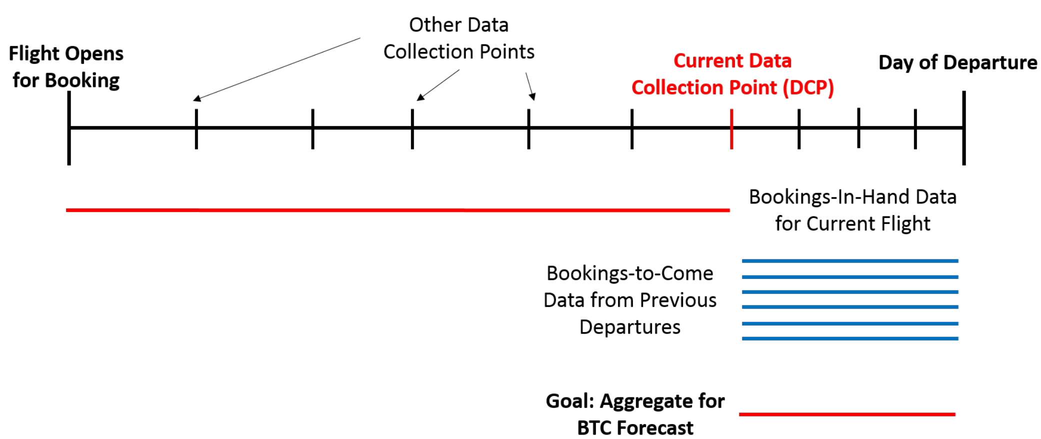


Figure 2.8: Conceptual Example of Pickup Forecasting

BTC are aggregated for each class on a given leg, and then fed into the optimizer as class demand. Pickup forecasting can be done on a leg level or on an itinerary level. Pickup forecasting *does not* take into account inter-class effects of buy-down or sell-up. Since pickup forecasting is used frequently in industry, it is the baseline forecaster for experiments in this thesis, and is called *standard forecasting.* A more detailed explanation and example may be found in [16].

2.4.2 Q- and Hybrid Forecasting

As mentioned before, with the influx of semi-restricted fare structures, passengers have more leeway to buy or demand multiple fare classes, making the assumption of independent demand in pickup forecasting unreasonable. Since, rationally, a passenger will always tend to buy a lower class ticket if the disutility costs are lower, the risk of buy-down and diversion in semi-restricted fare structures becomes more prevalent. Unfortunately, this affects the forecaster through a process called spiral-down. The forecaster sees more lower class bookings (from higher class passengers buying down) and misinterprets that as increased demand for the lower class, which causes the optimizer to protect fewer seats for higher classes, leading to even more bookings in the lower classes.

To solve this issue, Belobaba and Hopperstad developed *Q-Forecasting* [8], which attempts to evaluate the potential for passengers to sell-up in a fully undifferentiated fare structure, where price-sensitivity is the only common denominator. The process is as follows (also see Figure 2.9):

1. For each class, calculate the equivalent number of Q-bookings (lowest class bookings) based on input models of sell-up. For example, if there is 1 passenger demanding a seat in Class 3, and the probability of a Class 6 Q passenger selling up to Class 3 is 25%, then we say that there is $1/0.25 = 4$ Q-equivalent passengers from Class 3.
2. Aggregate Q-equivalent passengers from all classes, to obtain Q_{TOTAL}.
3. Then, based on differences in sell-up potential between classes, calculate the number of Q-equivalent passengers that are allocated into each class. For example, if only 10% would sell up to Class 2, then the demand that should be allocated to Class 3 should be 25% - 10% = 15% * Q_{TOTAL}.

Fare Class	Mean Demand	Probability of Class 6 Selling Up to Class X	Equivalent Q Bookings		Final Adjusted Forecast Value	
1	**0**	2.50%	=0/0.025	0	=29.375*(0.025-0)	**0.73**
2	**0**	10%	=0/0.10	0	=29.375*(0.10-0.025)	**2.20**
3	**1**	25%	=1/0.25	4	=29.375*(0.25-0.10)	**4.41**
4	**3**	50%	=3/0.50	6	=29.375*(0.50-0.25)	**7.34**
5	**7.5**	80%	=7.5/0.80	9.375	=29.375*(0.80-0.50)	**8.81**
6	**10**	100%	=10/1.00	10	=29.375*(1.00-0.80)	**5.88**
Total			***Q_TOT***	***29.375***		

Figure 2.9: Q-Forecasting Calculation

Notice the differences between original mean demand (left, red column) for each class compared to the final forecasted value for each class (right, green column). The demand has been reduced for Class 6 and increased for all the other classes, to account for the dual forces of buy-down from Classes 1-5 and sell-up from Class 6. However, Q-forecasting works specifically for price-sensitive passengers in an undifferentiated fare structure. *Hybrid forecasting* simply applies Q-forecasting for those price-sensitive passengers while applying traditional forecasting models to passengers who can be safely assumed to be product-oriented if the differences between products is great enough.

2.4.3 Fare Adjustment

Hybrid forecasting is usually used in combination with *fare adjustment*, an advanced RM optimization technique that modifies input revenues for each class based on projections of price-oriented passengers buying down. A full explanation is given by Fiig in [15], but a simple explanation and example are presented below.

In our example, the demands for each class are assumed deterministic. In a fully differentiated fare structure (see Figure 2.10, they are also assumed to be independent, so there is no risk of buy down. For each class, the fares and demands are given. Each subsequent column then gives the effect of opening Class X. For example, opening Class 1 would give an additional $1,200*30 = $36,000. The marginal revenue is obtained by dividing the incremental revenue gained from opening a class by the incremental number of passengers that will book. For this case, the marginal revenue is equal to input fare value. The total revenue for this flight is $87,000.

Fare Class	Fare	Demand	Open Class 1	Open Class 2	Open Class 3	Open Class 4	Open Class 5	Open Class 6	Total with Class 6 Open
1	$1,200	30	$36,000						$36,000
2	$1,000	10		$10,000		No losses due to buy-down.			$10,000
3	$800	15			$12,000				$12,000
4	$600	20				$12,000			$12,000
5	$400	25		Classes aren't open yet.			$10,000		$10,000
6	$200	35						$7,000	$7,000
Total Revenue			**$36,000**	**$10,000**	**$12,000**	**$12,000**	**$10,000**	**$7,000**	**$87,000**
Marginal Revenue			*$1,200*	*$1,000*	*$800*	*$600*	*$400*	*$200*	

Figure 2.10: Fully Differentiated Fares and Revenue

However, in a fully *undifferentiated* fare structure (Figure 2.11), demands are not independent by class; rather, since there is no product differentiation, all demand will buy down to the lowest available class. For example, in the column "Open Class 2", Class 2 is open, so it sees 30+10

Fare Class	Fare	Demand	Open Class 1	Open Class 2	Open Class 3	Open Class 4	Open Class 5	Open Class 6	Total with Class 6 Open
1	$1,200	**30**	$36,000	-$6,000	-$6,000	-$6,000	-$6,000	-$6,000	$6,000
2	$1,000	**10**		$10,000	-$2,000	-$2,000	-$2,000	-$2,000	$2,000
3	$800	**15**			$12,000	-$3,000	-$3,000	-$3,000	$3,000
4	$600	**20**				$12,000	-$4,000	-$4,000	$4,000
5	$400	**25**			Classes aren't open yet.		$10,000	-$5,000	$5,000
6	$200	**35**						$7,000	$7,000
Total Revenue			**$36,000**	**$4,000**	**$4,000**	**$1,000**	**($5,000)**	**($13,000)**	**$27,000**
Marginal Revenue			*$1,200*	*$400*	*$267*	*$50*	*($200)*	*($371)*	

Figure 2.11: Fully Undifferentiated Fares and Revenue

= 40 bookings from forecasted Class 1 and Class 2 demand. The revenue gained from Class 2 is 10*$1000 = $10,000. The revenue lost from Class 1 buying down to Class 2 is 30*$1000 - 30*$1200 = -$6,000. The marginal revenue per passenger, therefore, from booking 10 additional passengers is $10000 - $6000 = $4000/10 = $400. Correspondingly, the effects of opening the next four classes are calculated. The overall revenue in this case drops by $60,000 to $27,000.

We see that the effects of buy-down are hugely significant in an undifferentiated fare structure. From this table, additionally, we can also see the point where it becomes undesirable to open any more classes – namely, when the first four classes are open. We see that opening Class 5 gives a marginal revenue of -$200 per passenger, so at this point it would not be beneficial to open any more seats.

When fare adjustment is turned on for an RM system, the fare values used in the optimizer for each class are modified to account for buy-down (see Figure 2.12), specifically by using the marginal revenues calculated for each fare class. In the semi-restricted fare structures that are used in this thesis, the adjusted fare values are incorporated for price-sensitive demand only, and calculated in combination with product-oriented demand.

The adjusted fare values are utilized in the optimizer's calculation of booking class limits instead of the normal class fare. By using fare adjustment and hybrid or Q-forecasting, the airline can use optimizers for semi-restricted and unrestricted fare structures without worrying about the optimizer not accounting for buy-down and opening too many lower class seats, leading to spiral-

Fare Class	Fare	Adjusted Fare
1	$1,200	$1,200
2	$1,000	$400
3	$800	$267
4	$600	$50
5	$400	-$200
6	$200	-$371

Figure 2.12: Adjusted Fare Values

down. Essentially, fare adjustment values lower classes by taking into account the potential for buy-down. Hybrid forecasting with fare adjustment is used in combination as a forecasting scheme in our later experiments.

2.5 The Optimizer

The optimizer takes forecasted demand data and combines that with revenue data in order to calculate booking limits at each data collection point. As alluded to before, there are two main types of optimizers: those that optimize based on flight leg level forecasts and demand and those that optimize on a network level, based on forecasted demand for itineraries. In this section, we first present the EMSRb heuristic by Belobaba (more information in [3] which was originally applied for leg RM. Then, we present two network level RM schemes that we will use in our thesis, which build on the principles of EMSRb on a broader scale. The three optimizer schemes we will use in our experiments are as follows:

1. Leg-Based Fare Class Yield Management (FCYM) – EMSRb
2. Network-Based Displacement Adjusted Virtual Nesting (DAVN)
3. Network-Based Probabilistic Bid Price Control (ProBP)

2.5.1 Expected Marginal Seat Revenue (EMSRb) Heuristic for FCYM

Expected marginal seat revenue (EMSRb) takes as inputs the mean and variance of normally distributed demands as well as revenue values for each class and outputs booking class limits. The key assumption made by EMSRb is class independence, so in order to use EMSRb in semi-restricted fare structures effectively, we need to employ hybrid forecasting and fare adjustment.

Booking limits for EMSRb are determined by measuring the marginal seat value of a given class if the booking limit was increased by one seat. Given a normal distribution, the expected value is the probability of an additional passenger arriving multiplied by the fare value for that class. For example, if the mean demand of Class 1 is 5 and the fare is $1000, then the EMSR of passenger #5 is 50%*$1000 or $500. The probability of the n^{th} passenger arriving can be calculated and looked up with a *z-score*.

In Figure 2.13 (left), we calculate the z-scores for each Class 1 passenger, assuming a mean of 5 and standard deviation of 2. We then look up the corresponding probability of arrival, $1 - CDF$, and multiply by the fare, obtaining EMSR values for each passenger in Class 1. For subsequent classes, the calculation is slightly more complicated because demand needs to be aggregated in order to generate protection levels against the bottom classes. For example, we protect the combined inventory of Class 1 and Class 2 from Class 3. We protect the combined inventory of Classes 1-3 against Class 4. Though this aggregation is not presented here, in Figure 2.13 (right), we plot EMSR curves for Classes 1 through 3. The optimal number of seats to protect for a particular class against lower classes occurs at the intersection of the curves, circled in red.

Passenger #	Z Score	Probability of Arrival	EMSR
1	-2.0	98%	$977
2	-1.5	93%	$933
3	-1.0	84%	$841
4	-0.5	69%	$691
5	0.0	50%	$500
6	0.5	31%	$309
7	1.0	16%	$159
8	1.5	7%	$67
9	2.0	2%	$23
10	2.5	1%	$6

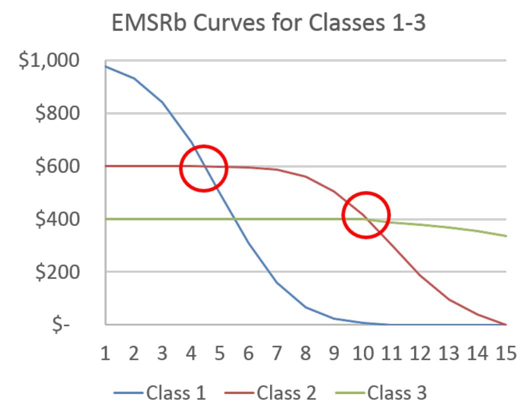


Figure 2.13: [Left] EMSR Calculations for Class 1 [Right] EMSR Curves for Classes 1-3

Protection levels at each class are joint protection levels – that is, the number of seats reserved at Class 2 can be booked by Class 1 as well, making this a top-down approach. Therefore, we see in Figure 2.14, although the mean demand for L class exceeds the booking limit, it is constrained by the physical capacity of the aircraft: 135.

On the leg level, applying EMSRb is known as fare class yield management (FCYM); although in this thesis due to its widespread use, we refer to this as our *standard baseline leg EMSRb* case.

CABIN CAPACITY =		135				
AVAILABLE SEATS =		135				
BOOKING CLASS	AVERAGE FARE	SEATS BOOKED	FORECAST DEMAND MEAN	SIGMA	JOINT PROTECT	BOOKING LIMIT
Y	$ 670	0	12	7	6	135
M	$ 550	0	17	8	23	129
B	$ 420	0	10	6	37	112
V	$ 310	0	22	9	62	98
Q	$ 220	0	27	10	95	73
L	$ 140	0	47	14		40
	SUM	0	135			

Figure 2.14: Sample Spreadsheet of Classes with Joint Protection Levels [7]

2.5.2 Network Value and Displacement Costs

There are issues when the airline's network includes a large number of connecting passengers, as the case when an airline operates a hub-and-spoke network. There are two main issues that arise:

1. **Booking classes are not of equal value across different itineraries**

   Consider the following: Sally wishes to book a Class 3 ticket worth $300 from BOS-ATL-MIA. In order to do so, there needs to be availability for Class 3 on both BOS-ATL and ATL-MIA legs. However, if the RM system is managing the ATL-MIA leg, there might be a local Class 3 fare that is only worth $200. For this reason, a simple leg RM system cannot apply EMSR calculations by grouping classes of equal value, since Class 3 values in this case are different for different itineraries.

2. **Connecting passengers occupy multiple seats on their itineraries, displacing local passengers**

   Additionally, if Sally successfully receives availability for BOS-ATL-MIA, she pays $300. But is she worth $300 to the airline? Potentially not, because she occupies two seats on this itinerary, and might displace a local BOS-ATL passenger and a local ATL-MIA passenger. For this reason, we need to account for *displacement costs* that are to be deducted from her fare when we evaluate the availability.

The following two sections present two network RM optimizer schemes that solve the two network problems in different ways.

2.5.3 Displacement Adjusted Virtual Nesting (DAVN)

Displacement Adjusted Virtual Nesting (DAVN) employs the following process to deal with the two problems (a more detailed description can be found in [17]):

1. For each itinerary, take the mean demand forecast of each path and set up a deterministic linear program with capacities of flights as constraints and fare values.
2. Solve the network optimization problem, and obtain shadow prices for each flight leg, which correspond to displacement costs for each leg.
3. When managing a specific leg, subtract the displacement costs of all other legs for connecting itineraries.
4. Organize the itineraries into similar value ranges called *virtual buckets* and disregard any previous notions of classes.
5. Apply EMSR calculations to these virtual buckets with aggregated demand forecasts to obtain protection limits.

Figure 2.15 shows an example of Sally attempting to book the BOS-ATL-MIA itinerary. The fare she is paying is \$300, but it needs to be adjusted to account for displacement costs (which are calculated in the LP). The *displacement adjusted* fare is now \$300 - \$185 = \$115. Now, to organize all the itinerary fares into similar values, the BOS-ATL leg is composed of 8 virtual buckets that have different value ranges. Sally's itinerary falls into Bucket 7, which is closed at this point (due to an EMSR calculation).

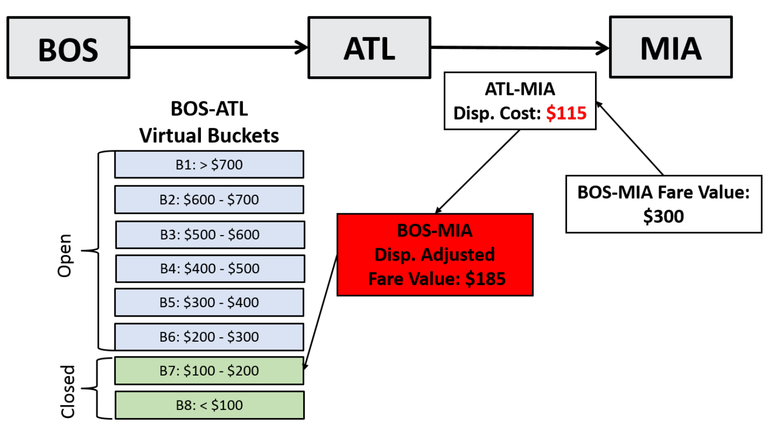


Figure 2.15: Optimizer Process for Displacement Adjusted Virtual Nesting (DAVN)

2.5.4 Probabilistic Bid Price Control (ProBP)

Probabilistic bid price control (ProBP) employs the following process (a more detailed description can be found in [10]:

1. For each leg, calculate EMSR values for *all* possible classes in all possible itineraries on a particular leg, at first without adjusting for displacement cost.
2. Find the opportunity cost (marginal revenue of the last seat on the leg) and set as the displacement cost.
3. Prorate the highest fares on the first iteration by the relative displacement costs across multiple legs, and find the new opportunity cost.
4. Continue until convergence – this is the *bid price* for each leg.
5. If the fare value is worth more than the sum of the bid prices across all legs, accept the booking; otherwise, reject it.

Figure 2.16 shows the control mechanism for ProBP. In order to book an itinerary (BOS-ATL-MIA) over two legs, the fare value needs to be compared with the bid prices of both legs. Since the additive bid price ($115 + $200 = $315) is more than the posted fare value – $300, for example – the request is rejected.

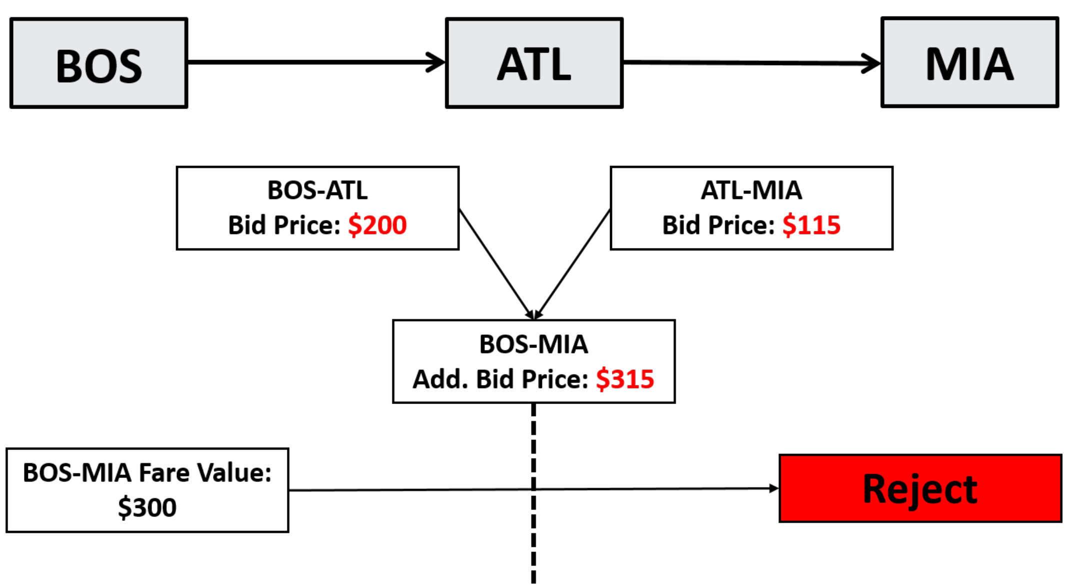


Figure 2.16: Optimizer Process for Probabilistic Bid Price (ProBP)

2.5.5 Summary

In the experiments, we test scenarios with variations on: (1) fully restricted and semi-restricted fare structures; (2) standard and hybrid forecasting (with fare adjustment) on generating leg and path forecasts; and (3) standard leg-based EMSRb (FCYM), displacement adjusted virtual nesting (DAVN), and probabilistic bid price (ProBP).

In this thesis, we test the incorporation of ancillary revenue into RM systems as well as in the availability decision process for DAVN and ProBP, studying revenue impacts under different scenarios which model the competitive environment and airline RM systems. In Chapter 3, we examine ancillary revenue in the context of overall goals of revenue management: maximization of revenue for a flight or a network. We explore the interface between RM systems and distribution from the airline side as well as the purchasing decision process from the passenger side. We then highlight the importance of ancillary revenue within these processes and outline different methods to optimize for ancillary revenue within the entire airline-passenger system.

3 Adding Ancillary Revenue into Revenue Management

3.1 Introduction

The common goal of RM systems is to retrieve as much **ticket** revenue possible from a mix of potential customers for an airline. For the past thirty years, revenue management systems have grown increasingly sophisticated, as explained in Chapter 2. Newer RM systems optimize revenue on a network level, solving problems dealing with network value and displacement costs. They incorporate class dependence and buy down with better models of passenger behavior in terms of sell up. However, so far there has been little work done on optimizing ancillary revenue **and** ticket revenue from the mix of potential customers for an airline. With the growing importance of ancillary revenues, as detailed in Chapter 1, it is logical that the next step in revenue management would be to consider these ancillary revenues (specifically from passenger add-ons) in addition to optimizing ticket revenue alone.

The goal of revenue management is to maximize revenues, given a schedule of flights, available capacity, and competitive fare structure, factors determined by other airline functions distinctly separate from RM. For example, consider two passengers: A, a frequent flyer with a high willingness to pay who makes his bookings close to departure, and passenger B, a college student with a low willingness to pay who books through an online travel agency very early for his vacation. The RM system considers both the base ticket fare as well as the probability of a passenger booking when calculating expected value; seats are protected in anticipation of the later booking passenger A who books in Class 1 if the expected value for A is greater than that of B. Assume that the expected value for A is, in fact, greater than that of B when considering the ticket fare only. This is shown in the first line of Figure 3.1.

Product	Class 1 Passenger A	Class 6 Passenger B
Base Ticket Fare	\$500	\$300
Checked Bag	Included	\$30
Priority Boarding	Included	\$15
Extra Legroom	Included	\$30
Onboard Food	Included	\$10
Total Revenue	**\$500**	**\$385**

Figure 3.1: Example of Revenue Data from Passenger A vs. Passenger B

To date, however, this prioritization and calculation of expected value has been based on ticket revenues only. Assume that booking a Class 1 ticket includes complimentary amenities – in other words, the fare includes not only the transportation from origin to destination, but also a checked bag, priority boarding, extra legroom, and onboard food. In this case, the $500 that Passenger A pays for a Class 1 ticket represents his willingness to pay for not only the base ticket, **but also the extra amenities** associated with a bundled product. On the other hand, Passenger B pays $300 for a Class 6 ticket, which only represents his willingness to pay for **the base transportation service** alone. Given this discrepancy, after the initial booking Passenger B may choose to purchase a checked bag for $30, priority boarding for $15, extra legroom for $30, and food onboard for $10. This increases the total revenue collected by the airline for Passenger B to $385.

When the airline RM system optimizes with $500 and $300 as inputs, the comparison is unequal because the figures represent the willingness to pay for different products. In fact, after the airline uses these inputs to calculate expected revenues and generate availability, Passenger B contributes additional revenue through purchase of ancillary services. To make a better decision in terms of overall revenue performance, the total revenue potential of passengers which includes both ticket revenue and ancillary revenue needs to be considered.

However, in order to make the better decision and incorporate ancillary revenues, the airline first needs a good estimate of the ancillary revenue potential of passenger B before he makes his booking request. After the airline has an estimate, the RM system can then adjust fares to account for both ticket revenue and ancillary revenue when it calculates availability.

In this chapter, we:

- Discuss the problem of incorporating ancillary revenue potential with respect to the current overall decision process of the passenger and the airline. Because the RM optimizer calculates booking limits and sends seat availability to distribution systems before the passenger makes a decision to purchase ancillary products, there are challenges to estimating the level of ancillary revenue potential for passengers before they even purchase their tickets.
- Consider the challenge on the airline side of estimating ancillary revenue potential in order to incorporate into RM systems. Depending on the level of detail in the available data, the airline has many different possibilities for estimating ancillary revenue. In this thesis, we will assume two alternatives in airline estimations for ancillary revenue: (1) on a class level and (2) on an individual passenger level.

