

# Stochastic Control of Throughput and Delay for Flows in Air Traffic Management

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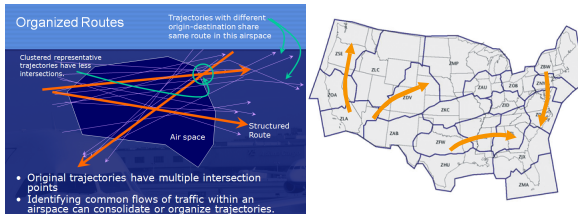
## Abstract

Attempts to manage air traffic by either decreasing delay or increasing flow can have the reverse effect on the other. In the NAS, flights typically depart at their chosen times, and flow management techniques are implemented in the air in and effort to maximize flow, while possibly leading to delay for individual aircraft. Other areas of the world allow flights to depart only at predetermined slot times knowing that there is a clear unobstructed path, leading to minimal delays but possibly underutilizing airspace.

We propose a new approach in leveraging the highway cell transmission model (CTM) to the airspace in the form of a multi-objective optimization that trades between maximizing throughput and minimizing delay. To construct the network for the model, the main flows of traffic in the airspace are first determined via a clustering method. These paths are then converted into a network of cells which can model the movement of aircraft along each route to determine the effects different control methods have on throughput and delay.

In practice, the model is envisioned to initially run offline to determine a preliminary solution to the current state of the system. Solutions for subsequent changes in actual state can be determined by running the model online for the incremental state change. Stochastic events such as convective weather clearing times or capacities can be included in the model to better see the benefits and impacts of pre-positioning traffic to take advantage of possible future clearing.

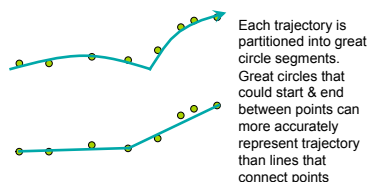
## I. Determination of Main Flows for Network



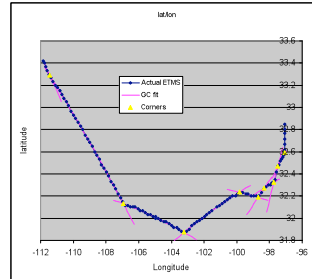
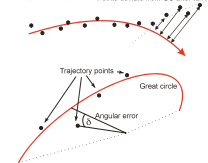
We propose a novel approach to identify the flows of air traffic using a clustering-based methodology. The trajectory is first broken into a series of great circle segments that provide for the best fit between points. An algorithm is developed that identifies turns in the trajectories using heuristics in order to identify the start and end of the segments.

Then, the segments are clustered using a density-based approach that takes into account the proximity, heading, timing, and other metrics of the segments. Finally, a representative trajectory is identified for each cluster.

### Step 1: Partition into Segments



Transition from one segment to the next is based on turns in trajectory.

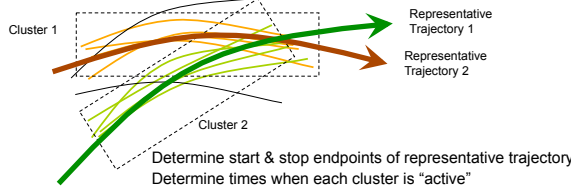


### Step 2: Clustering

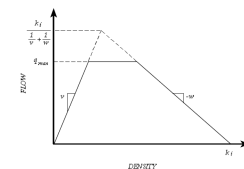
- Set of all trajectory segments  $D = \bigcup_{f \in F} \{s_{f1}, s_{f2}, \dots, s_{fseg}\}$
- Each cluster  $C_i \subseteq D$  consists of set of trajectory segments  $C_i = \{s_{fk}\}$
- Find a set of clusters representative of flows  $K = \{C_i\}$
- Find optimum clustering  $P(K^*) = \min_{K \in C} P(K)$

### Step 3: Determine Representative Trajectory

Generate representative trajectory composed of great circle segments that are "average" of segments in cluster

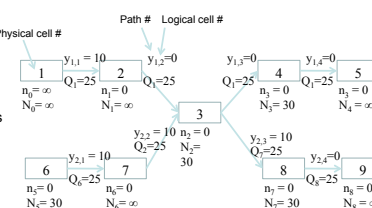


## II. Flow Optimization



### Application to Aviation

The network is composed of a set of logical cells and physical cells. Each aircraft moves from origin to destination along a path that is composed of a set of logical cells. When the paths of different aircraft cross the same physical region, the logical cells of the two paths belong to the same physical cell at the intersection.



Independent optimization of delay and throughput:

$$\min \sum_p \sum_i \sum_t c_{p,i} b_{p,i} n_{p,i}(t)$$

or

$$\max \sum_p \sum_i y_{p,i(p)}(t)$$

Subject to

$$n_{p,i}(t+1) = n_{p,i}(t) + y_{p,i}(t) - y_{p,i+1}(t) \quad \forall p, i, t$$

$$y_{p,i}(t) \leq n_{p,i-1}(t) \quad \forall p, i, t$$

$$\sum_p \sum_i a_{p,i,r} y_{p,i}(t) \leq Q_r(t) \quad \forall t, r$$

$$\sum_p \sum_i a_{p,i,r} n_{p,i}(t) \leq N_r(t) \quad \forall t, r$$

$n_{p,i}(t)$  num vehicles contained in logical cell  $i$  at time  $t$  that are on path  $p$

$y_{p,i}(t)$  inflow to logical cell  $i$  in the time interval  $(t,t+1)$  on path  $p$

$N_r(t)$  max vehicles that can be present in physical cell  $r$  at time  $t$

$Q_r(t)$  max vehicles that can flow into physical cell  $r$  from  $t$  to  $t+1$

$a(p,i,r)$  indicates whether logical cell  $(p,i)$  is included in physical cell  $r$

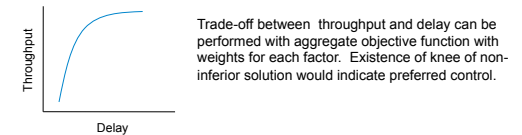
$b(p,i)$  indicates whether logical cell  $(p,i)$  is part of a valid path

$c(p,i)$  cost of using cell  $(p,i)$

$l(p)$  indicates the index of the last cell on path  $p$

Combined weighted optimization

$$\max \lambda \sum_p \sum_i y_{p,i(p)}(t) - (1-\lambda) \sum_p \sum_i c_{p,i} b_{p,i} n_{p,i}(t)$$



## Summary & Future Work

- Approach for identifying flow patterns of air traffic involving three steps:
  - Partitioning each trajectory into segments
  - Grouping the segments into clusters
  - Identifying the representative trajectory for each cluster
- A key ability of algorithm will be to dynamically and incrementally cluster new flight segments with existing clusters without having to re-cluster the entire data set each time.
- Flow paths are used to construct network with separate logical paths from origin to destination, each consisting of series of cells.
- Initial model for optimizing throughput with minimal delay that can be used to trade-off between the two.
- Future steps include
  - Include stochastic factors such as random convective weather clearing times or random capacity
  - Adapt to ability to incrementally update network state based on current conditions and re-optimize.
  - Develop heuristic to quickly find reasonably optimal solution
- Model can be used to evaluate variations in flow strategies between US and Europe that emphasize increased throughput vs minimal delay.