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

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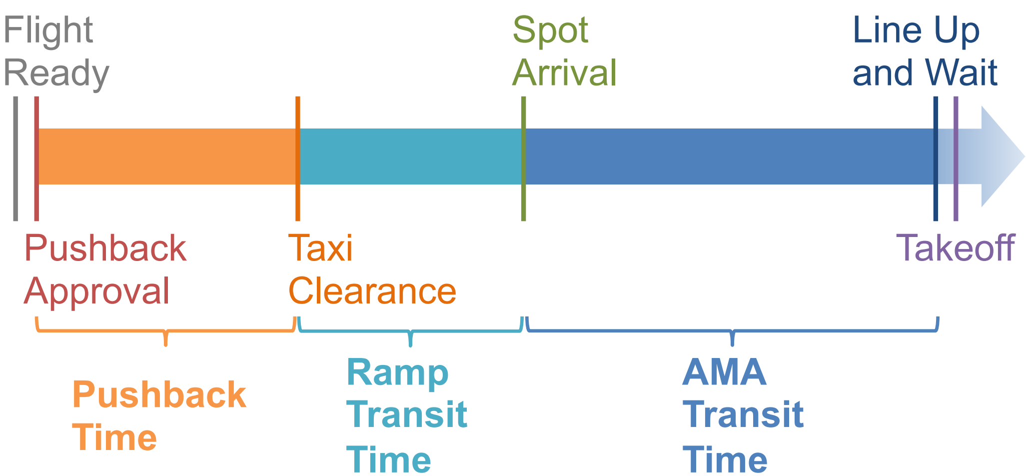
Outline

- Introduction
- Data analysis
  - Pushback time
  - Ramp taxi time
- Data-driven prediction models
- Evaluation using machine learning algorithms
- Conclusions

Taxi-Out Time of Departures

- 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

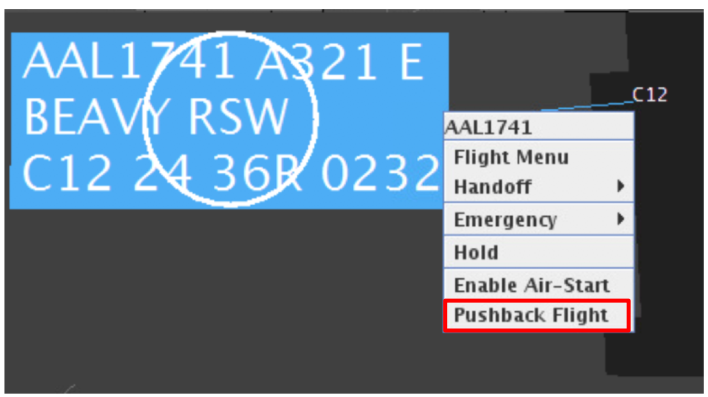
Taxi-out time = Pushback time + Ramp transit time + AMA transit time

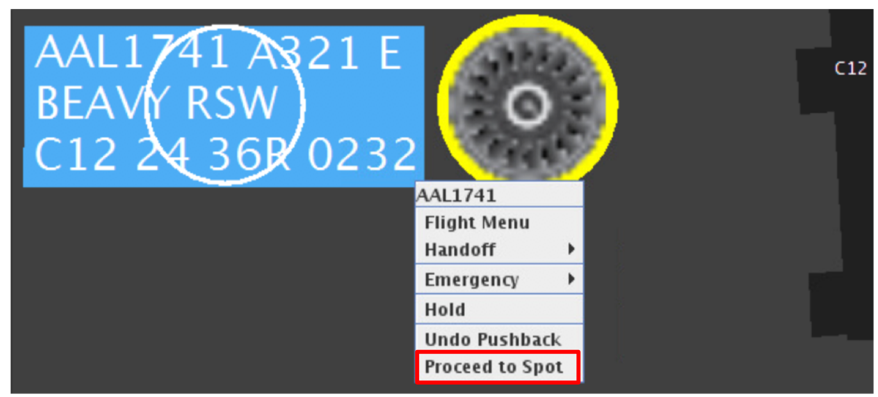


➢ Lack of accurate data for pushback time and ramp transit time

Accurate Data Available from ATD-2

- 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)

