Chapter 3 Review

![Graphical representation of Chapter 3 Review with various economic and operational metrics.]

**Key Concepts**
- **Demand**: RPM, QOS Elasticity, Time Elasticity, Price Elasticity, Revenue
- **QOS**: RPM, QOS Elasticity, # Flights, Yield
- **Operating Expense**: ASM, Economies Of Scale, Operating Expense
- **Profit**: Revenue, Cost

**Economies of Scale** and **Operating Expense** are interrelated, affecting overall profitability.
Fundamentals of Pricing and Revenue Management
Chapter 4
Lesson 3
Outline

• Airline Pricing and O-D Markets
  – Pricing Strategies
  – Price Discrimination vs. Product Differentiation

• Airline Differential Pricing
  – “willingness to pay” (WTP)

• Airline Revenue Management
Airline Pricing and O-D Markets Pricing Strategies
Airline Prices and O-D Markets

• **Pricing** – refers to the process of determining fare levels, combined with various service amenities and restrictions, for a set of fare products in an origin-destination market

• **Revenue Management** – is the subsequent process of determining how many seats to make available at each fare level

• **Regulated Pricing** – the Civil Aeronautics Board (CAB) used a mileage-based formula to ensure equal prices for equal distances

• **“Deregulated” or Liberalized Pricing** – Different O-D markets can have prices not related to distance traveled, or even the airline’s operating costs, as airlines match low-fare competitors to maintain market presence and share of traffic
  
  – Its possible that low-volume O-D markets are more costly to serve per passenger basis will see higher prices than high-density O-D markets, even if similar distances are involved
Theoretical Pricing Strategies

• For determining prices to charge in an O-D market, airlines can utilize one of following economic principles:
  – Cost-based pricing
  – Demand-based pricing
  – Service-based pricing

• In practice, most airline pricing strategies reflect a mix of these theoretical principles:
  – Prices are also highly affected by competition in each O-D Market
  – In the US, severe competition in some markets has led to “price-based costing”, meaning airlines must reduce costs to be able to match low-fare competitors and passengers’ price expectations
Price Discrimination vs. Product Differentiation

• Price discrimination:
  – The practice of charging different prices for same product with same costs of production
  – Based solely on different consumers’ “willingness to pay”

• Product differentiation:
  – Charging different prices for products with different characteristics and costs of production

• Current airline fare structures reflect both strategies:
  – Differential Pricing based on differentiated fare products
  – But higher prices for fare products targeted at business travelers are clearly based on their willingness to pay
Airline Pricing Practices

- Differential pricing presents a trade-off to customers between inconvenience and price levels:
  - Business travelers are “willing” to pay higher fares in return for more convenience, fewer restrictions on use of tickets
  - Leisure travelers less “willing” to pay higher prices, but accept disutility “costs” of restrictions on low fare products

- Economic concept of “willingness to pay” (WTP) is defined by the theoretical price-demand curve:
  - “Willingness” does not mean “happiness” in paying higher prices
  - Differential pricing attempts to make those with higher WTP purchase the less restricted higher-priced options
Differential Pricing Theory (circa 2000)

- 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
Airline Differential Pricing
Why Differential Pricing?

• It allows the airline to increase total flight revenues with little impact on total operating costs:
  – Incremental revenue generated by discount fare passengers who otherwise would not fly
  – Incremental revenue from high fare passengers willing to pay more
  – Studies have shown that most “traditional” high-cost airlines could not cover total operating costs by offering a single fare level

• Consumers can also benefit from differential pricing:
  – Most notably, discount passengers who otherwise would not fly
  – It is also conceivable that high fare passengers pay less and/or enjoy more frequency given the presence of low fare passengers

• If airline could charge a different price for each customer based on their WTP, its revenues would be close to the theoretical maximum
Market Segmentation

• Business and Leisure travelers are the two traditional segments targeted by the airlines in their different pricing efforts
  – First Class, Business Class, and Economy
  – Restrictions on advance purchase, use, and refundability