- Present three alternatives for incorporating ancillary revenue into revenue management: **(1) RM Input Fare Adjustment:** directly augment RM input fares that feed into the optimizer, which changes booking limits before they reach the customer; **(2) Availability Fare Adjustment:** bypass the RM optimizer and override booking limits before they are presented to the customer; and **(3) Customized Availability Adjustment**: bypass the RM optimizer and dynamically generate availability based on the ancillary revenue potential of each individual customer.

3.2 Interface of the Passenger Decision Process with Distribution

Airline revenue management systems interface with passengers via distribution systems in a cause-effect relationship loop. This feedback loop, which is illustrated in Figure 3.2, is detailed below.

- Airlines first upload their calculated booking limits into *global distribution systems (GDS)*, which are databases that aggregate path availability. Possible paths are itineraries for a given origin and destination which might consistent of different connections. Depending on the desired origin and destination for passengers, the GDS queries its database and delivers potential, available itineraries to the customer.
- Passengers who choose to book a ticket have their information collected by the airline, including their booking class, fare, and path.
- The airline RM system then uses these data as an expectation of passenger revenue for each market. In combination with demand detruncation and forecasting, the RM system can then calculate booking limits.

As discussed in Section 1, the competitive environment has moved in a way that allows airlines to sell add-ons to passengers before, during, or even after the actual flight. In Figure 3.3, examples of add-ons are illustrated in the context of the RM/passenger decision process interface. The primary implication is the timing of ancillary revenue: airlines collect ticket revenue first and then collect ancillary revenue later.

In order to incorporate ancillary revenue into RM effectively, a major issue for the airline is that it has to predict the ancillary revenue potential for passengers before they purchase the ticket. Although airlines collect aggregate revenue data on sources like baggage fees or revenue from priority boarding, these data are usually not tied to passenger itineraries or fare classes. Booking limits are currently calculated based on ticket data only and are independent of any ancillary purchases, which can occur during and after the time of booking. In order to

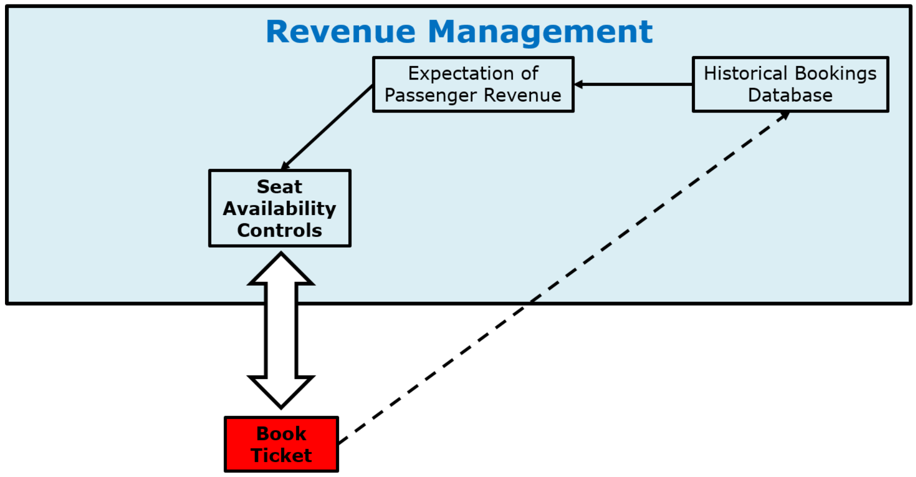


Figure 3.2: Feedback Loop and Interface of RM/Distribution with Passengers

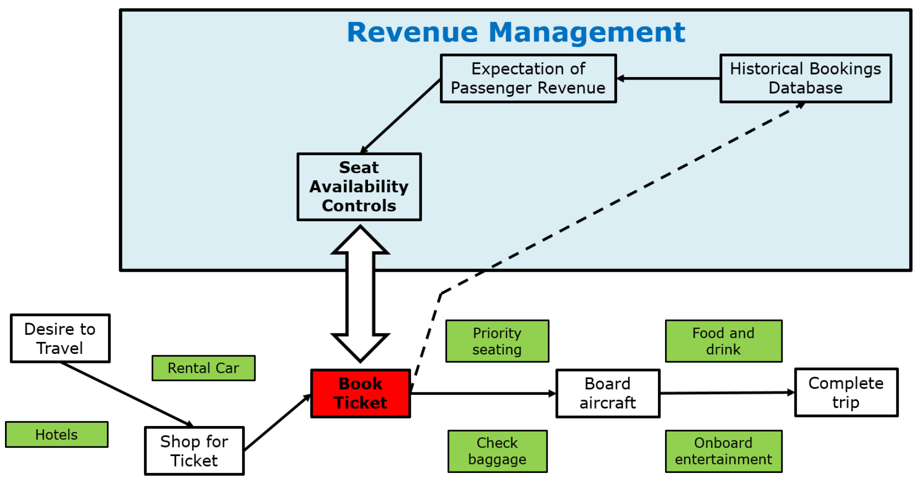


Figure 3.3: Multiple Points of Opportunity to Market Ancillary Products

incorporate ancillary revenue into calculations of booking class limits, it is imperative that there is the right level of detail within the data in order to estimate the level of ancillary revenue for passengers.

3.3 Different Airline Approaches to Estimating Ancillary Revenue Potential

In order to apply knowledge of ancillary revenue potential in their RM and distribution systems, airlines need to first estimate the spending behavior of their customers. In order to do this, the airline:

1. Identifies possible variables that affect ancillary revenue potential. For example, one hypothesis is that passengers flying on domestic long-haul flights are more likely to purchase food, because they get hungry. However, passengers on international flights do not, because complimentary meals are provided.

2. Collects data. The level of detail available in the data determines the level of predictive power that the model can estimate. For example, in order to model class level behavior – i.e. make assumptions about ancillary revenue potential by booking class – class level ancillary revenue data needs to be collected. In the extreme case, to model ancillary revenue potential by each individual passenger, passenger itineraries need to be tied with add-on revenue data.

3. Statistically analyzes the data. Given the required level of data, inferences are made that reaffirm or disprove the hypothesis.

4. Apply the inference to the RM and distribution system.

In this thesis, we explore the application to RM and distribution systems, assuming that the airline has already performed the necessary preceding steps. Although there are many ways to model ancillary revenue potential, we list a few possibilities in Figure 3.4.
Note that moving down the chart represents an increased level of granularity, or how detailed the airline's approach is in estimating ancillary revenue. Increasing the level of granularity increases the predictive power of the model in terms of capturing variability by passenger. For example, a "one-size-fits-all" approach such as estimating $30 for the entire month of June for all passengers in all fare classes – estimating by aggregate metrics – does not account for differences by market or region. Estimating differences in markets would account for those trends, but is not sufficient in estimating ancillary revenue for each passenger within that market. The more detail in the data, the more the airline can fine-tune its RM system or availability calculations to account for differences in ancillary revenue.

Although it is desirable for the airline to estimate ancillary revenue with the most detailed level of granularity as possible, the cost of acquiring and processing the data increases as well. For example, it is relatively easy to model aggregate levels of ancillary revenue potential by airline and year, given that these metrics are already reported to the Department of Transportation. Given (from Chapter 1) that about 7% of operating revenue is derived from ancillary revenue, the airline could simply apply a 7% multiplier to all ticket fares in its RM system. Even though this data is readily available, it has little use in terms of RM and distribution because it does not account for real world variability in ancillary revenue in markets or passengers.

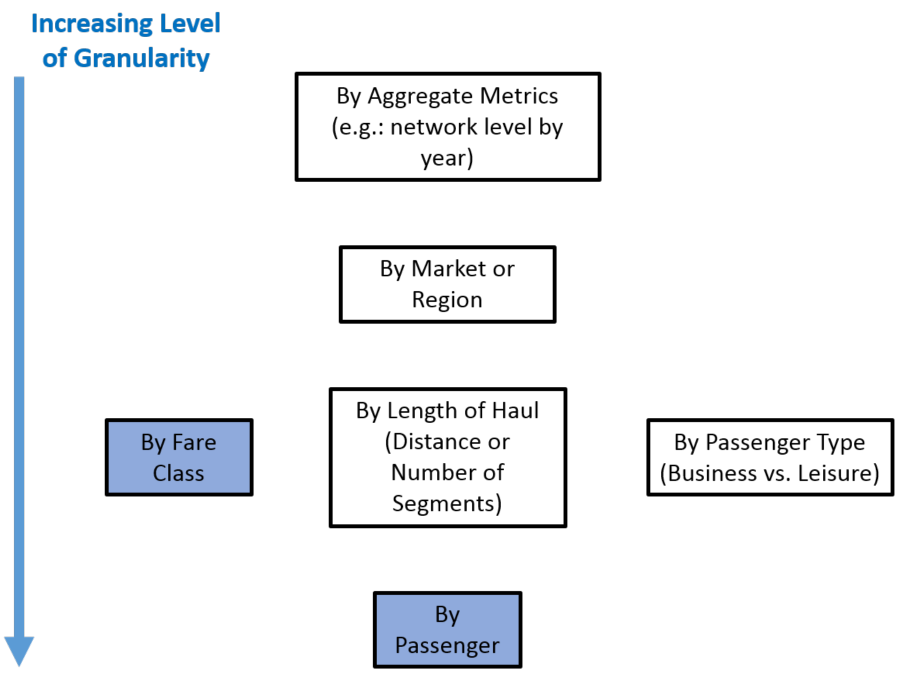


Figure 3.4: Different Ways to Model Ancillary Revenue Potential

In this thesis, we evaluate scenarios in which different levels of ancillary revenue potential are known on either a passenger level basis or a class/market level basis (highlighted in blue in Figure 3.4).

3.3.1 Class and Market Level Estimation of Ancillary Revenue Potential

Ancillary revenue potential can be estimated as a function of market as well as booking class. Airlines may estimate different levels of ancillary revenue potential by market. For example, if it believes that passengers who travel in markets to leisure destinations are more likely to check a bag, the airline may estimate on average a higher ancillary revenue potential for all leisure destinations. If longer haul passengers are more likely to purchase food and drink, a larger estimate of ancillary revenue potential might be assumed for markets with longer physical distances.

Additionally, airlines may estimate ancillary revenue potential as a function of booking class. An airline may offer a checked bag to passengers who purchase a Class 1 or Class 2 ticket. Priority boarding may be complimentary for a Class 1, 2, or 3 ticket. Because of these possibilities, airlines may already have some knowledge of the ancillary revenue potential by class and is able to account for the differences by class.

Assuming that the airline has adequate data and calculates the necessary parameters to estimate ancillary revenue potential, multipliers can be applied to the ticket fare to obtain an adjusted fare. This adjusted fare, instead of the original ticket fare, is then used as the fare value as an input to the RM system.

Class	Ticket Fare	Estimated Ancillary Revenue	Adjusted Fare
1	$ 400	$ 15	$ 415
2	$ 350	$ 15	$ 365
3	$ 300	$ 25	$ 325
4	$ 200	$ 25	$ 225
5	$ 150	$ 25	$ 175
6	$ 100	$ 25	$ 125

Figure 3.5: Estimate of $25 Ancillary Revenue on Class 6 BOS-SEA

Under this assumption, the airline has expected of ancillary revenue by each fare class. Figure 4.6, for example, shows the fare structure for a hypothetical Boston to Seattle market. For instance, note that the ticket fare value is given as $100 for Class 6. Assuming that the airline estimates $25 in expected ancillary revenue per passenger on Class 6, the RM fare value for this class is modified to be $125. This new value can then used for RM calculations, which has implications on availability as seen in later sections. It is important to note at the class level of implementation, there are no assumptions of ancillary revenue by individual passenger. Any bookings in the same class and the same market are given the same ancillary revenue value.

Obtaining knowledge about ancillary revenue behavior by fare class within each market is more complicated than the aggregate approach. These estimates require the airline to collect ancillary revenues by each market and fare class, which may be complicated given the plethora of add-on options available to passengers in general. Each of the options require tabulation to effectively aggregate on a market and fare class level. For example, food and drink are sold on board the aircraft, but a single flight leg serves passengers from many markets, making it difficult to connect purchases with specific markets, not to mention fare classes within those markets. Similarly, for example, purchasing decisions made at the gate to upgrade to first class or to purchase priority boarding are also difficult to tabulate because they are related to the operation of a flight leg, rather than amenities to a market. In this thesis, we assume that the airline has performed all the necessary preceding steps to be able to estimate ancillary revenue potential.

3.3.2 Passenger Level Estimation of Ancillary Revenue Potential

At the other extreme, the airline may have the capability to estimate different levels of ancillary revenue potential by individual passenger. Given two otherwise identical passengers with the same itinerary, day and time of travel, and booking class, each may have a different spending potential for add-ons due to their underlying characteristics, which, of course, can vary greatly. For example, consider Passenger A, a business traveler. Because he travels a lot, he saves money by packing efficiently and lightly with a carry-on bag only, avoiding checked baggage fees. He, however, purchases lunch on board the aircraft every time he flies. If the airline tracks his purchases via credit card and discovers that he habitually makes the same purchases, then the airline has a pretty good estimate of his ancillary revenue potential every time he flies.

Given that the airline has a good estimate of ancillary revenue potential, it can modify its fare values that are used in the optimizer and availability calculations on a passenger case by case basis. If the airline knows that Passenger A pays on more ancillary revenue potential than other passengers on average within his market and booking class, the airline can prioritize a seat for him specifically. Instead of assuming the same value of ancillary revenue for all bookings within the same class, as in class level estimation, the airline can adjust availability depending on knowledge of individual passenger spending behavior.

However, this level of granularity in estimation is even more difficult than class level estimates on a market level since ancillary revenue potential needs to be estimated by each individual passenger. For passenger level estimation of ancillary revenue, the airline requires certain methods to track its customers, like tying purchases to passenger name records, credit cards, or frequent flyer accounts. It could do so, for example, by streamlining its databases to connect transactions or offering incentives to customers who log in to their accounts before purchasing. However, given that these tasks are very data intensive, they require extreme coordination on the part of the IT system to tie passenger name records to purchases in order to ensure data accuracy.

Airlines having this level of knowledge is only assumed as a theoretical example. Although this assumption might not be realistic, testing this assumption can provide an indication of the maximum value of the adjustment approaches an airline might implement into its RM and distribution systems. Having good estimates of individual ancillary revenue potential is ideal when calculating availability because the airline can take advantage of the variability in revenue for each passenger.

3.4 Using Adjusted Fares Into RM and Distribution

In either the class level or passenger level ancillary revenue estimate cases, the airline applies its knowledge of ancillary revenue potential to modify the fares that feed into the RM system or the distribution system. There are two fares of interest: fares that are fed directly into the RM optimizer, or **RM Input Fares**, and fares that are used for availability evaluation, or **Availability Fares**.

To understand where these fares come into play, we examine in detail the interface between the RM optimizer and availability calculations for three RM optimizers: FCYM, DAVN, and ProBP. These RM optimizers were described in Chapter 2.

For FCYM, the optimizer:

- Takes **RM input fares** by class and by flight leg as well as forecasts by class and by leg as data inputs.
- Calculates the expected marginal seat revenues from accepting incremental passengers for each class on each flight leg.
- Constrains the real-time availability based on the capacity of the aircraft for paths that span across legs. Availability is determined based on the separate evaluations of each booking leg – in other words, the same class has to be available on both legs in a connecting itinerary.

For DAVN:

- The optimizer takes **RM input fares** and forecasts by class and path and calculates displacement costs for each flight leg using the inputs and other constraints.
- Then, the **availability fare** of each possible market and class is adjusted to account for displacement cost.
- For each leg, relevant markets that span the leg are organized into similar revenue categories, or virtual buckets.
- EMSR is applied to determine bucket availability for that leg.

- The availability of a given class for a certain market depends on if its classes on every leg fall into open buckets.

For ProBP:

- The optimizer takes **RM input fares** and forecasts by class and path and calculates bid prices for each flight leg using the inputs and other constraints.
- For each path, the additive bid price of the flight legs required within that itinerary is determined.
- The availability of a given class for a certain path depends on if the **availability fare** of that class is more than the sum of the bid prices.

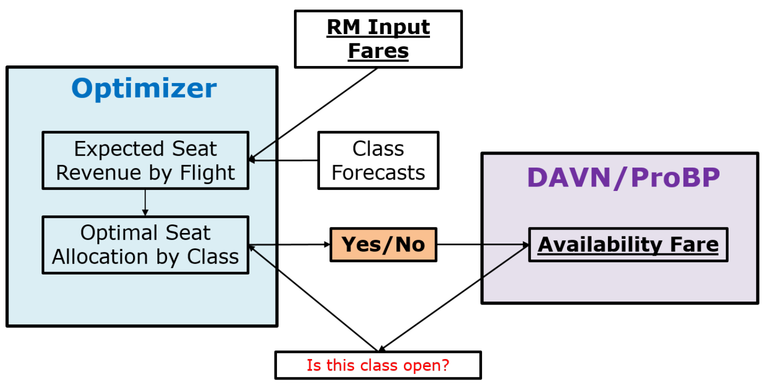


Figure 3.6: Generalized RM and Availability Process

In FCYM, fares are only used as RM input fares to the optimizer. Because there is no intermediate step for determining network effects in FCYM, there are no availability fares. Given the processes of these three RM systems, RM Input Adjustment can be applied to account for ancillary revenue in all three optimizers. However, Availability Fare Adjustment can only be applied for DAVN and ProBP. A generalized process flow is summarized in Figure 3.6.

3.4.1 RM Input Adjustment

In RM Input Fare Adjustment, both the RM input fare and the availability fare (when available) are modified, as in Figure 3.7. Because the input fares to the optimizer are modified to account for ancillary revenue potential, this fundamentally changes the booking class limits that the optimizer calculates.

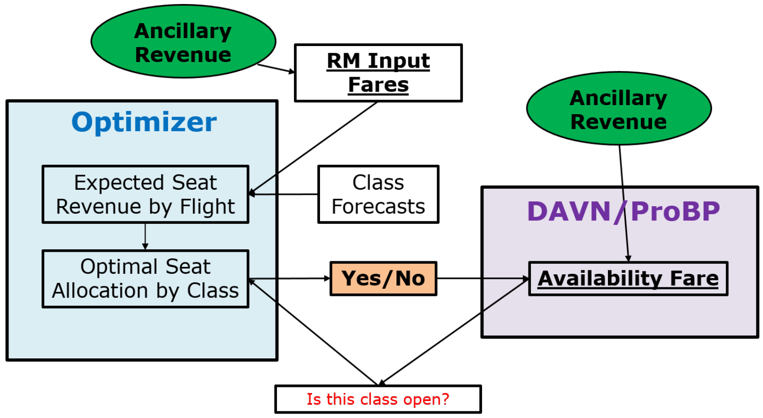


Figure 3.7: RM Input Fare Adjustment

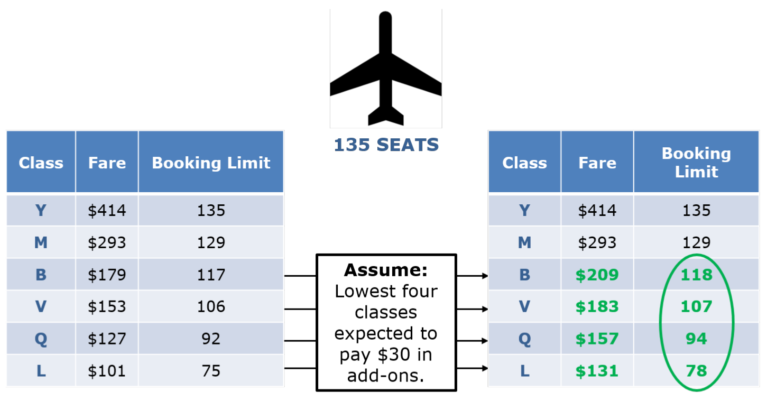


Figure 3.8: Adjusting RM Input Fares Alters Booking Limits

In the case of leg-based EMSRb (FCYM) for example, depending on which classes are assumed to have extra ancillary revenue potential, the booking limits may change. In Figure 3.8, we present sample booking class calculations if an extra ancillary revenue potential of $30 is assumed for the lowest four classes on a 135 seat aircraft. Because the four lowest classes are valued more, the relative fare ratios between the classes change, altering the EMSR calculations, leading to more availability for the lowest classes.

For DAVN and ProBP, altering the fare inputs also causes a shift in the calculation of displacement costs (DAVN) and bid prices (ProBP), which affect availability in slightly different ways. In DAVN, modifying the input fares causes a change in the linear program used to calculated displacement costs. Since input fares are adjusted positively, displacement costs rise. Additionally, modified input fares cause some itineraries to be placed into different buckets. In ProBP, modifying the input fares causes a change in the convergence algorithm used to calculate the bid prices for each leg. Consequently, bid prices rise. However, since the availability fare is also modified, lower class itineraries still see increased availability.

3.4.2 Availability Fare Adjustment

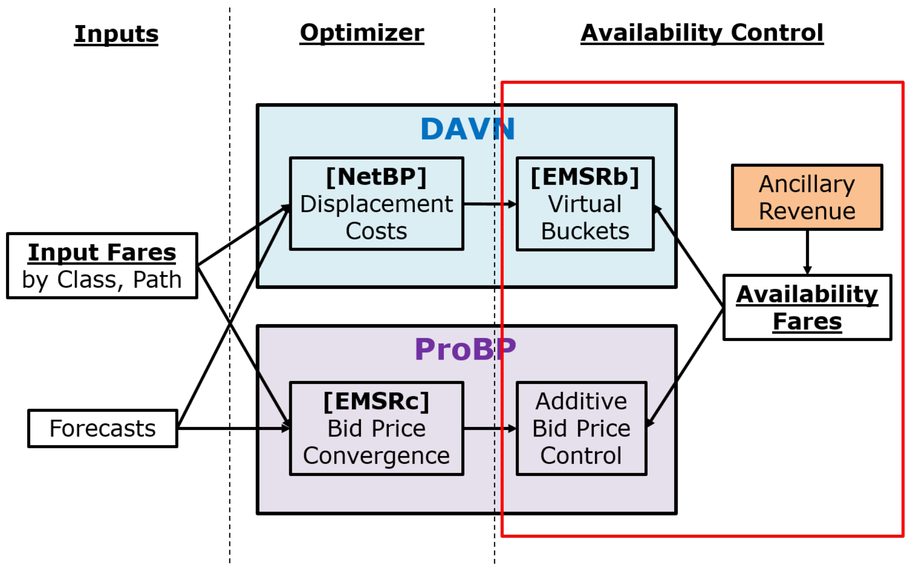


Figure 3.9: Availability Fare Adjustment in DAVN and ProBP

Availability Fare Adjustment can be implemented with network RM schemes like DAVN or ProBP optimization because availability fares are defined for network RM. In DAVN, availability fares are associated with different buckets grouped by value. In ProBP, availability fares are compared numerically with bid prices. Availability fare adjustment refers to modifying the availability fare only, without modifying the RM input fare. Consequently, availability fare adjustment essentially bypasses the RM optimizer when it calculates displacement costs or bid prices. Because the optimizer is not being modified, the displacement costs and bid prices are not modified, which implies that the RM optimizer solution is partially ignored in favor of a last-minute override.

In Figure 3.9, we show the interaction of ancillary revenue adjusted availability fares with availability controls in both DAVN and ProBP. Again, input fares and forecasts are fed into the optimizer. For DAVN, this is NetBP, which calculates displacement costs using a deterministic approach. ProBP uses a bid price convergence algorithm by prorating fares with each iteration in EMSRc. Then, the optimizer calculates controls with either virtual buckets or additive bid prices for each itinerary. At the time of booking request, the availability fare is compared with the controls.

In DAVN, the logic of adding ancillary revenue onto the availability fare is shown in Figure 3.10 with an example.