Data

- 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

Departures only — actual pushback times and spot times

Ramp controller input — pushback approval and taxi clearance

Valid flight state — no canceled/return to gate/suspended/unknown

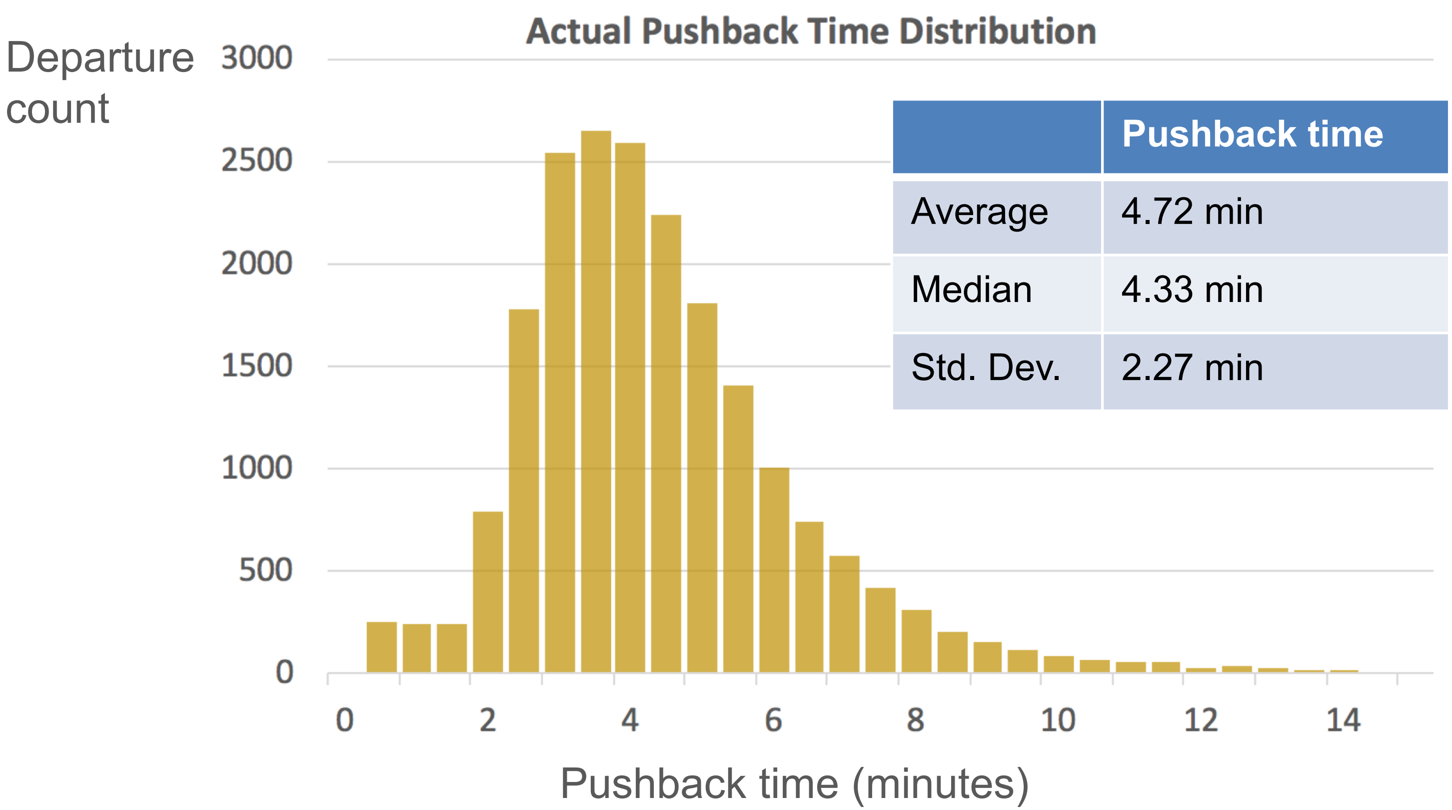
Valid time value — 30sec <= pushback or ramp transit time < 1hr

➢ 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 Time Distribution

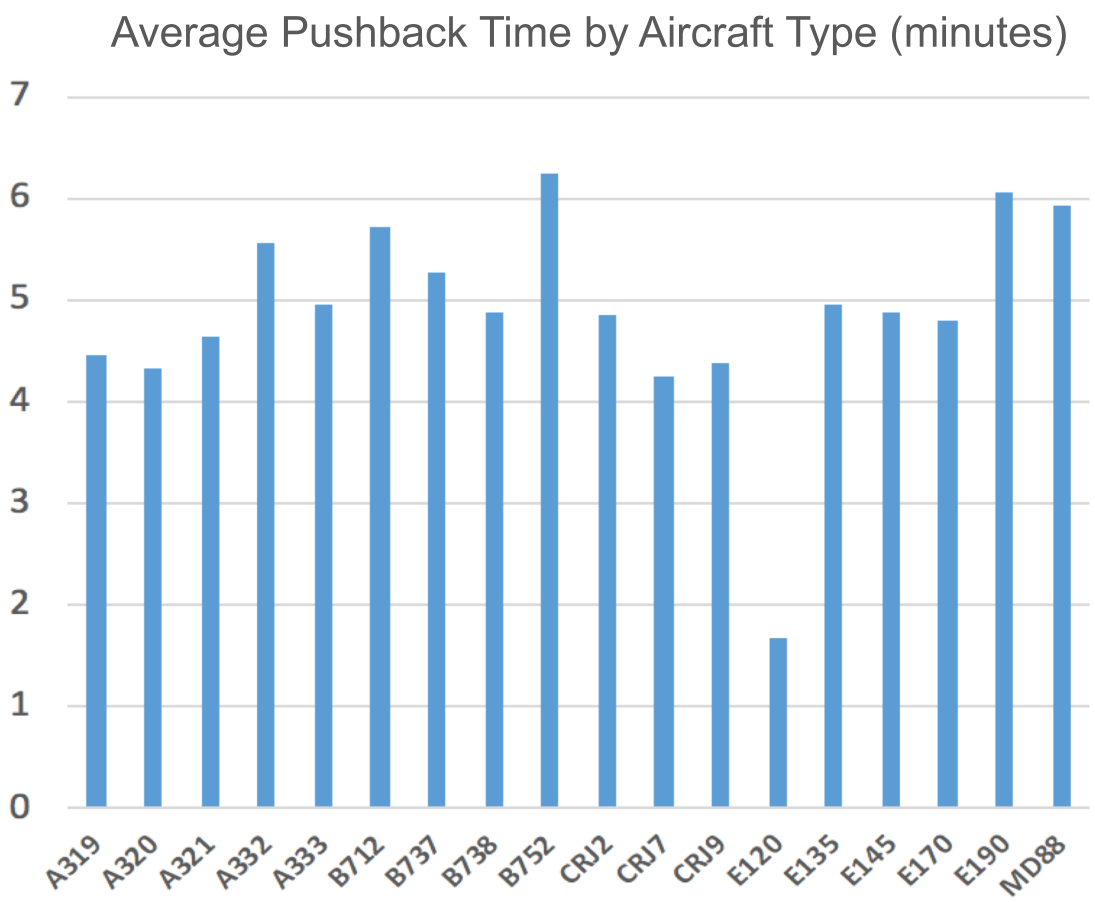
- Pushback processes include pushback by tug, engines spooling, communication delay between pilot and ground crew, and so on



