Measuring and Modeling En Route Flight Efficiency: the US Experience

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Outline

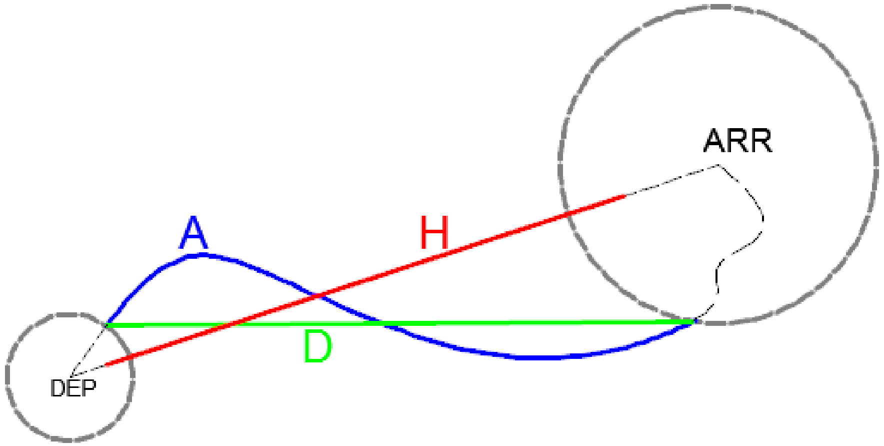
- Introduction
- Data Sources and Preliminary Statistical Analysis
- Macroscopic Model
- Microscopic Model
- Route Selection Model
- Conclusions

Background

- FAA and EuroControl published metrics to evaluate flight en route inefficiencies;
- Understanding the causal factors behind the inefficiency is of great importance.

Defining En route Inefficiency

$$\frac{A - H}{H}$$



- A: Actual flown distance;
- D: Great circle distance between local entry and exit point;
- H: Achieved distance (related to great circle distances from exit/entry points to arcs surrounding arrival/departure airports).

Sources: https://www.eurocontrol.int/sites/default/files/content/documents/single-sky/pru/news-related/2013-05-08-slides-workshop-achieved-distance.pdf

Project Goals

- "Evaluation of En Route performance Measures"
- Support FAA in developing en route efficiency performance metrics
- For selected metrics, identify reasons for inefficiency
  - NAS route structure
  - Traffic management initiatives
  - Winds
  - Convective weather
- Eventually allow comparison with other ANSPs such as Eurocontrol

Overview

- Develop models to evaluate how flight en route inefficiency varies based on geographic and seasonal factors;
- Apply clustering algorithms to raw trajectory data for selected OD pairs
- Include cluster membership as explanatory variable in multi-variate model of en route inefficiency
- Analyze within-cluster and between-cluster contributions to en route inefficiency

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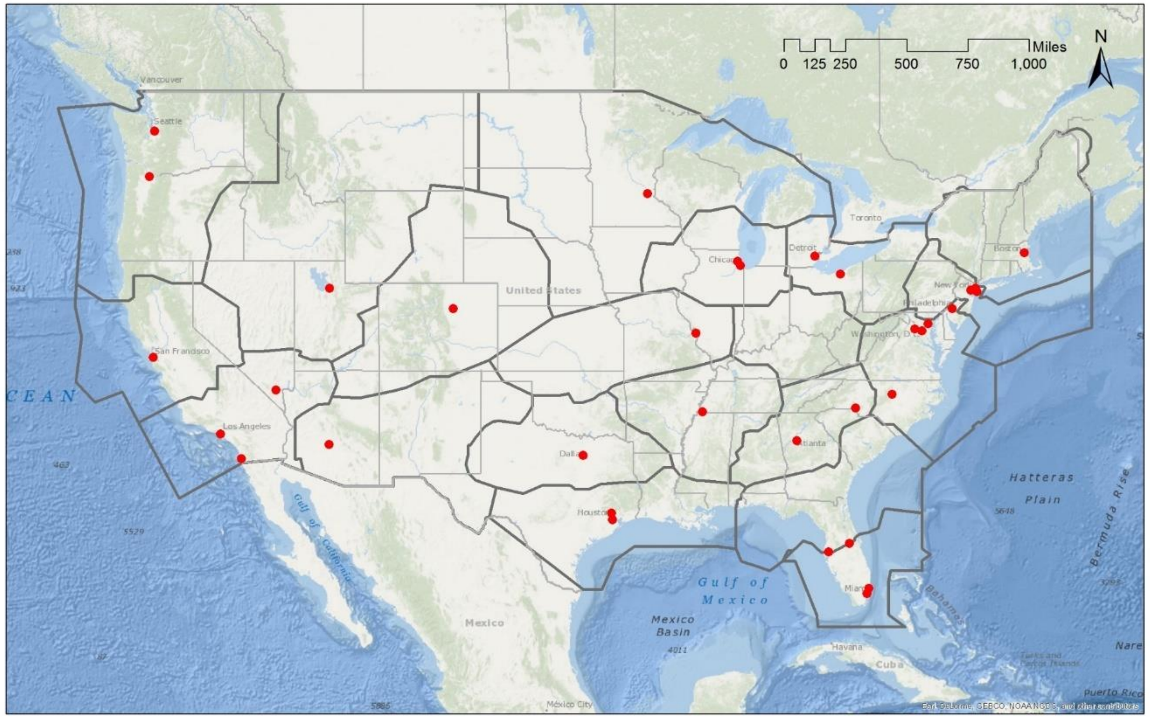
Data Sources

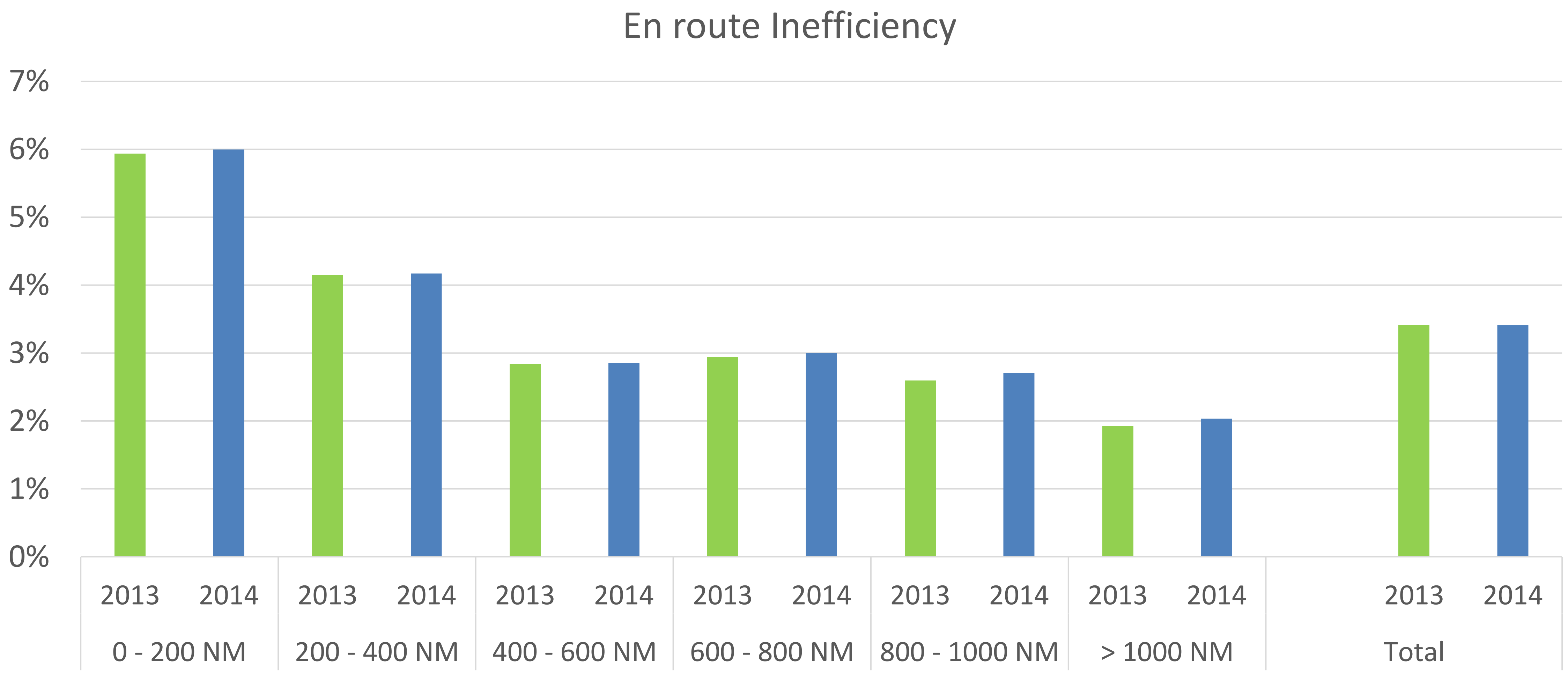
- Flight Event Data
  - From FAA Traffic Flow Management System (TFMS);
  - Flight level records: arrival/ departure airports, D40A100 Actual/Great Circle/ Achieved distances and etc.
- Flight Track Data
  - From FAA Traffic Flow Management System (TFMS);
  - Radar position data (4D trajectory): typically one-minute position updates from individual flights.

Summary Statistics

- Only focusing on 34 core airports scattering around US;
- Around 3 million flights per year in/out of core 34 airports, accounting for about 50% of total flights in/out of the US;

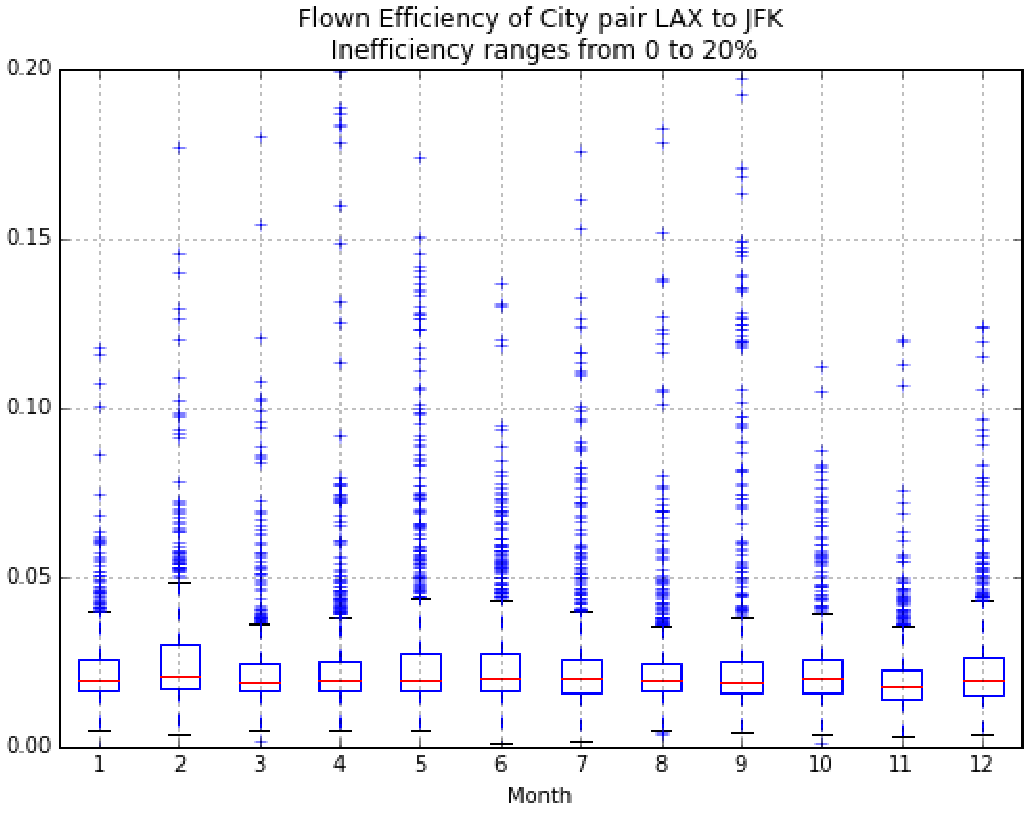


En Route Inefficiency vs Great Circle Distance

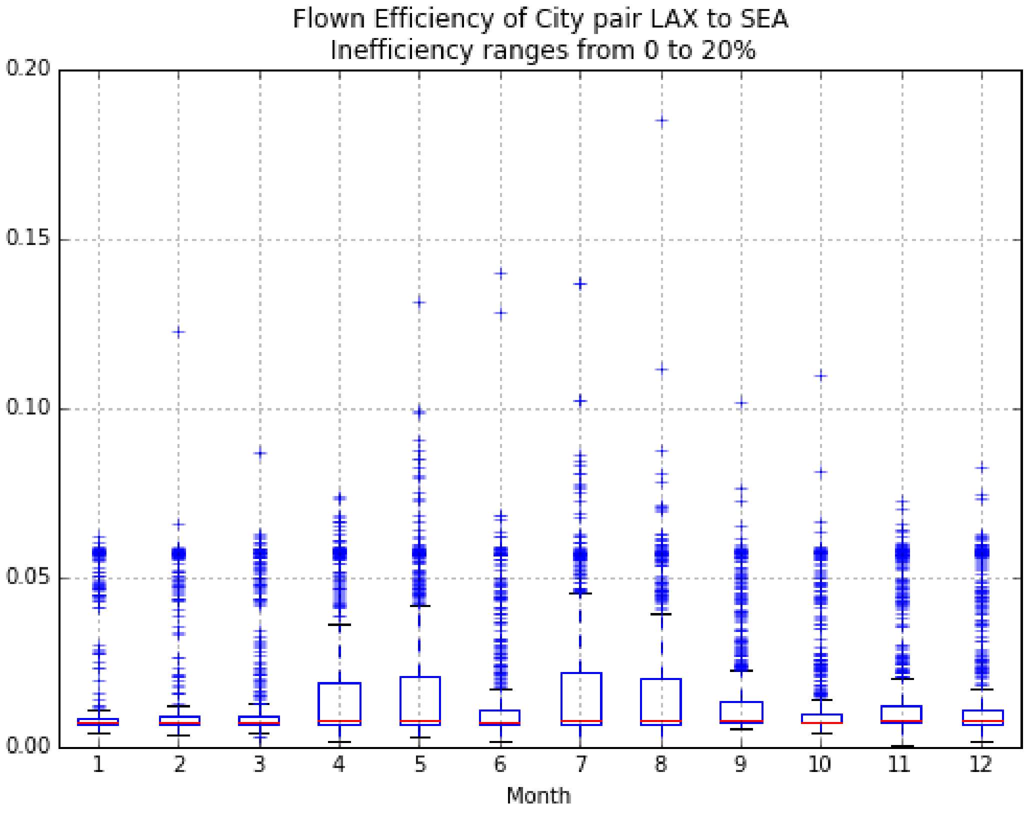


Inefficiency of Typical Airport Pairs (2013)

