FLIGHT TRANSPORTATION LABORATORY
REPORT R 90-3

PRESENTATIONS FROM THE MIT/INDUSTRY COOPERATIVE RESEARCH PROGRAM ANNUAL MEETING 1990

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Catherine H. Bohutinsky
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TABLE OF CONTENTS

AIRLINE YIELD MANAGEMENT

RESEARCH OVERVIEW

Dr. Peter P. Belobaba
MIT Flight Transportation Laboratory

Presentation to Annual Meeting
MIT/Industry Cooperative Research Program
May 31, 1990

OVERVIEW

- Simulation of airline yield management strategies

- Single flight leg with a set of nested inventory classes.

- Simulation results address the following questions:

1. What is the most appropriate OPTIMIZATION ALGORITHM?

2. How important is more accurate DEMAND FORECASTING?

3. What additional revenue can be realized from by DYNAMIC REVISION of booking limits?

TERMINOLOGY AND DEFINITIONS

AIRLINE YIELD MANAGEMENT:

- Limiting the availability of seats in different booking classes

BOOKING CLASS (also FARE CLASS):

- Each fare type is associated with a booking class. A single flight leg departure can have 5 to 14 booking classes.

BOOKING LIMIT:

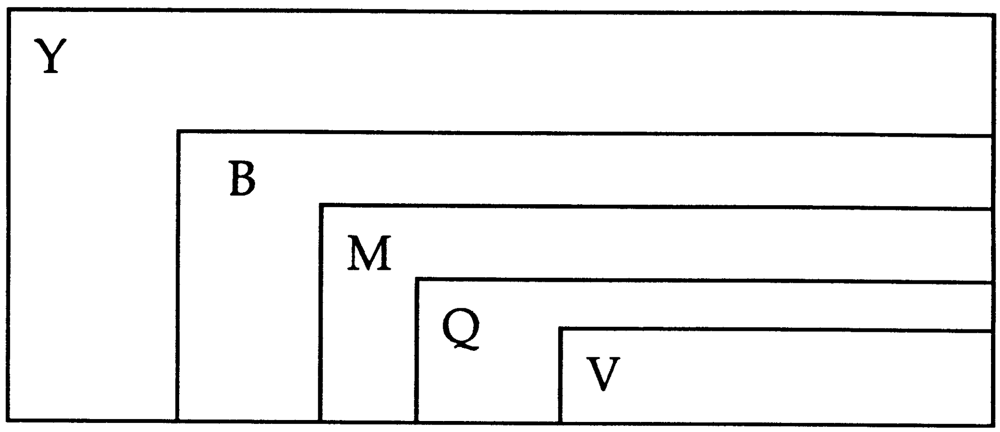
- Maximum number of reservations that may be accepted in a booking class.

FLIGHT LEG CONTROL:

- Booking limits are applied to booking classes for each flight leg, independent of other legs.

BOOKING CLASS STRUCTURE

EXAMPLE: 100 seats, 5 nested booking classes with Y-class having highest fare



BOOKING LIMITS: Y100 B85 M65 Q40 V10

- 15 seats are protected for exclusive use of Y-class bookings, but Y-class can book up to 100 (capacity).

OPTIMIZATION ALGORITHMS

1. DETERMINISTIC PROTECTION

EXAMPLE: 5 Fare Classes, 195 Seats

	CLASS 1	2	3	4	5
Demand	28	43	54	49	46
Std. Error	9.8	15.1	18.9	17.2	16.1
Fare	$289	236	205	141	127
Deterministic Protection	**28**	**43**	**54**	**49**	**21**

2. EMSR ALGORITHM (Belobaba 1987)

EXAMPLE: 5 Fare Classes, 195 Seats

	CLASS 1	2	3	4	5
EMSR Nested Protection	**19**	**31**	**64**	**34**	**47**

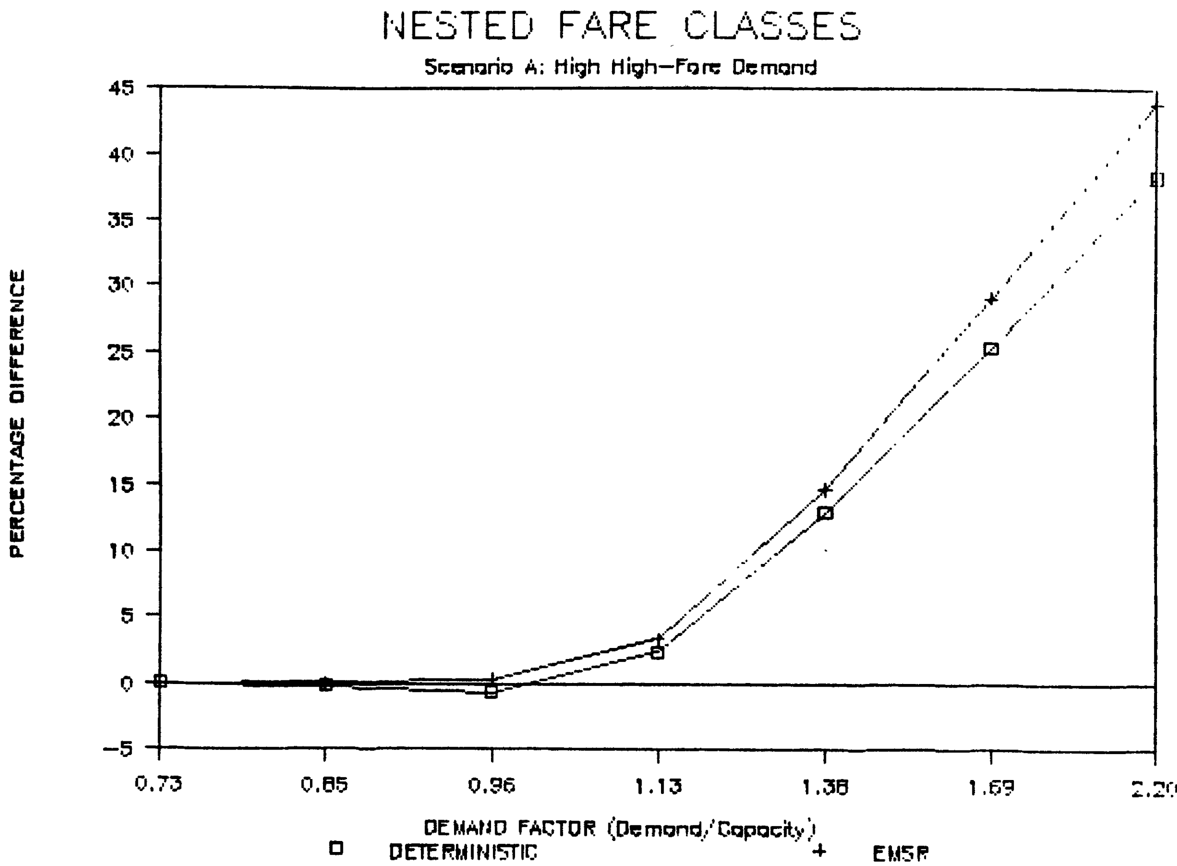
STATIC SIMULATION OF EXPECTED REVENUES

INPUTS:

- 5 booking classes on single flight leg
- Probabilistic demanddistribution, total demand of 220
- Varying capacities, from 100 to 300
- 2 demand scenarios:
  - (A) High high-fare demand
  - (B) High low-fare demand

SIMULATION:

- Demands drawn at a single point in time
- Lowest class books first; highest last
- Independent class demands; no "sell-up"
- No revisions of booking limits
- 1,000 flight sample


NESTED FARE CLASSES
Scenario A: High High-Fare Demand
PERCENTAGE DIFFERENCE
45
40
35
30
25
20
15
10
5
0
-5
0.73
0.85
0.96
1.13
1.38
1.69
2.20
DEMAND FACTOR (Demand/Capacity)
DETERMINISTIC
EMSR

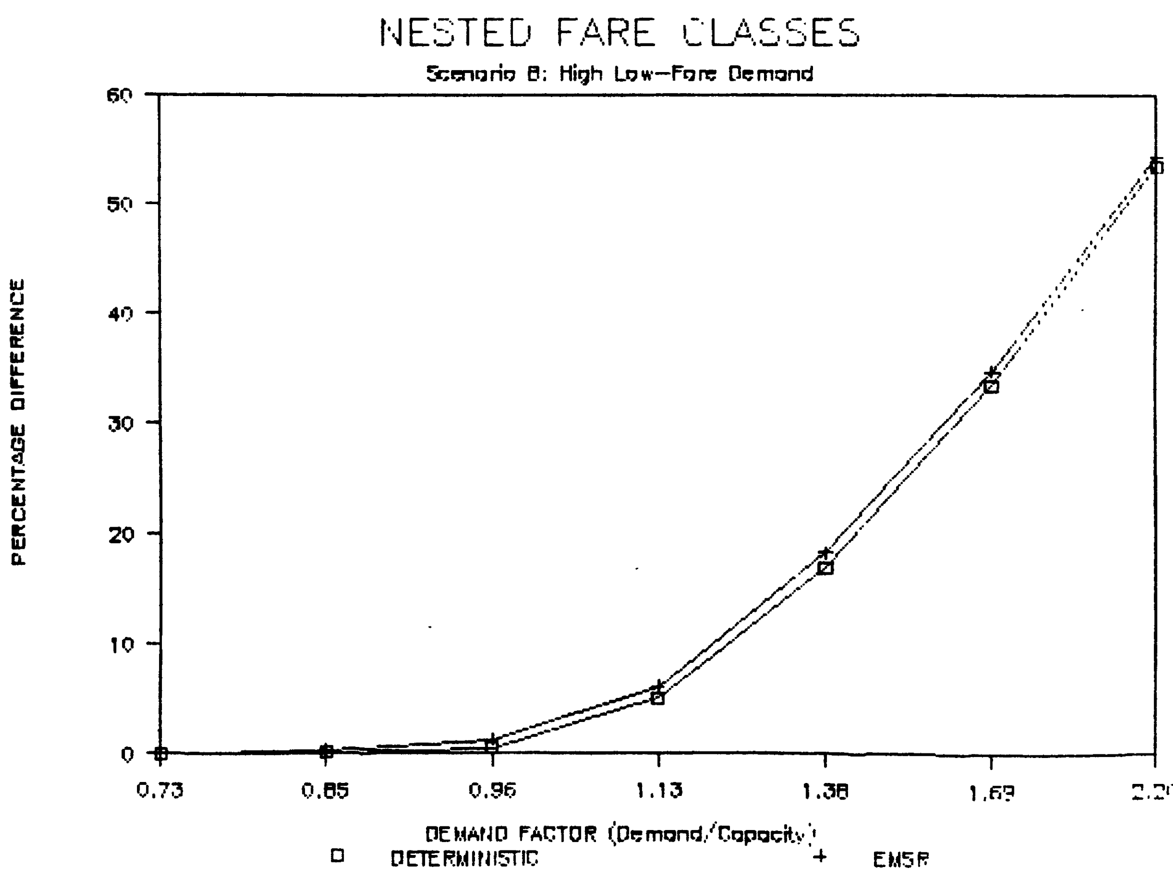

NESTED FARE CLASSES
Scenario B: High Low-Fare Demand
PERCENTAGE DIFFERENCE
60
50
40
30
20
10
0
0.73
0.85
0.96
1.13
1.38
1.69
2.20
DEMAND FACTOR (Demand/Capacity)
DETERMINISTIC
EMSR

FIGURE 1

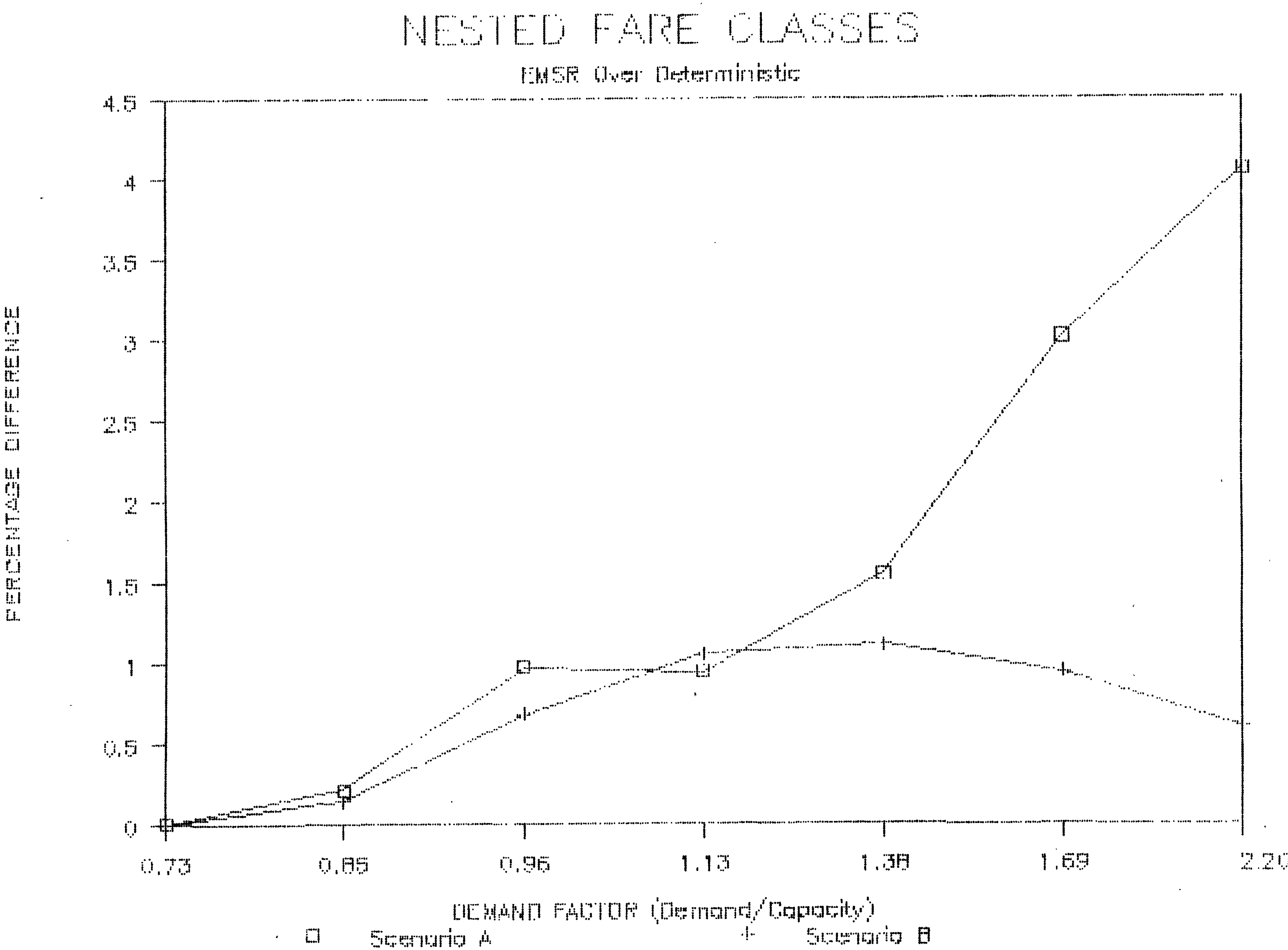

NESTED FARE CLASSES
EMSR Over Deterministic
PERCENTAGE DIFFERENCE
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
0.73
0.85
0.96
1.13
1.38
1.69
2.20
DEMAND FACTOR (Demand/Capacity)
Scenario A
Scenario B

FIGURE 2

RESERVATIONS FORECASTING

- Accurate flight-specific and class-specific forecasts of demand (bookings) at specific times before flight departure.

Common forecasting methods:

- Seasonally adjusted moving average models

- Regression models

- Combined causal and time series models.

Airlines are able to reduce forecast standard errors for each flight departure and fare class to 30-50% of the mean forecast.

- More precise forecasts lead to improved allocations of seats to fare classes and higher revenues.

SIMULATION OF THE VALUE OF FORECASTING

Four fare classes Y,B,M and Q with relative revenues of 100, 70, 50 and 30.

Four demand scenarios:

- Low (30% of capacity)
- Medium (60% of capacity)
- High (90% of capacity)
- Very high (120% of capacity)

Simulation of forecast fare class demands that differ from actual demands.

- Forecast mean and standard error used to calculate EMSR booking limits, where

  FORECAST = FACTOR x ACTUAL DEMAND

  and FACTOR ranges from 0.25 to 3.0.

- Demand drawn from a normal density of the actual mean and standard deviation of demand.

- Simulation of 2000 flights

TABLE 2- VALUE OF ACCURACY IN FORECASTING

(AIRCRAFT CAPACITY = 200)

(CHANGES IN THE MEAN ONLY)

FORECAST ACCURACY	PERCENTAGE CHANGE IN AVERAGE REVENUE FROM THE BASE CASE			
	LOW	MEDIUM	HIGH	VERY HIGH
50% OF BASE CASE	0%	0%	-3.6%	-9.2%
75% OF BASE CASE	0%	0%	-1.4%	-3.1%
90% OF BASE CASE	0%	0%	-0.3%	-0.6%
95% OF BASE CASE	0%	0%	-0.1%	0.2%
BASE CASE (PERFECT FORECAST)	----	----	----	----
105% OF BASE CASE	0%	0%	-0.1%	0.1%
110% OF BASE CASE	0%	0%	-0.4%	-0.5%
125% OF BASE CASE	0%	0%	-2.1%	-2.9%
150% OF BASE CASE	0%	-0.5%	-7.9%	-9.9%
200% OF BASE CASE	0%	-4.2%	-22.6%	-17.6%

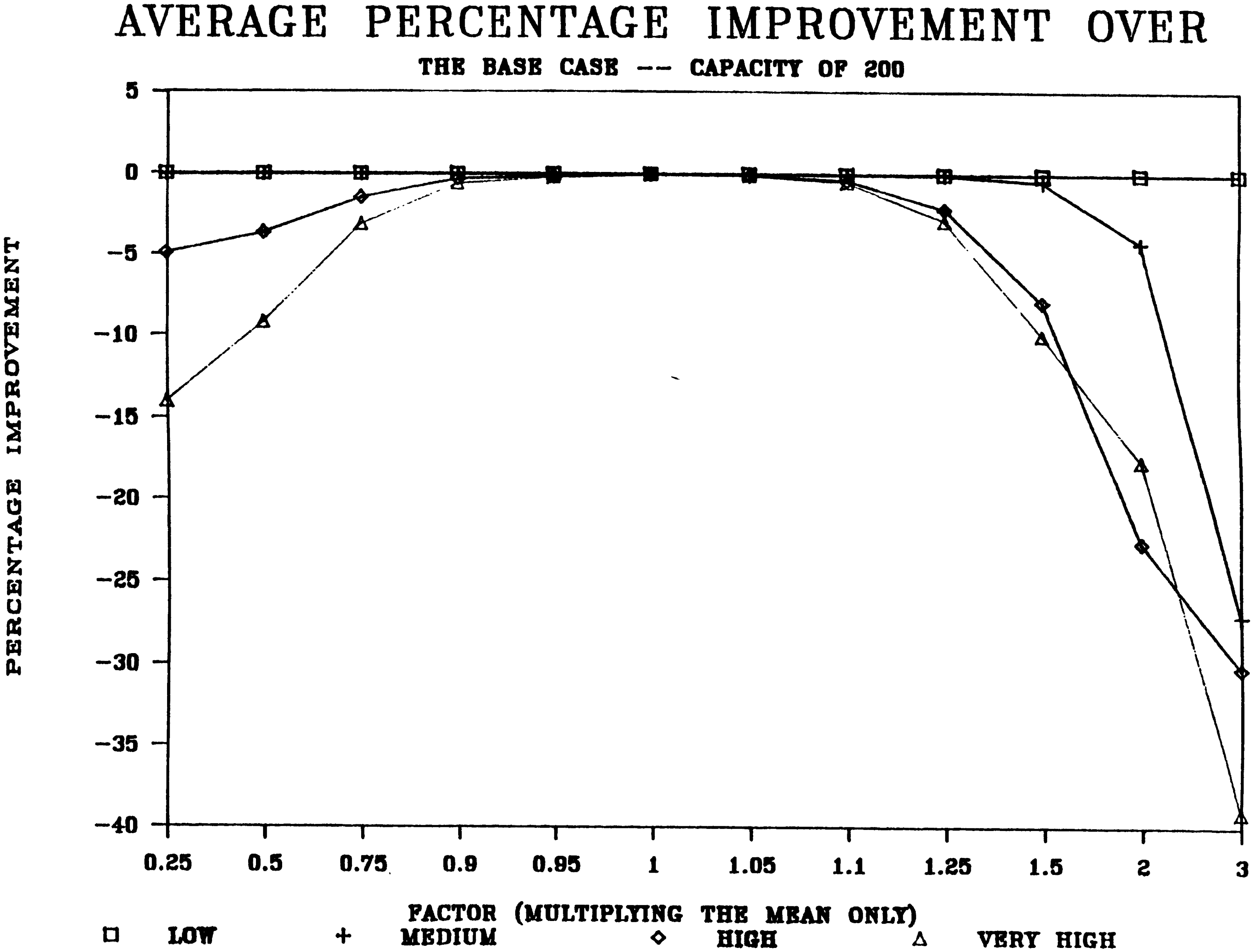

AVERAGE PERCENTAGE IMPROVEMENT OVER
THE BASE CASE -- CAPACITY OF 200
PERCENTAGE IMPROVEMENT
5
0
-5
-10
-15
-20
-25
-30
-35
-40
0.25
0.5
0.75
0.9
0.95
1
1.05
1.1
1.25
1.5
2
3
FACTOR (MULTIPLYING THE MEAN ONLY)
□ LOW
+ MEDIUM
◇ HIGH
△ VERY HIGH

FIGURE 3

DYNAMIC BOOKING LIMIT REVISION

Airlines are able to revise the fare class booking limits for a future flight as departure day nears.

A revised set of fare class booking limits can be found based on:

- a revised forecast of demand still to come
- number of available seats remaining

Examined the revenue impact of setting booking limits at 5 points in time prior to departure, compared to a single set of booking limits.

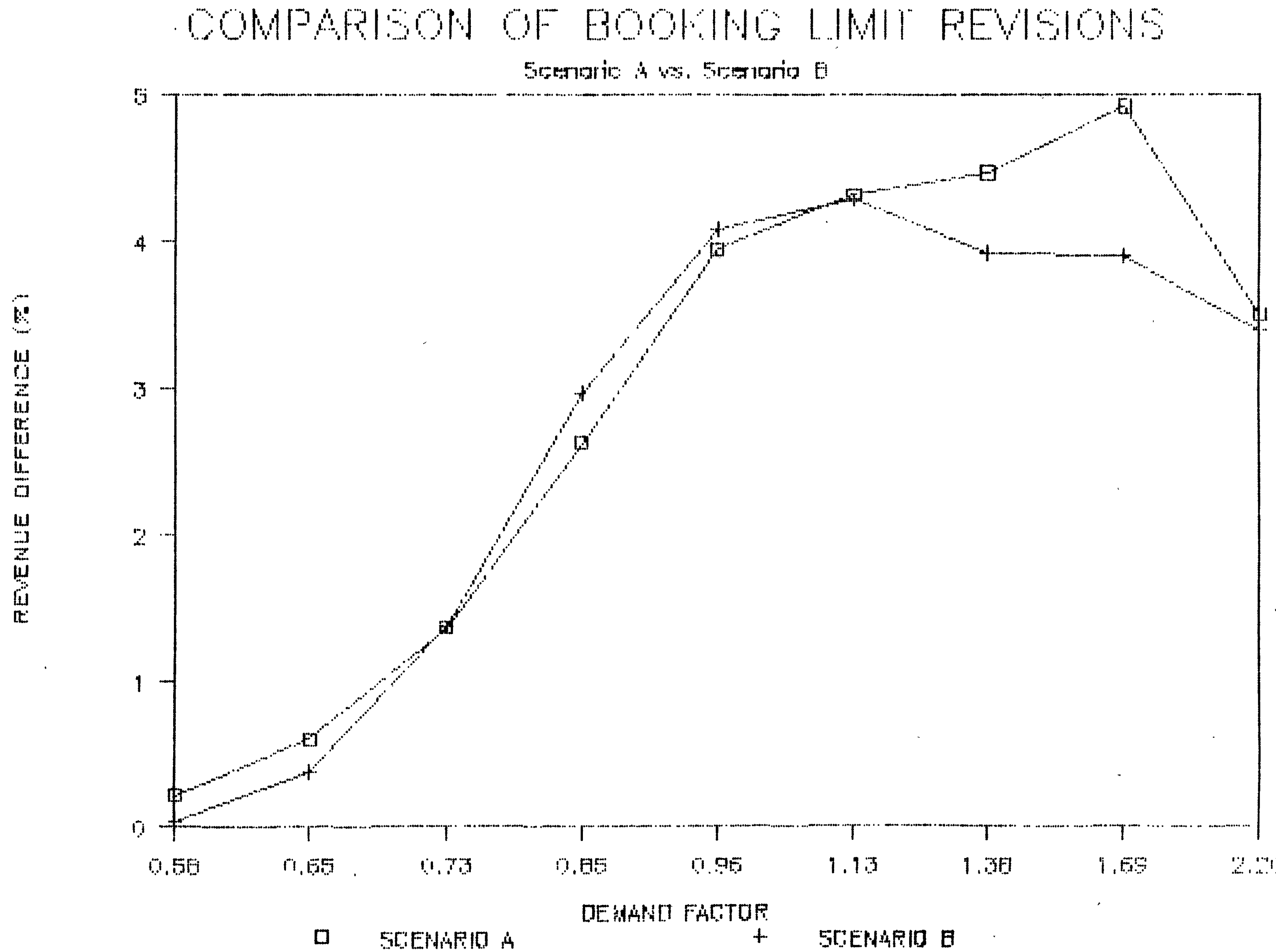
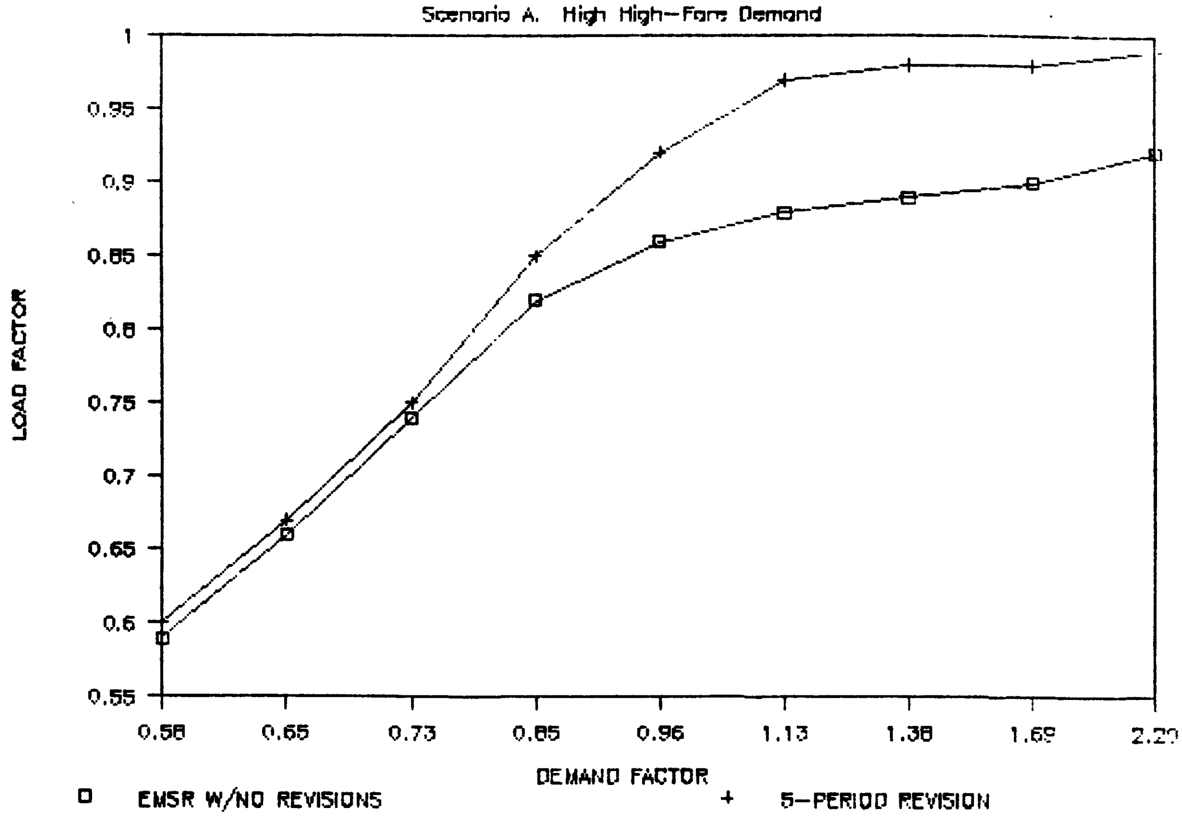

COMPARISON OF BOOKING LIMIT REVISIONS
Scenario A vs. Scenario B
REVENUE DIFFERENCE (%)
0
1
2
3
4
5
0.56
0.65
0.73
0.85
0.96
1.13
1.30
1.69
2.20
DEMAND FACTOR
SCENARIO A
SCENARIO B

FIGURE 4

COMPARISON OF BOOKING LIMIT REVISIONS

Scenario A. High High-Fare Demand



COMPARISON OF BOOKING LIMIT REVISIONS

Scenario B: Low High-Fare Demand

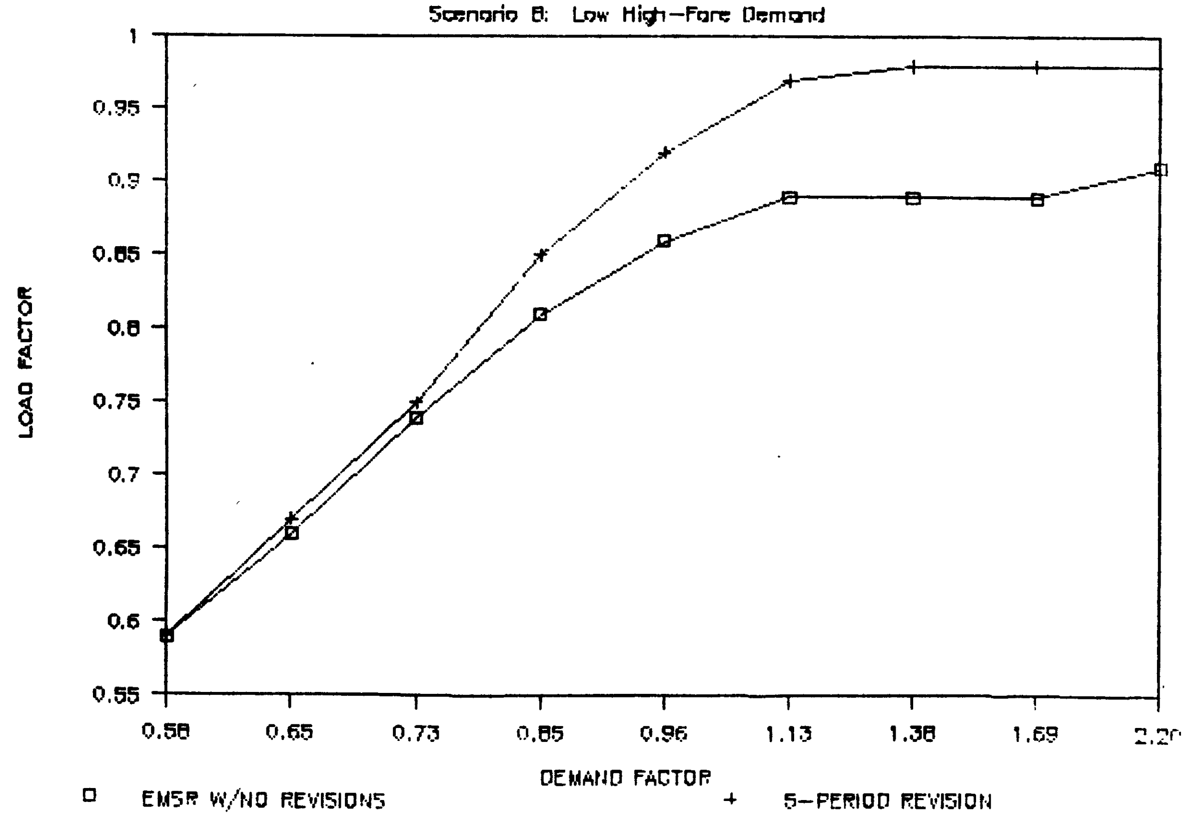


FIGURE 5

SUMMARY OF RESULTS

- Probabilistic optimization algorithm can increase expected revenues from 1 to 3 percent on high demand flights, compared to a determininistic approach.

- Each 10 percent improvement in the accuracy of forecasts can lead to revenue increases of 1 to 4 percent.

- Dynamic revision of booking limits can lead to expected revenue increase of up to 4 percent.

Further simulation analysis now under way to assess interaction of these three elements.

ANALYSIS OF AIRLINE DEMAND "SELL UP" POTENTIAL

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Presented to
MIT-Industry Cooperative Research Program

May 31, 1990

OUTLINE

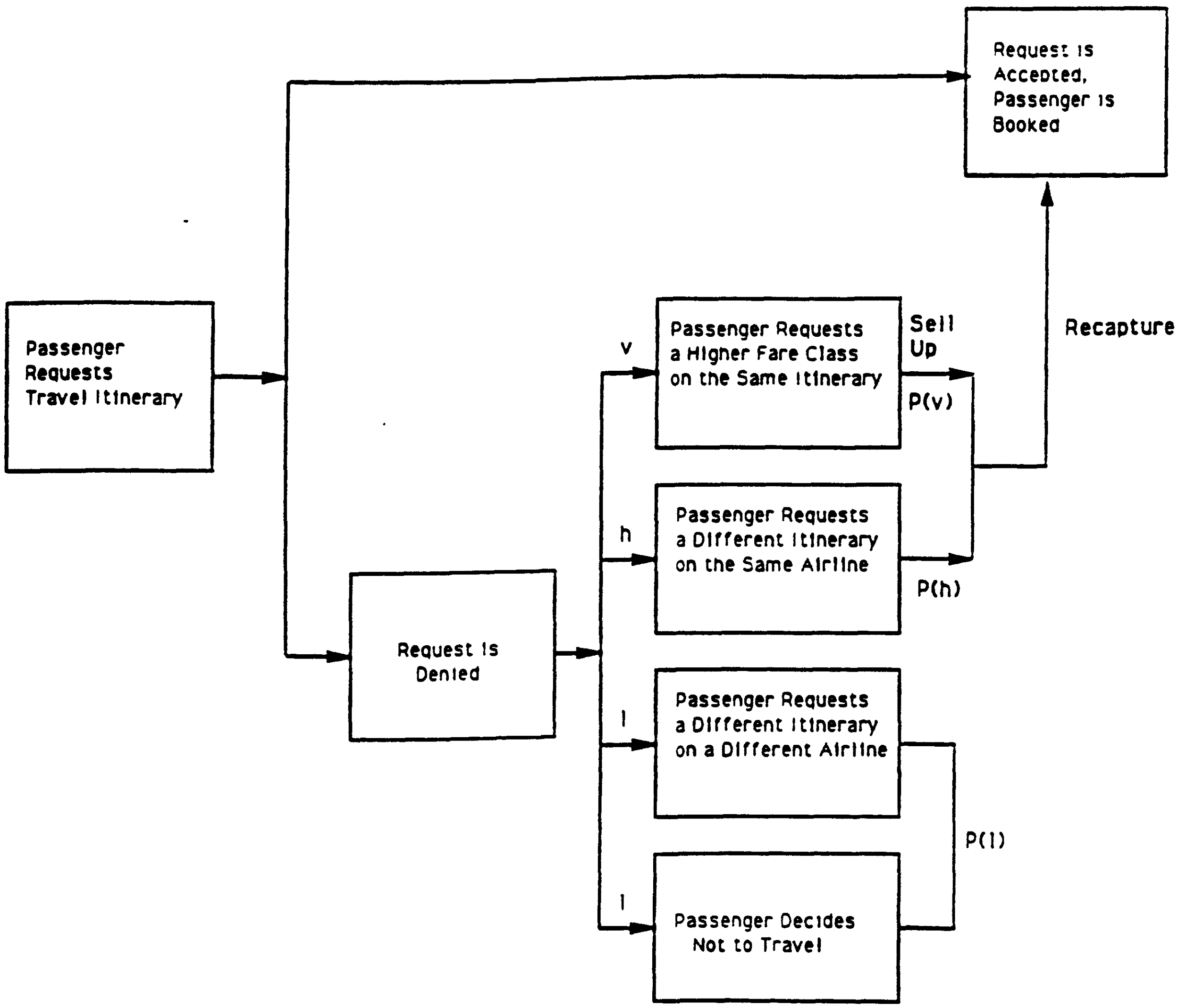
- Basic Definitions
- Example of a Sell Up Strategy
- Revenue Impact Measurements
- Sell Up Test Description
- Sell Up Test Results
- Conclusions

- **The purpose of this study was to address the issue of passenger choice shifts during the booking process.**

- **The unavailability of a desired flight and fare class to a consumer can lead to:**

    - **A shift to a higher fare class on the same flight (vertical shift)**
    - **A shift to a different flight on the same airline (horizontal shift)**
    - **A booking loss to the airline**

- **<u>Sell Up</u> refers to the vertical shift portion and occurs when a passenger purchases a ticket at a higher fare class on the same travel itinerary originally requested.**



Passenger Choice Options

- Benefits:
  - Airline gains higher revenue from the passenger
  - Costs of carrying this passenger remain the same
  - Thus, the airline increases profits by the difference of the two fare classes.

- Questions to be Answered:
  - How prevalent is sell up?
  - Does it occur in every market?
  - If not, which markets have a high occurrence of sell up and why?

- Identifying Flights with Sell Up Potential:
  1. The flight should experience historically high demand levels.
  2. A larger proportion of business travelers increases the probability of sell up.
  3. A large amount of competition from other carriers serves to decrease sell up potential.

EXAMPLE OF A SELL UP STRATEGY

- A sell up test can be performed on select flights to test for the existence (or nonexistence) of sell up.

- This test will compare the overall flight revenues of two types of flights in the same market.

  1. Sell up flight(s): The flight in which a sell up strategy will be implemented.

  2. Control flight(s): To be managed using usual seat inventory control measures. This flight will be used as a comparison measure.

SIMPLE EXAMPLE:

- Fare class structure (in descending order): Y; B; M; H; Q; K; L

- Sell Up Strategy: Close Class M seven days prior to the sell up flight's departure.

- Seat inventory management on the control flight will be performed as usual with no premature class closings.

Potential Impact:

- Passengers requesting reservations in Class M from Day 7 to Day 0 would be denied the option.

- These passengers would have the opportunity to sell up to Class B or Class Y.

- Lower fare classes are assumed to be closed to the passengers due to advanced purchase restrictions and nested fare class structure.

REVENUE IMPACT MEASUREMENTS

- **The revenue impact difference, ΔR between the sell up flight and the control flight is expressed as:**

$$\begin{aligned}\Delta R \;=\; & f_Y \sum_{j=7}^{0} (b^s_{Yj} - b^c_{Yj}) + \\ & f_B \sum_{j=7}^{0} (b^s_{Bj} - b^c_{Bj}) + \\ & f_M \sum_{j=7}^{0} (b^s_{Mj} - b^c_{Mj})\end{aligned}$$

where s = sell up flight
c = control flight
f_Y - fare value in class Y
b_{Yj}^s = bookings accepted in class Y day j prior to departure for the sell up flight
Day 7 = first day that the sell up policy was implemented
Day 0 = the day of the flights' departure

- This incremental revenue test allows one to compare flight revenues during the period the sell up policy was implemented, screening out differences in booking levels not due to sell up.

- The *difference* in bookings after the sell up policies are implemented is the basis of this test.

- Revenue impact is thus the sum of the revenue impact differences for Classes Y, B, and M, which are the classes affected by the sell up strategy. Differences in flight revenues are only measured from Day 7 to Day 0.

- The revenue impact difference for any given sell up policy can be generalized as:

$$\Delta R = \sum_{m=v}^{M} (f_m \sum_{j=t}^{0} (b^s_{mj} - b^c_{mj}))$$

where v = the lowest fare class that is affected by the sell up policy

t = first day that the sell up policy is implemented

SELL UP TEST DESCRIPTION

- Under a research agreement with Delta Air Lines, a sell up strategy was developed and tested.

- Eleven markets were selected on the basis of having historically high demand levels.

- Two flights a day, two days a week, for a two week period were chosen for each of these markets to be a part of the analysis, for a total of eighty-eight flights to be included in the test.

- Actions to be taken were as follows:

  AUTOMATED CONTROL - No modifications were to be made on recommended booking limits.
  SINGLE POINT SELL UP - Application of sell up strategies was done on an individual flight basis, taking into account each markets' historical booking patterns.

- These actions were distributed evenly across flight numbers, days of week, and across the two week period.

MARKET	FLIGHT	WEEK	DAY OF WEEK	ACTION TAKEN
ATLBOS	A	1	Tuesday	AUTOMATED CONTROL
		1	Wednesday	SINGLE POINT SELL UP
		2	Tuesday	SINGLE POINT SELL UP
		2	Wednesday	AUTOMATED CONTROL
	B	1	Tuesday	SINGLE POINT SELL UP
		1	Wednesday	AUTOMATED CONTROL
		2	Tuesday	AUTOMATED CONTROL
		2	Wednesday	SINGLE POINT SELL UP

Example of Actions to be Taken, Two Week Study

GROUP	MARKET	SELL UP ACTION FARE CLASS	SELL UP ACTION DAY CLOSED
I	ATLBOS	K,L	42
	BOSATL	H	14
		B	7
II	ATLLAX	K,L	21
	LGAATL	H	14
	ATLDCA	B	7
	DFWATL		
	ATLGSP		
	GSPATL		
III	LGAFLL	K,L	21
	ATLMLB	H	7
	MLBATL		

Sell Up Policies Developed on an Individual Market Basis

SELL UP TEST RESULTS

Total Revenues:

- % Difference Same Week - Compares the coach class revenue value of the sell up flight with the control flight of the same week.

- % Difference Across Weeks - Compares the revenue values of the single point sell up flight with the automated control flight across different weeks.

Relatively few flight pairs exhibit positive percentage differences, when compared in the same week or across weeks.

- 14 out of 44 percentage difference values for the % Difference Same Week comparison are positive

- 12 out of 44 percentage difference values for the % Difference Across Week comparison are positive.