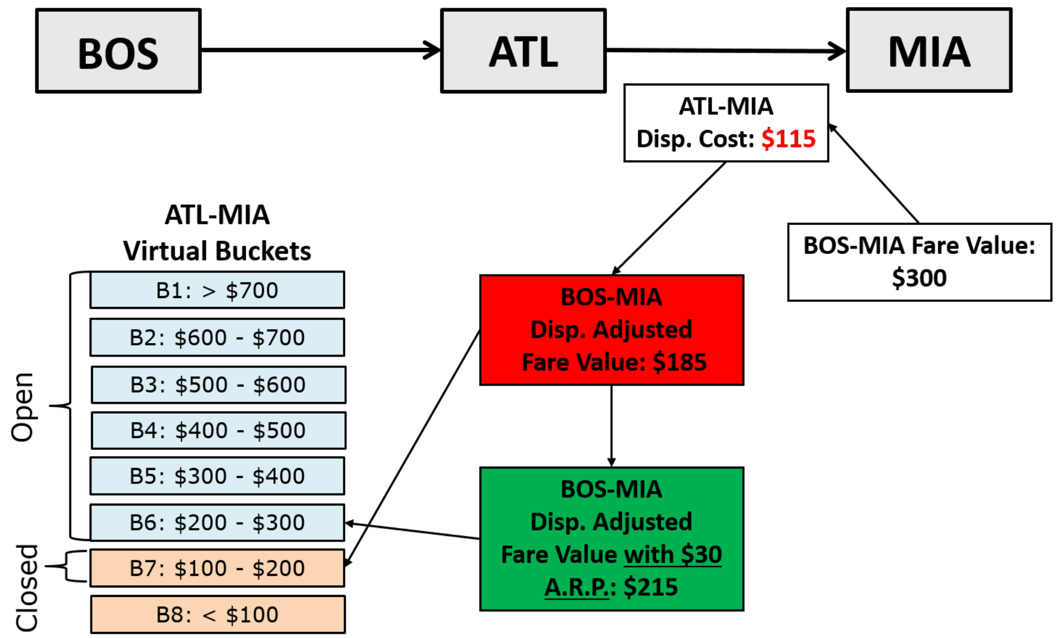


Figure 3.10: Ancillary Revenue Adjusted Availability Fare in DAVN

- DAVN calculates displacement costs based on input fares and forecasts. Since only the availability fare is adjusted for ancillary revenue, the displacement costs calculated by the deterministic LP (NetBP) are initially the same as with the case of no ancillary revenue adjustment.
- A passenger wants to book a Class 5 BOS-ATL-MIA fare for $300. Looking at the virtual buckets for ATL-MIA, subtract the displacement cost of $115 on the downstream ATL-MIA leg.
- The displacement adjusted fare is $185, which falls into Bucket B7. This bucket is currently closed (based on EMSRb calculations), so Class 5 is not available.
- Alternatively, if a $30 ancillary revenue potential is assumed for that passenger, the availability fare would be worth $215, falling into Bucket B6. B6 is open, and if the corresponding bucket on ATL-MIA is open as well, then the passenger is able to make the booking.

In ProBP, the logic of adding ancillary revenue is illustrated in Figure 3.11.

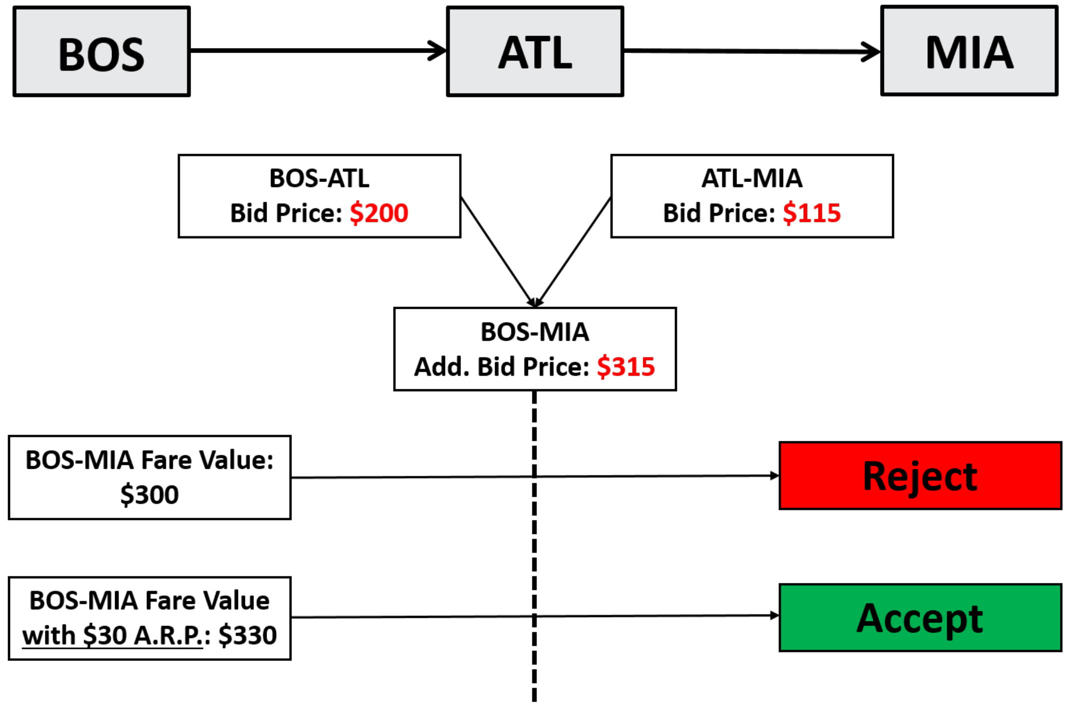


Figure 3.11: Ancillary Revenue Adjusted Availability Fare in ProBP

- ProBP calculates bid prices based on input fares and forecasts through a convergence algorithm. Again, since the bid price calculations were based on input fares (which are not modified), the bid prices calculated remain the same.
- A passenger wants to book a Class 5 BOS-ATL-MIA itinerary for \$300. The bid price for BOS-ATL is \$200 and for ATL-MIA is \$115. The additive bid price is \$315.
- Since \$300, the availability fare, is lower than the current bid price, Class 5 is not open.
- However, if a \$30 ancillary revenue potential is assumed for that passenger, the availability fare is \$330, which is greater than the additive bid price and the passenger is able to make the booking.

For both DAVN and ProBP, although the inputs to the RM optimizer are not modified, the availability decisions are ultimately modified to give greater availability to passengers who are expected to pay more for add-ons. Consequently, availability fare adjustment can be a powerful tool to prioritize availability without modifying the optimizer.

Given earlier discussion of class level versus passenger level assumptions of ancillary revenue, it is important to make the distinction with respect to availability fare adjustment. In class level availability fare adjustment, the availability fare is incremented by the same amount for each class. Although passengers within each class in reality have different ancillary revenue potential, the airline only has knowledge on the class level; so therefore all passengers are expected to have the same extra contribution by class. In customized availability fare adjustment, the availability fare is incremented by a certain amount unique to each individual passenger. For example, if the airline knows that a particular passenger is willing to spend large amounts of money on add-ons, the airline can fine-tune availability for that specific passenger.

3.5 Summary

This chapter reviewed the necessity of incorporating ancillary revenue potential into the RM optimizer and/or the availability distribution controls. The challenges of predicting ancillary revenue potential were examined and different levels of granularity in making these assumptions were given. In this thesis, we assumed that the airline has the capability to predict ancillary revenue potential on either a class level or a passenger level basis.

The interface between passenger decision process and the airline RM/distribution process was presented. Availability fares and RM input fares were given in the context of FCYM, DAVN, and ProBP. Three methods were postulated for adjusting the fares to account for ancillary revenue – given the context of class level or passenger level data: (1) Class Level RM Input Adjustment; (2) Class Level Availability Fare Adjustment (for Network RM only); and (3) Customized Availability Fare Adjustment (for Network RM only).

Chapter 4 continues the discussion by introducing the Passenger Origin Destination Simulator (PODS), a tool that simulates the interaction between sample airlines and generated passenger demand in a competitive environment. The generation of passengers is changed to reflect ancillary revenue potential for each individual passenger, and airlines are given the capability to utilize class level RM input fare adjustment, class level availability adjustment, or customized availability adjustment. Chapter 4 presents the framework of the simulation environment in order to test the effectiveness of the three methods in combination with other RM strategies.

4 Passenger Origin Destination Simulator (PODS)

This chapter provides a brief overview of the Passenger Origin Destination Simulator (PODS), the simulation tool used to run the experiments in this thesis. PODS simulates competitive airline networks and air travel demand in order to test the performance of revenue management strategies. In a brief summary, a researcher or user may employ PODS by defining cities as well as corresponding demand to travel between different cities as inputs into the simulation. The researcher also defines the structure of the airlines' network. This includes the number of airlines in the simulation scenario, the number of cities served by each airline, the competitive fare structure for each market, as well as the central hubs and schedules of each airline. Airlines offer flights and products to serve the travel demand and employ revenue management strategies, competing in a competitive environment to maximize their revenues.

A brief overview of the process flow for generating demand, applying RM controls, and booking passengers to collect performance data is given below:

- Passengers are generated for each market for each departure day. Certain characteristics about their booking behavior are randomized and assigned for each passenger.
- Given the forecast of passenger demand, capacity by flight leg, and fare structures, each airline sets booking limits dynamically during the booking process and books passengers up until the day of departure.
- Outputs about revenue, load factor, yield are aggregated and presented in a summary. Additionally, PODS generates outputs about forecasts, booking patterns by class, and booking patterns by flight. It is important to note that in PODS, it is possible to simulate data that may not be available to airlines in real life. For example, it is impossible to retrieve passenger rankings of their choice set as usable data.

In this thesis, we test the different methods of ancillary revenue incorporation using PODS and measure their relative performances. This chapter first presents an overview of PODS and highlights some important details within the simulator environment that are relevant to modeling ancillary revenue potential. First, we discuss the competitive airline environment in order to set up the experiment and measure revenue performance. Then, we examine the passenger generation process and the characteristics that determine passenger decisions. Additionally, we discuss new steps regarding generation of ancillary revenue potential by passenger. Finally, we list the available RM schemes that airlines employ in PODS as well as some of the baseline scenarios used to test these methods. More information about the details of PODS as well as many of the charts and figures used in this chapter can be found in [9].

4.1 Overview and Structure

In PODS, a single departure day is simulated with multiple flights served across each of the airline's networks. The booking process for passengers to purchase tickets is the period set 63 days from departure up until the day of departure. Within this booking period, passengers and airlines interact in a continuous feedback loop, as shown in Figure 4.1.

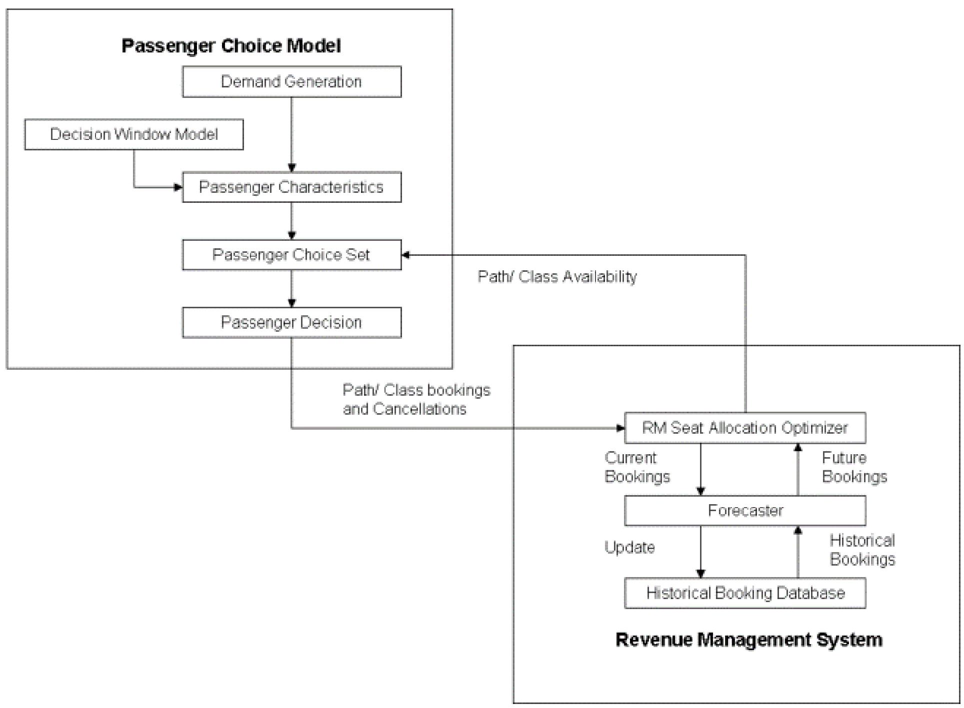


Figure 4.1: Interaction of Passengers with Airlines in PODS

First, passengers are generated by O-D market. Underlying characteristics – passenger type (business vs. leisure), willingness to pay, and other sensitivities – are drawn for each passenger. Then, these passengers consider the available itineraries offered by airlines, as a function of the point in time in the booking curve they search for itineraries. Based on their underlying characteristics, each passenger ranks these different itineraries and makes a decision to book with an airline (or does not fly).

On the airline side, the RM system forecasts the unconstrained demand for each market by retrieving bookings from the current booking period as well as historical bookings from previous departure days. The optimizer then takes the forecast and generates seat availability, which is communicated to the passenger. Based on the solutions that the RM system generates, certain flights or paths may not be available to passengers at different points in time during the booking period.

Using these processes, we simulate the same departure day many times, averaging output results to obtain statistically significant results. Additionally, since the forecaster depends on historical data to create forecasts, some "preliminary" simulations are used for forecasting purposes but are not tabulated within the averages. We clarify the experimental process and list key nomenclature below:

- A **sample** refers to a simulation of a single departure day for the entire network with multiple airlines. The forecaster, for example, forecasts future demand for the current sample, drawing upon both previous bookings in the current sample as well as historical bookings from previous samples. At the conclusion of each sample, performance data is recorded.

- Each **trial** has 600 samples, whose performance results are tabulated and averaged for statistical significance. Because the quality of the solution depends on the quality of past forecast data, the first 200 samples are disregarded in the tabulation. An **experiment**, as defined in this thesis, is an average of five trials.

- The **booking period** is defined to be the time that passengers are able to book flights within the network. It is set to be the period 63 days before departure up until the day of departure.

- The booking period is separated into 16 **time frames**. At the end of each time frame is a **data collection point**, where the airline might stop offering a product (advance purchase requirement) and will reoptimize its booking limits (though for network RM, we employ daily reoptimization as well). The breakdown of the booking period into time frames is given in Figure 4.2. Closer to departure, there are more reoptimization points within the same period of time.

4.2 Competitive Airline Networks

In the network used in this thesis, there are two airlines competing across forty-two cities shown in Figure 4.3. The routes and operation of flights are not changed across our experiments to maintain consistency.

Time Frame	Days until Departure	Time Frame Duration (days)
1	63	7
2	56	7
3	49	7
4	42	7
5	35	4
6	31	3
7	28	4
8	24	3
9	21	4
10	17	3
11	14	4
12	10	3
13	7	2
14	5	2
15	3	2
16	1	1

Figure 4.2: Structure of Time Frames in PODS

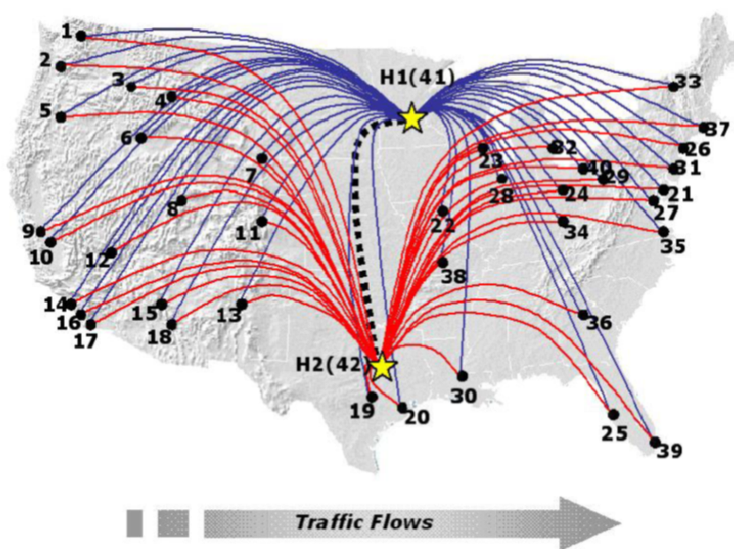


Figure 4.3: Competitive Network with Two Airlines

- These two "legacy" airlines operate on hub-and-spoke networks: **Airline 1** hubs at MSP and **Airline 2** hubs at DFW. In this environment, twenty cities lie west of the hubs and twenty lie east.

- For each sample, traffic flows from west to east – there is only passenger demand generated for markets from western cities to eastern cities (as well as hub to spoke, spoke to hub, or hub to hub).
- There are three connecting banks for each airline at its respective hub. For each of the three connecting banks per airline, 21 flights depart from the western cities (plus the competitor hub) to the airline's hub. The passengers then connect and 21 flights depart from the hub to the eastern cities. Therefore, in total, there are 252 flights (3 banks x 2 airlines x 42 flights) within each sample.
- There are 482 total markets (20 west to 22 other cities = 440 plus 21 markets from each of the two hubs).

Additionally, the fare structures are also set for both airlines. In our experiments, we use two scenarios: an environment with fully restricted fare structures across all markets; or an environment with semi restricted fare structures across all markets. In other words, both airlines adhere to the same fare structure for a given experiment.

For each market, there are six fare classes, with differences in restrictions as detailed in Figure 4.4. The difference between a fully restricted fare structure and a semi-restricted one is the allocation of restrictions onto each fare class. R1, R2, and R3 represent different levels of restrictiveness; in the real world, they are analogous to a Saturday night stay requirement, change fee, and a cancellation fee. In the real world, a Saturday night stay has been found historically to be more effective at segmenting demand; in PODS, R1 represents a stronger restriction than R2 or R3.

Although fares differ by market, the average fare across all 482 markets is shown in Figure 4.4. Again, the two airlines adhere to the same fares as well. Because we hold many of these factors constant, the baseline differences in revenues between Airline 1 and Airline 2 are due to fundamental differences in schedules and network structure. Rather than focusing on absolute numbers of total revenue, the performance of various RM methods is measured by the incremental revenue gain relative to a base case to control for the differences in network structure.

4.3 The Passenger Choice Model and Demand Generation

Potential passengers are generated with demand to travel in each of these 482 OD markets. These passengers have different characteristics: for example, they may be business travelers or leisure travelers; they have a certain level of willingness to pay; and they have a certain preference for departure time. Given these characteristics, passengers identify their ideal itineraries

Fully Restricted

Class	Average Fare	AP	R1	R2	R3
1	$ 414	0	-	-	-
2	$ 293	3	-	Yes	-
3	$ 179	7	Yes	Yes	-
4	$ 153	14	Yes	Yes	-
5	$ 127	14	Yes	Yes	Yes
6	$ 101	21	Yes	Yes	Yes

Semi-Restricted

Class	Average Fare	AP	R1	R2	R3
1	$ 414	0	-	-	-
2	$ 293	3	-	Yes	-
3	$ 179	7	-	Yes	Yes
4	$ 153	14	-	Yes	Yes
5	$ 127	14	-	Yes	Yes
6	$ 101	21	-	Yes	Yes

Figure 4.4: Fully Restricted and Semi-Restricted Fare Structures

to book, given the available itineraries offered at a certain point in time.

In this section we explore the assumptions and implementations of the four-step passenger process: (1) demand generation by market; (2) passenger characteristics; (3) the passenger choice set; and finally, (4) the decision to book.

4.3.1 Demand Generation

First, demand for each OD market is determined for each sample based on a series of random draws from normal distributions. These draws are calibrated such that the mix of business passengers to leisure passengers is about 40:60, figures based on industry data.

Then, passengers arrive for booking at different times along the period, depending on their classification as business or leisure. In attempting to align with real data, cumulative arrival curves are defined, which outline the proportion of passengers who will have arrived by a certain time frame in Figure 4.5.
For example, since the leisure arrival curve is above that of business, more leisure passengers seek to book itineraries early as compared to business passengers. By time frame 6, 55% of the leisure demand has arrived while only 25% of the business demand has arrived. During the last few time frames, there is significant business demand.

Finally, it is important to note that this typing of business versus leisure passenger is an underlying characteristic for modelling purposes only. In the real world, passengers do not identify themselves as business or leisure when booking, so it is not possible to obtain that

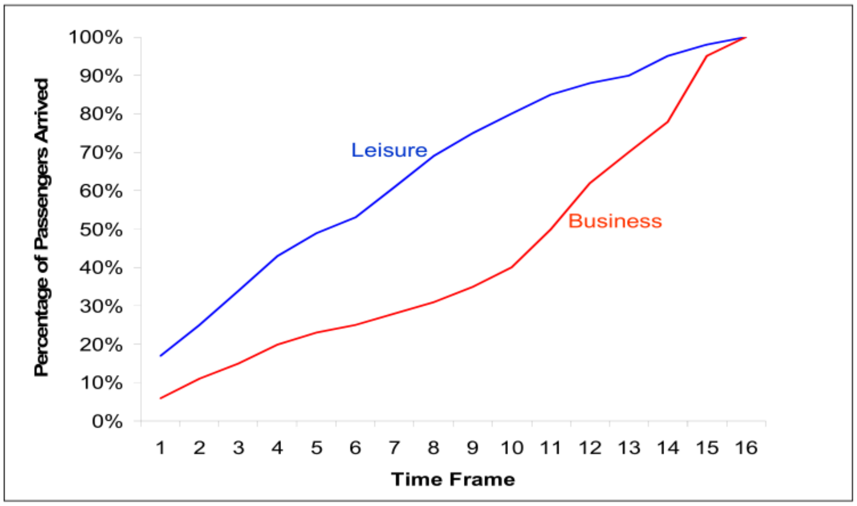


Figure 4.5: Cumulative Arrival Curves for Business and Leisure Travelers

data. The idea of typing passengers as business or leisure is used to model different groups of demand that behave differently and to recognize that even some business demand will choose lower fares targeted at leisure passengers.

4.3.2 Passenger Characteristics

Each passenger is also assigned three randomized, defining characteristics in addition to a business or leisure designation: (1) a decision window; (2) a maximum willingness to pay; and (3) a set of disutility costs.

1. The **decision window** refers to each passenger's time-of-day preference for travel: the combination of his earliest preferred departure time and his latest allowable preferred time. On average, decision windows for business travelers are shorter than that of leisure travelers to reflect their decreased flexibility in travel. All available flights that fall into this decision window are included in the choice set of feasible alternatives.

2. The **maximum willingness to pay** is the maximum dollar amount that the passenger is willing to pay for air travel. Willingness to pay is defined as a function of the fare ratio to the lowest fare in each market. For example, if the lowest fare in the DFW-BOS market is \$100, then a fare ratio of 2.0 would correspond to a fare of \$200. Business travelers are set on average to be more willing to pay a higher fare ratio than leisure travelers.

3. The **set of disutility costs** determines the monetized impact of restrictions, replanning, path quality costs, and unfavorite airline costs. Replanning disutility refers to a passen-

ger's preference in flying within his preferred decision window, incurring a cost if he has to replan for a flight outside of the window. Although a passenger may fly outside of the decision window, any flight option outside of the decision window is assigned a replanning cost. Transfer costs refers to the preference for nonstop flights versus connecting flights. Business travelers are set to have higher disutility costs because the underlying assumption is that they are more sensitive to time and restrictions as opposed to leisure travelers.

4.3.3 Passenger Choice Set and Decision

Given that a passenger wants to travel from a specific origin to a specific destination, he must evaluate multiple possible itineraries each of which have different departure times offered by different airlines. In PODS, the passenger monetizes the impacts by calculating a **total generalized cost** of each feasible alternative and ranks them in order of desirability to make a decision. The total generalized cost is used by a PODS passenger only to rank alternatives by their relative differences in utility - it does not represent the real dollar value paid to the airline.

Since there are two airlines flying three times a day offering six different fare products, there can be a maximum of 2*3*6 = 36 possible path/fare options, along with a "no-go" option. Given these 36 options, some are eliminated based on the fact that the actual dollar amount of the fare is higher than the dollar willingness to pay of the passenger (independent of total generalized cost). In addition, some itineraries might not be available due to advance purchase requirements or if the airline's RM system has closed them down.

For the remaining itineraries, the total generalized cost is the sum of the:

- **Base Ticket Fare**
- **Costs of Connection and Stops** - Connecting itineraries are less desirable than nonstop itineraries because of the stress associated with changing planes, added trip time, and so on.
- **Unfavorite airline costs** - If applied, the passenger has a preference for one airline over the other.
- **Replanning costs** - If the itinerary is outside of the decision window, the passenger assigns a penalty to the less desirable itinerary.
- **Disutility costs of restrictions** - Based on the underlying sensitivities of passengers, disutility costs are calculated for each restriction.

Restrictions in fare structures are set in a way to adequately segment the business traveler and the leisure traveler. Because the two types of customers have different sensitivities to restrictions, their disutility levels are different. In combination with the other factors that make up the total generalized cost, theoretically more business customers would buy a higher class ticket with a high dollar fare even though a lower class ticket may have a lower dollar value. In other words, fare structures are set such that the total generalized cost is lower for business travelers booking higher classes and lower for leisure travelers booking lower classes.

Given all feasible paths that the passenger is able to take, the total generalized cost is used to rank alternatives. From the available paths, the top-ranked alternative becomes the choice of the passenger and he books. Seat availability for that particular itinerary is decreased by 1, and the airline records a booking in its database.

To illustrate an example of calculating total generalized cost and making a decision, imagine two passengers potentially travelling from DFW to BOS: a business passenger and a leisure passenger. For simplicity's sake, assume that the only feasible path is on Airline 1's first non-stop flight – connection costs, unfavorite airline costs, replanning costs are all held constant.

Suppose there are two available options: Class Y with no restrictions and a ticket fare of $500 and Class Q with an R1 Saturday Night Stay restriction with a ticket fare of $250. Since the business customer travels for his work, he desires to be home for the weekend. An R1 Saturday Night restriction, which forces him to stay overnight away from home, imposes a disutility cost – say $400. Therefore, for the business traveler, the total generalized cost for Class Y is $500 and for Class Q is $650 (fare + R1 disutility). For the business traveler, it makes sense to pick Class Y.