LAX to JFK (2.45%)

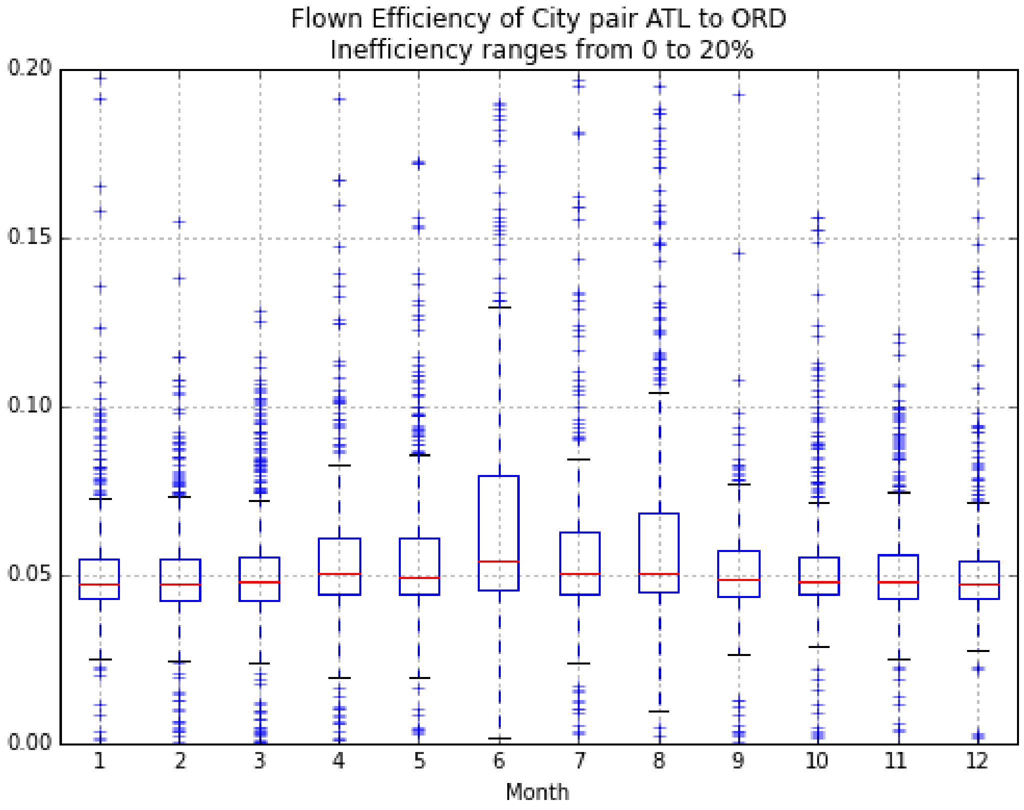


LAX to SEA (1.61%)

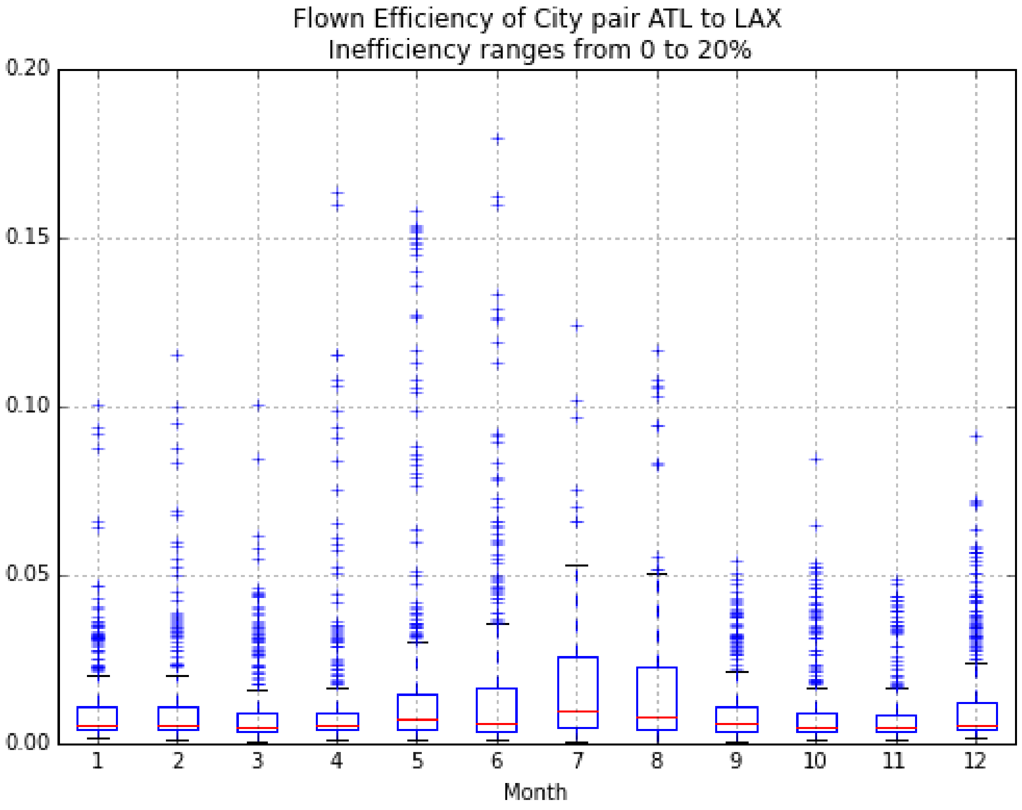


Inefficiency of Typical Airport Pairs (2013)

ATL to ORD (6.86%)



ATL to LAX (1.28%)



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Method

- Use Regression analysis to explore the fixed effects of departure/ arrival airports, month and great circle distance;
- First to build a model that no interaction terms are included. (Model I, 6M observations, 82 Variables)

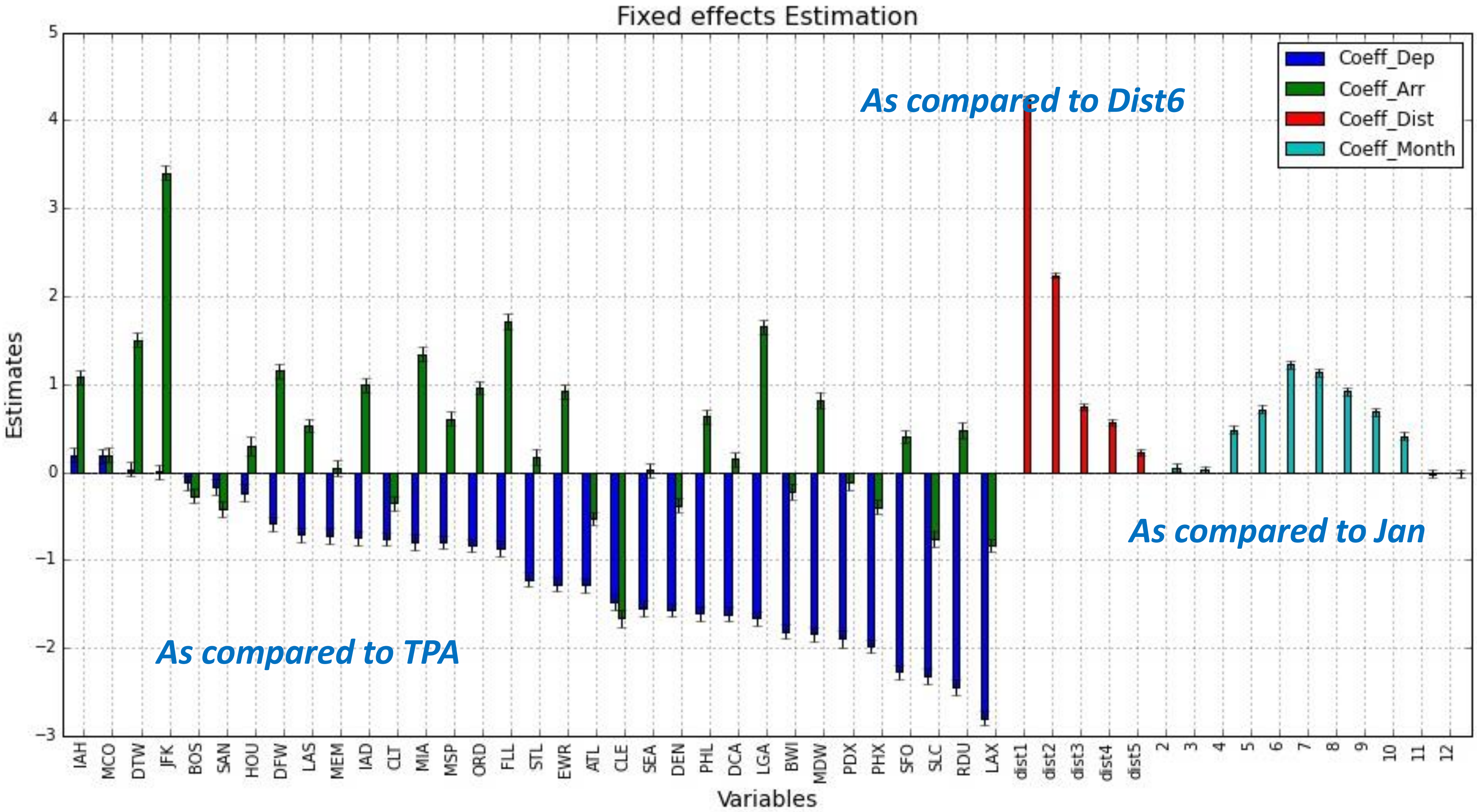
$$ineffi = \beta_{dep} \cdot X_{dep} + \beta_{arr} \cdot X_{arr} + \beta_{mon} \cdot X_{mon} + \sum_{i}^{5} \beta_i \cdot Dist_i$$

- Then build a model that considers the interaction between airports and month. (Model II, 6M observations, 808 Variables)

