Application of reinforcement learning algorithms for predicting taxi-out times

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Structure of the presentation

1) Introduction and problem definition

2) Modeling the taxi-out time estimation problem using approximate dynamic programming (reinforcement learning)

3) Prediction accuracy results
   a. Individual flights
   b. Average in 15 minute intervals of the day

4) Overview of the research methodology
Taxi-out time predictions: Java interface

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Taxi-out time prediction: motivation

- Taxi-out time (duration between gate-pushback and takeoff) contributes to 20% of total flight delay (FAA report).

- In order to minimize taxi-out delay it is necessary to first predict taxi time under dynamic airport conditions.

- Major benefits of accurately predicting taxi-out times:
  - Congestion mitigation by avoiding near-capacity operations (DOT)
  - Emissions compliance through optimal adjustment of departure schedules (NAAQP)
  - Reduction in returns to the gate for refueling (Dalton personnel communication)
  - Efficient resource utilization (ground personnel, gates) (NextGen)
  - Estimated departure clearance time compliance (Sherry and Belle, 2008)
Need for a stochastic dynamic approach

The FAA is looking towards a modernized ATC system with increased automation (NextGen, JPDO):

- Predictions in real-time, as the system evolves.
- Method that is adaptive to changing airport dynamics
- Due to uncertainties involved, and the complex nature of airport operations, it is often difficult to obtain mathematical models to completely describe airport dynamics.

The above can be addressed using reinforcement learning (a strand of stochastic dynamic programming):

- The problem of sequential prediction is well-suited to the stochastic dynamic programming formulation
- RL is a model free approach that is adaptive to changing airport dynamics.
- RL learns by interacting with the environment (alleviating need for good training data in neural networks).
- Suitable for large-scale optimization due to its simple recursive formulation.
# Comparison of stochastic dynamic programming method with literature

<table>
<thead>
<tr>
<th>Year, author</th>
<th>Approach</th>
<th>Data range/airport</th>
<th>Data used</th>
<th>Additional information</th>
</tr>
</thead>
<tbody>
<tr>
<td>Idris et al. (2002)</td>
<td>Queueing model</td>
<td>BOS, August 1998</td>
<td>ASPM, downstream restrictions, PRAS</td>
<td>Predictions are not a-priori of pushback</td>
</tr>
<tr>
<td>Signor and Levy (2006)</td>
<td>Bi-variate quadratic regression</td>
<td>DTW</td>
<td>Surface surveillance</td>
<td>Taxi-out time defined from ramp area/spot to takeoff</td>
</tr>
<tr>
<td>Futer (2006)</td>
<td>Running average</td>
<td>Used by the FAA at several airports</td>
<td>ETMS (based on flight plan)</td>
<td></td>
</tr>
</tbody>
</table>

**Acronyms:**
- **PRAS**: Preferential Runway Advisory System
- **ASPM**: Aviation System Performance Metrics
- **ETMS**: Enhanced Traffic Management System
- **FAA**: Federal Aviation Administration

**Additional Information:**
- BOS: Boston Logan International airport
- DTW: Detroit International airport
- JFK: John F. Kennedy International airport
Data Source

- OOOI (Out, Off, On, In) data from the Aviation System Performance Metrics (ASPM) database maintained by the Federal Aviation Administration (FAA) was used.

Snapshot of the ASPM data (Departing and Arriving Flights)

<table>
<thead>
<tr>
<th>FLTNO</th>
<th>SCHOUTTM</th>
<th>ACTOUTTM</th>
<th>NOMTO</th>
<th>ACTTO</th>
<th>SCHOFFTM</th>
<th>ACTOFFTM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flight Number</td>
<td>Scheduled Out time</td>
<td>Actual Out time</td>
<td>Nominal TO time</td>
<td>Actual TO time</td>
<td>Scheduled Off time</td>
<td>Actual Off time</td>
</tr>
<tr>
<td>275</td>
<td>07:19</td>
<td>07:30</td>
<td>14.4</td>
<td>13</td>
<td>07:33</td>
<td>07:43</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>ACTONTM</th>
<th>NOMTI</th>
<th>ACTTI</th>
<th>ACTINTM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual On time</td>
<td>Nominal Ti time</td>
<td>Actual Ti Time</td>
<td>Actual In Time</td>
</tr>
<tr>
<td>10:11</td>
<td>5.5</td>
<td>6</td>
<td>10:17</td>
</tr>
</tbody>
</table>

