

**TURKISH
AVIATION
ACADEMY**



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Evolution of Airline Revenue Management

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Lecture Outline

1. Review: Airline Pricing

- Differential Pricing Theory

2. Revenue Management Systems

- Load Factor vs. Yield Strategies
- RM System Components

3. Single-leg Fare Class Seat Allocation Problem

- EMSRb Model for Seat Protection

4. Overbooking Models and Practice

- Mathematical Approaches to Overbooking
- Denied Boarding vs. Spoilage Costs

Airline Revenue Maximization

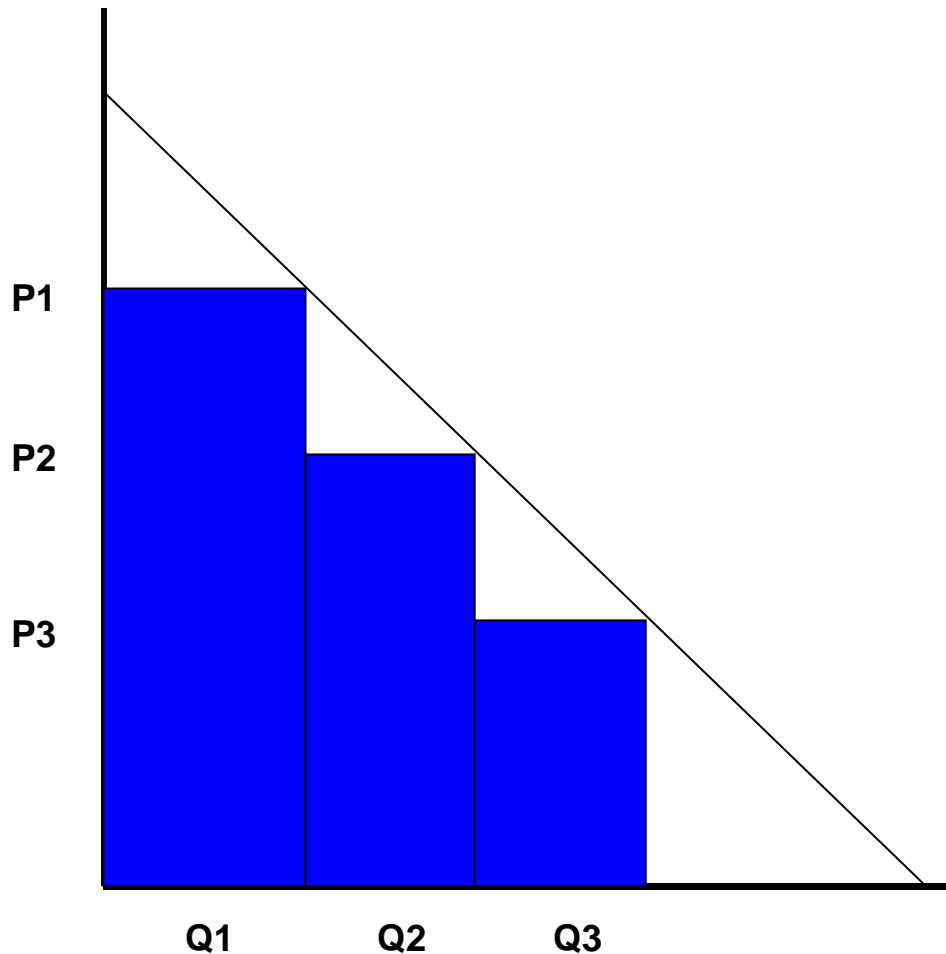
Differential Pricing:

- Various “fare products” offered at different prices for travel in the same O-D market

Revenue Management (RM):

- Determines the number of seats to be made available to each “fare class” on a flight, by setting booking limits on low fare seats
- **With high proportion of fixed operating costs for a schedule, maximize revenues to maximize profits**
- **With very few exceptions, virtually *all airlines* make use of differential pricing and RM:**
 - Including most new entrant Low-Cost Carriers (LCCs) with “simpler” fares

Differential Pricing Theory



- Market segments with different “willingness to pay” for air travel
- Different “fare products” offered to business versus leisure travelers
- Prevent diversion by setting restrictions on lower fare products and limiting seats available
- Increased revenues and higher load factors than any single fare strategy

BOS-IST Economy Class Fare Structure Turkish Airlines, April 2015

Class	One Way Fare	Advance Purchase	Minimum Stay	Change Fee	Refunds	RT Required
Y	\$1072	None	None	None	Yes	No
B	\$934	None	None	None	Yes	No
M	\$725	0/3 (TKT)	Sat Night	\$135	No	Yes
H	\$612	0/3 (TKT)	Sat Night	\$135	No	Yes
S	\$512	0/3 (TKT)	Sat Night	\$135	No	Yes
E	\$425	0/3 (TKT)	Sat Night	\$135	No	Yes
Q	\$350	0/3 (TKT)	Sat Night	\$135	No	Yes
L	\$238	0/3 (TKT)	Sat Night	\$135	No	Yes

