Prediction of Pushback Times and Ramp Taxi Times for Departures at Charlotte Airport

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Outline

• Introduction

• Data analysis
  – Pushback time
  – Ramp taxi time

• Data-driven prediction models

• Evaluation using machine learning algorithms

• Conclusions
• Taxi-out time prediction
  – Require to obtain takeoff time input for runway scheduling
  – Have focused on total taxi time prediction from gate to runway

• Taxi-out time calculation

Taxi-out time = Pushback time + Ramp transit time + AMA transit time

➢ Lack of accurate data for pushback time and ramp transit time
• Airspace Technology Demonstration 2 (ATD-2) project
  – For the integrated arrival, departure, and surface traffic management capabilities
  – Deployed the ATD-2 systems at Charlotte airport in 2017
• Ramp controller input data available since 10/2017
  – Through Ramp Traffic Console (RTC)
  – Manual input for pushback approval and taxi clearance

➤ Can obtain accurate pushback time and ramp taxi time, which can be used for taxi time prediction
Pushback Time and Ramp Taxi Time
Data Analysis for Charlotte Airport (CLT)
• Actual flight data used for prediction and evaluation
  – One-month data at CLT: 8/1/2018 ~ 8/31/2018
  – 24,642 departures and 24,962 arrivals

• Data filtering

After data filtering, we have 20,595 departures (83.6%) for pushback time analysis and 21,093 departures (85.6%) for ramp transit time analysis.
Pushback processes include pushback by tug, engines spooling, communication delay between pilot and ground crew, and so on.

### Pushback Time Distribution

<table>
<thead>
<tr>
<th>Pushback time</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>4.72 min</td>
</tr>
<tr>
<td>Median</td>
<td>4.33 min</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>2.27 min</td>
</tr>
</tbody>
</table>

![Histogram showing actual pushback time distribution](image)
Pushback times vary, mainly depending on **aircraft type** and ramp area (gate groups).
Pushback times vary, mainly depending on aircraft type and **ramp area** (gate groups).
Ramp taxi time depends on taxi distance and congestion

- Long taxi distance for westbound flights from concourse E
- Surface traffic congestion and complexity inside the ramp
Data-Driven Prediction Models for Pushback Time and Ramp Taxi Time
Decision Tree Model for Pushback Time Prediction

- Decision Tree (DT) model based on historical data, using two main criteria
  - Ramp area
  - Aircraft type
• Decision Tree (DT) model provides good prediction performance
• Prediction errors come from uncertainties in pushback processes

<table>
<thead>
<tr>
<th>Prediction errors</th>
<th>DT model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>0.37 min</td>
</tr>
<tr>
<td>Median</td>
<td>0.00 min</td>
</tr>
<tr>
<td>RMSE</td>
<td>2.24 min</td>
</tr>
<tr>
<td>Within ± 1min</td>
<td>52.1%</td>
</tr>
<tr>
<td>Within ± 3min</td>
<td>89.8%</td>
</tr>
</tbody>
</table>
• Assume a constant taxi speed in the ramp area
• Data Driven (DD) model calculates ramp transit times using a median ramp taxi speed (6.6knot) on the given taxi distance along standard taxi routes
Prediction Model Evaluation Using Machine Learning Algorithms
### Machine Learning Algorithms

- Six machine learning algorithms tested for comparison
  - Linear Regression (LR)
  - Support Vector Regression (SVR)
  - Lasso linear regression (Lasso)
  - \textit{k}-Nearest Neighbors (\textit{kNN})
  - Random Forest (RF)
  - Neural Networks (NN)

- Coded using \textit{sklearn} (scikit-learn) library in Python
- Training and test dataset from the actual data at CLT in August 2018
Features for Pushback Time Prediction

- **Ramp area** (gate groups): 18 binary variables
- Carrier: 23 binary variables
- **Aircraft type**: 23 binary variables
- Pushback time of day (in hour)
- Gate conflict: binary
- Traffic Management Initiative restrictions: 2 binary variables
  - Approval Request (APREQ)
  - Expect Departure Clearance Times (EDCT)

 gö Total 68 features defined and used for running machining learning algorithms
Pushback Time Prediction Accuracy Comparison

