

Three Models for Weather Impacted Airspace Capacity Estimation and Forecast

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Abstract – Following NASA’s request to develop and test airspace capacity estimation models of different fidelity (for use in the agency’s air traffic simulation toolsets), we have developed three different models - simple, mid-level, and complex - and have evaluated them on airspace units of different size, from large (Centers), to medium (Areas-of-Specialization) to small (Sectors). The simple model computes capacity degradation of an airspace unit as the area of convective weather coverage within its boundary divided by the unit’s total area. The mid-level Scanning model utilizes our multi-directional scanning algorithm developed in the course of prior research. The most complex model, Probe Reroutes, extends the directional scanning idea by “flying” groups of aircraft on parallel tracks through weather-impacted airspace, rerouting them if needed and finding the viable number of safe-passage “air lanes”; airspace capacity estimate is derived from that. A range of convective weather-impacted days were studied and model capacity estimates were compared to actual occupancy counts in airspace units. Initial validation results are encouraging and they also demonstrate the trade-off between model complexity and accuracy. It appears that capacity estimates become more accurate as we “zoom in” from Centers to Sectors; and the accuracy improves somewhat (but not dramatically) when a finer weather grid resolution is used. Reasonably good airspace capacity predictions can also be made if a forecast product is used as input instead of convective weather diagnostic.

Keywords – Airspace Capacity Estimation; Convective Weather Impact; Scanning Algorithm; Probe Reroutes.

I. INTRODUCTION

Convective weather is a major contributor to excess air traffic delays and costs because it blocks portions of airspace, thereby limiting its capacity. It is very important to be able to correctly estimate this airspace capacity degradation due to convective weather impact – so that avoidable delays and costs are minimized. Appropriate models need to be developed for this task. A model of this kind should ideally be able to produce reasonably accurate capacity estimates for airspace units of different size, from sectors to Centers; work well for a wide variety of convective weather scenarios; be usable with both actual and *forecast* weather for airspace capacity prediction; and

reflect the notion of directional capacity that conforms to directional traffic demand (for instance, east-west traffic flows are impacted by typical U.S. convective weather fronts more than north-south flows). The model should be fast enough to be relevant in fast-time simulation environment and in future real-time decision support tools, so a tradeoff between a model’s complexity and speed needs to be explored. Although promising new methods for airspace capacity estimation have been proposed and inroads have been made into implementing such models in software, many of the above listed requirements remain to be met. The present paper reflects our NASA-funded effort to develop and evaluate several candidate models of different complexity that are a step closer to satisfying these requirements.

II. BACKGROUND

A. Prior Research

Research on weather-impacted Airspace capacity estimation has become particularly active in the last 5-7 years. One fruitful direction of research is being followed in [1-3]. It focuses on route availability when traffic is impeded by convective weather; the related airspace capacity estimation is derived from actual and short-term forecast convective weather information. This directional route- (or flow-) based capacity approach is echoed, and developed further, in [4], which introduces an important notion of probabilistic traffic flow management (including probabilistic sector capacity estimation based on sector’s traffic flow patterns).

A new concept, MaxFlow/MinCut, is introduced in [5] as another take on flow-based sector capacity. A minimum weather-free cross-section (MinCut) of a sector partially blocked by weather is determined mathematically for a specific flow direction; this bottleneck determines capacity as a function of the number of “air traffic lanes” that can fit into the MinCut. The model was applied to hypothetical sectors and a wide range of experimental traffic flows vs. convective weather diagnostic data. This method is applied in [6]: main flows through a sector are identified; flow blockage by weather is determined using the MinCut method (each flow has its own MinCut estimate); and the reduced sector capacity is defined as weighted sum of flow blockage. Another approach to building a simple sector capacity model in terminal airspace is proposed in [7]; it is

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based on a Weather Severity Index which quantifies the degree of weather coverage computed for wedge-shaped regions around the airport’s arrival metering fixes.

All of the above models concentrate on sectors as the “nucleus” airspace unit of the NAS. In [8], we have introduced a new type of airspace capacity estimation model based on our directional scanning algorithm, and tested it on large airspace units, ATC Centers. Our interest was to explore how this model might be applied in strategic Air Traffic Management (ATM). We have now expanded this initial research to include two new airspace capacity models and a range of airspace unit sizes.

B. Weather Data and Airspace Units

In our models, National Convective Weather Diagnostic (NCWD) is used. NCWD is represented by the amount of 5-min reports of significant convective weather, collected on a 4-Km grid covering the National Airspace System (NAS) area. For ATM purposes, this resolution is too fine; it is therefore aggregated into larger hourly “bins” on a coarser hexagonal grid covering the NAS. The specifics of this aggregation are described in [8].

In addition to weather diagnostic, NCWD, we have developed a methodology to convert various convective forecast products into quasi-NCWD format, so that airspace capacity estimation models initially built for actual weather can be seamlessly applied to forecast weather [8, 9]. The probabilistic forecast product we chose for most of our experiments is the Localized Aviation MOS Product (LAMP).

Rather than limiting ourselves to just sectors, we have applied our models to airspace units of three different sizes: sectors, Areas-of-Specialization, and ATC Centers; this would cover both strategic and tactical ATM.

A pre-requisite to realistic airspace capacity estimation of an airspace unit is a good definition of its nominal (unimpeded) capacity. For sectors, Monitor Alert Parameter (MAP) value is the traditionally used, if not ideal, proxy for nominal capacity. For Areas and Centers, other metrics need to be established. For the Areas, our working assumption is that we can still use the sum of an Area sectors’ MAP values. For Centers, we use a lower number corresponding to the peak actual traffic load ever observed, possibly augmented by a small extra buffer. All these nominal capacity metrics, however, need further study.

III. WEATHER AGGREGATION, PERMEABILITY

We aggregate NCWD from 5-min reports on a rectangular 4-Km grid into hourly “bins” on a 180x110 hexagonal grid covering the continental US. This resolution is a default parameter that can be changed; and in fact, our experiments with a finer grid “bins” are described at the end of this paper.

A key concept we use is that of weather permeability for air traffic. Our method for determining the permeability thresholds is based on the research conducted by Sheth et al [10]. In it, actual flight tracks deviating around convective weather were superimposed on convective probability grids using the National

Convective Weather Forecast product (NCWF-6). The PCP (Probability Cut-Off Parameter) thresholds were established as follows: when convective probability reaches PCP, most aircraft flight plan or deviate around such weather areas. Sheth and co-authors found that for 1-hr NCWF-6 forecast, PCP was in the order of 40%; that is, when the forecast puts the probability of severe convective weather (VIP² Level 3 or higher) at 40% or greater, 90% of all aircraft will plan or deviate around the weather area. For 2-hr forecast, the PCP at 90% deviation was approx. 35%, and for 4-hr forecast it was approx. 25%.

