Modeling Passenger Disutilities in Airline Revenue Management Simulation

by

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ABSTRACT

Passenger behavior is the fundamental factor driving air transportation market reactions to the managerial decisions of airlines; therefore, it is important to understand passenger path choice process, and to develop a valid model to represent it. In this thesis, passenger disutilities are used to indicate passengers' sensitivity to alternative path options. Accordingly, passenger disutilities have a big impact on airline revenue performances, depending on an airline's revenue management methods and the path options it provides. As an attempt to understand and represent passenger disutilities with an analytical model, this thesis describes the procedure for modeling passenger disutilities based on survey answers from airline experts.

Modeling passenger disutilities assumes that they are function of market distances and that they take the form of a distribution. In this thesis, we assume that the passenger disutilities fit a linear function of market index fares in the form of Gaussian distribution for every market. In order to determine appropriate parameters for the model, the survey results obtained from airline experts are used. The coefficients of three disutility functions indicate that path quality and replanning disutilities have greater influence on passenger choice than unfavorite airline disutility does.

The Passenger Origin-Destination Simulator is used to test the impact of passenger disutilities on a hypothetical 42-city, hub-and-spoke network. With all disutility functions implemented, the simulation results suggest that the role of airline revenue managements become more important with passenger preference for attractive paths. Also, the relative benefits of Origin-Destination revenue management methods as supposed to Fare Class Yield Management method are higher when passenger disutilities are considered. Among the three disutility components modeled for this thesis, the replanning disutility predominantly drives market response in our hypothetical network.

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Chapter 1 Introduction

1.1. Passenger Disutilities in Airline Revenue Management

In the real world, the users of commercial air transportation service have a choice of one or more available flight itineraries (or "paths") serving the desired markets. Depending on individual characteristics, there can be various reasons for a path preference, such as a preference for an airline, for a certain schedule, and so forth. Also, each individual has a different degree of path preference. These path preferences strongly influence the passenger behavior within the air transportation system.

Airline revenue management is basically a repeated process of optimizing booking limits by fare class based on the forecast of expected demand. Modeling and forecasting demand for air transportation service greatly depends on how passenger behaviors are represented. Accordingly, airline revenue management, which is a way of maximizing passenger revenue through seat inventory control, is influenced by the passenger behavior patterns in path choice, hence it is important to have a reasonable understanding of passenger choice for effective revenue management.

It is true that passenger path preferences are subjective; however, it is possible to represent some of the most common factors in passenger choice as mathematical models. In this thesis, we take four of the major components influencing passengers' path choice into consideration – fare class restrictions, carrier preference, the number of stops/connections in a path, and schedule. By assigning "disutility costs", which are perceived inconvenience costs of traveling on a path that is relatively unattractive to passengers, we can measure the total inconvenience of available paths within passengers' choice sets. Along with the nominal (fare) costs of the path, this inconvenience cost serves as a rationale for modeling passengers' path choice.

In the first part of this thesis, we concentrate our efforts on building the passenger disutility model. Among the four disutility components previously discussed, estimating the latter three disutilities – carrier preference, number of stops/connects in a path, and schedule – is the objective. The disutility cost for the path provided by carriers other than a passenger's preferred carrier is called the "unfavorite airline" disutility cost, the disutility cost assigned to a connecting path is the "path quality" disutility cost, and the disutility cost assigned to a path that is outside the passenger's initial decision window[1] is called the "replanning" disutility cost. These three disutility costs are assumed to be a function of market index fares[2] and are in the form of assumed probabilistic distributions reflecting the stochastic nature of demand.

Once these disutility cost functions are defined and estimated, we can test the impact of passenger disutilities on various revenue management models through simulation. The computational tool used for this purpose is the Passenger Origin Destination Simulator (PODS).[3] PODS takes disutility functions and revenue management schemes as input to simulate a network of origin-destination markets for multiple airlines competing within the network. The results from the simulation are presented in the latter part of this thesis.

1.2. Objective of Thesis

The major goal of this thesis is to develop a model representing passenger disutilities for the three disutility components previously discussed. A survey of airline experts is conducted in order to obtain realistic disutility function parameters. The passenger

[1] Boeing Commercial Airplane Group (1993). See Section 2.3.3 for the definition of a decision window.
[2] Market index fares indicate the overall fare level of the market for each passenger type. In the scope of this thesis, Q class fare is used as a leisure passenger market index fare, and 2.5*Q class fare is used as a business passenger market index fare. Market index fares are also referred to as market basefares, as described in Section 4.1.3.
[3] See Section 3.3 for details.

disutility model is an attempt to understand passenger behavior pattern. With the passenger disutility model, airlines can get a better understanding of passengers' decision process and its impact on performances their revenue management sectors.

Six representative revenue management methods are tested in this thesis to understand the impact of passenger disutilities on different revenue management schemes: Fare Class Yield Management vs. Origin-Destination Revenue Management, or Expected Marginal Seat Revenue based methods vs. network bid price methods.[4]

1.3. Structure of Thesis

Chapter 2 explains the basic concept of passenger disutilities before going into mathematical detail in later chapters. The definition of passenger disutilities and disutility costs is explained, as well as its components of interest to us: unfavorite airline disutility, path quality disutility, and replanning disutility. Also in Chapter 2, we walk through some of the existing literature with approaches to demand modeling that are not included in this thesis. The two major measures of path attractiveness that are examined in this chapter are the utility concept used in the logit model[5] and quality of service index[6].

Chapter 3 is an overview of airline revenue management methods and the simulation tool of this thesis, PODS. A brief explanation of airline revenue management is followed by explanation of various revenue management methods and their implications. Descriptions for the EMSRb model with a FCYM approach and five other Origin-Destination revenue management methods (Greedy Virtual Nesting, Displacement Adjusted Virtual Nesting, Network Bid Price, and Prorated Bid Price) are presented in this chapter. An introduction to PODS, its architecture, and its input/output parameters, along with the PODS simulation environment, is included in this chapter as well.

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[4] For detailed explanation about revenue management methods and their implications, see Section 3.1 and 3.2
[5] See Section 2.4.1
[6] See Section 2.4.2

Chapter 4 describes the modeling procedure for passenger disutility functions. First, we look into how PODS models disutilities, as well as the PODS passenger assignment model with examples of disutility costs for each component for business and leisure passengers. In Section 4.2, the survey conducted for the purpose of estimating disutility function coefficients is presented along with the responses. The mathematical process to extract the disutility parameters from these responses is illustrated afterwards.

Chapter 5 presents the basic results of simulation with all disutility functions implemented in the PODS simulation. Revenue gains from using O-D revenue management methods, as well as load factors and fare mix, are compared to the base case, which does not incorporate passenger disutilities as a factor in its passenger choice model.

In Chapter 6, sensitivity analysis for each of the three disutility components modeled in this thesis is presented. We examine the impacts of each disutility component separately in simulations, implementing one of the three components at a time. Detailed analyses of results, as well as the impacts of each component are discussed in this chapter.

In Chapter 7, this thesis concludes with a summary of modeling passenger disutilities and findings from the disutility simulations. At the very end of this chapter, we address some of the issues for future research directions involving passenger disutility models.

Chapter 2 Passenger Disutilities

In the real world, air transportation passengers are constantly forced to make a choice from a wide range of alternate options of paths offered in a desired market, which we label as "path options". In making those decisions, each passenger has his/her own criteria for measuring attractiveness or unattractiveness of each path option. Disutilities represent the unattractiveness of the path, categorized by various components. The purpose of this chapter is to walk through the basic concepts of passenger disutilities before going in to mathematical details in Chapter 4.

Section 2.1 introduces the concept of passenger disutilities, followed by an introduction to how disutilities can be modeled, in Section 2.2. Section 2.3 introduces three major disutilities utilized in the PODS simulation; path quality disutility, replanning disutility, and unfavorite airline disutility. Finally Section 2.4 reviews and compares the passenger disutility concept with related literature, followed by Section 2.5, which summarizes this chapter.

2.1. Basic Concept of Passenger Disutilities and Disutility Costs

Passenger disutilities represent the unattractiveness of a path option to a passenger. By introducing the concept of passenger disutilities, we can quantify the unattractiveness of specific passenger choice options. Once the passenger disutilities are modeled and measured, it becomes possible to simulate a random passenger's behavior and perform a mathematical calculation to map the decision process into a computational simulation tool. Moreover, in order to capture the stochastic property of passenger behaviors, we assume that the passenger disutilities take a form of a probability distribution (namely, Gaussian distribution in this case) rather than a deterministic representation of passenger behavior.

There exist variety of reasons that a flight path option is attractive or unattractive to a passenger. Among various reasons, we can pick out the most important rationales that are common to most passengers. The Passenger Origination Destination Simulator, which serves as the computational simulation tool for disutility experiments presented later in this thesis (see Section 3.3 for detailed explanation), classifies passenger disutilities into four categories: restriction disutilities, path quality disutilities, replanning disutilities, and unfavorite airline disutilities[7]. Restriction disutilities represent the perceived unattractiveness of restrictions associated with a fare product. Path quality disutilities measure the unattractiveness of a connecting or stopover path relative to nonstop path. Replanning disutility is programmed to penalize the path options that are outside of passenger's decision window[8]. Unfavorite airline disutility, as its name suggests, says that the path option of an airline other than one's preferred airline is less attractive that a path option on one's preferred airline.

These four disutilities can be weighted by the relative importance of each category in passenger's decision. Then these disutilities can be quantified in terms of dollar costs, for a fair comparison with nominal fares of each path itinerary. This value is called the disutility cost, comparable to the out-of-pocket dollar cost of the path option.

For example, a passenger can choose between two fare products, let's say, $250 B class with Saturday night stay restriction and $400 Y class with no restrictions. Depending on how this certain passenger weighs the Saturday night stay restriction, this passenger will make a decision between the two options. If a passenger, let's say passenger 1, is willing to pay no more than $100 dollars more to book on a fare class without the Saturday night stay restriction, the Y class is less attractive than B class with the restriction (See Table

[7] Wilson [14]
[8] See Section 2.3.3 for definition of decision window

2.1). On the other hand, there can be another passenger, passenger 2, who is very reluctant to sleep over a Saturday night in the destination. Then this passenger will be willing to pay more than what passenger 1 would pay to fly in a Y class with no restrictions, let's say $200. In this case the disutility cost of Saturday night stay restriction is $100 for passenger 1, and $200 for passenger 2. The total "perceived" cost of passenger 1 for the fare class with Saturday night stay is then $350 whereas the total "perceived" cost of passenger 2 is $450. The total "perceived" cost is designated as "total cost" in PODS, with more explanations on Section 2.2 and 4.1.4. Under the assumption that both the passengers will make a rational decision, that is, choose a path option with less total cost, passenger 1 will choose B class with $350 total cost, whereas passenger 2 will choose to book on a Y class with $400 total cost. Table 2-1 illustrates how the disutility cost of Saturday night stay affects the path choice decision of each passenger.

		Passenger 1	Passenger 2
Path Option 1			
Y Class	Fare	$400	$400
No Restriction	Restriction Disutility Cost	$0	$0
	Total Cost	$400	**$400**
Path Option 2			
B Class	Fare	$250	$250
Saturday Night Stay Restriction	Restriction Disutility Cost	$100	$200
	Total Cost	**$350**	$450
Rational Path Choice		Path 2	Path 1

Table 2-1 Total cost of path option 1 (with no restrictions) and 2 (with Saturday night stay restriction), for passengers 1 and 2

This approach of modeling the passenger disutilities in a passenger choice model is an opposite approach of the traditional approach of demand modeling, using "utility" as a measure of path attractiveness. An overview of the traditional models and comparison with the passenger disutility model is provided in Section 2.4.

2.2. Disutility Modeling

Various attributes of individuals and travel paths can take part in the process of individual decision-making. In this thesis we concentrate on representing attributes of travel paths that are recognized as both important and objective. As for classification of individuals, we use the conventional grouping of passengers into two categories, business passengers and leisure passengers.

The four representative attributes of the path attractiveness, along with monetary costs of the path itinerary, are added into a single property for a reasonable comparison between alternate path options, representing actual passenger's decision process. This was defined earlier in Section 2.1 as the total cost. Once the total cost is defined the decision rule of a rational passenger becomes simple: choose the path with least total cost.

The methodology that Chapter 4 of this thesis focuses on is scaling the disutility costs of four attributes in a reasonable way. The estimates in dollar costs of each disutility categories (unfavorite airline, path quality, replanning and restrictions) can be approximated using data gathered from a survey conducted of potential users or airline experts. The survey that was performed for this purpose is explained more in detail in Section 4.2. The estimates of each disutility cost will be in a form of a distribution, which we can approximate as a Gaussian distribution. From the survey responses the average and standard deviation of the distribution are extracted, to represent an individual passenger's perceived cost of each disutility. This Gaussian distribution with mean and standard deviation derived from the survey can be thought as a representative distribution for the cost of each disutility component, hence can be used as an input to the total cost calculation.

Once each disutility is approximated into a distribution measured as dollar costs, the total cost is the sum of all disutility costs with the nominal fare. This process is done for every passenger for his/her own choice of path. Disutility cost distributions are assumed to be independent for both leisure and business passengers. With the total cost calculated for each passenger we can now approximate passengers' path choice process with a mathematical model; choosing least total cost path.

2.3. Disutility Components

The disutility components that are of our interest are fare class restriction disutilities, unfavorite airline disutilities, path quality disutilities, and replanning disutilities. Among these four disutilities this thesis concentrates on defining and modeling the latter three components. This section explains the definitions and implications of these three disutility components.

2.3.1. Unfavorite Airline Disutility

A person who is willing to travel via air has a choice among paths offered by various carriers. When all else is equal, the customer is likely to have a tendency to choose one carrier over other carriers. There can be many reason for one's inclination toward an airline, such as a membership of frequent flyer program, corporate association, perception of general service, safety, reliability, etc. The tendency to favor one airline over others is "airline preference" and we name this preferred airline as "favorite airline". In the same sense all other airlines are called "unfavorite" airlines.

For the paths offered by carriers other than the favorite airline of a passenger, we add the unfavorite airline disutility cost to the total cost of the path in order to reflect the inconvenience cost of traveling with an unfavorite airline. Depending on the total cost, a rational passenger will make a path choice to fly on a path with the least total cost.

For example, let's assume two passengers, both with a choice between Y class of a favorite airline and B class of an unfavorite airline. Furthermore let's apply the same example as in Section 2.2; with a Y class fare of $400 and a B class fare of $250, and for both passengers a B class restriction disutility cost of $100. Without an airline preference, the rational choice for both passengers would be path 2 with B class, which has total cost of $350 as we observed in Table 2-1. Now if we assume that path 2 is offered by an unfavorite airline, the total cost increases for path 2 with additional unfavorite airline disutility cost. Let's say that passenger 1 is less sensitive to airline preference, with unfavorite airline disutility cost of $25. On the other hand, let's assume that passenger 2 is a loyal customer of the "favorite" airline (possibly a member of the frequent flyer program of that airline), and in consequence is willing to pay higher than passenger 1 to fly on a favorite airline, for example, $75. Then the total cost of path 2 for passenger 1 is $375, still less than path 1, leading this passenger to choose path 2 over path 1. However, passenger 2 with higher unfavorite airline disutility cost now ends up with $425 of total cost for path 2, making this option less attractive than Y class of favorite airline. Table 2-2 illustrates this example, showing how unfavorite airline disutility cost affects a passenger's decision of path choice.

		Passenger 1	Passenger 2
Path Option 1			
Y Class	Fare	$400	$400
No Restriction	Restriction Disutility Cost	$0	$0
Favorite Airline	UFA Disutility Cost	$0	$0
	Total Cost	$400	**$400**
Path Option 2			
B Class	Fare	$250	$250
Saturday Night Stay Restriction	Restriction Disutility Cost	$100	$100
Unfavorite Airline	UFA Disutility Cost	$25	$75
	Total Cost	**$375**	$425
Rational Path Choice		Path 2	Path 1

Table 2-2 Total cost of path option 1 (with favorite airline) and 2 (with unfavorite airline), for passengers 1 and 2

2.3.2. Path Quality Disutility

Path quality indicates how convenient the path options are for a passenger. Generally a non-stop path is considered to have better path quality than a one-stop or a connecting path. When a passenger's path option has a stopover or a connection, additional path quality disutility cost is added to the total cost to convert the inconvenience the passenger has to put up with into dollar costs. In Chapter 4 we introduce path quality index to measure path quality in numbers. With path quality index, the path quality disutility cost can be estimated to be a product of path quality index and unit path quality index disutility cost. For further description of path quality index see Section 4.1.3.4.

We can continue with the example shown in Section 2.2 to illustrate how path quality disutility plays a role in passenger's path choice. Assume two passengers with path choice between Y class nonstop path and B class connecting path. The restriction disutility cost for B class is assumed to be $100. If passenger 1 is a leisure passenger who is relatively less sensitive to path quality, for example, with additional path quality disutility for connecting path being only $25, the total cost of second path for this passenger is $375 whereas the total cost for Y class nonstop path is $400. Hence passenger 1 will choose the B class connecting path rather than Y class nonstop path. On the other hand, passenger 2 is assumed to be more sensitive to path quality, willing to pay $75 more for a nonstop path. In this case the total cost of the second path becomes $425, making the connecting option less attractive for passenger 2. The detailed comparisons for two passengers are illustrated in Table 2-3.

		Passenger 1	Passenger 2
Path Option 1			
Y Class	Fare	$400	$400
No Restriction	Restriction Disutility Cost	$0	$0
Nonstop Path	Path Quality Disutility Cost	$0	$0
	Total Cost	$400	**$400**
Path Option 2			
B Class	Fare	$250	$250
Saturday Night Stay Restriction	Restriction Disutility Cost	$100	$100
Connecting Path	Path Quality Disutility Cost	$25	$75
	Total Cost	**$375**	$425
Rational Path Choice		Path 2	Path 1

Table 2-3 Total cost of path option 1 (nonstop path) and 2 (connecting path), for passengers 1 and 2

2.3.3. Replanning Disutility

When planning a trip (via air or other modes), a traveler implicitly or explicitly sets an earliest possible departure time and latest arrival time for his/her travel. The time interval between the possible earliest departure time and latest arrival time is called the passenger's decision window. If there are no available path choices within one's decision window, the passenger either has to cancel the trip (spill out) or replan the trip with path options outside his/her decision window. Direct or indirect replanning of the trip exerts an additional cost to passenger, and we can incorporate this inconvenience cost of replanning into total cost of the path by defining replanning disutility cost. Replanning disutility cost is added to the total cost of the path when the path is outside of one's decision window, making replanned path less attractive to the passenger compared to the path options within the decision window.

For example, let's continue with the example we have been using throughout this chapter. We assume two passengers with same choice set; Y class path within the decision window and B class path outside of the decision window. The restriction disutility for B class is assumed to be $100 for both passengers. Now if we assume that passenger 1 is on a personal trip being less time sensitive, hence assigning replanning disutility cost of $25, the total cost for second path becomes $375, which is less than the total cost of the Y class path within the decision window. For passenger 2, who we assume is a business passenger with less flexibility of schedule and with replanning disutility cost of $75, the total cost of the replanned path (path option 2) becomes $425, making the replanned path less attractive than first path option. Table 2-4 shows the process of deriving the total cost for two passengers in our example.

		Passenger 1	Passenger 2
Path Option 1			
Y Class	Fare	$400	$400
No Restriction	Restriction Disutility Cost	$0	$0
Path within Decision Window	Replanning Disutility Cost	$0	$0
	Total Cost	$400	**$400**
Path Option 2			
B Class	Fare	$250	$250
Saturday Night Stay Restriction	Restriction Disutility Cost	$100	$100
Path outside Decision Window	Replanning Disutility Cost	$25	$75
	Total Cost	**$375**	$425
Rational Path Choice		Path 2	Path 1

Table 2-4 Total cost of path option 1 (within decision window) and 2 (outside decision window), for passengers 1 and 2

2.4. Literature Review

In this thesis we evaluate passenger's path choice by assigning disutility costs to each path. There have been other approaches in attempting to measure attractiveness of choice options for a rational passenger. In this section we examine the traditional passenger choice modeling approaches and compare them with our disutility model. Especially this section is focused on two of the most commonly used measures used in passenger demand modeling in transportation passenger choices; utility and quality of service. The well-known logit model[9] uses utility functions as a measure of passenger's path preference. Others incorporate quality of service for the purpose of passenger choice modeling.

[9] For deeper understandings of logit model see Ben Akiva and Lerman [5] and/or Kanafani [10]

2.4.1. Utility – The Logit Model

Utility is a measure of attractiveness of an alternative, expressed as a function of attributes of the alternative. In the passenger choice model which uses the utility function as a referring index of attractiveness, the objective of a decision maker is to maximize the utility of a path. Logit model is a representative passenger choice model with utilities as a measure of path attractiveness.

Among many works introducing the logit model, Kanafani [10] and Ben Akiva and Lerman [5] give a good description of the logit model. The basic idea of logit model is to use the systematic utility as a measure of passenger's path preference. The logit choice model builds up from defining the probabilistic utility of each choice option. We represent the deterministic element of the utility with V_{in} and random component with ε_{in}. Then the utility of path *i* in the choice set of passenger C_n, U_{in}, can be expressed as sum as the deterministic component and the random component (disturbance).

$$U_{in} = V_{in} + \varepsilon_{in}$$

Utility of path j for passenger n is also expressed in the same manner:

$$U_{jn} = V_{jn} + \varepsilon_{jn}$$

For the case that the passenger has only two options, the logit model starts with an assumption that $\varepsilon_n = \varepsilon_{jn} - \varepsilon_{in}$ is logistically distributed:

$$F(\varepsilon_n) = \frac{1}{1+e^{-\mu\varepsilon_n}}, \qquad \mu > 0, -\infty < \varepsilon < \infty$$

$$f(\varepsilon_n) = \frac{\mu\varepsilon_n}{(1+e^{-\mu\varepsilon_n})^2}$$

where μ is a positive scale parameter. The logistic distribution approximates the normal distribution quite well, while being analytically convenient. With the logical distribution assumption, the choice probability for alternative i is given by:

$$
\begin{aligned}
P_n(i) &= \Pr(U_{in} \geq U_{jn}) \\
&= \frac{1}{1+e^{-\mu(V_{in}-V_{jn})}} \\
&= \frac{e^{\mu V_{in}}}{e^{\mu V_{in}} + e^{\mu V_{jn}}}
\end{aligned}
$$

In case of multinomial choices, the disturbances ε_{in} are assumed to be (1) independently distributed, (2) identically distributed, and (3) Gumbel-distributed with a location parameter η and a scale parameter μ>0. Then the multinomial logit model expresses the probability of passenger n choosing alternative i as:

$$
P_n(i) = \frac{e^{\mu V_{in}}}{\sum_{j \in C_n} e^{\mu j_{jn}}}
$$

The systematic utility used in the logit model plays a similar role that disutility has in the passenger choice model later presented in this thesis. The major difference is that utility measures the attractiveness of an alternative, whereas disutility measures the unattractiveness. The logit model assumes a logical (binomial choice) or Gumbel (multinomial choice) distribution for analytical purpose, whereas our model assumes a Gaussian distribution of disutilities.

2.4.2. Quality of Service Index (QSI)

Quality of service is another way of representing the perceived attractiveness of a path choice. The quality of service can be expressed as a scalar function of various quality of service variables, such as travel time, trip reliability, trip comfort, trip convenience, etc. The quality of service has been an important variable in demand modeling of transportation systems.

For more precise definition, Quality of Service Index was introduced to the area of transportation demand modeling. Quality of Service Index, or Quantitative Share Index (QSI), is an industry standard measuring the "attractiveness" of an itinerary relative to the entire set of other itineraries (including competing airlines) in that market[10]. QSI is a function of various attributes of the path, such as number of stops, level of service, time of departure, and etc. There is a QSI for each itinerary i in each market m for each airline a denoted QSI_i^a. The sum of QSI_i^a over all itineraries i in a market m over all airlines a is equal to 1, for all markets. With all itineraries measured in terms of service quality, QSI_i^a becomes the probability of a passenger in market m choosing airline a, itinerary i.

QSI is another representation of an attractiveness of an alternative, along with utility. However it is not represented in a distribution but as a deterministic value omitting stochastic nature of demand, hence QSI has generally been used in macroscopic demand modeling in transportation rather than individual passenger choice modeling.[11]

2.5. Summary

In this chapter the basic concept of passenger disutilities was explained. Along with itinerary fares, passenger disutility, which is a measure of path unattractiveness, is an important factor that affects passenger's path choice. The four major components consisting passenger disutility costs are restriction disutilities, unfavorite airline disutilities, path quality disutilities, and replanning disutilities. Each of the components

[10] Definition of QSI adapted from Kniker, Tom [11]. Original model for QSI was developed by the staff of CAB for application in domestic-route proceedings, such as the investigation of Reno-Portland/Seattle nonstop service, May 1970.

[11] QSI is used to estimate market shares, or to estimate demand for each itineraries for scheduling purposes. See Etschmaier and Mathaisel [7] and Kniker [11] for example.

are rated in dollar terms and added up with itinerary fare for each passenger to determine which path would be most favorable for each passenger. The detailed procedure of passenger choice is explained in Chapter 4, along with process of disutility modeling.

Chapter 3 Overview of Airline Revenue Management and PODS Simulation

Airline revenue management is a way of maximizing passenger revenue through the seat inventory control. In this thesis, we consider six major revenue management methods widely used in the airline industry, which are described in Sections 3.1 and 3.2. The revenue management system decides whether to accept or deny passenger bookings, based on their estimated revenue value to the airline. Since the passenger behavior has a direct influence on the performance of the revenue management system, the passenger disutilities modeled and tested throughout this thesis are expected to have a significant influence on the performance of the different revenue management systems.

Revenue maximization through seat inventory control is comprised of three fundamental process: 1) forecasting the expected passenger by fare class, 2) optimizing the booking limits based on these demand forecasts, and 3) revising both forecasts and the booking limits as actual bookings are accepted[12]. Where passenger disutilities play a major role is in the first step. Booking history and forecasting are outputs of passenger behavior; hence under the "rational passenger choice", that is, a passenger chooses to book a path option with the least perceived cost, passenger disutility costs play an important role in the passenger choice. The role of revenue management system is to adjust the protection levels to maximize the total revenue.

In this chapter we will walk through the basic concepts of each revenue management system before starting the discussion about impact of passenger disutilities on various revenue management systems.

[12] Source: Belobaba [3]

As a computational simulation tool for the disutility experiments presented in later chapters, the Passenger Origin-Destination Simulator (PODS) developed by The Boeing Company is used. Section 3.3 includes a brief description of PODS simulation and its sub-models. Section 3.4 illustrates the base case network used for the simulation in this thesis, followed by summary of the chapter in Section 3.5.

3.1. Airline Revenue Management – Fare Class Yield Management (FCYM)

Airline seat inventory control, otherwise known as airline revenue management, is the practice of managing the availability of seats to be sold at different fare levels to passengers wishing to travel a particular itinerary. The simpler and most widely used revenue management algorithms can be categorized into Fare Class Yield Management algorithms. FCYM models control seat inventory on a flight leg basis, rather than a path basis like some recently developed and tested models presented in Section 3.2. Generally FCYM methods require simpler data collection and optimization then O-D revenue management methods, hence currently are used by the majority of the airlines that practice revenue management. However there have been voices in recent years that claim that the leg based revenue management has been pushed to its extreme in terms of revenue gains, and more airlines are now considering, planning or even starting to implement O-D revenue management systems.

