**Pushback Rate Control**

The Design and Field-Testing of an Airport Congestion Control Algorithm

Hamsa Balakrishnan
Aeronautics & Astronautics, MIT

Aerospace Engineering Colloquium, University of Washington
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Goal

- Develop algorithms that increase efficiency and robustness, and ensure safety...
- ... while coping with uncertainty, human factors, and environmental concerns
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Our approach
- Leverage large amounts of operational data to
  - Build simple models for desired objectives and operational constraints
  - Develop and implement scalable control and optimization algorithms

Practical algorithms and decision-support automation are vital to meet future system demands
Practical algorithms for air transportation

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  - ... while coping with **uncertainty**, **human factors**, and **environmental concerns**

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- Air transportation: Cyber + physical + human components
Airport surface traffic operations

- **Modeling and analysis** of surface operations using data

- **Design and field testing** of congestion control strategies
Boston Logan (BOS) airport (6/30/2012)
Problem: Airport surface congestion

- Frequent congestion at major airports results in inefficient operations, and increased fuel burn and emissions.

**JFK departure throughput (2009)**

- When JFK is saturated:
  - In Visual Meteorological Conditions, the average taxi-out time is **56 min**.
  - In Instrument Met. Conditions, the average taxi-out time is **69 min**.
  - Unimpeded taxi-out time: **16-19 min**.

- JFK is saturated 18% of the time in VMC, and 24% of the time in IMC.
- 32% of departures at JFK takeoff during saturated periods.

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Simaiakis and Balakrishnan, *Transportation Research Record*, 2010 (Confirms Pujet, Delcaire and Feron, BOS 1999).
Airports can look very different
Queueing model of the departure process

Pushbacks

Taxi-out time = Travel time + Queuing delay

\[ \tau_{\text{travel}} = \tau_{\text{unimped}} + \tau_{\text{taxiway}} \]
\[ \tau_{\text{taxiway}} = \alpha R(t) \]

Module 1

Ramp and Taxiway delays

Runway schedule

Module 2

Departure queue

Departure throughput

Learn from data

Learn from data

Runway service process model

EWR, (VMC, 22L | 22R) in 2011

Severity of weather on departure routes

Departure throughput

# Arrivals in 15 min
- Arrivals<6
- Arrivals≥6

$\mu=10.34$
$\sigma=2.19$

$\mu=10.03$
$\sigma=1.86$

$\mu=9.75$
$\sigma=1.74$

16 $\leq N \leq 31$

EWR model predictions

- Model parameters identified from 2011 data, predictions carried out on 2010 data (pushback schedules)

- Similar prediction performance shown for BOS, CLT, DTW, LGA, PHL, ...

PHL operations (08/09/2011)
Airport congestion control

- Aircraft pushback from gates, start their engines, and then taxi until they takeoff

- Control pushbacks in order to maintain runway utilization while avoiding excessive levels of congestion

- Key challenges:
  - How do we design a congestion control strategy?
  - How do we implement control strategy?
  - How do we interface with human controllers?
1. Designing control strategy

- Threshold policy (N-control) possible option [Feron et al. 1997]
  - Departure throughput saturates when number of aircraft taxiing out, $N$, exceeds a certain threshold, $N^*$
  - Stop pushbacks when $N$ exceeds $N_{ctrl}$, where $N_{ctrl} \gg N^*$

- Example: $N_{ctrl} = 5$
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2. Implementing control strategy

- Threshold control (N-control) does not work in practice
  - Rather than release an aircraft every time that a flight takes off, controllers prefer a rate at which to let aircraft pushback from their gates
  - Rate is updated periodically
  - Pushback Rate Control (PRC)

- **Option 1:** Adapt N-control policy (PRC v1.0)
- **Option 2:** (PRC v2.0) Formulate control problem to
  - Minimize expected queue length
  - Maximize expected number of aircraft served (throughput)
Revisit Step 1. Designing control strategy: Pushback Rate Control

- Dynamic programming formulation to recommend pushback rate, given loading of taxiway and runway queues
- Challenges
  - Random travel time between actuation (at the gate) and queue being controlled (runway)
  - Runway process is a dynamic and stochastic process with a great variability (fleet mix, weather, arrival demand, route availability, human factors)
- State space, $N_t = (D_t, R_t)$: Number of aircraft in departure queue, $D_t$, and number of aircraft traveling toward departure queue, $R_t$.
- Time window, $\Delta$: Average travel time from gates to the runway

