Pushback Rate Control

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

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Practical algorithms for air transportation

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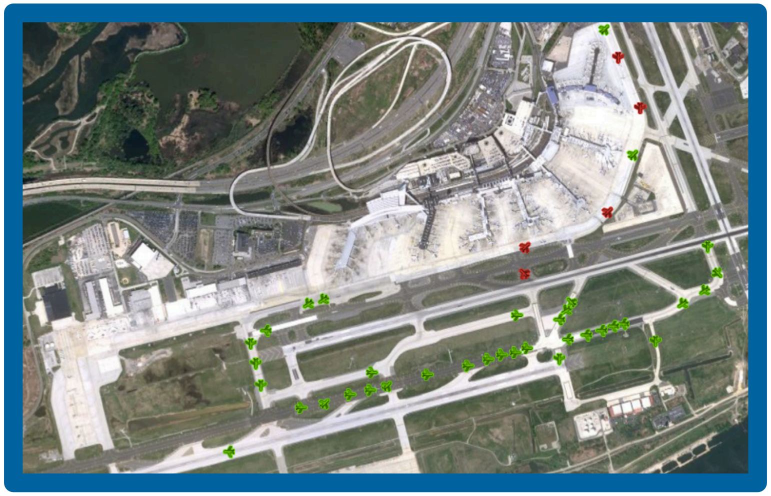
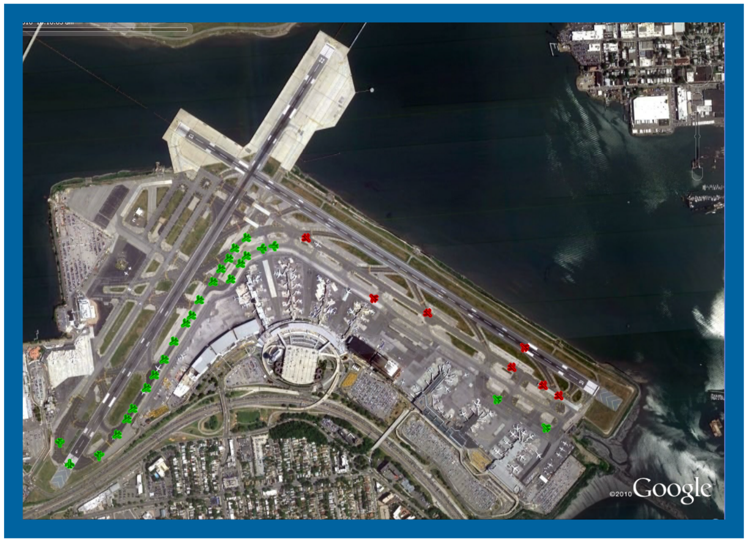
- Air transportation: Cyber + physical + human components

Airport surface traffic operations

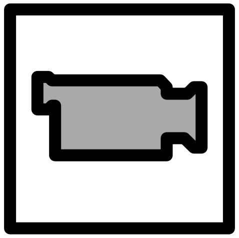
- **Modeling and analysis** of surface operations using data



- **Design and field testing** of congestion control strategies



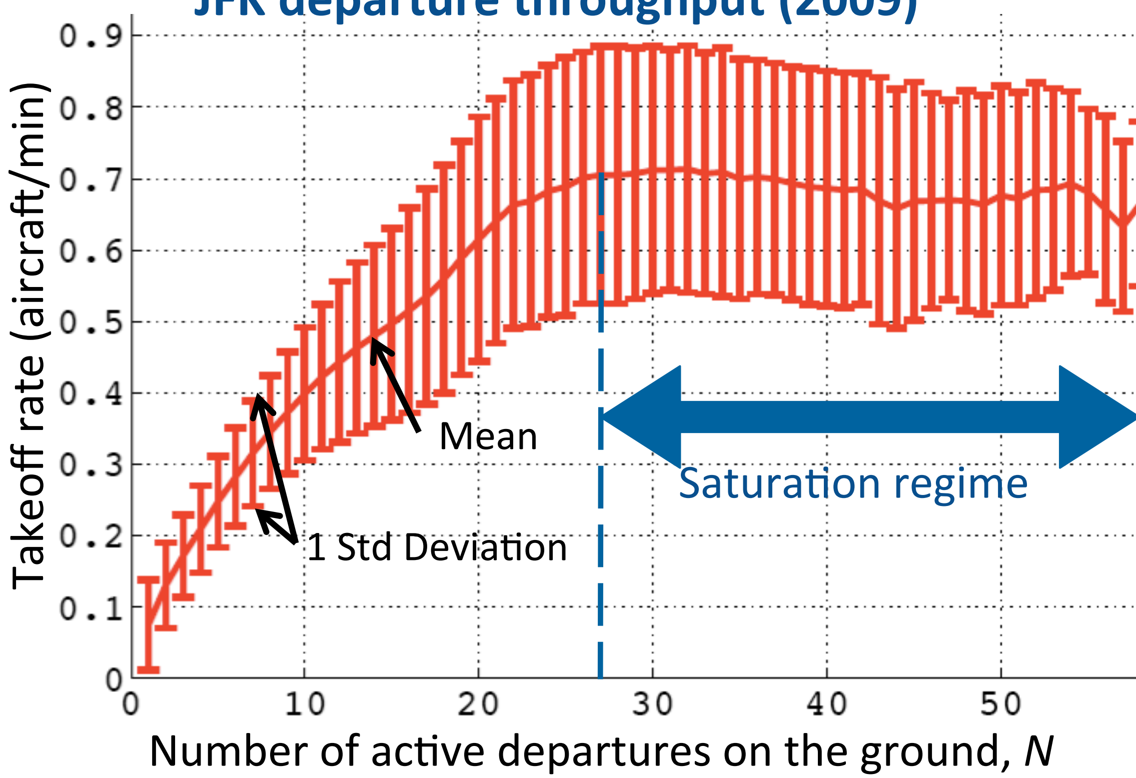
Boston Logan (BOS) airport (6/30/2012)



Problem: Airport surface congestion

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

JFK departure throughput (2009)



Simaiakis and Balakrishnan, *Transportation Research Record*, 2010 (Confirms Pujet, Delcaire and Feron, BOS 1999).

When JFK is saturated:

In Visual Meteorological Conditions, the average taxi-out time is **56 min**

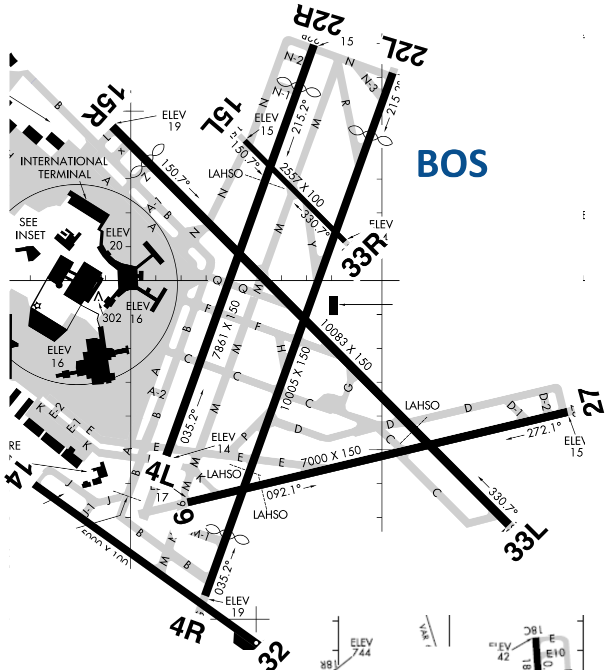
In Instrument Met. Conditions, the average taxi-out time is **69 min**

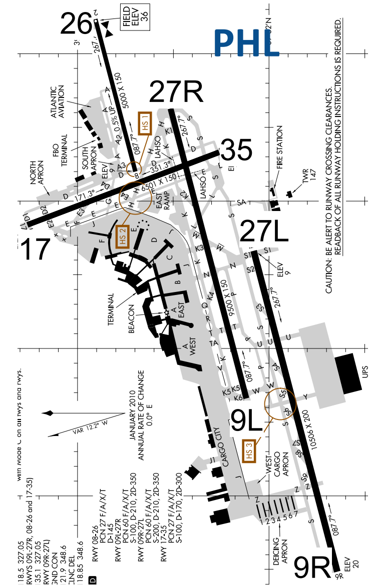
Unimpeded taxi-out time: **16-19 min**

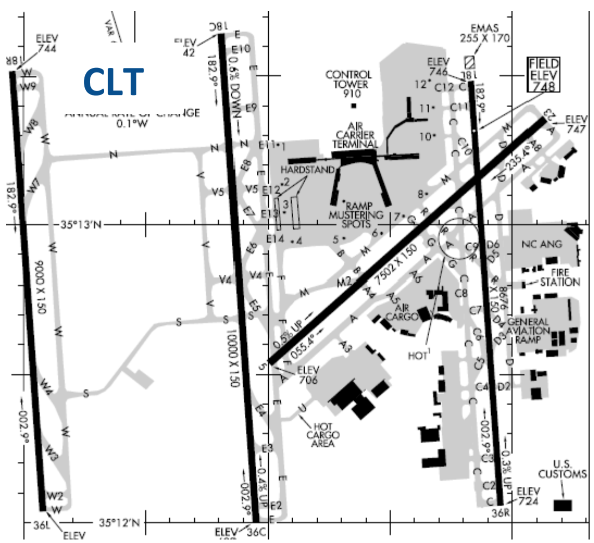
JFK is saturated 18% of the time in VMC, and 24% of the time in IMC