In contrast, since leisure customers travel for the purpose of vacation and plan to stay over a weekend anyway, Saturday Night Stay restrictions do not impose a disutility cost – $0. The total generalized cost for the leisure traveler is $500 for Class Y and $300 for Class Q, which allows him to pick Class Q.

It is important to note at this point that it is assumed in PODS there is no upper bound on the total generalized cost that a passenger is willing to accept. On the other hand, there is an upper bound to the maximum dollar amount (willingness to pay). This is important because the difference between the paid ticket fare and the maximum willingness to pay represents consumer surplus, measure that should be minimized for revenue management. For example, most leisure travelers want to book Class 6 because it is the lowest ticket fare; however, this is not ideal for the airline because consumer surplus is large. If the airline closes Class 6, it may be able to influence the leisure passenger to pick a higher class, Class 5, which reduces consumer surplus and results in more revenue for the airline. The passenger is "sold up" to a higher class, as long as the restrictions for Class 5 aren't too strong.

When analyzing results in PODS, it is possible to examine the proportion of passengers who received their "first choice", or whether they were sold up or decided to buy down to lower classes. This level of knowledge, again, is not available in the real world, but is available in the simulation world, giving additional insight to trends affected by different RM strategies.

4.4 Modelling Passenger Ancillary Revenue Potential in PODS

For this thesis, there is new PODS programming to model ancillary revenue within the simulation environment. In the context of our experiments, passengers are also assigned an **ancillary revenue potential** when their characteristics are generated. Ancillary revenue potential is a number internal to each passenger that indicates their propensity to purchase add-ons after booking their ticket. Ancillary revenue potential is **independent** of any airline action to optimize its RM system to account for ancillary revenue – in other words, even in the baseline cases with no airline adjustment, both airlines collect ancillary revenue potential from passengers. This section describes the passenger ancillary revenue potential generation process only.

Ancillary revenue potential is generated as a proportion of ticket fare value. Therefore, average ancillary revenue potential varies by market and by class. In our experiments, we assign different ancillary revenue multipliers on a network level by class, which affects all markets. The main ancillary revenue potential structure is detailed in Figure 4.6. For most cases, we assume an average ancillary revenue contribution of $30 for the lower four classes based on industry trends. Higher class tickets tend to sell as bundled products, which possibly already include checked baggage, priority boarding, and potentially food. It is important to note that because add-ons are priced independent of ticket class, the average absolute dollar amount is constant. Consequently, lower class passengers pay a higher proportion of their ticket fare for the products that are not unbundled in their ticket.

In addition to the average $30 potential on the lowest four classes, we also test other cases, as seen in Figure 4.7, for sensitivity analysis. These ancillary revenue potential structures range from modifying the absolute revenue potential from $30 - $60, as well as assuming ancillary revenue potential on Classes 1 and 2.

Class	Average Fare	Ancillary Multiplier Assumed	Average Ancillary Revenue	Adjusted Average Fare
1	$ 414	0%	-	$ 414
2	$ 293	0%	-	$ 293
3	$ 179	**16.8%**	$ 30.00	$ 179
4	$ 153	**19.6%**	$ 30.00	$ 153
5	$ 127	**23.6%**	$ 30.00	$ 127
6	$ 101	**29.7%**	$ 30.00	$ 131

Figure 4.6: Average of $30 A.R. Potential Varies by Market

Class	Average Fare	Structure 1: Low 4	Structure 2: All Classes	Structure 3: Top 4
1	$ 414	--	$30 - $60	$30 - $60
2	$ 293	--	$30 - $60	$30 - $60
3	$ 179	$30 - $60	$30 - $60	$30 - $60
4	$ 153	$30 - $60	$30 - $60	$30 - $60
5	$ 127	$30 - $60	$30 - $60	--
6	$ 101	$30 - $60	$30 - $60	--

Figure 4.7: Different Models of Ancillary Revenue Potential

Although we set the average ancillary revenue potential in the network to be $30 for Class 3-6 in Structure 1, the real ancillary revenue potential also varies by market. The average ancillary revenue potential is only calibrated at a system-wide level to calculate the multiplier (of 29.7% for Class 6) shown in Figure 4.6. This multipler of 29.7% in Class 6, for example, is applied to all markets in the network.

Since each market has a different fare, the average ancillary revenue potential is also different by each market. An example of this is shown in Figure 4.8, illustrating the difference in average ancillary revenue potential in Class 6 SEA-BOS versus Class 6 MSP-BOS. From the ancillary revenue structure, the multiplier is set to be 29.7% for Class 6. Because the Class 6 ticket fare for SEA-BOS is $130 – applying the multiplier nets an ancillary revenue contribution of $38.61. In contrast, the Class 6 ticket fare for MSP-BOS is $90 – applying the multiplier nets an ancillary revenue contribution of $26.73. The rationale for selecting a multiplier to apply to all markets equally is that ancillary revenue potential should intuitively scale with length of haul and also ticket price. We believe that passengers who fly on longer routes tend to be more likely to purchase add-ons such as food and drink or aircraft wireless LAN.

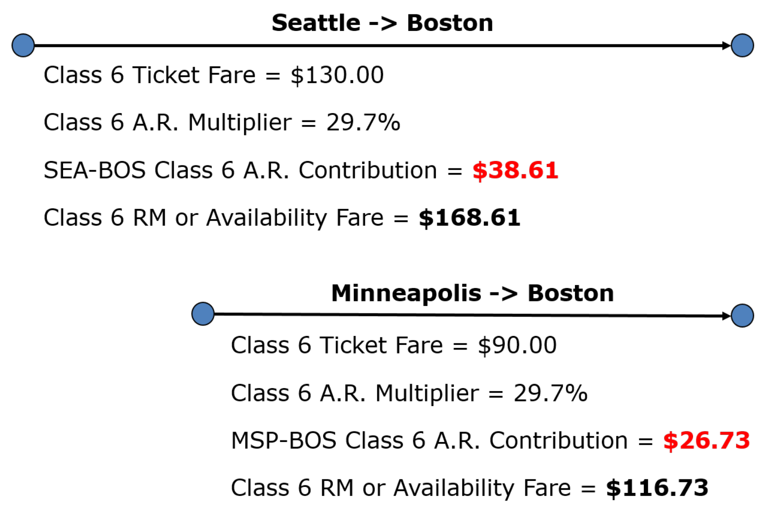


Figure 4.8: Average of $30 A.R. Potential Varies by Market

In addition to defining a different ancillary revenue potential by each market, we also model some variability in A.R. potential with respect to individual passengers. Note that this assignment of ancillary revenue potential is independent of any airline actions in estimating ancillary revenue on a class level or on a passenger specific level. Ancillary revenue potential on a passenger level is modelled as a normal distribution with a mean dollar amount (defined previously) and standard deviation for each class, denoted by a k-factor (standard deviation divided by mean). The k-factor, a measure of variability, is set on a network level, and the standard deviation is therefore derived for each market. For example, the average ancillary revenue potential for SEA-BOS is $38.61 for Class 6. Therefore, the probability density function for SEA-BOS is centered on $38.61. The k-factor, a measure of variability in passenger ancillary revenue potential, is set to be 0.2, so the standard deviation is defined to be about $7.72 for SEA-BOS Class 6 only. In the experiments, we vary the system k-factor and test different airline methods of incorporating ancillary revenue potential.

4.5 Summary

PODS simulates the competitive environment of multiple airlines competing for passengers demanding travel across many markets. These passengers are generated and given characteristics that determine their preferred paths and booking behavior. The revenue management systems of airlines control class availability and attempt to optimize revenue for the airlines. In PODS, the performances of different RM strategies, including incorporating ancillary revenue potential, can be measured.

Given the variety of different variables to be adjusted, it is useful to group and list some of the key variables that are changed with different experiments. The first group involves factors related to the competitive environment and passenger generation, items that define the overall environment of the simulation and are not controlled by any airline. The second group and third group involve the RM system - the forecaster and the seat allocation optimizer.

In each experiment, the optimizer and forecaster are changed for both airlines at the same time in order to control for that variable. Finally, in the fourth group, Airline 1 only has the option of incorporating ancillary revenue potential given the two adjustment strategies.

The next chapter tests the two strategies for incorporating ancillary revenue potential – RM Input Fare Adjustment and Availability Fare Adjustment. Results are reported with these two strategies in the context of differences in competitive environment as well as in the context of different RM systems.

Competitive Environment and Passenger Generation (parameters native to the simulation)

- Overall Demand - The overall demand generated can be altered proportionately to "set" the baseline system load factor anywhere from 75 - 90%.
- Fare Structures - Given as unchangeable. Airlines in our tests do not compete on price or on product. Both airlines either use a fully restricted fare structure or a semi restricted fare structure.
- Ancillary Revenue Potential - Whether or not the airline chooses to use ancillary revenue potential within their RM/distribution systems, each passenger has ancillary revenue potential. Ancillary revenue potential varies by class, market, and passenger.

Existing/Baseline RM System Strategies (changed for both airlines symmetrically)

- Standard Forecasting - As detailed in Chapter 2, standard forecasting aggregates forecasts from previous samples with forecasts of the current sample to forecast demand.

- Hybrid Forecasting with Fare Adjustment - Standard forecasting in conjunction with Q-forecasting accounts for the probability of selling up price-sensitive demand.
- Standard Leg-Based RM (FCYM) - Leg based, fare class control.
- Displacement Adjusted Virtual Nesting (DAVN) - Accounts for displacement costs of connecting itineraries and compares fare classes of similar value.
- Probabilistic Bid Price Control (ProBP) - Calculates the critical value of the bid price on each flight leg. Controls by adding flight leg bid prices across the itinerary.

New Ancillary Revenue Adjustment (applied for Airline 1 Only)

- RM Input Fare Adjustment - Altering the RM optimizer to account for ancillary revenue potential.
- Availability Fare Adjustment Only - Bypassing the RM optimizer and modifying the availability fares to give preference to passengers with high ancillary revenue potential.

5 Results of the Experiments

Chapter 5 presents the results of incorporating ancillary revenue potential into the RM optimizer and/or availability calculations using the PODS simulation tool defined in Chapter 4. Given the previous discussion of different ancillary revenue adjustment methods and different levels of ancillary revenue estimation, Chapter 5 is organized into four broad areas of testing: (1) RM Input Adjustment with Class Level Estimates of A.R. Potential; (2) Availability Fare Adjustment with Class Level Estimates; (3) Customized Availability Fare Adjustment with Passenger Specific Estimates of A.R.; and (4) Both RM Input and Customized Availability Fare Adjustment with Passenger Specific Estimates of A.R.

Within each research area these ancillary revenue related strategies are tested in the context of: (1) different airline choices of RM optimizer (leg versus network RM); (2) different choices of forecasting techniques (standard versus hybrid forecasting/fare adjustment); and (3) differences in fare structure environment (semi-restricted versus fully restricted). These scenarios are defined in a way to maintain symmetry across airlines: both airlines always adhere to the same optimizers, forecasters, and fare structures for a given experiment. However, ancillary revenue estimates are only incorporated for Airline 1 in order to measure the incremental benefit of adjusting for ancillary revenue. The revenue performance given these adjustment strategies is then measured against the baseline scenario with neither airline incorporating ancillary revenue. Within each scenario, we also perform sensitivity analysis by modifying the level of demand and level of ancillary revenue potential generated for passengers to examine the differences in effects.

As detailed in Chapter 4, ancillary revenue potential is generated in PODS as an inherent characteristic of each passenger. Average ancillary revenue potential for each market and each fare class is set as a function of ticket fare value and each passenger is given an ancillary revenue value based on a probability density function distribution around that mean. Whether or not an airline estimates ancillary revenue potential to include within their optimization and availability calculations has no effect on the underlying ancillary revenue value for each passenger.

5.1 Class Level Estimates and RM Input Fare Adjustment

Within this area of testing, Airline 1 estimates ancillary revenue on a class level basis. In other words, Airline 1 has knowledge of the average ancillary revenue potential by market and by class, but not by each individual passenger. Then, Airline 1 takes these class level ancillary revenue estimates and uses them to modify fare inputs to the RM optimizer. The combination of this level of estimate and adjustment is called Class Level Input Fare Adjustment. We emphasize that although only Airline 1 applies RM Input Fare Adjustment, both airlines always collect extra ancillary revenue from relevant booked passengers.

In our baseline scenario, passengers in the lowest four classes are expected to pay, on average across all markets, \$30 in ancillary revenue to account for the fact that passengers in lower classes buy an unbundled ticket. This \$30 ancillary revenue potential represents the average network-wide ancillary revenue by passenger in each market. This \$30 average scales by the ticket fare depending on the fares in a particular market. For example, the average fare in Class 6 is \$101: a particular market which sells a Class 6 fare can expect \$30 from each booking. An alternative market that sells a Class 6 fare for a higher dollar amount can expect a proportionately higher ancillary revenue from each booking. In addition, there is also variability with respect to ancillary revenue potential for each individual passenger within each fare class since not all passengers pay exactly the same amount for ancillary revenue.

Class	Ticket Fare (Average)	Ancillary Revenue Potential (Average)	AL1 RM Input Fare (Average)	AL2 RM Input Fare (Average)
1	\$414	\$0	\$414	\$414
2	\$293	\$0	\$293	\$293
3	\$179	\$30	\$209	\$179
4	\$153	\$30	\$183	\$153
5	\$127	\$30	\$157	\$127
6	\$101	\$30	\$131	\$101

Figure 5.1: Average Ticket Fares, A.R. Potentials, and Input Fares by Class

At this point, Airline 1 is assumed to have knowledge of average ancillary revenue potential on a class level basis only. Therefore, Airline 1 modifies its RM input fare by taking the ticket fare value for each class/market and adding the mean ancillary revenue potential for each class and each market, as in Figure 5.1. Alternatively in the base case without any A.R. adjustment, both Airline 1 and Airline 2 use only the ticket fares as inputs into their RM optimizers. When Airline 1 applies Input Adjustment, the average input fare for Classes 3 - 6 for Airline 1 increases by \$30. In all cases, the average input fare for Airline 2 remains the same.

5.1.1 Leg RM with Standard Forecasting and Fully Restricted Fare Structures

Experiment 1: Baseline Tests with and without A.R. Incorporation

We present the results from two baseline experiments, where both airlines use leg RM (FCYM) with standard forecasting under a fully restricted fare structure environment. In Experiment 1A - neither airline modifies its optimizer - both airlines use the ticket fare as the RM input fare. In Experiment 1B - AL1 modifies its optimizer - AL1's input fare is shown below in Figure 5.1.

First, we present key metrics in Experiment 1A to give a baseline for comparison.

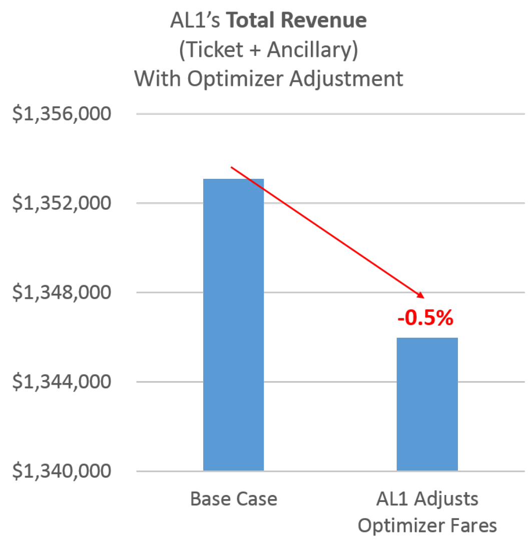
Metric	Airline 1	Airline 2
Available Seat Miles (ASM)	12,267,691	12,739,248
Revenue Passenger Miles (RPM)	9,812,613	10,103,120
Load Factor (LF)	80.0%	79.3%
Yield	$0.126	$0.121
Ticket Revenue	$1,236,505	$1,222,229
Ancillary Revenue	$116,595	$118,741

Table 1: Key Metrics in Baseline Scenario

In this single departure day, Airline 1 collects about $1.2M from ticket revenue, and, in addition, $117K worth of extra ancillary revenue. Ancillary revenue represents about 10% of ticket revenue, which is fairly reasonable given the earlier analysis of U.S. airline ancillary revenue. Load factor is about 80%, which is also calibrated to be reasonable.

Next, we present the comparison between Experiment 1A and Experiment 1B, where Airline 1 incorporates ancillary revenue potential into its optimizer. Figure 5.2 shows the change in **total revenue** for Airline 1, a reduction of -0.5%. Looking at the breakdown of ticket and ancillary revenue data for Airline 1 gives us clues as to why the results are negative. Ancillary revenue increased by +3.6%, indicating that the optimizer valued the lower class bookings more and accepted more of these passengers. However, ticket revenue decreased by -0.9%, which was enough to drive total revenue to a net negative.

More clues can be obtained by examining load factor and yield changes as in Figure 5.3. When Airline 1 applies RM Input Adjustment, it sees an increase in load factor with a corresponding drop in yield. Load factor increased by about 1.3 points and yield decreased by about 2%. Again, this reaffirms the fact that Airline 1 accepted more bookings overall, because it valued



	Ticket Revenue	Ancillary Revenue	Total Revenue
Base	$1,237K	$116.6K	$1,353K
AL1 Adjusts Optimizer Fares	$1,225K	$120.9K	$1,346K
Change	—$12K	+$4.3K	—$7K
% Change	**—0.9%**	**+3.6%**	**—0.5%**

Figure 5.2: AL1 Change in Total, Ancillary, and Ticket Revenue

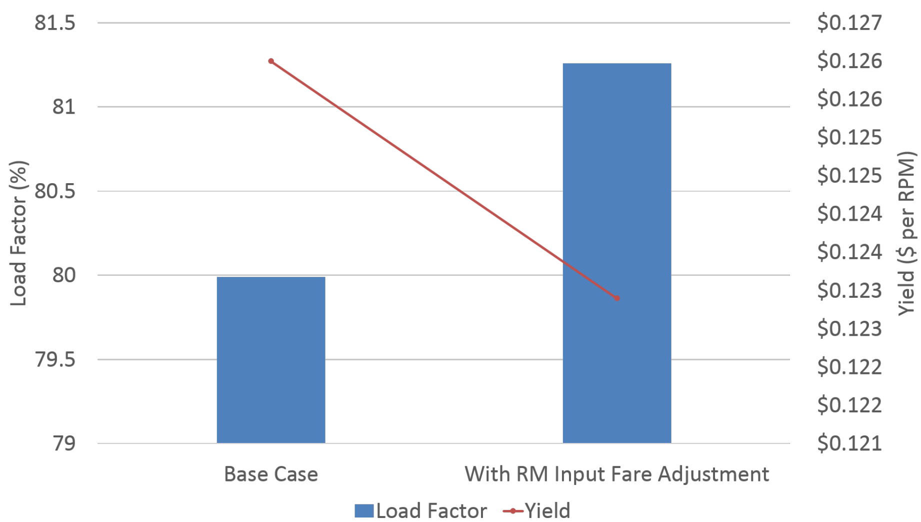


Figure 5.3: AL1 Changes in Load Factor and Yield

lower classes more in its RM optimizer. More bookings in lower classes resulted in a drop in yield.

Figure 5.4 shows the change in fare class revenue mix before and after RM Input Adjustment as well as the change in ancillary revenue and total revenue. There are a few key ideas to notice:

- The majority of extra revenue came from Class 6 bookings.

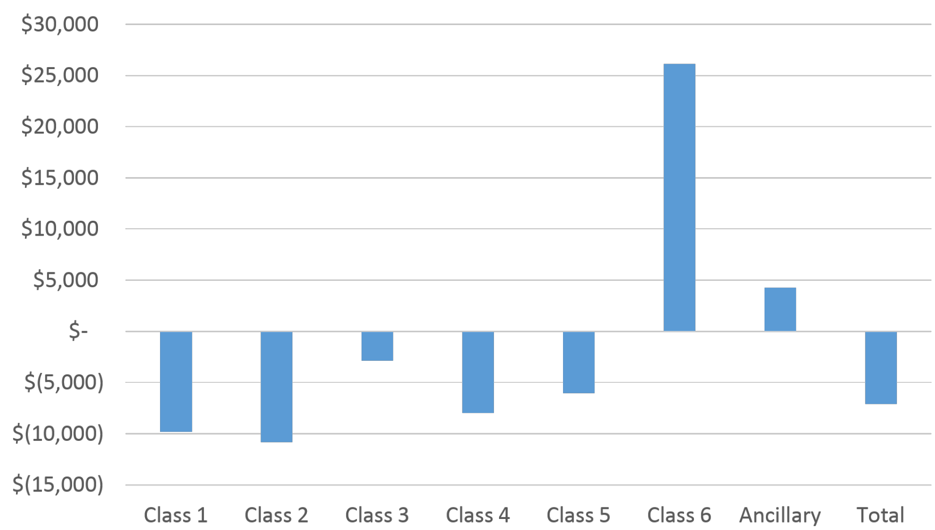


Figure 5.4: AL1 Change in Fare Class **Revenue** Mix (vs. No Adjustment)

- Since ancillary revenue is associated with bookings from Classes 3-6, ticket revenue losses in Classes 3-5 reduced the revenue gains from ancillary sources. Overall, the ancillary revenue gain was positive as well, due to the significant increase in Class 6 bookings.
- Class 1 and Class 2 saw a significant drop in the number of bookings and revenues.

There are two main reasons why there was a reduced number of bookings from Classes 1-5. Extra valuation for Class 6 allows more opportunity for other passengers to buy these seats early and take up inventory. Extra bookings result from Class 6 passengers from other sources, including those who were unable to book on Airline 2, those who were unable to book on another itinerary on Airline 1, as well as those who would not have flown due to lack of availability from any itinerary on either Airline 1 or Airline 2. Because of extra valuation for Class 6 and since the seat supply is constant, consequently the optimizer calculates less seat protection for the upper classes, and therefore lower yield.

Secondly, more Class 1 and Class 2 passengers buy down to Class 6 because the RM system does not account for inter-class demand. In other words, demands for each class are assumed to be independent, when in reality, higher value customers take the opportunity to buy down to lower classes when the itinerary adequately satisfies their preferences. This diversion of upper class passengers to lower classes as well as the extra influx of bookings from other airlines, other itineraries, and “no-go” passengers contributes to the “spiral down” effect.

The spiral down effect is a revenue losing effect that manifests over many sample iterations, because the strategy of the RM system depends on the historical data of previous samples (which leads to the forecast). Because of the influx of other Class 6 passengers as well as Class 1 and 2 passengers who buy down, there is an increased number of bookings assumed to be Class 6 demand. This causes future forecasts of demand to be higher for Class 6, leading to even more availability and more Class 6 bookings. This cyclical feedback effect is called the spiral-down effect.

Therefore, although there is extra revenue gained from Airline 1 taking more bookings in Class 6, the negative effects of spiral down contribute to a loss in total revenue. To summarize the results from Experiment 1:

- Incorporating ancillary revenue into leg-based RM with standard forecasting led to total revenue reduction for Airline 1.
- Load factor increased and yield decreased because there was more availability and more bookings in Class 6.
- Although there is an increase in ancillary revenue, there is a corresponding drop in ticket revenue.
- The unintended consequence is that bookings from Class 1-5 decreased and bookings from Class 6 increased because of the spiral down effect, caused by two reasons: (1) extra valuation for the lower classes leading to more Class 6 bookings from other sources; and (2) buy down from upper classes.

Experiment 2: Tests with Different Levels of Overall Demand

Experiment 2 explores the effects of RM Input Adjustment on scenarios with different demand levels. Previously, in Experiment 1, the system load factor (for both airlines) as calibrated to be about 80%. Figure 5.5 shows four alternative scenarios with different demand levels; their load factors range from 80% LF for Airline 1 on the low end to 92% LF on the high end. Within each scenario, results are shown with Airline 1 employing RM Input Adjustment; there is a corresponding increase in load factor as more bookings are accepted. Although not shown, each scenario exhibited the same patterns in fare class mix shift, which resulted in higher load factors and decreased yields.

