# Modeling and Mitigation of Air Traffic Delays

**Hamsa Balakrishnan**
Massachusetts Institute of Technology
Resilient Ops, Inc.

**(With Bala Chandran, Karthik Gopalakrishnan, Richard Jordan)**

MIT AEROASTRO

RESILIENT OPS

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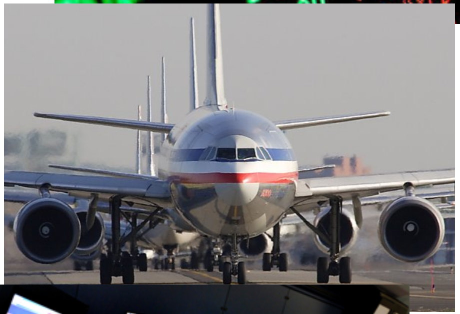
# Air transportation

- Drives global travel & commerce
  - 6.7B passenger enplanements/year
  - 85M flights/year worldwide (2014)
- US delays cost $30-40B /year
  - Waste 740M gallons of jet fuel
  - Additional 7.1M metric tons of $CO_2$
- Significant growth expected
  - Next-generation air transportation systems
  - Increased levels of autonomy and automation






# Practical algorithms for air transportation

- Goals: Efficiency, robustness, safety
- Challenges: Uncertainty, human operators, competition
- Approach:
  - Use real-world data
  - Build simple, interpretable models
  - Develop and implement scalable algorithms
- Practical algorithms and decision-support
- Cyber + Physical + Human

# Today: Two research vignettes

- **Understanding the dynamics of delay**
  - Delay propagation in networks with switching topologies
- **Mitigating the impacts of delay**
  - Large-scale, stochastic optimization algorithms for air traffic flow management

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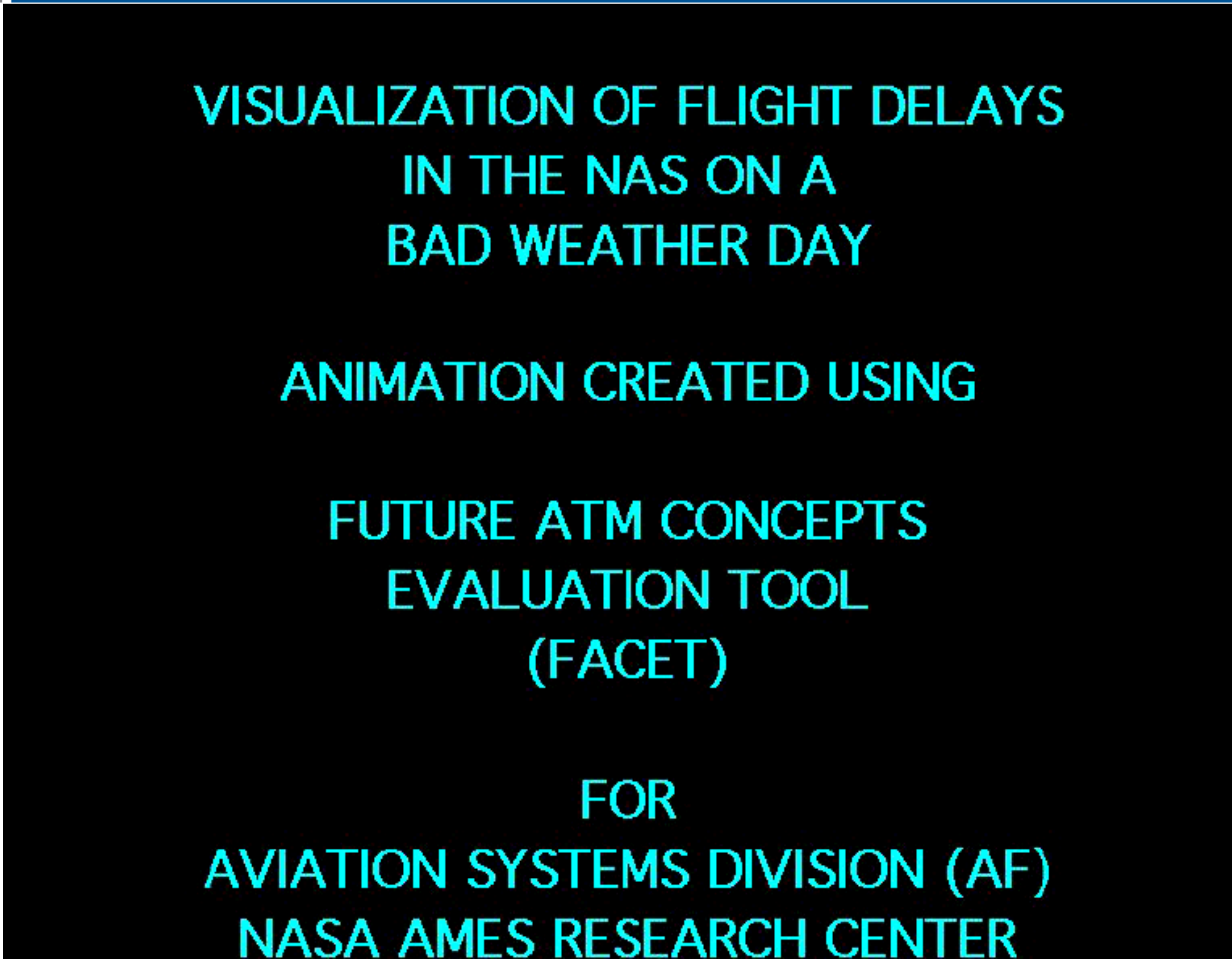
# Problem #1:
# Delays propagate

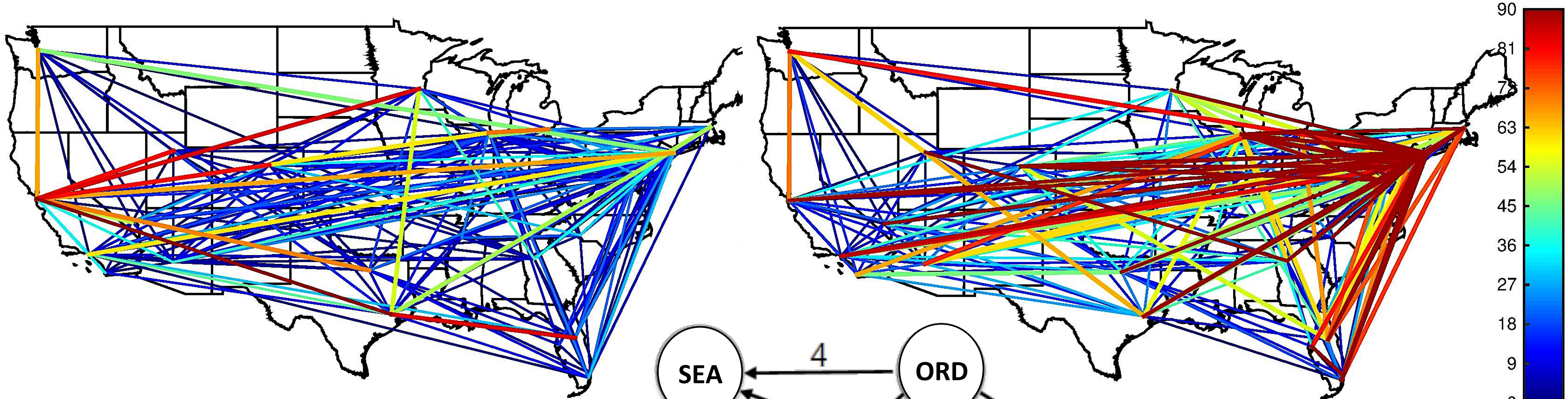


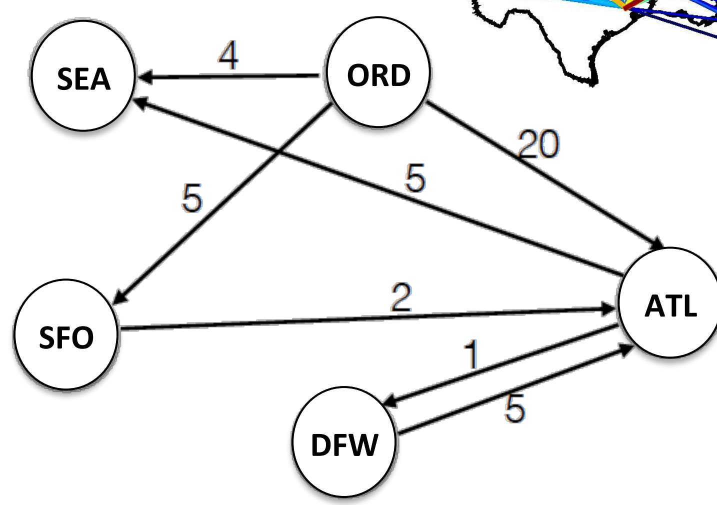
# Networks are ubiquitous, and yet…

- Networks have been used to model a vast range of systems (e.g., epidemics, rumors, power grids, communication systems, public transport, road, rail, air)
  - Nodal "state" typically assumed to belong to small set of discrete values (e.g., Susceptible, Infected, Recovered)
  - Typically unweighted and undirected networks
  - Network stucture is typically assumed to be static
- Air traffic delay networks are *different* because:
  - Delays are better modeled as continuous quantities
  - Underlying interactions are weighted and directed
  - Networks are time-varying

# A network-centric view of air traffic delays

- For example, delay levels on edges between airports
- Weighted, directed, time-varying networks