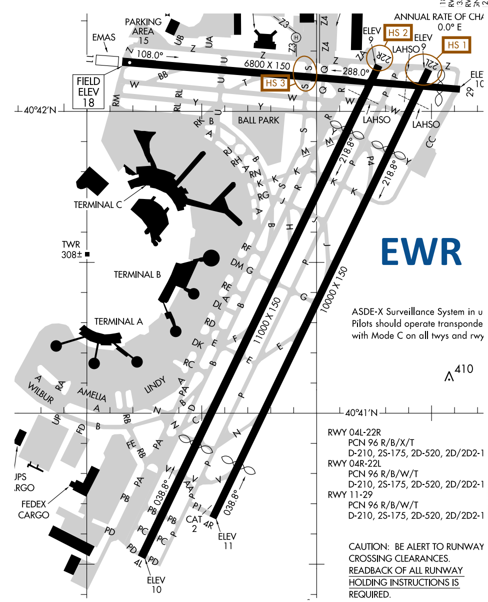
32% of departures at JFK takeoff during saturated periods

Airports can look very different

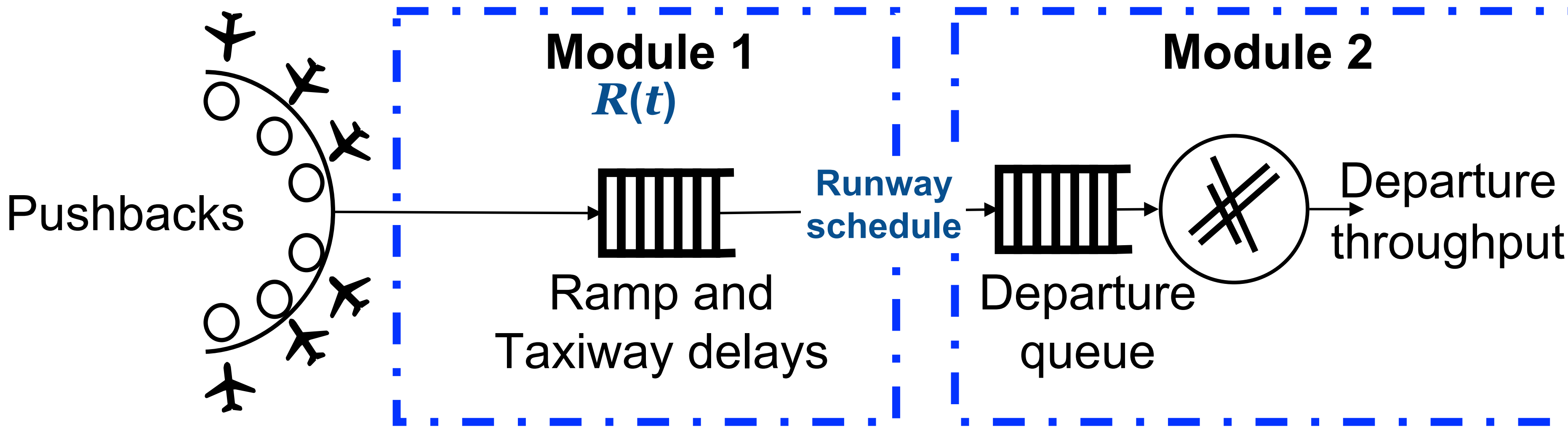








Queuing model of the departure process



Taxi-out time = Travel time + Queuing delay

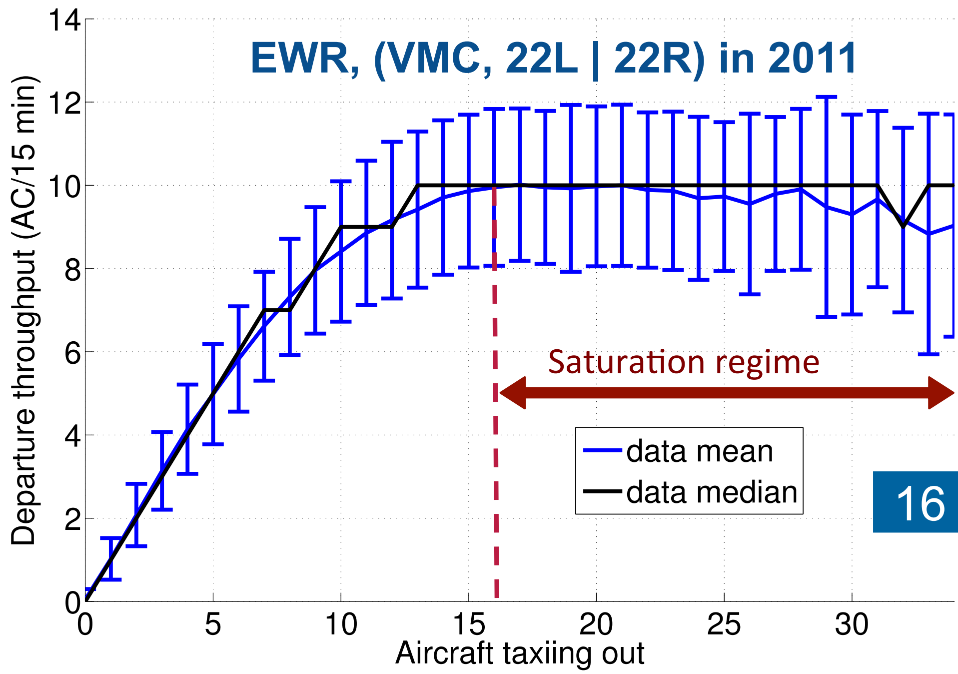
Learn from data　　*Learn from data*

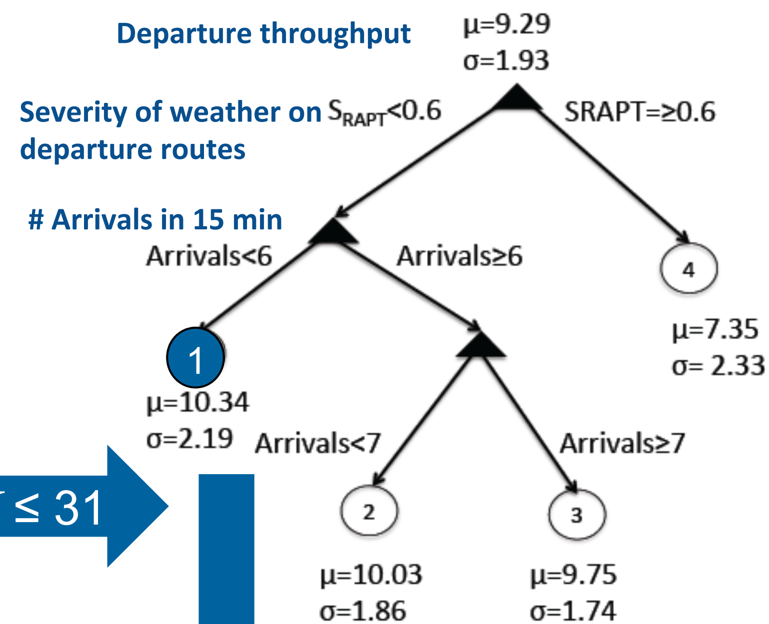
$$\tau_{\mathrm{travel}} = \tau_{\mathrm{unimped}} + \tau_{\mathrm{taxiway}} \qquad D(t)/E_k(t)/1$$

$$\tau_{\mathrm{taxiway}} = \alpha R(t)$$

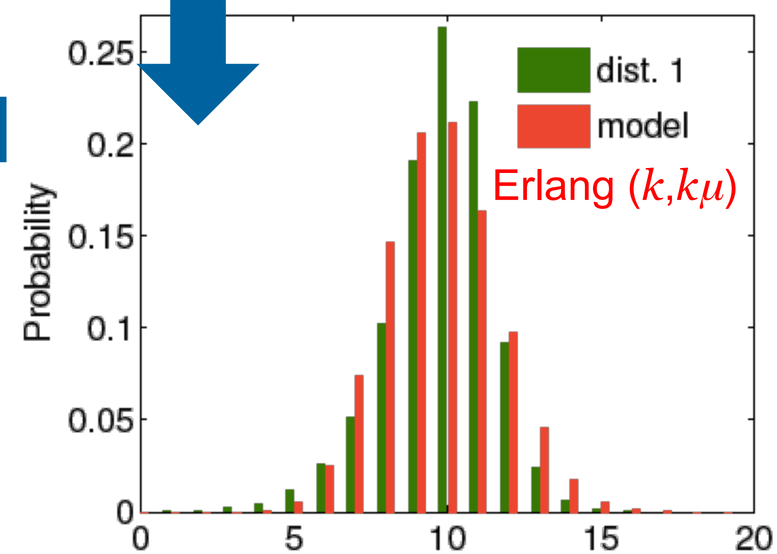
Simaiakis and Balakrishnan, *Transportation Science*, to appear, 2014

