Airspace Complexity and its Application in Air Traffic Management

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Abstract—Predicted growth in air traffic and the desire for more user preferred routes in the National Airspace System (NAS) will impose additional demand on air traffic control and management systems. This demand can be met by alternate airspace configurations, modified traffic patterns, and staff reassignment. There is a need to understand the effect of changing airspace configurations and traffic patterns on the workload of air traffic controllers. This complex relation is referred to as "Airspace Complexity". Research on dynamic density indicates that it is a good measure of airspace complexity. Dynamic density is a function of the number of aircraft and their changing geometries in a given airspace. In order to use dynamic density as a planning tool, it is necessary to project its behavior over the planning horizon. The objective of this work is to study how well dynamic density can be predicted into the future using the trajectory generation feature of the Center-TRACON Automation System (CTAS). This paper describes the application of trajectory prediction to computation of actual and predicted dynamic density using traffic data from Dallas/Fort Worth airspace. Results show that dynamic density can be predicted up to 20 minutes in advance and errors in predictions can be further reduced by accounting for departure traffic.

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1. Introduction

The Air Traffic Management (ATM) system in the United States provides services to enable safe, orderly and efficient aircraft operations within the airspace over the continental United States, large portions of the Pacific and Atlantic Oceans, and the Gulf of Mexico. The ATM system consists of two components, Air Traffic Control (ATC) and Traffic Flow Management (TFM). The ATC function ensures that the aircraft within the airspace are separated at all times, while the TFM function organizes the aircraft into flow patterns to ensure their smooth and efficient movement. In order to accomplish the ATC and TFM functions, the airspace over United States is distributed into 22 Air Route Traffic Control Centers (ARTCCs). The Center airspace is stratified into low-altitude, high-altitude and super-high altitude strata. Each vertical layer is further partitioned into several horizontal Sectors. A typical ARTCC airspace is partitioned into 20 to 50 Sectors. These Sectors are the basic control units within the ATM system.

Generally, one to three controllers are assigned to every Sector within the ARTCC. These controllers have the responsibility of separating every aircraft operating within the Sector. The

Sectors are designed such that the controllers are able to handle the usual flow of traffic. In the event of increased demand or re-routing required due to weather conditions or special use airspace constraints, proven TFM techniques such as staff reallocation and alternative airspace configurations are used for maintaining the workload of the controllers so that safety and flow efficiency remain uncompromised. An existing decision support system for traffic management, the Enhanced Traffic Management System (ETMS), compares the strategic prediction of traffic volume against the established traffic volume threshold for its monitor/alert function. These threshold values do not adequately represent the level of difficulty experienced by the controllers under different traffic conditions. The growth in air traffic and developments in the ATM, such as, free flight, requires a new understanding of the complex relationship between traffic pattern, Sector/Center geometry, procedures and controller workload. It has been suggested by the Radio Technical Commission on Aeronautics (RTCA)[1] that the monitor/alert function should be extended to include measures of Sector complexity and controller workload. These measures should be based not only on the number of aircraft, but their relation to each other, airspace geometry and varying traffic flow conditions. This concept has come to be known as *Dynamic Density*. For dynamic density and other airspace complexity measures to be useful as traffic management tools, it is necessary to predict their future behavior.

The approach of this paper is to adopt a measure of complexity of the Sector and Center airspace that can be related to controller workload, and to examine how well it can be used with the predicted traffic estimates to forecast future workload levels. This assessment can then be used for TFM decisions. A measure of airspace complexity has been developed at the NASA Ames Research Center (ARC)[2]. This paper assumes it to be a good measure of controller workload, and studies how well dynamic density can be predicted up to a specified period in advance. This analysis was applied to predict dynamic density at the Dallas/Fort Worth (ZFW) ARTCC using the Center-TRACON Automation System (CTAS)[3]. CTAS predicts future aircraft locations using radar tracks, flight plans, aircraft dynamic models, and weather data from National Centers for Environmental Prediction (NCEP). These predicted aircraft positions and speeds are used for computing dynamic density in the future.

