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Analysis of convective weather impact on pre-departure routing of flights from Fort Worth Center to New York Center

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In response to severe weather conditions, Traffic Managers specify flow constraints and reroutes to route air traffic around affected regions of airspace. Providing analysis and recommendations of available reroute options and associated airspace capacities would assist Traffic Managers in making more efficient decisions in response to convective weather. These recommendations can be developed by examining historical data to determine which previous reroute options were used in similar weather and traffic conditions. This paper describes the initial steps and methodology used towards this goal. The focus of this work is flights departing from Fort Worth Center destined for New York Center. Dominant routing structures used in the absence of convective weather are identified. A method to extract relevant features from the large volume of weather data available to quantify the impact of convective weather on this routing structure over a given time range is presented. Finally, a method of estimating flow rate capacity along commonly used routes during convective weather events is described. Results show that the flow rates drop exponentially as a function of the values of the proposed feature and that convective weather on the final third of the route was found to have a greater impact on the flow rate restriction than other portions of the route.

I.   Introduction

Currently, Traffic Managers (TMs) assess weather predictions and issue traffic management initiatives (TMIs) reducing flow rates through regions of airspace affected by severe weather. Flow rates can be reduced below nominal levels by holding flights on the ground or routing flights around these regions. TMs make these decisions based on their experience with similar weather conditions. Flow rates through sectors or flow constrained areas are reduced based on heuristics, the experience of the TM, and the experience of controllers at key sectors. Capacities are reduced with broad strokes and may be overly conservative, or vary under similar scenarios, based on individual TM preferences. Airlines are unable to reliably predict what the TM will prescribe in a given situation, causing delays in their own decision processes, which results in a lack of operational predictability. A new program for dealing with airspace constraints, Collaborative Trajectory Options Program[1] (CTOP), is currently in limited use. This program allows airlines to submit multiple preferred routes to the Federal Aviation Administration (FAA) through a trajectory options set (TOS) when severe weather is predicted to affect their flights' planned routes. With this shift towards greater

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airline participation in pre-departure routing during convective weather events, the need for a predictable system of constraint selection becomes apparent. This need for improved predictability is addressed in the plan outlined by the National Aeronautics and Space Administration (NASA) Aeronautics Research Mission Directorate (ARMD) in the NASA Aeronautics Strategic Implementation Plan.[2] The plan calls for the development of concepts and tools to realize trajectory-based operations (TBO), including such concepts as system modeling to improve predictive capabilities.

Predictable constraint selection would require a tool to identify viable routing options and include flow rate constraints along each route. There are a variety of route and rate choices that can satisfy constraints caused by a particular convective weather scenario. Whereas one might think to choose the optimal solution among feasible solutions, there is no one metric that can be used to determine optimality. Each airline has its own metric based on its individual business case. The FAA has its own objectives that may vary in relative importance across scenarios. Rather than attempt to find "optimal" solutions, this system should provide feasible solutions along with estimated quantitative performance values calculated using various metrics. Historical data can be leveraged to generate models to find usable routes given weather information. Such a tool would benefit both the user and the FAA. Airlines can benefit from knowing if previous trajectory-based routes were effective to inform future TOS generation in similar weather conditions. Air navigation service providers will also benefit from a tool that suggests historical solutions. This will allow TMs to make use of solutions used by other TMs, thus allowing an individual TM to learn from the prior experience of many TMs, not just his or her own experience. This would lead to more informed and consistent decision making, the latter of which would increase predictability for airlines.

The objective of this work is to quantify the weather impact on routing structures commonly observed in the absence of convective weather. Ideally, we would also like to identify conditions under which reroutes that do not conform to the commonly used route structure are used. However, work done to date that has attempted to model the use of non-conforming routes based on weather conditions has proven difficult. Challenging aspects of this work include taking the large amount of weather data available and creating a set of features that are relevant to the TM decision process, and the fact that a wide range of responses can be and are implemented by TMs during similar weather scenarios. For the former challenge, TMs have a variety of weather products available to them, each of which has strengths and weaknesses, and interpretation by each individual TM, in consultation with weather experts, is nuanced and difficult to articulate to researchers. The latter challenge makes the problem of finding patterns in the TM response difficult.

In this work, we focus on flights from Fort Worth Air Route Traffic Control Center (ZFW) to New York Air Route Traffic Control Center (ZNY) and find the dominant routes used in the absence of convective weather. This involves identifying clear-weather days and clustering flight tracks from those days. Details of this process are given in Section III. In Section IV, we develop a metric to quantify convective weather impact on these routes. Historical flow rates along these dominant routes are found by identifying tracks flown in convective weather conditions that conform to these clusters. These historical flow rates are examined and modeled as a function of this convective weather impact quantity. This relationship is modeled using an exponential curve which can then be used to predict flow rates based on given weather conditions. These results are given in Section V. Results show that the flow rate does not depend uniformly on convective weather found throughout the route; however, convective weather on the final third of the route was found to have a greater impact on the flow rate restriction than other portions of the route.