Runway service process model

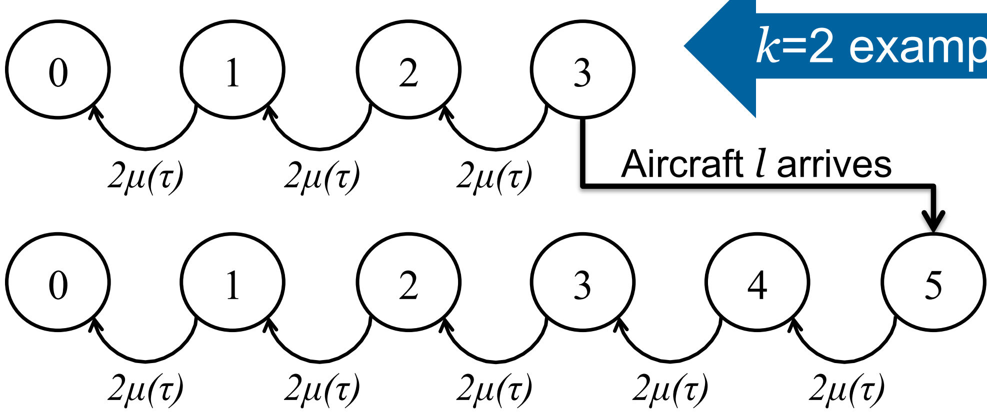




$16 \le N \le 31$



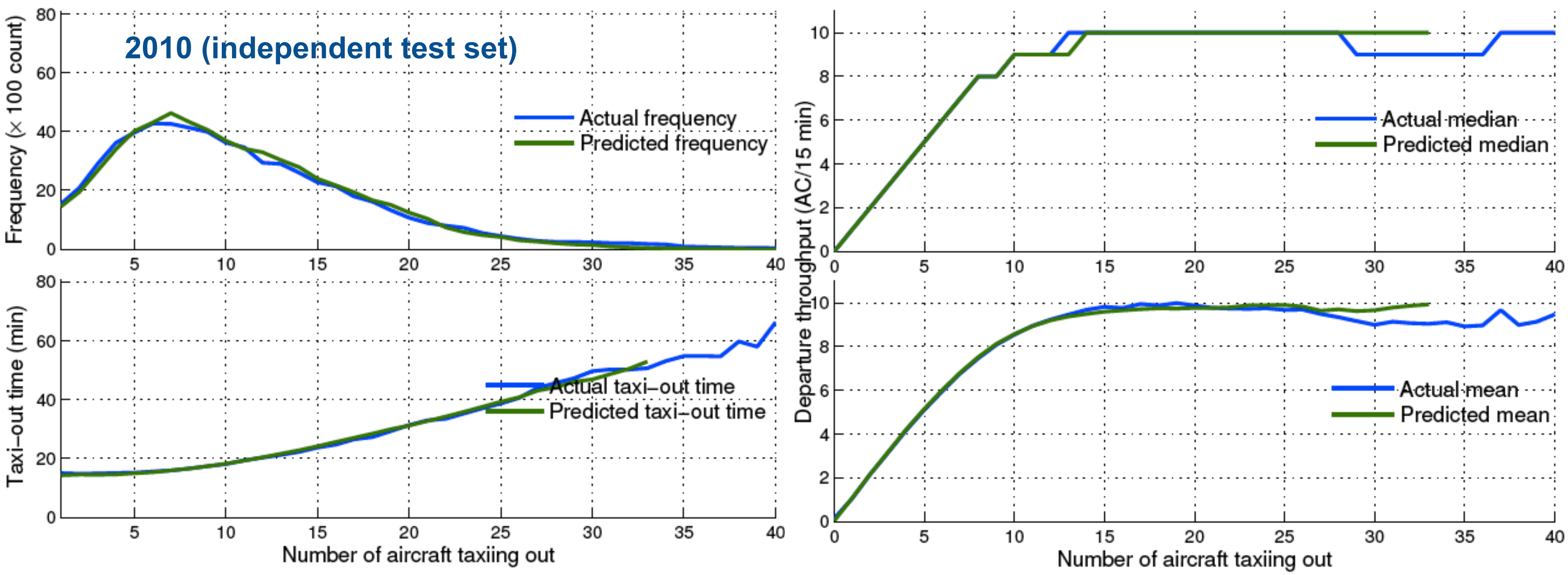
k=2 example



Simaiakis and Balakrishnan, *Transportation Science*, to appear, 2014

EWR model predictions

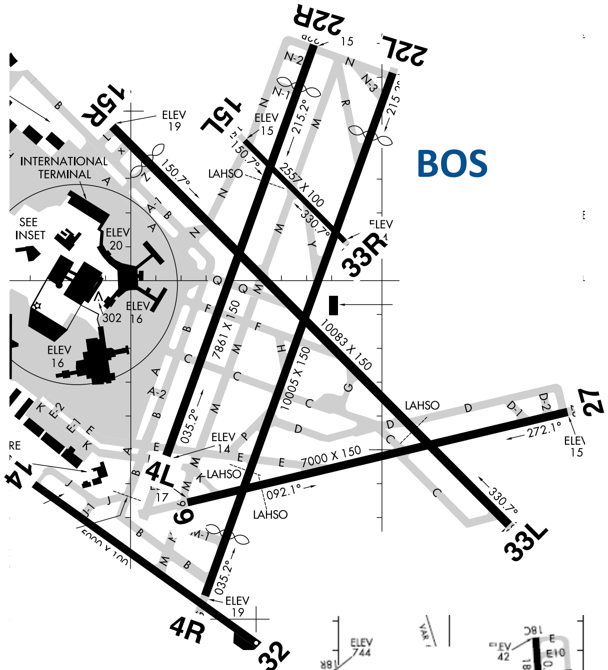
- Model parameters identified from 2011 data, predictions carried out on 2010 data (pushback schedules)



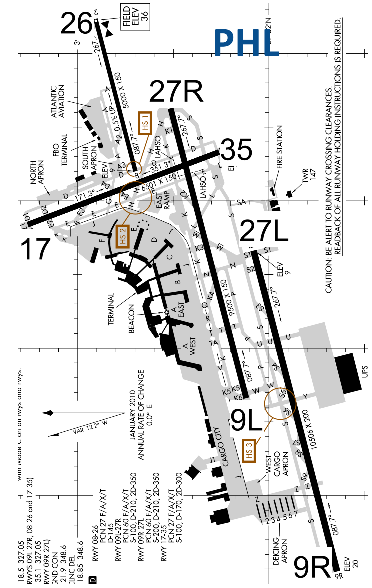
- Similar prediction performance shown for BOS, CLT, DTW, LGA, PHL, …

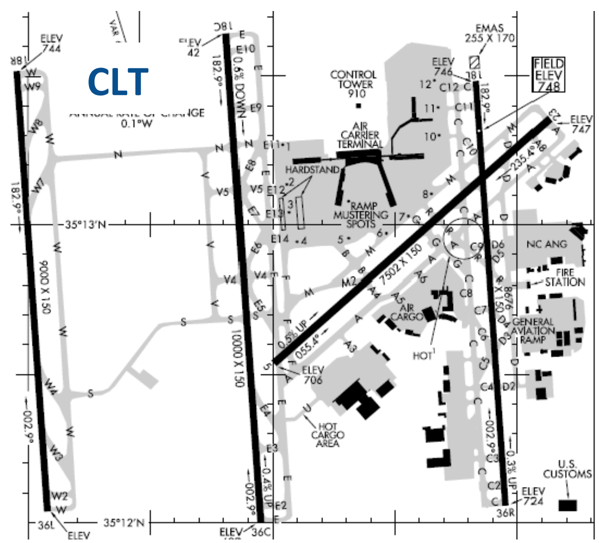
MIT AEROASTRO

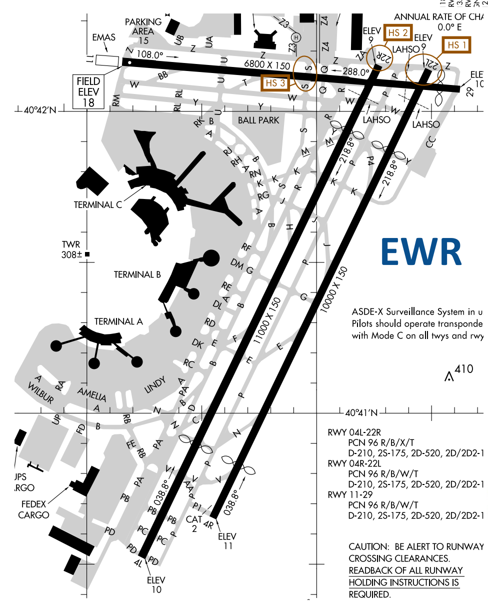
Simaiakis and Balakrishnan, *Transportation Science*, to appear, 2014


BOS
22R
22L
15R
15L
33R
4L
27
9
14
4R
32
33L

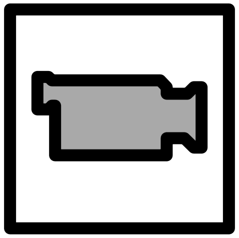

LGA
22
13
4
31


PHL
26
27R
35
27L
17
9L
9R


CLT

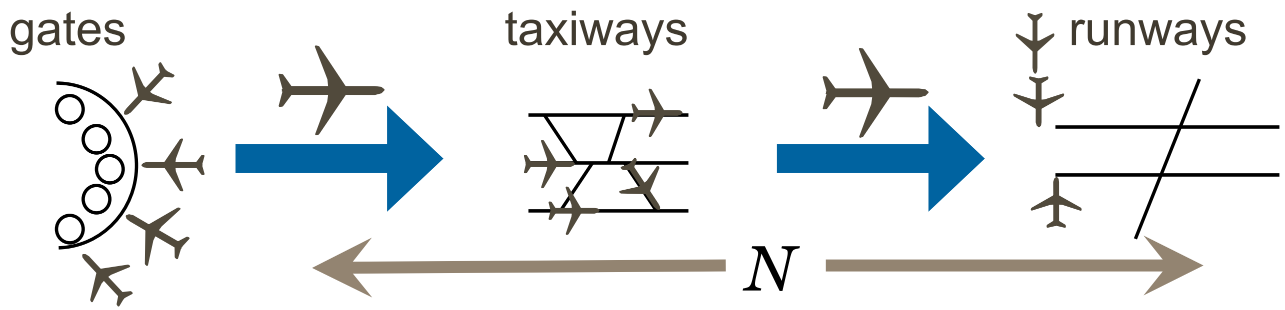

EWR

PHL operations (08/09/2011)



