FLIGHT TRANSPORTATION LABORATORY
REPORT R93-3

A STUDY OF THE PRACTICALITY AND PROFIT ENHANCEMENT POTENTIAL OF DEMAND DRIVEN DISPATCH IN AIRLINE HUB OPERATIONS

GARY L. WALDMAN

JUNE 1993

A STUDY OF THE PRACTICALITY AND PROFIT ENHANCEMENT POTENTIAL OF DEMAND DRIVEN DISPATCH IN AIRLINE HUB OPERATIONS

by

Gary L. Waldman

S.B., Massachusetts Institute of Technology (1988)

Submitted to the Department of Aeronautics and
Astronautics in Partial Fulfillment of the
Requirements for the Degree of
Master of Science
at the

Massachusetts Institute of Technology
May 1993

© Massachusetts Institute of Technology 1993
All rights reserved

Signature of Author ______________________________
Department of Aeronautics and Astronautics
14 May 1993

Certified by ______________________________
Professor Peter P. Belobaba
Thesis Supervisor

Accepted by ______________________________
Professor Harold Y. Wachman
Chairman, Departmental Graduate Committee

ARCHIVES

A STUDY OF THE PRACTICALITY AND PROFIT ENHANCEMENT POTENTIAL OF DEMAND DRIVEN DISPATCH IN AIRLINE HUB OPERATIONS

by

GARY L. WALDMAN

Submitted to the Department of Aeronautics and Astronautics on 14 May 1993 in partial fulfillment of the requirements for the Degree of Master of Science in Aeronautical and Astronautical Engineering

ABSTRACT

This thesis explores the use of demand driven dispatch in the hub and spoke environment prevalent in the route networks of major airlines in the United States. Demand driven dispatch is an operational mode where aircraft assignments can be changed in response to variation in demand. A computer program simulated the functions of a revenue management system and an optimal aircraft assignment routine over the course of the passenger booking process. An isolated hub with service exclusively between the hub and 15 spoke cities was assumed.

Two series of quantitative studies were done, one looking at the possible profit improvements at various demand levels with demand driven dispatch and the other examining the sensitivity of demand driven dispatch results to when the first and last optimal reassignment of hub aircraft was made in the booking process. In the first series, comparisons were made between results obtained from static aircraft assignments and fully dynamic demand driven dispatch assignments. Several scenarios were simulated. These involved various combinations of demand distribution, demand balance, and booking process assumptions. Booking process sensitivity studies were performed on a small subset of the scenario combinations. A discussion of practical issues which could affect implementation is also included.

Results show that demand driven dispatch performance is fairly uniform regardless of the scenario with the best projected yearly profit increases for a major hub and spoke operator of \$35-\$40 million over the current fixed assignment practice. This occurred at load factors similar to airline historical levels of 65%. The profit increases at normal demand levels were achieved mostly through better aircraft utilization patterns (lower costs) and not revenue enhancement. At higher average load factors demand driven dispatch improvement was less significant but was always positive. Studies on when demand driven dispatch was applied during the booking process showed that major benefits could be gained by evaluating assignments even once as long as this assignment period preceded any significant level of high yield passenger booking requests.

Thesis Supervisor: Professor Peter P. Belobaba
Title: Assistant Professor of Aeronautics and Astronautics

Acknowledgments

I am very grateful for the opportunity to have studied at MIT in the Flight Transportation Lab not just once but twice. When I left MIT after one semester of graduate school in 1988, I suppose many around here thought they would never see me again. I knew I would be back, but at the time it was more important for me to spend time with the love of my life, my girlfriend (and now wife) Laura. Professor Simpson graciously reaccepted me back into the lab in January 1992, a gesture which I will never forget. Since that time both Professors Simpson and Belobaba have been a tremendous source of information, advice, and yes, funding. Thank you both very much for making my grad school experience one which I am sure would make other students jealous.

Of course what I will miss most about this place are the people I have been fortunate to meet over the years. I spent way too much time talking about life, school, sports, careers, politics, and the future of the airline industry with you, but what the hell, it was fun. Thank you Ray Ausrotas, Ted Botimer, Ming-Cheng Chiang, Mike Clarke, Francois Cohas, Dave Cuthbert, Jim Davis, Seth Grandeau, Tom Svrcek, Ulf Weber, and Elizabeth Williamson for always lending an ear.

Finally, I wish to acknowledge three people working in the background who helped me get to this point: Steve Ellis in Academic Computing, who saved the day for me many times, and Walt Blake of Boeing and Catherine Bohutinsky of Delta Air Lines, who never turned down any request I had for information.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

Much has been written over the past few years about the financial woes of the airline industry. How poorly have the airlines performed? Losses over the past three years alone top $9 billion just for the domestic U.S. carriers.[1] What are the root causes of the industry's difficulties? For airlines in the United States, the current list of items is long and varied. Among the most cited reasons are high costs, low yields, overcapacity relative to demand, government mishandling of bankruptcy laws, foreign competition, and, of course, the Airline Deregulation Act of 1978.

With the outlook of the industry not likely to improve in the near future, does it make sense for the major carriers like American, Delta, and United to consider exiting the industry for strategic reasons? It has been the topic of discussion at many board meetings, and rightly so. If these firms choose not to formulate and implement bold and creative solutions to deal with ever changing market conditions, then they would indeed be doing a service to their shareholders to dissolve their companies. After all, there are airlines which have managed to make money and even prosper while the rest of the industry has suffered these horrendous losses. Most notable is Southwest Airlines, a Dallas-based carrier which has adopted a strategy of low frills, low costs, and high frequency service. Southwest has been profitable the last 18 years, and is the only major airline in the United States which had positive net earnings in 1992. As an indication of the paralytic state which the other majors find themselves, even though Southwest presents a significant threat to erode their market shares, they have yet to define a strategy to check Southwest's growth.

Many of the successful innovations which were introduced by individual carriers since deregulation, like frequent flyer programs and super saver fares, have lost their effectiveness to boost primary demand for travel. These programs benefit an airline only over the short term because they are easily replicable and therefore <u>not</u> sustainable competitive advantages. What is a sustainable competitive advantage is an organization's ability to continuously bring to the market cost effective innovations which the market will embrace. This thesis examines an airline operational philosophy which meets the previous criteria in that it goes beyond the traditional way of executing a flight schedule while at the same time lessening the negative impact of what is perhaps the greatest external impediment to sustained profitability in any organization, variation in demand.

In particular, the subject of this thesis is demand-driven dispatch (D^3) in a hub and spoke environment typically found in the United States today. First developed by Boeing[2], demand driven dispatch is a dynamic aircraft assignment procedure which utilizes the detailed and constantly updated data in the revenue management system in an attempt to increase airline profits relative to the current fixed aircraft assignment practice by more closely matching seat capacity to passenger demand.

The discussion in this thesis will commence with a background section on the evolution of the current route structure and a review of previous work on demand driven dispatch. The final sections of the thesis discuss computer simulations which illustrate the potential magnitude of benefits to the airlines, specific issues which would have to be addressed in order to convert to a D^3 operational mode, and a set of conclusions addressing the overall merit of such a shift.

Chapter 2: The Development of the Hub and Spoke System

2.1 The Era of Regulation

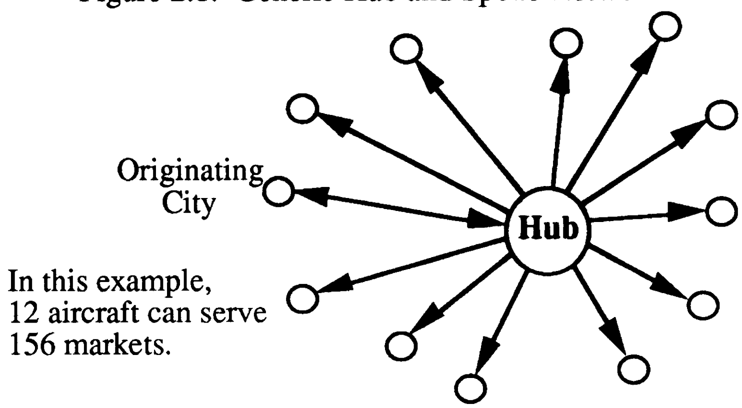
In the days when airline travel was regulated by the Civil Aeronautics Board (CAB), airline route networks reflected point to point service offered along trunk, or high demand, routes. Airlines tended to provide air services within confined geographical regions. Indeed their names alluded to the areas of the country where a company's service was focused. There are numerous examples: Eastern, Southern Airways, Western, Northwest Orient, Piedmont, etc. Carriers could be further classified into those whose route networks were primarily east-west (United) or north-south (Eastern), but there were no airlines that were truly national in terms of complete coverage of the country. Airlines were assured steady financial returns and little competition under the benevolent stewardship of the CAB. With no motivation to strive for organizational efficiency, airline costs gradually drifted upwards. Inevitably, fares rose as well to cover the cost increases.

In part because of the recognition that bureaucratic oversight of the airline industry did not maximize benefits to the traveling public, the U.S. government in 1978 dissolved the CAB with the passage of the Airline Deregulation Act. For the first time airlines were free to serve markets and set prices at their own discretion. Filings for new airline operating licenses rose tremendously in the aftermath. New carriers with low fare, low frill service, People Express Airlines for example, were enthusiastically embraced by the public. The established carriers that offered more traditional levels of service faced the prospect of large declines in passenger traffic and were forced to seek new operational and marketing strategies which would allow them to retain their passenger base in a cost effective manner. Innovations like super save fares and frequent flyer plans were introduced. It was also in this newly competitive environment that the hub and spoke system began to flourish.

2.2 The Hub and Spoke Solution

What was so appealing about the hub and spoke system? The answer is that it gave the airlines the ability to serve a large number of markets with relatively few

Figure 2.1: Generic Hub and Spoke Network



aircraft. Consider a generic hub with n spokes similar in layout to the one in the Figure 2.1. Each spoke city is linked via the hub to n markets comprised of the other n-1 spoke cities and the hub itself. For passengers beginning their trips in the hub city, there are an additional n markets to consider. Thus, over all spokes there are a total of n(n+1) markets or origin-destination pairs which can be served with n aircraft. The arrival and departure of aircraft at the hub must obviously be sequenced to provide enough time for passengers to connect to other aircraft. The window of time when all the aircraft are present at the hub and passenger transfers occur is commonly referred to as a connecting bank or connecting complex.

Another advantage of hub and spoke networks is that they allow airlines to operate fewer models of aircraft which can efficiently service flight legs of varied distances from the hub. This results in greater scheduling flexibility. Also, these aircraft are usually jets, which are desirable from a level of service perspective, not small propeller driven planes. Larger jet aircraft feeding traffic (passengers) into the hub can routinely be filled regardless of the local market being served by the aircraft because of spoke passenger opportunities to connect to numerous market destinations beyond the hub. Non hub operations of a similar schedule, in contrast, would not only require many more aircraft but aircraft of various capacities to match market size.

Today's hub and spoke systems are clearly an integral part of an airline's flight operations. The statistics below give a sense of the magnitude and scope of hub and spoke operations at Delta Air Lines.

Number of Hubs - 9 (5 major, 4 minor)
Percentage of system-wide flights originating or terminating at hub - 90%
Typical number of aircraft in a connecting bank - 30
Maximum number of aircraft in a connecting bank - 65
Typical number of connecting banks per day per hub - 8
Maximum number of connecting banks per day - 10

Recent bankruptcies of carriers who had been operating in the pre-deregulation era points to the importance of the hub and spoke system as an indicator of sustainable success in the 1980s. Those airlines which recognized the market and cost efficiencies of hub operations from the outset have managed to survive the initial shakeout period. Prominent examples are the "Big Three" - American, Delta, and United. Many airlines who were late or negligent in establishing a strong nationwide hub and spoke system have exited or are in the midst of exiting the industry. Airlines in this category include Pan American, TWA, and Eastern. For Pan American and TWA it was a clear problem of failing to grasp the importance of establishing feeder systems for their vast overseas route networks. Eastern, possibly because it had no choice but to concentrate on resolving labor issues, never grew its hub and spoke system beyond a couple on the East Coast.

2.3 Is the Hub and Spoke System Obsolete?

In the past few months the cost effectiveness of hub operations has come into question. The most outspoken person on this issue has been American Airlines Chairman Robert Crandall. He feels that part of the responsibility for American's losses rests upon the failure to account for higher costs incurred when routing passengers through a hub relative to the costs of point to point service. Specifically, Crandall argues that "hubs require the presence of a large number of employees and an infrastructure to handle the periodic bank of flights, which have sent airport costs soaring."[3] While this might be true, a counter argument might highlight other contributing factors to losses like low demand, ill-conceived pricing schemes, and overcapacity. Also, there are several studies which completely contradict this notion. Kanafani and Hansen[4] find that "airlines with strongly hubbed route systems incur roughly the same cost to provide a given amount of transportation as those with less hubbed systems, controlling for other factors." In other words, if the accounting *were* done correctly, one would find that the greater market reach of the hub and spoke system versus point to point can be achieved with little or no cost penalty.

Regardless of the whether this is the core problem for American Airlines or not, Crandall's contention that hubs are more costly to operate in general should be addressed. Indeed the key motivation for this study of demand driven dispatch is to evaluate its potential for increasing profits in a hub and spoke network. A.J. Reynolds-Feighan in her doctoral dissertation[5] on the effects of deregulation on route network concludes at one point that "for these hubs (where the carrier has a dominant market position) a better matching of equipment with passenger demand and route length is the most important aspect that can lead to improved efficiency levels." For all intents and purposes, this statement is an endorsement of the demand driven dispatch philosophy.

Point to point service is making a bit of a comeback today with new entrants like Reno Airlines, Kiwi, and the yet to be certificated Family Airlines. One should understand that this is *not* an indictment of the hub and spoke system. The markets these airlines are targeting justify this level of service. Airlines operating hub and spoke systems offer nonstop service in selected markets as well. However, hubs are by far the most effective method to link the greatest number of smaller markets with the fewest number of aircraft. If hubs are not turning a "profit", the airline should reexamine the allocation of seats to markets (aircraft size) as well as the way they are being used (D^3) before they abandon the hub and spoke system prematurely.

Chapter 3: The Evolution of Demand Driven Dispatch

3.1 Problems Inherent in Current Aircraft Assignment Process

Airlines typically fix the flight schedule on either a monthly or seasonal basis. The aircraft type assignments and tail number routings are also simultaneously set on the basis of the outcome of a network optimization mathematical programming routine. There are several drawbacks with this approach. Principally, the solution depends upon either forecasted or projected demand. Forecasting relies upon methodologies which estimate future demand based upon past traffic data while accounting for factors like seasonality, day of week, special events like holidays or the Super Bowl, and the time of day. Projections in this context are subtlely different in that they estimate demand for new flight services or a changing competitive environment. Projections also are a function of the aforementioned factors applied not to past traffic data, which would reflect an invalid competitive model, but rather to theoretical demand relationships which are based upon market size and flight frequency. In either case the results are never wholly accurate.

Another inherent problem is caused by the use of deterministic data in the assignment process. A more sophisticated approach might include some probabilistic techniques to assess spill potential. Spill is a measure of the level of passenger requests for air travel which cannot be met. However, current practice does not account for the situation where, for example, a specific flight has mean demand of 100 (adjusted for the various factors) where the actual demands are 65 and 135.

Demand-driven dispatch creates a flexible assignment environment which converts this variability into an opportunity to increase profits rather than the settling for the current situation of demand spill *and* low average load factors. In the above example, a demand driven dispatch-controlled system would have advance knowledge of flights where passenger demand was projected to vary significantly from the expected level.

This information would come from a revenue management system which monitors among other items deviations from historical or forecasted booking patterns for every flight. A D^3 optimization routine would then look for feasible aircraft assignment swaps which would result in an increase in operating profit for the airline. A feasible assignment would be one that in the context of the overall schedule could be executed with little impact to other operational areas like crew scheduling and maintenance.

3.2 Demand Driven Dispatch as Means to Sell Airplanes

Demand drive dispatch was introduced by the Boeing Company primarily as a vehicle which allowed the company to exploit its 'family of aircraft' product line advantage. A manufacturer is usually selected on a repeat basis by an airline customer for reasons like airframe/engine commonality, which reduces spare parts inventories and maintenance costs, and savings on flight training. Over time each major aircraft manufacturer has recognized the importance of the family concept and has acted to expand their product line accordingly. Examples of manufacturers and their family concept are show in Table 3.1. The aspect of flight training commonality across aircraft

Table 3.1: Airframe Manufacturers Aircraft Families

Manufacturer	Aircraft Family	Range of Capacities
Boeing	737-300,400,500	108-148
McDonnell Douglas	MD81,83,85,87,88	115-145
Airbus	A319,A320,A321	115-180
Fokker	F70,F100,F130	70-137
British Aerospace	RJ70,RJ85,RJ100	70-125

families is the most critical for D^3 operations to be successfully conducted. The reader may have noticed that any mention of changes to the scheduling of flight crews has been absent from the discussion. This is not an unintentional omission. Under D^3 the flight crews will still be flying their preassigned flight legs regardless of the member of the aircraft family at the departure gate. This can be only be done if aircraft families are designed with similar cockpits in order to qualify for certification by the Federal Aviation Administration (FAA) in the category of "common type rating." This essentially means that the flight crew is legally allowed to fly any aircraft in the family without any sort of intervening training. Without this stipulation, D^3 would not be possible.

3.3 Why the Airline Industry Needs D^3

There is a checklist of characteristics whose presence, absence, or extent in an industry will easily allow even a person with a layman's knowledge of economics to quickly determine the prospects for long term profitability in that industry. Included on this list are relative level of fixed costs, barriers to entry, nature of variability in channels of distribution, perishability of the product, and differentiability among competing products. Where does the airline industry fit in this picture? Before I answer this question, let us examine industries/firms at two extremes and speculate about their chances for success in economic terms. At one end of the spectrum is a software company like Microsoft. Its products require little capital to develop (a few computers), are considered in many cases to be the best available as well as industry standards, last for years (MS-DOS and Excel), and are in high demand. Their fortunes at least over the next few years are relatively secure. Now consider the independent fishermen. Their boats are relatively expensive, anybody with the inclination and money can enter the business overnight, both the supply of and demand for fish is variable, a fair portion of their catch dies before reaching market, and a fish is difficult to brand. Under these circumstances it is almost miraculous if a fisherman makes any money at all.

Unfortunately for the airline industry, it more closely resembles commercial fishing than software design. For the airlines the situation is as follows. On the positive side of the ledger, starting an airline is not a trivial task. While the used aircraft market today is certainly a buyers market, the management of a new entrant still must deal with Federal Aviation Administration operating approval, distribution costs through competitor-owned customer reservation systems, gate availability, and, in some cases, landing slot restrictions. The good news for prospective airline moguls ends there. New jet aircraft represent a large capital investment, anywhere from 20 to 120 million dollars depending on the capacity and range. While the supply of seats can be controlled, passenger demand at a disaggregate level is not highly predictable. An airline's product, available seat-miles, perish upon departure if not sold. Any new service features can be quickly copied by the competition, effectively preventing branding.

Much of what is seen in the industry today is driven by these industry circumstances. While fixed costs are high, marginal costs are low. This observation, in combination with perishability and importance of low cost to the passenger for air service, leads to the never ending fare wars. In an area of concern to this paper, airlines have also invested heavily in revenue management systems in order to better cope with the stochastic nature of passenger demand. Revenue management systems serve to determine seat availability in different fare classes with the objective of maximizing revenue. The number of seats allocated to each fare class is based upon the mean demand for the fare class, the variance of the demand, and the fare itself. However, one must realize that using a revenue management system is only an *acknowledgment* of variability, not a solution to eliminate it. Even with revenue management systems in place, on average over 30% of airline seats in the United States fly unfilled each day!

Demand driven dispatch is to aircraft seat supply like revenue management is to passenger demand, but they are not substitutes for each other. To ideally maximize profits a firm must be able to exert some control over both supply and demand. In fact, differential pricing mechanisms are currently meshed with revenue management systems to achieve this effect, but the results are not always desirable. For example, a passenger wanting to buy a super saver ticket for a 9 AM flight from Los Angeles to New York might be told that all the seats available at that fare on the requested date are sold. The traveler now has several alternatives: buy a more expensive ticket on the desired flight, fly at a less desirable time (e.g. a "red eye" or perhaps the same flight the next day), try the competition, or not fly at all. Every one of these alternatives from the airline's perspective should represent a failed opportunity to meet a customer's need. Additionally, the prospective passenger's ultimate decision will affect demand statistics which the airline relies upon for future forecasting. However, the airlines currently have no way of knowing whether the passengers who flew on today's 9 AM flight really wanted to fly on the flight or whether it was an "undesirable alternative." In this way, variability is introduced into the system with no way of flushing it out. D^3 will break this cycle because aircraft capacity would be moved to conform with basic demand patterns.

3.4 The Rubber Airplane

In 1986 an internal memo at the Boeing Company was written describing an operating concept based upon a "rubber" airplane,[6] A few years later, Berge and Hopperstad of Boeing wrote what is the seminal paper on demand driven dispatch, the formal name for the "rubber" airplane concept.[2] As a reminder, demand driven dispatch uses demand forecasts from the revenue management system and subsequent passenger bookings to dynamically adjust aircraft assignments as the date of departure approaches to optimize profit. How this is done will be developed in a subsequent chapter. In their paper Berge and Hopperstad conclude that demand driven dispatch could improve airline earnings and could be feasibly applied to any route network regardless of its fundamental structure or size. Other noteworthy conclusions from the paper are:

- The major elements necessary to run a demand driven dispatch operation, namely aircraft with common flight crew ratings, reservations systems capable of forecasting demands and flexible enough to accommodate aircraft changes, and computing capability, are all currently available.
- Operating profit on hub and spoke dominated networks can be improved in the range of 2 to 4 percent.
- The source of the benefits comes not only from increased revenue but better utilization of aircraft. In some case studies the latter was even the majority

component. This has implications for fleet planning as well. There was some indication that demand driven dispatch with smaller aircraft will generate as much revenue as the fixed assignment method using larger aircraft. Smaller aircraft require less capital investment.

- Relative to the fixed schedule, load factors (the number passenger miles flown divided by the number of seat miles flown) rise by a couple percentage points while spill (demand not satisfied because of unavailability of a fare product) dips slightly.
- Large-scale aircraft assignment problems can be solved heuristically to near optimal levels in a short time.
- Even with switching of aircraft assignments, tail number-specific activities like maintenance can be accomplished.

The demand driven dispatch model and case studies used in preparation of this report will be presented in the next section. Differences and similarities with the Berge and Hopperstad model will also be discussed.

Chapter 4: Demand Driven Dispatch Simulation

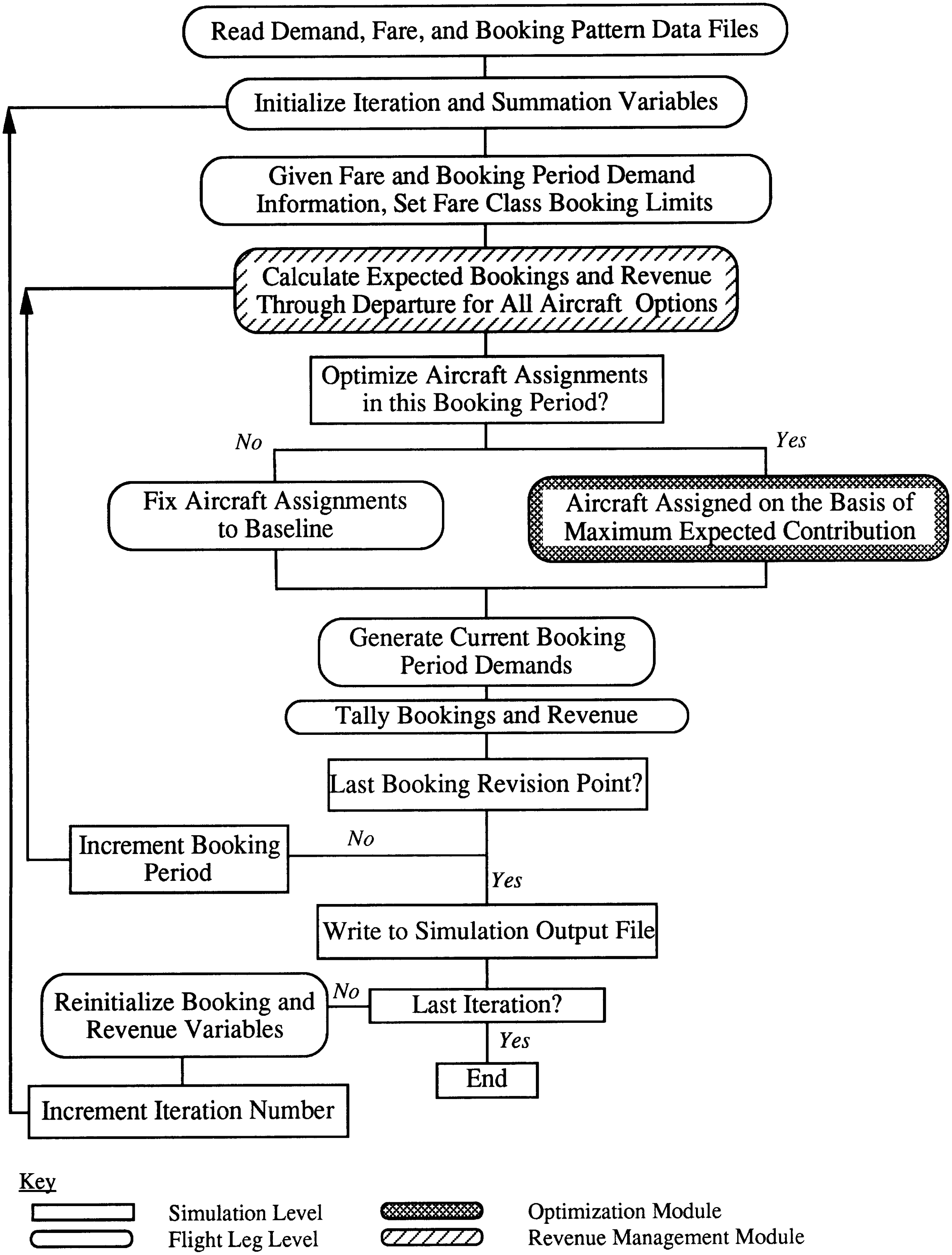
4.1 Simulation Overview

The simulation used to test the potential of demand driven dispatch under a variety of conditions is essentially composed of two separate functional modules, the revenue management module and the aircraft assignment module, which function independent of each other except during the exchange of data. Each module will be described in detail below. Before this is done, a flowchart of the integrated process (Figure 4.1) is presented.

Each simulation consists of a set of 200 iterations of the complete booking and assignment process. The number of iterations is a compromise between simulation run time (30 minutes per run on a multi-user VaxStation 9000) and data points needed to demonstrate statistical significance of results. As each iteration commences, the revenue management module at the initial booking revision point evaluates probabilistically the likelihood of passenger bookings by fare class and leg for the specified aircraft capacities for the entire booking process. Later revision points will subtract seats already filled from the various capacities.

