Approximate Network Delays Model

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Jan 26, 2008

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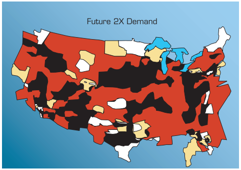
Motivation

- In 2007 26% of all commercial flights arrived with at least 15 minutes delay
- Flight delays cost $8 billion to airlines and $4 billion to passengers
- NAS has traffic bottlenecks both at congested airports and in congested parts of the airspace
- "Current airport and airway infrastructure cannot be scaled to meet the rapidly increasing demand", FAA



[Socio-Economic Demand Forecast, NASA and FAA 2004]

- The NAS is a highly connected network where disruptions at one node will affect other nodes of the network
- Need to estimate delays at individual airports and model their propagation in order to assess improvements in the NAS

Related Work

Individual airport performance models:

- Queuing theory, Kivestu 1976
- Fluid approximation, Kleinrock 1975
- Diffusion model, Kleinrock 1975

Networks of queues:

- Networks with infinite-server queues, Massey 1993
- Decomposition methods, Peterson 1995
- NASA ACES simulator of the NAS (2005-)

Challenge:

- To develop a fast and easy-to-use tool that models stochasticity, dynamic behaviour and the network effects in the NAS

Project Aims

Develop a model that incorporates the schocasticity and variability of airport demand and capacity using queuing theory in order to estimate the delays at individual airports and how these delays propagate through the network of airports

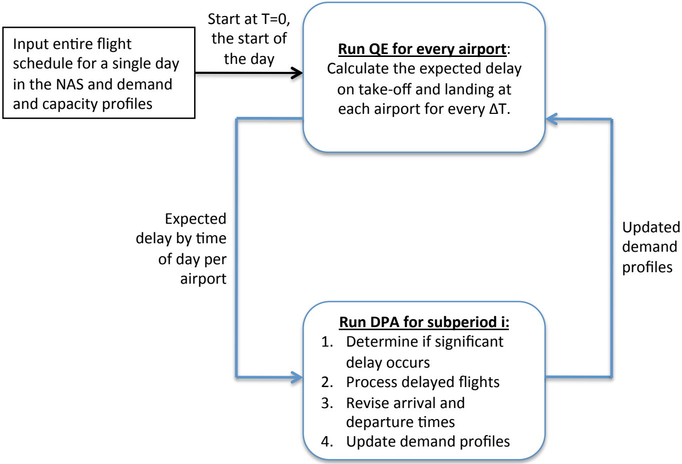
- What are the implications for system-wide delays of ATM-related or infrastructure capacity improvements at one or more airports?
- What will be the system-wide effects of a change in a major airline's network configuration?
- How would delays be affected if the daily peaking demand profiles at some airports were changed?

AND Concept

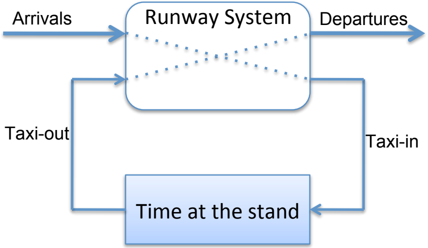
- Approximate Network Delays (AND) proposed by Malone, 1998 but not developed into a workable model
- Uses an iterative procedure that consists of two parts
  - The Queuing Engine (QE):
    - Each individual airport is viewed as a queuing system so that delays are analyzed at each airport separately
  - The Delay Propagation Algorithm (DPA):
    - Based on the flight schedule of individual aircraft flying in the network DPA propagates delays (which are estimated in the QE) to the rest of the network.
    - Susbsequently demand profiles at individual airports are updated.

AND Iteration

- The day is divided into subperiods of length ΔT (e.g. 96 15minute periods)



Why model an airport as a queuing system?