	Pushback time
Average	4.72 min
Median	4.33 min
Std. Dev.	2.27 min

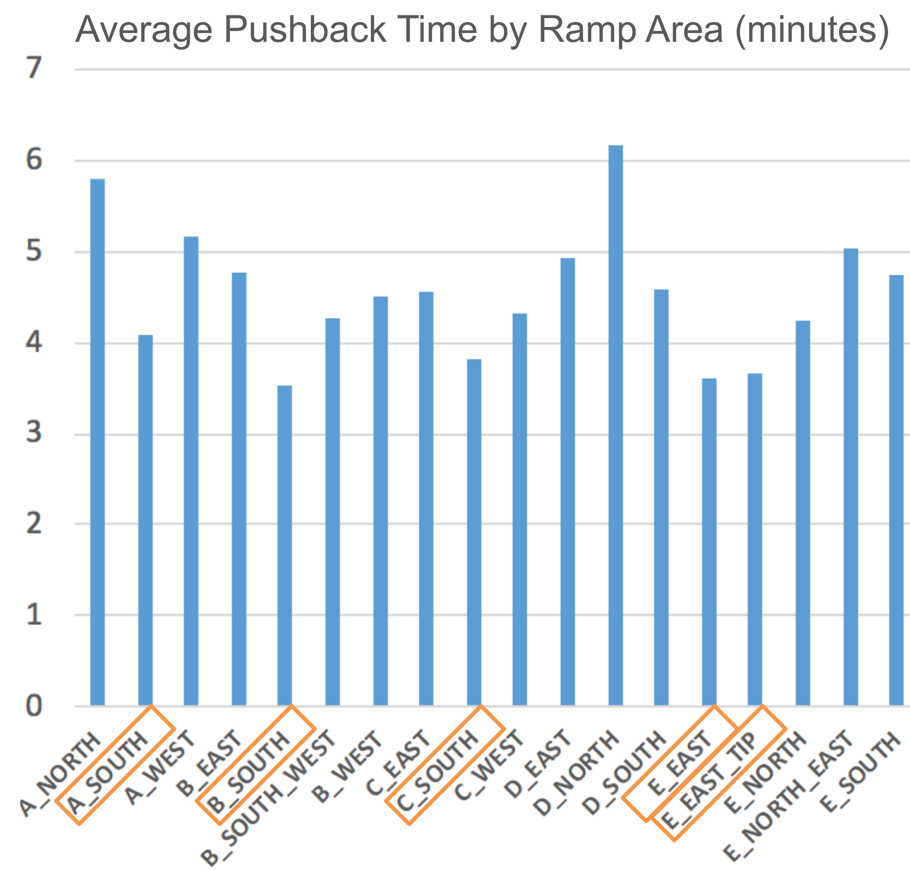
Pushback Time Variations by Aircraft Type

- Pushback times vary, mainly depending on **aircraft type** and ramp area (gate groups)



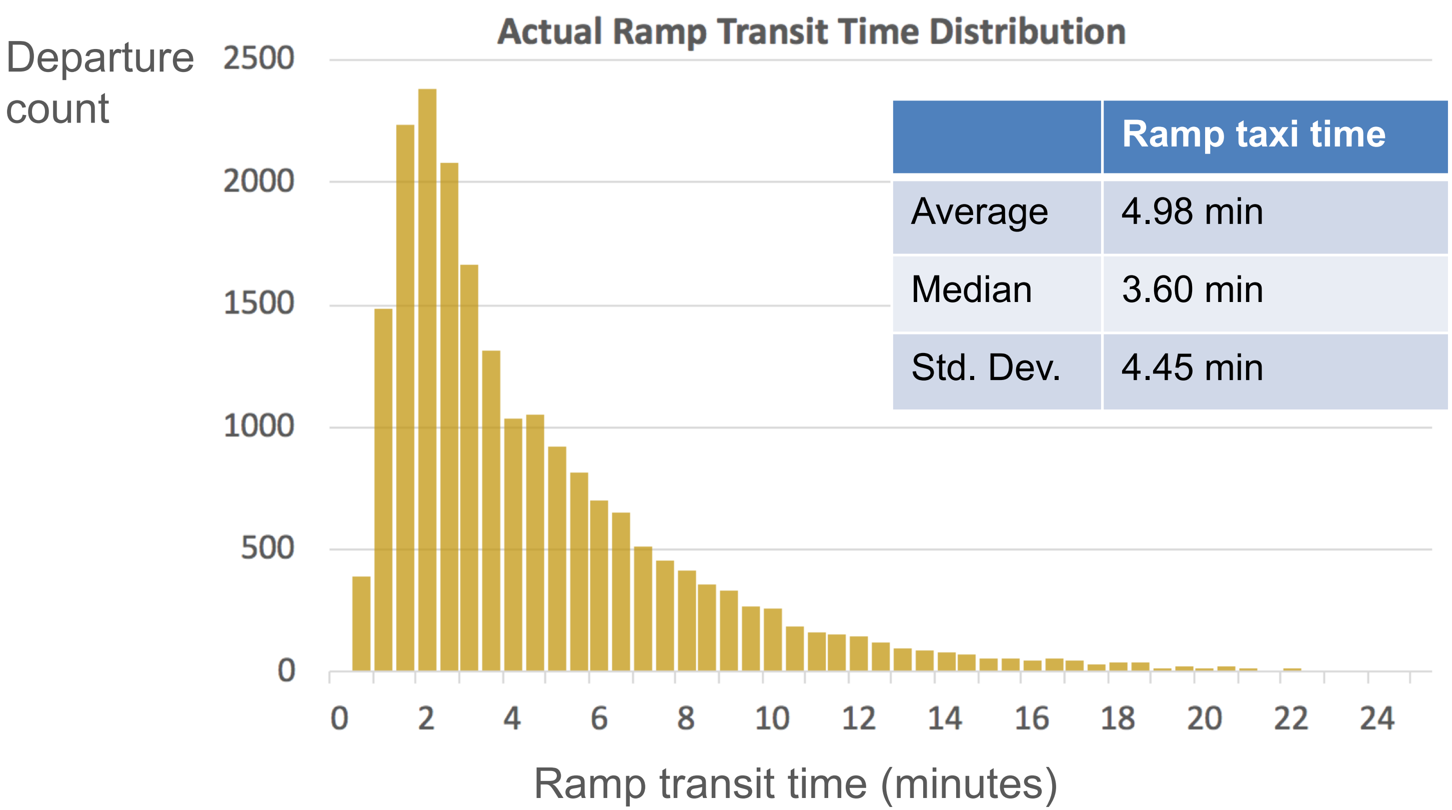
Pushback Time Variations by Ramp Area

- Pushback times vary, mainly depending on aircraft type and **ramp area** (gate groups)