This allows us to define the permeability thresholds as follows. The maximum possible hourly convective score for a hexagonal grid cell is derived from the NCWD product and is defined as M . This score would be reached if all 4-Km NCWD grid points inside the hexagon were to report continuous significant convective activity (VIP Level 3 or higher) for the entire hour. We compute the actual (or forecast) highest convective score in the hexagons that are crossed by a scan line. The permeability score of a weather area by this scan line is then defined as the ratio of the highest convective score found in hexagons along the scan line vs. maximum possible convective score of M :

$$P = 100 * \text{Highest_conv_score_along_scan_line} / M$$

IV. THE SIMPLE MODEL

The first capacity model is indeed simple; the capacity of an airspace unit (Center, Area, Sector) is reduced from a sector’s MAP value (or Area’s or Center’s nominal capacity) according to the percent weather coverage in that airspace unit. Nominal capacity for an Area is defined as the sum of its sector MAP values. Nominal capacity for the Centers was determined from empirical observations of peak occupancy counts.

To improve the sensitivity of this model to weather impacts, we have augmented this simple approach as follows. We compute observed weather score W_O in hourly increments:

- For each hexagonal cell whose midpoint is inside the given airspace unit, we check if its NCWD score (or quasi-NCWD score if a forecast product is used) is below or above the permeability threshold.
- If above, we add Maximum Possible Hourly NCWD Score, $NCWD_{Max}$ for this cell to W_O .
- If below, we add the actual NCWD score, $NCWD_{Actual}$, for this hexagonal cell to W_O .

We then compute the maximum possible weather score W_M for the given airspace unit. It is simply $NCWD_{Max} * K$, where K is the total number of hex cells inside the airspace unit. The resulting capacity (as % nominal) for the airspace unit for the given hour is $C = 1.0 - W_O / W_M$.

² Video Integrator and Processor which contours radar reflectivity (in dBZ) into six VIP levels.

V. THE SCANNING MODEL

A. Basic Idea

A simple idea is to estimate the airspace availability of an airspace unit by scanning it in a series of directions [8], e.g., every 20°, using scan lines with spacing commensurate with the granularity of weather grid and the size of the airspace unit (Figure 1). In this example, an airspace unit is scanned in the 320° direction (and the reciprocal 140° direction). Each scan line may or may not encounter convective weather significant enough to block traffic flow along this line. During the scanning, we are looking for the maximum intensity (“ridge”) of convection in the airspace unit along the scan line. This maximum will determine whether this area of weather is permeable by the given scan line.

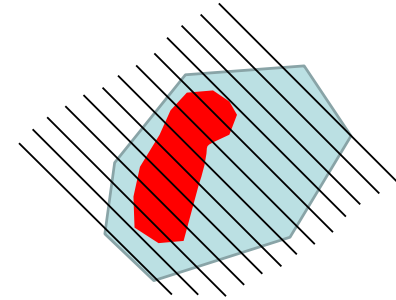


Figure 1. Scanning algorithm illustration

To determine that, we relate the maximum convective score found in the hexagonal grid cells that are crossed by each scan line (and are inside the unit being evaluated) to the maximum possible NCWD score. This ratio, ranging from 0 to 100%, is then compared to the permeability thresholds described in Section III that indicate at what probability or actual intensity of convective weather will most aircraft be likely to deviate (or plan the flight around the weather in the first place). In addition to using just “permeable” and “not permeable” we introduce the notion of weather being “half permeable”.

Then, Directional Airspace Availability percentage along any scan direction is N_{SIGWX} / N , where N_{SIGWX} is the sum of the scan line permeability scores (which can be 0, 0.5 or 1 for each scan line) that cross the significant weather area(s) and N is the total number of scan lines that cross the unit in the given direction. For example, if there is no weather in the airspace, permeability scores of all scan lines will be 1 (“yes”) and the unit’s capacity in this particular direction will be 100% nominal.

B. Converting Directional Airspace Availability into Aggregated Capacity

The scanning method gives us directional airspace availability *percentages* in 18 different directions at 20-degree steps. We multiply them by 1/18th of the airspace unit’s good-weather nominal capacity to obtain initial cut of weather-impacted *absolute* capacity in each direction. This directional capacity is molded, to the extent possible, to reflect directional demand, so capacity in certain directions is increased at the expense of other, less-busy directions (total capacity does not change). This produces finalized directional capacities [8]. The aggregated hourly capacity value is also computed - as the sum of the 18 directional capacities of the airspace unit.

C. “Blended” Capacity Estimation Method

The scanning algorithm introduced above finds the “ridge” (maximum impact) of convective weather along a scan line. The line crosses hexagonal cells; if their NCWD (actual weather) or quasi-NCWD (forecast) score exceeds a certain threshold, the related weather area can be declared not permeable. This can be characterized as an optimistic convective impact estimate (only one hexagonal cell – with the highest NCWD score – matters).

Now let us consider the following. If we know individual probabilities of scan line blockage by hexagonal cells with weather, what is the *cumulative* probability of the scan line being blocked? Such probability can be computed as (1.0 – probability of scan line not being blocked). This latter, in turn, is the product of individual probabilities of the scan line *not* being blocked by hexagonal cells’ weather. Even if we have a few hexagonal cells with low (e.g. 10%) probability of weather, the cumulative probability of a scan line not being blocked will deteriorate quickly (90% after first hexagonal cell, 81% after two consecutive cells, 72% after three consecutive hexagonal cells with only 10% weather probability in each, etc). This calculation reflects a more pessimistic view on airspace capacity.

In actuality, taking the product of the individual probabilities is only accurate if each probability is independent, which it is not. Given the spatial correlation in the convective weather probabilities, we know that using this approach overestimates the probability of the route being blocked [11]. We have therefore adopted the *blended* scan line permeability computation method using the average value of the two probabilities (“ridge” and cumulative) described in this section. As shown in [8], [11], this approach produces better correlation between actual and forecast weather impact estimates. This is the finalized value of airspace capacity according to the Scanning Model.

VI. THE “PROBE REROUTES” MODEL

This model is an extension of the scanning algorithm and a bridge, of sorts, toward the MinCut model described in [5]. It builds upon our Dynamic Airspace Rerouting Tool (DART) developed in 2010 under NASA SBIR³ sponsored research. DART features flight rerouting algorithms that take into account both actual and forecast weather. It employs an original “step-out-and-scan” algorithm to find an economical reroute around dynamic convective weather (it can combine diagnostic and forecast) and, if a reroute is not possible, adds a small ground delay and retries until either a reroute is found or the delay exceeds some threshold (so the flight has to be cancelled).