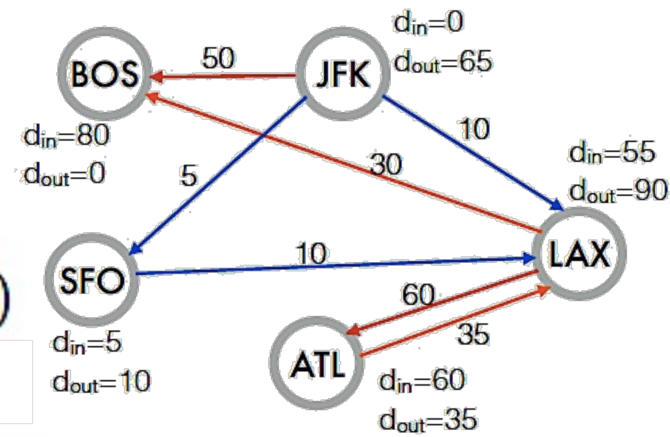




**Adjacency matrix, $A$:**

$$a_{ij} = \begin{cases} w_{ij}, & \text{if } (i,j) \in \mathscr{E}, \\ 0, & \text{otherwise} \end{cases}$$

# A simplistic model of delay dynamics

- Given adjacency matrix, $A = [a_{ij}]$




$$d^i_{in}(t+1) = \alpha^i_{in} d^i_{in}(t) + \sum_j \beta^{in}_{ji} \bar{a}_{ji}(t) d^j_{out}(t)$$

$$d^i_{out}(t+1) = \alpha^i_{out} d^i_{out}(t) + \sum_j \beta^{out}_{ij} \bar{a}_{ij}(t) d^j_{in}(t)$$

- "State" of system: $\vec{x}(t) = \begin{bmatrix} \vec{d}^{\text{out}}(t) \\ \vec{d}^{\text{in}}(t) \end{bmatrix}$

- For a fixed network topology, the system evolves as:

$$\vec{x}(t+1) = \left(\text{diag}([\vec{\alpha}^{\text{out}};\vec{\alpha}^{\text{in}}]) + \text{diag}([\vec{\beta}^{\text{out}};\vec{\beta}^{\text{in}}])\mathcal{A}\right)\vec{x}(t)$$

where $\mathcal{A} = \begin{pmatrix} 0 & \bar{A} \\ \bar{A}^{\text{T}} & 0 \end{pmatrix}.$



[Gopalakrishnan et al. CDC 2016]

# Effect of network structure on dynamics

- The matrix $A$ (and consequently, $\mathcal{A}$) depends on network structure
- Let us consider two different networks, $A_1$ and $A_2$: How do we measure if they are similar or different?
  - **Comparison of state evolution (delay dynamics)**
    - Effect of $\mathcal{A}$ is of the form
      $\vec{x}(t+1) = \beta \mathcal{A} \vec{x}(t)$, where $\mathcal{A} = \begin{pmatrix} 0 & \bar{A} \\ \bar{A}^{\mathrm{T}} & 0 \end{pmatrix}$
    - Principal eigenvector of $\mathcal{A}$ forms an invariant subspace
    - **Therefore, dynamics can be distinguished by spectral radius of $\mathcal{A}$**
  - **Comparison of network-theoretic properties**

# Network centrality metrics: Hub and Authority scores

- Strong **hubs point to** strong authorities; strong **authorities are pointed to** by strong hubs
- Extension of eigenvector centrality to directed graphs
- Hub and authority scores can be calculated as the **principal eigenvector of** (Benzi et al. 2013)

$$\mathcal{A} = \begin{pmatrix} 0 & \bar{A} \\ \bar{A}^{\mathrm{T}} & 0 \end{pmatrix}$$

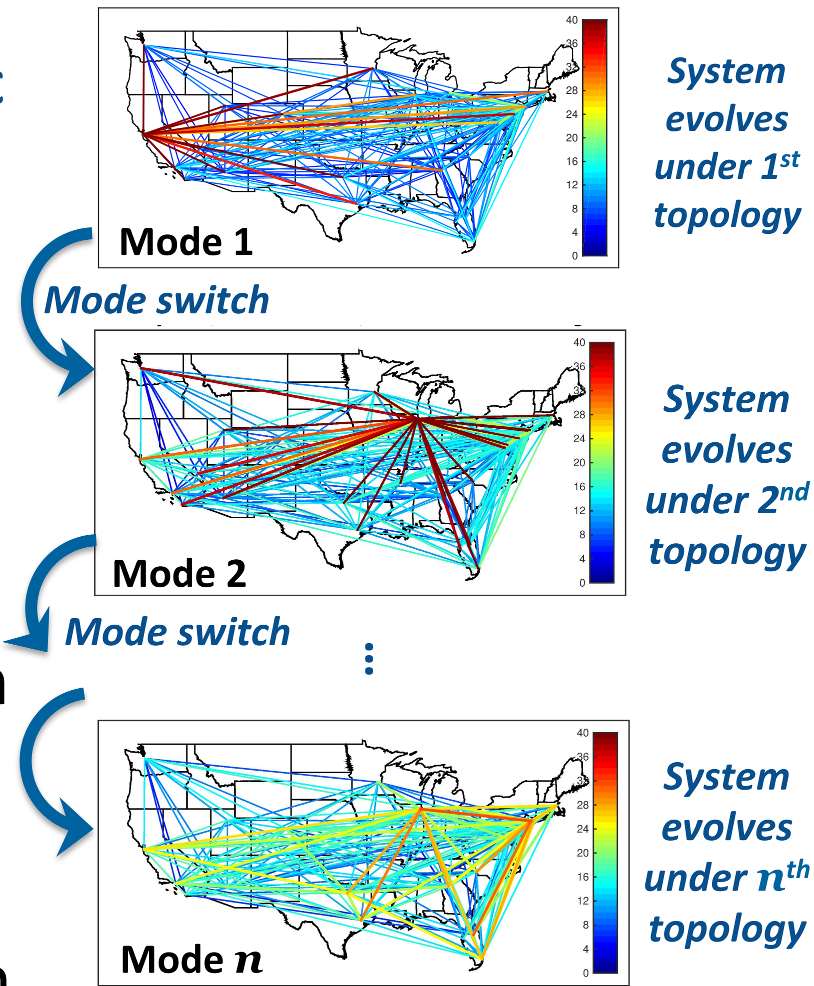
- Discrete modes determined by clustering based on:
  - Inbound and outbound delays at each airport
  - Hub and authority scores of each airport
  - System-wide delay trend (increasing/decreasing)



[Gopalakrishnan et al. ACC 2016]

# Dynamics with switching network topologies

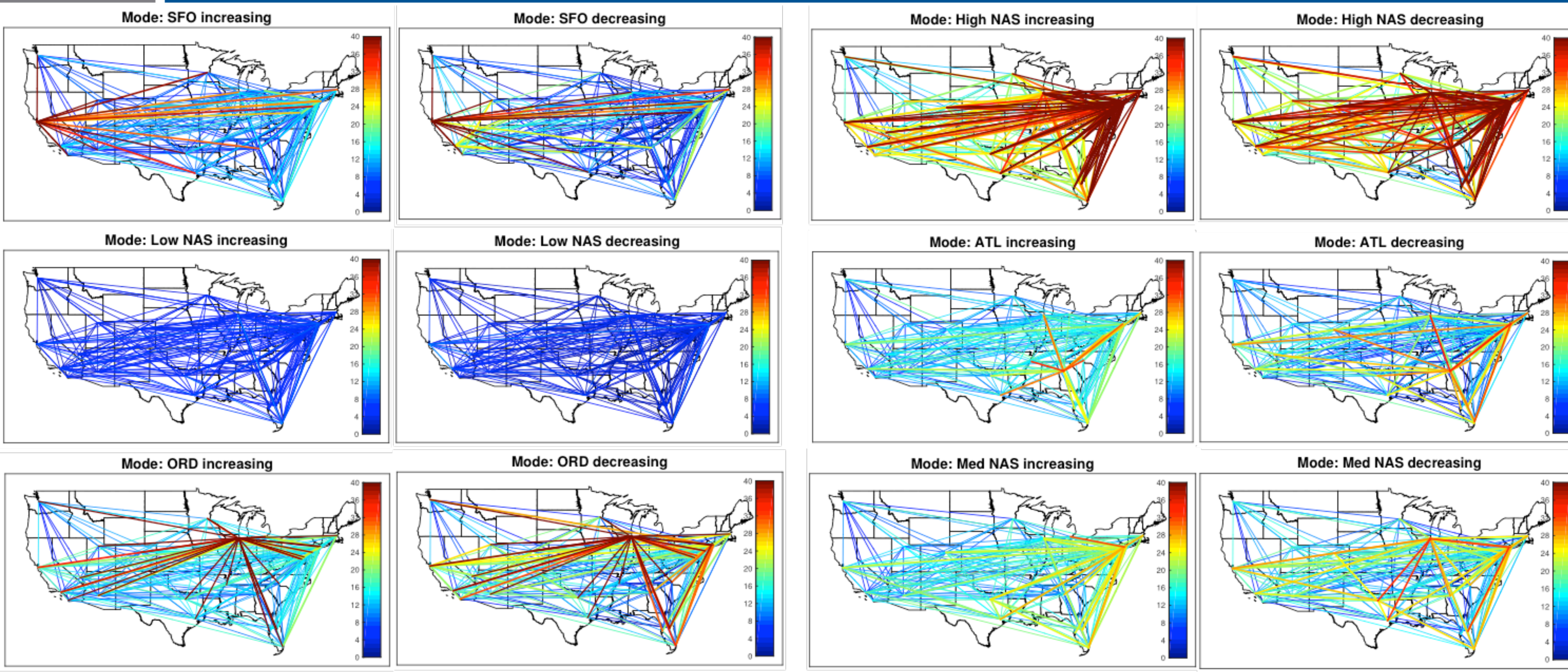
- Identify set of characteristic topologies ("discrete modes of operation")
- Determine linear continuous state dynamics under a fixed topology
- Switched linear system with random (Markovian) transitions
- Markov Jump Linear System (MJLS)