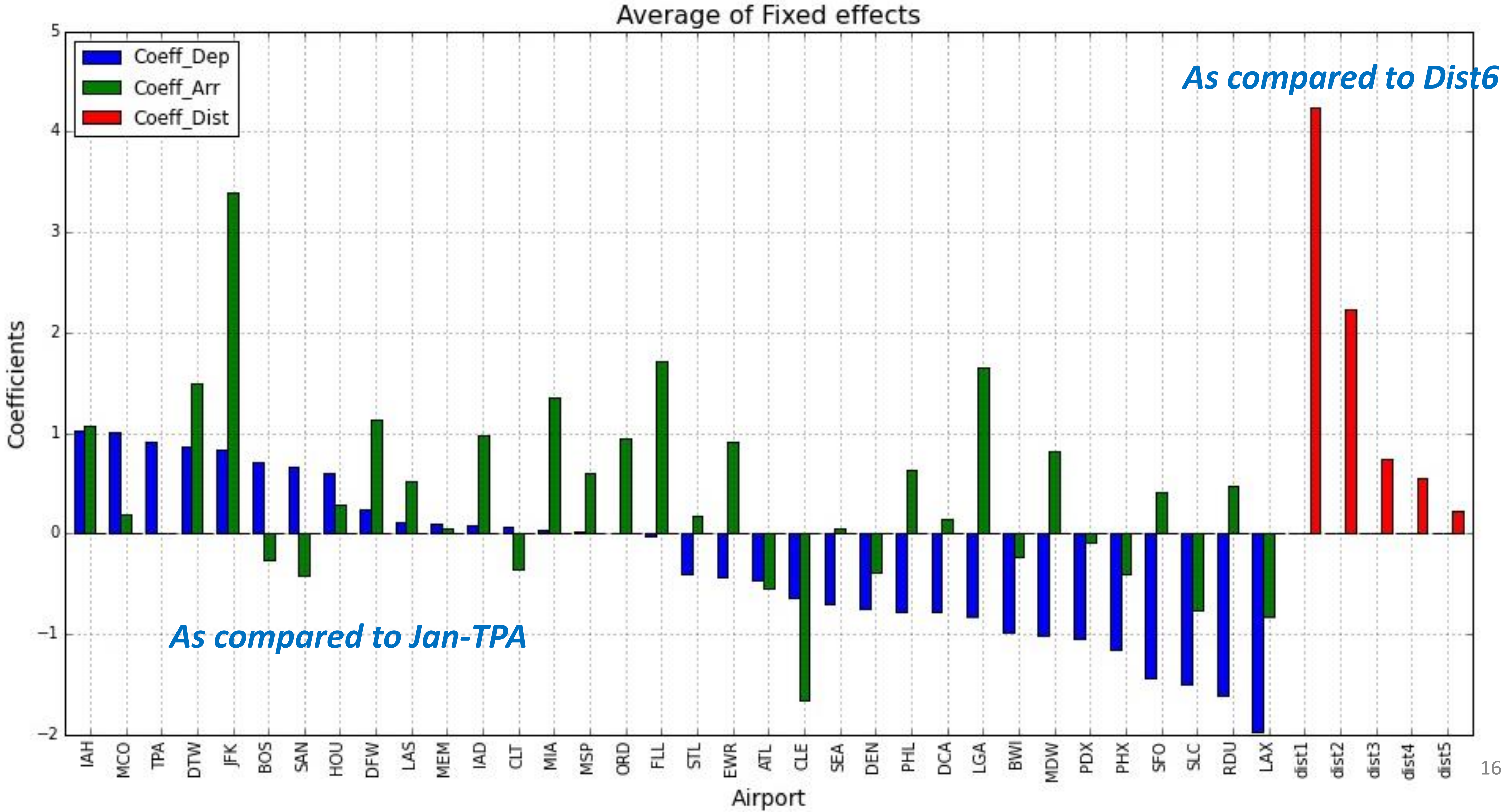
$$ineffi = \beta'_{int1} \cdot X_{dep} \cdot X_{mon} + \beta'_{int2} \cdot X_{arr} \cdot X_{mon} + \sum_{i}^{5} \beta_i \cdot Dist_i$$

- $Dist_1: 0\ - 200\ NM; Dist_2: 200\ - 400\ NM; Dist_3 = 400\ - 600\ NM;$
- $Dist_4: 600\ - 800\ NM; Dist_5: 800\ - 1000\ NM; Dist_6: > 1000\ NM$

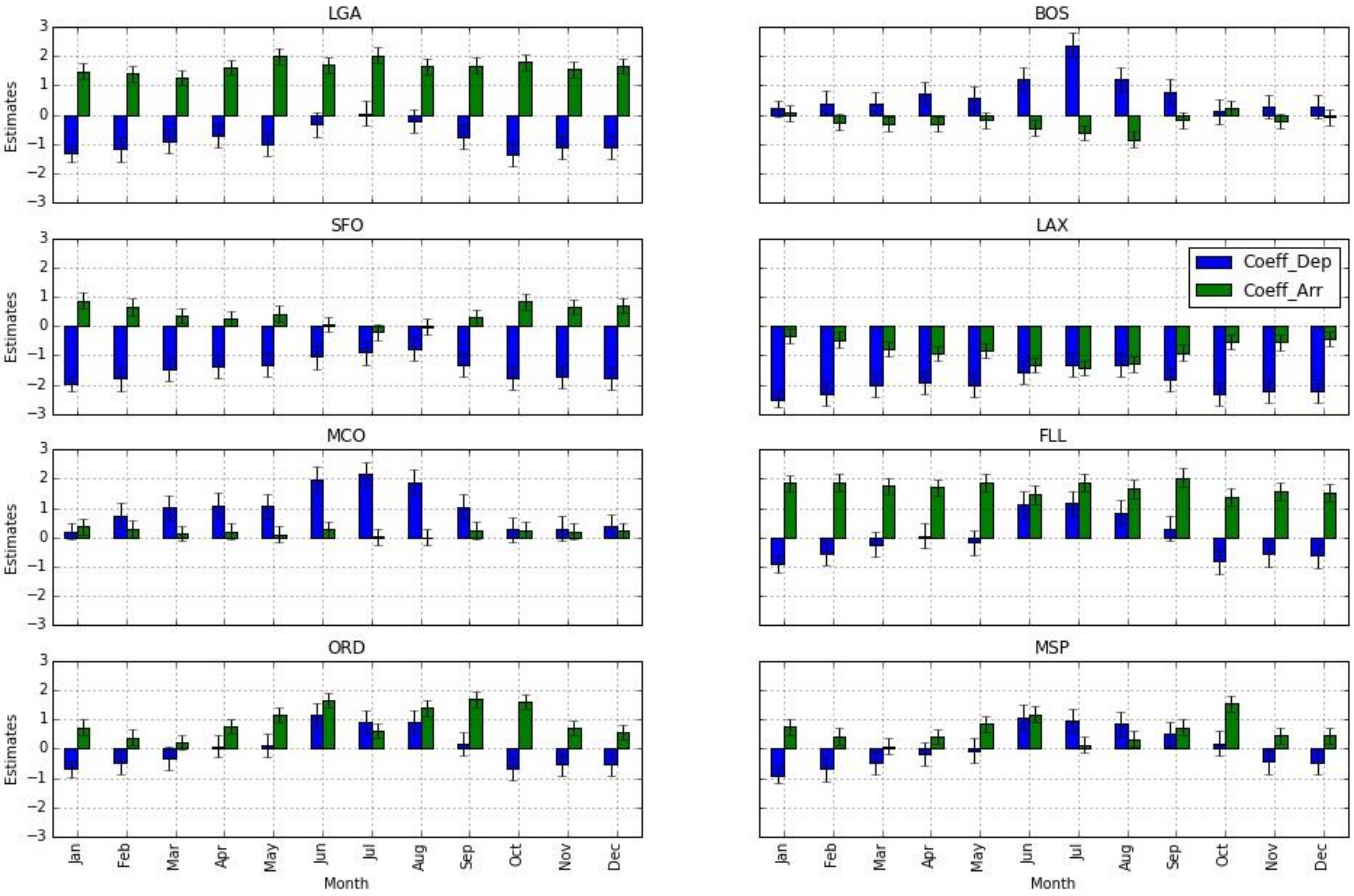
Model I - Estimation



Model II - Estimation



Model II – comparison



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Trajectory Clustering

- A Trajectory is defined as the set of horizontal tracking points and times for a specific flight
- A flight typically has ~10^2 tracking points
- No two flights have exactly the same trajectory
- We want to find sets of flights with similar trajectories
- Standard clustering techniques need to be adapted because
  - Different trajectories have different numbers of tracking points
  - There is no inherent correspondence between the points of different trajectories
  - The number of tracking points is very large

Clustering Algorithms

- ***<u>Step 0: Trajectory Cleaning</u>***
  - Exclude geometric-discontinuity and time-discontinuity trajectories;
  - Exclude trajectories starting/ending outside terminal areas.

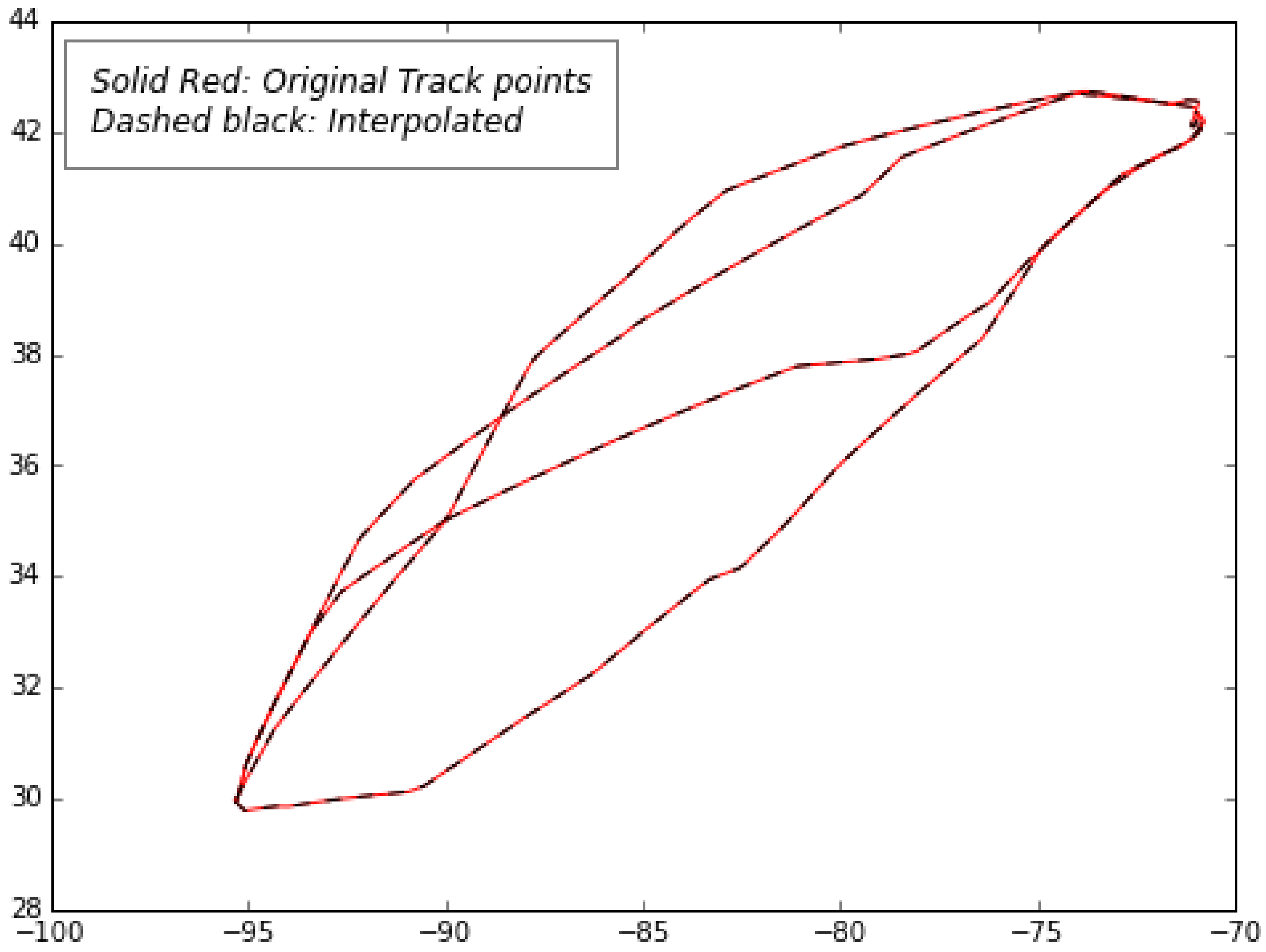
- ***<u>Step 1: Trajectory resampling</u>***
  - Get trajectories with equal numbers of points;
  - Linear Interpolation (with respect to tracking distance).

- ***<u>Step 2: Principal Component Analysis (PCA)</u>***
  - Dimension reduction & Trajectory smoothing;
  - First five modes can capture more than 97% of variations.

- ***<u>Step 3: Clustering</u>***
  - Trajectory classifications;
  - DBSCAN algorithm is applied to the PCA mode matrix to get representative clusters.