As part of this research we have developed a concept of Probe Reroutes, described next. Areas of airspace can be “probed” (tested) for permeability using series of probe flights; we can start and end them at any Lat/Long location. As an example, consider ZKC Center in case of minor weather (or high risk tolerance whereby most weather is considered permeable), Figure 2.

³ NASA SBIR Phase 1 #A3.01-9634, “Least-Impact TMIs”, awarded Jan 2010.



Figure 2. Probe flights on parallel tracks traversing ZKC in west-east direction, all weather is considered permeable; no impediment to traffic.

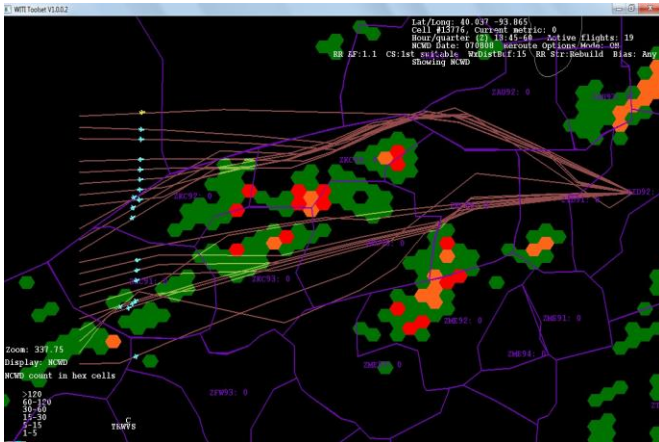


Figure 3. Probe flights on parallel tracks traversing ZKC in west-east direction, some weather is considered non-permeable. Most flights have to be rerouted and/or delayed. There are about 4 lanes available to traffic to traverse ZKC. Blue aircraft are those delayed (i.e., viable reroute at the time of launch is not available, so a delay is assigned incrementally and the reroute is re-attempted); yellow are aircraft not delayed.



Figure 4. Probe flights on parallel tracks traversing ZKC in west-east direction when more weather is considered non-permeable. All flights have to be rerouted and the majority have to be delayed as well. There is only one lane available to traffic in this west-east direction.

Permeable weather is shown in green, non-permeable weather in red. In this example, all flights converge at a point

outside ZKC but they don't have to: they could continue on parallel tracks if that mattered.

In fact, the parallel tracks for the probe flights can be created from the scan lines used in our Scanning Algorithm. If we compute how many distinct lanes of traffic can get through an airspace unit (e.g. Center) in a given direction – vs. total number of probe flights – this could give us an indication of the capacity of this airspace unit. Figures 3 and 4 show the same airspace with increasingly more significant weather impact and the resulting Probe Reroutes in east-west direction.

This idea is applied to airspace capacity estimation as follows.

1. We create series of probe flights along the scan lines, in 18 different directions (at 20-degree steps). The flights are launched some distance away from an airspace unit's boundary and are ended some distance after exiting the airspace unit at the other end. Spacing between parallel tracks depends on the CONUS grid resolution; we reduce it for smaller airspace units such as Sectors.
2. Each group of flights is launched in hourly increments (or 15-min increments if that time step is selected).
3. Directional capacity of the airspace unit is computed as

$$C = N_{\text{Valid}} / N_{\text{Total}}$$

where N_{Valid} is the number of "valid" flights (or rather lanes) that can get through the airspace, navigating around the weather and N_{Total} is the total number of flights along the scan lines covering the width of the perpendicular-to-scan-lines cross-section of the airspace unit.

The formula we use is:

$$N_{\text{Valid}} = N_{\text{Total}} - N_{\text{Delayed}} - N_{\text{Outside}} - N_{\text{Merged}}$$

where

N_{Delayed} is the number of delayed probe flights,

N_{Outside} is the number of probe flights whose reroutes take them entirely outside the airspace unit,

N_{Merged} is the number of probe flights whose reroutes become "bunched" together with another reroute for at least a portion of the flight inside the airspace unit. That is, when multiple flights are forced into a single lane of traffic which of course means reduced capacity, we count each such "bunch" as a single traffic lane.

4. As a last step, directional capacities are averaged, similar to Scanning Algorithm approach⁴.

The rationale for not counting the delayed flights is that, if a flight cannot proceed through the given airspace unit immediately, this means that right now, this hour, the airspace is blocked for it. Even if the flight could proceed later, after a

⁴ Note that we could also consider directional capacity vectors without the averaging; but this would require additional calibration and would expand the analysis material 18-fold.

delay, that delay would be exactly the consequence of the reduced airspace capacity which we are trying to estimate; therefore delayed flights are not counted.

VII. MODEL VALIDATION

A. Limited Scope of Applying the Capacity Models

All three models – Simple, Scanning and Probe-Reroutes – estimate weather-related capacity of airspace units (Centers, Areas, Sectors) in isolation, one by one. They do not attempt to assess the impact of capacity degradation in one airspace unit on other units. This job is left to TFM models (of which capacity estimation is one component). While this approach seems logical and consistent to us, it also creates some difficulties and pitfalls during model validation [8]. We must remember that when we compare degraded capacity with actual occupancy counts in airspace units, the occupancy counts reflect cross-unit dependencies.

B. Airspace Area of Study

We have selected a block of five Centers in middle and Eastern section of the U.S. (Figure 5). We deliberately avoided using Northeast Centers for validation because of “contamination” of actual traffic counts in the airspace by weather related delays at major airports on the Eastern seaboard, as well as by airspace design constraints, especially in New York Center (ZNY).

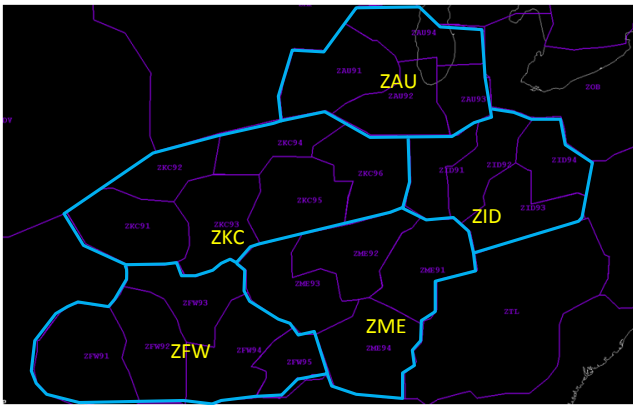


Figure 5. Airspace area of study: Centers (blue) and QuasiAreas (purple)

To create an interim airspace unit between a Center and a sector, we have devised “QuasiAreas”. These notional airspace units are approximately the size of actual Areas-of-Specialization but they only contain high-altitude sectors and are simplified as extruded polygons. Each QuasiArea contains 3-4 sectors (See Fig. 5).

