

# PREDICTING SECTOR CAPACITY FOR TFM

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## Abstract

A novel approach to sector capacity prediction for airspace congestion management is presented, in which traffic complexity is captured with traffic flow patterns. Predictability of flow features are quantified and considered in describing the traffic flow patterns. Quantifying sector capacity as a function of traffic flow pattern provides a good approximation of the amount of traffic that can be effectively handled in the sector. The sector capacity for each traffic flow pattern is established based on observed system performance to avoid direct measurement of controller's workload and predefining workload threshold. Such a "predictable" sector capacity metric also provides a basis for capturing weather impact on sector capacity.

## Introduction

In the U.S. National Airspace System (NAS), en route Traffic Flow Management (TFM) is the function which balances air traffic demand against available airspace capacity, to ensure a safe and expeditious flow of aircraft. However, airspace capacity is difficult to estimate and predict. In today's NAS, there is no automation tool to predict sector capacity, since there is no established and accepted indicator of sector capacity. The current Enhanced Traffic Management System (ETMS) [1] provides a congestion alerting function which uses peak one-minute aircraft count as a sector congestion alerting criterion (the "Monitor/Alert Parameter," or MAP). This is not meant to be a measure of airspace capacity, but rather a threshold which, when exceeded by predicted demand, alerts traffic managers to examine the sector for potential congestion. The actual capacity of a sector is dependent on the complexity of the traffic flows within, as well as the presence or absence of hazardous weather.

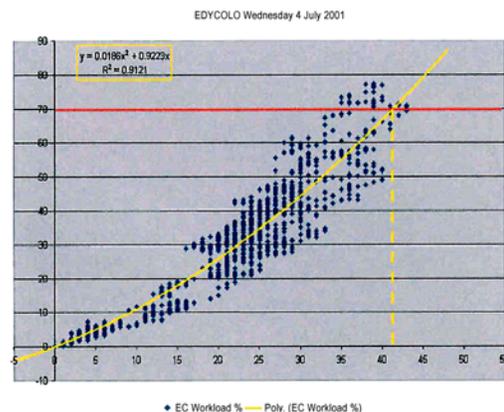
A metric of sector capacity is needed that (1) is a good approximation of the amount of traffic that can be effectively handled in the sector, (2) is predictable at useful look-ahead times (30 minutes to 2 hours), (3) is intuitive and relevant to human decision makers, (4) can provide insight into congestion resolution options, and (5) can include the

impact of convective weather on available sector capacity.

## Background

Sector capacity can be defined in terms of the number of aircraft which may enter a sector within the given time period, without causing excessive sector controller workload; that is, the maximum number of aircraft that can be safely handled by the controller. Controller workload reflects the overall level of demand for controller's perceptual and cognitive resources.

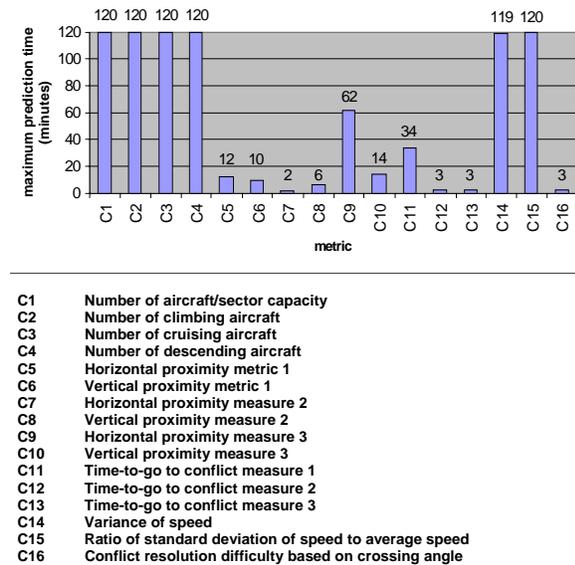
EUROCONTROL Experimental Center developed a mathematical model [2] to assess sector capacity based on measuring pre-defined, event driven, controller tasks of a specified duration. Figure 1 shows the cloud of controllers' workload as a function of aircraft count. As we can see, there are several spots on each column, because the same number of flights may generate different workloads. This is a consequence of complexity variations: when a situation is complex, the workload is higher for the same number of flights [2]. The CAPAN (ATC Capacity Analyzer tool) team used a parabolic curve (the yellow line in Figure 1) to fit the workload cloud and decide the sector capacity with the abscissa of the intersection between this curve and the predefined workload threshold.



**Figure 1. Sector Capacity Assessment by CAPAN**  
(cited from [2])

Since controllers' workload is not only a function of aircraft count, but also a function of traffic complexity, it's necessary to have sector capacity, as an indicator of controller's workload threshold, to be different for different traffic patterns with different levels of complexity.