• A wide enough range of fare product options at different price levels should be offered to capture as much revenue potential from the market price-demand curve as possible
Traditional Approach: Restrictions on Lower Fares

• Progressively more severe restrictions on low fare products designed to prevent diversion:
  – Lowest fares have advance purchase and minimum stay requirements, as well as cancellation and change fees
  – Restrictions increase the inconvenience or “disutility cost” of low fares to travelers with high WTP, forcing them to pay more
  – Studies show “Saturday night minimum stay” condition to be most effective in keeping business travelers from purchasing low fares

• Still, it is impossible to achieve perfect segmentation:
  – Some travelers with high WTP can meet restrictions
  – Many business travelers often purchase restricted fares
Example: Restriction Disutility Costs

Business Passenger Fare Structure, Eb vs. Eb, DF=1
Example: BOS-SEA Traditional Fares

<table>
<thead>
<tr>
<th>Round-Trip Fare ($)</th>
<th>Cls</th>
<th>Advance Purchase</th>
<th>Minimum Stay</th>
<th>Change Fee?</th>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
<td>$458</td>
<td>N</td>
<td>21 days</td>
<td>Sat. Night</td>
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<td>Tue/Wed/Sat</td>
</tr>
<tr>
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<td>Tue/Wed</td>
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<tr>
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<td>Sat. Night</td>
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</tr>
<tr>
<td>$2083</td>
<td>B</td>
<td>3 days</td>
<td>None</td>
<td>No</td>
<td>2xOW Fare</td>
</tr>
<tr>
<td>$2262</td>
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<td>None</td>
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<tr>
<td>$2783</td>
<td>F</td>
<td>None</td>
<td>None</td>
<td>No</td>
<td>First Class</td>
</tr>
</tbody>
</table>

Figure 4.5
Fare Simplification: Less Restricted and Lower Fares

• Recent trend toward “simplified” fares – compressed fare structures with fewer restrictions
  – Initiated by some LFAs and America West, followed by Alaska
  – Most recently, implemented in all US domestic markets by Delta, matched selectively by legacy competitors

• Simplified fare structures characterized by:
  – No Saturday night stay restrictions, but advance purchase and non-refundable/change fees
  – Revenue management systems still control number of seats sold at each fare level

• Higher load factors, but 10-15% lower revenues:
  – Significantly higher diversion with fewer restrictions
Example: BOS-ATL Simplified Fares
Delta Air Lines, April 2005

<table>
<thead>
<tr>
<th>One Way Fare ($)</th>
<th>Bkg Cls</th>
<th>Advance Purchase</th>
<th>Minimum Stay</th>
<th>Change Fee?</th>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
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<td>T</td>
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<td>$50</td>
<td>Non-refundable</td>
</tr>
<tr>
<td>$139</td>
<td>U</td>
<td>14 days</td>
<td>0</td>
<td>$50</td>
<td>Non-refundable</td>
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<tr>
<td>$184</td>
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<td>$50</td>
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<tr>
<td>$209</td>
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<td>0</td>
<td>No</td>
<td>First Class</td>
</tr>
</tbody>
</table>
Revenue Impact of Each “Simplification”
Impacts on Differential Pricing Model

- Drop in business demand and willingness to pay highest fares
- Greater willingness to accept restrictions on lower fares
- Reduction in lowest fares to stimulate traffic and respond to LCCs
- Result is lower total revenue and unit RASM despite stable load factors
Airline Revenue Management
Airline Revenue Management

• Two components of airline revenue maximization:
  
  Differential Pricing:
  – Various “fare products” offered at different prices for travel in the same O-D market

  Yield Management (YM):
  – Determines the number of seats to be made available to each “fare class” on a flight, by setting booking limits on low fare seats

• Typically, YM takes a set of differentiated prices/products and flight capacity as given:
  – With high proportion of fixed operating costs for a committed flight schedule, revenue maximization to maximize profits
Why Call it “Yield Management”? 