Resampling Example

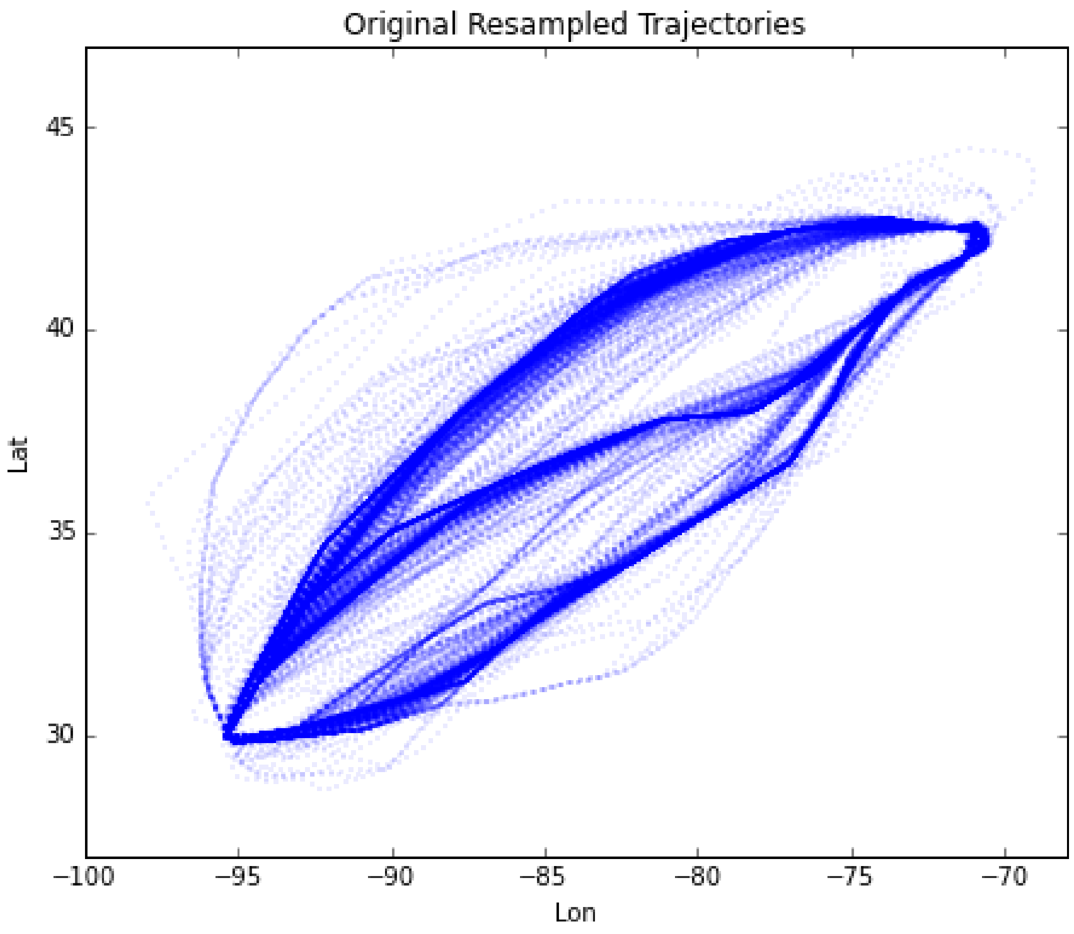
- Linear interpolation between the start and end tracking location for each route
- 100 pseudo points are predicted locations at:
  - Initial location (d0)
  - d0 + trajectory distance/99 (d1)
  - d1 + trajectory distance/99 (d2)
  - …
  - Final trajectory location (d100)

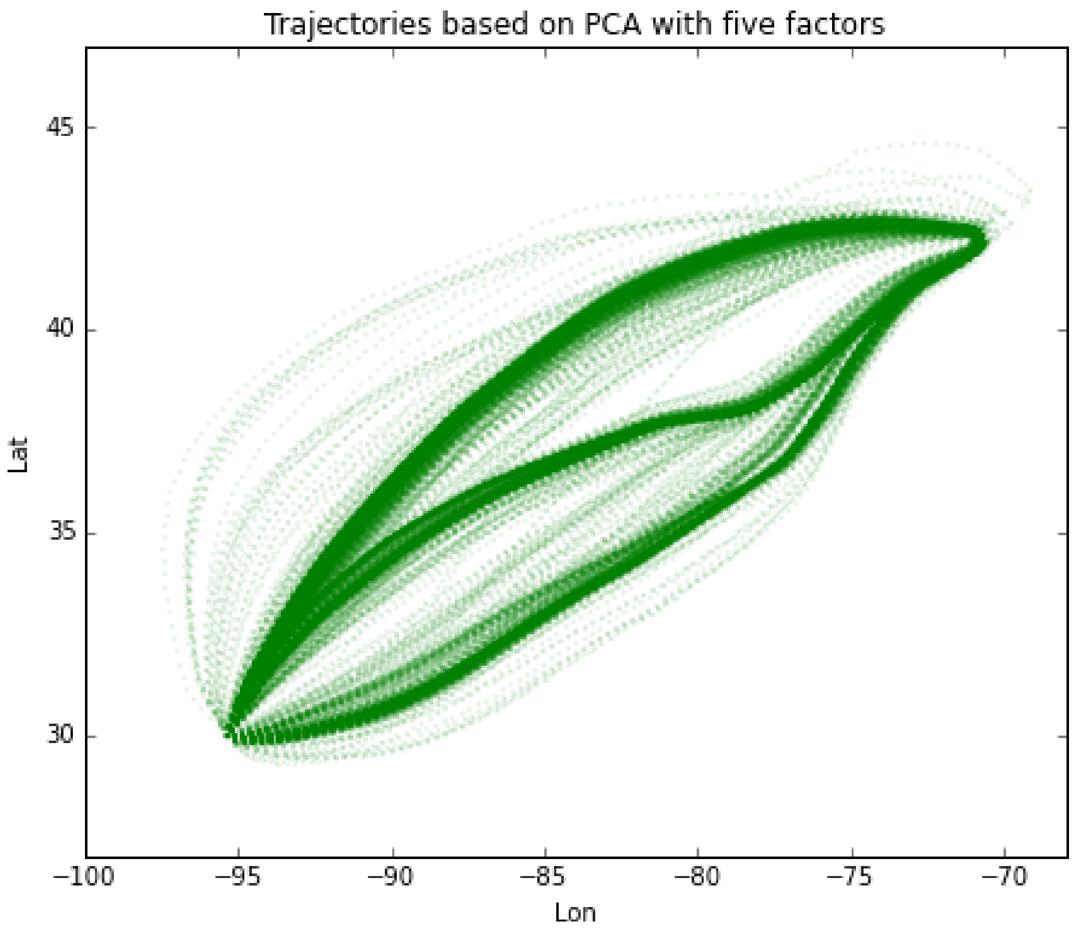


Dimension Reduction

- Reduce the dimension of trajectories – save computational time
- Improve the quality of clustering – Principal Component Analysis (PCA) can help to filter off noise and smooth the data
- Using PCA, we found that five factors can capture almost all the variation in the original 900 variables e.g.
  - 99% for IAH → BOS
  - 96% for FLL → JFK
  - 94% for ORD → DCA

Example of Dimension Reduction (IAH-BOS)





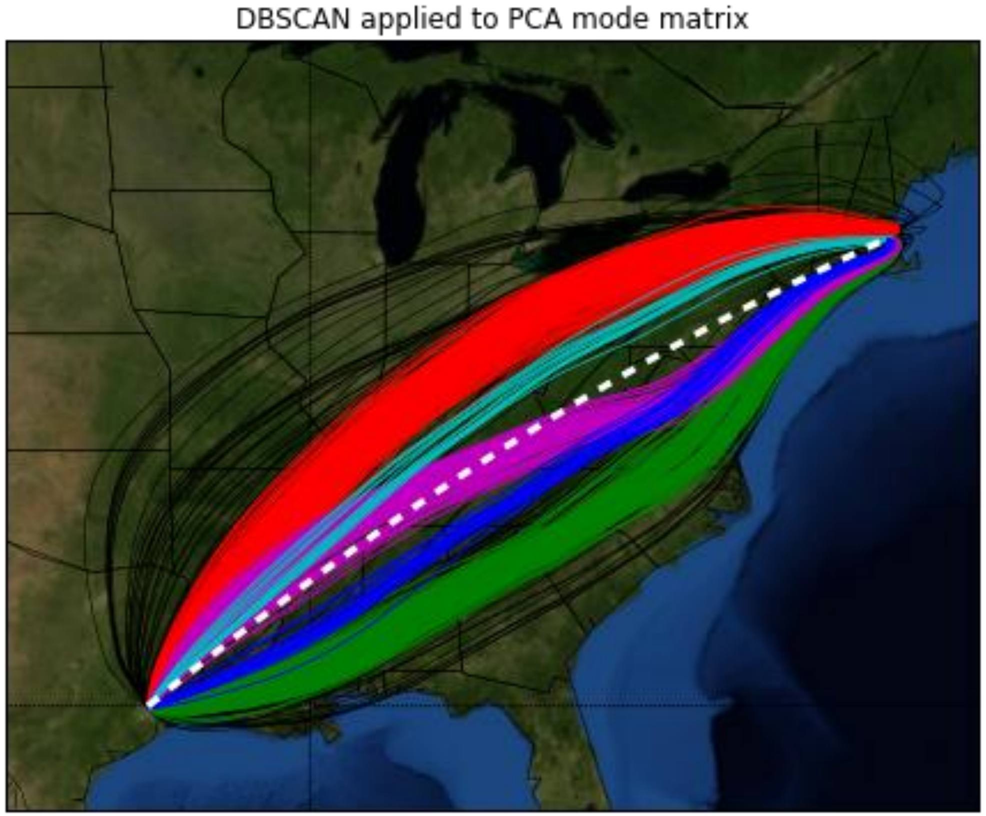
Clustering

- Use trajectory factor scores to find sets of trajectories that are similar to each other
- Measure similarity between any two trajectories using Euclidean distance between their respective factor scores
- Tried two clustering methods
  - K means
  - DBSCAN
- Prefer DBSCAN because
  - Do not need to pre-determine number of clusters
  - Allows trajectories to be identified as outliers
  - Can limit variation within each cluster
  - However DBSCAN does require two parameters to be specified

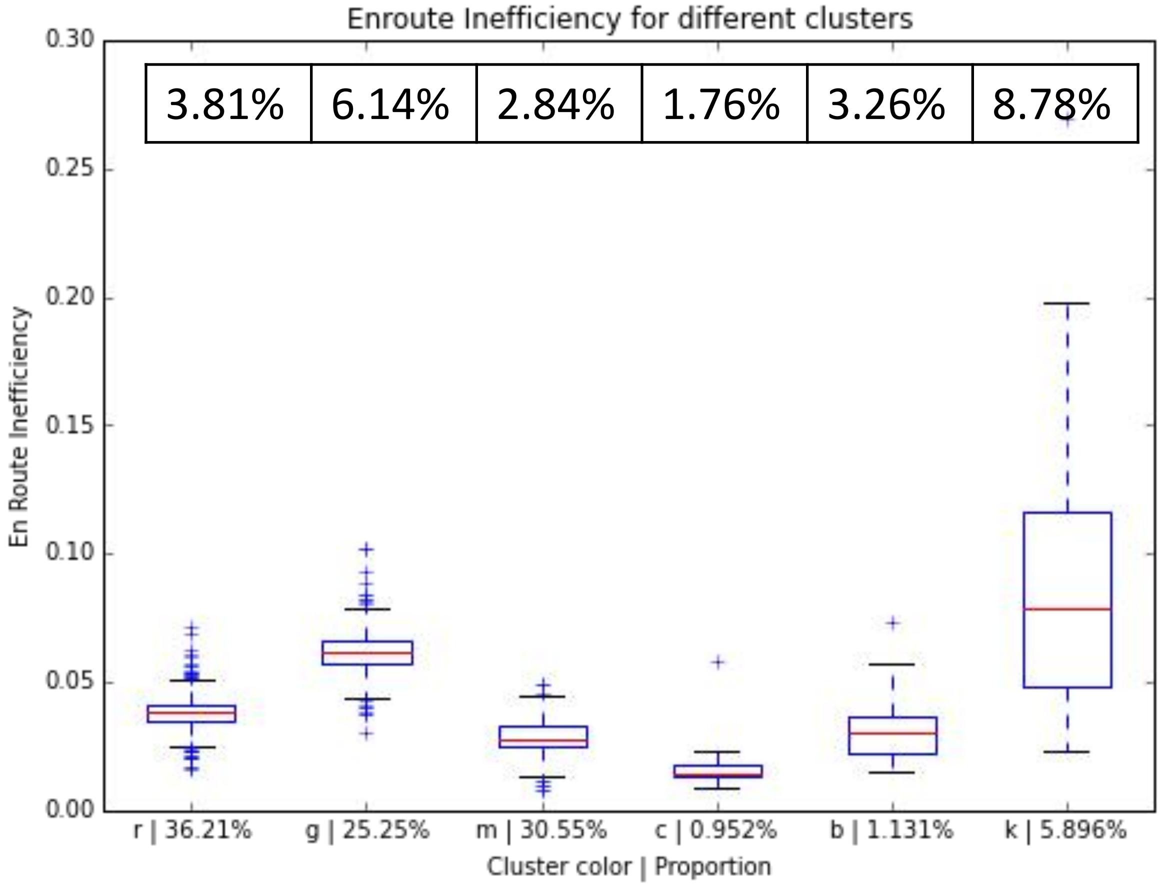
DBSCAN Results for Six Airport Pairs

- Input parameters (distance threshold and minimum points) determined using trial-and-error for each pair