C. Weather Impacted Days

We have focused on the 2008 convective season because traffic volumes were higher than in 2007 or 2009-2010 (good for validation). Further, we have identified those days when significant weather impacted the 5-Center airspace area of study rather than the Northeast. That way, we could obtain “cleaner”

actual occupancy counts for model validation. Figure 6 shows a daily NCWD summary for one of such days, June 9, 2008.

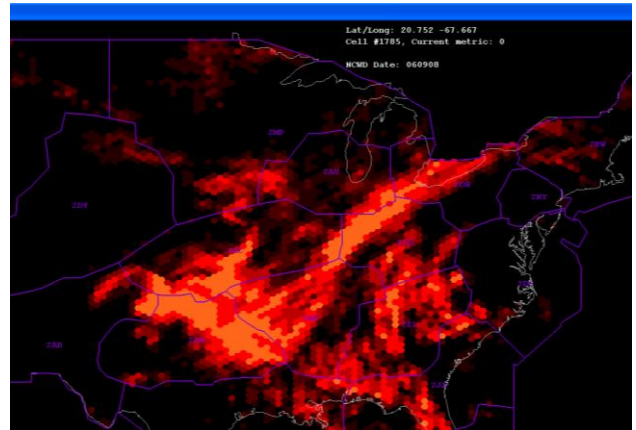


Figure 6. 06/09/08 NCWD daily summary (“smear”)

D. Centers

We began our validation with the largest airspace units, Centers. Figure 7 shows the three capacity estimates (green, blue and red lines) vs. actual occupancy (dashed purple line) at ZAU on August 4, 2008. The Scanning and Probe Reroutes (“RR”) models, especially the latter, reflect lower traffic in the morning due to convective weather.

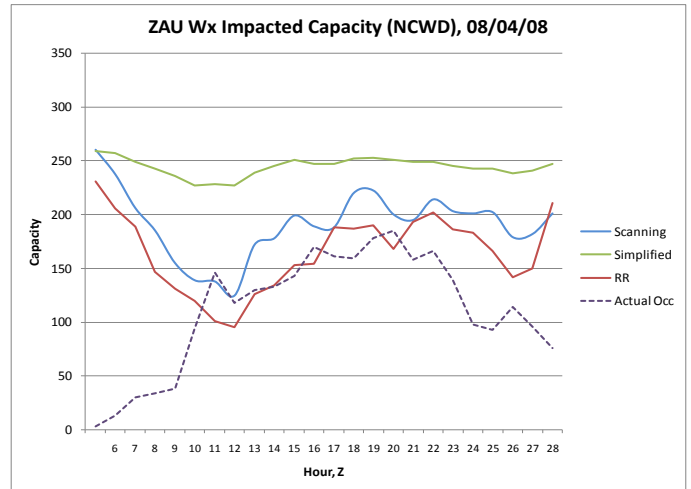


Figure 7. ZAU capacity and occupancy, 08/04/08

Figure 8 shows estimated capacity and actual occupancy for another Center, ZKC, on a different day, 08/07/08. In this case, the Scanning and Probe Reroutes models somewhat underestimate the impact of the weather, while the Simple model’s capacity estimate is excessively optimistic.

Figure 9 refers to afternoon weather impact in ZID airspace on 06/09/08. The decline in occupancy numbers is indicative of convective weather impact, which is what two out of our three capacity models show (the Simple model again being overly optimistic).