[Gopalakrishnan et al. CDC 2016]

# Discrete modes correspond to different network structures (and continuous dynamics)




$$\left.\begin{aligned} \vec{x}(t+1) &= \Gamma_{m(t)}\vec{x}(t) \\ \pi_{ij} &= \Pr[m(t+1)=j \mid m(t)=i] \end{aligned}\right\}$$

**Markov Jump Linear System (MJLS)**

$$\underbrace{\vec{x}(t+1) = J_{ij}\Gamma_i\vec{x}(t),}_{\text{Continuous state resets}} \text{ if } m(t)=i \text{ and } m(t+1)=j$$

# Stability of MJLS models

- "Physical interpretation": Will delays increase or decrease over time (e.g., over the course of a day)?
- **Almost-Sure Stability:** A system is said to be almost-surely stable if the state tends to zero as time tends to infinity with probability 1, that is,

$$\Pr[\lim_{k \to \infty} \|\vec{x}(k)\| = 0] = 1,$$

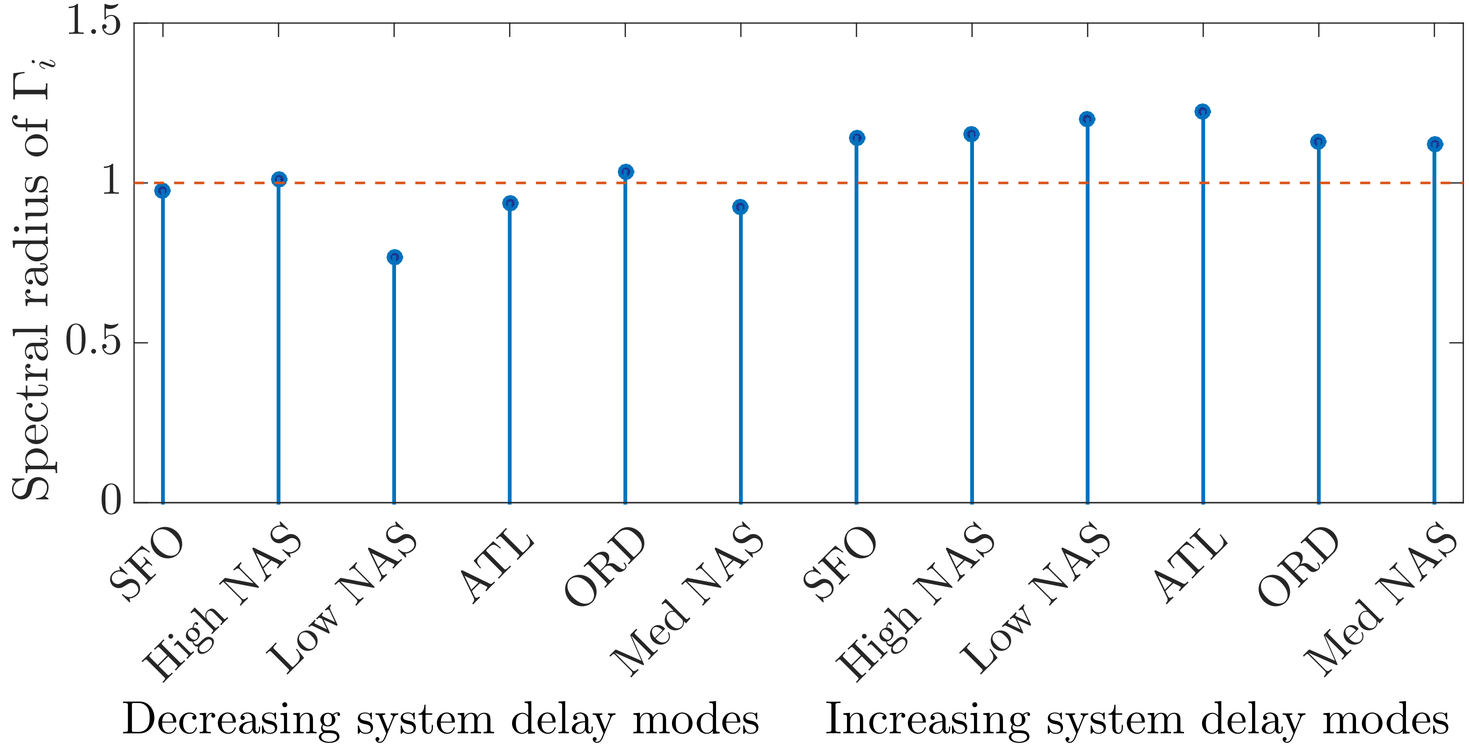
  for any nonnegative initial condition, $\vec{x}(0)$.
- Derive conditions for the stability of a discrete-time Markov Jump Linear System with time-varying transition matrices and continuous state resets (depends on $\Gamma_i$'s, $\pi_{ij}(t)$ and $J_{ij}$)



[Gopalakrishnan et al. CDC 2016]

# Some discrete modes are stable, while others are not…

- $\vec{x}(t+1) = \Gamma_{m(t)}\vec{x}(t)$ is stable if and only if the spectral radius of the matrix $\Gamma$ is less than 1



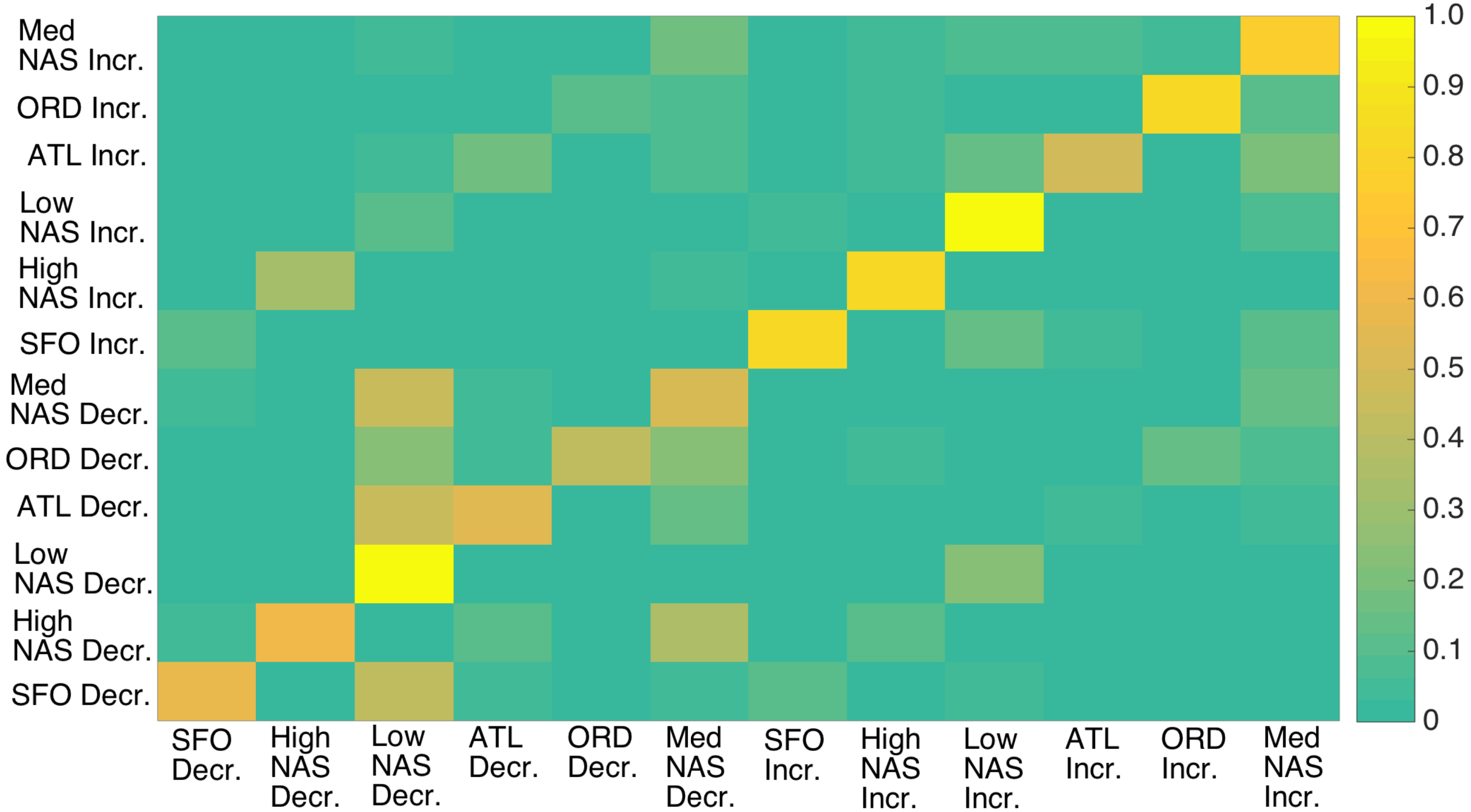

- Stability of component modes is neither necessary nor sufficient for the stability of a switched system