• Main objective of YM is to protect seats for later-booking, high-fare business passengers.
• YM involves tactical control of airline’s seat inventory:
  – But too much emphasis on yield (revenue per RPM) can lead to overly severe limits on low fares, and lower overall load factors
  – Too many seats sold at lower fares will increase load factors but reduce yield, adversely affecting total revenues
• Revenue maximization is proper goal:
  – Requires proper balance of load factor and yield
• Many airlines now refer to “Revenue Management” (RM) instead of “Yield Management”
# Seat Inventory Control Approaches

**EXAMPLE: 2100 MILE FLIGHT LEG**

**CAPACITY = 200**

<table>
<thead>
<tr>
<th>FARE CLASS</th>
<th>AVERAGE REVENUE</th>
<th>YIELD EMPHASIS</th>
<th>LOAD FACTOR EMPHASIS</th>
<th>REVENUE EMPHASIS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y</td>
<td>$420</td>
<td>20</td>
<td>10</td>
<td>17</td>
</tr>
<tr>
<td>B</td>
<td>$360</td>
<td>23</td>
<td>13</td>
<td>23</td>
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<tr>
<td>H</td>
<td>$230</td>
<td>22</td>
<td>14</td>
<td>19</td>
</tr>
<tr>
<td>V</td>
<td>$180</td>
<td>30</td>
<td>55</td>
<td>37</td>
</tr>
<tr>
<td>Q</td>
<td>$120</td>
<td>15</td>
<td>68</td>
<td>40</td>
</tr>
</tbody>
</table>

| 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 |

Figure 4.11
Computerized RM Systems

• Size and complexity of a typical airline’s seat inventory control problem requires a computerized RM system

• Consider a US Major airline with:
  500 flight legs per day
  15 booking classes
  330 days of bookings before departure

• At any point in time, this airline’s seat inventory consists of almost 2.5 million booking limits:
  – This inventory represents the airline’s potential for profitable operation, depending on the revenues obtained
  – Far too large a problem for human analysts to monitor alone
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
Example of Third Generation RM System

Figure 4.12
Revenue Management Techniques

• Overbooking
  – Accept reservations in excess of aircraft capacity to overcome loss of revenues due to passenger “no-show” effects

• Fare Class Mix (Flight Leg Optimization)
  – Determine revenue-maximizing mix of seats available to each booking (fare) class on each flight departure

• Traffic Flow (O-D) Control (Network Optimization)
  – Further distinguish between seats available to short-haul (one-leg) vs. long-haul (connecting) passengers, to maximize total network revenues
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 10-15% 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)
  - Actual # of seats on the flight, usually maximum capacity of the aircraft

- **Authorized Capacity** (AU)
  - Maximum # of bookings that an airline is willing to accept

- **Confirmed Bookings** (BKD <= AU)
  - Total # of passenger reservations that have been accepted

- **No Show Rate** (NSR)
  - Mean % of passengers with confirmed bookings that do not show up

- **Denied Boardings** (DB)

- **Spoilage** (SP)

- **Show up Rate** (SUR)
Overbooking Models

• Overbooking models try to minimize:
  – Total costs of overbooking (denied boardings plus spoilage)
  – Risk of “excessive” denied boardings on individual flights, for customer service reasons

• Mathematical overbooking problem:
  – Find $OV > 1.00$ such that $AU = CAP \times OV$
  – But actual no-show rate is highly uncertain
Manual/Judgmental Approach

• Relies on judgment of human analyst to set overbooking level:
  – Based on market experience and perhaps recent no-show history
  – Tendency to choose OV = 1+NSR (or lower)
  – Tendency to focus on avoidance of DB

• For CAP=100 and mean NSR=.20, then:
  \[ AU = 100 \times (1.20) = 120 \]
Deterministic 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 - 0.20) = 125
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

• Keep show-ups less than or equal to CAP, when BKD=AU:
  – Find SUR*, so that AU x SUR* = CAP,
    and Prob[AU x SUR* > CAP] = 5%

• From Gaussian distribution, SUR* will satisfy:
  \[ Z = 1.645 = \frac{\text{SUR}^* - \text{SUR}}{\text{STD}} \]
  where SUR = mean show-up rate
  STD = standard deviation of show-up rate
Probabilistic/Risk Model (cont.)