Yield Management = Revenue Management

- **Primary objective is to protect seats for late-booking high-fare demand, given limited capacity:**
 - Forecast future booking demand for each fare product
 - Optimize number of seats to be made available to each fare class
- **Optimal control of available seat inventory:**
 - On high demand flights, limit discount fare and group bookings to increase overall yield (average fare) and revenue.
 - On low demand flights, sell empty seats at any low fare to increase load factors and revenue.
 - Revenue maximization requires a balance of yield and load factor
- **Balance yield vs. load factor to maximize revenues**

Revenue Management Strategies

EXAMPLE: 2100 MILE FLIGHT LEG

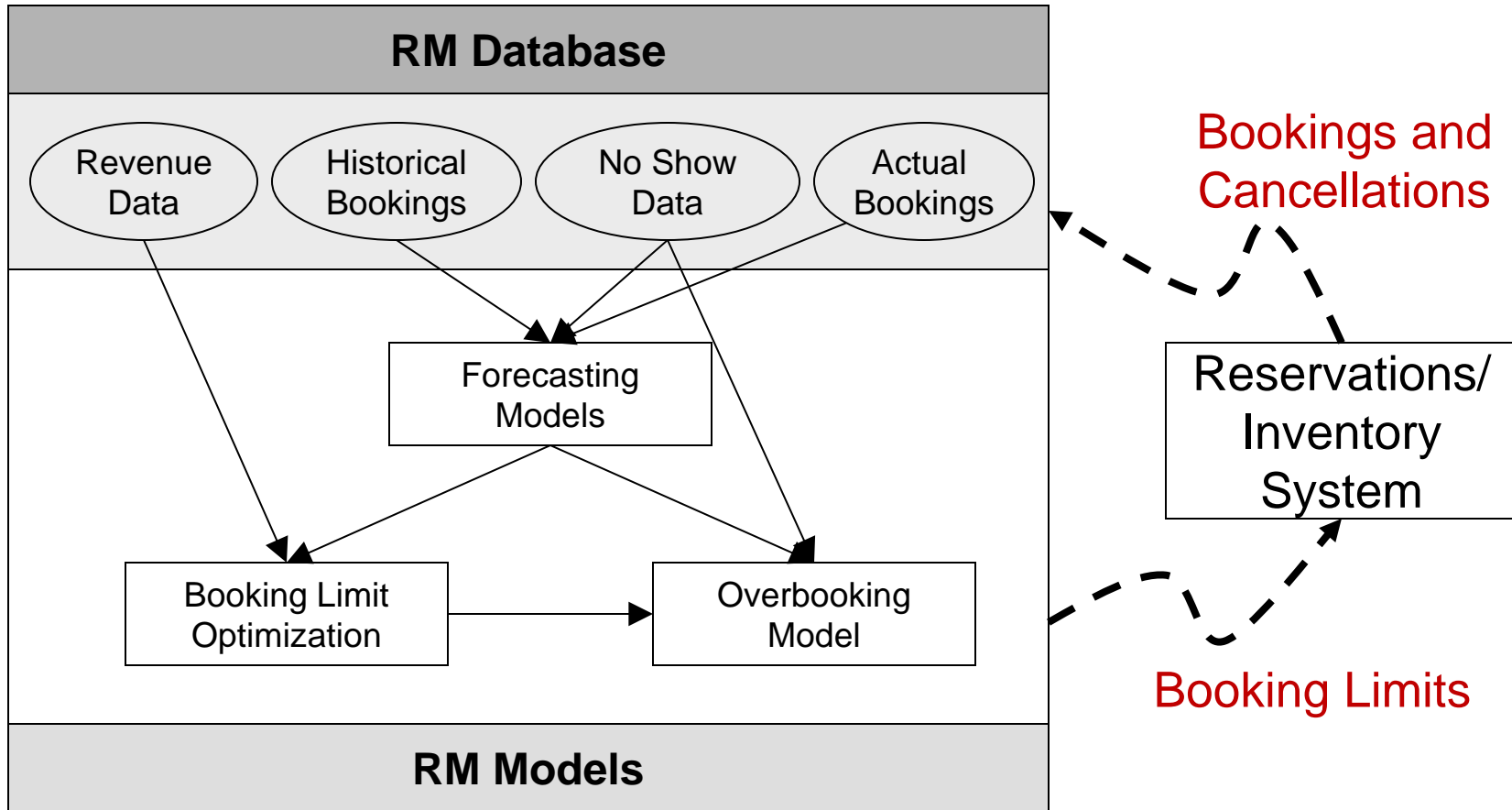
CAPACITY = 200

<u>NUMBER OF SEATS SOLD:</u>				
FARE CLASS	AVERAGE REVENUE	YIELD EMPHASIS	LOAD FACTOR EMPHASIS	REVENUE EMPHASIS
Y	\$420	20	10	17
B	\$360	23	13	23
H	\$230	22	14	19
V	\$180	30	55	37
Q	\$120	15	68	40
TOTAL PASSENGERS		110	160	136
LOAD FACTOR		55%	80%	68%
TOTAL REVENUE		\$28,940	\$30,160	\$31,250
AVERAGE FARE		\$263	\$189	\$230
YIELD (CENTS/RPM)		12.53	8.98	10.94

