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INTEGRATION OF TERMINAL AREA PROBABILISTIC METEOROLOGICAL FORECASTS IN NAS-WIDE TRAFFIC FLOW MANAGEMENT DECISION MAKING

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Abstract

This paper we describe how we use meteorological measurements and forecasts to model the impact of ceiling, visibility and surface winds on airport capacity. These impacts can be modeled both as deterministic influences on airport capacity and stochastic forecasted airport capacities. These impacts can be used, along with en route airspace impact models, in traffic flow management solutions. Our preliminary results suggest that traffic flow management is influenced by the airport congestion sensitivity. This parallels our earlier findings that traffic flow management is also influenced by the airspace congestion sensitivity.

Introduction

Many of the advanced air traffic management and traffic flow management concepts envisioned for future implementation require advanced meteorological data products. Weather has several important effects on system capacity so it is important to integrate these effects into the air traffic management decision making. This means that a wide range of automated meteorological forecast products, with forecast horizons ranging up to several hours, will be required for use in air traffic management tools.

Meteorological forecasts are uncertain and while improved forecast accuracy is desired, it is important for the uncertainty of the forecasts to be described for proper use in air traffic management forecasting and decision making. This is the subject of on-going research and key questions include: How should forecast uncertainties be described? What update rates and forecast horizons are required or desirable? How sensitive is the performance of the air traffic management to forecast accuracy? In this paper we focus on meteorological effects in the terminal area, and how these impact nationwide traffic flow management.

The air traffic management research community has developed detailed methods and practices for modeling terminal area and airport capacity. These methods model airport capacity in both visual and instrument conditions. Whether visual or instrument conditions prevail depends on the local ceiling and visibility distances. Beyond this, there are several meteorological phenomena that can reduce airport capacity.

High head winds can reduce final approach ground speed, and therefore inter arrival spacing and capacity. High cross winds make airport operations more difficult and reduce capacity. Very high winds can shutdown the airport altogether. Similarly, very low ceiling and visibility can shutdown the airport arrival capacity.

Heavy thunderstorms can also shutdown the airport if overhead, and otherwise can reduce the terminal area airspace capacity, or interfere with arrival or departure traffic streams. And local lightning can slow or shutdown ramp activities such as refueling. Degraded airport surface conditions, such as wet pavement, slows braking and turning, tends to increase runway occupancy time and so can reduce runway capacity. En route icing conditions causes departure delays for deicing operations. On the positive side, emerging wake vortex sensing and tracking technologies may be able to increase airport capacities in the future, in favorable conditions.

While all these effects are important, in most cases the most persistent effects are the local ceiling and visibility, and surface winds. In this paper we describe how we have used forecasts of these phenomena in our probabilistic traffic flow management experiments. And we provide preliminary results.

There are two key questions that must be addressed when using meteorological forecasts, such as ceiling, visibility and winds, in an air traffic management planning and decision support tool.

First, the impact of the meteorological phenomena on the system capacity must be understood. Models must be developed that translate the meteorological data to capacity data. These models are useful both for understanding the capacity under known conditions, such as the current capacity of an airport, as well as predicting the capacity under forecasted conditions.

Second, the uncertainty of the meteorological forecast must be understood. Models must be developed that characterize the forecast as a random variable rather than a deterministic value. These models should account for all available information that is relevant and influences the forecast accuracy. These may include, for example, a forecast accuracy, confidence or skill parameter, meteorological descriptions of the structure and intensity of the forecasted weather, the forecast look ahead time, seasonal and regional effects, and so forth. The end result is a stochastic version of the meteorological forecast, such as in the form of a probability distribution function.

In addressing these two key questions we use both rational (model-driven) and empirical (data-driven) approaches because both have strengths and weaknesses. The weakness of purely rational approaches is that they are oblivious to real-world mechanisms that are not captured in the model. The weakness of purely empirical approaches is that they rely on the particular scenarios in which the data were collected. Those scenarios may not be generally descriptive. For instance, empirical approaches cannot measure capacity, they can merely measure traffic throughput, and it is difficult to know whether the throughput was capacity-limited or demand-limited. Throughput may appear to be low merely because demand was low. Also, it is likely that pilots sometimes avoid weather not because they must, but because they can. Sometimes avoiding the weather is a preference rather than a requirement. This suggests that weather impacted capacity can be fuzzy, or alternatively that it is higher than the measured throughput indicates when alternatives are easily available.