Airport congestion control

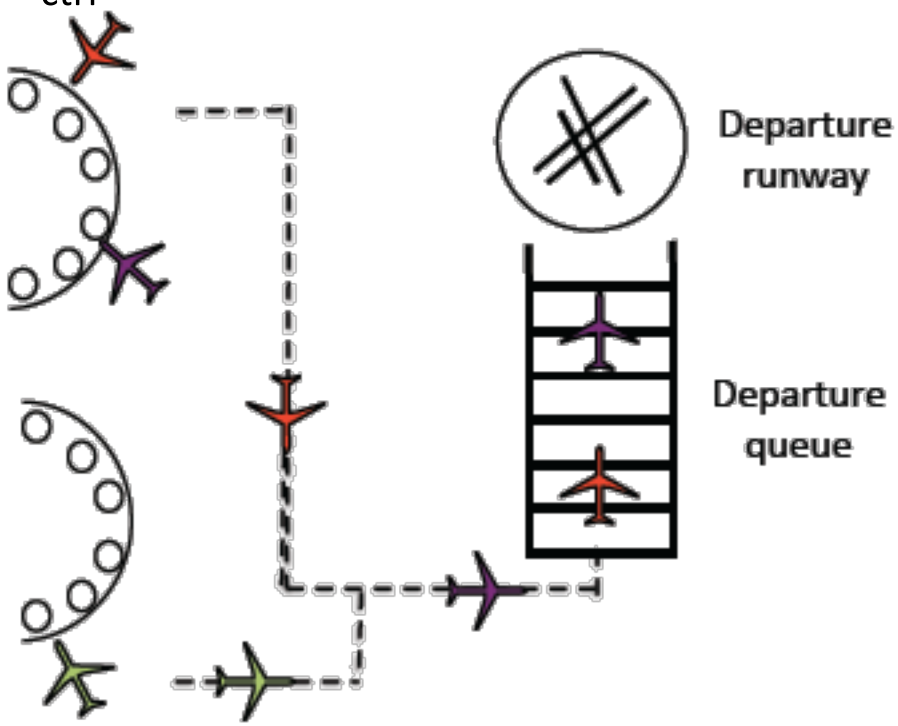
- Aircraft pushback from gates, start their engines, and then taxi until they takeoff



- 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 $N_{ctrl} >> N^*$
- Example: $N_{ctrl} = 5$



1. Designing control strategy: How about a threshold policy?

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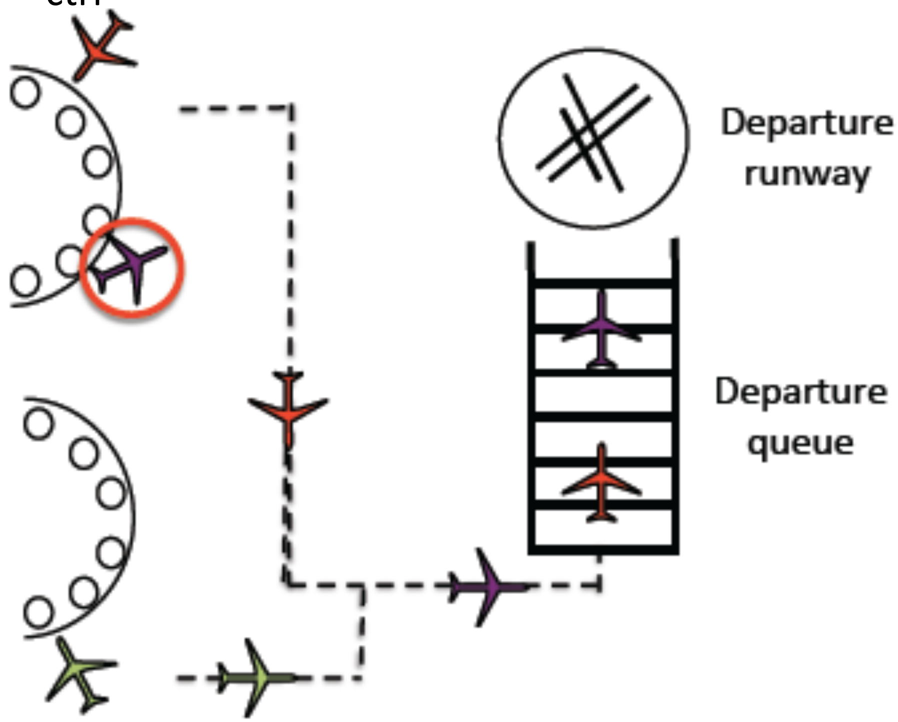

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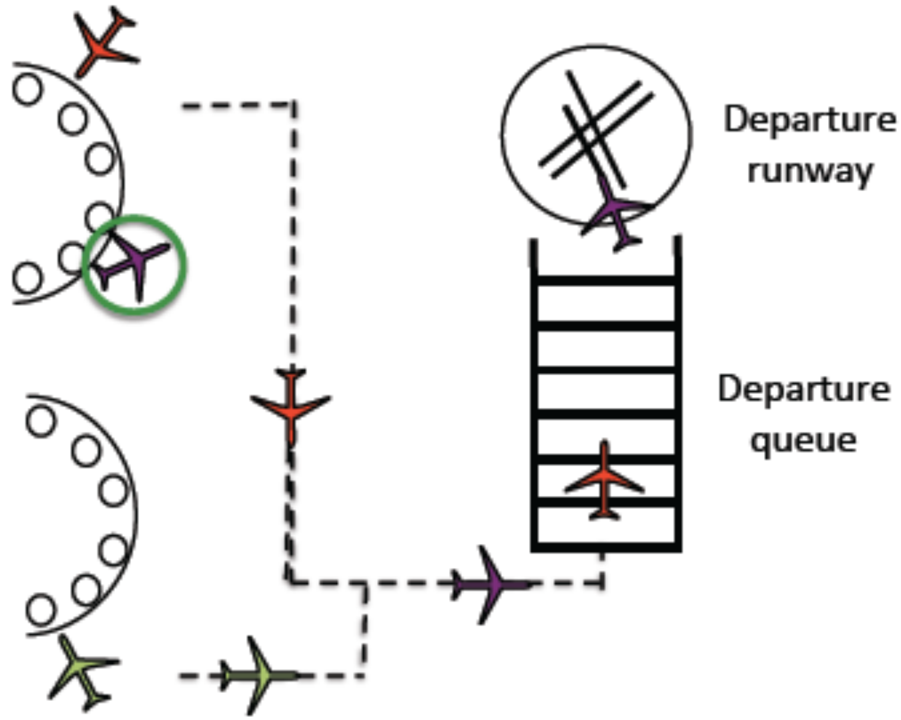

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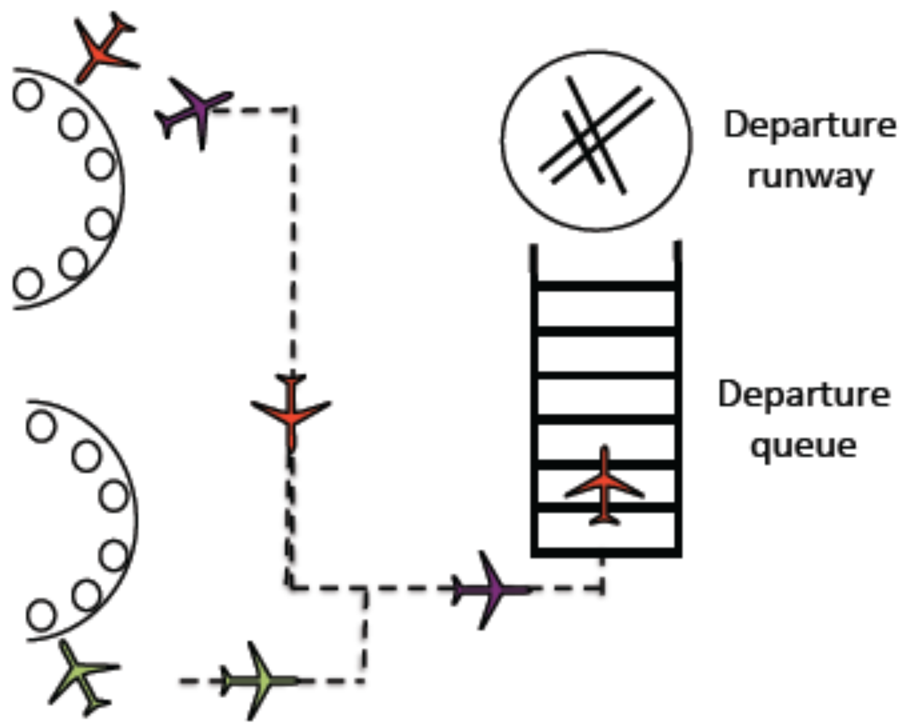