Typical 3rd Generation RM System

- **Collects and maintains historical booking data by flight and fare class, for each past departure date.**
- **Forecasts future booking demand and no-show rates by flight departure date and fare class.**
- **Calculates limits to maximize total flight revenues:**
 - Overbooking levels to minimize costs of spoilage/denied boardings
 - Booking class limits on low-value classes to protect high-fare seats
- **Interactive decision support for RM analysts:**
 - Can review, accept or reject recommendations

Third Generation Leg-based RM System



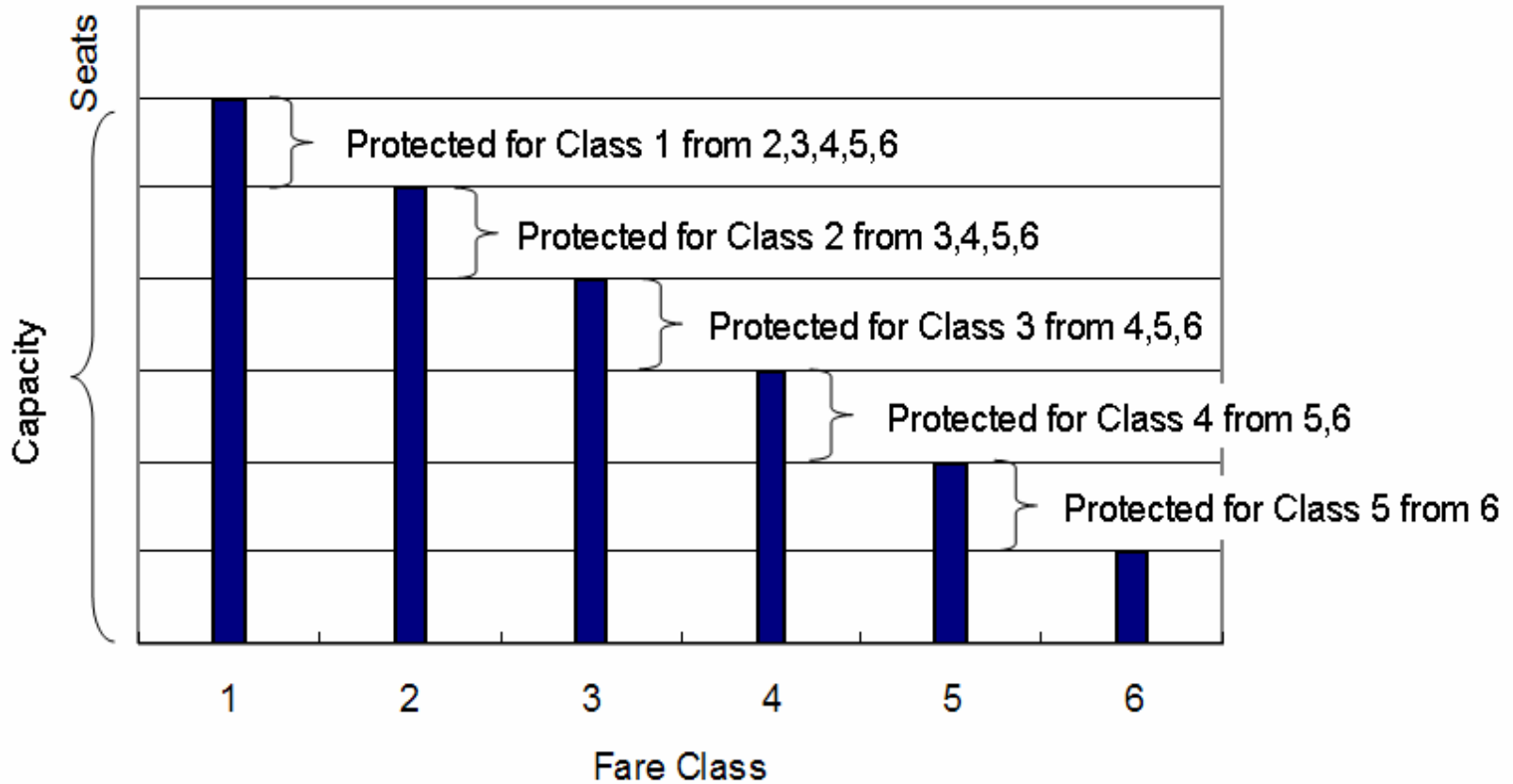
Components of 3rd Generation RM

- **Demand Forecasting**
 - Time series methods applied to historical booking data to forecast demand by fare class for each future flight/departure date
- **Flight Leg Optimization**
 - Expected Marginal Seat Revenue (EMSR) models determine revenue-maximizing mix of seats for each fare class
- **Overbooking**
 - Cost-based overbooking models minimize denied boarding and spoilage costs, based on probabilistic analysis of no-shows
- **Revenue increases of 4 to 6 percent typically quoted**
 - From overbooking and fare class mix optimization alone