MARKET	FLIGHT	DEP. WEEK	ACTION TAKEN	% DIFF SAME WEEK	% DIFF ACROSS WEEKS
ATLBOS	A	1	AUTOMATED CONTROL		
		1	SINGLE POINT SELLUP	-22.06%	-19.12%
		2	SINGLE POINT SELLUP	-51.05%	-52.82%
		2	AUTOMATED CONTROL		
	B	1	SINGLE POINT SELLUP	-9.46%	12.40%
		1	AUTOMATED CONTROL		
		2	AUTOMATED CONTROL		
		2	SINGLE POINT SELLUP	16.51%	-6.15%
ATLLAX	A	1	AUTOMATED CONTROL		
		1	SINGLE POINT SELLUP	5.47%	-0.24%
		2	SINGLE POINT SELLUP	16.67%	23.36%
		2	AUTOMATED CONTROL		
	B	1	SINGLE POINT SELLUP	-41.06%	-28.32%
		1	AUTOMATED CONTROL		
		2	AUTOMATED CONTROL		
		2	SINGLE POINT SELLUP	-19.70%	-33.98%
LGAATL	A	1	SINGLE POINT SELLUP	-7.03%	12.99%
		1	AUTOMATED CONTROL		
		2	AUTOMATED CONTROL		
		2	SINGLE POINT SELLUP	123.91%	84.25%
	B	1	AUTOMATED CONTROL		
		1	SINGLE POINT SELLUP	27.00%	-3.99%
		2	SINGLE POINT SELLUP	-30.41%	-7.95%
		2	AUTOMATED CONTROL		
MLBATL	A	1	AUTOMATED CONTROL		
		1	SINGLE POINT SELLUP	-33.09%	-38.27%
		2	SINGLE POINT SELLUP	-0.79%	7.53%
		2	AUTOMATED CONTROL		
	B	1	SINGLE POINT SELLUP	-16.34%	-40.15%
		1	AUTOMATED CONTROL		
		2	AUTOMATED CONTROL		
		2	SINGLE POINT SELLUP	-36.69%	-11.51%
DFWATL	A	1	SINGLE POINT SELLUP	-38.84%	-9.63%
		1	AUTOMATED CONTROL		
		2	AUTOMATED CONTROL		
		2	SINGLE POINT SELLUP	26.63%	-14.30%
	B	1	AUTOMATED CONTROL		
		1	SINGLE POINT SELLUP	-22.93%	-36.76%
		2	SINGLE POINT SELLUP	-29.20%	-13.72%
		2	AUTOMATED CONTROL		
LGAFLL	A	1	AUTOMATED CONTROL		
		1	SINGLE POINT SELLUP	-35.80%	-20.62%
		2	SINGLE POINT SELLUP	2.55%	-17.06%
		2	AUTOMATED CONTROL		
	B	1	SINGLE POINT SELLUP	-43.93%	-6.25%
		1	AUTOMATED CONTROL		
		2	AUTOMATED CONTROL		
		2	SINGLE POINT SELLUP	46.94%	-12.11%

MARKET	FLIGHT	DEP. WEEK	ACTION TAKEN	% DIFF SAME WEEK	% DIFF ACROSS WEEKS
ATLGSP	A	1	SINGLE POINT SELLUP	-18.28%	-18.42%
		1	AUTOMATED CONTROL		
		2	AUTOMATED CONTROL		
		2	SINGLE POINT SELLUP	7.32%	7.51%
	B	1	AUTOMATED CONTROL		
		1	SINGLE POINT SELLUP	-7.61%	-11.00%
		2	SINGLE POINT SELLUP	14.87%	19.25%
		2	AUTOMATED CONTROL		
BOSATL	A	1	AUTOMATED CONTROL		
		1	SINGLE POINT SELLUP	-25.40%	-17.38%
		2	SINGLE POINT SELLUP	-33.41%	-39.88%
		2	AUTOMATED CONTROL		
	B	1	SINGLE POINT SELLUP	-39.39%	-24.94%
		1	AUTOMATED CONTROL		
		2	AUTOMATED CONTROL		
		2	SINGLE POINT SELLUP	63.42%	31.96%
GSPATL	A	1	SINGLE POINT SELLUP	-9.14%	33.66%
		1	AUTOMATED CONTROL		
		2	AUTOMATED CONTROL		
		2	SINGLE POINT SELLUP	104.19%	38.82%
	B	1	AUTOMATED CONTROL		
		1	SINGLE POINT SELLUP	2.63%	-13.33%
		2	SINGLE POINT SELLUP	-38.49%	-27.17%
		2	AUTOMATED CONTROL		
ATLMLB	A	1	AUTOMATED CONTROL		
		1	SINGLE POINT SELLUP	-39.75%	-51.53%
		2	SINGLE POINT SELLUP	-39.94%	-25.35%
		2	AUTOMATED CONTROL		
	B	1	SINGLE POINT SELLUP	-39.08%	-45.65%
		1	AUTOMATED CONTROL		
		2	AUTOMATED CONTROL		
		2	SINGLE POINT SELLUP	-0.03%	12.05%
ATLDCA	A	1	SINGLE POINT SELLUP	-10.96%	-13.62%
		1	AUTOMATED CONTROL		
		2	AUTOMATED CONTROL		
		2	SINGLE POINT SELLUP	6.73%	10.02%
	B	1	AUTOMATED CONTROL		
		1	SINGLE POINT SELLUP	-22.38%	-18.70%
		2	SINGLE POINT SELLUP	-14.80%	-18.66%
		2	AUTOMATED CONTROL		

TOTAL REVENUE RESULTS

Revenue Impact Results:

- **Revenue impact tests were performed on a flight by flight basis to further assess sell up impact.**

- **The net *Change in Bookings* was determined on an individual class level, depending upon when the class was affected by the sell up actions.**

- ***Revenue Impact* for a specific class is the *Change in Bookings* multiplied by the average posted fare value for the class.**

- **Total Revenue Impact for a specific class is the sum of the revenue impact of the two sell up flights minus the sum of the revenue impact of the two control flights. If this value is positively valued, then sell up has had a positive impact in the specific class. In contrast, if this revenue value is negative, sell up has had a negative impact on the class.**

- **The revenue impact of a specific sell up strategy can be measured using Total Revenue Impact values. For example, the impact of closing B-class in the ATLBOS market at Day 7 can be calculated by adding up the Total Revenue Impact of Y and B-classes.**

- **Total Revenue Impact of All Classes is the sum of the revenue impact differences in classes Y through L.**

  - **This value was positive for only 2 out of the 22 flights numbers surveyed.**

MARKET	FLIGHT NUMBER	WEEK OF DEPARTURE	ACTION TAKEN	CHANGE IN Y	CHANGE IN B	CHANGE IN M	CHANGE IN H	CHANGE IN Q	CHANGE IN K	CHANGE IN L			REVENUE IMPACT					TOTAL REVENUE IMPACT
											Y	B	M	H	Q	K	L	L THROUGH Y
ATLBOS	B	1	SELL UP	51	-9	-5	-1	16	-2	-7	$15,453	$0	$0	$0	$2,288	$0	$0	$17,741
		1	CONTROL	39	-8	3	8	11	22	14	$11,817	$0	$555	$1,240	$1,573	$2,750	$1,288	$19,223
		2	CONTROL	32	-16	2	13	12	9	16	$9,696	$0	$370	$2,015	$1,716	$1,125	$1,472	$16,394
		2	SELL UP	30	-3	-2	-2	22	-6	-1	$9,090	$0	$0	$0	$3,146	$0	$0	$12,236
											$3,030	$0	($925)	($3,255)	$2,145	($3,875)	($2,760)	($5,640)

MARKET	FLIGHT NUMBER	WEEK OF DEPARTURE	ACTION TAKEN	CHANGE IN Y	CHANGE IN B	CHANGE IN M	CHANGE IN H	CHANGE IN Q	CHANGE IN K	CHANGE IN L			REVENUE IMPACT					REVENUE IMPACT
											Y	B	M	H	Q	K	L	L THROUGH Y
DFWATL	A	1	SELL UP	40	0	-1	0	3	-6	-1	$10,880	$0	$0	$0	$477	$0	$0	$11,357
		1	CONTROL	39	-1	0	12	18	25	10	$10,608	$0	$0	$1,836	$2,862	$3,100	$980	$19,386
		2	CONTROL	34	2	0	20	11	13	14	$9,248	$468	$0	$3,060	$1,749	$1,612	$1,372	$17,509
		2	SELL UP	38	0	2	-1	3	-7	-6	$10,336	$0	$422	$0	$477	$0	$0	$11,235
											$1,360	($468)	$422	($4,896)	($3,657)	($4,712)	($2,352)	($14,303)

MARKET	FLIGHT NUMBER	WEEK OF DEPARTURE	ACTION TAKEN	CHANGE IN Y	CHANGE IN B	CHANGE IN M	CHANGE IN H	CHANGE IN Q	CHANGE IN K	CHANGE IN L			REVENUE IMPACT					REVENUE IMPACT
											Y	B	M	H	Q	K	L	H THROUGH Y
LGAFLL	B	1	SELL UP	--	--	14	0	12	0	-17	--	--	$2,408	$0	$1,968	$0	$0	$4,376
		1	CONTROL	--	--	2	10	14	-5	-1	--	--	$344	$1,640	$2,296	$0	$0	$4,280
		2	CONTROL	--	--	1	8	39	5	8	--	--	$172	$1,312	$6,396	$640	$744	$9,264
		2	SELL UP	--	--	12	-3	23	-10	-3	--	--	$2,064	$0	$3,772	$0	$0	$5,636
													$3,956	($2,952)	($2,952)	($640)	($744)	($3,332)

Incremental Revenue Impact Results

- In general, sell up appeared to be most successful from Class B to Class Y.

    - Revenue impact was positive for 10 out of the 22 flights when Classes Y and B are considered alone.

- Sell up was less successful in the lower fare classes (Class H to Class M as well as Class L and K to Class Q).

    - When considering the revenue impact of Classes H and M alone, 2 out of the 22 flights had a positive revenue impact.

    - None of the flights surveyed had a positive revenue impact with respect to Classes L, K and Q only.

REVENUE IMPACT MEASUREMENTS
Y AND B FARE CLASSES

MARKET	FLIGHT	Y CLASS REVENUE IMPACT	B CLASS REVENUE IMPACT	TOTAL
ATLBOS	A	($4,545)	($234)	($4,779)
	B	$3,030	$0	$3,030
ATLLAX	A	$2,352	($3,641)	($1,289)
	B	($4,704)	$0	($4,704)
LGAATL	A	$16,038	($723)	$15,315
	B	($4,752)	$0	($4,752)
MLBATL	A	$1,442	($3,800)	($2,358)
	B	$0	($608)	($608)
DFWATL	A	$1,360	($468)	$892
	B	($2,176)	($1,170)	($3,346)
LGAFLL	A	$2,064	($3,444)	($1,380)
	B	$3,956	($2,952)	$1,004
ATLGSP	A	$0	($1,200)	($1,200)
	B	$6,291	($1,680)	$4,611
BOSATL	A	$302	$0	$302
	B	$3,322	($2,270)	$1,052
ATLMLB	A	$1,188	($3,634)	($2,446)
	B	$396	($2,212)	($1,816)
GSPATL	A	$10,992	$233	$11,225
	B	($3,893)	($1,864)	($5,757)
ATLDCA	A	$3,264	$0	$3,264
	B	$5,508	($1,120)	$4,388

CONCLUSIONS

- Sell up is flight specific. It is possible for one flight to exhibit sell up behavior and another flight in the *same* market to show no indication of sell up.

- The sell up strategies tested in this study had an overall negative revenue impact (revenue gained through sell up was less than revenue lost by prematurely closing out specific fare classes).

- Comparisons of flights within the same week and across weeks yielded relatively the same negative sell up impacts.

- Some positive indication of sell up was shown from Class B to Class Y. In general, lower fare classes showed little or no positive sell up impact.

OVERALL CONCLUSIONS

The following criteria should be met in the development of a successful sell up strategy:

1. **The policy should be developed on a flight by flight basis, taking into account that sell up is flight specific.**

2. **Booking limits should be restricted in upper fare classes only, in order to impose sell up in the higher fare classes.**

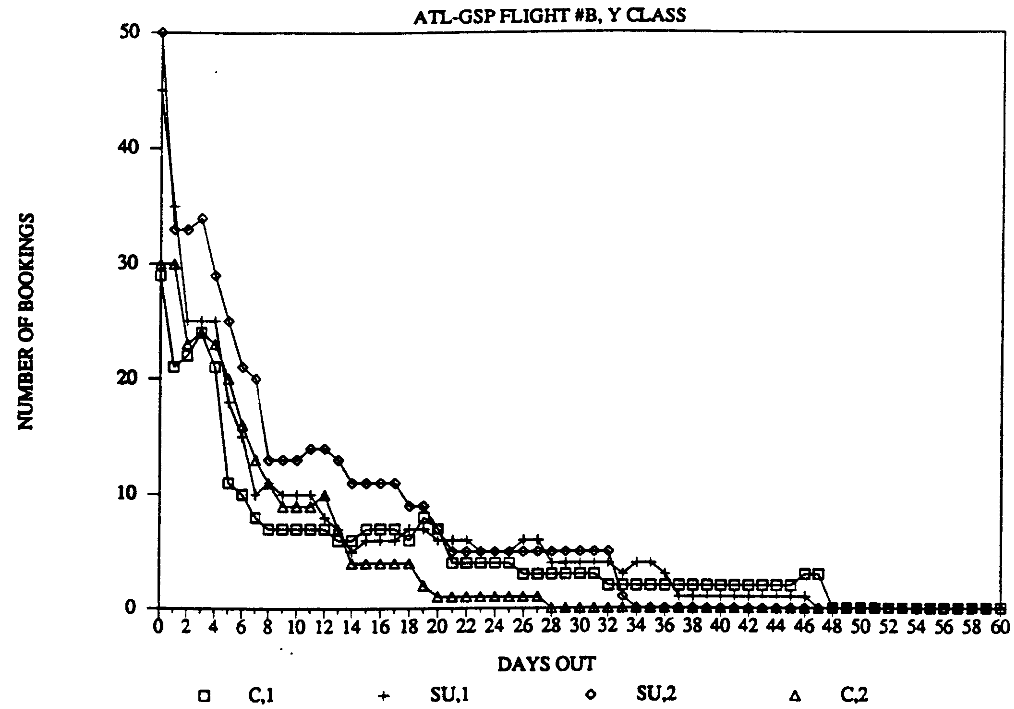
3. **Booking limit restrictions should not be made in lower fare classes, due to the lack of sell up behavior in these classes.**

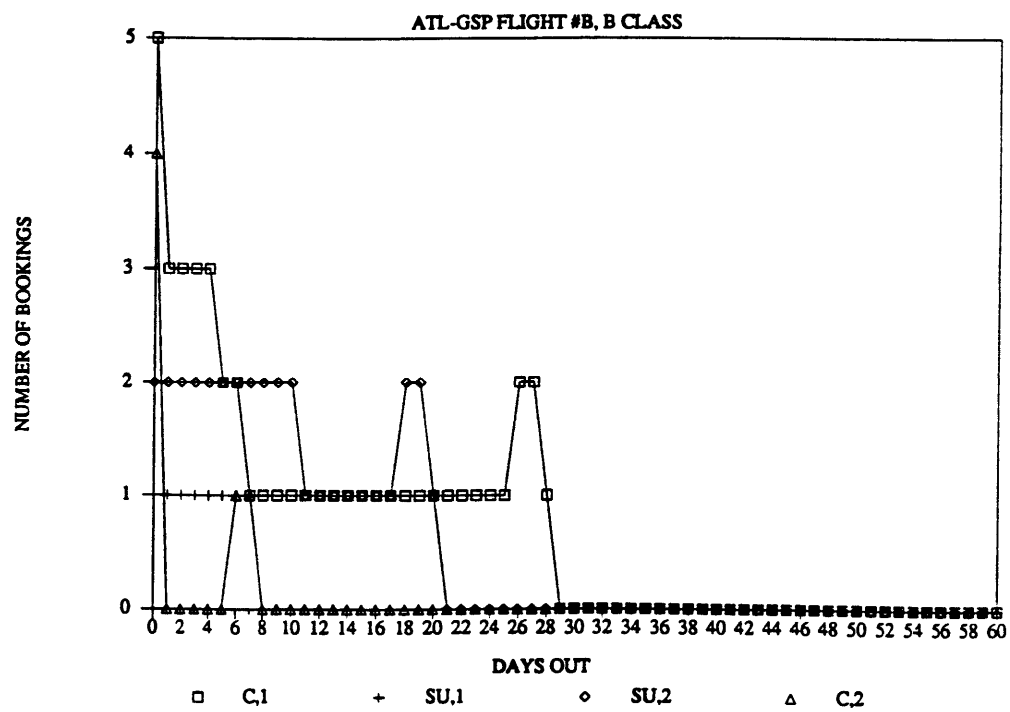
APPENDIX

BOOKING INFORMATION

Sell Up vs. Control Flights

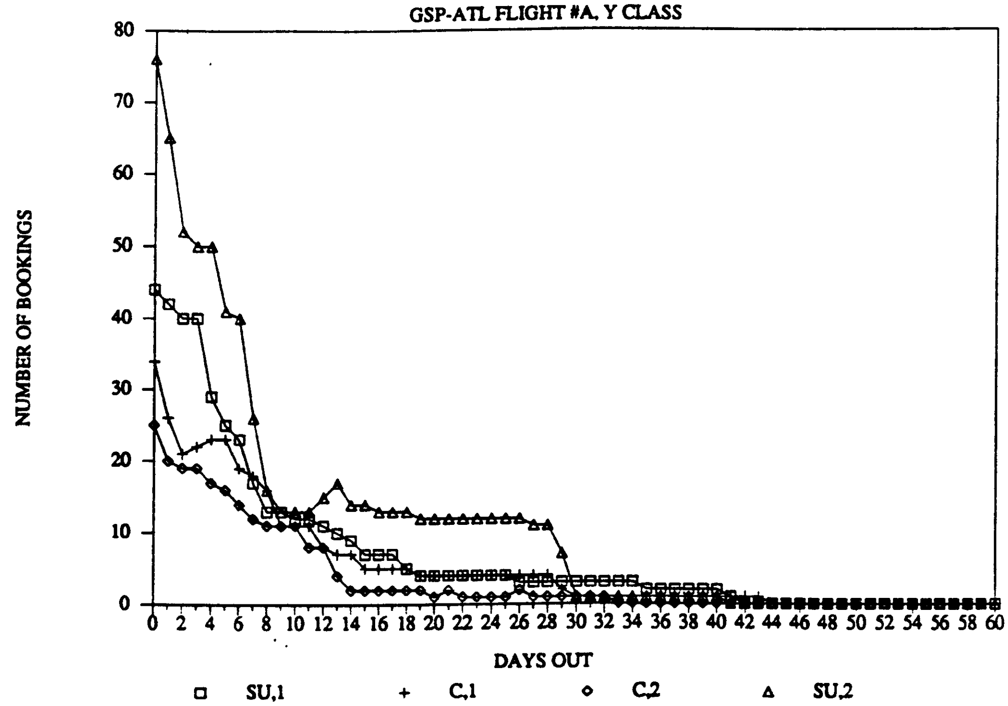
BOOKING INFORMATION

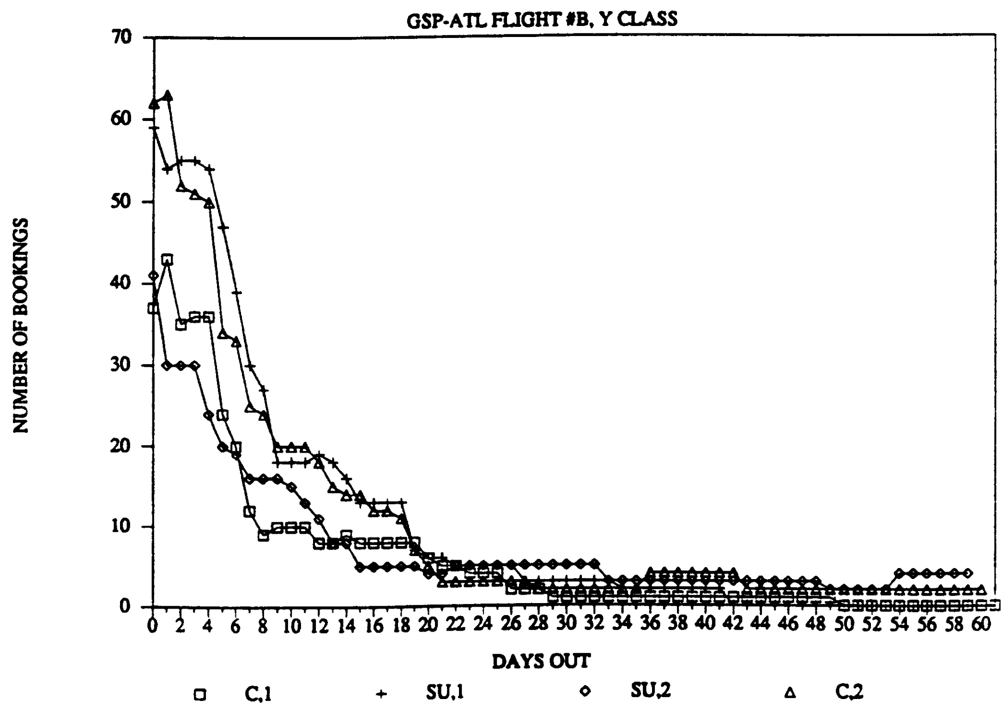




ATLGSP "Y", "B" Classes, Flight B

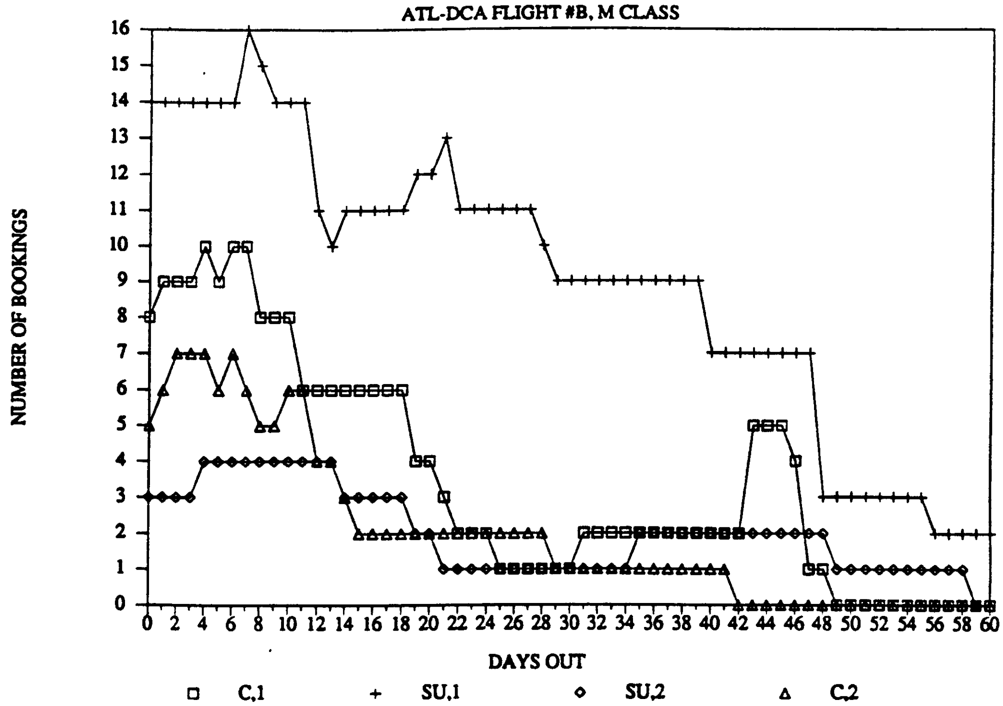
BOOKING INFORMATION

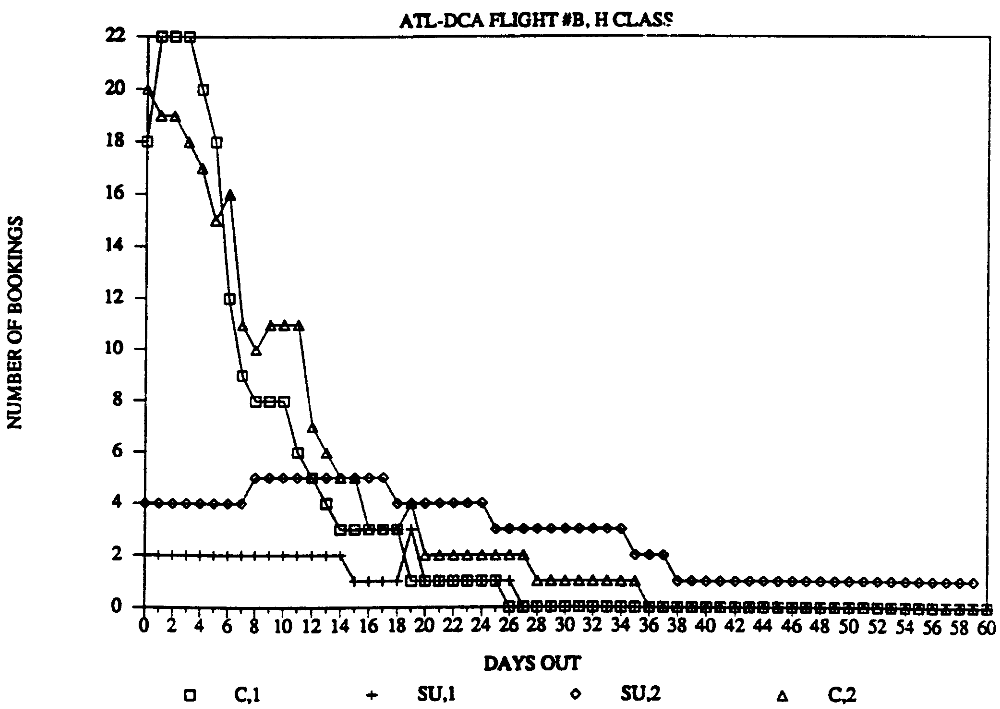




GSPATL "Y" Class, Flights A, B

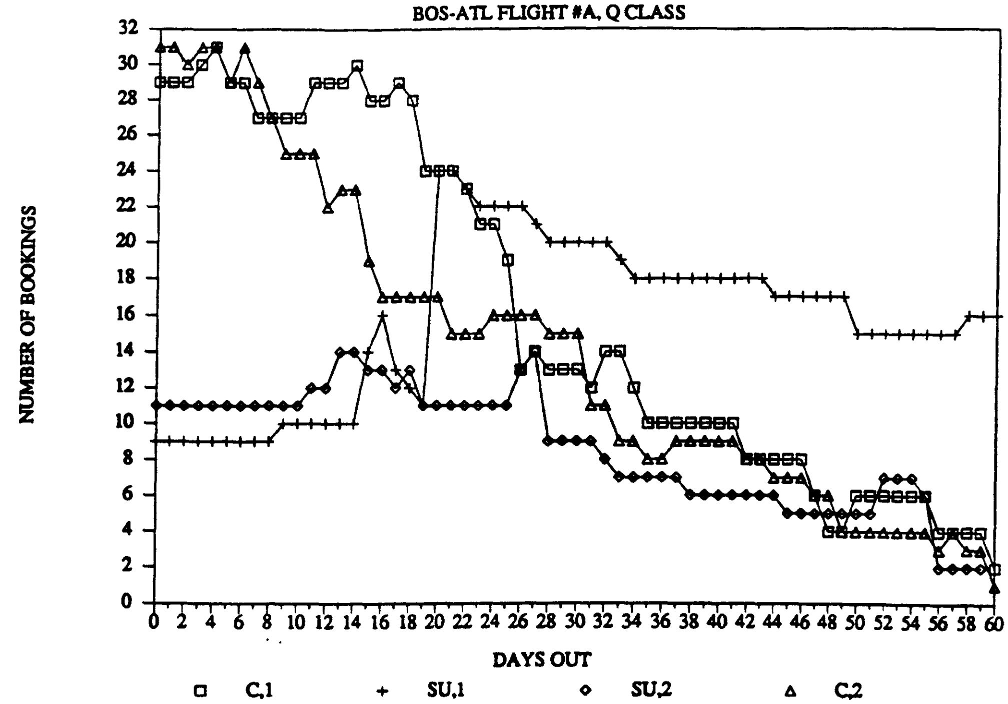
BOOKING INFORMATION

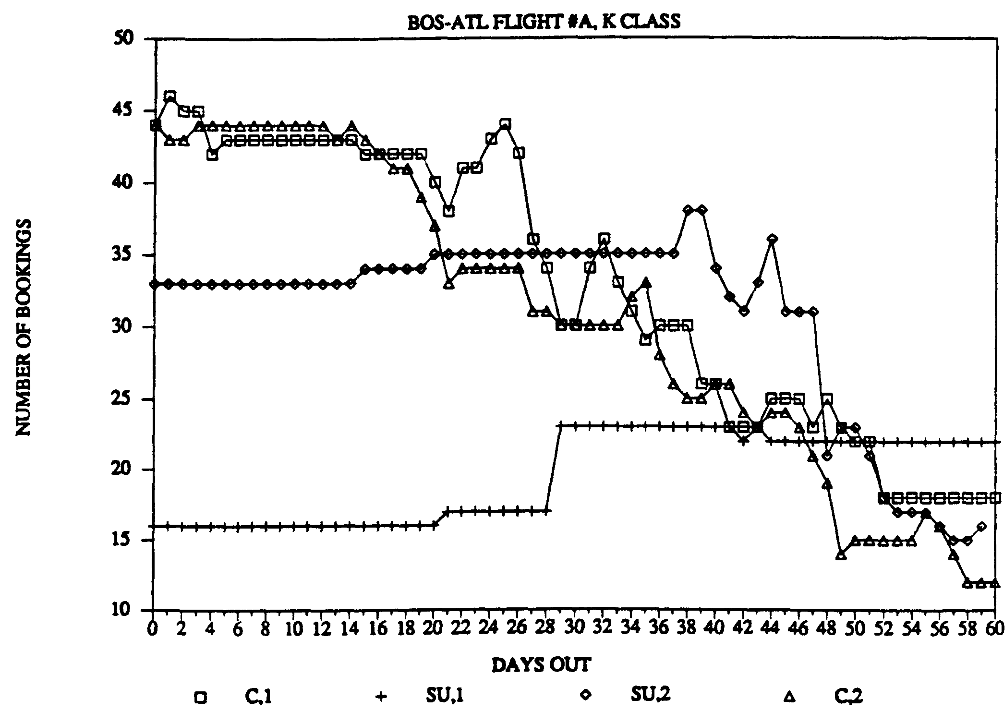




ATLDCA "M", "H" Classes, Flight B

BOOKING INFORMATION





BOSATL "Q", "K" Classes, Flight A

PROBABILISTIC MODELS OF THE AIRLINE RESERVATIONS PROCESS FOR SEAT INVENTORY CONTROL

by

Anthony Lee
Flight Transportation Laboratory
and
Center for Transportation Studies

May 31, 1990

OUTLINE OF PRESENTATION

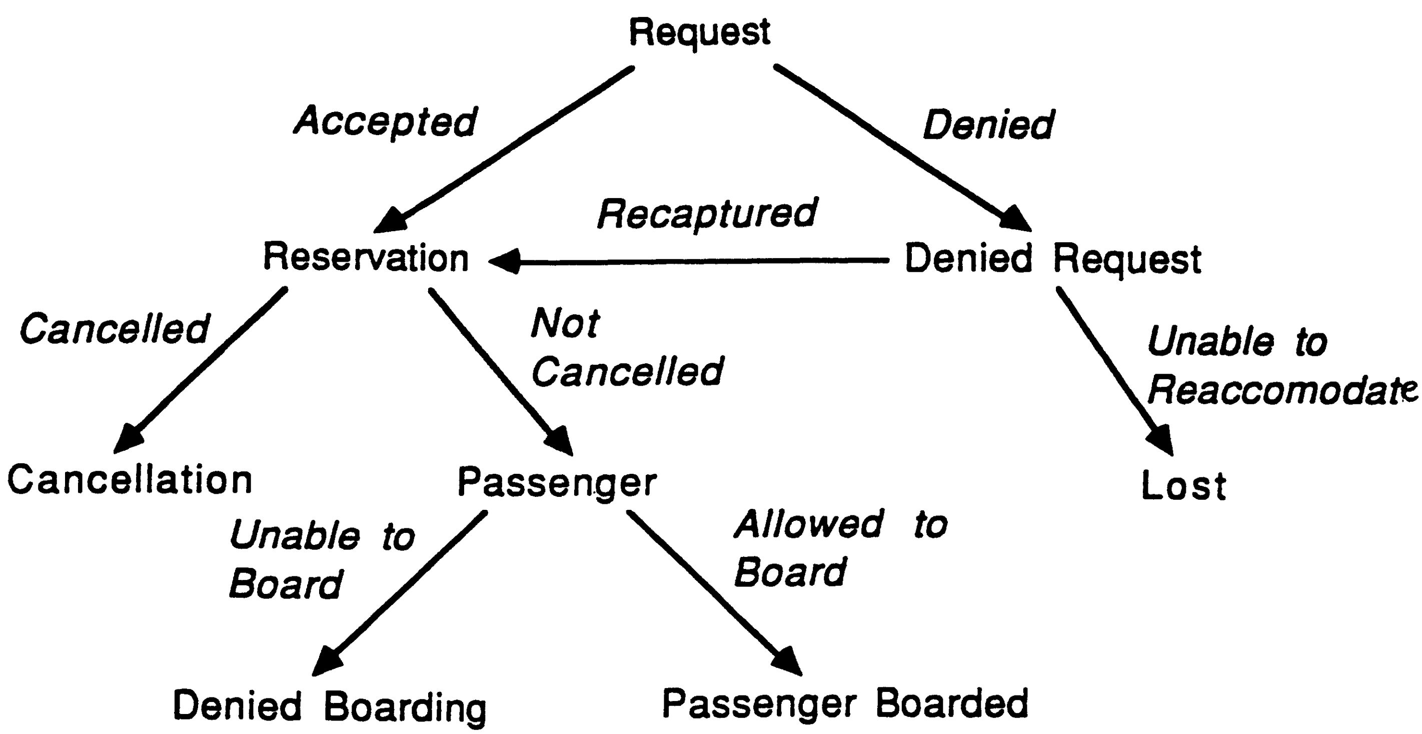
- PROBLEM DESCRIPTION
- AIRLINE DEMAND ASSUMPTIONS
- PROBABILISTIC FRAMEWORK
- APPLICABILITY OF PROBABILISTIC MODELS
- EXTENSIONS AND CONCLUSIONS

GOAL OF THIS RESEARCH

- DEVELOP A FRAMEWORK FOR ACCURATE FLIGHT-SPECIFIC, CLASS-SPECIFIC FORECASTS OF TOTAL BOOKINGS AT SPECIFIC TIMES BEFORE A FLIGHT DEPARTS.

  - Example: Today, we want to forecast how many more Y Class passengers will book on Flight 123 departing on June 30, 1990.

SCHEME OF THE PROBABILISTIC PROCESS



Bookings = Total Reservations - Total Cancellations

= number of reservations currently remaining in the system

AIRLINE DEMAND ASSUMPTIONS

- AIRLINE BOOKINGS ARE ASSUMED TO BE:

  - STATIONARY -- stable once cyclical and seasonal components are eliminated.

  - DISTINCT -- ability to isolate and distinguish demand for each fare class.

  - INDEPENDENT -- no (or very little) correlation between fare classes $\Rightarrow$ fare classes are only related through the booking limits.

INTRODUCTION TO PROBABILISTIC FRAMEWORK

- Booking Process as a *Stochastic Process*

  - Random Variable -- bookings in the res. system for each fare class at any time.

  - State Space -- set of all possible values of the number of bookings in the res. system.
    - Booking Limits censor the state space.

  - Time Element -- time is measured from 0 (the start of bookings) to T (flight time).

- <u>Discrete</u> State, <u>Continuous</u> Time Stochastic Process

- <u>Immigration and Death Process</u>
  - Each <u>request</u> is a potential immigrant. Note that requests do *not* depend on the current size of the population.
  - Requests are <u>accepted</u> if there is space left in the fare class.
  - Each <u>cancellation</u> is a death of an existing member of the population. Note that the number of cancellations per period depend on the size of the population.

PROBABILISTIC APPROACH

MODEL 1: SINGLE FARE CLASS, INFINITE CAPACITY

Assumptions:

1. Requests arrive in a Poisson manner with time-dependent rate $\lambda(t)$.
2. Given n bookings, cancellations occur in a Poisson manner with rate of $n\mu(t)$ per unit time.
3. Initially, there are no bookings in the system.

In a small period of time Δt, we write the following conditional probablities:

$$P[B(t+\Delta t) = n+1 \mid B(t) = n] = \lambda(t)\,\Delta t + o(\Delta t)$$

$$P[B(t+\Delta t) = n-1 \mid B(t) = n] = n\mu(t)\Delta t + o(\Delta t)$$

$$P[B(t+\Delta t) = n \mid B(t) = n] = 1 - \lambda(t)\,\Delta t - n\mu(t)\Delta t + o(\Delta t)$$

$$P[B(t+\Delta t) = k \mid B(t) = n] = o(\Delta t) \text{ for } |k-n| > 1$$

Given the previous equations, assuming Δt is small, and using the notation $P_n(t) = P(B(t) = n)$, we have:

$$P_n(t+ \Delta t) = P_{n+1}(t)\, n\mu(t)\, \Delta t + P_n(t)[1 - \lambda(t)\, \Delta t - n\mu(t)\Delta t]$$
$$+ P_{n-1}\lambda(t)\, \Delta t$$

ignoring the higher order terms $o(\Delta t)$.

Rearranging terms and letting $\Delta t \rightarrow 0$, we get the following differential equation:

$$P'_n(t) = - (\lambda(t) + n\mu(t))P_n(t) + (n+1)\mu(t)P_{n+1}(t)$$
$$+ \lambda(t)P_{n-1}(t)$$

with initial condition

$$P_0(0) = 1 .$$

The solution to the differential equations is the following:

$$P_n(t) = \frac{\mathrm{EXP}\left[-\int_0^t \lambda(s) e^{-\rho(s,t)} ds\right] \left[\int_0^t \lambda(s) e^{-\rho(s,t)} ds\right]^n}{n!}$$

This is a Poisson distribution. where $\rho(s,t) = \int_s^t \mu(\tau)\,d\tau$

OBSERVATIONS:

1. The expected number of bookings at time t is

$$E[B(t)] = \int_0^t \lambda(s) e^{-\rho(s,t)} ds$$

2. If $\lambda(t) \equiv \lambda$ and $\mu(t) \equiv \mu$, then

$$P_n(t) = \frac{\mathrm{EXP}\left[-\frac{\lambda}{\mu}(1-e^{-\mu t})\right] \left[\frac{\lambda}{\mu}(1-e^{-\mu t})\right]^n}{n!}$$

$$E[B(t)] = \frac{\lambda}{\mu}(1-e^{-\mu t})$$

MODEL 2: SINGLE FARE CLASS, FINITE CAPACITY

Assumptions:

1. Requests are Poisson with rate $\lambda(t)$.
2. A request is accepted if there is space available on the flight (bookings are less than capacity). Otherwise, the request is denied.
3. Cancellations are Poisson with rate $\mu(t)$.
4. Initially, there are no bookings in the system.

Following the same logic as before, we can write the following differential equations:

$$P'_n(t) = -(\lambda(t) + n\mu(t))\,P_n(t) + (n+1)\mu(t)\,P_{n+1}(t) + \lambda(t)\,P_{n-1}(t), \quad \text{for } n = 0, 1, 2, \ldots, CAP-1$$

$$P'_{CAP}(t) = \lambda(t)\,P_{CAP-1}(t) - (CAP)\mu(t)\,P_{CAP}(t)$$

Cannot find solution for general time-dependent parameters.

However, if $\lambda(t) \equiv \lambda$ and $\mu(t) \equiv \mu$, then the solution is the following:

$$P_n(t) = \underbrace{\frac{\left(\frac{\lambda}{\mu}\right)^n / n!}{\sum_{j=0}^{CAP} \left(\frac{\lambda}{\mu}\right)^j / j!}}_{\substack{\text{Truncated} \\ \text{Poisson} \\ \text{with parameter} \\ \lambda/\mu.}} + \frac{(CAP)!}{j!} \rho^{CAP} \sum_r \frac{D_n(r)\, e^{r\mu t}}{r\, D_{CAP}(r)\, D'_{CAP}(r+1)}$$

where r is summed over the c roots of $D_c(s+1) = 0$ and

$$D_n(r) = \sum_{k=0}^{n} \binom{n}{k} \rho^{n-k}\, r(r+1)\cdots(r+k-1)$$

The truncated Poisson distribution seems to agree with past empirical distributional studies.

APPLICABILITY OF PROBABILISTIC MODELS

Crucial Observations

- What we observe in the booking process is the model with *finite* capacity. That is, demand is censored at the booking limit.

- What we want is the expected demand from the infinite capacity model. To optimize seat allocations correctly, an airline wants to know the true, unconstrained demand.
  (What if we had an elastic aircraft???)

Algorithm for Predicting Demand

Two-Step Process

1. Estimate the parameters λ and μ from the *finite* capacity model.

2. Obtain a forecast of expected bookings for a future flight by substituting the estimated parameters into the *infinite* capacity model. In particular, the forecast is obtained from the *expected bookings to come* expression.

Mathematical Tractability

- If we make one simple approximation, then the probability expressions for both models become much more satisfying.

- We make the Poisson approximation to the Binomial distribution.
  - The infinite capacity model probability statement becomes Poisson.
  - The finite capacity model probability statement becomes *censored* Poisson.

- Estimates of the parameters λ and μ can be obtained via a straightforward application of maximum likelihood estimation.

Data Requirements

- Booking Curves from previous weeks of the same flight number.

- Separate data on requests and cancellations could be helpful, but not necessary.

- Seasonal Index by date and fare class.