The Dynamic Density (DD) concept attempts to measure control-related workload as a function of both the number of aircraft and the traffic complexity in a volume of airspace [3]. Recently, improved metrics of sector demand and capacity that consider the traffic complexity have been developed and evaluated by MITRE [4, 5, 6], the FAA [7, 8, 9], and other institutions [10, 11, 12]. These metrics account for the traffic complexity by examining details of individual flight characteristics or the interactions between pairs of flights. These metrics are generally not suitable for congestion management because the predictability of these flight characteristics is too low [13], given the uncertainties in the NAS over the long look-ahead times needed for traffic management.



- C1 Number of aircraft/sector capacity
- C2 Number of climbing aircraft
- C3 Number of cruising aircraft
- C4 Number of descending aircraft
- C5 Horizontal proximity metric 1
- C6 Vertical proximity metric 1
- C7 Horizontal proximity measure 2
- C8 Vertical proximity measure 2
- C9 Horizontal proximity measure 3
- C10 Vertical proximity measure 3
- C11 Time-to-go to conflict measure 1
- C12 Time-to-go to conflict measure 2
- C13 Time-to-go to conflict measure 3
- C14 Variance of speed
- C15 Ratio of standard deviation of speed to average speed
- C16 Conflict resolution difficulty based on crossing angle

**Figure 2. Maximum Prediction Time for a Set of DD Metrics**

In MITRE's study of the predictability of DD metrics [13], the correlation between predicted and actual values of a DD metric at a given look-ahead time was calculated. In this study, it was assumed that a correlation below 0.3 for a DD metric at a given look-ahead means that the metric cannot be usefully predicted at or beyond that look-ahead. The maximum prediction time for a set of DD metrics is shown in Figure 2. As we can see from Figure 2, the predictable metrics in the TFM time domain (30-120

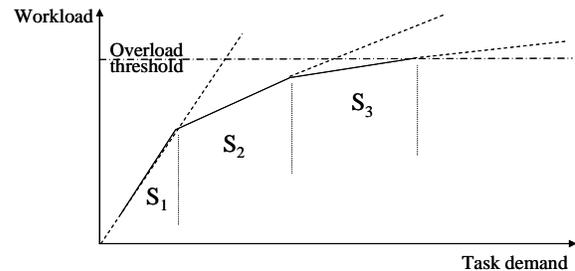
minutes) are those based on aggregated traffic information rather than aircraft interactions.

This work is focused on identifying the complexity factors that are related to the controller's workload and predictable in the TFM time domain, so that we can model sector capacity as a function of traffic complexity.

## Controller's control strategy

Since traffic complexity is a controller workload related concept, it's necessary to find the complexity factors that are related to controllers' control strategy. Two studies shed some light on this topic: one study observing controllers' control strategy [14] and another observing controllers' structure usage [15].

A series of field studies [14] examined how air traffic controllers modify their cognitive processes and other concomitant operational behavior when the number of aircraft controlled varies. As shown in Figure 3, controllers adjust their control strategies as task demand (aircraft count) increases. Otherwise, controllers' workload would reach the threshold very quickly. The studies revealed that controllers take into account a smaller and smaller number of variables for each aircraft as traffic increases. Controllers progressively treat each aircraft as one link in a chain whose characteristics remain stable and not as an independent body moving in free space among other independent moving bodies.



**Figure 3. Controller Strategy Changes to Regulate Workload**

To match controllers' control strategy, traffic managers should manage the traffic on the level of flow (chain) instead of each individual aircraft (independent body), making it easier for controllers to find the stable chain (flow) characteristics. This indicates that sector capacity should be based on how complex the distribution of chains (flows) within the sector is, instead of on how complex the interactions among individual aircraft are.

In another study [15], a series of site visits to ATC facilities were conducted to investigate the

relationship between structure and cognitive complexity. Discussions were held with traffic managers to understand how complexity is regulated through traffic management initiatives.

Field observation and analysis show that a recognized underlying structure can act as the basis for a set of abstractions internal to the controller that can simplify the task of predicting the future behavior of the traffic. The properties of standard flows, one of the observed three key structure-based abstractions, and the distribution of flows relative to the sector shape were stressed by controllers as being the key complexity factors.

This study also observed that a standard flow abstraction may tolerate a localized disturbance in the flow trajectory, such as a deviation around an isolated area of convective weather. However, when disturbances become so large that the underlying structure can no longer be used to support the standard flow abstraction, described by controllers as “losing the picture,” the cognitive complexity increases dramatically.

These two studies support the conclusion that controllers are using the flow properties and catching the “picture” of the traffic to simplify their cognitive complexity. Flows instead of aircraft should be used as the object for congestion management to match controllers’ usage of structured abstraction, help them to keep their “picture” and thus simplify their cognitive complexity. The “picture” usage of the traffic also supports the decision theory under stress and uncertainty.