Under the FCYM approach, the availability of a seat for a given booking class is calculated independently for each flight leg. Hence the availability of a seat for multiple-leg itinerary is limited by the minimum booking limit of all legs included in that itinerary for the same fare class. There are some obvious disadvantages of this approach due to the limitations just described, which led to development of various O-D revenue management methods described in Section 3.2. The most critical shortcoming of the leg-based FCYM approach is that it does not distinguish between connecting passengers and local passengers when they are in the same fare class, which can result in loss of potential revenues for over a network of connecting flights. Section 3.2 introduces some O-D based revenue management methods developed to overcome the limitation of leg based revenue management.

EMSR Model

The nested EMSR model for multiple fare classes was originally developed by Belobaba[13]. The model makes use of expected marginal revenue of incremental seats made available to each fare class, determining booking limits for the classes for all fare classes. The expected marginal revenue of an incremental seat is the expected value of the revenue from selling that seat given the probability density function of the flight leg demand forecast. Given the forecasted demand on a leg basis, the EMSRb algorithm sets a booking limit for each fare class as to a point where the next fare class's fare is greater than the expected marginal value of the last seat of the protecting fare class. With the protection level for each fare class determined, EMSRb algorithm calculates the nested protection level for each fare class to make sure that highest fare class always have seat availability. For details see Belobaba [2].

This model is used for revenue management by many of the airlines in the world. There still exist the same limitations in optimality of the EMSRb model applied to FCYM as previously described. However the significance of the EMSRb model lies in the fact that it is widely used, as well as the fact that it serves as a basis for some of the O-D methods examined in Section 3.2.

3.2. Origin-Destination Revenue Management Methods

Several revenue management systems were developed to modify some of the limitations that FCYM has. Where as FCYM is flight leg based revenue management method that does not distinguish between local and connecting passengers with different revenue

[13] See Belobaba [1] for original EMSR model, Belobaba [2] for nested EMSRb model.

potential, there have been additional efforts to implement path based forecast and/or path based optimization. Greedy Virtual Nesting (GVN) and Displacement Adjusted Virtual Nesting (DAVN) use virtual classes instead of fare classes. Network Bid Price (Netbid) and Prorated Bid Price (ProBP) method uses a bid price mechanism for O-D control. Heuristic Bid Price Method (HBP) uses both virtual classes and bid price mechanism. The following sections briefly go though the idea of each revenue management system. For more thorough explanations see Williamson [13] and/or Lee [12].

3.2.1. Greedy Virtual Nesting (GVN)

The word "Virtual" of Greedy Virtual Nesting comes from the fact that this approach uses "virtual" or hidden classes instead of published booking classes. The virtual classes are defined throughout the whole network, based on the total fares of the itineraries for every existing path. Hence the high fare long distance fares will be assigned to a higher virtual class than the low fare short distance fares. By mapping virtual classes according absolute fare values of the itinerary, GVN generally gives priorities to connecting markets with higher revenue potential. Data collection, forecast, optimization and availability control are all done on a per-virtual class, per-leg basis, with EMSRb algorithm for seat inventory control booking limit optimization.

There also exist drawbacks for GVN. As suggested by the term "Greedy", GVN favors connecting passengers to local passengers. Usually accepting a connecting passenger over a local passenger brings in higher revenues. However when there is high demand for both local legs, sometimes accepting two local passengers rather than a connecting passenger generates more revenue. This is when GVN shows its weakness; by rejecting two local passengers to accept a connecting passenger, GVN loses some of the revenue potential.

For the standard simulator testing of this thesis, GVN does seat inventory control based on 8 virtual classes with system-wide virtual boundaries. Table 3-1 shows the standard upper and lower boundary fare settings for virtual classes, for the hypothetical network that we have developed.

Virtual Class	1	2	3	4	5	6	7	8
Upper Boundary	1002.84	777.57	388.78	291.59	204.05	150.96	126.15	91.16
Lower Boundary	777.57	388.78	291.59	204.05	150.96	126.15	91.16	0.00

Table 3-1 Virtual class boundary fares

3.2.2. Displacement Adjusted Virtual Nesting (DAVN)

The basic structure of DAVN is exactly the same as GVN. However, unlike GVN, DAVN does not unconditionally favor connecting passengers over local passengers when accepting a booking for a seat, but considers the possibility of dislocating a second local passenger when accepting a connecting passenger. If the probability of both flight legs in a connecting path being full is high, DAVN gives bigger penalties to connecting fares of that path.

Given an O-D based demand forecast, DAVN solves a deterministic linear program to optimize the entire connecting network and to generate shadow prices for each leg for each departure. The shadow price can be translated as the revenue that airline is willing to accept a booking on an additional seat in a given flight leg. After the shadow prices are generated from the deterministic LP for each leg, the "pseudo fares" of each leg for multi-leg paths are calculated as the nominal fare on minus the shadow price. For example, if the connecting path is consisted of flight leg i and j, the pseudo fare (PF) for local and connecting passengers for each leg can be expressed as follows:

Leg i:	Local Passenger	PF_L^i = Fare on leg i
	Connecting Passenger	PF_C^i = Fare on leg i – Shadow price on leg j
Leg j:	Local Passenger	PF_L^j = Fare on leg j
	Connecting Passenger	PF_C^i = Fare on leg j – Shadow price on leg i

In this case the shadow price is assumed to be the displacement cost for the connecting fares, displacement cost meaning the potential revenue that the airline is losing by accepting a connecting passenger. The pseudo fares of connecting paths and nominal fares of local markets are then mapped into virtual classes for leg based seat inventory control following the EMSRb algorithm.

The standard version of DAVN for the purpose of this thesis uses 8 virtual buckets with initial boundaries defined as in Table 3-1. The virtual boundaries are initially defined the same for all flight legs, are then re-defined at every timeframe[14] specific for each leg. After the first timeframe, standard DAVN is set to re-solve the LP at every timeframe, calculating the new displacement costs and pseudo fares for leg based optimization at every timeframe.

3.2.3. Network Bid Price (Netbid)

The Network Bid Price mechanism uses bid prices for seat inventory control instead of booking limits. Netbid is a complete O-D revenue management algorithm; with O-D based demand forecast and O-D based seat inventory control. The biggest difference of Netbid compared to FCYM based revenue management methods introduced in this thesis is that instead of using EMSRb algorithm to set booking limits, Netbid generates a bid price to accept all bookings with fares greater than the bid price. Hence Netbid usually appears to be more "open" to accepting bookings compared to EMSR methods with strictly defined booking limits.

Netbid first solves a deterministic linear program to generate bid prices for each leg for each departure, using ODF demand forecasts. The bid price for an itinerary is assumed to be the sum of shadow prices of the legs traversed. Bookings with total itinerary fare greater than the bid price are accepted, and bookings with fares lower than the bid price are rejected. Until the network LP is re-optimized the bid price remains constant,

[14] Checkpoint for optimization. See Section 3.3.1 for more explanation.

therefore frequent update and reoptimization is crucial for Netbid to perform well. Standard Netbid re-optimizes every 200 bookings on our hypothetical network, approximating once-a-day revision of the airlines in the real world.

3.2.4. Heuristic Bid Price (HBP)

Heuristic Bid Price is also called Greedy Virtual Nesting with EMSR Heuristic Bid Price. HBP was developed by Belobaba[15]. It is almost identical to GVN; the difference between GVN and HBP is in optimization and availability control. HBP, like DAVN, takes account of the fact that network revenue contribution of a connecting fare is actually less than the whole itinerary fare of the connecting path. But instead of taking the network optimization approach, HBP enables path-based control without using network optimization, which is still a difficult option for many airlines.

HBP collects data at a leg/bucket basis while doing network based O-D control, unlike Netbid with path-based forecasting. For local paths HBP uses standard EMSRb booking limits on the leg; for connecting paths HBP uses a bid price method instead of EMSR booking limits. Bid prices are the weighted sum of EMSR value of two legs consisting the path, with one leg's EMSRb value weighted with the heuristic d-factor. For example, for leg *i* in a simple two-leg case (leg *i* and *j*), the bid prices are calculated as follows:

Leg i: Local Passenger $BP_{Li} = EMSR_{Ci}$

Connecting Passenger $BP_{Ci} = EMSR_{Ci} + d*EMSR_{Cj}$

Only passengers with itinerary fares greater than the bid price are accepted. For a connecting passenger, the itinerary fare must be greater than all bid prices of each leg consisting the connecting path.

[15] Belobaba [4]

Like Netbid, HBP has no control over the number of bookings between recalculation of bid price; hence frequent reoptimization is an important issue. The standard version of HBP uses the same virtual classes as GVN with reoptimizing every 200 bookings on our hypothetical network (just as Netbid). The heuristic d-factor is set to 0.25 for the experiments for this thesis.

3.2.5. Prorated Bid Price (ProBP)

Finally, the most recent developed revenue management algorithm tested and used in PODS is Prorated Bid Price (ProBP) method. This method was developed and examined by Bratu[16]. The basic concept of this method is to use a bid price method to determine looking limits on a given flight. However, unlike other bid price methods, ProBP determines the bid price for each leg used in each O-D path and divides the actual total fare in between the connecting legs. The bid price used in this "prorating" is the $EMSR_c$ value, which is the EMSR value of the last seat sold on a leg. With this "prorating" of the fares ProBP is able to take the network structure and leg demand into account. For set of legs traversed by an ODF *j*, *L(j)*, the prorated fare of ODF *j* in leg *k*, *PRF(j,k)*, is defined as follows:

$$\sum_{m \in L_j} EMSR_C(m) \neq 0 \Rightarrow PRF(j,k) = \frac{EMSRc(k)}{\sum_{m \in Lj} EMSRc(m)} \times F_j$$

$$\sum_{m \in L_j} EMSR_C(m) = 0 \Rightarrow PRF(j,k) = \frac{F_j}{card(L_j)}$$

where F_j is the original fare of ODF *j* and $EMSR_c(m)$ is the critical EMSR value of leg *m*.

The other issue worth noting here is the fact that EMSRb model used the full ODF fare when computing $EMSR_c$, therefore overestimating the critical EMSR value. Hence ProBP introduces a convergence model to adjust this problem of overestimating the $EMSR_C$ value; the model iterates until the difference between the calculated PRF value

[16] Bratu [6]

and the input PRF value for EMSRc calculation is below a certain criteria. This model works extremely well, better than many other methods, as shown in simulation results presented by Bratu[17].

The PODS standard version of ProBP reoptimizes every 200 bookings. ProBP repeats until the $EMSR_C$ value converges with $10 range, with maximum number of iteration limited to less than 10 times.

3.2.6. Summary

The revenue management models briefly described in Section 3.2 are the test bases for the disutility simulations to be described in Chapters 5 through 8. For more detailed explanations of revenue management methods see references noted in each section. Table 3-2 summarizes the specifications of each revenue management methods introduced in this section. EMSRb is the only strictly leg based revenue management algorithm of our interest. GVN and HBP also use leg based forecasting method, but maps the fares into virtual buckets, qualifying as O-D revenue management method. DAVN does leg based inventory control based on path based forecast, and both Netbid and ProBP fully uses path based forecasting and path based control. EMSRb, GVN, and DAVN sets physical booking limits to protect seats, whereas Netbid, HBP and ProBP only sets a minimum bid price to be paid by a customer.

Revenue Management Algorithm	Data Collection and Forecast	Control Type		
		Leg/O-D	Limit/Bid	
EMSRb	Leg-based	Leg-based	Limit	
GVN	Leg-based	Leg-based	Limit	
DAVN	Path-based	Leg-based	Limit	
Netbid	Path-based	Path-based	Bid	O-D algortihms
HBP	Leg-based	Path-based	Bid	
ProBP	Path-based	Path-based	Bid	

Table 3-2 Summary of revenue management algorithm specifications. Source: Gorin [9]

[17] Bratu [6]

The following Table 3-3 summarizes the standard O-D parameters for later experiments.

RM Method	Description
EMSRb	4 fare classes, 16 reoptimization
GVN	16 virtual classes System-wide virtual boundary definition
Netbid	LP bid price/Availability processor Reoptimizing every 200 bookings
DAVN	16 virtual classes Reoptimizing every timeframe Virtual classes re-defined every timeframe Virtual classes defined leg specific
HBP	16 virtual classes Reoptimizing every 200 bookings
ProBP	Reoptimizing every 200 bookings Maximum number of iterations = 10 Convergence criteria < $10

Table 3-3 Summary of standard O-D parameters

3.3. *Passenger Origin Destination Simulator (PODS)*

The Passenger Origin Destination Simulator, abbreviated as PODS, is a computer simulation tool for testing airline revenue management schemes. It was originally developed by C. Hopperstad and The Boeing Company and has served as the experimental tool for the recent works in MIT Flight Transportation Laboratory. PODS simulates a network of origin-destination markets for one or more airlines and produces outputs in terms of bookings, revenues and loads. With these outputs users are able to analyze the competitive implications of various revenue management methods. Wilson [14] provides a thorough and detailed explanation of evolution and major features of the simulator. In this section a brief introduction of PODS architecture (Section 3.3.1), input/outputs (Section 3.3.2), and simulation environment for the experiment (Section 3.3.3) are provided.

3.3.1. PODS Architecture

PODS provides the tools for simulating a competitive environment in which various airlines compete over a network of numerous O-D markets. With the given network users are able to test the competitive advantages or disadvantages of the different revenue management methods in terms of various outputs. PODS also lets users to implement passenger behavior models to see their impact on revenue management system performance. Basically PODS architecture can be divided into four sub models; passenger choice model, revenue management/seat inventory control model, forecaster model, and historical database. Figure 3-1 shows how the PODS sub models function interconnected.

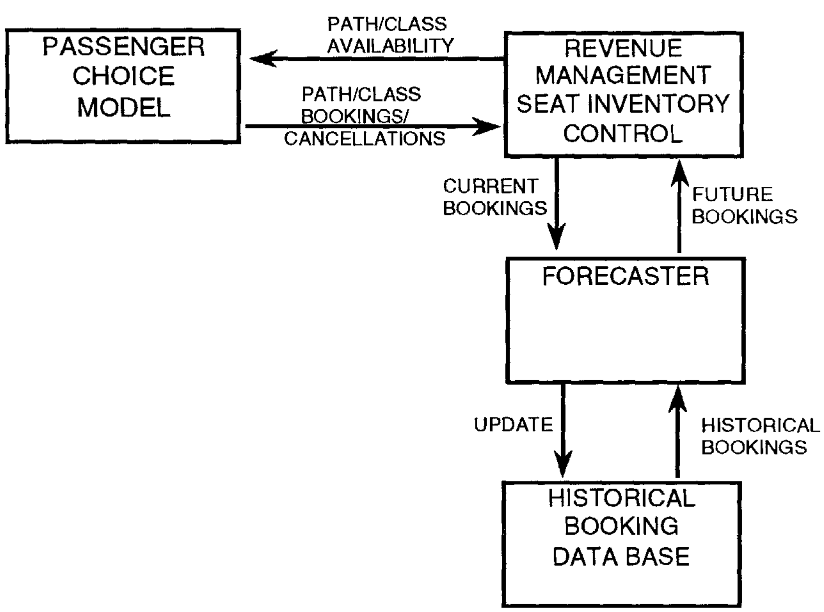

Figure 3-1 PODS Architecture. Source: Hopperstad, The Boeing Company

The simulator starts at the Passenger Choice Model, where passenger preferences for a path are decided depending on the passenger disutility model and other stochastic natures of passenger behavior. The Passenger Choice Model is described more thoroughly in

Section 4.1. In this process PODS generate passengers by passenger type with airline preferences, maximum willingness to pay, and disutility costs. There are two passenger types currently implemented in PODS; business passengers with higher maximum willingness to pay and lower price sensitivity, and leisure passengers with lower maximum willingness to pay and higher price sensitivity. With all these settings, disutility cost of a given path and path availability, generated passengers make a choice of whether to fly or not, and if so then on what path.

After a passenger inquires about an available fare class on some path, the Revenue Management Module comes into action. Each airline, based on the different revenue management algorithms in use, decides whether to accept the passenger booking or not. As described in Section 3.2, the decision is made based on booking limits or bid prices set by the revenue management algorithm. How booking limits/bid prices are determined differs from one revenue management algorithm to another. However, all revenue management algorithms use some kind of forecasting method to calculate booking limits of bid prices based on the previous booking history.

The historical database is created by keeping record of booking histories starting from the first booking of the simulation. The first part of sample departures, called burns, serves as a pure historical database, not incorporated in the simulation output. More detailed explanation of burns and samples are provided in the next section. The time line from the start to each departure is divided in to timeframes, and at the end of each timeframe the Revenue Management Module passes the booking information on to the historical database. The forecaster then updates the historical database to generate a new forecast, which in turn is used as a feedback to the Revenue Management Module.

The process described above repeats through user specified number of samples/trials, and finally produces statistical results at the end of the simulation. Figure 3-2 summarizes the sequential procedures in PODS simulation.

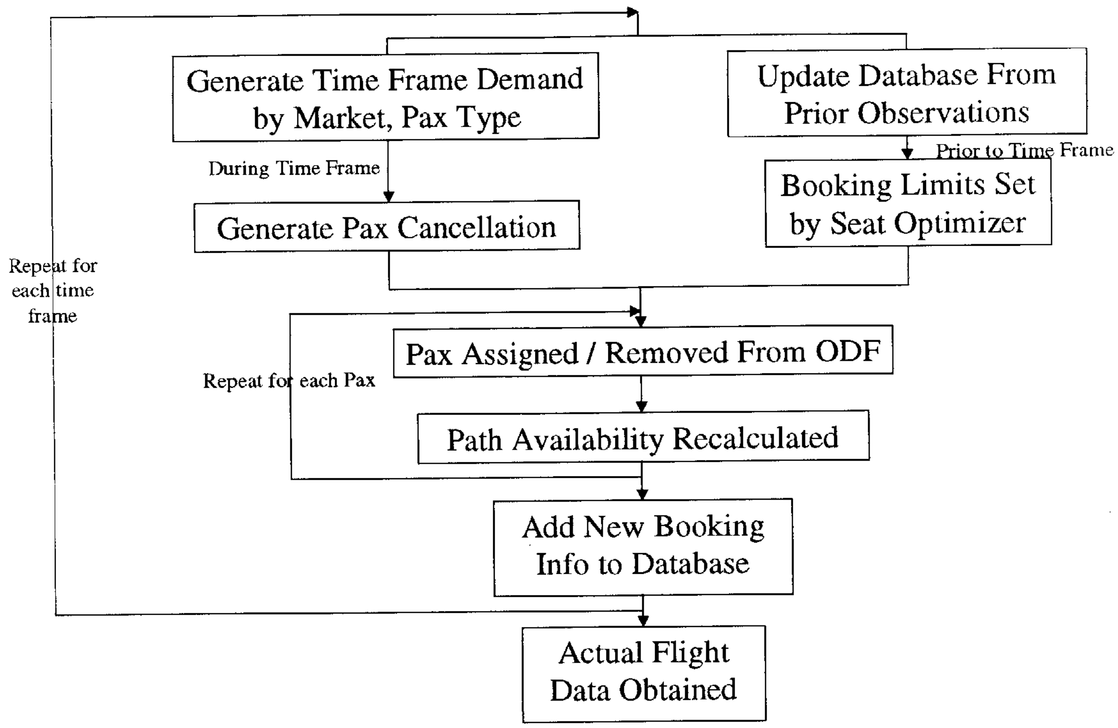

Figure 3-2 PODS Flow chart. Source: Zickus [15]

3.3.2. Trials, Samples, Burns

Each departure in the simulation is called a "sample" in PODS terms. Currently the standard number of samples per trial is set to 600. Every single sample becomes a booking history data for the following samples. Hence in order to reduce the correlation and obtain statistically sound results, we group samples by 600 each as a trial. A trial serves as a unit run for a single case, which in most of our simulations is composed of 20 trials. A set of 20 trials is called a "case" which completes a single simulation. Since the beginning part of each sample has little or no historical database to refer to, the first 200 samples are not used as a part of the results. Instead, PODS relaxes the capacity of first 50 sample departures to be four times the standard input capacity, and capacity of 51~100 sample to be twice of the standard input capacity in order to obtain an unconstrained demand forecast. Samples 101 to 200 are run with standard capacity, but still serve only as a historical record to produce stable and reliable forecasts. These first 200 samples are called "burns", and the number of samples burned is also a user defined input data. As a result, in standard settings with 600 samples, 20 trials, and 200 burns, we have total of (600-200)*20=8,000 samples departures in a single case simulation.

3.3.3. Input Parameters

PODS allows a great deal of flexibility for the simulation, mostly controlled by the user. The user-defined inputs are categorized in three parts; system-level inputs, airline inputs, and market/path/leg inputs.

System level inputs determine the general characteristics of the simulation such as simulation sizing variables, passenger behavioral coefficients, fare and reservation structure descriptions, stochastic factors, and experimental design inputs. Airline inputs define for each airline the revenue management system and airline carrier preferences. Market inputs specify the mean schedule tolerance and time-of-day demand profile for each market. Departure and arrival schedule, path quality index, component leg identifiers are defined by path inputs. Capacity and distance for each leg are defined by leg inputs. For more specific listings of input parameters see Zickus [15]. The key input parameters for the purpose of this thesis are summarized in Table 3-4.

System Level Input Parameters		Airline Input Parameters
Description	Base Settings	Description
Number of airlines	2	Index of RM optimization method
Number of legs	252	Index of forecasting method
Number of markets	482	Index of detruncator
Number of pax types	2	**Market/Path/Leg Parameters**
Number of fare classes	4	Leg capacity
Number of restriction categories	3	Leg distance
Attributed cost k-factor	0.3	Number of paths in market
Multiplier (to basefares) for Pr(willingness to pay=0.5), business pax	3	Basefare of market, per pax type
		Mean demand at basefare
Multiplier (to basefares) for Pr(willingness to pay=0.5), leisure pax	1.2	Coefficient of airline preference
		Market fare
		Path departure time
		Path arrival time
		Path quality index

Table 3-4 Important PODS input parameters. Adapted and summarized from Wilson [15]

3.3.4. Outputs

PODS records the output results of the simulation into two files; summary output file (.SOT) and a general output file (.OUT). The summary output file provides overall results of the simulation such as total revenues, average network load factors, Revenue Passenger Miles, Average Seat Miles, average yields and unit costs per airline. It also provides revenues and average network load factors broken up by banks[18], as well as summary of leg loads and actual choice of passengers given first choice. The general input file has detailed listings of primary outputs such as revenues by trials, loads by leg/market by fare class. Supplementary outputs like forecast and manifest demand are attached to the general output file. The most frequently used outputs will be the net revenues and average load factors by airline. However, the percentage of passengers with a particular path choice given first choice is a useful measure of tracking passengers who divert to other path/fare class options.

[18] Hub-and-spoke network based airlines have one or more connecting banks in a day at the hub. Connecting bank is a time window where incoming flights and outgoing flights are scheduled closely in order to construct feasible and reasonable connecting schedules for passengers.

3.4. Simulation Environment – Network D

For the purpose of testing various topics in revenue management and this thesis, Network D was developed. Network D is a 42-city network, replicating actual locations of major U.S. cities. Two of the 42 cities are hub cities for two airlines, the rest of them are the spoke cities where both airlines operate scheduled flights. All traffic flows from 20 western cities to 20 eastern cities, distances from the hub ranging from 125 to 1514 miles. On this network there are 3 bank schedules, at 10:30 AM, 2:00 PM, and 5:30 PM. There are total of 252 flight legs including inter-hub legs operated on this network in a day, with 482 O-D markets.

Network D with its large scale is representative of actual airline hub networks in the real world. The size of outputs as well as inputs is very large, compared to what was previously simulated in PODS (See Lee [12]). With interhub flights and multiple banks, passengers now have fare more choice of path options, resembling the variety of path choices of real world travelers. Figure 3-3 illustrates the geographical layout of Network D, followed by the summary of major characteristics.

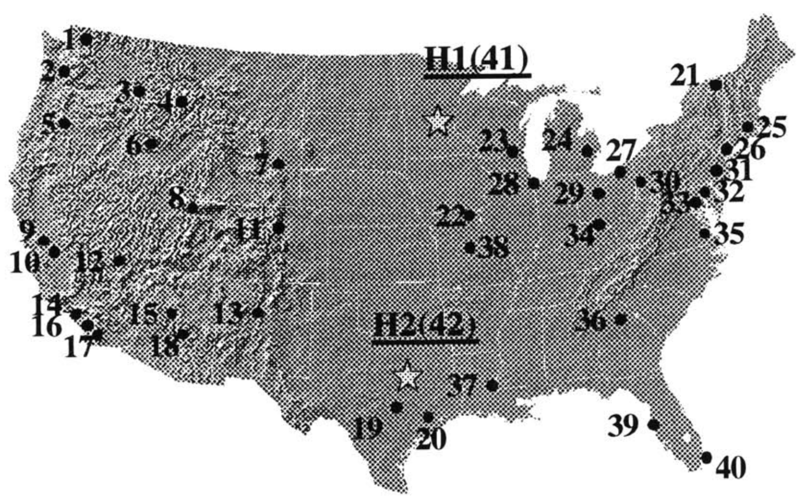

Figure 3-3 Network D layout

<Summary of Network D Characteristics>

- 40 spoke cities with 2 hubs, one for each airline
- 20 spoke cities on each side, located by geographical coordinates of actual US cities
- Distance -- 125~1514 miles to the hub from spoke cities
- Unidirectional : West to east flow of traffic
- Interhub services, one for each direction, for each bank, for each airline
- 3 banks starting at 10:30, 14:00, 17:30 per each airline
    - 21 flights arrive at 10:30AM, 2PM, and 5:30PM at each hub
    - Bank duration is 1 hour
    - 21 flights depart at 11:30AM, 3PM, and 6:30PM from each hub
- 252 flight legs, 482 O-D markets

3.5. Summary

This chapter gives an overview of airline revenue management and the simulation tool used later in this thesis, Passenger Origin Destination Simulator (PODS). Conventional airline revenue management methods can be categorized into two groups, Fare Class Yield Management (FCYM) and Origin-Destination revenue management methods. FCYM methods gather data and perform inventory control on a flight leg basis, which leads to some shortcomings such as neglecting high fare connecting passengers on multiple leg itineraries. Due to the reasons mentioned in Section 3.1 there had been efforts to develop O-D revenue management, and some products of those efforts were described in Section 3.2.

PODS provides the tools for simulating a competitive environment which two or more airlines compete over a network of O-D markets. Developing the passenger choice model and simulating with PODS is the major issue for later chapters of this thesis. A hypothetical 42-city network, Network D, serves as a simulation environment for the purpose of testing the impacts of disutility model discussed in Chapter 4.

Chapter 4 Modeling Airline Passenger Disutilities

Airline passenger disutilities have considerable impact on passenger path choice. The passenger path choice directly influences airlines' revenues. Therefore the challenge that we face in order to gain a logical perspective on how passenger disutilities can be related to airline revenues is to find a reliable model that represents passenger disutilities. First, this chapter will go through a basic approach to disutilities programmed in PODS (Section 4.1). Afterwards, actual parameters for three passenger disutilities will be derived (Section 4.3), using the survey results from the airline experts (Section 4.2), followed by a chapter summary in Section 4.4.