EXTENSIONS

- Tour Groups -- Bulk arrivals and cancellations
- Multivariate Process -- Same aircraft, requests for different fare classes
- Waitlisting -- Queueing problem
- Horizontal and Vertical Spill -- Retrial
- Cancellations -- age-dependent
- Nested inventory -- shared state space

CONCLUSIONS

- "Intuitive" Model of the Booking Process

- Dynamic over Time

- Mathematically Complex on a Large-Scale Basis, but straightforward ML estimation

- Starting Point for a Probabilistic View of the Booking Process

DYNAMIC SIMULATION

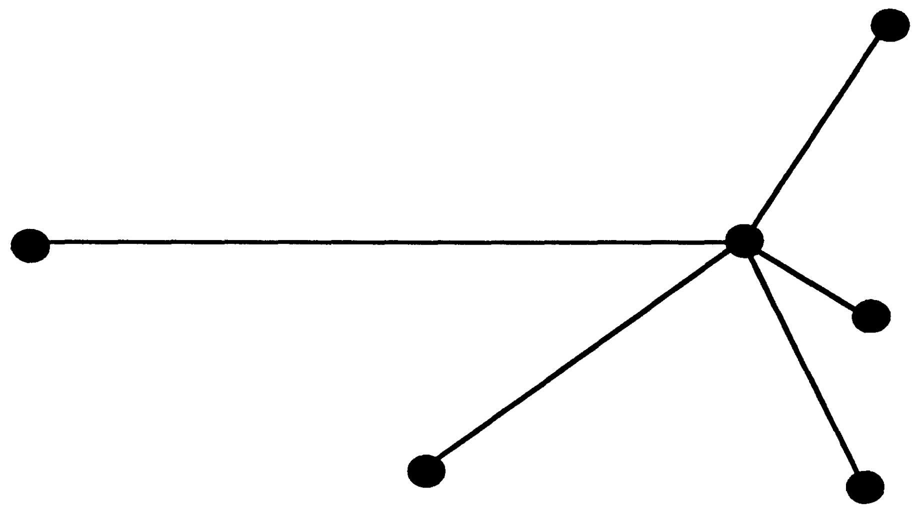
OF

ORIGIN-DESTINATION SEAT INVENTORY

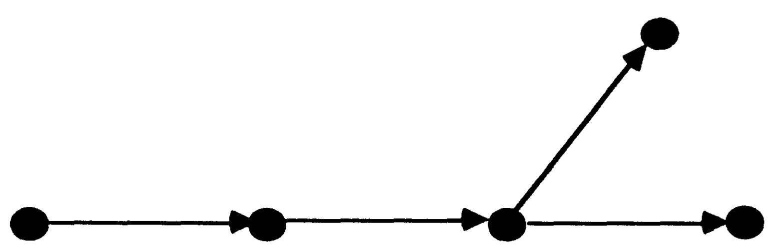
CONTROL

By

Elizabeth L. Williamson
Flight Transportation Laboratory
May 31, 1990



HUB NETWORK



MULTI-LEG NETWORK

DETERMINISTIC LP FORMULATION

Maximize total flight revenues

$$R = \sum_{OD} \sum_{i} FARE_{i,OD} \times SEATS_{i,OD}$$

subject to:

$$\sum_{OD} \sum_{i} SEATS_{i,OD} \leq CAP_{j}$$

for all O-D itineraries and i fare classes on each flight leg j

$$SEATS_{i,OD} \leq MEAN\ DEMAND_{i,OD}$$

for all O-D itineraries and i fare classes

PROBABILISTIC LP FORMULATION

Maximize total flight revenues

$$R = \sum_{OD} \sum_{i} \sum_{s=1}^{CAP_j} FARE_{i,OD} \times PROB(S)_{i,\,OD} \times X_{s,i,OD}$$

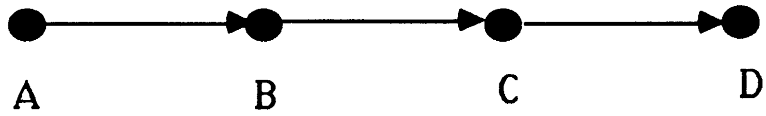
subject to:

$$\sum_{OD} \sum_{i} \sum_{s=1}^{CAP_j} X_{s,i,OD} \leq CAP_j$$

for all O-D itineraries and i classes on each flight leg j

$$X_{s,i,OD} = 0 \text{ or } 1$$

for all O-D itineraries, i classes, and $s = 1, 2, \ldots, CAP_j$ for each j



Means, Standard Deviations, Fares

	Y	M	B	Q
AB	25.21	2.66	6.78	25.67
	7.26	4.94	14.02	11.37
	216.00	203.00	194.00	152.00
AC	2.15	1.45	4.16	14.44
	2.67	5.84	3.42	10.45
	519.00	344.00	262.00	231.00
AD	2.61	1.27	3.68	2.32
	3.25	1.56	6.62	2.69
	582.00	379.00	302.00	269.00
BC	9.64	22.48	11.55	32.50
	5.08	18.99	9.55	16.37
	404.00	315.00	223.00	197.00
BD	5.78	4.49	4.50	5.81
	4.77	5.78	5.53	5.52
	440.00	307.00	221.00	199.00
CD	19.42	55.70	7.43	5.63
	10.78	31.63	13.34	3.93
	251.00	169.00	174.00	134.00

Deterministic Network Solution

	Y	M	B	Q
AB	25	3	7	26
AC	2	1	4	14
AD	3	1	0	0
BC	10	22	12	15
BD	6	0	0	0
CD	19	54	7	0

Probabilistic Network Solution

	Y	M	B	Q
AB	30	6	14	28
AC	3	1	2	3
AD	3	0	0	0
BC	13	26	9	24
BD	6	0	0	0
CD	23	49	5	4

REVENUE IMPACTS OF DISTINCT BUCKET CONTROL

DEMAND/CAPACITY	DISTINCT DETERMINISTIC	DISTINCT PROBABILISTIC
Low	- 12.2 %	- 0.6 %
Medium	- 6.3 %	- 2.6 %
High	+ 43.2 %	+ 47.9 %

*Percent Difference From No Seat Inventory Control

Nested Deterministic by Fare Class
Leg B-C

O-D/Fare Class	Seats Allocated	Booking Limit
ACY	2	90
ADY	3	90
BCY	10	90
BDY	6	90
ACM	1	69
ADM	1	69
BCM	22	69
BDM	0	69
ACB	4	45
ADB	0	45
BCB	12	45
BDB	0	45
ACQ	14	29
ADQ	0	29
BCQ	15	29
BDQ	0	29

Nested Deterministic By Fares
Leg B-C

O-D/Fare Class	Seats Allocated	Booking Limit
ADY	3	90
ACY	2	87
BCY	10	85
BDY	6	75
ADM	1	69
ACM	1	68
BCM	22	67
BDM	0	45
ADB	0	45
ADQ	0	45
ACB	4	45
ACQ	14	41
BCB	12	27
BDB	0	15
BDQ	0	15
BCQ	15	15

Nested Deterministic by Shadow Prices
Leg B-C

O-D/Fare Class	Seats Allocated	Booking Limit
ACY	2	90
BCY	10	88
ADY	3	78
ACM	1	75
BCM	22	74
BDY	6	52
ACB	4	46
ACQ	14	42
BCB	12	28
ADM	1	16
BCQ	15	15
BDM	0	0
ADB	0	0
ADQ	0	0
BDB	0	0
BDQ	0	0

STATIC BOOKING SIMULATION

- Optimal seat allocations for each O-D/fare class are determined from a deterministic or probabilistic network formulation.

- Booking limits for each O-D/fare class on each flight leg are determined from one of the O-D seat inventory control methods.

- Booking demands are randomly drawn for each O-D/fare class; the bookings are made if space is available, otherwise rejected.

- Lowest classes book first and there is no "sell-up".

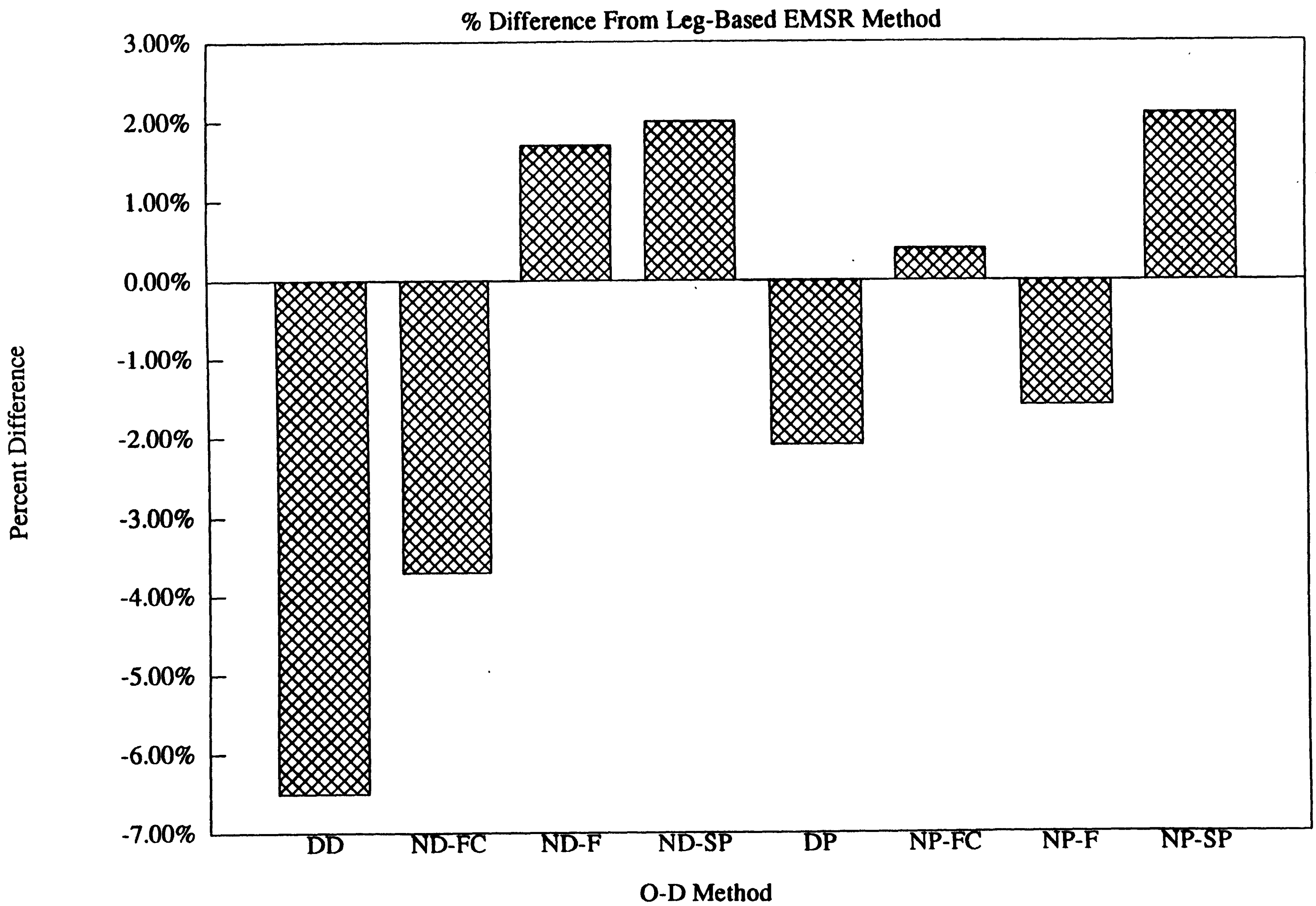
- Single point in time; therefore there are no revisions of booking limits during reservations process.

- 1000 repetitions of booking process.

O-D CONTROL OPTIONS TESTED

EMSR	EMSR Leg-Based Control of Nested Fare Classes (Base Level)
DD	Distinct Deterministic Seat Allocations Used as O-D/Fare Class Limits
ND-FC	Nested Deterministic on Fare Classes
ND-F	Nested Deterministic on Fares
ND-SP	Nested Deterministic on Shadow Prices
DP	Distinct Probabilistic Seat Allocations Used as O-D/Fare Class Limits
NP-FC	Nested Probabilistic on Fare Classes
NP-F	Nested Probabilistic on Fares
NP-SP	Nested Probabilistic on Shadow Prices

Base Case



% Difference From Leg-Based EMSR Method
3.00%
2.00%
1.00%
0.00%
-1.00%
-2.00%
-3.00%
-4.00%
-5.00%
-6.00%
-7.00%
Percent Difference
DD
ND-FC
ND-F
ND-SP
DP
NP-FC
NP-F
NP-SP
O-D Method

DEMAND SCENARIOS TESTED

- BASE CASE (AS IN FIGURE)
- HIGH DEMAND ON 1-LEG O-D ITINERARIES
- HIGH DEMAND ON 2-LEG O-D ITINERARIES
- HIGH DEMAND ON 3-LEG O-D ITINERARIES
- HIGH DEMAND IN TOP FARE CLASS (Y)
- HIGH DEMAND IN MIDDLE FARE CLASSES (M, B)
- HIGH DEMAND IN LOW FARE CLASS (Q)

SUMMARY OF SIMULATION RESULTS

PERCENT REVENUE DIFFERENCE FROM EMSR
SEVEN DEMAND SCENARIOS

DISTINCT DETERMINISTIC	-4.87 %
Nested by Fare Class	-0.63 %
Nested by Fares	+0.70 %
Nested by Shadow Prices	+2.99 %
DISTINCT PROBABILISTIC	-1.24 %
Nested by Fare Class	+1.61 %
Nested by Fares	-1.19 %
Nested by Shadow Price	+2.69 %

DYNAMIC BOOKING SIMULATION

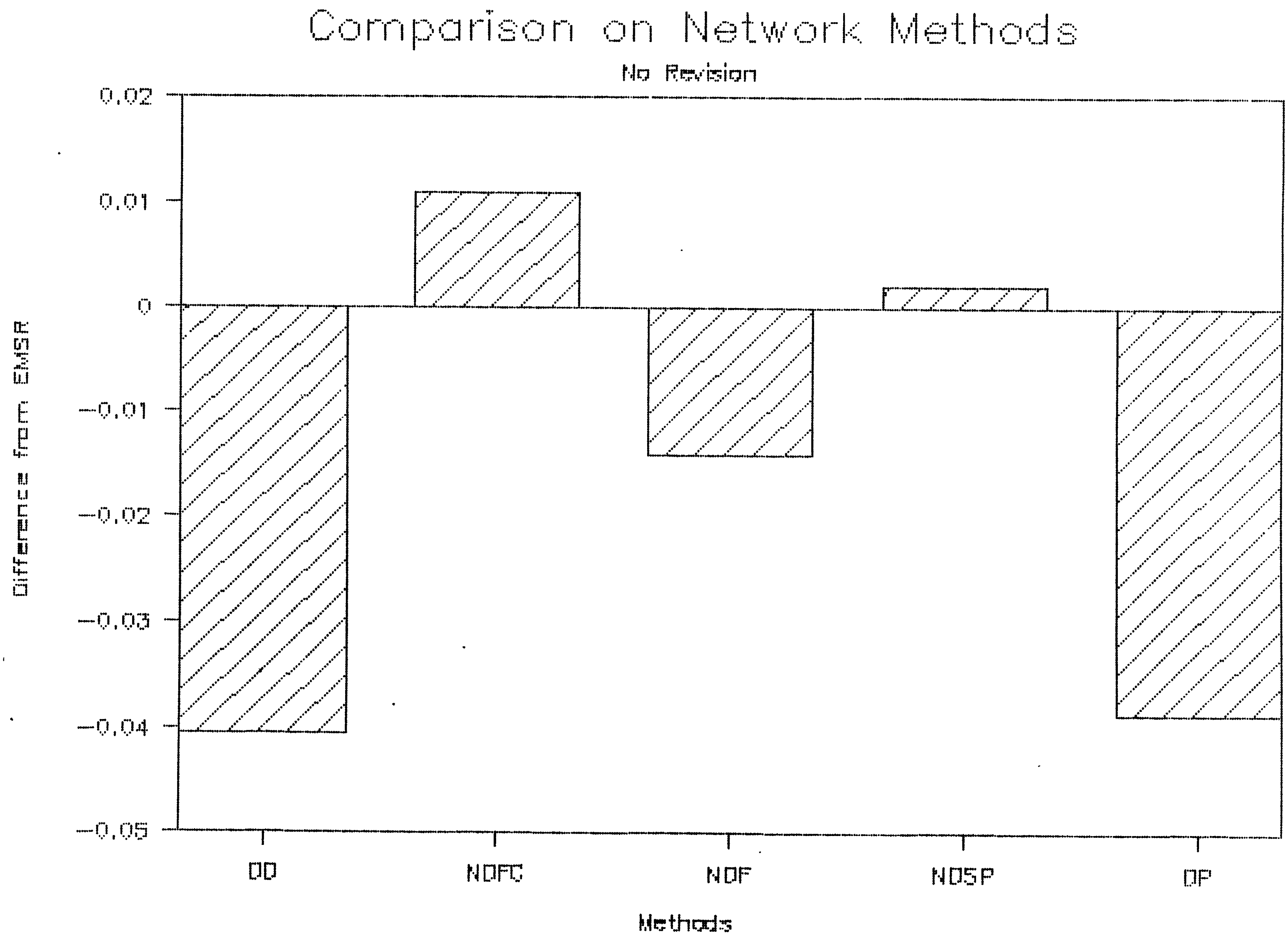
- Actual booking data for each O-D/fare class is used to generate distributions of demand <u>within</u> each of 15 booking periods prior to departure.

- Initially, booking limits are determined for aggregate demand for each O-D/fare class.

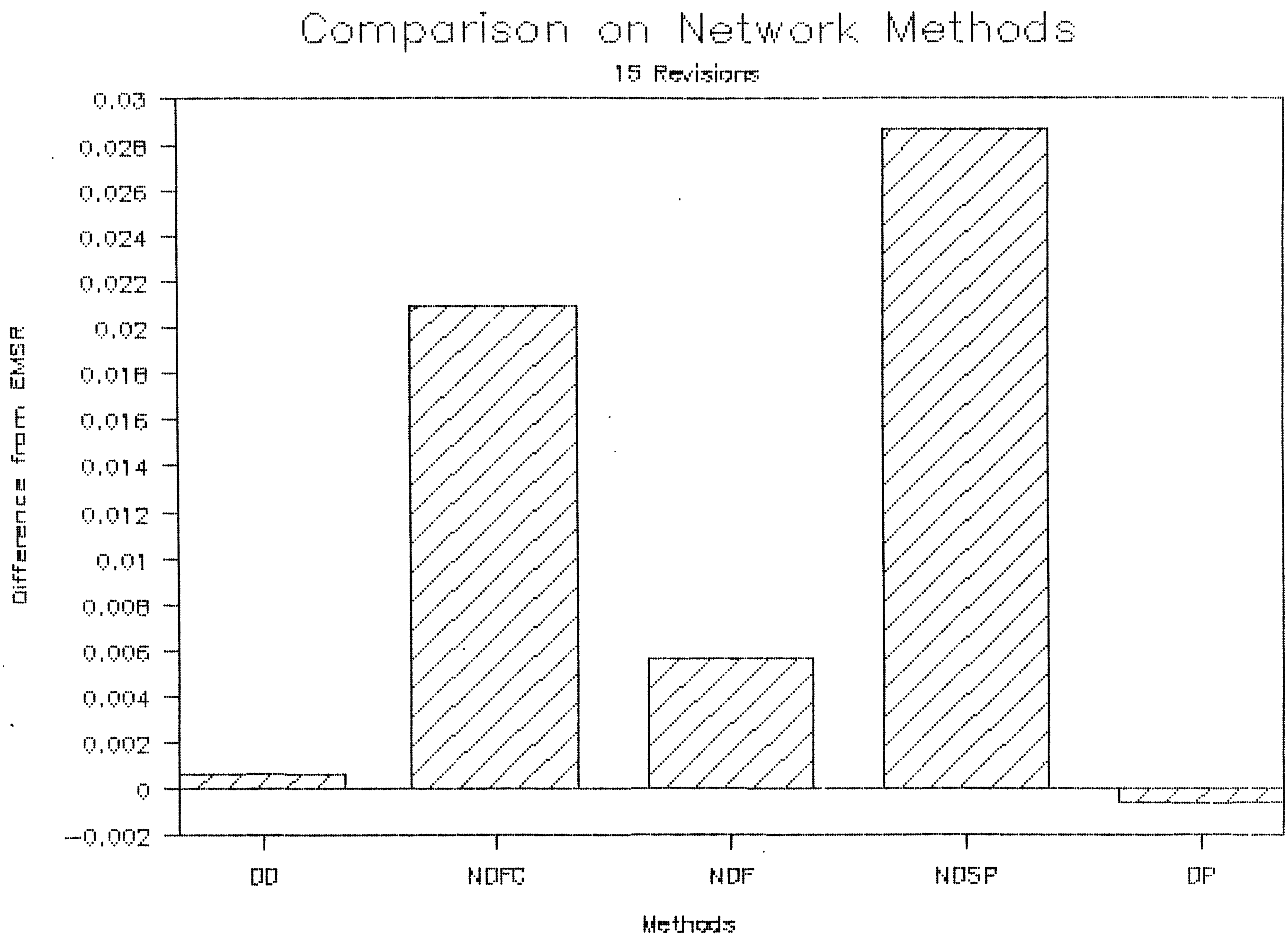
- Bookings are simulated for the first booking period only. Booking limits are then re-optimized based on aggregate demand in remaining booking periods and remaining empty seats.

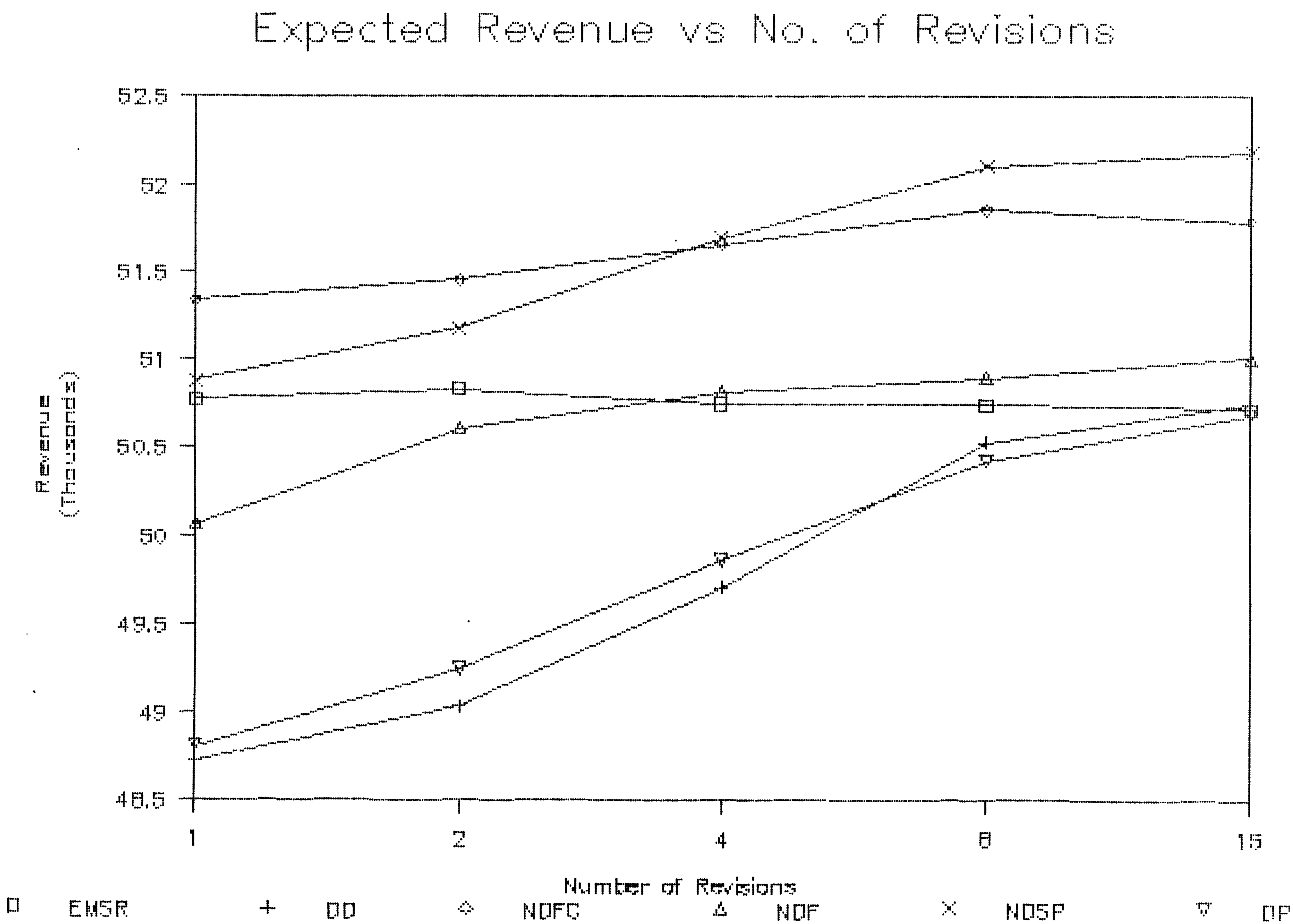
- Revision process is repeated 15 times for each departure.

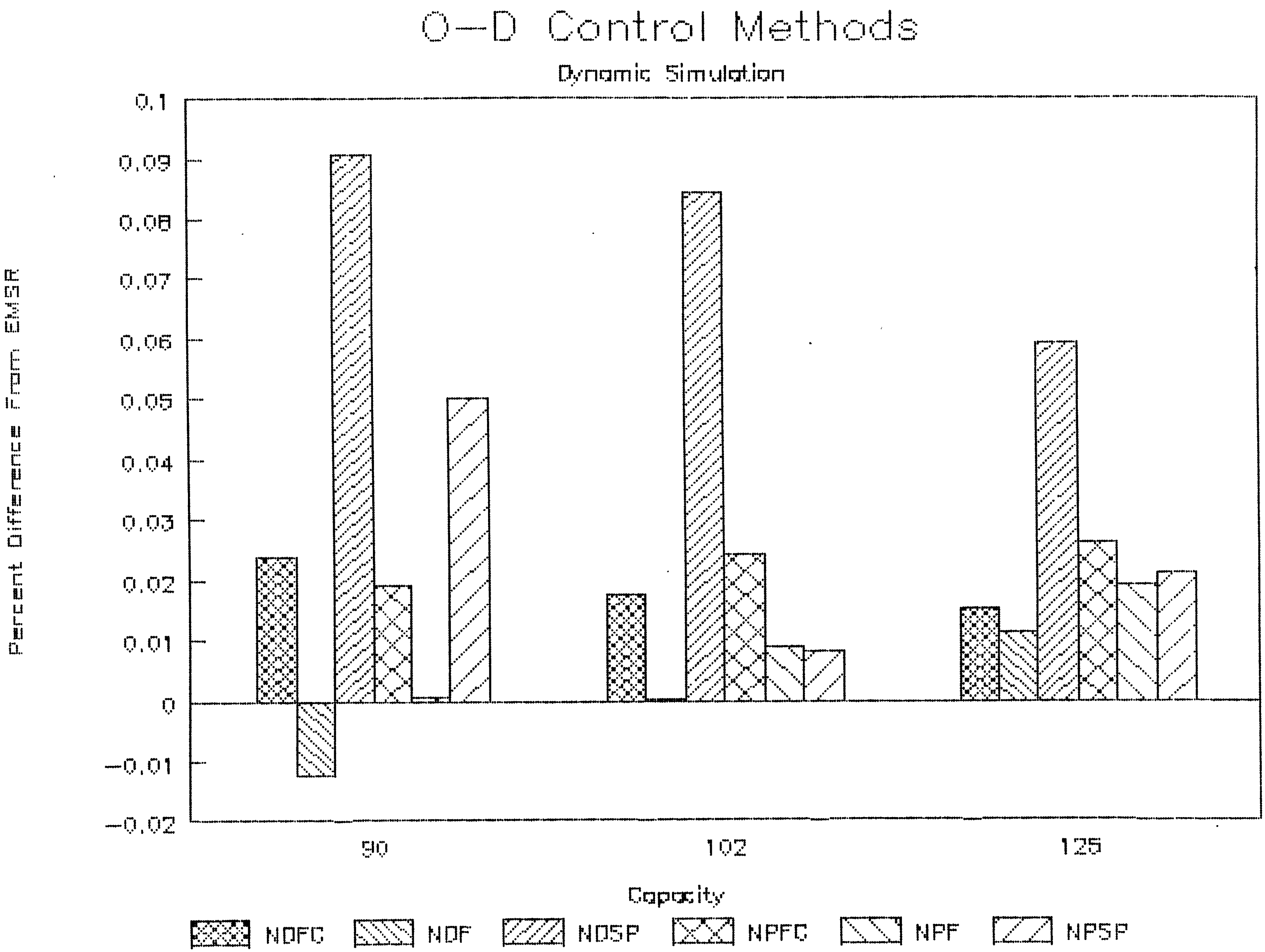
- One simulation run involves 100 departures.



Comparison on Network Methods
No Revision
0.02
0.01
0
-0.01
-0.02
-0.03
-0.04
-0.05
Difference from EMSR
DD
NDFC
NDF
NDSP
DP
Methods

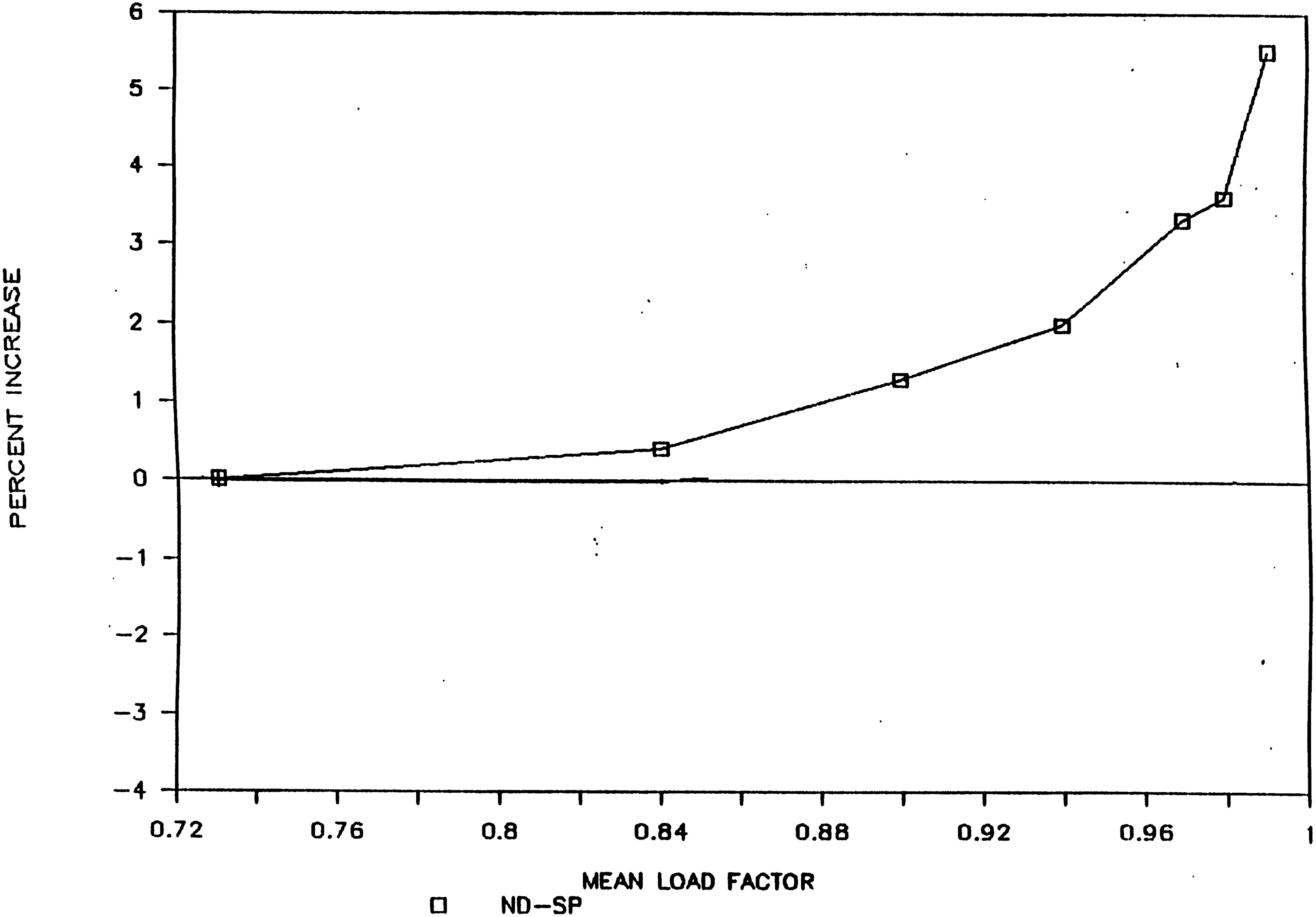

Comparison on Network Methods
15 Revisions
Difference from EMSR
0,03
0,028
0,026
0,024
0,022
0,02
0,018
0,016
0,014
0,012
0,01
0,008
0,006
0,004
0,002
0
-0,002
DD
NDFC
NDF
NDSP
DP
Methods


Expected Revenue vs No. of Revisions
Revenue
(Thousands)
52.5
52
51.5
51
50.5
50
49.5
49
48.5
1
2
4
8
15
Number of Revisions
EMSR
DD
NDFC
NDF
NDSP
DP


O-D Control Methods
Dynamic Simulation
Percent Difference From EMSR
0.1
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
-0.01
-0.02
90
102
125
Capacity
NDFC
NDF
NDSP
NPFC
NPF
NPSP

PERCENT INCREASE IN REVENUES OVER EMSR

DATA WITH 15 REVISION PERIODS



SUMMARY OF FINDINGS

- Use of "distinct" network solutions for O-D control can result in <u>negative</u> revenue impacts.

- Nesting of O-D/fare class limits is essential to overcome problems of distinct seat allocations.

- Our simulations show that nesting of network solutions by <u>shadow price</u> is most promising.

- Accurate estimates of revenue impacts require that a <u>dynamic</u> booking simulation be used.

- Effective O-D control can increase flight revenues by 2 to 4 percent on high demand flights.

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Ground Holding Strategies for ATC

Amedeo Odoni, MIT
Stephan Kolitz, CSDL
Mostafa Terrab, MIT

CSDL

Background

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- Flow Control Problem in ATC
  - information-intensive
  - uncertainty
  - need for DSS
  - extremely important in ATC

- Co-operative MIT/Draper work since early 1988

- Major technical report just issued on ground-holding strategies in connection with congested airports

Approaches to the Airport Capacity Problem

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- Long term
  - more runways
  - improved ATC technology

- Medium term
  - economic and administrative measures to influence airline scheduling practices and demand patterns at major airports

- Short term
  - adjust flow rate of aircraft on a **real-time** basis to make it compatible with available capacity

Strategic vs. Tactical Flow Control

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- The **strategic** flow control problem is concerned with the question of when to "release" aircraft into the ATC system, (i.e., by assigning ground-holding times to aircraft, when necessary, at the airport of departure).
  - motivation: If an aircraft is to suffer a long delay anyway, it is better that as much of this delay as possible be taken on the ground before takeoff.

- The **tactical** flow control problem is concerned with post-takeoff routing, en route/terminal area holding and sequencing, speed control, etc.
  - work has been done on route/trajectory optimization with weather and air traffic constraints

- The two problems should be addressed interactively.

Simplified Version of the Problem

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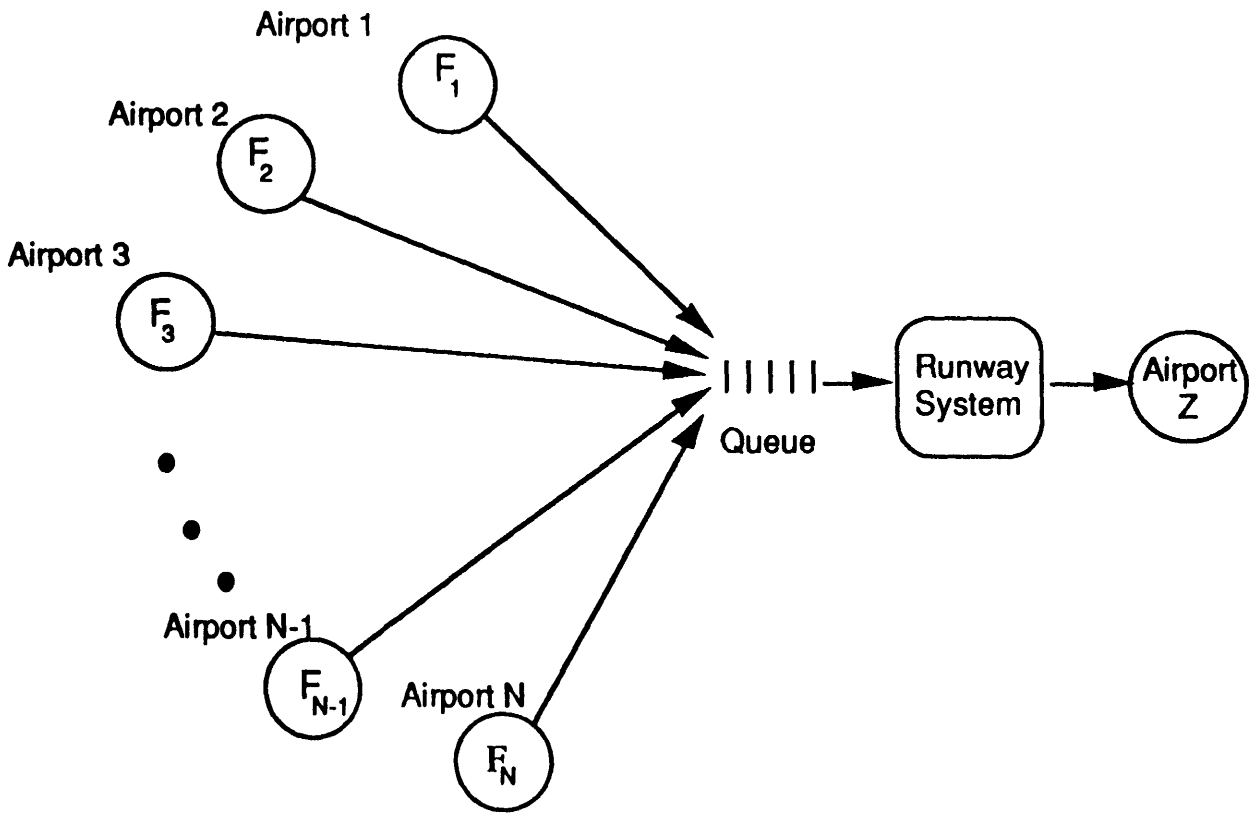

- Trade-off between ground holding delays and airborne delays
- Goal: develop a ground holding strategy to minimize total delay costs

General Problem Formulation

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minimize

total expected cost

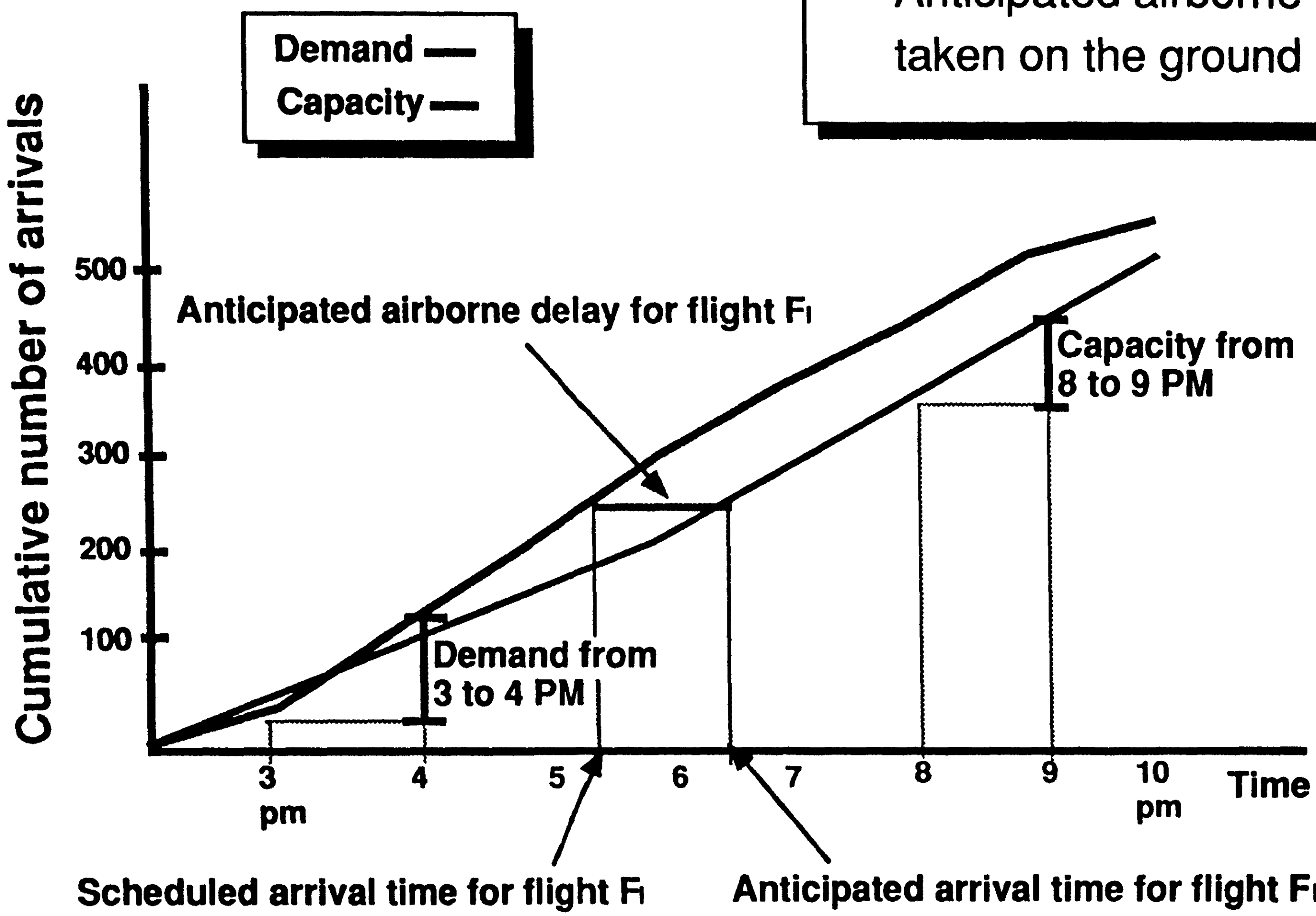
subject to

- every flight is assigned to one time period to land
- capacity constraints are not violated

Ground Holding Today

MIT

- Anticipated airborne delays are taken on the ground



Challenges in Problem

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- Uncertainty regarding airport capacity (AAR) at time of arrival at destination, especially for long-range flights
  - Range of possible AAR values can be large
  - At critical times considerable uncertainty about AAR may persist even for a time-horizon of one or two hours
- Information-rich environment
- Must be able to revise ground holding strategies quickly in response to changes (dynamic environment).
- Trade-offs

  "Type 1 error" : AAR turns out to be lower than anticipated and aircraft suffer long airborne delays

  "Type 2 error" : AAR turns out to be higher than anticipated and aircraft are delayed on the ground (prior to take-off) unnecessarily

Probabilistic Model is Needed

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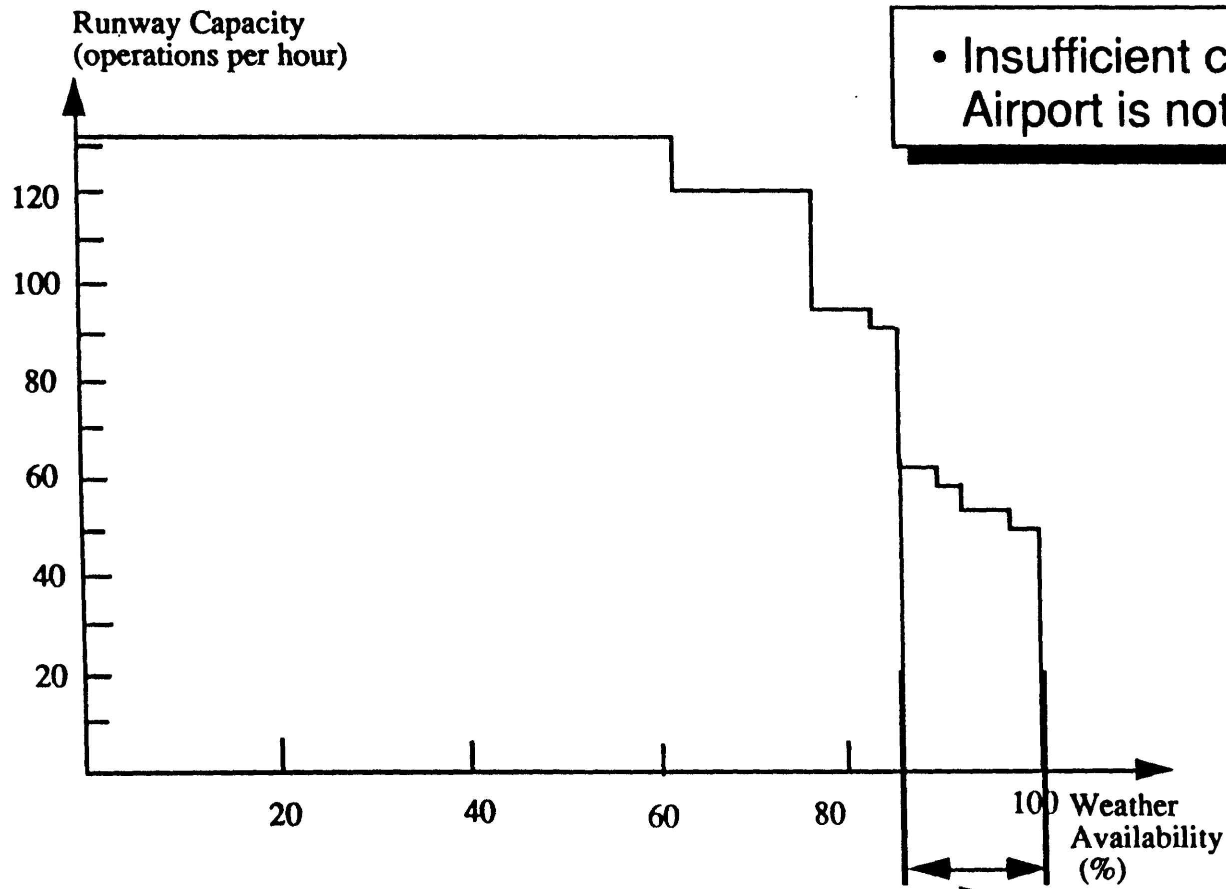

- Insufficient capacity at Logan Airport is not uncommon

% of time with very low capacity

Description of the Ground Holding Problem

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- For each flight F_i ($i = 1,\ldots,N$) we have cost functions

  $Cg_i(t)$ = cost of delaying F_i on ground at time t

  $Ca_i(t)$ = cost of delaying F_i in air at time t

- For each time period T_j ($j = 1,\ldots, P$) the airport has a capacity K_j, which may be a random variable. A period can be of any desired length (e.g. 10 minutes, 15 minutes, 30 minutes).

