Models of Sector Flows under Local, Regional and Airport Weather Constraints

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Abstract

Recently, the ATM community has made important progress in collaborative trajectory management through the introduction of a new FAA traffic management initiative called a Collaborative Trajectory Options Program (CTOP). FAA can use CTOPs to manage air traffic under multiple constraints (manifested as flow constrained areas or FCAs) in the system, and it allows flight operators to indicate their preferences for routing and delay options. CTOPs also permits better management of the overall trajectory of flights by considering both routing and departure delay options simultaneously. However, adoption of CTOPs in airspace has been hampered by many factors that include challenges in how to identify constrained areas and how to set rates for the FCAs. Decision support tools providing assistance would be particularly helpful in effective use of CTOPs. Such DSTs tools would need models of demand and capacity in the presence of multiple constraints.

This study examines different approaches to using historical data to create and validate models of maximum flows in sectors and other airspace regions in the presence of multiple constraints. A challenge in creating an empirical model of flows under multiple constraints is a lack of sufficient historical data that captures diverse situations involving combinations of multiple constraints especially those with severe weather. The approach taken here to deal with this is two-fold. First, we create a generalized sector model encompassing multiple sectors rather than individual sectors in order to increase the amount of data used for creating the model by an order of magnitude. Secondly, we decompose the problem so that the amount of data needed is reduced. This involves creating a baseline demand model plus a separate weather constrained flow reduction model and then composing these into a single integrated model. A nominal demand model is a flow model (g_{dem}) in the presence of clear local weather. This defines the flow as a function of weather constraints in neighboring regions, airport constraints and weather in locations that can cause re-routes to the location of interest. A weather constrained flow reduction model ($f_{wx\text{-}red}$) is a model of reduction in baseline counts as a function of local weather. Because the number of independent variables associated with each of the two decomposed models is smaller than that with a single model, need for amount of data is reduced. Finally, a composite model that combines these two can be represented as $f_{wx\text{-}red}(g_{dem}(e), l)$ where *e* represents non-local constraints and *l* represents local weather.

The approaches studied to developing these models are divided into three categories: (1) Point estimation models (2) Empirical models (3) Theoretical models. Errors in predictions of these different types of models have been estimated. In situations when there is abundant data, point estimation models tend to be very accurate. In contrast, empirical models do better than theoretical models when there is some data available. The biggest benefit of theoretical models is their general applicability in wider range situations once the degree of accuracy of these has been established.

Keywords—Weather, CTOP, TMI

I. MOTIVATION

Recently, the ATM community has made important progress in collaborative trajectory management through the introduction of an FAA traffic management initiative called a Collaborative Trajectory Options Program (CTOP). CTOP allocates delay and reroutes around multiple FCA (Flow Constrained Area) - based airspace constraints in order to balance demand with available capacity. Similar to what is done with Airspace Flow Programs (AFPs), Air traffic managers can create an FCA in a CTOP and control any air traffic that crosses that boundary by setting a flow rate for it. However, CTOP has the ability to manage multiple FCAs within a single program, permitting different parts of the program to be changed as conditions evolve. It also assigns delays or reroutes to flights in order to dynamically manage the capacity-demand imbalance as conditions change. For example, as conditions get better, CTOP can reroute traffic off of lengthy reroutes and back onto shorter routes, thereby decreasing their delays in the system. Secondly, a CTOP is collaborative in that it permits airlines to provide a set of preferred reroute options (called a Trajectory Options Set or TOS) around an FCA. CTOP also permits better management of the overall trajectory of flights by considering both routing and departure delay options simultaneously. However, adoption of CTOPs in airspace has been hampered by many factors that include challenges in how to identify constrained areas and how to set rates for the FCAs. Decision support tools (DST) providing assistance in executing CTOPs can help in addressing these challenges. Such DSTs would need models of demand and capacity in the presence of multiple constraints.