A description of factors that can contribute to airspace complexity and how they influence controller workload is presented in Section 2 of this paper. Section 3 describes the measures of dynamic density used in this work. Section 4 illustrates how dynamic density is computed in CTAS using predicted trajectories of aircraft. It also shows application of the concept to traffic data for a Sector in the ZFW airspace. Results comparing actual and predicted dynamic density are presented. Section 5 demonstrates how using ETMS supplied flight plans and aircraft track data can improve longer term prediction of dynamic density and number count of aircraft. Results for errors in computed estimates and a discussion of their sources are also included. Some concluding remarks and future research directions are presented in Section 6.

2. Airspace Complexity

Airspace complexity depends on both structural and flow characteristics of the airspace. The structural characteristics are fixed for a Sector/Center and they depend on the spatial and physical attributes of the Sector such as terrain, number of airways, airway crossings and navigation aids. The flow characteristics vary as a function of time and depend on features like number of aircraft, mix of aircraft, weather, separation between aircraft, closing rates, aircraft speeds and flow restrictions. A combination of these structural and flow parameters influences the controller workload.

Several efforts are underway to model airspace complexity as it relates to controller workload. This paper implements and extends previous work performed by Laudeman *et al.*[2] at NASA ARC. The proposed metric provides a quantitative description of the air traffic complexity along with the traffic density and is described in the next section. Another effort undertaken at Wyndemere, Inc.[4], described a method for evaluating and measuring the complexity of airspace. The framework was designed to evaluate a model of the perceived complexity of an air traffic situation, with specific emphasis on the traffic and airspace characteristics that impact the cognitive and physical demands placed on the controller. An attempt was made to include the level of knowledge about the intent of the aircraft. Both these studies include significant input from full performance level air traffic controllers to specify and improve the models. The FAA William J. Hughes Technical Center[5] is also conducting a study to identify a set of dynamic density metric variables and to quantify their contribution towards controller workload. The intent of the study is to evaluate validity and utility of the identified metrics for air traffic management.

3. Dynamic Density

This Section describes earlier work performed at NASA ARC[2], where dynamic density was studied as an ATM metric of controller activity level, characterizing the measures of airspace complexity that are based on the flow characteristics of the airspace. The dynamic density measure was developed based on interviews and survey techniques with input from 65 qualified air traffic controllers. The controllers were presented with questionnaires which contained preferences for factors affecting their performance. In addition to the number of aircraft (also referred to as Traffic Density) in a Sector, the number of aircraft undergoing trajectory change (i.e., heading, speed or altitude changes), and the number of aircraft requiring close monitoring due to reduced separation were also identified by controllers as significant contributors to the workload. An activity catalog tool was developed to measure controller activity, including radio communication and radar scope related actions. This tool captured on-duty controller activity, which was then correlated to dynamic density.

The following variables were selected for inclusion in the definition of the dynamic density function for a Sector:

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. Dynamic density is a linear combination of the above factors, i.e.,

$$DD = W_1 \bullet N + W_2 \bullet NH + W_3 \bullet NS + W_4 \bullet NA + W_5 \bullet S5 + W_6 \bullet S10 + W_7 \bullet S25 + W_8 \bullet S40 + W_9 \bullet S70$$

The weights, W_i, were computed both by regression analysis of activity data and by subjective weights from survey data. A comparative analysis of unit weights, subjective weights, and regression weights for the dynamic density terms was performed and the resulting weights are presented in Table 1.

Weight	Regression Analysis	Subjective Ratings
W1	0.79	1.00
W2	2.17	2.40
W3	0.00	2.45
W4	0.88	2.94
W5	1.02	2.45
W6	1.18	1.83
W7	0.00	4.00
W8	1.85	3.00
W9	1.85	2.11

Table 1: Weights for the dynamic density function (from Ref. 2).