4.1. Disutility Functions in PODS

When PODS generates demand for each market, it will also choose passenger disutility values for each passenger generated. PODS then uses its own algorithm to assign path choice for each of those passengers. If a passenger's favorite path is unavailable, the passenger will spill or seek his/her second favorite path. As explained briefly in this section, the passenger disutility model plays an essential role in the PODS passenger assignment model (Section 4.1.2). Section 4.1.3 examines how passenger disutilities are represented by a probabilistic model and how it is applied in PODS. Finally Section 4.1.4 will show an example of calculating total cost.

4.1.1. How Disutility Functions Work in PODS

In order to measure the attractiveness of each fare class/path option generated, PODS needs to calculate the "total cost" of the path options. The term "total cost" will be distinguished from the nominal cost, which is the actual dollar value of an airline ticket. Alternatively, "total cost" includes the dollar value of the inconvenience coming from each restriction of the lower fare options, as well as the out-of-pocket money paid (nominal cost). Disutility functions are used to convert these inconveniences into comparable dollar values.

PODS refers to disutility functions to compute each passenger's disutility costs for all disutility categories defined in the simulator. The four disutility categories anticipated in PODS are:

- Fare class restriction disutility
- Unfavorite airline disutility
- Path quality index disutility
- Replanning disutility

Disutility costs are calculated and summed with the nominal fare of the selected fare class option. This sum is designated as "total cost" of each path and fare class combination. Among the options of fare class/path with nominal cost not exceeding each passenger's generated maximum willingness to pay, PODS will compare the total fare of each option and choose the fare class/path of minimum total cost to represent the passenger's first choice path option.

4.1.2. PODS 8 Passenger Assignment Model

The PODS 8 passenger assignment model basically generates passengers and assigns them to the best path/fare class option. If there are no seats available within the passenger's choice set of paths, the passenger will be spilled. The detailed process of passenger assignment model is described below.

1. Generate demand by market, by passenger type (business passenger or leisure passenger).
2. Scramble the arrival order
3. For a given market and path type, pick

a. Favorite airlines – ordinarily set the same for each airline
b. The decision window – pick the earliest possible departing time and the latest possible arrival time
c. The path quality costs
d. The cost for non-favorite airline use
e. The cost for fare class restrictions
f. The cost for replanning

4. For a given market and passenger type, pick the maximum willingness to pay (XPAY)
5. Screen-out paths and fare classes with fares greater than maximum willingness to pay (fare>XPAY)
6. If no paths are remaining with seats available, spill out the passenger
7. If paths do remain, compute the following for each screened-in path and fare class combination

   Total Cost for path/fare class option
   = Fare
   + Path quality cost*Path Quality Index
   + Unfavorite airline cost (If unfavorite airline)
   + Restriction costs
   + Replanning costs

8. Assign passenger to the lowest total cost path/fare class
9. Proceed to the next passenger, go to step 3.

The process described above is also outlined in Figure 4-1. In the passenger choice model, step 3 is where the disutility functions are involved. The four categories, path quality cost, unfavorite airline cost, fare class restriction cost, and, replanning cost are essentially calculated according to disutility functions defined and input by the users. Disutility functions will be explained more thoroughly in the Section 4.1.3.

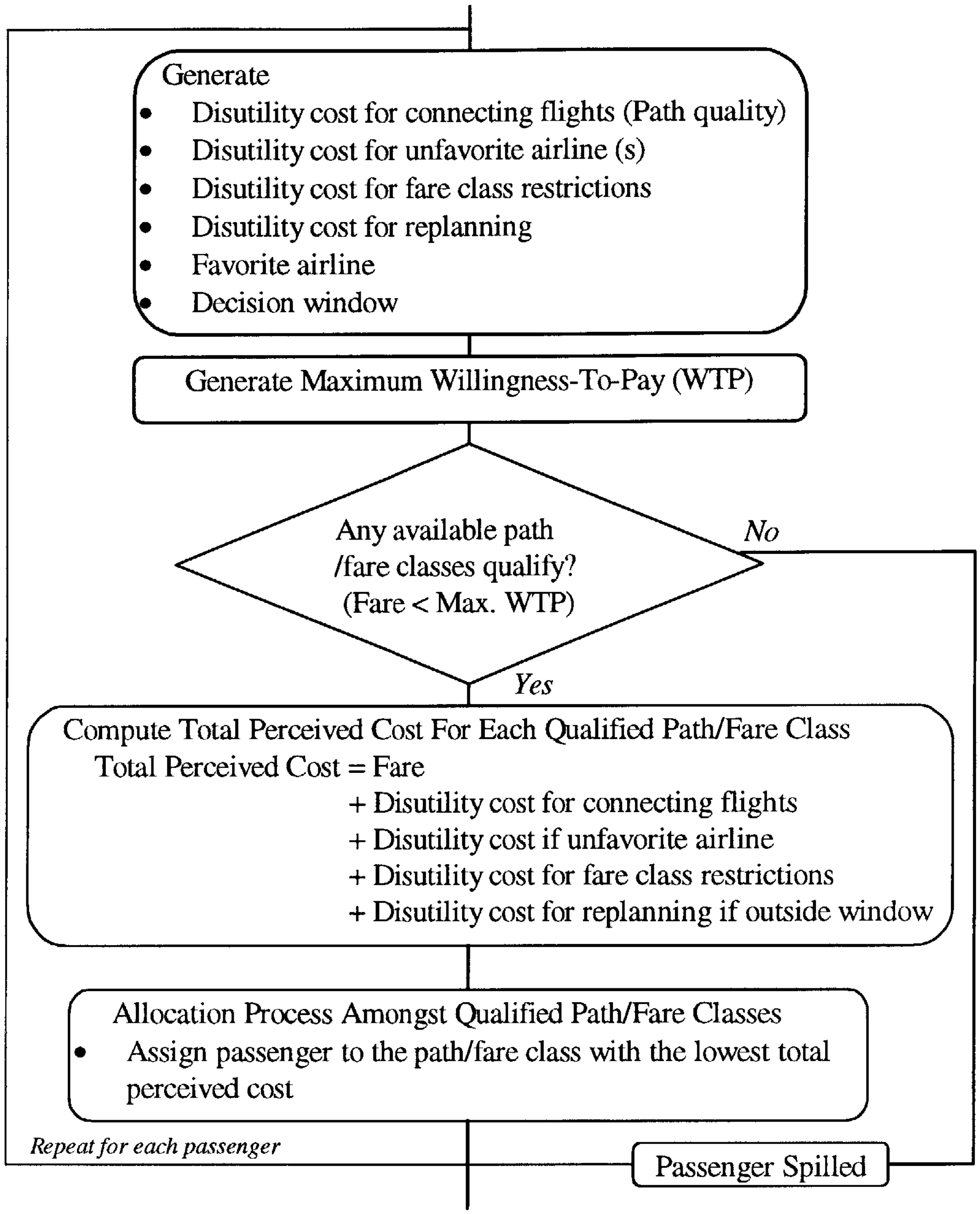

Figure 4-1 PODS8 Passenger Choice Model[19]

4.1.3. Disutility Costs

Disutility costs are chosen from a normal distribution. The mean value and standard deviation of the Gaussian distribution for disutility costs are defined to have different

[19] Adapted from Lee [12]

values for each market, depending on the distance of the O-D market. It also depends on passenger types and for the purpose of this thesis the passengers are classified into two types, leisure and business. We can represent the disutility cost for a passenger type in a certain O-D market to be $N(\mu,(k\mu)^2)$, where μ is the mean disutility cost at that market, and k is the k-factor of the normal distribution. When generating a passenger, PODS will pick a value from the disutility distribution curve with a probability according to the Gaussian probability distribution. The four disutility categories have different averages, while all disutility costs have a Gaussian distribution. The k factor for all cost distributions have taken the value 0.3 for all the simulations up to the present, which is the value widely recognized to represent the stochasticity of air transportation demand as numerous empirical studies have shown[20].

The representation of all disutility cost probability density functions are expressed as:

<Business>

Restriction 1 disutility cost = $N(\mu_{R1,B},(k\mu_{R1,B})^2)$

Restriction 2 disutility cost = $N(\mu_{R2,B},(k\mu_{R2,B})^2)$

Restriction 3 disutility cost = $N(\mu_{R3,B},(k\mu_{R3,B})^2)$

Unfavorite airline disutility cost = $N(\mu_{UFA,B},(k\mu_{UFA,B})^2)$

Path quality disutility cost per PQI = $N(\mu_{PQI,B},(k\mu_{PQI,B})^2)$

Replanning disutility cost = $N(\mu_{RP,B},(k\mu_{RP,B})^2)$

<Leisure>

Restriction 1 disutility cost = $N(\mu_{R1,L},(k\mu_{R1,L})^2)$

Restriction 2 disutility cost = $N(\mu_{R2,L},(k\mu_{R2,L})^2)$

Restriction 3 disutility cost = $N(\mu_{R3,L},(k\mu_{R3,L})^2)$

Unfavorite airline disutility cost = $N(\mu_{UFA,L},(k\mu_{UFA,L})^2)$

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[20] Wilson [14] p.46

Path quality disutility cost per PQI = $N(\mu_{PQI,L}(k\mu_{PQI,L})^2)$

Replanning disutility cost = $N(\mu_{RP,L},(k\mu_{RP,L})^2)$

The average of each distribution, $\mu_{DisutilityCategory,PaxType}$, can be expressed as a function of the market distance and/or fares since the perceived cost for a disutility will be heavily market dependent. In order to set a comparable representation of each market in dollar terms, the concept of "market basefare" is introduced. Market basefare is a parameter that serves as a basis of comparison for fares, passenger maximum willingness to pay, and passenger disutility costs between different markets. For instance the market basefares are used to determine the fares for each markets, as Q class fare set equal to leisure passenger's basefares. One important attribute of a market that determines the fare and cost level is the market distance, as can be observed in most of the real world air transportation markets. Therefore it is reasonable to express the market basefares as a linear function of market distances for each of the passenger types, as follows:

Basefare_Leisure = 50+0.075*distance (4. 1)

Basefare_Business = 2.5*(50+0.075*distance) (4. 2)

The average of each disutility cost distribution now can be expressed as a function of market basefares. The simulations presented later in this thesis assume that $\mu_{DisutilityCategory,PaxType}$ is an increasing linear function of market basefares; hence the average disutility cost is higher for long distance markets with high market basefares. Equation (4.3) shows that mean disutility cost is a linear function of the market distance, with coefficients to be determined for each disutility category and for each passenger type.

μ = a + b*basefare, a and b to be determined (4.3)

4.1.3.1. Restriction Disutility Cost

Definitions of restrictions in PODS simulations

There are three kinds of restriction categories currently applied in PODS simulations. Restriction 1 is defined as the 'Saturday night stay' restriction, which requires the passenger to stay over a Saturday night at the destination. Restriction 2 indicates that there will be a penalty fee when a passenger wants to change or cancel the trip. Restriction 3 is non-refundability of airline tickets, which is only applied to the lowest fare class. Among the four fare classes currently used in for PODS simulation, Y class has no restrictions applied, B class has only restriction 1 applied, M class has restriction 1 and 2 active, and, all three restrictions apply for Q class. The relations of restrictions and fare classes are summarized in Table 4-1.

Table 4-1 Summary of restriction categories and fare class applications

Restrictions	1	2	3
Decription	Saturday night stay	Cancellation/ change penalty	Nonrefundable
Y Class	x	x	x
B Class	o	x	x
M Class	o	o	x
Q Class	o	o	o

Restriction disutility costs

As explained in Section 4.1.3, disutility costs for each restriction category have a normal distribution. The mean value of each distribution is determined by the market distance, strictly speaking, by the basefare of the market. Recall that market basefares are defined as a linear function of market distances, as in equations (4.1) and (4.2).

The coefficients or disutility functions for all three restriction categories for each passenger type were determined by the earlier works of Wilson [14][21]. The coefficients of each restriction disutility cost were preliminarily based on the market research conducted at Boeing (1988), along with the constraint that the for business passengers lower fare classes should be less attractive and for leisure passengers the lower fare classes should be more attractive. This constraint was made to assure that the restriction disutility function reflects the fare class segmentation schemes of the actual airlines, which define fare classes such that a fare product is superior to fare products of lower fares in every restriction element. An example of coefficients being used in PODS is shown in Table 4-2.

Table 4-2 Coefficients of restriction disutilities

		Business		Leisure	
		Intercept	Slope	Intercept	Slope
Parameters	Restriction 1	0	0.9	0	1.75
	Restriction 2	0	0.3	0	0.25
	Restriction 3	0	0.3	0	0.25

For example, the mean value of disutility for Restriction 1 (Saturday night stay) for a business passenger in market with basefare equal to $500 can be found using equation (4.3), as follows:

$$\mu_{R1B}(\$500) = 0 + 0.9*\$500 = \$450 \tag{4. 4}$$

Examples of restriction disutility costs

With the disutility functional coefficients defined in Table 4-2, and with a k-factor of 0.3, we can provide an example of what restriction disutilities will be for a certain passenger. As Table 4-1 shows, only the first restriction applies for passengers traveling a market distance of 1000 miles, in a B class. For M class, restrictions 1 and 2 apply, and the

[21] Wilson [14], Chapter 4 *The Operational Competitive Simulation Environment*

disutility costs of both restrictions need to be added for total restriction disutility cost. However, for the sake of simplicity, let's begin our example with B class choice.

First, the basefare is determined by market distance (1000 miles) and passenger type (business), as denoted in equation (4.2).

$$\text{Basefare\_Business}(1000\text{ mi}) = 2.5*(50+0.075*1000\text{ mi})=\$312.5 \tag{4. 5}$$

Next, with the basefare determined, mean disutility cost for restriction 1 can be found using coefficients in Table 4-2 and equation (4.3).

$$\mu_{R1,B}(\$312.5) = 0 + 0.9*\$312.5 = \$281.25 \tag{4.6}$$

Since the mean value of the disutility cost distribution with k-factor of 0.3 is known, the mean disutility cost in this market for B class will be picked from the probabilistic distribution of:

$$\text{Disutility cost(Restrictions, business passenger, B class)} = N(\$281.25, \$84.375^2)$$

Example of restriction disutility cost relative to fare structure

As an example showing how restriction disutility costs compare to actual fares, Table 4-3 shows a sample PODS fare structure and restriction disutility cost at market distance of 1000 miles. In this case, the restriction disutilities are defined such that the highest fare class is most attractive for an average business passenger. For leisure passengers it would be opposite, Q class would have lowest average total cost.

Pax Type	Fare Class	Y	B	M	Q
Business	Average Dis(Re1)	N/A	$281.25	$281.25	$281.25
	Average Dis(Re2)	N/A	N/A	$93.75	$93.75
	Average Dis(Re3)	N/A	N/A	N/A	$93.75
	Fare	$500.00	$250.00	$187.50	$125.00
	Average Total Cost	**$500.00**	**$531.25**	**$562.50**	**$593.75**
Leisure	Average Dis(Re1)	N/A	$218.75	$218.75	$281.25
	Average Dis(Re2)	N/A	N/A	$31.25	$31.25
	Average Dis(Re3)	N/A	N/A	N/A	$31.25
	Fare	$500.00	$250.00	$187.50	$125.00
	Average Total Cost	**$500.00**	**$468.75**	**$437.50**	**$468.75**

Table 4-3 Sample fare structure and average restriction disutility costs for market distance of 1000 miles

4.1.3.2. Unfavorite Airline Disutility Cost

Unfavorite airline is a term used to describe the airline, which is not the passenger's first preference. If a passenger's path option is with the unfavorite airline, the unfavorite airline disutility cost is added into the total cost of the path. PODS assumes that each passenger always has a favorite airline, and the other airline will be the unfavorite airline. The probability of airline A (or airline B) being the favorite airline is decided with the input parameter. Previously, all simulations set the preference of each airline to be 0.5 and unfavorite airline disutility costs to be $0, effectively ignoring any passenger preference for airlines.

For example, for the market distance of 1000 miles, the basefares for business passengers in equation (4.5) were already calculated, to be $312.5. If the intercept and slope of the unfavorite airline disutility function are $a_{UFA,B}$ and $b_{UFA,B}$, respectively, the mean value of this disutility cost is:

$$\mu_{UFA,B}(\$3125) = a_{UFA,B} + b_{UFA,B}{}^{*}\$312.5 \qquad (4.7)$$

In most previous PODS simulations with $a_{UFA,B} = b_{UFA,B} = 0$, and k factor of 0.3, the mean and standard deviation of the unfavorite airline disutility in this market is 0.

4.1.3.3. Path Quality Index Disutility Cost

Path Quality Index

Path Quality Index is an indication of the convenience of the given path. In PODS path quality is measured strictly in terms of number of stops and connects in the path.

PQI = 1 + # of stops + 2*# of connections (4.8)

For example, the PQI of a path with one connection will be 3.

PQI disutility costs

PQI disutility cost per PQI is determined in a manner similar to the methods of determining other disutility costs. We input the intercept and slope for the disutility function to determine the mean value of the disutility cost distribution at a give market distance. For example, for a business passenger at market distance of 1000 miles with a basefare of $312.5, the mean of disutility cost per unit PQI is calculated as:

$$\mu_{PQI,B}(\$312.5) = a_{PQI,B} + b_{PQI,B} * \$312.5 \qquad (4.9)$$

where $a_{PQI,B}$ and $b_{PQI,B}$ are the intercept and slope of the PQI disutility function. With the setting of $a_{PQI,B}$=$25 and $b_{PQI,B}$=0, $\mu_{PQI,B}$ will be $25. If the path option includes with one connection (therefore PQI=3) the PQI disutility cost distribution is:

Disutility cost(PQI, business passenger) = N(3*$25, 3*$$7.5^2$)

4.1.3.4. Replanning Disutility Cost

If a passenger's path option is outside his/her initially determined decision window, the replanning disutility cost is added into the total cost of the path. The disutility cost of replanning is also normally distributed with a mean determined by input parameters. For example, for business passengers replanning for a market distance of 1000 miles, the mean of replanning disutility cost is:

$$\mu_{RP,B}(\$312.5) = a_{RP,B} + b_{RP,B} * \$312.5 \qquad (4.10)$$

where $a_{RP,B}$ and $b_{RP,B}$ are the intercept and slope of the replanning disutility function. With $a_{RP,B}$=\$0 and $b_{RP,B}$=0, $\mu_{PQI,B}$ is \$0.

4.1.4. Total Cost

Using the previous examples of a business passenger in a market distance of 1000 miles in B class with one connection with the unfavorite airline and a path outside the decision window, the total disutility cost is the sum of the restriction disutility cost, the unfavorite airline disutility cost, the PQI disutility cost, the replanning disutility cost, and the nominal fare.

Total Cost = B class nominal fare \$250
+ Restriction disutility $N(\$281.25, \$84.375^2)$
+ Unfavorite airline disutility $N(\$0, \$0)$
+ PQI disutility $N(\$75, 3*\$7.5^2)$
+ Replanning disutility $N(\$0, \$0)$

In order to obtain realistic distributions for each of the disutility categories in the above equation, a survey asking probabilistic passenger behavior was conducted to a group of airline experts, with more explanation in Section 4.2. The estimations generated from survey results are needed for the realistic values of slopes and intercepts of the unfavorite airline, PQI, and replanning disutility functions. After these coefficients of disutility functions are determined (Section 4.3), the impact of disutility costs of each disutility category will be tested and analyzed (Chapters 5~6).

4.2. The Survey

4.2.1. Background

In order to get the idea of passengers' sensitivity to unfavorite airlines, path qualities, and replanning, we conducted a survey asking the probability that passengers would pay for a higher fare class rather than put up with disutilities. The respondents of the survey were thirteen airline experts from six airlines of the PODS consortium. The answers given by the respondents are based on their perceptions of actual consumer choice behavior. These answers are the basis of the disutility model derived in Section 4.3.

4.2.2. Assumptions

Base Case Network Assumptions

The notional base case assumptions for the questions given in the survey are:

- A bow tie design with 5 spoke cities on each side
- Two airlines operating on this network
- Two separate hub cities, with inter-hub flights
- Two banks per day per airline (possibly non-synchronized)
- Two paths per day per airline per market
- Four fare classes and three nested restrictions

The layout for this network is shown in Figure 4-2.

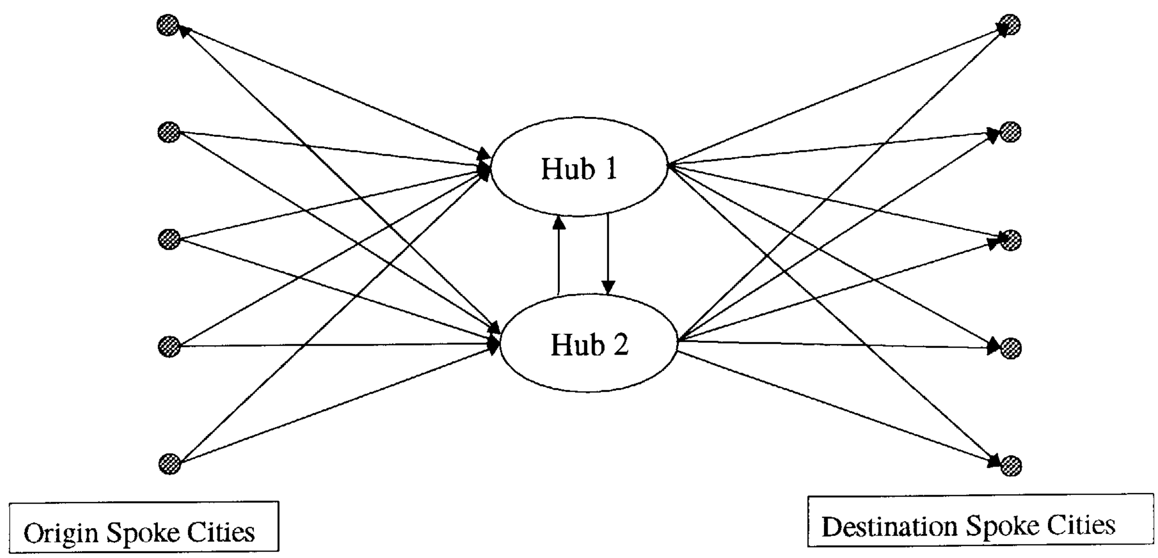

Figure 4-2 Layout for the notional base case network for the survey

Passenger Assumptions

There are also assumptions presented in the survey for the passengers traveling throughout this hypothetical network. For the survey, a typical business passenger is assumed to have maximum willingness-to-pay exceeding the fare for fare class 1. Furthermore, the disutility attributed for restriction 1, which is assigned to fare class 2, is less than the fare difference between fare class 1 and fare class 2. These assumptions can be interpreted such that under ideal circumstances with all fare classes open and all paths open, a typical business passenger will choose fare class 2 as his/her first choice. However, in the survey we limit the favorite path choice to be closed, forcing the passengers to either purchase higher fare class of same path choice or spill to another path choice. Finally, a typical business passenger's choice set is limited to fare classes 1 and 2 and to two paths given in each question of the survey, of which (path 1, class 2) is closed.

	Path 1	Path 2
Fare Class 1	Open	Open
Fare Class 2	Closed	Open

Table 4-4 Choice set of a business passenger

Assumptions for leisure passengers are symmetrical to the business passenger assumptions. A typical leisure passenger's maximum willingness-to-pay includes only fare class 3 and 4, and the disutility attributed to restriction 3, which is applied only to fare class 4, is less then the fare difference between fare class 3 and fare class 4. Hence, under ideal circumstances a typical leisure passenger's first choice will be in fare class 4. Finally, a typical leisure passenger's choice set is limited to fare classes 3 and 4 (explicit from the maximum willingness-to-pay assumption) and two path choices given by each question.

	Path 1	Path 2
Fare Class 3	Open	Open
Fare Class 4	Closed	Open

Table 4-5 Choice set for leisure passengers

4.2.3. Questions and Answers

The survey consists of three parts; the probability of a random passenger buying a fare class higher rather than the fare class of his/her choice with the unfavorite airline, path quality, and replanning disutility applied. Each part has two questions: one for business passengers and one for leisure passengers. All questions are answered for four different market distances, 500, 1000, 2000, and 4000 miles.

- ***Question 1 – Unfavorite Airline***

Question 1 asks the respondent to provide the probability that the unfavorite airline disutilities are greater than the fare differences of two fare class choices for each passenger type.

Business

What do you estimate is the probability of a random business passenger choosing fare class 1 of his/her favorite airline rather that fare class 2 of the unfavorite airline if all else is equal?

Distance	500	1000	2000	4000
Average	34.2%	36.9%	40.0%	43.5%
Std	12.8%	9.3%	10.9%	16.3%

Table 4-6 Average and standard deviation of answers for the probability of selling up instead of taking unfavorite airline for business passengers

Airline experts estimated that 34.2% to 43.5% of business passengers will sell up to farc class one instead of flying with the unfavorite airline, given that his/her first choice fare class on favorite airline is closed down.

Leisure

What do you estimate is the probability of a random leisure passenger choosing fare class 3 of his/her favorite airline rather that fare class 4 of the unfavorite airline if all else is equal?

Distance	500	1000	2000	4000
Average	11.5%	11.2%	13.8%	15.8%
Std	6.4%	4.9%	7.0%	19.8%

Table 4-7 Average and standard deviation of answers for the probability of selling up instead of taking unfavorite airline for leisure passengers

From the survey results, 11.5% to 15.8% of the leisure passengers are expected to sell up when their favorite airline's first choice fare class (fare class 4) is closed down.

For both type of passengers, the presumed probability of selling up is higher for longer distance markets. The factors that would work against flying on the unfavorite airline would be frequent flyer advantages or loyalty towards one's favorite airline. The survey results show that the advantages and "loyalty" of a favorite airline would be more important at longer distances with higher nominal fares. Hence, the disutility cost of an unfavorite airline increases as market distance increases. Moreover, the probability of selling up is higher for business passengers, meaning that business passengers tend to be more sensitive to which airline they are flying.

□ *Question 2 – Path Quality*

Question 2 asks about the probability that the disutility of a connecting path is greater than the fare difference of two fare class choices for each passenger type.

Business

What do you estimate is the probability of a random business passenger choosing fare class 1 for a non-stop path over fare class 2 of a connecting path if all else is equal?

Distance	500	1000	2000	4000
Average	72.3%	60.0%	47.7%	39.6%
Std	15.8%	14.6%	18.5%	17.9%

Table 4-8 Average and standard deviation of answers for the probability of selling up instead of taking a connecting path for business passengers

The airline experts answered that up to 72.4% of business passengers would sell up to fare class 1 rather than flying a one-stop path. This percentage was higher for shorter market distances.

Leisure

What do you estimate is the probability of a random leisure passenger choosing fare class 3 of a non-stop path over fare class 4 of a connecting path, if all else is equal?

Distance	500	1000	2000	4000
Average	38.5%	28.1%	19.2%	15.0%
Std	17.2%	17.5%	19.3%	19.9%

Table 4-9 Average and standard deviation of answers for the probability of selling up instead of taking a connecting path for leisure passengers

Both business and leisure passengers are expected to have a higher probability of selling up in shorter distance markets. Presumably, the time delay from a stopover seems longer for shorter trips, making the advantages of a non-stop path decrease for longer haul markets. Another interpretation would be that path quality disutility tends to decrease for longer distances.

