Predicting & Quantifying Risk in Airport Capacity Profile Selection for Air Traffic Management

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Motivation

• NASA’s Integrated Demand Management (IDM) program is exploring CTOP to precondition demand into time-based metering programs at Newark airport

• Estimates from strategic decision support systems (TFMS) may be inconsistent with delivery capability of tactical decision support systems (TBFM)

• Good estimates of airport capacity are needed to effectively control demand to the appropriate level

• Proposed Approach
  – Leverage weather translation tools and algorithms to estimate airport capacity
  – Provide quantification of the uncertainty associated with the estimate
  – Develop TMI planning models that account for uncertainty
Need for Improved Airport Acceptance Rate (AAR) Decision Support

- Currently no common, quantitative, objective basis for AAR planning forecasts
  - Existing resources (HRRR, ITWS TWINDS, CoSPA winter weather) not fully leveraged

- Ineffective strategic planning results in disruptive ground stops / TRACON holding, Miles-in-trail or under-delivery of aircraft to airports

- Primary Decision Support Benefits
  - Improved airport planning reduces need for ground stops, airborne holding and TMI revisions
  - Enables efficient post-event reutilization of airport capacity
  - Common, objective guidance improves coordination, likelihood of airline acceptance of TMI

**Convective and winter weather**

**Low ceilings and visibility**

**Winds: Arrival compression and configuration changes**

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HRRR = High Resolution Rapid Refresh model
ITWS TWINDS = Integrated Terminal Weather System
CoSPA = Consolidated Storm Prediction for Aviation
TMI = Traffic Management Initiative
Traditional Approach to AAR Planning

- Scenario-Based approach provides decision maker with recommended AAR based on TAF, historical capacity and flight demand
  - Suffers from dimensionality
  - Frequently ignores demand uncertainty
  - Model assumptions may not be transparent to the decision maker
Proposed Approach to AAR Planning

- Quantile-based AAR planning model
  - Airport capacity derived from quantiles of a distribution
  - Decisions associated with specific risk tolerance
  - Reduced dimensionality wrt capacity
  - Incorporates demand uncertainty
  - Evaluates quality of profiles in terms of risk and operational cost
Research Contributions

• Quantile-based AAR planning model
  – Airport capacity derived from quantiles of a distribution
  – Decisions associated with specific risk tolerance
  – Reduced dimensionality wrt capacity
  – Incorporates demand uncertainty
  – Evaluates quality of profiles in terms of risk and operational cost
Airport Acceptance Rate (AAR) Prediction

- Airport capacity is an uncertain forecast into the future
Under-Delivery

- If actual AAR exceeds planned AAR: may under-deliver

- Incur costs due to unused airspace capacity and unnecessary ground delays
Over-Delivery

- If actual AAR is less than planned AAR: may over-deliver

- May need tactical intervention (e.g. holding, miles-in-trail restrictions)

- Incur costs due to airborne delay, diversion, …
• To quantify AAR uncertainty, we apply quantile estimates:
  For example, 80\% quantile estimate $\rightarrow$ at least 80\% of
  future (actual) observations will lie above estimate
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Goal: Find the profile that best matches the planned AAR to the observed AAR to minimize total cost of ground and airborne delay.
AAR Planning Model

Inputs:
- List of flights and scheduled times of arrival
- List of Historical Days for TMI intervention

Quantify Demand and Capacity Uncertainty

Inputs:
- Baseline Features
- Site Adaptation Derived Features
AAR Planning Model

Inputs:
- List of flights and scheduled times of arrival
- List of Historical Days for TMI intervention

Problem 1 (Machine Learning)
Quantify Model Uncertainty
- Estimate Airport Capacity Quantiles
- Generate Airport Demand perturbations by sampling from historical data

Capacity Quantiles And Demand Scenarios

Inputs:
- Baseline Features
- Site Adaptation Derived Features
AAR Planning Model

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- List of flights and scheduled times of arrival
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Find best capacity profile to set the planned AAR

Inputs:
- Baseline Features
- Site Adaptation Derived Features
AAR Planning Model

Problem 1 (Machine Learning)
Quantify Model Uncertainty
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Problem 2 (Optimization)
Objective: Minimize total expected cost of ground and air delay
- All flights scheduled to take off must either take-off or be delayed on ground
- All scheduled arrivals that have taken off must land at their scheduled times or be delayed in the air
- Number of arrivals can’t exceed the assigned capacity (based on quantile estimate)
- Decision Variable: Number of flights that take off in a given time period

Inputs:
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AAR Prediction Framework

• Leverage features from terminal weather forecast products
• Derive site-specific features from winds aloft along the arrival routes
• Estimates are informed based on information about previous states
• One of the best predictors of the current state is the previous state

• Propagate airport capacity state information forward through estimates until we reach the hour of interest
AAR Estimation Model Features