II.   Background

Previous and ongoing work is focused on finding similarities between days based on weather conditions or NAS performance metrics.[3–5] With a vast amount of weather information, the challenge is to condense the data in such a way that operationally relevant features are preserved (or highlighted) in order to compare days. It is often difficult to identify operationally relevant features, which typically depend heavily on the objective. In Ref. [5], days are clustered based on the Weather Impacted Traffic Index (WITI) values at each Air Route Traffic Control Center (ARTCC or Center). Once similar days are discovered, the use of particular advisory reroutes on similar days is quantified. Previous research[6–8] has also involved creating or selecting reroutes for flights that avoid airspace affected by severe weather. However, little work has been done to predict the use of specific routes in the presence of convective weather.

Previous work[9] focused on predicting reroute advisories put in place in response to convective weather. However, airline dispatch may make routing choices to avoid convective weather that do not conform to an

issued reroute. Additionally, the paradigm shift from the historical use of reroutes issued by the FAA to airline participation, for example, via CTOP, is making the study of flown flight tracks important. The goal of this work is to capture that behavior by focusing on previously flown flight tracks, making this problem more difficult than that of predicting reroute advisories.

Advisories are put in place for several hours (typically 4 to 8), and thus represent an aggregate control of many flights. However, looking at individual flights, aggregation is left to the researcher, which requires determining appropriate spatial and temporal ranges over which flights are to be grouped. This is extremely difficult when weather can change drastically at the time scale of quarter hours, whereas only a handful of flights traveling through the affected area depart per hour. These factors make the problem of predicting the use of a particular route more difficult than predicting the implementation of an advisory route.

Traffic from ZFW to ZNY is studied in this work. Recent and ongoing work at NASA has focused on various problems affecting air traffic into and out of airports in the New York metropolitan area.[10–16] This particular region of airspace was chosen as the focus for various research studies because operations in this area have been subject to chronic delay, problems in this region are complex due to the close proximity of high volume airports, and problems in this region have far-reaching impacts throughout the National Airspace System (NAS). In order to complement that research, this work is focused on traffic with destinations within the New York metropolitan area. In order to gain understanding of pre-departure routing choices, we selected ZFW as the origin Center since it is close enough to the New York metropolitan area such that a reasonably accurate two-hour forecast would be sufficient to predict en route weather conditions but far enough that significantly different alternate routes exist. Flights departing from Dallas/Fort Worth and Dallas Love Field make up the majority of this traffic with flight times from these airports to New York metroplex airports between 2 hours and 2 hours 45 minutes.

While it is impossible to completely decouple the traffic in any region of the NAS from all other traffic in the NAS, this region of airspace is heavily used by flights departing from ZFW and landing within ZNY. Forty-two percent of all traffic that traverses ZFW and subsequently traverses ZNY is traffic that originates and terminates in ZFW and ZNY, respectively. In this paper we focus on analyzing the impact of convective weather on this traffic specifically, which has the opportunity for pre-departure rerouting based on reasonably accurate two-hour weather predictions. Future work could include an investigation into the impact of the shift of other fights into this airspace on the capacity available for traffic originating in ZFW and terminating in ZNY.

III.   Clear-weather flight track analysis

The first objective is to identify flight paths commonly used in the absence of convective weather. Days with little or no convective weather activity throughout the NAS will be referred to as "clear-weather days." An understanding of en route routing options during clear-weather days will allow us to quantify impact of weather on nominal routing, and provide insight into the response of airlines and TMs to convective weather events.

This process includes the identification of clear-weather days, collection of tracks flown on these days, and the removal of any bad data from this set of tracks. The portions of the flight tracks near the departure and arrival airports vary and are removed so as not to be quantified as a difference between tracks that may overlap significantly in the en route portion of the flights. Clusters are then identified and "lanes" are formed to describe the clear-weather routing structure. These steps are described in detail in the remainder of this section.

Step 1: Identify clear-weather days

Clear-weather days were identified using total daily Center WITI, which is the sum of Center WITI for all 20 Centers across the NAS. Note that a Center WITI value is an indication of the convective weather impact on a Center, and does not take into account other weather features, such as winds or turbulence. Days with low total daily Center WITI values (below 2.5% of the maximum observed value) are considered to be clear-weather days. A total of 78 days in 2014 were identified as clear-weather days. Tracks for flights departing from any airport in ZFW destined for any airport in ZNY were then analyzed. In total, there were 2,984 flights from ZFW to ZNY on these 78 days. The airport pairs making up 90% of the traffic from ZFW

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to ZNY were selected to represent the dominant flows. The breakdown of the number of flights for each of these origin and destination pairs is given in Table 1.

Step 2: Identify invalid flight tracks

Flight track information was obtained from Aircraft Situation Display to Industry[17] (ASDI) data. RADAR systems are used to track flights and the speed, altitude, and position of flights are recorded. Updates are provided every one minute for flights in en route airspace. This information is then made available through ASDI. Flight tracks can be described by a sequence of points, specified by latitude, longitude, and altitude coordinates.

As with any data set, there is likely to be missing or invalid information. Before clustering the clear-weather tracks selected in the previous step, flight tracks with invalid values should be removed. Invalid flight tracks are identified by inter-track point distance and to-

Table 1: Origin and destination city pairs constituting 90% of the traffic departing from airports within ZFW to destination airports within ZNY.