## Decision Theory under Stress and Uncertainty

Traffic managers and controllers work in complex dynamic environments. They act or react on the basis of prior experience, monitoring, planning, and modifying plans to meet specific and changing constraints. Time stresses constrain their attention resources and working memory. A proposed situation awareness model suggests that optimal decision making is dependent upon pattern matching between critical environmental cues and the person’s mental model of the situation. This situation awareness model, called the *recognition-primed decision-making* (RPD) model, describes what people actually do under time stress situations, uncertain information, and dynamic conditions [16].

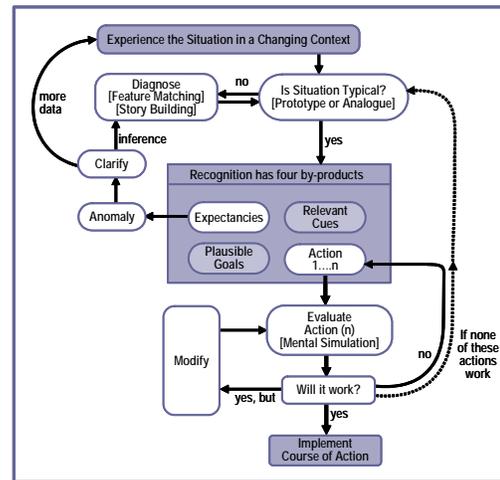


Figure 4. Recognition-Primed Decision Model (cited from [16])

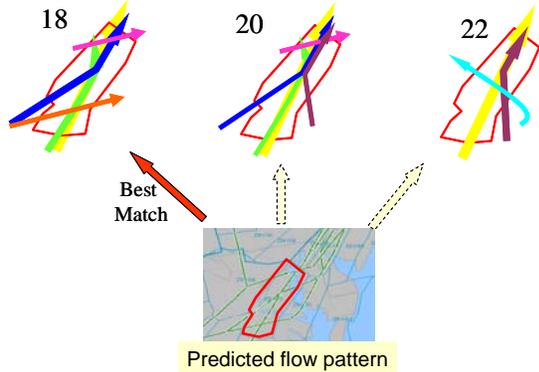
The RPD model contains three levels of cognitive functioning: simple pattern matching, pattern discrimination, and mental simulation (Figure 4). During the simple pattern matching stage of decision-making, the person identifies a pattern encompassed within the environmental cues and reacts accordingly. For instance, when a controller is in a high time-stress situation and sees a kind of traffic flow pattern which is exactly the same as one experienced before, the controller can make conflict resolution decisions without much cognitive processing. When people match patterns of environmental cues to an appropriate action, rapid and optimal decision-making can occur [16]. If the predicted traffic flow pattern matches any pattern a traffic manager has experienced before, the traffic manager can react quickly based on the historic sector capacity associated with that flow pattern. According to this decision-making theory, pattern recognition is a proper mental model of traffic managers’ congestion management process.

## Proposed Approach

We propose an approach of modeling the sector capacity as a function of traffic flow pattern and predicting sector capacity through pattern recognition [17]. The basic idea is shown in Figure 5.

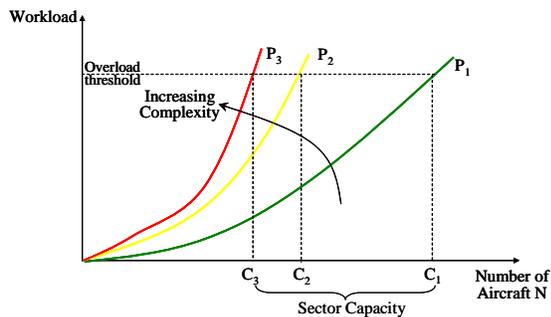
First, we identify the primary set of traffic flow patterns that have different levels of complexity for a given sector through cluster analysis. For the example shown in Figure 5, the three primary traffic flow patterns are shown on the top of the figure. The left flow pattern is more complex than the right one, because the left one has more merging and crossing flows than the right one. Thus, the corresponding

sector capacity for the left one (18) is less than the capacity for the right one (22). The sector capacity for a given traffic flow pattern can be assessed through observing the system performance [17]. As long as the primary set of traffic flow patterns and the corresponding sector capacities have been determined, the future sector capacity can be predicted with pattern recognition, finding the best match from the primary set with the predicted traffic flow pattern.