• Optimal AU given CAP, SUR, STD with objective of DB=0 with 95% confidence is:
  \[
  AU = \frac{\text{CAP}}{\text{SUR} + 1.645 \times \text{STD}} = \frac{\text{CAP}}{1-\text{NSR} + 1.645 \times \text{STD}}
  \]

• In our example, with STD= 0.05 & NSR=.20:
  \[
  AU = \frac{100}{(1-0.20 + 1.645\times0.05)} = 113
  \]

• The larger STD, the larger the denominator and the lower the optimal AU, due to increased risk/uncertainty about no-shows.
# More Overbooking Terminology

- Waitlisted passengers: **WL**
- Go-show passengers: **GS**
- Stand-by passengers: **SB**
- No-shows: **NS**
- Show-ups: **SU**
- Passengers Boarded: **PAX**
- Voluntary DB: **VOLDB**
Probabilistic Model Extensions

• Reduce level of confidence of exceeding DB limit:
  – $Z$ factor in denominator will decrease, causing increase in AU

• Increase DB tolerance to account for voluntary DB:
  – Numerator becomes $(\text{CAP} + \text{VOLDB})$, increases AU

• Include forecasted empty F or C cabin seats for upgrading:
  – Numerator becomes $(\text{CAP} + \text{FEMPTY} + \text{CEMPTY})$, increases AU
  – Empty F+C could also be “overbooked”

• 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:
  \([\text{Cost of DB} + \text{Cost of SP}]\)

• For any given AU:
  
  \[
  \text{Total Cost} = \$DB \times E[DB] + \$SP \times E[SP]
  \]

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

  \(E[DB] = \text{expected number of DBs, given AU}\)

  \(E[SP] = \text{expected number of SP seats, given AU}\)

• Mathematical search over range of AU values to find minimum total cost.
Example: Cost-Based Overbooking Model

Denied Boarding and Spoilage Costs
DB Cost = $50, SP Cost = $100
Cost Inputs to Overbooking Model

• 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 costs

• Many airlines have difficulty providing accurate DB cost inputs to these models.
Dynamic Revision and Intervention

• RM systems revise forecasts and re-optimize booking limits at numerous “checkpoints” of the booking process:
  – 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
Current State of RM Practice

• Most of the top 25 world airlines (in terms of revenue) have implemented 3rd generation RM systems.
• Many smaller carriers are still trying to make effective use of leg/fare class RM
  – Lack of company-wide understanding of RM principles
  – Historical emphasis on load factor or yield, not revenue
  – Excessive influence and/or RM abuse by dominant sales and marketing departments
  – Issues of regulation, organization and culture
• About a dozen leading airlines are looking toward network O-D control development and implementation
  – These carriers could achieve a 2-5 year competitive advantage with advanced revenue management systems
Single-Leg Seat Allocation Problem

• Given for a future flight leg departure:
  – Total booking capacity of (typically) the coach compartment
  – Several fare (booking) classes that share the same inventory of seats in the compartment
  – Forecasts of future booking demand by fare class
  – Revenue estimates for each fare (booking) class

• Objective is to maximize total expected revenue:
  – Allocate seats to each fare class based on value
Cost Inputs (cont’d)

• Spoilage Costs:
  – Loss of revenue from seat that departed empty
• What is best measure of this lost revenue:
  – 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)?
• Specifying spoilage costs is just as difficult.
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:
  – 2007 involuntary DB rate was 1.12 per 10,000
  – Over 90% of DBs in U.S. are volunteers
  – Good treatment of volunteers generates goodwill
Flight Leg Revenue Optimization

• Given for a future flight leg departure:
  – Total booking capacity of (typically) the coach compartment
  – Several fare (booking) classes that share the same inventory of seats in the compartment
  – Forecasts of future booking demand by fare class
  – Revenue estimates for each fare (booking) class

• Objective is to maximize total expected revenue:
  – Allocate seats to each fare class based on value
Partitioned vs. Serial Nesting

• In a partitioned CRS inventory structure, allocations to each booking class are made separately from all the other classes.