Origin Airport	Destination Airport	Number of Flights	
DFW	LGA	1531	
DFW	EWR	749	↑
DFW	JFK	189	90% of traffic
DAL	TEB	120	↓
DAL	LGA	94	

tal path length. These values are calculated for all flight tracks and compared within origin-destination city pairs. Flight tracks that are found to have inter-track point distances greater than the 90th percentile value or total path length below the 10th percentile value or above the 90th percentile value for the corresponding origin-destination city pair are removed from the data set. A total of 20% of the flight tracks were found to be invalid tracks. This is a large portion of the total flight tracks, however, their removal aggressively cleans the clear weather track data in order to extract trends.

Step 3: Isolate en route portion of flight tracks

We are interested in routing choices for the en route airspace. Flight tracks may vary greatly within the departure and arrival segments of the flights based on, for example, departure and arrival procedures and runway configuration, which would not otherwise affect the flight trajectory. We remove these segments so variations in these portions of the routes are not quantified as major differences between tracks if they are otherwise co-located on the en route portions.

The portions of tracks just after departure and just prior to landing are characterized by turns while flights follow departure and arrival procedures. Flight tracks become more uniform and similar to other flight tracks as the distance from the origin or destination airport increases. To identify the point at which a track becomes smooth enough to cluster, we calculate the rate of change of the heading angle and find the distance from the airport at which this value is within some threshold. We define this threshold to be the average rate of change of the heading angle 30 minutes after departure and 30 minutes prior to arrival.

Using the departure portion of the tracks as an example, this value was found to be 8 degrees per minute. In Fig. 1, the rate of change of the heading angle versus distance is shown. From this we can see that for this specific example, at a distance of 72 nmi from the origin airport, the rate of change of the heading angle falls below 8 degrees per minute for 95% of the flight tracks. For each track, we cut off the points in the track whose distance to the origin airport is less than 72 nmi. The same procedure is used to remove the final portion of the flight tracks, which also tends to vary significantly. These results are shown in Fig. 2.

For the purpose of comparing flight tracks in the subsequent steps, only the en route portions of the flight tracks are used. Figure 3 shows the full tracks with en route and arrival or departure portions indicated.

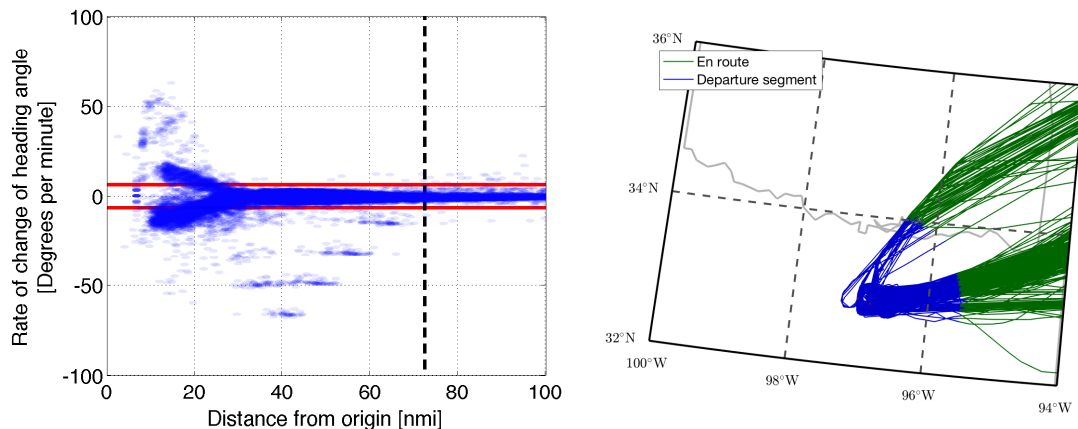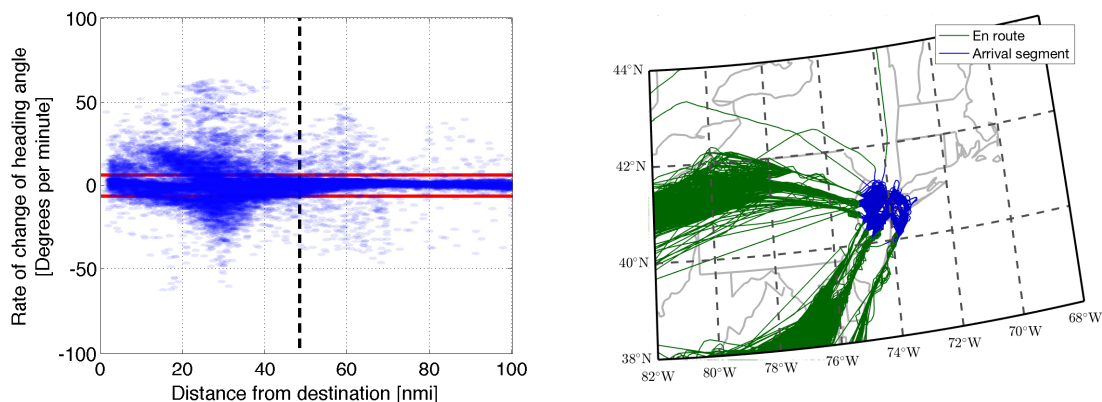American Institute of Aeronautics and Astronautics

Figure 1: (left) Rate of change of heading angle for each track up to 100 nmi from mean location of origin airports. The red lines indicate the mean en route rate of change of the heading angle, and the black dashed line indicates the distance at which 95% of the flight tracks have a rate of change of heading angle that drops below the mean rate of change of en route heading angle.
(right) Departure portion of flight tracks. The blue indicates the departure portion that is not included in the flight track comparison, green indicates en route portion (beyond 72 nmi from origin).