This research does not use surface surveillance (track) data
Stochastic Dynamic Programming Formulation

\[ V(S_t) = \min_x [C(S_t, x) + \gamma E[V(S_{t+1})]] \]

\[ \gamma \text{ is a fixed discount parameter} \]
\[ C = \text{Error} = |\text{actual TO} - \text{predicted TO}| \]

Learning version based on Q-factors

\[ Q(S, x) = (1 - \alpha)Q(S, x) + \alpha [C(S, x) + \gamma \{\min_b Q(S, b)\}] \]

\[ C(S, x) = |\text{actual TO} - \text{predicted TO}| \]
\[ \alpha \text{ is the learning parameter} \]

\[ V(S) = \min_x Q(S, x) \]

Taxi-out time prediction Implementation
Implementation - RL Estimating Taxi-out

1. Map dynamics of airport system from t to t+60 min
2. For every flight in t to t+15, calculate system state S
   S={s1,s2,s3}
3. Predict its taxi-out, using RL estimator
4. Predicted taxi-out values
5. Actual taxi-out values
6. Immediate Reward C = |Actual-Predicted| (output)
7. Update Utility Function (Reward), Q(S,x)
8. Learning loop

Reinforcement Learning Functional Block Diagram

Taxi-out time prediction Implementation
Learnt phase of the Q-Learning Approach

- To obtain taxi-out time prediction for a flight,
  - Identify its system state
  - Look for smallest non-zero Q value in corresponding row
  - The corresponding prediction $x^*$ is the taxi-out time estimate

$S = \{s_1, s_2, s_3\}$

$x$ (prediction values in minutes)

$\text{minimum } Q(S, x)$

$x^*$

Q matrix
Airports analyzed

- DTW (Detroit International)
- JFK (John F. Kennedy International)
DTW: Detroit International airport

- Days used for learning –
  - Scenario 1: March-August (Spring-Summer)
  - Scenario 2: September – February (Fall-Winter)

- In each scenario, 42 days were selected at random for testing

- Years studied:
  - September 2005 – August 2008
Daily airport analysis: percentage prediction accuracy within ± 4 min, DTW airport

Results: Detroit International Airport (DTW)
### Daily airport analysis: percentage prediction accuracy, DTW airport

#### Average prediction accuracy in 15 min intervals of the day

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Date</strong></td>
<td>Dec 15th</td>
<td>Dec 4th</td>
</tr>
<tr>
<td><strong>Prediction accuracy within ± 4 min (%)</strong></td>
<td>53.62</td>
<td>68.12</td>
</tr>
</tbody>
</table>
DTW airport: Daily taxi-out time standard deviation (Fall-Winter)

Source: ASPM database, FAA

Results: Detroit International Airport (DTW)
DTW airport behavior, December 5, 2007

Data source: ASPM

Results: Detroit International Airport (DTW)
JFK: John F. Kennedy International airport (challenges)

- Literature (Andrew Compart, Aviation Week) suggests that
  - Percentage of on-time departures at JFK is about 65% (both in July 2007 and July 2008)
  - On time departure performance worsened significantly in the late-afternoons and evenings.
- Wide variations in taxi-out times across a single day (about 20 min to as high as 130 min)

<table>
<thead>
<tr>
<th>Airport</th>
<th>Date</th>
<th>Mean of actual TO times (min)</th>
<th>Standard deviation of actual TO times (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DTW</td>
<td>29th Jan 2006</td>
<td>17.9</td>
<td>8.9</td>
</tr>
<tr>
<td>DTW</td>
<td>27th Jul 2006</td>
<td>17.1</td>
<td>8.2</td>
</tr>
<tr>
<td>JFK</td>
<td>4th Jul 2007</td>
<td>31.0</td>
<td>14.2</td>
</tr>
<tr>
<td>JFK</td>
<td>4th Dec 2007</td>
<td>37.3</td>
<td>19.5</td>
</tr>
</tbody>
</table>
JFK airport: actual operations