The impact of final approach headwinds on airport capacity serves as an example of how we use both rational and empirical approaches. Headwinds cause the aircraft groundspeed to decrease. Therefore, for aircraft flying at a given airspeed profile, with given in-trail spacing on final approach, the presence of a headwind increases the inter-arrival time spacing, and thus reduces the runway throughput. This model compares well with the empirical throughput data, though it predicted slightly higher capacity reduction. This could be explained by several possible mechanisms not captured in the model. For instance, pilots sometimes increase airspeed in the presence of high headwinds. The model is easily adjusted to better fit the data.

In this paper we present our research in modeling ceiling, visibility and surface winds effects and forecasts. We present how we use these models in our probabilistic traffic flow management decision support tool with results and performance sensitivities.

Translation of Terminal Area Weather to NAS Capacity Impact

The impact of final approach headwinds on airport capacity serves as an example of the importance of using both rational and empirical approaches. Headwinds cause the aircraft groundspeed to decrease. Therefore, for aircraft flying at given airspeed profile, with given in-trail spacing on final approach, the presence of a headwind increases the inter-arrival time spacing, and thus reduces the runway throughput. This model compares well with our empirical throughput data, though the model predicted slightly higher capacity reduction.

This could be explained by several possible mechanisms not captured in the model. For instance, pilots sometimes increase airspeed in the presence of high headwinds. Also, the wind data include the cross wind component, which means the headwind is sometimes less than the wind speed value input to the model. We are currently upgrading our model to include wind direction as well as magnitude.

Our results also show that there are outlier airports, such as San Diego and Boston. In addition to the headwind, particularly heavy crosswinds can reduce runway capacity and even cause temporary shutdown. Previous research has shown the significant impact of these phenomena [1].

Wind shifts cause airport configuration changes which effectively shutdown the airport for 20 minutes or more. This may cause significant en route delays. Predicting airport configuration selection, however, is complicated by several factors. First, the exact time of an airport configuration change due to wind is often carefully selected according to the traffic pattern, including both tactical and daily flow patterns. Washington Dulles airport (IAD), for instance, switches from a morning to an afternoon configuration due to heavy international traffic arrivals. Also, some large airports have more than a single dominant configuration, and in major urban areas configuration changes are typically coordinated with other nearby airports. Finally, when the wind is weak the airport configuration may not change with a wind shift.

This means that advanced TFM methods need good predictions of airport configuration changes. We need to correlate airport configuration change events with traffic and surface wind data, both nowcast and forecast, to construct configuration predictors.

Airport ceiling and visibility (C&V) is another important meteorological cause of capacity reduction and en route delays. When the ceiling is higher than 3,000 ft and visibility is greater than 5 miles then visual flight rules (VFR) prevail. If either the ceiling or visibility is less then marginal VFR (MVFR) prevails, unless the ceiling is below 1,000 ft or visibility is less then 3 miles in which case instrument flight rules (IFR) prevail. In practice IFR typically extends across MVFR as well.

Limited ceiling and visibility reduces airport capacity. This impact varies between airports and we use airport-specific capacity data for visual and instrument conditions. For instance, San Francisco (SFO) airport has closely spaced parallel runways. In clear weather, SFO runs simultaneous (side-by-side) landings, but in fog conditions SFO must maintain a minimum diagonal spacing between the adjacent arrivals thus reducing capacity.

In addition to winds and C&V, airport capacity is also reduced by wet or icy runway conditions. These cause longer taxi times, which in turn cause longer final approach spacing, thus reducing runway capacity. Airborne icing conditions cause ground delays for departures when de-icing is required. Extremely cold temperatures or lightning slow ramp operations, and extremely hot temperatures can make take-off impossible because of insufficient lift resulting from reduced dynamic pressure.