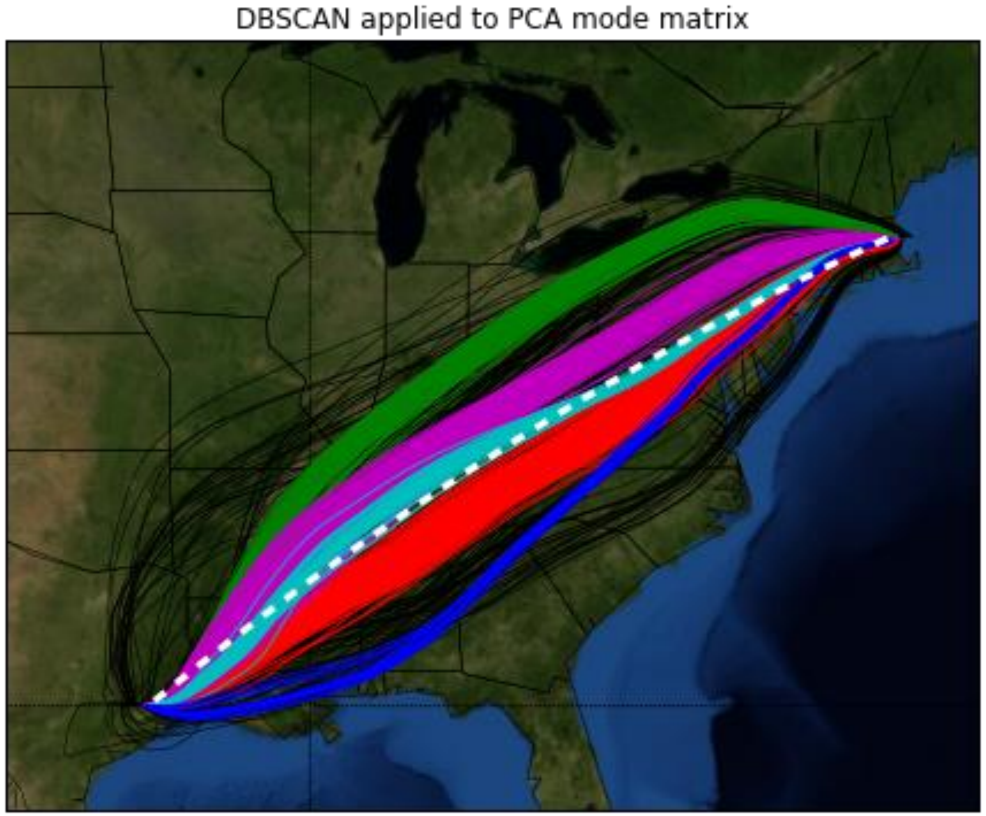
IAH → BOS (1679 of original 1817)



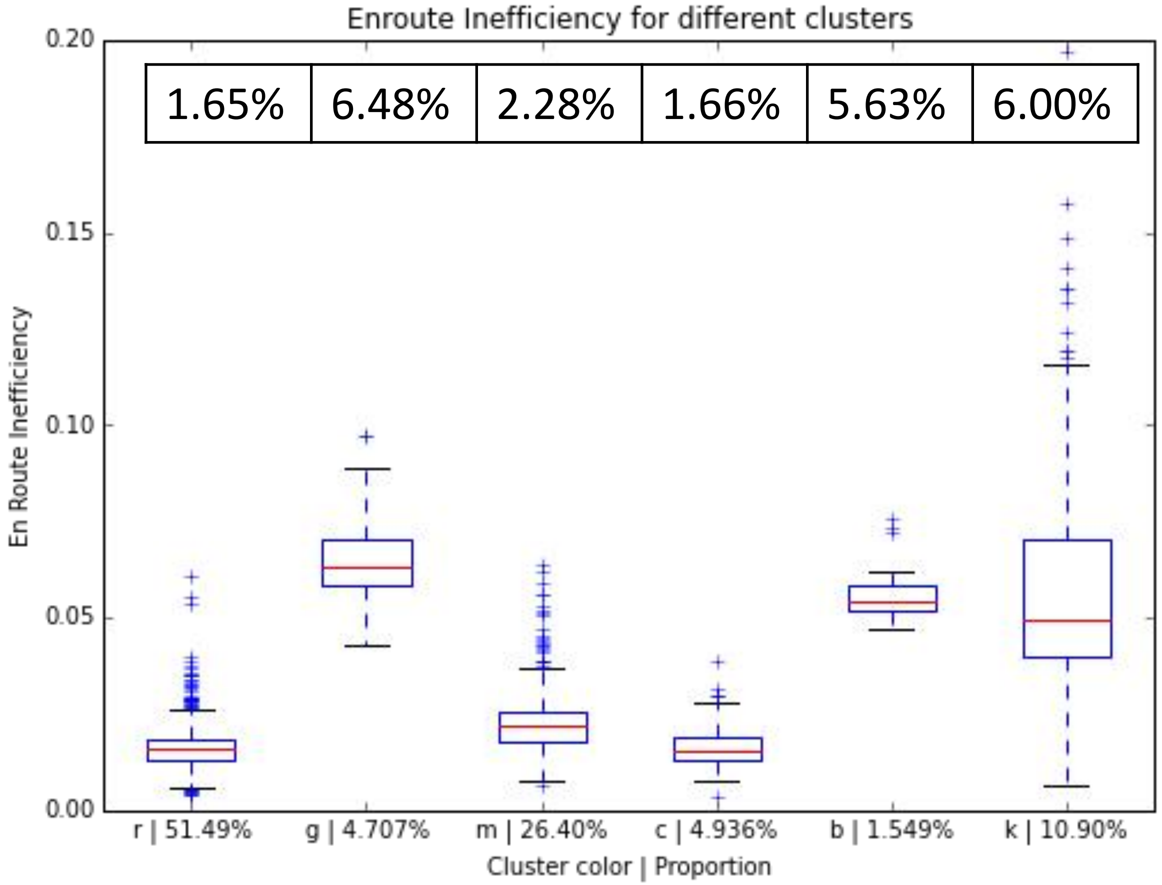
Black lines are classified as outliers



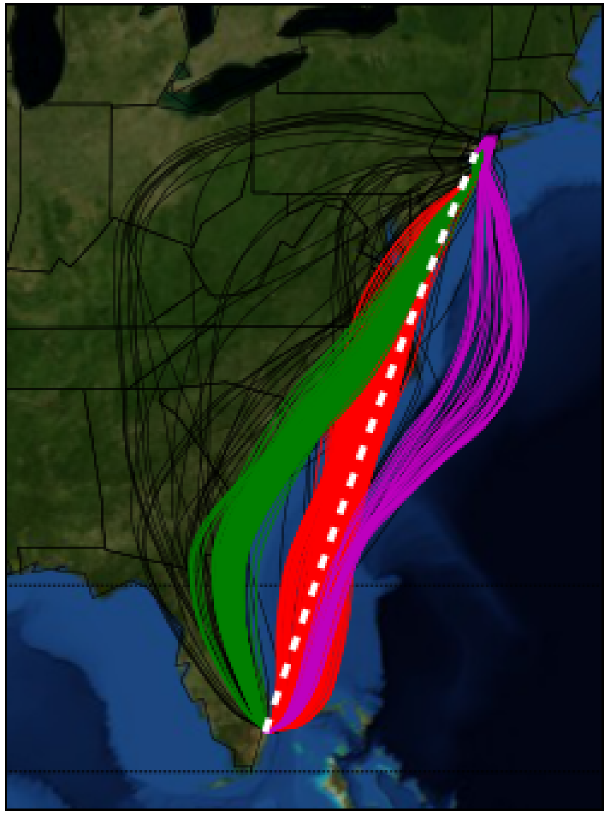
BOS → IAH (1742 of original 1883)



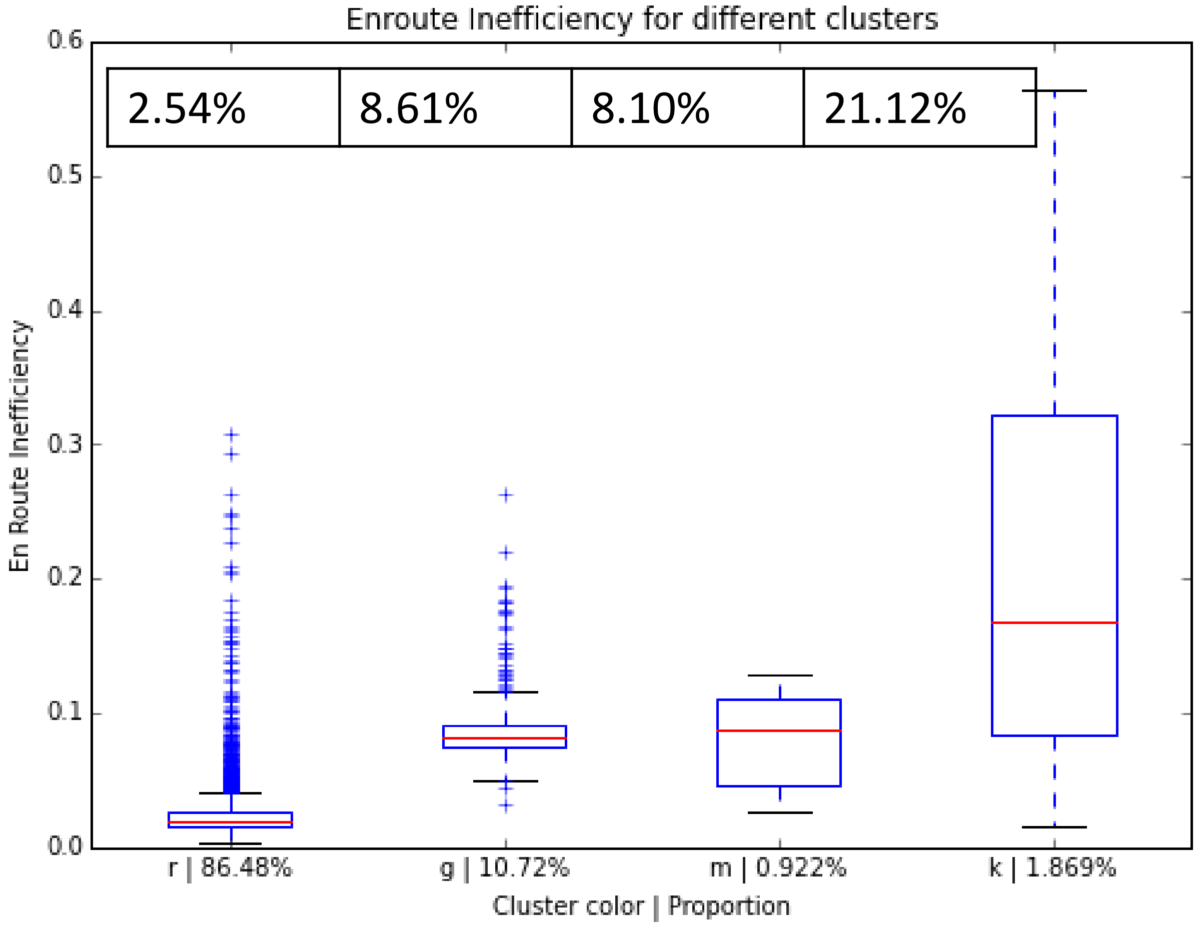
Black lines are classified as outliers



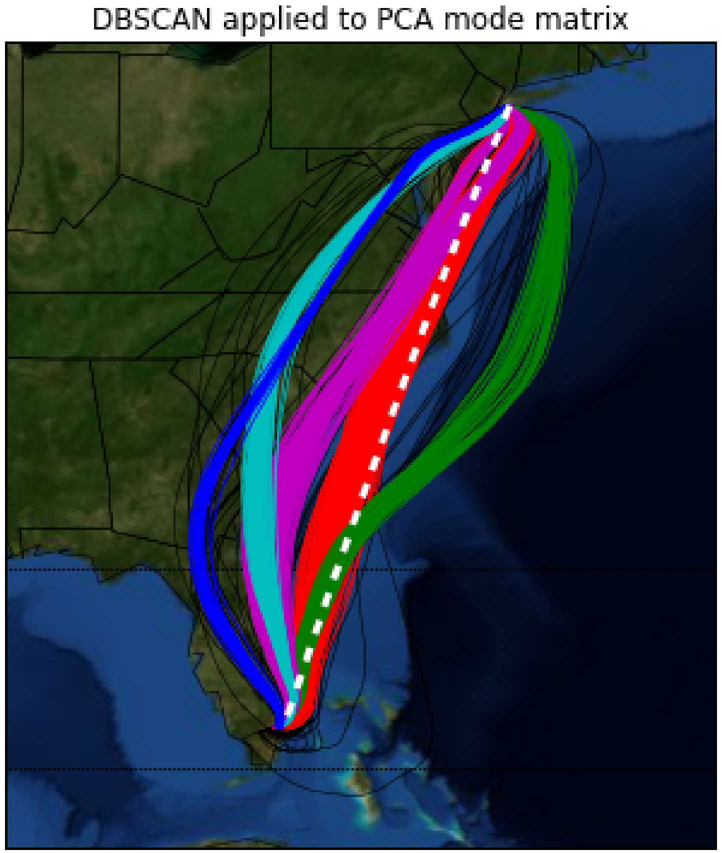
FLL → JFK (4011 of original 4267)