Leg-Based Fare Class Mix Optimization

- **Determine the optimal number of seats to make available to each booking class.**
- **Given for each future flight leg departure:**
 - Total remaining booking capacity of (typically) the coach compartment
 - Forecasts of future booking demand by fare class between current DCP and departure
 - Revenue estimates for each fare (booking) class
- **Objective is to maximize total expected revenue:**
 - Protect seats for each fare class based on revenue value, taking into account forecast uncertainty and probability of realizing the forecasted demand

Serially Nested Buckets



EMSRb Model Calculations

- **To calculate the optimal protection levels:**

Define $P_i(S_i) = \text{probability that } X_i \geq S_i$,
where S_i is the number of seats made available to class i , X_i is
the random demand for class i

- **The expected marginal revenue of making the S th seat available to class i is:**

$EMSR_i(S_i) = R_i * P_i(S_i)$ where R_i is the average revenue (or fare)
from class i

- **The optimal protection level, π_1 for class 1 from class 2 satisfies:**

$$EMSR_1(\pi_1) = R_1 * P_1(\pi_1) = R_2$$

Example Calculation

Consider the following flight leg example:

<u>Class</u>	<u>Mean Fcst.</u>	<u>Std. Dev.</u>	<u>Fare</u>
Y	10	3	1000
B	15	5	700
M	20	7	500
Q	30	10	350

- To find the protection for the Y fare class, we want to find the largest value of π_Y for which
$$\text{EMSR}_Y(\pi_Y) = R_Y * P_Y(\pi_Y) \geq R_B$$

Example (cont'd)

$$\text{EMSR}_Y(\pi_Y) = 1000 * P_Y(\pi_Y) \geq 700$$
$$P_Y(\pi_Y) \geq 0.70$$

where $P_Y(\pi_Y)$ = probability that $X_Y \geq \pi_Y$.

- **Assume demand in Y class is *normally* distributed, then we can create a standardized normal random variable as $(X_Y - 10)/3$:**
 - for $\pi_Y = 7$, $\text{Prob} \{ (X_Y - 10)/3 \geq (7 - 10)/3 \} = 0.841$
 - for $\pi_Y = 8$, $\text{Prob} \{ (X_Y - 10)/3 \geq (8 - 10)/3 \} = 0.747$
 - for $\pi_Y = 9$, $\text{Prob} \{ (X_Y - 10)/3 \geq (9 - 10)/3 \} = 0.63$
- **$\pi_Y = 8$ is the largest integer value of π_Y that gives a probability ≥ 0.7 and we will protect 8 seats for Y class.**

General Case for Class n

- Joint protection for classes 1 through n from class $n+1$

$$\overline{X}_{1,n} = \sum_{i=1}^n \overline{X}_i$$

$$\hat{\sigma}_{1,n} = \sqrt{\sum_{i=1}^n \hat{\sigma}_i^2}$$

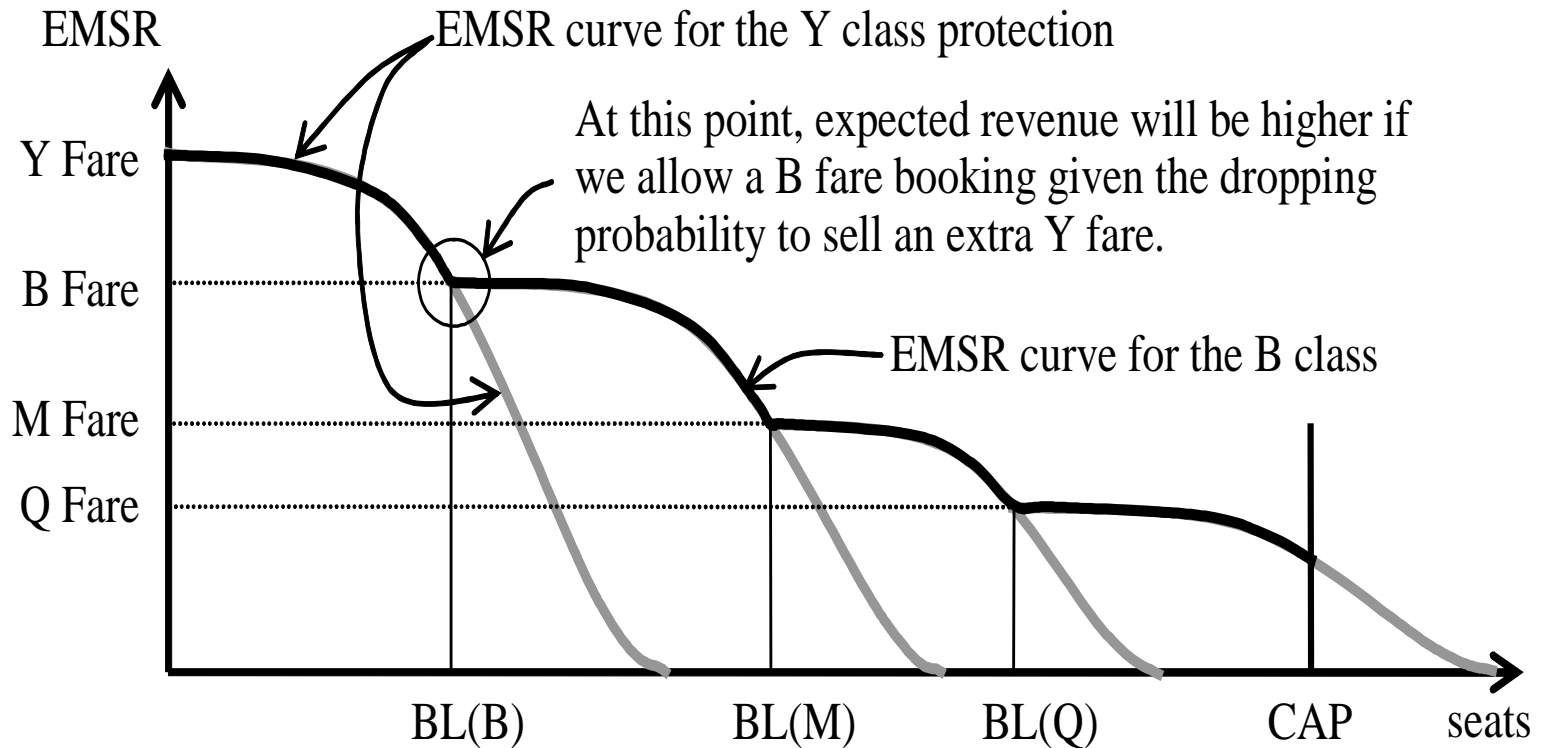
$$R_{1,n} = \frac{\sum_{i=1}^n R_i * \overline{X}_i}{\overline{X}_{1,n}}$$