2. Implementing control strategy

- 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)

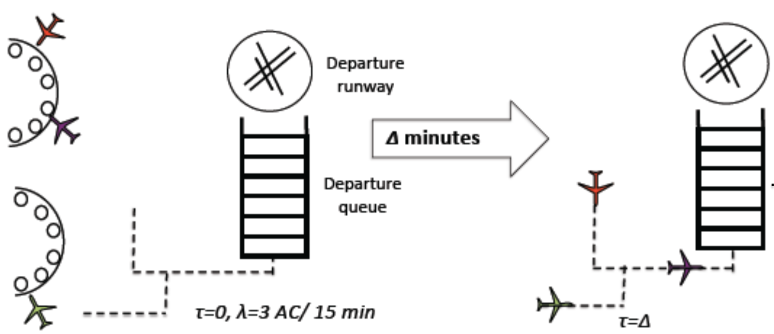
Revisit Step 1. Designing control strategy: Pushback Rate Control

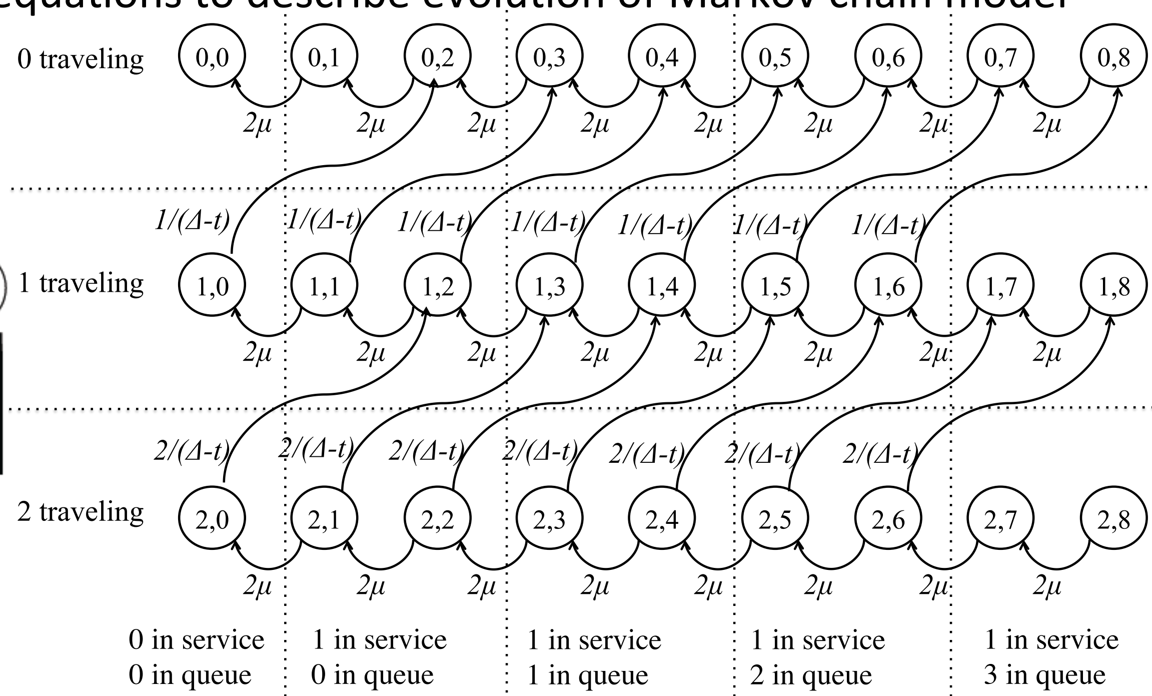
- Dynamic programming formulation to recommend pushback rate, given loading of taxiway and runway queues
- Challenges
  - Random travel time between actuation (at the gate) and queue being controlled (runway)
  - Runway process is a dynamic and stochastic process with a great variability (fleet mix, 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, Δ: Average travel time from gates to the runway

Simaiakis, Sandberg and Balakrishnan, *IEEE Trans. on Intelligent Transportation Systems*, 2014.

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 $(M(t)|R_\tau)/E_k/1$
  - Chapman-Kolmogorov equations to describe evolution of Markov chain model





Simaiakis, Sandberg and Balakrishnan, *IEEE Trans. on Intelligent Transportation Systems*, 2014.

System dynamics

- 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:

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

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

Simaiakis, Sandberg and Balakrishnan, *IEEE Trans. on Intelligent Transportation Systems*, 2014.

Dynamic programming formulation

- Bellman equation for infinite horizon average cost problem with discount factor α

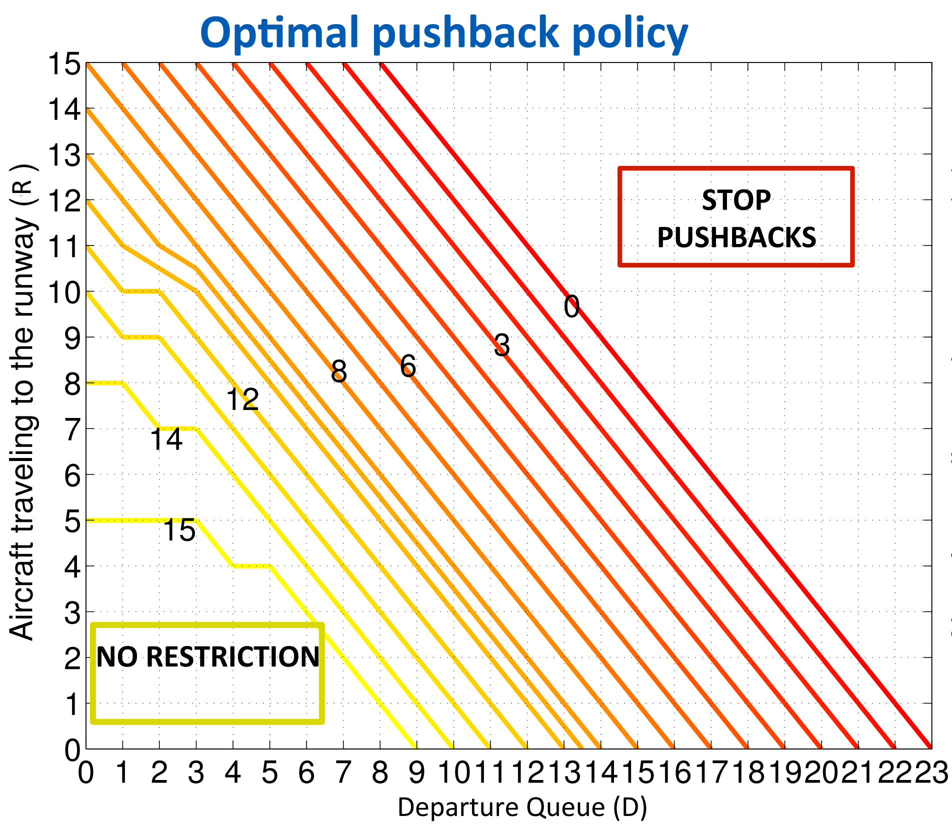
$$J^*(q,r) = \min_{\lambda \in \Lambda} \Big\{ \quad (1 - \sum \beta_i - \sum \gamma_i)[\bar{c}(q,r) + \alpha \mathbf{p}_q(q,r) \cdot \mathbf{J}^*(\lambda)]$$
$$+ \sum \beta_i [\bar{c}(q, r+i) + \alpha \mathbf{p}_q(q, r+i) \cdot \mathbf{J}^*(\lambda - i)]$$
$$+ \sum \gamma_i [\bar{c}(q, r-i) + \alpha \mathbf{p}_q(q, r-i) \cdot \mathbf{J}^*(\lambda + i)] \Big\}$$

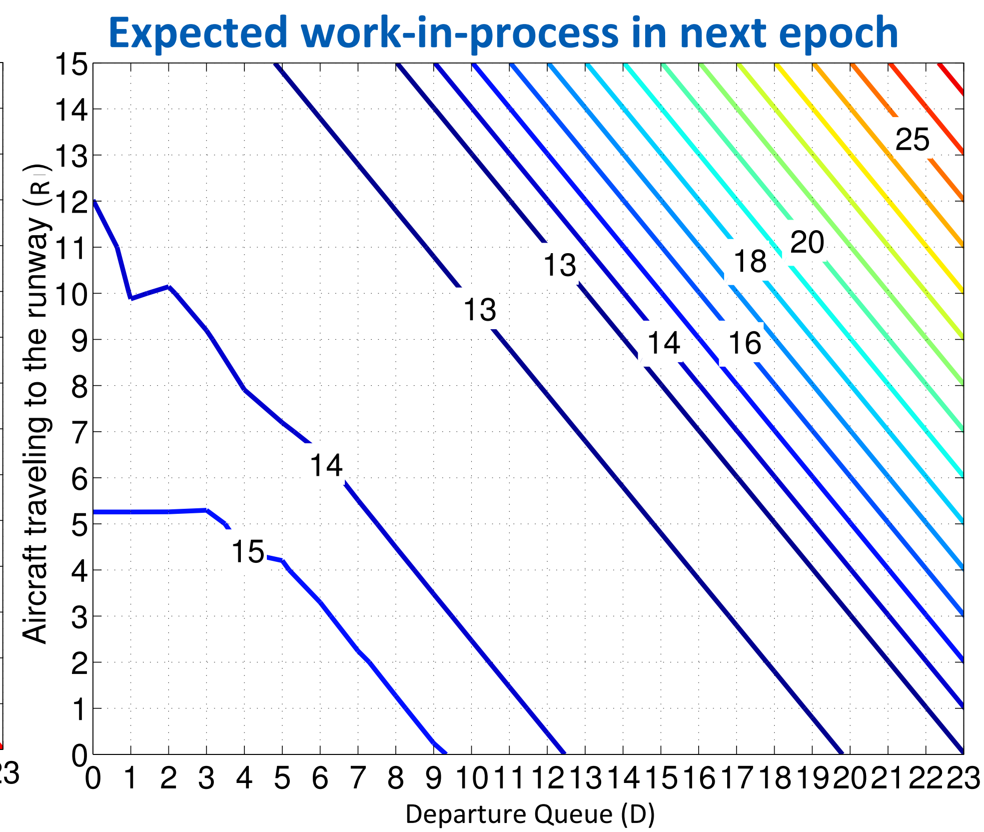
- Policy iteration converges in fewer than 10 iterations
- Can also be formulated as minimum average cost per stage problem
- Multiple ramp towers can be incorporated

Simaiakis, Sandberg and Balakrishnan, *IEEE Trans. on Intelligent Transportation Systems*, 2014.