Ramp Transit Time Distribution

- 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

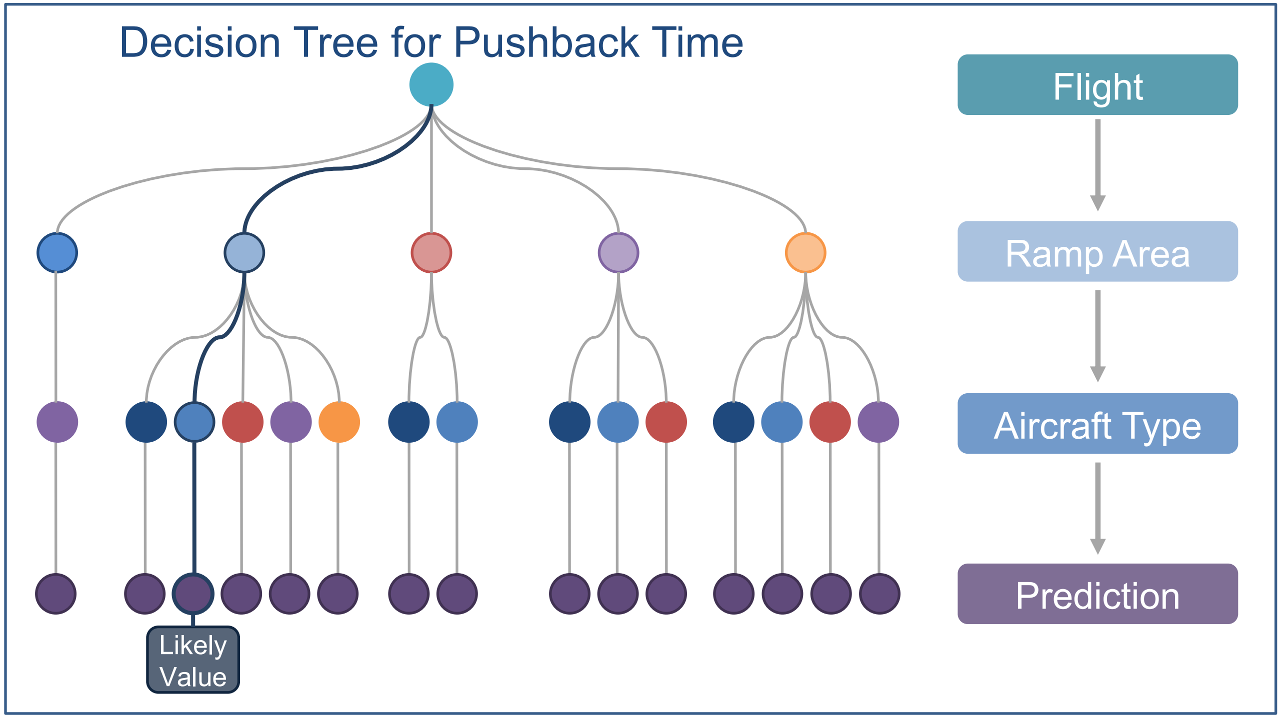


	Ramp taxi time
Average	4.98 min
Median	3.60 min
Std. Dev.	4.45 min

Data-Driven Prediction Models for Pushback Time and Ramp Taxi Time

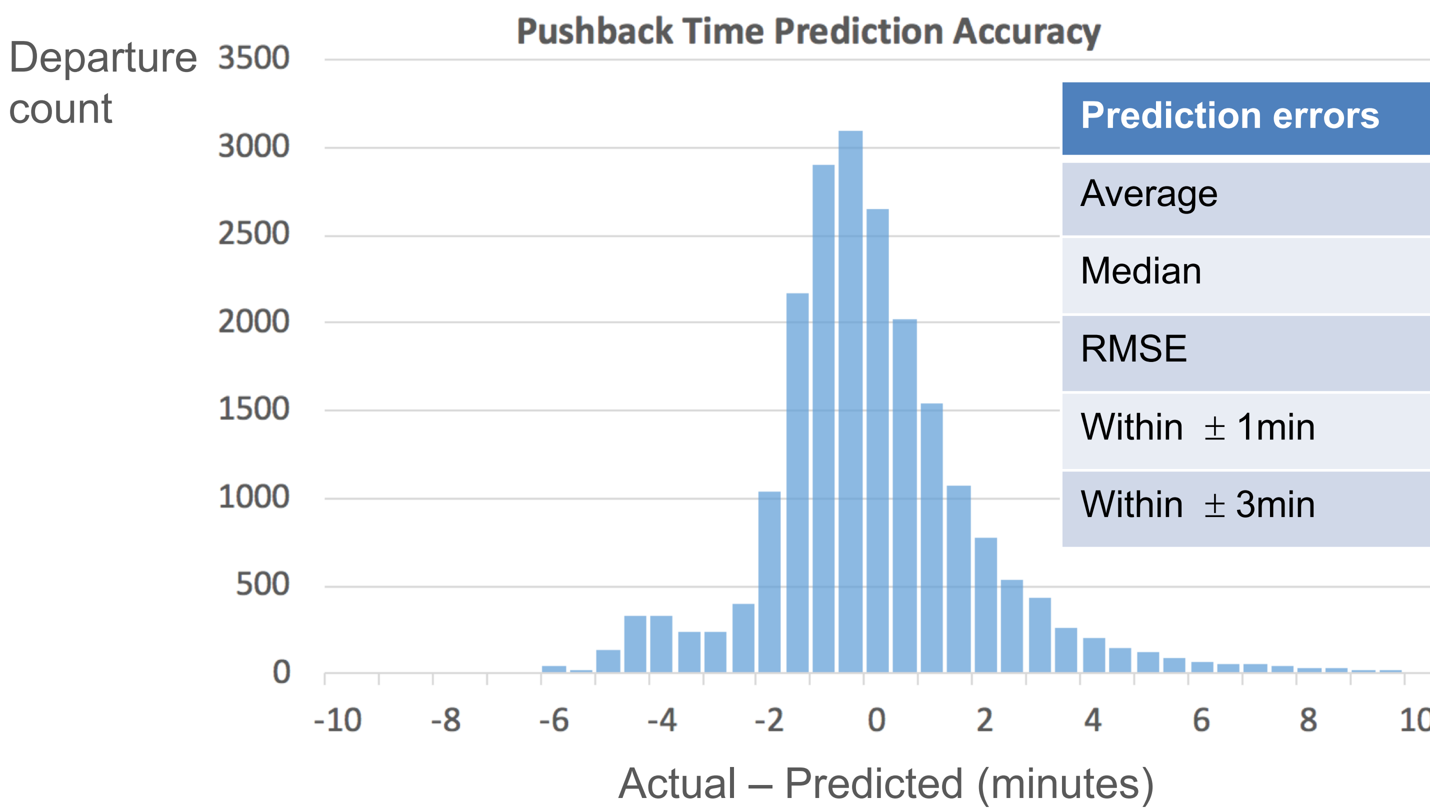
Decision Tree Model for Pushback Time Prediction