❑ *Question 3 – Replanning*

Question 3 asks for estimates of the probability that the disutilities of replanning are greater than the fare differences of two fare class choices for each passenger type.

Business

What do you estimate is the probability of a random business passenger choosing fare class 1 in his/her decision window rather than fare class 2 with replanning?

Distance	500	1000	2000	4000
Average	67.7%	60.1%	55.3%	49.6%
Std	23.6%	18.0%	16.4%	19.8%

Table 4-10 Average and standard deviation of answers for the probability of selling up instead of replanning for business passengers

Leisure

What do you estimate as the probability of a random leisure passenger choosing fare class 3 in his/her decision window rather than fare class 4 with replanning?

Distance	500	1000	2000	4000
Average	27.7%	24.2%	20.4%	18.5%
Std	17.9%	16.9%	18.1%	19.7%

Table 4-11 Average and standard deviation of answers for the probability of selling up instead of replanning for leisure passengers

Replanning disutility costs, as presented, tend to decrease for longer haul trips, meaning that long distance trips with longer durations are planned with more flexibility. The percentage of passengers who would pay more rather than replan their trips tends to decrease, as market distances get longer.

- ***Summary***

Generally all disutility costs resulting from the survey probabilities are estimated higher for business passengers than leisure passengers. In other words, business passengers are judged to be more sensitive to various inconveniences, whereas leisure passengers are more sensitive to fares. Using these results, we are ready to model the individual disutility functions for all cases mentioned in the survey, illustrated in Section 4.3.

4.3. Building Disutility Models

The average probability values given in the survey, allow estimation of the slope and intercept of the three disutility functions for business and leisure passengers. Recall from Section 4.1 that the mean value of a disutility functions is linear function of market basefares, which turns out to be a linear function of market distances. Therefore, the next step requires establishing a reasonable representation of disutility function, i.e. the value of the slope and intercept of each disutility functions. The survey results provide the data necessary for this derivation.

4.3.1. Parameters Required

As shown in equation (4.3), the mean value of a disutility distribution is a linear function of the basefare at that distance for a given passenger.

$$\mu = a + b*\text{basefare, a and b to be determined} \quad (4.3)$$

The coefficients *a* and *b* are defined for all disutility categories, and values can be derived for the three disutility categories in the survey. Each of the three categories has a pair of coefficients (*a,b*); for each categories, and for the two passenger types, the resulting 6 pairs of coefficients can be determined. These coefficients are determined by deriving the mean value of each disutility at market distance of 500, 1000, 2000 and 4000 miles, then performing a linear regression over the basefares for those market distances.

4.3.2. Determining Parameters from Survey

From the probabilities that a passenger will sell up at any of the four different market distances, we can obtain the intercept and slope of each disutility through the following procedure. First we calculate the base fare for distances of 500, 1000, 2000 and 4000 miles, for each passenger type. Then we derive the mean value for each disutility distribution for each passenger type for distances of 500, 1000, 2000 and 4000 miles, for each passenger type, based on survey results. Finally, we do a linear regression of the mean disutility cost over basefares to produce the intercept and slope of each mean disutility cost.

4.3.2.1. <u>Sample Calculation For Unfavorite Airline Disutility, Business Passenger</u>

Background and Assumptions

This example demonstrates the procedure of how this is done for the case of business passenger with the unfavorite airline disutility. Starting with market distance of 500 miles, the basic assumptions for the given case are shown in Table 4-12.

Market distance = 500 miles Basefare_Business = 2.5*(50+0.075*500)=$218.75 Basefare_Leisure = 50+0.075*500=$87.5		
Fare Class	Restrictions	Fares
1	N/A	4*Class 4 Fare = $350
2	1	2*Class 4 Fare = $175
3	1,2	1.5*Class 4 Fare = $131.25
4	1,2,3	50 + 0.075*500 = $87.5

Table 4-12 Basic parameters needed for the calculation of the mean disutility cost

The Total Cost

This survey has given the probability that a business passenger whose first choice is airline 1 fare class 2 will choose (airline 1, fare class 1), instead of (airline 2, fare class 2), when fare class 2 of favorite airline (airline 1) is closed. It is the probability that the total cost of the path choice for (airline 1, fare class 1), given that first path choice of this passenger which is path choice (airline 1, fare class 2) is closed, is smaller than the total cost of path choice (airline 2 fare class 2). The total cost for these two case are compared in Table 4-13.

	Airline 1, Fare class 1	Airline 2, Fare class 2
Unfavorite Airline?	No	Yes
Path Quality Index	1 (non-stop)	1 (non-stop)
Replanning?	No	No
Nominal Fare	$350	$175
Restriction Disutility	$0	$x
UFA Disutility	$0	$y
PQI Disutility	$z	$z
Rpln Disutility	$0	$0
Total Cost	350+z	175+x+y+z

Table 4-13 Total cost calculation for the two path choice options

The variables x, y, and z in Table 4-13 represent conditional restriction 1 disutility, unfavorite airline disutility, and path quality index disutility. With these calculations, the question in the survey is asking the probability that $350+z$ is less than $175+x+y+z$. In Table 4-6, we can see that this probability is estimated by the survey respondents as 34.2% with standard deviation of 12.8%. Mathematically:

$$\Pr(350+z > 175+x+y+z) = \Pr(x+y < 175) = 0.342 \tag{4.11}$$

where x is the conditional disutility of restriction 1, given that the first choice is fare class 2 of airline 1, and y is the unfavorite airline disutility. In other words, the survey is asking the probability that the sum of the conditional disutility cost for restriction 1 and the disutility cost of the unfavorite airline is greater than the fare difference of class 1 and class 2.

Conditional Distribution of Restriction 1 Disutility Cost, f(x)

This approach looks at each disutility as a Gaussian distribution, hence both x and y can be presented in the form of a probability density function. The variable x comes from the distribution for the restriction 1 disutility; only it is a <u>conditional</u> distribution. For the probability density function for x, first define:

- Event A: A business passenger's first choice is fare class 2 of airline 1 (the favorite airline)

- $$f(Dis_{R1}) = N(\mu_{R1,B,500mi}, \sigma_{R1,B,500mi}{}^2) = \frac{1}{\sqrt{2\pi}\sigma_{R1,B,500mi}} \exp\left(\frac{-(Dis_{R1} - \mu_{R1,B,500mi})^2}{2\sigma_{R1,B,500mi}{}^2} \right) \qquad (4.12)$$

(the probability density function of the restriction 1 disutility cost for business passengers at market distance of 500 miles, expressed as a normal distribution)

- $\mu_{R1,B,500mi} = 0 + 0.9 * \$218.75 = \$196.88$, from (4.4) and Table 4-12 (4.13)
- $\sigma_{R1,B,500mi} = k * \mu_{R1,B,500mi}$, where k=0.3 (system-wide k factor)

  =\$59.06 (4.14)

Then, by definition, the distribution of x, f(x), will be in the following form:

$$f(x) = f(Dis_{R1} \mid A)$$

The probability of event A, which is the probability that a random business passenger's first choice is fare class 2 of his/her favorite airline, can be interpreted as that the total cost of the path choice for airline 1 fare class 2 is less than the total cost of path choice for airline 1 fare class 1. Then as shown in 4-13, the total cost for these two options can be compared by category.

	Airline 1, Fare class 1	Airline 1, Fare class 2
Unfavorite Airline?	No	No
Path Quality Index	1 (non-stop)	1 (non-stop)
Replanning?	No	No
Nominal Fare	\$350	\$175
Restriction Disutility	\$0	$\$x_1$
UFA Disutility	\$0	\$0
PQI Disutility	$\$z_1$	$\$z_1$
Rpln Disutility	\$0	\$0
Total Cost	$350+z_1$	$175+x_1+z_1$

Table 4-14 Total cost calculation table for fare class 1 and 2

As a result, the probability of event A is expressed as:

$$\Pr(A) = \Pr(350 + z_1 > 175 + x_1 + z_1) = \Pr(x_1 < \$175) \tag{4.15}$$

The probability density function of x, f(x), becomes:

$$f(x) = f(Dis_{R1} \mid A) = \frac{f(x_1 \mid x_1 < 175)}{\Pr(x_1 < 175)} \tag{4.16}$$

where $f(x_1) = f(Dis_{R1,B,500mi}) = N(196.88, 59.06^2)$, from (4.12), (4.13), and (4.14), and

$$\Pr(x_1 < 175) = P(Z < \frac{175 - 196.88}{59.06}) = P(Z < -0.37) = 0.356, \tag{4.17}$$

Equations (4.16) and (4.17) generate the probability density function, mean value, and the standard deviation of the variable x as following:

$$f(x) = \frac{1}{0.356} * \frac{1}{2\pi * 59.06} * \exp\left(\frac{-(x - 196.88)^2}{2 * 59.06^2}\right) \tag{4.18}$$

$$E(x) = \int_{-\infty}^{175} x * f(x)dx = \$134.84 \tag{4.19}$$

$$\sigma(x) = \sqrt{E(x^2) - \{E(x)\}^2} = \$32.09 \tag{4.20}$$

Unfavorite Airline Disutility Distribution

So far, the analysis has looked at the variable x in the equation (4.11) given. Now, attention needs to turn to how variable y, which is the unfavorite airline disutility cost, can be represented in order to solve equation (4.11). Solving this equation will provide the mean value of the unfavorite airline disutility for business passengers, at market distance of 500 miles. Let this parameter be $\mu_{UFA,B,500mi}$. By assuming that the unfavorite airline disutility cost has Gaussian distribution, the probability density function of y looks like:

$$f(y) = N(\mu_{UFA,B,500mi}, \sigma_{UFA,B,500mi}{}^2), \text{ where } \sigma_{UFA,B,500mi} = k\mu_{UFA,B,500mi}, k = 0.3 \qquad (4.21)$$

Back to the Survey Question

Now, if $x+y=w$, the master equation (4.11) can be expressed as following:

$$\Pr(x + y < 175) = \Pr(w < 175) = 0.342 \qquad (4.22)$$

Random variable y is already assumed to have a Gaussian distribution. Additionally, by assuming that the conditional distribution of the restriction 1 disutility cost also has a Gaussian distribution, the average and the standard deviation of the variable w, which is the linear sum of the two variables, can be obtained.

$$E(w) = E(x) + E(y) = 134.84 + \mu_{UFA,B,500mi} \qquad (4.23)$$

$$\sigma(w) = \sqrt{\{\sigma(x)\}^2 + \{\sigma(y)\}^2} = \sqrt{32.09^2 + (0.3\mu_{UFA,B,500mi})^2} \qquad (4.24)$$

Since by definition the sum of independent Gaussian probability density functions is also a Gaussian probability density function, variable w has a normal distribution. Now the equation (4.22) becomes

$$P(w > 175) = P\left(Z > \frac{175 - E(w)}{\sigma(w)}\right) = 0.34 \qquad (4.25)$$

Inserting (4.23) and (4.24) into (4.25), and solving for $\mu_{UFA,B,500mi}$,

$\mu_{UFA,B,500mi}$ **=$26.12**

Calculations for 1000, 2000, 4000 miles

Similar procedures produce the mean disutility cost for market distances of 1000, 2000, and 4000 miles. The calculated mean unfavorite airline disutility cost and business passenger basefares for those markets are shown in Table 4-15.

Market Distance(mi)	500	1000	2000	4000
Basefare_Business	$218.75	$312.50	$500.00	$875.00
Mean UFA Disutility	$26.12	$40.92	$71.87	$138.01

Table 4-15 Mean unfavorite airline disutility cost for business passengers

Linear Regression – Intercept and Slope

Table 4-15 shows the mean unfavorite airline disutility cost for four basefare levels. Linear regression over these four sets of data give the intercept and slope of the unfavorite airline disutility function for business passengers. Results and the significance tests of the regression are shown in Table 4-16.

Regression Statistics	
Multiple R	0.999776171
R Square	0.999552391
Adjusted R Square	0.999328587
Standard Error	1.286714238
Observations	4

	Coefficients	*Standard Error*	*t Stat*
Intercept	-12.29149892	1.379122548	-8.912550184
X Variable 1	0.17106473	0.002559717	66.82955534

Table 4-16 Resulting intercept and slope of mean unfavorite airline disutility, for business passengers, with statistical test results

The calculation gives an intercept of –12.29 and a slope of 0.17 with an R square value over 99% for the business passenger for unfavorite airline disutility function. The t-statistics for both the intercept and slope are large enough to assume the statistical significance of the derived coefficients.

4.3.2.2. Unfavorite Airline Disutility, Leisure Passengers

Calculations for the leisure passengers go through similar procedure, except restriction 1 and 2 disutility costs are added for both options (airline 1, fare class 3) and (airline 2, fare class 4). For the latter path choice, conditional disutility cost for restriction 3, given that the passenger's first choice is fare class 4, is added to the cost. A "total cost calculation table" can be constructed similar to Table 4-13.

	Airline 1, Fare class 3	Airline 2, Fare class 4
Unfavorite Airline?	No	Yes
Path Quality Index	1 (non-stop)	1 (non-stop)
Replanning?	No	No
Nominal Fare	$131.25	$87.5
Restriction Disutility	$R1+$R2	$R1+$R2+$x
UFA Disutility	$0	$y
PQI Disutility	$z	$z
Rpln Disutility	$0	$0
Total Cost	131.25+R1+R2+z	87.5+R1+R2+x+y+z

Table 4-17 Total cost calculation table for leisure passengers on the unfavorite airline

R1 and R2 are restriction disutility costs for restrictions 1 and 2, x is the conditional disutility for restriction 1, y is the unfavorite airline disutility for leisure passengers, and z is the path quality index disutility cost. The master equation representing the survey question is (from Table 4-17 and Table 4-6):

$$\Pr(131.25 + R1 + R2 + z > 87.5 + R1 + R2 + x + y + z) = \Pr(x + y < 43.75) = 0.115 \quad (4.26)$$

In other words, the probability that the sum of the unfavorite airline disutility and the conditional disutility cost of restriction 3, given that the passenger's first choice is fare class 4 of his/her favorite airline, is greater than the fare difference of class 3 and class 4.

Through the same derivation as in the business passenger case, the mean disutility cost for four distances used in the survey are shown in Table 4-18.

Market Distance(mi)	500	1000	2000	4000
Basefare_Leisure	$87.50	$125.00	$200.00	$350.00
Mean UFA Disutility	$7.68	$10.87	$19.09	$35.19

Table 4-18 Mean unfavorite airline disutility cost for leisure passengers

Linear regression gives the intercept and slope of the unfavorite airline disutility function for leisure passengers, as in Table 4-18. Statistical test results are also displayed in Table 4-19.

Regression Statistics			
Multiple R	0.999633286		
R Square	0.999266706		
Adjusted R Square	0.998900059		
Standard Error	0.40796829		
Observations	4		
	Coefficients	*Standard Error*	*t Stat*
Intercept	-1.983608324	0.437267461	-4.53637305
X Variable 1	0.105923624	0.002028973	52.2055426

Table 4-19 Resulting intercept and slope with statistical test results of the mean unfavorite airline disutility, for leisure passengers

As in the business passenger case, the significant R square value is over 99%, and t-statistics are large enough for both the intercept and slope coefficients. The intercept of the leisure unfavorite airline disutility function is –1.98 with a slope of 0.11.

4.3.2.3. Path Quality Index Disutility, For Business Passenger

Deriving the intercept and slope coefficients for the path quality index disutility function follows the same steps as in the unfavorite airline disutility described in Section 4.3.2.1. The only difference is that the path quality index disutility function applies for unit PQI. For example, the survey is asking the disutility of a connecting path, which has PQI of 3 (equation 4-8). In this case, the total PQI disutility would be the sum of three unit PQI disutility distributions. With two path choices of (non-stop, fare class 1) and (connecting, fare class 2), the "total cost calculation table" in this case for a market distance of 500 miles is constructed as shown in Table 4-20.

	Non-stop, Fare class 3	Connecting, Fare class 4
Unfavorite Airline?	No	No
Path Quality Index	1 (non-stop)	3 (connecting)
Replanning?	No	No
Nominal Fare	$350	$175
Restriction Disutility	$0	$x
UFA Disutility	$0	$0
PQI Disutility	$z	$3z
Rpln Disutility	$0	$0
Total Cost	350+z	175+x+3z

Table 4-20 Total cost calculation table for two path options

With the total cost for each path option calculated as in Table 4-20, the survey question is interpreted in mathematical form as follows:

$$\Pr(350 + z > 175 + x + 3z) = \Pr(x + 2z < 175) = 0.723 \qquad (4.27)$$

Equations (4.18)-(4.20), which are for the conditional disutility for restriction 1, can be applied for our variable x in Equation (4.27).

$$f(x) = \frac{1}{0.356} * \frac{1}{2\pi * 59.06} * \exp\left(\frac{-(x - 196.88)^2}{2 * 59.06^2}\right) \qquad (4.18)$$

$$E(x) = \int_{-\infty}^{175} x * f(x)dx = \$134.84 \qquad (4.19)$$

$$\sigma(x) = \sqrt{E(x^2) - \{E(x)\}^2} = \$32.09 \qquad (4.20)$$

Let the mean unit PQI disutility cost be $\mu_{PQI,B,500mi}$, and let the standard deviation be $\sigma_{PQI,B,500mi}$. Then, the probability density function for unit PQI is expressed as equation (4.28).

$$f(z) = N(\mu_{PQI,B,500mi}, \sigma_{PQI,B,500mi}{}^2), \text{ where } \sigma_{PQI,B,500mi} = k\mu_{PQI,B,500mi}, k = 0.3 \qquad (4.28)$$

Again, as in Section 4.3.2.1, let $x+2z=w$ and assume x to have a Gaussian distribution. Then, the variable w will also have a normal distribution with mean and standard deviation of:

$$E(w) = E(x) + 2E(z) = 134.84 + 2\mu_{PQI,B,500mi} \qquad (4.29)$$

$$\sigma(w) = \sqrt{\{\sigma(x)\}^2 + 2\{\sigma(z)\}^2} = \sqrt{32.09^2 + 2(0.3\mu_{UFA,B,500mi})^2} \qquad (4.30)$$

The next step is to solve the equation (4.31) for $\mu_{PQI,B,500mi}$.

$$P(w > 175) = P\left(Z > \frac{175 - E(w)}{\sigma(w)}\right) = 0.723 \qquad (4.31)$$

This equation gives the result $\mu_{PQI,B,500mi}$ **=$30.31**

Similar calculations give the mean disutility cost for market distances of 1000, 2000, and 4000 miles. The calculated mean unit PQI disutility cost and business passenger basefares for those markets are shown in Table 4-21.

Market Distance(mi)	500	1000	2000	4000
Basefare_Business	$218.75	$312.50	$500.00	$875.00
Mean UFA Disutility	$30.31	$34.78	$43.70	$63.05

Table 4-21 Mean PQI disutility cost, for business passengers

Table 4-22 summarizes the results of linear regression over four data points. Consistent with the previous results, the regression produces a high R square value over 99% and significant t-statistics. The obtained intercept and slope for business PQI disutility function are 19.15 and 0.05.

Regression Statistics			
Multiple R	0.999783877		
R Square	0.999567802		
Adjusted R Square	0.999351702		
Standard Error	0.369253679		
Observations	4		
	Coefficients	*Standard Error*	*t Stat*
Intercept	19.15121462	0.395772472	48.38945595
X Variable 1	0.049959046	0.000734572	68.01105472

Table 4-22 Resulting intercept and slope of mean PQI disutility with statistical test results for business passengers

4.3.2.4. Path Quality Index Disutility, For Leisure Passengers

With calculations similar to those in Section 4.3.2.2, Table 4-23 give the mean leisure PQI disutility costs. The following Table 4-24 shows statistics and the values of intercept and slope, assuring statistical significance.

Market Distance(mi)	500	1000	2000	4000
Basefare_Leisure	$87.50	$125.00	$200.00	$350.00
Mean PQI Disutility	$6.16	$8.37	$12.69	$37.34

Table 4-23 Mean PQI disutility cost for leisure passengers

Regression Statistics			
Multiple R	0.999986283		
R Square	0.999972567		
Adjusted R Square	0.99995885		
Standard Error	0.043698924		
Observations	4		
	Coefficients	*Standard Error*	*t Stat*
Intercept	1.011066002	0.046837262	21.58678703
X Variable 1	0.058680237	0.00021733	270.0046874

Table 4-24 Resulting intercept and slope of mean PQI disutility with statistical test results for leisure passengers

4.3.2.5. Replanning Disutility, For Business Passengers

The same calculations as in the unfavorite airline example give mean leisure PQI disutility costs, as in Table 4-25. The following table, 4-26, displays statistics and values of the intercept and slope, assuring statistical significance.

Market Distance(mi)	500	1000	2000	4000
Basefare_Business	$218.75	$312.50	$500.00	$875.00
Mean Rpln Disutility	$56.07	$69.96	$102.14	$152.29

Table 4-25 Mean replanning disutility cost for business passengers

Regression Statistics			
Multiple R	0.999705669		
R Square	0.999411424		
Adjusted R Square	0.999117137		
Standard Error	1.362987046		
Observations	4		
	Coefficients	*Standard Error*	*t Stat*
Intercept	21.56292485	1.460873061	14.76030015
X Variable 1	0.158011092	0.00271145	58.27550538

Table 4-26 Resulting intercept and slope of replanning airline disutility with statistical test results for business passengers

4.3.2.6. Replanning Disutility, For Leisure Passengers

Mean leisure PQI disutility costs are calculated in Table 4-27. Table 4-28 shows statistics and values of the intercept and slope, assuring statistical significance.

Market Distance(mi)	500	1000	2000	4000
Basefare_Leisure	$87.50	$125.00	$200.00	$350.00
Mean Rpln Disutility	$6.16	$8.37	$12.69	$37.34

Table 4-27 Mean replanning disutility cost for leisure passengers

Regression Statistics			
Multiple R	0.999975051		
R Square	0.999950103		
Adjusted R Square	0.999925154		
Standard Error	0.101687371		
Observations	4		
	Coefficients	*Standard Error*	*t Stat*
Intercept	1.900849536	0.108990281	17.44054171
X Variable 1	0.101247346	0.000505728	200.2012665

Table 4-28 Resulting intercept and slope of mean replanning disutility for leisure passengers

4.3.3. Summary

Table 4-29 summarizes the resulting intercepts and slopes of the disutilities for each passenger type. Figure 4-2 and 4-3 plots the mean disutilities and shows the regression line as a function of distance for each disutility.

Pax Type	Unfavorite Airline		Path Quality		Replanning	
	Intercept	Slope	Intercept	Slope	Intercept	Slope
Business	-12.29	0.17	19.15	0.05	21.56	0.16
Leisure	-1.98	0.11	1.01	0.06	1.9	0.1

Table 4-29 Summary of coefficients for all disutility functions

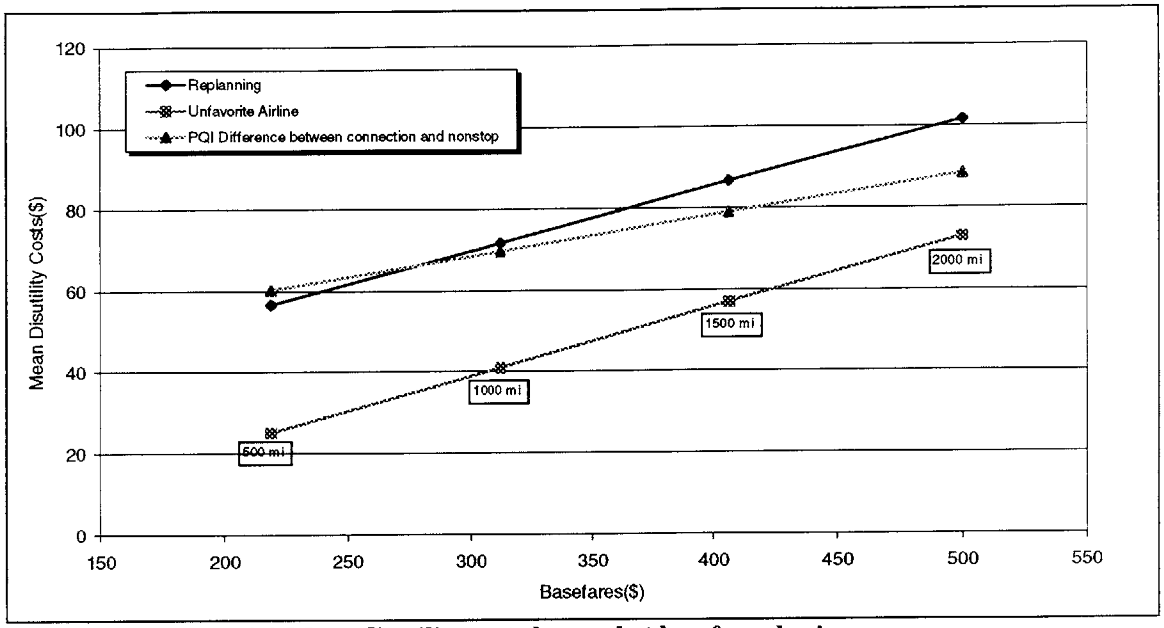

Figure 4-3 Mean disutility costs by market basefares business passengers

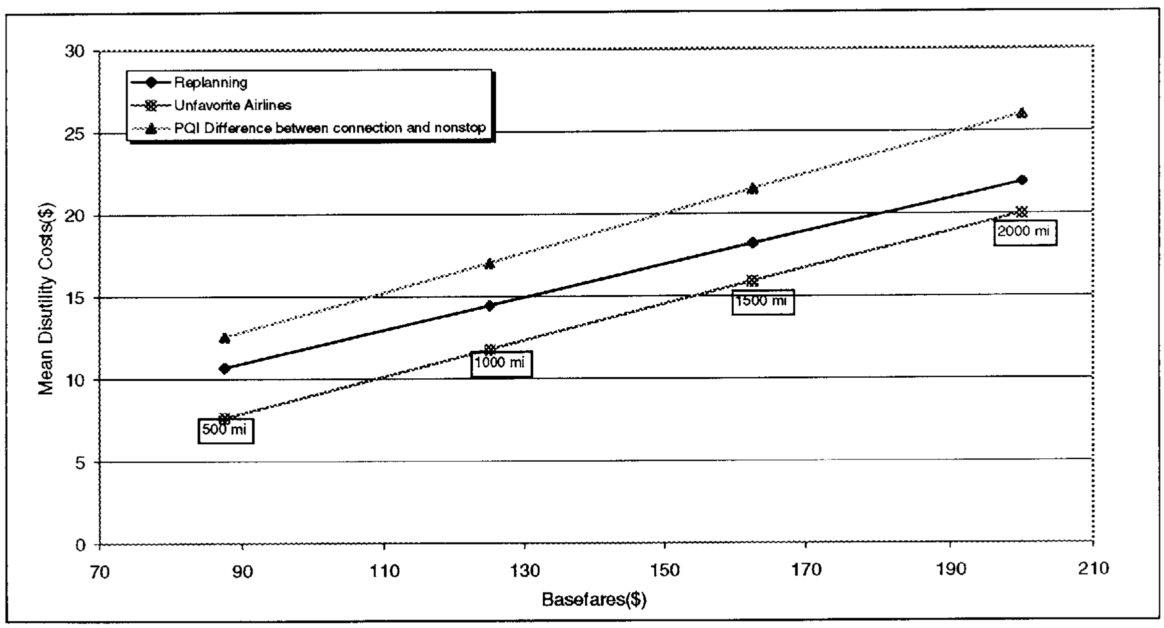

Figure 4-4 Mean disutility costs by market basefare leisure passengers

Figures 4-3 and 4-4 depict the average disutility cost for three disutility categories over market basefares. The PQI disutility costs were plotted for 2*PQI disutility cost instead of unit disutility cost, since the perceived difference of disutility costs between nonstop and a connecting path is 2*PQI. With these three disutilities plotted on the same scale, we are able to weigh the relative importance of each disutility in passenger choice.