[Liberzon and Morse 1999; Gopalakrishnan et al. CDC 2016]

# Is the MJLS stable?

- Consider "average" transition matrix for each hour of day

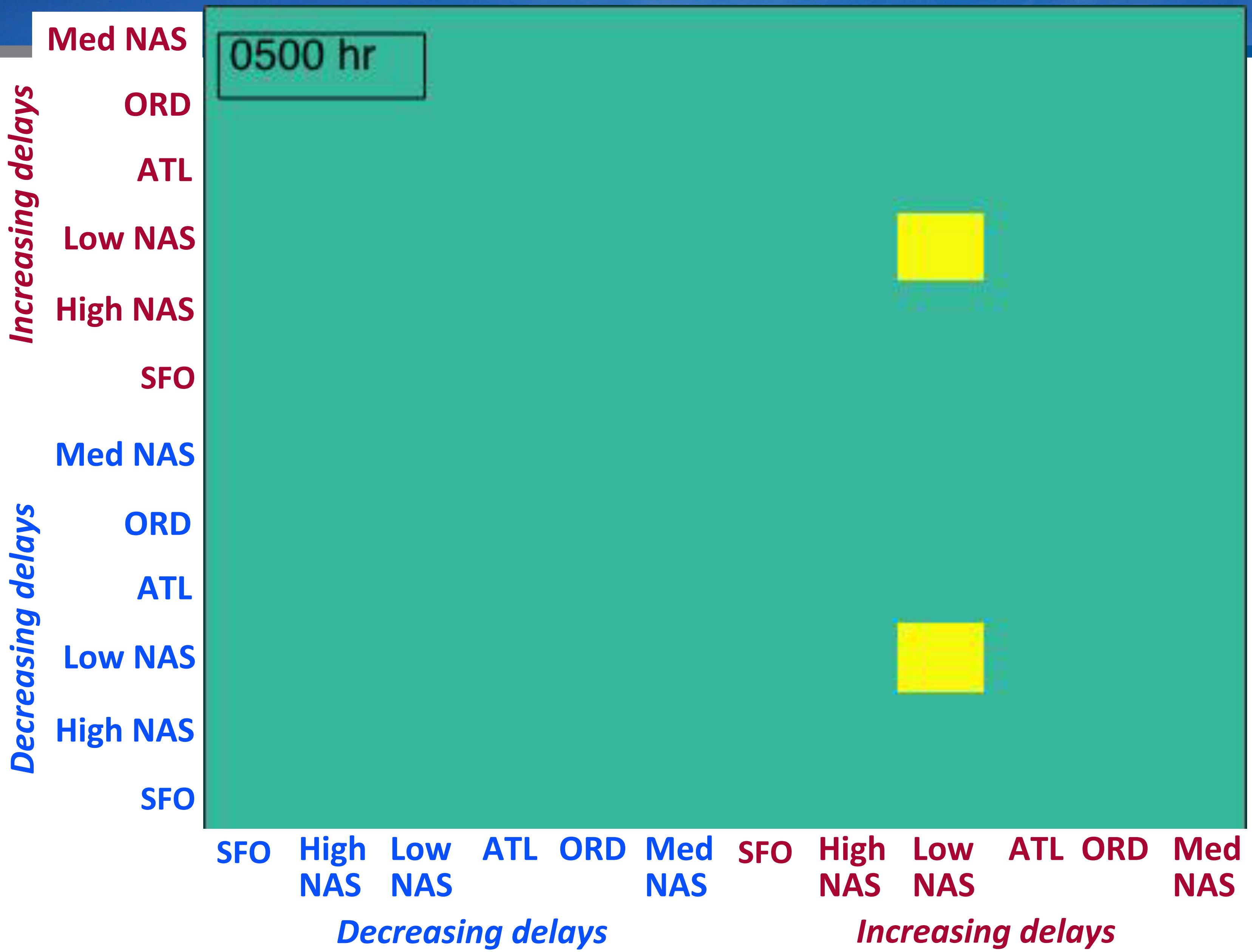



- The resulting MJLS model is ***not*** stable



[Gopalakrishnan et al. CDC 2016]

# Transition matrices exhibit temporal patterns



# Stability of MJLS model

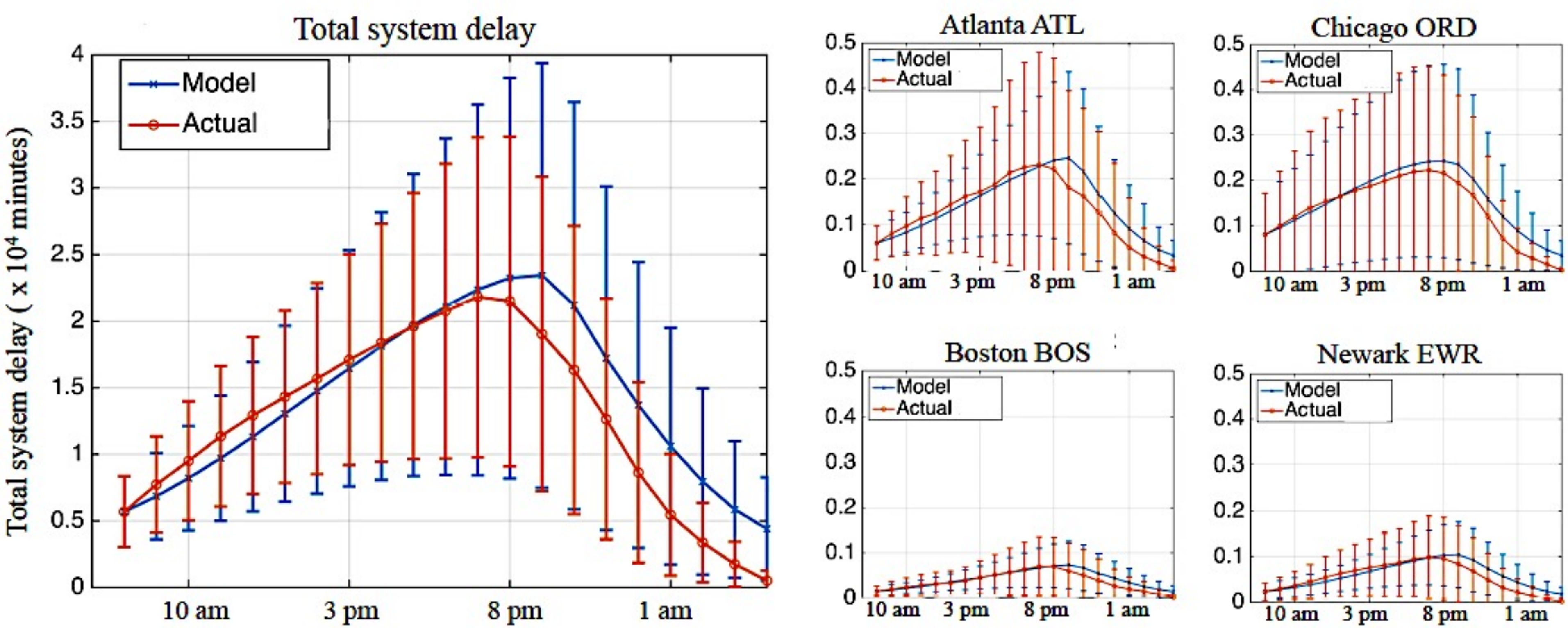
- Consider stability of MJLS model with periodic time-varying mode transition matrices (determined by hour of day)
- Resulting MJLS model shown to be stable
- System appears to be stabilized by the temporal variations in the mode transition matrices



[Gopalakrishnan et al. CDC 2016]

# MJLS model validation

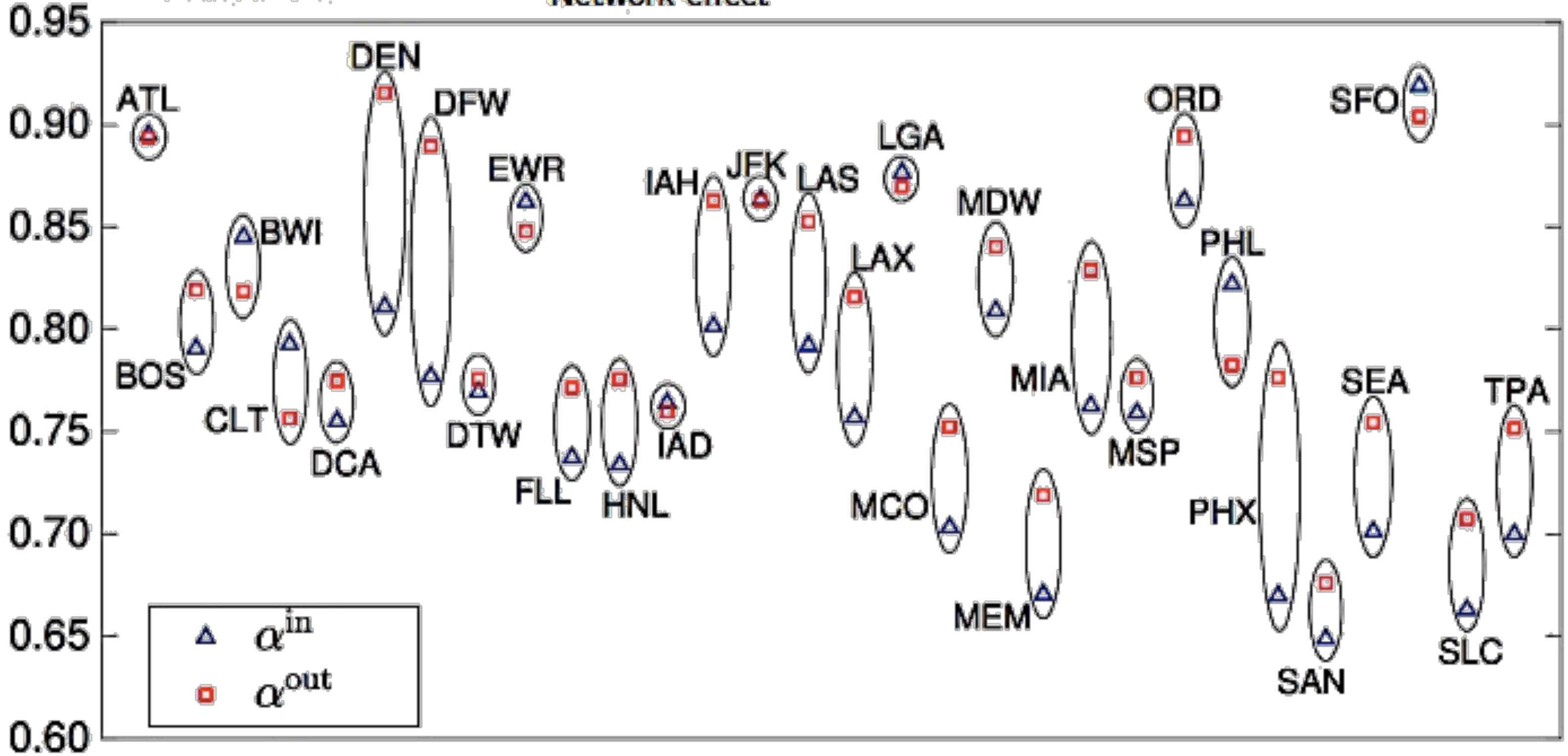
- Model learned using 2011 data; validation using 2012 data