- Decision Tree (DT) model based on historical data, using two main criteria
  - Ramp area
  - Aircraft type



Pushback Time Prediction Using Decision Tree (DT) Model

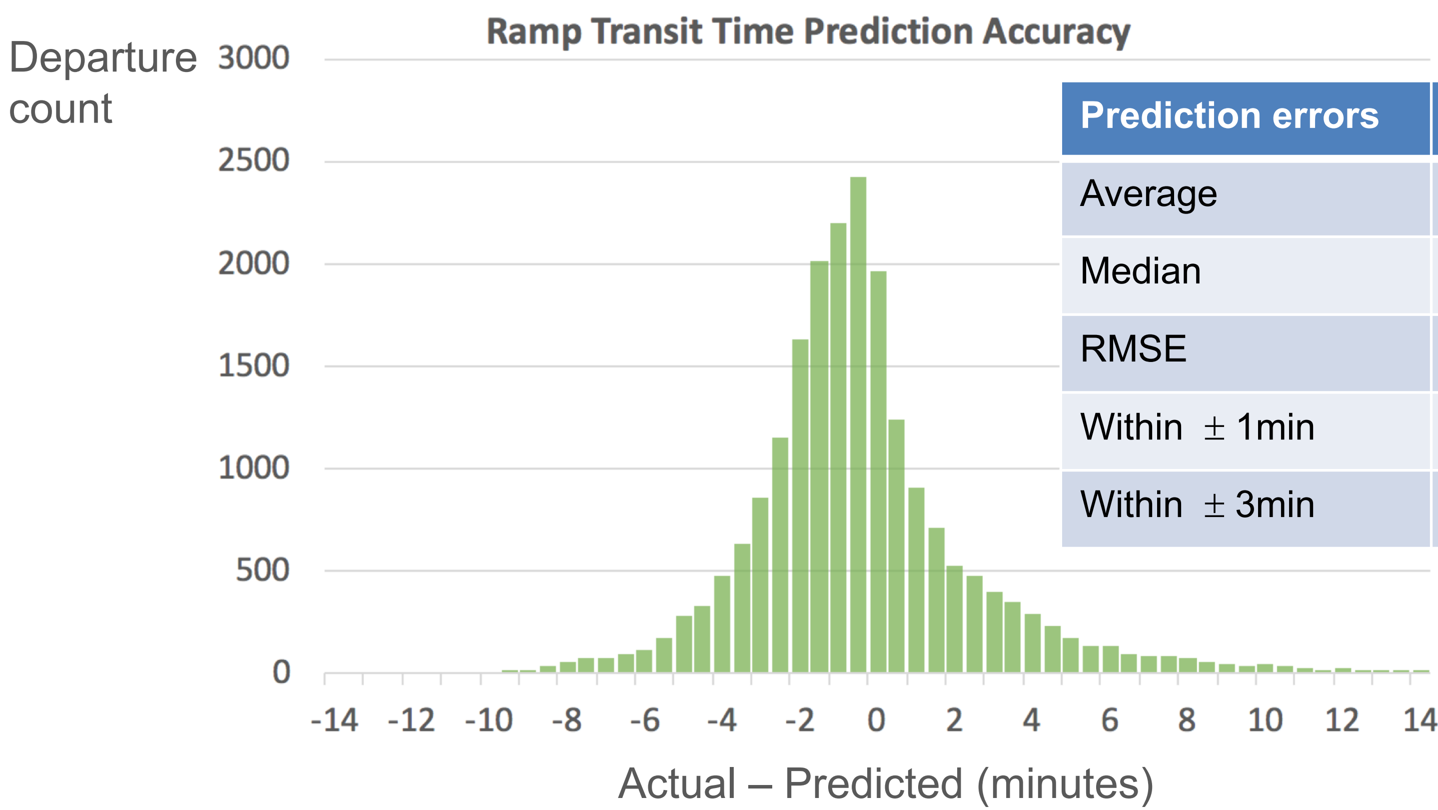
- Decision Tree (DT) model provides good prediction performance
- Prediction errors come from uncertainties in pushback processes



Prediction errors	DT model
Average	0.37 min
Median	0.00 min
RMSE	2.24 min
Within ± 1min	52.1%
Within ± 3min	89.8%

Ramp Transit Time Prediction Using Data Driven (DD) Model

- 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 errors	DD model
Average	0.07 min
Median	-0.45 min
RMSE	4.00 min
Within ± 1min	37.4%
Within ± 3min	76.4%

Integrated Arrival/Departure/Surface

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)
  - *k*-Nearest Neighbors (*k*NN)
  - Random Forest (RF)
  - Neural Networks (NN)