- We wish to develop a ground holding strategy (i.e., decide how long to keep each flight on ground beyond its scheduled take-off time) to minimize total delay costs.

Notation of Mathematical Formulation

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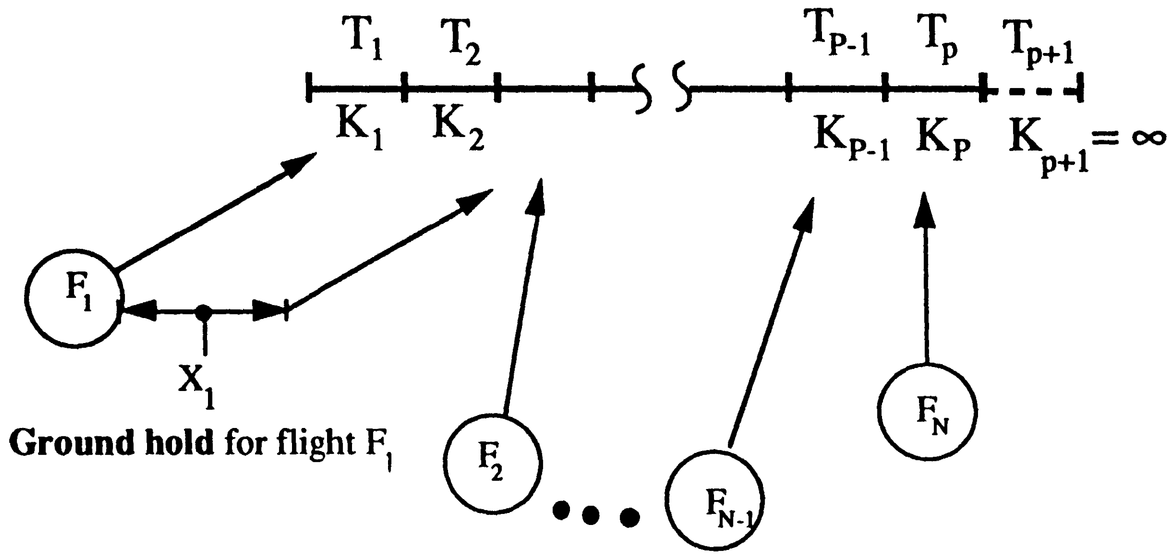

Notation:

T_j time period

K_j capacity during T_j

F_i flight

N number of flights

P number of periods

X_i ground hold of flight F_i

Deterministic Excess Demand Causes Delays

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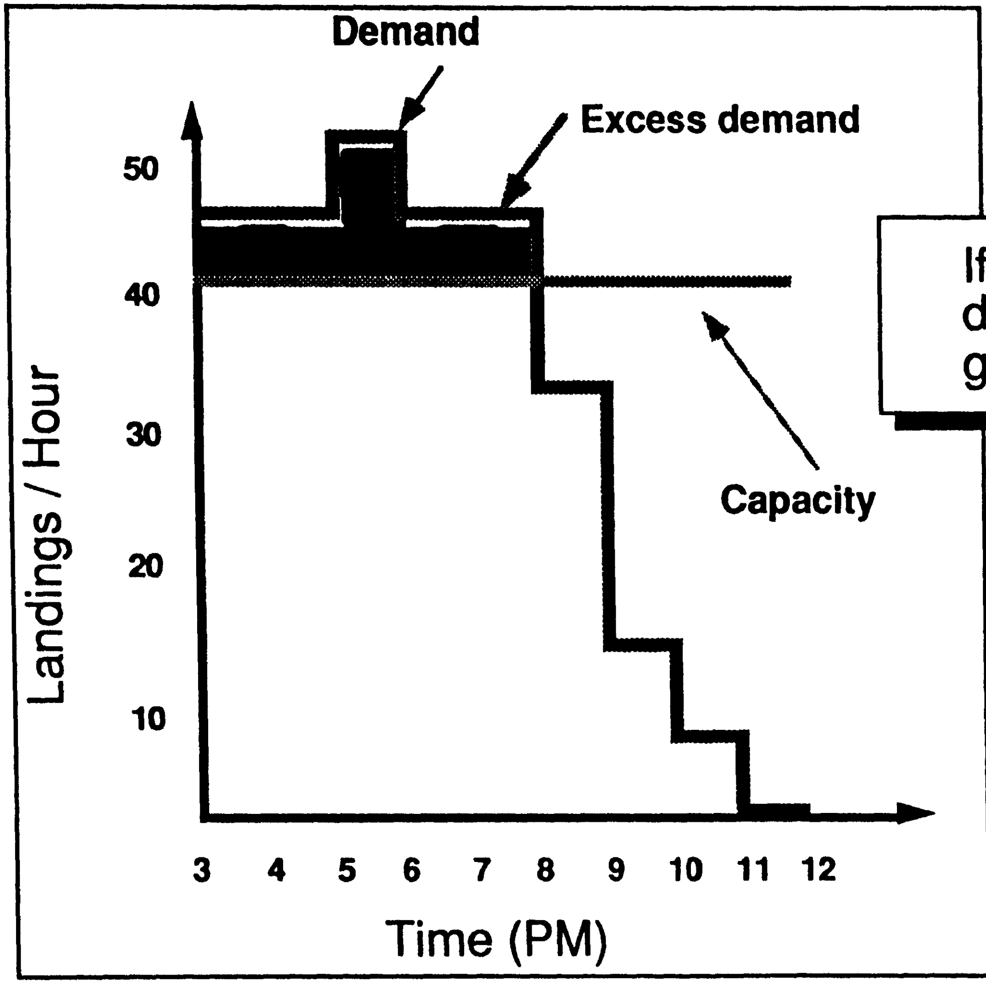

If everything is deterministic, then delays should be taken on the ground

-96-

If Capacities are Deterministic, Can Use Min-Cost Flow

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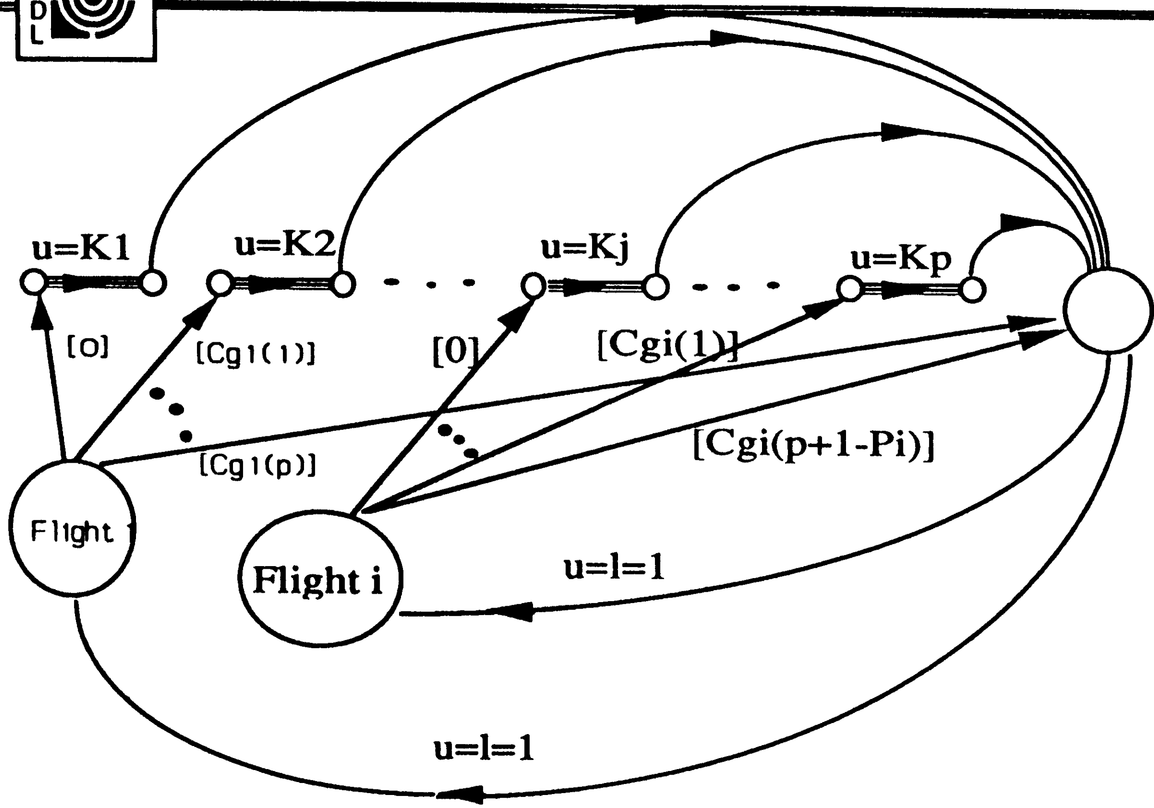
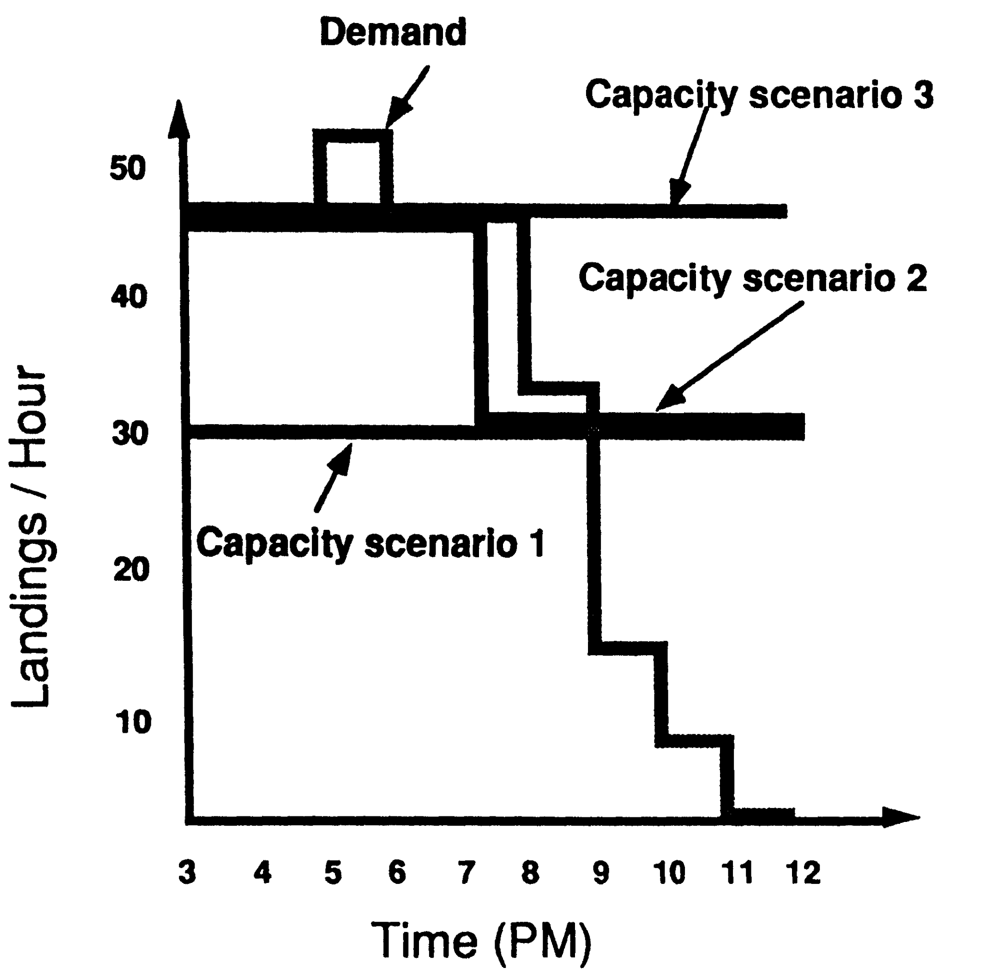


- Each flight is represented by a node, with arcs representing all possible time period assignments of the flights
- Well known low-order polynomial algorithms can solve for general cost function

u	upper bound on flow
l	lower bound on flow
$Cg_i(x)$	cost of delaying F_i on the ground for x time periods
$Ca_i(x,y)$	cost of delaying F_i in the air for y time periods if it has already been delayed x time periods on the ground

Stochastic Capacity: Typical Scenarios

MIT



- Model stochastic capacities through "scenarios"
- This example: a bad weather front is expected to come through; uncertainty in timing.
- In general, there are not many candidate capacity scenarios for a given day

-98-

An Example of Deterministic Demand/Capacity

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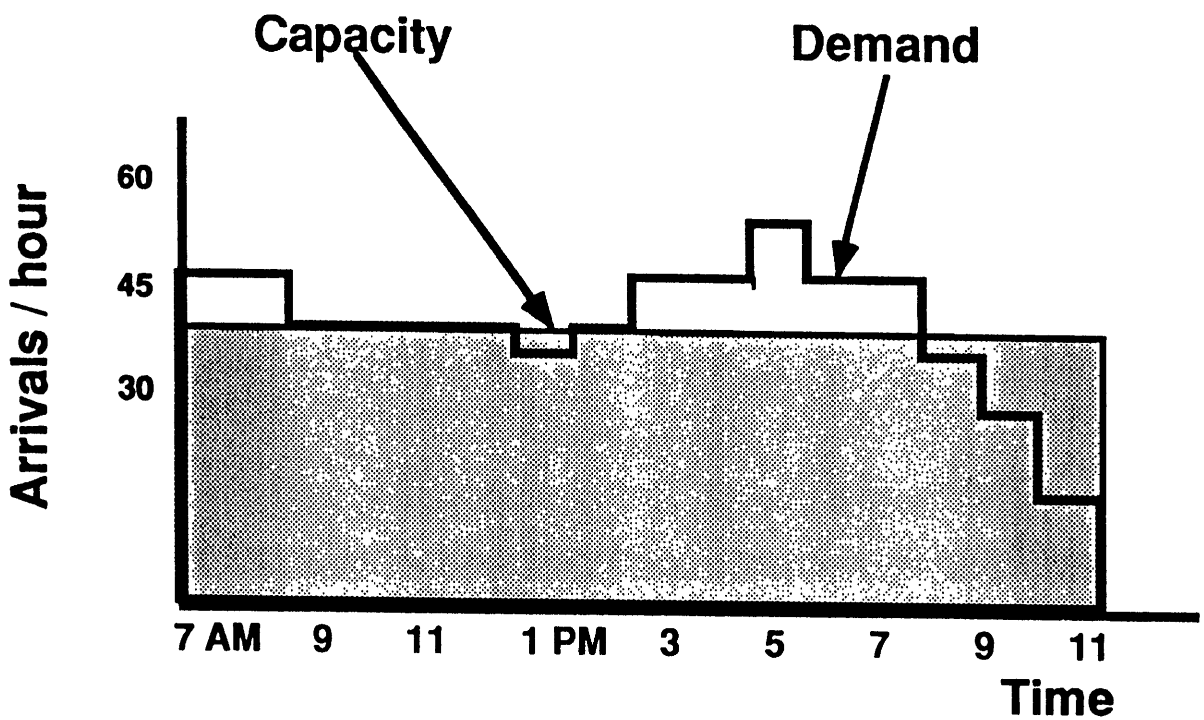

The MMR Algorithm for the Stochastic Case

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- A fast algorithm to solve the stochastic capacity case
- Basic principle: Maximum Marginal Return (MMR)
- Works with general cost functions
- Uses the following important property:
  - the expected delay cost for flight F_i depends only on the ground hold imposed on F_i and on the status of the flights with priority higher than F_i

- It determines ground delays by finding those that minimize the expected delay cost for flights in decreasing order of priority
  - start with highest priority flight; find lowest cost ground hold
  - go to second highest priority flight; find lowest cost ground hold, given the highest priority flight solution
  - go the third highest priority flight; find lowest cost ground hold, given the two highest two priority flights solution
  - and so on ...

Cost Savings from Ground Hold Policy (Deterministic)

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Average delay per flight (minutes)

First Come First Served	Fast Algorithm Solution	**Plane type**	**Hourly Ground-hold Cost**
17.5	28.9	General Aviation and Commuters	$ 400
16.4	9.7	Standard Jets	$ 1200
17.6	5.9	Wide-body Jets	$ 2000
Total Cost $191,500	$127,100		

- **Data from simulated typical day at Logan Airport**

MMR Algorithm with FCFS at Landing

MIT

FCFS at landing

	Ground Costs	Total Costs (ground + airborne)
MMR	$ 61,900	$ 326,220
FCFS	$ 243,300	$ 415,940
TRESH	$ 226,700	$ 421,220
No Holds	$ 0	$ 529,520

- **Data from simulated typical day at Logan Airport**
- **Airborne costs assumed to be twice ground hold costs**
- **Hourly ground hold costs same as in deterministic case**

C S D L

Benefits Increase With Congestion

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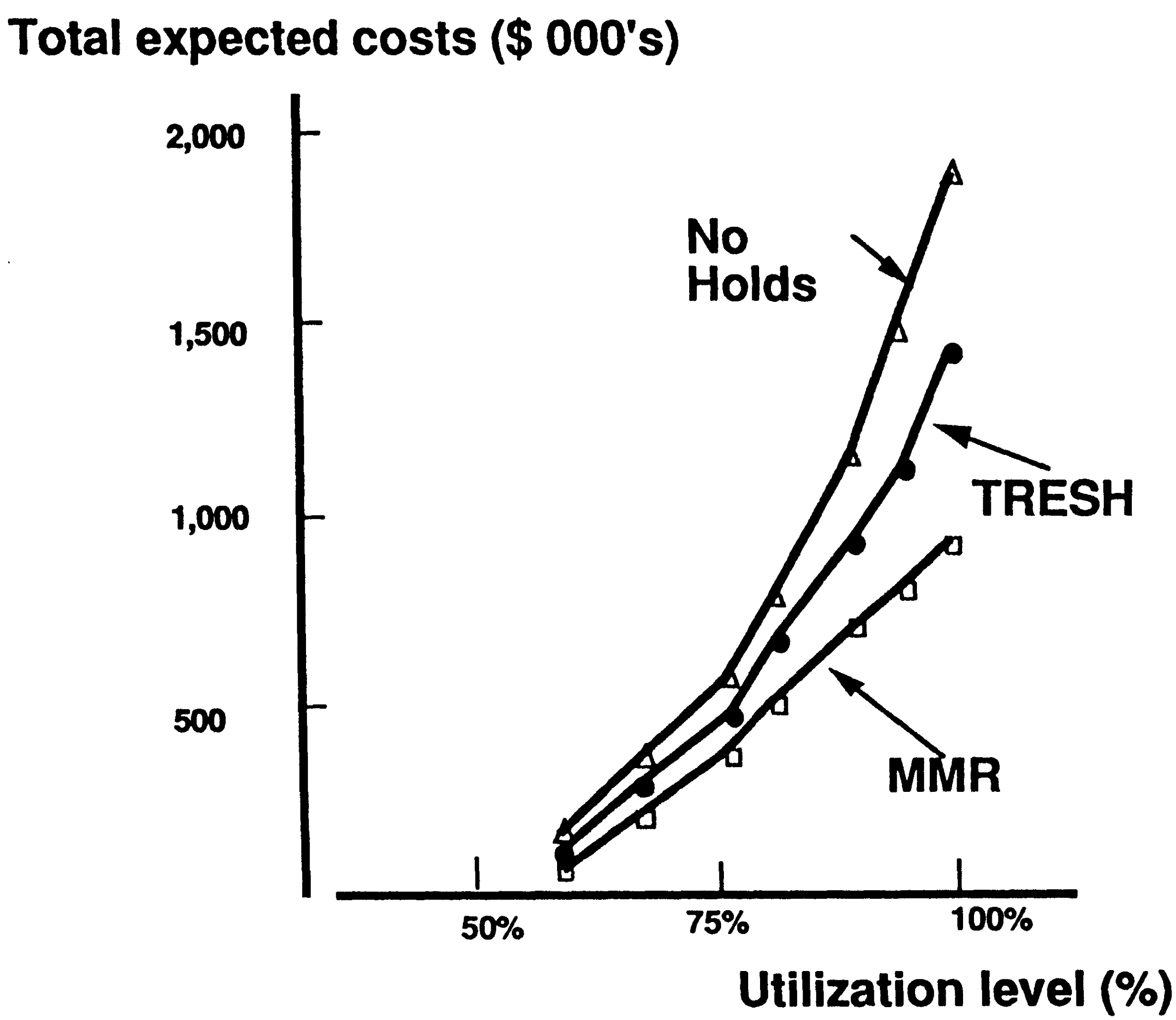

-103-

MMR Algorithm with Optimal Tactics at Landing

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Optimal tactics at landing

	Ground Costs	Total Costs (ground + airborne)
MMR	$ 61,900	$ 152,300
FCFS	$ 243,300	$ 309,220
TRESH	$ 226,700	$ 300,660
No Holds	$ 0	$ 203,520

- **Data from simulated typical day at Logan Airport**
- **Airborne costs assumed to be twice ground hold costs**
- **Hourly ground hold costs same as in deterministic case**

Results and Products

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- If there are delays in the system due to capacity problems, then there is a large payoff from using intelligent scheduling policies that take uncertainty into consideration.

- Models and associated algorithmic solutions have been developed:
  - deterministic capacity case

    assignment problem $O(N^{2.5})$ (N = # of flights)

    "Fast Algorithm" $O(P N \ln N)$ (P = # of time periods)
  - stochastic capacity case

    dynamic programming $O((P+1)^2 ((N/P)+1)^P)$

    "MMR Algorithm" $O(N (P+1)^2)$

- Models and algorithms support real-time adaptive use of methodology

Further Work

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- Higher fidelity model
- Cost functions
- Dynamic aspects of the problem
- The problem of "downstream" effects (some work already)
- Integration of tactical and strategic problems
- Realistic testbed
- Implementation issues

Summary

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- There can be significant pay-offs from successful Decision Support Systems (DSS) for CFCF.

- Models and associated algorithmic solutions which support real-time adaptive solutions have been developed.

- The combination of Draper and MIT provides a full range of capabilities: from pure research to implementation of real-time integrated systems.

-107-

An Integrated Environment for Planning Passenger Terminals

John D. Pararas

May 31, 1990

SUMMARY

- Passenger Terminal Planning Process
- Modelling Techniques and Existing Planning Systems
- Modern Software and Hardware Technology
- A General Framework for Passenger Terminal Planning

Passenger Terminal Planning Process

- Long-term (10-20 years)
  - Master plans, detailed designs for new airports or new buildings.
  - Extremely uncertain data
- Medium-term (5 years)
  - Significant additions to existing terminals
  - More reliable data, fewer alternatives.

Passenger Terminal Planning Process (Continued)

- Short-term (6 months-1 year)
  - Manpower planning,
  - Schedule evaluation,
  - Procedural alternatives (e.g. checkin allocation schemes),
  - Gate assignment planning
- Operational Management
  - Manpower allocation
  - Gate Assignment
  - Coping with Delayed Aircraft

Modelling Techniques

- Space Programming Approach:
  - Rules of thumb,
  - Graphs and Charts,
  - distilled knowledge from research, surveys, etc.

  Problems:

  - Not always applicable to situation at hand
  - Assumptions not always clear or understood

Modelling Techniques (Continued)

- Queuing Systems Theory

  Approach:

  - Steady state analysis,
  - Time dependent analysis,
  - Approximations

  Problems:

  - Computationally expensive,
  - Need substantial amounts of data,
  - Steady state assumption suspect,
  - "Single Commodity Flow"

Modelling Techniques (Continued)

- Simulation
  - Flow Models:
    * Simulations of Discrete Markov Process.
    * Fixed time slice,
    * State transitions occur by random sampling from transition probabilities
    * Passenger based statistics are a problem.

Modelling Techniques (Continued)

- Simulation (continued)
  - Discrete Event Simulations:
    - * Detailed modelling of individual passenger actions,
    - * Can produce accurate statistic on all aspects of the terminal operation.
    - * Prone to the GIGO effect.
    - * Prone to "wishful modelling".

Problems with Existing Models

- Isolated implementations rather than an integrated planning environment
- Large data requirements, No defaulting capability.
- "Shallow" knowledge representation. Makes translation from reality to model and back hazardous.
- Distinction between "system" and control logic is blurred.

Problems with Existing Models (Continued)

- Fine tuning and control is impossible without reprogramming

- Batch oriented systems.

- Limited reporting, graphics and animation capabilities

Hardware Technology

Computer prices over the last 30 years:

1960	US$	1,000,000
1970	US$	250,000
1980	US$	25,000
1990	US$	500

Software Technology

- Object Oriented Programming

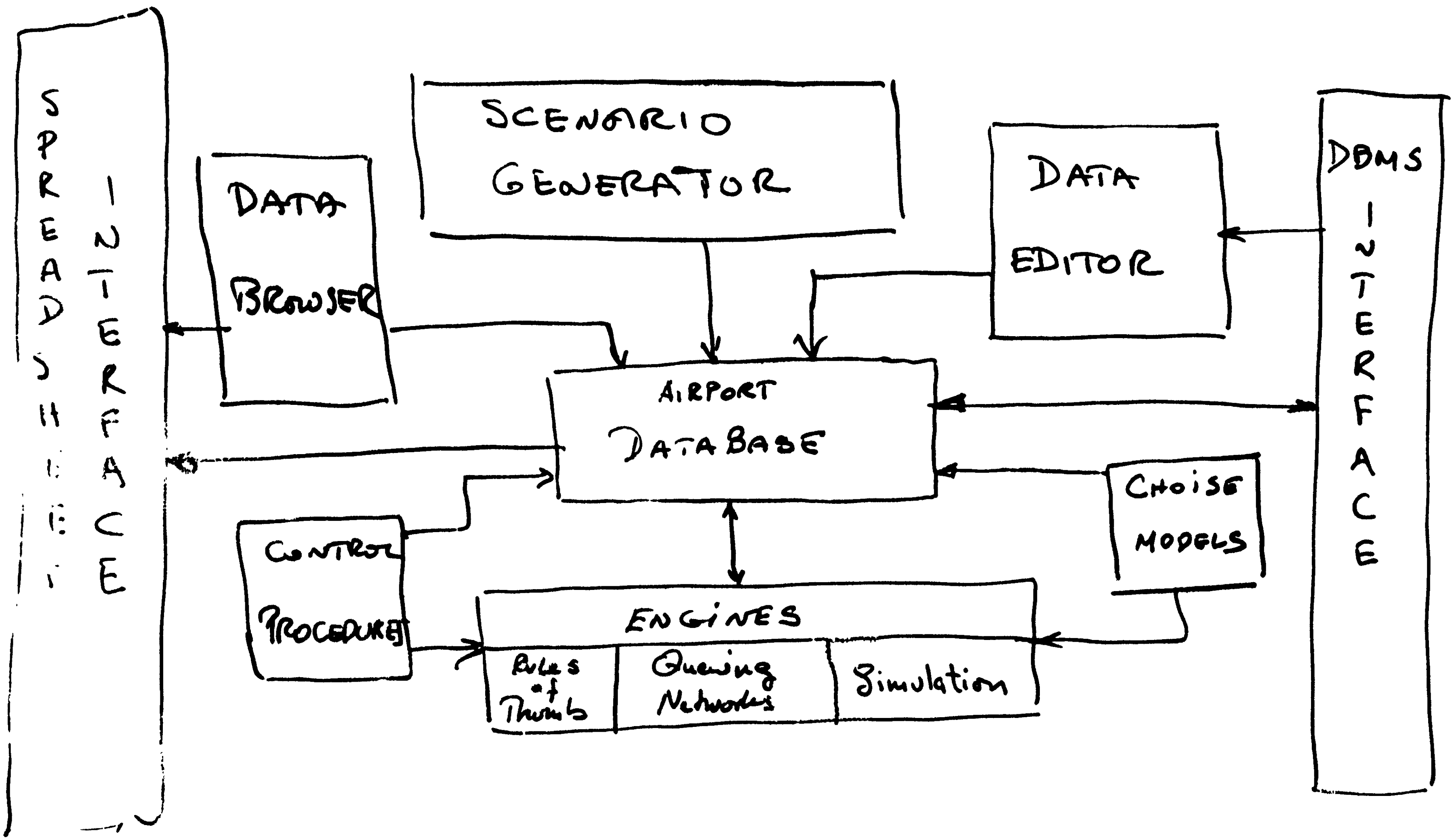
- Expert Systems Programming (Logic Programming)

- Fourth Generation Languages (Code Generators)

- Graphical Interfaces

Generalizations and abstractions of what the software engineer does.

A FRAMEWORK FOR PASSENGER TERMINAL PLANNING.



System Engines

- Implement the *mechanics* of the models
- Logic and choice decisions are deferred to the appropriate subsystems.
- Simulations
  - Queuing system implementation
  - Statistics gathering,
  - Passenger path following
  - Random sampling,

System Engines (Continued)

- Analytical Models
  - System state equations
  - Convolution

- Object-Oriented approach is uniquely suited for system engine development (particularly for simulations).

Choice Models

- Implement the logic to effect choice and procedural control

- Need to provide "entry points" for retrieval of information from system engines at run time.

  - route selection

  - facility selection

  - delay (for flights)

  - Gate selection

  - Baggage claim selection

  - Spare time utilization.

Choice Models (Continues)

- Expert Systems may be best for choice models

- Automatic code generation would allow the user to create and tailor them to suit particular needs.

System Editor

- Allows creation of new objects and editing of existing ones at all levels of detail.
- Coordinates changes to maintain a consistent dataset
- Allows creation and editing of choice models.
- Makes extensive use of GUI's (menus, CVV windows, etc.)
- Object-oriented Design almost a necessity for this subsystem

System Browser

- Allows interactive presentation of the results of a run.

- Allows creation of reports for printing, etc.

- Multiple views of system performance

  - Facility based (average waiting times, average queue lengths)

  - Passenger based, (delays per passenger type, etc.)

  - Histograms (occupancy vs. time of day, etc)

  - Probability distribution functions

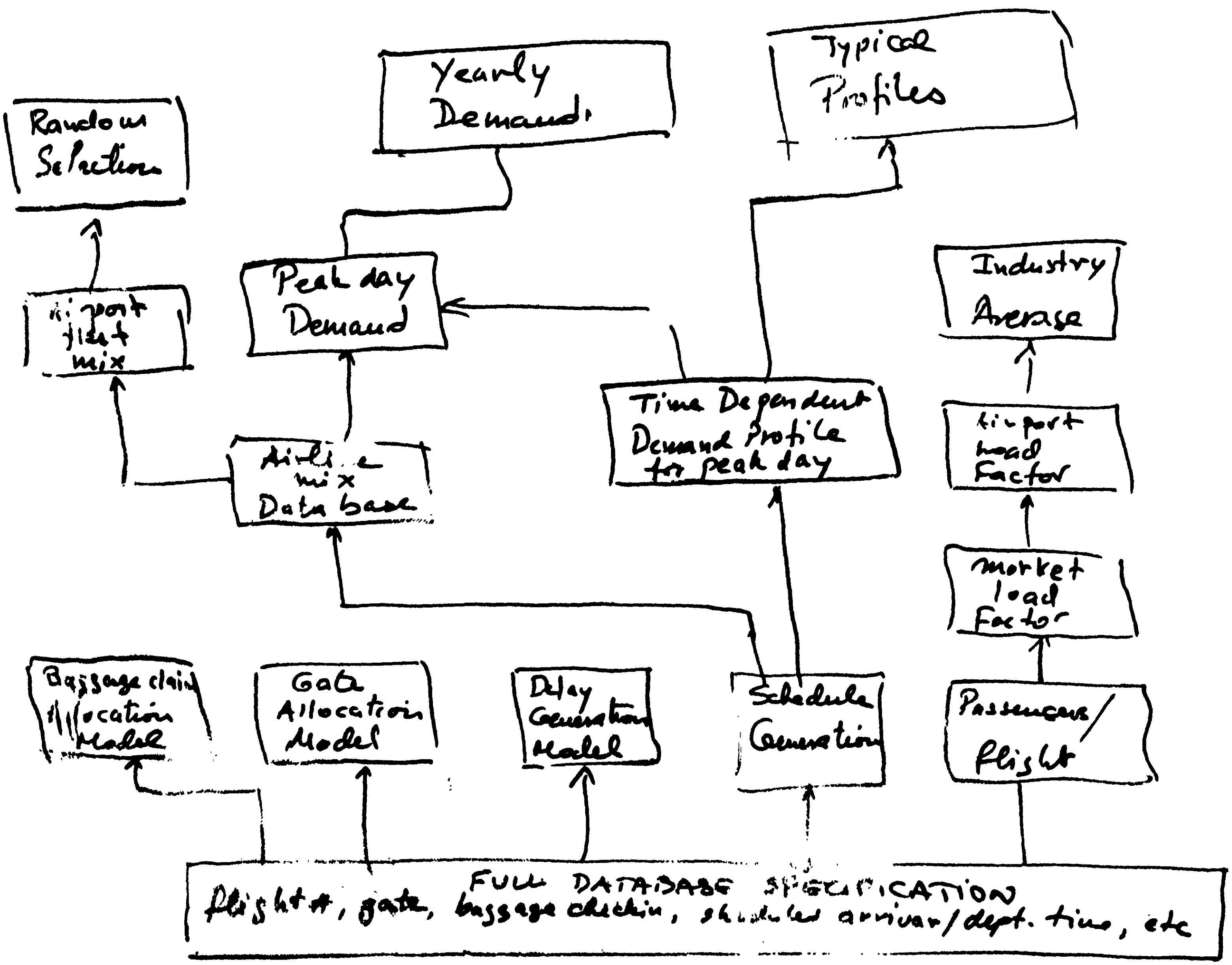
System Browser (Continued)

- Sensitivity analysis results appropriate to various scenarios.
  - Overall statistics vs. % transfers,
  - Passenger waiting time vs. facility allocation schemes,

Scenario Generator

- Mapping of problems into models.
- Help user select appropriate representation
- Query for undefined information (via the editor)
- Implements a data specification hierarchy
- Implements models and methods for generating data appropriate for the selected model.
- Interprets and aggregates results for presentation

SCHEDULE DATA DEFAULT HIERARCHY EXAMPLE



INTRODUCTION TO AIR TRAFFIC CONTROL ENGINEERING

Robert W. Simpson

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Draft of 5/19/90

Planned CHAPTERS

1.3 The Cost of ATC Service

The cost of operating the current US ATC system can be estimated in various ways. Table 1.4 lists only those portions of the FAA expenses for 1988 which are directly attributable to the operation of the ATC system, and there are yet other costs of an overhead nature. Their sum for 1988 is $2.5 billion out of total FAA expenses of $3.2 billion. (There was another $2.8 billion expended by the FAA in the form of Grants-in-Aid to US airport agencies, and another $1.1 billion of capital investment in ATC Facilities and Equipment).

TABLE 1.4 - FAA ANNUAL ATC OPERATING COSTS

TOTAL ANNUAL SYSTEM OPERATING COSTS	
OPERATION OF THE ATC SYSTEM------	1,433,000,000
MAINTENANCE OF THE ATC SYSTEM---	628,000,000
LEASED TELECOMMUNICATIONS-------	225,000,000
NAS LOGISTICS SUPPORT--------------	193,000,000
TOTAL—	$2,469,000,000

UNIT OPERATING COSTS - 1988	
COST PER AIRCRAFT	= $ 9876
COST PER PILOT	= $ 4598
COST PER AC HANDLED BY ARTCC's	= $ 68
COST PER TOWER OPERATION	= $ 40
COST PER AIRCRAFT HOURS FLOWN	= $ 50
COST PER PASSENGER ENPLANEMENT	= $ 5.50

SOURCE: FAA ADMINISTRATOR FACT BOOK

Table 1.4 also shows unit operating costs in a very gross way by dividing the annual operating cost of $2.5 billion by the various measures of activity given in Table 1.3. It can be seen that the annual operating costs alone in 1988 amounted to almost 10,000 $/aircraft, or 5000 $/pilot, or 70 $/operation, or 40 $/takeoff or landing, or 50 $/flying hour. These are gross numbers, and are not additive. A better analysis of how these annual costs are incurred would provide the true marginal costs for each type of activity, but it should be clear that the current operation of the US ATC system is very expensive. In doing a proper job of engineering a new ATC system, it is important to understand these costs and how they are incurred, and to try to find cheaper modes of operation. Since most of these operating costs are salaries, the answers lie with automation and increased productivity of ATC controllers.

Note that we can also find the unit cost per passenger enplanement for operating the US ATC system. Table 1.4 shows this to be only 5.50 $/enplanement. US airline passengers currently are required to pay an 8% tax on their ticket price into an Airways and Airports Trust Fund which contributes towards the operating costs and capital investment in the US ATC system. In 1988 this ticket tax collected $3.2 billion against a sum of operating costs and capital investment of $6.1 billion.

A Brief Sketch of the Work of an ATC Controller

THE SEVEN BASIC FUNCTIONS

1. **Receive and comprehend flight plans and other requests by pilots.**

2. **Generate conflict-free intended paths, or clearances for each aircraft.**

3. **Transmit (& confirm receipt) clearances to each pilot.**

4. **Monitor the "traffic situation" to maintain a mental awareness of:**

   a) **Current set of aircraft-identity and type;**

   b) **their positions, speeds, altitudes, altitude changes;**

   c) **their current clearance limits and final destination;**

   d) **their pending requests for information or changes.**

5. **Monitor conformance of each aircraft to intended path.**

6. **Detect and resolve hazards arising from unexpected events (eg. unknown aircraft, severe weather, equipment failure)**

7. **Manage traffic congestion by generating spacing, metering, scheduling corrections to intended paths which matches actual traffic flow rates with desired flow rates.**

CHAPTER 2

An Analytical Framework for ATC Processes

ANALYTICAL DESCRIPTION OF ATC SYSTEMS

DEFINITION OF ATC VARIABLES - AIRCRAFT PATH

AIRCRAFT PATH - $P_i(t)$

- DEFINE $P_i(t)$ AS A VECTOR QUANTITY DESCRIBING THE PAST HISTORY OF THE POSITION OF AIRCRAFT i AS A FUNCTION OF TIME, t.
- IT HAS COMPONENTS:
  - $r(t)$ = RANGE FROM A REFERENCE ORIGIN, SUCH AS AIRCRAFT, RADAR, WAYPOINT,ETC
  - $\Theta(t)$ = BEARING FROM A REFERENCE DIRECTION, SUCH AS MAGNETIC NORTH, AIRCRAFT HEADING, ETC
  - $h_p(t)$ = PRESSURE HEIGHT FROM A REFERENCE DATUM SUCH AS STANDARD MEAN SEA LEVEL PRESSURE

AIRCRAFT VELOCITY - $\dot{P}_i(t)$

- DEFINE $\dot{P}_i(t)$ AS A VELOCITY VECTOR QUANTITY DESCRIBING THE PAST HISTORY OF POSITION RATE FOR AIRCRAFT i AS A FUNCTION OF TIME.
- IT HAS COMPONENTS:
  - $V_g(t)$ = GROUND SPEED ALONG TRACK
  - $\Phi(t)$ = TRACK DIRECTION RELATIVE TO MAG. NORTH
  - $\dot{h}_p(t)$ = RATE OF CLIMB IN PRESSURE HEIGHT /TIME

ANALYTICAL DESCRIPTION OF ATC SYSTEMS

DEFINITION OF ATC VARIABLES - AIRCRAFT INTENDED PATH

FLIGHT PLAN CLEARANCE- $F_i(t)$

- DEFINE $F_i(t)$ AS A VECTOR QUANTITY

WHICH DESCRIBES THE FUTURE INTENDED PATH, OR FLIGHT PLAN TO BE FOLLOWED BY AIRCRAFT i, AT TIME, t.

PLANNING HORIZON- T_h

- THERE IS A FINITE PLANNING HORIZON, T_h , FOR DEFINING THE FUTURE EXTENT OF THE FLIGHT PLAN. IF IT IS SMALL, THE SYSTEM IS CALLED "TACTICAL"; IF IT IS LARGE, IT IS CALLED "STRATEGIC"

FLIGHT PLAN VELOCITY- $\dot{F}_i(t)$

DEFINE $\dot{F}_i(t)$ AS THE FUTURE INTENDED VELOCITY PLANNED FOR AIRCRAFT i. IT MAY BE USED TO SPECIFY THE FUTURE TRACK, OR IT IS IMPLICIT IN THE SPECIFICATION OF $F_i(t)$

ANALYTICAL DESCRIPTION OF ATC SYSTEMS

DEFINITION OF ATC VARIABLES -TRAFFIC SEPARATION

FLIGHT PLAN DEVIATION- $\Delta FP_i(t)$

- DEFINE $\Delta FP_i(t)$ AS THE ACTUAL DEVIATION FROM FLIGHT PLAN TRACK OBSERVED AT TIME t

$$\Delta FP_i(t) = F_i(t) - P_i(t)$$

- THIS QUANTITY IS USED BY THE CONTROLLER TO MONITOR THE CONFORMANCE OF AIRCRAFT i TO THE ASSIGNED TRACK OR ALTITUDE. THERE IS A CONFORMANCE LIMIT, **C** .

FLIGHT PLAN SEPARATION- $\Delta F_{ij}(t)$

- DEFINE $\Delta F_{ij}(t)$ AS THE PLANNED SEPARATION BETWEEN

  THE FLIGHT PLANS FOR AIRCRAFT i AND AIRCRAFT j AT SOME FUTURE TIME t.

- THIS QUANTITY IS USED BY THE CONTROLLER TO ENSURE THAT THERE IS NO CONFLICT BETWEEN FLIGHT PLANS. THERE ARE SEPARATION CRITERIA,**S** .

AIRCRAFT SEPARATION- $\Delta P_{ij}(t)$

- DEFINE $\Delta P_{ij}(t)$ AS THE ACTUAL SEPARATION OBSERVED

  BETWEEN AIRCRAFT i AND AIRCRAFT j AT TIME, t.

- THIS QUANTITY IS USED BY THE CONTROLLER TO MONITOR THE ACTUAL SEPARATION BETWEEN AIRCRAFT. THERE ARE HAZARD CRITERIA , **H** ,WHICH ARE MUCH SMALLER THAN **C** .