With this information, initial booking limits are set and revenue estimates become available. Revenue management systems in general seek to maximize the revenue generated by passenger bookings by attempting to balance the opportunity cost of an empty seat which could have been sold to a low fare, discretionary passenger against the ability to offer a seat to high fare, non-discretionary customer who typically books closer to the departure date. It should be noted that the revenue management system does not attempt to fill each seat in the aircraft since this will not likely maximize revenue. A thorough explanation of the revenue management methodology used in this paper, Expected Marginal Seat Revenue (EMSR) can be found in Belobaba[7]. EMSR is a

Fig. 4.1: Flowchart of Demand Driven Dispatch Simulation



heuristic model for maximizing revenue on the flight leg level given nested fare classes. Briefly, the general concept of EMSR is that expected revenue is the product of the probability of the unconstrained passenger demand for a seat in a specific fare class and the fare associated with that seat. The example in Table 4.1 shows why holding a seat for

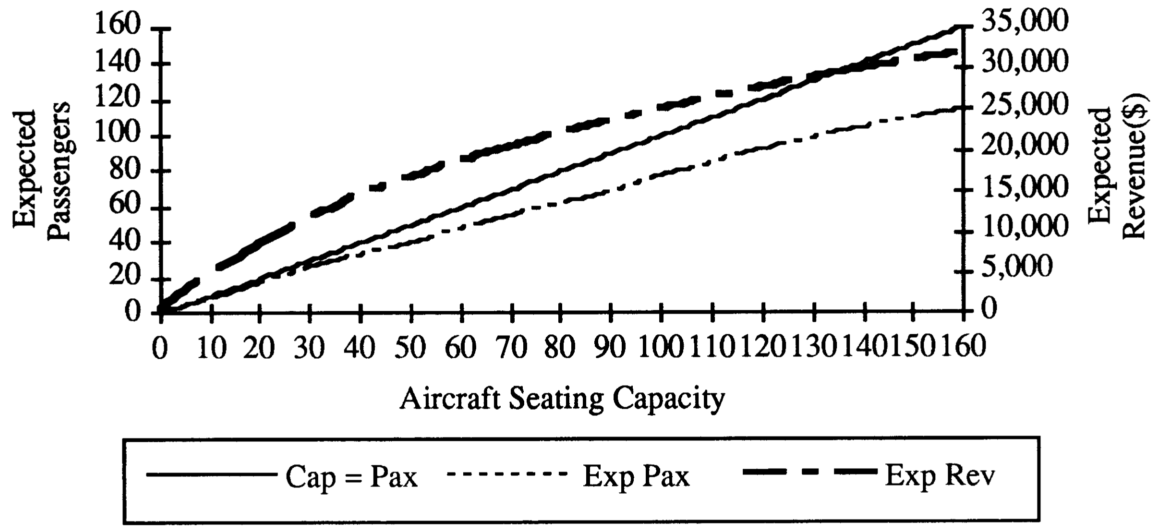
Table 4.1: Simple Revenue Management Example

	Passenger 1	Passenger 2
Booking Probability	0.20	0.80
Fare	$1000	$200
Expected Revenue	**$200**	**$160**

a passenger who is less likely to book could make sense from a revenue standpoint. Even though a particular seat held for Passenger 1 will remain empty 80% of the time, on average the airline will come out $40 ahead in revenue than if it sold the seat to Passenger 2. This example illustrates that it is not always obvious from which fare class the next most valuable expected revenue seat will come.

Costs of operating the different type of aircraft are then calculated considering performance characteristics of the aircraft (expected fuel burn for a flight leg based upon operating weights, block time) and the expected passenger load. Referring to the example in Figure 4.2, this latter figure will be always be less than the aircraft seating capacity. The magnitude of the difference will grow with aircraft size since the probability of booking successive passengers trends downward. The expected passenger curve is *not* smooth. While not obvious in Figure 4.2, it is actually quite jagged because the probability of a booking a passenger is not the dominant concern. Maximizing revenue is the goal. In contrast, Figure 4.2 shows that the derivative of the expected revenue line will always be negative, a direct result of the revenue management system prioritizing seats on the basis of revenue. Contributions to operating profit are then simply the difference between the expected revenues and costs. Variable costs for items like meals need not be included since they are the same regardless of the type of aircraft the passenger ultimately flies. They are also small enough in magnitude (a few dollars)

Figure 4.2: Expected Revenue and Passenger Load versus Aircraft Capacity



so that we can reasonably expect the revenue from any seat sold to cover them.

The next step in the process is the communication of the revenue and cost information to the optimization module. The optimization module within the bounds of a set of specified operational constraints then finds the aircraft assignment combination which is expected to maximize profit. Some of the studies which will be discussed later in the paper look at the effects on profits of "turning off" the optimal assignment module at different points in the booking cycle. A decision box modeling this option appears in the flowchart for this reason.

With booking limits set and aircraft assignments completed, the simulator proceeds to randomly generate passenger bookings based upon the probabilistic demands that have been fed into the revenue management model. The outcome statistics for events like seats booked, revenue earned, and demand spilled are then tabulated. The simulation then returns to the initial step of estimating demands for the remaining periods and so on. This loop will be executed at every booking revision point. When the final revision point is reached, the final statistics for the run are saved for post processing, the model is reset, and the next iteration commences.

4.2 Simulation Specifics

We have tried to simulate as realistically as possible the booking patterns, fare classes, fares, costs, etc. that one is likely to find in typical hub and spoke operation of a major airline. The revenue management module is an extension of the revenue management and booking process work done by Williamson[8]. The demand driven dispatch module was written specifically for this thesis. A comparison of characteristics between the revenue management model in this thesis and the one utilized by Boeing appears in Table 4.2. While the Boeing studies were designed to highlight general trends over an entire route network, this model has purposely been created to encompass more revenue management detail with the goal of characterizing parametric changes in demand driven dispatch performance in a hub and spoke network. The greater number of booking revision points and fare classes used in my revenue management module will assure that any discernible differences in profit will be largely attributable to the demand driven dispatch optimal assignment routine. With this level of resolution, EMSR revenue benefits will approach the possible maximum magnitude.[11] Because the booking process and fare class definitions more accurately reflect actual airline practice, the magnitudes of the numerical differences are also likely to be closer to what would be expected under realistic conditions.

A major feature of the Boeing model was the use of a continuously moving "planning window." The planning window extended one week into the future. In this concept the demand driven dispatch routine searches throughout the next seven days of the schedule for globally optimal switch opportunities and makes appropriate assignment changes. In this manner schedule feasibility will always be assured while permitting switching anywhere in the system.

Schedule feasibility in the demand driven dispatch version in this thesis is assured because the aircraft are on a daily cycle. While the flexibility of switching outside the hub is a nice feature, one should realize that both versions of demand driven dispatch are constrained in some way. In the Boeing version, future decisions are dependent upon previous decisions. The degree to which this is so depends upon the number of days between decisions. Given that a decision has been made for Day 1, the ability to optimally assign aircraft to maximize profit from Day 2 is somewhat compromised. The chances of having aircraft placed optimally for Day 10 operations are much better. In this model, the slate is wiped clean each day, but we contend with the same aircraft being assigned to the outbound and inbound leg.

As the number of legs the aircraft must fly before returning to the hub increases, the effectiveness of the thesis method decreases because of demand imbalance. Consider a plane which must fly to other cities beyond the initial spoke destination before returning the hub for the next connecting bank. The probability of one aircraft type being well-matched in terms of capacity to each of the legs is not high. For this reason, the aircraft itineraries in my simulation are restricted to fly only roundtrips between a hub and spoke. Even so, in all likelihood one would expect some demand imbalance even over a single roundtrip. Several of the scenarios to be examined in this thesis will address the demand imbalance issue. Unless an airline has an infinite supply of aircraft, a compromise on assignment flexibility will exist in every operational scheme in one form or another.

Finally, the Boeing model penalizes spill and denied boardings. Spill relates to the number of passengers whose requests for a specific fare could not be satisfied. Denied boardings occur as a consequence of flights being oversold or, in the case of demand driven dispatch, swapping a smaller aircraft for a larger aircraft on a leg whose bookings exceed the capacity of the smaller aircraft. The costs of spill and denied boardings are based upon things like lost revenue potential and passenger inconvenience. Quantifying these costs is a difficult and sometimes arbitrary exercise. The demand driven dispatch routine in this thesis does not take the costs of these two items into consideration when solving for the optimal assignment. Spill data will, however, be recorded, and the specific formulation of the assignment algorithm (See Explanation of Constraints in Section 4.2.4.2) precludes denied boardings.

Table 4.2: Comparison of Study Simulations

	Boeing Generic Case Study	MIT Hub and Spoke Model
Revenue Management Methodology	EMSR	EMSR
Assignment Time Frame	Planning Window	Daily Cycle
Booking Revision Points	3	10
Fare Classes	2	7
Spill	Penalized	Measured
Denied Boardings	Penalized	Not Allowed

4.2.1 Hub and Spoke Network

A daily cycle at a mythical Dallas-Fort Worth "in and out" connecting hub with 15 spokes will be assumed in all studies. Because the flight legs outbound from and inbound to the hub will be purposely constrained to be flown by the same set of physical aircraft, the number of required aircraft is equivalent to the number of spokes. This set of aircraft will be defined as the switching pool. The daily cycle begins during a connecting complex and not necessarily at a specific time of day. Because aircraft flying in hub networks often overnight in spoke cities, the daily cycle might be defined by the 24 hour period commencing at the 5 PM connecting complex as opposed to the time the airport opens in the morning. The simulation aircraft are Boeing 737s with an equal number (5) of each type assigned to the pool of aircraft available for switching. The passenger capacities for each aircraft in the series are shown in Table 4.3 The spoke cities were selected on the criteria that they have varied distances from the hub, and that operations with every member of the 737 family were possible. Baseline aircraft

Table 4.3: Aircraft Capacities

Aircraft	Capacity
737-300	128
737-400	148
737-500	108

assignments for both the outbound and inbound leg and flying distances are shown in Table 4.4. Baseline demands in these markets, which will be discussed later in Chapter 6, will be influenced by these assignments. This specific assignment combination attempts to evenly allocate aircraft types over the flight distances and will remain the same in all static scenarios. The static scenario simulations will be used for comparison with demand driven dispatch scenario simulations and are meant to represent the fixed assignment operations currently practiced by airlines.

Table 4.4: Spoke Cities and Baseline Assignments

Spoke City	Distance (Miles)	Baseline Assignment
Austin TX	183	737-500
San Antonio TX	246	737-300
Wichita KS	329	737-400
Albuquerque NM	569	737-500
Denver CO	645	737-300
Phoenix AZ	868	737-400
Mexico City MEX	935	737-500
Salt Lake City UT	988	737-300
Las Vegas NV	1050	737-400
San Diego CA	1171	737-500
Los Angeles CA	1235	737-300
Oakland CA	1457	737-400
San Francisco CA	1465	737-500
Portland OR	1616	737-300
Seattle WA	1660	737-400

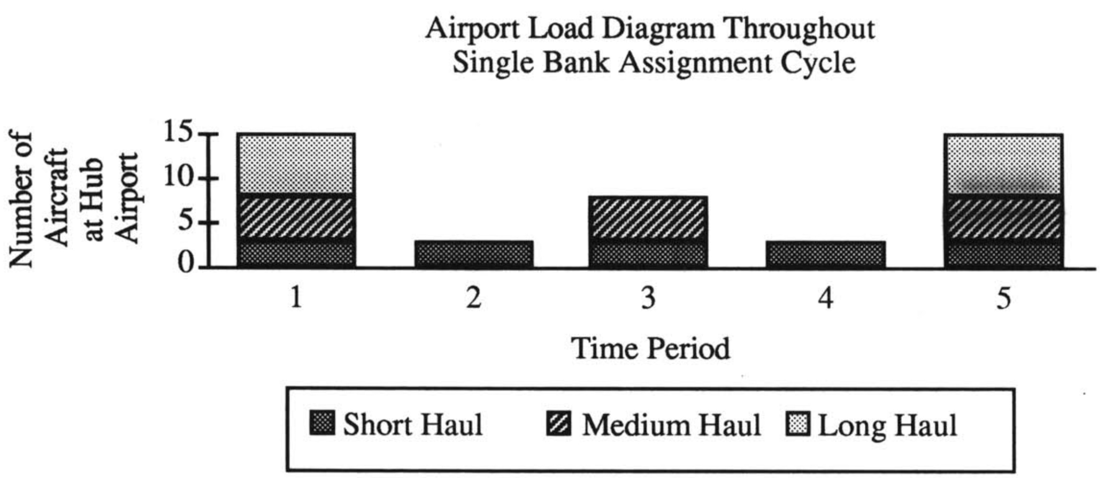
Because the flight legs in the base case vary greatly in distance, it is reasonable to expect that over the course of a daily cycle an airplane could fly more Dallas-Austin legs than Dallas-Seattle legs. This has been reflected in my model by weighting spoke city service frequency according to distance from the hub. Table 4.5 shows the classification of hub flight segment lengths into 3 general categories and the assumed daily cycle service

Table 4.5: Spoke Frequency Weighting Factors

Distance Category	Mileage Range	Number of Daily Frequencies
Short Haul	0 to 350	4
Medium Haul	350 to 1000	2
Long Haul	Over 1000	1

frequencies. The demand driven dispatch simulation studies done for this thesis only consider assignments made at the beginning of a daily cycle for the entire cycle. In the case of short haul and medium haul flights, each of the multiple flights are equivalent in the sense that the simulated demands are the same. Aircraft assignments were extended to cover all of the flights in multiple frequency markets over the daily cycle. In reality, it would be possible to consider aircraft switches at times of the day other than the when the full complement of aircraft are in place to execute the main connecting bank. Figure 4.3 shows the airport load diagram for our mythical hub. Each peak represents a demand

Figure 4.3: Load Diagram for Simulation Hub



driven dispatch opportunity for switching of aircraft. Swapping within these peaks would be desirable in order to avoid the problem discussed earlier where aircraft are assigned to many flight legs with non-uniform demands. As long as demand forecasts are available for each occasion of service in multiple frequency markets, swapping internal to the daily cycle can be readily written into the D^3 assignment routine.

4.2.2 Revenue Management Module

Since the revenue management module in this simulation functions largely independent of the aircraft assignment module, the simulation can be run with any revenue management methodology without modification. The EMSR nested leg heuristic was chosen because it has been widely discussed in academic literature, is used in many actual airline revenue management systems, and most importantly, was used in the Boeing studies. While D^3 performance might be better in concert with other revenue management methodologies, it is not the point of this study to search for an optimal match.

The specification of 10 booking limit revision points is similar to what is done in present revenue management systems. The spacing of the revision points is typically one week starting at 8 weeks before the flight with the exceptions to this pattern at the beginning and end of the process. The initial "revision" is on the day the flight becomes available for bookings (330 days before departure). The final revision usually occurs 3 days before the flight.

Passenger demands were generated assuming a Poisson arrival pattern. These demands are defined for each booking period which commences after fare class purchase limits have been set at the corresponding booking revision point. The Poisson arrival pattern allows for random arrivals (in this case requests by passengers for various fare class products) with the restriction that the mean arrival rate λ be specified. Also, the arrival events are independent of each other, and the probability of arrival in an interval Δt is proportional to Δt. Given these assumptions, it can be shown that the distribution of inter-arrival times is exponential[9]. The probability of n arrivals occurring in an interval of length t under these conditions is defined by[10]

$$P(n) = \frac{(\lambda t)^n e^{-\lambda t}}{n!} \qquad (n = 0,1,2,\ldots)$$

This distribution is the Poisson distribution. The use of the Poisson distribution in the simulation of a booking process is described in Williamson[8]. Information pertaining to the construction of the EMSR heuristic and its revenue impact can be found in Belobaba[7] and Mak[11].

4.2.3 Aircraft Costs and Performance Characteristics

Estimates of total block hour aircraft operating costs minus fuel for the 737 series of aircraft were provided by the Boeing Company. Fuel burn and flying times were estimated using performance curves from 737 Operations Manuals[12,13,14] with the following cruise condition assumptions:

- Long range cruise planning (M=.78)
- Flight Level 330
- Both engines operating
- Cabin air-conditioning on
- M=.74 climb and descent

Weight of an individual passenger with baggage is 200 lbs. The cost of a gallon of jet fuel is 0.70 USD. Block hours were determined by adding 30 minutes of taxiing time to flying time. Other aspects, like seating configuration, operator's empty weight, and engine model, were selected to represent the options most often requested by airline customers.

4.2.4 Aircraft Assignment Module

This is the key aspect of the demand driven dispatch scheme. Optimal assignment decisions were determined using output from the following linear program. In the current booking period p, we seek to

Maximize $C_{ij}x_{ij}$

$$\text{where } C_{ij} = \sum_{n=1}^{p} BKDREV_{jn} + \sum_{n=p+1}^{f} EXPREV_{ijn} - AC\_COST_{ij}$$

Subject to:

$$\sum_{j} x_{ij} = NAC_i \qquad (1)$$

$$\sum_{i} x_{ij} = 1 \qquad (2)$$

$$\sum_{i} CAP_i x_{ij} \geq BKDPAXO_j \qquad (3)$$

$$\sum_{i} CAP_i x_{ij} \geq BKDPAXI_j \qquad (4)$$

$$0 \leq x_{ij} \leq 1 \qquad (5)$$

i =1,2,3 and represents the three different aircraft types
j = 1,2,...,15 and represents the 15 spoke aircraft itineraries from the hub
n = 1,2,...,10 and represents the number of booking periods

where

C_{ij} is the contribution to profits expected with aircraft type i from flying out of and back to the hub on the spoke connecting hub with city j.

$BKDREV_{jn}$ is the booked revenue on the roundtrip legs on spoke j over the booking periods n = 1 to p. Booked revenue is equal to the sum of the fares paid by each booked passenger.

$EXPREV_{ijn}$ is the expected revenue figure from the revenue management system for the roundtrip on spoke j for an aircraft with capacity CAP_i from the next booking period n = p+1 to the final booking period n = f.

AC_COST_{ij} is the total aircraft operating cost for aircraft type i for the roundtrip on spoke j. AC_COST_{ij} is a function of aircraft performance characteristics, the price of fuel, weight of passengers (firm plus expected bookings) and baggage, and roundtrip flight mileage.

NAC_i is the number of aircraft type i in the switching pool

$BKDPAXO_j$ is the number of bookings on the hub to spoke city j leg

$BKDPAXI_j$ is the number of bookings on the spoke city j to hub leg

The decision variables x_{ij} are not specified as integer. However, because the linear programming formulation represents a balanced transportation problem, we are assured that the optimal solution will have integer values as long as the supplies and demands are integers[15]. This is indeed the case. The "supplies" are the numbers of each aircraft type, and the "demands" are the requirements that one aircraft be assigned to each flight leg.

4.2.4.1 Explanation of Decision Variable Coefficients

The decision variable coefficients C_{ij} reflect the total operating profit obtained from operating a specific aircraft type on the roundtrip legs. Since our model assumes that the same tail number aircraft must fly the inbound and outbound leg, the revenues and costs from the inbound and outbound leg can be collapsed into one variable. There are three components of the coefficient: the booked revenue for all previous periods for the number of passengers that have been booked on each leg, the expected revenue for the remaining periods for each aircraft type on each leg, and the cost of operating each aircraft type on each leg. Note that the BKDREV figure, which accounts for revenue for a specific leg accumulated in all previous booking periods, does not vary by aircraft type. Thus, if on a particular leg there are 130 passengers booked up to the current booking revision point, the corresponding BKDREV will be a component in the coefficient for the 108 seat 737-500 in the present aircraft swapping analysis. Constraints 3 and 4, however, preclude the 108 seat aircraft from being assigned to this particular set of inbound and outbound legs.

4.2.4.2 Explanation of Constraints

Constraint 1 specifies that each aircraft in the switching pool must be assigned. Constraint 2 prevents the assignment of more than one aircraft to an outbound/inbound itinerary. Constraints 3 and 4 forbid the assignment of an aircraft to a leg whose capacity is less than the number of bookings on both the outbound and inbound flights. The consequence of this is that denied boardings (i.e. overselling) is not allowed. While overbooking strategies were not used in this study, expanding the capability of the simulation to include this feature would simply require multiplying capacities at each booking revision point on each leg by an "overbooking factor" and adjusting bookings for cancellations.

4.2.5 Fares and Booking Patterns

Fares in each fare class were derived from flown revenue figures in each of the actual origin-destination markets. This data was provided to MIT by Delta Air Lines. The seven fare classes represent the range of fare products available in the coach cabin of the aircraft. In theory the fare levels are a function of mileage with prescribed discounts applied to fare classes in proportion to the level of restrictions. Twenty-one day advance purchase and Saturday night stay are examples of restrictions placed on the cheapest tickets. Flown revenue per passenger in a fare class often differs from the "formula" due to circumstances like competitive pressure or promotional programs. Booking patterns by fare class were also constructed based upon actual booking trends (See Chapter 5).

Generation of demands in the simulation via a Poisson process requires the definition of λ, the mean arrival rate. A Poisson random variable process has the property that $\lambda = \sigma^2$ where σ^2 is the variance. Obviously the mean arrival rate of booking requests in each period in each fare class on each leg should be equal to the similarly defined mean demand data μ used by the revenue management module ($\lambda = \mu$). Therefore, in order to have the revenue management module set fare class booking limits which faithfully reflect the random nature of the booking process, the variance of passenger booking arrivals must equal the mean demand.($\sigma^2 = \mu$) The point of this derivation is to show that once the demands are specified (forecasting from historical data), the use of a Poisson process for simulation implicitly fixes what the variance of the demands should be. If the actual variances differ greatly from the Poisson variances, then one should consider another probability distribution function to model the process.

Chapter 5: Practical Aspects of D^3 in a Hub Environment

5.1 Airline Reluctance in the United States

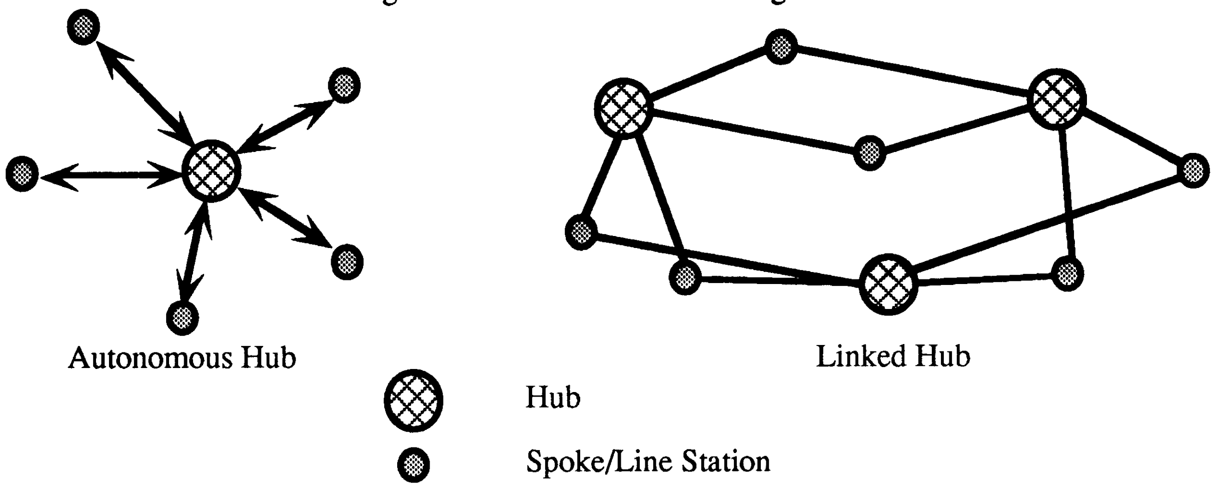
Though some major airlines in the United States have expressed interest in the D^3 philosophy, not a single one has yet incorporated D^3 into their daily operations. D^3 is clearly a radical idea, and part of the blame for its lack of acceptance has been a less than thorough evaluation by the airlines of the changeover and long term costs of running a D^3 assignment process relative to the fixed aircraft assignment mode. Berge and Hopperstad address the major issue of aircraft maintenance and conclude that multiple opportunities for maintenance would still exist in a D^3 environment. However, there are many other practicalities which must conform to D^3 without adverse effects on operating costs and passenger expectations. It is an all or nothing proposition as well. If a single aspect of the airline operation cannot be performed acceptably in a D^3 environment, then it is doubtful that an airline would ever implement the methodology. The necessary adaptations of current practices in fundamental operational areas which need to be made to allow for D^3 operations are the subject of the following section of the thesis.

5.2 Scheduling

At every point in the booking process the reservation and revenue management system must have knowledge of the number of seats on the aircraft which will be assigned to each flight leg. This condition also must be met by D^3 . Upon initial scrutiny, this condition seems to impose a difficult obstacle to the implementation of D^3. On the one hand we are saying that in a D^3 system the aircraft assignments are potentially changing at each booking revision point. However, at the same time, we must always know the complete set of available specific leg capacities. A simple way to bridge these two restrictions in a hub and spoke system is to create fixed switching pools of aircraft from which the D^3 decision tool can then assign optimally to flight legs.

Additionally, the exact composition of the pool (i.e. the number of each aircraft family member) must not vary from day to day. This suggests two basic tail routings (Figure 5.1) which I have termed the autonomous and linked hybrid hubs.

Figure 5.1: Hub Aircraft Routings

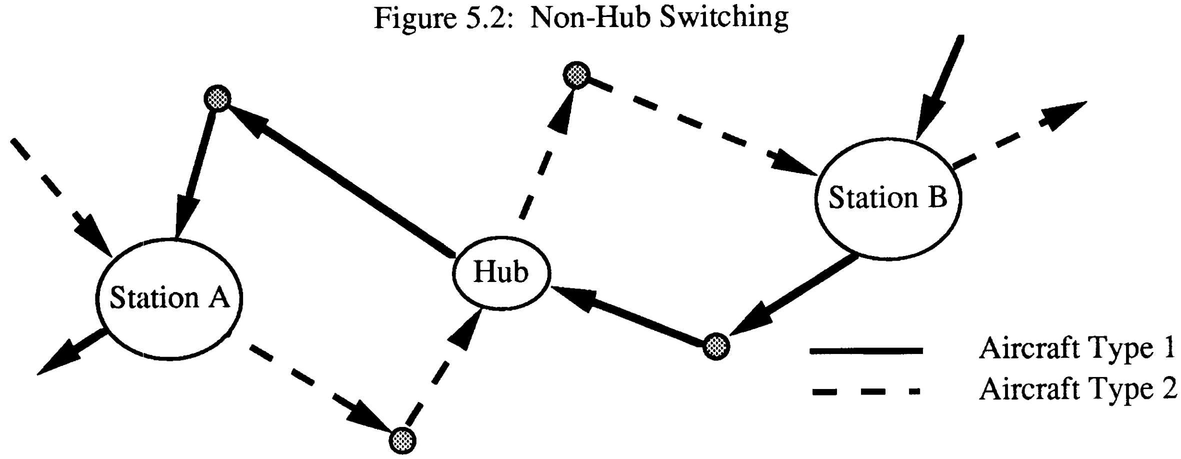


In the autonomous hub, specific tail numbers are assigned to the hub so that every 24 hours the *same* aircraft are collocated at the hub for possible assignment switches. In a linked hub system, identically composed pools of aircraft travel from hub to hub over the daily cycle. The principal benefit to this latter form is a flight schedule which will more likely meet marketing requirements for ideal arrival and departure times when the connecting banks through the hub serve short and long haul flights among city pairs spread across several time zones.

Today's major airline hub and spoke networks in the United States are actually a superimposition of the autonomous and linked concept. Therefore, running a D^3 system would in all likelihood require little alteration to current flight schedules. The ultimate extension of assignment flexibility for this model would be similar to the switching posed by Berge and Hopperstad. As stated earlier, their Boeing model allows for the possibility of switches anywhere in the route system, not just the hub. For the purpose of analyzing the impact of non-hub switching within the framework of this simulation, a constraint assuring that the composition of the pool of aircraft at the hub remain unchanged would still be required. Figure 5.2 shows an example of how this switching could be accomplished. At spoke station A aircraft types 1 and 2 are switched. In order to meet the composition restriction, the D^3 routine must also recommend a switch of types 1 and 2 at another station (B) in a way that the overall profit to the airline is still increased.