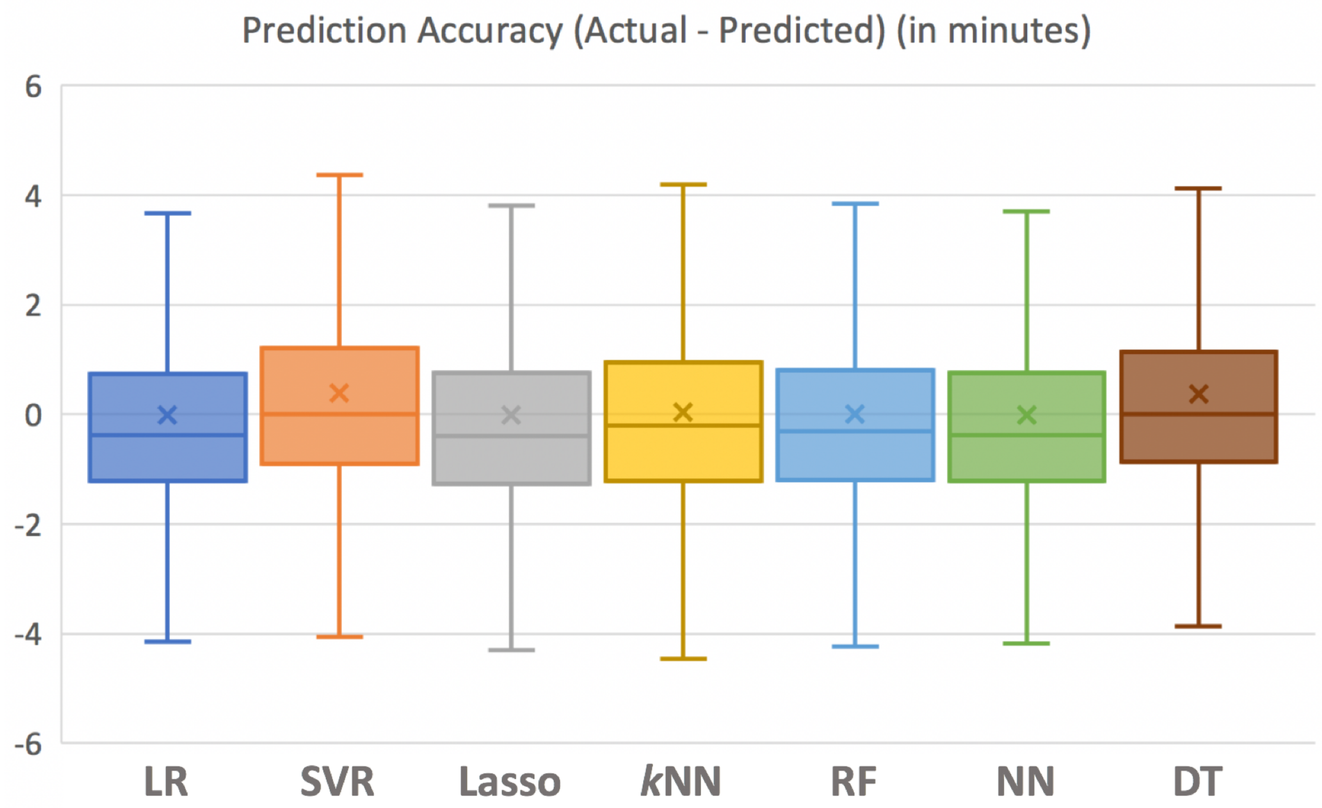
- Coded using *sklearn* (scikit-learn) library in Python
- Training and test dataset from the actual data at CLT in August 2018

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)

➢ Total 68 features defined and used for running machining learning algorithms

Pushback Time Prediction Accuracy Comparison



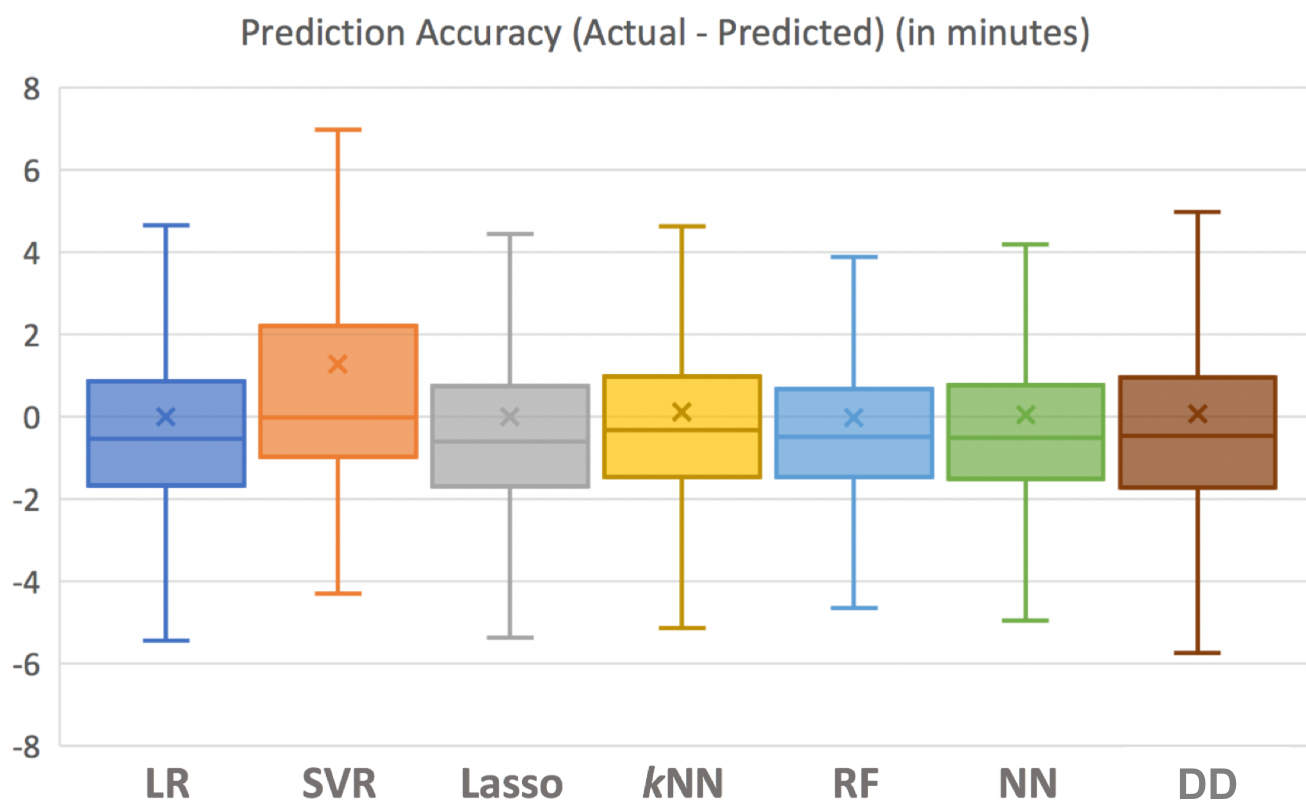
	LR	SVR	Lasso	*k*NN	RF	NN	DT
Mean (min)	0.00	0.39	-0.01	0.05	0.00	-0.01	0.37
RMSE (min)	2.19	2.28	2.22	2.37	2.25	2.20	2.24
Within ± 1min	47.9%	49.4%	45.4%	45.8%	47.9%	47.4%	52.1%
Within ± 3min	90.6%	89.1%	90.4%	87.7%	89.3%	90.5%	89.8%