• EXAMPLE (assuming uncertain demand):
  – Given the following allocations for each of 3 classes--Y = 30, B = 40, M = 70 for an aircraft coach cabin with booking capacity = 140.
  – If 31 Y customers request a seat, the airline would reject the 31st request because it exceeds the allocation for the Y class.
  – It is possible that airline would reject the 31st Y class customer, even though it might not have sold all of the (lower-valued) B or M seats yet!

• Under serial nesting of booking classes, the airline would never turn down a Y fare request, as long as there are any seats (Y, B or M) left for sale.
Serially Nested Buckets

Q1

Q2

Q3

Protected for class 1 from 2, 3, ..., l

Protected for class 2 from 3, 4, ..., l
Deterministic Seat Allocation/Protection

• If we assume that demand is deterministic (or known with certainty), it would be simple to determine the fare class seat allocations
  – Start with highest fare class and allocate/protect exactly the number of seats predicted for that class, and continue with the next lower fare class until capacity is reached.

• EXAMPLE: 3 fare classes (Y, B, M)
  – Demand for Y = 30, B = 40, M = 85
  – Capacity = 140

• Deterministic decision: Protect 30 for Y, 40 for B, and allocated 70 for M (i.e., spill 15 M requests)

• Nested booking limits Y=140 B=110 M=70
EMSRb Model for Seat Protection: Assumptions

• Basic modeling assumptions for serially nested classes:
  – demand for each class is separate and independent of demand in other classes.
  – demand for each class is stochastic and can be represented by a probability distribution
  – lowest class books first, in its entirety, followed by the next lowest class, etc.
  – booking limits are only determined once (i.e., static optimization model)
EMSRb Model Calculations

• Because higher classes have access to unused lower class seats, the problem is to find seat protection levels for higher classes, and booking limits on lower classes

• To calculate the optimal protection levels:
  Define $P_i(S_i) = \text{probability that } X_i > S_i$,
  where $S_i$ is the number of seats made available to class $i$, $X_i$ is the random demand for class $i$
EMSRb Calculations (cont’d)

• The expected marginal revenue of making the Sth seat available to class i is:
  \[ \text{EMSR}_i(S_i) = F_i^* \ P_i(S_i) \] where \( R_i \) is the average revenue (or fare) from class i

• The optimal protection level, \( \pi_1 \) for class 1 from class 2 satisfies:
  \[ \text{EMSR}_1(\pi_1) = F_1^* \ P_1(\pi_1) = R_2 \]

• Once \( \pi_1 \) is found, set \( \text{BL}_2 = \text{Capacity} - \pi_1 \).
• Of course, \( \text{BL}_1 = \text{Capacity} \) (authorized capacity if overbooking)
Example Calculation

• Consider the following flight leg example:

<table>
<thead>
<tr>
<th>Class</th>
<th>Mean Fcst.</th>
<th>Std. Dev.</th>
<th>Fare</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y</td>
<td>10</td>
<td>3</td>
<td>1000</td>
</tr>
<tr>
<td>B</td>
<td>15</td>
<td>5</td>
<td>700</td>
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<tr>
<td>M</td>
<td>20</td>
<td>7</td>
<td>500</td>
</tr>
<tr>
<td>Q</td>
<td>30</td>
<td>10</td>
<td>350</td>
</tr>
</tbody>
</table>

• To find the protection for the Y fare class, we want to find the largest value of $\pi_Y$ for which $\text{EMSR}_Y(\pi_Y) = F_Y \ast P_Y(\pi_Y) > R_B$
Example (cont’d)

\[ \text{EMSR}_\gamma(\pi_\gamma) = 1000 \times P_\gamma(\pi_\gamma) > 700 \quad P_\gamma(\pi_\gamma) > 0.70 \]

where \( P_\gamma(\pi_\gamma) \) = probability that \( X_\gamma > \pi_\gamma \).