From Figure 4-3 for business passengers, we observe that the replanning disutility is the highest among the three disutility categories for most of the markets. Replanning the whole trip would be more painful than taking an unfavorite airline or one-stop path. For short haul markets with under 1000 miles range, path quality disutility cost for connecting markets are even higher than the replanning disutility cost, implying that the path quality is most important criteria among these three disutility categories for those markets. For leisure passengers the replanning disutility cost is consistently the highest cost disutility among the three categories followed by the path quality disutility, as shown in Figure 4-4. Generally, all three disutilities show an increasing trend as market distance increases.

4.4. Summary

In this chapter we introduced disutility functions and inspected how disutility functions apply within PODS 8 Passenger Assignment Model. Basically, disutility functions implemented in PODS require intercept and slope since they are expressed as a linear function of market basefare. These parameters were estimated from the survey conducted of airline experts. The coefficients of the disutility functions extracted and estimated from the survey will serve as input parameters indicating the impact of each disutility component on passengers' path choice. The following chapters present the results of PODS simulations with disutility function coefficients applied.

Chapter 5 Simulation Results

In Chapter 4 we estimated the coefficients for the three disutility functions – unfavorite airline, path quality index, and replanning. These coefficients determine the effects of each disutility component on passenger's path choice, and therefore have an influence on the performance of various revenue management methods. In this chapter we examine the results of the PODS simulation with all four disutility functions implemented.

Section 5.1 is an explanation of the base case settings and some of the important input parameters for the PODS simulation. Section 5.2 presents the simulation results with all disutility functions, with estimated coefficients as simulation input, followed by interpretation in Section 5.3 and a chapter summary in Section 5.4.

5.1. Base Case Settings

Before presenting any of the simulation results, it is necessary to understand the base case that serves as a basis for comparison of simulations performed for this thesis. Since the purpose of the simulations presented in this thesis is to observe the impacts of disutility components, we set up our base case such that three disutility costs of our interest have either zero or constant values. Additionally, our base case will be reflecting the most common revenue management conditions (including forecasting and detruncation) that the majority of the airlines in the world operate under. All simulations addressed in this thesis were performed on Network D, which is described in Section 3.4.

5.1.1. Disutility Functions

The four disutility components that we can manipulate in PODS simulations are restriction disutilities, unfavorite airline disutilities, path quality index disutilities, and replanning disutilities. All disutility functions are set as a linear function of the market basefares. Recall from Section 4.1.3 that market basefares are an index fare that indicates fare levels of markets. Among the four disutility functions, we adapt restriction disutility function coefficients from Wilson [14]. Table 4-2 shows the coefficients for three restrictions used in PODS. Definitions of the three restrictions and their relation to fare classes were illustrated in Table 4-1 and Section 4.1.3.1. The base case disutility functions for three disutility components of our interest and related parameters are set as follows:

Unfavorite Airline Disutility Function: Unfavorite airline disutility function coefficients are all set to zero for the base case, hence it is assumed that passenger's airline preference does not influence path choice.

Airline Preference Coefficients: We assume that both airlines are equally preferred. That is, half of the passengers in the network prefer Airline A to Airline B, and visa versa. In our simulation inputs the airline preference coefficients for both airlines are set to be 0.5, each.

Replanning Disutility Function: Similarly, replanning disutility function coefficients have zero values in order to initially assume that passengers choose paths outside his/her decision window without any kind of penalty for those paths.

Path Quality Index Disutility Function: For minimum discrepancy between nonstop and connecting paths, we used an initial intercept value of $25 for unit Path Quality Index. However with base case slope for PQI disutility function set to zero, all unit PQI disutility costs are assumed to have constant value of $25 for all markets. With PQI=3 for connecting paths and PQI=1 for nonstop paths, the constant difference in PQI disutility costs between a connection and nonstop will be $50.

5.1.2. Revenue Management

We will be testing the impact of passenger disutilities, when airlines are using one of the six revenue management methods (EMSRb, GVN, Netbid, DAVN, HBP and ProBP) introduced in Section 3.1 and 3.2. The leg-based EMSRb model serves as a base case revenue management method for all simulations presented in this thesis. Especially, the revenue gains achieved with O-D revenue management are measured as a percentage gain over the case when both airlines use EMSRb control.

5.1.3. Forecasting and Detruncation

Forecasting in the airline management world is predicting the demand for future flights given booking histories of previous flights. However, since "closed flights" exist which had demand exceeding the capacity of the flight, the number of bookings from a closed flight is different from actual demand for the flight. Therefore the number of bookings from the past flights is biased to lower values than actual demands, and airlines need to remove the bias (or unconstrain) of historical data. This process is called detruncation. Hence forecasting actually consists of two phases, detruncation of historical data and application of forecasting models. Some sophisticated models exist for forecasting and detruncation[22], but since forecasting and detruncation is not a major focus of this thesis, we limit the forecasting and detruncation methods to basic models used in PODS.

Detruncation – Booking Curve Detruncation

Booking Curve detruncation uses booking curves from unclosed flights as a reference for future demands. This method simply uses the estimates from the unclosed flights to

[22] For deeper inspections on forecasting and detruncation methods, refer to Gorin [9].

predict how many more people will book from a certain time point on. For example, if the estimated bookings 14 days prior to departure from unclosed flights are 40% of the total bookings (hence total demand in the cased of unclosed flights), and we have 40 passengers booked 14 days prior to departure for a future flight, the estimated unconstrained historical demand for this flight will be 100 bookings.

Forecasting – Pick-up Forecasting

Pick-up forecasting in method is similar to Booking Curve detruncation, but more time-specific. That is, pick-up forecasting estimates the number of passengers "picked up" (additionally booked) from a time period to the next. Hence to get a forecast of incremental bookings from a current time period, pick-up forecasting uses the average of number of incremental bookings for that specific time period from previous open flights. Depending on the revenue management method, pick-up forecasting is done on a leg or ODF basis, and also revised at every time frame.

5.1.4. Demand Factors

Demand factor in PODS is the ratio of average demand over average aircraft capacity. For example, at demand factor of 0.9, the average demand for a flight where a 100 seat capacity aircraft flies will be 90 passengers. The simulations performed for this thesis are done on a four demand factor level: demand factor (DF) 0.8, 0.9, 1.0 and 1.1. Approximately, with both airlines using EMSRb control, with base case disutility parameters, the average system-wide load factors at those demand factorare 70%, 78%, 84% and 88% at DF 0.8, 0.9, 1.0, and 1.1, respectively. The average system-wide load factors broken down by banks are shown in Table 5-1.

DF	0.8	0.9	1.0	1.1
ALF	70%	78%	84%	88%
Bank 1	64%	74%	82%	88%
Bank 2	78%	83%	86%	89%
Bank 3	69%	76%	83%	87%

Table 5-1 Base case average system-wide load factors at four demand factors, both airlines using EMSRb control

5.2. Simulation Results with Disutilities

5.2.1. Settings

Input settings for simulations with disutilities are exactly the same as the base case, except that we use disutility functions extracted from the survey (Section 4.3, Table 4-29) to characterize unfavorite airline, path quality index, and replanning disutilities of passengers. Again airline A uses all six revenue management methods described in Section 3.1 and 3.2, whereas airline B keeps using EMSRb control in all cases.

5.2.2. Results

Revenue Gains

With the estimated disutility functions in the simulation, DAVN followed by ProBP shows the largest revenue gains over EMSRb vs. EMSRb case for all demand factors. The relative rankings of O-D methods agree with the base case disutility parameters. O-D methods that performed worse than EMSRb at base case show positive revenue gains in disutility simulation, benefiting from stronger passenger path preferences.

Revenue gains for airline A using O-D methods, increase over the base case with all disutility functions implemented. At all demand factors, DAVN and ProBP show the largest increase in revenue gains, implying these methods with path forecasting are more effective under stronger passenger path preferences. Netbid, which suffered with negative revenue gains, shows slightly positive revenue gains when disutility parameters are included. Figures 5-1 to 5-4 illustrate the competitive revenue gain increases when disutility parameters are introduced, for demand factors 0.8, 0.9, 1.0, and 1.1.

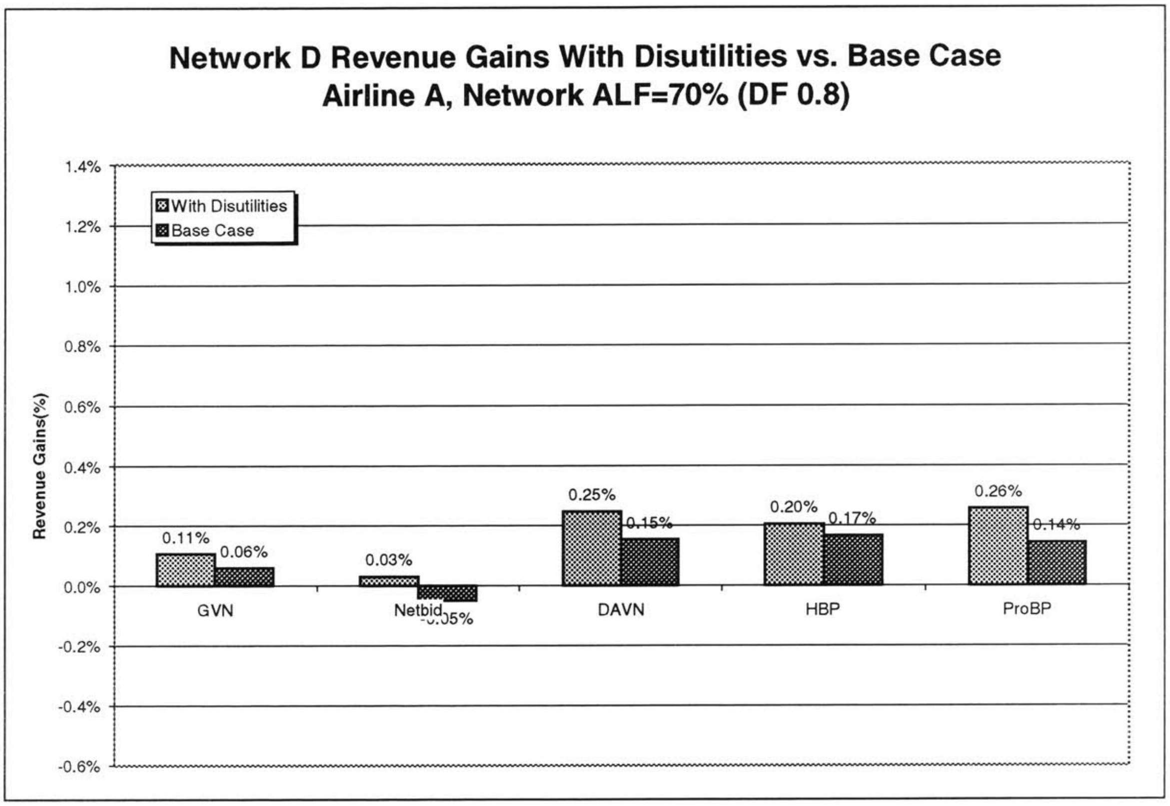

Figure 5-1 Revenue gains over EMSRb vs. EMSRb, with disutility functions vs. base case, DF 0.8

At DF 0.8, all revenue management methods show increased revenue gains when disutility functions are applied in the simulation. Netbid, which showed negative revenue gains in the base case, shows positive revenue gains with input disutilities. DAVN and ProBP perform the best among the O-D methods.

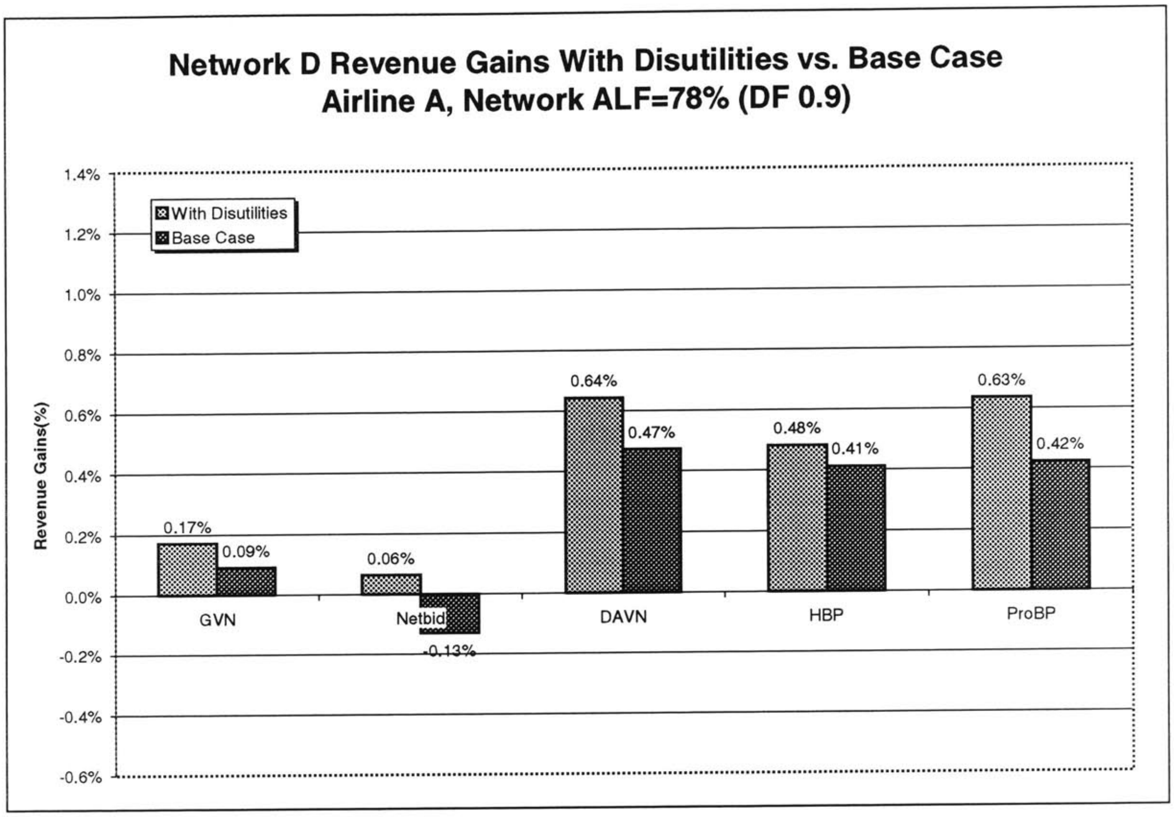

Figure 5-2 Revenue gains over EMSRb vs. EMSRb, with disutility functions vs. base case, DF 0.9

At DF 0.9, the relative rankings of O-D methods do not change from the base case. Again DAVN and ProBP show the best performance, ProBP catching up with DAVN revenue gains when disutilities are applied. ProBP, DAVN, and Netbid show the highest increases in percentage revenue gains from the base case.

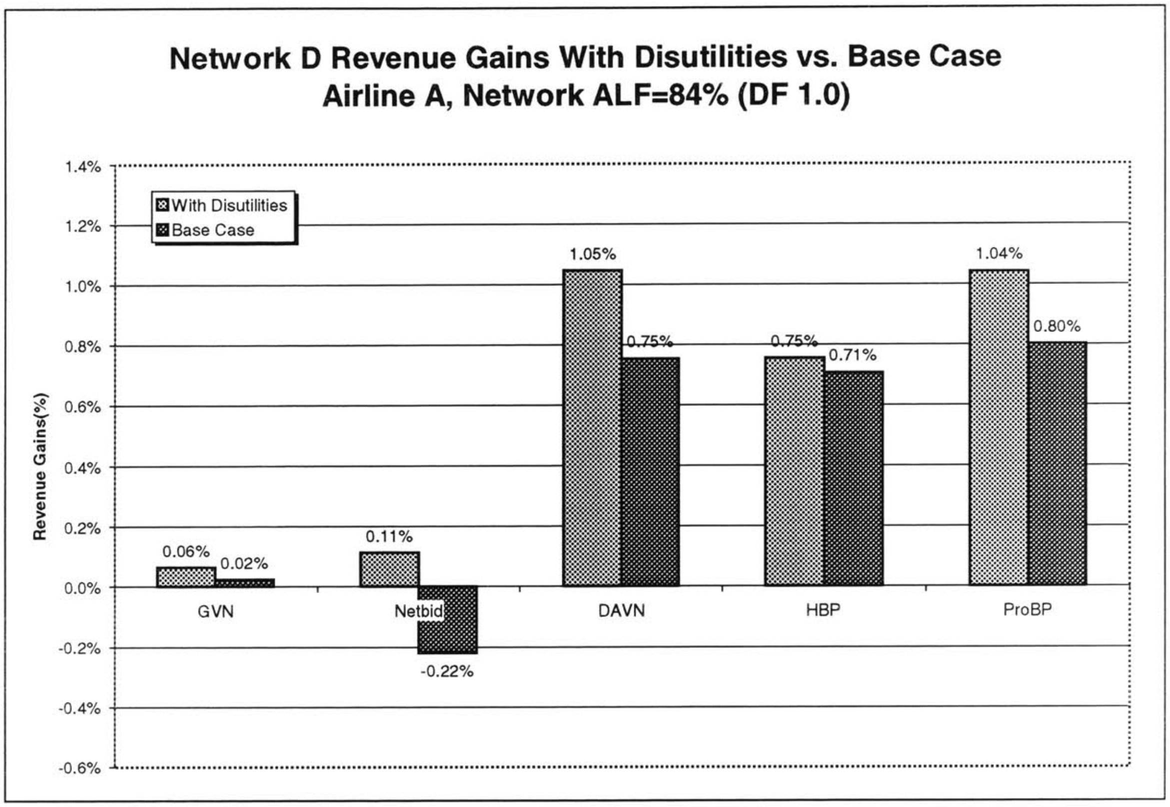

Figure 5-3 Revenue gains over EMSRb vs. EMSRb, with disutility functions vs. base case, DF 1.0

At DF 1.0, the discrepancies between the O-D methods start to grow larger. Significantly, DAVN, ProBP, and Netbid show gains with passenger disutilities included, whereas GVN and HBP do not show as much increase in revenue gains over the base case. Still HBP performs better than Netbid, as in the base case.

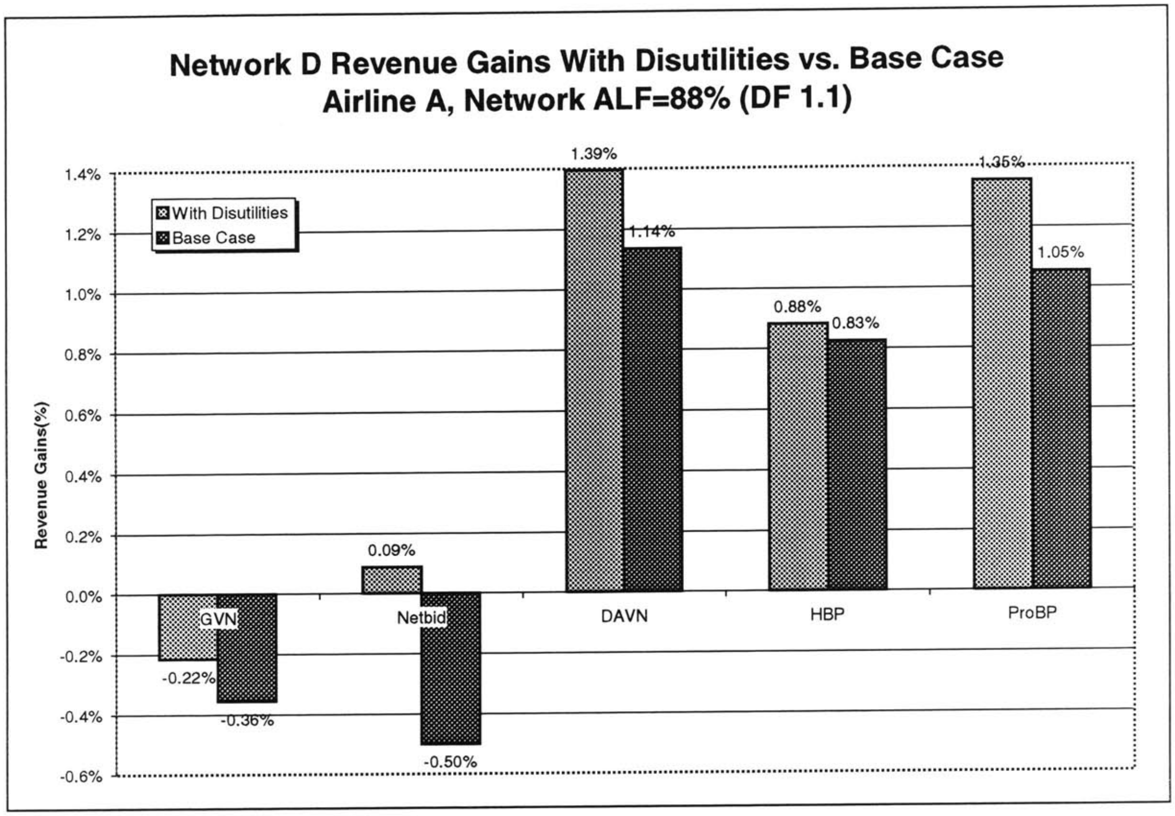

Figure 5-4 Revenue gains over EMSRb vs. EMSRb, with disutility functions vs. base case, DF 1.1

DAVN consistently shows the highest revenue gains both in the base case and with disutilities. As in other demand factors, DAVN, ProBP, and Netbid benefit the most from passenger disutilities at DF 1.1.

Loads

Average network load factors, which are the total Revenue Passenger Miles (RPM) divided by total Available Seat Miles (ASM), generally increase up to 1% when the disutility costs are accounted for. Especially at lower demand levels where there is more opportunity for improvement of inventory control, these increase rates are higher. Airline A with EMSRb control achieves 0.9% higher load factors at DF 0.8, than the base case without any disutilities considered. At DF 0.9, 1.0, and 1.1, this increase reduces to 0.75%, 0.39%, and 0.15%. Generally more sophisticated O-D control methods such as

DAVN, HBP, and ProBP which already carried more passengers at base case benefit less than EMSRb. At DF 1.1 where load mix becomes more important in terms of revenue gains rather than absolute load factors, some of these methods end up carrying less passengers than the base case, implying more strict O-D control for better fare mix. GVN and Netbid generally show the highest increase in load factors with disutility parameters included. Table 5-2 illustrates the simulation results in terms of average network load factors for all demand factors.

	YM methods		With Disutility		Base Case		Difference	
DF	Airline A	Airline B	ALF A	ALF B	ALF A	ALF B	ALF A	ALF B
0.8	EMSRb	EMSRb	70.97	69.6	70.07	69.73	0.9	-0.13
	GVN	EMSRb	71.27	69.49	70.33	69.68	0.94	-0.19
	Netbid	EMSRb	71.39	69.38	70.4	69.64	0.99	-0.26
	DAVN	EMSRb	71.25	69.46	70.37	69.63	0.88	-0.17
	HBP	EMSRb	71.08	69.59	70.23	69.74	0.85	-0.15
	ProBP	EMSRb	71.18	69.53	70.28	69.67	0.9	-0.14
0.9	EMSRb	EMSRb	77.87	76.88	77.12	76.89	0.75	-0.01
	GVN	EMSRb	78.77	76.61	77.92	76.97	0.85	-0.36
	Netbid	EMSRb	79.28	76.32	78.35	76.7	0.93	-0.38
	DAVN	EMSRb	78.87	76.48	78.11	76.83	0.76	-0.35
	HBP	EMSRb	78.38	76.79	77.68	76.97	0.7	-0.18
	ProBP	EMSRb	78.63	76.66	77.93	76.71	0.7	-0.05
1.0	EMSRb	EMSRb	82.81	82.17	82.42	82.28	0.39	-0.11
	GVN	EMSRb	84.23	81.55	83.81	82.33	0.42	-0.78
	Netbid	EMSRb	85.46	81.3	85.07	81.82	0.39	-0.52
	DAVN	EMSRb	84.41	81.55	84.15	82.02	0.26	-0.47
	HBP	EMSRb	83.79	81.91	83.46	82.34	0.33	-0.43
	ProBP	EMSRb	84.14	81.8	83.92	81.9	0.22	-0.1
1.1	EMSRb	EMSRb	86.1	85.75	85.95	85.9	0.15	-0.15
	GVN	EMSRb	87.75	85	87.58	85.79	0.17	-0.79
	Netbid	EMSRb	89.81	84.71	89.73	85.22	0.08	-0.51
	DAVN	EMSRb	87.91	85.17	87.95	85.63	-0.04	-0.46
	HBP	EMSRb	87.36	85.43	87.17	85.93	0.19	-0.5
	ProBP	EMSRb	87.59	85.41	87.6	85.45	-0.01	-0.04

Table 5-2 Average network load factors at all demand factors, for simulations with disutilities and base case

Loads by Fare Class

As we saw in the average load factor results, the general trend with disutility costs considered is increase in load factors. Generally the incremental loads by fare class are in the same range for all revenue management methods, implying that additional passengers are results of stronger path preference (since disutility costs are considered) rather than discrepancies of revenue management methods. This is true especially at lower demands, where flights are more open and the role of seat inventory control are not as important as in higher demand factors.

At a relatively high demand of DF 1.0, we observe loss of passengers in Q class (Figure 5-8) whereas Y class continues to carry more passengers (Figure 5-5). In conclusion, with disutility costs, the path preference of passengers result in "better" seat inventory control to lead to higher load factors and better fare mix. Figures 5-5 to 5-8 show the average loads by fare class for all simulations at DF 1.0.