In managing a CTOP, FAA managers need to locate regions of airspace where likely demand exceeds the number of aircraft they currently allow under operational procedures. In existing operations, the maximum number of allowed aircraft may be lower than the actual capacity (the maximum aircraft it is possible to safely fly). The maximum number of aircraft that controllers allow in a sector under current procedures is close to the Monitor Alert Parameter (MAP) value [1], but studies on controller workload [6] have shown that this does not always correspond to the maximum they are actually able to handle.

In this paper, we focus on developing models of maximum aircraft counts currently allowed in a single sector under multiple constraint situations. Given inaccuracies in weather predictions and uncertainties in other factors, there is uncertainty in the maximum number of aircraft that can be handled given the known information about air traffic situation. Uncertainties in such a situation can be represented by a probability distribution. In this paper, we will illustrate an approach to develop a model for 95th percentile of the counts and we will refer to these as maximum flows. Similar approach can be taken develop models for other percentiles and the entire probability distribution.

II. REVIEW OF PAST RESEARCH

A. Airspace Capacity in Clear Weather

Early research efforts focused on estimating capacity of sectors and larger airspace regions based on traffic flow patterns and traffic complexity. Histon et al. [2] examined the capacity of airspace sector, and how within the airspace itself, safety concerns and the need to separate aircraft generates yet more constraints. Three factors were considered: (1) Properties of the airspace, (2) traffic conditions (based on instantaneous distribution of traffic), and (3) short-term variations in operational conditions. Histon showed how these factors help in computing the capacity of a sector and influence the complexity of the controller's task. Recognizing that traffic density in a region of airspace, by itself, did not adequately characterize the difficulty of managing traffic in that region, the notion of dynamic density (DD) was created. Laudeman [8] defined DD as a weighted combination of traffic density and various traffic complexity factors (e.g., numbers of heading and altitude changes, minimum separation distances, and conflict predictions at various ranges). He showed that DD correlated better with controller workload than traffic density alone.

Sridhar et al [6] showed that controller workload can be modelled as a function of aircraft geometries in clear weather conditions and can be predicted up to 20 minutes ahead of time. There is a very high correlation (.86) between workload and following parameters:

N = Traffic Density,
NH = Number of aircraft with Heading Change greater than 15º,
NS = Number of aircraft with Speed Change greater than 10 knots or 0.02 Mach,
NA = Number of aircraft with Altitude Change greater than 750 feet,
S5 = Number of aircraft with 3-D Euclidean distance between 0-5 nautical miles excluding violations,
S10 = Number of aircraft with 3-D Euclidean distance between 5-10 nautical miles excluding violations,
S25 = Number of aircraft with lateral distance between 0-25 nautical miles and vertical separation less than 2000/1000 feet above/below 29000 ft,
S40 = Number of aircraft with lateral distance between 25-40 nautical miles and vertical separation less than 2000/1000 feet above/below 29000 ft,
S70 = Number of aircraft with lateral distance between 40-70 nautical miles and vertical separation less than 2000/1000 feet above/below 29000 ft, where each of these parameters are measured during a sample interval of one minute.

More recently, Welch developed a controller workload impact model as a function of traffic density, sector geometry, flow direction, and air-to-air conflict rates. [7]

B. Airspace Capacity under Adverse Weather Conditions

Klein et al [3] created a weather translation measure that accounts for traffic and weather patterns within a sector through the calculation of the sector-level weather impacted traffic index (WITI). They have shown that a linear model of WITI correlates well with sector capacity on selected days they studied in detail. WITI, as defined here, represents the percent of clear day aircraft that would encounter weather if these flew the same routes on the weather impacted day as they do on a clear weather day. Song et al. [5] describe a model for weather-impacted sector capacity as a function of traffic flow pattern. The model uses a Weather Avoidance Altitude Field (WAAF) that most pilots would deviate around based on CWAM model. The model uses mincut approach to calculate the flow capacity ratio of each flow in the predicted traffic flow pattern. Matthews et al. [4] developed techniques for translating multiple weather forecast products into airspace permeability metric. These can be used to estimate achievable or sustainable traffic flow rates for FCAs.