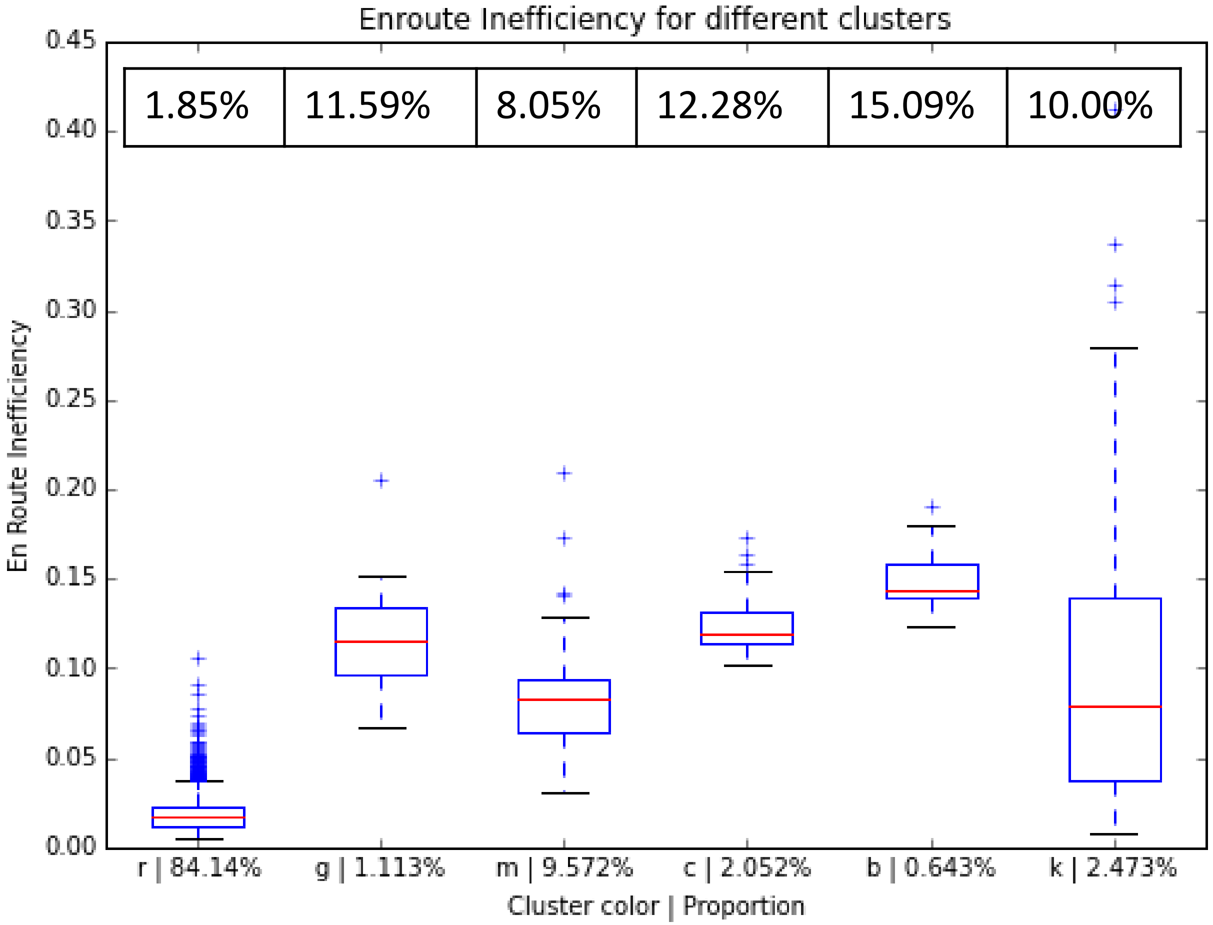
Black lines are classified as outliers



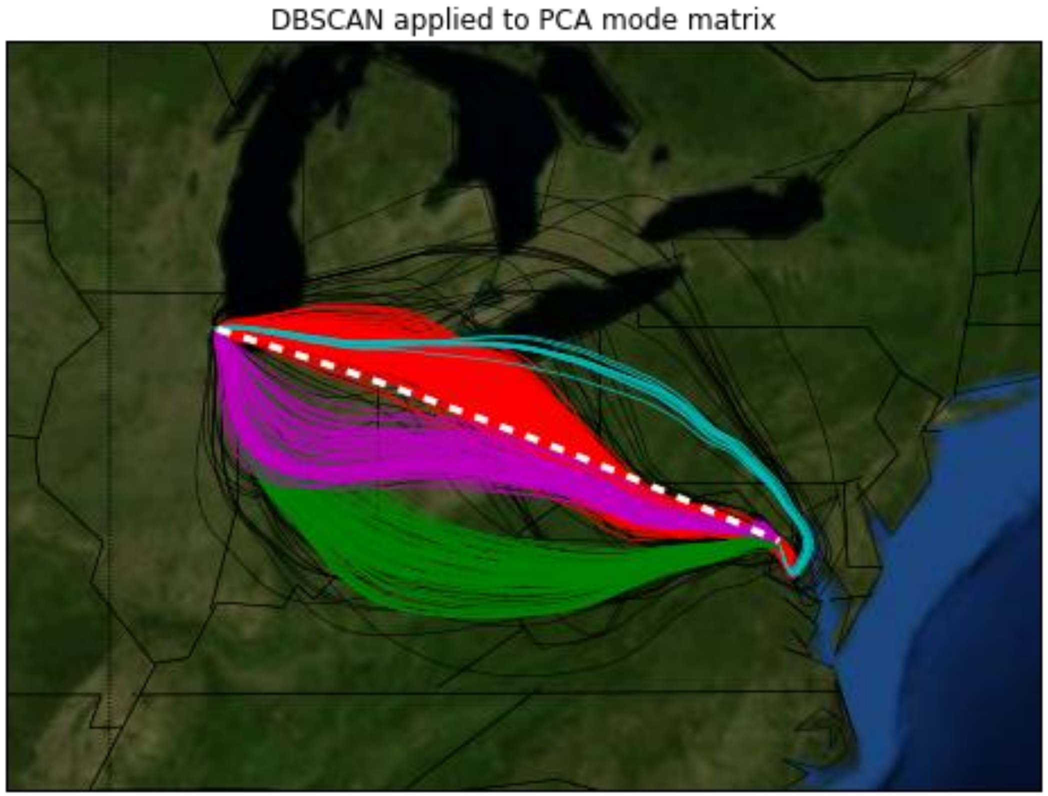
JFK → FLL (4043 of original 4273)

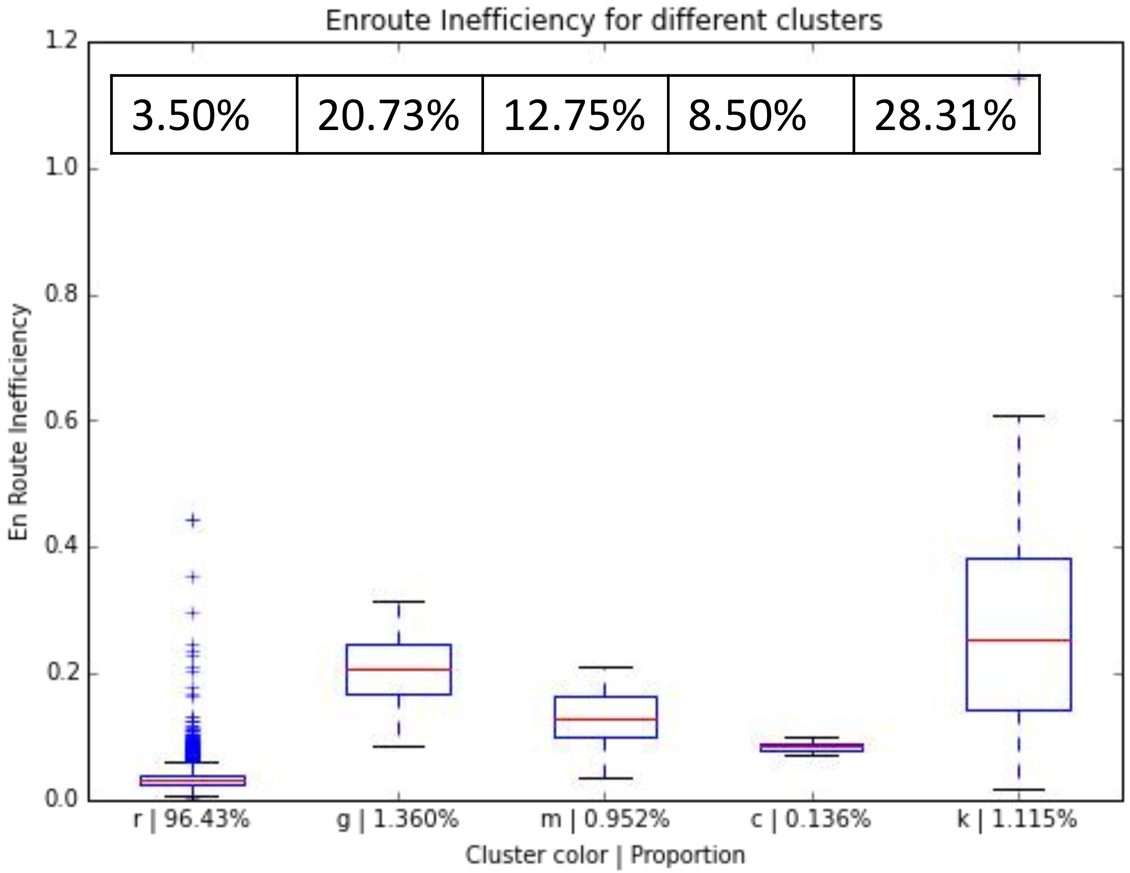


Black lines are classified as outliers



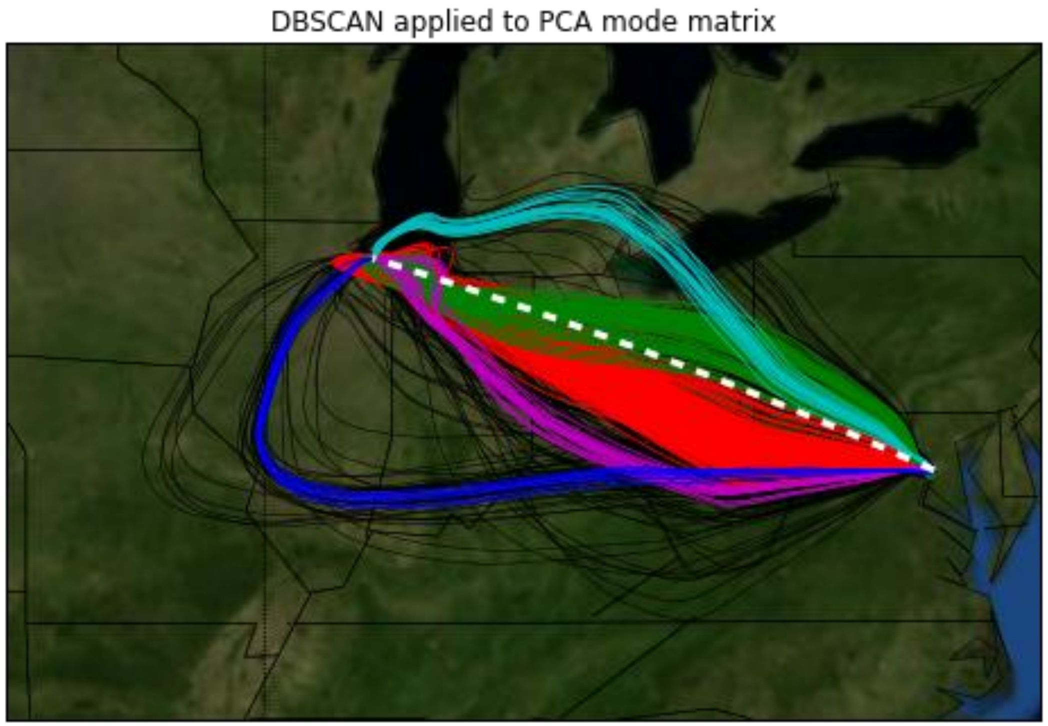
ORD → DCA (7349 of original 7574)



