OPTIMIZATION APPROACHES TO AIRLINE INDUSTRY CHALLENGES:

Airline Schedule Planning and Recovery

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Models and Algorithms for Optimization in Logistics
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Outline

• Scheduling Planning Process
  – Capabilities
  – Impacts
  – Shortcomings

• New trends in airline schedule planning and operations recovery
  ➢ Robust Scheduling
    • Optimizing actual rather than planned schedule performance
  ➢ Dynamic Scheduling
    • Adjust schedules to reflect improved demand forecasts
  ➢ Integrated operations recovery planning
Aircraft and Crew Schedule Planning

- Schedule Design
  - Fleet Assignment
  - Aircraft Routing
  - Crew Scheduling

- Select optimal set of *flight legs* in a schedule
- Assign aircraft types to flight legs such that *contribution* is maximized
- Route individual aircraft to satisfy maintenance restrictions
- Assign crew (pilots and/or flight attendants) to flight legs
Aircraft and Crew Schedule Planning

Schedule Design

Fleet Assignment

Aircraft Routing

Crew Scheduling

- Select optimal set of *flight legs* in a schedule
- Assign aircraft types to flight legs such that *contribution* is maximized
- Route individual aircraft to satisfy maintenance restrictions
- Assign crew (pilots and/or flight attendants) to flight legs
Crew Pairing Problem: State-of-the-Practice and Economic Impact

• Optimization widely used in crew planning
  – In 1969, Arabeyre et al. published a survey of research activities on the topic
• Routinely solve problems with thousands of constraints and billions of decision variables
  • Branch-and-price
  • References: Desaulniers et al. 1998, Clarke and Smith 2000 and Barnhart et al. 2003
• Significant economic impact
  – Anbil et al. (1991) achieved cost savings at American Airlines of $20 million dollars annually, representing an increase in crew utilization of 1.5%
  – Typical result: $50 million annual reduction in planned crew pairing costs using branch-and-price for major US airline
• Focus shift with time to
  • Re-defining the problem through integration with other problems
Fleet Assignment Research

• In 1956, Ferguson and Dantzig published a paper describing a model for a variant of this problem
• Initially, focus on developing solution approaches
  – Exploit problem structure
  – Multi-commodity flow based approaches widely adopted by the industry
    • Rushmeier and Kontogiorgis (1997) report realized savings of at least $15 million annually at USAir
    • Wiper et al (1994) report annual savings of $100 million at Delta Airlines
    • Abara (1989) reports a 1.4% improvement in operating margins at American Airlines
• Focus shift with time to
  • Expanding models to capture added realism
  • Origin-destination FAM
Schedule Design Literature

- Schedule design affects and is affected by essentially all aircraft and crew scheduling decisions of the airline, and competing airlines as well
  - Schedule design primarily a manual process, typically with limited optimization
- More recent research on “incremental” schedule design
  - Berge (1994), Marsten et al. (1996), Erdmann et al. (1999), Rexing et al. (2000) and Lohatepanont and Barnhart (2001)
- United Airlines (Lohatepanont and Barnhart 2001)
  - $100 - $350 million annual projected savings
    - Additional reduction in number of aircraft to operate schedules
So much optimization success
... so little economic success
... and so many unhappy passengers
Airline Schedule Optimization

• Long history
  – With capabilities increasing due to advances in data acquisition, computing, and optimization
  – With impact increasing over time due to added realism in models capturing more of the complexity, integration of some of the decisions in the sequential process

• Have we ‘solved’ the airline schedule optimization problem yet?
  – No.
  – Optimized fight schedules are never operated
Optimizing Plan Execution

• Optimized solutions are rarely executed as planned
  – A finely tuned, optimized solution has little slack and often lacks flexibility to recover, often translating in practice into less robustness and increased costs

• Growing congestion at major US airports translates into several billion dollars of delay costs annually
  – Total aircraft delay in 2007: 134M minutes
  – Total passenger delays in 2007: 17B minutes
  – 29% increase in passenger delays from 2006 to 2007
  – Additional direct operating costs: $8.1B
  – Estimated passenger delay costs: $8.5B
  – Average trip delays of greater than 25 minutes at the 5 worst affected airports (JFK, ORD, LGA, EWR, DFW)

[¹Source: Air Transport Association, 2008]
[²Source: U.S. Airline Passenger Trip Delay Report, 2008]
Airline Operations

1. Aircraft delays result from
   - Weather, unscheduled maintenance requirements, unavailable crews, gates, ground resources, etc.