In contrast to prior work aimed at modelling workload and capacity as a function of local conditions, we develop a unified model of the maximum traffic currently allowed in an airspace region under multiple constraints including those at destination airports and other airspace regions in addition to local constraints. In general, such constraints can include weather at upstream locations, weather at downstream locations and weather at locations that can cause re-routes to location of interest.

III. APPROACH

A challenge in creating an empirical model of aircraft counts under multiple constraints is a lack of sufficient historical data that captures diverse situations involving combinations of multiple constraints, especially those with severe weather. The approach taken here to deal with this is two-fold. First, we create a generalized sector model for multiple sectors, thus increasing the amount of available data by an order of magnitude. Secondly, we decompose the problem in order to reduce the need for data. This involves creating a baseline demand model, a separate weather constrained flow reduction model and then composing these into a single integrated model. The baseline demand model is a flow model (g_{dem}) in the presence of clear local weather. This defines the flow as a function of weather constraints in a neighborhood region, airport constraints and weather in locations that can cause re-routes to the sector of interest. A weather constrained flow reduction model (f_{wx-red}) is a model of reduction in baseline counts as a function of local weather. Finally, a composite model that combines these two can be represented as $f_{wx-red}(g_{dem}(\boldsymbol{e}), \boldsymbol{l})$ where $\boldsymbol{e}$ represents external weather including airport constraints and $\boldsymbol{l}$ represents local weather.

Table 1. Quantile Regression for Sector Counts

	Value	Std. Error	T value	P-value
Intercept	.07	.009	8	< .001
WITIn	-.00072	.00012	-6	< .001
AIRPORTR	.004	.00008	51	< .001
WITIr	.002	.0003	6	< .001

IV. BASELINE DEMAND MODEL

This section describes a model of counts in a generic sector in the presence of clear local weather. The benefit of creating a generalized sector model for a generic sector is that it increases the amount of available data used in developing models, significantly increasing the validity of statistical conclusions. Sectors considered in this study are ZNY42, ZNY75, ZOB27, ZOB28, ZOB29, ZOB77, and ZOB79. Sector counts are defined as maximum instantaneous counts in a 15 minute interval. These are then scaled using the maximum observed such counts for a sector during all such 15 minute intervals.

A baseline demand model is defined as a function of airport constraints, weather constraints in a neighboring region outside the current sector and weather in locations that can cause re-routes to the location of interest. Airport constraints are captured by a variable AIRPORTR that corresponds to the sum of AARs (Airport Acceptance Rates) at destination airports. Weather at various locations is quantified using a weather translation measure called Weather Impacted Traffic Index (WITI) that was described earlier.

In our study, two independent variables are used to capture impact of weather in creating the baseline demand model: Percent WITI in the neighborhood sectors (WITIn), and percent WITI in regions from where local traffic is sometimes rerouted to the sectors we are studying (WITIr). Thus, baseline demand is function of three variables defined above: AIRPORTR, WITIn, WITIr. A quantile regression method was used to create 95th percentile linear model of sector counts in terms of AIRPORTR, WITIn and WITIr as shown in Table 1. P-values associated with quantile regression show that all coefficients are statistically significant. Also, the signs of model coefficients are consistent with expected trends in counts relative to regional weather, airport AAR and weather at reroute source locations.