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



	LR	SVR	Lasso	*k*NN	RF	NN	DD
Mean (min)	0.02	1.29	0.00	0.13	-0.01	0.04	0.07
RMSE (min)	3.56	4.36	3.60	3.80	3.54	3.52	4.00
Within ± 1min	37.7%	40.2%	37.3%	41.7%	43.0%	41.1%	37.4%
Within ± 3min	80.9%	79.2%	80.8%	78.5%	81.7%	81.1%	76.4%

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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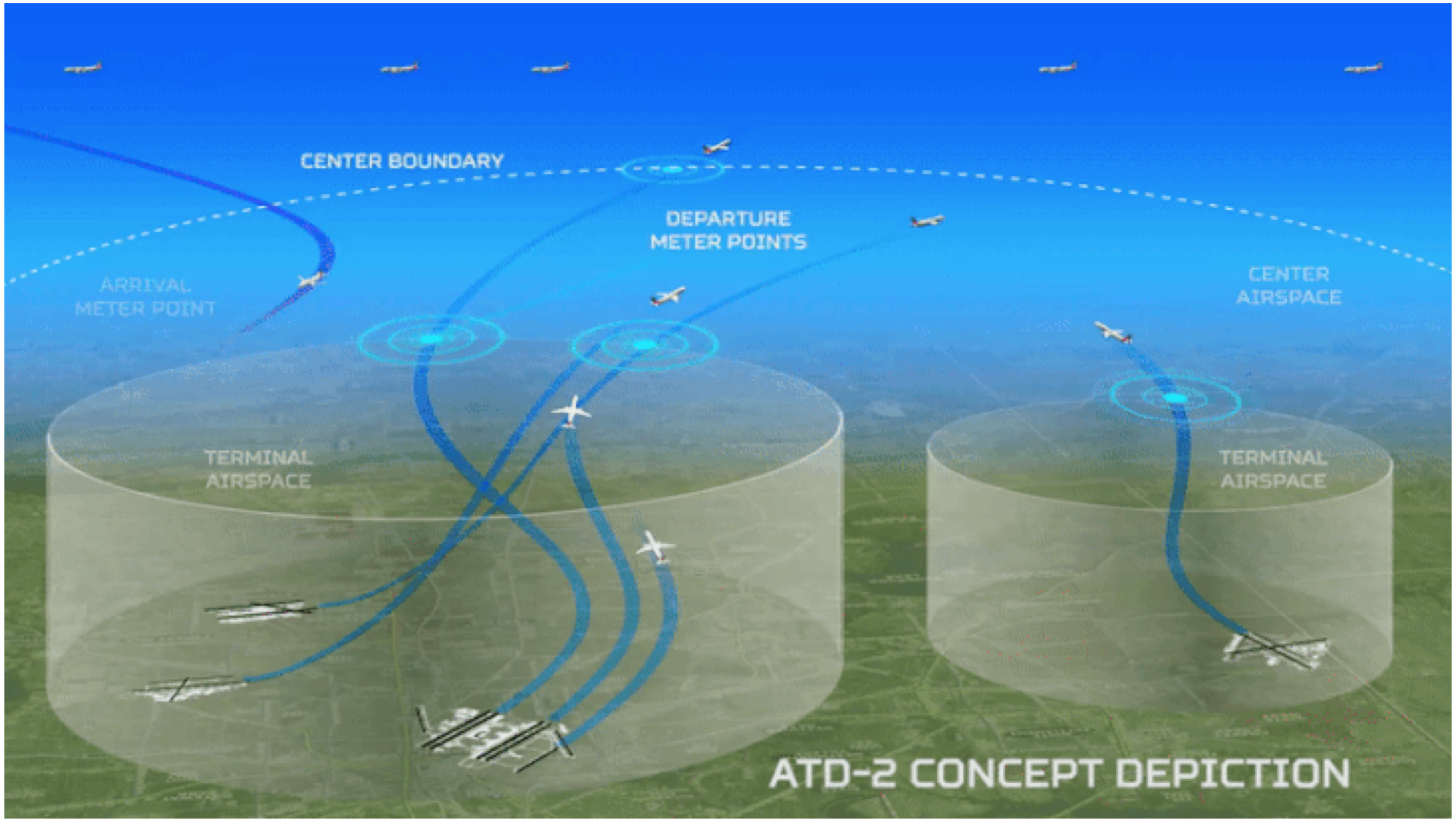
Backup