Effects on total revenue are also intuitive and larger in Figure 5.6: with increased demand levels, there was more revenue loss due to the spiral-down effect. In the highest demand case,

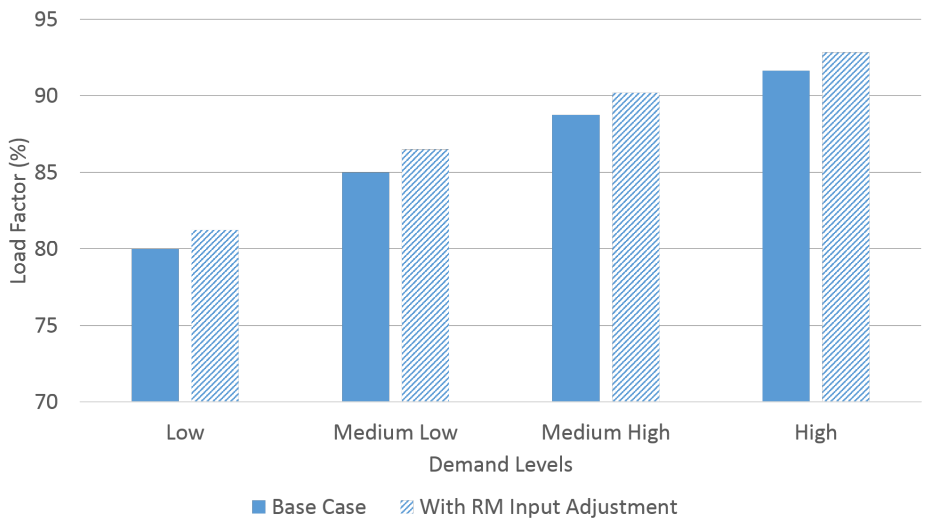


Figure 5.5: Different Levels of Demand and AL1 Load Factor

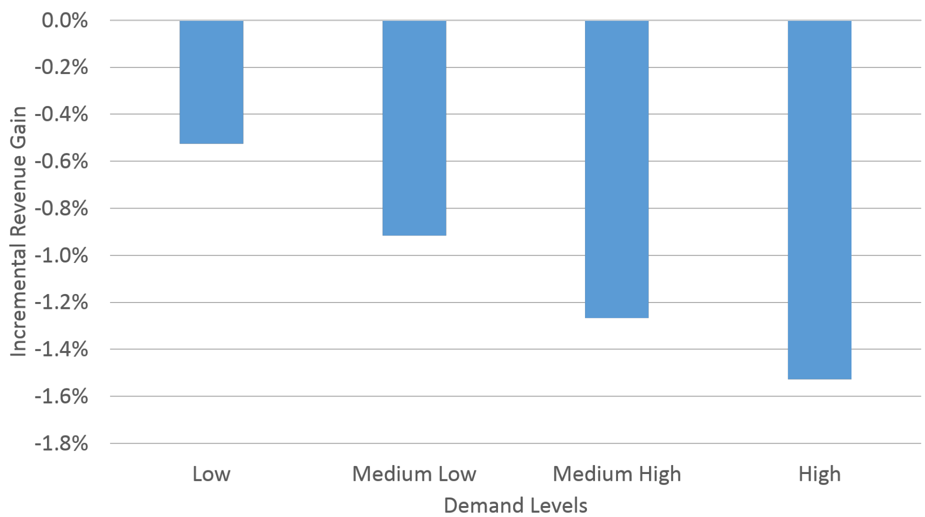


Figure 5.6: Effects of Demand and A.R. Input Adjustment on Revenue

revenue losses of -0.96% occurred.

The reasons for increased losses are logical. In the baseline case with more demand the RM system should be protecting more higher class seats to take advantage of the greater demand and increase yield. However, with RM Input Adjustment in an optimizer that does not account for inter-class demand, there is a larger risk of spiral down because there are more valuable passengers in the high demand scenario that can be lost to buy down. Indeed, with a standard forecaster that does not account for class dependence, spiral down effects are evident in increasing losses as demand increases.

Experiment 3: Tests with Different Levels of Ancillary Revenue Potential

Experiment 3 explores the effects of RM Input Adjustment with higher actual ancillary revenue potential. Holding AL1's load factor at 80%, we present the results of incremental revenue gain below in Figure 5.7, assuming average ancillary revenue potential ranging from \$30 to \$60. As seen, with increasing ancillary revenue potential, there is, again, a larger decrease in incremental revenue. Although not shown for brevity, the same patterns of spiral down occur.

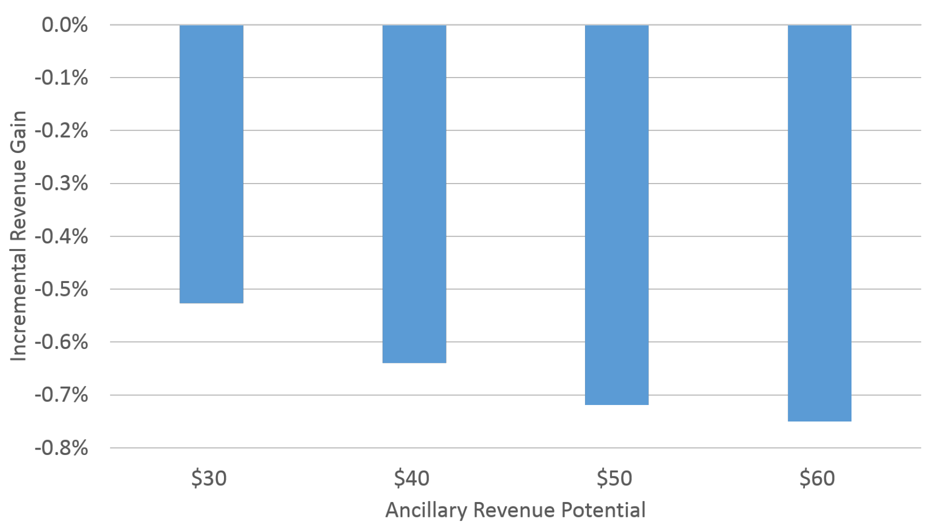


Figure 5.7: Different Levels of Ancillary Revenue Potential and Revenue

In Figure 5.8, we summarize the effects of different demand levels and different ancillary revenue potentials on incremental revenue gain. In the worst case scenario, with high demand and \$60 A.R. potential, revenue losses of up to –2.6% occur. In summary, larger demand levels and large ancillary revenue potential present cases where more spiral down occurs when RM Input Adjustment is applied.

5.1.2 Network RM with Standard Forecasting and Fully Restricted Fare Structures

We evaluate the performance of RM Input Adjustment when both airlines use DAVN, a network RM implementation, as opposed to previous tests with leg RM.

	Low	Medium Low	Medium High	High
$30	-0.5%	-0.9%	-1.3%	-1.5%
$40	-0.6%	-1.2%	-1.6%	-1.9%
$50	-0.7%	-1.4%	-1.9%	-2.3%
$60	-0.8%	-1.6%	-2.2%	-2.6%

Figure 5.8: Incremental Revenue Gain with Demand Levels and Ancillary Revenue Potential

Experiment 4: Tests with Different Demand Levels

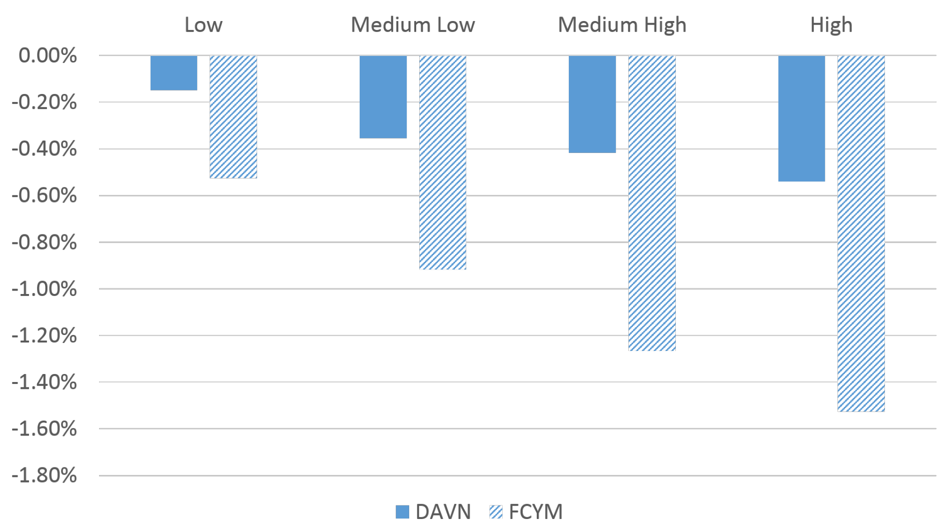


Figure 5.9: A.R. Incorporation in DAVN - Differing Demand Affects on Incremental Revenue Gain

We alter levels of demand on the network while having both Airline 1 and Airline 2 use DAVN. As seen in Figure 5.9, the same general trend occurs: with increasing demand, incorporating A.R. is detrimental to total revenues. However, with DAVN, these losses are greatly reduced compared to leg RM.

There is significantly less buy-down when the optimizer is set to DAVN vs. leg RM, which is why we do not see the similar pattern of increasingly larger losses. This trend is intuitive because of the adjustment parameters inherent to DAVN - Class 6 connecting passengers, which are the least desirable traffic to the airline - are rejected more frequently in DAVN because of the displacement cost adjustment. In fact, with ancillary revenue RM Input Adjustment in DAVN, the percentage share of connecting bookings decreased from 39.1% to 38.9%, only a slight decrease as opposed to leg RM, which increased connecting booking share from 44.6% to 45.0%. For this reason, the effects of buy-down are smaller when these passengers receive an ancillary revenue bonus as compared to leg RM, which has no such displacement cost adjustment.

Experiment 5: Tests with Different Levels of Ancillary Revenue Potential

Holding demand constant at 80% system load factor, we test scenarios with different levels of ancillary revenue potential, designated as low ($30), medium low ($40), medium high ($50), and high ($60) as before. With Input Fare Adjustment in DAVN, we see that overall revenue in each scenario hovers at the break-even point in Figure 5.10. Interestingly, although we see the same patterns of buy-down (decreasing ticket revenue), the gain in ancillary revenue made up enough for Airline 1 to break even. Figure 5.11 compares these cases with FCYM, which yielded the same general trend as before with Experiment 4, for the same reasons.

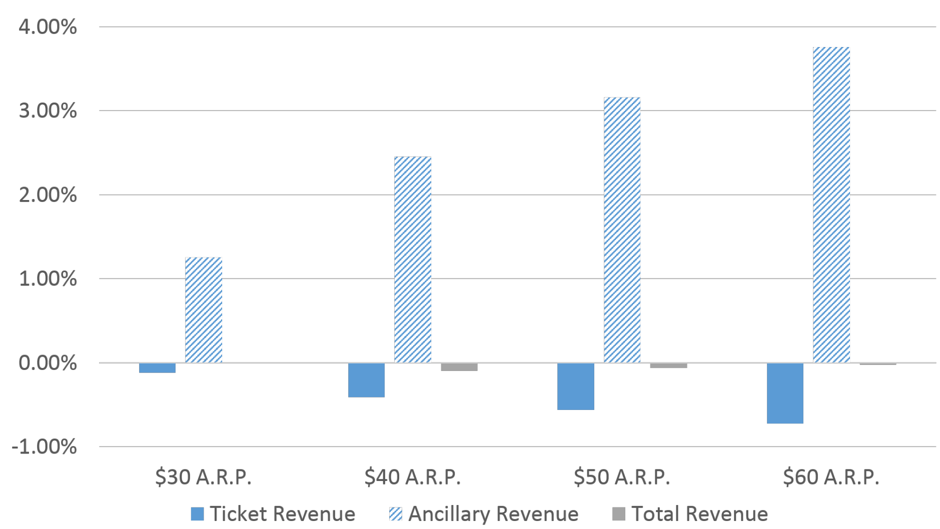


Figure 5.10: With A.R. Incorporation in DAVN, Change in Ticket, Ancillary, and Total Revenue

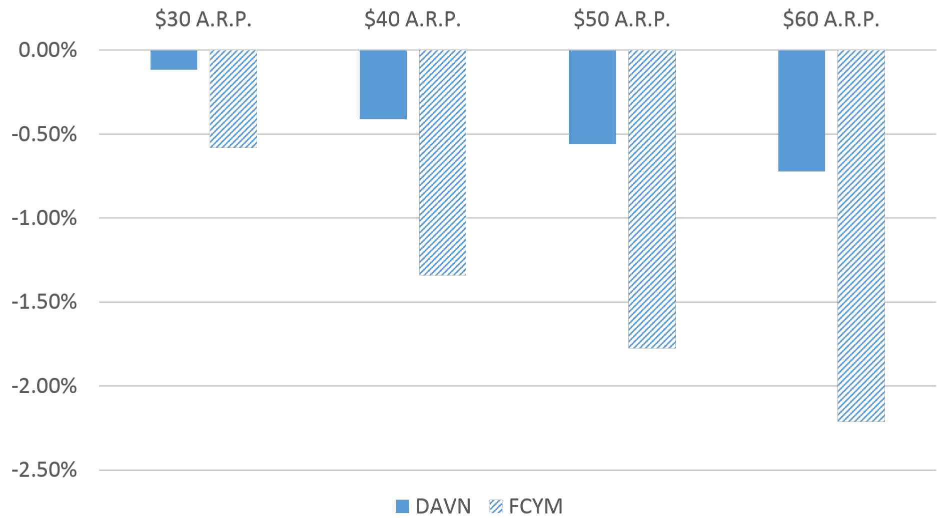


Figure 5.11: Comparison of Changes in Ticket Revenue with Leg RM (FCYM)

Summary of Fully Restricted Experiments

- There are two main forces acting upon the RM system when A.R. is incorporated: (1) Because lower class passengers are valued more, there is more availability and an increase of bookings from passengers in those classes, who contribute some ancillary revenue; and (2) because lower classes are more available, passengers from higher classes are able to buy-down, resulting in a decrease in ticket revenue and undesirable change of fare class mix.

- For each scenario of RM optimizer, ancillary revenue magnitude, or demand level, the balance of the two forces determines whether Airline 1 gains or loses in total revenue.

- In the cases with fully restricted fare structures and standard forecasting, we did not see a case with positive revenue gain.

- RM Input Adjustment in DAVN performs better in terms of revenue gain than in FCYM because DAVN inherently protects more against forces of buy-down by prioritizing more valuable local bookings.

- Scenarios with increased demand or increased A.R. potential generate less revenue for Airline 1 because the effects of buy-down are magnified.

5.1.3 Leg/Network RM with Standard Forecasting and Semi-Restricted Fare Structures

Experiment 6: Performance of Leg RM in Semi-Restricted Fare Structures

Figure 5.12 shows the effects of A.R. incorporation in a semi-restricted fare structure with FCYM. The losses with Input Adjustment in semi-restricted fare structures are similar to those with fully restricted fare structures because of the same buy down effects. However, it is important to note that the incremental revenue gain is measured versus different baselines for the semi-restricted or for the fully restricted case. For example, in a semi-restricted fare structure, there are fewer upper class bookings because the effects of differential pricing are smaller due to fewer restrictions. Consequently, the baseline yield and baseline revenues are lower.

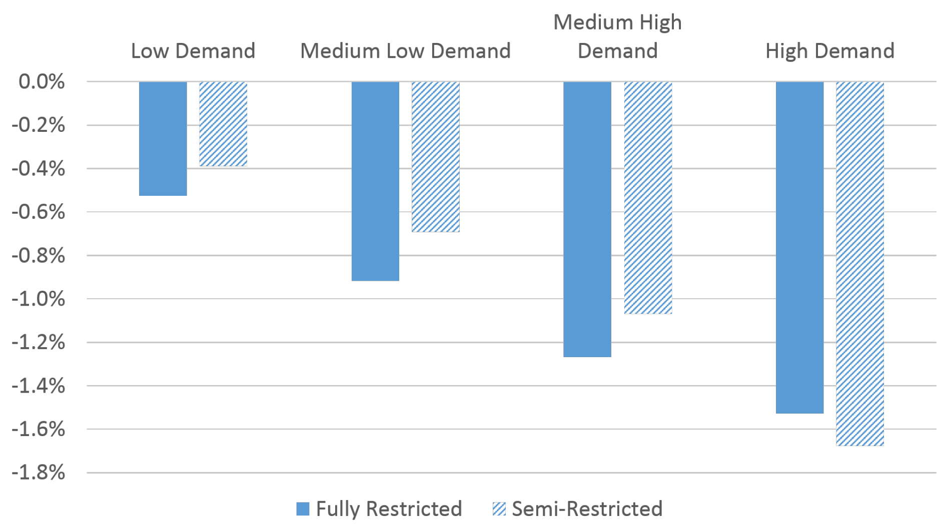


Figure 5.12: Total Revenue Changes with Semi-Restricted and Fully Restricted Structure

Figure 5.13 shows the effects of ancillary revenue incorporation in a semi-restricted fare structure. Note that there is a greater percentage loss from Class 1 and 2 in a semi-restricted fare structure due to buy down as well as fewer seats available due to spiral down. The reasoning is that with fewer and less effective restrictions, potential Class 1 and Class 2 passengers take the opportunity to book now-available lower class seats. This creates a larger forecast of low fare demand, contributing to fewer seats protected, and so on.

However, the reason that there is slightly more overall revenue loss with the fully restricted cases is because the fare class mix is different depending on fare structure. With better re-

Figure 5.13: Percent Changes in Class Bookings and Ancillary Revenue in High Demand

strictions, high value passengers are segmented into higher classes to begin with, resulting in more bookings in Class 1 and 2. Therefore, with the incorporation of ancillary revenue, there is more absolute revenue loss from Class 1 and 2, even though the percentage lost is not as large. This explains why in low, medium low, and medium high scenarios that there is slightly more incremental revenue loss with a fully restricted fare structure. The same general trend with demand is apparent, though: with higher demand, there is more opportunity for upper class bookings and therefore opening up Class 6 because of ancillary revenue incorporation represents more incremental losses. Ancillary revenue incorporation in a semi-restricted environment for leg RM leads to revenue losses from -0.4% to -1.6%.

Experiment 7: Performance of DAVN and ProBP in Semi-Restricted Fare Structures and Standard Forecasting

In Experiment 7, we report the results of RM Input Adjustment for DAVN and ProBP in semi-restricted fare structures to establish a baseline with standard forecasting. The results in Experiment 7 are then compared with the case where the airlines use hybrid forecasting and fare adjustment. Tests with DAVN in a semi-restricted fare structure show Airline 1 losing more revenue, ranging from -0.2% to -0.6% for DAVN and -0.2% to -1.5% with ProBP in Figure 5.14, for the same reasons as seen in the cases with FCYM.

With DAVN, in cases of higher demand, there is more incremental loss in revenue – this makes sense given previous examples of high demand cases exacerbating spiral down effects. However, in the case of ProBP with very low demand, there is a surprisingly large loss (-1.5%) that breaks the pattern of lower demand scenarios. We see in Figure 5.15 that the trend reversed for many key metrics: load factor decreased instead of increased; yield and ticket revenue increased; and ancillary revenue actually decreased. In contrast to cases of spiral down that were observed before with incorporating ancillary revenue, Input Adjustment in ProBP low demand resulted in too high of protection levels.

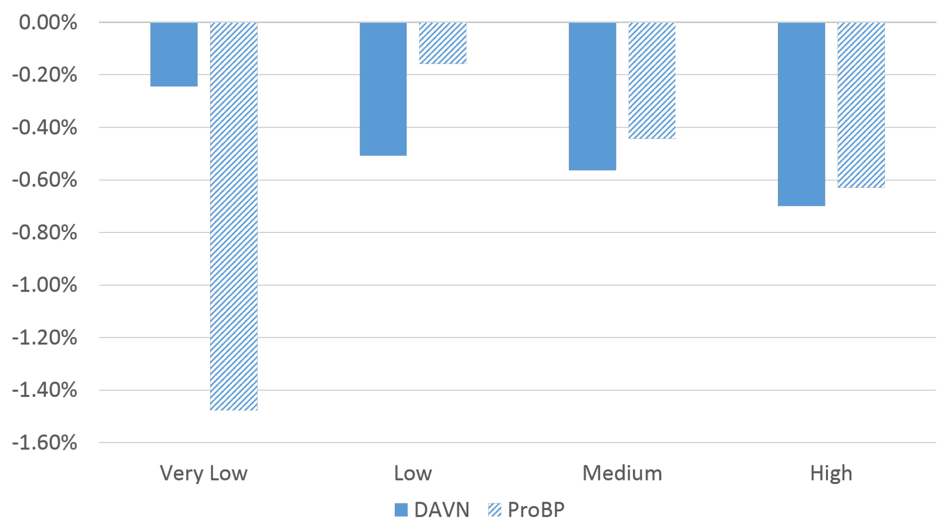


Figure 5.14: Change in Total Revenue with DAVN or ProBP Tests

	Low Demand	Medium Demand	High Demand
Load Factor	-1.64	1.21	1.21
Yield	0.8%	-1.9%	-2.3%
Ancillary Revenue	-2.1%	2.1%	2.7%
Ticket Revenue	-1.4%	-0.5%	-0.9%
Total Revenue	-1.5%	-0.2%	-0.4%
Average Bid Price at TF=1	46%	23%	22%
Class 1 PAX	2%	-2%	-2%

Figure 5.15: ProBP Change in Key Metrics

The key to understanding this phenomenon stems from the large increase (46%) in bid prices calculated by ProBP with A.R. adjustment, which comes from the fundamental difference between the optimization schemes of ProBP and DAVN. In ProBP, the bid price is calculated by considering all possible paths and fares values on a particular leg. Since the bid price was low in cases of low demand (because the opportunity cost is low), adding an average of $30 ancillary revenue proportionally increased the bid price by a large amount, since this A.R. was added for all possible itineraries. A 46% increase in bid price affects the availability of all potential bookings. Higher bid prices results in fewer accepted bookings overall, explaining the loss in load factor and the increase in yield. Particularly in ProBP, the bid price is the only control mechanism, so a large change in bid price results in a change in the behavior of the RM system. In contrast, with DAVN, the displacement cost is nested into virtual buckets as an intermediate step before calculating protection levels with EMSRb, so the effect is not as large.

In summary, with standard forecasting on ProBP, Input Adjustment causes less predictable effects especially in cases of low demand because of the sensitivity of ProBP's bid prices to modification.

5.1.4 Network RM with Hybrid Forecasting/Fare Adjustment (Semi-Restricted)

Because hybrid forecasting and fare adjustment represents an RM strategy developed for network RM (compared to classic leg RM), we do not test cases that combine FCYM with hybrid forecasting and fare adjustment. Additionally, since HF/FA was developed in response to the rise of LCCs and the movement of the industry towards semi-restricted and unrestricted fare structures, we only test HF/FA in the context of a semi-restricted fare structure.

With HF/FA, RM fares are adjusted by the optimizer to account for buy down in fare adjustment. Details were given in Chapter 2, but fare values are modified based on marginal revenue expectation which accounts for both the expected revenue from extra bookings as well as the expected loss in revenue from buy down. Given in RM Input Adjustment that input fares are modified twice (once by fare adjustment and once by ancillary revenue adjustment), it is debatable which adjustment should be theoretically applied first. Tests showed that the differences between the two approaches are not significantly different, and in this thesis we assume that fare adjustment that accounts for buy down is applied first and then followed by ancillary revenue adjustment.

Experiment 8: DAVN vs. ProBP with Hybrid Forecasting/Fare Adjustment

Figure 5.16 shows the incremental revenue gain from Input Adjustment when the optimizer is set at either DAVN or ProBP with hybrid forecasting and fare adjustment. In contrast with cases without fare adjustment, results are positive for all demand levels tested. Incremental revenue gains range from +0.25% to +0.65%.

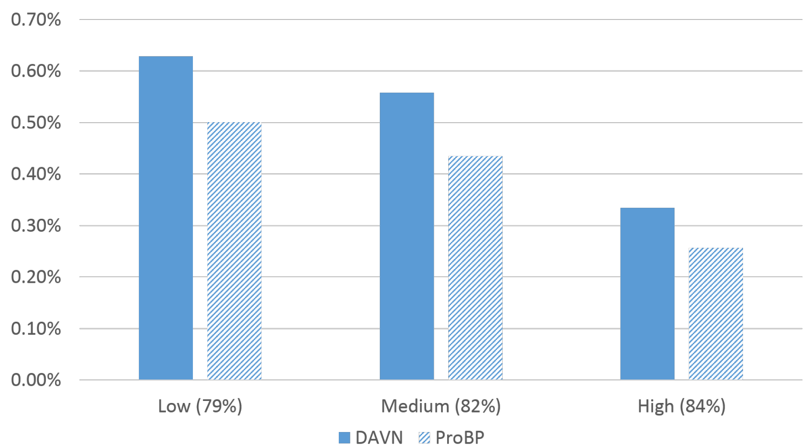


Figure 5.16: DAVN and ProBP Incremental Revenue Gain with HF/FA

Similar to previous cases, the percent increase in incremental revenue decreases with higher demand. The greatest gains are around 0.6% at the low demand level. Incremental revenue gains (and underlying patterns) are similar for DAVN or ProBP, so our deeper analysis focuses on cases with ProBP.

Figure 5.17 shows the change in load factor with RM Input Adjustment in an optimizer with hybrid forecasting and fare adjustment. Since the optimizer performs better in reducing the revenue losses of spiral-down, Airline 1 received the benefits of higher loads while retaining enough yield and obtaining ancillary revenue for positive incremental revenue. With all of the demand cases tested, again, there was about a +2 point increase in load factor for Airline 1.

Figure 5.18 shows the change in revenue for both ticket sources and ancillary sources. With all demand cases, there is an increase in ancillary revenue - which is expected since the optimizer opens availability for lower classes. The effect of capturing more ancillary revenue, as with before, increases when the demand level increases, because there are more lower classes bookings accepted.