ANALYTICAL DESCRIPTION OF ATC SYSTEMS

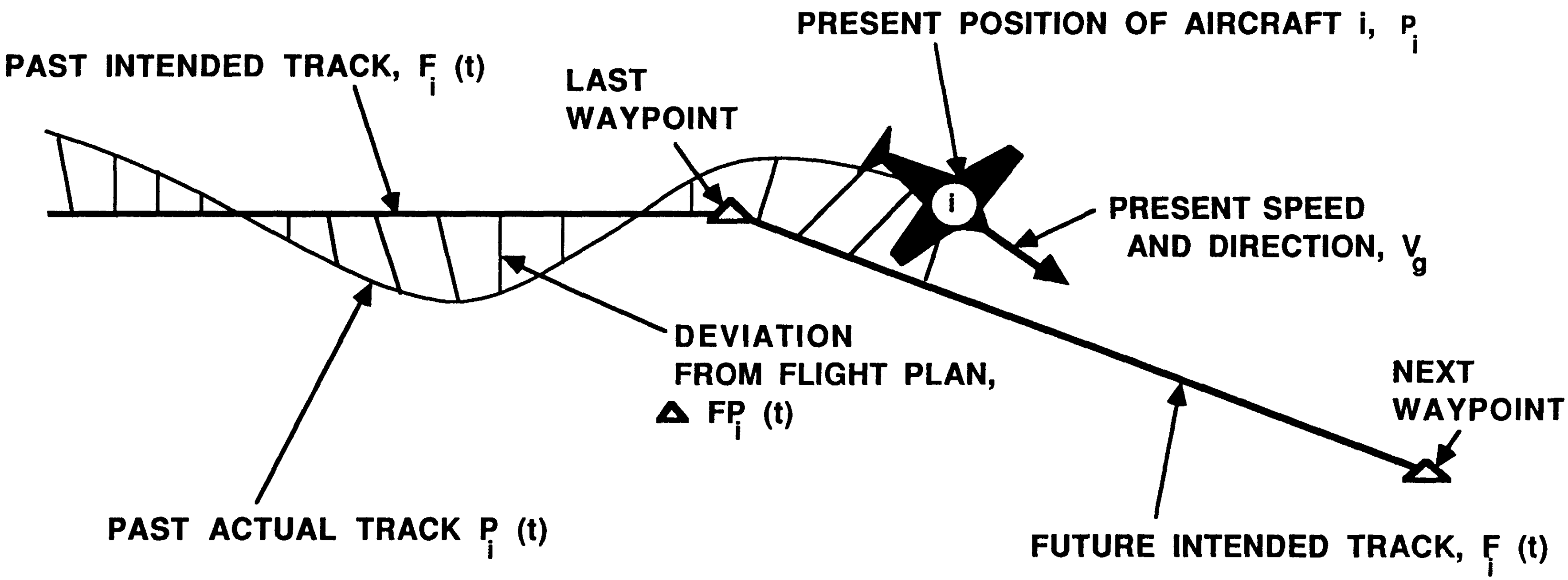
DEFINITION OF ATC VARIABLES - INFORMATIONAL QUANTITIES

- IN A COMPLEX, MULTISENSOR ATC SYSTEM, IT IS NECESSARY TO DISTINGUISH BETWEEN THE TRUE VALUES OF QUANTITIES AND THE ESTIMATED INFORMATION ABOUT THOSE QUANTITIES KNOWN BY VARIOUS ELEMENTS OF THE SYSTEM AT DIFFERENT TIMES. A CIRCUMFLEX , ^ , WILL BE USED TO DENOTE THE FACT THAT IT IS ESTIMATED INFORMATION, AND A SUPERSCRIPT TO DENOTE THE ELEMENT WHERE THE INFORMATION IS KNOWN.

- AS AN EXAMPLE OF WHY IT IS NECESSARY TO MAKE THIS DISTINCTION CONSIDER THE PROBLEM OF MONITORING HAZARDS. SUPPOSE A TRUE HAZARD ALARM EXISTS FROM TIME T1 TO TIME T2 . SINCE THERE CAN BE ERRORS IN THE ACTUAL SEPARATION INFORMATION KNOWN TO A MONITORING SECTOR, THERE CAN BE PERIODS OF TIME WHEN A "FALSE ALARM" EXISTS IN THE SECTOR. TO MINIMIZE THE OCCURENCE OF SUCH PERIODS, A BUFFER CAN BE USED ON THE VALUES OF **H** , BUT THIS WILL NECESSARILY RESULT IN INCREASING THE PERIODS OF TIME WHEN A "MISSED" ALARM EXISTS.

- ALSO, THERE WILL BE PERIODS OF TIME WHEN INFORMATION DOES NOT EXIST YET IN CERTAIN ELEMENTS OF THE SYSTEM, OR HAS YET TO BE UPDATED

FIGURE 2.1 - DEFINITIONS FOR ATC POSITIONAL INFORMATION

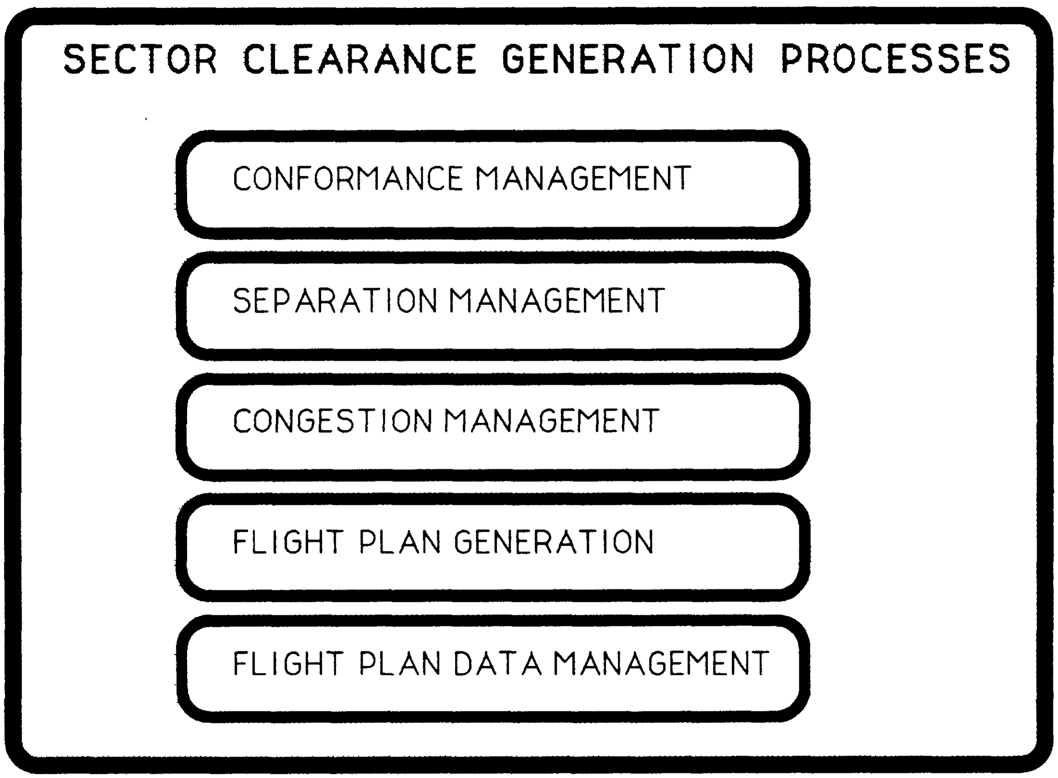


2.3 Sector Clearance Generation Processes

The functionality of the ATC **Sector Clearance Generation Process** can now be examined in further detail. There are numerous inputs:

Aircraft Position and Separation;
Aircraft Flight Plans and Flight Plan Requests;
Wind and weather information;
Aircraft performance;
ATC procedures, and sector flow capacities;
ATC conflict criteria.

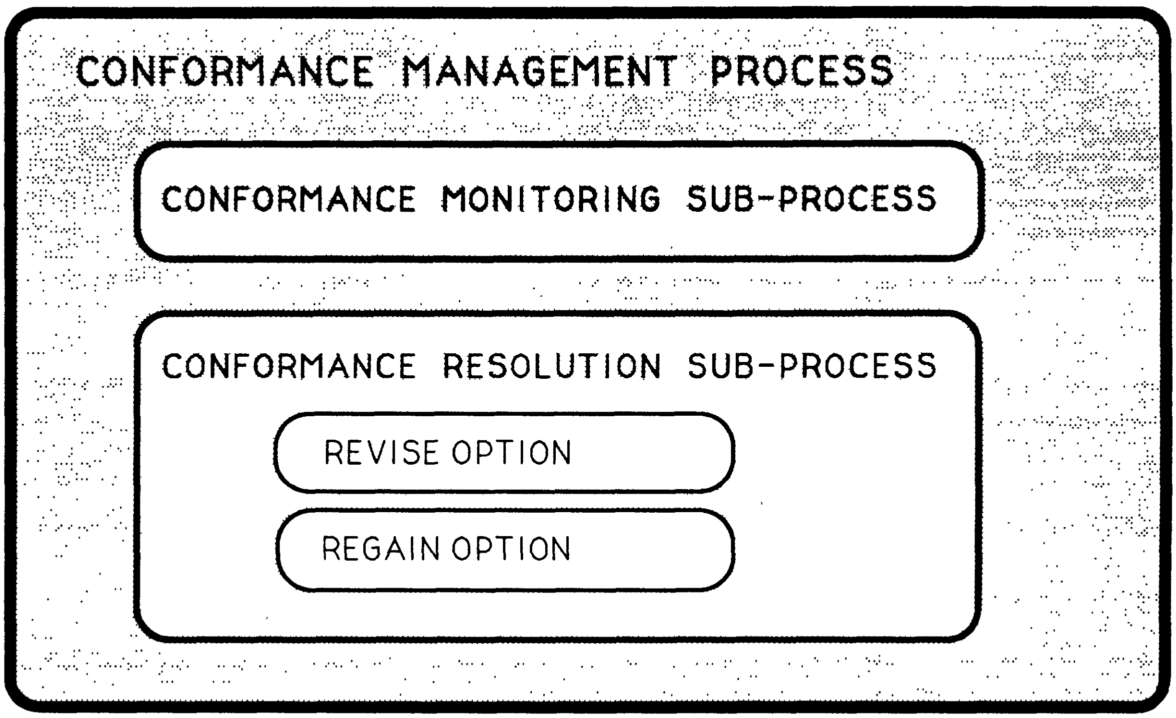
The process involves human controllers, electronic displays, computer systems, and, in the future, automated decision support systems. Clearance Generation can be organized into five basic modules:



Each of these modules contains various other sub-processes which may be nested hierarchically. Later, the sector block diagram will be shown (see Figure 2.4) which shows the information flows between these modules which are necessary to produce the ATC clearances for all aircraft i in sector s. First, these basic functional modules and their nested sub-processes will be described in more detail. These decision processes are currently executed by the human controller given current ATC displays and procedures, but are future candidates for real-time, automated decision-support. It is important that rigorous definitions of these decision processes be created to allow the construction of these automated decision support tools in a coherent manner. To date, attempts to describe these functional processes of ATC have been quite incoherent.

2.3.1 Conformance Management Process

The purpose of the Conformance Management process is to detect and resolve flight plan deviations which exceed a Conformance Limit C. The deviation can be lateral (across-track), vertical, or longitudinal (i.e., along-track, where it is usually expressed as a time deviation). Conformance Management can be 1, 2, or 3 dimensional.



There are two sub-processes of Conformance Management: a) Monitoring; b) Resolution

a) Conformance Monitoring (Sub-process)

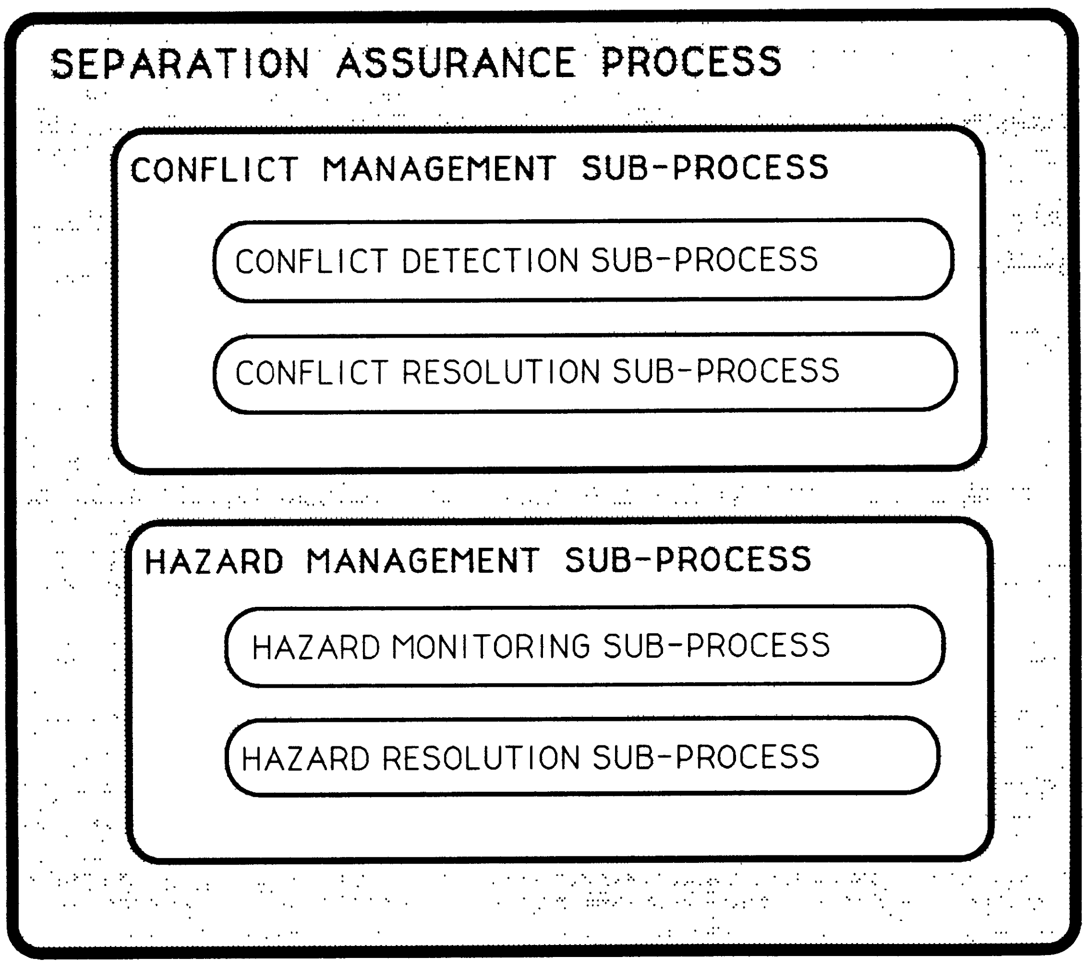
The first sub-process is a continuous, or recurrent periodic function concerned with detection or prediction of deviations by any aircraft in the sector. (The word **monitoring** will be associated with such continuous or recurrent processes). Its output is a **Conformance Alert** which declares and describes the deviation situation. The Conformance Limit C is expressed in its simplest terms as a maximum allowable deviation which can be observed without causing an Alert (eg. a deviation of 300 feet from an assigned altitude). It can also be expressed as a maximum predicted deviation given current position and position rate if conformance is time-critical (e.g., monitoring the conformance on parallel approaches to landing operations where both the cross-track deviation and cross track velocity is monitored).

The Conformance Limit C can be a single value which applies everywhere, or in an automated system, it can be applied differently in various areas of the airspace, or as a function of the traffic situation. It can be varied over time as a function of traffic density, or as a function of the actual proximity of other traffic. The update rate of recurrent Conformance Monitoring can be reduced if traffic density is low, and then increased whenever certain traffic requires closer monitoring. The human controller already uses these spatial and time variations in performing Conformance Monitoring.

2.3.2 Separation Assurance Process

The purpose of the Separation Assurance Process is to ensure safe separation between aircraft, terrain, and restricted airspace. Separation Criteria can be expressed in terms of distance, altitude, and time, and their rates of change. There are two types of Separation Assurance, depending on whether P_i or F_i information is used:

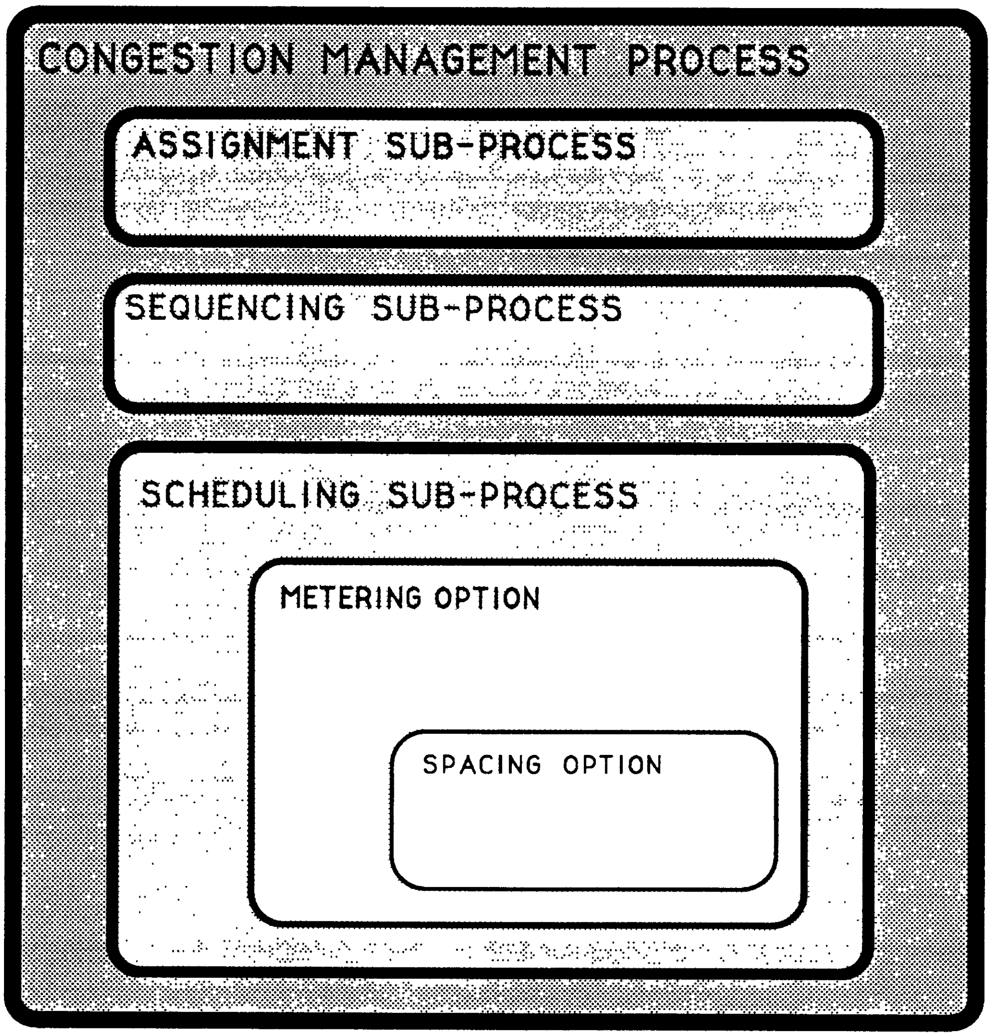
1) **Conflict Management,** which imposes Conflict Criteria S on F_i;
2) **Hazard Management,** which imposes Hazard Criteria H on P_i.



As with Conformance Management, there are two sub-processes for both types of Separation Assurance.

2.3.3 Congestion Management Process

The purpose of the Congestion Management process is to avoid congestion, i.e., avoid crowding too many aircraft into a given airspace. Although there may be no conflicts or hazards, congestion may jeopardize safety by creating short-term overload work rates for ATC controllers in handling the traffic. There are many ways to perform Congestion Management and a sequential and hierarchical relationship exists amongst its sub-processes, as shown below:



Congestion Management processes always exercise control over the arrival times for aircraft, either at a particular waypoint, or at a set of entry points into an airspace area or sector. A timed waypoint will be called a **timepoint**. A set of timepoints may be established for traffic at any waypoint **x** (eg. t_{xi}, t_{xj}, t_{xk}, t_{xl}) for successive aircraft (i, j, k, l) passing over that point. Timepoints can be defined in either the $\mathbf{P_i}$ or $\mathbf{F_i}$ information. Congestion Management processes are solely concerned with creating or modifying timepoints for aircraft, - not for the purposes of Separation Assurance, but to smooth peaks in the flow of traffic. Unlike the other processes, Congestion Management usually transcend the bounds of any one sector of the ATC system.

FIGURE 2.4 - SECTOR CLEARANCE GENERATION - INFORMATION FLOW

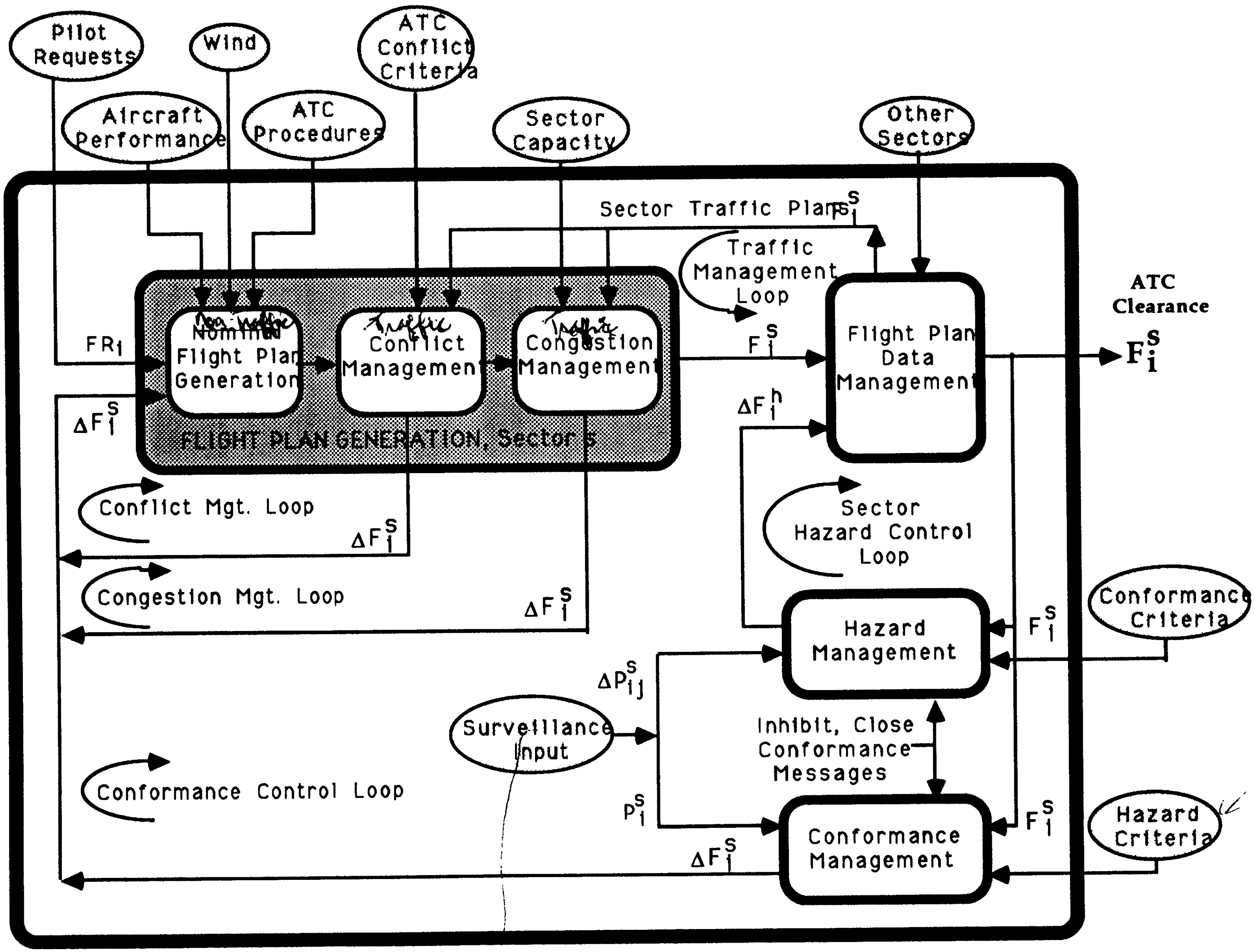
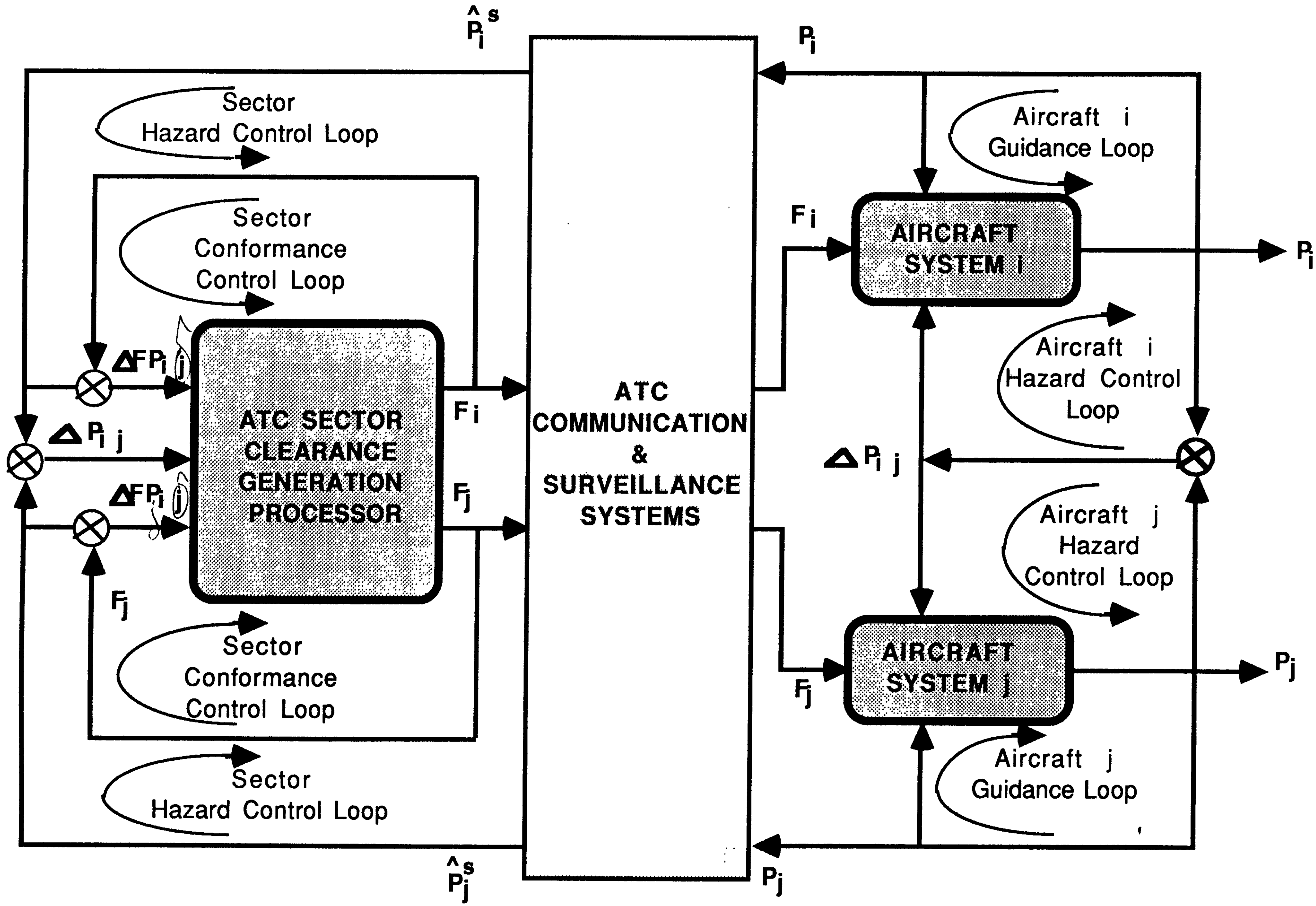


FIGURE 2.3 - GENERAL ATC SECTOR BLOCK DIAGRAM



NEW YORK AIRPORTS

TRAFFIC FLOW ANALYSIS

OBJECTIVE

- Identify and evaluate trends/changes in scheduled passenger traffic flows through all 3 New York area airports over past 5 years.

HISTORICAL DATA

- DOT T9 reports from carrier Form 41 filings provide domestic airline departure information by quarter from 1984-1 to 1989-1.

- Ten percent ticket coupon sample provides passenger itinerary information by quarter from 1984-1 to 1989-3.

- Database Products Inc. database used to extract data, provided by Port Authority of NY and NJ.

DOMESTIC TRAFFIC FLOW ANALYSIS

SUPPLY MEASURES

- Domestic departures by carrier from each airport
- Total seats departed by carrier from each airport

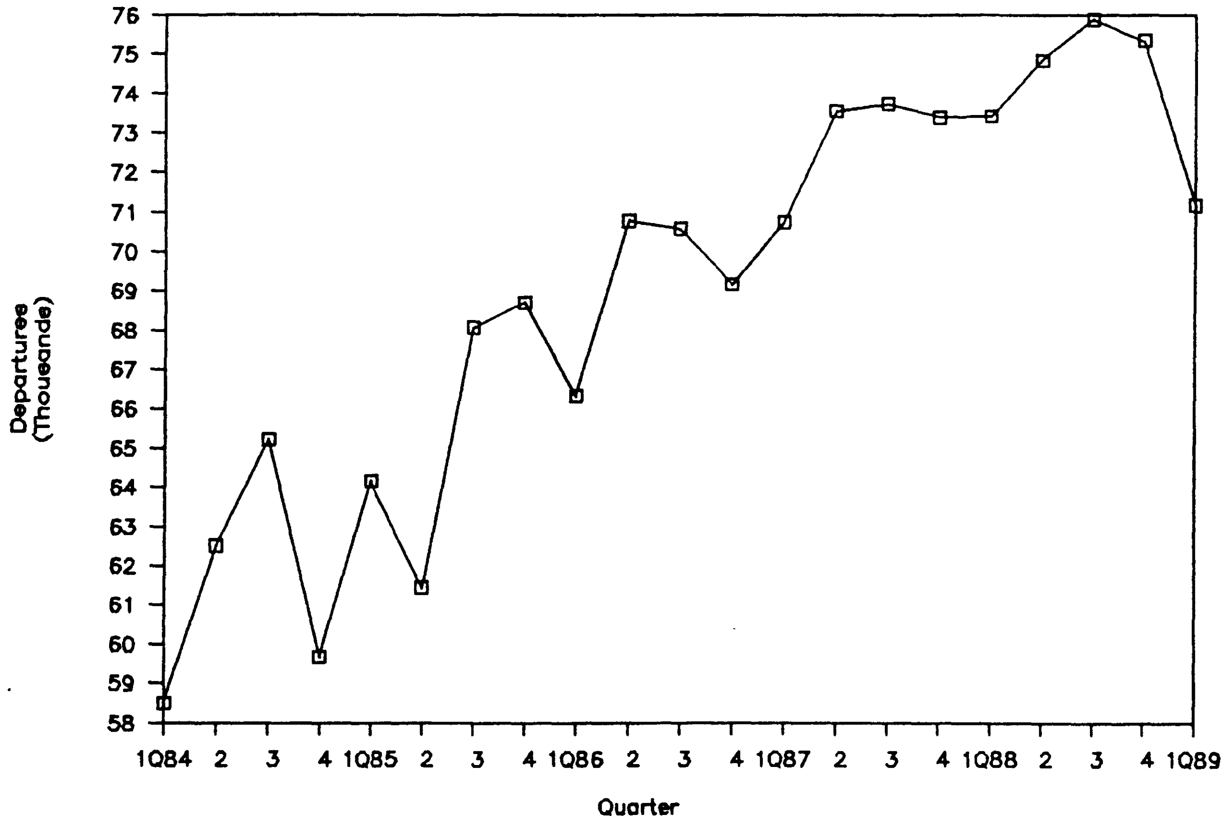
DEMAND MEASURES

- Total on-board domestic passengers departing, by carrier from each airport
- Local originating vs. connecting passengers (domestic only) "Local originating" includes domestic connections to/from international flights

AIR CARRIERS

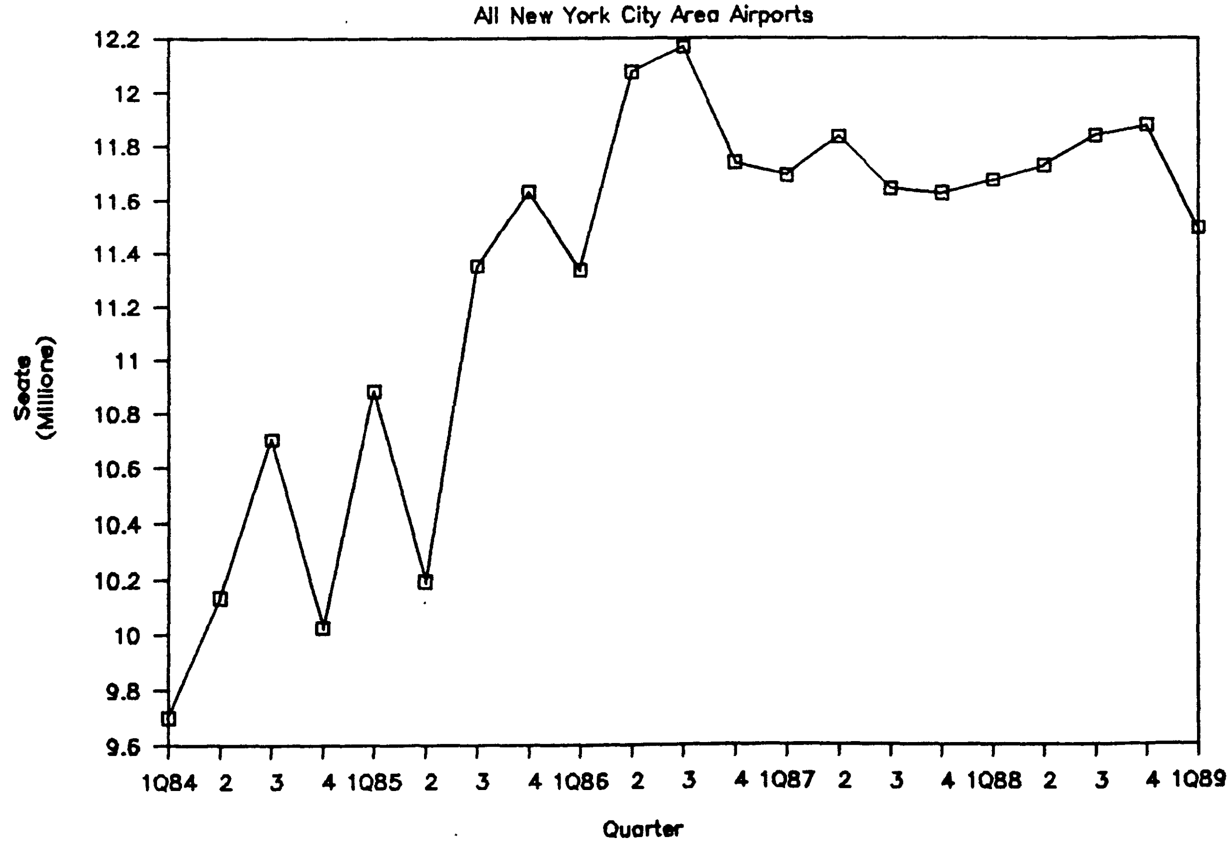
- "Major" U.S. carriers offering service to domestic destinations, defined to include smaller airlines with large market presences.

Total Departures for Majors (All NYC)



Total Seats Departed for Majors

All New York City Area Airports



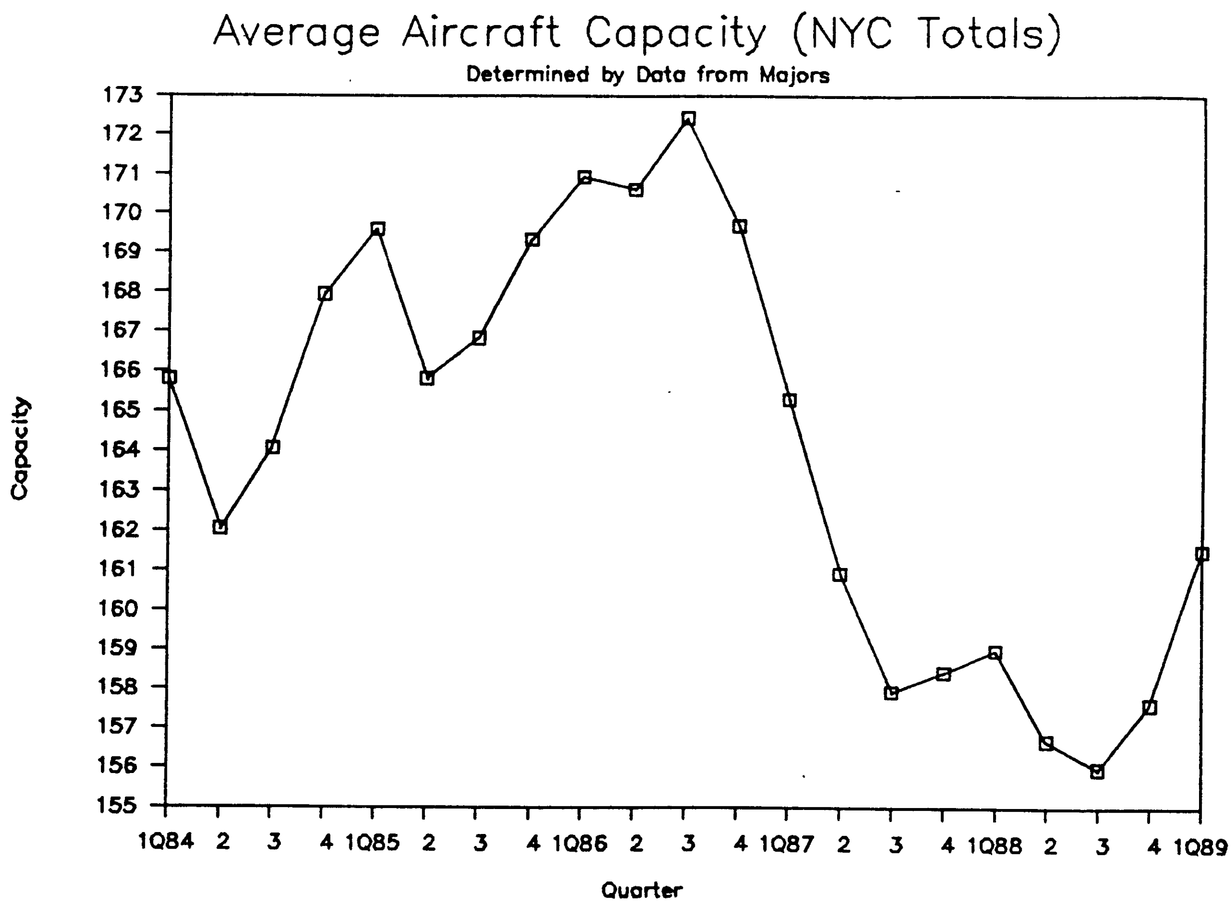
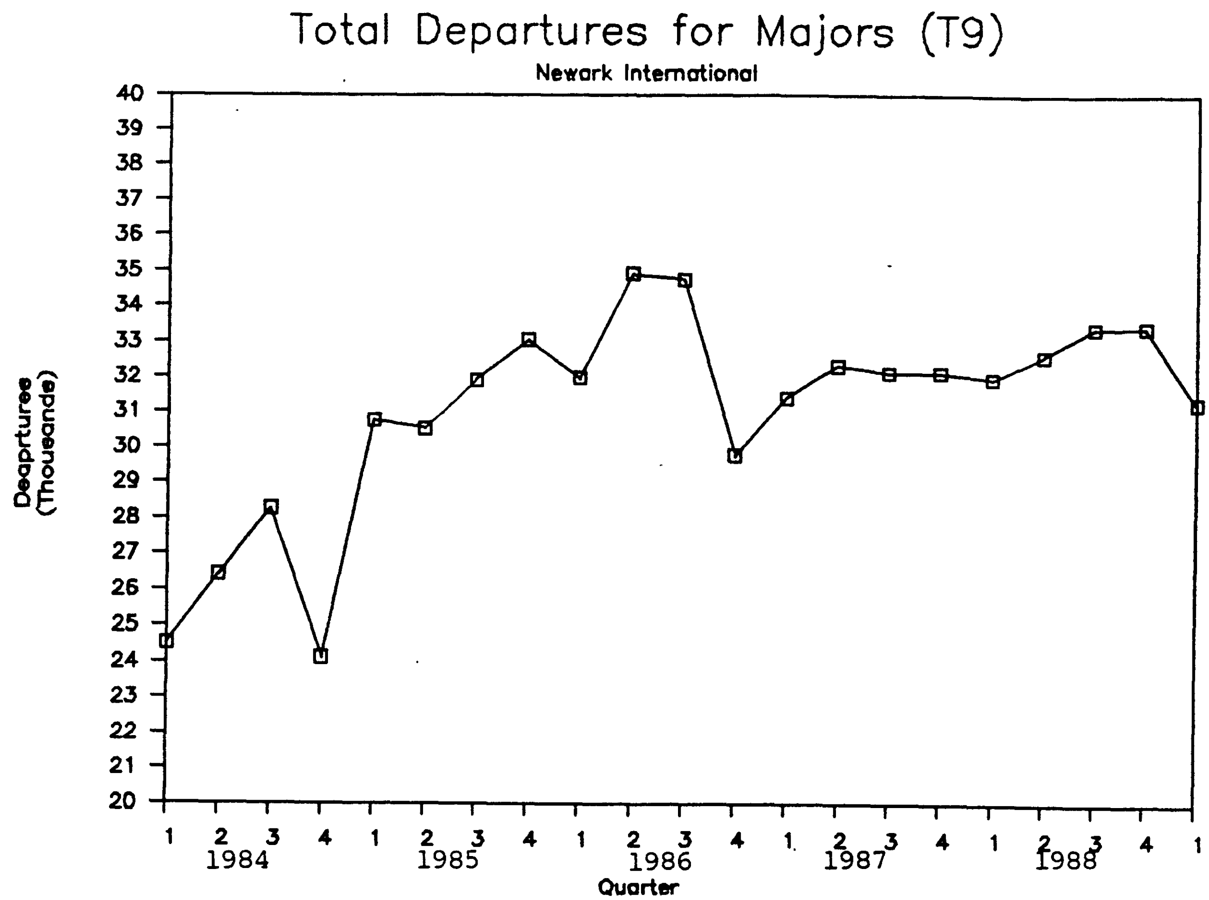
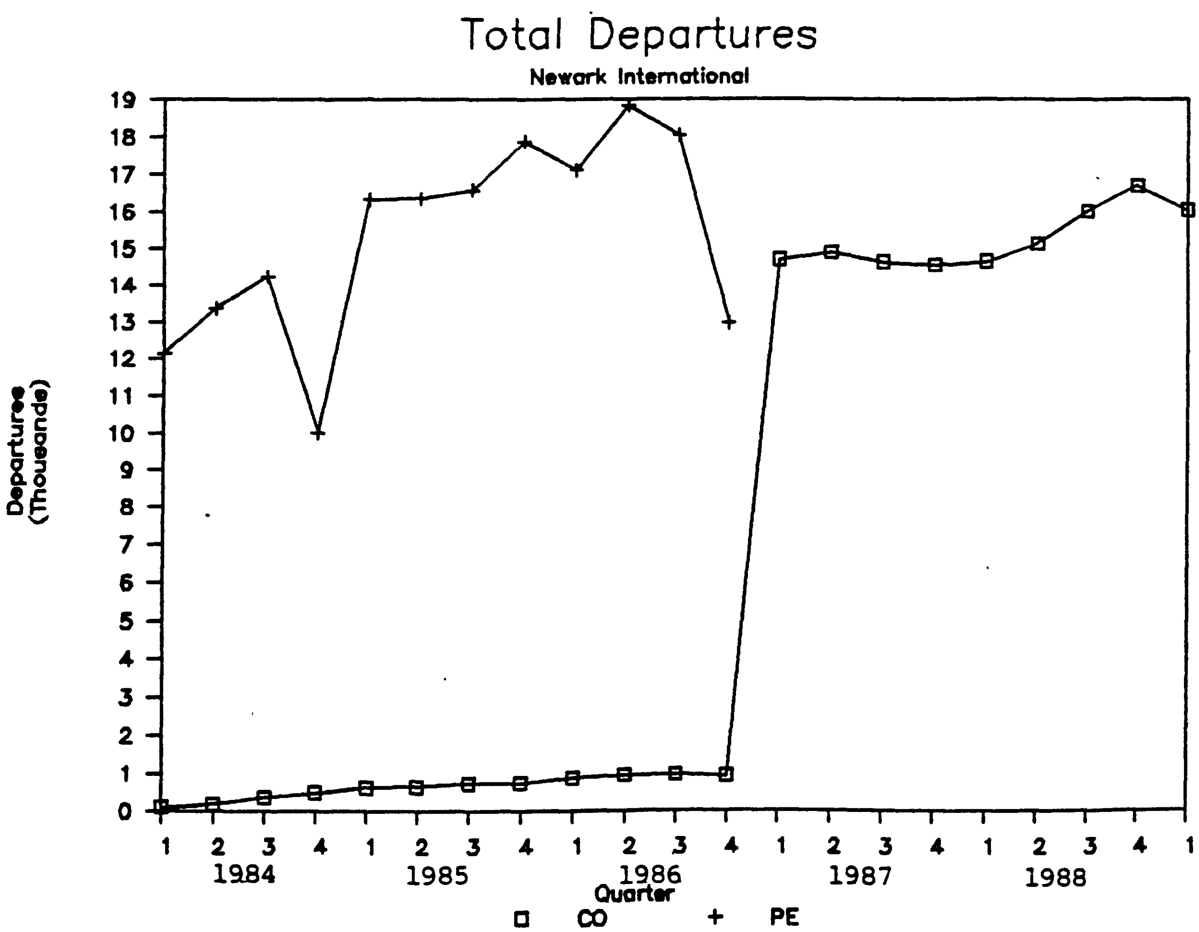
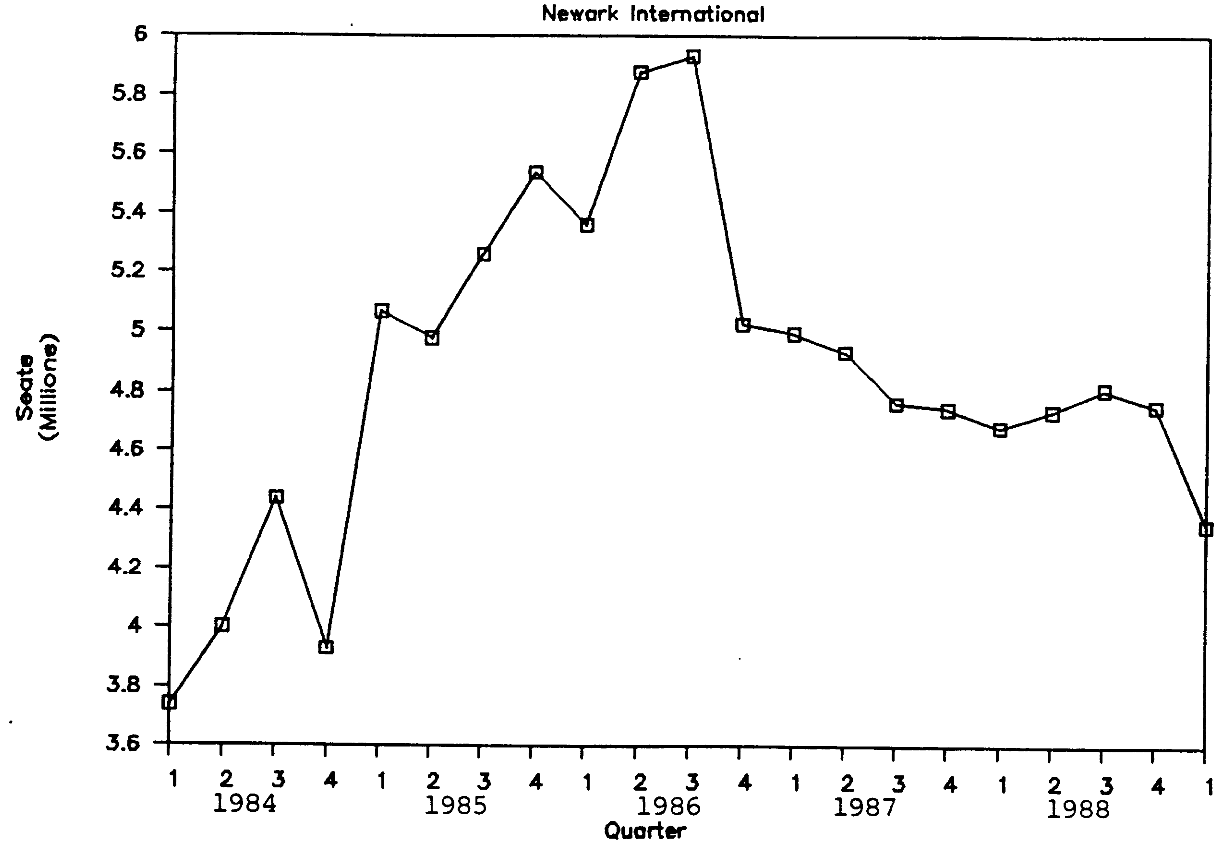