2. Flights are delayed or cancelled

3. Delays propagate through the network

4. Aircraft, crew and passengers are delayed/disrupted …
Some Problems…

Solving the wrong problem, or more exactly, optimizing a piece of a non-optimized system

1. Lack of coordination of airline schedules at most airports in US
   • More scheduled operations than (best-case) capacity at our busiest airports
     – Slot controls not used except in a few cases
     – Trend toward smaller aircraft
       » Increased frequency
   – Result: disruptions, such as bad weather, induce delays that propagate through the network
Utilization as percentage of IFR capacity

January 31, 2008
[Source: ASPM, 2009]
What Can Be Done?

- Challenge assumptions of conventional models
  - Future demands are known and deterministic
  - Schedules are operated as planned

- Create Robust or Flexible Schedules
  - Optimizing actual rather than planned schedule performance

- Create Dynamic Schedules
  - Adjust schedules to reflect improved demand forecasts overtime

- Create Optimized Operations Recovery Plans
  - Passenger-centric recovery
AIRLINE ROBUST PLANNING
Re-designing Aircraft Routings and Planned Block Times to Reduce Delays
Delay Propagation

- Flights with underestimated block times or delayed departures lead to arrival delays that can propagate to subsequent flights if insufficient slack is planned on the ground.
Aircraft swapping during the day of operation
Passenger misconnections due to a flight delay
Dampening Delay Propagation through Routing

Original routing

New routing
Aircraft Re-routing

- Doesn’t create more slack, just changes the location of slack
Computational Results

Test Networks

<table>
<thead>
<tr>
<th>Network</th>
<th>Num of flights</th>
<th>Num of strings</th>
</tr>
</thead>
<tbody>
<tr>
<td>N1</td>
<td>20</td>
<td>7,909,144</td>
</tr>
<tr>
<td>N2</td>
<td>59</td>
<td>614,240</td>
</tr>
<tr>
<td>N3</td>
<td>97</td>
<td>6,354,384</td>
</tr>
<tr>
<td>N4</td>
<td>102</td>
<td>51,730,736</td>
</tr>
</tbody>
</table>

Model Building and Validation

July 2000 data → Model → Routes → Aug 2000 data

Propagated delays (August 2000)

<table>
<thead>
<tr>
<th>Network</th>
<th>Old PD</th>
<th>New PD</th>
<th>PD reduced</th>
<th>% of PD reduced</th>
</tr>
</thead>
<tbody>
<tr>
<td>N1</td>
<td>6749</td>
<td>4923</td>
<td>1826</td>
<td>27%</td>
</tr>
<tr>
<td>N2</td>
<td>4106</td>
<td>2548</td>
<td>1558</td>
<td>38%</td>
</tr>
<tr>
<td>N3</td>
<td>8919</td>
<td>4113</td>
<td>4806</td>
<td>54%</td>
</tr>
<tr>
<td>N4</td>
<td>14526</td>
<td>9921</td>
<td>6940</td>
<td>48%</td>
</tr>
<tr>
<td>Total</td>
<td>34300</td>
<td>21505</td>
<td>15130</td>
<td>44%</td>
</tr>
</tbody>
</table>
Results - Delays

- Total delays and on-time performance

<table>
<thead>
<tr>
<th>Network</th>
<th>Total num of D-pax</th>
<th>D-pax reduces</th>
<th>D-pax reduced (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>N1</td>
<td>986</td>
<td>147</td>
<td>14.9%</td>
</tr>
<tr>
<td>N2</td>
<td>1070</td>
<td>79</td>
<td>7.4%</td>
</tr>
<tr>
<td>N3</td>
<td>1463</td>
<td>161</td>
<td>11.0%</td>
</tr>
<tr>
<td>N4</td>
<td>3323</td>
<td>355</td>
<td>10.7%</td>
</tr>
<tr>
<td>Total</td>
<td>6842</td>
<td>742</td>
<td>10.8%</td>
</tr>
</tbody>
</table>

Passenger misconnects

Old:
- >15 min: 22.3%
- >60 min: 7.9%
- >120 min: 2.9%
- On-time performance:
  - 15 min: 77.7%
  - 60 min: 92.1%
  - 120 min: 97.1%