- If we assume demand in Y class is *normally distributed with mean, standard deviation given earlier, then we can create a standardized normal random variable as \((X_\gamma - 10)/3\).*
Probability Calculations

• Next, we use Excel or go to the Standard Normal Cumulative Probability Table for different “guesses” for $\pi_Y$. For example,

\[
\begin{align*}
&\text{for } \pi_Y = 7, \text{ Prob } \{ (X_Y -10)/3 > (-10)/3 \} = 0.8417 \\
&\text{for } \pi_Y = 8, \text{ Prob } \{ (X_Y -10)/3 > (-10)/3 \} = 0.7478 \\
&\text{for } \pi_Y = 9, \text{ Prob } \{ (X_Y -10)/3 > (-10)/3 \} = 0.639 \\
\end{align*}
\]

• So, we can see that $\pi_Y = 8$ is the largest integer value of $\pi_Y$ that gives a probability >0.7 and therefore we will protect 8 seats for Y class!
Network Revenue Management: Origin-Destination Control

• Vast majority of world airlines still practice “fare class control”:
  – High-yield (“full”) fare types in top booking classes
  – Lower yield (“discount”) fares in lower classes
  – Designed to maximize yields, not total revenues

• Seats for connecting itineraries must be available in same class across all flight legs:
  – Airline cannot distinguish among itineraries
  – “Bottleneck” legs can block long haul passengers
Yield-Based Fare Class Structure (Example)

<table>
<thead>
<tr>
<th>BOOKING CLASS</th>
<th>FARE PRODUCT TYPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y</td>
<td>Unrestricted &quot;full&quot; fares</td>
</tr>
<tr>
<td>B</td>
<td>Discounted one-way fares</td>
</tr>
<tr>
<td>M</td>
<td>7-day advance purchase round-trip excursion fares</td>
</tr>
<tr>
<td>Q</td>
<td>14-day advance purchase round-trip excursion fares</td>
</tr>
<tr>
<td>V</td>
<td>21-day advance purchase or special promotional fares</td>
</tr>
</tbody>
</table>
## Connecting Flight Network Example

### Flight Leg Inventories

<table>
<thead>
<tr>
<th></th>
<th>LH 100</th>
<th>LH 200</th>
<th>LH 300</th>
</tr>
</thead>
<tbody>
<tr>
<td>CLASS</td>
<td>NCE-FRA</td>
<td>FRA-HKG</td>
<td>FRA-JFK</td>
</tr>
<tr>
<td>AVAILABLE</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Y</td>
<td>32</td>
<td>142</td>
<td>51</td>
</tr>
<tr>
<td>B</td>
<td>18</td>
<td>118</td>
<td>39</td>
</tr>
<tr>
<td>M</td>
<td>0</td>
<td>97</td>
<td>28</td>
</tr>
<tr>
<td>Q</td>
<td>0</td>
<td>66</td>
<td>17</td>
</tr>
<tr>
<td>V</td>
<td>0</td>
<td>32</td>
<td>0</td>
</tr>
</tbody>
</table>

### Itinerary/Fare Availability

- **NCE/FRA LH 100**
  - Y: 1
  - B: 1

- **NCE/HKG LH 100**
  - Y: 1
  - B: 1

- **NCE/JFK LH 100**
  - Y: 1
  - B: 1

- **NCE/FRA LH 200**
  - Y: 1
  - B: 1
  - M: 1
  - Q: 1
  - V: 1

- **NCE/HKG LH 200**
  - Y: 1
  - B: 1
  - M: 1
  - Q: 1
  - V: 1

- **NCE/JFK LH 300**
  - Y: 1
  - B: 1
  - M: 1
  - Q: 1
  - V: 1
The O-D Control Mechanism

• Revenue maximization over a network of connecting flights requires two strategies:
  1. Increase availability to high-revenue, long-haul passengers, regardless of yield;
  2. Prevent long-haul passengers from displacing high-yield short-haul passengers on full flights.