- We then find the value of π_n that makes

$$\text{EMSR}_{1,n}(\pi_n) = R_{1,n} * P_{1,n}(\pi_n) = R_{n+1}$$

- Once π_n is found, set $\text{BL}_{n+1} = \text{Capacity} - \pi_n$

Graphical Representation of EMSR Curves and Booking Limits



EMSRb Seat Protection Model

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

Dynamic Revision and Intervention

- **RM systems revise forecasts and re-optimize booking limits at numerous “checkpoints”:**
 - Monitor actual bookings vs. previously forecasted demand
 - Re-forecast demand and re-optimize at fixed checkpoints or when unexpected booking activity occurs
 - Can mean substantial changes in fare class availability from one day to the next, even for the same flight departure
- **Substantial proportion of fare mix revenue gain comes from dynamic revision of booking limits:**
 - Human intervention is important in unusual circumstances, such as “unexplained” surges in demand due to special events

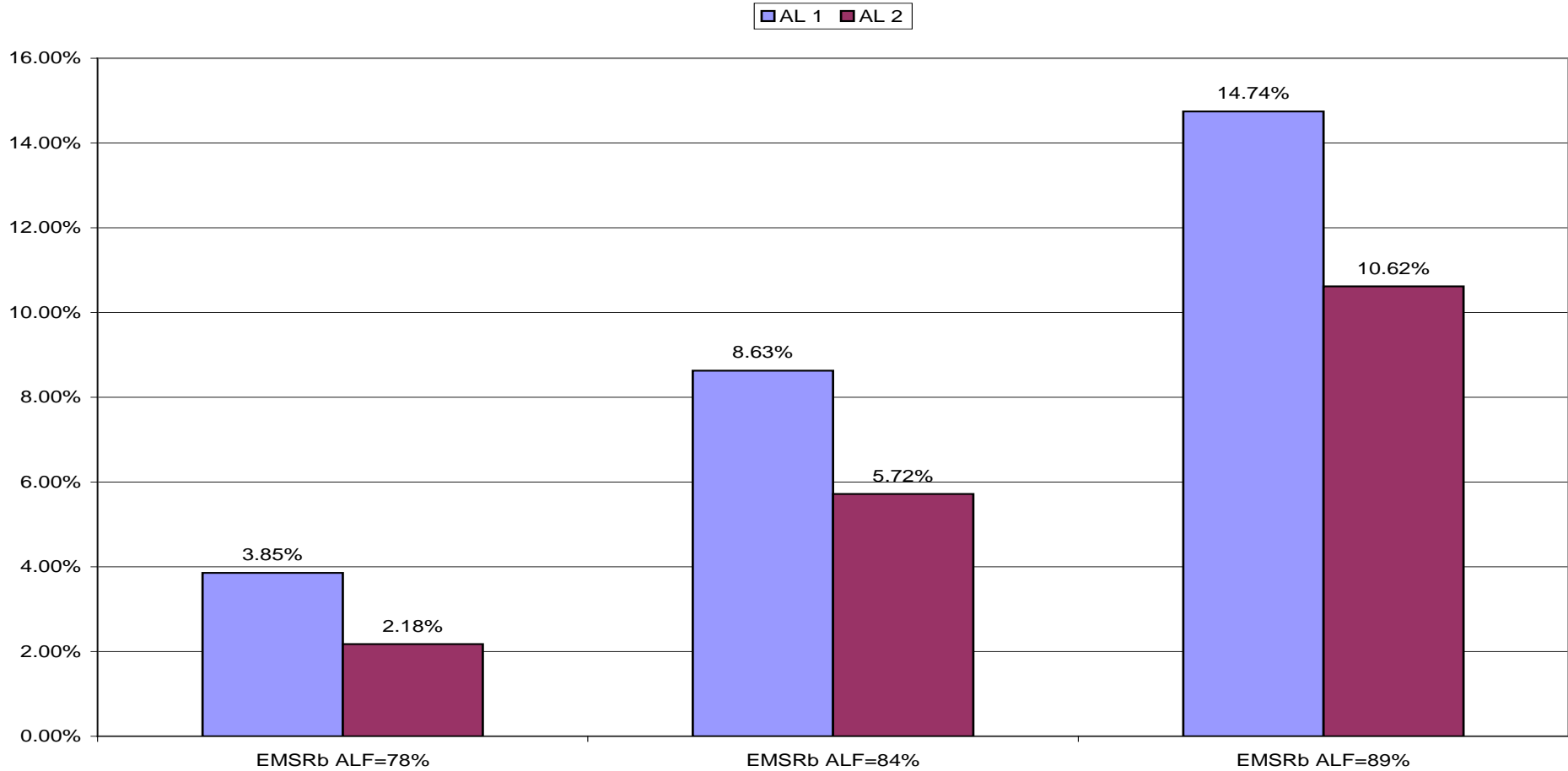
Revision of Forecasts and Limits as Bookings Accepted