Average Aircraft Capacity (NYC Totals)
Determined by Data from Majors
Capacity
173
172
171
170
169
168
167
166
165
164
163
162
161
160
159
158
157
156
155
1Q84 2 3 4 1Q85 2 3 4 1Q86 2 3 4 1Q87 2 3 4 1Q88 2 3 4 1Q89
Quarter

Figure 1.3

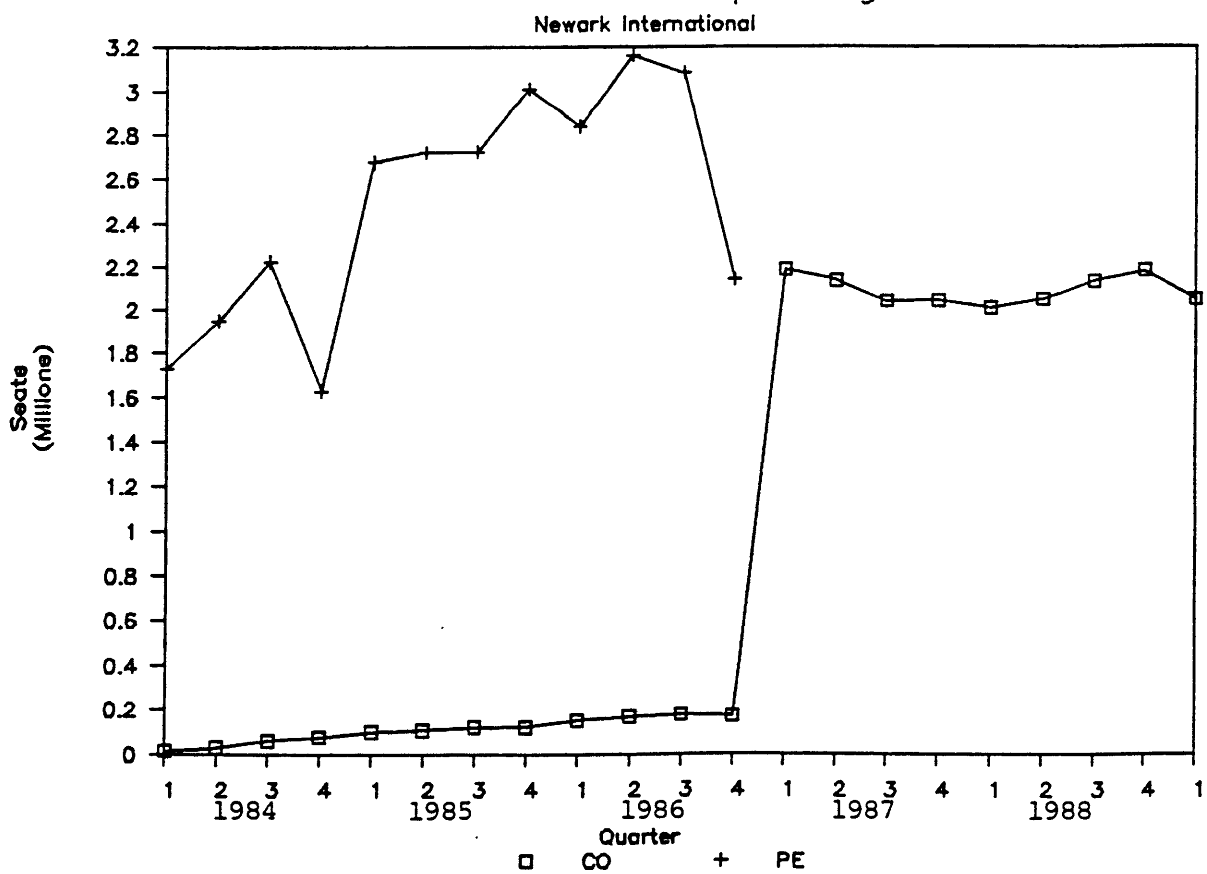

Total Departures for Majors (T9)
Newark International
Deaprtures (Thousands)
40
39
38
37
36
35
34
33
32
31
30
29
28
27
26
25
24
23
22
21
20
1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1
1984
1985
1986
1987
1988
Quarter


Total Departures
Newark International
Departures (Thousands)
19
18
17
16
15
14
13
12
11
10
9
8
7
6
5
4
3
2
1
0
1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1
1984
1985
1986
1987
1988
Quarter
CO
PE

Total Seats Departed for Majors (T9)



Total Seats Departing



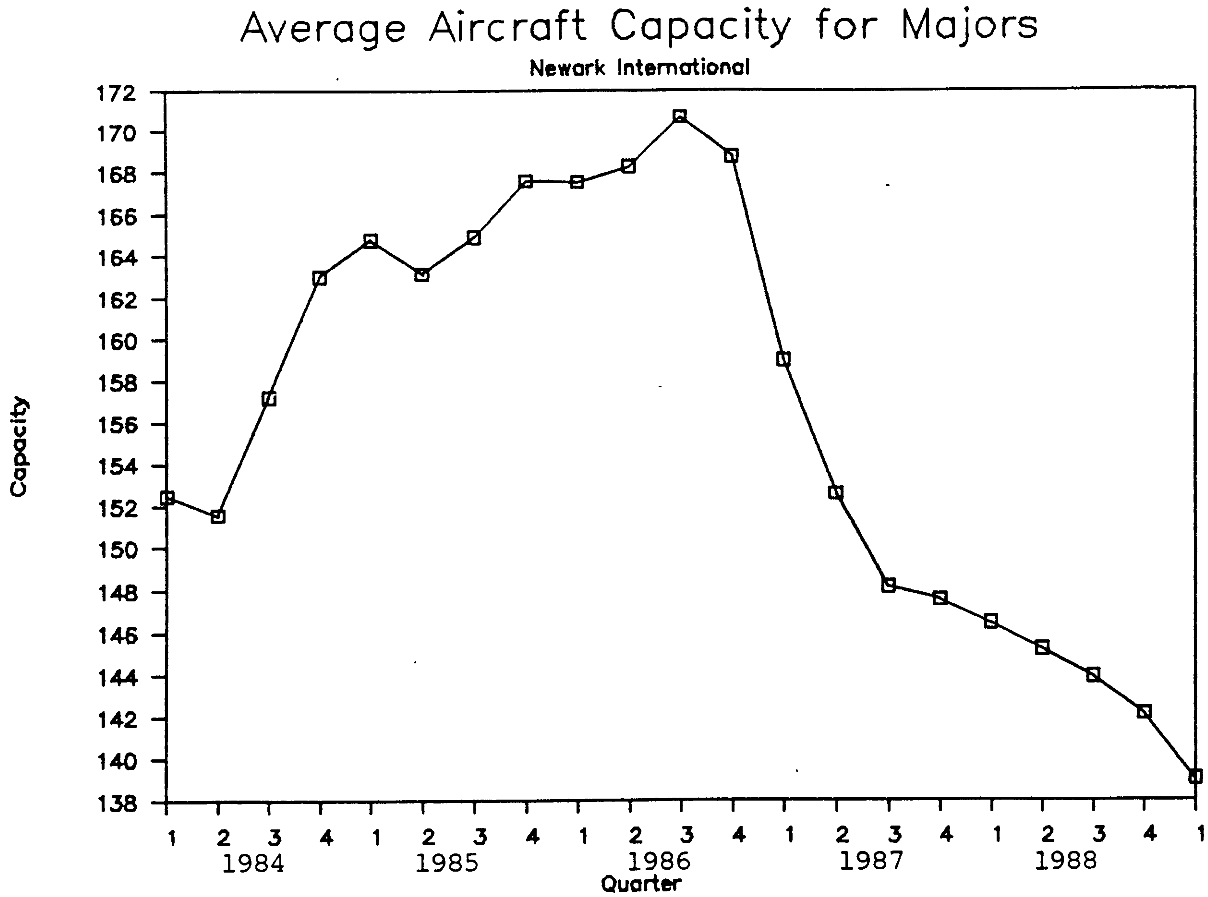
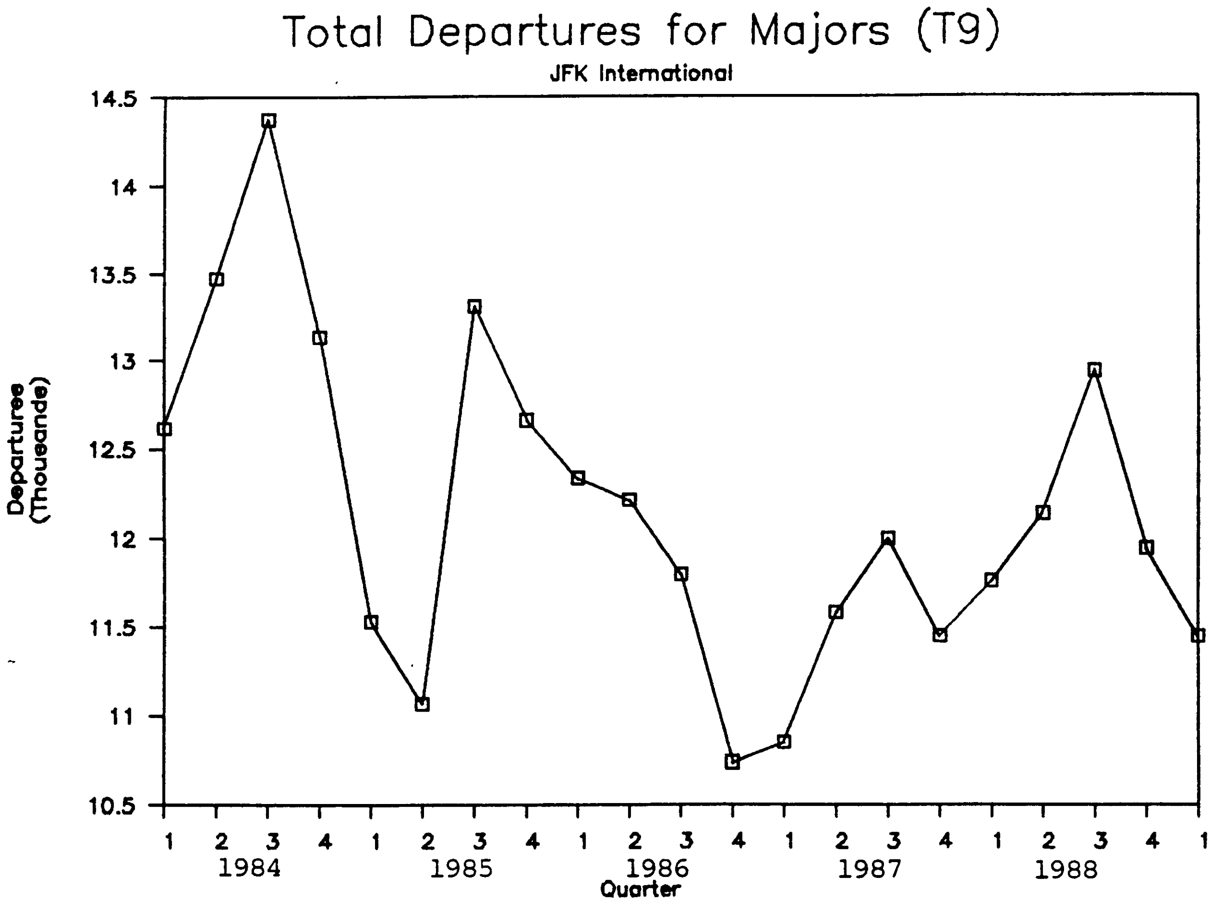
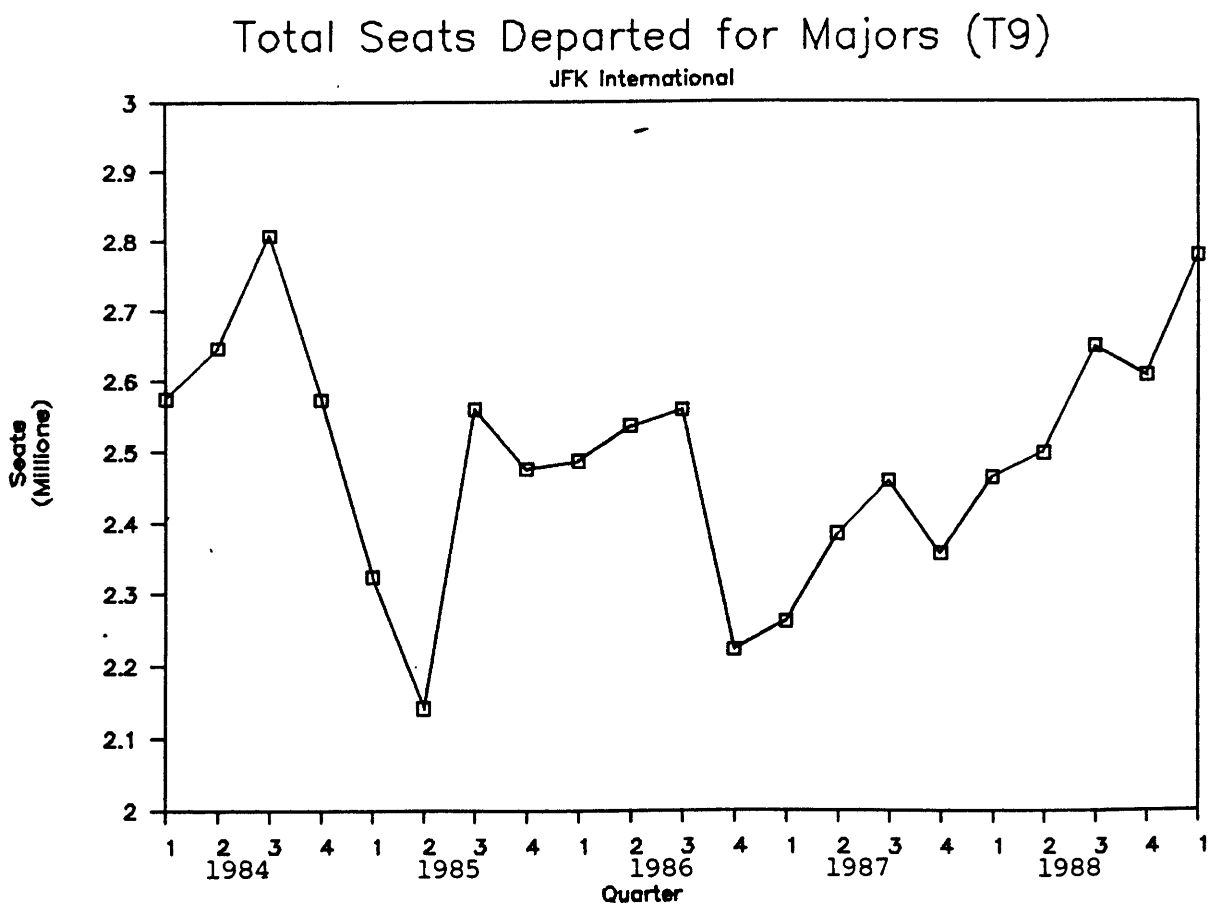
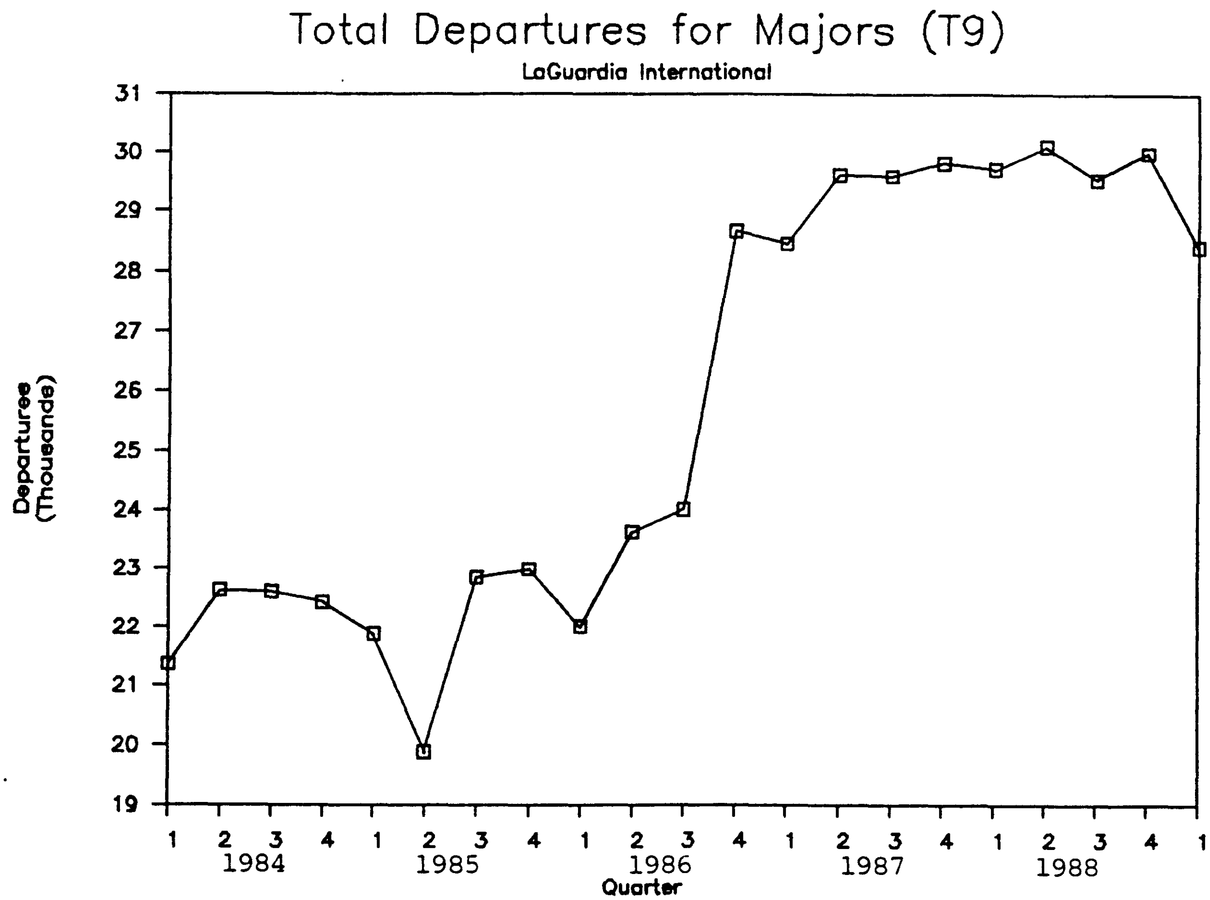
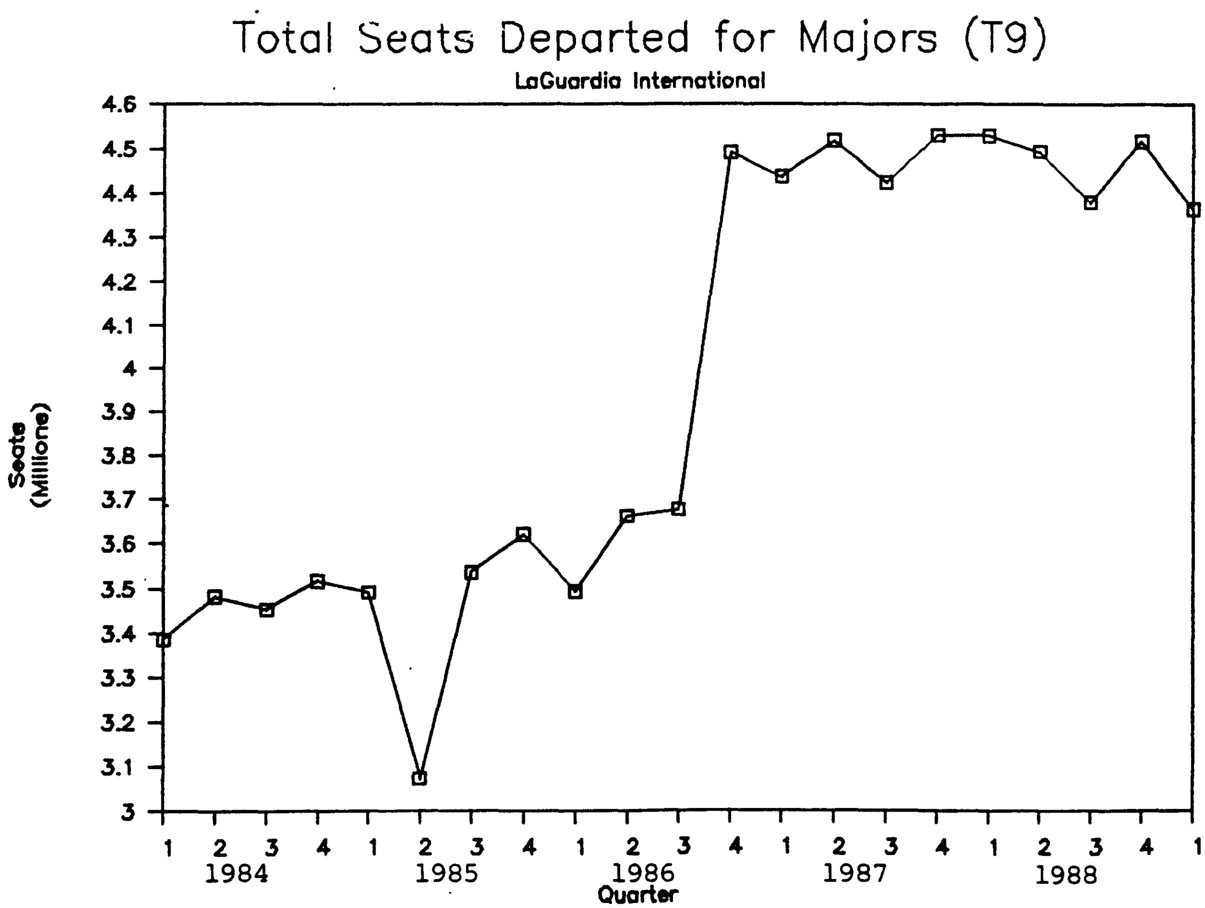

Average Aircraft Capacity for Majors
Newark International
Capacity
172
170
168
166
164
162
160
158
156
154
152
150
148
146
144
142
140
138
1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1
1984
1985
1986
1987
1988
Quarter

Figure 1.10

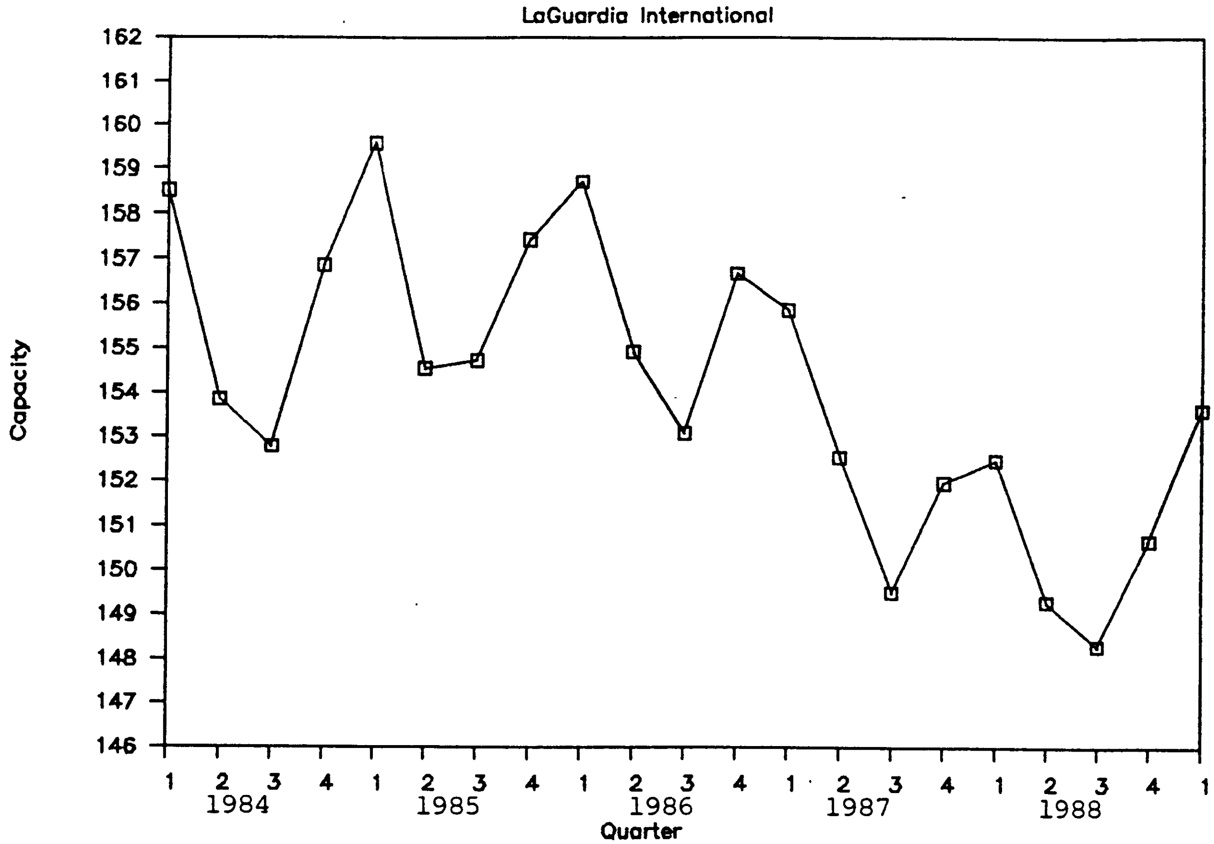

Total Departures for Majors (T9)
JFK International
Departures (Thousands)
14.5
14
13.5
13
12.5
12
11.5
11
10.5
1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1
1984
1985
1986
1987
1988
Quarter


Total Seats Departed for Majors (T9)
JFK International
Seats (Millions)
3
2.9
2.8
2.7
2.6
2.5
2.4
2.3
2.2
2.1
2
1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1
1984
1985
1986
1987
1988
Quarter

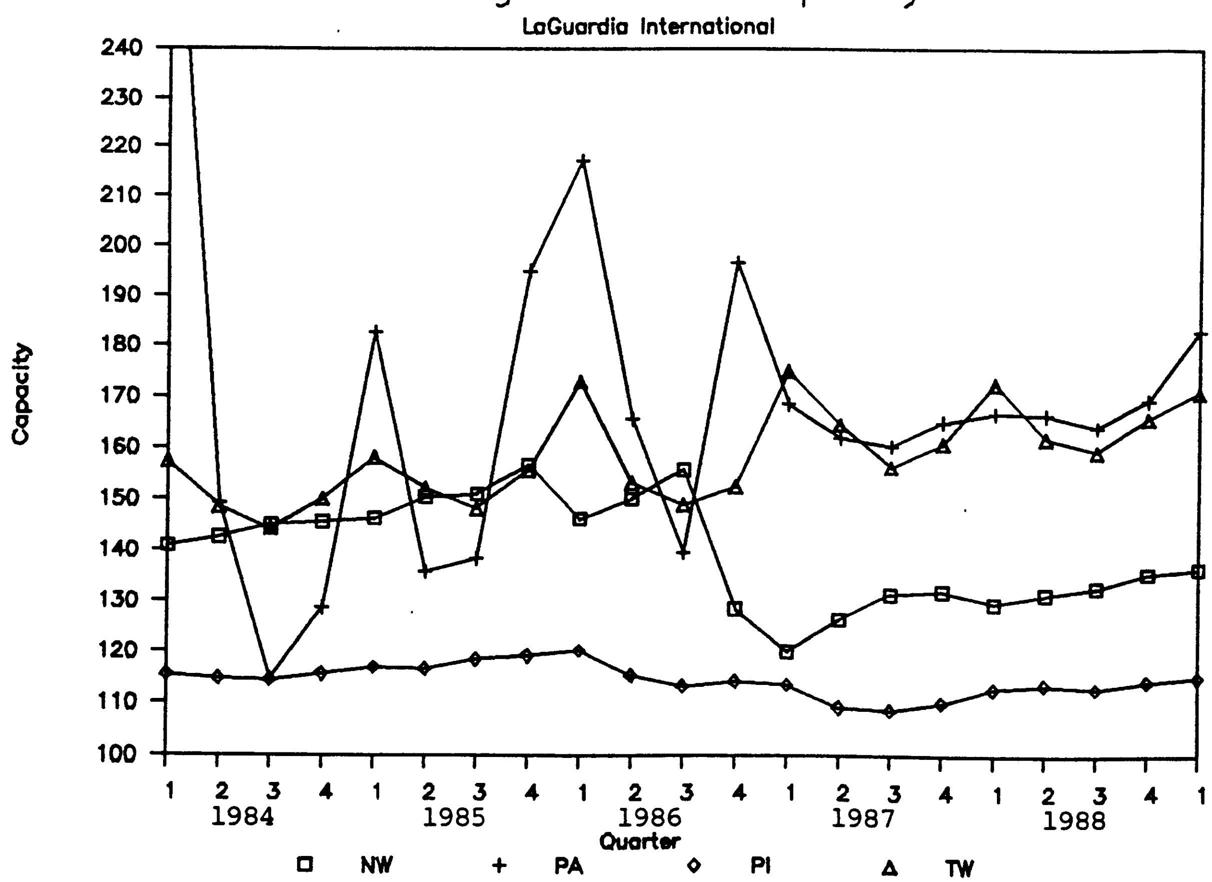

Total Departures for Majors (T9)
LaGuardia International
Departures (Thousands)
31
30
29
28
27
26
25
24
23
22
21
20
19
1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1
1984
1985
1986
1987
1988
Quarter


Total Seats Departed for Majors (T9)
LaGuardia International
Seats (Millions)
4.6
4.5
4.4
4.3
4.2
4.1
4
3.9
3.8
3.7
3.6
3.5
3.4
3.3
3.2
3.1
3
1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1
1984
1985
1986
1987
1988
Quarter