Of course the switches at stations A and B will force further switches at other spoke stations which must be feasible and profit enhancing. Spoke switching is a completely feasible activity at an airline today with the aid of the multitude of scheduling applications on the market. For readers interested in this aspect of the problem, Berge and Hopperstad discuss at length the complexity and associated practicalities of identifying switching opportunities over the entire route network.

Figure 5.2: Non-Hub Switching



The results in this report are based on an autonomous hub system. The autonomous hub was chosen because it is a reasonably simple introduction to D^3 and the order of magnitude of the payoff could be quickly quantified over a variety of demand characteristics. Airlines would probably seek to implement more complicated D^3 strategies once convinced of its worth.

5.3 Flight Crews

For each aircraft type in an airline's fleet, pilots bid on flights with priority given to those with the highest seniority. In D^3 there should be no major change to the trip bid process since the pilots can still fly their desired itineraries. The schedule will still be set well ahead of the departure date. However, as mentioned previously, there is a fundamental assumption being made with regard to this issue. Families of aircraft like the Boeing 737 carry similar type ratings. This means that pilots are legally allowed to fly any plane in the series without recurrent training or a familiarization check on a simulator. With D^3 it is possible that over the course of the day/trip the flight crew might end up flying each aircraft series several times but never fly the same series back to back. A potential safety concern might arise with continued exposure to slightly different aircraft handling characteristics and critical performance parameters like rotation, takeoff, and landing speeds. It is felt that this obstacle can be overcome since the aircraft in the 737 or any other family are by definition very similar. Also, adjusting to a new aircraft would not require additional pilot workload, just additional vigilance. This might even be a desirable action because changing aircraft types frequently might reduce the buildup over the day of complacency and fatigue which could result in operational mishaps.

5.4 Cabin Crew

This issue is actually more complicated than the flight crew issue since the FAA mandates the minimum number of cabin staff which must be assigned to an aircraft on the basis of passenger load and aircraft capacity. Under D^3 an airline might find itself in the situation where aircraft assignments are changed because of a surge of demand late in the booking process. Like pilots, flight attendants also bid on trips on the basis of seniority. Flight attendant union rules likely prohibit the last minute forced switching of personnel.

A way to avoid this situation is to extend itinerary bidding rights only to the number of most senior flight attendants needed to minimally staff all aircraft in the pool. Those attendants low in seniority would not have specific itinerary bid privileges but would be able to bid on itinerary lengths, dates, etc. With this system in place, these attendants could then be assigned as late as the day of the flight. Since the aircraft for a specific pool would be collocated at regular intervals, these "pool attendants" could be reassigned to other aircraft as necessary and would stay with the aircraft pool until it returned to a personnel switchout station (i.e. a major hub).

5.5 Ticketing/Seat Assignment

Since the exact seating layout for a flight might not be known until the day of departure under D^3, some consideration must be given to how seating assignments would be handled. A proposed solution requires the renumbering of aircraft rows so that a boarding pass sent to a passenger would remain valid regardless of when it was issued or of the final aircraft assignment. Seats would also have to be assigned to passengers from the rear section of the plane to the front. The desire to handle seat assignments in this manner can be explained with the help of the table below. In the initial stages of the booking process, it is possible that any of the three aircraft types could hold the current

Table 5.1: Alternative Row Numbering Scheme

Aircraft	Number of Rows	First Row Number	Last Row Number
737-400	25	1	25
737-300	21	5	25
737-500	18	8	25

assignment for a flight leg. In this situation no seat should be assigned with a row number less than 8. With each booking period aircraft assignments will be reevaluated and larger aircraft will be made available in most cases to those legs whose projected demand is greatest. When the number of passengers booked on a leg exceeds the minimum capacity of the smallest aircraft but is less than the largest aircraft, seat assignments can be made for rows 5 through 7. Assuming that bumping of passengers is not allowed, passengers assigned to rows 5 through 7 will always hold a valid boarding pass since it is not possible for their flight to be assigned the 737-500. The same argument holds once bookings for a flight exceed 128 (the capacity of the 737-300). Any passenger assigned a seat in rows 1 through 4 will know that the assigned aircraft cannot be any one other than the 737-400. On the other hand, a passenger assigned to a row higher than row 8 cannot predict in advance which aircraft from the 737 family will be assigned to his/her flight.

Booking from the rear of the aircraft also carries with it the advantage that passengers who book latest in the booking process, i.e. the high-yield passenger, will get a seat near the front of the aircraft. This creates a last-in, first-out situation which is considered desirable by the business traveler. However, in situations where a flight is being heavily overbooked, an airline would likely require seats to be assigned at the gate.

5.6 Ground Servicing

This aspect of operations will be largely unchanged with minor exceptions. In the case where specific aircraft are assigned to a single hub, the destination of the next flight leg for an aircraft at a spoke station will always be the hub. Since the aircraft type might vary from day to day, fueling requirements will be different. However, this is usually the case anyway because of variations in enroute weather, passenger load, etc. What will also be changing frequently is the aircraft destination beyond the hub. For example, on one occasion the aircraft will arrive at the hub as part of a connecting complex and depart for City A. The next day the final destination might be City B. To expedite passenger processing at the hub, it is advantageous to place bags going to the final destination at the rear of the cargo hold to minimize baggage handling time at the hub. Ground crews should be aware that the final destination, and thus the direct flight that the aircraft represents, will likely change on a daily basis. Thus, the switches that will be made at the hub must be known before the incoming flights depart.

In general, the communications structure of the airline's organization would have to be capable of quickly updating information systems and personnel on the multitude of changes likely to occur each day. This is not a major problem since airlines tend to be quite sophisticated in information systems technologies anyway. If a small airline is not capable of disseminating updated information to all its line stations, it probably also does not have the sophisticated revenue management technology and staff necessary to run in a D^3 environment.

5.7 A European Example

The non-overseas operations of many airlines in Europe are conducted in a manner analogous to the hub and spoke model described in this thesis. One airline, KLM, applies D^3 to their European network through their Amsterdam hub. The process KLM uses to identify switch opportunities is similar to that embodied in this simulation. Based on demand data from the revenue management system, certain legs are flagged for service by larger aircraft. Information on assignment recommendations is sent to the scheduling department with a list of possible replacement legs for the smaller aircraft.

In an interesting twist, KLM swaps assignments among 737-300s, 737-400s, and Airbus A310s. They do not operate 737-500s. Because of a restriction imposed by the airline's agreement with its pilots concerning itinerary changes, assignments must be fixed 10 days in advance of the flight. Itinerary changes occur in this case because the Boeing and Airbus aircraft do not carry similar pilot type ratings.

While results from D^3 have not been quantified, the fact that KLM has been using D^3 for some time must attest to their satisfaction. Even with the additional crew scheduling obstacle, KLM has demonstrated that D^3 operations are possible in an actual airline environment. Airlines in the United States should take notice.

Chapter 6: Outline of Study Scenarios

Two types of studies on the impacts of demand driven dispatch were conducted for this thesis. The first block of eight studies span a simulation matrix in three dimensions: load factor distribution, leg demand balance, and booking pattern. Within each dimension there are two assumption states which presents a total of $2^3 = 8$ combinations. Each of the studies compares results over a range of demand multipliers between a fully dynamic simulation (aircraft assignments evaluated in every booking period) to the corresponding static simulation where aircraft assignments are invariant. Demand multiplier and leg load factor are defined as

$$\text{Demand Multiplier} = \frac{\text{Scenario Demand}}{\text{Baseline Demand}}\text{, and}$$

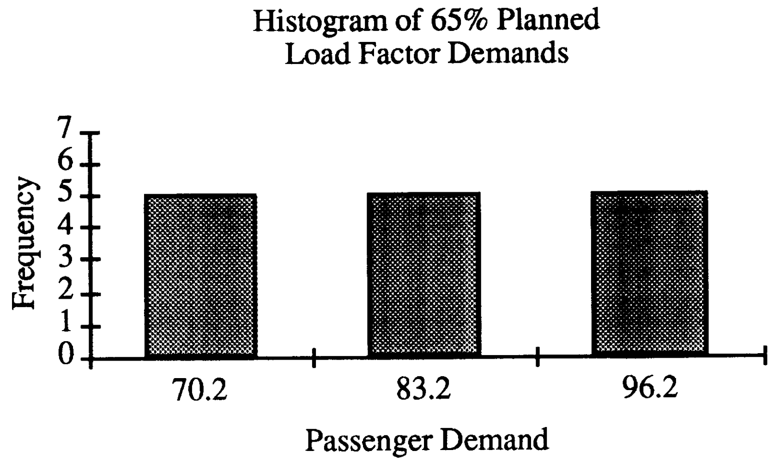
$$\text{Leg Load Factor} = \frac{\text{Bookings}}{\text{Capacity}}.$$

The other group of two studies look at the sensitivity of the demand driven dispatch process itself to varying the number of booking periods when aircraft assignments may be revised.

6.1 Dimension One: Load Factor

Average load factors (demand multiplier = 1.0) were selected to be 0.65, a representative annual average figure for U.S. airlines. This was modeled two ways. The first method assumes that a route planner is deciding among aircraft in the fleet which should serve a leg on the basis of achieving a load factor of 0.65. Working in reverse, the mean demands on a leg between the hub and the spoke were "found" to have values equal to 65% of the capacities of the three aircraft types. Assigning aircraft to the inbound and outbound flight itinerary could then simply be done by inspection. With five aircraft of each type, the demand distribution would have several peaks as shown in the histogram in Figure 6.1. The mean demand in this scenario is 0.65 * 128 = 83.2 passengers.

Figure 6.1: Planned Load Factor Alternative

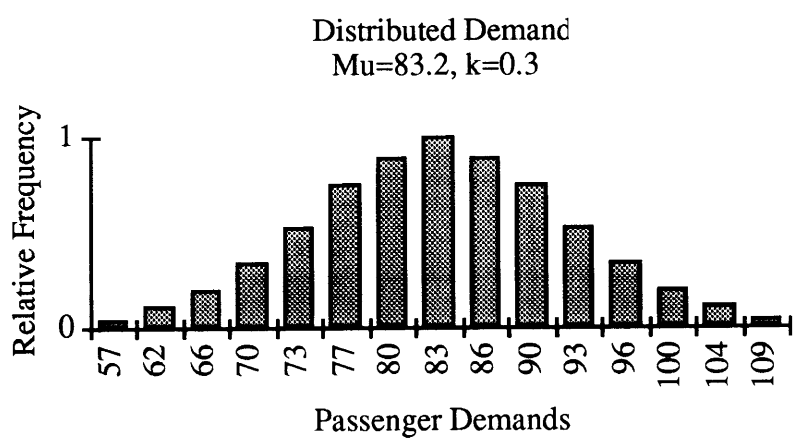


The second approach was to smooth out demand by assuming a normal distribution with the same mean as the first alternative of 83.2 and a k factor of 0.3 The k factor is defined as

$$\text{k factor} = \frac{\text{Standard Deviation}}{\text{Mean}}.$$

The 15 leg demands were created by selecting equally spaced probability percentiles along on the normal distribution curve between 15 and 85 percent. The distribution of demands in this instance would resemble Figure 6.2. Aircraft were assigned such that the smallest capacity 737 would fly the legs with the five lowest demands, the mid-sized 737

Figure 6.2: Distributed Load Factor Alternative



the legs with the next five larger demands, and the largest 737 the legs with the five greatest demands.

6.2 Dimension Two: Balance of Leg Demands

The baseline assumption for this study was to assume that the mean passenger demand on the leg from the hub to a particular spoke would be equal to the demand from that spoke city to the hub. This could be applicable to the situation where the daily cycle for aircraft assignments begins in the morning and ends in the evening of the same day. The level of demand for air travel during these periods is often markedly higher than at other times during the day. Because of the peaking characteristics shared by both time periods, the assumption that demand would be roughly equivalent over time on the basis of balance of flow considerations does not seem unreasonable. If the hub served many nearby markets (i.e. predominantly local traffic), one might expect this trend to be reinforced because of a commuter-type effect.

In other situations, the assumption of bi-directional demand equality might not hold. If the aircraft daily assignment cycle begins and ends in the middle of the day, there is not likely to be a consistent pattern of demand in each direction common to all market pairs, especially if they are separated by one or more time zones. Another argument against equal leg demands is that in a multi-hub network where much of the passenger traffic is connecting through the hub, there are several itinerary options connecting spoke cities. For example, if many passengers preferred for some reason to connect through Dallas on their way from Los Angeles to Boston and through Chicago on the return trip, the demand on the Los Angeles-Dallas leg might vary from the demand on the Dallas-Los Angeles leg.

There is also a day of the week effect. Consider a market where business travel predominates. Very few business trips are likely to be initiated Friday morning but a large number will likely conclude before the weekend. Thus, demand might be lower in the morning and higher in the evening relative to the average over the entire week.

In some sense there is probably a lot of "canceling out" of these effects, but the imbalance applicable to the situation modeled in this thesis is not likely to vanish completely. To examine what impacts the demand imbalance might have on demand driven dispatch, alternate demand data scenarios for the simulation were generated where the demand on one leg of a closed hub-spoke flight itinerary was increased by 10% and demand on the other leg was decreased by 10%. Because the same aircraft is constrained to fly both legs, it does not matter which leg demand is increased and which is suppressed.

6.3 Dimension Three: Booking Patterns

Booking patterns or curves describe the demand for fare class products over the booking process. If the overall percentage of passengers seeking a seat in fare class i is FC_i and the fraction of overall bookings which occur in fare class i in booking period j is PER_{ij}, then the demand DEM_{ij} for a particular fare class i in period j with a cabin level demand DEM is $DEM_{ij} = DEM \times FC_i \times PER_{ij}$. Two booking patterns, one which exemplifies a typical booking demand pattern on short and medium haul fights and another more representative of a booking pattern shifted closer to the date of departure, were chosen for the study. Tables 6.1 and 6.2 contain the percentage breakdowns of aggregate demand into fare class and booking period demand. Fare classes are arranged in descending order by fare. The accompanying Figure 6.3 shows the cumulative buildup of bookings over all fare classes throughout the booking process. One can observe in the late booking curve the noticeable shift of the curve to the right relative to the typical booking curve. This represents a difference in total bookings on a specific day before the departure of the flight.

Tables 6.1 and 6.2: Simulation Incremental Booking Curves

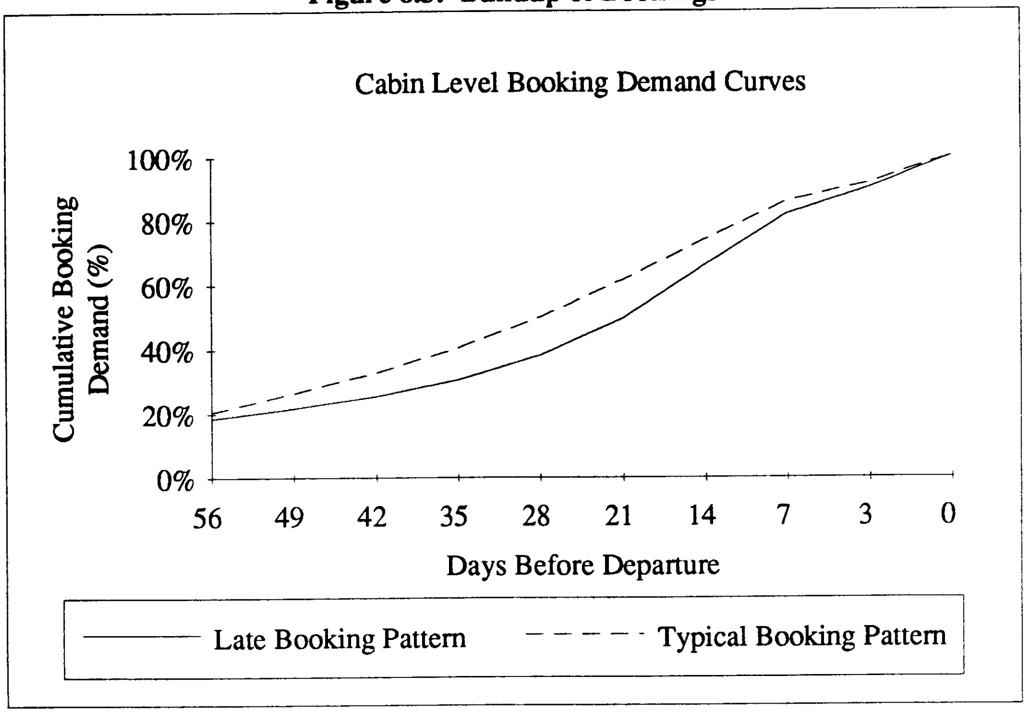
Table 6.1: Typical Booking Pattern

		Days Before Departure									
CLASS	***MIX***	**56**	**49**	**42**	**35**	**28**	**21**	**14**	**7**	**3**	**0**
Y	*0.12*	0.12	0.03	0.03	0.05	0.05	0.06	0.09	0.18	0.12	0.27
B	*0.24*	0.08	0.05	0.05	0.05	0.05	0.09	0.11	0.20	0.14	0.18
M	*0.10*	0.10	0.06	0.08	0.10	0.12	0.13	0.16	0.20	0.02	0.03
H	*0.02*	0.32	0.08	0.08	0.08	0.10	0.10	0.08	0.10	0.04	0.02
Q	*0.06*	0.36	0.09	0.09	0.08	0.10	0.10	0.08	0.06	0.02	0.02
K	*0.21*	0.24	0.05	0.05	0.08	0.12	0.15	0.17	0.06	0.04	0.04
L	*0.25*	0.22	0.06	0.06	0.09	0.12	0.18	0.20	0.02	0.03	0.02

Table 6.2: Late Booking Pattern

		Days Before Departure									
CLASS	***MIX***	**56**	**49**	**42**	**35**	**28**	**21**	**14**	**7**	**3**	**0**
Y	*0.10*	0.04	0.02	0.02	0.04	0.04	0.06	0.13	0.22	0.14	0.29
B	*0.26*	0.05	0.02	0.02	0.03	0.05	0.08	0.15	0.24	0.16	0.20
M	*0.07*	0.14	0.04	0.04	0.05	0.09	0.13	0.20	0.24	0.04	0.03
H	*0.02*	0.26	0.04	0.07	0.07	0.10	0.10	0.12	0.14	0.06	0.04
Q	*0.08*	0.39	0.05	0.05	0.05	0.06	0.08	0.12	0.10	0.06	0.04
K	*0.21*	0.20	0.02	0.03	0.05	0.09	0.18	0.21	0.10	0.06	0.06
L	*0.24*	0.21	0.04	0.04	0.06	0.09	0.17	0.24	0.06	0.05	0.04

Figure 6.3: Buildup of Bookings



Chapter 7: Presentation of Results

7.1 Raw Simulation Outputs

Tables 7.1 and 7.2 are examples of simulation output results for the scenario where demands are distributed and balanced, and a late booking pattern is assumed. Most of the items are self explanatory with the possible exception of the first five columns underneath Flight Leg Summary. From left to right, the columns show the airport codes for the origin and destination city and the number of daily roundtrips, the average capacity of the aircraft assigned to the flight leg over all iterations, and the number of assignments made to each aircraft type in the 200 iteration runs for the 737-500, 737-300, and 737-400. Table 7.1 is the static case where assignments are fixed. Therefore, each leg has only one aircraft type, the baseline aircraft type, assigned 200 times. Contrast this with the results on Table 7.2 The total number of assignments on each leg is 200, but the assignments on several legs are spread over more than one aircraft type. This spreading of aircraft assignments is the result of demand driven dispatch optimization efforts.

The leg designation of multiple aircraft types in our hub, or "swapping volatility" if you will, is actually not that high as it might first appear. Three city pairs (DFW-SAN, DFW-LAX, and DFW-LAS) have no swapping occurring whatsoever, and only four city pairs (DFW-PHX, DFW-SAT, DFW-SFO, and DFW-ICT) are ever assigned all three aircraft types. Maximum volatility would occur when each aircraft type is assigned to a leg 200/3 = 66 2/3 times. I would characterize a substantial level of swapping activity as the case where each aircraft type is assigned to a leg a minimum of 30 times. The swapping activity in the case shown in Table 7.2 is representative for what was seen in most other studies. Some studies did exhibit increased volatility on some legs, but averaged over the entire hub the activity levels were not remarkably high.

TABLE 7.1: DISTRIBUTED DEMANDS (MU=.65*128,SIGMA=.3*MU)/BALANCED/TYPICAL

SIMULATION SIZE: 200
DEMAND DISTRIBUTION: POISSON

LEG DEMANDS ADJUSTED BY 1.00
STANDARD DEVIATION FACTOR: 0.
NUMBER OF CAPACITY REVISIONS (0=EMSR): 0

MEAN REVENUE: 492979.16
MEAN FLIGHT COST: 219875.41
MEAN PROFIT: 273103.75
STD DEV ON MARGIN: 10578.20

	TOTAL	ONE LEG	TWO LEG
MEAN DEMAND:	4845.28	4845.28	0.
MEAN LOAD:	4845.24	4845.24	0.
MEAN SPILL:	0.04	0.04	0.
% SPILL:	0.00	0.00	0.

FLIGHT LEG SUMMARY:

	AVG	ASSIGNMENT			LOAD FACT	PAX LOAD	DEMAND	SPILL	YIELD
DFW-SAN(1)	108.	200	0	0	0.53	57.36	57.36	0.	12.87
DFW-LAX(1)	128.	0	200	0	0.60	76.25	76.25	0.	12.40
DFW-PDX(1)	128.	0	200	0	0.62	79.11	79.11	0.	10.88
DFW-AUS(4)	108.	200	0	0	0.58	62.29	62.29	0.	32.89
DFW-SEA(1)	148.	0	0	200	0.62	92.39	92.39	0.	9.98
DFW-LAS(1)	148.	0	0	200	0.64	95.39	95.39	0.	13.05
DFW-PHX(2)	148.	0	0	200	0.67	99.28	99.28	0.	13.51
DFW-SLC(2)	128.	0	200	0	0.65	83.67	83.67	0.	12.66
DFW-DEN(2)	128.	0	200	0	0.68	87.54	87.54	0.	16.47
DFW-SAT(4)	128.	0	200	0	0.71	90.99	91.00	0.01	24.17
DFW-ICT(4)	148.	0	0	200	0.70	103.97	103.98	0.01	22.61
DFW-MEX(2)	108.	200	0	0	0.63	67.55	67.55	0.	9.26
DFW-ABQ(2)	108.	200	0	0	0.64	69.50	69.50	0.	15.98
DFW-OAK(1)	148.	0	0	200	0.73	108.07	108.07	0.	10.90
DFW-SFO(1)	108.	200	0	0	0.68	73.83	73.83	0.	11.57
SAN-DFW(1)	108.	200	0	0	0.52	56.58	56.58	0.	12.88
LAX-DFW(1)	128.	0	200	0	0.60	76.97	76.97	0.	12.39
PDX-DFW(1)	128.	0	200	0	0.63	80.80	80.80	0.	10.83
AUS-DFW(4)	108.	200	0	0	0.57	61.90	61.90	0.	32.95
SEA-DFW(1)	148.	0	0	200	0.63	92.90	92.90	0.	10.00
LAS-DFW(1)	148.	0	0	200	0.65	95.65	95.65	0.	13.00
PHX-DFW(2)	148.	0	0	200	0.68	100.28	100.28	0.	13.46
SLC-DFW(2)	128.	0	200	0	0.65	82.81	82.81	0.	12.57
DEN-DFW(2)	128.	0	200	0	0.67	85.83	85.83	0.	16.55
SAT-DFW(4)	128.	0	200	0	0.70	89.43	89.43	0.	24.22
ICT-DFW(4)	148.	0	0	200	0.70	104.00	104.00	0.	22.51
MEX-DFW(2)	108.	200	0	0	0.62	67.11	67.11	0.	9.29
ABQ-DFW(2)	108.	200	0	0	0.65	70.21	70.21	0.	16.02
OAK-DFW(1)	148.	0	0	200	0.73	108.71	108.71	0.	10.96
SFO-DFW(1)	108.	200	0	0	0.68	73.26	73.26	0.	11.59

AVERAGE HUB LOAD FACTOR: 0.65
AVERAGE HUB YIELD: 14.22
UNIT AIRCRAFT COST: 4.13
AVERAGE REVENUE PER PAX: 101.75
AVERAGE REVENUE PER AVAILABLE SEAT: 66.76

HOURS: 737-500-> 6.60 737-300-> 7.30 737-400-> 7.33

TABLE 7.2: DISTRIBUTED DEMANDS (MU=.65*128,SIGMA=.3*MU)/BALANCED/TYPICAL

SIMULATION SIZE: 200
DEMAND DISTRIBUTION: POISSON

LEG DEMANDS ADJUSTED BY 1.00
STANDARD DEVIATION FACTOR: 0.
NUMBER OF CAPACITY REVISIONS (0=EMSR): 10

MEAN REVENUE: 492979.31
MEAN FLIGHT COST: 217708.09
MEAN PROFIT: 275271.22
STD DEV ON MARGIN: 10536.25

	TOTAL	ONE LEG	TWO LEG
MEAN DEMAND:	4845.28	4845.28	0.
MEAN LOAD:	4845.22	4845.22	0.
MEAN SPILL:	0.06	0.06	0.
% SPILL:	0.00	0.00	0.

FLIGHT LEG SUMMARY:

	AVG	ASSIGNMENT			LOAD FACT	PAX LOAD	DEMAND	SPILL	YIELD
DFW-SAN(1)	148.	0	0	200	0.39	57.36	57.36	0.	12.87
DFW-LAX(1)	148.	0	0	200	0.52	76.25	76.25	0.	12.40
DFW-PDX(1)	111.	163	37	0	0.71	79.11	79.11	0.	10.88
DFW-AUS(4)	120.	75	125	0	0.52	62.29	62.29	0.	32.89
DFW-SEA(1)	119.	83	117	0	0.78	92.39	92.39	0.	9.98
DFW-LAS(1)	148.	0	0	200	0.64	95.39	95.39	0.	13.05
DFW-PHX(2)	123.	54	142	4	0.81	99.28	99.28	0.	13.51
DFW-SLC(2)	108.	193	7	0	0.77	83.67	83.67	0.00	12.66
DFW-DEN(2)	121.	68	132	0	0.72	87.54	87.54	0.	16.47
DFW-SAT(4)	113.	142	57	1	0.81	91.00	91.00	0.	24.17
DFW-ICT(4)	127.	19	168	13	0.82	103.97	103.98	0.01	22.61
DFW-MEX(2)	108.	200	0	0	0.63	67.55	67.55	0.	9.26
DFW-ABQ(2)	147.	0	3	197	0.47	69.50	69.50	0.	15.98
DFW-OAK(1)	137.	0	106	94	0.79	108.07	108.07	0.	10.90
DFW-SFO(1)	136.	3	106	91	0.54	73.83	73.83	0.	11.57
SAN-DFW(1)	148.	0	0	200	0.38	56.58	56.58	0.	12.88
LAX-DFW(1)	148.	0	0	200	0.52	76.97	76.97	0.	12.39
PDX-DFW(1)	111.	163	37	0	0.73	80.80	80.80	0.	10.83
AUS-DFW(4)	120.	75	125	0	0.52	61.90	61.90	0.	32.95
SEA-DFW(1)	119.	83	117	0	0.78	92.90	92.90	0.	10.00
LAS-DFW(1)	148.	0	0	200	0.65	95.65	95.65	0.	13.00
PHX-DFW(2)	123.	54	142	4	0.82	100.28	100.28	0.00	13.46
SLC-DFW(2)	108.	193	7	0	0.77	82.81	82.81	0.	12.57
DEN-DFW(2)	121.	68	132	0	0.71	85.83	85.83	0.	16.55
SAT-DFW(4)	113.	142	57	1	0.79	89.43	89.43	0.	24.22
ICT-DFW(4)	127.	19	168	13	0.82	104.00	104.00	0.	22.51
MEX-DFW(2)	108.	200	0	0	0.62	67.11	67.11	0.	9.29
ABQ-DFW(2)	147.	0	3	197	0.48	70.21	70.21	0.	16.02
OAK-DFW(1)	137.	0	106	94	0.79	108.71	108.71	0.	10.96
SFO-DFW(1)	136.	3	106	91	0.54	73.26	73.26	0.	11.59

AVERAGE HUB LOAD FACTOR: 0.67
AVERAGE HUB YIELD: 14.22
UNIT AIRCRAFT COST: 4.18
AVERAGE REVENUE PER PAX: 101.75
AVERAGE REVENUE PER AVAILABLE SEAT: 68.45

HOURS: 737-500-> 8.05 737-300-> 7.15 737-400-> 6.03

7.2 Output Form Explanation

Output forms with data from the simulation scenarios are presented later in this chapter. Two graphs will accompany each scenario output form. These graphs highlight the effects of demand driven dispatch relative to the static simulations on two key parameters, the change in airline profit and utilization of the three types of aircraft. In the latter part of this chapter, the results of the dynamic sensitivity analysis are presented and explained.

