Benefits of Collaborative Flow Management During Convective Weather Disruptions

7th USA / Europe ATM2007 R&D Seminar
July 2-5, 2007

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Modeling
National Flow Model (NFM) Overview

Traffic represented by ETMS flight plans (FZ) and departure records (DZ) or OAG schedule

Airports and sectors represented as queues

Aircraft move between queues over the network

Delay Throughput...
Flow and Schedule Re-Planning in the NFM

- During an NFM simulation, re-planning of all flight schedules for the remainder of the day is triggered by events such as convective weather disruptions.
- The NFM contains re-planning modules for ground delay programs (i.e., Ration by Schedule, RBS) and modules for complete flow planning and airline schedule recovery.
- The flight schedule is then executed and delays are measured relative to the original flight schedule.
- Schedules may include block time padding.
- Schedules are also tail-routed so that the NFM can model the impact of delay propagation.
Airline Schedule Recovery (AOC) Model

- Development Objective
  - Develop airline schedule recovery (a major function of the Airline Operations Center, AOC) model to represent current and future airline responses to airport and airspace capacity reductions due to weather events or system outages
  - Embed in the Boeing National Flow Model (NFM) and use to assess operational concepts for collaborative flow management

- Airline Schedule Recovery Model Overview
  - Primary inputs
    - Original airline schedule
    - Allocation of forecast capacity to each airline by the centralized flow management authority (SCC)
  - Primary output is a re-planned schedule which includes
    - Cancellation, ground delay, and/or flight re-routing
AOC Model Features
(also called the Advanced Planner)

- Strategies include ground delay, re-routing, and cancellations
- Models implemented so far assume
  - Same aircraft (tail) flies an entire daily itinerary (1A)
  - Planner can swap equivalent aircraft types (1B)
- Optimization approach has multiple objective function choices
  - Delays, delay costs, or resultant schedule value
- Computationally feasible for fast-time analysis on a high-end laptop even in a complete NAS-wide setting

Result is a set of optimized airline schedules that are jointly feasible with respect to all forecast airport and airspace capacities
AOC Model Formulation
(Flight Plan Timeline and Temporal Discretization)

• **Complete** - goes from scheduled departure to aircraft availability
• **Aggregated** - does not include the "fine structure" of airways and waypoints

Resource Usage (Discretized):

```
G 0 0 T 0 0 0 1 1 1 1 2 2 2 2 2 2 2 2 0 0 L 0 0 0 G G G 0
```

**Strategies for Optimization:**
• Numerous alternative flight plans and departure times
• Problem is to select at most one alternative per flight leg to maximize a system objective based on flight leg value (adjusted for delays)
• Subject to many constraints including resource capacity
• Very large and combinatorial
Centralized Flow Management (SCC) Module

- Major function is to create equitable allocation of total forecast capacity to the airline users
- Total forecast capacity first reduced by prediction of capacity usage from committed operations
- Remaining capacity allocated to airlines in iterative process
  - Each airline proposes a plan, and associated resource usage, for its baseline schedule
  - SCC computes total resource usage by combining the plans
  - If the total usage for a resource exceeds the forecast residual capacity then capacity is allocated to each airline user in proportion to their request
  - Iterative process that is guaranteed to converge and which can be viewed as a “locally equitable” scheme with respect to the airlines
- This scheme has been implemented and works well; almost always converges in less than 20 iterations
  - Further research on the resource allocation scheme is of interest
Convective Weather Modeling

- Weather representations used in the model
  - Actual convective weather
  - Associated convective weather forecasts
  - Impact of weather on airport and airspace capacities
- Actual weather is based on historical archives of convective weather radar images in pixel format
- Forecast data is either
  - Based on archived forecasts for actual weather events
  - Generated in the NFM from actual weather data using adjustable forecast error parameters
- Primary weather model output is a time line of capacity reductions of airports and airspace sectors
- Provides the capability to study system behavior under a wide range of assumptions about weather prediction quality
Sector Capacity Determination in the NFM
(Example for Polygonal Forecast Data)

Note: Actual weather utilizes pixel data for coverage calculation.
Analysis
Study Overview

• The purpose of this analysis was to measure the NAS-wide single-day benefits potential of
  • Increased flow management automation
  • Improved convective weather forecasting
• Total delay cost was utilized as the primary measure of effectiveness (using inputs for cancellations, ground delay, airborne delay, passenger value of time, etc.)
• The bad convective weather day was June 14, 2000
• The Boeing Future Schedule Generation capability, utilizing the Boeing Current Market Outlook (CMO) was used to create traffic scenarios for year 2000, 2010, and 2020
• Used actual convective weather data and CCFP for 6/14/2000
• Represented “current” system (year 2000) by calibrating a modified version of the AOC model
Progress of the storm on the afternoon of June 14, 2000
Calibrating the Baseline System Model