# Measure of airport resilience: Delay persistence

$$d^i_{in}(t+1) = \underbrace{\alpha^i_{in} d^i_{in}(t)}_{} + \sum_j \underbrace{\beta^{in}_{ji} \overline{a}_{ji}(t) d^j_{out}(t)}_{}$$

$$d^i_{out}(t+1) = \underbrace{\alpha^i_{out} d^i_{out}(t)}_{\text{Persistence}} + \sum_j \underbrace{\beta^{out}_{ij} \overline{a}_{ij}(t) d^j_{in}(t)}_{\text{Network effect}}$$






[Gopalakrishnan et al. CDC 2016]

# Next steps

- Analysis of dwell times in each discrete mode
  - How long does a "delay state" tend to persist?
- Factors that trigger mode transitions
  - Weather impacts, Traffic Management Initiatives
- Prediction of future delays and delay states
  - Current delay state can help predict link delays 6 hr in advance with 23 min avg. error [Rebollo/Balakrishnan 2014]
- **Multi-layer, multi-timescale networks**
  - Cancellations, operations, capacity impacts [ICRAT 2016]
  - Interactions between networks

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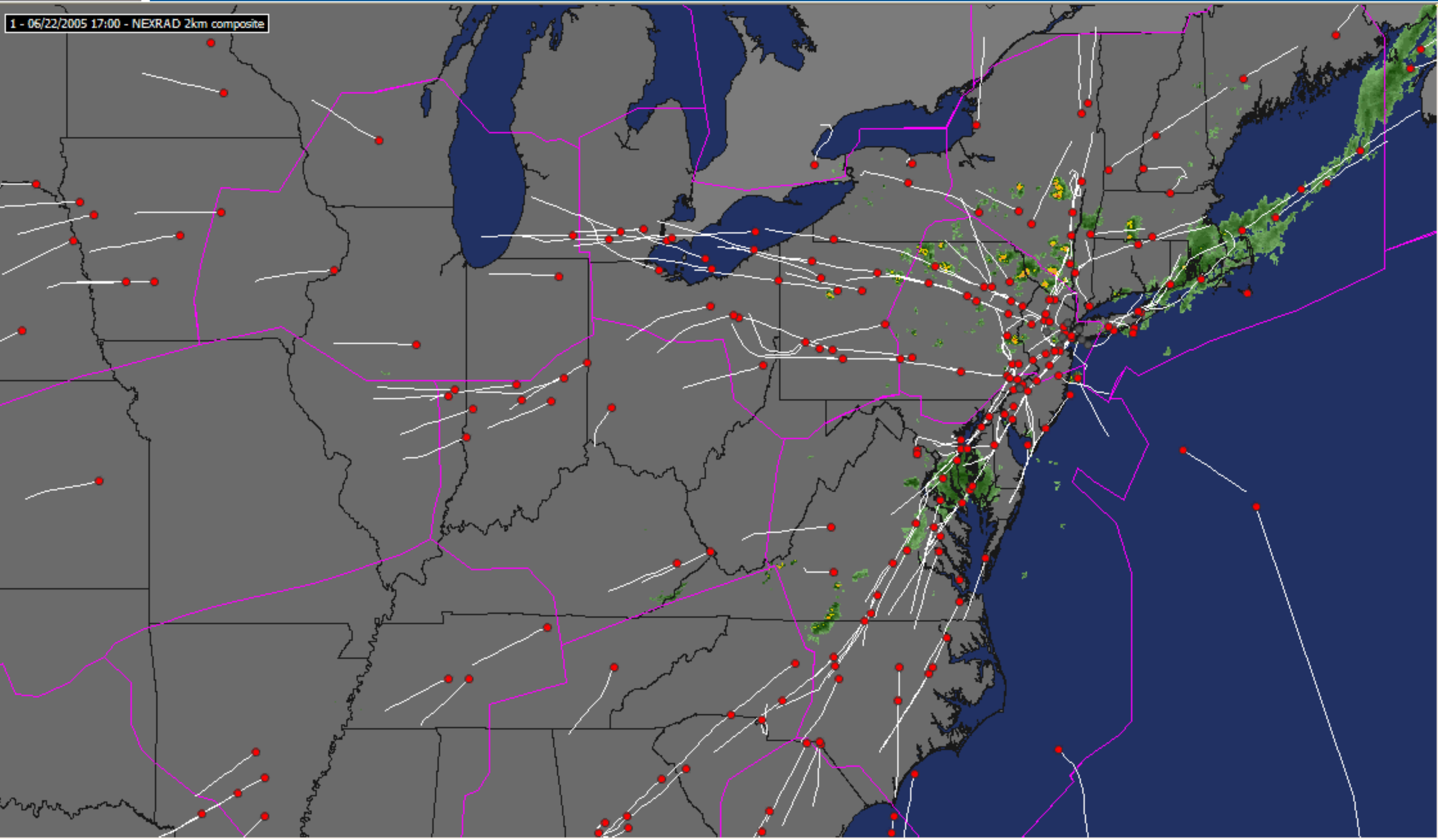
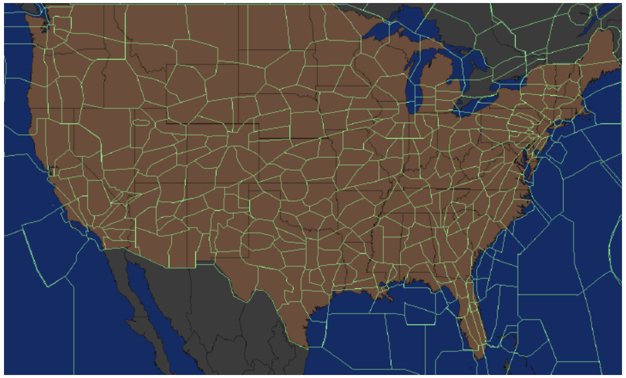
# Problem #2:
# Capacity constraints can cause large delays

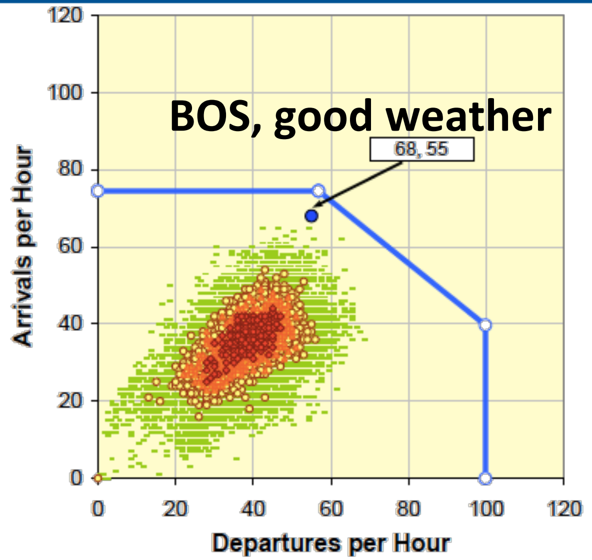


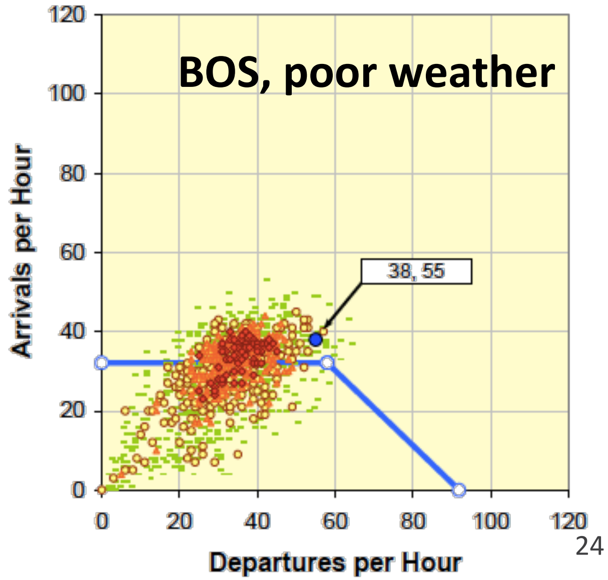

[Movie courtesy Rich DeLaura, MIT Lincoln Lab]

# Airport and airspace capacities

- Airport arrival/departure rate tradeoffs (capacity envelopes)
  - Depend on visibility, wind, etc.
- Airspace is divided into sectors; subject to max occupancy limits
  - Depend on geometry, traffic patterns, air traffic controller workload, weather, etc.