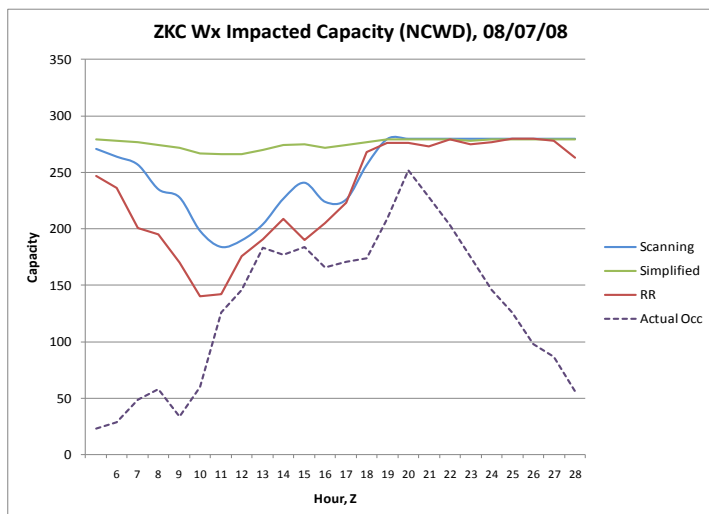


Figure 8. ZKC capacity and occupancy, 08/07/08

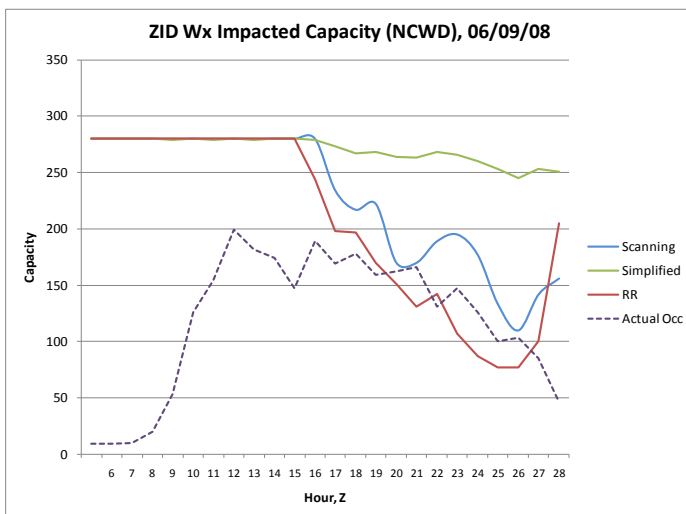


Figure 9. ZID capacity and occupancy, 06/09/08

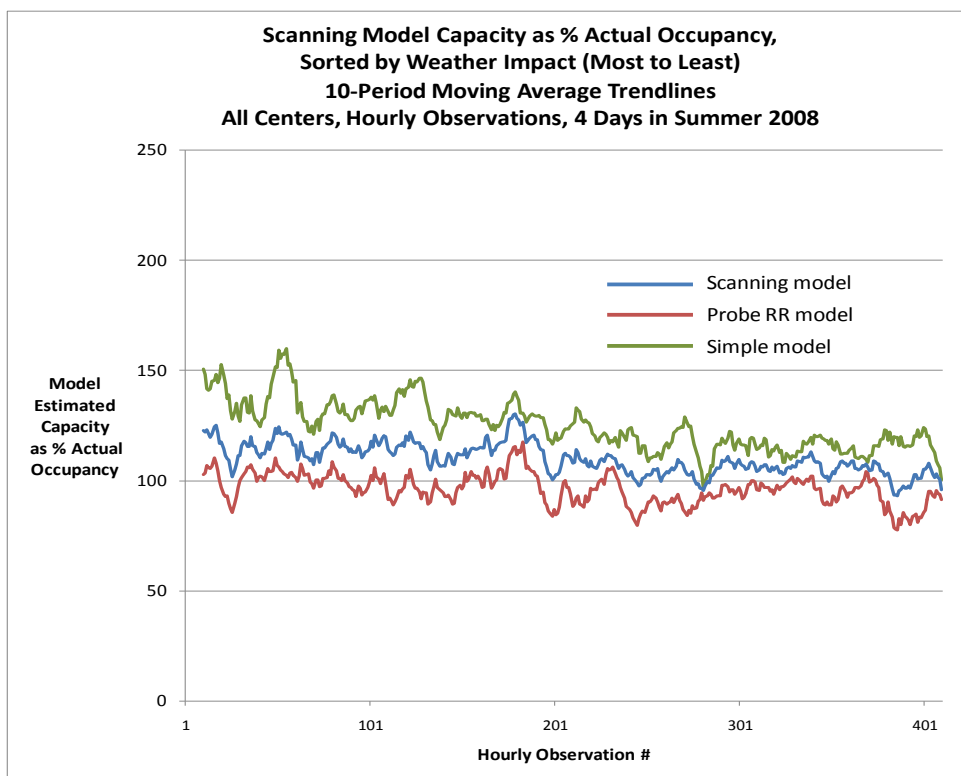


Figure 10. Center capacity-vs-occupancy trend lines

Overall statistics for all four days (hourly Center capacity estimates vs. actual occupancy counts, five Centers, only the busy hours with at least some weather impact) is shown in Fig. 10. To create this chart, we sorted all hourly Center occupancy observations and corresponding capacity estimates during weather impacted hours from lowest to highest occupancy. This corresponds approximately to sorting from most weather impact (typically associated with lowest airspace occupancy during otherwise busy hours) to least weather impact. We have then re-scaled our model-based airspace capacity estimates by showing

them as % of actual occupancy for the same Center / hour. For example, if Center occupancy was 220 and Scanning model capacity estimate for that Center/hour was 260, this is converted to $260/220 = 118\%$ on our new scale. To make viewing easier, we only display 10-period moving average trend lines; this is what Fig. 10 illustrates.

From this we can see that the Scanning and Probe-Reroutes models' capacity estimates (blue and red trend lines, respectively) are noticeably closer to actual observations (the 100 horizontal benchmark line) than the Simple model's estimates: the latter overestimates available airspace capacity by a wide margin.

Figure 10 shows the difference in airspace capacity estimation magnitudes. The correlations, which indicate if our model capacity estimates change in sync with actual occupancies, are also an important metric. In case of Centers, the

correlation coefficients ("R") between model estimates and actual occupancies for all three models are: 66% (Scanning), 60% (Probe Reroutes) and 52% (Simple).

E. QuasiAreas

The following two Figures (Fig. 11, 12) show QuasiArea capacity estimates and actual occupancies for two out of ZID's three QuasiAreas, ZID1 and ZID2, on 06/09/08. When compared to ZID Center chart for the same day (see Fig. 9), we can see that the models now reveal more nuances in convective

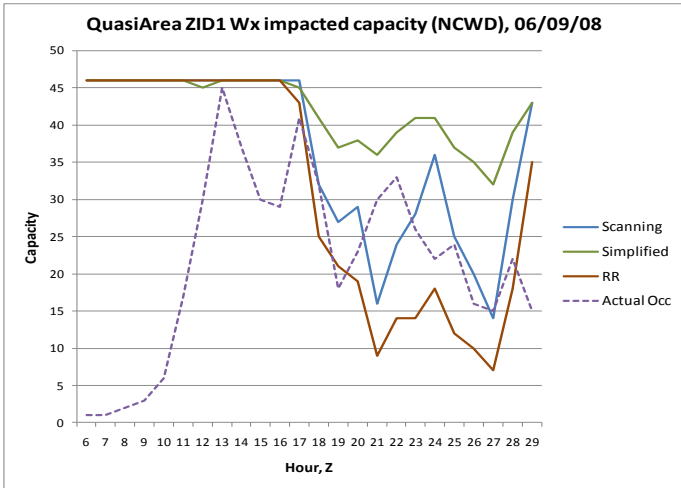


Figure 11. ZID1 QuasiArea capacity and occupancy

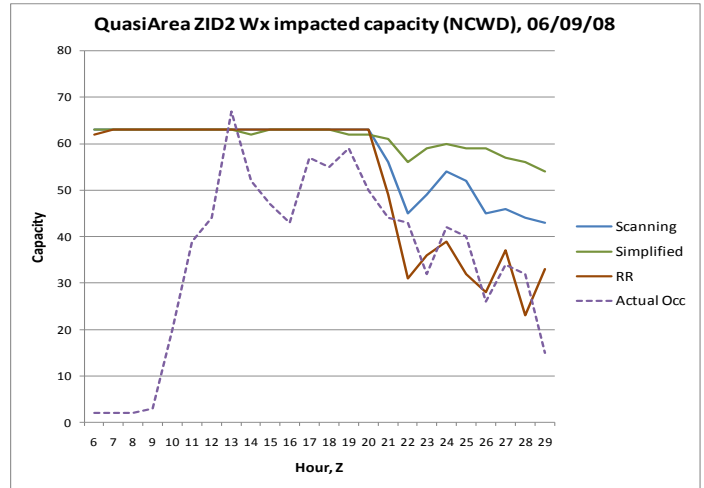


Figure 12. ZID2 QuasiArea capacity and occupancy

weather impact distribution across the area-like portions of the Center, in both spatial and temporal dimensions.

Figure 13 shows the model-vs-observations trend lines for QuasiArea capacity estimates (compare to Fig. 10, Centers).

The Probe Reroutes model produces the closest estimates vs. actual observations, followed by the Scanning model; the Simple model is behind the other two as far as its weather impact prediction quality is concerned.