CABIN CAPACITY =		135				
AVAILABLE SEATS =		63				
BOOKING CLASS	AVERAGE FARE	SEATS BOOKED	<u>FORECAST DEMAND</u>		JOINT PROTECT	BOOKING LIMIT
			MEAN	SIGMA		
Y	\$ 670	2	10	5	5	63
M	\$ 550	4	13	7	19	58
B	\$ 420	5	5	2	27	44
V	\$ 310	12	10	5	40	36
Q	\$ 220	17	20	6	63	23
L	\$ 140	32	15	4		0
	SUM	72	73			

Higher than expected Q bookings close L class

Leg-Based RM Benefits Increase with Average Load Factor

Revenue Gain When Both Airlines Implement EMSRb



Flight Overbooking

- **Determine maximum number of bookings to accept for a given physical capacity.**
- **Minimize total costs of denied boardings and spoilage (lost revenue).**
- **U.S. domestic no-show rates can reach 15-20 percent of final pre-departure bookings:**
 - On peak holiday days, when high no-shows are least desirable
 - Average no-show rates have dropped, to about 10% with more fare penalties and better efforts by airlines to firm up bookings
- **Effective overbooking can generate as much revenue gain as fare class seat allocation.**

Overbooking Terminology

- **Physical Capacity** CAP
- **Authorized Capacity** AU
- **Confirmed Bookings** BKD \leq AU
- **No-show rate** NSR
- **Show-up rate** SUR
- **Passengers Boarded** PAX
- **Denied Boardings** DB
- **Spoilage** SP

Deterministic Overbooking Model

- **Based on estimate of mean NSR from recent history:**
 - Assume that BKD=AU (“worst case” scenario)
 - Find AU such that $AU - NSR * AU = CAP$
 - Or, $AU = CAP / (1 - NSR)$

- **For CAP=100 and NSR=0.20, then:**

$$AU = 100 / (1 - .20) = 125$$

- **How would this model perform in the real world, where NSR is not known with certainty?**

Probabilistic/Risk Model

- **Incorporates uncertainty about NSR for future flight:**
 - Standard deviation of NSR from history, STD
- **Find AU that will keep DB=0, assuming BKD=AU, with a 95% level of confidence:**
 - Assume a probability (Gaussian) distribution of no-show rates
- **Optimal AU given CAP, SUR, STD with objective of DB=0 with 95% confidence is:**

$$AU = \frac{CAP}{SUR + 1.645 \text{ STD}} = \frac{CAP}{1 - NSR + 1.645 \text{ STD}}$$

- **In our example, with STD= 0.05:**

$$AU = 100 / (1 - 0.20 + 1.645 * 0.05) = 113$$

Probabilistic Model Extensions

- 1. Reduce level of confidence of exceeding DB limit:**
 - Z factor in denominator will decrease, causing increase in AU
- 2. Increase DB tolerance to account for voluntary DB:**
 - Numerator becomes (CAP+ VOLDB), increases AU
- 3. Include forecasted empty F or C cabin seats for upgrading:**
 - Numerator becomes (CAP+FEMPTY+CEMPTY), increases AU
 - Empty F+C could also be “overbooked”
- 4. Deduct group bookings and overbook remaining capacity only:**
 - Firm groups much more likely to show up
 - Flights with firm groups should have lower AU