Departure process model

- At the start of each time window, a pushback rate is chosen
- Pushbacks occur randomly within this time window
- Departure runway service times are Erlang ($k, k\mu$)

- Departure runway queuing system modeled as $(M(t)|R_t)/E_k/1$
- Chapman-Kolmogorov equations to describe evolution of Markov chain model

Queue at next epoch depends on state at current epoch
State probabilities computed numerically using C-K equations
Model assumes that $(D_{\tau+\Delta}, R_{\tau+\Delta}) = (f(D_\tau, R_\tau), \lambda_\tau)$
However, in reality, nonzero probabilities of flights being early or late to reach the runway:

$$(D_{\tau+\Delta}, R_{\tau+\Delta}) = \begin{cases} (f(D_\tau, R_\tau), \lambda_\tau), & \text{w.p. } 1 - \sum \beta_i - \sum \gamma_i \\
(f(D_\tau, R_\tau + i), \lambda_\tau - i), & \text{w.p. } \beta_i, i = 1, \ldots, \lambda_\tau \\
(f(D_\tau, R_\tau - i), \lambda_\tau + i), & \text{w.p. } \gamma_i, i = 1, \ldots, R_\tau \\
\end{cases}$$

Cost function:

$$c(D) = \begin{cases} M, & D = 0 \\
\frac{D^2}{D^2} = 1, \ldots, C \\
\end{cases}$$

- $M$ is the (very high) cost of not utilizing runway (set to equivalent of 25 aircraft in queue)

Dynamic programming formulation

- Bellman equation for infinite horizon average cost problem with discount factor $\alpha$

$$J^*(q, r) = \min_{\lambda \in \Lambda} \left\{ (1 - \sum \beta_i - \sum \gamma_i)[\bar{c}(q, r) + \alpha p_q(q, r) \cdot J^*(\lambda)] + \sum \beta_i[\bar{c}(q, r + i) + \alpha p_q(q, r + i) \cdot J^*(\lambda - i)] + \sum \gamma_i[\bar{c}(q, r - i) + \alpha p_q(q, r - i) \cdot J^*(\lambda + i)] \right\}$$

- Policy iteration converges in fewer than 10 iterations
- Can also be formulated as minimum average cost per stage problem
- Multiple ramp towers can be incorporated

Optimal pushback rate

- BOS (22L, 27 | 22L, 22R) configuration

3. Interfacing with human controllers

- Suggest pushback rate (color-coded cards or a tablet display)
  - Pushbacks in current time interval can be released (grayed out)
  - Unused rate is carried over to the next time interval, up to 2/min
  - Pushbacks in future time intervals can be reserved (angled)
  - Pushbacks can be reserved for the following 15-min time period

Sample test results: 7/21/2011

Reduced queue sizes

![Graph showing the number of aircraft over time with and without pushback rate control.](image)

- Blue line: Queue with Pushback Rate Ctrl
- Red line: Queue without Pushback Rate Ctrl
Visualization of operations (7/21/2011)
Visualization of operations (9/2/2010)
BOS field test results

- Aug-Sep`10 & Jul-Aug`11
- 4PM-8PM departure push
- Average gate-held: 4.7 min
- 23-25 US tons (6,600-7,300 gal) reduction in fuel burn
- 52-58 kg decrease in fuel burn / gate-held flight
- 71-79 tons CO₂ reduction
- Fair distribution of benefits
- 1 min gate-held => 1 min of taxi-out time savings
- Positive stakeholder feedback, from both airlines and Tower personnel

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<th>Configuration</th>
<th># of gate holds</th>
<th>Taxi-out time savings (min)</th>
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2010 | 247 | 1003 min = 16.7 hours

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2011 | 142 | 760 min = 12.7 hours

Some other projects: 
Prediction of air traffic network delays

- Predict departure delay on a link considering:
  - Current delay state of the network
  - Interdependencies between network elements
  - Time-of-day and day-of-the-week
  - Delays at origin, destination, and on link
  - Delay state of National Airspace System
  - Type of delay day in the NAS

- Delay states obtained by \( k \)-means clustering of delays

- 100 most-delayed OD pairs and major carriers
  - Avg. classification test errors to decide whether delays exceed 15 min or not:
    - 18%, 2 hours ahead
    - 21%, 6 hours ahead
  - Avg. (regression) median test error:
    - 13.5 min, 2 hours ahead
    - 17.1 min, 6 hours ahead