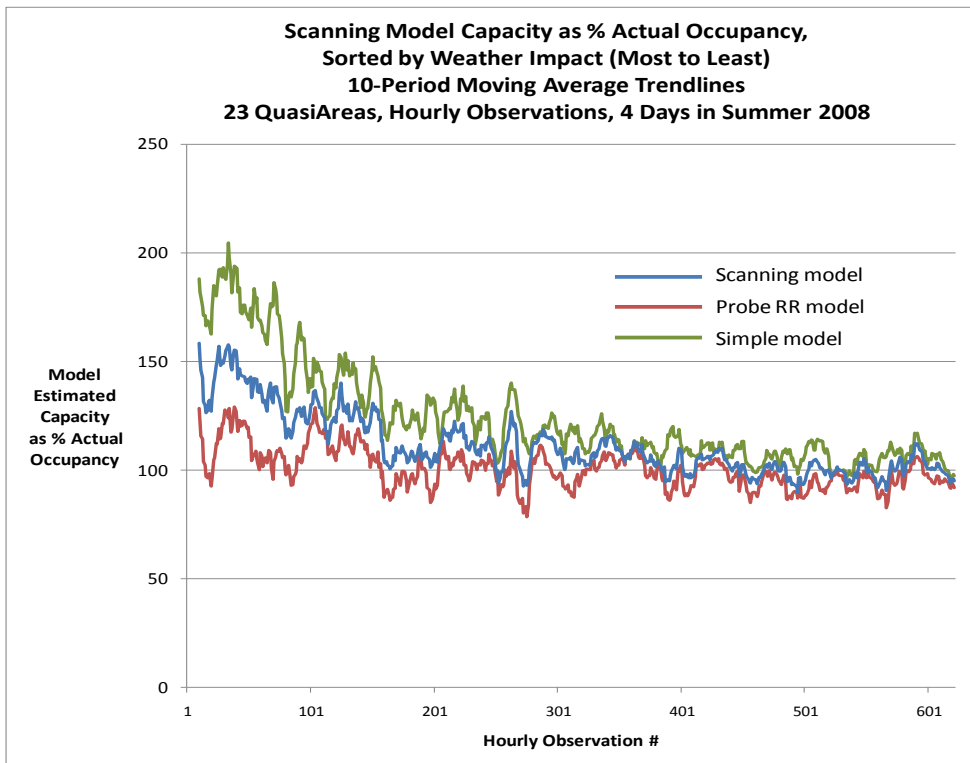


Figure 13. QuasiArea capacity-vs-occupancy trend lines

The QuasiArea model-vs-observations correlation coefficients (“R”) for all three models are: 79% (Scanning), 78% (Probe Reroutes) and 68% (Simple). We see that QuasiArea capacity model estimates differ more significantly from actual observations when weather impact is highest (the first 150 or so observation points in Fig. 13). The variability of model-vs-observation estimates is also higher.

F. Sectors

Continuing downward in terms of airspace unit size, the next two Figures (Fig. 14, 15) show Sector capacity estimates and actual occupancies for some of ZID’s high-altitude sectors on 06/09/08. Note how Simple model’s sector capacity estimates come closer to those made by the Scanning model (if compared to estimates for Centers and QuasiAreas).

Figure 16 depicts the trend lines for Sector capacity model estimates vs. actual observations; compare to Fig. 10 and 13. Again, only hours with busy traffic and some weather impact are considered. We can see that for sectors, the Probe-Reroutes model tends to slightly over-estimate weather impact (i.e., capacity loss) but is overall more accurate than the other two models. The Scanning model does a better job when weather impact is moderate (blue trend line is closer to 100 benchmark in the middle of the observation range).

The Probe Reroutes model produces the closest estimates vs. actual observations, followed by the Scanning model; the Simple model is behind the other two as far as its weather impact prediction quality is concerned.

The correlations (“R”) for model-vs-actual-occupancy estimates for sectors are: 83% (Scanning), 81% (Probe Reroutes) and 75% (Simple).