The dynamic density function with subjective weights was selected for validation in an operational environment. Dynamic density was computed within CTAS using air traffic data from the Denver (ZDV) ARTCC host computer and validated against the controller activity that was recorded using the catalog tool. Figure 1 shows this data as a function of time for Sector 28, a high altitude Sector within the Denver ARTCC airspace. This data was recorded during a field test[6] of CTAS at ZDV in September, 1997.

In Figure 1, the solid line shows the actual number of aircraft (N) in Sector 28. The dotted line shows the smoothed actual controller activity counts and the dashed line shows the smoothed predicted dynamic density (DD). A high value of Pearson correlation coefficient, r = 0.86, between estimated and actual activity counts indicates that these measures can be used for predicting controller activity with a high degree of confidence. The derived dynamic density values captured a substantial variation in observed controller activity.

Figure 1: Computed dynamic density and observed activity levels (data from Ref. 2).

4. Prediction of Dynamic Density

The high correlation of dynamic density with actual Sector controller activity levels indicates that dynamic density can be used as a good indicator of controller activity. For dynamic density to be useful, one should be able to predict its behavior. This section examines the ability to predict dynamic density. Since dynamic density is a function of position and velocity of all aircraft in a Sector, a trajectory prediction algorithm can be used to predict dynamic density. The CTAS trajectory synthesis algorithm[7, 8] uses flight plans, track data provided by the ARTCC Host computer, predicted atmospheric data provided by the NCEP's Rapid Update Cycle (RUC-II) model, and dynamic aircraft models for predicting aircraft trajectories as a function of time. Since this method uses the long-term intent information along with wind data, CTAS is able to predict aircraft trajectories for long look-ahead times. Utilizing the estimated aircraft positions and speeds, all of the factors contributing to dynamic density can be computed and estimated over the prediction interval. Dynamic density prediction results were computed using CTAS predicted traffic for short-term (5 minutes) and long-term (20 minutes) prediction intervals. These predictions were then compared with the actual value of dynamic density at the corresponding time instants. These computations were performed using real traffic data from the Host computer of the ZFW ARTCC shown in Figure 2.

Figure 2: Map of Dallas/Fort Worth ARTCC controlled airspace and its constituent Sectors.

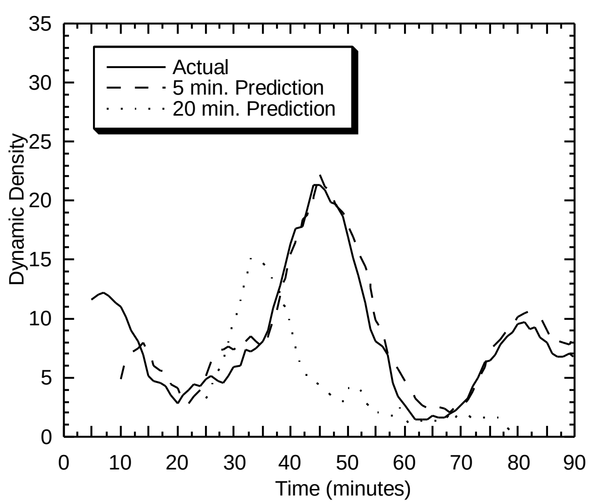

Figure 3: Prediction of dynamic density.

The solid line in Figure 3 shows time-averaged actual values of dynamic density for Paxto-High (Sector 86). The dashed and dotted lines represent dynamic density values for 5 and 20 minute predictions, respectively. It can be observed from Figure 3 that the 5 minute curve accurately predicts dynamic density whereas the 20 minute prediction fails to capture its behavior. The predictions deviate from estimated values primarily because the intent information for several aircraft is not known to the CTAS software. The reason for this limitation is that currently, the Host computer provides radar track data only for the aircraft within corresponding ARTCC boundary and for those aircraft within about 50 nautical mile (nm) distance from the boundary. This results in CTAS being unaware of some of the aircraft which appear in a Sector in the subsequent estimation interval (20 minutes) with the corresponding degradation in dynamic density prediction. These errors are more pronounced for a Sector closer to the Center boundary. This limitation can be overcome if inter-Center data is available to the system. This aspect and some other sources of error are discussed in the next Section.