**Figure 5. Predicting Sector Capacity through Pattern Recognition**

A notional relationship between traffic complexity, traffic flow pattern, controller workload, and sector capacity is shown in Figure 6. Different traffic flow patterns (e.g.,  $P_1$ ,  $P_2$  and  $P_3$  in Figure 6) with different levels of traffic complexity (e.g.,  $P_3$  is more complex than  $P_1$  in Figure 6) may appear in different time periods for the same sector. Given the same number of aircraft, the more complex the traffic pattern, the higher the controller's workload. In other words, the more complex the traffic pattern, the smaller number of aircraft the controller can handle within the specified duration, that is, the smaller the sector capacity.



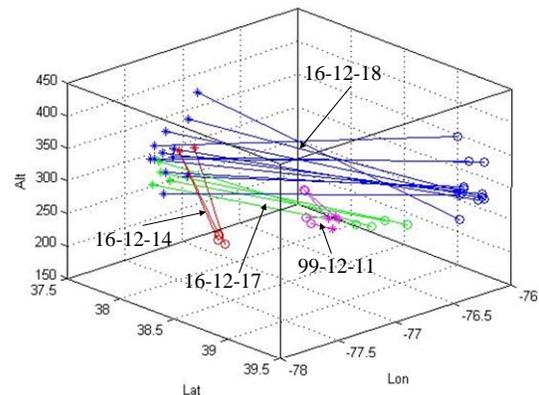
**Figure 6. Relationship between Traffic Complexity, Controller Workload, and Sector Capacity**

The following sections will focus on the discussion of flows, flow features to describe the flow patterns, and the predictability of flow features.

### Flow and Flow Features

An aircraft flow refers to a group of aircraft that exhibit similar characteristics as they travel through an airspace region. Aircraft can be grouped as a flow in different levels for different purposes. For the purpose of describing sector traffic flow patterns to represent sector traffic complexity, we want to define the flow to reflect sector controllers' control strategy. Since controllers' major task is to move aircraft through their controlled sector from previous sectors to the next sectors safely and efficiently, it's operationally acceptable to define the flow to be a group of aircraft within a sector that have the same entry and exit sectors. Thus, given a sector, each flow within the sector is identified by a sector transit triplet: entry sector - current sector - exit sector. For example, in Washington Center (ZDC), one flow for sector ZDC12 is ZDC16-ZDC12-ZDC18, which shows the flow is from sector ZDC16, through ZDC12, and into sector ZDC18. This definition of flow is also compatible with the sector transit level demand prediction model [18] developed in CAASD for a TFM decision support tool. With this approach, flight paths are abstracted as a series of time-stamped sector entries. The aircraft trajectories within a sector are straight lines from the entry points to the exit points.

The initial observation of actual flight sector entries and exits shows that the sector transit triplet can differentiate flows in most sectors. An example 15 minutes of actual flight entries and exits in sector ZDC12 is shown in Figure 7.



**Figure 7. Sector Transit Triplets to Represent Flows**

The stars in Figure 7 are entry points and circles are exit points. Different colors are for different sector transit triplets (flows). As we can see in Figure 7, aircraft with the same triplets are grouped together.

Sector transit triplets may not be an adequate identifier for some flows. The same sector transit triplet could represent two different flows, depending on what the fourth sector is. For example, triplet 99-12-11 in Figure 7, there are four aircraft in the triplet, but two of them are descending and the other two are climbing. For these cases, the fourth sector or an attached altitude may need to be considered to identify the flow uniquely.

For the initial analysis, we define *flow* to be any sector transit triplet that has at least two aircraft, and the triplet that has only one aircraft is defined as a *singleton*. The following flow features were explored to describe the traffic flow patterns and indicate the traffic complexity:

- *The Major Flow*: The flow with the maximum number of aircraft. The major flow is numbered to be 0 (no major flow), 1 (the most frequently-observed major flow), 2 (the second most frequent), 3 (the third most frequent), and 4 (any other, less frequently-observed flow).
- *The Major Flow Size*: The number of aircraft within the major flow.
- *The Number of Flows*: The number of triplets that have at least two aircraft.
- *The Number of Merging Flows*: Two flows are merging if they have the same exit sector.
- *The Number of Climbing Flows*: The flow is climbing if the average exit altitude is at least 500 ft above the average entry altitude.
- *The Number of Descending Flows*: The flow is descending if the average exit altitude is at least 500 ft below the average entry altitude.
- *The Number of Crossing Flows*: Each flow within the sector is treated as a line segment between the average entry point and exit point. Two flows are crossing if the minimum distance between two line segments is smaller than 5 nmi.
- *Ratio of singleton*: The number of singletons divided by the total number of aircraft.

### Predictability of Flow Features

To be able to predict the sector capacity in advance, the traffic flow pattern has to be predictable for the given look-ahead time. Thus, it's important to decide the predictability of the flow features that will

be used to describe the traffic flow patterns. The same approach as in MITRE's previous study of DD metrics predictability [13] is used to study the flow features predictability. The correlations between predicted and actual flow features are calculated as functions of Look-Ahead Time (LAT). An example sector (ZDC16) flow features predictability on January 18<sup>th</sup>, 2004 is shown in Figure 8.

