Predicting Sector Capacity for TFM

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En Route Congestion

Uncertain weather forecasts indicate current and future loss of airspace capacity...

Uncertain traffic forecasts provide airspace demand...

If demand exceeds capacity, delays will occur and safety may be compromised.

Role of TFM:
Balance demand vs. capacity.
Key function:
Predicting capacity/congestion.
Required:
A good metric of capacity/congestion.
What is Sector Capacity?

Cited from EUROCONTROL Experimental Center Note No. 21/03
EDYCOLO Wednesday 4 July 2001
A Good Sector Capacity Metric for En Route TFM Decision Support…

- Better represents sector workload, and workload threshold, than peak aircraft count with a static threshold (e.g., MAP)
- Is intuitive and relevant to human decision-makers
- Provides insight into congestion resolution options
- Is predictable at useful look-ahead times (30 min – 2 hr)
- Captures impact of convective weather
Dynamic Density Study

- Metric variables included a wide range of different traffic measurement types:
  - Aircraft count and density
  - Sector structure-based (e.g., handoff workload, sector shape)
  - Aircraft-aircraft proximity & conflicts
  - Aircraft state variables (e.g., speed variations, altitude transitions)
- DD metrics were more effective than aircraft count for measuring and predicting controller-perceived workload.
- Many metric variables are essentially unpredictable beyond 30 minutes (example follows)
  - Guidelines for which variables to include in predictive applications
  - Insight into what traffic features are predictable
## Example DD Variables

<table>
<thead>
<tr>
<th>C1</th>
<th>Number of aircraft/sector capacity</th>
</tr>
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<tbody>
<tr>
<td>C2</td>
<td>Number of climbing aircraft</td>
</tr>
<tr>
<td>C3</td>
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</tr>
<tr>
<td>C4</td>
<td>Number of descending aircraft</td>
</tr>
<tr>
<td>C5</td>
<td>Horizontal proximity metric 1</td>
</tr>
<tr>
<td>C6</td>
<td>Vertical proximity metric 1</td>
</tr>
<tr>
<td>C7</td>
<td>Horizontal proximity measure 2</td>
</tr>
<tr>
<td>C8</td>
<td>Vertical proximity measure 2</td>
</tr>
<tr>
<td>C9</td>
<td>Horizontal proximity measure 3</td>
</tr>
<tr>
<td>C10</td>
<td>Vertical proximity measure 3</td>
</tr>
<tr>
<td>C11</td>
<td>Time-to-go to conflict measure 1</td>
</tr>
<tr>
<td>C12</td>
<td>Time-to-go to conflict measure 2</td>
</tr>
<tr>
<td>C13</td>
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</tr>
<tr>
<td>C14</td>
<td>Variance of speed</td>
</tr>
<tr>
<td>C15</td>
<td>Ratio of standard deviation of speed to average speed</td>
</tr>
<tr>
<td>C16</td>
<td>Conflict resolution difficulty based on crossing angle</td>
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Minimally-Useful Prediction Horizon:

R threshold = 0.3 (R² = 0.09)

Correlations between predicted and actual values were done for each look-ahead time; the point at which R falls below 0.3 is plotted.
## Useful Variables (120 min)

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**Predictable variables are aggregate flow features rather than aircraft-to-aircraft interactions.**
Flow Structure to Represent Traffic Complexity for TFM

Traffic Complexity

Air Traffic Control

Controller Workload

Detailed factors (traffic characteristics) for Dynamic Density

Traffic Flow Management

– Aggregate flow variables are more easily predicted at TFM time frames than aircraft interaction variables
– Flow structure is tightly related to controllers control strategy
– Flow structure provides insight into congestion resolution options
Decision Theory under Stress and Uncertainty


Pattern recognition is a proper mental model of traffic managers’ congestion management process.
Proposed Approach

- Identify the primary set of traffic flow patterns for each sector
- Assess the sector capacity for each pattern of the set
- Predict the sector capacity through pattern recognition
Sector Transit Triplets to Represent Flows

1/6/04 14Z ZDC12 Major Triplets (actual traffic)

• Flows are the triplets that have at least two aircraft within the given time period.
Predictable Flow Features to Describe Traffic Flow Patterns

ZDC16 1/18/04 Flow Features Predictability

- Peak
- MajorFlow
- NumFlow
- MergeFlow
- CrossFlow
- ClimbFlow
- DescendFlow
- SingletonRatio

Correlation of Predicted with Actual

LAT=30, LAT=60, LAT=90, LAT=120
Identify Primary Set of Traffic Flow Patterns with Self-Organizing Maps (SOMs)

- Unified distance matrix visualizes distances between neighboring traffic flow patterns, and helps to see the cluster structure of the traffic flow patterns.
- Each component plane shows the values of each feature in the patterns organized in U-Matrix.
Assessing Sector Capacity Through Observing System Performance

ZDC16 with Major Flow 36-16-12

Aircraft Count

Major Flow 36-16-12 Average Distance Flown in ZDC36 (nmi)
Performance Curves of Flow Patterns with Different Levels of Complexity

ZID66 with Different Number of Flows

- NumFlow <= 3
- NumFlow > 3

Flow 83-66-89 Average Distance Flown in ZID66 (nmi)

Aircraft Count

P1 and P2 markers on the graph.
Predict Sector Capacity through Pattern Recognition with SOM

- Given a predicted traffic flow pattern with the flow feature vector $\mathbf{x}(t)$
- The map takes the input vector $\mathbf{x}(t)$ and goes through each map unit to find the Best Matched Unit (BMU) $\mathbf{m}_c(t)$

$$\forall i, ||\mathbf{x}(t) - \mathbf{m}_c(t)|| \leq ||\mathbf{x}(t) - \mathbf{m}_i(t)||.$$ 

- The BMU belongs to $P_2$, so the predicted sector capacity is $C_2$
Example Sector Capacity under Severe Weather Impact (1)

Case A

Case B
Example Sector Capacity under Severe Weather Impact (2)

Case A

Case B
Conclusion

• Sector capacity is still defined in terms of number of aircraft, but as a function of traffic flow pattern to consider complexity.
• Predictable flow features are used to describe traffic flow patterns, which makes the traffic complexity and sector capacity predictable.
• Pattern recognition is intuitive and relevant to controllers and managers decision making process.
• It helps not only on predicting the congestion, but also resolving the congestion
  – through both reducing the demand and increasing the capacity
• Assessing the capacity through observing system performance avoids measuring how hard controllers’ working and predefining the workload threshold.
• Traffic flow pattern provides a basis for capturing weather impact on sector capacity.