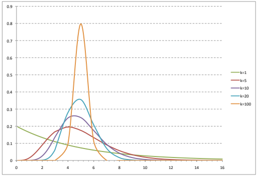


- Each airport is a queuing system with capacity equal to that of the runway system (assumed to be the dominant capacity constraint)
- Demand (arrivals and departures) and capacity at an airport is stochastic and may vary by time of day
- Numerical solutions can be obtained for such queuing systems so there is no need for simulation

The Queuing Engine

- Airport demand is approximated by a non-stationary Poisson process

- Airport service times are modeled by a k-th order Erlang distribution; k is the ratio of $E^2[S]$ to σ_S^2



- An airport is modeled as a FCFS M(t)/$E_k(t)/1$ system with infinite queue capacity:
  - Differential equations that provide approximate solution were used, Kivestu 1976:

$$P_j(t_{l+1}) = P_0(t_l) * \alpha_{l+1}(j) + \sum_{i=1}^{j+1} P_i(t_l) * \alpha_{l+1}(j-i+1), \quad j = 0, 1, ..., N-1$$
$$P_N(t_{l+1}) = P_0(t_l) * \Upsilon_{l+1}(N) + \sum_{i=1}^{N} P_i(t_l) * \Upsilon_{l+1}(N-i+1)$$

- Inputs: Demand and capacity profiles, Erlang order
- Outputs: Expected delays per time of day

Delay Propagation Algorithm

Scan all flights that takeoff or land within subperiod i:

- Determine if significant delays occur.
- If yes: revise arrival and departure times of all flights during this subperiod and to their immediate successors:

$$AA(f) = max(SA(f), AD(f) + (Expected\ takeoff\ delay) + (flight\ time) - (time\ made\ up\ in\ air))$$

$$AD(f) = max(SD(f), SD(f) + (AA(g) - SA(g)) + (Expected\ landing\ delay) - slack(g, f))$$

- Update demand profiles for each airport based on the revised arrival and departure times.
- If no significant delays occur move to the next subperiod.

AND Model Development

- Programmed in Java
- Inputs:
  - Airports in the network with their VFR and IFR capacities (FAA Capacity benchmark report 2004)
  - Complete aircraft itineraries and airport schedules
- Outputs:
  - Initial and revised demand profiles per airport
  - Initial and revised expected delay per airport per time of day
  - Upstream delays per airport, defined as the total amount of delay caused to flights prior to their arrival at that airport
  - Fraction of arrivals with more than 15 mins delay per airport
  - Complete flight itineraries showing where and by how much an airport has been delayed

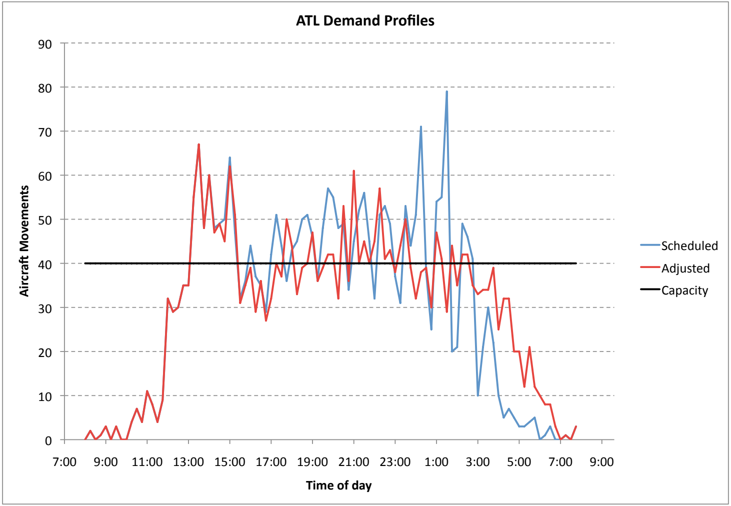
AND Model Status

22 airports that account for 823 mio pax (53% of US total) and 10.9 mio movements (34% of US total) for 2007

Test Case: Bad weather in Atlanta (ATL)