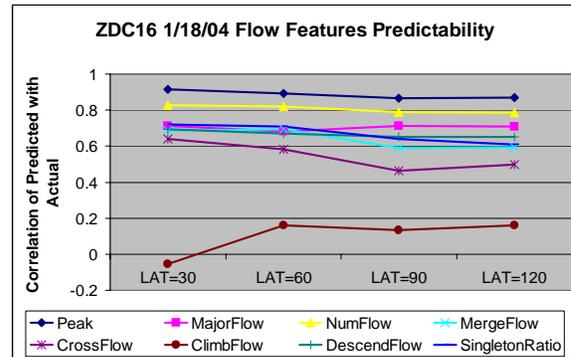


Figure 8. Predictability of ZDC16 Flow Features on 1/18/04

As shown in Figure 8, the peak minute count (dark blue diamond in Figure 8) has the highest correlation between the prediction and the actual. In general, the longer the look-ahead time, the lower the correlation between the prediction and the actual. If the same correlation threshold (0.3) as the one for DD metrics in [13] is used to decide the maximum prediction time, most of the flow features are predictable within two hours except the number of climb flows (ClimbFlow in Figure 8), which is not predictable with any look-ahead time. One reason for the low predictability of number of climb flows is that most of the traffic handled in ZDC16 is descending traffic.

The predictability of flow features on different days for the same sector appears to be a little different but with the similar trends. Figure 9 shows the predictability on January 21<sup>th</sup>, 2004.

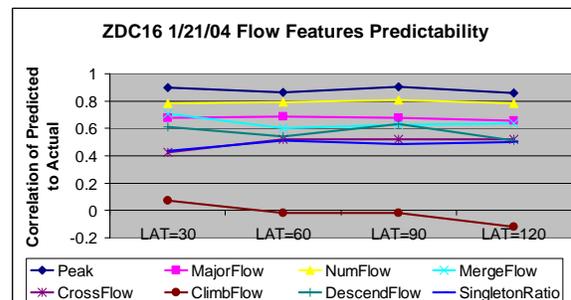


Figure 9. Predictability of ZDC16 Flow Features on 1/21/04

As shown on Figure 9, the major flow and the number of flows have better predictability than other flow features and there is no linear correlation between predictions and actual for the number of climb flows.

The predictability of flow features for different sectors could be different because the location, the shape, traffic types, and route structures of sectors are different. Figure 10 shows the flow features predictability of ZID66 on January 19<sup>th</sup>, 2004.

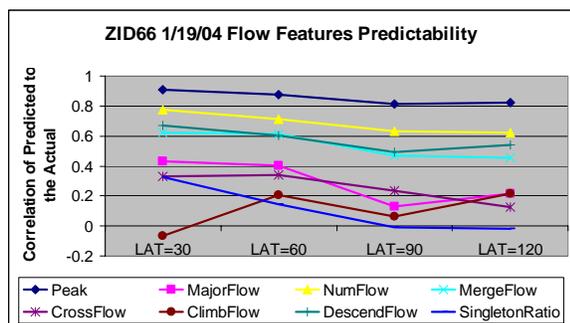


Figure 10. Predictability of ZID66 Flow Features

Comparing Figure 10 with Figure 8 and Figure 9, the overall predictability of flow features in ZID66 is lower than ZDC16. Only the number of flows (NumFlow), the number of descending flows (DescendFlow), and the number of merging flows (MergeFlow) are predictable within two hours. The maximum predictable time for the number of crossing flows (CrossFlow) and the major flow (MajorFlow) is one hour.

In conclusion, the flow features are generally more predictable than individual aircraft characteristics or aircraft interactions as most of the DD metrics. Intuitively, traffic aggregation reduces the amplitude of traffic fluctuations around the mean rate. The predictability of flow features is different for different sectors. Only the predictable flow features should be used for the cluster analysis to identify the primary set of traffic flow patterns. Thus, the primary set of traffic flow patterns would be described with different flow features for different sectors, which will be shown in the next section.

### Identify the Primary Set of Traffic Flow Patterns with Predictable Flow Features

As proposed in [17], the Self-Organizing Map (SOM) can be applied to cluster the historical traffic flow patterns with flow features to identify the primary set of traffic flow patterns for a given sector. Now we have identified the predictable flow features, we want to limit the predictable flow features to be

included in the input feature matrix for SOM. For example, in ZDC16, the predictability of the number of flows, the major flow, and the number of descend flows is comparable to the peak minute count and stable over LAT, so only these three flow features are included in the flow feature matrix as the input data to SOM. The Unified distance matrix (U-matrix) [17] is used to visualize the clusters of historical traffic flow patterns. Figure 11 shows the U-matrix of ZDC16 traffic flow patterns from SOM trained with five months 15-minutes traffic flow patterns.