5. Improved Predictions and Error Analysis

In the previous section, results were presented for the prediction of dynamic density using traffic data from the Host computer. The source of error due to lack of aircraft intent information is reduced in this research by supplementing data on aircraft outside the Center boundary with ETMS data. The Enhanced Traffic Management System (ETMS) collects aircraft information from all 22 ARTCC Host computers in the United States airspace and combines it to address traffic management issues.

Software was developed to acquire this data and include all aircraft within a specified distance from an ARTCC of interest. This is conceptualized by an approximate ellipse around the ZFW ARTCC in Figure 2. For the purpose of this study, distances of 50 nm and 250 nm outside of ZFW airspace were used. The 50 nm range was chosen to select ZFW ARTCC Host data only. The 250 nm range would provide approximately 30 minutes of travel time before an aircraft enters the Center airspace, which would facilitate the estimation of aircraft counts and dynamic density even in Sectors close to the ARTCC boundary (e.g. Sector 86). With the inclusion of inter-Center data, the long-term predictions can be improved significantly.

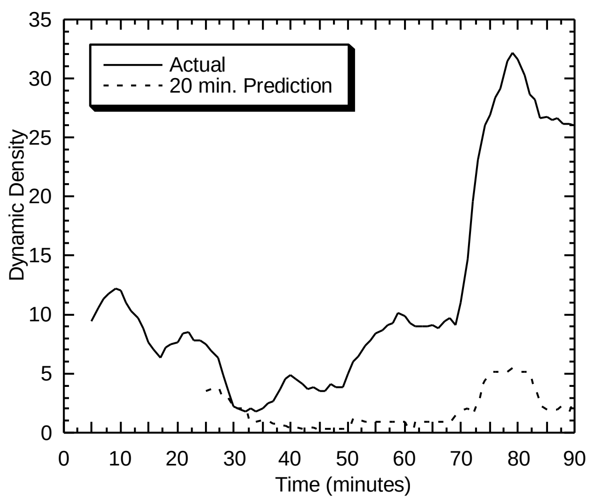

Figure 4(a): Prediction of dynamic density excluding inter-Center data.

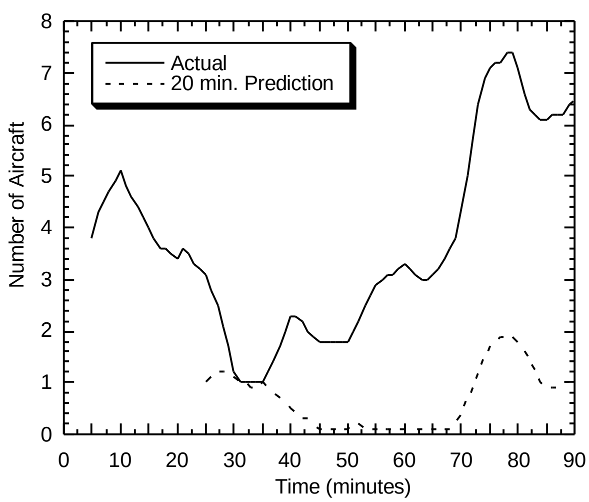

Figure 4(b): Prediction of aircraft count excluding inter-Center data.

Figures 4 and 5 present cases for Sector 86 in ZFW airspace where ETMS data was interfaced with CTAS.

Figures 4(a) and 4(b) show actual and 20 minute predicted dynamic density and aircraft count values, respectively, for ZFW ARTCC data only. Figures 5(a) and 5(b) show the corresponding values by including inter-Center data with a 250 nm range outside the Center airspace. Comparing Figures 5(a), (b) with Figure 4(a), (b) suggests that the long-term predictions are significantly improved by using extended data from outside the ARTCC.