Optimal pushback rate

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

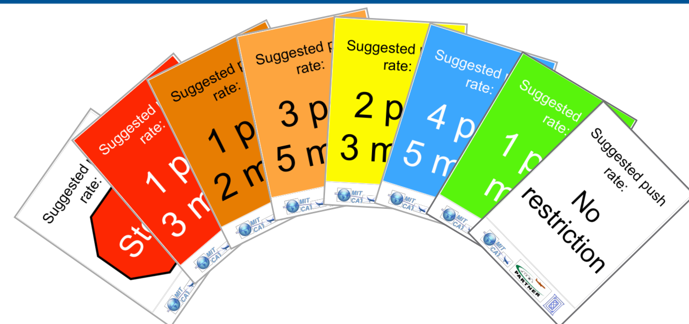


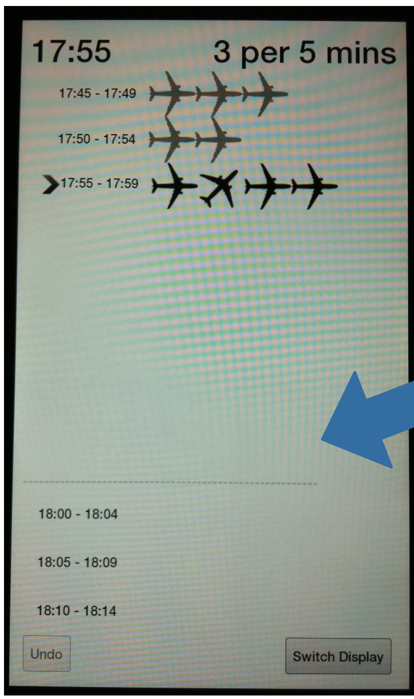


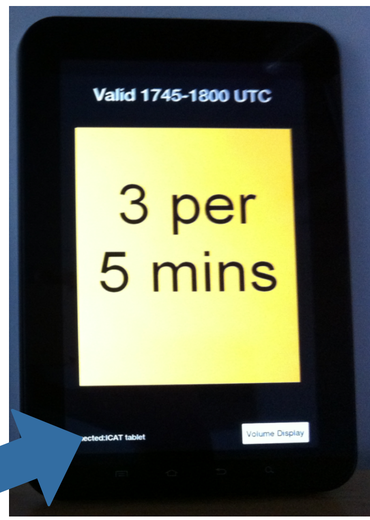
Simaiakis, Sandberg and Balakrishnan, *IEEE Trans. on Intelligent Transportation Systems*, 2014.

3. Interfacing with human controllers

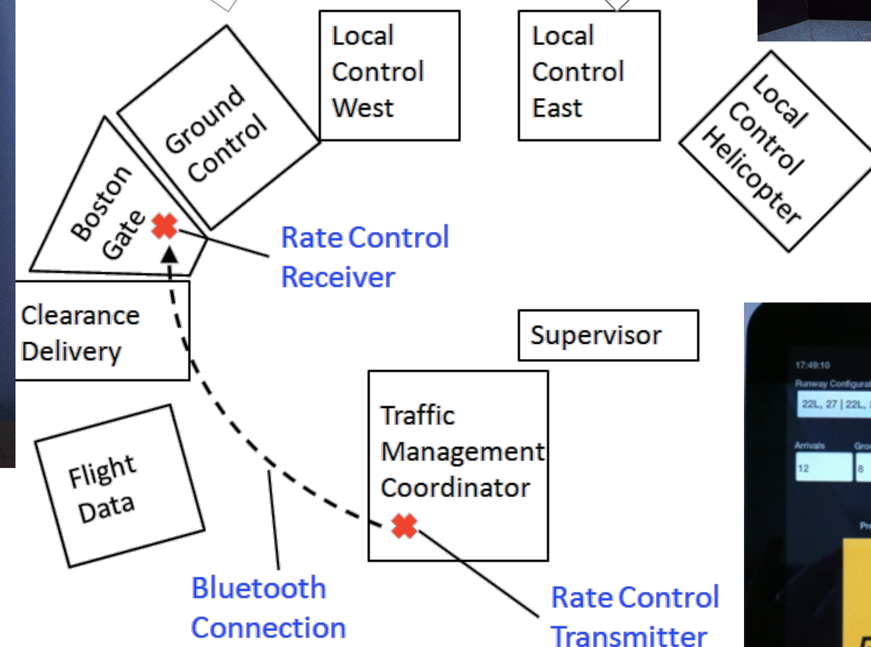
- Suggest pushback rate (color-coded cards or a tablet display)