ATD-2 Concept

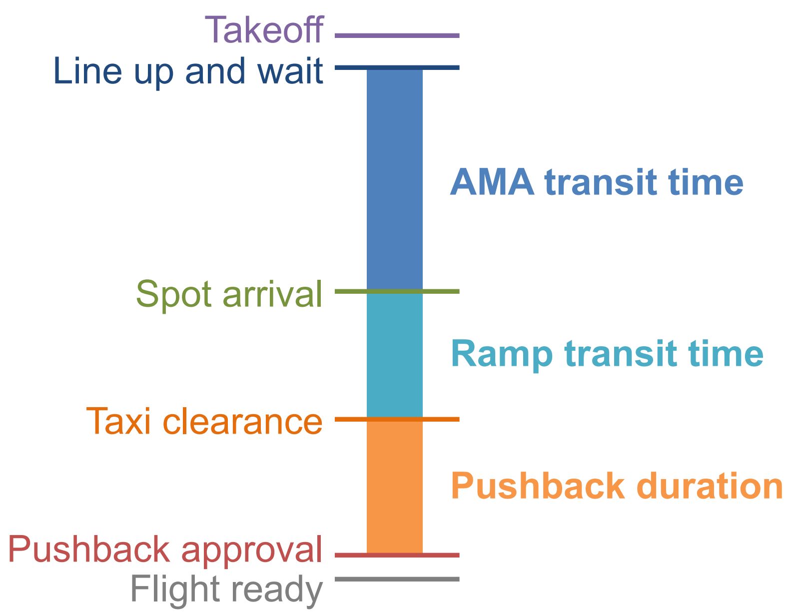
- To develop the Integrated Arrival, Departure, and Surface (IADS) traffic management capabilities



Taxi-Out Time of Departures

- Taxi time calculation for departures

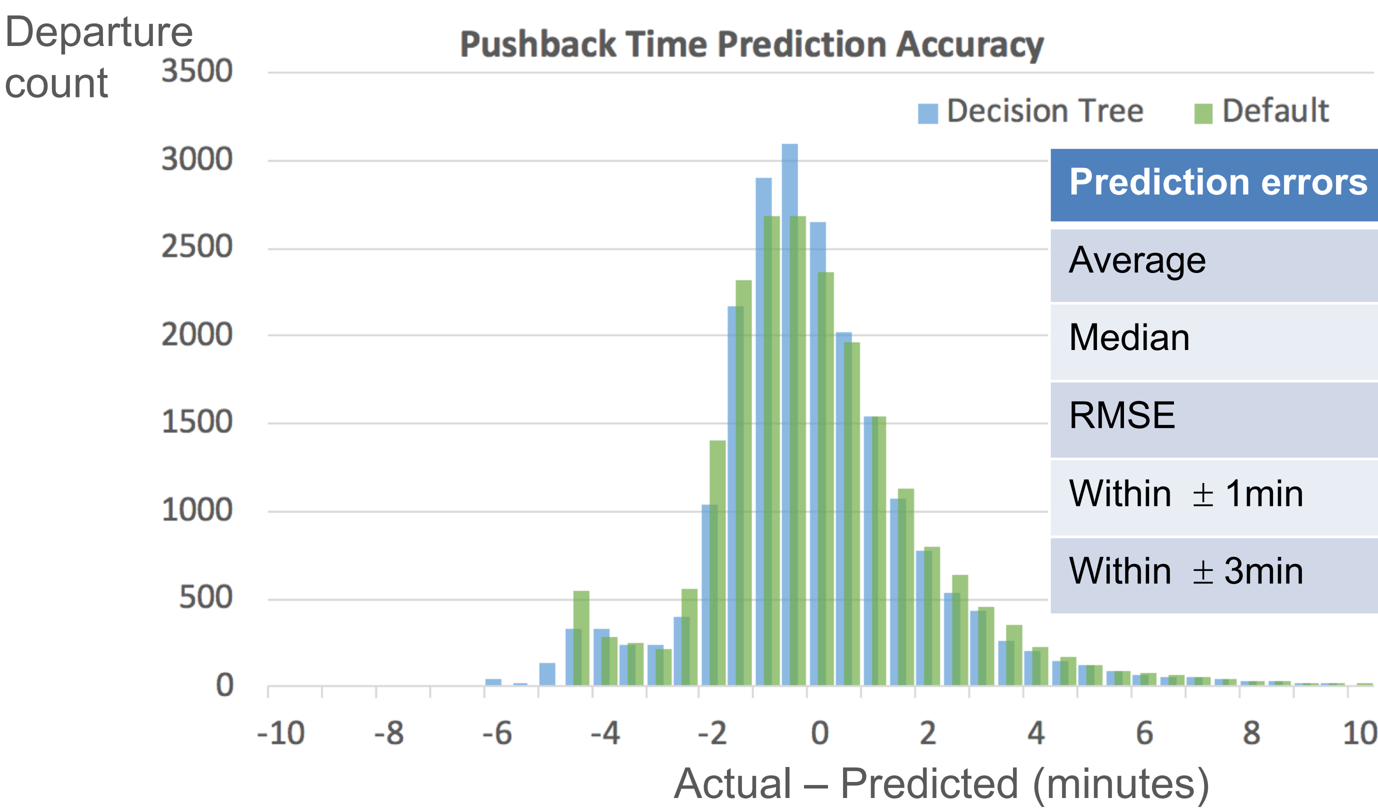
Taxi-out time = Pushback duration + Ramp transit time + AMA transit time



➢ Lack of accurate data for pushback time and ramp transit time

Pushback Time Prediction using Decision Tree (DT) and Default Models

- Decision Tree (DT) model provides good prediction performance
- Default model using a median pushback time value (260sec) also shows similar results



Prediction errors	DT	Default
Average	0.37 min	0.39 min
Median	0.00 min	0.00 min
RMSE	2.24 min	2.31 min
Within ± 1min	52.1%	47.3%
Within ± 3min	89.8%	89.0%

Ramp Taxi Time vs. Congestion Level

- A weak positive correlation between ramp transit time and the number of departures and arrivals in the ramp