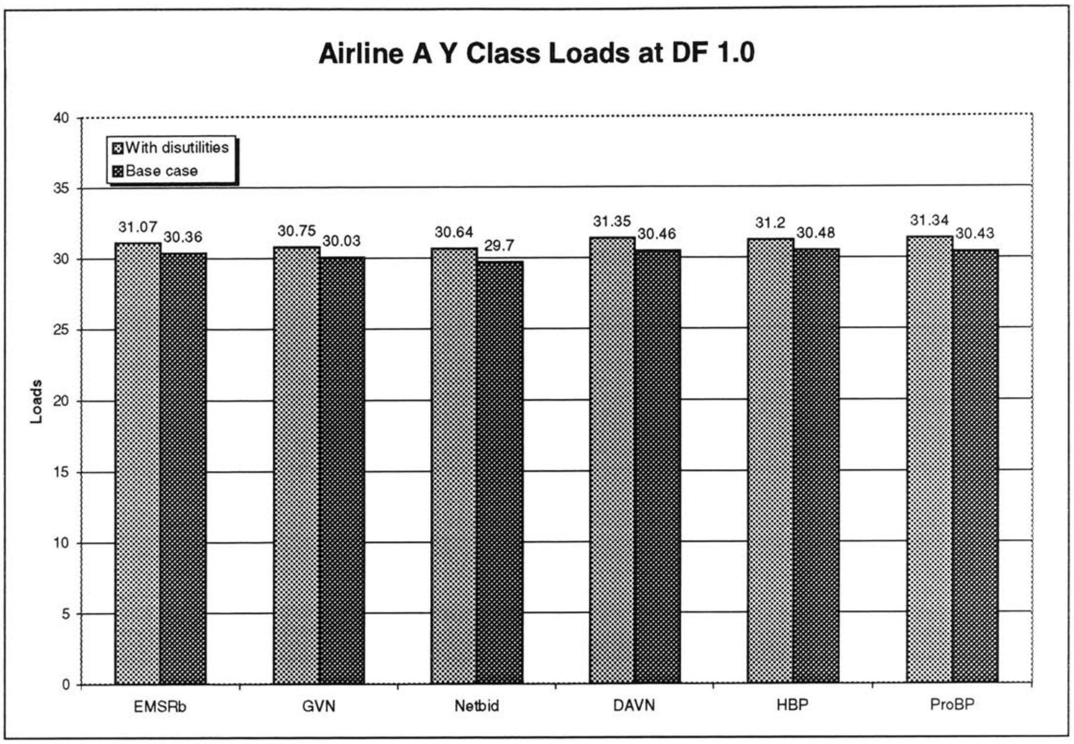

Figure 5-5 Average Y class loads for airline A, at DF 1.0, for simulations with disutilities and base case

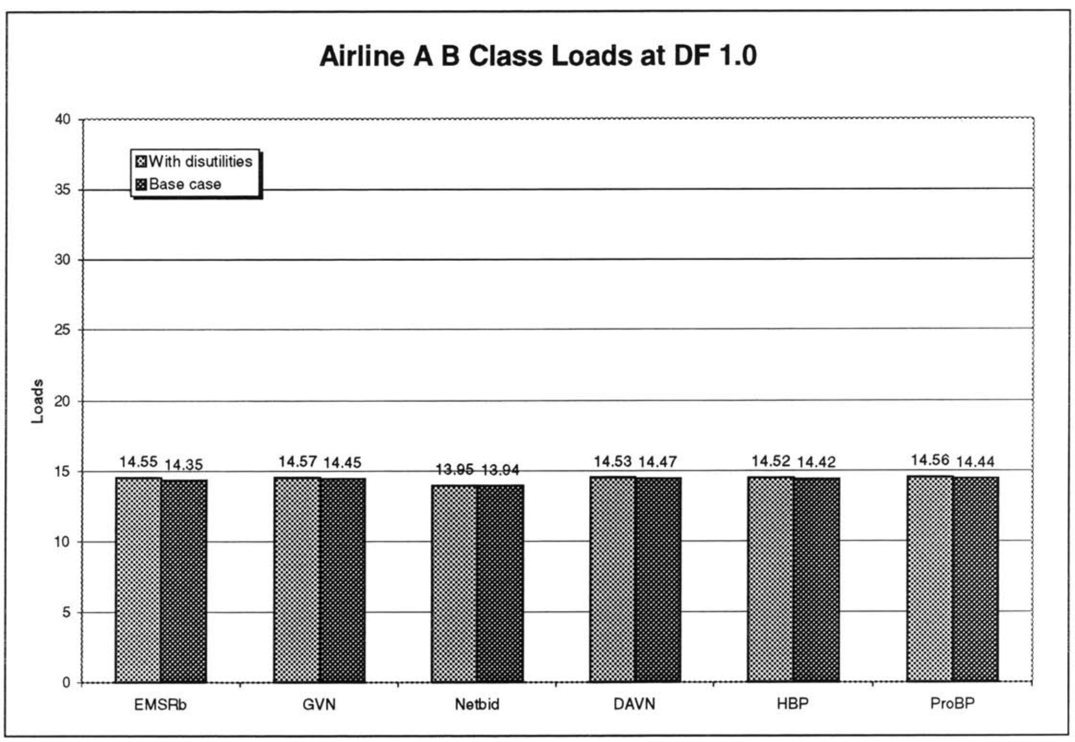

Figure 5-6 Average B class loads for airline A, at DF 1.0, for simulations with disutilities and base case

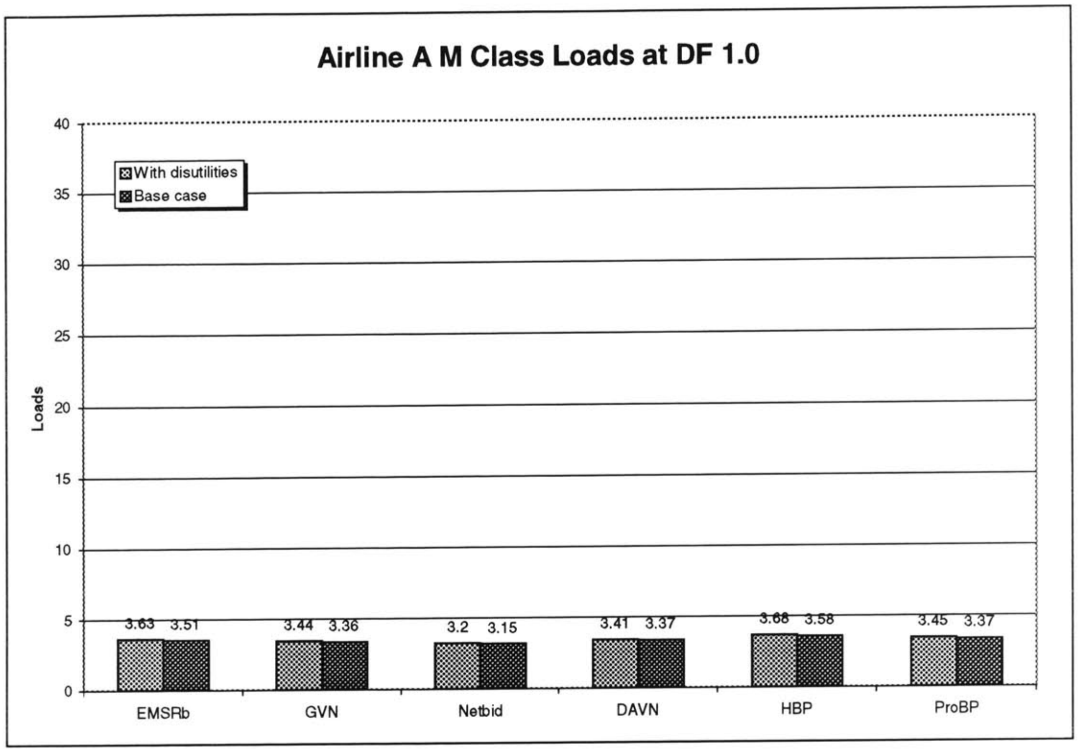

Figure 5-7 Average M class loads for airline A, at DF 1.0, for simulations with disuilities and base case

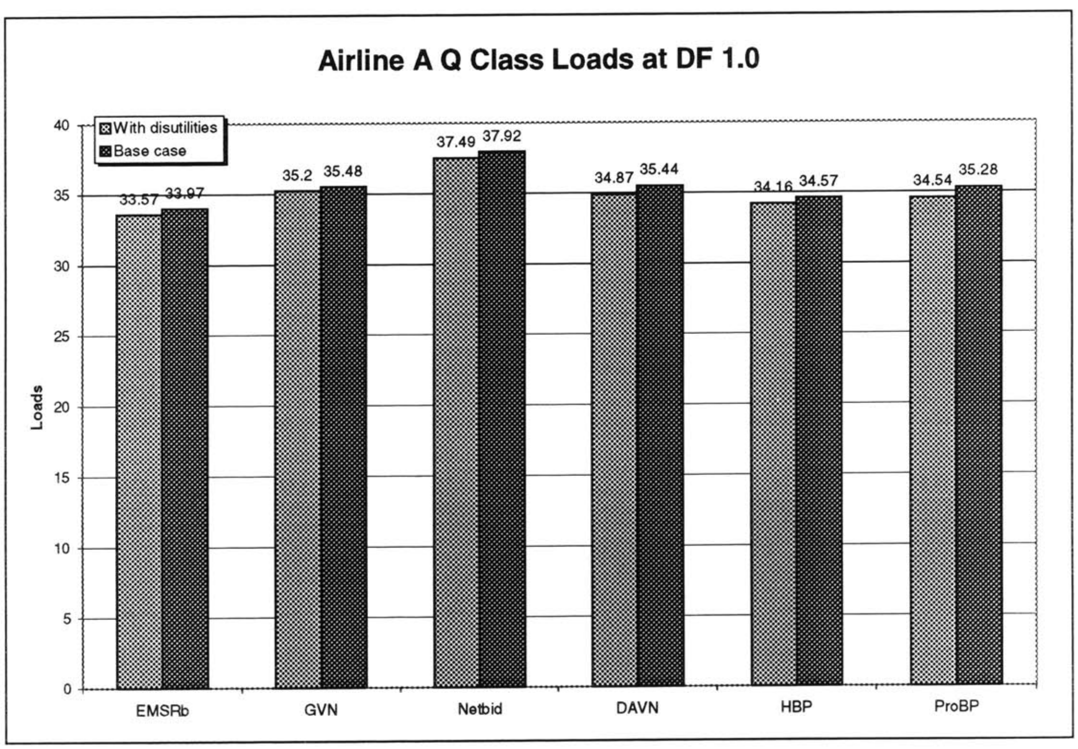

Figure 5-8 Average Q class loads for airline A, at DF 1.0, for simulations with disutilities and base case

5.3. Discussions

As we observed in Section 5.2.2, the performances of O-D revenue management methods as well as EMSRb improve when we account for passenger disutilities. When passenger disutilities are implemented in the simulation, the passenger preference for "popular" paths becomes stronger, resulting in higher demands for some paths and lower demands for others, compared to the base case. Hence the role of revenue management becomes more important than the base case, and this is proven by the higher revenue gains of O-D methods. The increases in absolute revenues as well as revenue gains are results of higher load factors. This is a combined effect of both higher demands with disutilities, and better fare mix.

5.4. Summary

In this chapter we inspected the simulation results with all disutility parameters defined as the estimated values obtained from the survey, as well as the base case for comparison of results. We saw that in general all revenue management methods are more effective when passengers have stronger preferences for better quality paths. In the next chapter we present simulation results for individual disutility components, to find out the impacts of each component separately.

Chapter 6 Sensitivity Analysis

In Chapter 5, we examined the results from simulations with all disutility components applied, and found out that the benefits of revenue management become greater in that case. In order to find out the sensitivity of each disutility component in those results, simulations were performed separately with each disutility component. In this chapter we examine and analyze the impact of each disutility component through sensitivity simulations.

6.1. Unfavorite Airline Disutility

6.1.1. Settings

The settings for unfavorite airline disutility simulations are the same as the base case described in Section 5.1, except that the disutility parameters for unfavorite airline disutility functions (both business and leisure) are specified by the survey results. Hence in this simulation we are assuming that along with restrictions, the preference for carrier is the only factor that has influence over passengers' path preference. Airline preference factors for both airlines (the probability that a passenger will prefer the given airline) are set to be 0.5.

6.1.2. Results

Revenue Gains

The simulations with estimated unfavorite airline disutility costs show interesting results. First of all, among the O-D methods tested, only Netbid and ProBP show higher revenue gains than the base case. Secondly, Netbid performs even better than under the case when all disutilities are accounted for, implying that the deterministic network bid price optimization method is most sensitive to airline preference factors. Something else that is noticeable is that DAVN performs better than the base case in most of the cases, except at DF 0.9. Overall, O-D methods under low demand levels do not perform as well as the base case (without disutilities included), or slightly better. However, as demand grows higher, DF 1.0 or 1.1, all O-D methods start to show higher revenue gains than the base case, and even better than the case with all disutilities at DF 1.1. Hence we can say that the performances of revenue management methods under unfavorite airline disutility costs are very sensitive to demand levels.

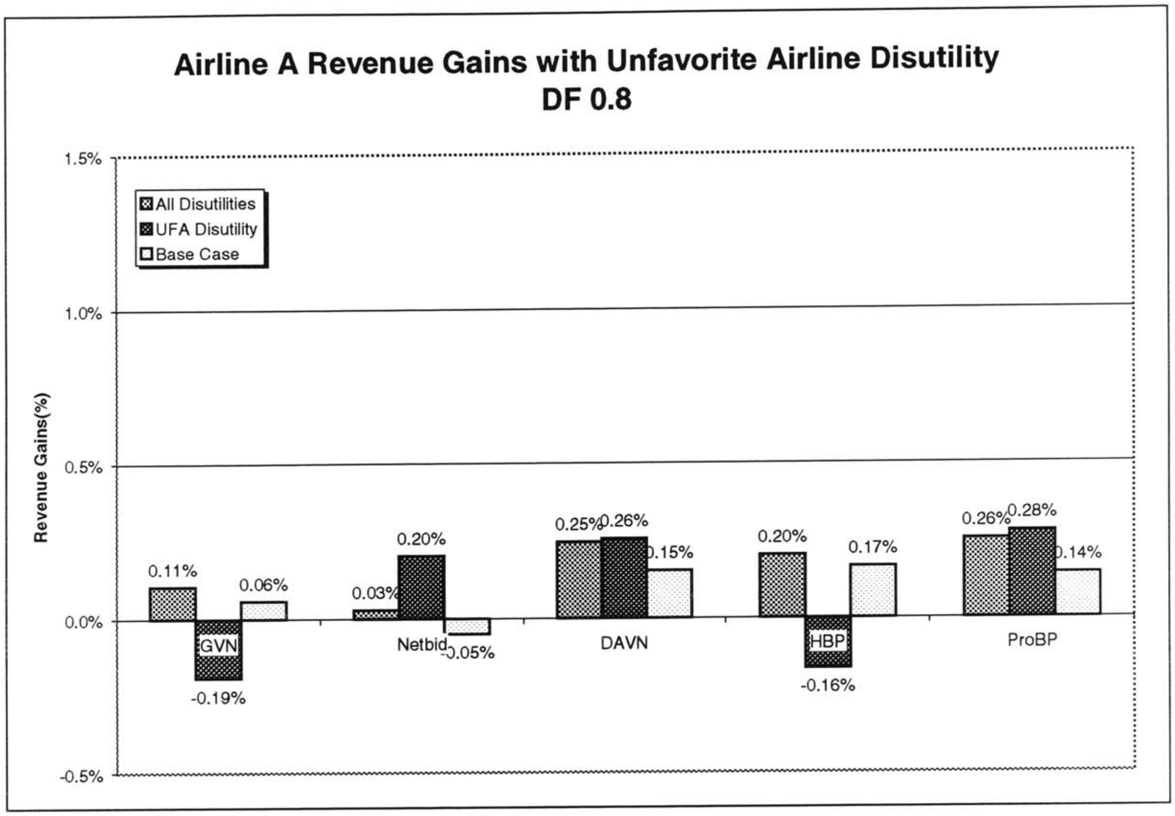

Figure 6-1 Revenue gains over EMSRb vs. EMSRb, with unfavorite airline disutility vs. base case, DF 0.8

At DF 0.8, Netbid, with its "open" bid-price mechanism, outperforms base case revenue gains as well as revenue gains with all disutilities. DAVN and ProBP show robust performance with unfavorite airline disutilities. GVN and HBP both show negative revenue gains under unfavorite airline disutilities.

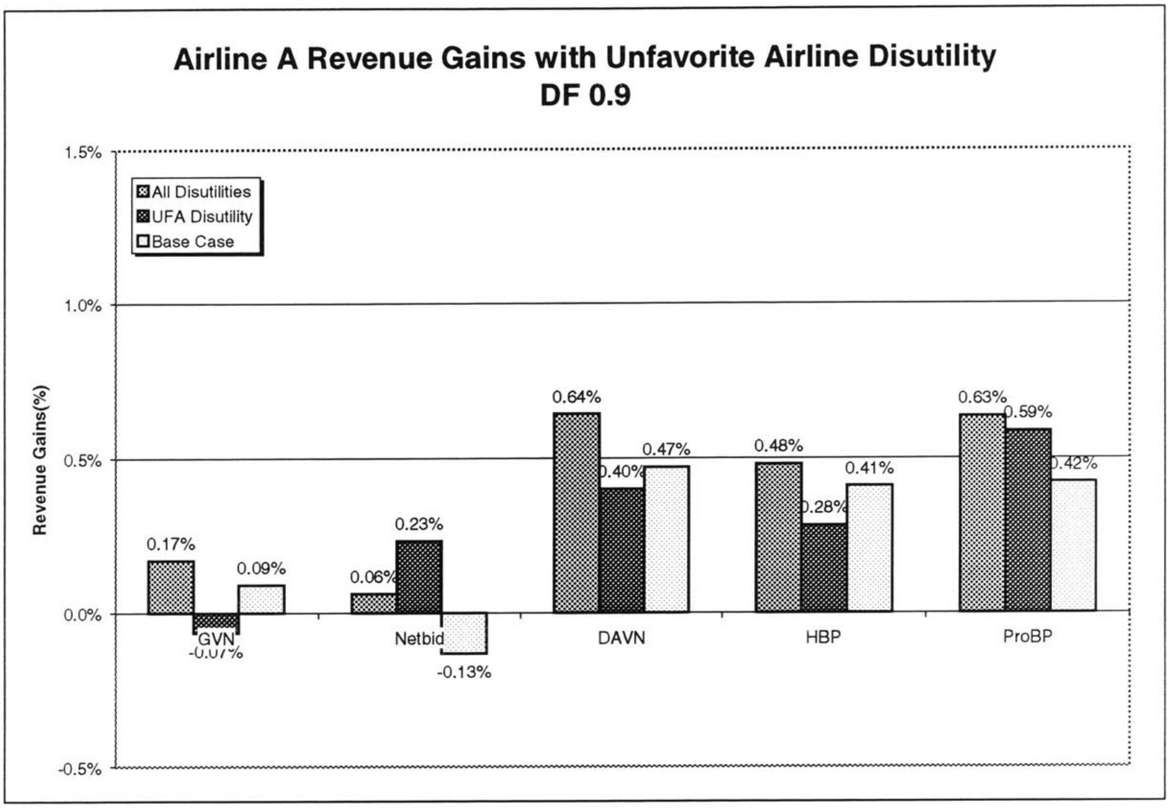

Figure 6-2 Revenue gains over EMSRb vs. EMSRb, with unfavorite airline disutility vs. base case, DF 0.9

Revenue gains of O-D methods at DF 0.9 show similar trends as in DF 0.8. The notable difference is that HBP now turns over to positive revenue gains due to increased demand, whereas GVN still records negative revenue gains with its “greediness”.

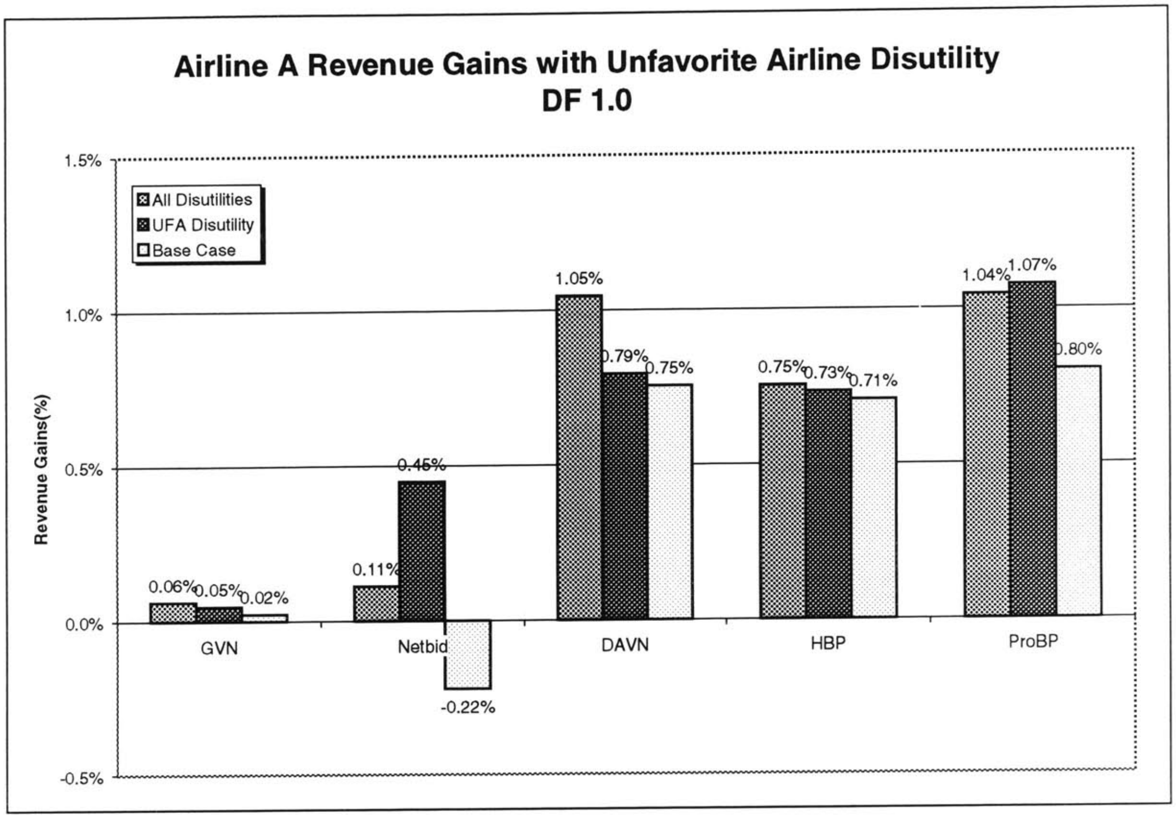

Figure 6-3 Revenue gains over EMSRb vs. EMSRb, with unfavorite airline disutility vs. base case, DF 1.0

At DF 1.0, ProBP starts to outperform other O-D revenue management methods. HBP, GVN and DAVN catch up with base case revenue gains, whereas Netbid shows higher revenue gains than the base case.

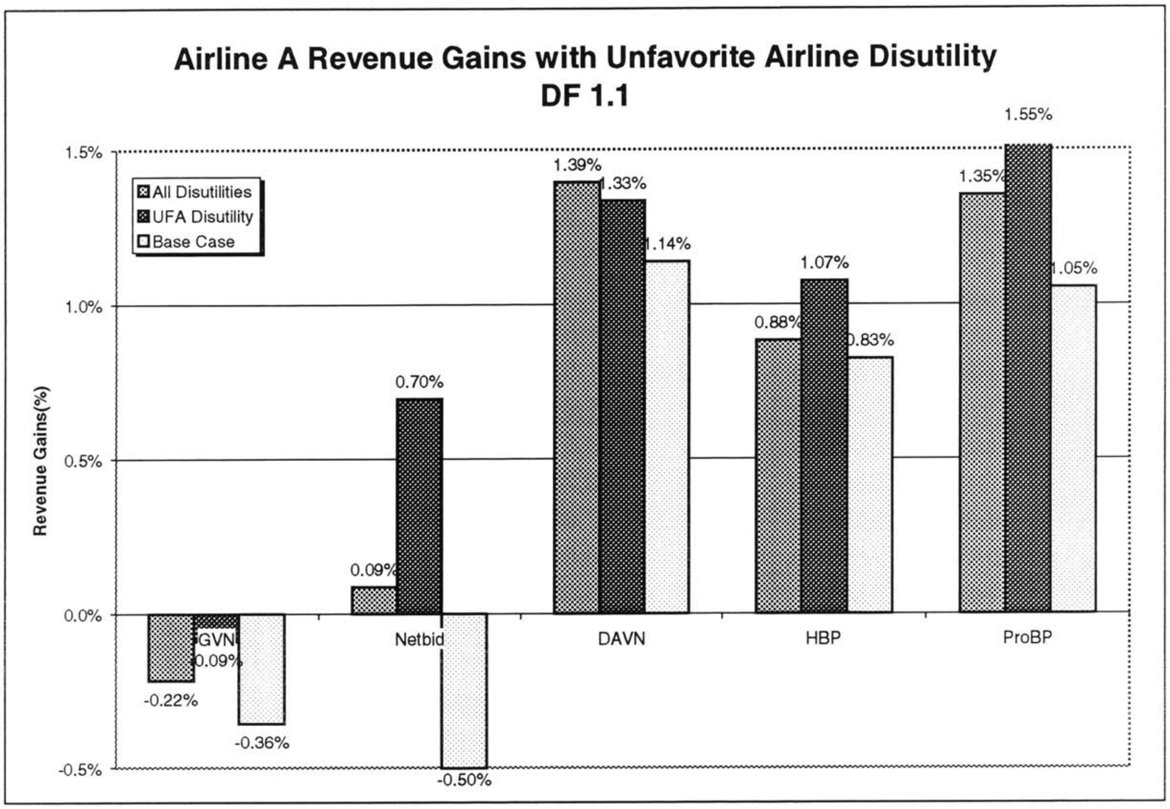

Figure 6-4 Revenue gains over EMSRb vs. EMSRb, with unfavorite airline disutility vs. base case, DF 1.1

At the highest demand level, DF 1.1, all bid-price methods do better than the base case, and even better than the all-disutilities simulations. DAVN also performs better than the base case, almost to the level where all disutilities are implemented. Overall, all O-D methods under unfavorite airlines are able to perform better at higher demand factors.

Loads

Average network load factors for airline A with unfavorite airline disutilities are higher than the base case, up to 1.7% at DF 0.8 for GVN. Airline B also records higher load factors than the base case, indicating that the there are network-wide increases in demand. EMSRb shows the highest increase in load factors with unfavorite airline disutilities from the base case, hence the relative increase in loads for O-D methods are negligible or negative compared to EMSRb. This explains some of the O-D method revenue gains, which are lower than the base case.

	YM methods		With UFA Disutility		Base Case		Difference	
DF	Airline A	Airline B	ALF A	ALF B	ALF A	ALF B	ALF A	ALF B
0.8	EMSRb	EMSRb	71.65	71.78	70.07	69.73	1.58	2.05
	GVN	EMSRb	72.01	71.4	70.33	69.68	1.68	1.72
	Netbid	EMSRb	71.93	71.44	70.4	69.64	1.53	1.8
	DAVN	EMSRb	71.81	71.56	70.37	69.63	1.44	1.93
	HBP	EMSRb	71.82	71.58	70.23	69.74	1.59	1.84
	ProBP	EMSRb	71.91	71.48	70.28	69.67	1.63	1.81
0.9	EMSRb	EMSRb	78.37	78.67	77.12	76.89	1.25	1.78
	GVN	EMSRb	78.97	78.24	77.92	76.97	1.05	1.27
	Netbid	EMSRb	79.51	77.86	78.35	76.7	1.16	1.16
	DAVN	EMSRb	79.24	78.09	78.11	76.83	1.13	1.26
	HBP	EMSRb	78.77	78.39	77.68	76.97	1.09	1.42
	ProBP	EMSRb	79.07	78.22	77.93	76.71	1.14	1.51
1.0	EMSRb	EMSRb	83.38	83.65	82.42	82.28	0.96	1.37
	GVN	EMSRb	84.37	83.2	83.81	82.33	0.56	0.87
	Netbid	EMSRb	85.73	82.53	85.07	81.82	0.66	0.71
	DAVN	EMSRb	85.17	82.74	84.15	82.02	1.02	0.72
	HBP	EMSRb	84.11	83.3	83.46	82.34	0.65	0.96
	ProBP	EMSRb	84.59	83.06	83.92	81.9	0.67	1.16
1.1	EMSRb	EMSRb	86.79	85.17	85.95	85.9	0.84	-0.73
	GVN	EMSRb	88.07	84.11	87.58	85.79	0.49	-1.68
	Netbid	EMSRb	90.13	84.59	89.73	85.22	0.4	-0.63
	DAVN	EMSRb	89	86.79	87.95	85.63	1.05	1.16
	HBP	EMSRb	87.73	88.07	87.17	85.93	0.56	2.14
	ProBP	EMSRb	88.09	90.13	87.6	85.45	0.49	4.68

Table 6-1 Average network load factors at all demand factors, for simulations with unfavorite airline disutilities and base case

Discussions

When unfavorite airline disutilities are implemented, half of the flights operating within the network are less attractive to passengers, due to the 0.5 airline preference factor. Hence when compared to the base case, passengers are more reluctant to fly on an unfavorite airline, causing more passengers to spill from the favorite airline, or to sell-up to a higher fare class. Since there is more willingness to sell-up, the relative benefits of

O-D revenue management methods tend to be higher than base case. This effect is maximized at higher demand levels, where "optimal" fare mix becomes an important factor in revenue benefits. At lower demands, revenue gains for O-D revenue management methods are not as significant since flights are more open and revenue increase for FCYM is in a similar range with O-D methods. One more thing worth noting is that the average load factors under unfavorite airline disutilities are larger compared to all disutility simulations, up to 1.63%. This can be explained by the fact that with considerable preference for a favorite airline and at the same time without any preferences or disutilities for path quality, the demand for a connecting path offered by a favorite airline becomes higher (at the same time demand for nonstop path offered by unfavorite airline is lower) than without any disutilities. Hence increased loads for connecting path results in higher RPMs, leading to higher load factors in the unfavorite airline disutility simulations.

