Strategic and Tactical Congestion Management in the New York Airport System

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Outline

- Research Questions
- Dynamic Optimization of Capacity Utilization
  - Presentation
  - Model Formulation
  - Implementation at JFK
  - Conclusion
- Looking forward: Strategic Congestion Management
Motivation

- Large and costly delays in the US (Ball et al., 2010)

<table>
<thead>
<tr>
<th>Cost Component</th>
<th>Cost of delays in 2007 (in $ billion)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost to Airlines</td>
<td>8.3</td>
</tr>
<tr>
<td>Cost to Passengers</td>
<td>16.7</td>
</tr>
<tr>
<td>Cost from Lost Demand</td>
<td>3.9</td>
</tr>
<tr>
<td>Impact on GDP</td>
<td>4.0</td>
</tr>
<tr>
<td>TOTAL</td>
<td>32.9</td>
</tr>
</tbody>
</table>

- Main source of delays: demand / capacity mismatch
  - Capacity limitations: Infrastructure, Safety, Weather etc.
  - Weak scheduling constraints in the US
Congestion at New York’s Airports

- New York’s airports are the most congested nationwide

Delays at New York / PHL are responsible for approximately 1/3 of NAS delays (MITRE, 2013)

- FAA should reexamine its flight caps at New York’s airports
- FAA should improve its capability to model delay propagation throughout the NAS
Airport Congestion

- Primary bottleneck of airport operations: Runway System
- Characterization of the runway system as a queuing system
- Queue stochasticity: Use of an $M(t)/E_k(t)/1$ queuing model

- Descriptive models of airport congestion

Diagram:

- Regulatory Policies
- Airline Scheduling
- Infrastructure
- Airport Operations
- Demand
- Capacity
- Runway System
- Flight Delays
Airline / Airport Planning
Airport Congestion Management

- Given a model of queue dynamics, how can we \textit{prescriptively} control schedules and airport capacity to mitigate airport delays?

**LONG TERM**
- Capacity Planning
  - Infrastructure Investments

**SHORT TERM**
- Capacity Allocation
  - Airline Scheduling & Regulatory Policies
- Capacity Utilization
  - Airport Operational Procedures
Research Plan

1. Airport Capacity Utilization
   ■ Dynamic Control of Runway Configurations and Arrival and Departure Service Rates to Minimize Congestion Costs under Queue Stochasticity

2. Airport Capacity Allocation
   1. Reducing Flight Delays through Flight Re-Scheduling, under a “Central Planning” Perspective
   2. Airline Schedule Planning and Airport Congestion Management: Incorporating Airline Competition within this Framework

3. Airport Capacity Planning
   ■ Evaluation of Airport Investment Planning: Capacity Expansion vs. Schedule Limitations
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Representation of Airport Capacity

- Airport capacity primarily depends on:
  - The runway configuration in use
  - The departure / arrival balance
  - Weather conditions

- Representation of capacity: Operational Throughput Envelope (Simaiakis, 2012)
  - Relationship between average arrival and departure service rates
  - Specific to a runway configuration

- Integrates stochasticity of service processes
Problem Statement

- **Objectives**: Minimizing airport congestion costs by jointly controlling:
  - Selection of runway configurations
  - Arrival and departure service rates
- **“Cost” of switching runway configurations**
- **NO control of**:
  - Throughput rates that can be achieved in a given runway configuration
  - Schedules of flights
Literature Review

- Descriptive statistical analysis (Ramanujam & Balakrishnan, 2011)

- Prescriptive optimization tools:
  - Dynamic Programming (Li and Clarke, 2010)
  - Integer Programming (Bertsimas, Frankovich and Odoni, 2011)

- In general: No account for queue stochasticity

- Contributions of the paper:
  - A *tactical* tool to control runway configurations and service rates, which combines (a) queue stochasticity, (b) Operational Throughput Envelopes and (c) stochasticity of operational conditions
  - Improvement of models of airport congestion at the *strategic* level, which typically do not exercise that control
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DP Framework