Figure 2: (left) Rate of change of heading angle for each track up to 100 nmi from mean location of destination airports. The red lines indicate the mean en route rate of change of the heading angle, and the black dashed line indicates the distance at which 95% of the flight tracks have a rate of change of heading angle below the mean rate of change of en route heading angle.
(right) Arrival portion of flight tracks. The blue indicates the arrival portion that is not included in the flight track comparison, green indicates en route portion (beyond 42 nmi from destination).
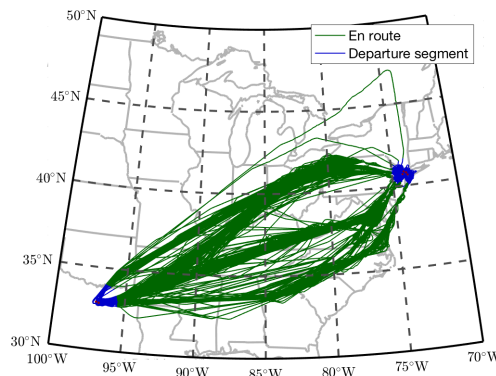
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Figure 3: Full flight tracks with green indicating en route portions of tracks and blue indicating departure or arrival portions of tracks.

Step 4: Remove outliers and cluster flight tracks

In this work, we are interested in finding flight tracks that are similar in the horizontal spatial plane. Whereas it would be useful to take altitude and elapsed time since departure into consideration, we simply do not have enough data to segregate tracks further and still have enough information to find statistically significant trends. This will become evident in Section V when results are presented.

Focusing on similarity in the horizontal plane, we need to choose a metric with which to compare flight tracks. Several distance metrics were assessed for use in this application. A more detailed discussion of the requirements for distance metrics with respect to this type of application are given in Ref. [9]. The Frechét distance is a good candidate for this application. The Frechét distance is often described as the length of the smallest leash that is required to connect a dog and its owner as they walk along two separate paths. The calculation of this metric is computationally intensive. Similar results were found using Euclidean distance between corresponding track points, as was done in Ref. [18]. One advantage of using the Euclidean distance is that it can can be calculated faster than the Frechét distance. In order to make use of the Euclidean distance metric, each flight track must be represented by the same number of coordinates. Here, we choose to take each track and describe it by 100 evenly spatially distributed points. These latitude and longitude coordinates are then transformed to the Lambert azimuthal equal-area coordinate system. Since this is an equal-area projection, the Euclidean distance can be used to compare relative distances between points near the reference point.

The challenge of unsupervised clustering is to determine the appropriate number of clusters. Metrics such as the silhouette score or inter-cluster versus intra-cluster distances can indicate that clusters are tight and well separated. The existence of outliers in a data set results in low scores on these metrics, thus possibly artificially indicating that a given clustering is not appropriate. If outliers are removed from the data set before clustering, these metrics will more accurately indicate the quality of the resulting clusters.

Prior to clustering the tracks, we first remove outlier tracks from the data set. An outlier is identified by examining the nearest neighbor distances for each track in each origin-destination pair. Tracks with few nearest neighbors are removed from the data set before clustering. This outlier detection method is described in detail in Ref. [19,20]. All flight tracks of interest and those identified as outliers are shown in Fig. 4.
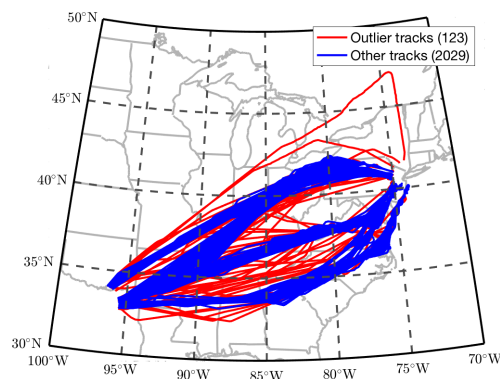

Figure 4: Flight tracks from ZFW to ZNY (top 5 origin destination pairs only).