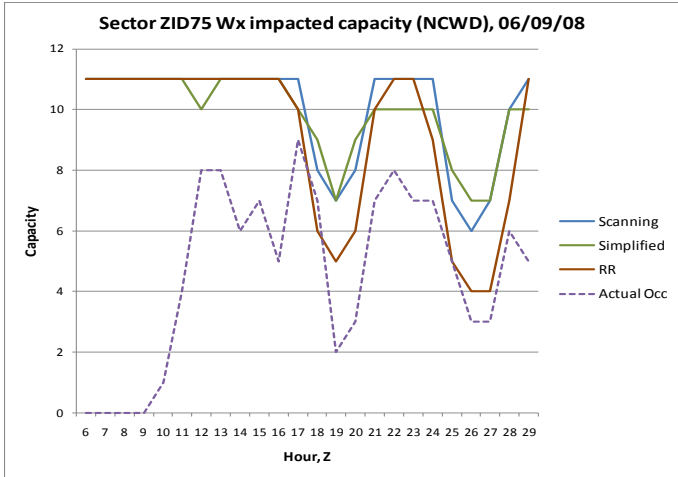


Figure 14. ZID75 sector capacity and occupancy

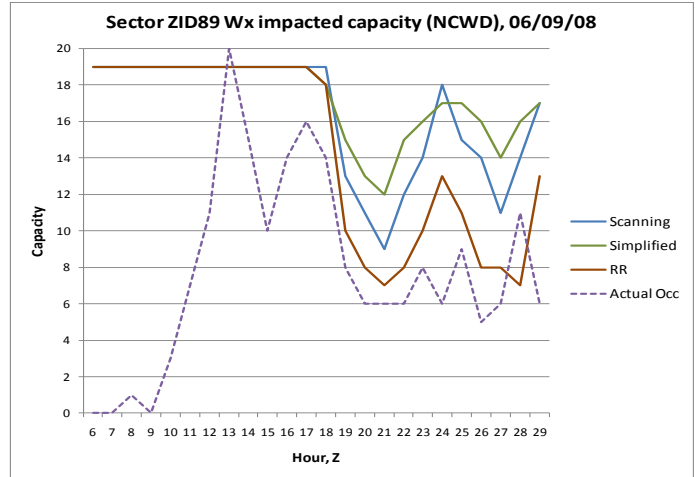


Figure 15. ZID89 sector capacity and occupancy

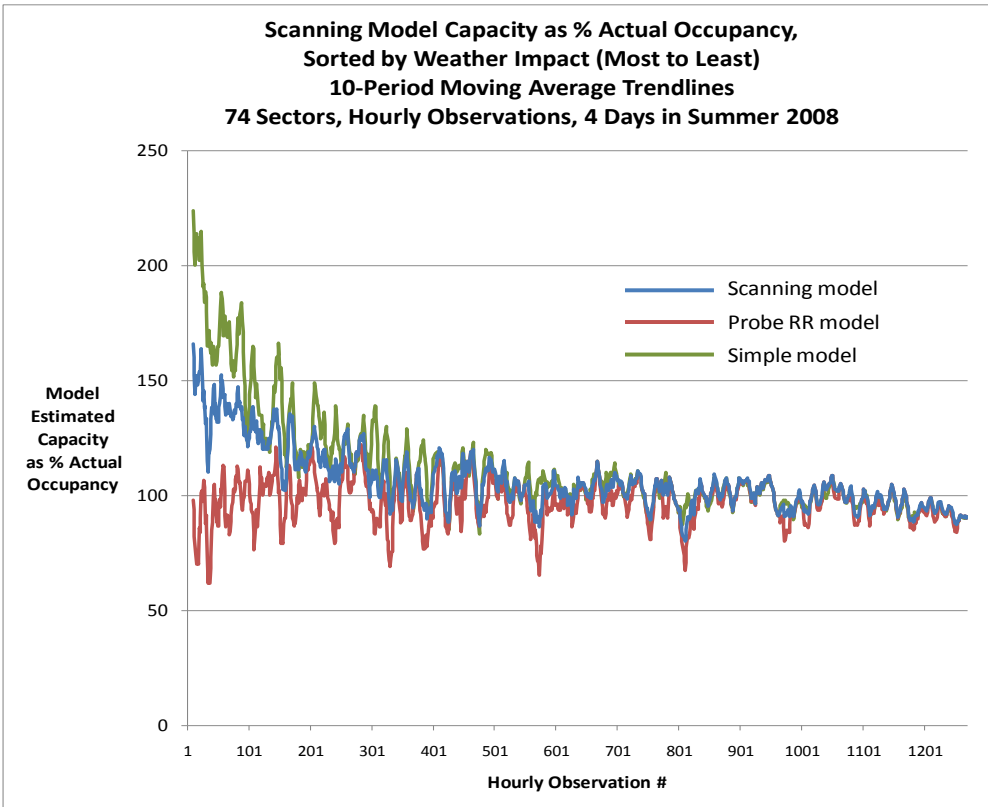


Figure 16. Sector capacity-vs-occupancy trend lines

It is interesting to note that, while the correlations are higher for sectors (e.g., Fig. 14 and 15) than for QuasiAreas and especially Centers, we do still see occasional significant discrepancies between the magnitudes during high weather impact hours (Fig. 16). But, since the correlations are high, it may be possible to achieve closer match between model capacity estimate and actual occupancy magnitudes by applying additional calibration through model parameter fine-tuning.

VIII. 2D VS. 3D WEATHER

Our convective weather data was only available in 2D (no echo tops information). While echo tops are important in determining airspace capacity, in the summer months – the time frame for our analysis – echo tops in areas of significant weather are typically very high (at least 35,000 Ft, often 40,000+ Ft). Few aircraft will fly above these areas of weather: the majority will deviate around it – or will be directed so by the ATC. Our observations of multiple days’ worth of actual aircraft tracks confirm that. Therefore, while not ideal, 2D weather data is usable for initial model calibration.

IX. GRANULARITY ANALYSIS

An obvious question arising from the above results is how they are affected by the granularity of our weather translation model’s grid.

To generate results presented so far in this paper, we used a 180x110 hexagonal grid covering the NAS as a default (approximate diameter of the hexagons is 18 NM). This grid resolution corresponds to the standard WITI grid [9]. To test our model behavior at finer grid granularity, we doubled the accuracy to a 360x220 grid and reduced spacing between scan lines and probe reroutes by half as well, and ran the same set of weather impacted days to obtain airspace unit capacity estimates. Our initial finding is that there is an improvement in accuracy, although it is not dramatic (but the models take almost three times longer to run).

For example, Figure 17 shows a comparison of the lower-granularity model (left) with higher-granularity (right) for QuasiArea ZME3. For reference, Figures 18 and 19 show the hourly snapshot of convective weather in that area at around 0800Z with 180x110 and 360x220 NCWD grids, respectively.

grid granularity is not (purple arrow, Fig. 19). This causes a greater capacity loss at higher grid granularity because the weather now blocks the entire northern section of ZME3 QuasiArea.

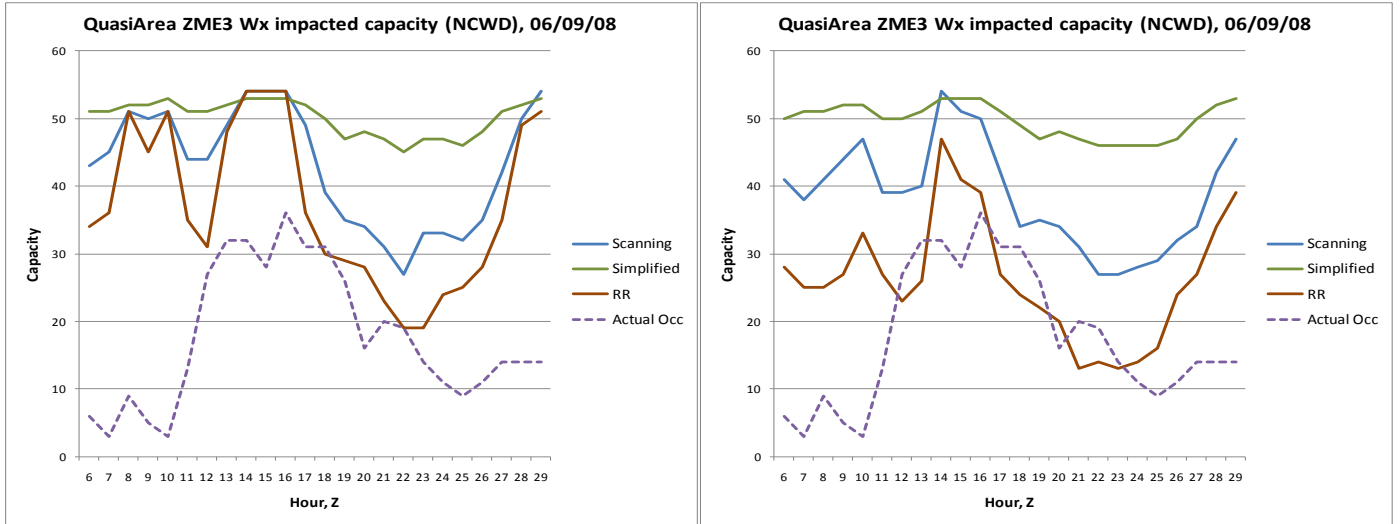


Figure 17. QuasiArea capacity estimates using coarser (180x110, left) and finer (360x220, right) weather grids