- Finite-horizon (72 15-minute periods)
- State variables
  - Arrival and departure queues
  - Current runway configuration
  - Weather and wind conditions
- Control variables
  - New runway configuration
  - Arrival and departure service rates
- Objective: Minimizing congestion costs – use of a quadratic cost function of arrival and departure queues

\[ \alpha \sum_{t=1}^{T} a_t^2 + \delta \sum_{t=1}^{T} d_t^2 \]

\(a_t\): number of aircraft in the arrival queue
\(d_t\): number of aircraft in the departure queue
System Dynamics (1/3)

- Arrival and departure queues: M/E_k/1 queuing model

```
0 <-> k(t) <-> 1 <-> k(t) <-> 2 <-> ... <-> k <-> k(t) <-> k+1 <-> k(t) <-> ...
```

\( \lambda(t) \)
System Dynamics (1/3)

- Arrival and departure queues: M/E_k/1 queuing model
- Chapman Kolmogorov equations:

\[
\begin{align*}
\frac{dP_0(t)}{dt} &= -\lambda(t)P_0(t) + k\mu(t)P_1(t) \\
\frac{dP_i(t)}{dt} &= -\left(\lambda(t) + k\mu(t)\right)P_i(t) + k\mu(t)P_{i+1}(t) \quad \forall i \in \{1, ..., k\} \\
\frac{dP_i(t)}{dt} &= \lambda(t)P_{i-k}(t) - \left(\lambda(t) + k\mu(t)\right)P_i(t) + k\mu(t)P_{i+1}(t) \quad \forall i \in \{k + 1, ..., (N - 1)k\} \\
\frac{dP_i(t)}{dt} &= \lambda(t)P_{i-k}(t) - k\mu(t)P_i(t) + k\mu(t)P_{i+1}(t) \quad \forall i \in \{(N - 1)k + 1, ..., kN - 1\} \\
\frac{dP_{kN}(t)}{dt} &= \lambda(t)P_{k(N-1)}(t) - k\mu(t)P_{kN}(t)
\end{align*}
\]

- Off-line pre-processing: Lookup table
- Problem aggregation:

<table>
<thead>
<tr>
<th>Queue States</th>
<th>Queue Length</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>k</td>
<td>2</td>
</tr>
<tr>
<td>k+1</td>
<td>...</td>
</tr>
<tr>
<td>2k</td>
<td>...</td>
</tr>
</tbody>
</table>
System Dynamics (2/3)

- Switching runway configurations: A challenging operational procedure
- Modeled as a time period of idleness

<table>
<thead>
<tr>
<th>Previous runway configuration</th>
<th>Period of idleness</th>
<th>New runway configuration</th>
</tr>
</thead>
<tbody>
<tr>
<td>$t-1)S$</td>
<td>$(t-1)S + \tau_l$</td>
<td>$tS$</td>
</tr>
</tbody>
</table>

$\mu_i^a = 0$  
$\mu_i^d = 0$  
$\mu_t^a = \mu^{(a)}$  
$\mu_t^d = \mu^{(d)}$

- Operational trade-off: Improving throughput efficiency might imply a time period of inefficiency
- Adjustments of parameters $\tau_l$ as a function of the “proximity” of the runway configuration switch
Weather Conditions: A Markov Chain

3 categories of days:
- “All-VMC days”: p=0
- “All-IMC days”: q=0
- “VMC/IMC days”: p=0.044 and q=0.056

Wind Conditions: A Markov Chain

Constraint: FAA safety requirements

Approach similar to Li and Clarke (2010)