Capacity Uncertainty Modeling

The sections above describe capacity impact models for the meteorological phenomena. Given a meteorological state, the models compute the corresponding expected capacity. But when forecasting NAS capacity the weather data are available only as a forecast. An important step in probabilistic TFM is the forecasting of system capacities over the duration of the national TFM planning window (approximately 1–8 hours). Regardless of forecasting accuracy level, TFM decision making needs to know the uncertainty level. A capacity forecast with high certainty, even if low capacity, is often more useful for TFM decision making than a high capacity forecast that has low certainty. It is important that capacity forecasts provide the level of certainty in addition to the expected value of the capacity. This can be done by providing the forecast in the form of capacity probability distribution functions (CPDFs) of the terminal area and of the en route airspace.

For instance the fog at SFO has an uncertain burnoff time. When it does occur, the fog burnoff is relatively rapid, so it is difficult to use immediately the additional capacity which suddenly is available. If traffic is scheduled with the assumption that the fog will burnoff at a particular time, then there is a risk of requiring airborne delay or even costly diversions. Substantial research efforts have focused on both the problem of predicting fog burnoff time and optimizing TFM decision making given the fog burnoff uncertainty [2,3]. Given the demand level during the period when the SFO fog typically burns off, there is a relatively high benefit to solving this problem. What makes it particularly challenging is that the capacity reduction comes at the very end of the flight for SFO arrivals, and the only alternatives (i.e., diversions) are costly.

Aside from the particular case of fog burnoff, we develop uncertainty models for C&V forecasts, in general. The ceiling and visibility forecasts for the major airports are available as part of the terminal area forecast (TAF) product. This gives ceiling and visibility forecasts over specified time windows. We archive TAF forecasts and the corresponding METAR reports of the surface weather that occurs. We compare these data to analyze the TAF forecast uncertainty. Figure 1 shows that the visibility forecast has a standard deviation of about one mile which is not very sensitive to the forecast look ahead time (LAT). In other words, the TAF visibility forecasts are typically good for several hours into the future.

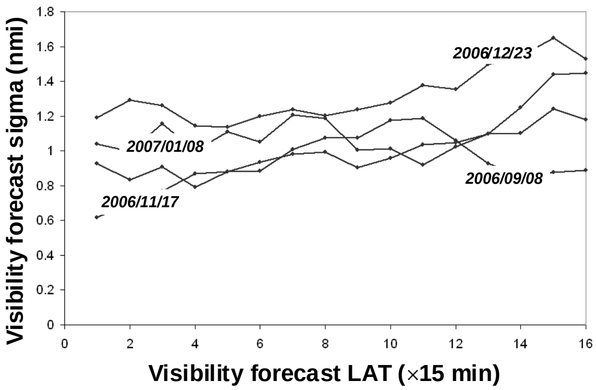

Figure 1. Visibility forecast error vs LAT

The uncertainty of the TAF visibility forecasts is, however, sensitive to the weather conditions. Specifically, as Fig. 2 shows, clear conditions are easier to predict than low-visibility conditions. Fig. 2 shows that the one mile standard deviation in Fig. 1 is typical of clear conditions, but in poor visibility conditions the standard deviation rapidly increases to about 1.75 miles.

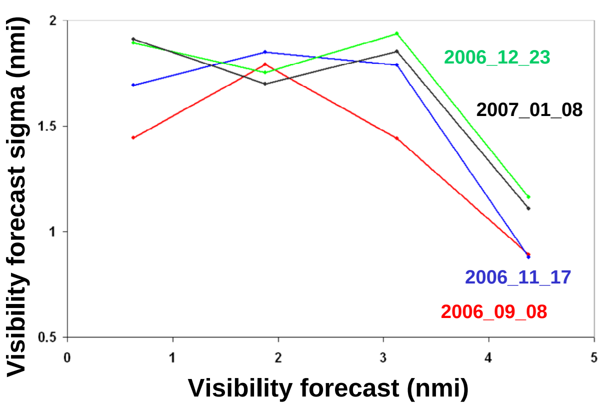

Figure 2. Visibility forecast error vs visibility

The ceiling forecast shows similar trends, and we use this information to construct PDF models for the visibility and ceiling forecasts. The surface wind forecast also has only a minor increase with the forecast LAT, and is overall quite accurate, with standard deviation less than 2 kt, as Fig. 3 shows for our January 7, 2007 data sample.