Average Aircraft Capacity for Majors

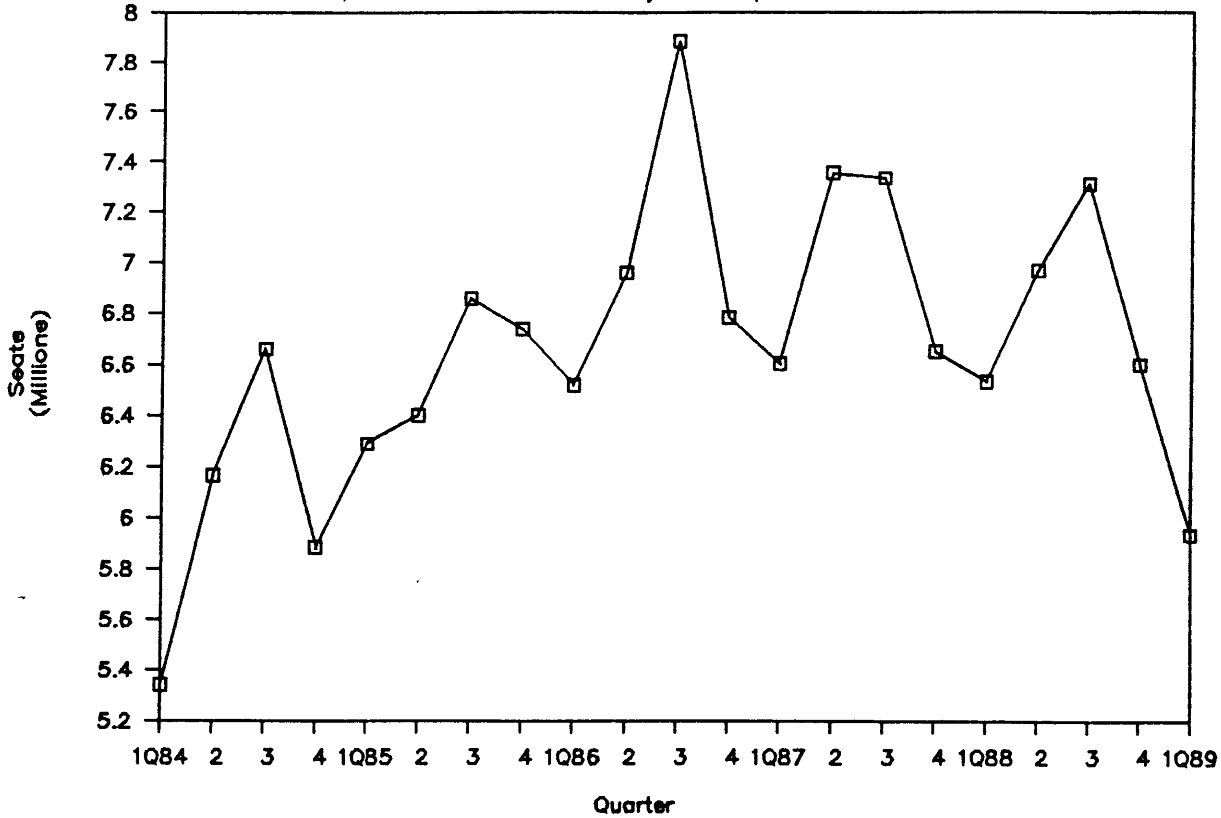


Average Aircraft Capacity



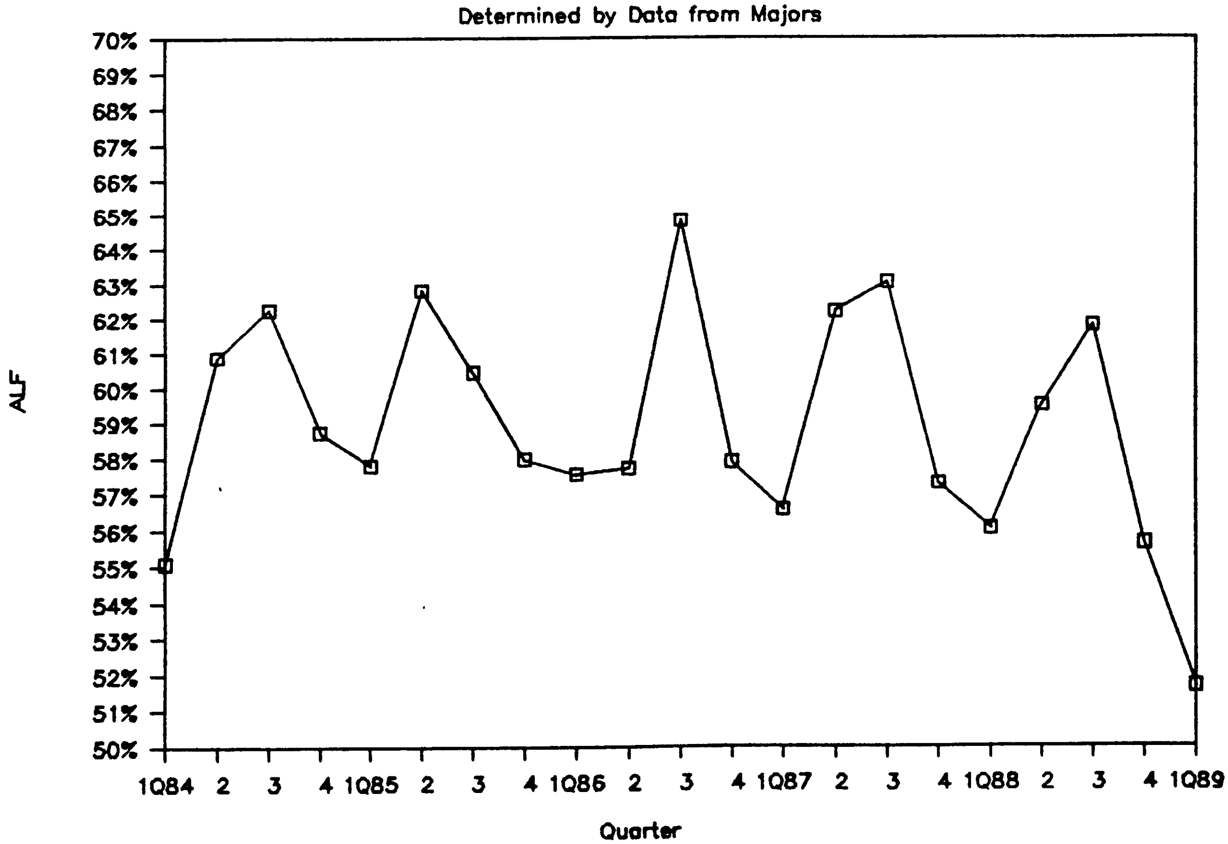
Total Onboard Pax for Majors

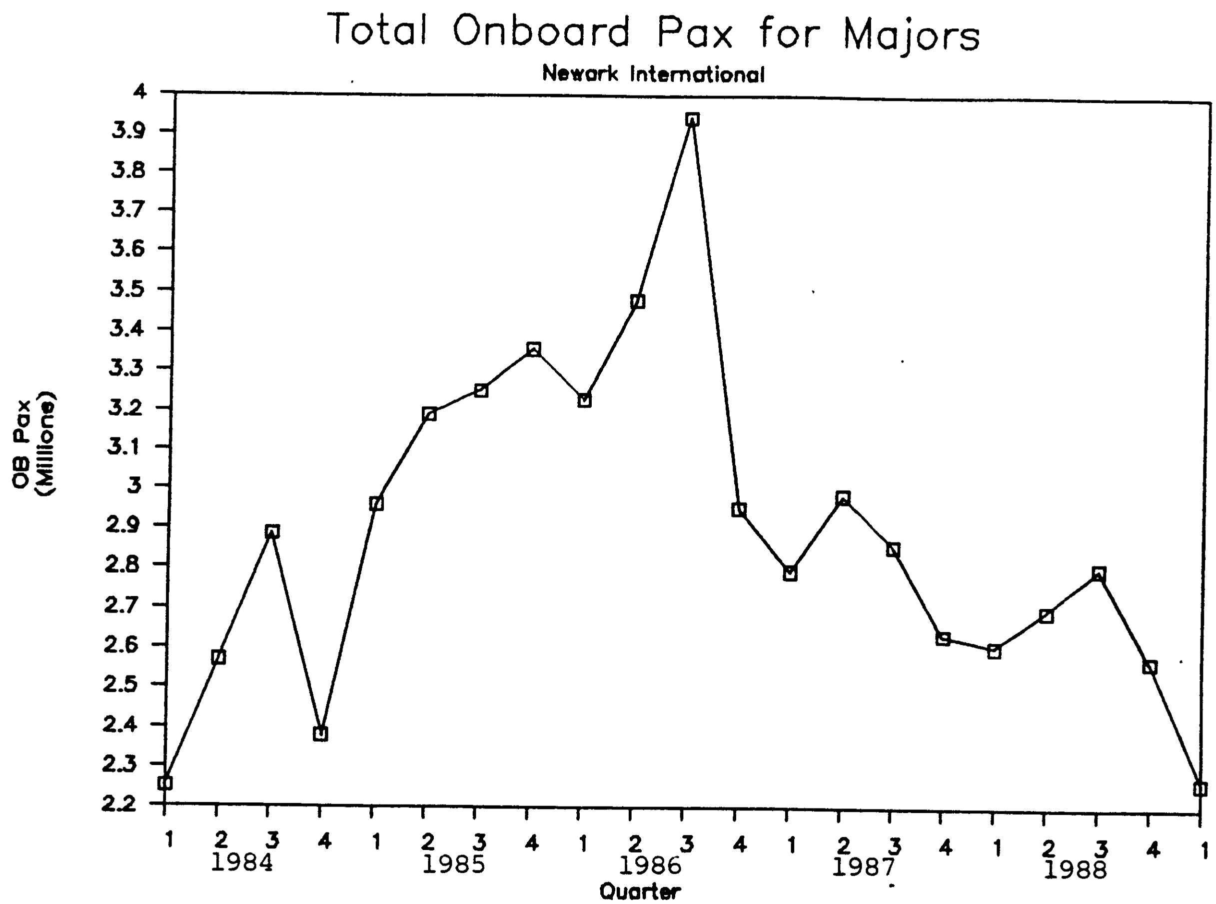
All New York City Area Airports

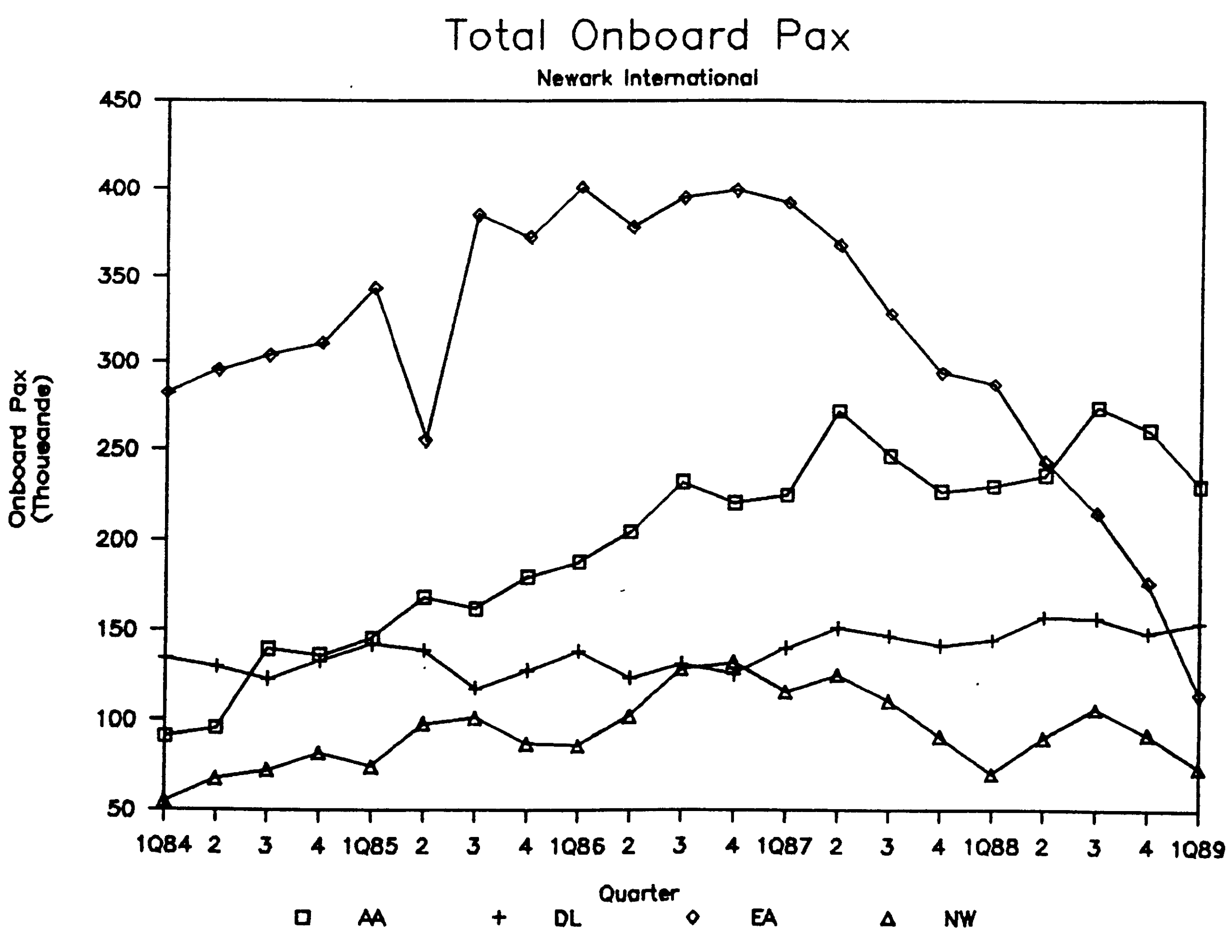


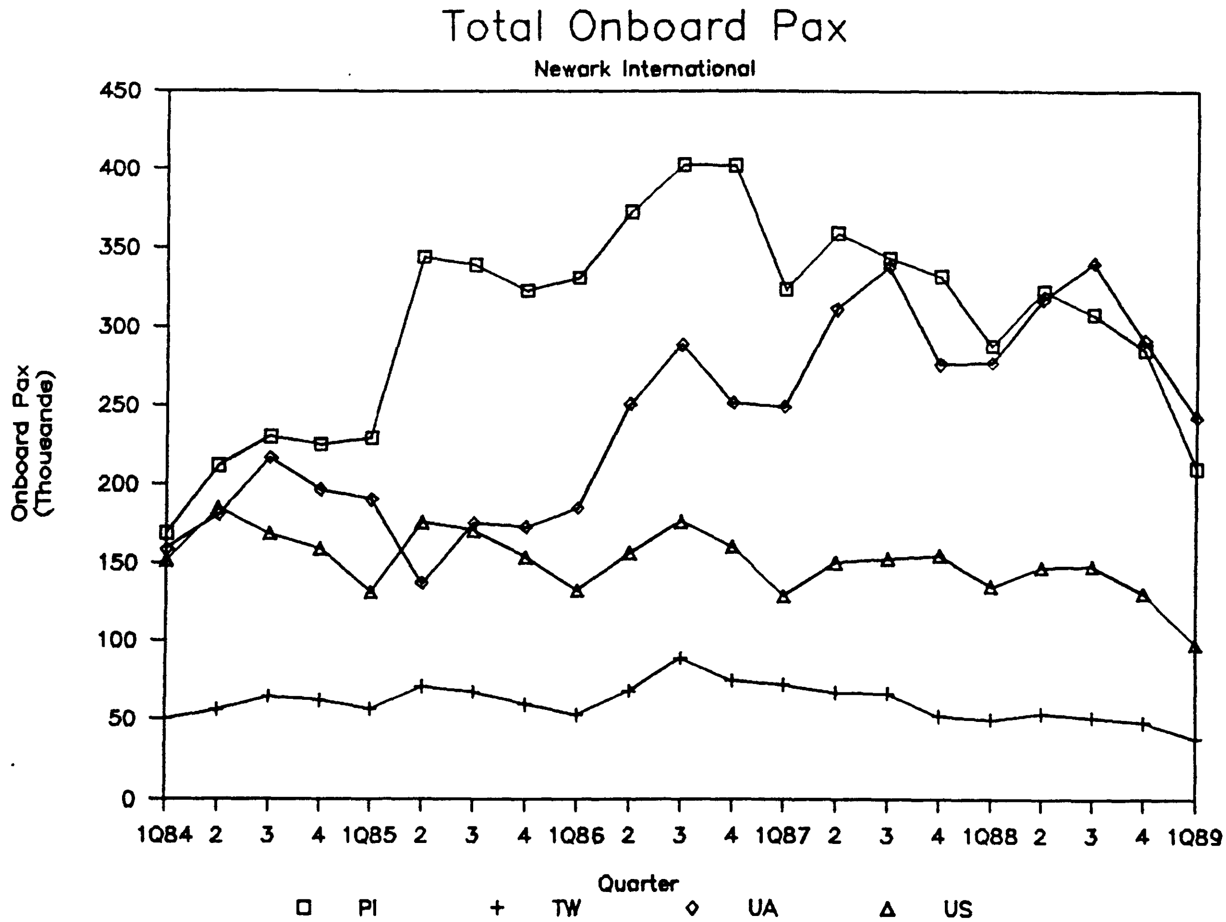
Average Load Factor (NYC Totals)

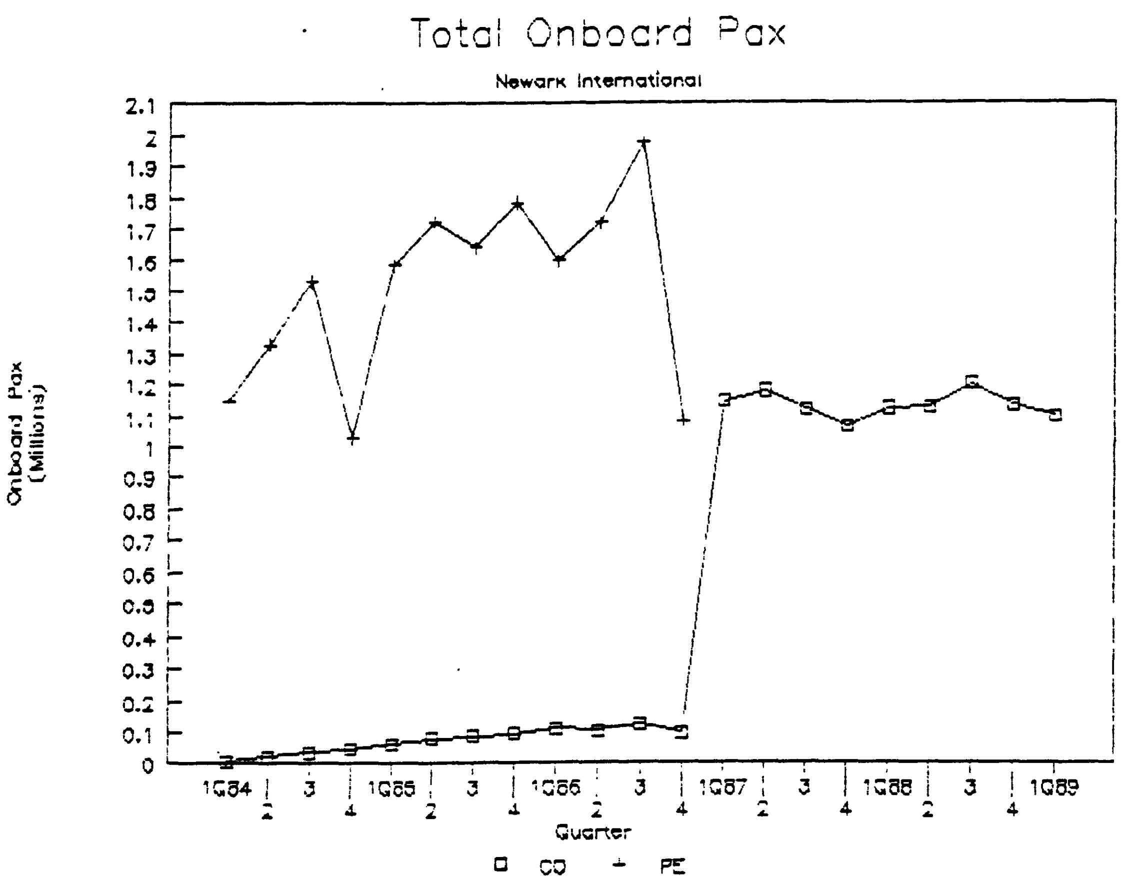
Determined by Data from Majors




Total Onboard Pax for Majors
Newark International
OB Pax
(Millions)
4
3.9
3.8
3.7
3.6
3.5
3.4
3.3
3.2
3.1
3
2.9
2.8
2.7
2.6
2.5
2.4
2.3
2.2
1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1
1984
1985
1986
1987
1988
Quarter


Total Onboard Pax
Newark International
Onboard Pax
(Thousands)
450
400
350
300
250
200
150
100
50
1Q84 2 3 4 1Q85 2 3 4 1Q86 2 3 4 1Q87 2 3 4 1Q88 2 3 4 1Q89
Quarter
AA
DL
EA
NW


Total Onboard Pax
Newark International
Onboard Pax (Thousands)
450
400
350
300
250
200
150
100
50
0
1Q84 2 3 4 1Q85 2 3 4 1Q86 2 3 4 1Q87 2 3 4 1Q88 2 3 4 1Q89
Quarter
PI
TW
UA
US


Total Onboard Pax
Newark International
Onboard Pax (Millions)
2.1
2
1.9
1.8
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1Q84 2 3 4 1Q85 2 3 4 1Q86 2 3 4 1Q87 2 3 4 1Q88 2 3 4 1Q89
Quarter
CO
PE

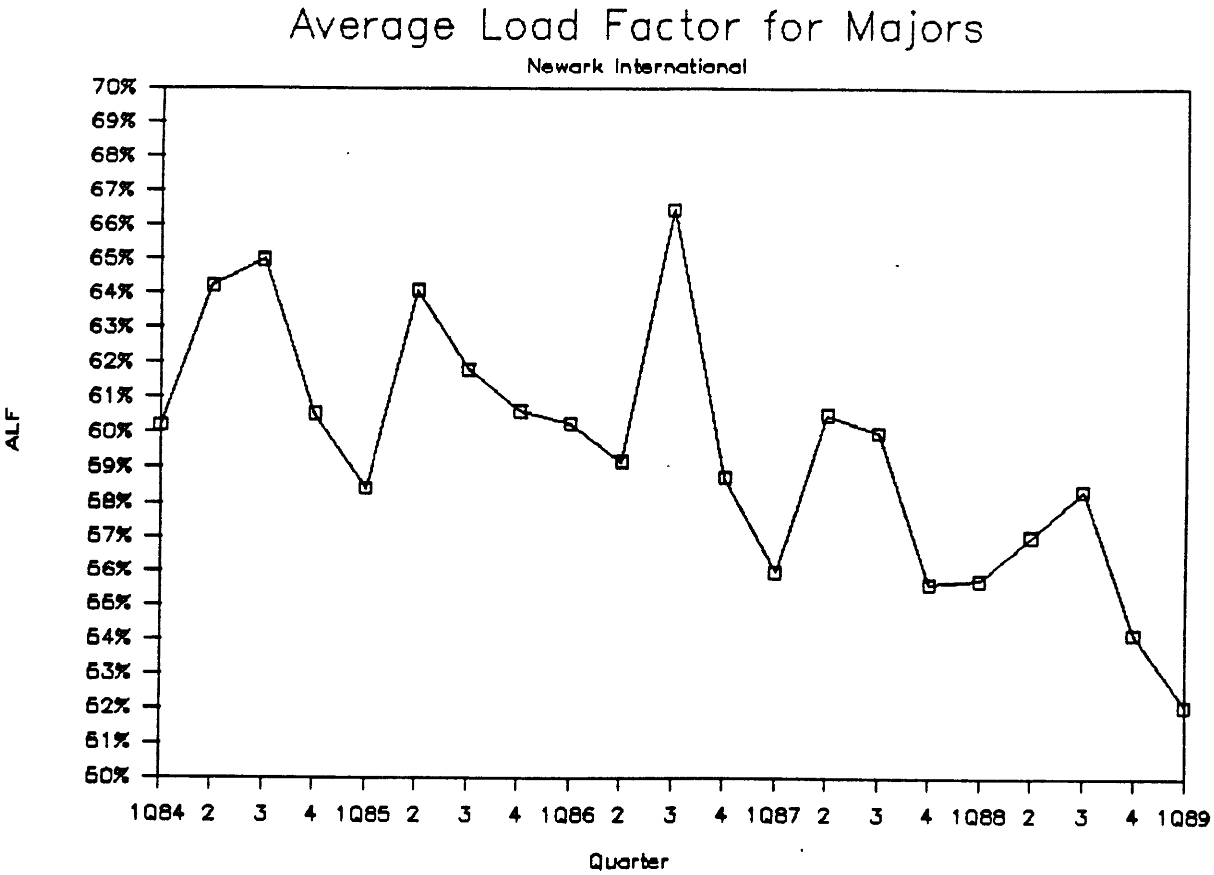
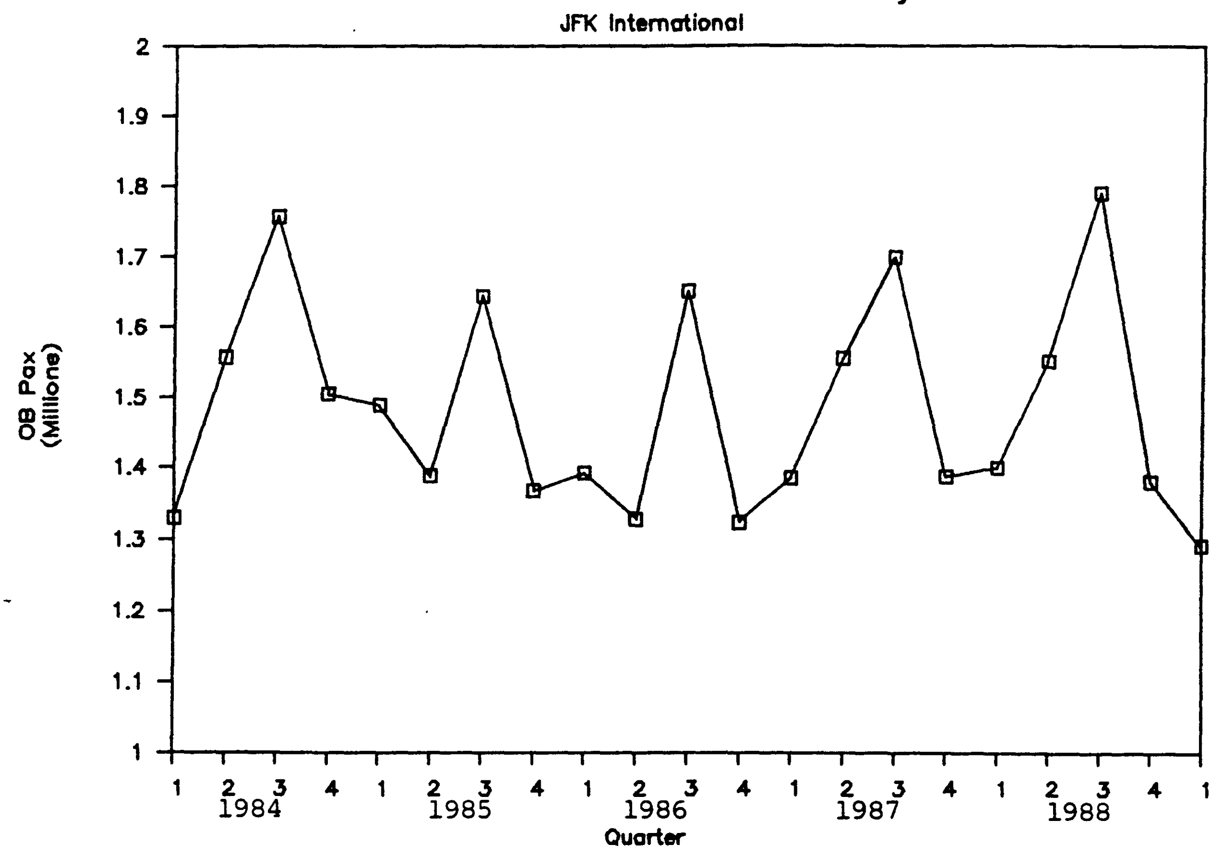
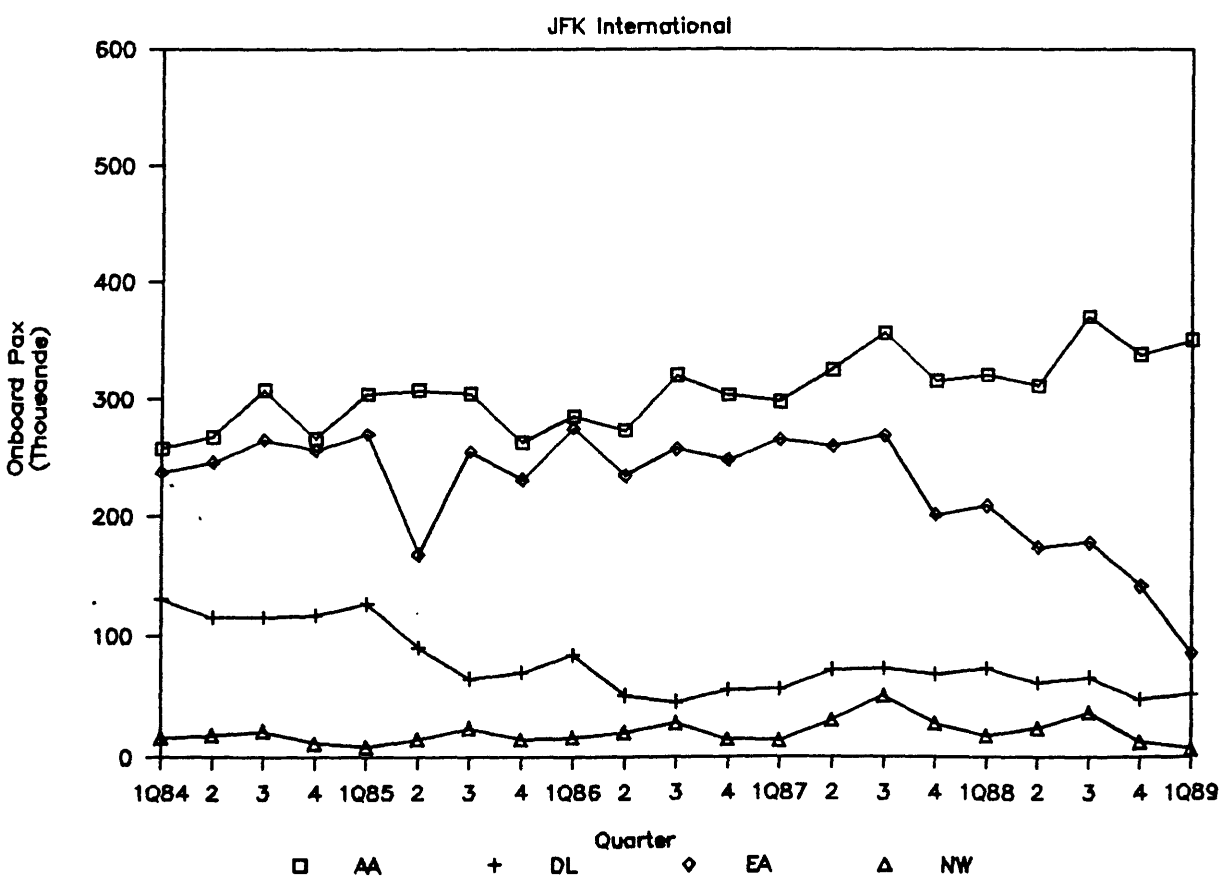

Average Load Factor for Majors
Newark International
70%
69%
68%
67%
66%
65%
64%
63%
62%
61%
60%
59%
58%
57%
56%
55%
54%
53%
52%
51%
50%
ALF
1Q84 2 3 4 1Q85 2 3 4 1Q86 2 3 4 1Q87 2 3 4 1Q88 2 3 4 1Q89
Quarter

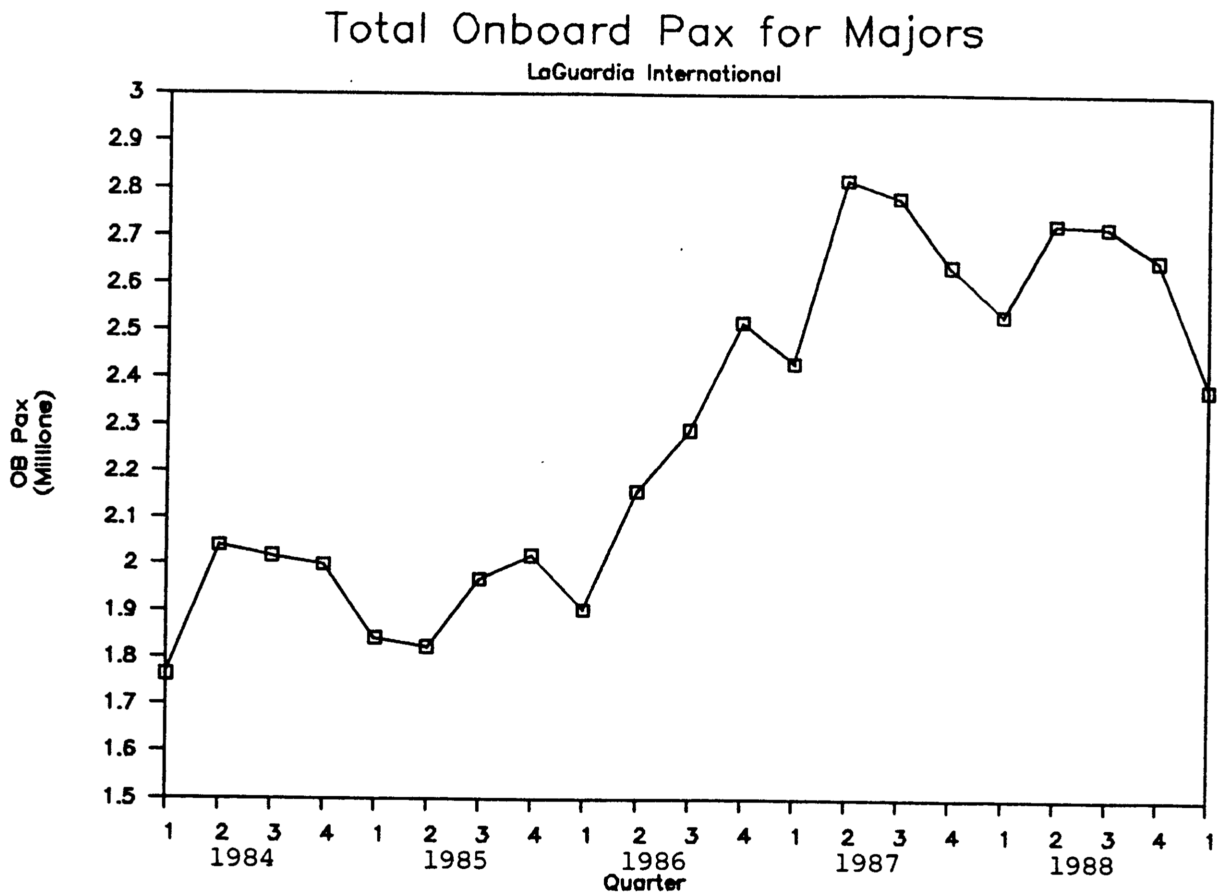
Figure 2.7

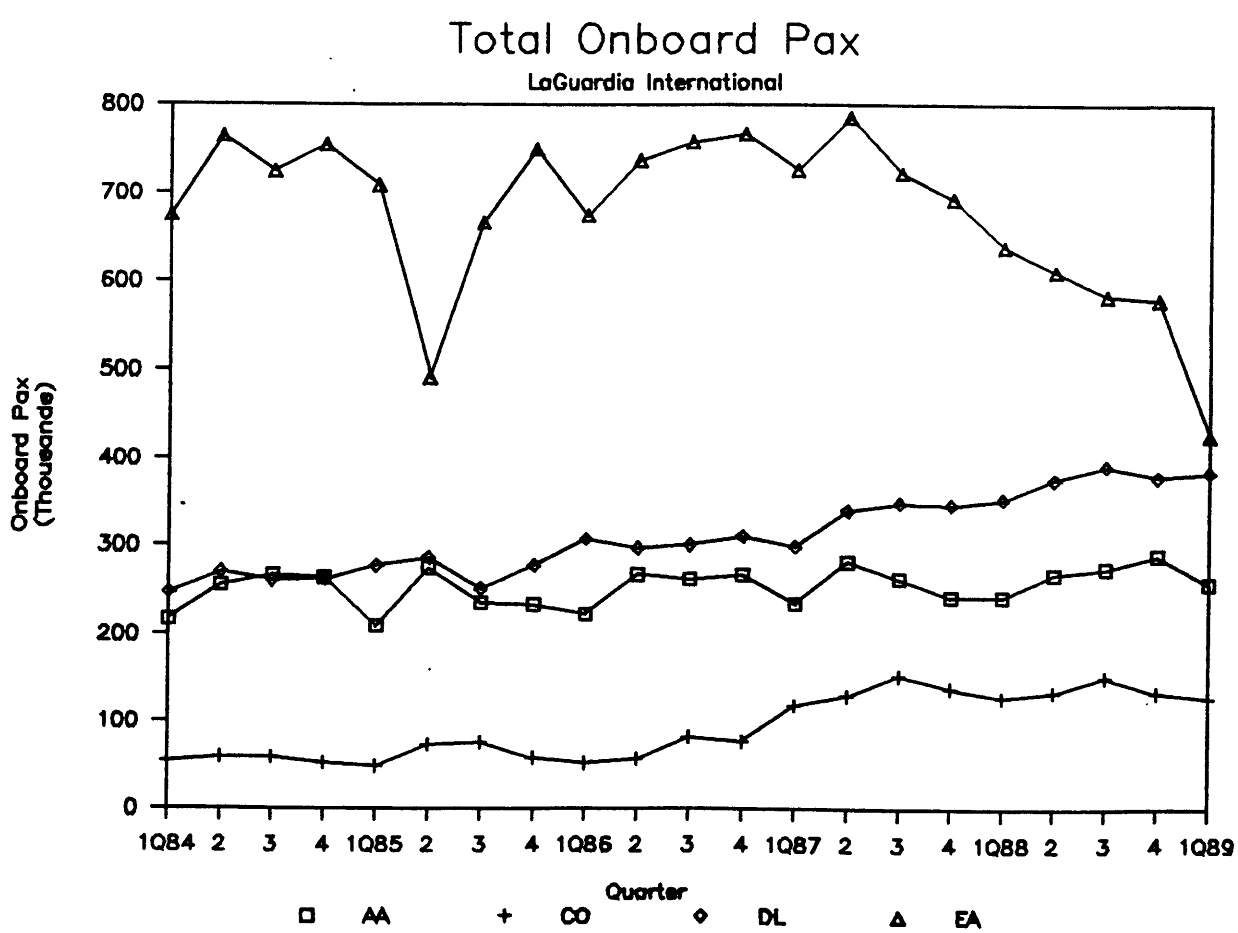
Total Onboard Pax for Majors



Total Onboard Pax

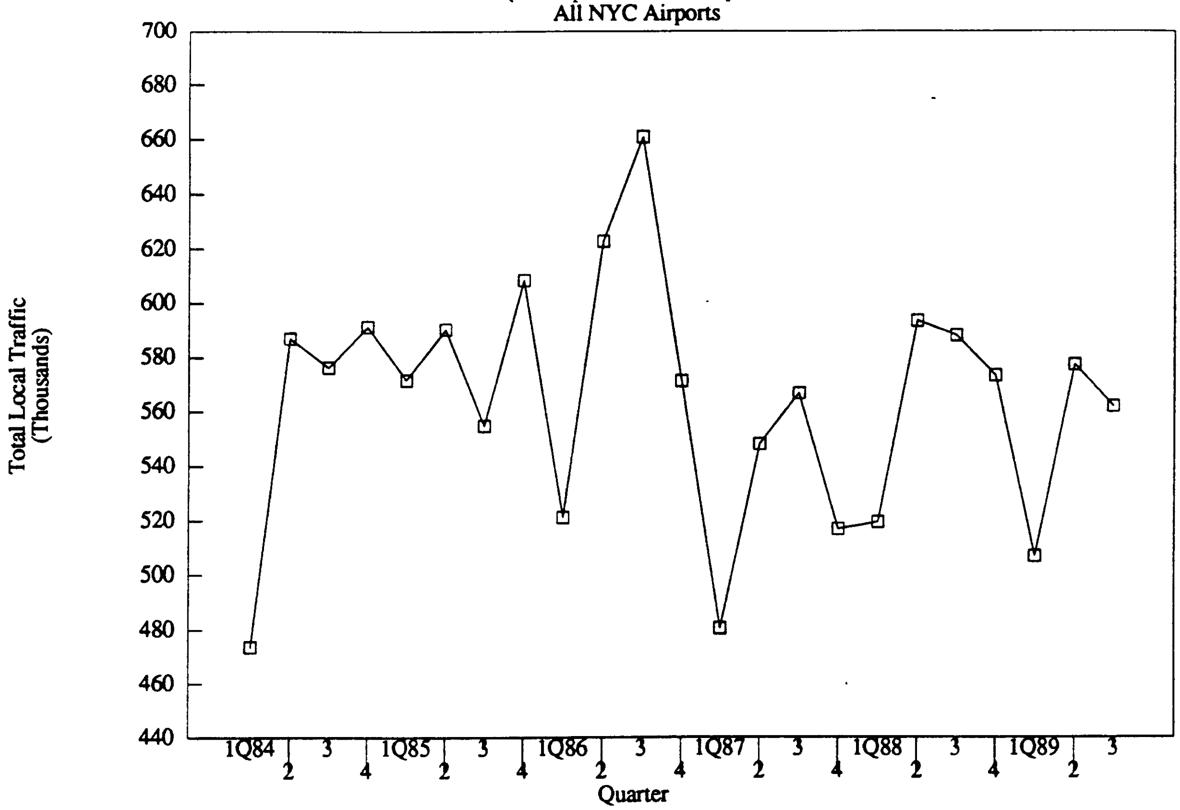



Total Onboard Pax for Majors
LaGuardia International
OB Pax (Millions)
3
2.9
2.8
2.7
2.6
2.5
2.4
2.3
2.2
2.1
2
1.9
1.8
1.7
1.6
1.5
1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1
1984
1985
1986
1987
1988
Quarter


Total Onboard Pax
LaGuardia International
Onboard Pax (Thousands)
800
700
600
500
400
300
200
100
0
1Q84 2 3 4 1Q85 2 3 4 1Q86 2 3 4 1Q87 2 3 4 1Q88 2 3 4 1Q89
Quarter
AA
CO
DL
EA

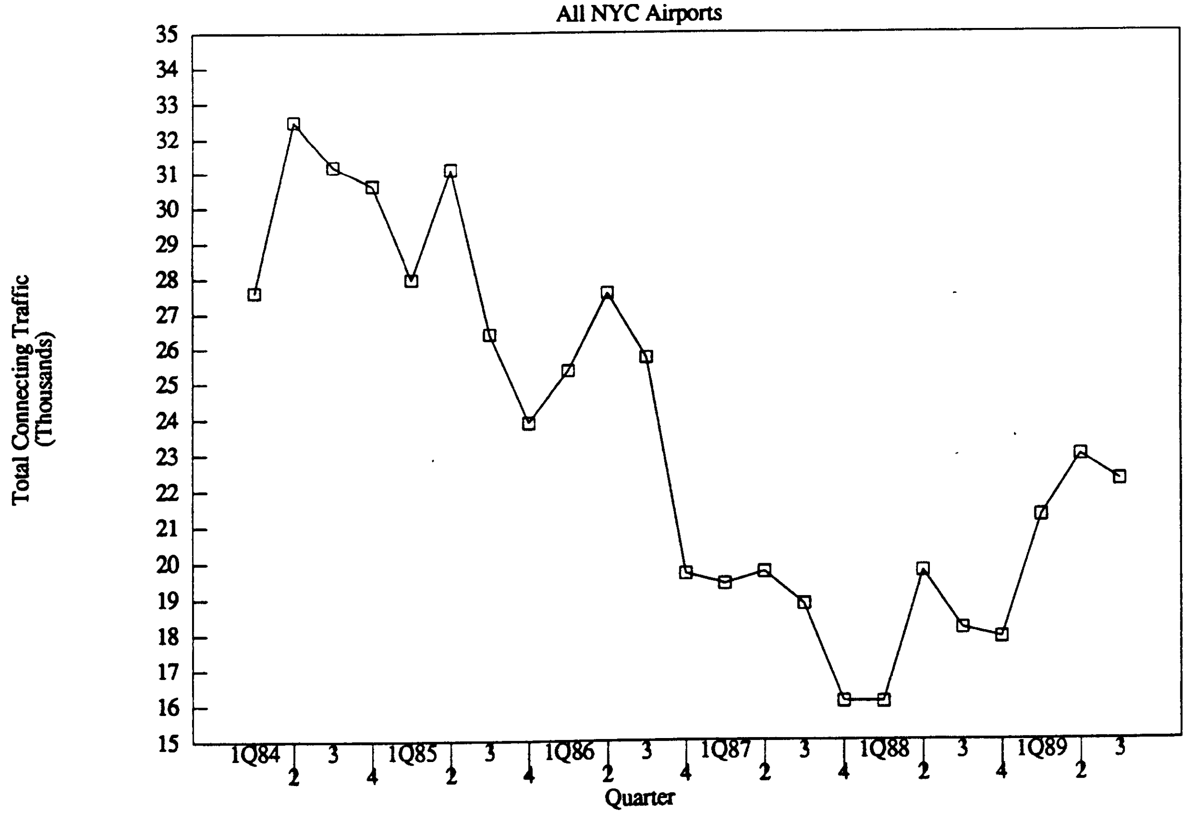
Total Local Originating Pax

(Ten percent sample)
All NYC Airports

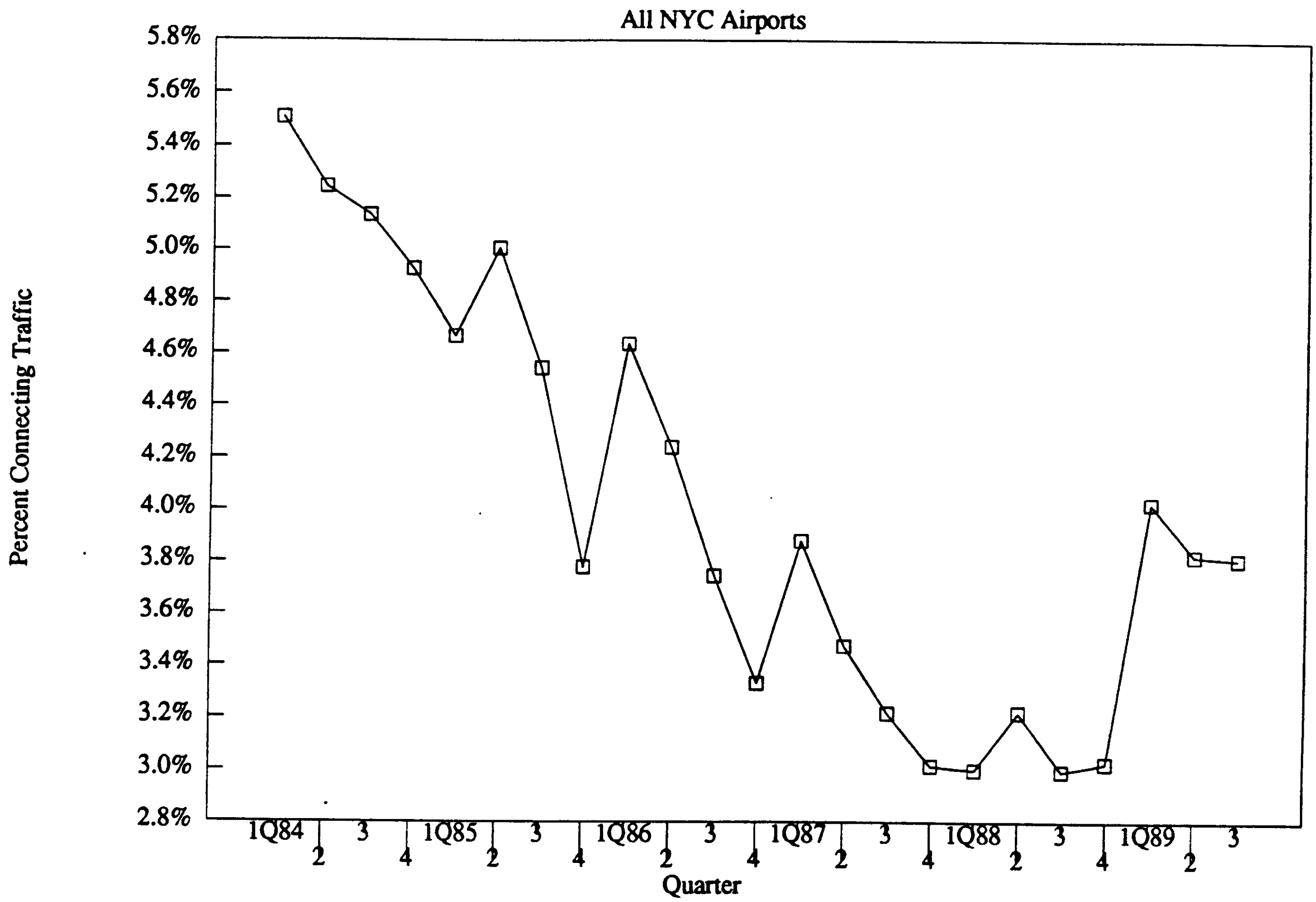


Total Connecting Pax

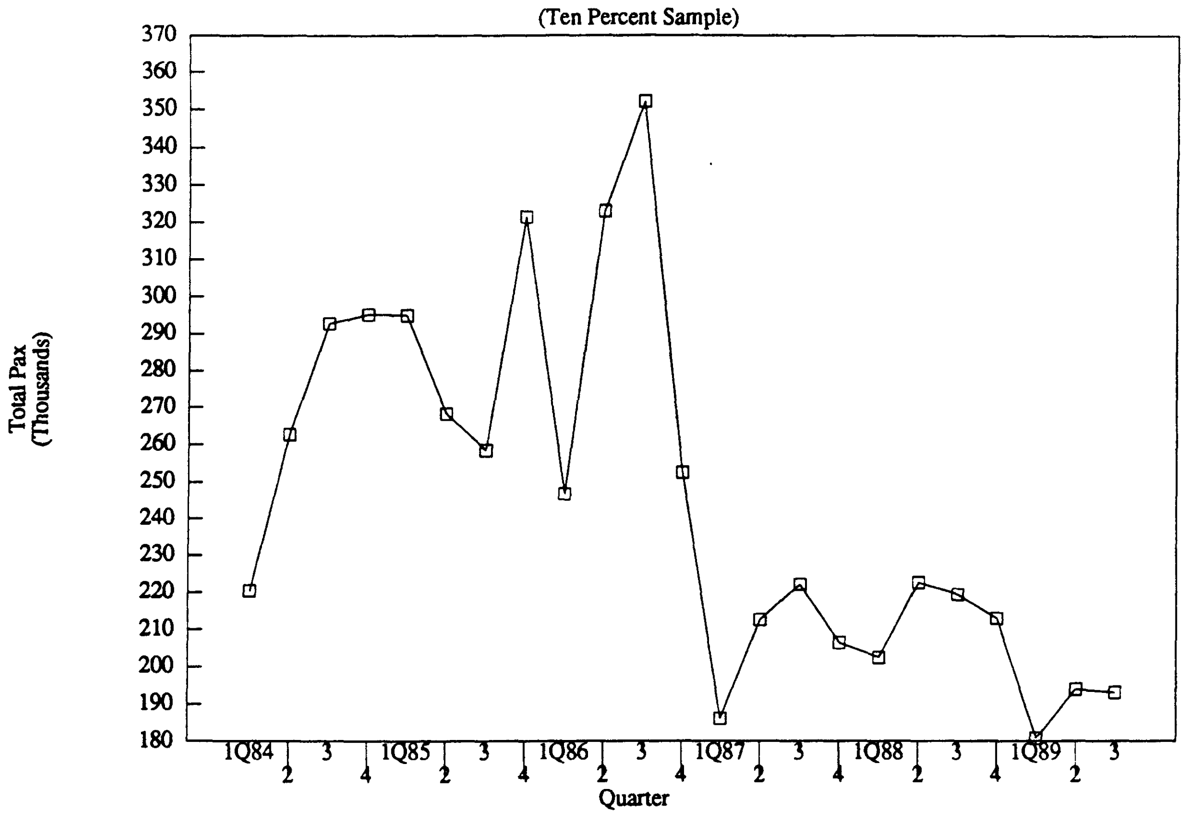
(Ten percent sample)
All NYC Airports



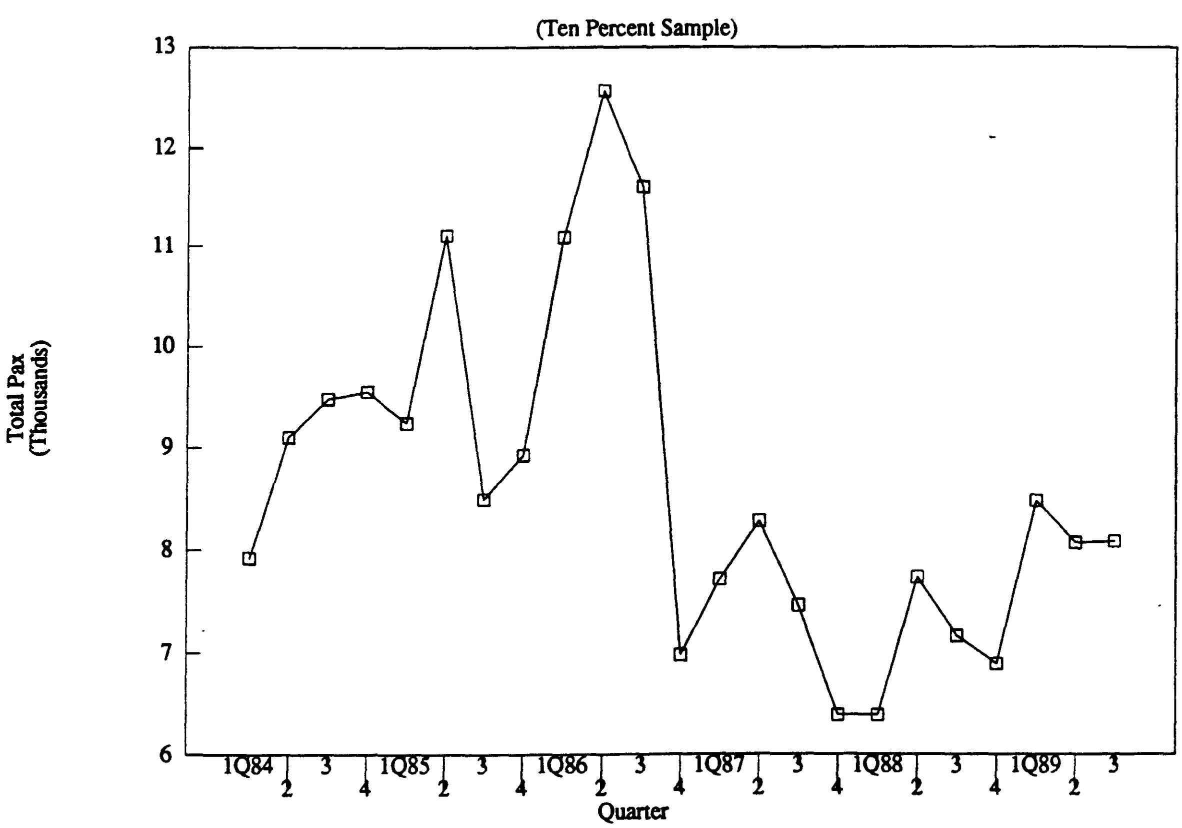
Total Percent Connecting Pax



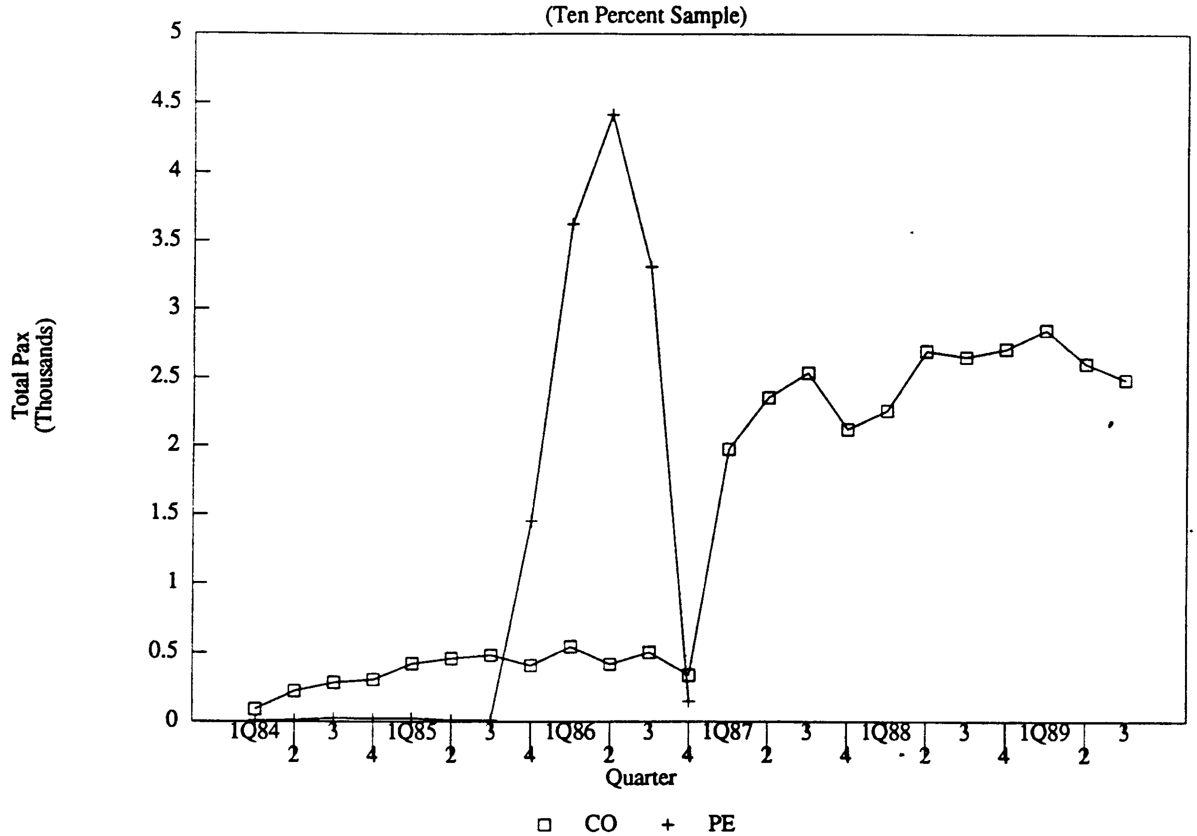
Total Local Originating Pax (EWR)