Cost-Based Overbooking Model

- **Find AU that minimizes :**

[Cost of DB + Cost of SP]

- **For any given AU:**

$$\underline{\text{Total Cost}} = \$DB * E[DB] + \$SP * E[SP]$$

\$DB and \$SP= cost per DB and SP, respectively

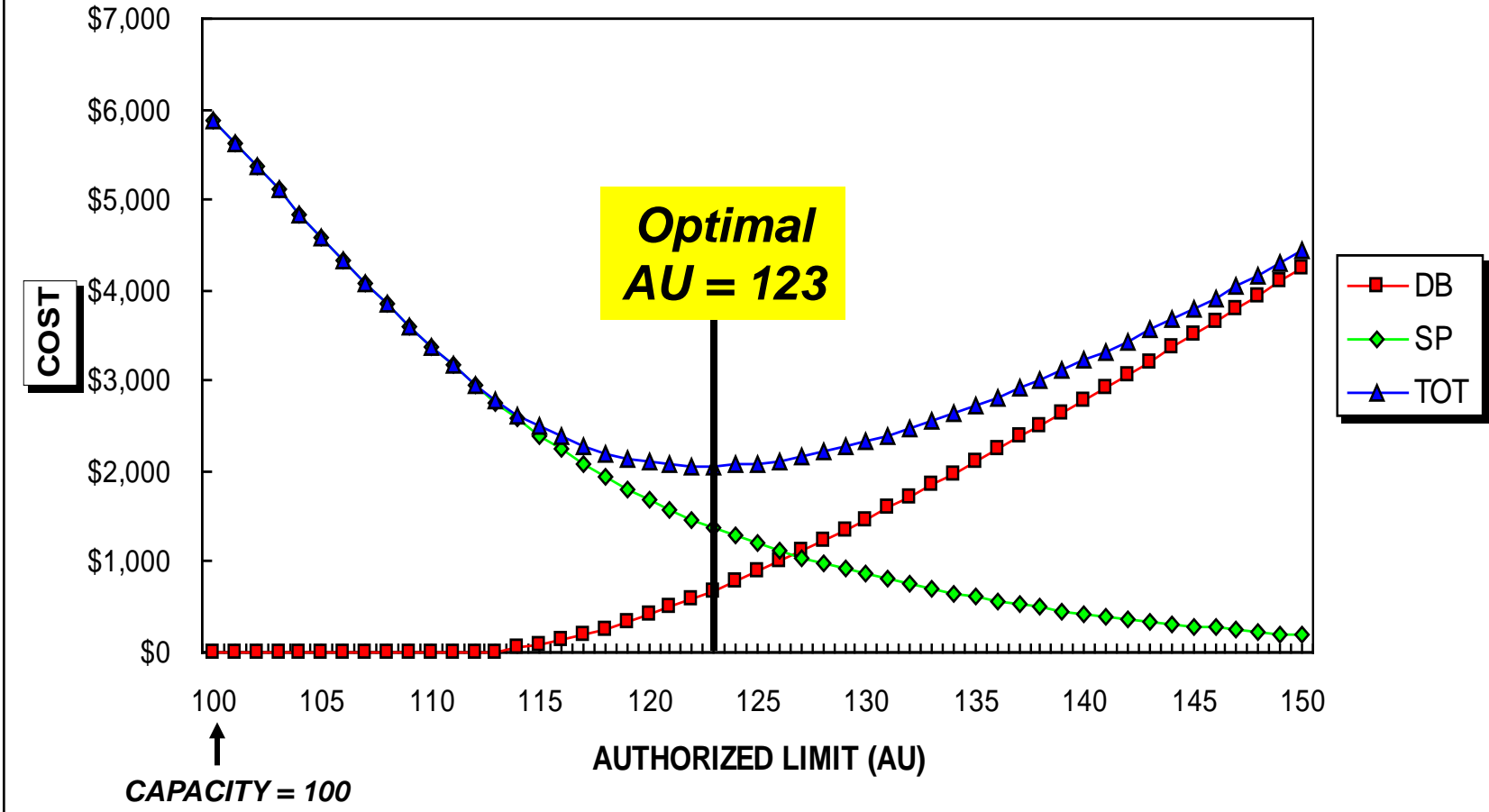
E[DB] = expected number of DBs, given AU

E[SP] = expected number of SP seats, given AU

- **Mathematical search over range of AU values to find minimum total cost.**

Example: Cost-Based Overbooking Model

Denied Boarding and Spoilage Costs



Costs of Denied Boardings and Spoilage

- **Denied Boarding Costs:**

- Cash compensation for involuntary DB
- Free travel vouchers for voluntary DB
- Meal and hotel costs for displaced passengers
- Space on other airlines
- Cost of lost passenger goodwill