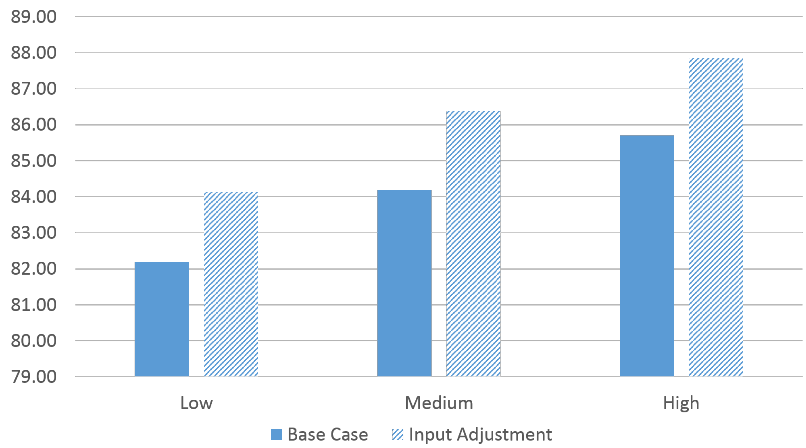


Figure 5.17: Load Factor Changes with ProBP

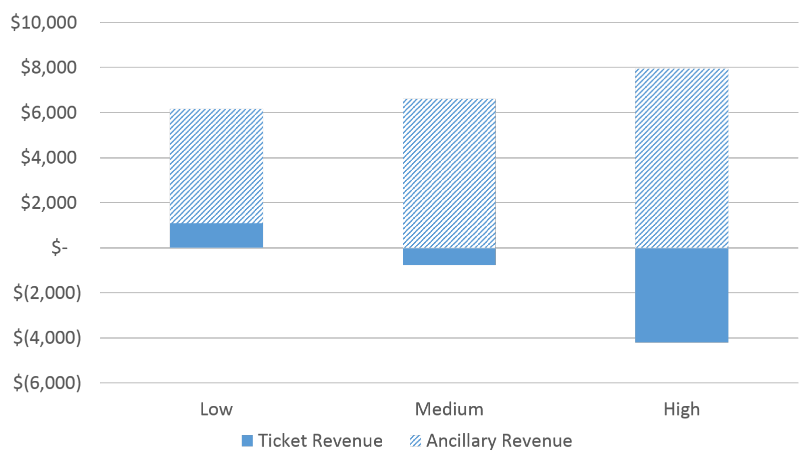


Figure 5.18: Ticket and Ancillary Revenue Changes with ProBP

With respect to ticket revenue, however, there is an increase in the low demand case. This is surprising because it is the first instance tested where this has occurred. This shows that the fare class mix actually improved to a more favorable one, signalling that there are smaller amounts of buy-down, spiral-down, and the availability is opened more effectively for the targeted demand segment. Hybrid forecasting and fare adjustment accounts for the effects of buy down, and in the low demand case, contributed to positive gains in ticket revenue with ancillary revenue incorporation. In the medium and high demand scenarios, even though there was a loss in ticket revenue, the gain in ancillary revenue contributed to the net gain in total revenue.

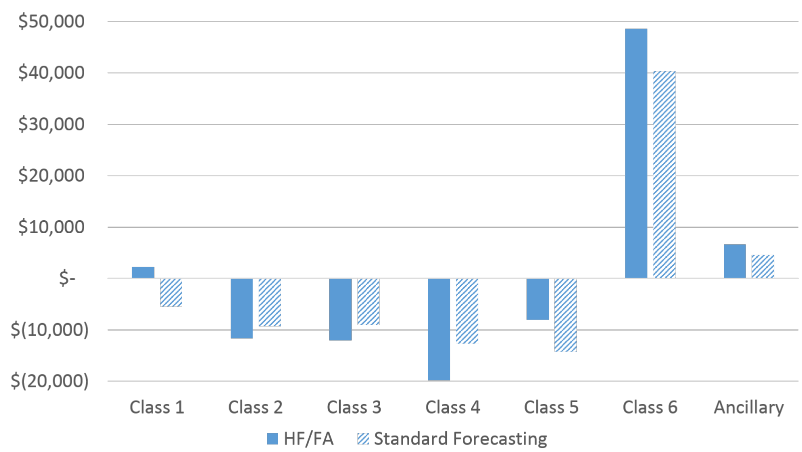


Figure 5.19: Changes in Fare Class Mix (Revenue) and Ancillary Revenue with HF/FA and Standard Forecasting in Medium Demand

Figure 5.19 shows the change in revenue by class and by ancillary sources with ancillary revenue adjustment. The revenue values are grouped together with HF/FA (left bars) and standard forecasting (right bars) cases. Although there are still buy down effects in the HF/FA case, there is sell up occuring with the positive revenue gains at Class 1 and Class 5. HF/FA prioritizes inventory for Classes 1, 5, and 6 while restricting inventory to Class 2-4. With this format, there is significantly more Class 6 revenue and ancillary revenue, which outweighs the slight loss in revenue from changes in fare class mix.

5.1.5 Summary: Class Level Estimates and Input Fare Adjustment

The key points from tests on Input Fare Adjustment, assuming class level knowledge by the airline of ancillary revenue potential data is as follows:

- Incorporating ancillary revenue potential with Input Fare Adjustment with only standard forecasting results in revenue loss for all scenarios tested, be it network versus leg RM, different amounts of A.R. potential, different demand levels.
- The revenue losses come primarily from the negative effects of buy down and spiral down, where failure to account for inter-class demand results in higher value passengers purchasing a lower fare, resulting in lost revenue.
- Increasing the overall demand level or increasing the ancillary revenue potential exacerbates the effects of spiral down.

- With sell up modelling, or hybrid forecasting and fare adjustment, there is revenue gain for all scenarios tested.
- After accounting for the effects of buy down, the RM system can adequately prioritize enough seats for lower classes to gain ancillary revenue while recovering extra higher value passengers.

The next step is to test and compare the effects of Availability Fare Adjustment only with Input Fare Adjustment. Again, we assume class level estimation of ancillary revenue potential by market by the airline when it adjusts its availability fares.

5.2 Class Level Estimates and Availability Fare Adjustment

This area of testing explores the results when Airline 1 utilizes Availability Fare Adjustment only. To provide context, results are compared with those from RM Input Adjustment. Since Availability Fare Adjustment is feasibly implemented only for network revenue management, we begin our analysis with cases where Airline 1 and Airline 2 use DAVN and ProBP with standard forecasting in semi-restricted fare structures.

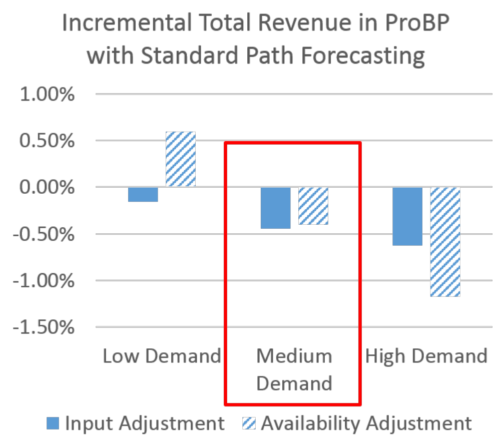
5.2.1 Network RM with Standard Forecasting and Semi-Restricted Fare Structures

As with before, both airlines utilize the same forecaster or optimizer. In the environment with semi-restricted fare structures, AL1 and AL2 have the choice of DAVN or ProBP and standard forecasting or hybrid forecasting/fare adjustment. Availability Adjustment for ancillary revenue is altered for Airline 1 only.

Experiment 1: Availability vs. Input Adjustment in ProBP

Figure 5.20 (left) shows the incremental total revenue from either RM Input Adjustment or Availability Adjustment for Airline 1. With Availability Adjustment, there is positive revenue gain in the low demand case and negative incremental revenue with medium and high demand. This is interesting because the low demand case is the first scenario with standard forecasting where ancillary revenue adjustment resulted in significantly positive total revenue gain. Also to note is that the high demand case resulted in lower incremental revenues with Availability Adjustment than the comparable Input Adjustment case.

Clues for the differences between the two methods can be found by looking at the changes in load factor, yield, ticket and ancillary revenue. In Figure 5.20 (right), the changes in these met-



Change in Key Metrics in Medium Demand

	Load	Yield	Ticket Rev.	Ancillary Rev.
Input	+1.2 PT	-2.3%	-0.9%	+2.7%
Availability	+5.5 PT	-7.7%	-1.7%	+8.4%

Figure 5.20: (Left) Incremental Total Revenue Gain. (Right) Changes in Key Metrics in Medium Demand with Adjustment

rics are compared in the medium demand case for the two different ancillary revenue adjustment scenarios. Availability adjustment results in the same general patterns as Input Adjustment: more lower class bookings are accepted, increasing load factor and ancillary revenue at the cost of lower yields and lower ticket revenue. The important thing to note here is that Availability Adjustment results in a stronger net effect than Input Adjustment on revenues – twice the loss in ticket revenue but triple the gain in ancillary revenue – given the same levels of demand.

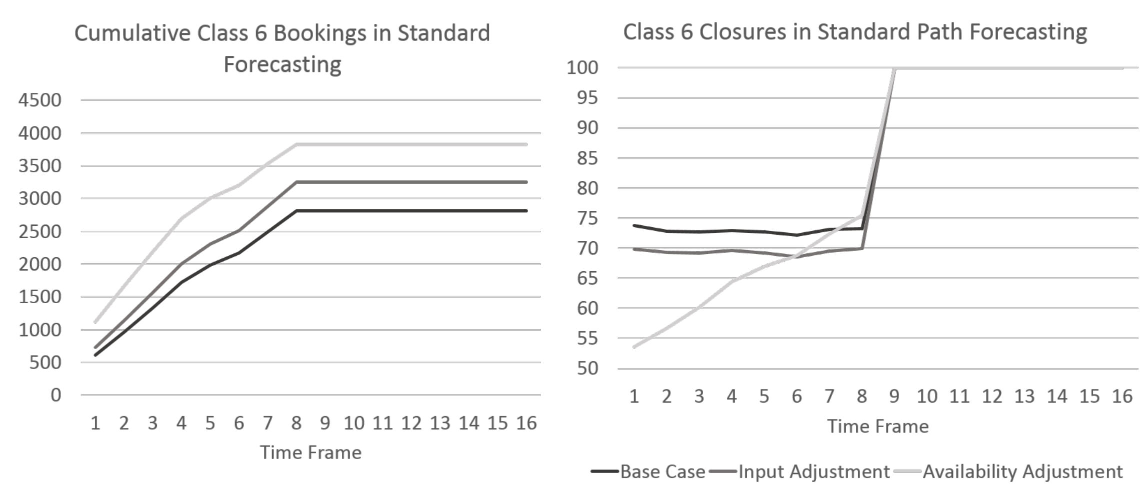


Figure 5.21: (Left) Cumulative Class 6 Bookings Taken by Time Frame. (Right) % of Class 6 Closed by Time Frame.

Figure 5.21 (left) shows the total number of Class 6 bookings taken in each case – base case with no adjustment, Input Adjustment, and Availability Adjustment – with the ProBP medium demand scenario, as a function of time frame. The key trend to note is that Availability Adjustment results in more Class 6 bookings being taken in the early time frames. Looking at Figure 5.21 (right) reaffirms this trend: there is significantly more availability for Class 6 with Availability Adjustment than either of the other two cases. The reasoning for this is that ancillary revenue adjustment affects availability immediately at the beginning of the booking process, since all lower class bookings receive extra availability. Because lower class passengers have a higher proportion of leisure travelers that show up early, there are more bookings accepted in the early time frames.

The reason why this occurs is because of the nature of Availability Adjustment. Input Adjustment modifies bid prices and displacement costs as RM inputs in addition to extra valuation of lower class , which causes more Class 6 bookings to be accepted than the base case, but not as much as Availability Adjustment. Availability Adjustment results in a bonus to the availability fare without a corresponding modification of bid prices or displacement costs and therefore results in significantly more Class 6 availability early.

However, by time frame 6 and 7, class 6 closures for Availability Adjustment equal that of Input Adjustment (and later, the base case). This is a result of a feedback effect within the simulation – because there were many more bookings in the early time frames, this caused the optimizer to readjust and progressively become more "aggressive" in protecting seats and closing down Class 6. The net result is that Availability Adjustment results in significantly more availability for Class 6 early, booking enough to indirectly adjust the optimizer and close down before advance purchase takes into effect at time frame 9 for Class 6.

The nature of the two adjustment methods explains why Availability Adjustment results in much more effect on revenues than Input Adjustment.

Experiment 2: Availability vs. Input Adjustment in ProBP or DAVN

Figure 5.22 shows the comparison of Input Adjustment and Availability Adjustment for DAVN and ProBP. Although the magnitudes are slightly different for both optimizers, the general trends are the same for both Input Adjustment and Availability Adjustment. The key points to note in cases with standard forecasting are as follows:

- In Input Adjustment with standard forecasting, all cases saw negative change in incremen-

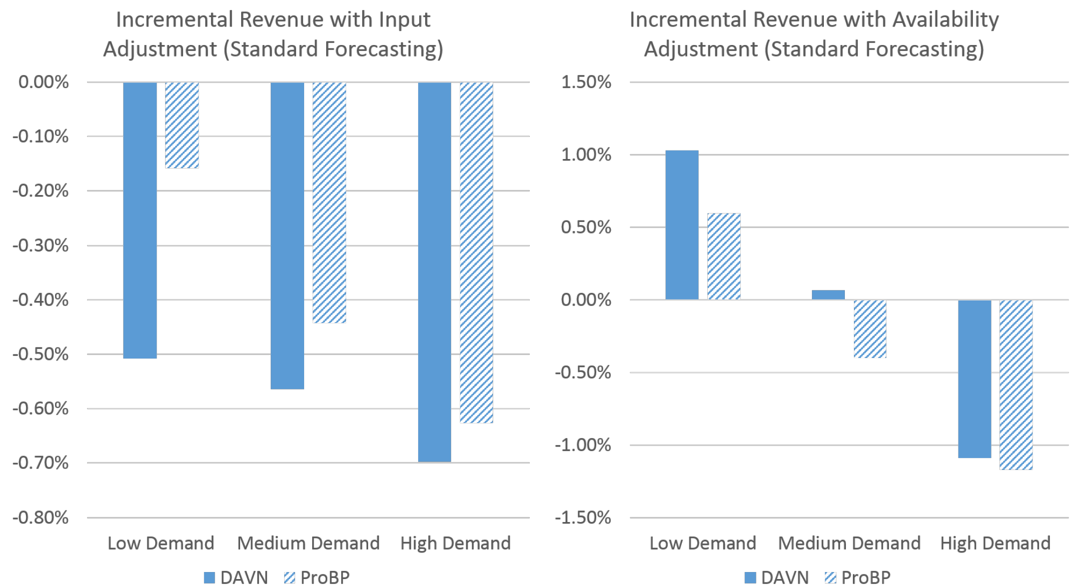


Figure 5.22: (Left) Differences in Revenue Gain in Input Adjustment. (Right) Differences in Revenue Gain in Availability Adjustment.

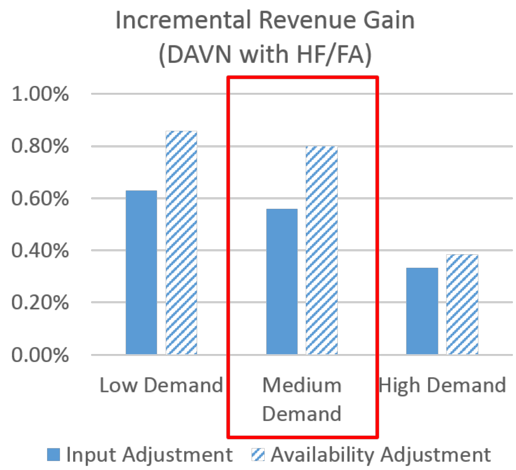
tal total revenue with adjustment. This is because the RM system is unable to account for inter-class demand, which results in spiral down.

- In Availability Adjustment, the same patterns occurred but the level of effect was much greater because of extra availability in the early time frames.
- In low demand cases, where the extra bookings are beneficial and the effects of buy down are small compared to the benefit from extra bookings, this resulted in positive revenue gain for both DAVN and ProBP.
- Medium and high demand scenarios saw the usual loss in revenue for the same reasons as Input Adjustment.
- Adjustment in DAVN and ProBP resulted in similar trends.

5.2.2 Network RM with Hybrid Forecasting/Fare Adjustment

In this section, both airlines use hybrid forecasting and fare adjustment. Tests and results are shown for DAVN, because the trends are similar to ProBP. As explained previously, the following scenarios with HF/FA assume that ancillary revenue adjustments occur after the fare adjustment calculations.

Experiment 3: Availability vs. Input Adjustment in DAVN with Hybrid Forecasting/Fare Adjustment



Change in Key Metrics in Medium Demand

	Load	Yield	Ticket Rev.	Ancillary Rev.
Input	+2.3 PT	-2.5%	+0.1%	+4.1%
Availability	+4.2 PT	-4.7%	+0.0%	+6.2%

Figure 5.23: (Left) Differences in Revenue Gain in Input Adjustment. (Right) Differences in Revenue Gain in Availability Adjustment.

Figure 5.23 shows the incremental revenue gain for RM Input Adjustment and Availability Adjustment. Note that Availability Adjustment (+0.4% to +0.83%) results in more incremental revenue than Input Adjustment (+0.37% to +0.62%). Note that the same patterns occur as with standard forecasting: Availability Adjustment results in more load captured and extra ancillary revenue than Input Adjustment. However, the magnitude of the effect is lessened - ancillary revenue only increases by an additional 2.1 percentage points, for example. Secondly, the positive incremental total revenue gain results from the zero change in ticket revenue. In contrast to the standard forecasting case, Availability Adjustment (and Input Adjustment) with HF/FA resulted in smaller losses from buy down and therefore no loss in ticket revenue. Coupled with the positive increase in ancillary revenue, total revenue increased.

Figure 5.24 reaffirms the benefits of HF/FA with ancillary revenue adjustment in the medium demand scenario. Class 6 and Class 5 bookings increased at the expense of Class 3 and Class 4, resulting in slightly less ancillary revenue gain. However, in combination with more bookings from Class 1 and Class 2, this fare class mix overall resulted in an overall zero gain in ticket revenue by overcoming the losses in buy down.

Figure 5.25 shows the net effect of Availability Adjustment under HF/FA. As with the stan-

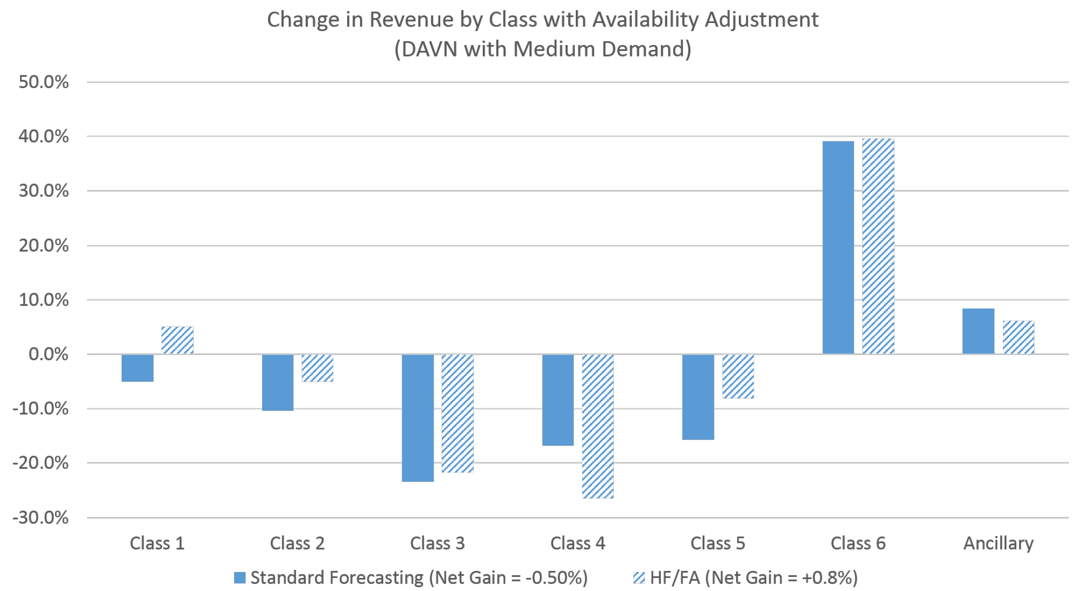


Figure 5.24: Medium Demand DAVN: Changes in Class Revenue with Availability Adjustment

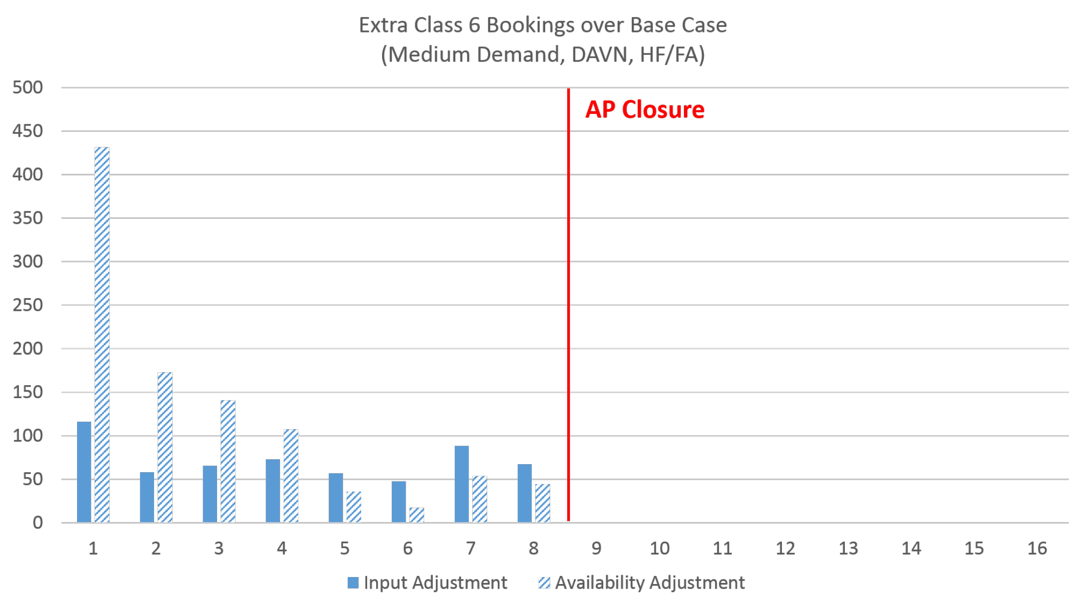


Figure 5.25: Extra Class 6 Bookings over Base Case (DAVN + HF/FA)

dard forecasting case, Availability Adjustment opens up availability for Class 6 in the early time frames by bypassing the optimizer and assigning a bonus at the start of booking for all lower class itinerary requests. The feedback loops manifests itself, and the optimizer ends up closing down many classes in time frames 7 and 8 to sell some passengers up to Class 5.

Ancillary revenue adjustment in hybrid forecasting and fare adjustment results in the largest revenue gains simulated in these tests.

5.2.3 Summary: Class Level Estimates and Availability Fare Adjustment

In this area of testing, we evaluated the revenue performance of Availability Fare Adjustment only in the context of standard forecasting or hybrid forecasting and fare adjustment with network RM.

With standard forecasting, Availability Adjustment results in positive revenue gains of +0.5% to +1.0% because the extra load obtained is beneficial when load factor is low overall. Extra bookings are accepted early in the booking curve, which still allows the RM optimizer to close down in the middle time frames and capture higher value demand. This is in contrast to Input Adjustment (all demand levels) and Availability Adjustment in medium and high demand, where incorporating ancillary revenue led to revenue loss. In those scenarios, the revenue losses from spiral down were too large and offset the gains obtained from Class 6 bookings.

With hybrid forecasting and fare adjustment, Availability Adjustment resulted in revenue gaoins from +0.4% to +0.9%, which is slightly higher than the gains with Input Adjustment and HF/FA. Similarly with Input Adjustment, HF/FA results in positive revenue gains because it models passenger sell up and closes down classes in the middle time frames before Class 6 AP.

So far, tests have been run assuming airline estimates on a market and class level basis. Based on estimates of mean ancillary revenue potential, Airline incorporates these estimates within their RM input fares by modifying the RM optimizer or in availability fares only. The next area of testing explores the scenario that Airline 1 has estimates of ancillary revenue potential by each individual passenger, which represents an unrealistic and infeasible circumstance. Although airlines do not currently have the capacity to estimate on this level, it is possible to test this level of estimation in PODS and obtain a theoretically maximum possible incremental revenue gain.

5.3 Passenger Specific Ancillary Revenue Potential and RM Input Fare Adjustment

In this area of testing, we assume that Airline 1 has an estimate of ancillary revenue potential by each individual passenger. However, in the case of Input Adjustment, the input fares are still based on mean fare values by market and by class when used as inputs to calculate displacement costs and bid prices. In other words, the airline aggregates estimates for fare values by booking class and by market when making these calculations; so, deriving the mean from an estimate of ancillary revenue by passenger is the same as simply estimating the mean ancillary revenue potential. For this reason, results of RM optimizer input should not be affected by the randomization of actual passenger ancillary revenue values.