<table>
<thead>
<tr>
<th>Wind States</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
</tr>
</thead>
<tbody>
<tr>
<td>4L, 4R</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>X</td>
<td>✓</td>
<td>X</td>
<td>X</td>
<td>✓</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>22L, 22R</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>X</td>
<td>✓</td>
<td>X</td>
<td>✓</td>
<td>X</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>13L, 13R</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>✓</td>
<td>X</td>
</tr>
<tr>
<td>31L, 31R</td>
<td>✓</td>
<td>X</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Proportion</td>
<td>10.6%</td>
<td>7.6%</td>
<td>16.0%</td>
<td>8.9%</td>
<td>15.6%</td>
<td>2.5%</td>
<td>13.6%</td>
<td>8.1%</td>
<td>8.8%</td>
<td>10.3%</td>
<td>0.8%</td>
<td>0.5%</td>
<td>5.7%</td>
</tr>
</tbody>
</table>
Dynamic Programming equation

- **Bellman equation:**

\[
J_t(a_{t-1}, d_{t-1}, RC_{t-1}, wc_t, ws_t) = \min_{RC_t \in \mathcal{R}(ws_t), \mu_t^a \in [0, A_{RC_t, wc_t}]} \left( a \mathbb{E} \left( a_t^2 \right) + \delta \mathbb{E} \left( d_t^2 \right) + \mathbb{E} \left( J_{t+1} \left( a_t, d_t, RC_t, wc_{t+1}, ws_{t+1} \right) \right) \right), \forall t = 1, \ldots, T
\]

\[
J_{T+1}(a_T, d_T, RC_T, wc_{T+1}, ws_{T+1}) = 0
\]

- **System dependencies:**

- \( ws_t \rightarrow RC_t \)
- \( RC_{t-1}, RC_t \rightarrow \tau^{RC_{t-1}, RC_t}_I \)
- \( RC_t, wc_t \rightarrow \mu_t^a, \mu_t^d = DT_{RC_t, wc_t}(\mu_t^a) \)
- \( x_t, \tau^{RC_{t-1}, RC_t}_I, wc_t, \mu_t^a, a_{t-1} \rightarrow a_t \)
- \( y_t, \tau^{RC_{t-1}, RC_t}_I, wc_t, \mu_t^d, d_{t-1} \rightarrow d_t \)
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JFK Airport: Presentation

Operational Throughput Envelopes of JFK’s major runway configurations (Simaiakis, 2012)
JFK Schedule on 07/13/2007
Optimal Policy

- Representation of the optimal policy at 14:00
  - More arrivals than departures in the following two hours

(a) $RC_{t-1} = 13L, 22L | 13R$

(b) $RC_{t-1} = 22L | 22R, 31L$
Use of runway configurations

\[ \tau_I = 0 \]

\[ \tau_I = 3 \]

\[ \tau_I = 5 \]