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Finally, the flight tracks are clustered using the hierarchical clustering technique.[21] The silhouette score for each track, which is a value that indicates how well each track fits in its assigned cluster, and visual inspection were used to select the total number of clusters. Silhouette scores range from -1 to 1, with a high value indicating that the cluster member is close to other members of the cluster and distant from members of other clusters. If all tracks have high silhouette scores, this is an indication that clusters are tight and well separated and thus an appropriate clustering of the data. The silhouette scores for each track are shown in Fig. 5. The final flight track clusters are shown in Fig. 6.
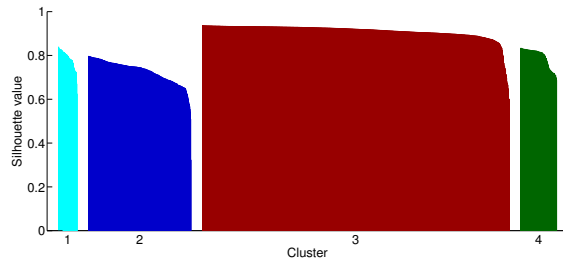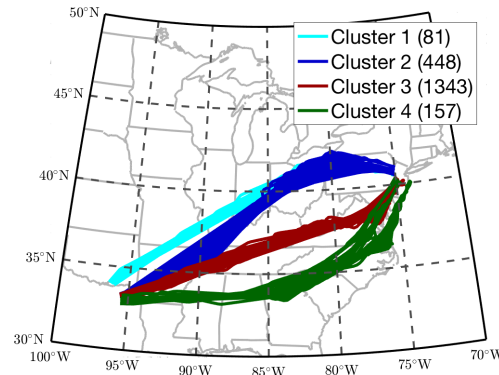

Figure 5: Silhouette scores for each track.

Figure 6: Flight track clusters from ZFW to ZNY.

Step 5: Create clear-weather track cluster lanes

In the next section, flight tracks flown during the convective weather season from April to September will be analyzed. Each track flown during this season will be identified as either conforming to a clear-weather cluster or not. Additionally, weather impact on the clear-weather track clusters must be quantified. To facilitate these processes, a "lane" is created for each clear-weather cluster.

One potential method of classifying a flight track as conforming to a cluster is based on cluster metrics. Each new flight track would be considered a member of each cluster and cluster metrics could be calculated with this trial member. For example, the silhouette score of the new track could be compared to others in the cluster or the changes to inter-cluster and intra-cluster distances as a result of the addition of this track could be calculated. Either of these values could be used to indicate a conforming or non-conforming track. This process would require all of the clear-weather flight tracks to be saved and each new track to be compared to all of the clear-weather flight tracks. Depending on the distance metric used, this could become a computationally intensive procedure.

As an alternative to this method, we chose to create lanes for each cluster based on the dispersion of flight track coordinates of the members of the clusters. Using these lanes, a new flight track can be classified as conforming to a given lane based on whether or not the new track lies within the lane. This procedure is described in Section IV.

These lanes will also be used to quantify convective weather impact on the clear-weather track clusters. We will use Convective Weather Avoidance Model[22] (CWAM) forecasts for this calculation. We break each lane up into segments of roughly 15 minute flight time per segment so that CWAM forecasts at 15 minute intervals can be used to quantify the interaction of convective weather with the clear-weather lanes. More details will be provided in Section IV.

The most commonly used clear-weather track cluster, cluster 3, will be used as an example throughout the explanation of lane formulation. Each track (with beginning and end portions cut) is re-sampled to be described by coordinates spaced by 15 minutes of flight time. With en route flight times between 115 minutes and 165 minutes, each flight track is then described by 8 to 12 points. Most flight tracks in cluster 3 were described by 9 segments. Only flights described by this number of points are then used to develop segments of the lane. The 15 minute interval description of each of these tracks for this example is shown in Fig. 7. For

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this cluster, 775 tracks out of the total 1343 tracks are described by 9 points spaced 15 minutes apart. The end points of each 15 minute traversal time segment is found by averaging locations of the corresponding points of all tracks in this group. The width of the lane is then based on the lateral spread of points at each end point. The lane width is twice the mean distance of each point to this mean location, plus two standard deviations.

IV. Convective weather season flight track analysis

We now focus on the use of the commonly-used clear-weather clusters from ZFW to ZNY identified above during the convective weather season. The convective weather season for this region runs from April through September. Data was collected for convective weather seasons in both 2014 and 2015. Tracks for flights departing between 7 AM and 10 PM, EDT were used in the analysis. A total of 8,334 flights fit this criteria.

In order to identify trends in the data, we must aggregate information over some time period. We choose to aggregate over one-hour long time intervals. For each hour long time interval, we find the number of departing flights using each commonly used clear-weather route cluster. We quantify the convective weather impacts along each cluster. We found that during any one-hour time window, a maximum of 12 aircraft using a particular cluster take off. These processes are described in the following two steps.
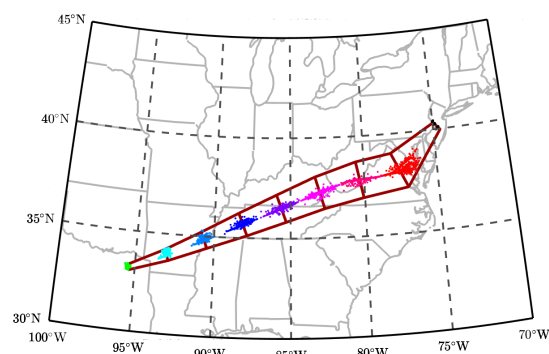