- Established the baseline system performance using historical statistical data for the selected convective weather day
- Actual delay and flight cancellation statistics were analyzed using the Airline Service Quality Performance (ASQP) database
- Alternative baselines
  - Baseline “white” (W) planner
    - Ignores airspace during the schedule re-planning process (infinite capacity)
    - Only airports and their forecast capacities are considered for planning
    - Actual airspace capacities are enforced in executing the plan
  - Baseline “black and white” (BW) planner
    - Assumes that sectors are either open (white) or closed (black)
    - Re-planning process uses only sectors that are open
    - Actual airspace capacities are enforced in executing the plan
Calibrating the Baseline System Model

- BW (black & white) baseline utilizes a capacity threshold to differentiate open versus closed sectors.
- Calibration is by varying the threshold and the B-intercept (an additional cancellation penalty also considered).
- Advanced planner uses forecast capacities (blue line) for planning.
- Both plans are subject to the actual capacities in execution.

The presentation will focus on the BW planner.
Calibration Results for Baseline BW

Calibrated using Threshold, B-intercept and Cancellation Penalty
Delay Cost Comparison (Baseline BW versus Advanced Planner)

- BW / CCFP: Black and White planner with CCFP forecast
- AdvPlan / PF : Advanced planner with Perfect forecast
- AdvPlan / CCFP : Advanced planner with CCFP forecast
Discussion of Analysis Results

• Baseline W and BW were both calibrated to match the ASQP statistics on total delay cost and cancellations.

• Our observation: Baseline BW seems to be the more realistic of the two approaches, and appears to be closer to current practice.

• Results for Baseline BW:
  • Advanced automation delivers good results for all conditions.
  • Single-day benefits of $30-$100M with CCFP forecast and much greater benefits for improved forecasting.

• Although not based on an explicit model of current practice, these baselining approaches can provide insight into the magnitude of potential benefits for greater flow management automation and improved weather forecasting.

• Our next steps can address some of the analysis shortcomings.

• Both the distributed schedule recovery application and improved forecasting have a large potential to deliver results.
Summary and Next Steps

• Summary
  • Developed large-scale flow model with comprehensive optimization capabilities for distributed flow management
  • Calibrated baseline system model and compared with advanced planner for multiple future timeframes and forecasts
  • Large benefits potential for both improved automation and improved forecasting

• Next Steps
  • Improved route databases for pre-departure re-routing and dynamic flight plan generation for post-departure re-routing
  • Potential acquisition of additional actual and forecast weather data (NOAA) and re-calibration with multiple points; evaluate additional forecasting products besides the CCFP
  • Consideration of pre- and post- airspace flow program
  • Characterization of probabilistic forecasting and development of a “stochastic planner” that considers forecast uncertainty
Backup
Major Assumptions for AOC Model

- Applicable only to pre-departure (uncommitted) operations
  - Separate tactical planning function assumed for committed operations; current work addresses post-departure re-routing
- Focus on aircraft and gate resources (no crew considerations)
- The SCC collaborates with the airlines through an allocation of forecast capacities
- AOC re-plans adhere to allocated forecast capacities
- System capacity elements include airport departure and arrival rates and sector occupancy limits
- Optimization is used to maximize the value of the re-planned schedule subject to capacity and other operational constraints
Basics of the Formulation
(Discretized Time)

- List of system resources and associated forecast capacities
- List of aircraft itineraries
  - Legs in each itinerary
  - Type of equipment
  - Aircraft availability time (slice)
- List of strategies for each flight leg with associated:
  - Departure, arrival, and availability time (slice)
  - Flight plan (route through the airspace)
  - Schedule value and list of resources used
- Optimization problem: select at most one strategy for each flight leg to maximize total schedule value subject to resource & flyability (including fleet count and aircraft flow) constraints
- The flow constraint essentially means that new itineraries can be formed which satisfy a constraint that says the next leg departs at a time greater than or equal to the availability time of the previous flight leg in the itinerary
Flow Constraints for Aircraft Flyability

- Challenge: develop a representation for flow constraints for which model 1B is a generalization of 1A (as opposed to a whole new model)
- Solution: aircraft flow is represented by conservation of flow in space-time networks constructed for sets of legs (or strategies) to be flown by operationally equivalent aircraft (i.e., aircraft with same flying times and turnaround times for any given leg)
- Realization for model 1A
  - Construct a separate space-time network from the set of legs assigned to each individual aircraft
- Realization for model 1B
  - Construct a separate space-time network from the set of legs flown by each individual type of equipment (e.g., 737-400), or even each “aggregated” equipment type (e.g., 737 family)
- Note: space-time network generator can be independently applied to any subset of N aircraft itineraries, that is, applied to the pooled set of itinerary legs (and associated strategies) to be flown by N operationally equivalent aircraft
### Integer (Linear) Programming Formulation