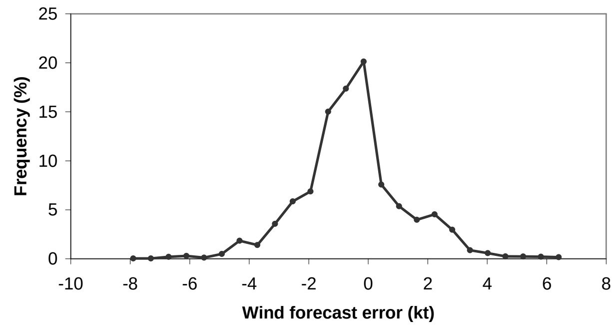

Figure 3. Wind forecast error histogram

As with the ceiling and visibility forecasts, the accuracy of the surface wind forecast varies with the wind conditions, as Fig. 4 shows, again for January 7, 2007 data.

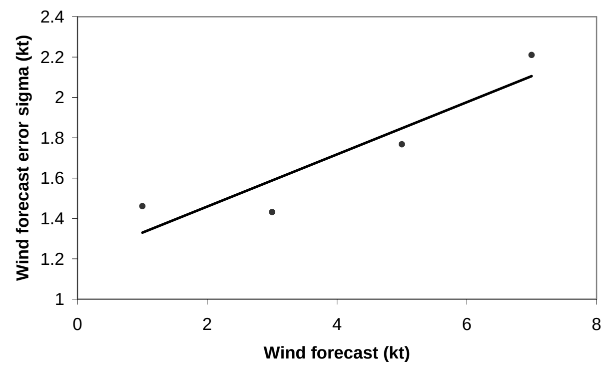

Figure 4. Wind forecast error vs wind speed

Multi-modal CPDFs

Beyond summing to unity, a CPDF may take on a wide variety of forms, ranging from a single value with probability of one to a multi-modal form. As Fig. 5 illustrates, airport capacity PDFs, for instance, are bi-modal when both visual and instrument conditions (VMC and IMC, respectively) have non zero probabilities.

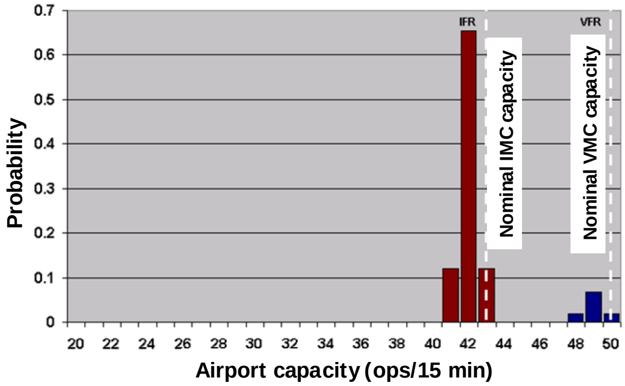

Figure 5. Example bi-modal airport CPDF

It is also possible that NAS loading PDFs may be multi-modal. The presence of multi-modal CPDFs and LPDFs may influence the performance of TFM solutions determined by TFM optimizers. Such algorithms need to be tested with multi-modal PDFs.

NAS TFM Decision Making

We constructed weather impact models that translate (i) C&V and surface winds into airport capacity reductions and (ii) C&V and surface winds forecasts into airport CPDFs. We implemented these impact models in our probabilistic NAS platform (PNP) tool and our *ProbTFM* TFM decision support tool. These tools use real-time data for TFM decision support, or use archived data in a fast-time mode to replay historical days. For this experiment we used Nov. 12, 2006, which was a light-moderate traffic day and, as Fig. 6 illustrates, a moderate-heavy convective weather day.

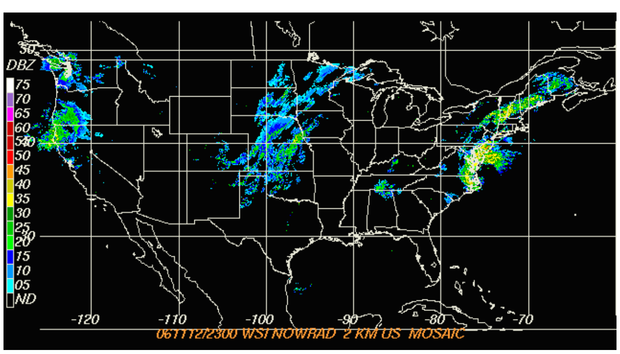

Figure 6. Nov 12, 2006 convective weather

As Fig. 7 shows, according to our models the airport capacity weather impact was predominantly on the east coast on Nov. 12, 2006. The top 10 airports, in terms of overall capacity reduction throughout the day, were New York-JFK, Providence, Buffalo, Washington-Dulles, Tampa, Boston, Windsor Locks, Orlando, Raleigh-Durham and Teterboro.

