Building a Smarter Air Transportation System

From Research to Practice

Hamsa Balakrishnan

Massachusetts Institute of Technology • Lumo
Air transportation, pre-pandemic

• Drives global travel & commerce
  • 4.6B enplanements/year (2019)
  • 51M flights/year worldwide (2019)
  • 82.6% average load factor (2018)

• US delays cost $30-40B/year
  • Waste 740M gallons of jet fuel
  • Additional 7.1M metric tons of CO2

• Undergoing significant transformation
  • Next-generation air transportation systems
  • Drones, Urban Air Mobility (UAM)
  • Increased levels of autonomy and automation
Types of emerging demand

Future of urban mobility
My kind of flyover

[Airbus, Amazon, Google, Uber]
Scale of emerging demand

20,000 flights per hour over Paris by 2035

2-3 million sUAS by 2023

[Airbus UTM Blueprint for the Skies, 2018]

[FAA UTM Concept of Operations, 2020]
Analysis, Optimization, Prediction

Analysis and Benchmarking [How can we tell when we do well?]
Optimization [How do we make the best use of limited resources?]
Prediction [How do we predict how the system is going to behave?]

[Movie courtesy Rich DeLaura, MIT Lincoln Lab]
Local events have far-reaching impacts

- Cancellations: Fire in Chicago Center
- Delays: Power outage in Atlanta
- Delays: Thunderstorms in the NE US
The need to look beyond local weather

• Local weather can look similar (even in NYC) but the days may have very different delay impacts

5/22/2014
Mean dep. delay: 20.3 min; A14: 72.3%
Cancellations: 3.5%

7/28/2016
Mean dep. delay: 27.4 min; A14: 71.4%
Cancellations: 7%

9/6/2014
Mean dep. delay: 9.2 min; A14: 84.8%
Cancellations: 1.5%

7/30/2015
Mean dep. delay: 19 min; A14: 74.8%
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I. Benchmarking performance

Ground Delay Program-level

Airline-level

Airport-level

K. Gopalakrishnan, M. Li, H. Balakrishnan.

Network-centric Benchmarking of Operational Performance in Aviation, Transportation Research Part C, 2021
Analysis, Optimization, Prediction

[Movie courtesy Rich DeLaura, MIT Lincoln Lab]
II. Optimizing resource allocation

• Airport and airspace capacities are limited (depend on weather, traffic, workload, etc.)

• Capacity forecasts are subject to uncertainty

• Large amount of flight connectivity
  • Only 6% of aircraft in the US fly just one flight/day
  • Results in delay propagation
  • Makes rolling horizon optimization suboptimal

[Bureau of Transportation Statistics 2016]
Air Traffic Flow Management

• Given set of flights with assigned aircraft and capacity profiles, identify a trajectory for each aircraft to maximize system-wide benefit (or minimize system-wide costs), and satisfy operational constraints
  • Constraints:
    • Airport/airspace sector capacity limits (including geofencing)
    • Flight connectivity and turn-around times
    • Maximum/minimum transit times and speeds
  • Control actions:
    • Ground/airborne delays
    • Rerouting
    • Cancellations

Distributed Resilient Framework for TBO (DRIFT)

H. Balakrishnan and B. Chandran.  

*TBO: Trajectory-Based Operations*
Solves much larger problems than before

<table>
<thead>
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<th>Control</th>
<th>Scale</th>
<th>Horizon/disc.</th>
<th>Run times</th>
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<tr>
<td>Maugis (1995)</td>
<td>Ground holds; cancellations</td>
<td>4,743 flights; 1,153 sector-saturated time periods (no airport capacity limits)</td>
<td>1 day/ 5 min</td>
<td>2+ hr</td>
</tr>
<tr>
<td>Bertsimas &amp; Stock-Patterson (1998)</td>
<td>Ground/air holds</td>
<td>1,002 flights; 18 airports; 305 sectors</td>
<td>8 hr/ 5 min</td>
<td>8+ hr</td>
</tr>
<tr>
<td>Bertsimas &amp; Stock-Patterson (2000)</td>
<td>Ground/air holds; limited rerouting</td>
<td>71 flights; 4 airports; 42 sectors</td>
<td>8 hr/ 5 min</td>
<td>4 min</td>
</tr>
<tr>
<td>Bertsimas et al. (2011)</td>
<td>Ground/air holds; rerouting network</td>
<td>6,745 flights; 30 airports; 145 sectors</td>
<td>8 hr/ 15 min</td>
<td>10 min</td>
</tr>
<tr>
<td>Wei et al. (2013)</td>
<td>Aggregate model; air holds</td>
<td>3,419 flights; 284 sectors</td>
<td>2 hr/ 1 min</td>
<td>21 min</td>
</tr>
<tr>
<td>Balakrishnan &amp; Chandran (2014)</td>
<td>Ground/air holds; unrestricted rerouting network; cancellations</td>
<td>17,500 flights; 370 airports; 375 sectors</td>
<td>24 hr/ 5 min</td>
<td>5 min (Macbook Pro w/ 8 virtual cores)</td>
</tr>
<tr>
<td>Balakrishnan &amp; Chandran (ATM-2017)</td>
<td>Ground/air holds; unrestricted rerouting network; cancellations</td>
<td>76,900 flights; 2,400 airports (+4,000 UAS ones); 955 sectors</td>
<td>24 hr/1 min</td>
<td>4 min (Linux X-Large machine w/ 40 cores on AWS)</td>
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Solving tomorrow’s ATFM problems

• Manned air traffic demand from FAA’s SWAC simulation*
  • ~48,000 flights within the US; ~27,500 unique airframes
  • Assumes two types of constraints
  • 955 sectors, with same capacities as today
  • Airport capacity envelopes (2030 improvements)

• Realistic unmanned operations dataset**
  • ~29,000 flights + varying missions (typically smaller airports)
  • Communications, fish spotting, cargo, etc.
  • Altitudes: 100-60,000 ft
  • No alternative routing for unmanned aircraft
  • Incorporate geofencing where needed

• ~50 combinations of costs, schedules and capacities

* Noonan, 2011
** Wieland et al., 2013
A day in the life of the National Airspace System (2030 version)

• Optimize ~77K flights (≤ 0.1% of optimal) in under 4 min
• “Rolling horizon” mode: ~6-8 hr with ~25K flights: < 1 min
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III. Prediction of system behavior

- Predictability is often as desirable as efficiency.
- Ultimately, our optimization is only as good as our ability to forecast airport/airspace resource capacities.
- Depend on weather and traffic, but also on human decision-makers, workload, and procedures.

[www.thinklumo.com]
Emerging challenges
Efficiency will always be important, but...

- **Efficiency**
  - How do we best utilize congested resources?

- **Fairness**
  - How can we be fair in allocating resources to different users?

- **Privacy**
  - How much information do users have to share, and with whom?