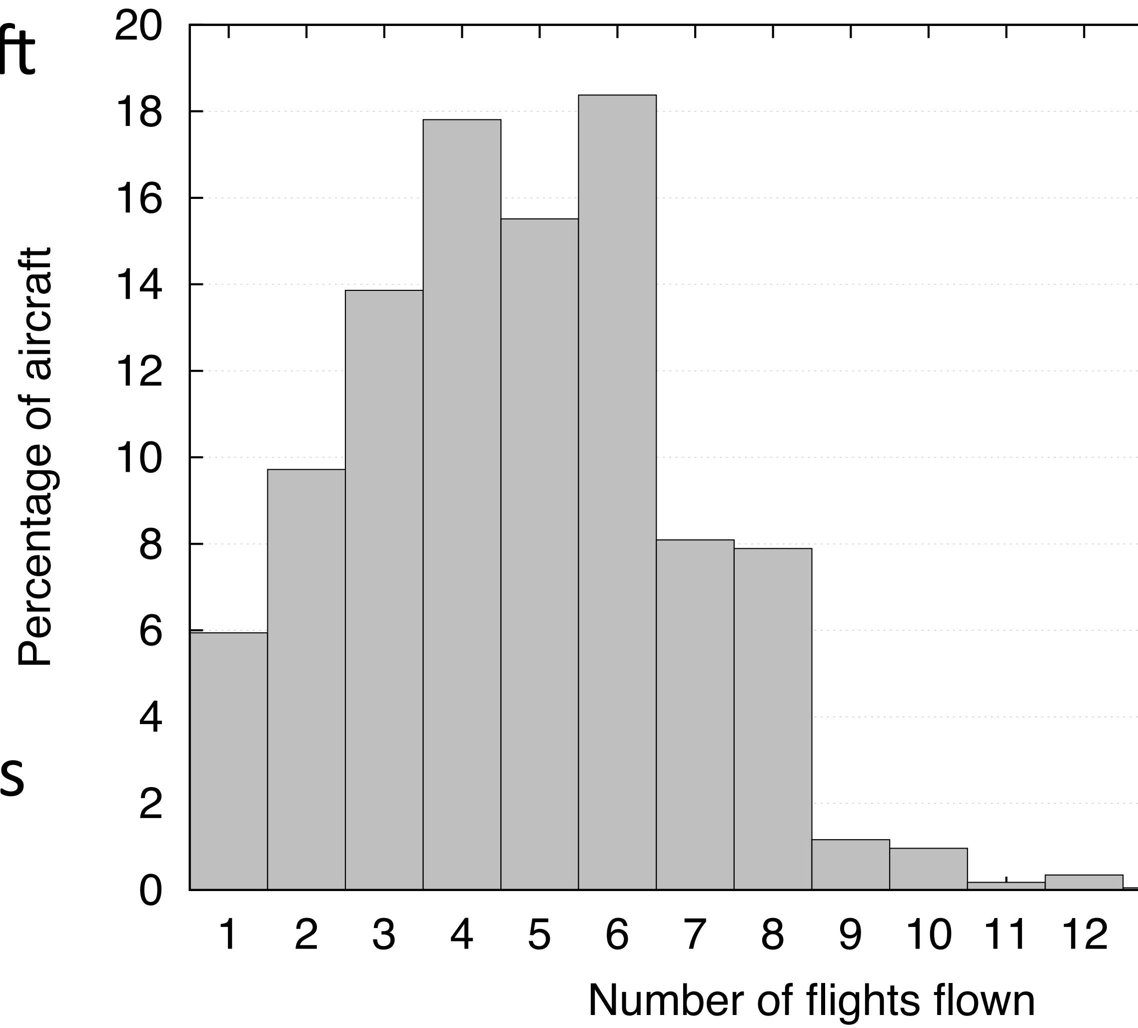






[FAA Airport Capacity Benchmark 2004]

# Challenges: Flight connectivity + uncertainty

- Only 6% of aircraft fly just one flight per day
  - Results in delay propagation
  - Rolling horizon optimization is suboptimal
- Capacity forecasts are subject to uncertainty






[Balakrishnan and Chandran, 2014]

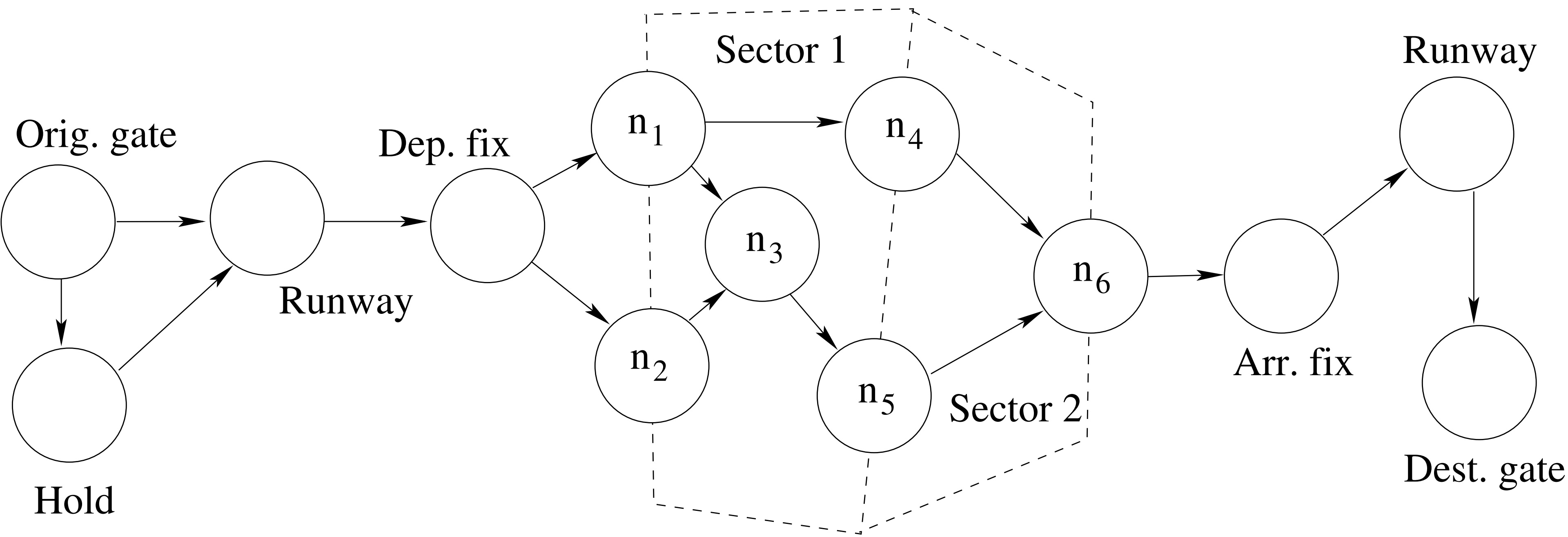
# Problem statement: Air Traffic Flow Management

- Given set of flights with assigned aircraft, (scenario tree and) capacity profiles, identify trajectory for each aircraft to maximize (expected) system-wide profit, and satisfy operational/capacity constraints (in all scenarios)
  - Constraints:
    - Airport/airspace sector capacity limits
    - Flight connectivity and turn-around times
    - Maximum/minimum transit times and speeds
  - Control actions:
    - Ground/airborne delays
    - Rerouting
    - Cancellations

[Odoni 1987; Helme 1992; Vranas 1994; Maugis et al. 1995; Bertsimas & Stock Patterson 1998; Bayen et al. 2006; Bertsimas et al. 2011; Wei et al. 2013; Balakrishnan & Chandran 2014]

# Trajectory definition

- Time is discretized (e.g., 5-minute intervals)
- Sequence of node-time combinations representing the flight path of an aircraft