• Revenue benefits of (1) outweigh risks of (2):
  – Probability of both connecting flights being fully booked is low, relative to other possible outcomes
What is O-D Control?

• The capability to respond to different O-D requests with different seat availability.

• Can be implemented in a variety of ways:
  – Revenue value buckets (“greedy approach”)
  – EMSR heuristic bid price
  – Displacement adjusted virtual nesting
  – Network “optimal” bid price control

• All of the above can increase revenues, but each one has implementation trade-offs.
Revenue Value Bucket Concept

• Fixed relationship between fare type and booking class is abandoned:
  – Booking classes ("buckets") defined according to revenue value, regardless of fare restrictions
  – Each itinerary/fare type (i.e., “ODF”) assigned to a revenue value bucket on each flight leg
  – ODF seat availability depends on value buckets

• Value concept can be implemented within existing classes or through “virtual” classes
Value Bucket Implementation

• Within Existing Booking Classes:
  – Fare codes need to be re-published according to revenue value; no changes to inventory structure
  – Does not require seamless CRS links, but can be confusing to travel agents and consumers

• Development of Virtual Inventory Classes:
  – Substantial cost of new inventory structure and mapping functions to virtual classes
  – CRS seamless availability links are essential
Virtual Class Mapping by ODF Revenue Value

**FARE VALUES BY ITINERARY**

<table>
<thead>
<tr>
<th>NCE/FRA (via FRA)</th>
<th>CLASS</th>
<th>FARE (OW)</th>
<th>NCE/HKG (via FRA)</th>
<th>CLASS</th>
<th>FARE (OW)</th>
<th>NCE/JFK (via FRA)</th>
<th>CLASS</th>
<th>FARE (OW)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Y</td>
<td>$450</td>
<td></td>
<td>Y</td>
<td>$1415</td>
<td></td>
<td>Y</td>
<td>$950</td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>$380</td>
<td></td>
<td>B</td>
<td>$975</td>
<td></td>
<td>B</td>
<td>$710</td>
</tr>
<tr>
<td></td>
<td>M</td>
<td>$225</td>
<td></td>
<td>M</td>
<td>$770</td>
<td></td>
<td>M</td>
<td>$550</td>
</tr>
<tr>
<td></td>
<td>Q</td>
<td>$165</td>
<td></td>
<td>Q</td>
<td>$590</td>
<td></td>
<td>Q</td>
<td>$425</td>
</tr>
<tr>
<td></td>
<td>V</td>
<td>$135</td>
<td></td>
<td>V</td>
<td>$499</td>
<td></td>
<td>V</td>
<td>$325</td>
</tr>
</tbody>
</table>

**MAPPING OF ODFs ON NCE/FRA LEG TO VIRTUAL VALUE CLASSES**

<table>
<thead>
<tr>
<th>VIRTUAL CLASS</th>
<th>REVENUE RANGE</th>
<th>MAPPING OF C-D MARKETS/CLASSES</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1200+</td>
<td>Y NCEHKG</td>
</tr>
<tr>
<td>2</td>
<td>900-1199</td>
<td>B NCEHKG Y NCEJFK</td>
</tr>
<tr>
<td>3</td>
<td>750-899</td>
<td>M NCEHKG</td>
</tr>
<tr>
<td>4</td>
<td>600-749</td>
<td>B NCEJFK</td>
</tr>
<tr>
<td>5</td>
<td>500-599</td>
<td>Q NCEHKG M NCEJFK</td>
</tr>
<tr>
<td>6</td>
<td>430-499</td>
<td>V NCEHKG Y NCEFRA</td>
</tr>
<tr>
<td>7</td>
<td>340-429</td>
<td>B NCEFRA Q NCEJFK</td>
</tr>
<tr>
<td>8</td>
<td>200-339</td>
<td>V NCEJFK M NCEFRA</td>
</tr>
<tr>
<td>9</td>
<td>150-199</td>
<td>Q NCEFRA</td>
</tr>
<tr>
<td>10</td>
<td>0-149</td>
<td>V NCEFRA</td>
</tr>
</tbody>
</table>