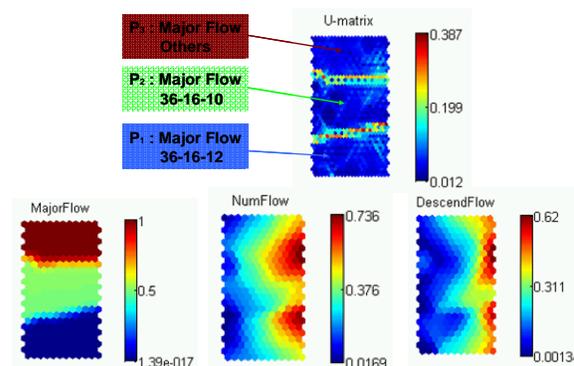


Figure 11. The Primary Set of Traffic Flow Patterns of ZDC16

The U-matrix shows distances between the neighboring units and thus visualizes the cluster structure of the map. The distance between the adjacent neurons is calculated and presented with different colors. A hot (high value) color corresponds to a large distance between the neurons and thus represents a gap between the values in the input space. A cool (low value) color signifies that the feature vectors are close to each other in the input space. Thus, clusters are typically uniform areas of low values in the U-matrix, and high values in the U-matrix indicate a cluster border [17]. As shown in Figure 11, the U-matrix is divided into three uniform areas by two high valued cluster borders. Each component plane in figure 11 shows the values of one variable in each map unit using the same color-coding as in U-matrix. Comparing to the U-matrix in Figure 11, we can see that the major flow makes the largest contributions to the distance differences. Cluster 1 ( $P_1$ ) on the U-matrix is basically the blue area on the major flow plane (with major flow to be the most frequent one, 36-16-12); cluster 2 ( $P_2$ ) is the green area on the major flow plane (with the major flow to be the second frequent one, 36-16-10); and cluster 3 ( $P_3$ ) is the dark red area on the major flow plane (with the major flow to be others). Thus, based on the historical traffic flow patterns that appeared in ZDC16, there are three primary traffic flow patterns

( $P_1$ ,  $P_2$ , and  $P_3$ ), with the major flow to be 36-16-12, 36-16-10, and any others.

As another example, the ZID66 flow features predictability is different from ZDC16, in that only the predictability of number of flows is comparable with the predictability of peak count. Two primary traffic flow patterns are generalized with the number of flows,  $P_1$  with the number of flows to be less than or equal to three, and  $P_2$  with the number of flows to be more than three.

### Assess the Sector Capacity for a Given Traffic Flow Pattern

A usual way of assessing sector capacity is to measure controller’s workload as a function of aircraft count and decide the sector capacity (the corresponding aircraft count) as the workload reaches a predefined threshold, as in CAPAN [2]. The method proposed in [17] avoids measuring controller’s workload directly, which is sensitive and subjective, and avoids predefining the controller’s workload threshold. Figure 12 shows the performance curves of ZDC16 with the major flow 36-16-10 ( $P_1$ ).

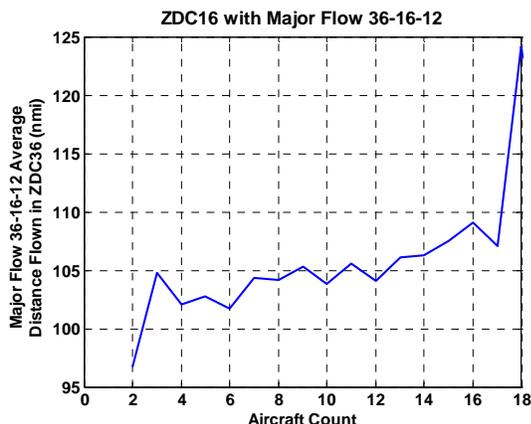


Figure 12. ZDC16 Performance Curves for the Pattern with Major Flow 36-16-12

The performance metric here is the major flow 36-16-12 average distance flown in the previous sector (ZDC36). As we can see, the performance curve exhibits three regimes of operation, opportunity (Peak Count < 3), route structure (3 < Peak Count < 17), and congestion (Peak Count > 17) regime as described in [19]. In the Opportunity Regime, controllers can handle additional aircraft without changing control strategies, but the average distance flown within the sector increases rapidly as the number of aircraft increases. In the Route Structure Regime, controllers start using the route structure to

handle more aircraft without increasing workload and without delaying aircraft in the previous sector. Thus, the major flow average distance flown in the previous sector (ZDC36) keeps stable in the route structure regime. The Congestion Regime begins when the number of aircraft within the sector keeps increasing, where the average distance flown in the previous sector increases abruptly. This jump indicates the sector was congested and the controllers were trying to delay or hold some of the aircraft in the previous sector. The transition point between the route structure and congestion regimes can be considered as an indicator that the controller team has reached the workload threshold. Thus, the corresponding number of aircraft within the sector would be the historical sector capacity for that flow pattern (17 for ZDC16 with the major flow to be 36-16-12,  $P_1$ ). Figure 13 shows ZDC16 performance curves for the other two primary traffic flow patterns ( $P_2$  and  $P_3$ ).