The output forms have four separate blocks for displaying static base case data, demand driven dispatch data, absolute difference between demand driven dispatch data and static base case data, and percentile difference data. Formulations from which the data were calculated are outlined below.

- REVENUE is the average over all iterations and legs of the money earned throughout a complete booking process cycle from passenger bookings in each fare class multiplied by the respective fare.

- COST comes from the average flight operating costs for the hub over all iterations scaled to full total operating costs. Flight operating costs comprise about 45% of total operating costs with ground and system operating costs making up the difference[16]. The non-flying costs which were calculated for the static base case were also used to generate total costs in the demand driven dispatch case under the assumption that ground and system operating costs would not markedly change in demand driven dispatch operations.

- PROFIT equals REVENUE minus COST.

- SPILL (%) is the average over all iterations and legs of the percentage of passengers who desired to purchase a fare product but could not because either the aircraft had been filled or the booking limit for a fare class as recommended by the revenue management module had been reached.

- LOAD FACTOR equals RPMs divided by ASMs. RPMs is the average number of passengers on each leg multiplied by the leg mileage flown in each iteration. ASMs is the average number of seats on each leg multiplied by the leg mileage flown in each iteration. This is the definition of load factor at the network level.

- YIELD equals REVENUE divided by RPMs expressed in cents per passenger mile.

- UNIT COST equals COST divided by ASMs expressed in cents per available seat mile.

- UTILIZATION equals the average over all iterations of the number of hours flown by a single aircraft of each aircraft type during the execution of the schedule as represented by the frequency-weighted legs into and out of the hub

7.3 Significance Testing

The results were also tested for statistical significance. Specifically, the null and alternative hypotheses subjected to a difference of means testing are

$$H_0 : \overline{\mathrm{PROFIT}}_{\mathrm{static}} = \overline{\mathrm{PROFIT}}_{D^3} \qquad \text{and}$$

$$H_1 : \overline{\mathrm{PROFIT}}_{D^3} \geq \overline{\mathrm{PROFIT}}_{\mathrm{static}} .$$

The calculated test statistic for this test is[17]

$$C = K_{1-\alpha}\sqrt{\sigma^2_{\mathrm{static}}/n + \sigma^2_{D^3}/m}$$

where

$\overline{\mathrm{PROFIT}}$ is the average profit,

C is the constant chosen to reject H_0 if $\overline{\mathrm{PROFIT}}_{D^3}$ - $\overline{\mathrm{PROFIT}}_{\mathrm{static}}$ C to a specified significance level α,

$K_{1-\alpha}$ the value taken from the normal distribution table for a specified significance level α,

σ^2 the variance in the simulation of $\overline{\mathrm{PROFIT}}$, and

n,m the number of data points (simulation iterations). In all simulation runs n = m = 200.

The designated significance level for the scenario studies is 90%, and the corresponding $K_{1-\alpha}$ is 1.3.

7.4 Results

7.4.1 Results and Analysis of Scenario

- **65% Planned Load Factor**
- **Balanced Demands**
- **Typical Booking Pattern**

The level of added contribution from demand driven dispatch peaks at $2,379 per daily cycle at demand multiplier 1.0 and gradually declines over the range of demand multipliers (Figure 7.1.1). Significance testing to a 90% confidence level in this (and all other) cases requires a contribution difference of approximately $1500. Since all contribution differences above demand multiplier 1.2 fall below this level, no performance difference between the static and demand driven dispatch model can be statistically claimed at this significance level. Even so, the downward sloping trend in the Additional Profit versus Demand Multiplier graph are seems to fit expected behavior.

As demand is increased, the revenue management module sets lower booking limits for the lower yielding passengers because the opportunity to fill the aircraft with higher yielding passengers improves. As demand starts to spill, the simulation reaches the point where almost any seat still available can be sold to a high fare passenger. Also, the variability in demand on the legs where the demands are greatest is reduced relative to the other legs. Recall that the variance in demand in each fare class and booking period is equal to the mean of that demand. However, the spread in demand about the mean as signified by the k factor goes down as demand rises since the standard deviation is equal to the *square root* of the variance. Thus at higher demand multipliers the booking demands take on a more deterministic appearance with the largest demand legs approaching this state more rapidly than the others. The end result is that as overall variability in the hub is lowered, the static case aircraft assignments which were based on deterministic demands become increasingly attractive. With the demand driven dispatch assignments looking more and more like the static case assignments, the profit differential disappears.

Another result is that the role of revenues and costs in the composition of profit gains complete reverses over the range of demand multipliers. This can be seen in the D^3 Relative Difference data block. At lower demand multipliers, the model attempts to increase profits by reducing costs. There is really no other option since there is little demand spill in either the static base case or dynamics D^3 case, which means the revenue is going to be the same regardless of the aircraft assignments. As demand multipliers rise, note how D^3 attempts to increase revenue. At this point the high yield passenger demands are strong enough to allow the model to diminish in importance the smaller cost flight cost differences.

The data also offers a very important lesson on why financial statistics taken in isolation can be misleading. Every airline these days is rightfully talking about cutting costs. Unit cost is commonly used as the figure of merit in these exercises. Imagine a group of airline managers who are asked to evaluate whether to switch to demand driven dispatch operations solely on the basis of cost effectiveness. They are told that current unit costs are 8.26 ¢/ASM, and that under D^3 they would rise to 8.36 ¢/ASM. My guess is that a majority would choose to remain with the present fixed assignment system. If this were indeed the case, the majority would be wrong.

A paradoxical feature of a D^3 system is that it can reduce overall costs by increasing unit costs. This is accomplished by increasing the utilization of smaller, higher unit cost aircraft in situations where a larger aircraft cannot be filled. Overall costs are reduced because trip costs for smaller aircraft are generally lower than they are for larger aircraft. Figure 7.1.2 shows how the D^3 utilization of the 108 seat 737-500 goes up 1.5 hours per day (22.7%) relative to the static case. At the same time the D^3 utilization of the 148 seat 737-400 drops by almost the same number of hours -1.3 (18.1%). This trading of hours between these two aircraft will be seen in each of the eight case studies. As the demand multiplier rises, the bar graph of Figure 7.1.2 takes on the appearance of a damped system response as the utilizations slowly revert to those of the static case.

A positive differential in load factors in the D^3 simulations implies that smaller aircraft are being used on longer legs in situations of weaker than average demand. Since no passengers are being spilled at low demand multipliers, the number of revenue passenger miles is the same in the static and D^3 case. The only way that the overall hub load factors can rise in D^3 is if fewer seat miles are flown. This is accomplished where economically justifiable by having higher than average leg load factors on smaller aircraft on long legs and lower than average load factors on larger aircraft on short legs.

We have established that the \$2,379 contribution increase at demand multiplier 1.0 is statistically significant, but is it financially significant? The static run at demand multiplier 1.0 confirms that the cost and revenue models in the simulation are roughly correct in that it predicts a profit of only \$1,563 on revenues of \$490,170. Of course the results would have been more realistic if a loss had been shown. This happens in other scenarios. In this case, though, the \$2,379 represents an increased profit from one daily cycle of 152%! Since one daily cycle involves on average two roundtrips to the hub, it would probably be roughly equivalent to two connecting banks. Referring to average hub and spoke characteristics presented in Chapter 2, if we were to assume that an airline could operate 4 similar daily cycles D^3 per day of 30 aircraft each at 5 hubs, the direct scaled yearly revenue profit increase would be approximately \$35 million. While not a major windfall (about 0.3% of sales at an airline like American), this benefit can be achieved every year with low one time startup costs. Other harder to quantify benefits might be derived from more accurate demand forecasts.

At higher demand multipliers, the added contribution, even if it had remained at the \$2,379 level, does not amount to much. This is because the static case contribution is very high, equivalent to 32% return on sales.

Table 7.3: 65% Load Factor, Balanced Demands, Typical Booking Scenario

Base Case Actual Data

	Demand Multiplier 1.0	1.1	1.2	1.3	1.4	1.5
Revenue ($)	490,170	540,029	588,543	636,111	680,507	719,296
Operating Cost ($)	488,607	488,740	488,873	489,002	489,118	489,196
Contribution ($)	1,563	51,289	99,670	147,109	191,389	230,100
Spill (% Demand)	0.00	0.00	0.03	0.30	1.30	3.99
Load Factor	0.65	0.71	0.78	0.84	0.90	0.93
Yield (¢/RPM)	14.17	14.19	14.18	14.19	14.25	14.46
Unit Cost (¢/ASM)	8.26	8.26	8.26	8.26	8.26	8.26
Aircraft Utilization (Hours)						
737-300	7.3	7.3	7.3	7.3	7.3	7.3
737-400	7.3	7.3	7.3	7.3	7.3	7.3
737-500	6.6	6.6	6.6	6.6	6.6	6.6

D3 Actual Data

	Demand Multiplier 1.0	1.1	1.2	1.3	1.4	1.5
Revenue ($)	490,170	540,019	588,589	636,502	680,968	719,556
Operating Cost ($)	486,228	486,839	487,693	488,717	489,170	489,382
Contribution ($)	3,942	53,180	100,896	147,785	191,798	230,174
Spill (% Demand)	0.00	0.00	0.01	0.20	1.19	3.84
Load Factor	0.66	0.73	0.79	0.85	0.90	0.94
Yield (¢/RPM)	14.17	14.19	14.18	14.19	14.25	14.47
Unit Cost (¢/ASM)	8.36	8.32	8.32	8.30	8.30	8.30
Aircraft Utilization (Hours)						
737-300	7.1	7.6	7.4	7.2	7.2	7.2
737-400	6.0	6.1	6.7	7.2	7.4	7.4
737-500	8.1	7.5	7.2	6.8	6.6	6.6

D3 Difference Relative to Base Case

	Demand Multiplier 1.0	1.1	1.2	1.3	1.4	1.5
Revenue ($)	0	-10	46	391	461	260
Operating Cost ($)	-2,379	-1,901	-1,180	-285	52	186
Contribution ($)	2,379	1,891	1,226	676	409	74
Statistically Significant?	Yes	Yes	No	No	No	No
Spill (% Demand)	0	0	-0.02	-0.1	-0.11	-0.15
Load Factor	0.01	0.02	0.01	0.01	0.00	0.01
Yield (¢/RPM)	0	0	0	0	0	0.01
Unit Cost (¢/ASM)	0.1	0.06	0.06	0.04	0.04	0.04
Aircraft Utilization (Hours)						
737-300	-0.2	0.3	0.1	-0.1	-0.1	-0.1
737-400	-1.3	-1.2	-0.6	-0.1	0.0	0.1
737-500	1.5	0.9	0.6	0.2	0.0	0.0

D3 Percent Differences

	Demand Multiplier 1.0	1.1	1.2	1.3	1.4	1.5
Revenue	0.0%	0.0%	0.0%	0.1%	0.1%	0.0%
Operating Cost	-0.5%	-0.4%	-0.2%	-0.1%	0.0%	0.0%
Contribution	**152.2%**	**3.7%**	**1.2%**	**0.5%**	**0.2%**	**0.0%**
Spill	0.0%	0.0%	-66.7%	-33.3%	-8.5%	-3.8%
Load Factor	1.5%	2.8%	1.3%	1.2%	0.0%	1.1%
Yield	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%
Unit Cost	1.2%	0.7%	0.7%	0.5%	0.5%	0.5%
Aircraft Utilization (Hours)						
737-300	-2.7%	3.4%	1.1%	-1.2%	-1.2%	-1.6%
737-400	-18.1%	-16.0%	-8.9%	-1.5%	0.7%	1.8%
737-500	22.7%	13.9%	8.6%	3.0%	0.6%	-0.3%

Figure 7.1.1

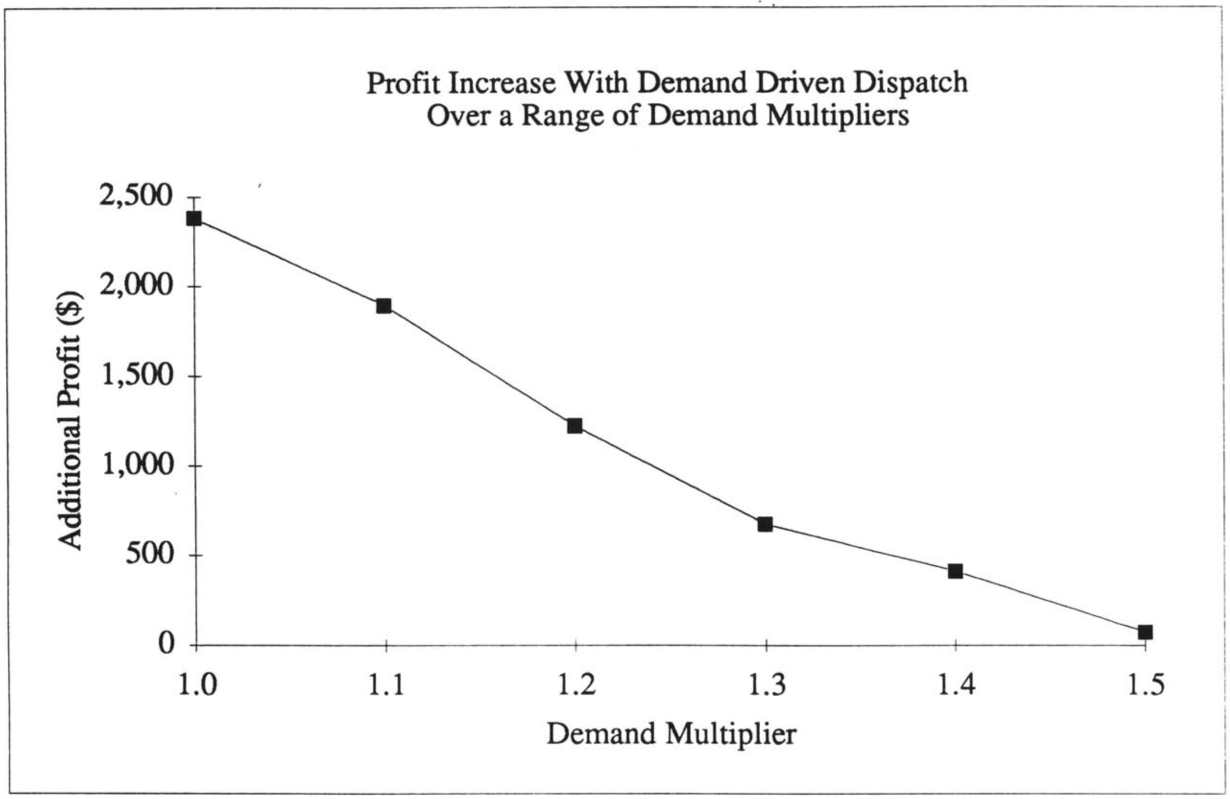
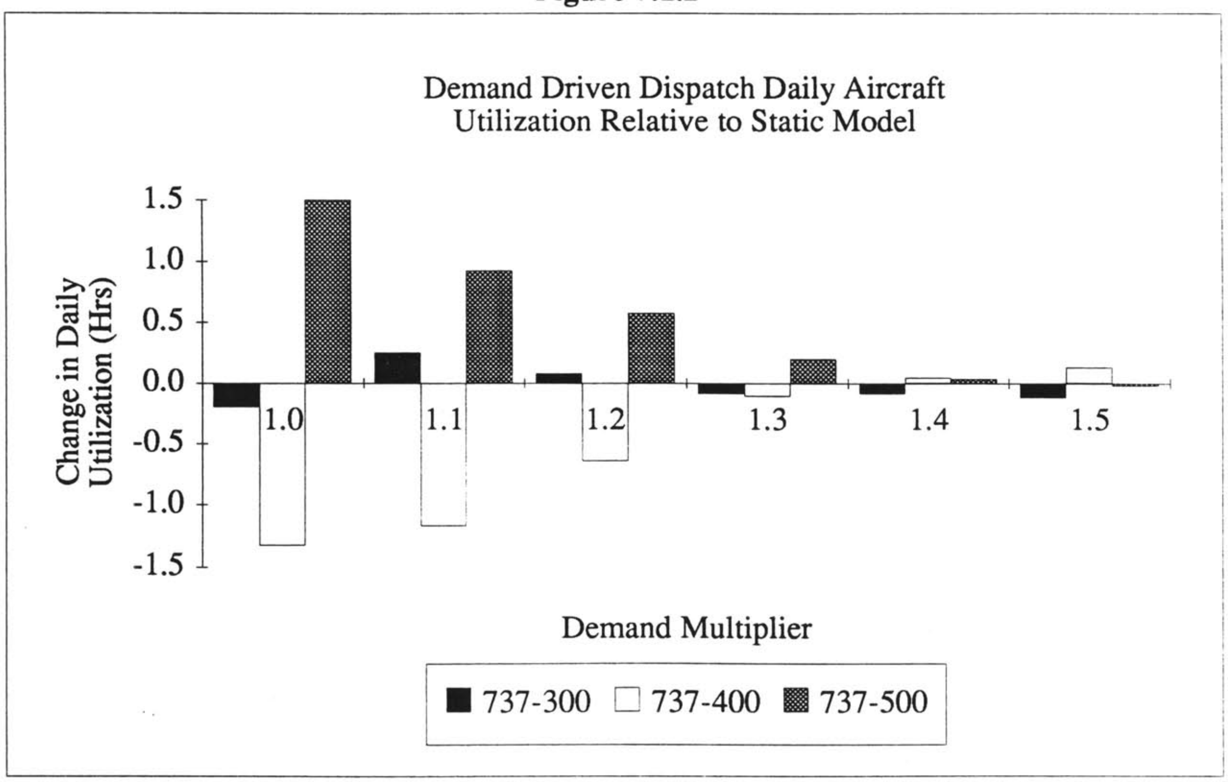


Figure 7.1.2



7.4.2 Results and Analysis of Scenario

- **65% Planned Load Factor**
- **Unbalanced Demands**
- **Typical Booking Pattern**

This is the first scenario where the demands in each fare class on one hub-spoke leg were increased by 10% and reduced by 10% on the return leg. Each hub and spoke leg pair is still balanced in terms of overall passenger demand, but the total expected revenue from the booking process will be different because variability changes which will impact revenue management booking limits. It was initially anticipated that this might be a favorable set of conditions for the D^3 model given the relatively high spillage occurring at high demand multipliers. Yet the results were quite similar to the planned load factor, balanced demand, typical booking pattern case. The proposed explanation is that as demand multipliers are increased, the legs with the higher demands begin to overshadow the decreased demand legs in terms of revenue opportunities. Instead of 15 sets of inbound and outbound legs of equal weight, the coefficients for expected contribution become dominated by the 15 increased demand legs.

This being the case, the same downward sloping trend in contribution differential as a function of demand multiplier (Fig 7.2.1) as seen in the balanced leg demand scenario since the 10% factor is uniformly applied to all legs. Aircraft utilization patterns are also similar.

Table 7.4: 65% Load Factor, Unbalanced Demands, Typical Booking Scenario

Base Case Actual Data

	Demand Multiplier					
	1.0	1.1	1.2	1.3	1.4	1.5
Revenue ($)	492,154	541,212	591,132	636,525	677,300	714,296
Operating Cost ($)	488,611	488,747	488,880	489,000	489,091	489,160
Contribution ($)	3,543	52,465	102,252	147,525	188,209	225,136
Spill (% Demand)	0.00	0.02	0.19	1.09	3.01	6.18
Load Factor	0.65	0.72	0.78	0.84	0.88	0.92
Yield (¢/RPM)	14.19	14.18	14.21	14.24	14.4	14.62
Unit Cost (¢/ASM)	8.26	8.26	8.26	8.26	8.26	8.26
Aircraft Utilization (Hours)						
737-300	7.3	7.3	7.3	7.3	7.3	7.3
737-400	7.3	7.3	7.3	7.3	7.3	7.3
737-500	6.6	6.6	6.6	6.6	6.6	6.6

D3 Actual Data

	Demand Multiplier					
	1.0	1.1	1.2	1.3	1.4	1.5
Revenue ($)	492,169	541,255	591,478	637,247	677,675	714,623
Operating Cost ($)	486,417	487,214	488,296	488,949	489,161	489,297
Contribution ($)	5,752	54,041	103,182	148,298	188,514	225,326
Spill (% Demand)	0.01	0.01	0.09	0.90	2.97	6.01
Load Factor	0.67	0.73	0.79	0.84	0.89	0.92
Yield (¢/RPM)	14.19	14.18	14.2	14.24	14.4	14.62
Unit Cost (¢/ASM)	8.34	8.32	8.30	8.30	8.30	8.30
Aircraft Utilization (Hours)						
737-300	7.3	7.5	7.4	7.2	7.3	7.2
737-400	6.0	6.4	7.0	7.3	7.3	7.4
737-500	7.9	7.4	6.9	6.7	6.6	6.6

D3 Difference Relative to Base Case

	Demand Multiplier					
	1.0	1.1	1.2	1.3	1.4	1.5
Revenue ($)	15	43	346	722	375	327
Operating Cost ($)	-2,194	-1,533	-584	-51	70	137
Contribution ($)	2,209	1,576	930	773	305	190
Statistically Significant?	Yes	Yes	No	No	No	No
Spill (% Demand)	0.01	-0.01	-0.1	-0.19	-0.04	-0.17
Load Factor	0.02	0.01	0.01	0.00	0.01	0.00
Yield (¢/RPM)	0	0	-0.01	0	0	0
Unit Cost (¢/ASM)	0.08	0.06	0.04	0.04	0.04	0.04
Aircraft Utilization (Hours)						
737-300	0.0	0.2	0.1	-0.1	0.0	-0.1
737-400	-1.3	-0.9	-0.3	0.0	0.0	0.1
737-500	1.3	0.8	0.3	0.1	0.0	0.0

D3 Percent Differences

	Demand Multiplier					
	1.0	1.1	1.2	1.3	1.4	1.5
Revenue	0.0%	0.0%	0.1%	0.1%	0.1%	0.0%
Operating Cost	-0.4%	-0.3%	-0.1%	0.0%	0.0%	0.0%
Contribution	**62.4%**	**3.0%**	**0.9%**	**0.5%**	**0.2%**	**0.1%**
Spill	0.0%	-50.0%	-52.6%	-17.4%	-1.3%	-2.8%
Load Factor	3.1%	1.4%	1.3%	0.0%	1.1%	0.0%
Yield	0.0%	0.0%	-0.1%	0.0%	0.0%	0.0%
Unit Cost	1.0%	0.7%	0.5%	0.5%	0.5%	0.5%
Aircraft Utilization (Hours)						
737-300	0.0%	2.3%	1.0%	-1.8%	-0.4%	-1.6%
737-400	-18.1%	-12.3%	-4.1%	0.0%	0.0%	1.8%
737-500	19.7%	12.1%	4.5%	1.5%	0.0%	-0.3%

Figure 7.2.1

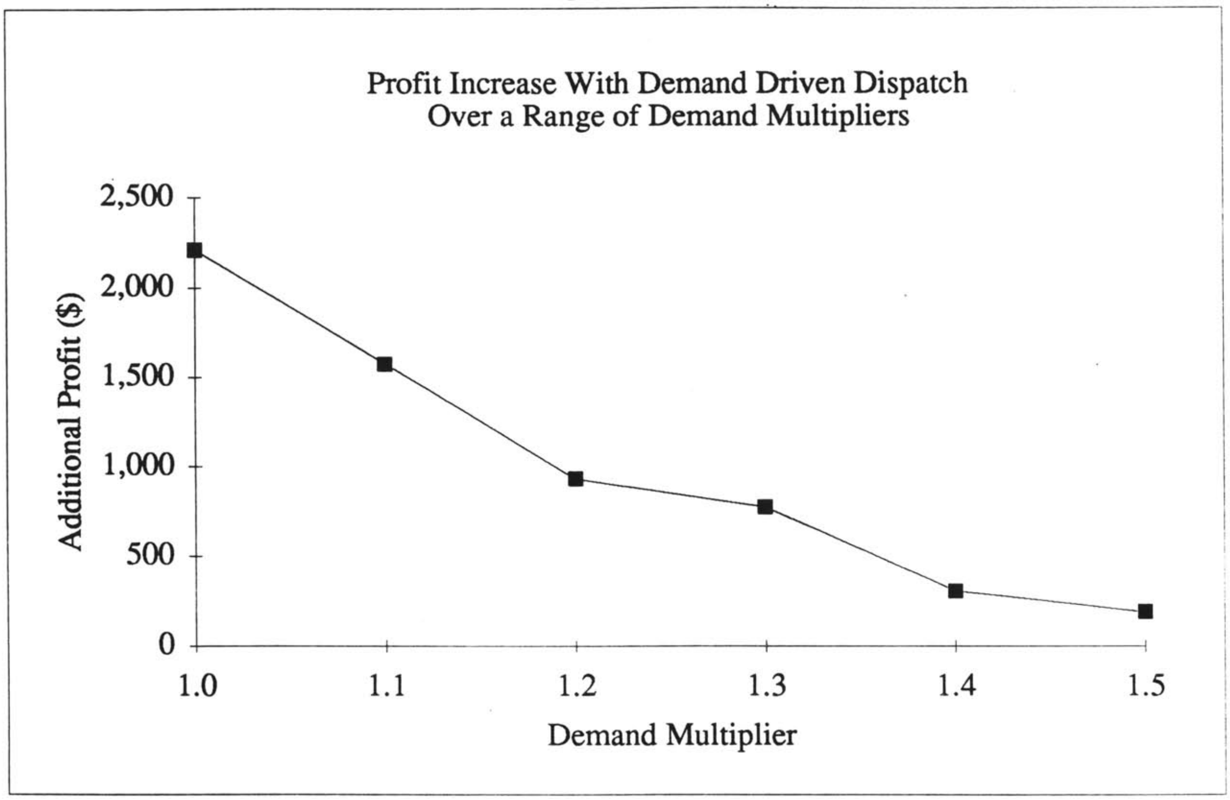
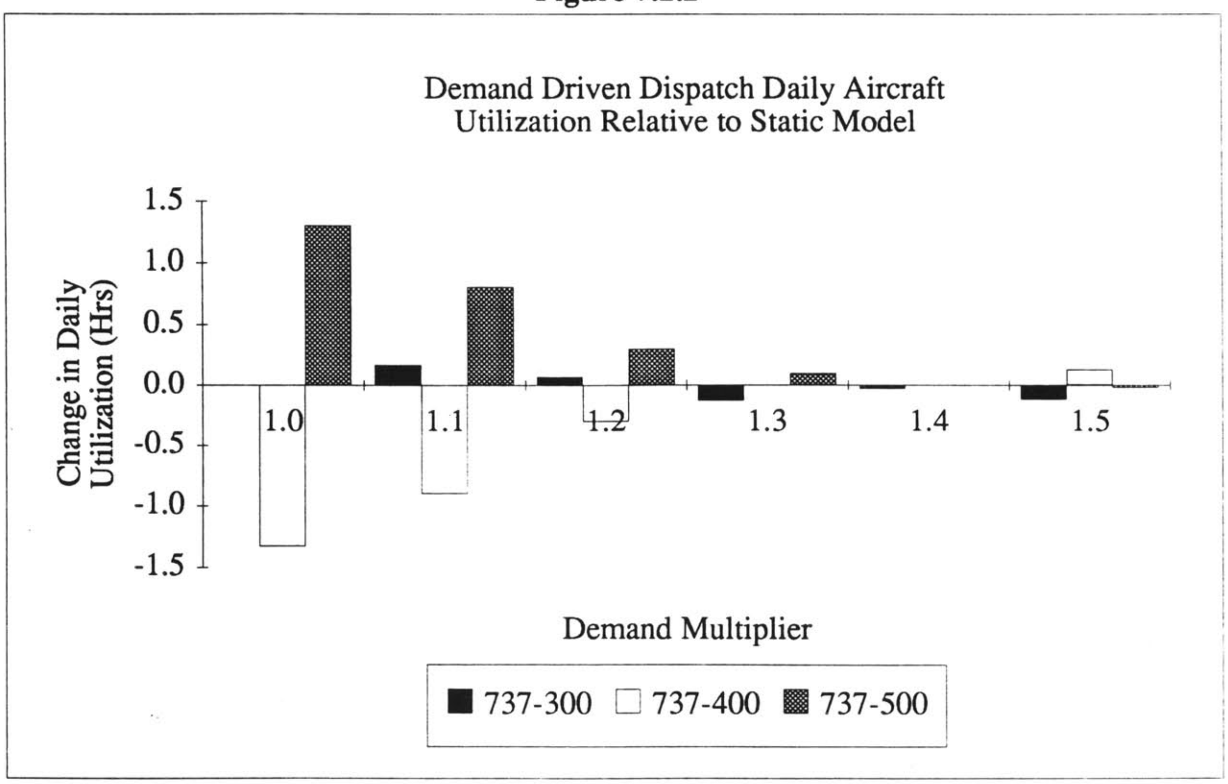


Figure 7.2.2



7.4.3 Results and Analysis of Scenario

- **Distributed Load Factor**
- **Balanced Demands**
- **Typical Booking Pattern**

The magnitude of the results from this scenario (demand multiplier =1.0) are similar to those in the planned load factor case. There are couple of new trends which do emerge. Most noticeable is the upturn in added contribution that takes place at demand multipliers beyond 1.3 (Figure 7.3.1). Again, the data are not statistically different from the static case to the 90% level of significance. It would probably be possible to demonstrate significance at higher demand multipliers with something like a pair wise t-test, but the magnitudes of the contributions are so small as to be nearly inconsequential. Yet there does seem to be an explanation for the behavior of the curve. At demand multiplier =1.5, the D^3 version is spilling 12% fewer passengers. Overall spill in the distributed demand pattern is higher than the planned load factor demand model because the load factors of some flights at demand multiplier 1.0 are already in the 80% range. Thus, significant spill will start appearing at lower demand multipliers.