- Wind Speed and Direction
- Wind Gusts
- Ceiling and Visibility
- Demand (Flight Schedule)
- Time of Day
- Estimates of the previous state
  - AAR
  - ADR
  - VMC vs IMC Conditions
Site Adaptation and Derived Features

- DCB headwind
- DCB-to-surface headwind difference
- Mergepoint-to-DCB headwind difference
- Headwind at TRACON entry capture box
- Maximum merge headwind difference
- Maximum STAR-to-DCB difference
- Maximum segment gain
- Maximum compression segment headwind gain
Analysis Conditions

- Data Sources: ASPM, TAF, HRRR, NTML
- Airport: EWR
- Training Data: October through December 2013
- Test Data: January through March 2014
- Method: Gradient Tree Boosting Regression
- Software: Python with Scikit-Learn package
- Two Cases
  - All Days
  - Days in which Ground Delay Programs (GDPs) were imposed
    - Identified with NTML data
    - Trained on GDP days
    - 8 test days
- Estimated AAR and quantiles to quantify uncertainty
Accuracy of AAR estimates is high and remains stable with increasing forecast horizon.

GDP scoring was lower as there was greater consistency on GDP days.
• Prediction intervals behave as expected
• Forecast horizon makes no difference
• Tighter width for GDP due to smaller range of capacity values
Prediction Interval Variation with Size on GDP Days

- Prediction Interval Coverage is larger than interval size for intervals of 70% or less as AAR is concentrated at a few discrete values
- Large growth in interval width beyond 90%
  - May have less value to the user
  - Leads to very conservative solutions with lots of planned ground delay

<table>
<thead>
<tr>
<th>Prediction Interval Size</th>
<th>PIC</th>
<th>PIW</th>
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</thead>
<tbody>
<tr>
<td>50%</td>
<td>71.5%</td>
<td>2.05</td>
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<tr>
<td>60%</td>
<td>77.3 %</td>
<td>2.11</td>
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<tr>
<td>70%</td>
<td>80.2%</td>
<td>3.60</td>
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<tr>
<td>80%</td>
<td>81.5%</td>
<td>3.71</td>
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<tr>
<td>90%</td>
<td>86.5%</td>
<td>6.18</td>
</tr>
<tr>
<td>95%</td>
<td>94.2%</td>
<td>15.6</td>
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Inputs:
• Baseline Features
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AAR Costs: Under-delivery

Cost

Cost of Under-Delivering

C_{under}

Percentile

Predicted high capacity

Predicted low capacity
AAR Costs: Over-delivery

- Predicted high capacity
- Predicted low capacity

Cost of Over-Delivering
Aggregated AAR Costs

\[ C_{\text{total}} = C_{\text{over}} + C_{\text{under}} \]

- Predicted high capacity
- Predicted low capacity
Optimized AAR Costs

Predicted high capacity

Predicted low capacity
Applying Profiles to AAR planning

- AAR prediction model quantiles inserted into AAR planning model
- AAR planning model run in a number of different test configurations

<table>
<thead>
<tr>
<th>Test Cases Examined</th>
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<tbody>
<tr>
<td>Parameter</td>
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<tr>
<td>Air-to-Ground delay cost ratio</td>
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<tr>
<td>Airport Capacity profiles</td>
</tr>
<tr>
<td>Number of Scheduled Arrivals</td>
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<tr>
<td>Flight Schedule</td>
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<tr>
<td>Demand Scenarios</td>
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<td></td>
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<td>TMI Types</td>
</tr>
</tbody>
</table>
Individual GDP Costs

- Cost generally increases with percentile
- Level is somewhat stable between 80\textsuperscript{th} and 85\textsuperscript{th} percentiles

Variation in costs with capacities ignoring profile mismatch.
Profile mismatch imposes significant additional cost at 75\textsuperscript{th} percentile.

Trend is more pronounced when the cost of fuel increases.

Cost of delay is minimized using the 80\textsuperscript{th} percentile profile.

Variation in costs over all GDPs with capacities including cost of profile mismatch.
Aggregated GDP Costs

- Profile mismatch imposes significant additional cost at 75\textsuperscript{th} percentile
- Trend is more pronounced when the cost of fuel increases
- Cost of delay is minimized using the 80\textsuperscript{th} percentile profile

Variation in costs over all GDPs with capacities including cost of profile mismatch.
Summary and Future Work

• Developed a new model for AAR assignment
  – Site adaptation incorporates effects of winds aloft and compression
  – Quantile estimation of capacity: transparent representation of uncertainty
  – Methodology accounts for influence schedule drift
  – Currently, planning models must be tailored to specific types of TMLs

• Future enhancements
  – Improved GDP / Ground Stop classification will support better parameter tuning
    • Accurate classification of days will support better parameter tuning
    • Facilitates a more general airport decision support capability
  – GDP and GS models could run simultaneously to provide different options which decision makers could evaluate based on preferences for strategic vs tactical intervention
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