On the availability side, we assume that the airline only has class level, mean value data. In other words, all passengers receive the same ancillary revenue bonus, as modelled by each class, in this scenario with RM Input Fare Adjustment (the last section tests the case where the airline applies RM Input Adjustment with passenger specific modification of availability fare). Passenger A, even though he may eventually pay \$50 for add-ons, is still only given a \$30 bonus to his availability fare in this scenario. For these tests, Airline 1 uses RM Input Fare Adjustment. DAVN with semi-restricted fare structures are applied for both airlines. Tests are performed with standard forecasting, HF/FA and different demand levels.

Ancillary revenue potential is generated by passenger as follows: a normal random distribution of ancillary revenue by passenger with a mean of \$30 with a standard deviation of \$0, \$9, \$18, and \$27 for Classes 3 through 6, which correspond to k-factors of 0, 0.3, 0.6, 0.9. There is a floor of \$0 because there are no negative values possible. In each case, the airline has unbiased estimates of the ancillary revenue potential for each passenger.

5.3.1 Results

Results are shown for the case where Airline 1 uses Input Adjustment with DAVN and standard forecasting in Figure 5.26. The case where passenger ancillary revenue is deterministic is k=0, which was tested in the previous section and shown for comparison. The results with different k-factors are very similar, except there is a slight increase in revenue with higher k-factors.

The reason for this can be found by looking at the distributions of ticket revenue and ancillary revenue separately in Figure 5.27. Note that the ticket revenue gain by Airline 1 is the exact same for each k-factor case, as is fare class mix, yields, and load factor. The factor that changed, however, is the incremental ancillary revenue gain. With increasing variability in passenger spend, the airline captured more ancillary revenue.

Figure 5.28 shows the distribution of ancillary revenue given the three probabilistic cases. Since a minimum of \$0 is applied, this created a skewness in the distribution since many values are at zero. The effective mean, for example, of the k=0.9 case rises to \$31.80, introducing a slight

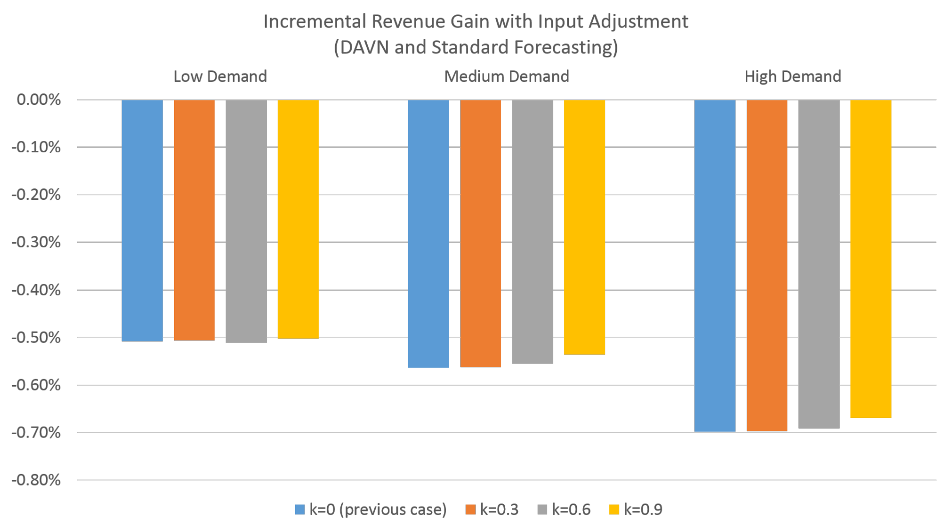


Figure 5.26: Incremental Revenue Gain given Different K-Factors with Standard Forecasting

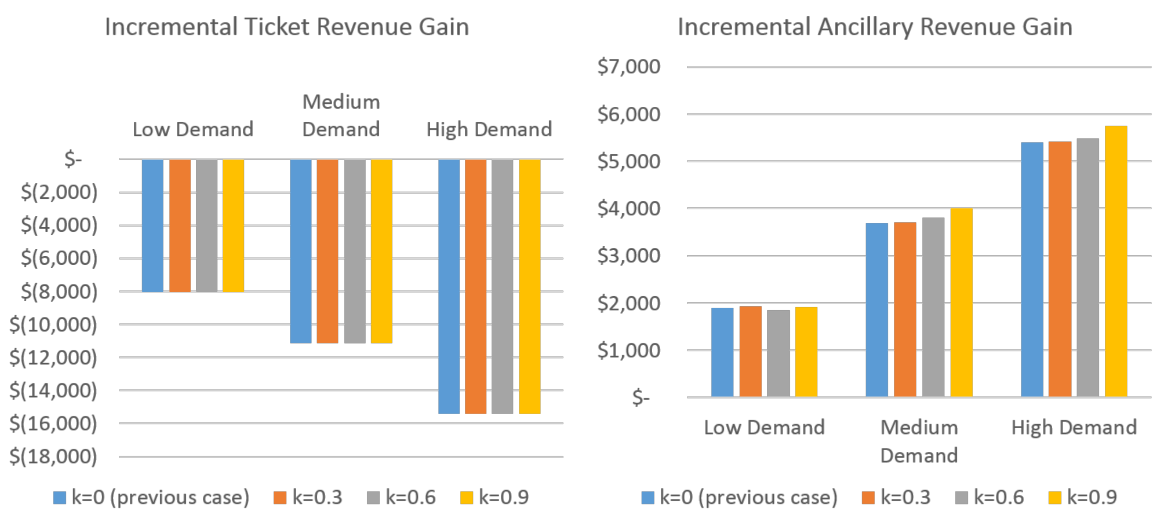


Figure 5.27: (Left) Ticket Revenue and (Right) Ancillary Revenue

bias. Although the conclusions drawn from these scenarios are as expected, knowledge of this bias is useful in comparing revenue gains for future scenarios.

In summary, the results are as expected: given Input Adjustment with mean values as RM input fares, there is no change in the optimizer methodology. In addition, given the availability fare is unchanged from the deterministic case, effectively the same results are produced. Although the case with HF/FA is not shown, there is no difference in trend from using a more sophisticated

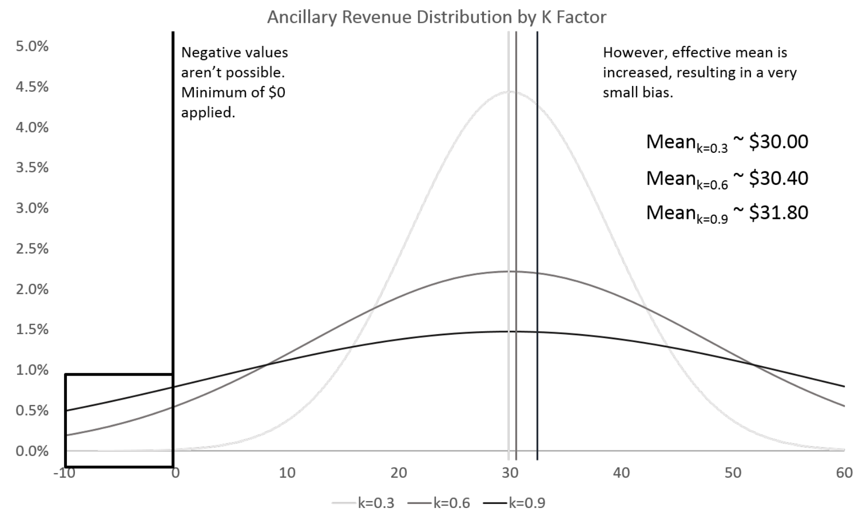


Figure 5.28: Normal Distributions of Ancillary Spending given K-Factors

forecaster.

5.4 Passenger Specific Estimates and Customized Availability Fare Adjustment in Semi-Restricted Fare Structures

In Customized Availability Fare Adjustment, the airline does not alter its bid prices or displacement costs. The optimizer remains unaffected; rather, the availability fare is given a bonus depending on the level of expected ancillary revenue potential of each individual passenger. The airline can effectively discriminate traffic even further, on an individual passenger by passenger basis.

We apply the same optimizers and environment as the previous case, starting with standard forecasting for both airlines. The variability of individual passenger ancillary revenue is the same as before: k=0, k=0.3, k=0.6, k=0.9.

5.4.1 DAVN with Standard Forecasting

Figure 5.29 shows the incremental revenue gain with Customized Availability Adjustment for each case of passenger distribution of ancillary revenue. For comparison, RM Input Adjustment (deterministic case, k=0) is also shown. The more variable the distribution of ancillary revenue, the more revenue that Airline 1 obtains with Customized Availability Adjustment. Revenue gains range from 1 - 2% with the highest k-factors, a significant increase over the deterministic cases.

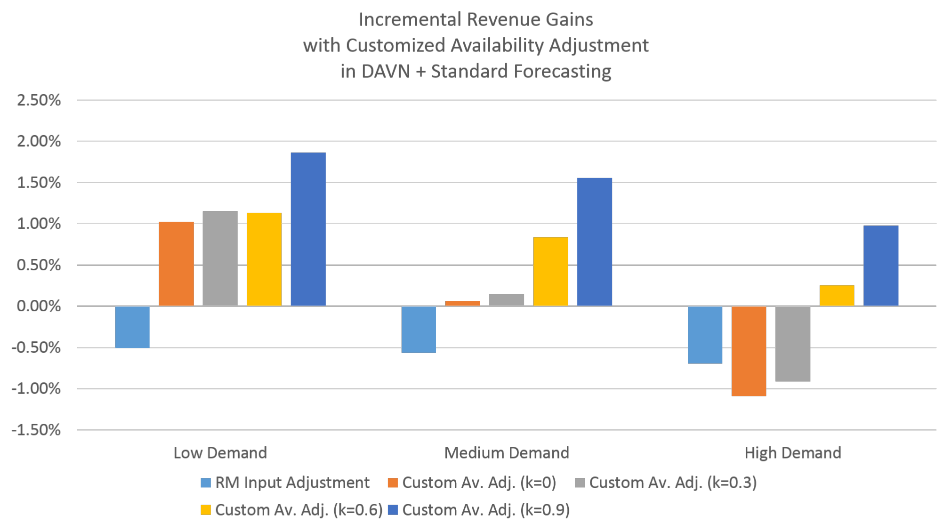


Figure 5.29: Revenue Gains from Customized Availability Adjustment with Standard Forecasting

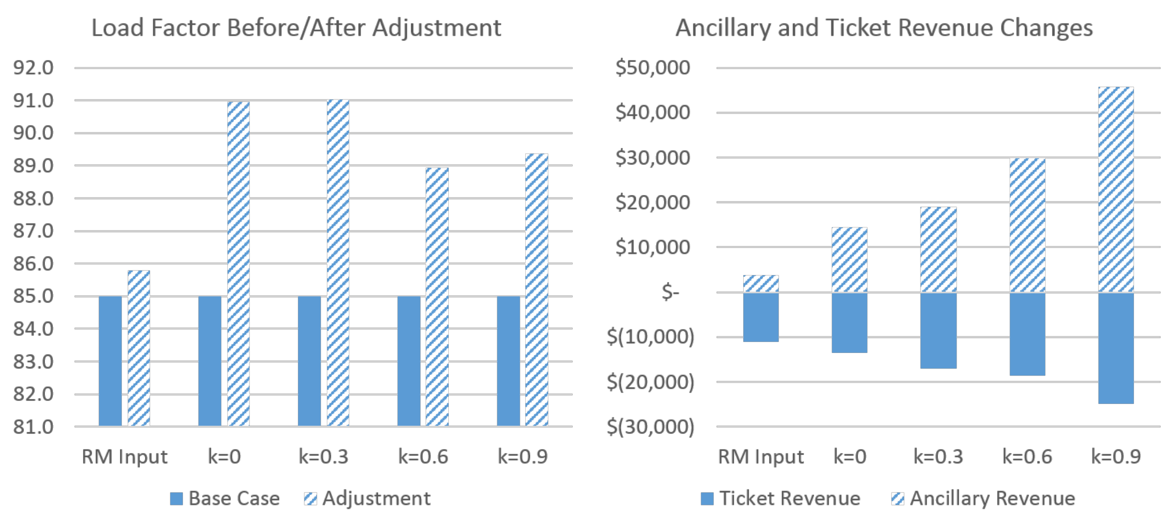


Figure 5.30: Medium Demand - (Left) Changes in Load Factor with Adjustment. (Right) Changes in Ancillary and Ticket Revenue.

Figure 5.30 (left) shows the change in load factor given Customized Availability Adjustment. In the deterministic cases, RM Input Adjustment results in slightly more load, while Availability Adjustment results in a significantly higher load increase. However, the revenue gain from

Customized Availability Adjustment given ancillary revenue variability does not come from increased load - with higher k-factors, the load increase remains constant or lower than the k=0 case. This reaffirms the fact that Airline 1 is able to discriminate in favor of higher value traffic more effectively.

Figure 5.30 (right) shows the gains in ancillary revenue and ticket revenue. Because Airline 1 is operating its RM system with a standard forecasting, the same trends of buy down occur from higher value classes (who do not have ancillary revenue) as with all cases of standard forecasting. However, even with the large losses in ticket revenue, the gain in ancillary revenue more than makes up the difference.

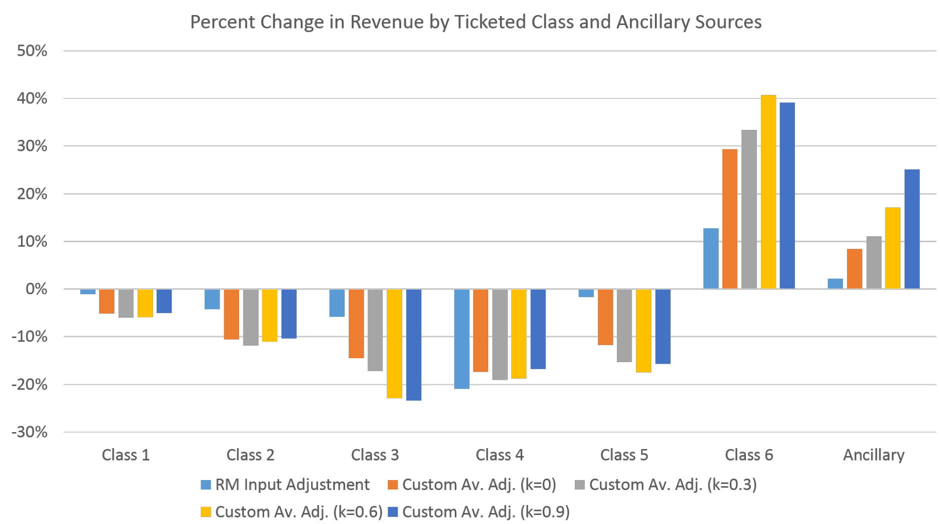


Figure 5.31: Medium Demand - Changes in Revenue by Class and Ancillary Sources

Figure 5.31 shows the percent change in revenue by ticketed class. There is evidence of losses due to buy down from the upper classes. However, with Customized Availability Adjustment, the significant increase in ancillary revenue indicates that the extra value carried by the extra Class 4-6 bookings makes a large difference. Although there are significant losses from buy down, the large gains in ancillary revenue are enough to overcome and result in positive total revenue increases.

5.4.2 DAVN with Hybrid Forecasting/Fare Adjustment

The next step is to apply Customized Availability Adjustment in the context of DAVN with hybrid forecasting and fare adjustment. Figure 5.32 shows the incremental revenue gains with

Customized Availability Adjustment (with different k factors), as well as RM Input Adjustment for comparison. As shown, the gains with HF/FA are even higher than standard forecasting, with revenue increases of 2.2% to 2.7% with k=0.9. Although there was revenue gain in the deterministic cases for both Input Adjustment and Availability Adjustment, Customized Availability Adjustment showed the largest increases in total revenue.

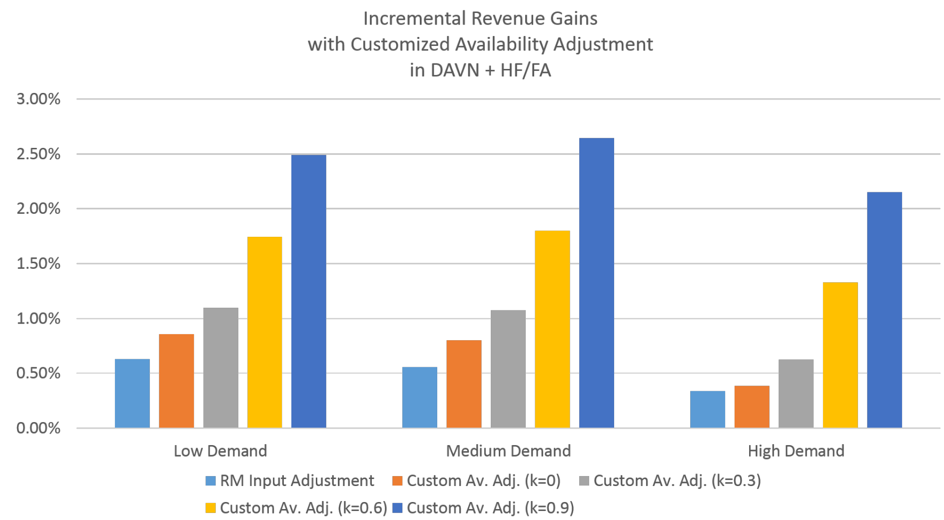


Figure 5.32: Incremental Revenue Gains with Customized Availability Adjustment in HF/FA

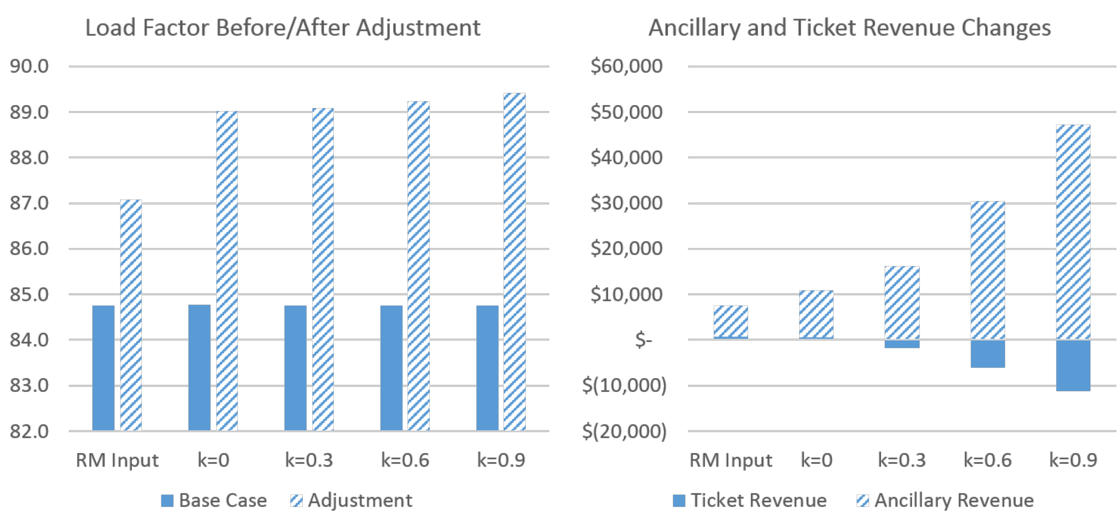


Figure 5.33: Medium Demand: Load Factor Changes, Ticket and Ancillary Revenue Changes

Customized Availability Adjustment benefited the airline with the same patterns in increased load as with standard forecasting (Figure 5.33). Rather than capturing more quantity of load, the quality of traffic accepted increases because the airline does not offer increased availability for those who are not expected to pay more for add-ons. The same levels of ancillary revenue captured are apparent with HF/FA, but the ticket revenue losses are greatly minimized compared to the case with standard forecasting, leading to the larger gains in total revenue.

5.5 Passenger Specific Estimates and Combined RM Input + Customized Availability Adjustment

Given passenger specific estimates of ancillary revenue, airlines could utilize them both when modifying RM inputs as well as when modifying individual availability. Since RM inputs can only be modified on an aggregate class level, we still modify the fares based on class level averages of ancillary revenue. However, we combine the increased RM input fares with the Customized Availability Adjustment given airline estimates of passenger specific ancillary revenue potential.

5.5.1 DAVN with Standard Forecasting and Semi-Restricted Fare Structures

Both airlines use DAVN with standard forecasting under semi-restricted fare structure environment. Only Airline 1 uses a combination of RM Input Adjustment and Customized Availability Adjustment. Results are shown alongside customized Availability Adjustment only.

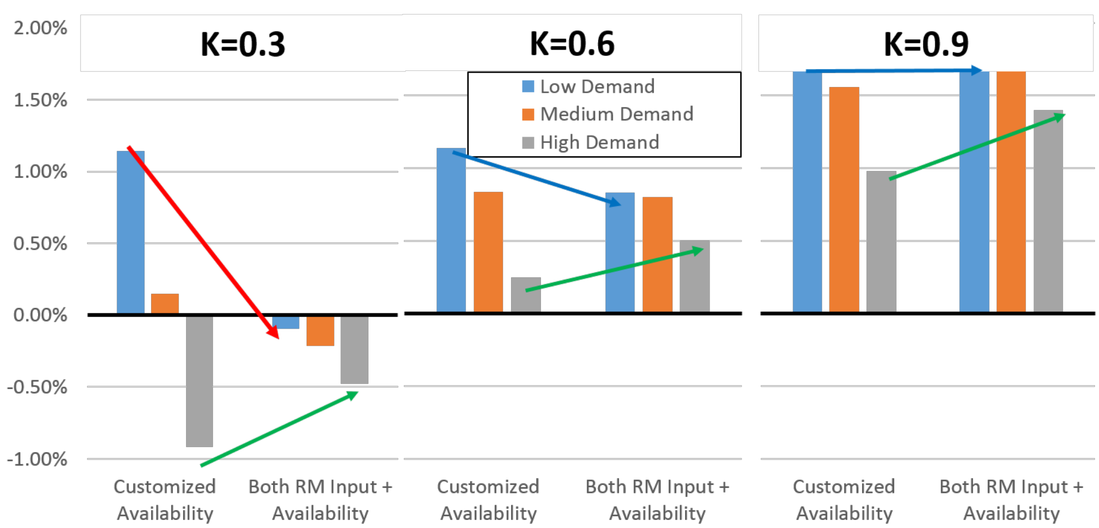


Figure 5.34: Given Different K-Factors and Different Demand Levels, Incremental Total Revenue with Combined RM Input and Availability Adjustment

Figure 5.34 shows the incremental total revenue gain, given different scenarios with k-factor, demand level, and ancillary revenue adjustment. Note that in most cases shown, Customized Availability Adjustment alone results in higher incremental revenue gains. However, given higher demand levels and higher k-factors, the gap in incremental total revenue closes, and in some cases the combined adjustment method results in even higher incremental revenues.

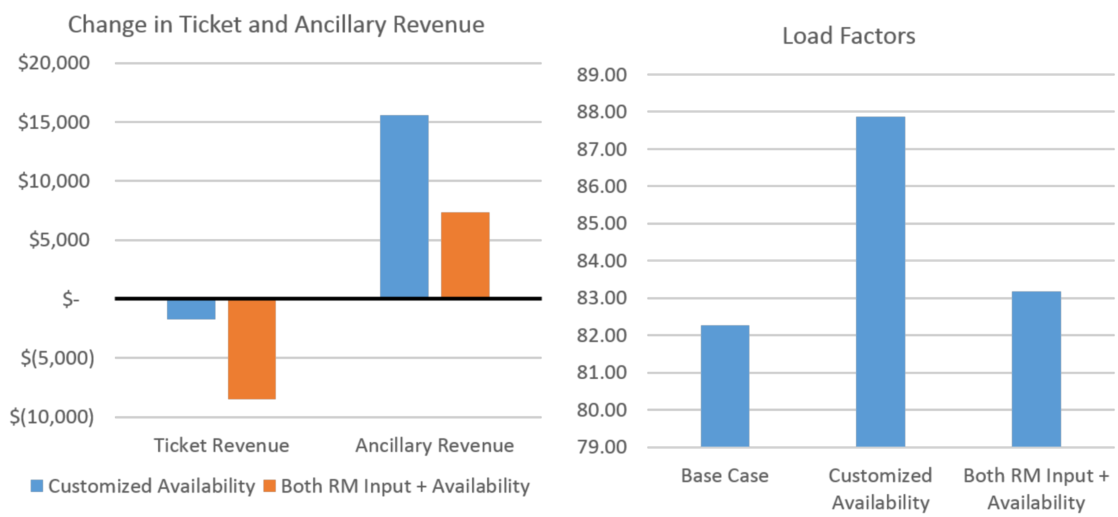


Figure 5.35: Low Demand, K=0.3 Case: Change in Ticket and Ancillary Revenue and Load Factors

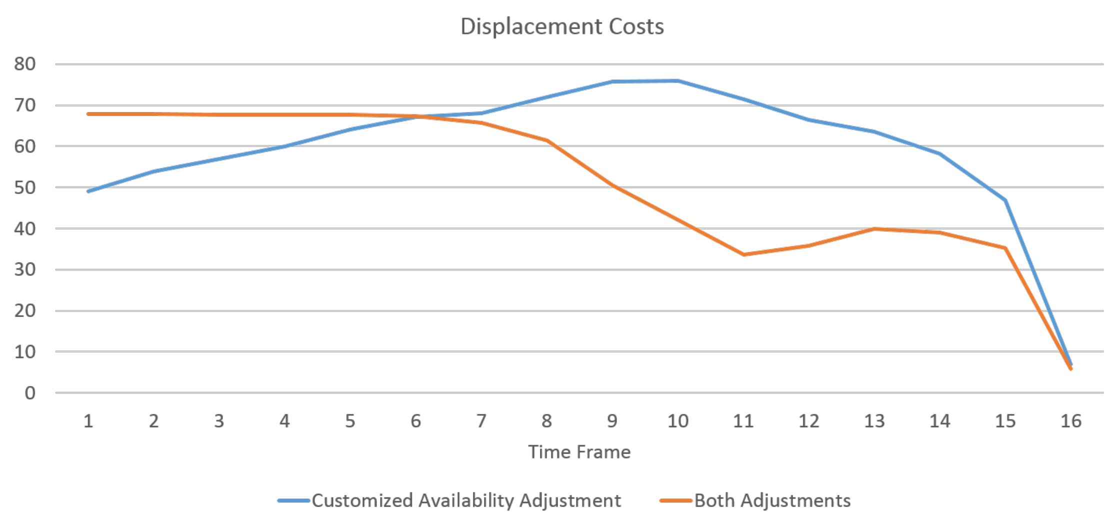


Figure 5.36: Low Demand, K=0.3 Case: Displacement Costs by Time Frame

Figure 5.35 shows the incremental revenues, split by ticket revenue and ancillary revenue in the low demand, k=0.3 case. With the combined adjustment method, there is both a decrease in ticket revenue as well as smaller gains in ancillary revenue. Load factor increase is also smaller than the Customized Availability Adjustment scenario.