The contribution difference at the higher demand multipliers is derived mostly from revenue gains from the additional number of passengers booked. The operating costs with D^3 are actually higher than those in the equivalent static case.

Table 7.5: Distributed Loads, Balanced Demands, Typical Booking Scenario

Base Case Actual Data

	Demand Multiplier					
	1.0	1.1	1.2	1.3	1.4	1.5
Revenue ($)	492,979	542,934	592,099	638,880	682,125	717,596
Operating Cost ($)	488,611	488,747	488,880	489,002	489,107	489,173
Contribution ($)	4,368	54,187	103,219	149,878	193,018	228,423
Spill (% Demand)	0.00	0.01	0.09	0.69	2.42	5.89
Load Factor	0.65	0.72	0.78	0.84	0.89	0.92
Yield (¢/RPM)	14.22	14.23	14.23	14.26	14.37	14.58
Unit Cost (¢/ASM)	8.26	8.26	8.26	8.26	8.26	8.26
Aircraft Utilization (Hours)						
737-300	7.3	7.3	7.3	7.3	7.3	7.3
737-400	7.3	7.3	7.3	7.3	7.3	7.3
737-500	6.6	6.6	6.6	6.6	6.6	6.6

D3 Actual Data

	Demand Multiplier					
	1.0	1.1	1.2	1.3	1.4	1.5
Revenue ($)	492,979	542,918	592,199	639,402	682,956	719,059
Operating Cost ($)	486,444	487,123	488,090	488,990	489,230	489,448
Contribution ($)	6,535	55,795	104,109	150,412	193,726	229,611
Spill (% Demand)	0.00	0.01	0.06	0.51	2.04	5.17
Load Factor	0.67	0.73	0.79	0.85	0.90	0.93
Yield (¢/RPM)	14.22	14.23	14.23	14.26	14.4	14.61
Unit Cost (¢/ASM)	8.36	8.34	8.34	8.32	8.32	8.32
Aircraft Utilization (Hours)						
737-300	7.1	7.4	7.2	7.3	7.4	7.3
737-400	6.3	6.3	6.8	7.2	7.2	7.3
737-500	8.0	7.6	7.2	6.7	6.6	6.6

D3 Difference Relative to Base Case

	Demand Multiplier					
	1.0	1.1	1.2	1.3	1.4	1.5
Revenue ($)	0	-16	100	522	831	1,463
Operating Cost ($)	-2,167	-1,624	-790	-12	123	275
Contribution ($)	2,167	1,608	890	534	708	1,188
Statistically Significant?	Yes	Yes	No	No	No	No
Spill (% Demand)	0	0	-0.03	-0.18	-0.38	-0.72
Load Factor	0.02	0.01	0.01	0.01	0.01	0.01
Yield (¢/RPM)	0	0	0	0	0.03	0.03
Unit Cost (¢/ASM)	0.1	0.08	0.08	0.06	0.06	0.06
Aircraft Utilization (Hours)						
737-300	-0.2	0.1	-0.1	0.0	0.1	0.0
737-400	-1.0	-1.0	-0.5	-0.1	-0.1	0.0
737-500	1.4	1.0	0.6	0.1	0.0	0.0

D3 Percent Differences

	Demand Multiplier					
	1.0	1.1	1.2	1.3	1.4	1.5
Revenue	0.0%	0.0%	0.0%	0.1%	0.1%	0.2%
Operating Cost	-0.4%	-0.3%	-0.2%	0.0%	0.0%	0.1%
Contribution	**49.6%**	**3.0%**	**0.9%**	**0.4%**	**0.4%**	**0.5%**
Spill	0.0%	0.0%	-33.3%	-26.1%	-15.7%	-12.2%
Load Factor	3.1%	1.4%	1.3%	1.2%	1.1%	1.1%
Yield	0.0%	0.0%	0.0%	0.0%	0.2%	0.2%
Unit Cost	1.2%	1.0%	1.0%	0.7%	0.7%	0.7%
Aircraft Utilization (Hours)						
737-300	-2.7%	1.0%	-1.8%	-0.4%	1.0%	-0.4%
737-400	-14.1%	-13.7%	-6.8%	-1.4%	-1.4%	0.0%
737-500	21.2%	15.2%	9.1%	1.5%	0.0%	0.0%

Figure 7.3.1

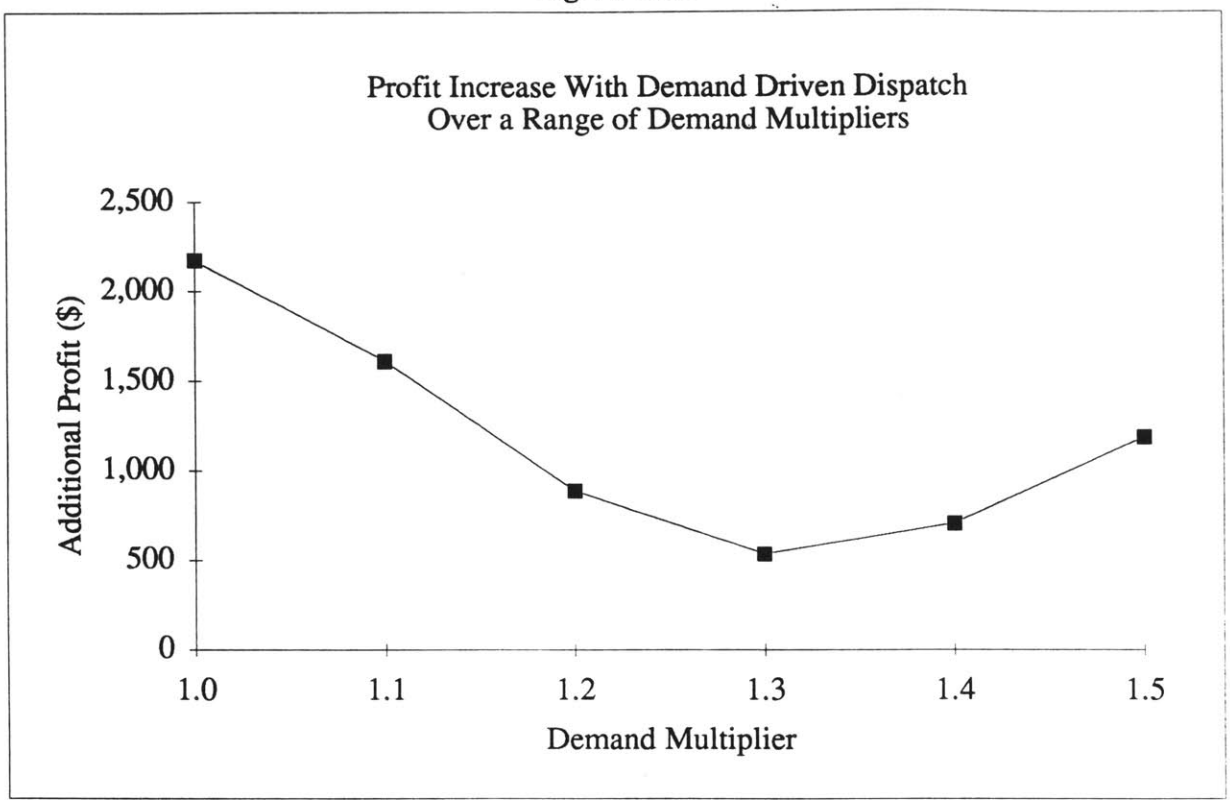
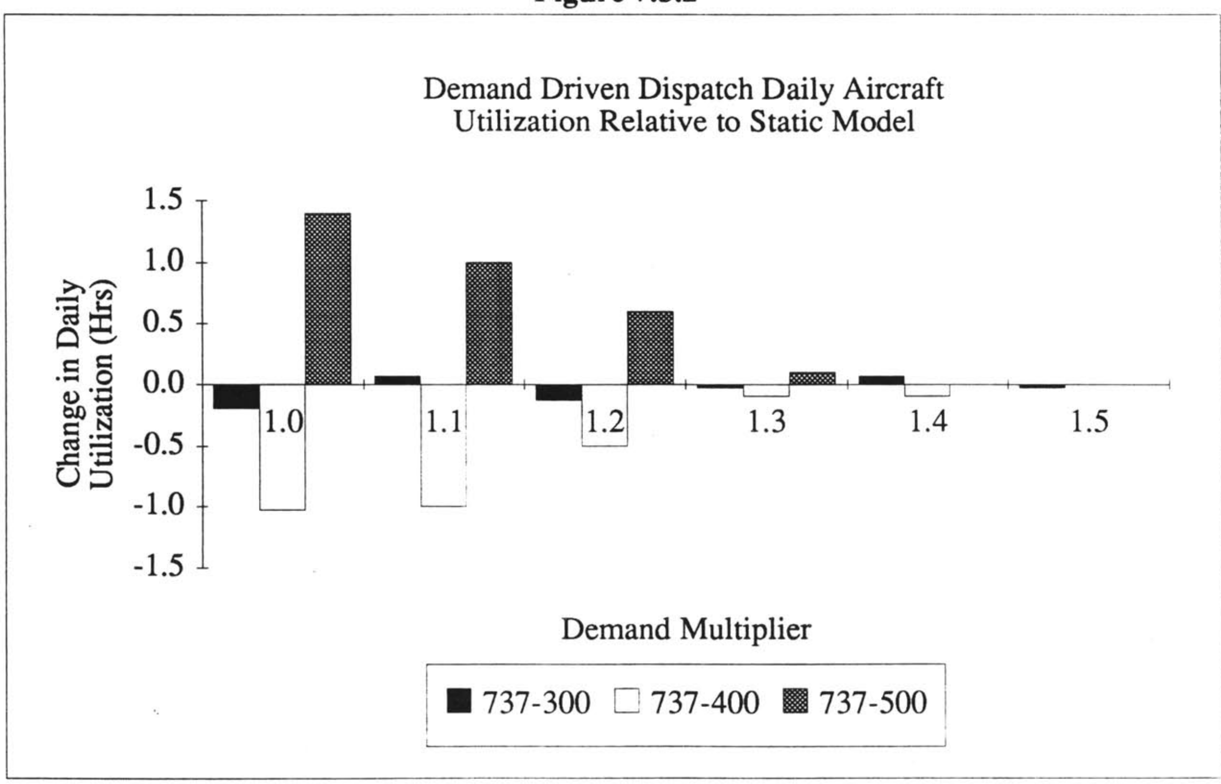


Figure 7.3.2



7.4.4 Results and Analysis of Scenario • Distributed Load Factor • Unbalanced Demands • Typical Booking Pattern

Any major deviation in the pattern of results in this scenario could be of interest since the distributed load factor and unbalanced demand combination is likely to be what would be encountered to some extent in actual airline operations. The contribution at demand multiplier 1.0 is lower (\$1961 versus about \$2200) than in other cases. This would lead to a smaller yearly profit increase than calculated in Section 7.4.1. The magnitude of the difference in aircraft utilization of the 737-500 is also smaller (1.2 versus 1.5 in planned load factor, balanced demands), a good indicator of lessened D^3 impact.

In other scenarios, graphs of Contribution Difference versus Demand Multiplier displayed either a roll-off with unbalanced demands or increase with distributed loads at high demand multipliers. What is seen in Figure 7.4.1 is a complete flattening out of the curve. This suggests that the effects of unbalanced demand and distributed load are largely independent and of similar magnitude to roughly cancel each other out. Thus, even at high demand multipliers, demand driven dispatch will still deliver some incremental benefit.

Table 7.6: Distributed Loads, Unbalanced Demands, Typical Booking Scenario

Base Case Actual Data

	Demand Multiplier 1.0	1.1	1.2	1.3	1.4	1.5
Revenue ($)	496,040	544,175	592,828	638,650	678,487	716,722
Operating Cost ($)	488,618	488,749	488,878	488,993	489,080	489,149
Contribution ($)	7,422	55,426	103,950	149,657	189,407	227,573
Spill (% Demand)	0.00	0.07	0.51	1.84	4.09	7.40
Load Factor	0.65	0.72	0.78	0.84	0.88	0.91
Yield (¢/RPM)	14.23	14.23	14.25	14.34	14.49	14.75
Unit Cost (¢/ASM)	8.26	8.26	8.26	8.26	8.26	8.26
Aircraft Utilization (Hours)						
737-300	7.3	7.3	7.3	7.3	7.3	7.3
737-400	7.3	7.3	7.3	7.3	7.3	7.3
737-500	6.6	6.6	6.6	6.6	6.6	6.6

D3 Actual Data

	Demand Multiplier 1.0	1.1	1.2	1.3	1.4	1.5
Revenue ($)	496,031	544,253	593,306	639,481	679,534	717,829
Operating Cost ($)	486,657	487,579	488,626	489,072	489,295	489,374
Contribution ($)	9,374	56,674	104,680	150,409	190,239	228,455
Spill (% Demand)	0.01	0.04	0.33	1.53	3.56	6.72
Load Factor	0.67	0.73	0.79	0.84	0.88	0.92
Yield (¢/RPM)	14.23	14.23	14.25	14.35	14.51	14.79
Unit Cost (¢/ASM)	8.36	8.34	8.32	8.32	8.32	8.32
Aircraft Utilization (Hours)						
737-300	7.3	7.3	7.3	7.4	7.4	7.4
737-400	6.1	6.6	7.1	7.2	7.2	7.2
737-500	7.8	7.3	6.9	6.6	6.6	6.6

D3 Difference Relative to Base Case

	Demand Multiplier 1.0	1.1	1.2	1.3	1.4	1.5
Revenue ($)	-9	78	478	831	1,047	1,107
Operating Cost ($)	-1,961	-1,170	-252	79	215	225
Contribution ($)	1,952	1,248	730	752	832	882
Statistically Significant?	Yes	No	No	No	No	No
Spill (% Demand)	0.01	-0.03	-0.18	-0.31	-0.53	-0.68
Load Factor	0.02	0.01	0.01	0.00	0.00	0.01
Yield (¢/RPM)	0	0	0	0.01	0.02	0.04
Unit Cost (¢/ASM)	0.1	0.08	0.06	0.06	0.06	0.06
Aircraft Utilization (Hours)						
737-300	0.0	0.0	0.0	0.1	0.1	0.1
737-400	-1.2	-0.7	-0.2	-0.1	-0.1	-0.1
737-500	1.2	0.7	0.3	0.0	0.0	0.0

D3 Percent Differences

	Demand Multiplier 1.0	1.1	1.2	1.3	1.4	1.5
Revenue	0.0%	0.0%	0.1%	0.1%	0.2%	0.2%
Operating Cost	-0.4%	-0.2%	-0.1%	0.0%	0.0%	0.0%
Contribution	**26.3%**	**2.3%**	**0.7%**	**0.5%**	**0.4%**	**0.4%**
Spill	0.0%	-42.9%	-35.3%	-16.8%	-13.0%	-9.2%
Load Factor	3.1%	1.4%	1.3%	0.0%	0.0%	1.1%
Yield	0.0%	0.0%	0.0%	0.1%	0.1%	0.3%
Unit Cost	1.2%	1.0%	0.7%	0.7%	0.7%	0.7%
Aircraft Utilization (Hours)						
737-300	0.0%	-0.4%	-0.4%	1.0%	1.0%	1.0%
737-400	-16.8%	-9.6%	-2.7%	-1.4%	-1.4%	-1.4%
737-500	18.2%	10.6%	4.5%	0.0%	0.0%	0.0%

Figure 7.4.1

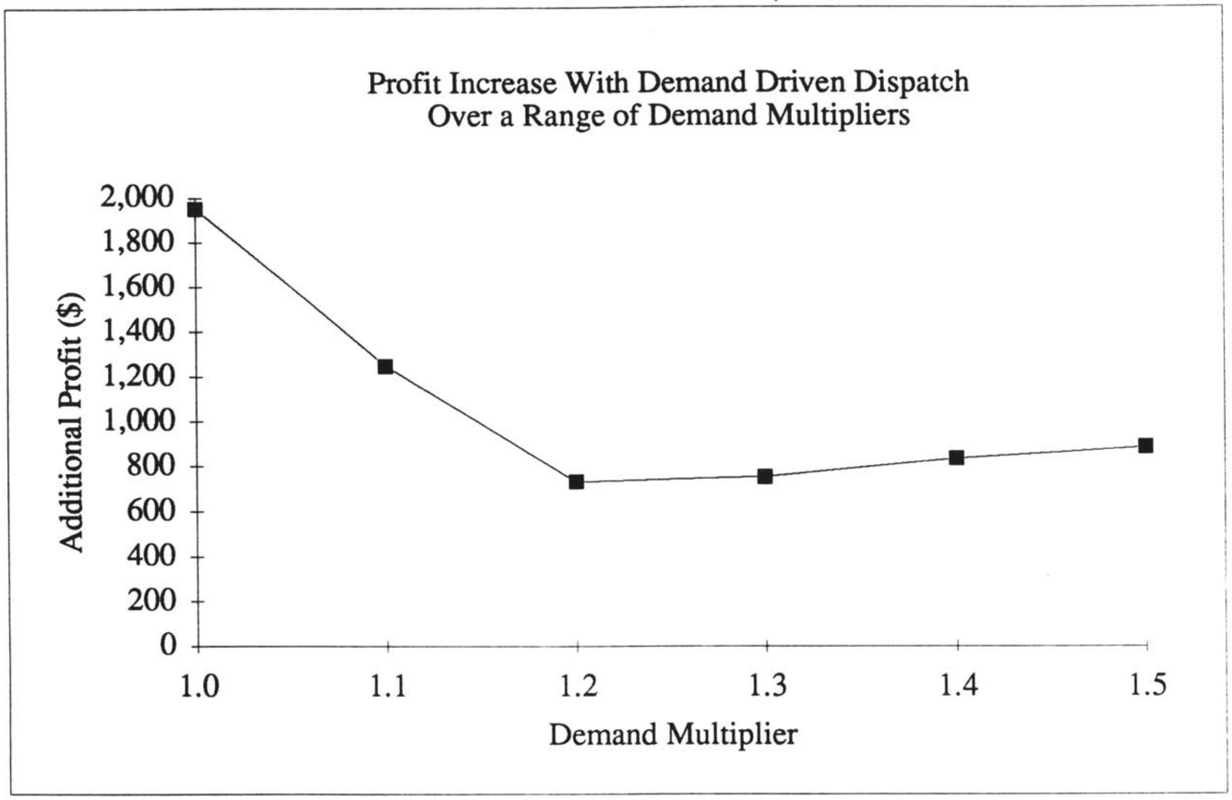
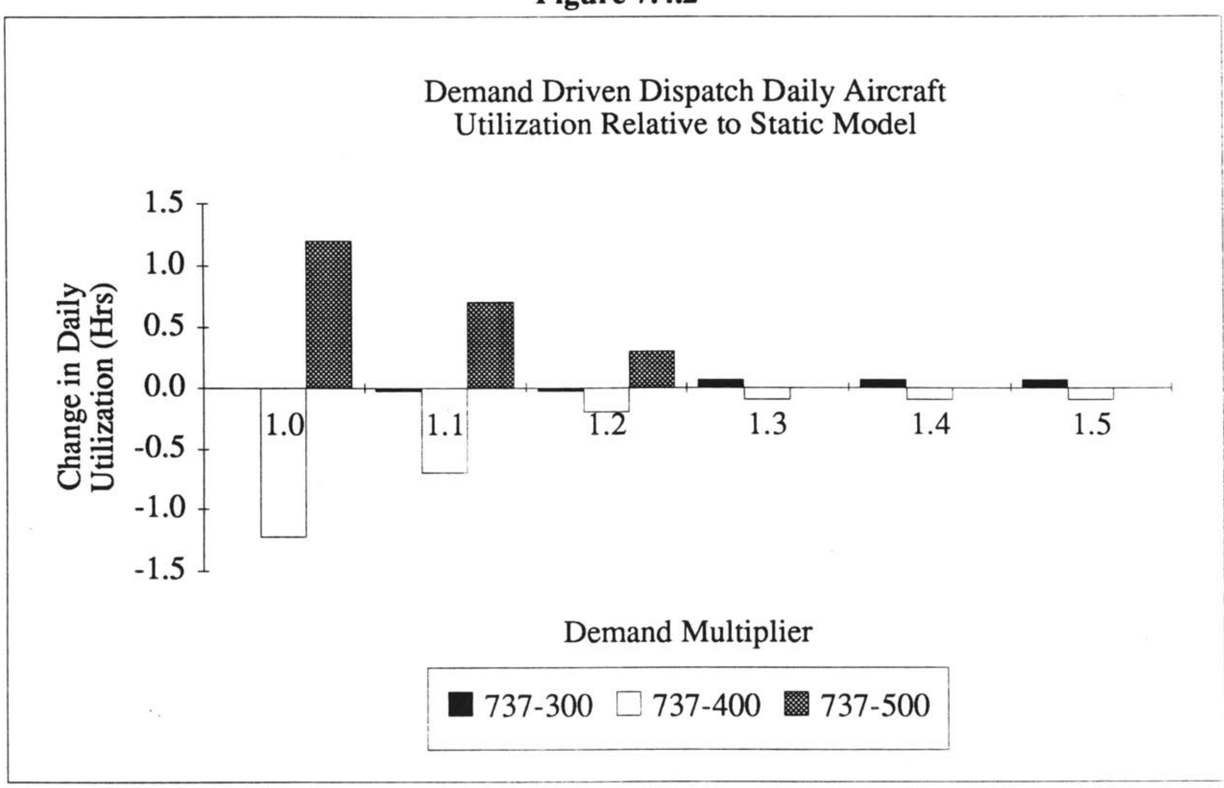


Figure 7.4.2



7.4.5 Results and Analysis of Scenario

- **Distributed Load Factor**
- **Balanced Demands**
- **Late Booking Pattern**

This scenario repeats the pattern seen in earlier distributed load factor /balanced demand simulations where D^3 performance reaches a minimum at demand multiplier 1.3. Balanced demands also produce slightly better contributions relative to unbalanced scenarios. This is a direct result of lower demand spill.

The distributed load factor scenario contributions at most demand multipliers are below those of planned load factors everything else being equal. In conjunction with slightly higher variances between D^3 and static results, the number of demand multiplier points which meet the statistical significance test drops from two to one. The contribution at demand multiplier 1.1 falls just outside the confidence interval. Because the transgression is small and the shape of the curve on the whole in Figure 7.5.1 is about as expected, I would tend to dismiss this point as an aberration caused by possible unique data circumstances specific to this run.