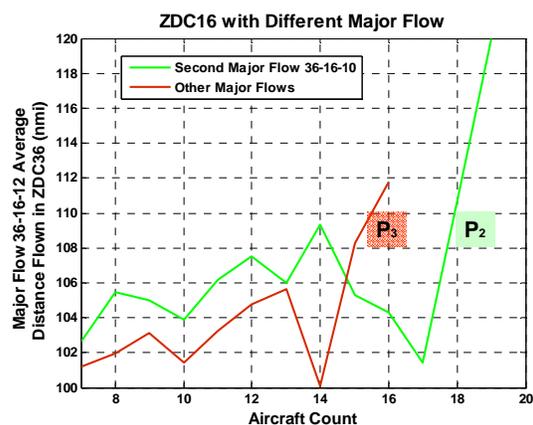
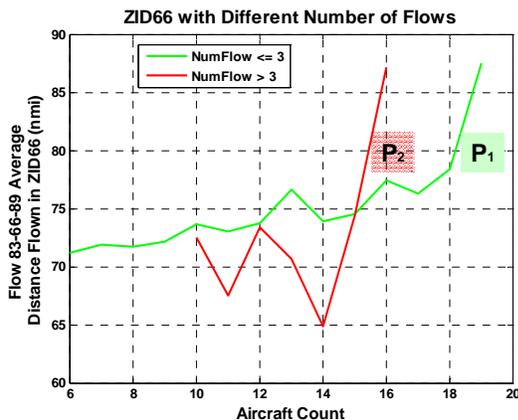


Figure 13. ZDC16 Performance Curves for the Pattern with Other Major Flows

The route structure and congestion regimes are shown in Figure 13. The average distance in the route structure regimes for  $P_2$  and  $P_3$  is different because they have different previous sectors. For the pattern with the major flow to be the second frequent one (36-16-10), controllers start to delay aircraft in ZDC36 when the number of aircraft in ZDC16 reaches 18, so the capacity for ZDC16 with this pattern ( $P_2$ ) is 18. The flow pattern with the major flow to be others is more complex than the other two flow patterns, or maybe controllers are not used to working with this kind of flow pattern in ZDC16 (not the usual “picture”), the congestion regime starts when the number of aircraft reaches 15, so the capacity for  $P_3$  is 15.

Different performance indexes exhibit the transition behavior in different sectors. In ZDC16,

controllers are used to delaying the aircraft in the most frequent flow 36-16-12 when the sector is congested. So, the major flow 36-16-12 average distance flown in ZDC36 exhibits the transition behavior. In ZID66, controllers vector or delay the aircraft in the second frequent flow 83-66-89 within ZID66 when the sector is congested. Figure 14 shows the flow 83-66-89 average distance flown in ZID66 as the function of aircraft count.



**Figure 14. ZID66 Performance Curves**

There are two primary traffic flow patterns for ZID66,  $P_1$  with the number of flows to be less than or equal to three and  $P_2$  with the number of flows to be more than three. For  $P_1$ , controllers do not have to delay the aircraft in 83-66-89 until the number of aircraft in ZID66 reaches 18, so the capacity for  $P_1$  is 18. Historically, there are more than nine aircraft in ZID66 when the number of flows is more than three. Similarly, the capacity for  $P_2$  is 15.

Field observations and interviews with traffic managers and controllers are necessary to verify the results based on the performance data analysis. Controllers' opinions from different sectors can also help us to select the right performance index to examine the transition point from the route structure regime to the congestion regime. The transition behavior of the performance curves can be compared with the controllers' workload cloud as in Figure 1 to cross validate the sector capacity and controllers' workload threshold.