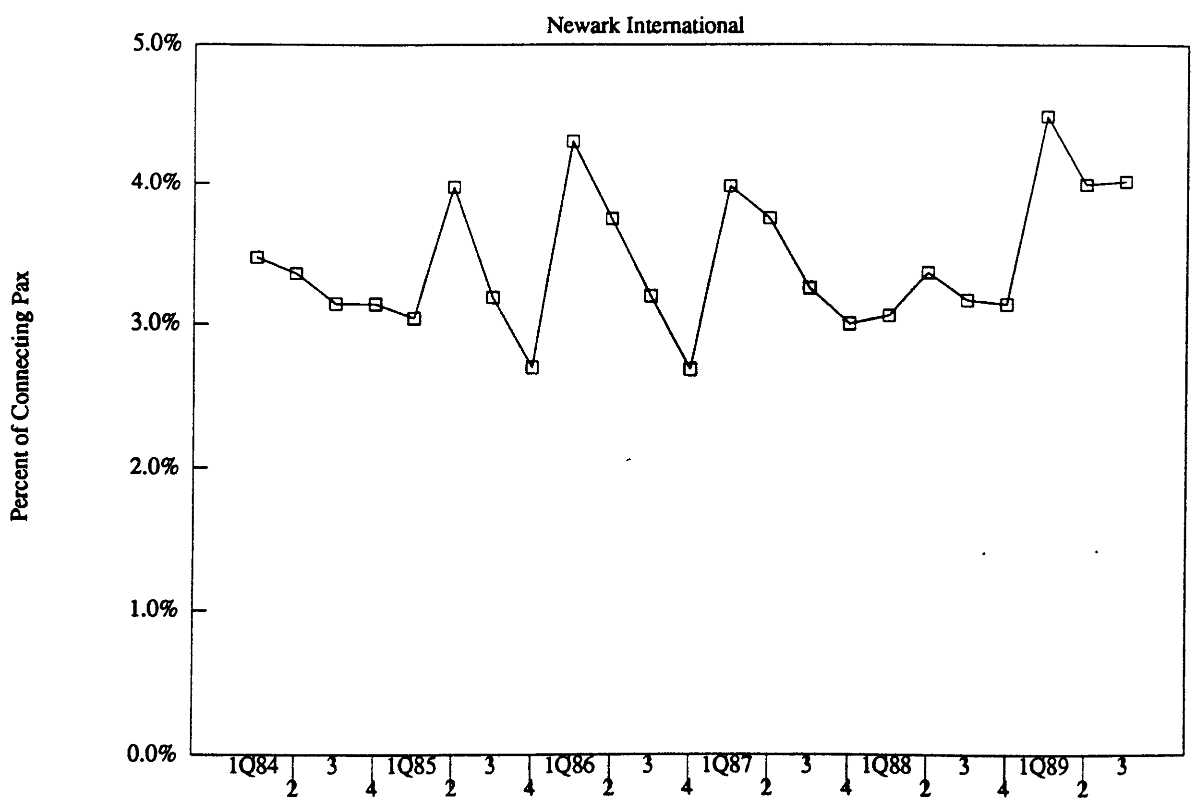
Total Connecting Pax (EWR)



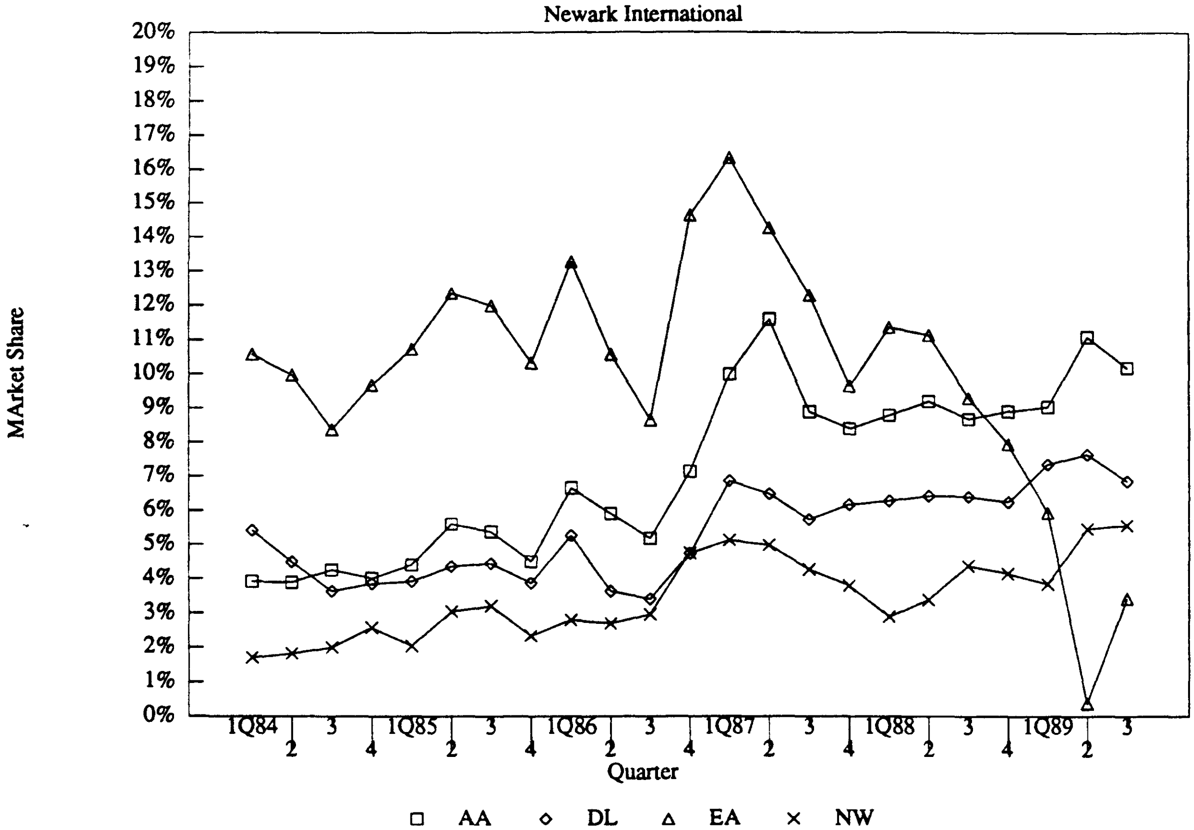
Total Connecting Pax (EWR)



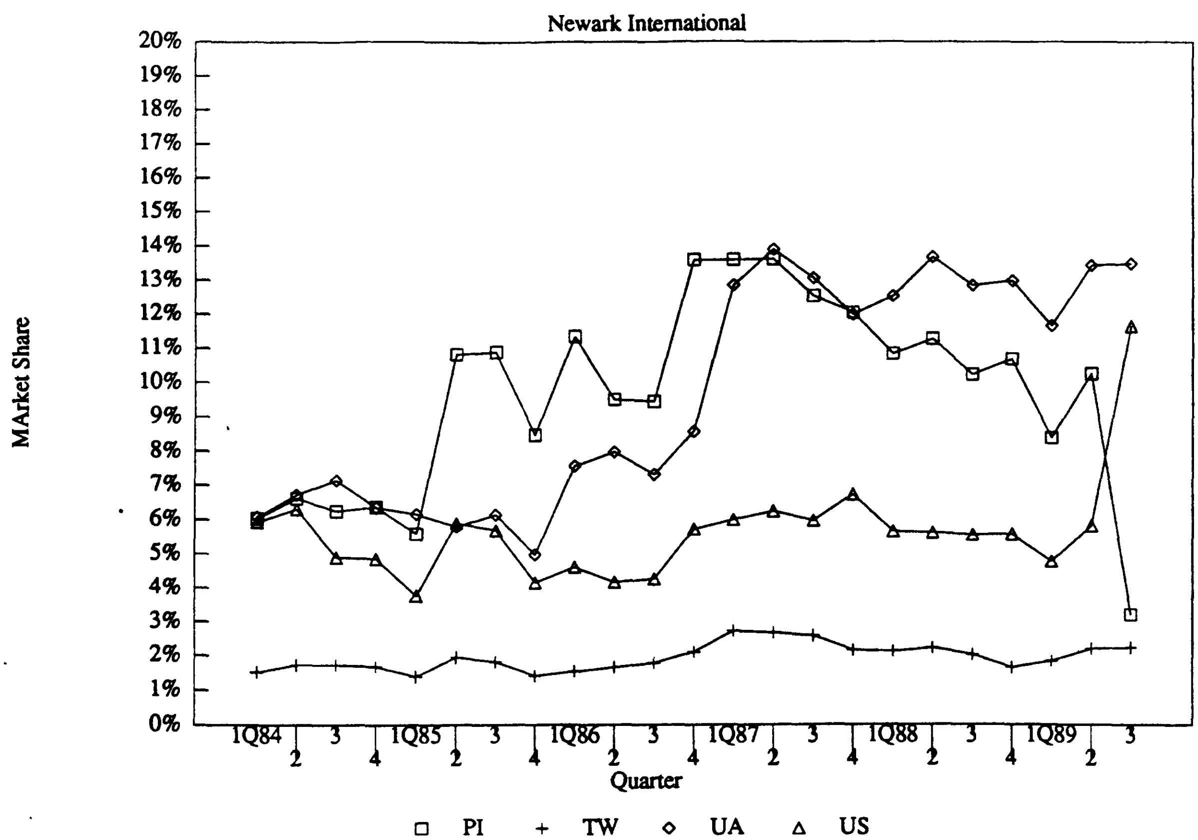
Total Percent of Connecting Pax



Market Share of Originating Pax



Market Share of Originating Pax



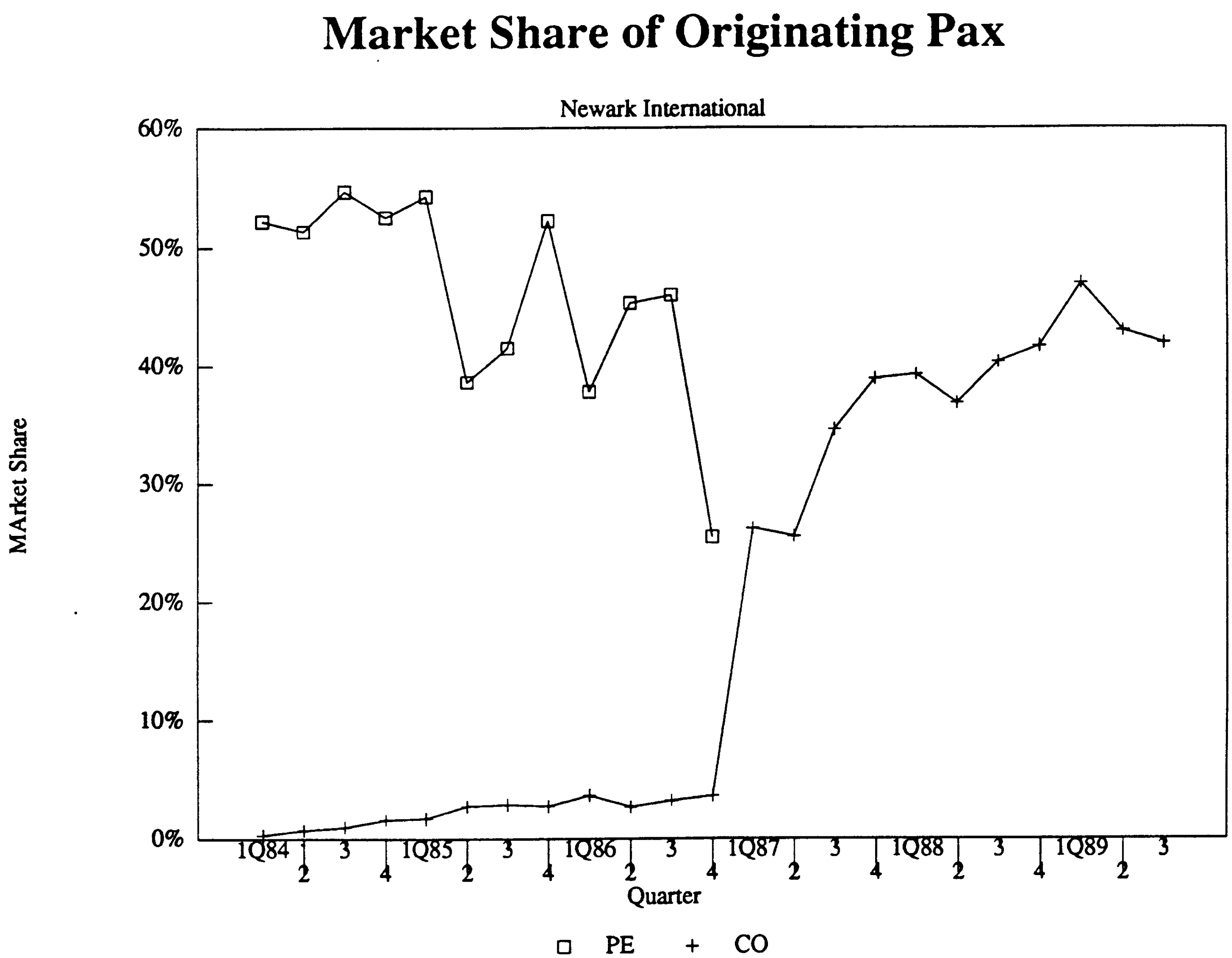
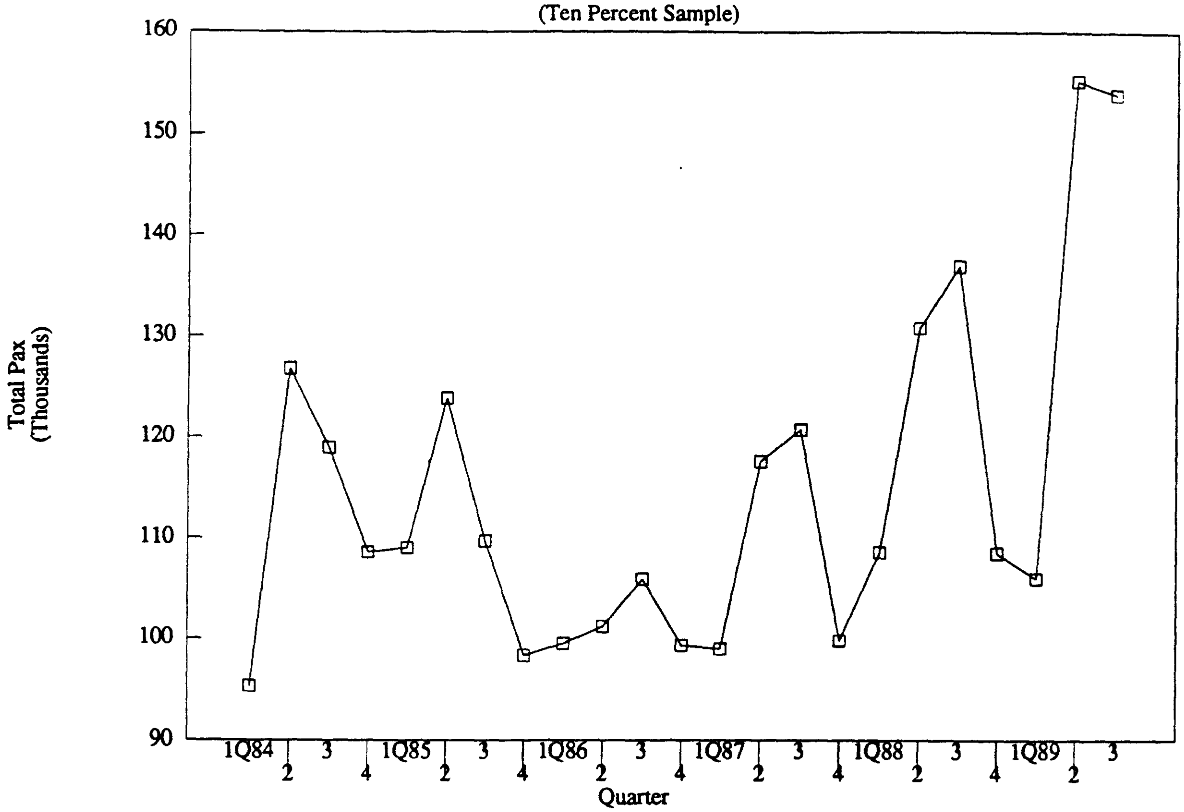
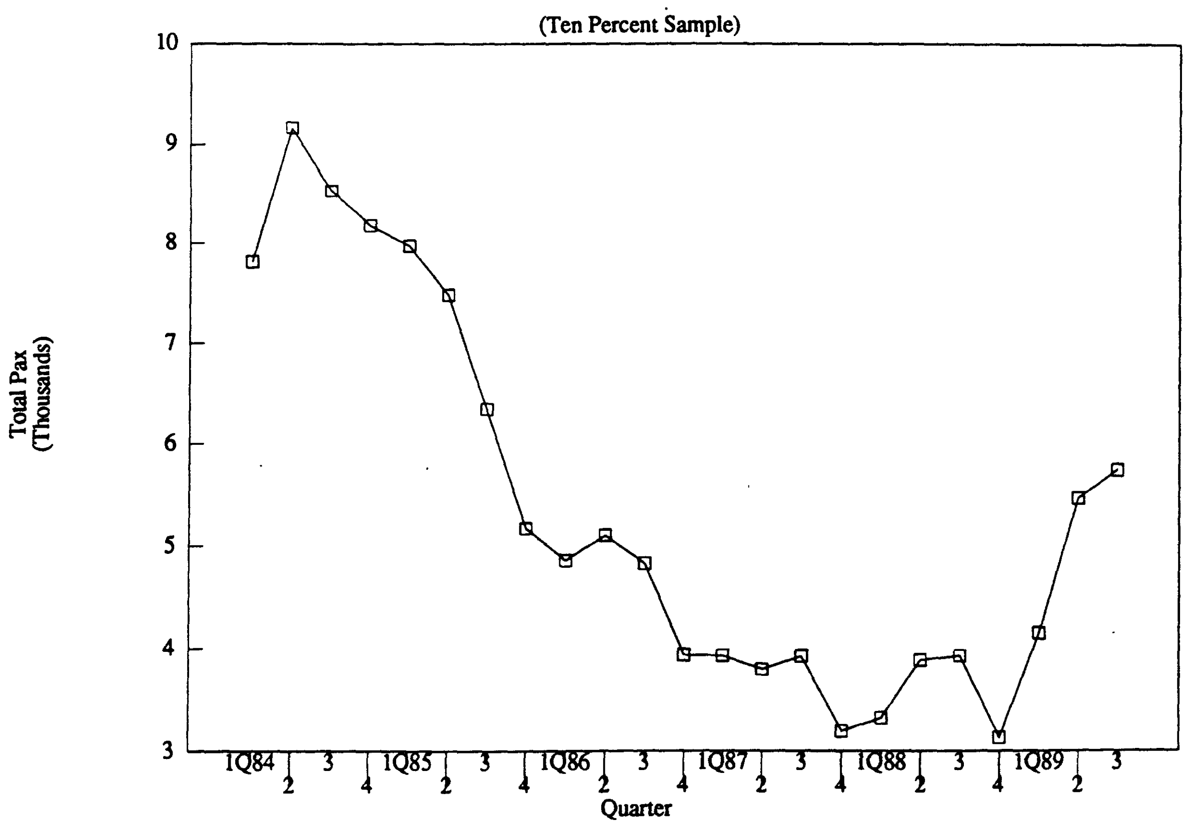

Market Share of Originating Pax
Newark International
MArket Share
60%
50%
40%
30%
20%
10%
0%
1Q84
2
3
4
1Q85
2
3
4
1Q86
2
3
4
1Q87
2
3
4
1Q88
2
3
4
1Q89
2
3
Quarter
PE
CO

Figure 3.15

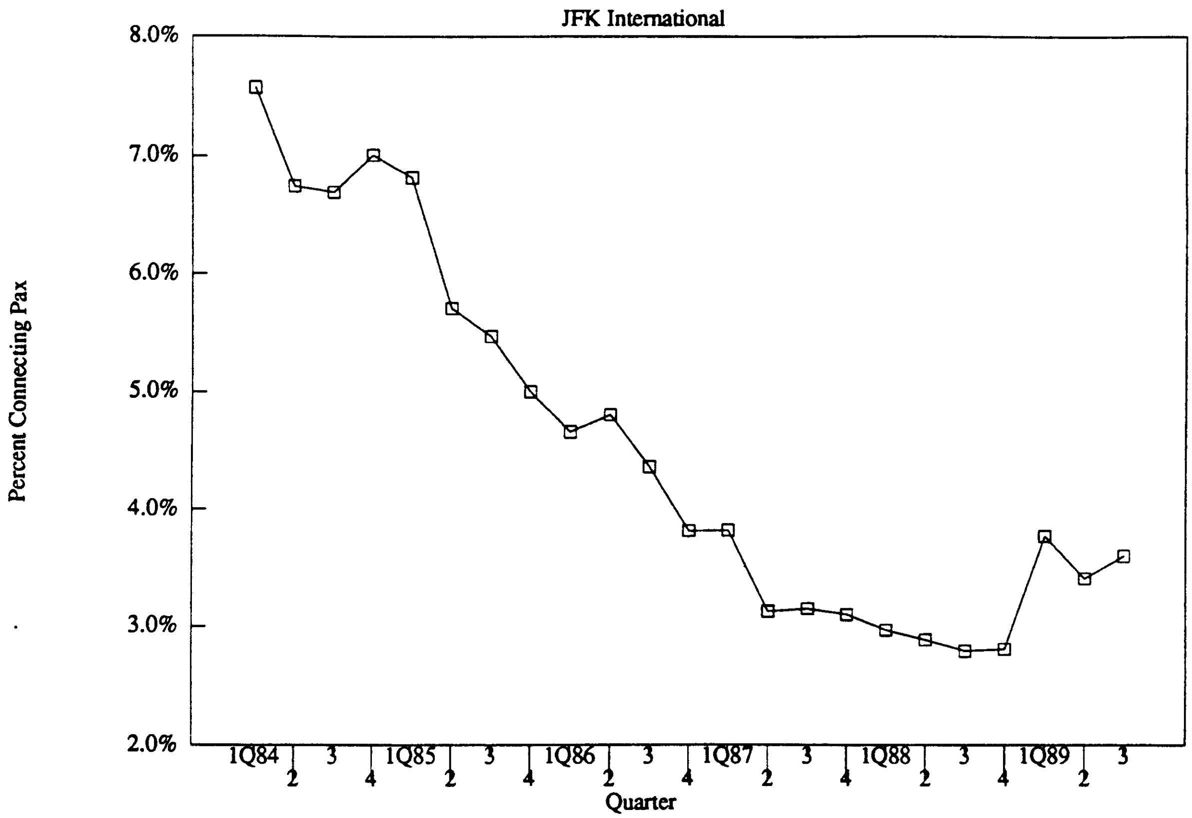
Total Local Originating Pax (JFK)



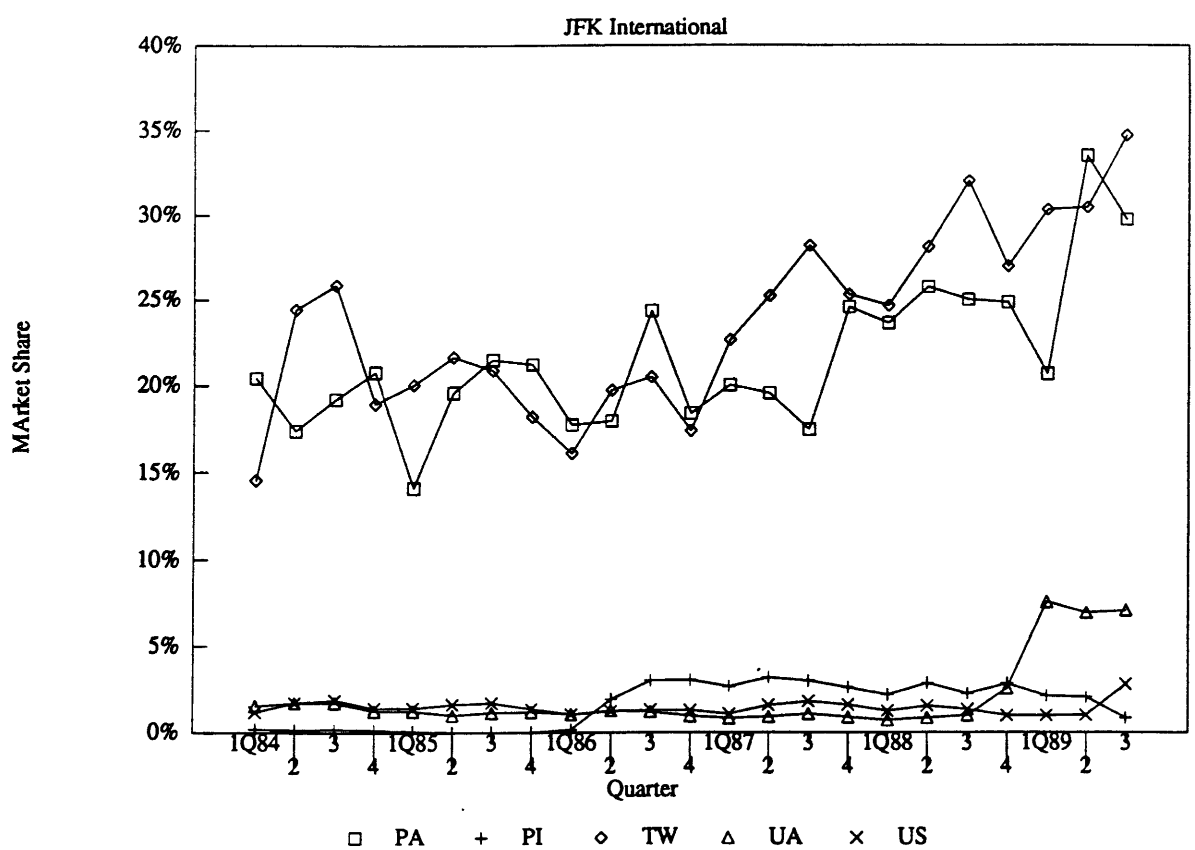
Total Connecting Pax (JFK)



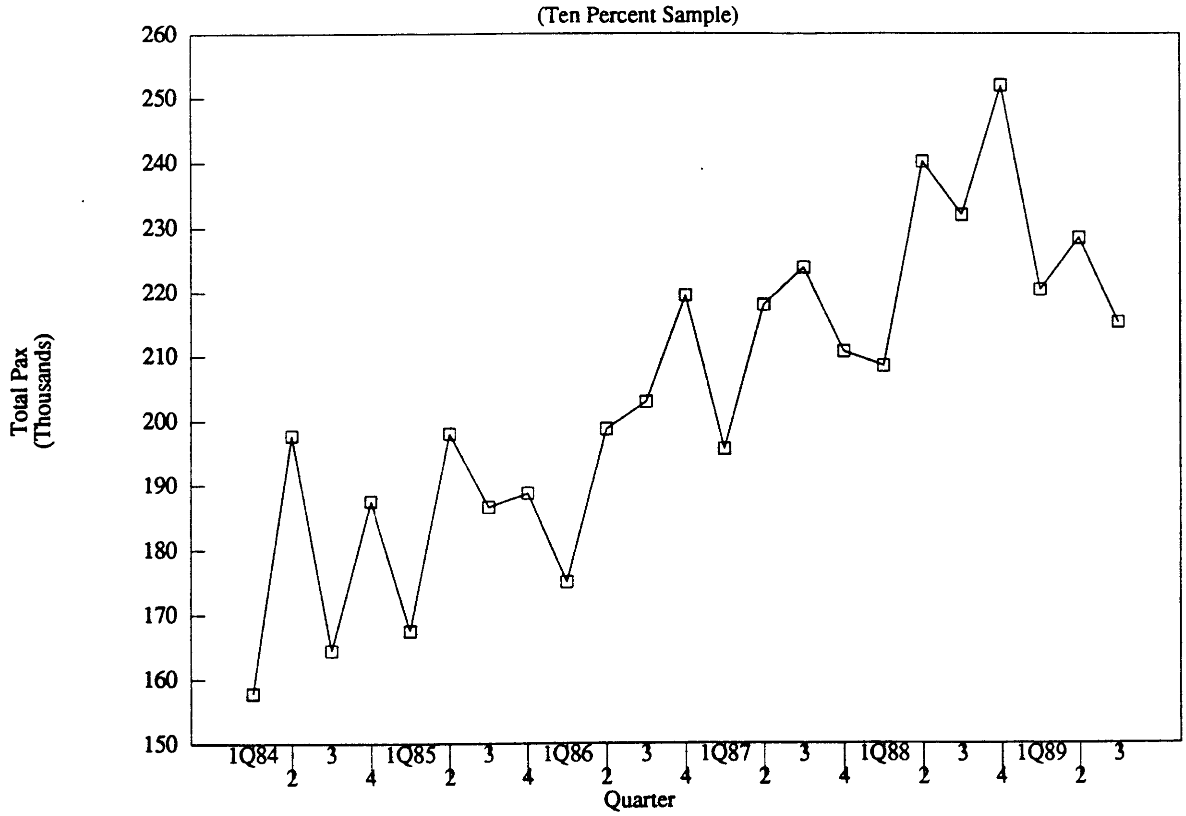
Total Percent of Connecting Pax



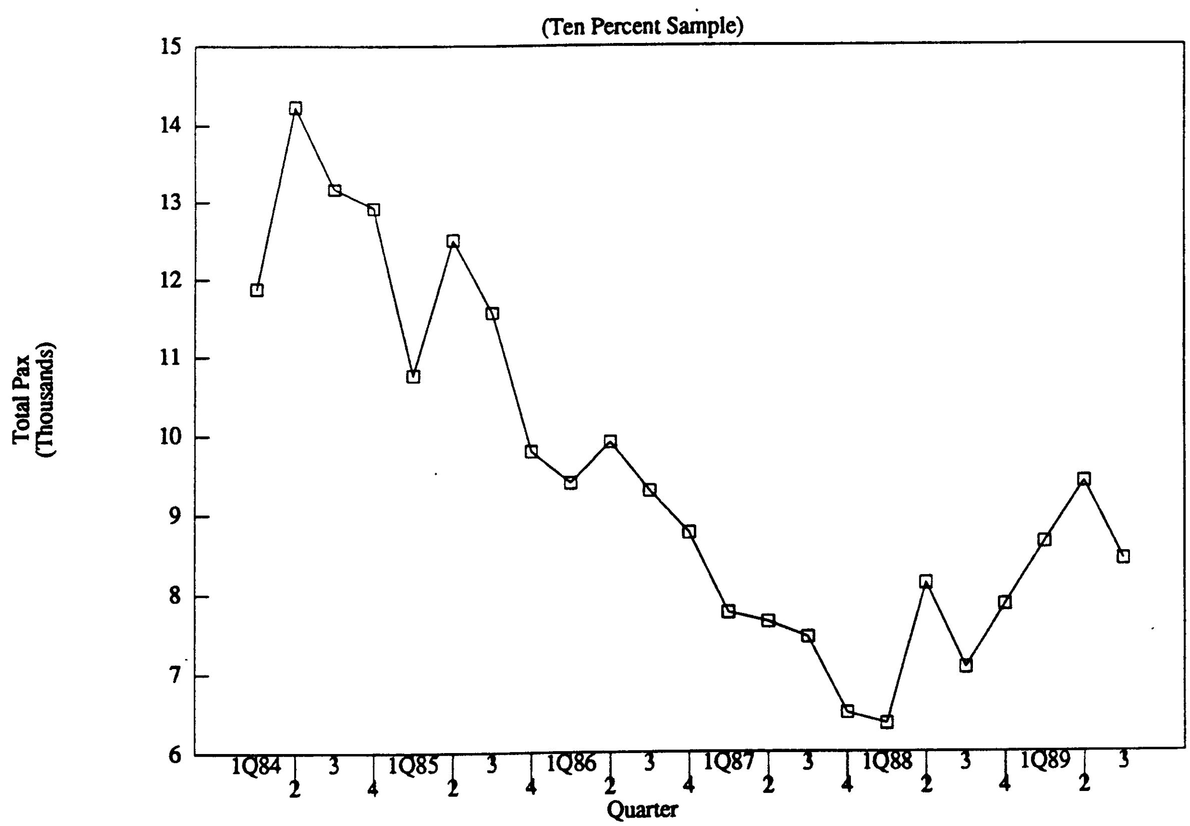
Market Share of Originating Pax



Total Local Originating Pax (LGA)



Total Connecting Pax (LGA)



Total Percent of Connecting Pax

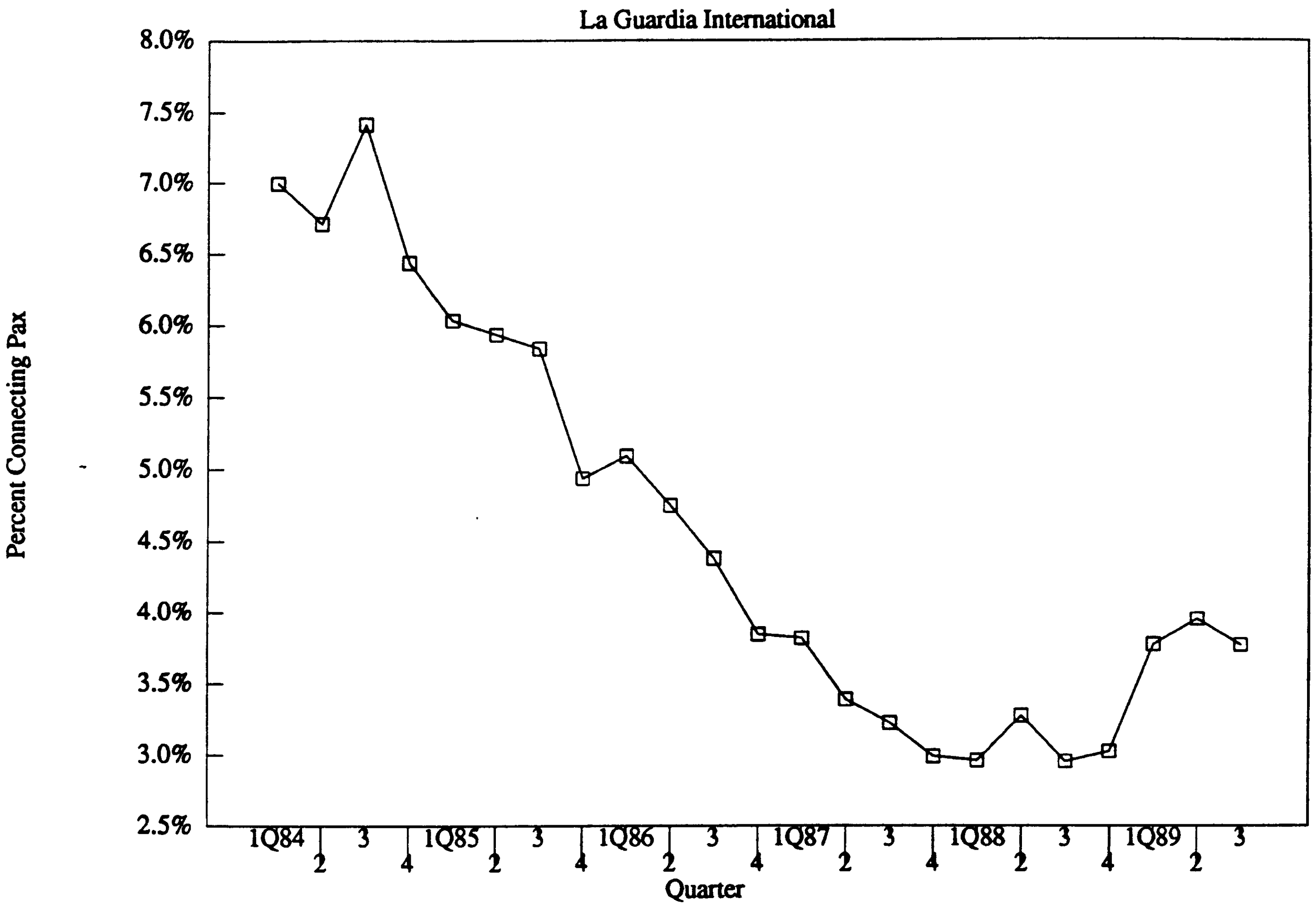


Figure 3.31

SUMMARY OF FINDINGS

AGGREGATE - 3 AIRPORTS

- Upward trend in domestic departures, with stability in total seats, indicating reduced aircraft sizes.
- Seasonal variations in total passengers, with no significant trend after peak in 1986-3.
- Local originating passenger counts plunged after PE's buyout, and have recovered only to pre-PE levels.
- Total domestic connecting passengers decreased throughout the analysis period, rebounding somewhat in 1989.

NEWARK AIRPORT (EWR)

- Stable departure levels since PE withdrawal, but fewer seats and much reduced aircraft sizes.
- Major drop in on-board passengers after 1986-3; downward trend continues through 1989-1 for virtually all carriers.
- Local originating passengers cut by half when PE failed; levels have barely returned to pre-1984 levels.
- Domestic connecting passengers were similarly affected by PE withdrawal from EWR.

KENNEDY AIRPORT (JFK)

- Highly seasonal but relatively stable departure levels, but more seats and larger aircraft.
- Highly seasonal on-board passenger counts, but no discernable overall trend.
- Upward trend in local originating passengers, reaching peak in 1989-2.
- Downward slide in domestic connecting passengers from 1984 to 1988, reversed somewhat in 1989.

LAGUARDIA AIRPORT (LGA)

- Growth in departures through 1986, relatively stable since; but slight downward trend in seats and average aircraft size.
- Strong growth in on-board passenger counts flattens out and possibly reverses after 1986.
- Upward trend in local originating passengers continues through 1987 and 1988.
- Domestic connecting passengers, however, dropped by more than half 1984 to 1988, but also rebounded a little in 1989.

CONCLUSIONS

- Removal of PeoplExpress from the New York area market has had the most significant negative impact on traffic flows.

- Newark traffic levels continue to drop, in contrast to JFK and LaGuardia, where local originating traffic remains strong.

- Domestic connecting passengers have dropped in both absolute and percentage terms at all 3 airports, suggesting a shift by carriers away from using New York airports as domestic hubs.