Table 7.7: Distributed Load, Balanced Demands, Late Booking Scenario

Base Case Actual Data

	Demand Multiplier					
	1.0	1.1	1.2	1.3	1.4	1.5
Revenue ($)	479,302	527,377	574,362	620,653	663,671	701,975
Operating Cost ($)	488,584	488,716	488,844	488,971	489,078	489,160
Contribution ($)	-9,282	38,661	85,518	131,682	174,593	212,815
Spill (% Demand)	0.00	0.00	0.00	0.42	1.64	4.54
Load Factor	0.64	0.70	0.76	0.93	0.87	0.92
Yield (¢/RPM)	14.09	14.12	14.10	14.12	14.19	14.36
Unit Cost (¢/ASM)	8.26	8.26	8.26	8.26	8.26	8.26
Aircraft Utilization (Hours)						
737-300	7.3	7.3	7.3	7.3	7.3	7.3
737-400	7.3	7.3	7.3	7.3	7.3	7.3
737-500	6.6	6.6	6.6	6.6	6.6	6.6

D3 Actual Data

	Demand Multiplier					
	1.0	1.1	1.2	1.3	1.4	1.5
Revenue ($)	479,299	527,376	574,439	621,065	664,456	703,228
Operating Cost ($)	486,356	486,968	487,968	488,814	489,183	489,387
Contribution ($)	-7,057	40,408	86,471	132,251	175,273	213,841
Spill (% Demand)	0.00	0.00	0.04	0.30	1.36	3.96
Load Factor	0.65	0.71	0.77	0.83	0.88	0.92
Yield (¢/RPM)	14.09	14.12	14.10	14.11	14.20	14.40
Unit Cost (¢/ASM)	8.38	8.34	8.32	8.32	8.32	8.32
Aircraft Utilization (Hours)						
737-300	7.1	7.4	7.3	7.3	7.4	7.3
737-400	6.0	6.2	6.7	7.2	7.2	7.3
737-500	8.1	7.6	7.2	6.8	6.6	6.6

D3 Difference Relative to Base Case

	Demand Multiplier					
	1.0	1.1	1.2	1.3	1.4	1.5
Revenue ($)	-3	-1	77	412	785	1,253
Operating Cost ($)	-2,228	-1,748	-876	-157	105	227
Contribution ($)	2,225	1,747	953	569	680	1,026
Statistically Significant?	Yes	Yes	No	No	No	No
Spill (% Demand)	0	0	0.04	-0.12	-0.28	-0.58
Load Factor	0.01	0.01	0.01	-0.10	0.01	0.00
Yield (¢/RPM)	0	0	0	-0.01	0.01	0.04
Unit Cost (¢/ASM)	0.12	0.08	0.06	0.06	0.06	0.06
Aircraft Utilization (Hours)						
737-300	-0.2	0.1	0.0	0.0	0.1	0.0
737-400	-1.3	-1.1	-0.6	-0.1	-0.1	0.0
737-500	1.5	1.0	0.6	0.2	0.0	0.0

D3 Percent Differences

	Demand Multiplier					
	1.0	1.1	1.2	1.3	1.4	1.5
Revenue	0.0%	0.0%	0.0%	0.1%	0.1%	0.2%
Operating Cost	-0.5%	-0.4%	-0.2%	0.0%	0.0%	0.0%
Contribution	**-24.0%**	**4.5%**	**1.1%**	**0.4%**	**0.4%**	**0.5%**
Spill	0.0%	0.0%	0.0%	-28.6%	-17.1%	-12.8%
Load Factor	1.6%	1.4%	1.3%	-10.8%	1.1%	0.0%
Yield	0.0%	0.0%	0.0%	-0.1%	0.1%	0.3%
Unit Cost	1.5%	1.0%	0.7%	0.7%	0.7%	0.7%
Aircraft Utilization (Hours)						
737-300	-2.7%	1.0%	-0.4%	-0.4%	1.0%	-0.4%
737-400	-18.1%	-15.1%	-8.2%	-1.4%	-1.4%	0.0%
737-500	22.7%	15.2%	9.1%	3.0%	0.0%	-0.3%

Figure 7.5.1

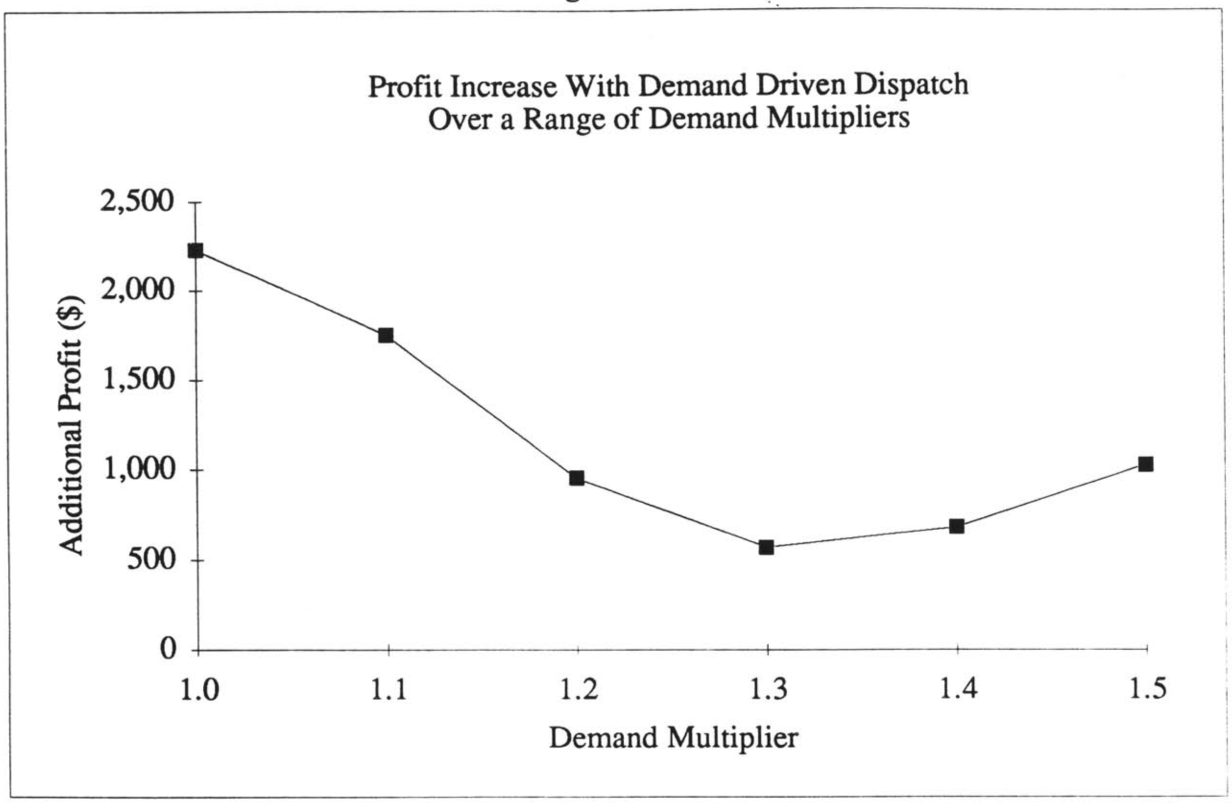
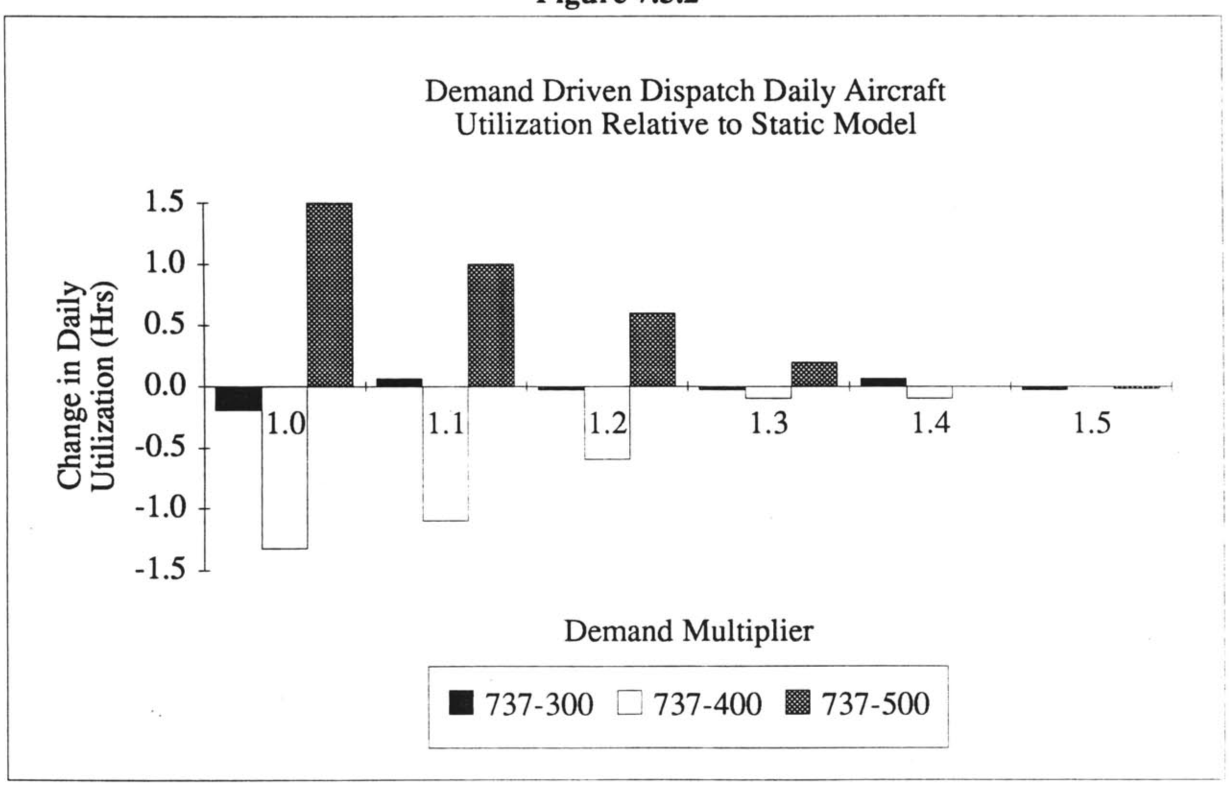


Figure 7.5.2



7.4.6 Results and Analysis of Scenario • Distributed Load Factor • Unbalanced Demands • Late Booking Pattern

The results of this simulation do not vary from those of other scenarios. The demand driven dispatch algorithm works fairly well at demand multiplier 1.0 with performance yielding constant returns at higher demand multipliers. Gains at the higher end are made possible because D^3 is spilling a smaller percentage of the demand at the higher demand multiplier 1.5, 5.8% versus 6.22% for the static case. The difference in the number of passengers spilled at this test point is 30.2. With an average revenue difference of $969, this equates to an opportunity cost of $32 per passenger. The average revenue per passenger is approximately $104 in both scenarios. This is a strong indication the revenue management system is working properly since the passengers being spilled must be coming from low fare demand.

The cost side results are also in line with what has been seen in the previous studies. Unit costs are slightly higher in the D^3 runs with hours being exchanged between the 737-500 and 737-400.

Table 7.8: Distributed Load, Unbalanced Demands, Late Booking Scenario

Base Case Actual Data

	Demand Multiplier 1.0	1.1	1.2	1.3	1.4	1.5
Revenue ($)	481,591	529,394	575,545	620,842	660,754	697,923
Operating Cost ($)	488,589	488,722	488,847	488,964	489,060	489,131
Contribution ($)	-6,998	40,672	86,698	131,878	171,694	208,792
Spill (% Demand)	0.00	0.03	0.36	1.32	3.40	6.22
Load Factor	0.64	0.71	0.77	0.82	0.87	0.90
Yield (¢/RPM)	14.12	14.09	14.11	14.16	14.28	14.5
Unit Cost (¢/ASM)	8.26	8.26	8.26	8.26	8.26	8.26
Aircraft Utilization (Hours)						
737-300	7.3	7.3	7.3	7.3	7.3	7.3
737-400	7.3	7.3	7.3	7.3	7.3	7.3
737-500	6.6	6.6	6.6	6.6	6.6	6.6

D3 Actual Data

	Demand Multiplier 1.0	1.1	1.2	1.3	1.4	1.5
Revenue ($)	481,579	529,403	575,943	621,654	661,683	698,896
Operating Cost ($)	486,568	487,355	488,425	489,025	489,219	489,313
Contribution ($)	-4,989	42,048	87,518	132,629	172,464	209,583
Spill (% Demand)	0.00	0.03	0.22	1.05	3.04	5.80
Load Factor	0.65	0.72	0.77	0.83	0.87	0.91
Yield (¢/RPM)	14.12	14.09	14.11	14.16	14.29	14.52
Unit Cost (¢/ASM)	8.36	8.34	8.32	8.32	8.30	8.30
Aircraft Utilization (Hours)						
737-300	7.3	7.4	7.3	7.3	7.4	7.3
737-400	6.1	6.5	7.0	7.2	7.3	7.3
737-500	7.9	7.4	7.0	6.7	6.6	6.6

D3 Difference Relative to Base Case

	Demand Multiplier 1.0	1.1	1.2	1.3	1.4	1.5
Revenue ($)	-12	9	398	812	929	973
Operating Cost ($)	-2,021	-1,367	-422	61	159	182
Contribution ($)	2,009	1,376	820	751	770	791
Statistically Significant?	Yes	No	No	No	No	No
Spill (% Demand)	0	0	-0.14	-0.27	-0.36	-0.42
Load Factor	0.01	0.01	0.00	0.01	0.00	0.01
Yield (¢/RPM)	0	0	0	0	0.01	0.02
Unit Cost (¢/ASM)	0.1	0.08	0.06	0.06	0.04	0.04
Aircraft Utilization (Hours)						
737-300	0.0	0.1	0.0	0.0	0.1	0.0
737-400	-1.2	-0.8	-0.3	-0.1	0.0	0.0
737-500	1.3	0.8	0.4	0.1	0.0	0.0

D3 Percent Differences

	Demand Multiplier 1.0	1.1	1.2	1.3	1.4	1.5
Revenue	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%
Operating Cost	-0.4%	-0.3%	-0.1%	0.0%	0.0%	0.0%
Contribution	**28.7%**	**3.4%**	**0.9%**	**0.6%**	**0.4%**	**0.4%**
Spill	0.0%	0.0%	-38.9%	-20.5%	-10.6%	-6.8%
Load Factor	1.6%	1.4%	0.0%	1.2%	0.0%	1.1%
Yield	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%
Unit Cost	1.2%	1.0%	0.7%	0.7%	0.5%	0.5%
Aircraft Utilization (Hours)						
737-300	0.0%	1.0%	-0.4%	-0.4%	1.0%	-0.4%
737-400	-16.8%	-11.0%	-4.1%	-1.4%	0.0%	0.0%
737-500	19.7%	12.1%	6.1%	1.5%	0.0%	-0.3%

Figure 7.6.1

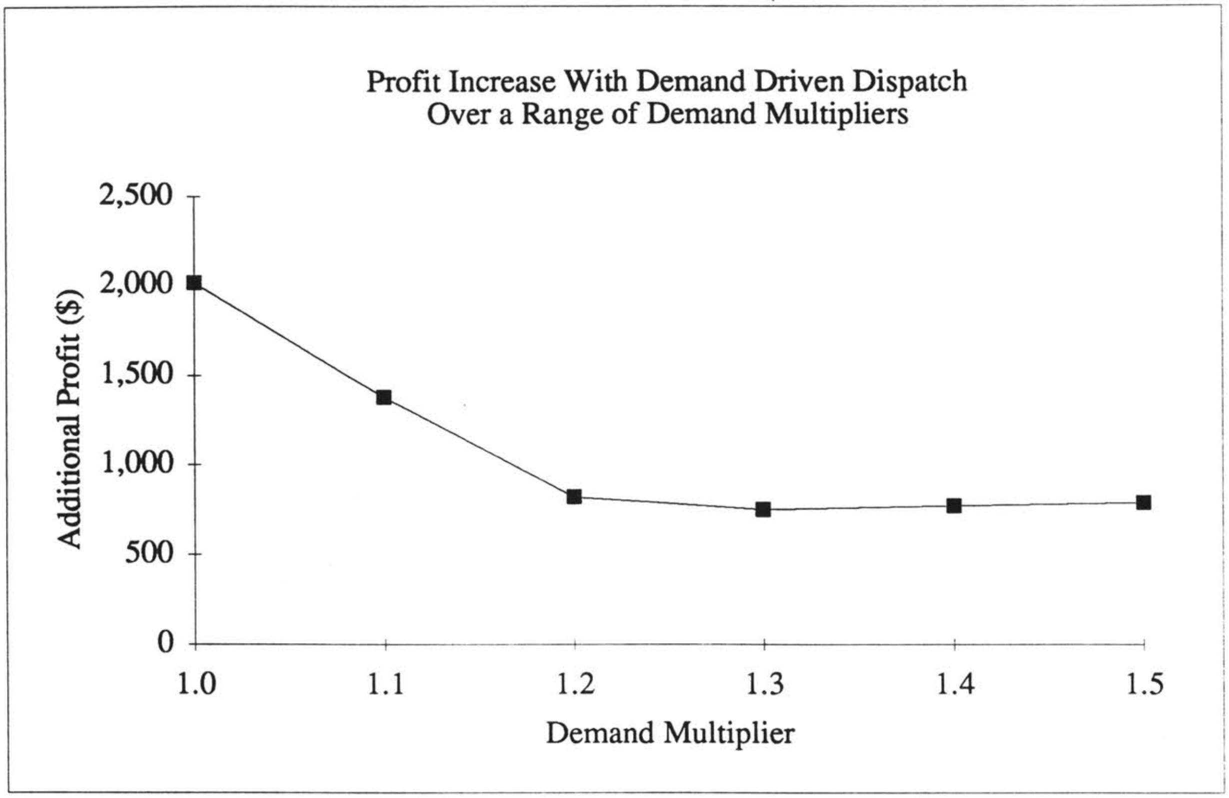
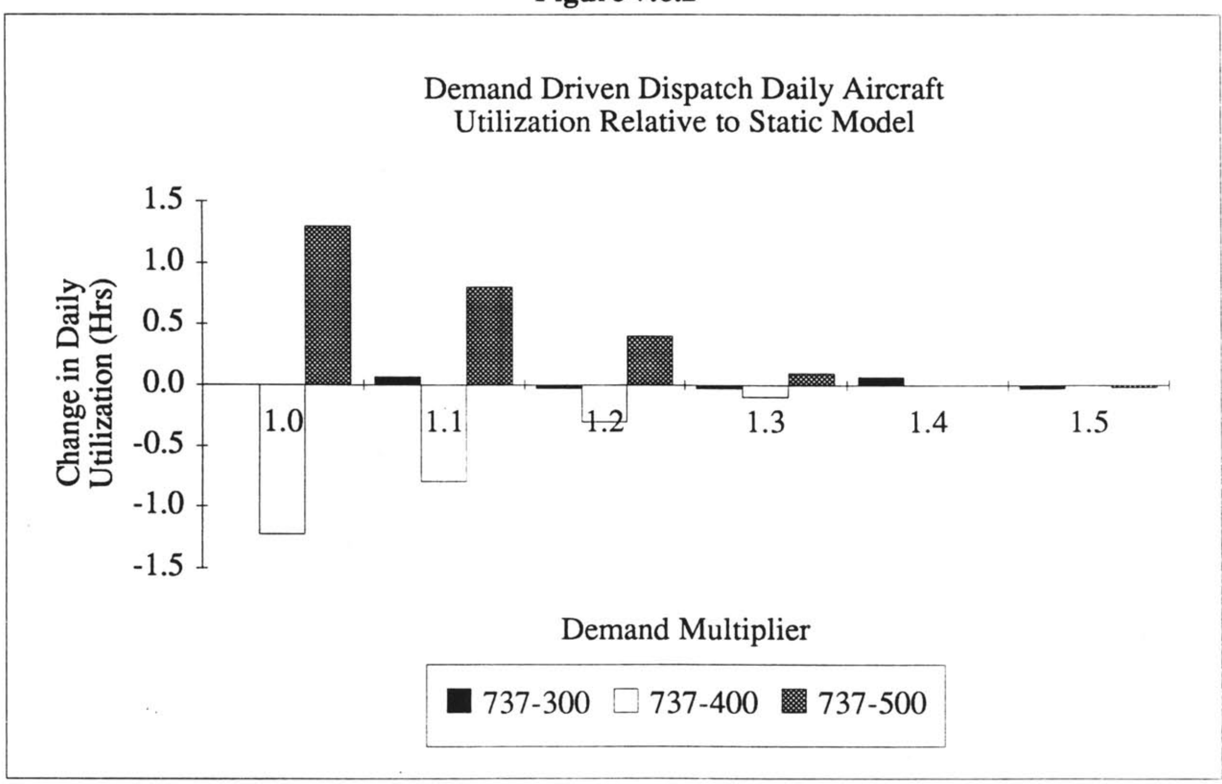


Figure 7.6.2



7.4.7 Results and Analysis of Scenario

- **65% Planned Load Factor**
- **Balanced Demands**
- **Late Booking Pattern**

The highest contribution difference at demand multiplier 1.0 ($2,411) is generated in this scenario. Because this occurs at a demand multiplier where there is no spill, the improvement is entirely a result of lower costs. Not surprisingly, the 737-500 achieves its highest utilization per day, 8.2 hours, in this scenario. Again, this means higher unit costs in the D^3 run versus the static case, but the overall costs come out lower because the trip costs for the smaller aircraft are less than the larger aircraft.

Table 7.9: 65% Planned Load Factor, Balanced Demands, Late Booking Scenario

Base Case Actual Data

	Demand Multiplier					
	1.0	1.1	1.2	1.3	1.4	1.5
Revenue ($)	476,184	524,683	570,646	618,519	662,890	702,168
Operating Cost ($)	488,582	488,716	488,840	488,971	489,089	489,178
Contribution ($)	-12,398	35,967	81,806	129,548	173,801	212,990
Spill (% Demand)	0.00	0.00	0.02	0.13	0.84	2.97
Load Factor	0.64	0.70	0.76	0.83	0.88	0.93
Yield (¢/RPM)	14.04	14.04	14.05	14.05	14.09	14.23
Unit Cost (¢/ASM)	8.26	8.26	8.26	8.26	8.26	8.26
Aircraft Utilization (Hours)						
737-300	7.3	7.3	7.3	7.3	7.3	7.3
737-400	7.3	7.3	7.3	7.3	7.3	7.3
737-500	6.6	6.6	6.6	6.6	6.6	6.6

D3 Actual Data

	Demand Multiplier					
	1.0	1.1	1.2	1.3	1.4	1.5
Revenue ($)	476,184	524,682	570,685	618,708	663,314	702,462
Operating Cost ($)	486,171	486,691	487,550	488,627	489,065	489,292
Contribution ($)	-9,987	37,991	83,135	130,081	174,249	213,170
Spill (% Demand)	0.00	0.00	0.01	0.08	0.76	2.81
Load Factor	0.65	0.71	0.77	0.83	0.89	0.93
Yield (¢/RPM)	14.04	14.04	14.05	14.05	14.09	14.25
Unit Cost (¢/ASM)	8.36	8.32	8.32	8.30	8.30	8.30
Aircraft Utilization (Hours)						
737-300	7.1	7.6	7.5	7.3	7.3	7.2
737-400	6.0	6.1	6.5	7.1	7.3	7.4
737-500	8.2	7.5	7.2	6.8	6.6	6.6

D3 Difference Relative to Base Case

	Demand Multiplier					
	1.0	1.1	1.2	1.3	1.4	1.5
Revenue ($)	0	-1	39	189	424	294
Operating Cost ($)	-2,411	-2,025	-1,290	-344	-24	114
Contribution ($)	2,411	2,024	1,329	533	448	180
Statistically Significant?	Yes	Yes	No	No	No	No
Spill (% Demand)	0	0	-0.01	-0.05	-0.08	-0.16
Load Factor	0.01	0.01	0.01	0.00	0.01	0.00
Yield (¢/RPM)	0	0	0	0	0	0.02
Unit Cost (¢/ASM)	0.1	0.06	0.06	0.04	0.04	0.04
Aircraft Utilization (Hours)						
737-300	-0.2	0.3	0.2	0.0	0.0	-0.1
737-400	-1.3	-1.2	-0.8	-0.2	0.0	0.1
737-500	1.6	0.9	0.6	0.2	0.0	0.0

D3 Percent Differences

	Demand Multiplier					
	1.0	1.1	1.2	1.3	1.4	1.5
Revenue	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%
Operating Cost	-0.5%	-0.4%	-0.3%	-0.1%	0.0%	0.0%
Contribution	**19.4%**	**5.6%**	**1.6%**	**0.4%**	**0.3%**	**0.1%**
Spill	0.0%	0.0%	-50.0%	-38.5%	-9.5%	-5.4%
Load Factor	1.6%	1.4%	1.3%	0.0%	1.1%	0.0%
Yield	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%
Unit Cost	1.2%	0.7%	0.7%	0.5%	0.5%	0.5%
Aircraft Utilization (Hours)						
737-300	-2.7%	3.7%	2.3%	-0.4%	-0.4%	-1.8%
737-400	-18.1%	-16.4%	-11.0%	-2.7%	0.0%	1.4%
737-500	24.2%	13.6%	9.1%	3.0%	0.0%	-0.3%

Figure 7.7.1

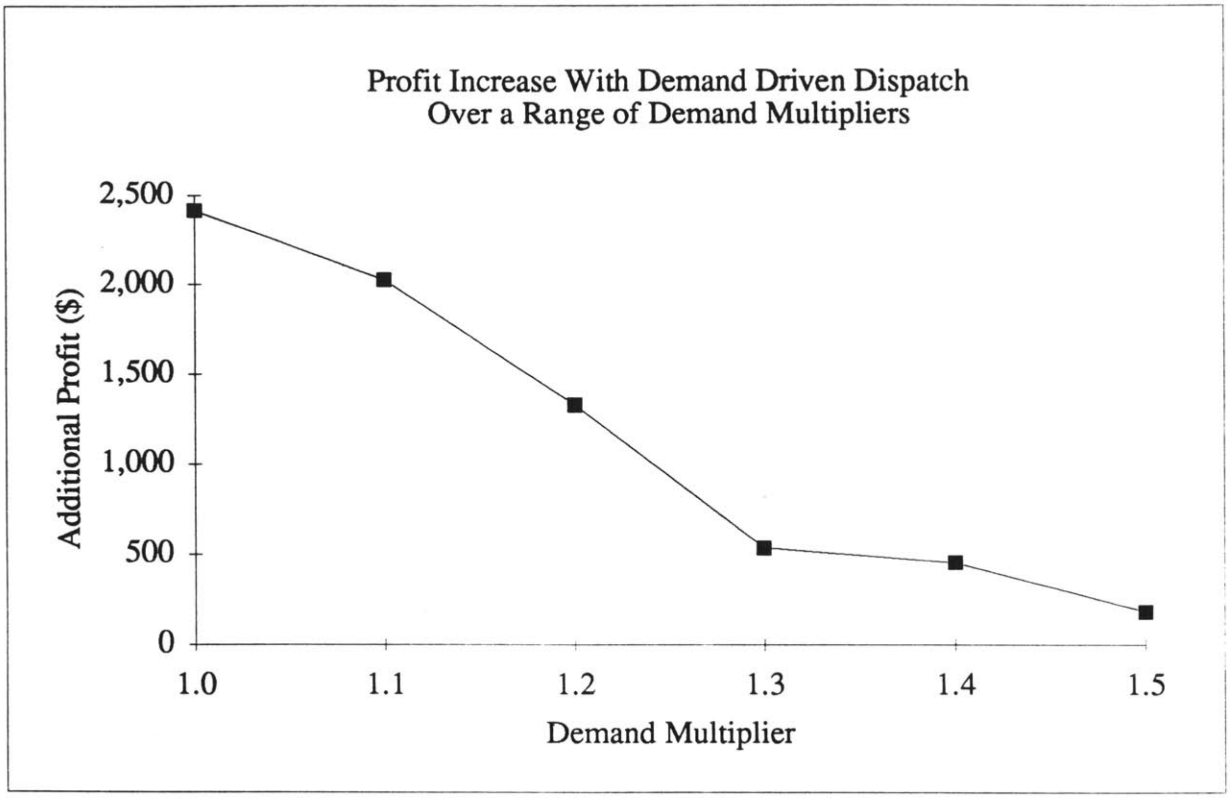
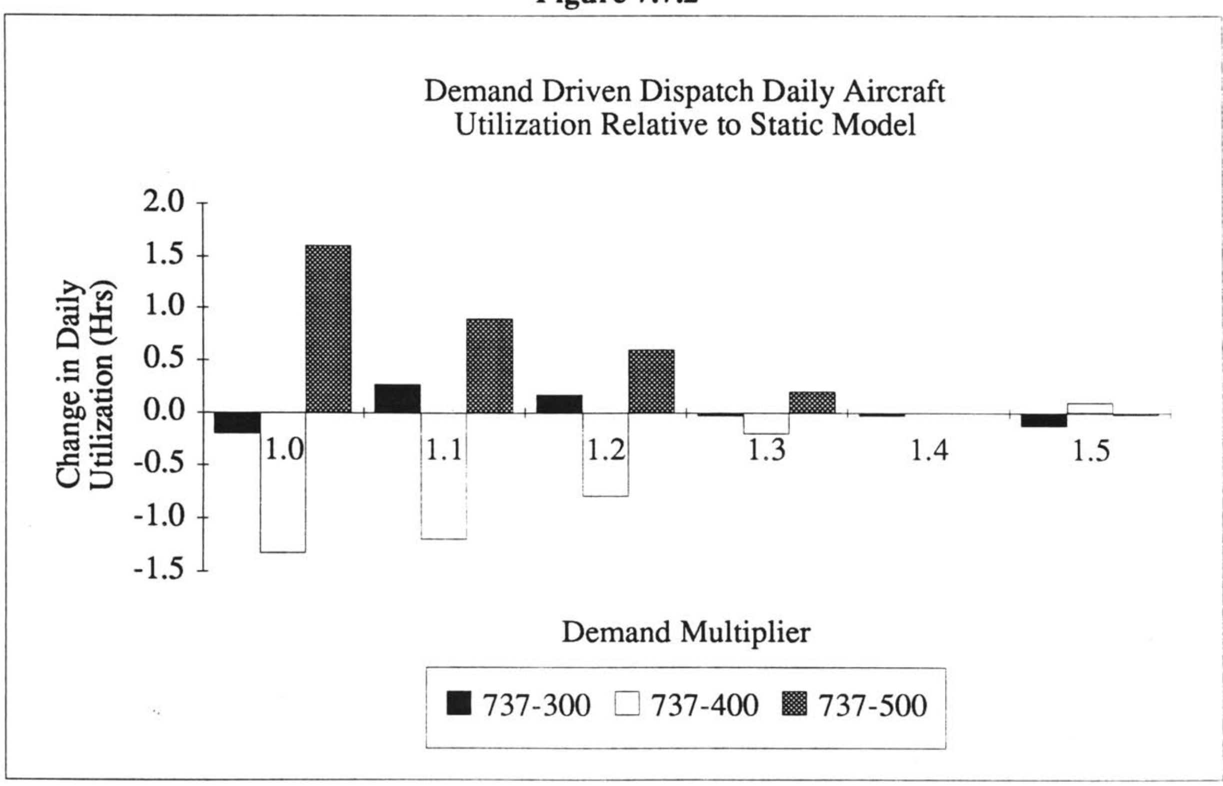


Figure 7.7.2



7.4.8 Results and Analysis of Scenario

- **65% Planned Load Factor**
- **Unbalanced Demands**
- **Late Booking Pattern**

The results from this scenario simulation are not remarkably different from other simulations - contributions drop with increasing demand multiplier, spill is relatively high at high demand factors, and utilization patterns are typical.