### ***Predicting Sector Capacity with Pattern Recognition***

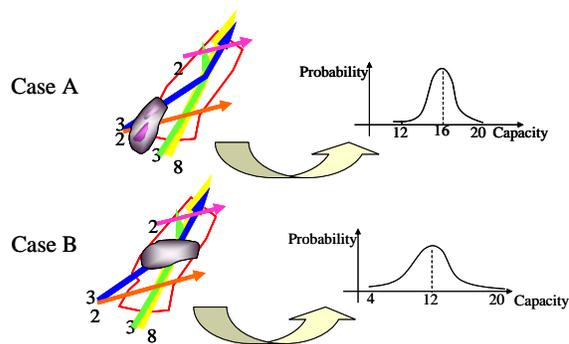
Now that the primary set of traffic flow patterns and their corresponding sector capacities have been identified, the future sector capacity can be predicted through pattern recognition given the predicted traffic flow pattern described by predicted flow features. If

the primary traffic flow patterns are as simple as the ones for ZDC16 and ZID66, pattern recognition can be realized through simple rule matching. Otherwise, the pattern recognition can be realized with SOM as described in [17], finding the best matched unit on SOM U-matrix even if the predicted traffic flow pattern is not the same as any of the historical traffic flow patterns.

### ***Under Severe Weather Impact***

The most important large scale NAS uncertainty is the complicated and sensitive nature of weather's impact on traffic. The biggest advantage of using flow as the object of TFM is to make the sector capacity under weather impact more predictable. It may not be easy or even possible to predict how each individual flight could be impacted by the weather beyond 2 hours without good knowledge of the actual trajectory of each aircraft and the weather. But it is possible and meaningful to predict the flow blockage by the weather when the flow features are predicted in the weather impacted area. Then algorithms can be developed to identify the capacity of the weather impacted area based on the flow blockage by the weather.

With the same size and same shape weather impacting on the different location in the sector, the sector capacity could be different. The flow pattern based sector capacity prediction provides the basis to catch this difference. Figure 15 shows a notional sector capacity distribution under severe weather impact.

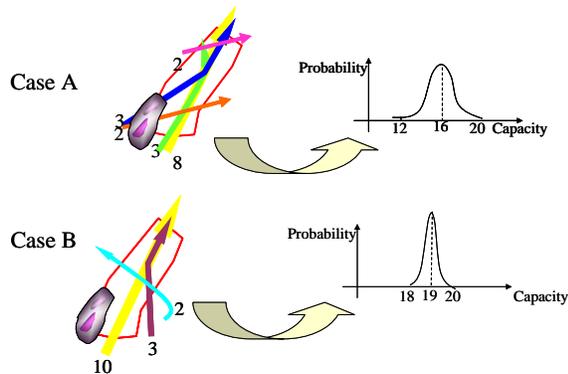


**Figure 15. Sector Capacity under Weather Impact on Different Location**

The severe weather in case A blocked only a corner of the sector and the major flow with eight aircraft in it is still open. So the capacity for case A could be higher and less uncertain than that for case B, where the weather blocked the major flow.

With the same size and same shape weather impacting on the same location in the sector, but if

the traffic flow demand is different, the sector capacity would also be different. Predicting sector capacity as a function of traffic flow patterns also provides the base to catch this difference. Figure 16 shows the notional capacity difference with different flow demand under the same weather impact.



**Figure 16. Sector Capacity with Different Flow Patterns under Same Weather Impact**

The weather impacts the same corner of the sector. However, since there is no traffic on that corner in case B, the sector capacity would not be affected as much as the capacity for case A.

The flow blockage depends on how close the aircraft could/would get to the severe weather, and how accurately the weather products could forecast the severe weather situation. An exploratory study has been implemented by MIT Lincoln Laboratory to develop a “Weather Avoidance Field (WAF)” model [20]. This model quantitatively characterizes pilots’ behavior within or around the severe weather as a function of explanatory variables (such as storm reflectivity level, storm echo top, lightning, and type of convective cells) through observing actual flight tracks around the severe weather area. When this pilot behavior model is available, weather resolution algorithms could be developed to predict how many aircraft could still be handled within the area affected by severe weather, and thus the flow blockage distribution of the severe weather area.

## Conclusion

One challenge in balancing sector demand and capacity in TFM is to accurately measure and predict the sector capacity as the flow structure changes, producing variations in traffic complexity. A novel approach to predicting sector capacity for TFM has been presented. Sector capacity is predicted as a function of traffic flow patterns, which is described with predictable flow features. Given a traffic flow pattern, the sector capacity is assessed through

observing system performance, which avoids measuring controller’s workload directly and predefining controller’s workload threshold.

This approach captures the impact of traffic complexity on sector capacity, and is predictable in the TFM time frame. Given a probabilistic severe weather forecast, the sector capacity can be predicted probabilistically. When combined with probabilistic traffic demand prediction, this can be used to provide probabilistic decision support, thereby explicitly accounting for the significant uncertainties in both traffic and weather prediction at TFM time scales.

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## Keywords

Traffic flow management, sector capacity, traffic complexity, controller workload, predictability, traffic flow pattern

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