- \( x_j \) - binary strategy variables (arc \( j \), for leg and ground strategies)
- \( v_j \) - strategy value (ground strategies have zero value)
- \( a_{rj} \) - binary resource usage for resource \( r \) and strategy \( j \)
- \( c_r \) - capacity (for resource \( r \))
- \( e_{ij} \) - node-arc incidence matrix (E) entry for node \( i \) and arc \( j \)
- \( b_i \) - node supply and/or demand
- \( S(l) \) - index set of strategies for leg \( l \)

Maximize \( \sum_{j=1}^{N} v_j x_j \)

Subject to:
- \( \sum_{j \in S(l)} x_j \leq 1 \) (coverage, leg \( l \), \( \forall l \))
- \( \sum_{j=1}^{N} a_{rj} x_j \leq c_r \) (capacity, resource \( r \), \( \forall r \))
- \( \sum_{j=1}^{N} e_{ij} x_j = b_i \) (flow and fleet count, node \( i \), \( \forall i \))
- \( x_j \in \{0,1\} \) (binary variables), \( \forall j \)
Lagrangian Relaxation Approach
(for 1A Model: assume same tail routings)

Primal Problem:
\[
\begin{align*}
\text{max} & \quad v \cdot x \\
\text{s. t.} & \quad A \cdot x \leq \text{cap} \\
& \quad x \in F
\end{align*}
\]

Relaxed Problem (for fixed $u \geq 0$):
\[
\begin{align*}
\max_{x \in F} & \quad \left\{ u \cdot \text{cap} + (v - u \cdot A) \cdot x \right\}
\end{align*}
\]

Lagrangian Dual:
\[
\begin{align*}
\min_{u \geq 0} & \quad \left\{ u \cdot \text{cap} + \max_{x \in F} (v - u \cdot A) \cdot x \right\}
\end{align*}
\]

Decomposing by Itinerary:
\[
\begin{align*}
\min_{u \geq 0} & \quad \left\{ u \cdot \text{cap} + \sum_{I} \max_{x \in F^I} (v^I - u \cdot A^I) \cdot x^I \right\}
\end{align*}
\]
Itinerary Subproblem
(for 1A Model: Assume same tail routings)

- Canceled flights have $V=0$; ground arcs have $V=0$; otherwise $V$ is the leg value minus the sum of the dual variable values for the resources consumed.
- Find the longest path through the acyclic network (essentially discrete-time DP).

**Itinerary Legs (A-H-B-H-A)**

- Entry
- Exit

- Delay and/or alter flight plan
- Cancel the flight leg
- Wait on the ground
Lagrangian Heuristic
(for 1A Model: Assume same tail routings)

- Solving the Lagrangian dual will not necessarily provide a feasible solution to the primal problem; need a "Lagrangian heuristic" to accomplish that task
- Order the itineraries (e.g. decreasing in total value)
- Solve (sequentially) the itinerary subproblems
  - continue to adjust strategy score by the dual values
  - remove strategies requiring 0-cap resources
  - solve this "restricted" version of the subproblem
  - recover the solution and decrement utilized caps
  - go the next itinerary
- Itinerary solver implemented to support 1) nonsmooth function evaluations and 2) Lagrangian heuristic
Geometric Modeling of Weather Forecasts – Boeing’s CWFR
Delay and Cancellation Statistics → Delay Costs

- Cancellation cost = $29.21 /seat
- Airplane plus crew operating cost = $6.67 /seat /hr
- Percentage of operating cost for crew = 31.62%
- Passenger value of time = $18.59 /seat /hr


- Arrival delay cost = $20.70 /seat /hr
  [= (0.3162 x 6.67) + 18.59]
- Cancellation cost = $103.57 /seat
  [= 29.21 + (4 x 18.59)]
- Airborne delay cost = $4.56 /seat /hr
  [= .6838 x 6.67]
Calibration Results for Baseline W
(Calibrate with B-intercept and Cancellation Penalty)

- Number of Cancellations
- Total Delay Cost
- Calibration Point
- ASQP Run
- Cancellation Penalty=1
- Cancellation Penalty=0.5

Calibration Parameter
B-Intercept 50%
Calibration Parameters

• White Planner Parameters:
  • B-Intercept (B-Int)
  • Cancellation Penalty (Can)

  At calibration point: \((B-Int, Can) = (22.5\%, 0.8)\)

• Black-and-White Planner Parameters:
  • Black/White threshold value (BW)
  • B-Intercept (B-Int)
  • Cancellation Penalty (Can)

  At calibration point: \((BW, B-Int, Can) = (47.3\%, 50\%, 1.01)\)
Delay Cost Comparison
(Baseline W versus Advanced Planner)

- Wht / CCFP: White planner with CCFP forecast
- AdvPlan / PF: Advanced planner with Perfect forecast
- AdvPlan / CCFP: Advanced planner with CCFP forecast