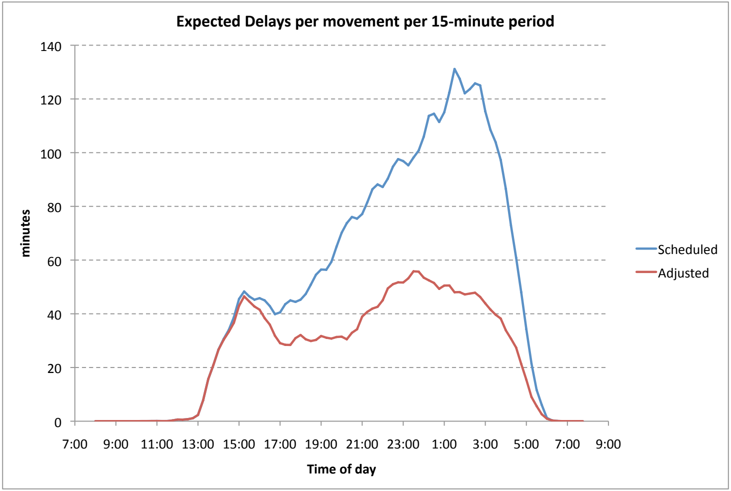
- 21 airports in optimal conditions
- Atlanta in low IFR conditions
- 17300 flights
- Runtime = 227 secs

Test Case: Shifted Profile



- Smoother demand profile due to the propagation of delays

Test Case: Delays



- Due to smoothing of the demand profile we get a lower delay curve compared to what would happen without propagation of delays

Test Case: An aircraft through ATL

- SA (AA): Scheduled (Adjusted) Arrival in GMT
- SD (AD): Scheduled (Adjusted) Departure in GMT
- Delays given in minutes
- Slack = 10 mins
- En route save time = 5 mins

Tail No	Airport	SA	AA	SD	AD	Upstream Delay on Arrival	Delay upon Arrival	Upstream Delay on Departure	Delay Upon Departure
N137DL	LAX	-	-	7:55	7:55	-	-	0	0
N137DL	ATL	12:01	12:01	13:45	13:45	0	0.6	0	18.6
N137DL	PHX	16:59	17:12	18:00	18:04	13.6	1.1	4.7	0.3
N137DL	ATL	22:41	22:41	23:50	0:31	0	51.2	41.2	53.3
N137DL	LAX	4:47	6:16	6:55	8:15	89.5	0.6	80.1	0.1
N137DL	ATL	11:03	12:18	-	-	75.2	0	-	-

- Minimal delays incurred at other airports and during early hours in ATL
- Very large expected delays in afternoon arrivals and departures

Network statistics for 2 scenarios

	All Airports on VFR		**ATL on low IFR**	
	Expected Upstream Delay	*Fraction of Arivals w >15min delay*	*Expected Upstream Delay*	*Fraction of Arivals w >15min delay*
ATL:	1244.3	37.6%	33863.1	88.2%
BOS:	449.0	3.2%	2104.9	10.0%
DCA:	333.4	3.1%	1850.5	9.3%
DEN:	224.9	0.9%	1153.4	2.5%
DFW:	283.8	1.0%	2057.9	4.1%
DTW:	270.5	1.2%	1526.7	3.9%
EWR:	201.4	1.3%	1436.5	4.9%
IAH:	145.9	0.6%	1061.5	3.3%
JFK:	323.3	30.6%	584.7	31.2%
LGA:	266.4	3.0%	2111.7	7.8%
MCO:	432.6	3.4%	2463.6	11.7%
MIA:	233.4	5.0%	1136.5	10.6%
ORD:	347.5	1.0%	1554.8	2.6%
SFO:	388.7	2.7%	1269	4.7%

- Large increase of upstream delays when ATL operates under low IFR

AND Limitations

- Does not capture airline responses
  - flight cancellations
  - spare aircraft at hubs
  - swapping of aircraft assignments to flights during irregular operations
- First-come, first-served sequencing of aircraft movements at airports
- AND provides upper bounds on delays
- AND is best used to estimate relative performance measures for different scenarios in the NAS
- Hard to validate the model with real data for delays

Conclusions

Conclusions

- AND runs very fast (60-230 seconds depending on the scenario)
- Large upstream delays observed when one or multiple airports operate in low visibility conditions
- Smoothing of demand profile at a hub airport under low visibility conditions
- A nice testbed for investigating many alternative scenarios for the future