The reasoning for this pattern of load factors is because Input Adjustment results in higher displacement costs, shown in Figure 5.36. Higher displacement costs cause the RM system to protect more seats for higher value passengers and therefore less willing to take low value Class 6 passengers.

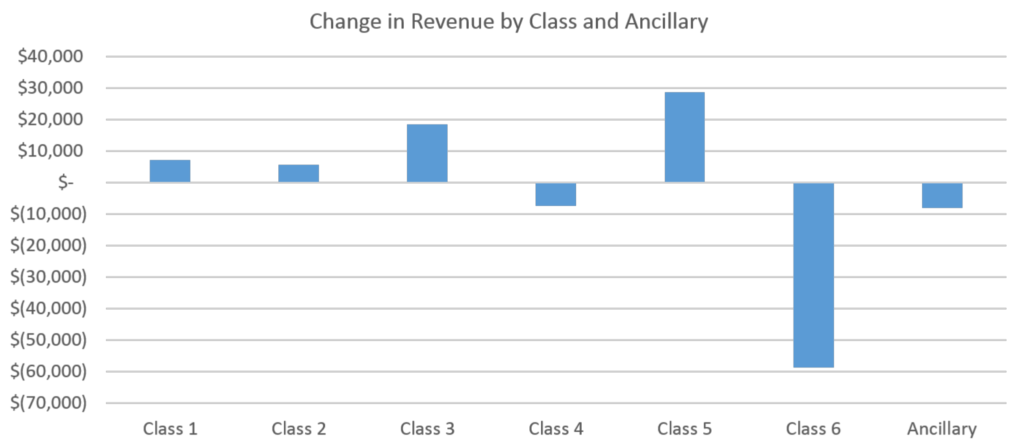


Figure 5.37: Low Demand, K=0.3 Case: Fare Class Mix Change (Availability Adjustment to Combined Adjustments)

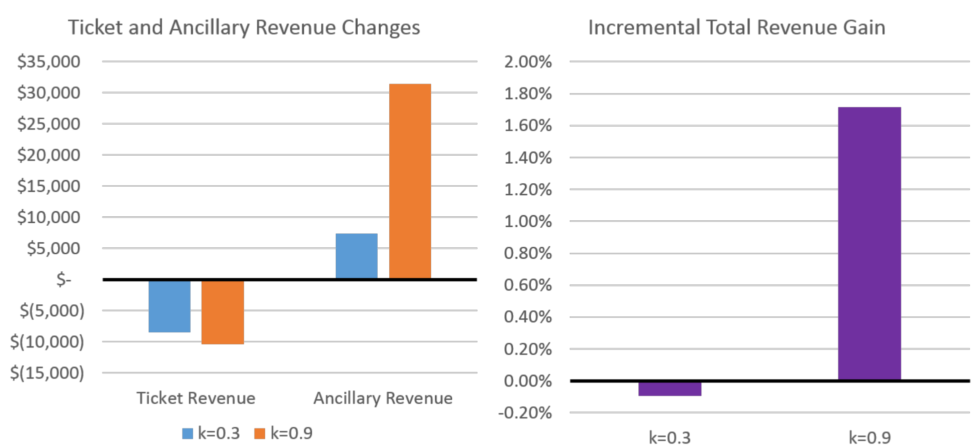
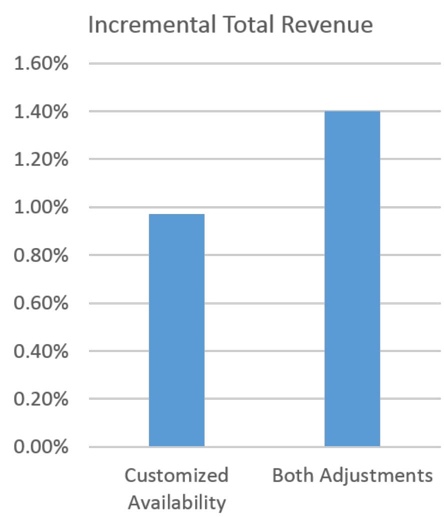


Figure 5.38: Low Demand, K=0.9 Case: Changes in Ticket and Ancillary Revenue and Total Incremental Revenue Gain

As a result, in Figure 5.37, combined adjustment results in much lower ticket revenues from Class 6 than Customized Availability Adjustment because more of the less valuable passengers are unable to book. Although there is an increase in the number of higher value passengers, overall ancillary revenue is smaller.

Figure 5.38 shows the results of combined adjustment in a higher k-factor scenario. When there are more valuable Class 6 passengers (due to some having higher ancillary revenue potential), the RM system benefits and is able to capture more ancillary revenue. Compared to the k=0.3 case, total revenue gain increases dramatically to +1.7%.



	Load Factor	Yield	Ticket Revenue	Ancillary Revenue	Total Revenue
Customized Availability	91.74	$ 0.109	$1,222K	$235.4K	$1,457K
Both Adjustments	90.07	$ 0.112	$1,233K	$230.7K	$1,463K
Change	-1.67	+2.9%	**+0.9%**	**-2.0%**	+0.43%

Figure 5.39: High Demand, K=0.9 Case: Changes in Total Revenue and Key Metrics

Similarly, given a high demand scenario and increased k-factor, there is an even higher potential for total revenue gain. Because there is also more demand overall, the RM system benefits from increased protection levels added by RM Input Adjustment and increased displacement costs. In fact, Figure 5.39 shows that the combined adjustment method even fares better than Customized Availability Adjustment only: +1.4% versus +1.0%. Although there is a compromise in ancillary revenue, the extra ticket revenue gained more than makes up for the losses.

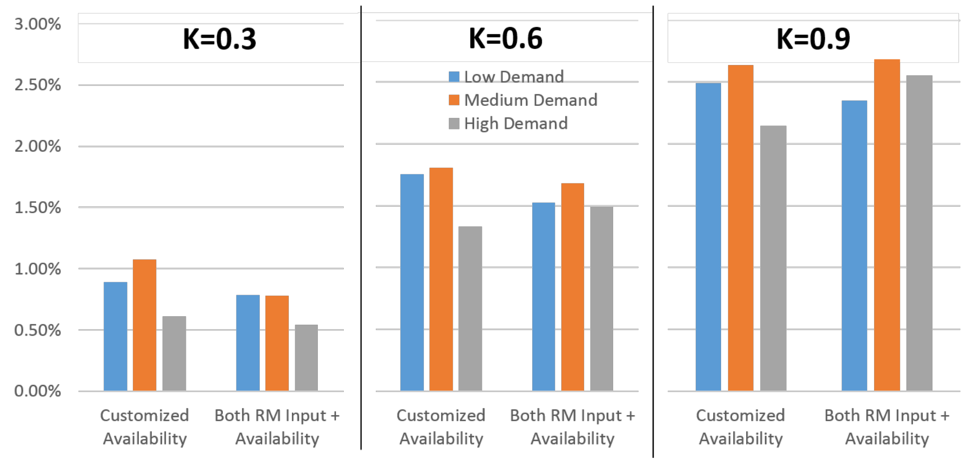


Figure 5.40: Given Different K-Factors and Different Demand Levels, Incremental Total Revenue with Combined RM Input and Availability Adjustment

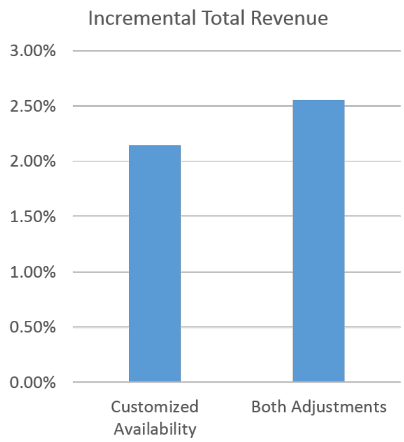
5.5.2 DAVN with Hybrid Forecasting/Fare Adjustment in Semi-Restricted Fare Structures

For scenarios with hybrid forecasting and fare adjustment, Figure 5.40 shows the results of Customized Availability Adjustment as well as combined RM input and Availability Adjustment given different k-factors and different demand levels. The same patterns occur as in the cases with standard forecasting, given enough demand and high k-factors, there are more valuable passengers that should take priority. With combined adjustments, increased displacement costs result in more seat protection and the ability for the RM system to capture more of these higher value passengers.

Figure 5.41 shows the case of high demand with k=0.9. Again, combined adjustments results in higher incremental total revenue (+2.5%), with decreased load factors and increased yield, because more valuable passengers are taken. Ancillary revenue decreased slightly, because the RM system with HF/FA is able to more accurately prioritize passengers of higher value.

5.6 Summary: Passenger Specific Estimates and A.R. Adjustment

In summary, introducing variability in ancillary revenue estimation for passengers produces different results than class level estimation. For Input Adjustment, because mean values are input into the optimizer, there is no effect on ticket revenues or fare class mix. The little difference in ancillary revenue gain is explained by the small bias in implementing a normal distribution.



	Load Factor	Yield	Ticket Revenue	Ancillary Revenue	Total Revenue
Customized Availability	91.41	$ 0.114	$1,283K	$228.0K	$1,511K
Both Adjustments	89.70	$ 0.117	$1,290K	$227.7K	$1,517K
Change	-1.71	+2.45%	**+0.5%**	**-0.1%**	+0.41%

Figure 5.41: High Demand, K=0.9 Case: Changes in Total Revenue and Key Metrics

In Customized Availability Adjustment, there are revenue gains that exceed that of deterministic passenger value (k=0) Input Adjustment and deterministic Availability Adjustment with either standard forecasting or hybrid forecasting and fare adjustment. With standard forecasting, revenue gains of +1.0% to +1.9% were simulated with k set to be 0.9. With standard forecasting, there are still forces of buy down which affect the results negatively through losses in ticket revenue. However, the ancillary revenue captured by the increased proportion of passengers spending more on add-ons increased greatly, which is enough to overcome those losses in ticket revenue.

With hybrid forecasting and fare adjustment in conjunction with Customized Availability Adjustment, revenue gains are even greater than the standard forecasting cases, with increases from +2.1% to +2.6%. This is due to the fact that the optimizer can more correctly account for losses in buy down, and minimize losses in ticket revenue.

Combined RM Input and Customized Availability Adjustment provides another alternative. The RM system prioritizes more valuable customers further, by incorporating estimates into its RM system and increasing the displacement costs or bid prices. In this method, fewer bookings are taken than in Customized Availability Adjustment. In cases where there is insufficient valuable Class 6 demand, as in low demand or k=0.3, combined adjustment results in lower and sometimes negative revenue performance compared to Customized Availability Adjustment. When there is sufficient valuable demand, as in high demand or k=0.9, combined adjustment results in better revenue performance because the system has more customers to choose from when allocating availability.

6 Conclusion

In this thesis, we explored the recent growth in ancillary revenue in the airline industry, particularly within in the last five years. Since airlines have continuously developed their revenue management systems to account for industry trends, ancillary revenue represents one of the upcoming challenges for incorporation into revenue management and distribution systems. In this thesis, we presented multiple methods for incorporating ancillary revenue into the RM and distribution process and tested the efficacy of these methods in a simulation environment.

6.1 Growth of Ancillary Revenues

Since airline deregulation in 1978, the airline industry has struggled to consistently maintain profits. The airline industry has faced challenges from both the revenue side as well as the expense side of the equation, such as the effects of September 11th on passenger behavior or record-high jet fuel prices. The volatility of the industry is apparent in that many major U.S. airlines have undergone bankruptcy filings and restructuring in order to cut expenses and return to profitability.

Ancillary revenue is a relatively recent phenomenon within the airline industry. As a proportion of operating revenues, ancillary revenues increased from about 2% to more than 6% in the five year period from 2007 to 2012. Given that airline profitability often hinges on a few percentage points, ancillary revenue can be the deciding factor in profitability for a given year and is becoming an important part of the business model for U.S. carriers and, increasingly, worldwide.

Strictly speaking, ancillary revenue includes revenue from any source that is not from the service of transporting a passenger from origin to destination. Because this definition is extremely broad, we segmented ancillary revenue into two major categories: revenue derived from add-ons or items purchased directly by passengers; and revenue derived from sources that are indirectly related to passengers. For example, examples of add-ons include charging for checked baggage or for food and drink onboard the aircraft. Revenue from indirect sources could refer to sales of Frequent Flyer awards to credit card companies, for example.

In this thesis, we focused on passenger-related ancillary revenue – revenue derived from add-ons – because of their relation to revenue management and distribution systems. The common goal of RM systems is to obtain as much ticket revenue as possible from a mix of potential customers on a given flight or network. However, there has been little work done on optimizing both ticket revenue and passenger-related ancillary revenue from customers. With the growing importance of ancillary revenues, it is logical that the next step in the evolution of revenue management systems be to include ancillary revenues in the calculations.

There is a disconnect between ticket revenues and passenger related ancillary revenues: namely, decisions to purchase add-ons come later and are made separately. This is problematic for the RM system because it forecasts demand based on the expectation of revenue, which so far has been based on ticket revenues only. In order to fully maximize total revenue, the airline RM and distribution systems should consider total revenue from each passenger, by linking his ticket fare value with his total ancillary revenue potential, the sum of all extra purchases that result in revenue for the airline.

6.2 Methods for Incorporating Ancillary Revenue

In order to effectively incorporate ancillary revenue potential into the RM and distribution systems, the airline needs to estimate a value for ancillary revenue potential for passengers. To do this, the airline collects data, runs statistical analysis on the data to generate inferences, and applies these inferences to the RM and distribution systems. Given the level of detail in the available data, the airline could make estimates that vary in granularity: the most extreme level of detail is an airline estimate of ancillary revenue potential by each individual passenger; a more reasonable level of detail estimated is an estimate by booking class and by market.

Ancillary revenue potential can be estimated by market on a class level. For example, if an airline believes that passengers who travel to leisure destinations are more likely to check a bag, then it may choose to estimate a certain expected fee from passengers travelling to those destinations. Alternatively, in passenger specific estimation, the airline associates passenger name records with ancillary revenue purchases in order to link them with tickets. Airlines can then estimate an ancillary revenue potential for each passenger. It is important to emphasize that this level of estimation is not feasible yet. To estimate ancillary revenue potential on a passenger specific basis, the airline needs to significantly invest in its database systems in order to gather ancillary revenue potential data from passengers. Even with the available data, it might not be possible for airlines to associate a specific ancillary revenue with each individual passenger. This type of estimation was tested in this thesis to represent a theoretical upper bound to revenue gain, assuming that airlines are able to obtain this level of knowledge. In this thesis, we assumed two different levels of ancillary revenue estimation by airlines: Class and Market Level Estimation; and Passenger Specific Estimation.

Given that an airline has some estimation of ancillary revenue potential, it can then incorporate the estimates into their RM and availability calculations. In this thesis, we present two possible methods for adjusting the RM and availability calculations scheme to account for ancillary revenue estimates.

RM Input Adjustment involves changing the optimizer input fare in the airline's RM system to account for both ticket revenue and ancillary revenue. The RM optimizer calculates availability limits based on the forecast of passenger demand by fare class and the revenue contribution of each fare class. RM Input Adjustment involves altering the revenue contribution of each fare class to more accurately reflect the expectation of ancillary revenue, based on airline estimates.

Availability Fare Adjustment alters the availability fare of a possible itinerary in the distribution system, as displayed at the time of booking. The revenue value of an itinerary is compared to the availability limits to determine whether or not it is available. In Availability Fare Adjustment, the revenue value of the itinerary at the time of booking is adjusted upward to account for ancillary revenue potential. Availability Fare Adjustment essentially overrides the availability limits set by the optimizer.

Given two types of estimation of ancillary revenue potential and two methods used to incorporate these estimates, we presented four methods for including ancillary revenue: (1) RM Input Adjustment with Class Level Estimates; (2) Availability Fare Adjustment with Class Level Estimates; (3) Customized Availability Fare Adjustment with Passenger Specific Estimation; and (4) Combined Customized Availability and RM Input Adjustment.

We tested the performance of these four methods in the Passenger Origin Destination Simulator (PODS), a simulation tool developed by Boeing in the 1990s used to test different revenue management strategies. In PODS, we tested the performance of these methods in the context of different optimizers, forecasters, and different fare structure environments.

6.3 Summary of Simulation Results

We assumed and modelled ancillary revenue potential on lower class passengers. The rationale is two-fold: (1) higher class tickets typically bundle amenities together which include complimentary add-ons – passengers booking in these classes contribute less ancillary revenue; and (2) since add-on prices are mostly constant by passenger, ancillary revenue potential is a greater proportion of ticket revenue for lower classes, given their ticket value is lower. Because RM systems base their calculations on the relative revenue differences between fare classes, the same absolute value of ancillary revenue potential has a greater effect on lower classes because their ticket prices are lower on average which leads to a greater ratio of ancillary revenue to total revenue.

Results indicated that including ancillary revenue estimates in either RM Input Adjustment or Availability Fare Adjustment, given a more primitive RM system (such as leg RM with standard forecasting) resulted in revenue losses. More primitive RM systems refers to those that lack the capability to model intra-class demand effects of sell up and buy down. In leg RM or network RM with standard forecasting, net total revenue losses occur because of a loss in ticket revenue. Although extra ancillary revenue is collected due to more availability and bookings in lower classes, there were significant losses due to higher class passengers buying down as well as fewer protection levels. We found that the losses intensified given greater levels of demand and given larger values of ancillary revenue potential. In the case of high demand, there were more higher class passengers that had the opportunity to buy down. In the case of higher ancillary revenue potential, a higher A.R. potential allowed the RM system to open up more availability and cased more buy down. With these standard RM systems, incorporating ancillary revenue estimates resulted in up to a -1.3% loss in revenue.

Incorporating ancillary revenue estimates given adequate modelling of sell up and buy down effects (hybrid forecasting with fare adjustment) resulted in significantly better results for both RM Input Adjustment and Availability Fare Adjustment. Given that the airline models intra class interaction, we observed little to no loss in ticket revenue; coupled with the increase in ancillary revenue, this resulted in a net increase in total revenue. Given class level and market level estimation of ancillary revenue, revenue gains of +0.3% to +0.9% were simulated. Given estimation of ancillary revenue on a passenger specific basis, we observed revenue gains up to +2.6%.

6.4 Application to Industry

Ancillary revenue, as of 2014, is an increasingly large proportion of airline operating revenue. With respect to revenue management, there is potential for significant revenue gains if airlines consider ancillary revenue when trying to maximize total revenue.

The first step for airlines is to develop some estimate of ancillary revenue in order to implement into their RM systems. This requires some level of effort related to data collection. One alternative is to tie ticket purchases with add-on purchases by passenger: since passengers decide to purchase add-ons after purchasing their ticket, it is a challenge for airlines to tie back these extra purchases to passenger itineraries in order to connect the two sources of revenue. Another alternative could be to connect add-on revenue trends with different markets; for example, leisure markets could possibly be more willing to check bags, so the RM system could justify increased availability to those passengers.

The next step for airlines is to use the data and draw statistical inferences. Given inferences, airlines could use estimates of ancillary revenues to predict expected revenue and implement them into revenue management and availability calculations. Airlines can then use the methods defined in this thesis to incorporate ancillary revenue into revenue management and distribution.

Overall, the contributions from this thesis are believed to be important practically to airlines, given many carriers emphasizing the sale of add-ons. Developing these methods to incorporate ancillary revenue is an important contribution, given that there is large potential for revenue gains.

References

[1] Airlines for America. *2011 Economic Report.* Washington, DC, 2012. Available: http://www.airlines.org/Documents/economicreports/2011.pdf.

[2] Barnhart, Cynthia, Belobaba, P., Odoni, A. "Applications of Operations Research in the Air Transport Industry". *Transportation Science*, Vol. 37:4, pp. 368 - 391. 2003.

[3] Belobaba, Peter. *Air Travel Demand and Airline Seat Inventory Management.* Ph. D. Dissertation, Massachusetts Institute of Technology, Cambridge, MA, 1987.

[4] Belobaba, Peter. "Applications of a Probabilistic Decision Model to Airline Seat Inventory Control," *Operations Research*, Vol. 37, pp. 183 - 197. 1989.

[5] Belobaba, Peter, Amedeo R. Odoni, and Cynthia Barnhart. "Introduction and Overview." *The Global Airline Industry*, 1st Edition. Chichester, U.K.: Wiley, 2009. 4. Print.

[6] Belobaba, Peter, Amedeo R. Odoni, and Cynthia Barnhart. "Fundamentals of Pricing and Revenue Management." *The Global Airline Industry*, 1st Edition. Chichester, U.K.: Wiley, 2009, pp.78-81. Print.

[7] Belobaba, Peter, Amedeo R. Odoni, and Cynthia Barnhart. "Fundamentals of Pricing and Revenue Management." *The Global Airline Industry*, 1st Edition. Chichester, U.K.: Wiley, 2009, pp.91. Print.

[8] Belobaba, Peter and Craig Hopperstad. *Algorithms for Revenue Management in Unrestricted Fare Markets.* Informs Revenue Management Section Meeting. Cambridge, MA. June 10 - 11, 2004.

[9] Belobaba, Peter. *Passenger Origin Destination Simulator (PODS): Summary of Processes and Models.* September 2010.

[10] Bratu, Stephanie. *Network Value Concept in Airline Revenue Management.* S.M. Thesis, Massachusetts Institute of Technology, Cambridge, MA, 1998.

[11] Bureau of Transportation Statistics. *Air Carrier Financial Reports: Schedule P-1.2.*

[12] Bureau of Transportation Statistics. *Air Carrier Financial Reports: Schedule T2 & P52.*

[13] Cléaz-Savoyen, Richard. *Airline Revenue Management Methods for Less Restricted Fare Structures.* S.M. Thesis, Massachusetts Institute of Technology, Cambridge, MA, 2005.

[14] Cooper, William, Tito Homem-de-Mello, and Anton Kleywegt. *Models of the Spiral-Down Effect in Revenue Management.* Operations Research (54:5), pp. 968-987. October 2006.

[15] Fiig, Thomas, Karl Isler, Craig Hopperstad, and Peter Belobaba. *Optimization of Mixed Fare Structures: Theory and Applications.* Journal of Revenue and Pricing Management, (9) pp. 152-170. June 2009.

[16] Gorin, Thomas. *Airline Revenue Management: Sell-up and Forecasting Algorithms.* S.M. Thesis, Massachusetts Institute of Technology, Cambridge, MA, 2000.

[17] Hung, Lee Alex Yen. *Investigation of Competitive Impacts of Origin-Destination Control using PODS.* S.M. Thesis, Massachusetts Institute of Technology, 1998.

[18] Merriam-Webster. *Ancillary - Definition*. Merriam-Webster - An Encyclopedia Britannica Company. Retrieved January 13, 2014. Available: http://www.merriam-webster.com/dictionary/ancillary.

[19] Sorenson, Jay. *The Amadeus Yearbook of Ancillary Revenue by IdeaWorks Company*. August 29, 2012. Print.

[20] *Spirit Airlines, Inc. Form 10-K*. United States Securities Exchange Commission. 2012.

[21] *United Continental Holdings Form 10-K*. United States Securities Exchange Commission. 2011.