\[ \tau_I = 10 \]
# Frequency of Decisions

<table>
<thead>
<tr>
<th>Policy</th>
<th>$\mu_i^a$</th>
<th>$\mu_i^d$</th>
<th>6:45</th>
<th>11:45</th>
<th>14:00</th>
<th>21:30</th>
</tr>
</thead>
<tbody>
<tr>
<td>$RC_t$</td>
<td>$\mu_i^a$</td>
<td>$\mu_i^d$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>8.0</td>
<td>-</td>
<td>38%</td>
<td>-</td>
<td>-</td>
<td>1%</td>
</tr>
<tr>
<td>11</td>
<td>9.9</td>
<td>-</td>
<td>-</td>
<td>7%</td>
<td>-</td>
<td>3%</td>
</tr>
<tr>
<td>10</td>
<td>10.1</td>
<td>-</td>
<td>-</td>
<td>7%</td>
<td>-</td>
<td>6%</td>
</tr>
<tr>
<td>9</td>
<td>10.2</td>
<td>-</td>
<td>-</td>
<td>1%</td>
<td>-</td>
<td>8%</td>
</tr>
<tr>
<td>4</td>
<td>10.6</td>
<td>17%</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>13L, 22L</td>
<td>13R</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>5.2</td>
<td>-</td>
<td>11%</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>10</td>
<td>8.9</td>
<td>-</td>
<td>-</td>
<td>6%</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>9</td>
<td>9.5</td>
<td>-</td>
<td>-</td>
<td>6%</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>7</td>
<td>10.7</td>
<td>-</td>
<td>-</td>
<td>11%</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>31L, 31R</td>
<td>31L</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>8.8</td>
<td>-</td>
<td>28%</td>
<td>1%</td>
<td>-</td>
<td>8%</td>
</tr>
<tr>
<td>12</td>
<td>9.4</td>
<td>-</td>
<td>-</td>
<td>8%</td>
<td>-</td>
<td>5%</td>
</tr>
<tr>
<td>11</td>
<td>9.9</td>
<td>-</td>
<td>-</td>
<td>6%</td>
<td>-</td>
<td>2%</td>
</tr>
<tr>
<td>10</td>
<td>10.5</td>
<td>-</td>
<td>-</td>
<td>9%</td>
<td>-</td>
<td>5%</td>
</tr>
<tr>
<td>9</td>
<td>11.0</td>
<td>-</td>
<td>-</td>
<td>8%</td>
<td>-</td>
<td>9%</td>
</tr>
<tr>
<td>7</td>
<td>11.7</td>
<td>1%</td>
<td>-</td>
<td>2%</td>
<td>-</td>
<td>5%</td>
</tr>
<tr>
<td>5</td>
<td>12.3</td>
<td>6%</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>2%</td>
</tr>
<tr>
<td>4</td>
<td>12.6</td>
<td>47%</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>2%</td>
</tr>
<tr>
<td>22L</td>
<td>22R, 31L</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>8.2</td>
<td>-</td>
<td>20%</td>
<td>-</td>
<td>-</td>
<td>5%</td>
</tr>
<tr>
<td>10</td>
<td>10.0</td>
<td>-</td>
<td>-</td>
<td>3%</td>
<td>-</td>
<td>6%</td>
</tr>
<tr>
<td>4</td>
<td>12.4</td>
<td>22%</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>4%</td>
</tr>
<tr>
<td>4R</td>
<td>4L, 31L</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Remarks on Optimal Policies

- Path-dependency: Optimal Policies depend on
  - Prior stochastic evolution of queues
  - Stochastic operational conditions

- Impact of $\tau_I$ on optimal policies, optimal queues and congestion costs

<table>
<thead>
<tr>
<th>$\tau_I$</th>
<th>Expected total cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 minute</td>
<td>Baseline</td>
</tr>
<tr>
<td>5 minutes</td>
<td>+5.77%</td>
</tr>
<tr>
<td>10 minutes</td>
<td>+9.39%</td>
</tr>
<tr>
<td>15 minutes</td>
<td>+13.60%</td>
</tr>
</tbody>
</table>
Comparison with Heuristics

- Priority to arrivals
- Heuristic 1 – no cost of runway configuration switches
- Heuristic 2 – extensive cost of runway configuration switches
- The optimal control results in significant cost savings compared to both heuristics

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>$\tau_I = 0$ minute</th>
<th>$\tau_I = 5$ minute</th>
<th>$\tau_I = 10$ minutes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exact</td>
<td>Baseline</td>
<td>Baseline</td>
<td>Baseline</td>
</tr>
<tr>
<td>Heuristic 1</td>
<td>16.23%</td>
<td>33.49%</td>
<td>66.41%</td>
</tr>
<tr>
<td>Heuristic 2</td>
<td>25.57%</td>
<td>18.42%</td>
<td>15.24%</td>
</tr>
</tbody>
</table>
Comparison with Baseline

- Comparison of optimal queues to 3 baseline policies (Simaiaakis, 2012)

<table>
<thead>
<tr>
<th>Policy</th>
<th>Arrival</th>
<th>Departure</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Balanced Operations</td>
<td>10</td>
<td>10</td>
<td>20</td>
</tr>
<tr>
<td>Arrival Priority</td>
<td>16</td>
<td>6</td>
<td>22</td>
</tr>
<tr>
<td>Departure Priority</td>
<td>6</td>
<td>12</td>
<td>18</td>
</tr>
</tbody>
</table>