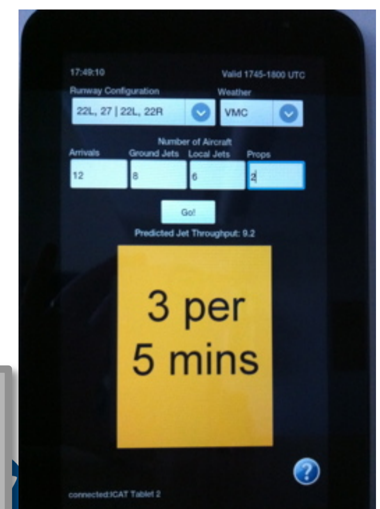






Alternative display modes

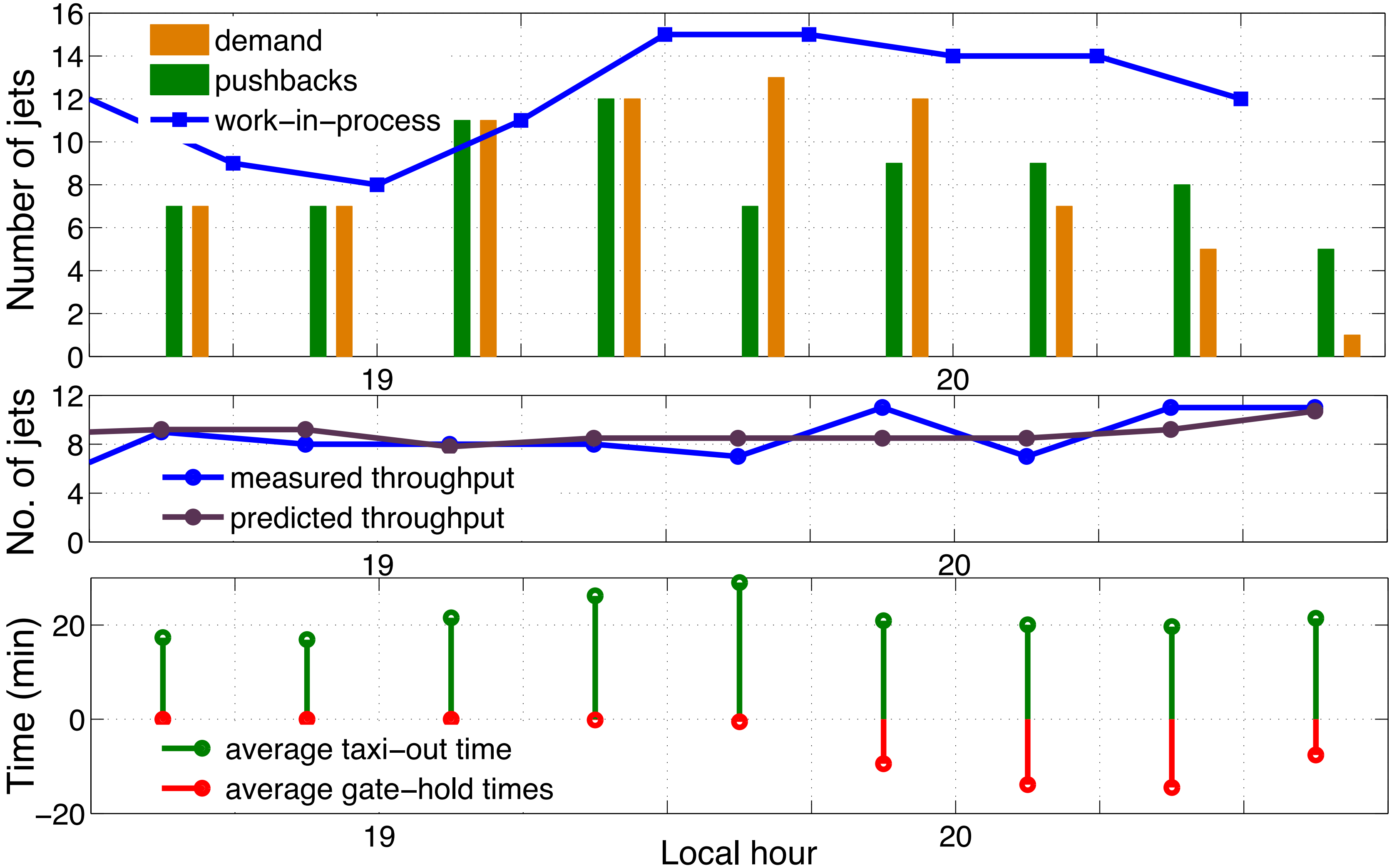




Sandberg et al.
IEEE Trans. on Human-Machine Systems 2014

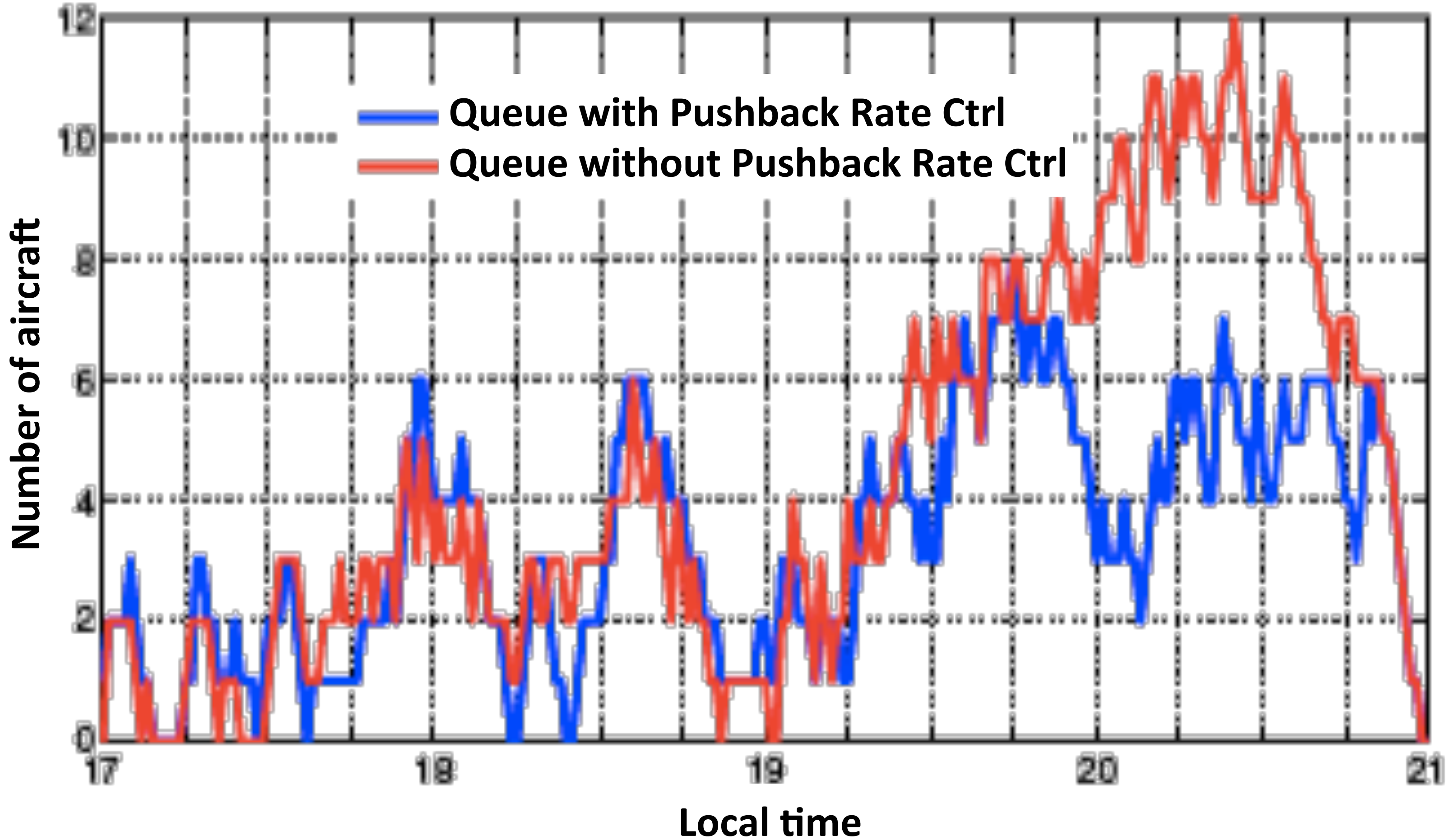
- Pushbacks in current time interval can be released (grayed out)
- Unused rate is carried over to the next time interval, up to 2/min
- Pushbacks in future time intervals can be reserved (angled)
- Pushbacks can be reserved for the following 15-min time period

Sample test results: 7/21/2011

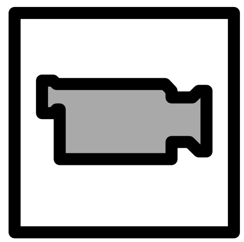


Simaiakis, Sandberg and Balakrishnan, *IEEE Trans. on Intelligent Transportation Systems*, 2014.

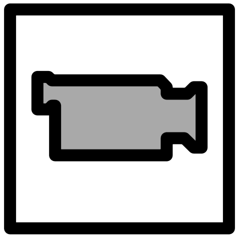
Reduced queue sizes



Visualization of operations (7/21/2011)



Visualization of operations (9/2/2010)



BOS field test results

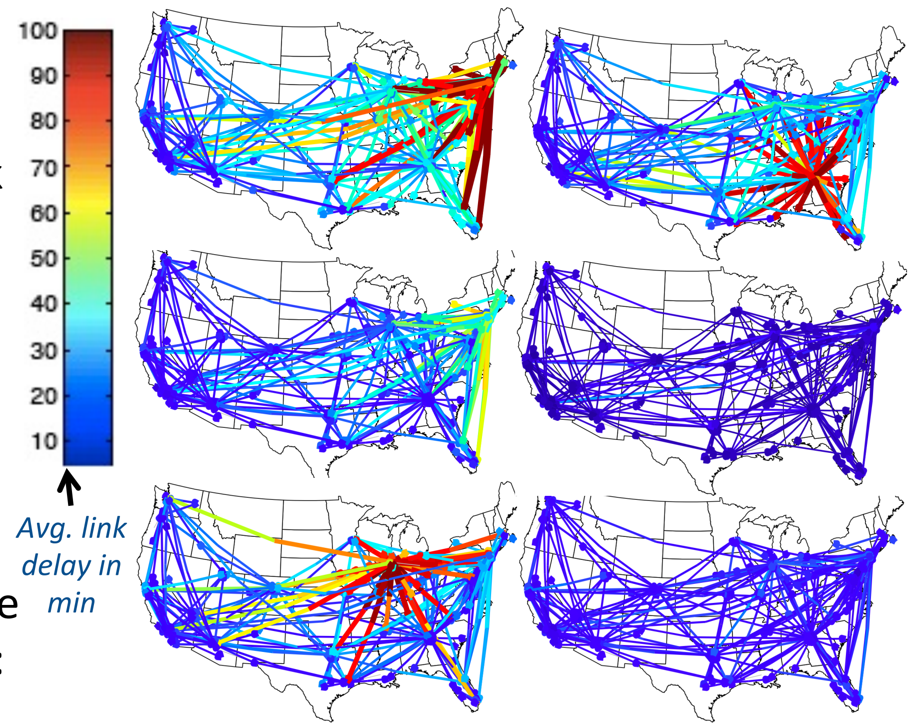
- Aug-Sep`10 & Jul-Aug`11
- 4PM-8PM departure push
- Average gate-hold: 4.7 min
- 23-25 US tons (6,600-7,300 gal) reduction in fuel burn
- 52-58 kg decrease in fuel burn / gate-held flight
- 71-79 tons CO_2 reduction
- Fair distribution of benefits
- 1 min gate-hold => 1 min of taxi-out time savings
- Positive stakeholder feedback, from both airlines and Tower personnel

Configuration	# of gate holds	Taxi-out time savings (min)
27, 22L I 22R	63	256
27, 32 I 33L	34	114
27, 32 I 33L	8	38
27, 22L I 22R	45	295
27, 22L I 22R	19	42
27, 22L I 22R	11	23
27, 32 I 33L	11	24
27, 32 I 33L	56	210
2010	**247**	**1003 min = 16.7 hours**
27, 22L I 22R	14	28
27, 22L I 22R	42	384
27, 22L I 22R	50	290
4L, 4R I 4L, 4R,9	11	13
4L, 4R I 4L, 4R,9	7	13
27, 22L | 22R	6	9
27, 22L | 22R	12	23
2011	**142**	**760 min = 12.7 hours**

Simaiakis et al., *IEEE Trans. on Intelligent Transportation Systems* 2014 and *Transportation Research A* 2014.