<table>
<thead>
<tr>
<th>Method</th>
<th>LR</th>
<th>SVR</th>
<th>Lasso</th>
<th>kNN</th>
<th>RF</th>
<th>NN</th>
<th>DT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (min)</td>
<td>0.00</td>
<td>0.39</td>
<td>-0.01</td>
<td>0.05</td>
<td>0.00</td>
<td>-0.01</td>
<td>0.37</td>
</tr>
<tr>
<td>RMSE (min)</td>
<td>2.19</td>
<td>2.28</td>
<td>2.22</td>
<td>2.37</td>
<td>2.25</td>
<td>2.20</td>
<td>2.24</td>
</tr>
<tr>
<td>Within ± 1min</td>
<td>47.9%</td>
<td>49.4%</td>
<td>45.4%</td>
<td>45.8%</td>
<td>47.9%</td>
<td>47.4%</td>
<td>52.1%</td>
</tr>
<tr>
<td>Within ± 3min</td>
<td>90.6%</td>
<td>89.1%</td>
<td>90.4%</td>
<td>87.7%</td>
<td>89.3%</td>
<td>90.5%</td>
<td>89.8%</td>
</tr>
</tbody>
</table>
Features for Ramp Transit Time Prediction

- Ramp area (gate groups): 18 binary variables
- **Spot**: 25 binary variables
- Carrier: 23 binary variables
- Aircraft type: 23 binary variables
- **Runway configuration**: 3 binary variables
- Pushback time of day (in hour)
- Gate conflict, APREQ, EDCT: 3 binary variables
- **Ramp taxi distance**: a dominating factor for ramp transit time
- **Number of departures taxiing in the ramp**: to account for ramp congestion level
- **Number of arrivals taxiing in the ramp**: to account for ramp congestion level

- Total 99 features defined and used for running machining learning algorithms
## Ramp Transit Time Prediction Accuracy Comparison

### Prediction Accuracy (Actual - Predicted) (in minutes)

<table>
<thead>
<tr>
<th>Model</th>
<th>LR</th>
<th>SVR</th>
<th>Lasso</th>
<th>kNN</th>
<th>RF</th>
<th>NN</th>
<th>DD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (min)</td>
<td>0.02</td>
<td>1.29</td>
<td>0.00</td>
<td>0.13</td>
<td>-0.01</td>
<td>0.04</td>
<td>0.07</td>
</tr>
<tr>
<td>RMSE (min)</td>
<td>3.56</td>
<td>4.36</td>
<td>3.60</td>
<td>3.80</td>
<td>3.54</td>
<td>3.52</td>
<td>4.00</td>
</tr>
<tr>
<td>Within ± 1min</td>
<td>37.7%</td>
<td>40.2%</td>
<td>37.3%</td>
<td>41.7%</td>
<td>43.0%</td>
<td>41.1%</td>
<td>37.4%</td>
</tr>
<tr>
<td>Within ± 3min</td>
<td>80.9%</td>
<td>79.2%</td>
<td>80.8%</td>
<td>78.5%</td>
<td>81.7%</td>
<td>81.1%</td>
<td>76.4%</td>
</tr>
</tbody>
</table>
Conclusions

• Data-driven prediction models developed for pushback and ramp transit time prediction at CLT
  – Pushback time prediction using a decision tree by ramp area and aircraft type
  – Ramp transit time prediction based on the median taxi speed and the standard taxi distance
  – Showed the similar prediction performance to machine learning algorithms

• These simple models can be
  – Used in real-time operations systems, with acceptable prediction accuracy
  – Applied to other airports, if high quality data are available
Thank You

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Backup
ATD-2 Concept

• To develop the Integrated Arrival, Departure, and Surface (IADS) traffic management capabilities
Taxi-Out Time of Departures

- Taxi time calculation for departures

\[
\text{Taxi-out time} = \text{Pushback duration} + \text{Ramp transit time} + \text{AMA transit time}
\]

- Lack of accurate data for pushback time and ramp transit time
• Decision Tree (DT) model provides good prediction performance
• Default model using a median pushback time value (260sec) also shows similar results
• A weak positive correlation between ramp transit time and the number of departures and arrivals in the ramp