6.2. Path Quality Index Disutility

6.2.1. Settings

Disutility parameters for PQI disutility in the simulations use estimated coefficients from the survey, for both business and leisure passengers. Hence in this simulation we are assuming that along with restrictions, the path quality (indicating whether the path is non-stop or connecting) is the only factor that has influence over passengers' path preference. PODS defines the PQI of a nonstop path to be 1, and connecting PQI to be 3. All PQI disutility costs chosen from the Gaussian distribution are multiplied by PQI to obtain PQI disutility costs, as described in Section 4.1.3.3.

6.2.2. Results

Revenue Gains

Revenue gains for O-D methods with PQI disutilities are not very different from revenue gains from the base case. GVN, DAVN and ProBP show similar ranges of revenue gains with the base case, for all demand factors. HBP does not perform as well as the base case, falling short of 0.05~0.26%. Netbid performs slightly better than the base case, except at DF 1.0. In most cases the revenue gains are not higher than the base case.

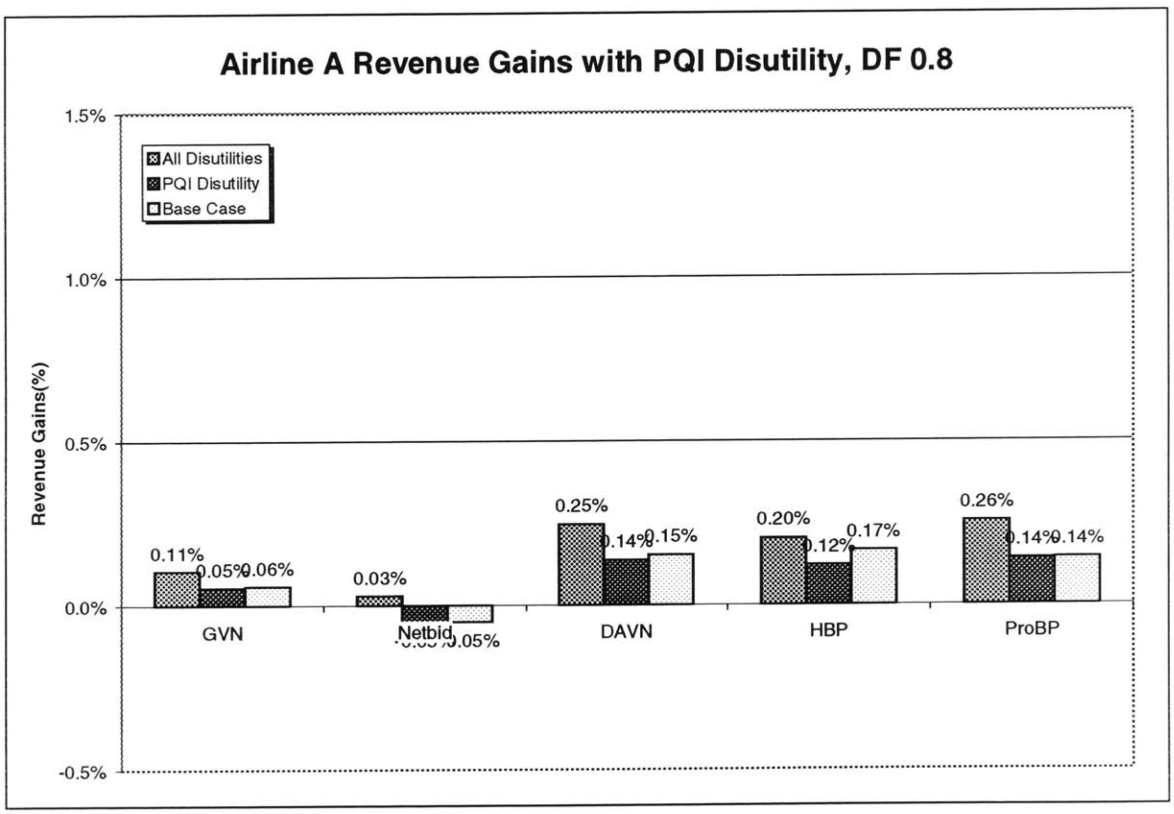

Figure 6-5 Revenue gains over EMSRb vs. EMSRb, with PQI disutility vs. base case, DF 0.8

All O-D method revenue gains are similar to the base case revenue gains at DF 0.8. With low demand, PQI disutility has very little impact on the relative revenue benefits of O-D methods.

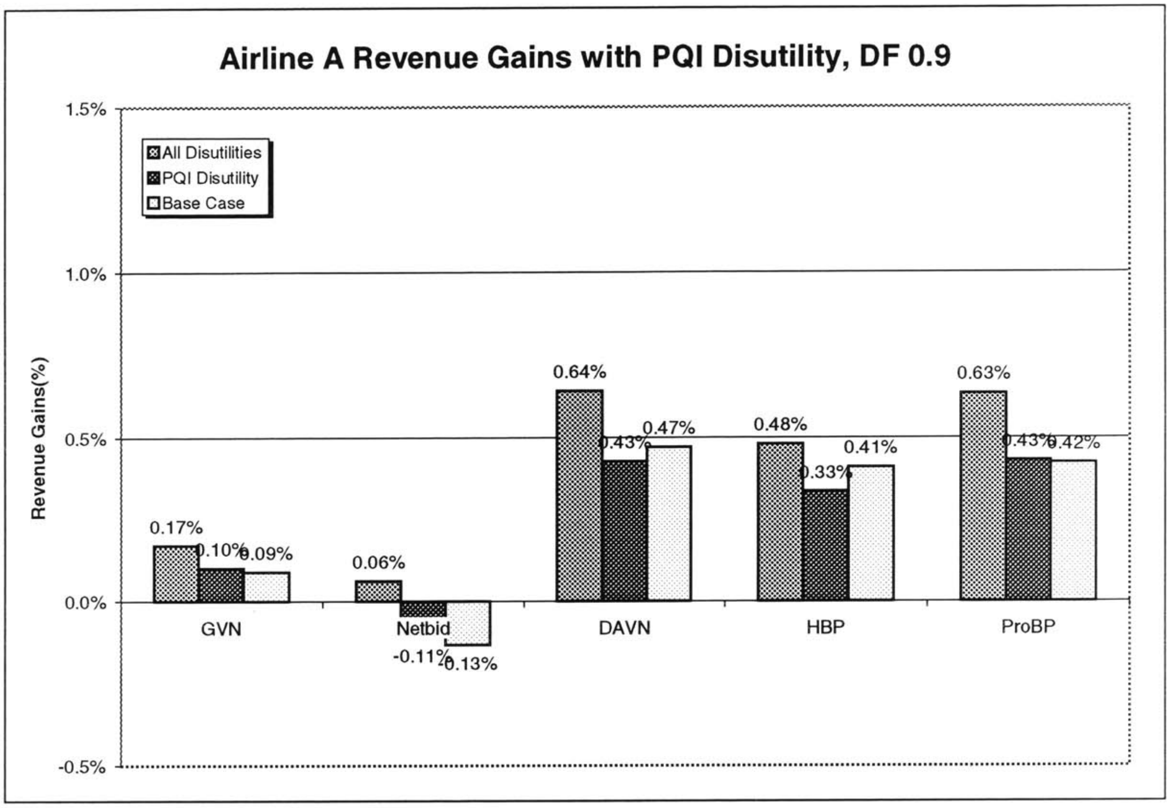

Figure 6-6 Revenue gains over EMSRb vs. EMSRb, with PQI disutility vs. base case, DF 0.9

Revenue gains under PQI disutilities at DF 0.9 show similar patterns with revenue gains at DF 0.8. The notable difference is that HBP now falls short of base case revenue gains with PQI disutilities.

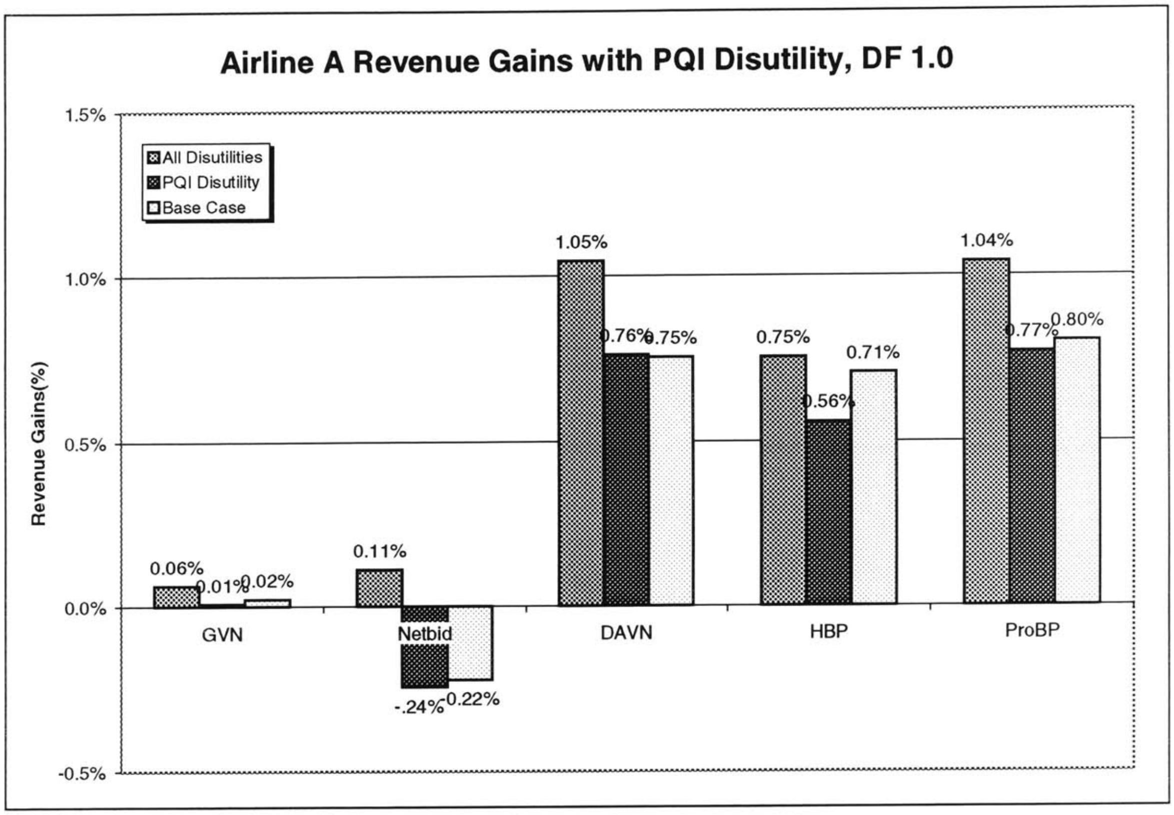

Figure 6-7 Revenue gains over EMSRb vs. EMSRb, with PQI disutility vs. base case, DF 1.0

As demand grows higher, the difference between HBP revenue gain with PQI disutility and under base case grows, at DF 1.0. Other O-D methods still show similar performance compared with the base case.

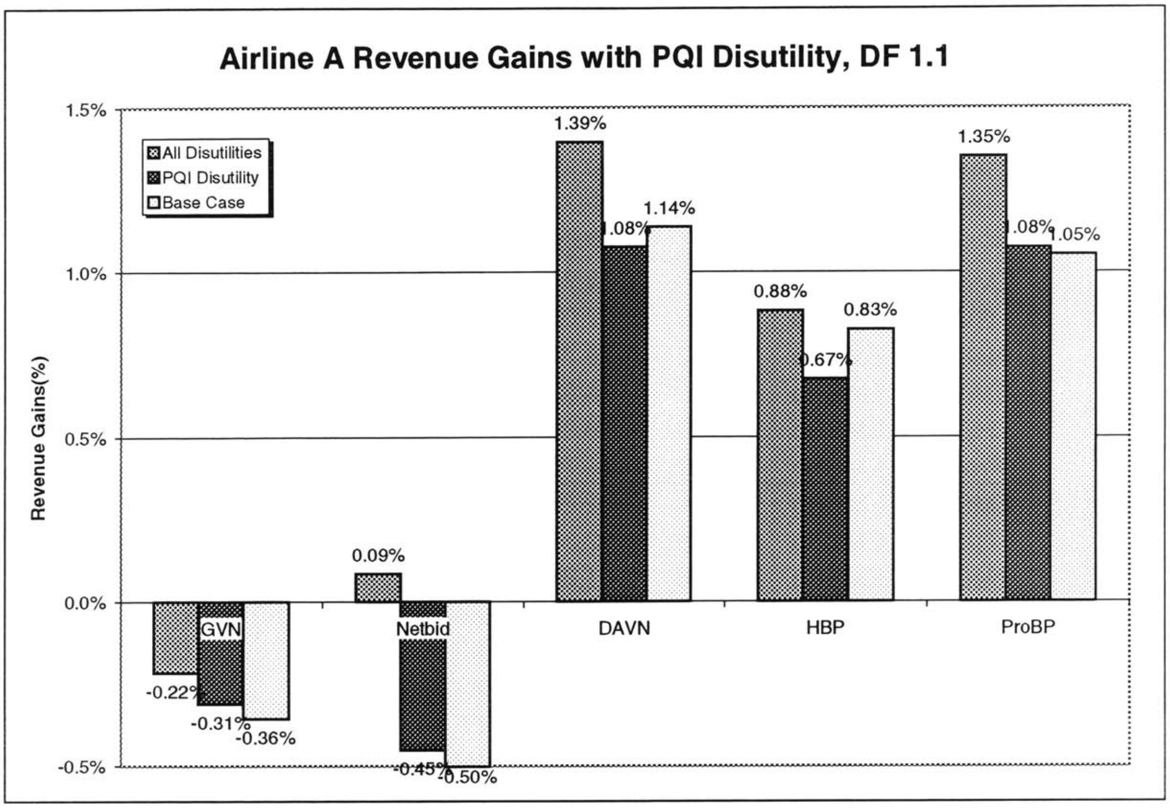

Figure 6-8 Revenue gains over EMSRb vs. EMSRb, with PQI disutility vs. base case, DF 1.1

At the highest demand factor of 1.1, GVN and Netbid show 0.05% recovery from the negative revenue gains they recorded in the base case, but still show negative revenue gains. HBP continues to fall short of the base case revenue gains, whereas DAVN and ProBP consistently show similar revenue gains with the base case.

Loads

The average network load factors for PQI disutility simulations are also almost the same as the load factors in the base case. The differences between the base case load factors and PQI disutility simulation load factors are less than 0.1%, indicating that PQI disutility in Network D has little impact on loads, for all O-D methods.

	YM methods		With PQI Disutility		Base Case		Difference	
DF	Airline A	Airline B	ALF A	ALF B	ALF A	ALF B	ALF A	ALF B
0.8	EMSRb	EMSRb	70.09	69.71	70.07	69.73	0.02	-0.02
	GVN	EMSRb	70.35	69.66	70.33	69.68	0.02	-0.02
	Netbid	EMSRb	70.41	69.62	70.4	69.64	0.01	-0.02
	DAVN	EMSRb	70.33	69.63	70.37	69.63	-0.04	0
	HBP	EMSRb	70.23	69.72	70.23	69.74	0	-0.02
	ProBP	EMSRb	70.3	69.65	70.28	69.67	0.02	-0.02
0.9	EMSRb	EMSRb	77.18	76.94	77.12	76.89	0.06	0.05
	GVN	EMSRb	77.99	77.02	77.92	76.97	0.07	0.05
	Netbid	EMSRb	78.42	76.74	78.35	76.7	0.07	0.04
	DAVN	EMSRb	78.1	76.83	78.11	76.83	-0.01	0
	HBP	EMSRb	77.7	76.98	77.68	76.97	0.02	0.01
	ProBP	EMSRb	77.99	76.75	77.93	76.71	0.06	0.04
1.0	EMSRb	EMSRb	82.4	82.25	82.42	82.28	-0.02	-0.03
	GVN	EMSRb	83.79	82.31	83.81	82.33	-0.02	-0.02
	Netbid	EMSRb	85.05	81.81	85.07	81.82	-0.02	-0.01
	DAVN	EMSRb	84.15	82.01	84.15	82.02	0	-0.01
	HBP	EMSRb	83.44	82.27	83.46	82.34	-0.02	-0.07
	ProBP	EMSRb	83.9	81.88	83.92	81.9	-0.02	-0.02
1.1	EMSRb	EMSRb	85.97	85.9	85.95	85.9	0.02	0
	GVN	EMSRb	87.59	85.79	87.58	85.79	0.01	0
	Netbid	EMSRb	89.74	85.24	89.73	85.22	0.01	0.02
	DAVN	EMSRb	87.93	85.61	87.95	85.63	-0.02	-0.02
	HBP	EMSRb	87.27	85.88	87.17	85.93	0.1	-0.05
	ProBP	EMSRb	87.62	85.45	87.6	85.45	0.02	0

Table 6-2 Average network load factors at all demand factors, for simulations with PQI disutilities and base case

Discussions

Basically we observe that with only PQI disutilities included in the simulation, the results are very close to the base case. This is mainly because the PQI disutilities in our Network D only affect "local" markets[23], which has both nonstop and connecting path options for the same market. All other markets have only connecting path options with single connections (spoke-to-spoke markets) or only nonstop path options (interhub markets), therefore PQI disutility costs have no impact on passengers' path choice. Hence even

[23] Spoke-to-hub markets. Passengers have the choice of a nonstop flight by a hub-dominating carrier or a connecting flight offered by the other carrier on these local markets.

though PQI disutility costs have relatively high values compared to other disutility costs (see Figure 4-3 and 4-4), the effective impact on the whole network is not as large.

In most cases, revenue gains of O-D methods are slightly smaller or similar to the base case. This is explainable by the fact that the revenue increase of EMSRb algorithm with FCYM overrules the relative benefits of O-D revenue management methods.

6.3. *Replanning Disutility*

6.3.1. Settings

Simulations for replanning disutility sensitivity tests use parameters from the base case, with replanning disutility function coefficients from the survey, for both business and leisure passengers. Hence in this simulation we are assuming that along with restrictions, the replanning disutility (indicating whether the path is within passengers' decision window or not) is the only factor that has influence over passengers' path preference.

6.3.2. Results

Revenue Gains

Revenue gains of O-D method in all replanning disutility simulations show higher values than the base case revenue gains. Especially at lower demand levels, at DF 0.8 and DF 0.9, the revenue gains are even higher than simulations with all disutilities. GVN achieves the highest revenue gains with replanning disutilities only. DAVN and ProBP consistently record the highest revenue gains among the O-D methods, and at the same time consistently perform better than the base case, similar to revenue gains with all disutilities. HBP revenue gains are in a similar range to the base case and all disutility simulations.

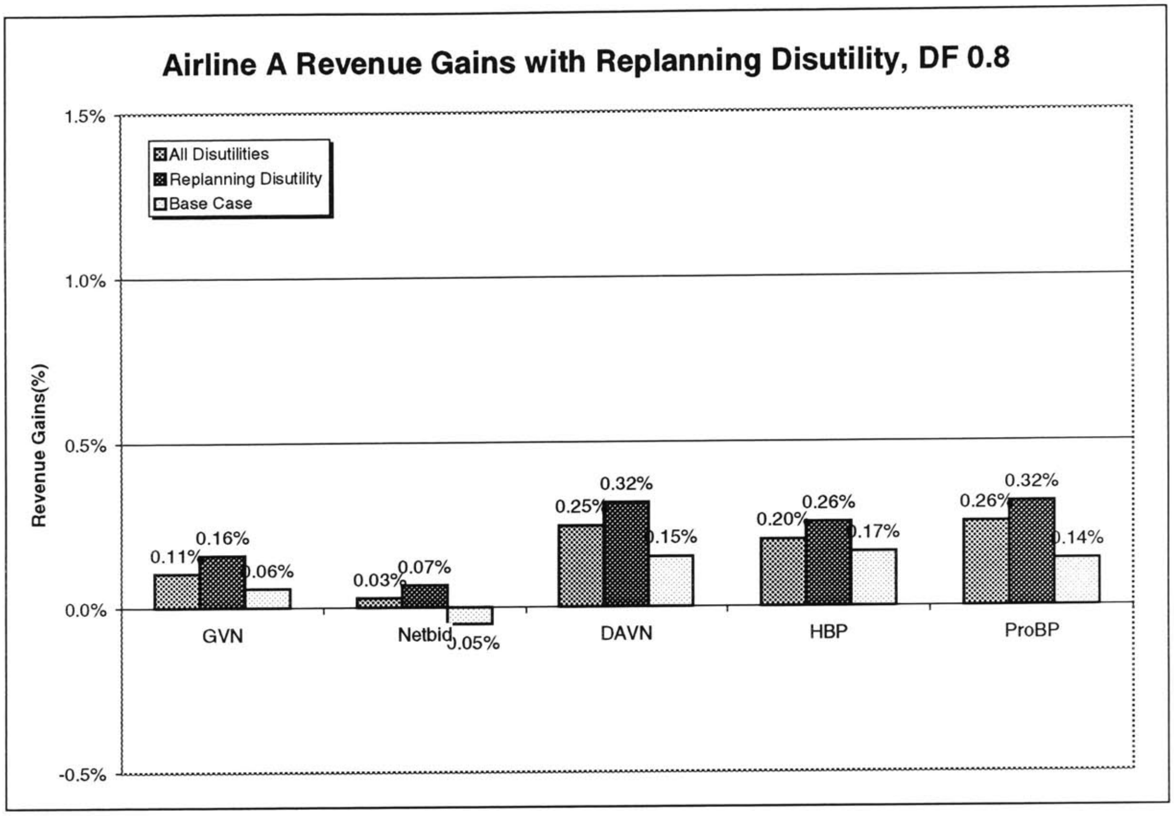

Figure 6-9 Revenue gains over EMSRb vs. EMSRb, with replanning disutility vs. base case, DF 0.8

All O-D revenue gains are higher than the base case at DF 0.8, and even higher than simulations with all disutilities. Especially revenue management methods with path-based forecasting, DAVN and ProBP show the highest revenue gains, improving up to 0.18% from the base case revenue gains.

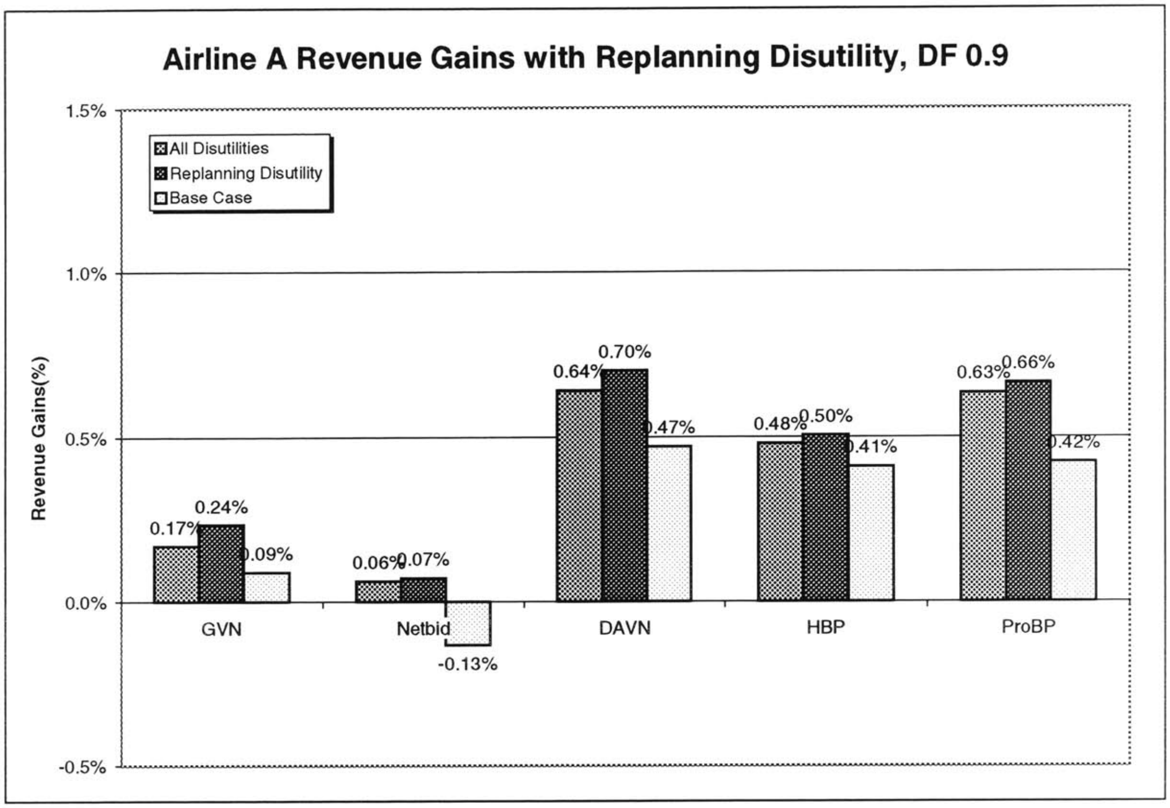

Figure 6-10 Revenue gains over EMSRb vs. EMSRb, with replanning disutility vs. base case, DF 0.9

At DF 0.9, DAVN achieves the highest revenue gains followed by ProBP. Still all O-D methods outperform both the base case and all-disutility revenue gains. HBP performs about the same for all three cases.