Figure 18. NCWD weather at 0800Z on 06/09/08, 180x110 hex grid

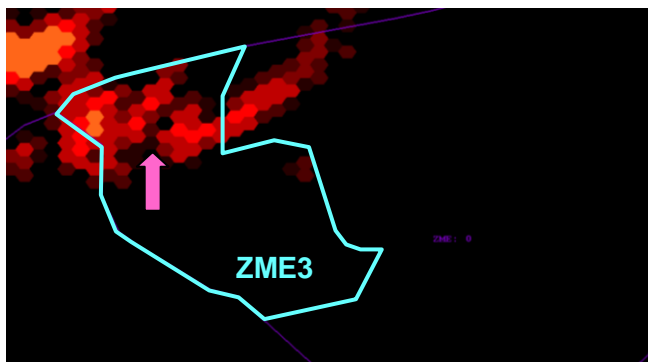


Figure 19. NCWD weather at 0800Z on 06/09/08, 360x220 hex grid

Compare the difference in weather depiction (Fig. 18, 19) to the difference in airspace capacity estimate at 0800Z in Fig. 17, Left vs. Right. For instance, at lower grid granularity the north-south corridor marked by a green arrow in Fig. 18 is permeable for probe flights, while the same corridor at higher

X. USING FORECAST WEATHER

The models presented above can be applied to airspace capacity *forecasting* if, instead of actual weather (diagnostic) we use forecast weather. We have developed Weather-to-TFM-Constraints translation models for a variety of convective forecast products such as LAMP [8, 11]. The quality of airspace capacity estimation depends on the forecast accuracy. Generally, the difference between capacity “diagnostic” based on actual weather (NCWD) and capacity forecast based on LAMP tends to increase - and exhibit greater variability - as the airspace unit’s size decreases from Center to Area to Sector, which is to be expected. Fig. 20-22 show sample diagnostic / forecast capacity estimates for an individual sector.

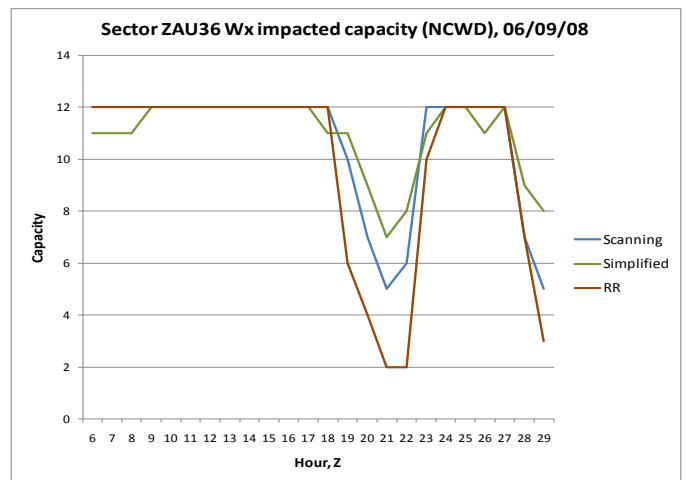


Figure 20. NCWD-based capacity estimate, sector ZAU36, 06/09/08

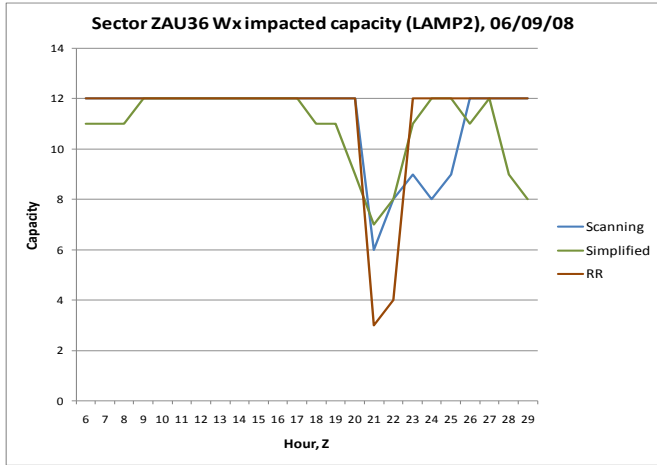


Figure 21. 2-hr LAMP based capacity forecast, ZAU36, 06/09/08

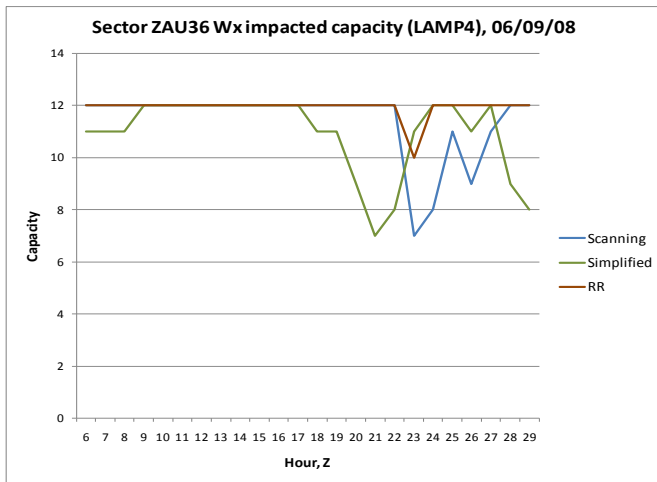


Figure 22. 4-hr LAMP based capacity forecast, ZAU36, 06/09/08

XI. CONCLUSIONS

We have developed three airspace capacity models of increasing complexity and have tested them on a variety of weather scenarios applied to airspace units of different size.

Initial validation shows that the mid-level (Scanning) and the complex (Probe Reroutes) models produce reasonably good capacity degradation estimates for all airspace unit sizes, although the trend is for model accuracy to improve as the size decreases. For sectors, the Scanning model and especially the Probe Reroutes model perform well; the latter tends to exhibit slightly higher variance, leaning toward over-prediction of weather impact, but can reflect localized weather impacts better on some occasions. The Simple model performs better for sectors than for larger units but its overall utility is questionable.

In addition to using convective weather *diagnostic*, we have developed weather translation methods for a number of convective *forecast* products, so that our models can be used for airspace capacity degradation *prediction*. This makes them

potentially usable in ATM decision support tools. An added benefit of the Probe Reroutes model is that it could help traffic managers identify viable flight paths through weather impacted airspace.

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