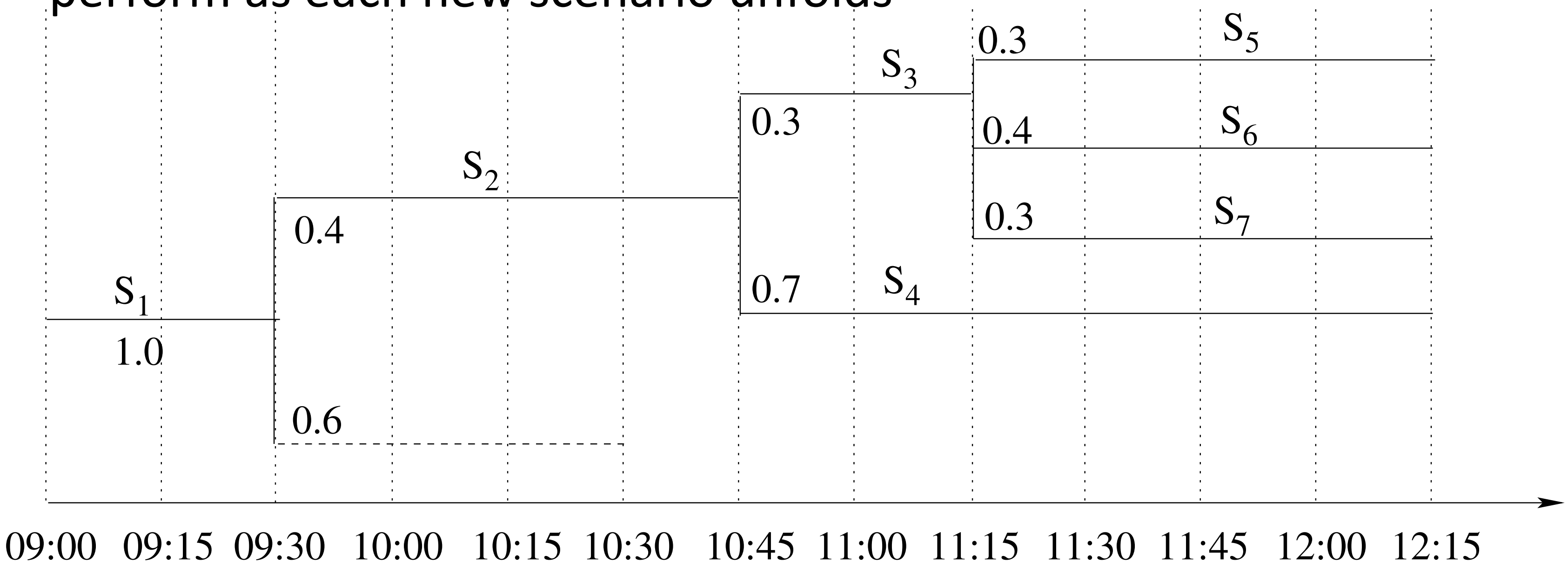





[Balakrishnan and Chandran, 2014]

# Handling uncertainty: Trajectory trees

- Location of aircraft at each time during a scenario + action to perform as each new scenario unfolds




  - *Depart gate @9:05, reach runway @9:15, reach departure fix @9:30; if scenario $S_2$ materializes, then go toward $n_1$ and reach @9:45, else go toward $n_2$ and reach @10:05;…*

- Decision can be based only on information available at the time



[Balakrishnan and Chandran, 2014]

# Mathematical formulation: Deterministic ATFM

maximize total benefit of selected trajectories

s.t. Select only one trajectory for each aircraft

Sector capacity constraints

Airport capacity envelope constraints

Binary variable indicating selected trajectory



[Balakrishnan and Chandran, 2014]

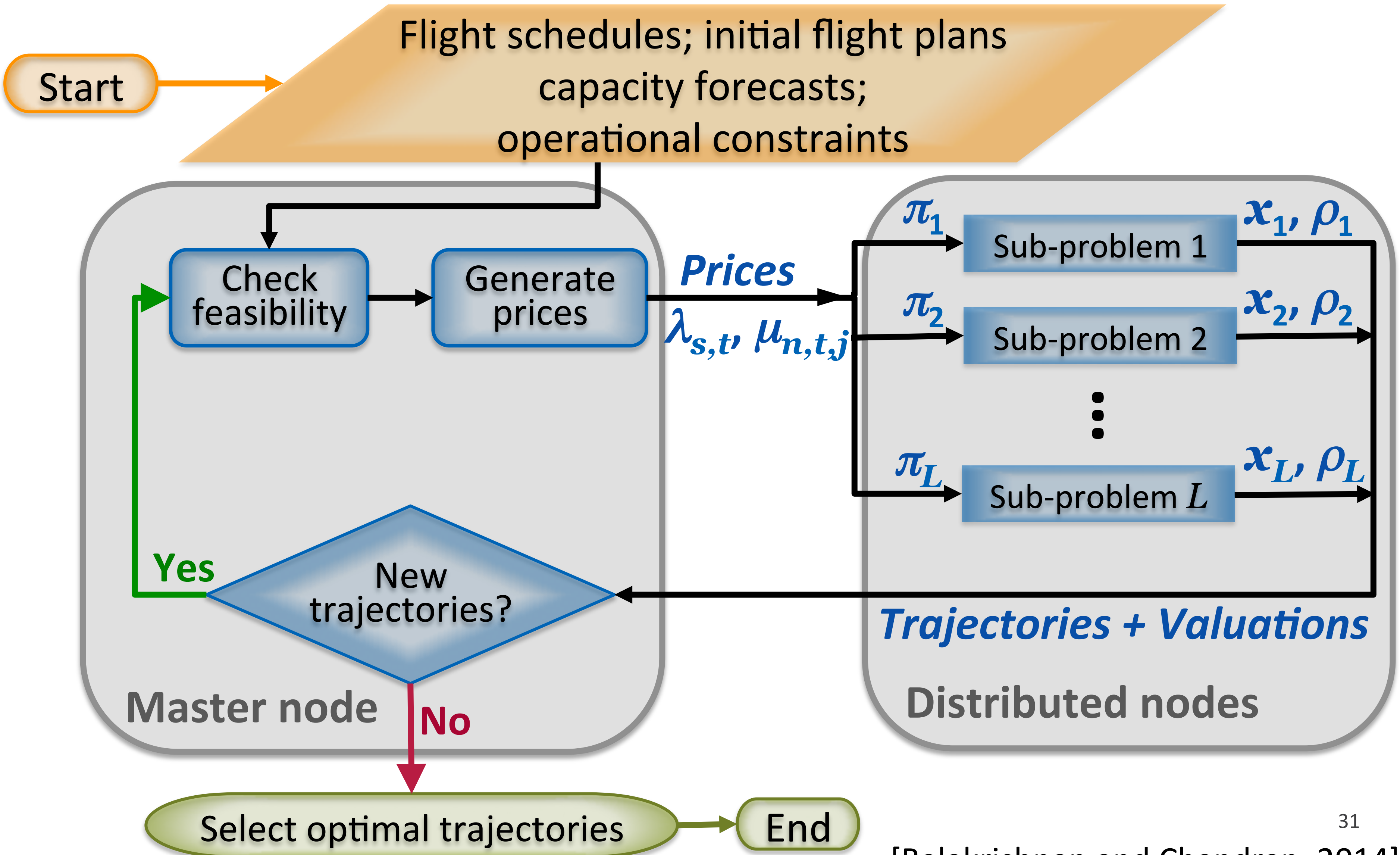
# Solution process

- Very large-scale Integer Program
- LP relaxation (Restricted Master Problem) solved using column generation
  - Sub-problems solved independently for each aircraft ("tail")
    - Formulated as longest-path problem on a DAG
    - Solved using dynamic programming
    - Enables parallel implementation
- Effective heuristic to obtain bounds and assess optimality gap



[Balakrishnan and Chandran, 2014]

# Schematic of solution process for Restricted Master Problem






[Balakrishnan and Chandran, 2014]

# Computational results (Deterministic ATFM)

- 24-hr planning horizon; 5 minute time-discretization

| Reference | Control | Scale | Horizon/disc. | Run times |
|---|---|---|---|---|
| Maugis (1995) | Ground holds; cancellations | 4,743 flights; 1,153 sector-saturated time periods (no airport capacity limits) | 1 day/5 min | 2+ hours (no cancel-lations) |
| Bertsimas and Stock Patterson (1998) | Ground/air holds | 1,002 flights; 18 airports; 305 sectors | 8 hours/5 min | 8+ hours |
| Bertsimas and Stock Patterson (2000) | Ground/air holds; limited rerouting | 71 flights; 4 airports; 42 sectors | 8 hours/5 min | 4 min |
| Bertsimas et al. (2011) | Ground/air holds; rerouting network | 6,745 flights; 30 airports; 145 sectors | 8 hours/15 min | 10 min |
| Wei et al. (2013) | Aggregate model; air holds | 3,419 flt paths; 284 sectors | 2 hours/1 min | 21 min |
| **Balakrishnan and Chandran (2014)** | Ground/air holds; unrest-ricted rerouting network; cancellations | 17,500 flights; 370 airports; 375 sectors | 24 hours/5 min | 5 min |



[Balakrishnan and Chandran, 2014]