Table 7.10: 65% Load Factor, Unbalanced Demands, Late Booking Scenario

Base Case Actual Data

	Demand Multiplier					
	1.0	1.1	1.2	1.3	1.4	1.5
Revenue ($)	478,380	526,394	573,552	617,574	659,754	696,388
Operating Cost ($)	488,587	488,720	488,849	488,969	489,069	489,142
Contribution ($)	-10,207	37,674	84,703	128,605	170,685	207,246
Spill (% Demand)	0.00	0.00	0.12	0.70	2.28	5.21
Load Factor	0.64	0.70	0.77	0.83	0.87	0.91
Yield (¢/RPM)	14.04	14.04	14.05	14.05	14.17	14.39
Unit Cost (¢/ASM)	8.26	8.26	8.26	8.26	8.26	8.26
Aircraft Utilization (Hours)						
737-300	7.3	7.3	7.3	7.3	7.3	7.3
737-400	7.3	7.3	7.3	7.3	7.3	7.3
737-500	6.6	6.6	6.6	6.6	6.6	6.6

D3 Actual Data

	Demand Multiplier					
	1.0	1.1	1.2	1.3	1.4	1.5
Revenue ($)	478,373	526,390	573,752	618,234	660,185	696,629
Operating Cost ($)	486,349	487,007	488,050	488,807	489,078	489,246
Contribution ($)	-7,976	39,383	85,702	129,427	171,107	207,383
Spill (% Demand)	0.00	0.00	0.06	0.53	2.21	5.08
Load Factor	0.65	0.72	0.77	0.83	0.88	0.91
Yield (¢/RPM)	14.04	14.04	14.05	14.05	14.18	14.40
Unit Cost (¢/ASM)	8.34	8.32	8.32	8.30	8.30	8.30
Aircraft Utilization (Hours)						
737-300	7.3	7.5	7.3	7.3	7.3	7.2
737-400	6.0	6.3	6.9	7.2	7.3	7.4
737-500	7.9	7.4	7.0	6.7	6.6	6.6

D3 Difference Relative to Base Case

	Demand Multiplier					
	1.0	1.1	1.2	1.3	1.4	1.5
Revenue ($)	-7	-4	200	660	431	241
Operating Cost ($)	-2,238	-1,713	-799	-162	9	104
Contribution ($)	2,231	1,709	999	822	422	137
Statistically Significant?	Yes	Yes	No	No	No	No
Spill (% Demand)	0	0	-0.06	-0.17	-0.07	-0.13
Load Factor	0.01	0.02	0.00	0.00	0.01	0.00
Yield (¢/RPM)	0	0	0	0	0.01	0.01
Unit Cost (¢/ASM)	0.08	0.06	0.06	0.04	0.04	0.04
Aircraft Utilization (Hours)						
737-300	0.0	0.2	0.0	0.0	0.0	-0.1
737-400	-1.3	-1.0	-0.4	-0.1	0.0	0.1
737-500	1.3	0.8	0.4	0.1	0.0	0.0

D3 Percent Differences

	Demand Multiplier					
	1.0	1.1	1.2	1.3	1.4	1.5
Revenue	0.0%	0.0%	0.0%	0.1%	0.1%	0.0%
Operating Cost	-0.5%	-0.4%	-0.2%	0.0%	0.0%	0.0%
Contribution	**-21.9%**	**4.5%**	**1.2%**	**0.6%**	**0.2%**	**0.1%**
Spill	0.0%	0.0%	-50.0%	-24.3%	-3.1%	-2.5%
Load Factor	1.6%	2.9%	0.0%	0.0%	1.1%	0.0%
Yield	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%
Unit Cost	1.0%	0.7%	0.7%	0.5%	0.5%	0.5%
Aircraft Utilization (Hours)						
737-300	0.0%	2.3%	-0.4%	-0.4%	-0.4%	-1.6%
737-400	-18.1%	-13.7%	-5.5%	-1.4%	0.0%	1.8%
737-500	19.7%	12.1%	6.1%	1.5%	0.0%	-0.3%

Figure 7.8.1

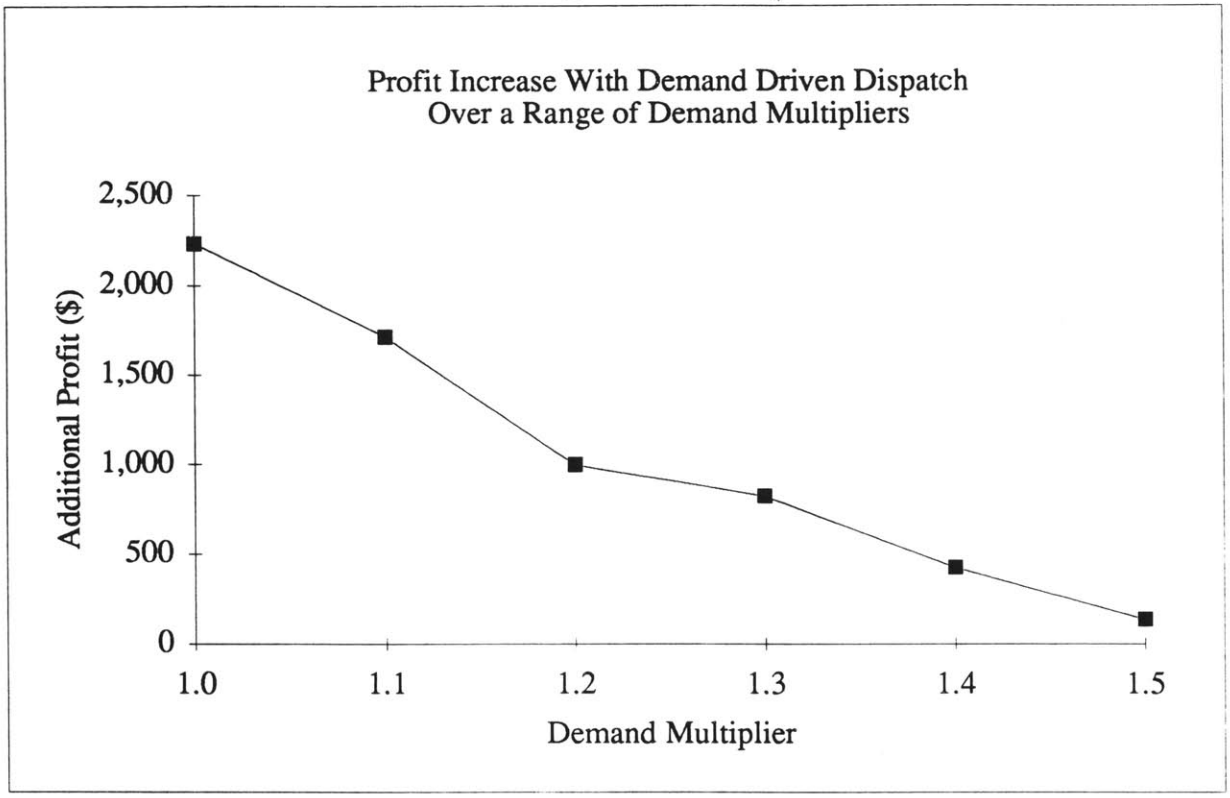
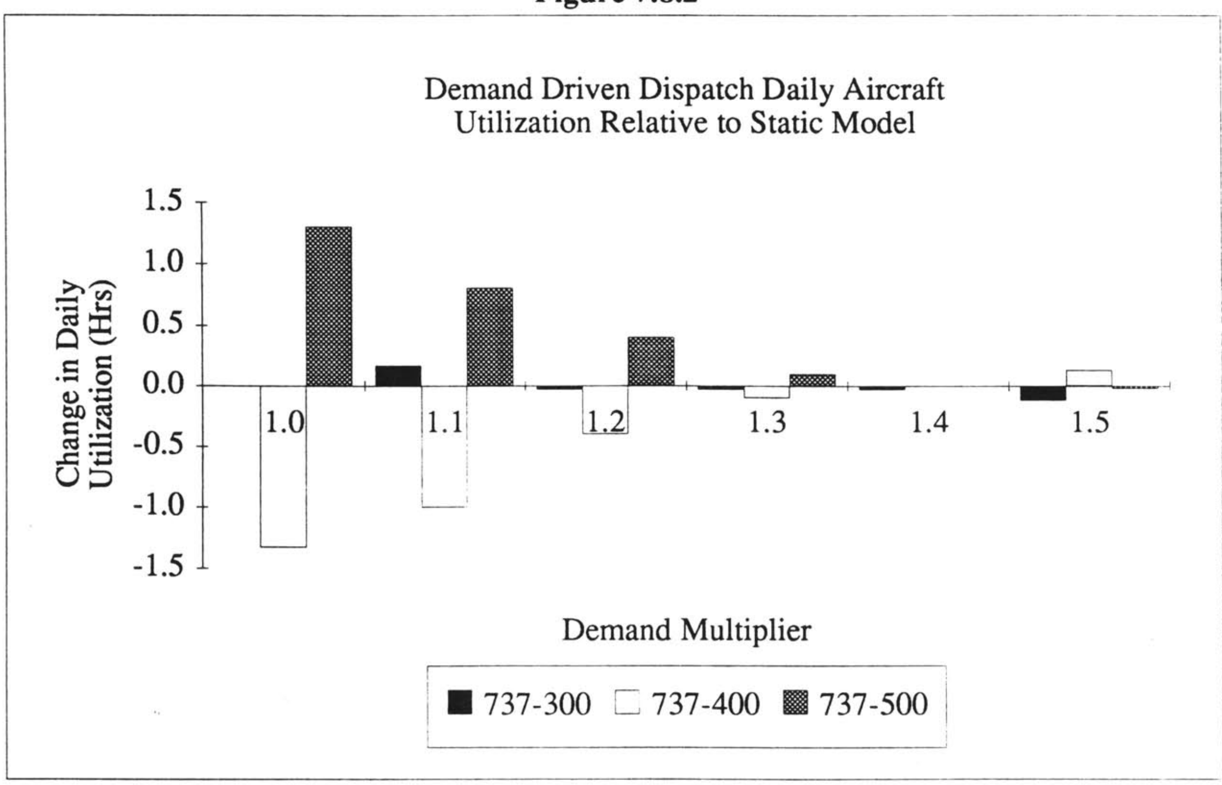


Figure 7.8.2



7.5 Sensitivity Analysis of Dynamic Nature of Demand Driven Dispatch

Tables 7.11 and 7.12 show data from simulations runs where the demand driven dispatch module was "turned on" and "turned off" over the entire range of possible booking revision points. Regardless of whether D^3 was being used or not, the revenue management module was invoked. The reason for doing such an analysis is to determine for airlines which might not wish to run D^3 assignment programs at every booking revision point for every flight on a daily basis the fewest number of assignment revision points and their occurrence in the booking process necessary to achieve good profit enhancement results. In all likelihood the answer to this question will heavily depend upon the distribution of and booking patterns for demand. The two scenarios examined here are planned load factor / balanced demand / typical booking and distributed load factor / balanced demand / typical booking at demand multipliers 1.0 and 1.5.

"Turning off" the D^3 process is defined as running the D^3 module at every booking revision point prior to the specified revision point and thereafter skipping over D^3 in the simulation at every revision point. "Turning on" represents the opposite action. The D^3 module is not run until a certain booking revision point is reached, and then it is run until the end of the booking process. By definition the contribution from the situation where the final booking period is the last revision point in the "turn off" case must equal the contribution from the situation where the initial booking period is the first booking revision point in the "turn on" case. Both of these points are equivalent to running D^3 over the entire booking process.

7.4.1 Planned load factor / Balanced demand / Typical booking

At demand multiplier 1.0, Figure 7.9.1 shows a sharp rise in contribution with the between the zeroth and first assignment revision point. In fact, 85% of the total possible contribution increase from using the D^3 process is gained between these two points. Of course turning off D^3 at assignment point 0 is the same as saying that the simulation is being run under static conditions. Terminating D^3 at assignment point 1 is analogous to running D^3 just once at the start of the booking process. This is a very important result since it means that if airlines could assign their aircraft at the beginning of the booking process for a flight many months away just on the basis of probabilistic fare class demand analysis (as opposed to aggregate level analysis used at many airlines), they can gain a large percentage of the D^3 benefits without running a full blown D^3 assignment process. Detailed demand data is supplied by the revenue management system, so it is crucial that the revenue management and demand driven dispatch functions be highly integrated to ensure timely relay of updated information. Over the rest of the booking periods, there is a gradual upward trend towards the final contribution figure. Thus, at every booking revision point where D^3 is run, there is on average some marginal benefit.

Where Figure 7.9.1 shows that large benefits can be gained by running D^3 just once, Figure 7.9.2 shows how contribution drops depending upon how late in the booking process the first D^3 assignment is made. Clearly if an airline chose to run D^3 at the final booking revision point, which corresponds to the day of the flight, it would bear some opportunity cost. Figure 7.9.2 suggests that as late as the seventh revision point, or 14 days before the flight, the airline can determine D^3 assignments without a perceptible drop in contribution.

That this transition point occurs 14 days before departure is not likely a matter of coincidence. Many airlines set purchase restrictions which require passengers seeking discount fares to book seats by 14 days before the flight. Even though passengers have the option of booking well before the 14 day cutoff, the uncertainty inherent in planning any future event promotes increased booking activity as fare class advance purchase deadlines approach. Figure 6.3 shows that almost 50% of passenger bookings in the typical model occur in the last four booking periods. More importantly, since these bookings represent predominantly higher yield passengers, the percentage of revenue booked over these periods is even greater.

In fairness it should be pointed out that the worst result is relatively small, only $170 (4.3%) lower in contribution. Why so low? One must remember that at demand multiplier 1.0 there is no spill whatsoever (Table 1.3). This in turn is a result of my demand models not having enough variability and/or high enough base load factors. Under these circumstances we are in the situation where running D^3 just once at any point in the booking process is sufficient. Spill is more common in real life because load factors are not so controlled. Additionally, fare class demands are broken out to the full origin-destination level as opposed to the leg level. This is important because it means that for a given demand level the variability will be higher when the demand is composed of many smaller, more volatile (higher k factor) market demands as opposed to a single aggregate demand.

At demand multiplier 1.5, there is no dramatic jump in contribution between the static case (last assignment revision point = 0) and any demand driven dispatch "turn off" point. The curve in Figure 7.9.3 even shows a drop in contribution at last assignment revision point = 2. There are separate phenomena at work in this situation. First, the level of spill at high demand multipliers is such that most of the contribution improvements come from the revenue side, and there are plenty of high revenue passengers to fill seats. Load factors in this instance are over 90%. Secondly, aircraft seats come in discrete quantities. Therefore, it is possible that a more costly assignment solution is found in anticipation of simulated bookings which do not materialize. With no further revisions possible after the last revision point, the revenue management system must make the best of the flawed assignments.

Figure 7.9.4 shows an uneven decline in contribution as the first assignment revision point is varied. A definitive break appears again appears at assignment revision point 7 for most likely the reason stated previously. In both Figures 7.9.3 and 7.9.4 the absolute changes are so low, on the order of a couple hundred dollars in comparison to the static value of about $230,000, as to be essentially insignificant in economic terms.

7.4.2 Distributed load factor / Balanced demand / Typical booking

As seen with the results in the demand multiplier sensitivity section, there are no major differences in the results between distributed load factor and planned load factor scenarios. The nominal demand multiplier (1.0) cases in fact look identical with slight differences only in absolute contribution levels (Figures 7.10.1 and 7.10.2). In this scenario too there is no spill at this demand multiplier to cause a larger drop at late assignment points in Figure 7.10.2.

At demand multiplier = 1.5, the "turn off" response of demand driven dispatch (Figure 7.10.3) differs from the planned load factor case in the fact that the upward trend in contribution rises more steadily. However, the number of dollars is so small that it would be stretching the point to attach any significance.

Table 7.11: Sensitivity Analysis - Changing Number of A/C Assignment Revision Points

Planned Load Factor of 65%/Balanced Demands/Typical Booking
Demand Multiplier = 1.0

Last Revision Period	0	1	2	3	4	5	6	7	8	9	10
Operating Revenue	$490,170	$489,816	$489,960	$490,156	$490,077	$490,092	$490,163	$490,160	$490,157	$490,170	$490,170
Flight Cost	$219,873	$217,477	$217,562	$217,766	$217,653	$217,597	$217,721	$217,617	$217,626	$217,580	$217,494
Total Cost	$488,607	$486,211	$486,296	$486,500	$486,387	$486,331	$486,455	$486,351	$486,360	$486,314	$486,228
Contribution	$1,563	$3,605	$3,664	$3,656	$3,690	$3,761	$3,708	$3,809	$3,797	$3,856	$3,942

Planned Load Factor of 65%/Balanced Demands/Typical Booking
Demand Multiplier = 1.5

Last Revision Period	0	1	2	3	4	5	6	7	8	9	10
Operating Revenue	$719,296	$719,296	$719,147	$719,186	$719,324	$719,282	$719,358	$719,429	$719,474	$719,504	$719,556
Flight Cost	$220,138	$220,138	$220,197	$220,126	$220,183	$220,167	$220,213	$220,248	$220,261	$220,269	$220,324
Total Cost	$489,196	$489,196	$489,255	$489,184	$489,241	$489,225	$489,271	$489,306	$489,319	$489,327	$489,382
Contribution	$230,100	$230,100	$229,892	$230,002	$230,083	$230,057	$230,087	$230,123	$230,155	$230,177	$230,174

Planned Load Factor of 65%/Balanced Demands/Typical Booking
Demand Multiplier = 1.0

First Revision Period	0	1	2	3	4	5	6	7	8	9	10
Operating Revenue	$490,170	$490,170	$490,170	$490,170	$490,170	$490,170	$490,170	$490,156	$490,078	$490,050	$489,996
Flight Cost	$217,494	$217,494	$217,494	$217,494	$217,494	$217,494	$217,494	$217,494	$217,493	$217,491	$217,490
Total Cost	$486,228	$486,228	$486,228	$486,228	$486,228	$486,228	$486,228	$486,228	$486,227	$486,225	$486,224
Contribution	$3,942	$3,942	$3,942	$3,942	$3,942	$3,942	$3,942	$3,928	$3,851	$3,825	$3,772

Planned Load Factor of 65%/Balanced Demands/Typical Booking
Demand Multiplier = 1.5

First Revision Period	0	1	2	3	4	5	6	7	8	9	10
Operating Revenue	$719,556	$719,296	$719,515	$719,483	$719,381	$719,411	$719,432	$719,033	$718,906	$718,719	$718,679
Flight Cost	$220,324	$220,138	$220,327	$220,326	$220,329	$220,338	$220,333	$220,345	$220,292	$220,317	$220,321
Total Cost	$489,382	$489,196	$489,385	$489,384	$489,387	$489,396	$489,391	$489,403	$489,350	$489,375	$489,379
Contribution	$230,174	$230,100	$230,130	$230,099	$229,994	$230,015	$230,041	$229,630	$229,556	$229,344	$229,300