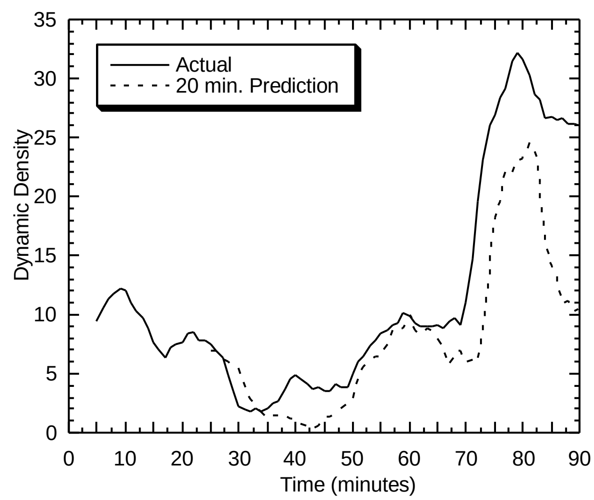

Figure 5(a): Prediction of dynamic including inter-Center data.

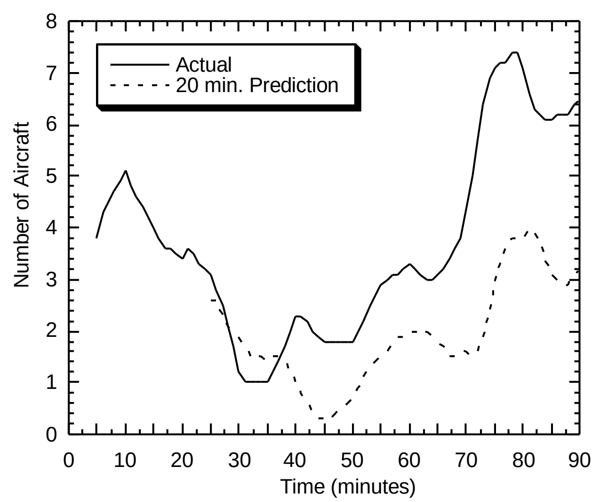

Figure 5(b): Prediction of aircraft count including inter-Center data.

Figure 6 presents error estimates in the prediction of dynamic density. The errors (? e = actual – predicted) are calculated for the long-term prediction of dynamic density using the Host-like (50 nm) and inter-Center (250 nm) data. It is observed that the dashed curve representing 20 minute prediction using a 250 nm range remains consistently closer to zero compared to the solid curve representing the same prediction interval for a 50 nm range. This confirms that using ETMS supplied data to obtain information for aircraft farther out from the ARTCC, considerably reduces errors in the prediction estimates.

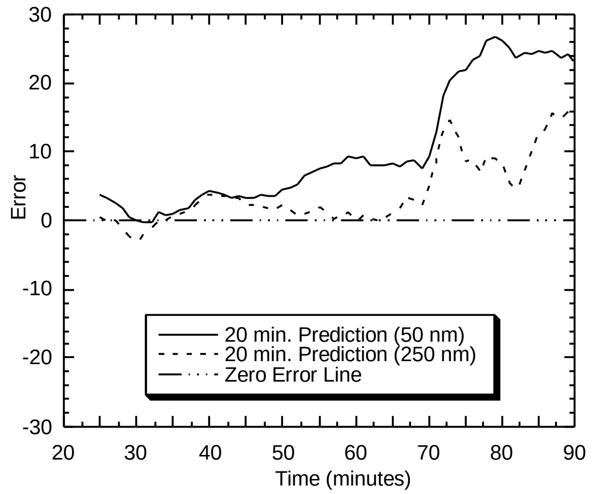

Figure 6: Error estimates in dynamic density prediction for Sector 86.