- **Spoilage Costs: Loss of revenue from seat that departed empty**

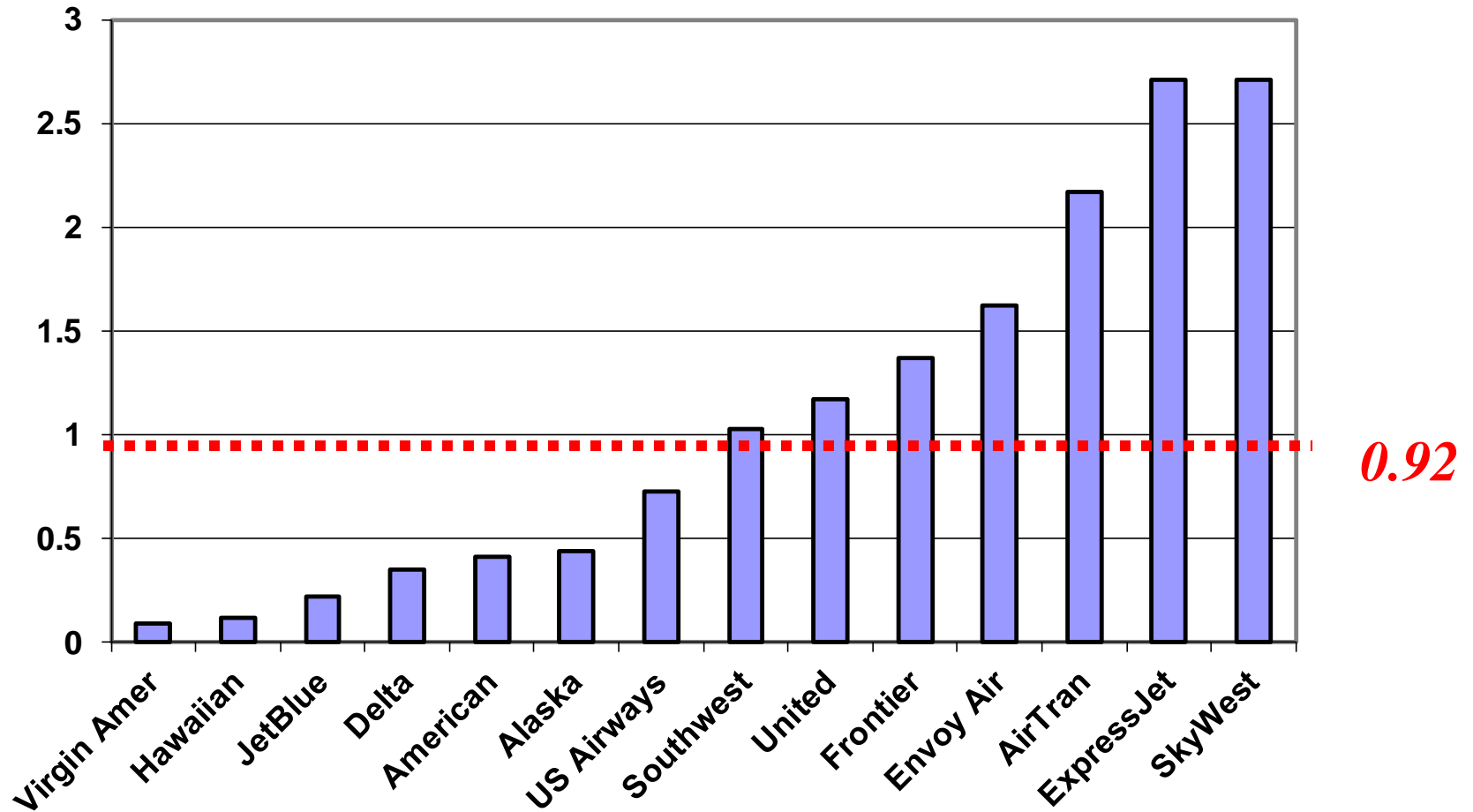
- Average revenue per seat for leg?
- Highest fare class revenue on leg (since closed flights lose late-booking passengers)?
- Lowest fare class revenue on leg (since increased AU would have allowed another discount seat)?

Voluntary vs. Involuntary DBs

- **Comprehensive Voluntary DB Program:**
 - Requires training and cooperation of station crews
 - Identify potential volunteers at check-in
 - Offer as much “soft” compensation as needed to make the passenger happy

- **US airlines very successful in managing DBs:**
 - 2013 involuntary DB rate was 0.92 per 10,000
 - About 90% of DBs in U.S. are volunteers
 - Good treatment of volunteers generates goodwill

2014 US Involuntary DBs per 10,000



Source: www.bts.gov

Current State of RM Practice

- **Most of airlines (legacy and LCC) have implemented 3rd generation Leg RM systems:**
 - Revenue gains of 4 to 6 percent, at 75-80% average system load factors
 - Tactical matching of demand to supply – channel low-fare demand to empty flights
 - Maintain competitive pricing while controlling dilution
- **About 15-20 leading airlines are implementing 4th generation Network RM systems**
 - Further distinguish between local and connecting requests based on network revenue value