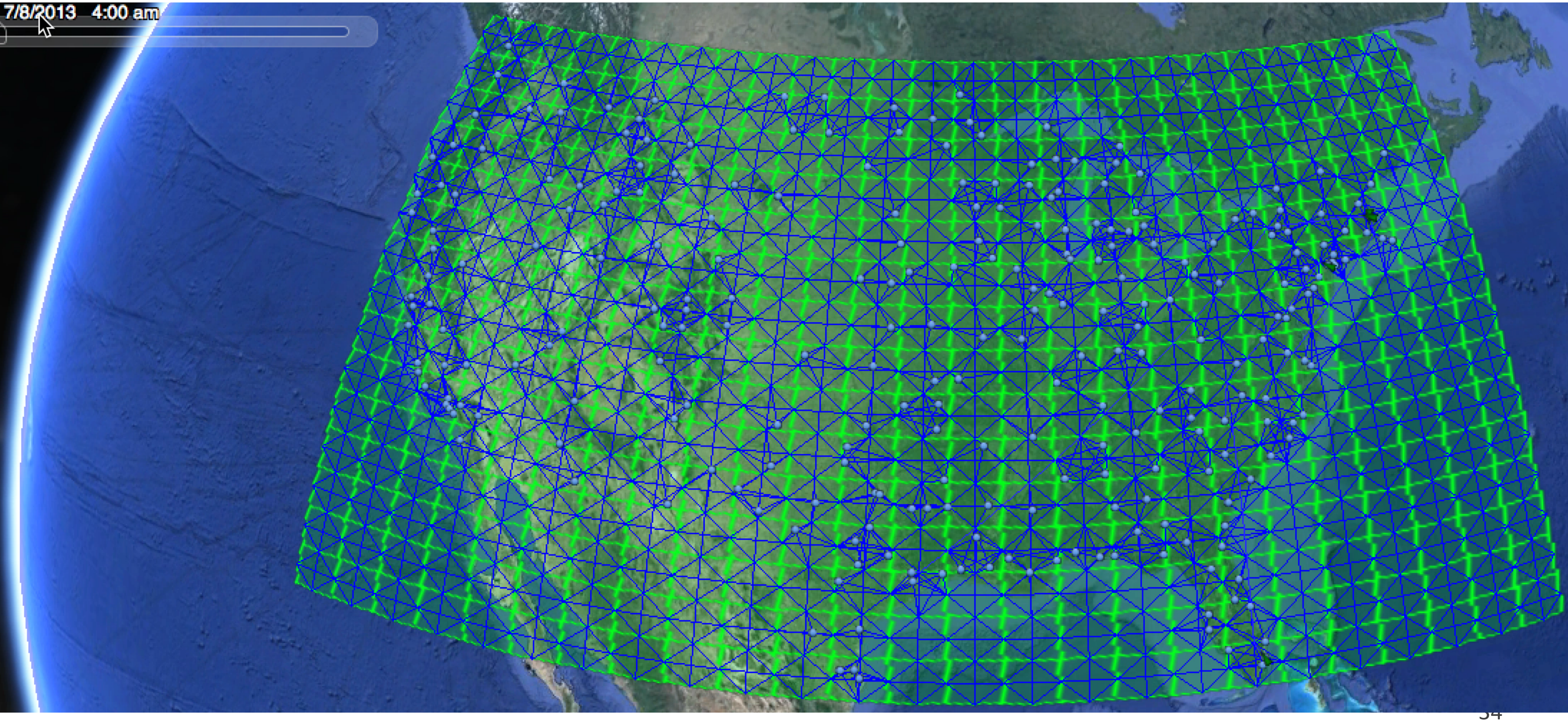
# Computational results (Stochastic ATFM)

- 24-hr planning horizon; 10 minute time-discretization

| Reference | Control | Scale | Horizon/disc. | Run times |
|---|---|---|---|---|
| Alonso et al. (2000) | Ground/air holds; max. delay 20 min | 160 flights; 4 airports; 5 sectors; 13 scenarios | 4 hours/5 min | 31 min |
| Marron (2004) | Ground/air holds; rerouting | 148 flights; 40 sectors; 3 scenarios | Not spec./5 min | 12 min |
| Agustin et al. (2012) | Ground/air holds; rerouting; cancellations | 425 flights; 45 airports; 40 sectors; 40-60 scenarios | 32 time-periods | 5-15 min |
| **Balakrishnan and Chandran (2014)** | Ground/air holds; unrestricted rerouting network; cancellations | 17,500 flights; 370 airports; 375 sectors; 5–25 scenarios | 24 hours/10 min | 5–16 min |

# Computational example: 7/8/2013

- Optimal solution: 33,060 min ground delay; 8,245 min airborne delay; 2% cancelled;  657 reroutes






[Balakrishnan and Chandran, submitted, 2014]

# Solving tomorrow's ATFM problems

- Manned air traffic demand from SWAC simulation
  - ~40,000 flights within the US
  - ~25,000 unique airframes (accounts for connectivity)
- Assumes two types of constraints
  - Sector capacities (same as today)
  - Airport capacity envelopes (2030 improvements)
- Realistic UAS dataset from Raytheon/IAI (NASA/JPDO)
  - ~35,000 flights + varying missions (typically smaller airports)
  - Comm., fish spotting, cargo, etc., altitudes: 100-60,000 ft
  - No alternative routing for unmanned aircraft
- ~50 combinations of costs, schedules and capacities

# A day in the life of the NAS (2030 version)

- Optimize ~77K flights (≤0.1% of optimal) in under 4 min
  - 1-minute trajectory fidelity, 5-minute constraint fidelity
  - "Rolling horizon" mode: ~6-8 hr with ~25K flights: < 1 min

# Learning models of human decision processes

- Decisions (for example, selection and use of runways) drive system capacity
- Reverse-engineering decision processes enables
  - **Better optimization** algorithms that account for true objectives
  - **Better prediction** of future decisions
- Learn maximum-likelihood models of decision processes and utility functions
  - Models that best explain real-world observations
  - Identify influence of “unwritten” factors



Ramanujam & B. *IEEE Trans. on Human-Machine Sys* 2015; Avery & B. *Transp. Res. Record* 2016

# Factors that influence runway configuration selection

- Wind direction and speed; visibility
- Demand
- Inertia
  - Switches need coordination
- Noise abatement
- Inter-airport coordination


- Primarily responsibility of Tower Supervisor or Controller-in-Charge



[DeLaura et al. 2014; FAA 2004; *Standard Operating Procedures*]

[Sandberg 2012]

# Solution approach: Discrete-Choice Modeling

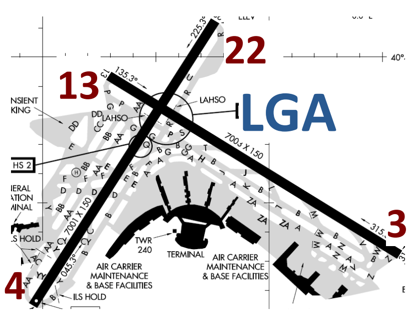
- Decision-makers are assumed to consistently choose the utility-maximizing option (from set of feasible alternatives)
- Utility function is modeled as a linear function of the independent variables plus an error term

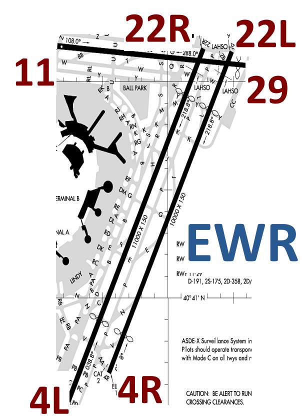
$$U_i = \underbrace{(\alpha_i + \beta_i \cdot X_i)}_{\text{Observed component, } V_i} + \underbrace{\epsilon_i}_{\text{Unobserved error}}$$

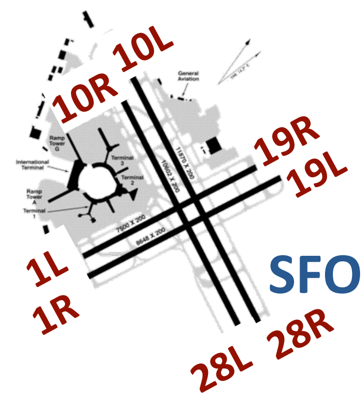
- For each observation, the decision-maker is assumed to choose the alternative that maximizes utility

# Predicting runway configuration choice

- Can identify statistically significant factors in configuration selection, and their "weights"
- Good prediction accuracies, even few hours ahead
  - Models tested for range of airports




  - Accuracy ~97% for 15-min horizon; ~80% for 3-hr horizon

Ramanujam & Balakrishnan *IEEE Trans. on Human-Machine Sys* 2015;
Avery & Balakrishnan *ATM R&D Seminar* 2015 and *Transp. Research Record* 2016.

# Just scratching the surface: Many important open challenges

- ***Autonomy***: Integration of unmanned/manned aircraft


Robot-Piloted Plane Makes Safe Crossing of Atlantic

No Hand on Controls From Newfoundland to Oxfordshire—Take-Off, Flight and Landing Are Fully Automatic

By ANTHONY LEVIERO
Special to THE NEW YORK TIMES.

***New York Times***
**Sept. 23, 1947**


MAKES TRANSATLANTIC FLIGHT UNDER CONTROL OF 'MECHANICAL BRAIN'

**"Air Force officers speculated on the possibility of loading robot planes, like the Skymaster, with bombs and sending them to distant targets. For peaceful purposes, it was suggested that they might be used as cargo carriers."**

# Just scratching the surface: Many important open challenges

- ***Autonomy***: Integration of unmanned/manned aircraft
- ***Fairness***: In networked resource allocation with multiple constrained resources
- ***Incentives***: To participate, to report truthfully
  - Pareto-optimality in the stochastic context
- ***Privacy***: Of valuations and flight delay costs
- ***Security***: Of system in the presence of faults/incorrect information and adversaries
- ***Interactions***:
  - Between humans & automation/autonomous systems
  - Between strategic and tactical control
  - Between different infrastructures

# Summary

- Practical ATM algorithms can enhance system efficiency, robustness and safety, and address uncertainty, human operators and competition
  - Leveraging *cyber-physical* + *human* elements is key!
- Several other important facets, including:
  - Airport congestion control [*IEEE Trans. on Intelligent Tranp. Sys*. 2014, *Tranp. Res. A* 2015, *IEEE Trans. Human-Machine Sys* 2014, *Transp. Sc.* 2016]
  - Weather-ATM integration [*Transp. Sc.* 2012; *Transp. Res. Rec*. 2015]
  - Statistical modeling of engine performance [*Transp. Res. D* 2012; ICAS 2016]
  - Interactions between aviation and high-speed rail [Transp. Res. Record 2012; *Transport Policy 2014]*
  - High-confidence control algorithms for aviation systems [*IEEE Trans. on Automatic Control* 2015]