December 4th, 2007

Results: John F. Kennedy International Airport (JFK)
JFK: John F. Kennedy International airport

- Days used for learning –
  - Scenario 1: May-October
    - 42 days were selected at random for testing
    - Years studied: 2007, 2008
  - Scenario 2: April-November
    - 10 days were selected at the end of the period for testing
    - Years studied: 2007

Results: John F. Kennedy International Airport (JFK)
Daily airport analysis: percentage prediction accuracy within accuracy of ± 5 min and ± 8 min, JFK airport

Individual flight prediction accuracy across 42 days of testing

![Graph showing individual flight prediction accuracy across 42 days of testing for May 07 - Oct 07 and May 08 - Oct 08. The graph compares prediction accuracy within 5 min and within 8 min accuracy.](image)

Results: John F. Kennedy International Airport (JFK)
Average prediction accuracy in 15 min intervals of the day

<table>
<thead>
<tr>
<th>Year 2007 Date</th>
<th>Time Period of Day</th>
<th>Dec 5th</th>
<th>Dec 7th</th>
<th>Nov 29th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prediction accuracy within ± 5 min (%)</td>
<td>Before 4:00 P.M.</td>
<td>67.50</td>
<td>77.50</td>
<td>100.00</td>
</tr>
<tr>
<td></td>
<td>After 4:00 P.M.</td>
<td>41.38</td>
<td>58.62</td>
<td>55.17</td>
</tr>
<tr>
<td></td>
<td>Across Whole Day</td>
<td>56.52</td>
<td>69.57</td>
<td>81.16</td>
</tr>
</tbody>
</table>
JFK airport: Effect of ADR, Change in runway configuration

Data source: ASPM
(Observations based on viewing AEROBAHN®, Sensis Corporation)
Macro-view of the research

Sequential decision making

Mathematical Programming

Dynamic Programming
(Markov decision process)

Approximate DP

Curse of modeling arises due to need for transition probabilities
Suitable for deterministic problems and small scale problems

Classical DP

Q-learning
Explicit Storage

Value function
(Reward learning)

Value function Approximation
(Approach for large scale problems)

Aggregation
Interpolation
Function fitting

Linear, nonlinear, piecewise linear, neural networks

Diffusion Wavelets
Thank you!
Results - Prediction Accuracy of average TO in 15 min intervals

Predicted taxi-out times
Flights Predicted to takeoff
Actual observed taxi-out (takeoff)
Flights that Actually took-off
This is indicative of how well airport behavior is predicted in advance

Implementation
Adapting RL to Taxi-out Prediction

- Markov Chain: The evolving airport system dynamics is perceived as a Markov chain (i.e. Future system state depends on the present system state and not on the past)

- Markov Decision Process: A taxi-out time prediction \( x \) is made 15 minutes before scheduled gate departure of a flight based on a system state \( S \) (explained later)

- The objective is to find the best prediction in every state \( S \), which minimizes the error in prediction

- The above is modeled as a stochastic dynamic programming problem
Macro-view of analysis

Taxi-out time estimation (TOTE)

Regression model for TOTE

Q-learning
(explicit storage of Q-matrix)

Approximate Dynamic Programming model

Value function
(Reward learning)

Value function Approximation (VFA)
(for large state spaces)

Diffusion wavelets
(for large and multi-dimensional state spaces)
DTW airport: individual flight prediction accuracy within ± 4 min

Results: Detroit International Airport (DTW)
JFK airport: individual flight prediction accuracy within ± 8 min

Results: John F. Kennedy International Airport (JFK)
Future work

- Expansion of the state space for the taxi-out time estimation model, to include features such as day of the week and forecasted weather information.

- Application of wavelet analysis for detection of anomalies in the airport departure process data, to gain a better understanding of taxi-out time behavior.
Future work

- Use of taxi-out predictions as inputs to a decision making problem for departure sequencing and downstream adjustments.

Ideally,
Future work: Surface Surveillance Data

Surveillance data supplements ASPM data by providing detailed information on nominal taxi times between specific gate/ramp area and runway pairs.

**Implications:**

- Improved accuracy of the RL algorithm in determining when a flight enters the runway queue
- More accurate predictions on an individual flight basis
- More precise records of OOOI event times which are more readily accessible than proprietary data (from airlines for example)