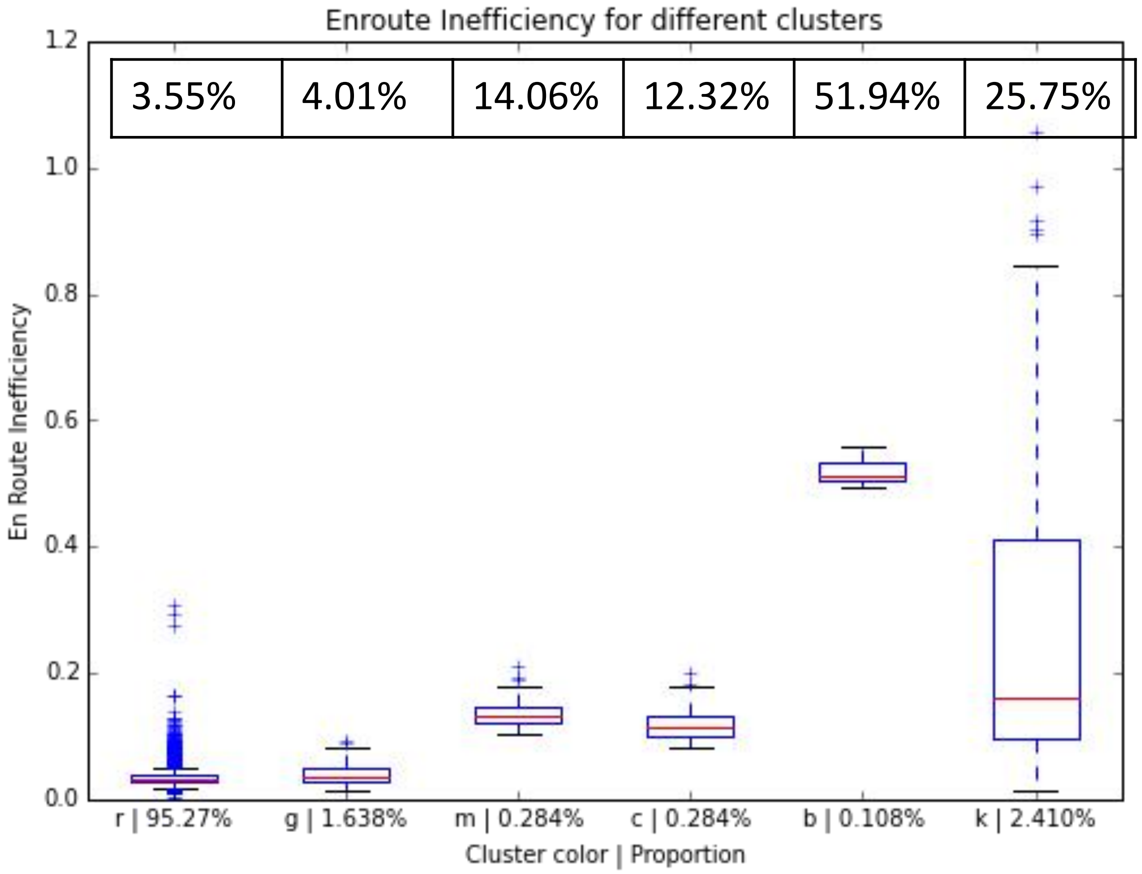


Black lines are classified as outliers

DCA → ORD (7383 of original 7557)



Black lines are classified as outliers



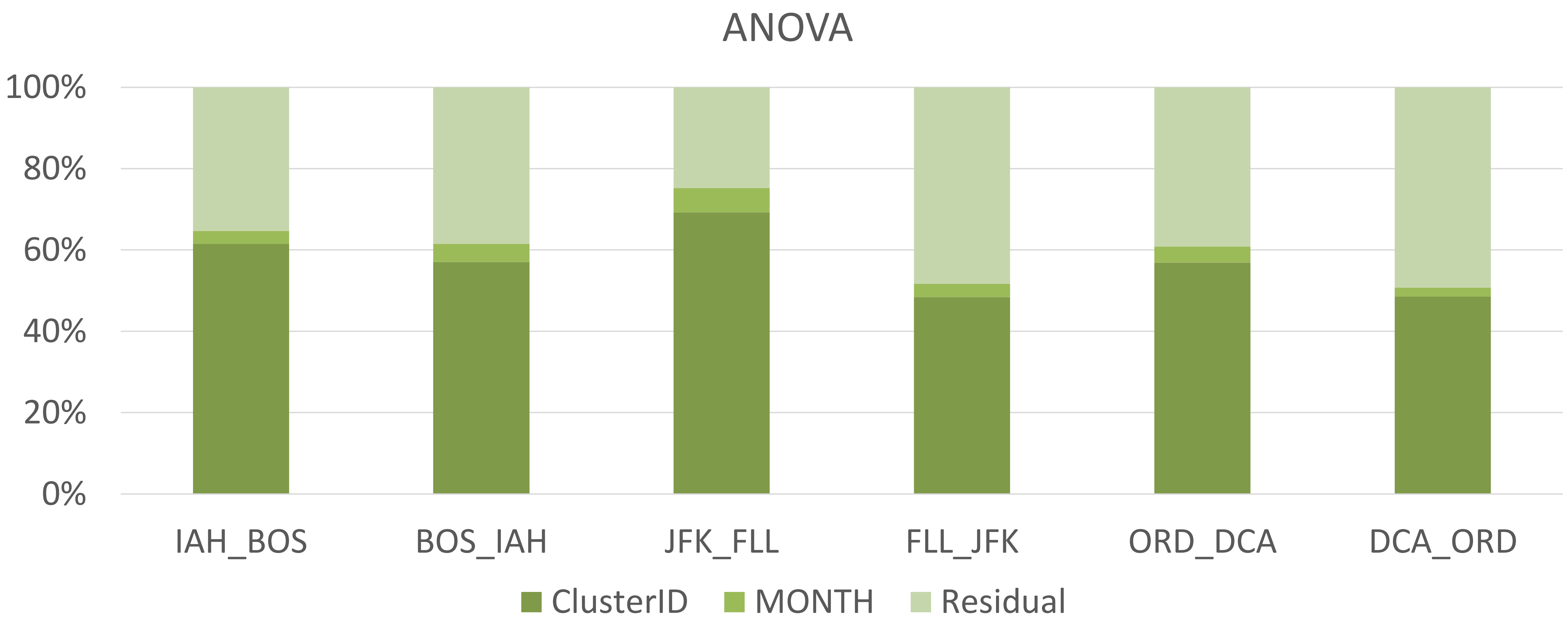
Impact of Cluster Membership on En Route Efficiency

- Build route-specific fixed effect models to capture variations in en route inefficiencies among representative clusters;
- Model specification
  - Separate models for each airport pair
  - $Inefficiency(\%) = \beta_0 + \beta_1' \cdot X_{month} + \beta_2' \cdot X_{ClusterID};$
  - X_{month} and $X_{ClusterID}$ are categorical variables;
  - Cluster ID can be found in previous slides.

Estimation Results

	IAH_BOS	BOS_IAH	JKF_FLL	FLL_JFK	ORD_DCA	DCA_ORD
Intercept	6.019***	8.452***	9.768***	20.924***	27.959***	25.485***
MONTH -2	-0.148	0.023	0.220*	0.042	0.009	-0.096
MONTH -3	-0.266*	-0.191	0.193*	0.317	-0.006	0.165
MONTH -4	0.121	0.312*	0.636***	0.259	0.045	-0.008
MONTH -5	0.184	-0.023	0.112	0.131	0.083	-0.114
MONTH -6	0.105	0.853***	0.367***	0.096	0.688***	0.621***
MONTH -7	0.025	0.215	0.336***	0.393*	0.344**	0.108
MONTH -8	-0.166	0.568***	0.105**	0.374*	0.151	0.964***
MONTH -9	0.093	0.306*	0.083	-0.073	-0.051	0.367*
MONTH -10	-0.090	0.018	0.012	-0.273	-0.109	-0.377*
MONTH -11	-0.074	-0.029	0.223*	-0.020	-0.116	-0.342
MONTH -12	-0.261	-0.071	0.130	-0.228	-0.041	-0.179
Cluster ID – r	-4.328***	-4.831***	-8.108***	-18.470***	-24.538***	-22.026***
Cluster ID – b	0.525***	-2.463***	1.558***	-12.457***	-7.521***	-21.908***
Cluster ID – g	-3.697***	-5.801***	-1.970***	-12.956***	-15.434***	-11.593***
Cluster ID – m	-4.292***	-7.017***	2.240***	-	-19.705***	-13.695***
Cluster ID - c	-0.409	-5.498***	5.058***	-	-	26.114***
R squared	0.6463	0.6147	0.7523	0.5167	0.6083	0.5076

Analysis of Variance



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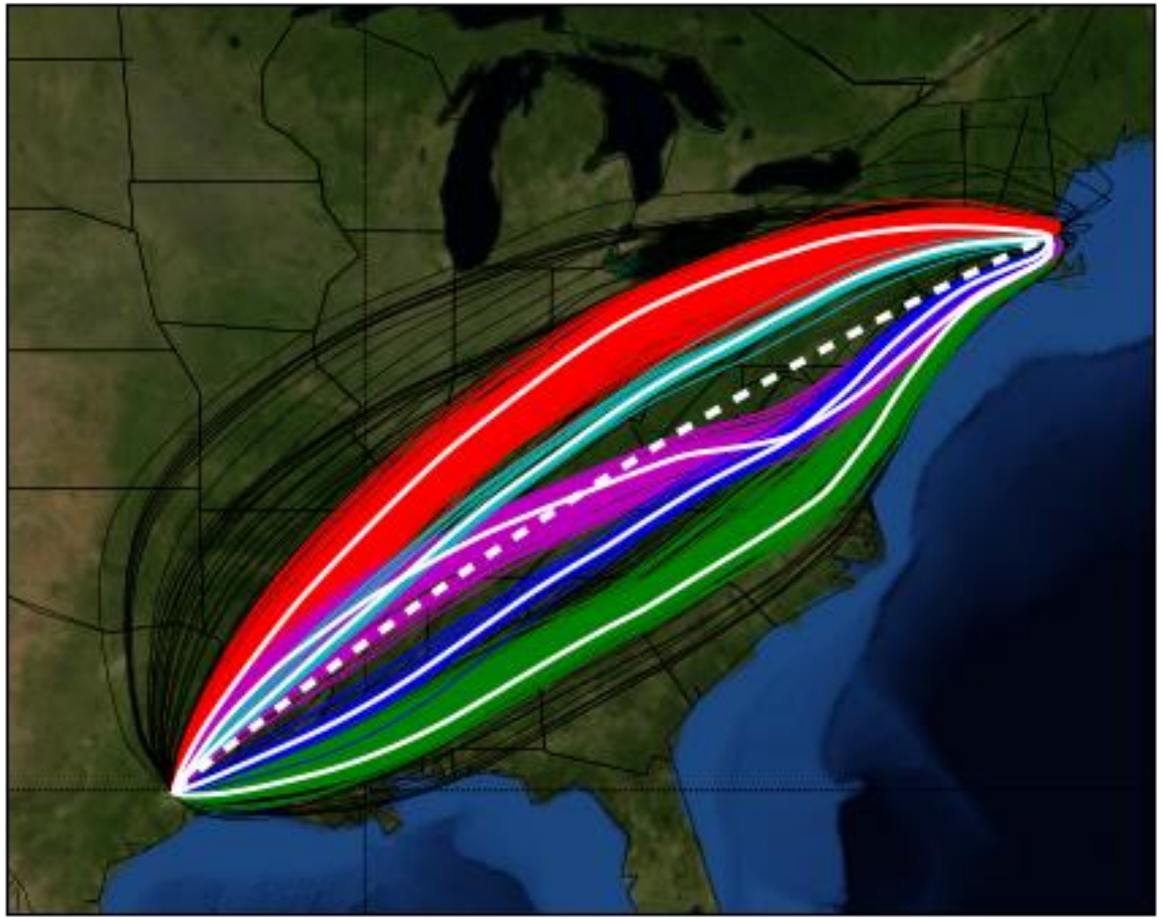
Route Selection Model

- We try to understand what factors may influence the route selection;
- We are specifically interested in the impacts of convective weather such as thunder storm, shower and etc.

Methodologies

- *Step 0: Trajectory Clustering*
  - Apply trajectory clustering algorithm to classify trajectories into groups;
  - Typically four to five groups can be classified
- *Step 1: "Center" of Clusters*
  - Apply 1-Median algorithm to determine the center for each cluster
- *Step 2: Data Fusion*
  - Obtain (historical) real time weather data for the same time period with trajectory data;
  - Merge the real-time weather data with 4D trajectory data (time series);
  - For each trajectory, determine the aggregated level of weather intensity
- *Step 3: Route Selection Model*
  - Estimate the impact of weather factors and other interesting factors;
  - Multinomial logit model is applied to the final dataset.