Figure 7: Example of clear-weather track cluster lane segments for cluster 3. Each colored grouping of points were used to define the end points and widths of each segment.
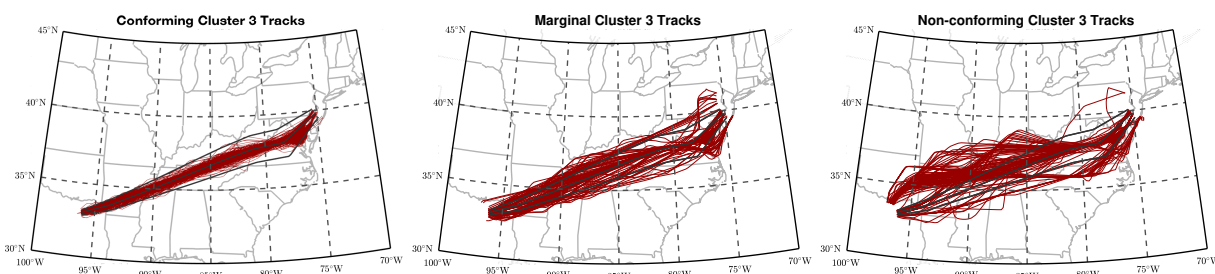
Step 1: Label tracks

In order to gain insight into the use of each of the clear-weather route lanes during the convective weather season, we need a method of identifying whether a given flight track conforms to a clear-weather route cluster or not. First, the departure and arrival portions of each convective weather season track are removed using the distance from origin and destination airport group found in Section III. Next, we compare a given flight track to each cluster center to find the closest cluster center. We then classify the track as *conforming*, *marginally conforming*, or *nonconforming* to that cluster based on the fraction of flight track points lying within the segments making up the closest cluster's lane and "extended lane." The extended lane is 40% wider than the original lane. If 90% of the track points are within the lane, the track is labeled conforming. If more than 10% of the track points are outside the extended lane, the track is labeled nonconforming. Otherwise, the track is labeled marginally conforming. Labeled tracks for cluster 3 are shown in Fig. 8.

Figure 8: Labeled 2014 convective weather season tracks for cluster 3: 2,484 conforming, 129 marginal, 147 non-conforming tracks.

Step 2: **Generate weather features**

As discussed in Section II, the major challenge of this work is to select, or calculate, appropriate features to describe the weather impact on commonly used routes. In this work, the Convective Weather Avoidance Model[22] (CWAM) is used. This product consists of polygons defined at various flight levels and forecast times. Each polygon represents a region of airspace that a specific percentage of pilots are expected to avoid. Contours are given for probability of pilot deviation of 60%, 70% and 80%. To model the probability of pilot deviation around weather, CWAM makes use of both the measured heights of the tops of clouds and the amount of Vertically Integrated Liquid (VIL) within the cloud. CWAM forecast extends up to two hours, making this product most useful for planning short haul flights. With flight times from ZFW to ZNY of roughly two and a half hours, this product is useful for our purposes. However, extending a similar technique to more distant origin and destination pairs will involve the selection of a weather product more appropriate for strategic planning of long haul flights.

We quantify the weather impact on a route cluster lane based on the predicted total time that a flight traveling along that route cluster would spend within CWAM polygons. This will be referred to as "dwell time" within CWAM polygons. In order to simplify calculations, 70% probability deviation polygons at the most common flight level observed in the clear-weather data (37 thousand feet) are used. Figure 9 shows the flight levels observed in the data.

As previously described, each route cluster lane is broken down into segments of roughly 15 minute traversal time. For a given segment, 10 flow lines are drawn, with beginning and end points spaced evenly on the respective upstream and downstream edges of the segment. The CWAM data available at the middle of the hour of interest are used. That is, if we are interested in flights departing between 9 AM and 10 AM, the CWAM file available at 9:30 AM is used. With segments of roughly 15 minute traversal times, we can calculate the expected time that a flight taking off in the middle of this hour would reach each segment. The CWAM forecast associated

Figure 9: Mode value of flight levels observed during en route portion of each flight track.

with this time is used to quantify predicted dwell time within a given segment. The dwell time of each flow line through each CWAM polygon is calculated. That is, the total time that a flight traveling along a particular flow line would be within a CWAM polygon is found. This value can be calculated for each probability of deviation threshold. The lane, segment and flow lines of cluster 3 are shown in Figure 10 overlaid with the CWAM polygons of the prediction used to calculate estimated dwell times in segment 4. For each segment, we then calculate 10 values: (10 flow lines)×(1 altitude)×(1 probability of deviation thresholds). This is calculated for each segment of each cluster. There are a total of 350 dwell time values used to describe the predicted interaction of flights taking off within a certain hour long time window with CWAM polygons.
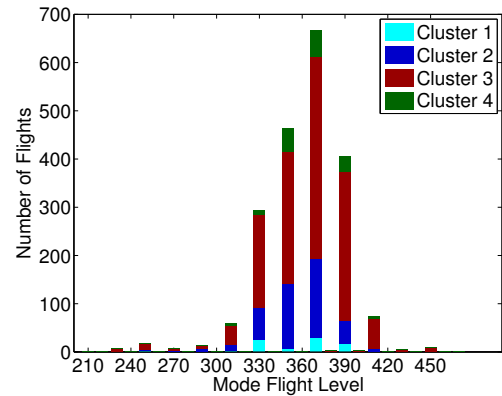
V.   Results