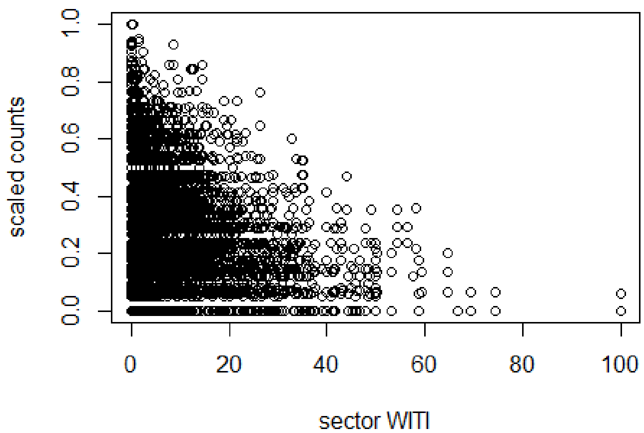

Fig. 1 Impact of sector witi on counts

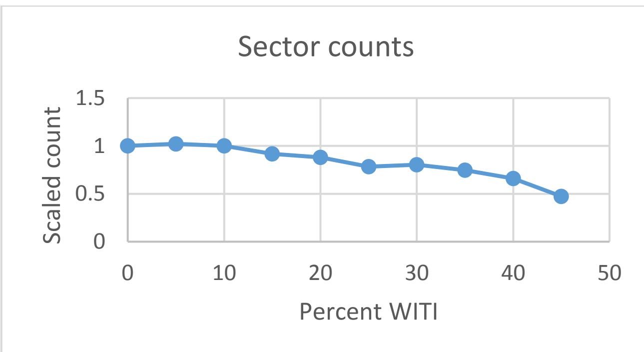

Fig. 2 WITI vs 95th percentile Scaled Counts

Table 2. Comparison of different models

WITI Range	Number of points	Point estimation of 95th percentile	Point estimation lower bound	Point estimation upper bound	Predicted count with linear model	Predicted count with theoretical model
0-5	75733	1.00	1.00	1.00	1.07	1.00
5-10	1905	1.02	0.99	1.09	1.02	0.95
10-15	1029	1.00	0.98	1.09	0.96	0.90
15-20	459	0.92	0.86	1.13	0.91	0.85
20-25	321	0.88	0.78	1.07	0.86	0.80
25-30	204	0.78	0.68	0.99	0.80	0.75
30-35	141	0.80	0.65	0.99	0.75	0.70
35-40	54	0.75	0.54	0.97	0.69	0.65
40-45	51	0.66	0.59	0.87	0.64	0.60

V. IMPACT OF LOCAL WEATHER IN REDUCING FLOWS

This section describes a model of how sector counts are reduced in the presence of local sector weather. Fig. 1 is a plot of sector counts vs. sector WITI. Sector counts are scaled using baseline demand function described in the previous section.

Now, we will compare three different approaches to estimating weather reduced flows: (1) Theoretical model (2) Point estimation model (3) Linear model.

A. *Theoretical model*

In theory, aircraft whose clear day trajectory does not encounter weather should be able to fly unhindered through a sector. On the other hand, aircraft whose trajectory encounters weather would choose to fly an alternate trajectory. Assuming that alternative trajectories are outside the sector through which the clear day trajectory passes, we could expect a percentage reduction of traffic to correspond with percent WITI. Thus, we would expect reduction in flow to be given by this theoretical model: **1 – .01 * percent WITI**. In the past, WITI has been defined in slightly different ways than defined here (e. g. [9]) and one could potentially come up with a different theoretical model with a different definition of WITI.

B. *Point estimation models*

Sector percent WITI bins of width 5 are created starting with [0,5] going to [45,50]. For each bin, 95th percentile value is computed among the sector counts during periods when sector percent WITI is in a particular range. For each point (x,y) in the fig. 2, y is the 95th percentile value among the sector counts when sector percent WITI is in the range [x, x+5]. Accuracy of the computation of 95th percentile value is higher when the number of available data points is higher. There are a lot of data points when there is clear weather and fewer data points when there is heavy weather. Correspondingly, the error in point estimates varies from 0 for clear weather to .21 for heavy weather.