New:
- >15 min: 20.7%
- >60 min: 6.9%
- >120 min: 2.6%
- On-time performance:
  - 15 min: 79.3%
  - 60 min: 93.1%
  - 120 min: 97.4%
Robust Block Time Adjustment: Formulation

- Change block times
  - Adjusts slacks in both aircraft connections and passenger connections
  - Moves slack between ground time and flying time
- Modify the re-timing model to allow changing both departure time and arrival time

\[
\begin{align*}
\text{minimize} & \quad \sum_{i \in F} \tau_{di} \\
\tau_{di} & \geq d_i + x_i - y_i \quad \forall i \in F_0 \\
\tau_{dj} & \geq p_d + d_j + x_i - y_i \quad \forall (i, j) \in A \\
\tau_{dj} & \geq 0 \quad \forall i \in F \\
\text{slack}_{ij} & = \text{slack}_{ij} - y_i + x_j \quad \forall (i, j) \in A \\
p_{dij} & \geq \tau_{di} - \text{slack}_{ij} \quad \forall (i, j) \in A \\
p_{dij} & \geq 0 \quad \forall (i, j) \in A \\
\text{slack}_{ij} - y_i + x_j & \geq 0 \quad \forall (i, j) \in P \\
\text{slack}_{ij} & \geq 0 \quad \forall (i, j) \in A \\
l_{x_i} & \leq x_i \leq u_{x_i} \quad \forall i \in F \\
l_{y_i} & \leq y_i \leq u_{y_i} \quad \forall i \in F \\
\end{align*}
\]

Coefficient matrix is totally unimodular
## Results

### Summary

<table>
<thead>
<tr>
<th>Model</th>
<th>19</th>
<th>20</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Average Total Slack</strong></td>
<td>8871.96</td>
<td>5576.16</td>
</tr>
<tr>
<td><strong>Average Total Retiming</strong></td>
<td>0.00</td>
<td>1903.96</td>
</tr>
<tr>
<td><strong>Average Total Block Time Change</strong></td>
<td>0.00</td>
<td>3308.20</td>
</tr>
<tr>
<td><strong>Average Lost Connections</strong></td>
<td>3.04</td>
<td>3.60</td>
</tr>
<tr>
<td><strong>Average Lost Passengers</strong></td>
<td>5.84</td>
<td>7.64</td>
</tr>
<tr>
<td><strong>Max Lost Connections</strong></td>
<td>7</td>
<td>9</td>
</tr>
<tr>
<td><strong>Max Lost Passengers</strong></td>
<td>18</td>
<td>22</td>
</tr>
<tr>
<td><strong>Average Total Dep Propagated Delay</strong></td>
<td>610.16</td>
<td>718.04</td>
</tr>
<tr>
<td><strong>Average Total Arr Propagated Delay</strong></td>
<td>569.96</td>
<td>552.72</td>
</tr>
<tr>
<td><strong>Average Total Arrival Delay</strong></td>
<td>3108.64</td>
<td>1754.84</td>
</tr>
<tr>
<td><strong>% of Flights with PD &gt; 0</strong></td>
<td>8.90%</td>
<td>11.07%</td>
</tr>
<tr>
<td><strong>15-min On-Time Performance</strong></td>
<td>76.44%</td>
<td>88.48%</td>
</tr>
<tr>
<td><strong>60-min On-Time Performance</strong></td>
<td>97.07%</td>
<td>97.92%</td>
</tr>
<tr>
<td><strong>Average Total Disrupted Pax</strong></td>
<td>22.44</td>
<td>24.92</td>
</tr>
<tr>
<td><strong>Average Total Canceled Pax</strong></td>
<td>25.00</td>
<td>31.40</td>
</tr>
<tr>
<td><strong>Average Total Pax Delay (Incl. Canceled Pax)</strong></td>
<td>257377.36</td>
<td>168194.24</td>
</tr>
<tr>
<td><strong>Average Non-Disrupted Pax Delay</strong></td>
<td>15.02</td>
<td>9.04</td>
</tr>
<tr>
<td><strong>Average Disrupted Pax Delay</strong></td>
<td>188.89</td>
<td>166.32</td>
</tr>
<tr>
<td><strong>Average Total Pax Delay (Excll. Canceled Pax)</strong></td>
<td>239377.36</td>
<td>145586.24</td>
</tr>
</tbody>
</table>
Dynamic Scheduling
Flight Scheduling and Demands