With the analysis of Section IV complete, we can now look for trends in clear-weather route cluster use given the calculated convective weather features. We are interested in pre-departure routing choices and thus focus on the number of flights which take off during an hour long time window using each of the clusters. Fifty-six percent of the hour long time windows examined had nonzero CWAM dwell times and only these time windows were used in the following analysis. Figure 11 shows a plot of the number of flights taking off and using (conforming or marginally conforming to) cluster 3 during an hour long time window versus the associated predicted average dwell time in CWAM polygons at or above a 70% probability of deviation during a traversal of this cluster. For each number of take-offs, the 95th percentile dwell time is found and plotted in red. An exponential curve is fit to these values.

The exponential decrease in departing flights with an increase in dwell time is quite evident. Note that the estimated dwell time is not necessarily the same as the *actual* dwell time for any given flight. Each flight has room to maneuver while still being categorized as using a particular route. Thus, actual dwell time may
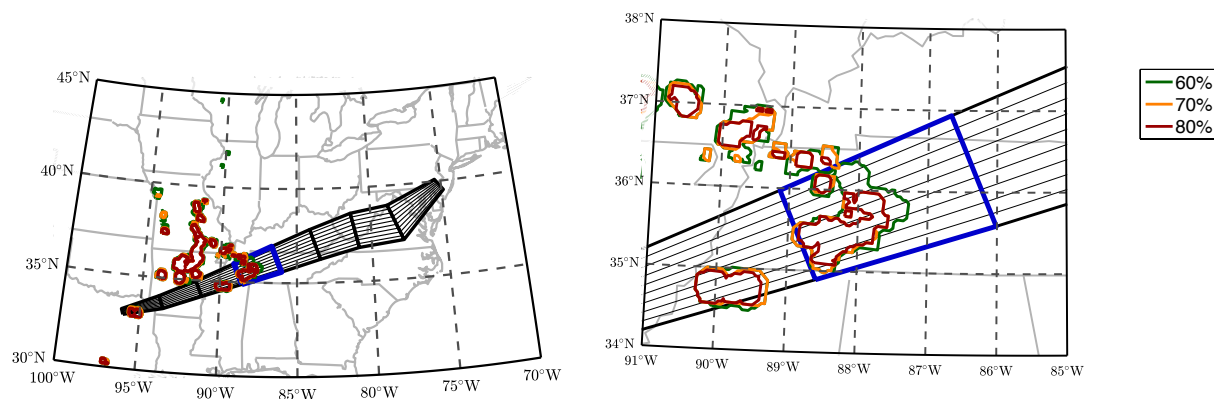
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Figure 10: (left) Segments and flow lines of cluster 3, with segment 4 highlighted in blue overlaid with CWAM polygons. The colored CWAM polygons are from the 45 minute forecast in order to estimate flight interaction with CWAM polygons when a flight departing in the middle of the hour of interest is predicted to enter segment 4. (right) A closer view of segment 4 overlaid with the 45 minute forecast CWAM polygons. CWAM dwell times for each flow line in segment 4 are calculated using these CWAM polygons and an estimated segment traversal time of 15 minutes.

be lower for a particular flight as it can fly around regions of severe convective weather. This may be the major cause in the exponential decay of route cluster use as a function of dwell time, as opposed to a linear relationship, or a simple "open" or "closed" status for each cluster separated by some critical value of dwell time.

An exponential model was fit to take-offs for each cluster versus predicted dwell time along the beginning segments, middle segments, and end segments of the respective clusters. These results are shown in Fig. 12. Data points that fall below the 95th percentile curve could be due to a variety of factors such as lower overall demand, shift in traffic to an alternate route cluster predicted to have lower CWAM dwell times, or increased over flight traffic.

It is interesting to note that the number of departures drops off steepest as a function of the dwell time in the final segments of the cluster for all clusters. This is an indication that the predicted weather conditions on the arrival portion of the flight have a strong influence on routing selection.

In practice, these results could be used to inform TM decisions. For example, given a specific CWAM forecast, the dwell time values could be calculated for each route cluster. These values could be input into the respective models of the number of take offs per hour as a function of dwell time. The resulting number of departures per hour could be used to set flow rate constraints along heavily used route clusters in a CTOP. Results shown here are for CWAM,
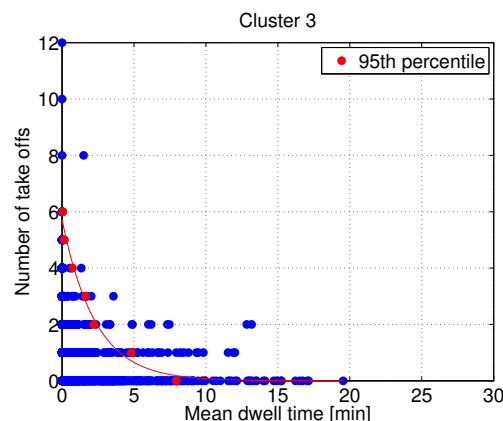

Figure 11: Each data point plotted represents the number of flights that depart during a particular hour long time interval and follow cluster 3 that are predicted to encounter CWAM dwell time of a particular value. For each number of departures, the 95th percentile dwell time is plotted in red.

which has a forecast of up to two hours. For longer flight times, a weather product with a longer forecast horizon should be chosen.