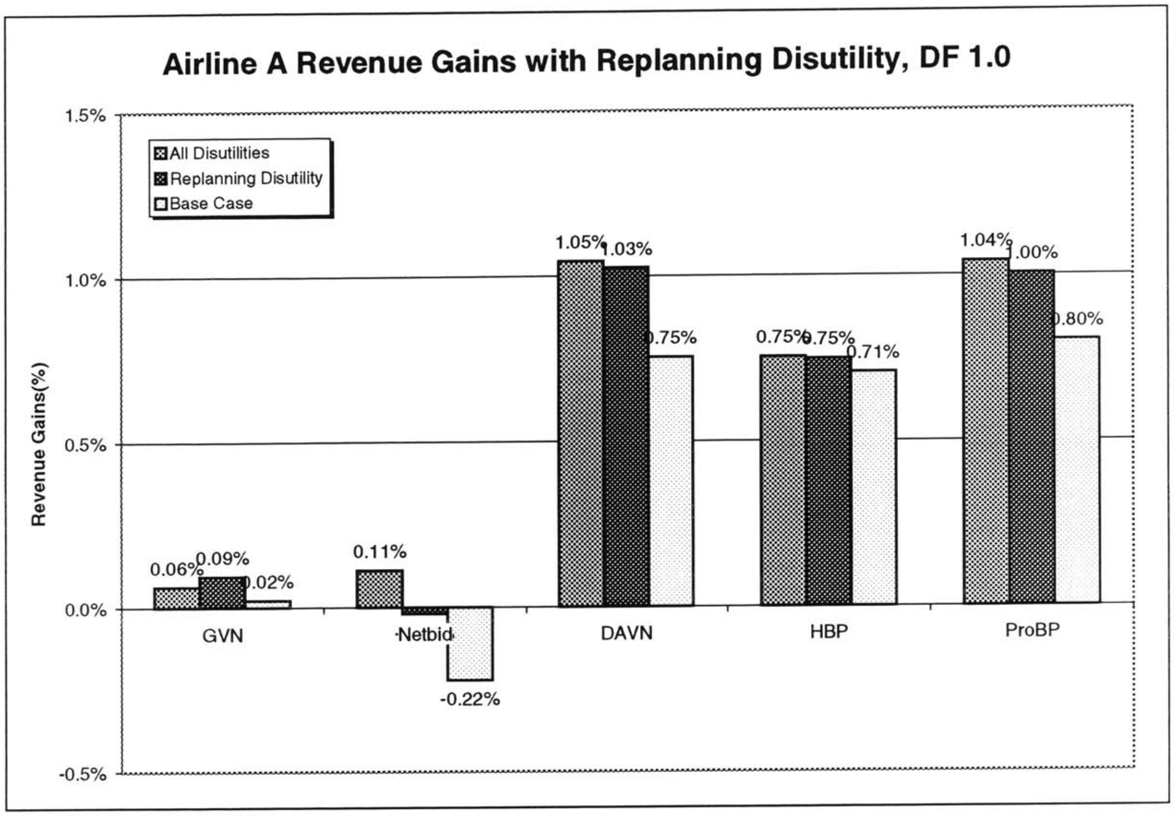

Figure 6-11 Revenue gains over EMSRb vs. EMSRb, with replanning disutility vs. base case, DF 1.0

At DF 1.0, revenue gains for DAVN, ProBP, and HBP catch up with revenue gains for the simulations with all disutilities. However GVN revenue gain difference is not as noticeable. Netbid revenue gain falls in between the base case and all-disutility revenue gains, with a slightly negative value.

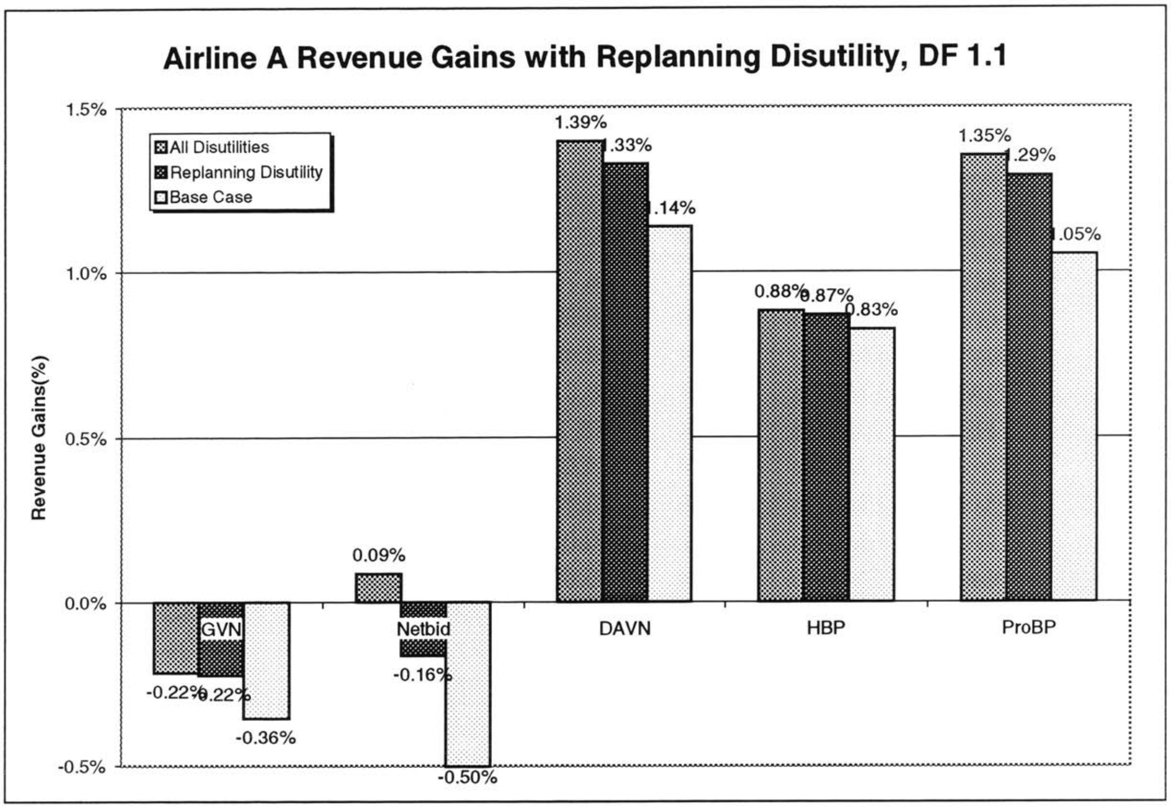

Figure 6-12 Revenue gains over EMSRb vs. EMSRb, with replanning disutility vs. base case, DF 1.1

At DF 1.1, the trends of revenue gains for replanning disutility simulations are almost the same as DF 1.0. All O-D revenue gains, with exception of Netbid, are in the same range as revenue gains under all disutilities, indicating that replanning disutilities have the largest impact among the three disutilities.

Loads

Average network load factors of airline A are generally higher with replanning disutilities than the base case. Moreover, when airline A uses O-D method incremental airline A load factors are higher than EMSRb, whereas airline B loses more passengers. This result indicates that the increase in load factors (and revenues) for airline A are mostly due to O-D method benefits, rather than replanning disutility itself. Also the load factor values are close to those of all-disutility simulations, also showing that replanning disutilities have greatest impact among the three disutilities when all disutilities are installed in the simulation.

	YM methods		With RPN Disutility		Base Case		Difference	
DF	Airline A	Airline B	ALF A	ALF B	ALF A	ALF B	ALF A	ALF B
0.8	EMSRb	EMSRb	70.45	68.72	70.07	69.73	0.38	-1.01
	GVN	EMSRb	70.88	68.53	70.33	69.68	0.55	-1.15
	Netbid	EMSRb	71.01	68.42	70.4	69.64	0.61	-1.22
	DAVN	EMSRb	70.87	66.81	70.37	69.63	0.5	-2.82
	HBP	EMSRb	70.64	68.7	70.23	69.74	0.41	-1.04
	ProBP	EMSRb	70.74	68.62	70.28	69.67	0.46	-1.05
0.9	EMSRb	EMSRb	77.38	76.18	77.12	76.89	0.26	-0.71
	GVN	EMSRb	78.4	76.03	77.92	76.97	0.48	-0.94
	Netbid	EMSRb	78.94	75.63	78.35	76.7	0.59	-1.07
	DAVN	EMSRb	78.57	75.82	78.11	76.83	0.46	-1.01
	HBP	EMSRb	77.99	76.17	77.68	76.97	0.31	-0.8
	ProBP	EMSRb	78.31	75.96	77.93	76.71	0.38	-0.75
1.0	EMSRb	EMSRb	82.46	81.72	82.42	82.28	0.04	-0.56
	GVN	EMSRb	83.97	81.37	83.81	82.33	0.16	-0.96
	Netbid	EMSRb	85.32	80.94	85.07	81.82	0.25	-0.88
	DAVN	EMSRb	84.27	81.22	84.15	82.02	0.12	-0.8
	HBP	EMSRb	83.55	81.62	83.46	82.34	0.09	-0.72
	ProBP	EMSRb	84.04	81.32	83.92	81.9	0.12	-0.58
1.1	EMSRb	EMSRb	85.93	85.52	85.95	85.9	-0.02	-0.38
	GVN	EMSRb	87.59	84.96	87.58	85.79	0.01	-0.83
	Netbid	EMSRb	89.82	84.46	89.73	85.22	0.09	-0.76
	DAVN	EMSRb	87.9	85.01	87.95	85.63	-0.05	-0.62
	HBP	EMSRb	87.25	85.31	87.17	85.93	0.08	-0.62
	ProBP	EMSRb	87.62	85.1	87.6	85.45	0.02	-0.35

Table 6-3 Average network load factors at all demand factors, for simulations with replanning disutilities and base case

Discussions

Referring to Figure 4-3 and 4-4, the reader will recall that replanning disutility costs are also high (along with PQI disutility costs), especially for business passengers in mid to long haul markets. Hence it is expected that replanning disutilities have significant impact among the three disutilities, which is proven by results shown in previous sections. With replanning disutility costs, the convenient scheduled paths (in general) become more favorable to passengers, resulting in passengers being less willing to shift to inconvenient paths. Therefore we can expect the demand for peak time paths to be higher than the base case, and consequently, demand for off-peak time paths to be lower than the base case. Due to these reasons O-D revenue management methods benefit more when replanning disutility costs are implemented, as shown in Figures 6-9 to 6-12.

6.4. Summary

In this chapter, simulations with each of the three disutility components installed were performed in order to observe the sensitivity of each disutility components. In Chapter 5 we observed that O-D revenue gains generally increased with all disutilities. However, with each of the three disutilities, this is not always true. Among the three disutilities, replanning disutility proves to have greatest impact on O-D revenue gain increases, as expected from the estimated disutility functions. PQI disutility, with the highest disutility costs, however, did not show as much influence on revenue gains of O-D revenue management methods due to our network configuration. Simulation results with unfavorite airline disutilities show interesting results with lower or similar revenue gains than base case values, mainly due to the fact that FCYM revenue increase overrules O-D benefits. Due to the reasons explained in Section 6.1.2, the whole system carried more loads than the base case with unfavorite airline disutilities, and the relative gains in revenues with O-D methods are less significant than the overall revenue and load factor growth with unfavorite airline disutilities. In all of these simulations revenue management methods with path-base forecasting (DAVN and ProBP) consistently proved to be more effective, compared to other methods.

Average load factors generally tend to show small increases when accounting for estimated disutility functions. However, with unfavorite airline disutility, relatively large increase of load factors throughout the whole network, including airline B's load factors, was observed. The reason for this increase is explained by the fact that without PQI disutilities, the demand for connecting local paths are higher than the base case due to unfavorite airline disutility costs.

Figures 6-13 to 6-16 summarize the revenue gains of five O-D revenue management methods for all simulations presented in Chapter 5 and Chapter 6. Five columns represent revenue gains with all disutilities, PQI disutility, replanning disutility, unfavorite airline disutility, and no disutilities (base case). Again it is shown that revenue gains for replanning disutilities resemble the revenue gains with all disutilities, whereas revenue gains with PQI disutilities are close to base case revenue gains.

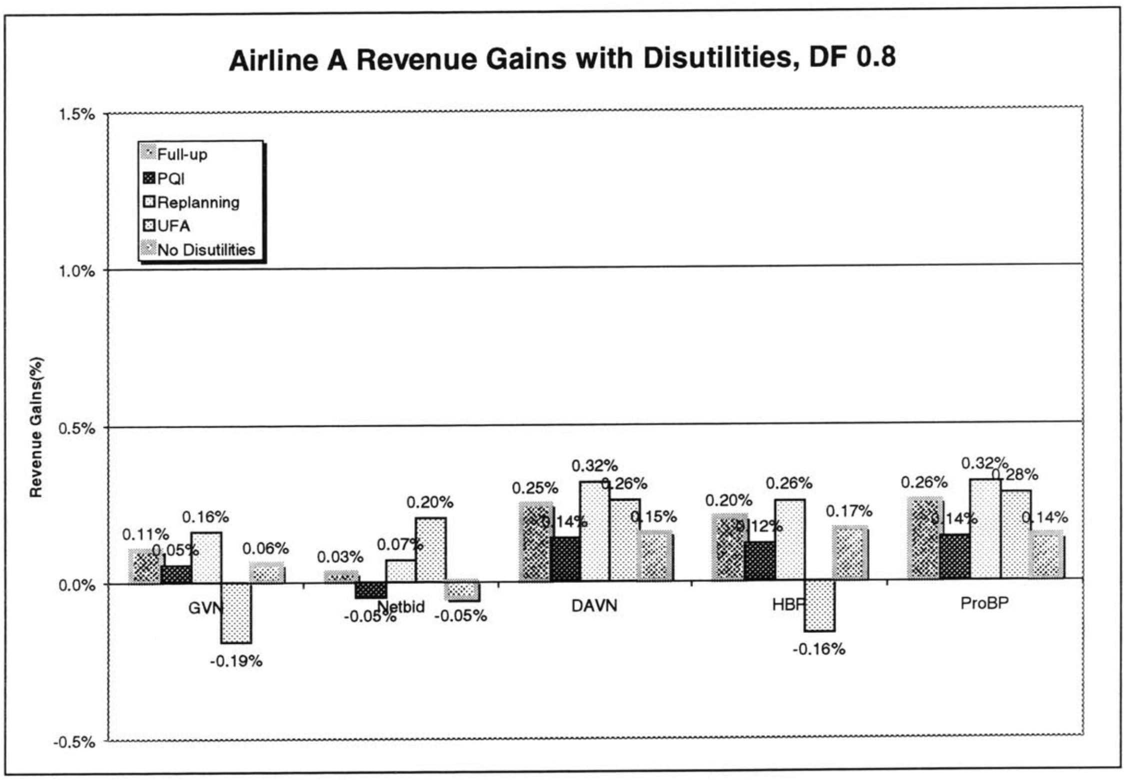

Figure 6-13 Revenue gains over EMSRb vs. EMSRb, for all simulations, DF 0.8

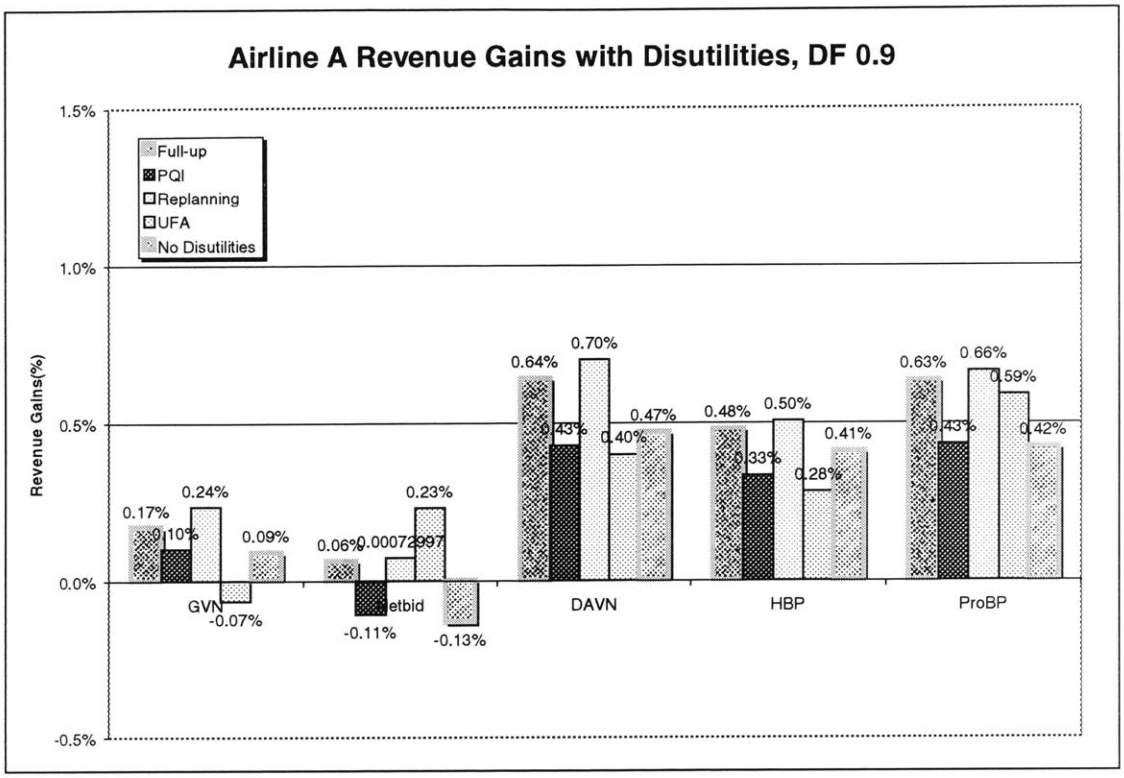

Figure 6-14 Revenue gains over EMSRb vs. EMSRb, for all simulations, DF 0.9

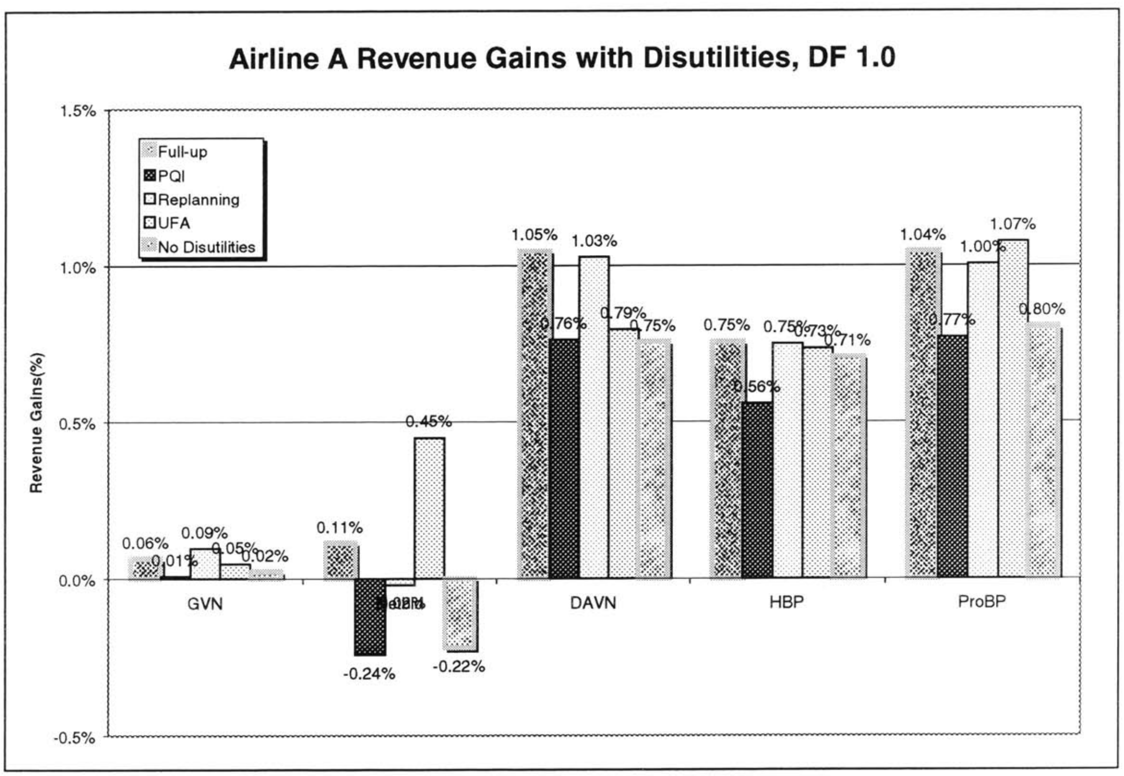

Figure 6-15 Revenue gains over EMSRb vs. EMSRb, for all simulations, DF 1.0

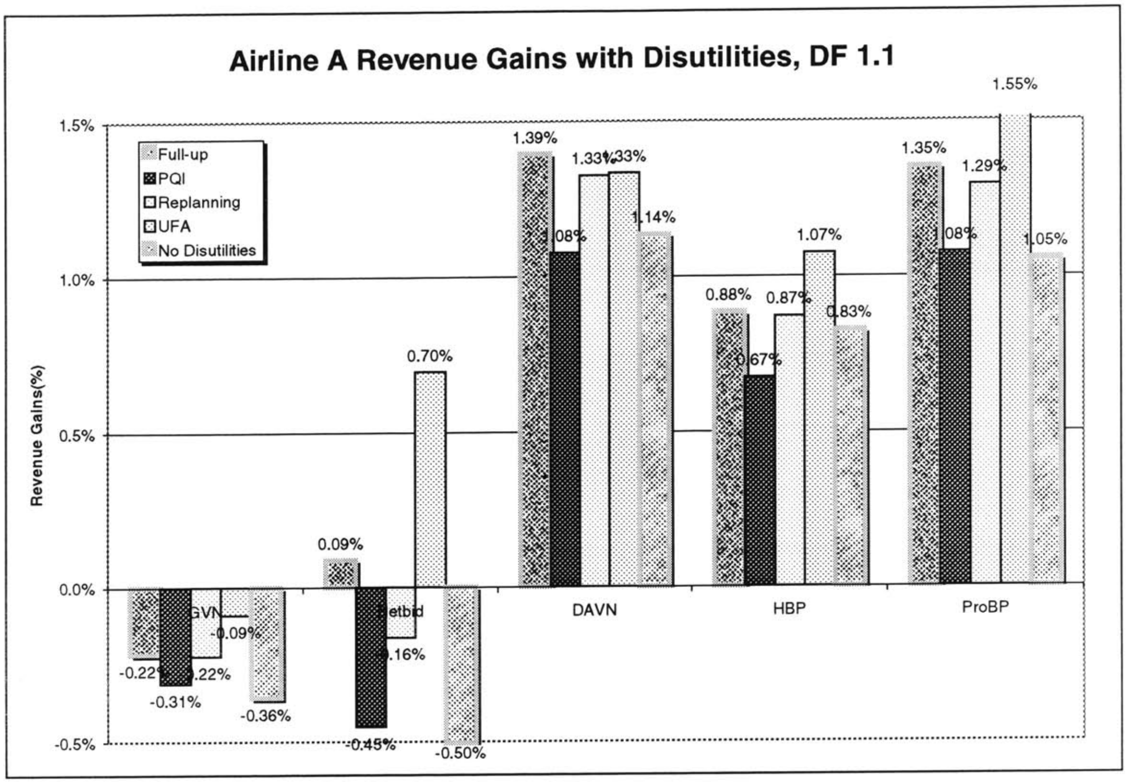

Figure 6-16 Revenue gains over EMSRb vs. EMSRb, for all simulations, DF 1.1

Chapter 7 Conclusion

7.1. Contribution of Thesis

The objective of this thesis was to develop an appropriate passenger disutility model for airline revenue management simulations, and test the impact of passenger disutilities with Passenger Origin Destination Simulator. The initial assumption for the passenger disutility model was that there are four major components consisting of passenger disutilities, restriction, unfavorite airline, path quality index, and replanning disutility. In order to develop a general passenger disutility model, it is assumed that all disutility components are defined with mean values, which is a function of market index fares. For the disutility model of this thesis all disutility functions are assumed to be linear. Also, to reflect the stochastic nature of individual passengers, disutility costs are assumed to be in a Gaussian distribution form, with average values defined with disutility functions.

This thesis uses survey answers from 13 airline experts to estimate the coefficients of each disutility components, for both business and leisure passengers. With mathematical analogy the survey answers are interpreted into the average and standard deviation of disutility distribution at a single market index fare level (which matches with market distance in our case). With average disutility costs for four market index fare levels, a simple linear regression gives the intercept and slope of each disutility functions with very high statistical significance. The estimated disutility functions – unfavorite airline, path quality index, and replanning disutility functions for both business and leisure passengers – summarized in Section 4.3 are the product of the first part of this thesis.

The passenger disutility model developed from this thesis now allows us to perform simulations with realistic representation of passengers' path choice patterns. Passenger choice is the fundamental element of all air transportation market responses; hence the disutility model developed in this thesis can be used in various simulations and analysis of air transportation systems. In this thesis we concentrated on testing revenue management simulations with passenger disutilities applied.

When all of the major disutility functions defined in PODS were incorporated in the simulation, it was shown in Chapter 5 that the relative revenue gains of O-D revenue management methods were higher than without any disutilities. Existence of passenger disutility costs means that passengers' path preferences for more convenient paths are higher, resulting in higher demands for those paths and lower demands for inconvenient paths. With concentrated demand on some of the attractive paths, the role of revenue management becomes more important, leading to bigger difference in terms of revenues between advanced O-D methods and FCYM approach. This is especially true at high demand levels, where O-D methods are able to achieve more "optimal" fare mix than the EMSRb algorithm with FCYM approach.

Among the three disutilities tested in this thesis, the impact of replanning disutility costs had the biggest impact in our Network D. This was partly expected from the magnitude of replanning disutility coefficients estimated from the survey. Even though the PQI disutility function is generally larger than the replanning disutility function, the PQI disutility had minimal impact since distinction between connecting and nonstop path was limited to local markets only. The replanning disutility, on the other hand, is applied to all paths offered in this network, since all markets are served three times a day. In conclusion it was verified that the magnitude of disutility functions are the indicators of its impact on the system, and also the impact very much depends on the network configuration. The estimation from the survey implies that path quality followed by replanning is the biggest factor in the air transportation system.

7.2. Future Research Directions

Our attempt to represent passenger disutility is only a first step in understanding and representing passenger behavior with an analytic model. Assumptions for our model – disutility function as a linear function of market index fares, and Gaussian distribution of disutility costs – seems reasonable for an initial approach, but there is always room for more sophisticated representation and its investigation.

Besides the assumptions, there also is room for improvement in reliability of the estimated disutility parameters. In this thesis the survey answers of thirteen airline experts have been the basis for disutility function coefficients. If it is possible to gather extensive data from actual airline PNR[24] databases or passenger choice records from electronic purchasing, it may be possible to take a step forward towards more realistic passenger choice representation.

Apart from the modeling approach, there are some more issues on the simulation and testing side that this thesis leaves for future research. With our Network D we have observed that the replanning disutility costs is the one that is driving O-D method performance over the system, due to both the magnitude of replanning disutility function and Network configuration. In order to test comparable impacts of path quality disutilities, a new network with wider choice between nonstop/connecting paths is required. Therefore more complicated version of Network D, possibly with nonstop paths provided in spoke to spoke markets, can better show the impact of PQI disutilities to a certain extent. As for replanning disutilities, it would be interesting to see how the O-D revenue gains along with market response changes with different set of banks and bank timings. Also even though the impact of unfavorite airline disutilities are not as large as the others, simulations with different airline preference factors may give clearer insight

[24] Passenger Name Record

about the impact of airline preferences on the air transportation market and revenue benefits of various revenue management methods.

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