Future Research

Future model enhancements

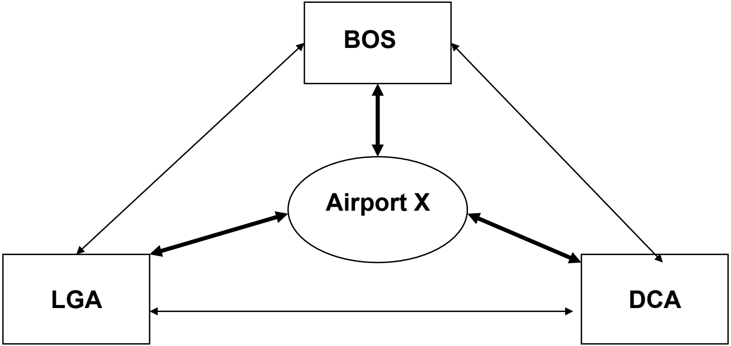
- Test different queuing engines (e.g. deterministic demand)
- Include flight cancelations
- Include some en-route capacities
- Develop different scenarios to explore

Future research questions

- At which points on the network will capacity increases lead to the highest improvements of the network performance?
- How would the delays be affected if US airports operated slot allocations for demand management?
- If congestion pricing was applied at the most congested airports how would the delays in the network change if we treated demand as a function of price?

QUESTIONS?

A Three Airport Network



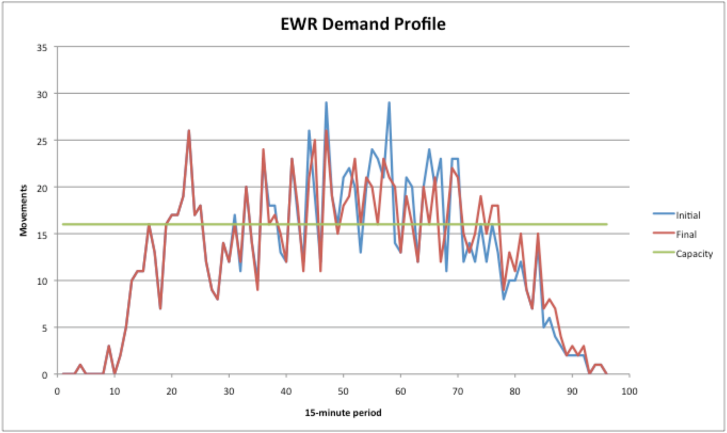
- Airport X represents all the "external airports"; it acts as an un-capacitated source and sink of traffic.

Scenario I: Network Statistics

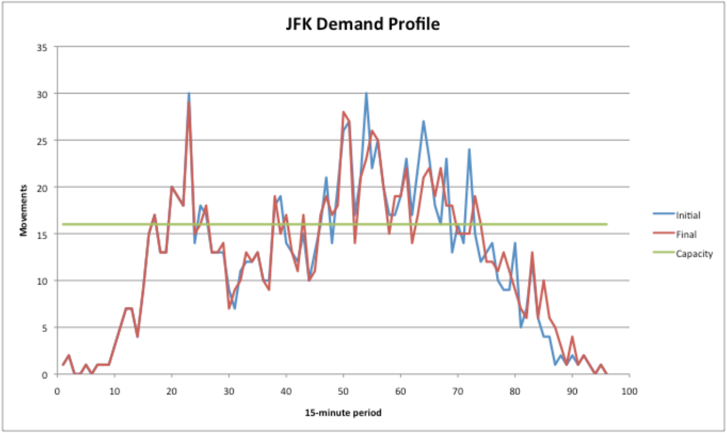
	ATL on IFR		All Airports on VFR	
	Expected Upstream Delay	*Fraction of Arivals w >15min delay*	*Expected Upstream Delay*	*Fraction of Arivals w >15min delay*
ATL:	33863.1	88.2%	1244.3	37.6%
BOS:	2104.9	10.0%	449.0	3.2%
CLE:	698.4	3.2%	158.5	2.3%
CLT:	1228.5	5.1%	211.1	1.6%
DCA:	1850.5	9.3%	333.4	3.1%
DEN:	1153.4	2.5%	224.9	0.9%
DFW:	2057.9	4.1%	283.8	1.0%
DTW:	1526.7	3.9%	270.5	1.2%
EWR:	1436.5	4.9%	201.4	1.3%
IAH:	1061.5	3.3%	145.9	0.6%
JFK:	584.7	31.2%	323.3	30.6%
LAS:	1159.7	3.5%	229.0	1.4%
LAX:	1650.9	4.3%	391.1	1.5%
LGA:	2111.7	7.8%	266.4	3.0%
MCO:	2463.6	11.7%	432.6	3.4%
MIA:	1136.5	10.6%	233.4	5.0%
MSP:	1173.6	4.6%	183.4	1.3%
ORD:	1554.8	2.6%	347.5	1.0%
PHL:	1325.7	6.4%	200.1	2.0%
PHX:	909	2.4%	232.9	1.2%
SEA:	559.6	3.6%	152.6	1.6%
SFO:	1269	4.7%	388.7	2.7%