Rebollo and Balakrishnan, *Transportation Research Part C*, 2014
Some other projects: Large-scale Air Traffic Flow Management

- Optimize aircraft trajectories (in space and time) with recourse on a system-wide scale, to accommodate capacity-demand imbalances
  - Use stochastic capacity forecasts (for airspace and ground resources)
  - Consider ground delays, speed changes, reroutes and cancellations
  - Account for operational constraints (flight connectivity, speeds, etc.)
- We solve largest instances of the ATFM to-date, with faster run times
- Case studies drawn from real data:
  - ~17,500 flights
  - 24-h/5-min discretization
  - 370 airports, 375 airspace sectors
  - Deterministic: Optimal in ~5-10 min
  - Stochastic: Optimal in ~30 min
  - Distributed decision-making

Balakrishnan and Chandran, working paper, 2014
Some other projects:
Integrated control & communication protocols

- Objectives: Safety and efficiency
  - Conflict detection and resolution
  - Optimize State Update Interval
  - Minimize flight times

- Decentralized at longer range
  - Low traffic density
  - ADS-B surveillance
  - Max transmit power

- Handover zone
  - Decentralized control
  - Adaptively adjust transmit power

- Centralized close to the airport
  - High traffic density
  - Min transmit power

- Ground radar surveillance
  - Augmented by ADS-B

Park et al., IEEE Trans. on Intelligent Transp. Systems 2014
Some other projects:
High-confidence network control for NextGen

- Secure, fault-tolerant control in the presence of adversaries
  - Distributed control using onboard threat detection
    - GPS and inertial sensor data fusion
    - Verification using Doppler effect and RSS of ADS-B messages from neighboring aircraft
  - Control objectives
    - Conflict avoidance, maintaining separation in the presence of uncertainty
    - Minimizing flight times
    - Fault detection

Park et al., IEEE Trans. on Automatic Control 2014
Some other projects: Robust routing through thunderstorms

- Integrating weather forecasts into air traffic management algorithms
  - Given a forecast, can we identify which routes are most likely to remain open, and the associated probabilities?
  - Development and validation of classification algorithms for predicting route blockage using weather and operations data
  - Dynamic airspace reconfiguration using convective weather forecasts

Pfeil and Balakrishnan, *Transportation Science* 2012
Lin and Balakrishnan, *Transportation Research Record* 2014
Some other projects: Arrival/Departure scheduling

- Given a set of flights with estimated arrival times at the airport, the aircraft need to be sequenced into the landing (takeoff) order, and the landing (takeoff) times need to be determined
  - Need minimum (wt. class dependent) wake vortex separation (Safety)
  - Currently FCFS; resequencing could increase throughput (Efficiency)
  - “Fair” resequencing: Constrained Position Shifting (CPS) [Dear 1976]
- Show that scheduling under constrained position shifting can be solved in (pseudo-)polynomial time as shortest-path problems

Balakrishnan and Chandran, *Operations Research* 2010
Lee and Balakrishnan, *Proceedings of the IEEE* 2008
Summary

- Practical ATM algorithms can enhance system efficiency, robustness and safety, and address uncertainty, competition and environmental impact
  - Leveraging cyber-physical aspects of the system is key!
- These challenges arise in all stages of flight as well as on a system-wide scale, including:
  - Data-driven modeling of human decision processes
    [Ramanujam and Balakrishnan, American Control Conference 2010]
  - Characterizing and providing feedback on operational performance
    [Khadilkar and Balakrishnan, Air Traffic Control Quarterly 2013]
  - Network modeling and congestion control of airport surface operations
    [Khadilkar and Balakrishnan, AIAA Journal of Guidance, Control and Dynamics 2014]
  - Mechanisms for resource allocation and reallocation
    [Balakrishnan, Conference on Decision and Control 2007; Ramanujam and Balakrishnan, Conference on Decision and Control 2014]
  - Distributed feedback control of the National Airspace System
    [Le Ny and Balakrishnan, AIAA Journal of Guidance, Control and Dynamics 2011]
  - Models of engine performance from flight recorder data
    [Khadilkar and Balakrishnan, Transp. Research Part D 2012; Chati and Balakrishnan, ATIO 2013 and ICRAT 2014]