C. *Empirical Linear models*

A linear model of counts was developed in terms of percent WITI using the point estimates described in the previous section. The equation of this model is: **1.07 – .011 * percent WITI**. R-squared for this model is .71 indicating a good correlation. This model is just slightly different than the theoretical model described earlier. As we noted in the literature survey, previous work has focused on relation of capacity to WITI without considering other constraints in the system and have also found a linear relationship between maximum counts and WITI. [3]

D. *Comparison of different models*

Table3. Comparison with test data

Lower bound of witi	Number of points	95^{th} percentile in test data	Point estimation of 95^{th} percentile	Point estimation lower bound	Point estimation upper bound
0	75733	1.00	1.00	1.00	1.00
5	1905	1.01	1.02	0.99	1.09
10	1029	1.02	1.00	0.98	1.09
15	459	0.88	0.92	0.86	1.13
20	321	1.01	0.88	0.78	1.07
25	204	0.88	0.78	0.68	0.99
30	141	0.82	0.80	0.65	0.99
35	54	0.69	0.75	0.54	0.97
40	51	0.71	0.66	0.59	0.87

Table 2 shows that 95^{th} percentiles estimated for different WITI ranges using the approaches discussed above. The first column defines a range of percent WITI in a sector. The second column shows number of points that represent time periods with WITI in the range in specified in the first two columns. Next three columns show 95^{th} percentile point estimate value and lower as well as upper bounds of estimation. The last two columns show predicted values with empirical and theoretical models. The difference between upper and lower bounds of point estimates is due to sampling errors that are dependent on the size of the data. This difference varies depending on the amount of data available. For low weather situations, there is an abundant data available and 95^{th} percentile values can be estimated accurately. However, for situations with heavy weather, there are far fewer data points and 95^{th} percentile values can't be estimated accurately and can't be used to compare the models. There is another implication of this lack of sufficient data points involving heavy weather impact. If we have two models that agree with each other in low and moderate weather situations but differ in heavy weather situations, lack of sufficient data involving heavy weather impact would make it hard to empirically conclude which of these is better. For our comparison of performance of theoretical and empirical models. We use data in the first five rows that corresponds to low and moderate weather conditions. In these rows, we find that the difference between the empirical model and point estimates is .03 on the average, whereas the difference between theoretical model and point estimates is .06 on the average. Thus, the empirical model is slightly more accurate as compared to the theoretical model. However, the theoretical model can be used more broadly in a wider set of situations as compared to empirical model e.g. it can be used for arbitrarily defined FCAs and FEAs for traffic management initiatives. As there is some variation in airspace operations over time, we use a estimate variation in the point estimates across different samples by using a sample test data from a different time period. Table 3 shows point estimates from training data and test data. The average difference between point estimates in training data and test data is .05.

VI. Composite Model of Maximum Demand

As discussed earlier, a composite model that combines the baseline demand model and local weather impact model can be represented as $f_{wx\text{-}red}(g_{dem}(\boldsymbol{e}), \boldsymbol{l})$ where $\boldsymbol{e}$ represents non-local constraints and $\boldsymbol{l}$ represents local weather. Section IV and Section V discussed g_{dem} and $f_{wx\text{-}red}$. Here, we will illustrate composition of the baseline demand model with the theoretical model.

The composed model would have the following equation:

witi_local * (a*AIRPORTR + b* WITIn + c*WITIr + d)

On a large enough test data sample, it would be expected that percentage of data that would fall below values predicted by this model would have a mean of 95% and a standard deviation dependent on the size of data sample. Three month data was used for testing this model. On this data, 92% of observed counts were below the model prediction and 8% of counts were above the model prediction.

Illustration with a case study: July 14, 2015

We will illustrate performance of this model with data from 14^{th} July, 2015. The general expectation about predictions of the model exceeding 95% of actual counts is likely to be valid for large enough datasets but not necessarily for a single day. Fig. 3 shows predicted 95^{th} percentile flows (solid line) and actual counts (dashed line). The X-axis shows UTC time in hours on July 14, 2015. Fig. 4 shows predicted 95^{th} percentile flows (solid line) and actual counts (dashed line). With 48 points shown in these plots, we would expect about 3 points to be at the predicted value or above it. This is consistent with the observations shown in the plots.