Trajectory Clustering and Center



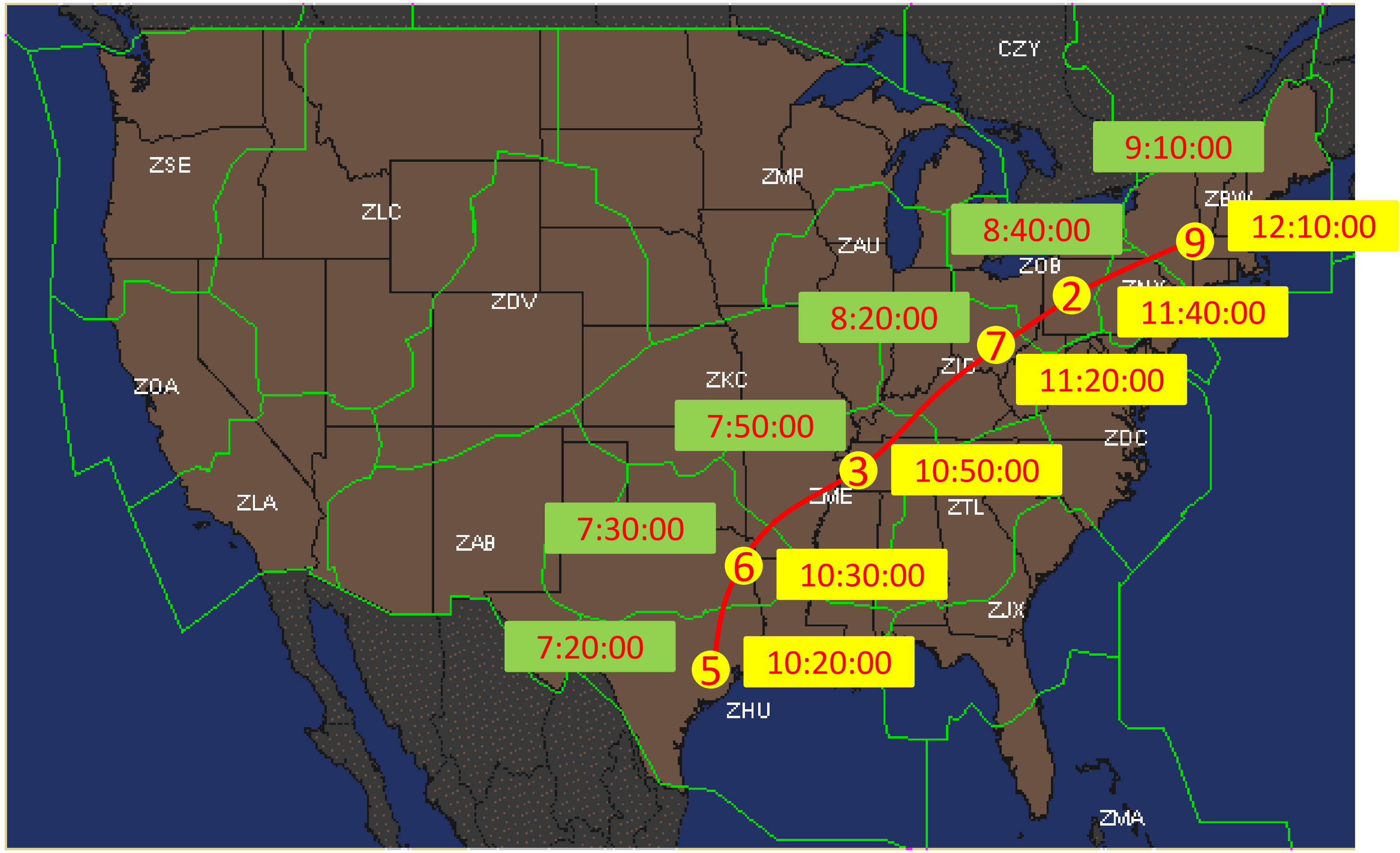
- The case for IAH → BOS in 2013;
- Solid white lines are the centers for cluster groups;
- Five representative clusters are identified (red, blue, green, magenta and cyan), with only 6% of outliers (black).
- 4d information (lat, lon, alt, time) is extracted for the five center trajectories.

Data Fusion

- Hourly weather data
  - Obtained from NOAA;
  - Include hourly (usually less than 30 minute) data indicating whether a station had thunder storms, showers, rains, hails… during a time period;
  - There are more than 2000 weather stations around United States;
- Center-trajectory data
  - “center” is determined by clustering algorithm;
  - 4d information is extracted for each center

- Data Fusion
  - First to exclude trajectories that are classified as outliers, then for each member trajectories, we extract the time stamp of its first track point;
  - Then we replace the departure time of center-trajectories with such time stamp, and calculate the time stamps for the rest of track point for center-trajectories;
  - For each track point of center-trajectories, we calculate the total number of convective weather happened within the ARTCC zone associated with the tracking location in a time interval that is 2 hours prior and after the tracking time stamp;
  - Finally we aggregate the total number of convective weather appeared during the whole trajectory.

Example for Data Fusion



- Red line: one of the center trajectory;
- Yellow dots: track points;
- Yellow boxes: original time stamp for track points along center trajectory;
- Green boxes: time stamp for track points after replacing the departure time;
- Numbers in yellow dots: number of convective weather (e.g. thunder storm) appeared for the ARTCC associated with the track point in a 2-hour time interval;
- Total convective weather intensity:
  - 5+6+3+7+2+9 = 32

Model Specification

- For the case of IAH → BOS, we have five clusters, including 1579 trajectory members;
- Model Specification

$$V_0 = \beta_0 + \beta_1 \cdot ThunderStormLevel_0 + \beta_2 \cdot Shower_0 + \beta_3 \cdot Squall_0 + \boldsymbol{\beta}' \cdot \boldsymbol{Month} + \boldsymbol{\gamma}' \cdot \boldsymbol{Morning\ Flight}$$
$$V_1 = \beta_1 + \beta_1 \cdot ThunderStormLevel_1 + \beta_2 \cdot Shower_1 + \beta_3 \cdot Squall_1$$
$$V_2 = \beta_2 + \beta_1 \cdot ThunderStormLevel_2 + \beta_2 \cdot Shower_2 + \beta_3 \cdot Squall_2$$
$$V_3 = \beta_3 + \beta_1 \cdot ThunderStormLevel_3 + \beta_2 \cdot Shower_3 + \beta_3 \cdot Squall_3$$
$$V_4 = \beta_1 \cdot ThunderStormLevel_4 + \beta_2 \cdot Shower_4 + \beta_3 \cdot Squall_4$$

- Independent variable
  - Thunder Storm Level: the aggregated thunder storm level for one nominal trajectory;
  - Shower: the aggregated number of total shower appearance for one nominal trajectory;
  - Squall: the aggregated squall ratio for one nominal trajectory;
  - Month: monthly fixed effects, 11 dummy variables;
  - Morning flight: dummy variable, equals to 1 if the local departure time is before 12 pm.

Estimation Results

Multinomial Logit Model Regression Results

Dep. Variable:	CHOICE	No. Observations:	1,579
Model:	Multinomial Logit Model	Df Residuals:	1,560
Method:	MLE	Df Model:	19
Date:	Fri, 15 Jul 2016	Pseudo R-squ.:	0.281
Time:	11:53:10	Pseudo R-bar-squ.:	0.273
converged:	True	Log-Likelihood:	-1,827.522
		LL-Null:	-2,541.302

	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
ASC_R0	3.8766	0.287	13.501	0.000	3.314	4.439
ASC_R1	3.0809	0.235	13.135	0.000	2.621	3.541
ASC_R2	3.2143	0.234	13.729	0.000	2.755	3.673
ASC_R3	-0.2599	0.340	-0.764	0.445	-0.926	0.406
Month 1 - fixed effects	-0.0957	0.267	-0.359	0.720	-0.618	0.427
Month 2 - fixed effects	-0.6622	0.281	-2.356	0.018	-1.213	-0.111
Month 3 - fixed effects	-1.2952	0.282	-4.591	0.000	-1.848	-0.742
Month 4 - fixed effects	-0.4955	0.257	-1.925	0.054	-1.000	0.009
Month 5 - fixed effects	-0.0165	0.248	-0.067	0.947	-0.502	0.469
Month 6 - fixed effects	-0.5894	0.252	-2.338	0.019	-1.083	-0.095
Month 7 - fixed effects	-0.2547	0.241	-1.059	0.290	-0.726	0.217
Month 8 - fixed effects	-0.1762	0.238	-0.742	0.458	-0.642	0.289
Month 9 - fixed effects	-0.6282	0.248	-2.535	0.011	-1.114	-0.143
Month 10 - fixed effects	-0.5649	0.243	-2.323	0.020	-1.042	-0.088
Month 11 - fixed effects	-0.0949	0.242	-0.393	0.695	-0.568	0.379
Morning Flight	-0.3495	0.111	-3.155	0.002	-0.567	-0.132
Thunder Storm	-0.0662	0.015	-4.327	0.000	-0.096	-0.036
Shower	-1.7684	0.807	-2.193	0.028	-3.349	-0.188
Squall	-0.2585	0.133	-1.943	0.052	-0.519	0.002

- Thunder Storm Level, Shower and Squall are continuous variables, all have negative sign and are significant @10% level;
- Comparing to December, it seems that summer seasons have stronger negative correlations with route selection.

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Conclusions

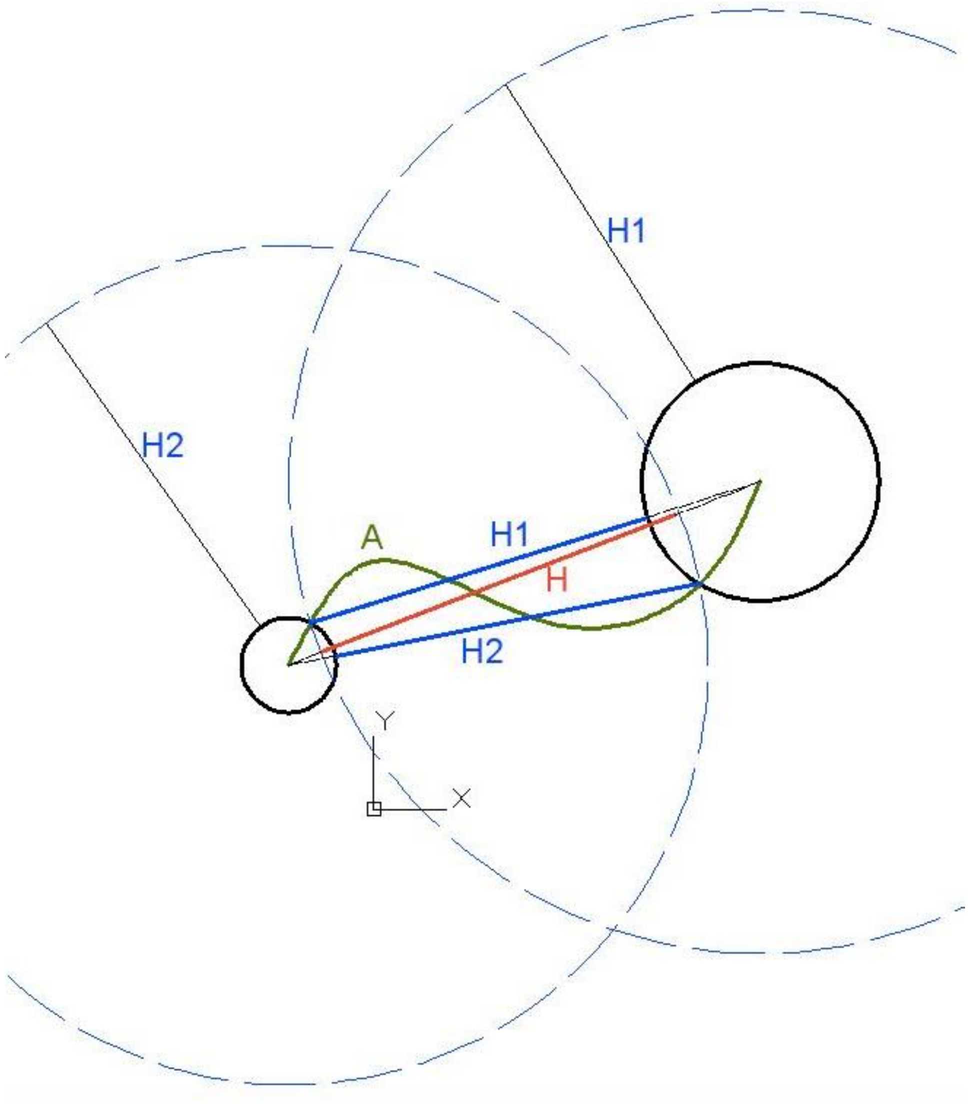
- Flight en route inefficiency is on average 3.5%, but varies significantly with airport pairs and seasons;
- Long-haul flights tend to be more efficient than short-haul flights;
- Flights depart from/ arrive at airports in the east coast tend to be more inefficient than the others;
- Flights in summer seasons are more inefficient;

Conclusions

- For most airport pairs, individual flight trajectories, while unique, can be divided into natural clusters whose members are very similar to one another;
- “Outlier” trajectories not belonging to a cluster account for from 1-10% of the total, depending on the airport pair;
- Cluster membership accounts for about 60% of overall variation in inefficiency
- Flights in summer seasons (May to August) are in general more inefficient than the others, but seasonal variation accounts for only 2-6% of the variation

Backup Slides

Method – on “Achieved distance”



- $H = \frac{H_1 + H_2}{2}$

- Indicate how much closer is the ***Entry point*** to destination and how much further is the ***Exit point*** away from origin.

Gap Between Actual and Flight Plan Distance