Figure 7.9.1

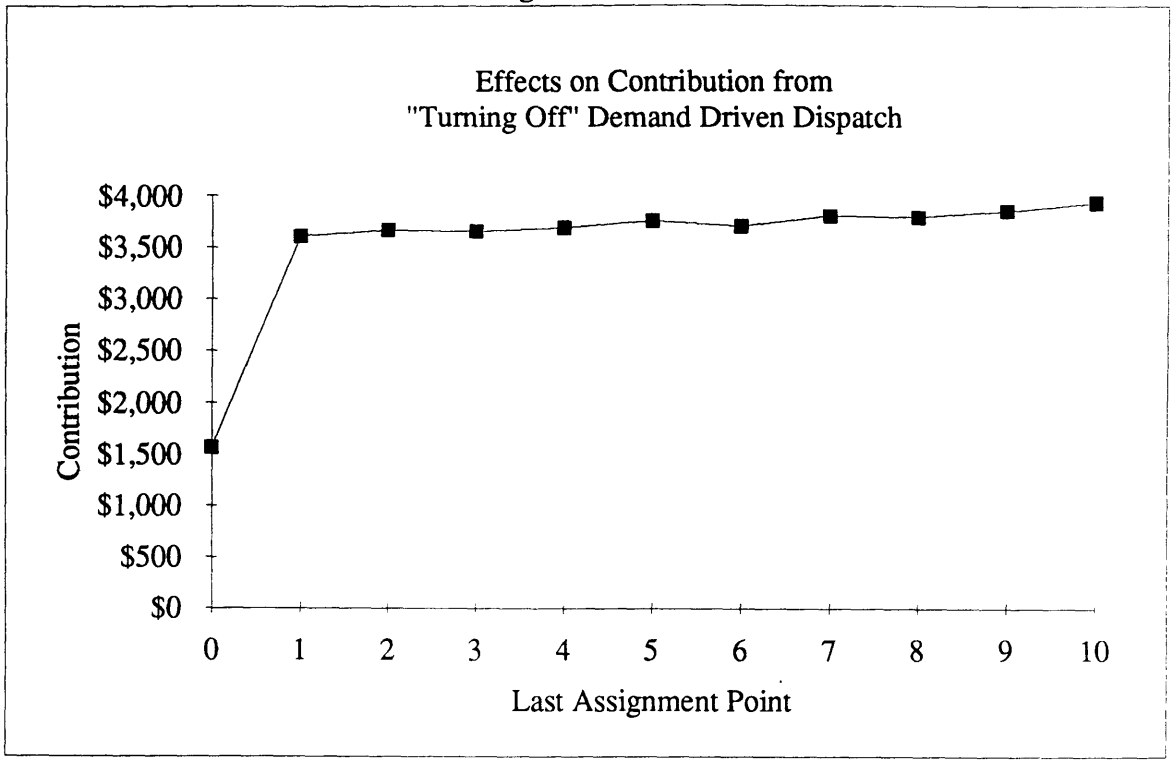


Figure 7.9.2

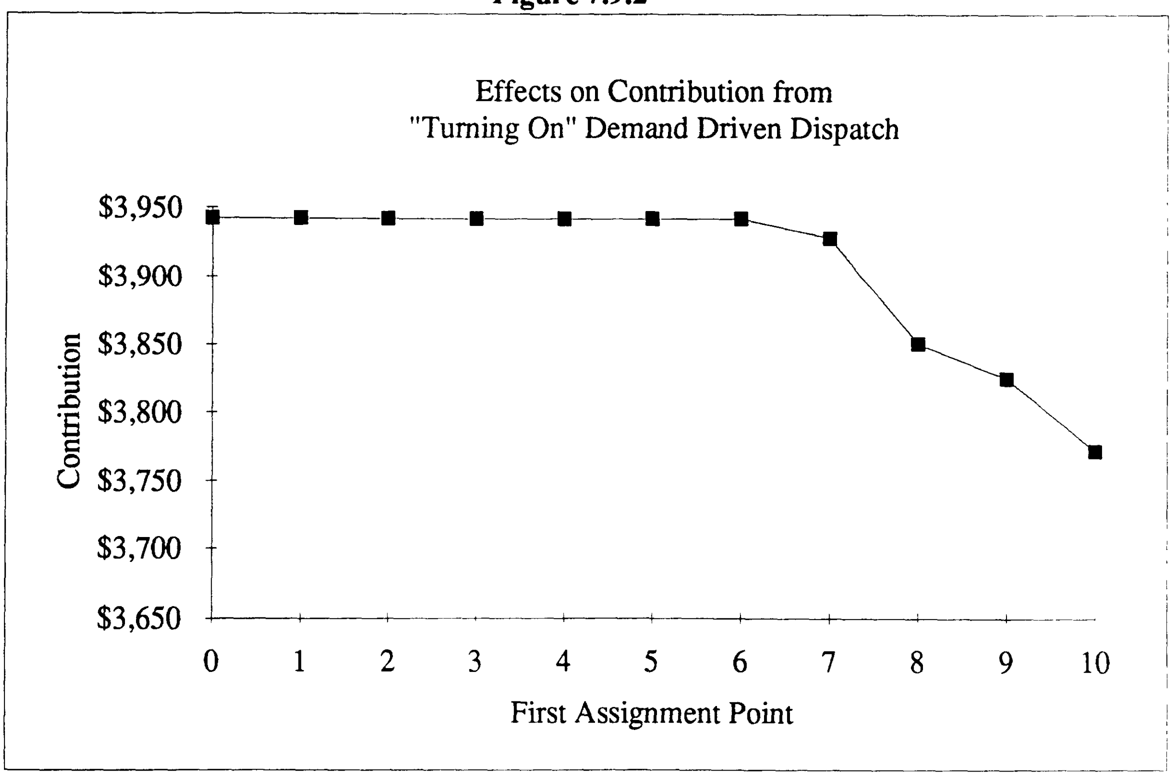


Figure 7.9.3

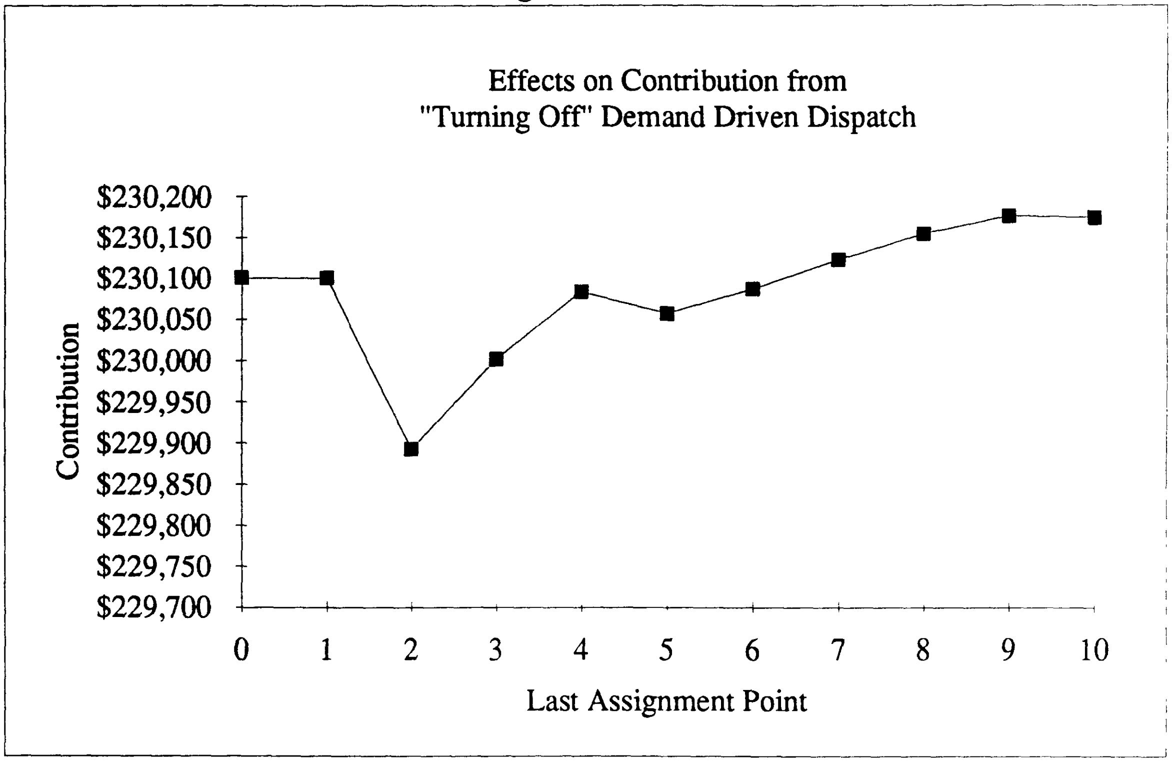


Figure 7.9.4

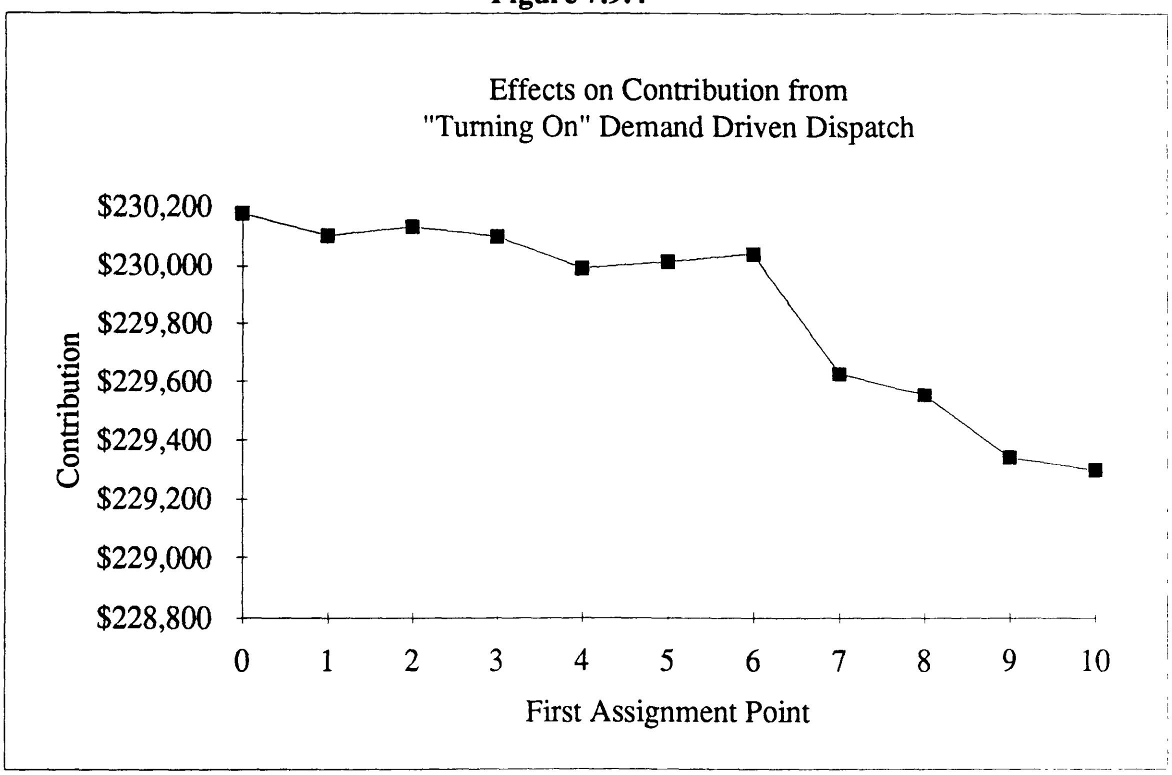


Table 7.12: Sensitivity Analysis - Changing Number of A/C Assignment Revision Points

Distributed Load Factor/Balanced Demands/Typical Booking
Demand Multiplier = 1.0

Last Revision Period	0	1	2	3	4	5	6	7	8	9	10
Operating Revenue	$492,979	$492,776	$492,822	$492,813	$492,876	$492,869	$492,915	$492,967	$492,969	$492,977	$492,979
Flight Cost	$219,875	$217,753	$217,806	$217,756	$217,814	$217,793	$217,818	$217,894	$217,856	$217,781	$217,708
Total Cost	$488,611	$486,489	$486,542	$486,492	$486,550	$486,529	$486,554	$486,630	$486,592	$486,517	$486,444
Contribution	$4,368	$6,287	$6,280	$6,321	$6,326	$6,340	$6,361	$6,337	$6,377	$6,460	$6,535

Distributed Load Factor/Balanced Demands/Typical Booking
Demand Multiplier = 1.5

Last Revision Period	0	1	2	3	4	5	6	7	8	9	10
Operating Revenue	$717,596	$717,596	$718,575	$718,234	$718,438	$718,410	$718,819	$718,876	$718,874	$718,974	$719,059
Flight Cost	$220,128	$220,128	$220,429	$220,235	$220,301	$220,253	$220,346	$220,395	$220,390	$220,399	$220,403
Total Cost	$489,173	$489,173	$489,474	$489,280	$489,346	$489,298	$489,391	$489,440	$489,435	$489,444	$489,448
Contribution	$228,423	$228,423	$229,101	$228,954	$229,092	$229,112	$229,428	$229,436	$229,439	$229,530	$229,611

Distributed Load Factor/Balanced Demands/Typical Booking
Demand Multiplier = 1.0

First Revision Period	0	1	2	3	4	5	6	7	8	9	10
Operating Revenue	$492,979	$492,979	$492,979	$492,979	$492,979	$492,979	$492,971	$492,918	$492,756	$492,704	$492,631
Flight Cost	$217,708	$217,708	$217,708	$217,708	$217,708	$217,708	$217,708	$217,704	$217,688	$217,686	$217,682
Total Cost	$486,444	$486,444	$486,444	$486,444	$486,444	$486,444	$486,444	$486,440	$486,424	$486,422	$486,418
Contribution	$6,535	$6,535	$6,535	$6,535	$6,535	$6,535	$6,527	$6,478	$6,332	$6,282	$6,213

Distributed Load Factor/Balanced Demands/Typical Booking
Demand Multiplier = 1.5

First Revision Period	0	1	2	3	4	5	6	7	8	9	10
Operating Revenue	$719,059	$719,044	$719,044	$719,026	$718,993	$718,904	$718,818	$718,399	$717,985	$717,935	$717,800
Flight Cost	$220,403	$220,401	$220,401	$220,403	$220,403	$220,416	$220,449	$220,380	$220,317	$220,359	$220,307
Total Cost	$489,448	$489,446	$489,446	$489,448	$489,448	$489,461	$489,494	$489,425	$489,362	$489,404	$489,352
Contribution	$229,611	$229,598	$229,598	$229,578	$229,545	$229,443	$229,324	$228,974	$228,623	$228,531	$228,448

Figure 7.10.1

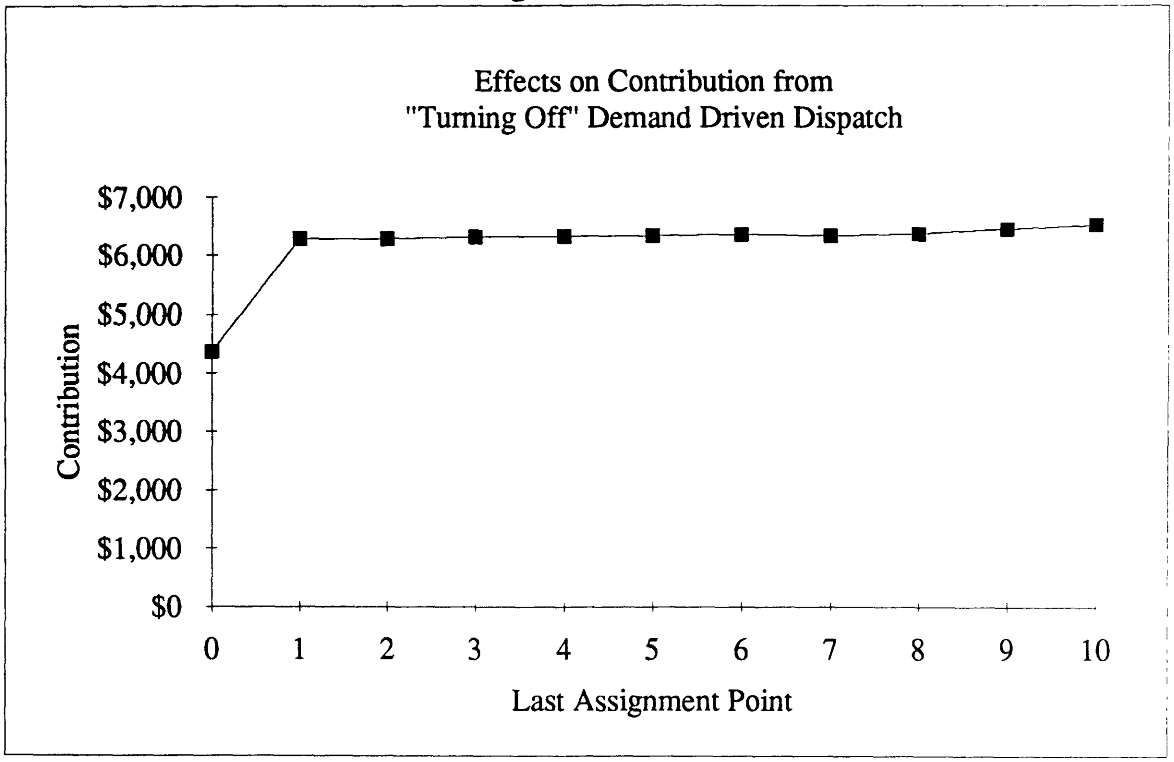


Figure 7.10.2

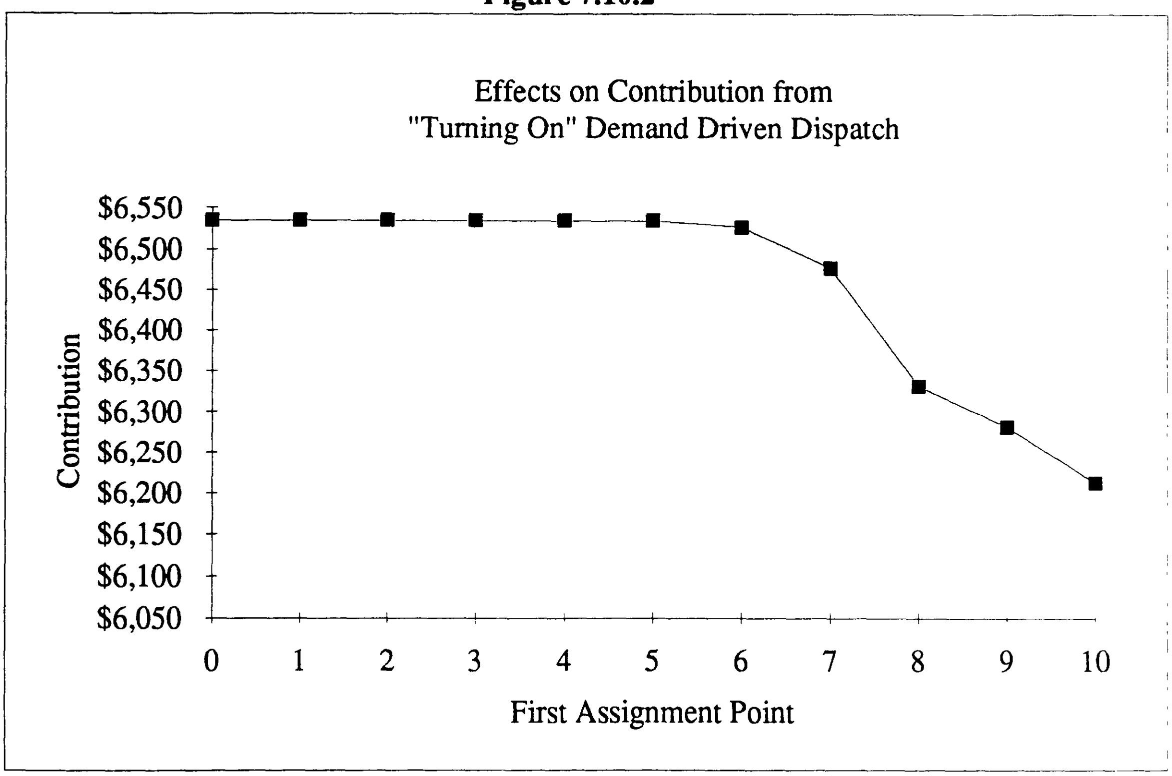


Figure 7.10.3

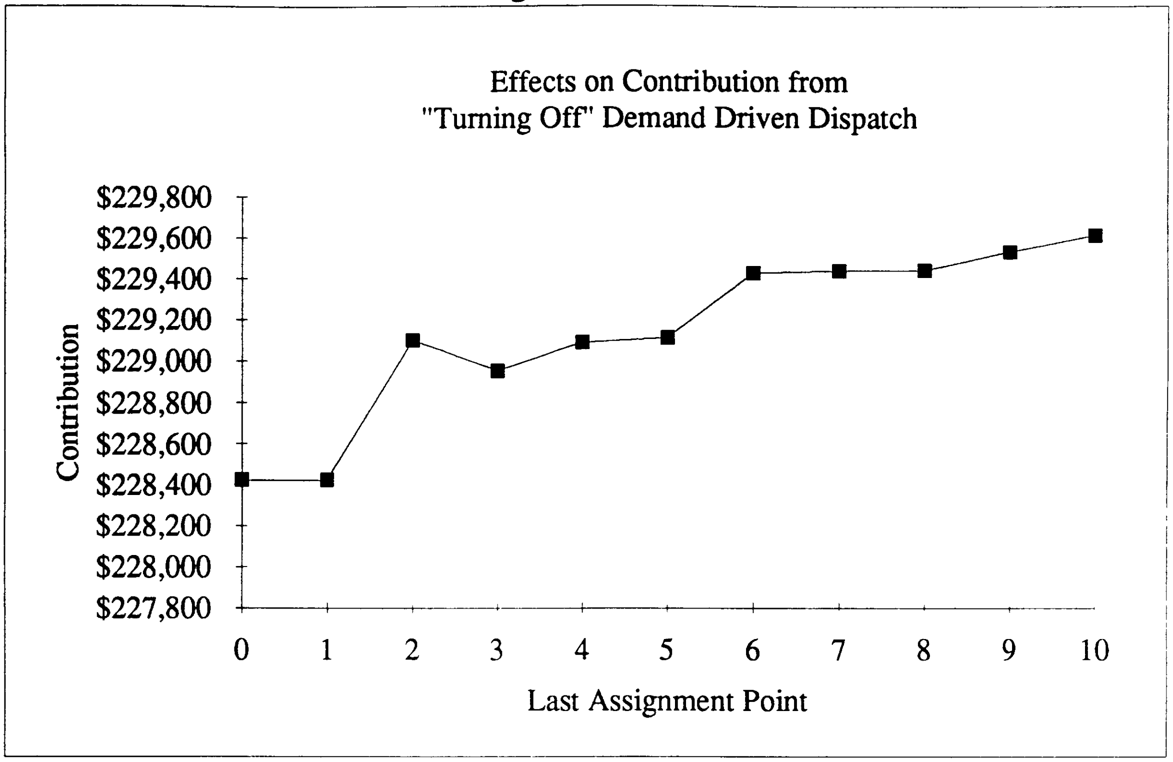
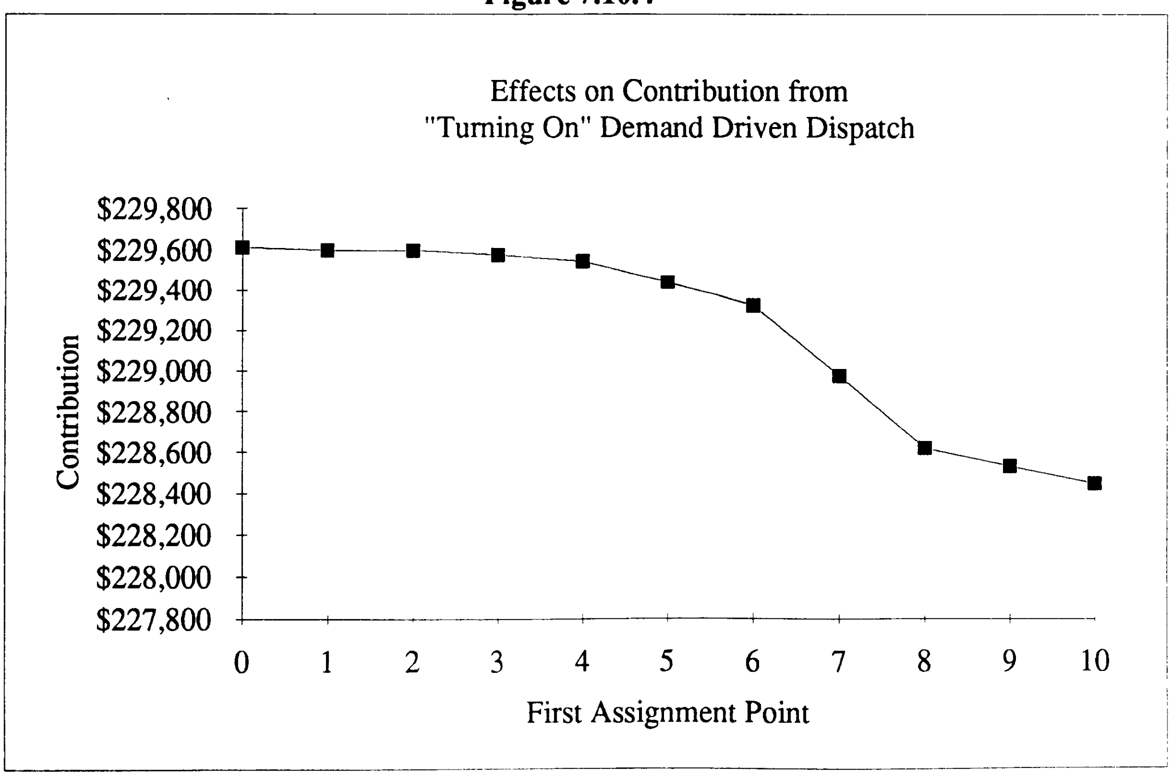


Figure 7.10.4



Chapter 8: Conclusions

Demand driven dispatch in airline hub operations can improve airline profit margins under certain conditions on the order of tens of millions of dollars annually. The best results obtained in this study were at load factors similar to those seen in the airline industry today. It was initially thought that the positive impacts of demand driven dispatch would carry through to higher demand situations as well. This was discovered not to be the case because opportunities for revenue generation are plentiful even in the static scenario that as long as revenue management systems are in place, the difference will be negligible.

In situations where profit was most significantly improved, the demand driven dispatch algorithm achieved these results by minimizing costs. This was done by radically changing the aircraft utilization pattern of the Boeing 737 family with respect to the static case. Daily utilization was greatly increased in the demand driven dispatch simulations for the smallest aircraft, the 737-500, by over an hour per airplane (approximately 20% change). Consequently, the daily utilization of the largest aircraft, the 737-400, was reduced by the roughly same amount on a per plane basis. This produced the situation where unit costs were higher in the demand driven dispatch runs relative to the static runs, but overall costs were lower because the demand driven dispatch model considers only trip costs. In situations where there was variability and low spill (i.e. demand multiplier 1.0) it made sense profit-wise to use the smaller aircraft more extensively because of lower trip costs. Variability in bookings and revenues drops when passenger demand greatly exceeds available capacity. Thus, as demands rise, the utilization rates drift back towards the static case assignment values since this set of aircraft assignments will capture by definition the greatest revenue under more deterministic conditions.

The results did not vary significantly with changes to the scenario definition. The profit improvement was always greatest at demand multiplier 1.0 regardless of any combination of demand distribution, leg demand balance, and booking process assumptions. This suggests a high degree of robustness of demand driven dispatch performance with regard to variable market conditions.

While it is difficult to make a direct comparison with the results from the Boeing studies, the impact on profit improvement from this version of demand driven dispatch was in general less (40%) than found with the Boeing model on a per airplane basis. There are two possible explanations. First, the Boeing model does not capture enough detail in the fare structure and booking process definitions. This suggests that demand driven dispatch profit projections cited in the Boeing studies could be more optimistic than those likely to be encountered in practice. However, it could also be true that the planning window approach is simply better than the daily cycle approach used in this thesis. Further study would be needed to determine the actual source(s) of the discrepancy.

Studies on the effectiveness of demand driven dispatch when initiated and terminated at different points in the booking process revealed two major conclusions. The first is that most of the benefit to be gained from running a demand driven dispatch reassignment routine at every booking revision point can be gained from performing the analysis just once early in the booking process. This is a clear message that airlines are limiting profit opportunities if aircraft assignments are made on the basis of aggregate demand data alone. It logically follows that independent of whether aircraft assignments are made upon consideration of deterministic or stochastic analyses, they must be made on at least a day of week basis if demand variation is high. Assigning a single aircraft type to a specific flight leg for an entire month will result in tremendous opportunity costs under this circumstance.

The second conclusion is that demand driven dispatch can be first used in the booking process as late as the revision point where advance purchase constraints initially come into play without a detrimental impact to profits. For example, the results from starting demand driven dispatch at 56 days before the flight will not vary greatly from those where demand driven dispatch assignments are initially made at 14 days before the flight, a common advance purchase restriction imposed by the airlines. This is an intuitive conclusion since passengers will typically not book restricted tickets until as late as possible because of penalties for itinerary changes.

Practical issues concerning the day to day operation of an airline in a demand driven dispatch environment were also examined. There seem to be no insurmountable obstacles preventing implementation of demand driven dispatch operations at airlines in the context of a multiple hub and spoke system. In fact, single hub and spoke systems with demand driven dispatch aircraft assignments are in use today in Europe. While the simulation runs only accounted for differences in flight operating costs, there is no reason to believe that ground and/or system operating costs will rise with demand driven dispatch. The major issue to be resolved in a large scale implementation would be the scheduling of flight and cabin crews. Ultimately this question comes down to the respective unions allowing for more work rule flexibility than exists in current contracts.

Chapter 9: Directions for Future Research

Perhaps the most interesting extension of this research would be to incorporate the ability to use demand driven dispatch not just once for a daily cycle, but for every intervening point in the day when aircraft flying shorter legs have returned to the hub. This would not require any great modification to the existing code but would necessitate a greater number of market demand assumptions.

The utilization patterns of the aircraft suggest that the composition of the aircraft pools might be altered so that the average capacity is reduced in such a way as to further increase profits. Methods for finding the optimal composition under different demand assumptions could explored.

There are also several leg assignment problems which could be addressed. For instance, a method could be developed to decompose a highly connected network into a set of either autonomous or linked hubs in such a way as to increase profit and while maintaining as much as possible the original flight schedule. Allowing for spoke switching among aircraft from different pools while maintaining overall fleet composition in each hub is also an interesting problem.

Finally, simulations could be run with traffic demand based upon connecting service for purposes of further realism. At present demands are only specified for each directed leg between the hub and the spoke city. Origin-destination demands could be specified on a spoke to spoke basis. More advanced revenue management techniques could also be tested. From the demand driven dispatch perspective, these two particular study directions would in all likelihood produce similar results to the cases in this study, but one never knows for sure without testing.

References

1 Jones Yang, Dori, and Rothman, Andrea. "Reinventing Boeing: Radical Changes Amid Crisis", Business Week, McGraw-Hill Publishing, 1 March 1993, page 60.

2 Berge, Matthew E. and Hopperstad, Craig A. "Demand Driven Dispatch: A Method for Dynamic Aircraft Capacity Assignment - Models and Algorithms", The Boeing Company, Seattle, Washington, 1990.

3 Ott, James T. "Carriers Streamline U.S. Hub Operations", Aviation Week and Space Technology, McGraw-Hill Publishing, 18 Jan 1993, pages 36-7.

4 Kanafani, A. and Hansen, M. "Hubbing and Airline Costs", Institute of Transportation Studies, University of California at Berkeley, 1985, (UCB-ITS-RR-85-12).

5 Reynolds-Feighan, Aisling J. "The Effects of Deregulation on U.S. Air Networks", Ph.D dissertation in Economics, University of Illinois, 1992.

6 Peterson, R.M. The Penultimate Hub Airplane. Internal Memo, Boeing Commercial Airplane Group, Seattle, Washington, 1986.

7 Beloba, Peter P. "Airline Travel Demand and Airline Seat Inventory Management", Ph.D dissertation in Aeronautical and Astronautical Engineering, Massachusetts Institute of Technology, 1987.

8 Williamson, Elizabeth L. "Airline Network Seat Inventory Control: Methodologies and Revenue Impacts", Ph.D. dissertation in Civil Engineering, Massachusetts Institute of Technology, 1992.

9 Morse, Philip M. *Queues, Inventories, and Maintenance,* New York, John Wiley and Sons, Inc, 1958, page 13.

10 Gordon, Geoffrey. *System Simulation*, Englewood Cliffs, New Jersey, Prentice-Hall, Inc., 1969, pages 105-8.

11 Mak, Chung Y. "Revenue Impacts of Yield Managment", Flight Transportation Laboratory Report R92-1, Massachusetts Institute of Technology, 1992.

12 Boeing 737-300 Operations Manual, CFM56-3B-2 Perfomance, The Boeing Company, Seattle, Washington, Last revised April 1992.

13 Boeing 737-400 Operations Manual, CFM56-3B-2 Perfomance, The Boeing Company, Seattle, Washington, Last revised April 1992.

14 Boeing 737-500 Operations Manual, CFM56-3C-1 Perfomance, The Boeing Company, Seattle, Washington, Last revised April 1992.

15 Winston, Wayne L., *Introduction to Mathematical Programming: Applications and Algorithms,* Boston, Massachusetts, PWS-Kent Publishing Company, 1991, page 356.

16 Simpson, R.W. Air Transportation Operating Cost, Class notes for Air Transporstation Economics taught at Massachusetts Institute of Technology, June 1985.

17 Meyer, Paul L. *Introductory Probability and Statistical Applications,* Reading, Massachusetts, Addison-Wesley Publishing Company, 1970, pages 325-6.