Scenario II: Northeast Storm

- 6 airports in low IFR conditions: BOS, DCA, EWR JFK, LGA, PHL



Scenario II: Northeast Storm



Scenario II: Northeast Storm

	ATL on IFR		All Airports on VFR		Northeast Storm	
	Expected Upstream Delay	*Fraction of Arivals w >15min delay*	*Expected Upstream Delay*	*Fraction of Arivals w >15min delay*	*Expected Upstream Delay*	*Fraction of Arivals w >15min delay*
ATL:	33863.1	88.2%	1244.3	37.6%	3585.6	34.5%
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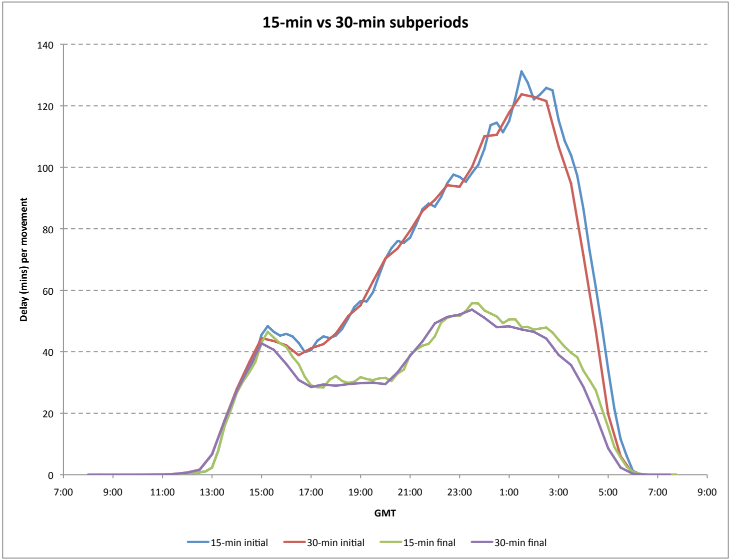
DCA:	1850.5	9.3%	333.4	3.1%	2663.8	20.2%
DEN:	1153.4	2.5%	224.9	0.9%	815.9	2.6%
DFW:	2057.9	4.1%	283.8	1.0%	1286.6	3.4%
DTW:	1526.7	3.9%	270.5	1.2%	1359.7	5.3%
EWR:	1436.5	4.9%	201.4	1.3%	3545.4	70.6%
IAH:	1061.5	3.3%	145.9	0.6%	1165.8	4.5%
JFK:	584.7	31.2%	323.3	30.6%	3119.9	65.0%
LAS:	1159.7	3.5%	229.0	1.4%	1074.6	3.1%
LAX:	1650.9	4.3%	391.1	1.5%	1715.5	3.3%
LGA:	2111.7	7.8%	266.4	3.0%	1857.6	84.5%
MCO:	2463.6	11.7%	432.6	3.4%	1615.7	9.1%
MIA:	1136.5	10.6%	233.4	5.0%	937.5	10.6%
MSP:	1173.6	4.6%	183.4	1.3%	749.1	3.8%
ORD:	1554.8	2.6%	347.5	1.0%	2685.1	4.7%
PHL:	1325.7	6.4%	200.1	2.0%	476.1	3.1%
PHX:	909	2.4%	232.9	1.2%	994.6	2.4%
SEA:	559.6	3.6%	152.6	1.6%	677.1	2.9%
SFO:	1269	4.7%	388.7	2.7%	1766.4	6.0%

Dependency on sub-period



Scenario III: ORD in low IFR