	Inter-Center data excluded		Inter-Center data included		
Sector No.	Mean	Std. Dev.	Mea n	Std. Dev.	Sector Types
42	8.5	5.8	2.6	4.0	A
47	6.7	15.9	2.5	10.5	A
65	4.7	5.0	4.5	4.2	A,O
89	5.3	4.3	0.9	4.3	A
39	13.3	10.7	11.9	9.9	D,O
46	25.4	8.5	23.9	8.4	D,O
48	10.9	4.0	9.5	4.5	D,O
90	11.5	5.9	9.5	8.1	D
94	2.2	3.5	2.3	4.7	D, O
86	10.4	9.0	4.1	5.0	A,D,O
All	9.9	10.2	7.2	9.5	

Table 2: Dynamic density error statistics by excluding and including inter-Center data with classification (A=Arrival, D=Departure, O=Overflight) for 10 Sectors in ZFW airspace.

Table 2 presents the mean and standard deviation obtained by excluding (50 nm) and including (250 nm) inter-Center data for 10 Sectors surrounding Dallas/Fort Worth (DFW) Terminal Radar Approach Control (TRACON). The first four Sectors listed in the Table refer to arrival Sectors in the ZFW's four corner-post design. It can be observed that the mean and standard deviation of dynamic density errors reduce considerably using the 250 nm range, with the exception of Sector 65. The arriving aircraft already have about 200 nm from the Center boundary before they enter Sector 65; hence the predictions are not significantly affected by a lack of information about aircraft outside the Center boundary. The next five Sectors listed in Table 2 reference the north, south, east and west-bound departure Sectors surrounding DFW (Sectors 39 and 94 are generally merged together for west-bound departures).

It is important to note that a significant source of error exists in the prediction results for Sectors with departing aircraft, and is demonstrated by a high value of the mean of dynamic density errors. Currently, departure aircraft information is available in the Host computer but the CTAS software does not perform trajectory predictions for an aircraft until the first radar track is received from the Host. Thus, using a larger range to incorporate intent information from distances further than 250 nm would not improve departure Sector predictions. To remedy this situation, CTAS software is being modified to include aircraft departure information.

The last Sector in Table 2, Sector 86 (Paxto-High), for which prediction data was presented in earlier Sections, is very complex from a controller's perspective. This is due to the merging of arriving aircraft to DFW, departure traffic from Houston, and overflights, over its airspace. A substantial reduction in the mean and standard deviation is observed for this Sector. The most important factor for this reduction is its proximity to the ZFW ARTCC boundary. For example, this Sector encounters many aircraft originating from Houston (which is about 125 nm away), and hence, the 250 nm range improves estimates significantly. The last entry in Table 2 presents the mean and standard deviation values for all Sectors combined. It can be concluded that using data from further outside the Center improves prediction estimates overall.

Currently, computations do not include controller action *during* the prediction interval and could contribute as a source of error in estimating the dynamic density. This could explain why in some cases the mean and standard deviation values were found to increase, e.g. Sector 94, with the use of 250 nm range. Other sources of error are errors in weather prediction and radar tracker estimates. Lack of flight intent information and aircraft modeling errors can also contribute to an incorrect prediction. All these factors reduce the accuracy of predicted aircraft trajectories[9].

6. Conclusion

The ability to predict trends in controller workload is necessary for the management of air traffic. Earlier research has shown that controller workload is related to dynamic density. Results have been presented with predictions of aircraft counts and dynamic density for the Dallas/Fort Worth ARTCC airspace. This prediction capability can be used by the Area Supervisors for resource allocation and by TFM staff for airspace/traffic planning. Currently the predictions have been made up to 20 minutes into the future. Availability of inter-Center data (specifically, aircraft intent), can help extend this analysis for larger prediction intervals. With improved wind estimates, reduced radar tracker errors, and better aircraft models, the parameters can be estimated more accurately.

This paper has assumed a specified definition of dynamic density as a good measure of controller workload. The current measure represents only the traffic flow conditions and could be improved by incorporating effects of structural characteristics like airway intersections, as well as other dynamic flow events such as weather. There is also a need for developing measures of airspace complexity that can be used for addressing not only the physical aspect but also the cognitive aspect of controller workload. The cognitive workload aspects are important because past research indicates that infrequent but critical events such as loss of separation, altitude deviations, VFR pop-ups and incorrect pilot read backs impose considerable mental workload on the controllers.

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