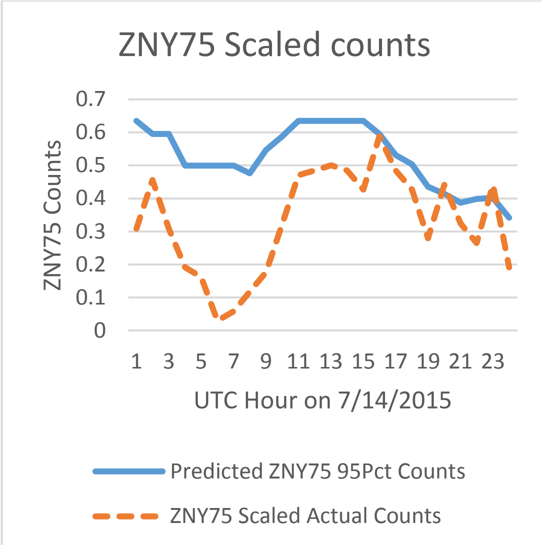

Fig. 3 ZNY75 predicted and actual counts

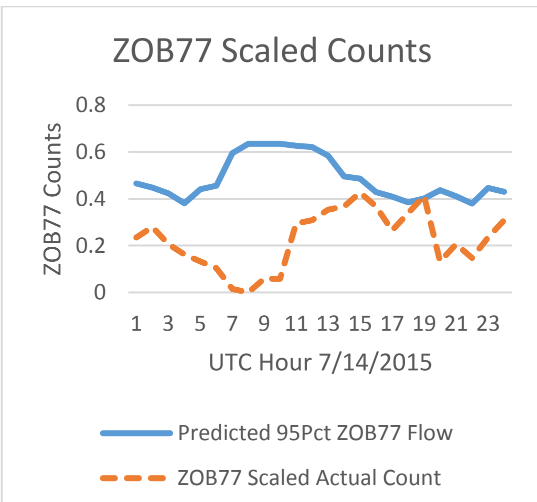

Fig. 4 ZOB77 predicted and actual Counts

VII. CONCLUSIONS

Air traffic controllers use traffic management initiatives when expected demand exceed the maximum aircraft they are willing to allow in a region of airspace. For new TMIs such as CTOP, it would be desirable to have models of maximum aircraft allowed in airspace regions in the presence of multiple constraints. This study examines different approaches to using historical data to create and validate models of maximum flows in sectors and other airspace regions in the presence of multiple constraints. A challenge in creating an empirical model of flows under multiple constraints is a lack of sufficient historical data that captures diverse situations involving combinations of multiple constraints especially those with severe weather. The approach taken here to deal with this is two-fold. First, we create a generalized sector model encompassing multiple sectors rather than individual sectors in order to increase the amount of data used for creating the model by an order of magnitude. Secondly, we decompose the problem so that the amount of data needed is reduced.

The approaches studied to developing these weather reduction models are divided into three categories: (1) Point estimation models (2) Empirical models (3) Theoretical models. Errors in predictions of these different types of models have been estimated. In situations when there is abundant data, point estimation models tend to be very accurate. In contrast, empirical models do better than theoretical models when there is some data available. The biggest benefit of theoretical models is their general applicability in wider range situations once the degree of accuracy of these has been established.

Adoption of CTOPs in the national airspace system would be accelerated by creation of decision support tools. One such capability would be a what-if-reasoning tool to understand impacts of CTOP related decisions. Such a capability can use models like the one describing worst case situation with maximum counts in the presence of multiple constraints. Secondly, optimization tools to recommend optimal FCA rates would also be useful. These can use probability distributions of likely flows in multi-constraint situations.

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