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

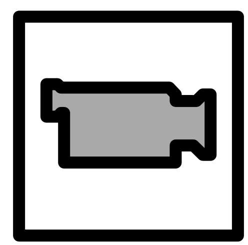


Centroids of NAS delay states.
Color represents avg. link departure delay over 2-hr time-window

Rebollo and Balakrishnan, *Transportation Research Part C*, 2014

Some other projects:
Large-scale Air Traffic Flow Management

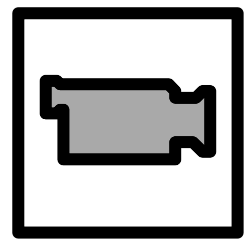
- Optimize aircraft trajectories (in space and time) with recourse on a system-wide scale, to accommodate capacity-demand imbalances
    - Use stochastic capacity forecasts (for airspace and ground resources)
    - Consider ground delays, speed changes, reroutes and cancellations
    - Account for operational 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

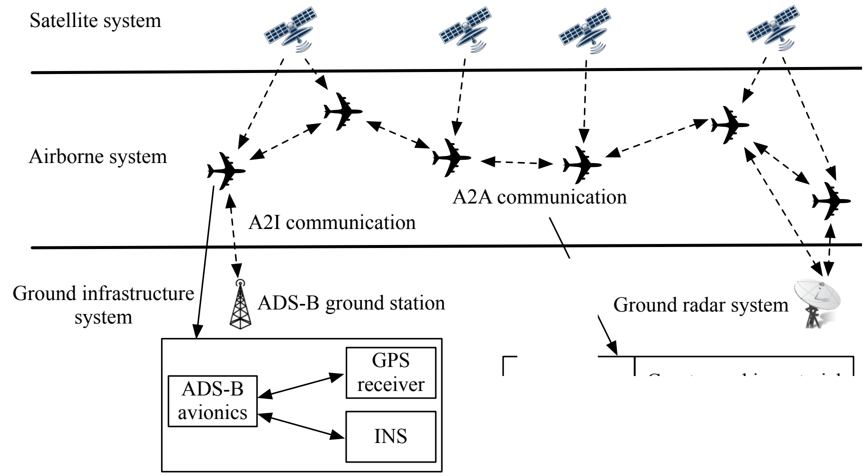
- Objectives: Safety and efficiency
  - Conflict detection and resolution
  - Optimize State Update Interval
  - Minimize flight times
- Decentralized at longer range
  - Low traffic density
  - ADS-B surveillance
  - Max transmit power
- Handover zone
  - Decentralized control
  - Adaptively adjust transmit power
- Centralized close to the airport
  - High traffic density
  - Min transmit power
- Ground radar surveillance
  - Augmented by ADS-B

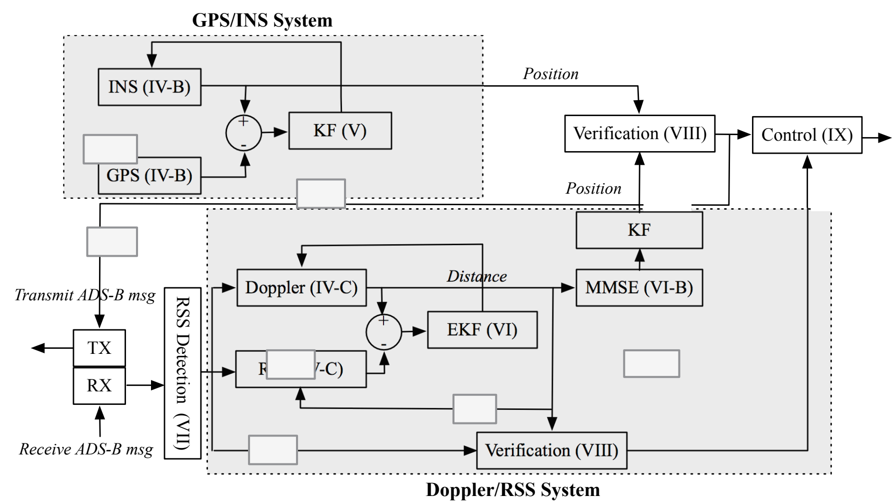


Park et al., *IEEE Trans. on Intelligent Transp. Systems* 2014

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

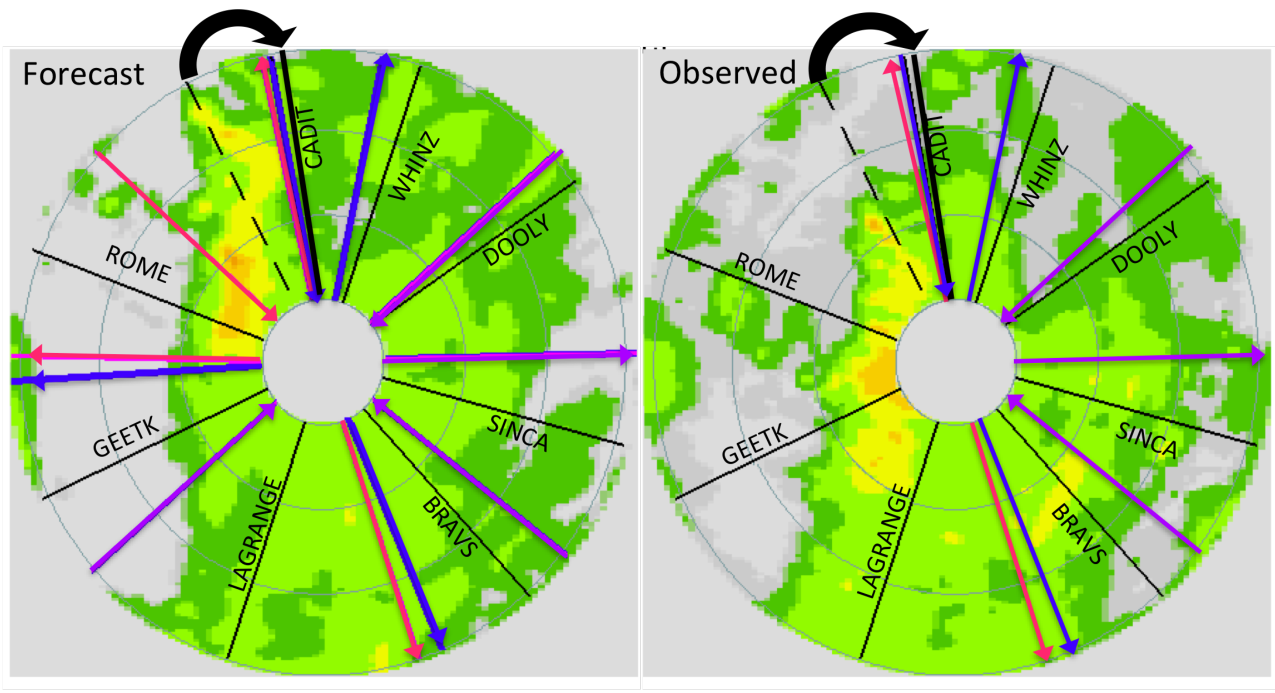




Park et al., *IEEE Trans. on Automatic Control* 2014

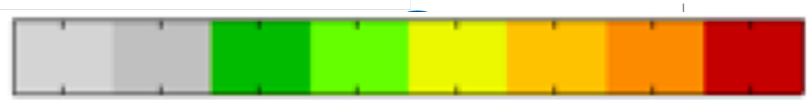
Some other projects:
Robust routing through thunderstorms

- 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



Legend
New Sector boundary
Old sector boundary
New Fix
Old Fix

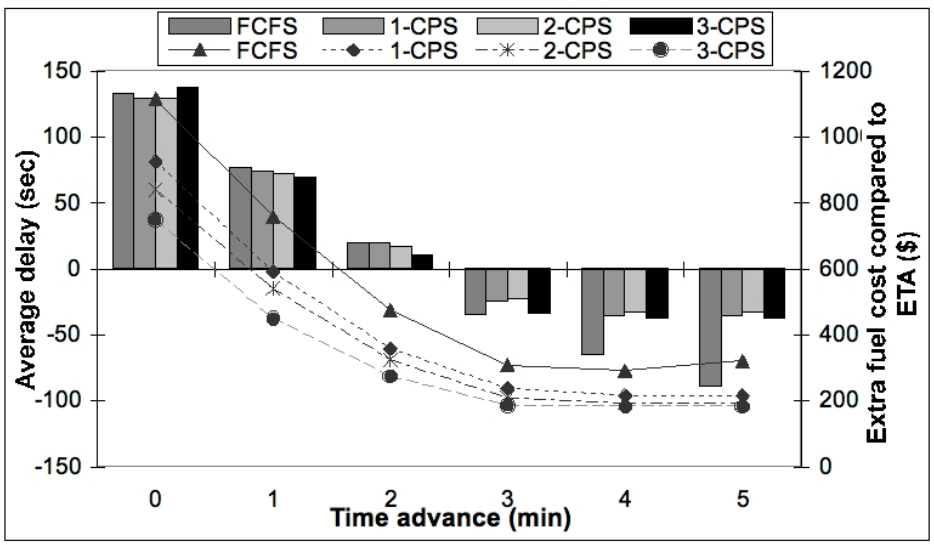
Fix	Probability	
	Old	New
WHINZ	0.975	0.975
CADIT	0.275	0.975
ROME	0.025	0.875
GEETK	0.825	0.975
LAGRA	0.975	0.975
BRAVS	0.825	0.925
SINCA	0.975	0.975
DOOLY	0.975	0.975



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]