• Flight schedules and fleet assignments are developed based on deterministic, static passenger demand forecasts (made months or longer in advance)
  – Air travel demand is highly variable
  – Each daily demand is different

• Significant mismatch exists between supply and demand
  – Even with sophisticated revenue management systems
Dynamic Airline Scheduling

• Idea: Dynamically adjust airline networks in the booking process to match supply with demand
“Matching Capacity and Demand”

- Assign new aircraft with different numbers of seats to the flight legs
- Re-time flight legs and create a new itinerary
  - Potentially many opportunities in a de-peaked hub-and-spoke network
De-banked (or De-peaked) Hubs

American de-peaked

Continental de-peaked
EWR


Delta de-peaked ATL (2005)

Lufthansa de-peaked FRA (2004)
Case Study

• Major US Airline
  – 832 flights daily
  – 7 aircraft types
  – 50,000 passengers
  – 302 inbound and 302 outbound flights at hub daily
    • Banked hub operations—must de-bank

• Re-time
  – +/- 15 minutes

• Re-fleet
  – A320 & A319
  – CRJ & CR9

• One week in August, with daily total demand:
  – higher than average (Aug 1)
  – average (Aug 2)
  – lower than average (Aug 3)

• Protect all connecting itineraries sold in Period up to d-t
  – t =21 or 28 days

• Two scenarios concerning forecast demand
  – Perfect information
  – Historical average demand
Improvement In Profitability

- Consistent improvement in profitability
  - Forecast A
    • 4-8% improvement in profit
    • 60-140k daily
  - Forecast B
    • 2-4% improvement in profit
    • 30-80k daily
    • Benefits remain significant when using Forecast B - a lower bound
  - not including benefit from aircraft savings, reduced gates and personnel ...
Airline Operations: Passenger Centric Optimization
Airline operations decision models

• Develop online optimization tools to reduce passenger disruptions and delays through improved flight cancellation and departure postponement decisions
  – Passenger-centric approaches

• Enforce crew and aircraft maintenance feasibility of the recovery plan
Airline Operations Simulation

Period 1
Operating stage

Time T1
Resource State
Forecasts
FP&C optimizer
Decisions
Routing passenger
Unexpected events

Time T2
Resource State
Forecasts
FP&C optimizer Pax itineraries
Decisions
Routing passenger
Unexpected events

Time Tn
Resource State
Forecasts
FP&C optimizer Pax itineraries
Decisions
Routing passenger
Unexpected events

End of time horizon

Passenger delay statistics
Resource state

Routing passenger
Unexpected events
Routing passenger
Unexpected events
Routing passenger
Unexpected events
Optimizer Performance

- Number of disrupted passengers reduced by 40%
- Runtime less than 30 CPU sec
- Base Case = Major airline operations

<table>
<thead>
<tr>
<th></th>
<th>Base Case</th>
<th>Optimizer solution</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average passenger delay (minutes)</td>
<td>Loc. 25.9</td>
<td>22.4 22.6</td>
<td>24.4 18.5</td>
</tr>
<tr>
<td>Number of disrupted passengers</td>
<td>1,896</td>
<td>1,131</td>
<td>40.4%</td>
</tr>
<tr>
<td>Number of overnights</td>
<td>900</td>
<td>491</td>
<td>45.4%</td>
</tr>
<tr>
<td>Total delay minutes of disrupted passengers</td>
<td>762,152</td>
<td>505,664</td>
<td>33.7%</td>
</tr>
<tr>
<td>Total delay minutes of non disrupted passengers</td>
<td>986,609</td>
<td>1,022,741</td>
<td>-3.7%</td>
</tr>
</tbody>
</table>
Summary

• Trends in optimizing airline schedules
  – Challenge assumptions of conventional models
    • Future demands are known and deterministic
    • Schedules are operated as planned

• Opportunities for airline operations researchers
  ➢ Dynamic Scheduling
    • Adjust schedules to reflect improved demand forecasts
  ➢ Robust Scheduling
    • Optimizing actual rather than planned schedule performance
  ➢ Integrated operations recovery planning
Questions?