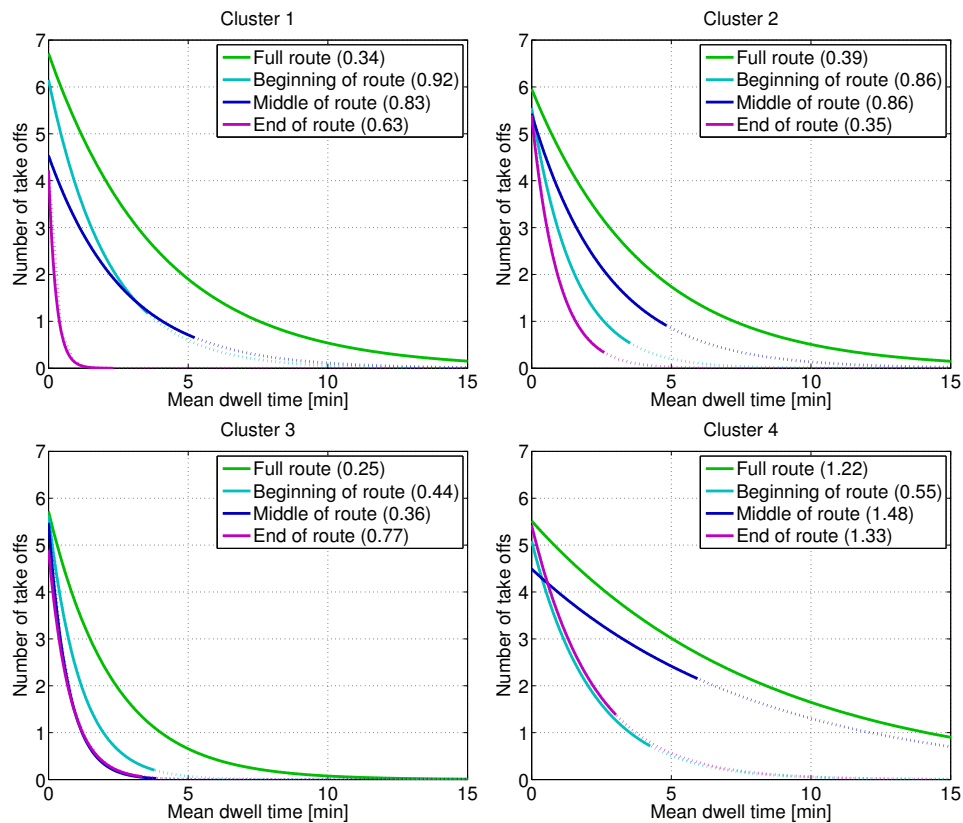American Institute of Aeronautics and Astronautics

Figure 12: Exponential fit of the number of departures in hour long intervals as a function of the estimated CWAM dwell time at the beginning, middle, and end of the route and throughout the full route. Values in parentheses following each legend label indicate the mean error in number of flights of each trend.

VI.   Conclusions and future work

In this paper, a method of processing flight tracks from 78 clear-weather days in 2014 and clustering these tracks to identify commonly used flight paths in the absence of convective weather was presented. We then identified whether or not flight tracks from convective weather seasons of 2014 and 2015 conformed to these clear-weather flight paths. Weather impact on these clear-weather paths was calculated based on predicted dwell time of a flight using each cluster during convective weather conditions. Here, the CWAM weather product was used.

Given predicted dwell times and labeled flight tracks in convective weather conditions, we were able to model the decay in the use of each cluster as an exponential function of the dwell time along the full route, and also along the beginning, middle, and end portions of the route. Results show that the use of the commonly used paths falls exponentially with dwell time. Thus, any machine learning predictive model that relies solely on linear combinations of dwell times will likely not perform as well as one that uses this exponential function to calculate a capacity for commonly used paths during convective weather events. The relations between dwell time and path use found here could be used in a CTOP application to set reduced flow rates along commonly used flight paths in the presence of convective weather.

Some work has been done to model the use of commonly used paths in convective weather with predictive accuracy of roughly 60%. Future work will involve incorporating this calculated capacity feature in machine learning models in an attempt to improve prediction accuracy. At this point, the models developed are binary classifiers, that is, the prediction is simply whether or not a given commonly used flight path is used during a specific time window. Prediction accuracy may improve if either regression or multi-class classification methods are applied to the problem.

Furthermore, the method of identifying commonly used flight paths in clear convective weather will be applied to additional origin centers, with flights bound for airports in the New York Center. This analysis

will hopefully identify structure in airspace and allow researchers to better understand routing options in regions of airspace with dense traffic.

Acknowledgements

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