- 4th scenario: *Baseline Control*, in which a control among the three above policies is exercised at each period
- These 4 scenarios are typical choices made in macroscopic models of airport congestion at the strategic level
Comparison with baseline

<table>
<thead>
<tr>
<th>Control</th>
<th>$\tau_I = 0$ minute</th>
<th>$\tau_I = 5$ minute</th>
<th>$\tau_I = 10$ minutes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimal Control</td>
<td>Baseline</td>
<td>Baseline</td>
<td>Baseline</td>
</tr>
<tr>
<td>Balanced Operations</td>
<td>+62.94%</td>
<td>+51.94%</td>
<td>+45.37%</td>
</tr>
<tr>
<td>Baseline Control</td>
<td>+40.00%</td>
<td>+30.55%</td>
<td>+24.90%</td>
</tr>
</tbody>
</table>
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Conclusion

- Dynamic airport congestion management tool at the tactical level
- Combination of queue stochasticity within this framework
- Exact and approximate algorithms
- Implementation at JFK
  - Path-dependency of optimal policy
  - Impact on arrival and departure queues
  - Significant cost savings compared to heuristics
- Optimal capacity utilization does not eliminate flight delays if scheduling levels are too high
- Use in strategic delay modeling as a way to control arrival and departure service rates
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Research Overview

LONG TERM

- Capacity Planning

SHORT TERM

- Capacity Allocation
- Capacity Utilization
Question: How can flight schedules be strategically modified to mitigate flight delays?

Demand Smoothing Model (Pyrgiotis and Odoni, 2013):
- Imposes “mild” schedule limitations
- Minimizes flight displacement
- Maintains aircraft connections
- Maintains passenger connections

Fix schedule limitations
Minimize Schedule Displacement
Subject to Schedule Limitations Constraints
Quantifies effects on flight delays
## Demand Smoothing: Effects

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Limits</th>
<th>Maximal Displacement</th>
<th>Total Displacement</th>
<th>Average Queuing Delay</th>
<th>Change from Baseline</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original</td>
<td>--</td>
<td>0</td>
<td>0</td>
<td>20.3 min / flight</td>
<td>--</td>
</tr>
<tr>
<td>Scenario 1</td>
<td>20, 20, 20, 20, ...</td>
<td>1</td>
<td>359</td>
<td>18.3 min / flight</td>
<td>-10%</td>
</tr>
<tr>
<td>Scenario 2</td>
<td>20, 19, 20, 19, ...</td>
<td>2</td>
<td>533</td>
<td>16.5 min / flight</td>
<td>-18.8%</td>
</tr>
<tr>
<td>Scenario 3</td>
<td>19, 19, 19, 19, ...</td>
<td>2</td>
<td>1,010</td>
<td>14.7 min / flight</td>
<td>-27.8%</td>
</tr>
</tbody>
</table>

![Graph showing number of scheduled flights vs. hour](Image)

![Graph showing delays vs. hour](Image)
Demand Smoothing: Extensions

- Objective: Including delay reduction objectives within the scheduling model
- Simulation of Level 2 Coordination
  - Airlines submit their schedules to a schedule coordinator
  - Schedule coordinator suggests schedule adjustments
- Integration of stochastic queue dynamics within the scheduling model

Fix delay reduction objectives

Minimize Schedule Displacement
Subject to Delay Constraints

Quantifies effects on flight delays
Future Steps?

Objective: Integrating airline competition within this scheduling algorithm

Possible questions:
- Mechanism design: Do airlines have the proper incentives to reveal their preferences?
- Game theory: Schedule planning & timetable development under airline competition and airport congestion constraints
Applications to Capacity Planning

- CLT: New runway opened on 01/06/2010
- Cost: $325 million – 40% government, 60% passengers
- Question: Capacity Expansion vs. Demand Smoothing?
Impact on Flight Delays

Arrival Queue Length

Baseline
Schedule Limitations
Capacity Expansion

Departure Queue Length

Baseline
Schedule Limitations
Capacity Expansion

Hour

5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
Thank you!

Questions?