Figure 4.17
Value Bucket O-D Control

• Allows O-D control with existing RM system:
  – Data collection and storage by leg/value bucket
  – Forecasting and optimization by leg/value bucket
  – Different ODF requests get different availability

• But also has limitations:
  – Re-bucketing of ODFs disturbs data and forecasts
  – Leg-based optimization, not a network solution
  – Can give too much preference to long-haul passengers (i.e..., “greedy” approach)
Displacement Cost Concept

• Actual value of an ODF to network revenue on a leg is less than or equal to its total fare:
  – Connecting passengers can displace revenue on down-line (or up-line) legs

• How to determine network value of each ODF for O-D control purposes?
  – Network optimization techniques to calculate displacement cost on each flight leg
  – Leg-based EMSR estimates of displacement
Value Buckets with Displacement

• Given estimated down-line displacement, ODFs are mapped based on network value:
  – Network value on Leg 1 = Total fare minus sum of own-line leg displacement costs
  – Under high demand, availability for connecting passengers is reduced, locals get more seats

• Revision of displacement costs is an issue:
  – Frequent revisions capture demand changes, but ODF re-mapping can disrupt bucket forecasts
Alternative Mechanism: Bid Price

- Under value bucket control, accept ODF if its network value falls into an available bucket:
  - Network Value > Value of Last Seat on Leg; or
  - Fare - Displacement > Value of Last Seat

- Same decision rule can be expressed as:

- Fare > Value of Last Seat + Displacement, or
- Fare > Minimum Acceptable “Bid Price” for ODF

- Bid Prices and Value Buckets are simply two different O-D control mechanisms.
O-D Bid Price Control

- Much simpler inventory control mechanism than virtual buckets:
  - Simply need to store bid price value for each leg
  - Evaluate ODF fare vs. itinerary bid price at time of availability request
  - Must revise bid prices frequently to prevent too many bookings of ODFs at current bid price
- Bid prices can be calculated with network optimization tools or leg-based heuristics
Example: Bid Price Control

A--------B--------C--------D

• Given leg bid prices

A-B:$35  B-C:$240  C-D:$160

• Availability for O-D requests B-C:

Bid Price = $240  Available?
Y  $440  Yes
M  $315  Yes
B  $223  No
Q  $177  No
<table>
<thead>
<tr>
<th>Combination</th>
<th>Bid Price</th>
<th>Available</th>
</tr>
</thead>
<tbody>
<tr>
<td>A-C</td>
<td>$275</td>
<td></td>
</tr>
<tr>
<td>Y</td>
<td>$519</td>
<td>Yes</td>
</tr>
<tr>
<td>M</td>
<td>$374</td>
<td>Yes</td>
</tr>
<tr>
<td>B</td>
<td>$292</td>
<td>Yes</td>
</tr>
<tr>
<td>Q</td>
<td>$201</td>
<td>No</td>
</tr>
<tr>
<td>A-D</td>
<td>$435</td>
<td></td>
</tr>
<tr>
<td>Y</td>
<td>$582</td>
<td>Yes</td>
</tr>
<tr>
<td>M</td>
<td>$399</td>
<td>No</td>
</tr>
<tr>
<td>B</td>
<td>$322</td>
<td>No</td>
</tr>
<tr>
<td>Q</td>
<td>$249</td>
<td>No</td>
</tr>
</tbody>
</table>
Network vs. Heuristic Models

• Estimates of displacement costs and bid prices can be derived using either approach:
  – Most O-D RM software vendors claim “network optimal” solutions possible with their product
  – Most airlines lack detailed data and face practical constraints in using network optimization models
  – Still substantial debate among researchers about which network O-D solution is “most optimal”

• Revenue gain, not optimality, is critical issue