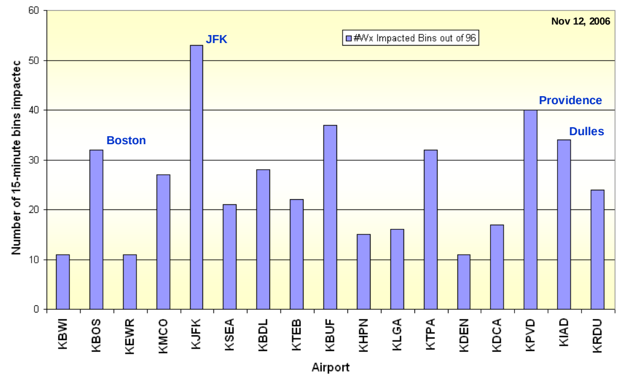

Figure 7. Nov 12, 2006 airport impacts

While the New York area was primarily impacted in the first half of the day, Boston was impacted during the afternoon and evening, heavy traffic hours, as Fig. 8 shows.

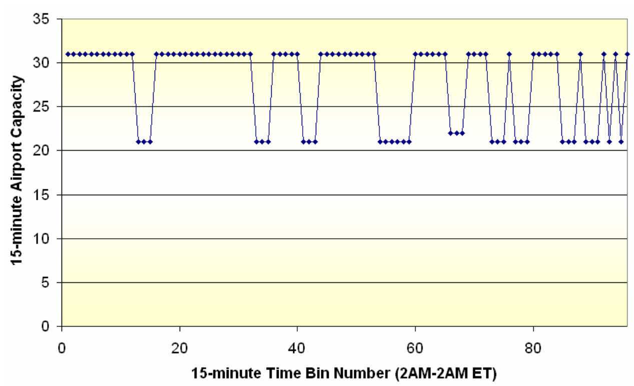

Figure 8. Nov 12, 2006 BOS capacity

Figure 9 shows our November 12, 2006 ProbTFM NAS-wide results. We ran three experiments, resulting in three NAS performance tradeoff curves. Each tradeoff curve illustrates the tradeoff between airspace congestion and system delay (see [4] for details). In our three experiments we used an airport congestion tolerance factor of zero, medium and high, respectively. Also shown is the observed sector congestion level and system delay, derived from ETMS and ASPM data, respectively.

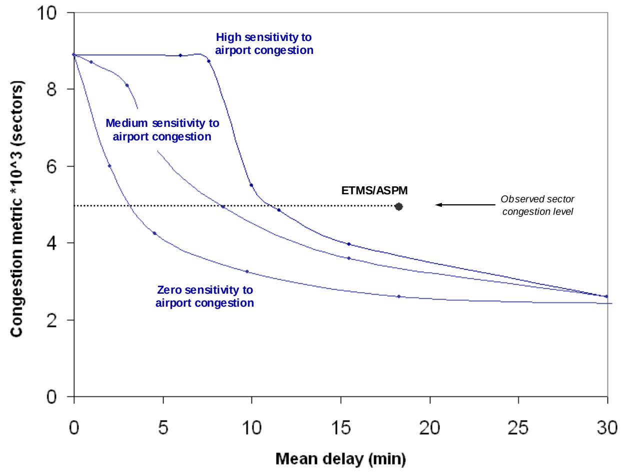

Figure 9. ProbTFM NAS-wide results

Figure 9 shows that the NAS performance is highly sensitive to the airport congestion tolerance. If very little airport congestion is tolerated (i.e., high sensitivity), then delay increases for a given level of airspace congestion. On the other hand, if there is no sensitivity to airport congestion, then delay is minimized for a given level of airspace congestion. Figure 10 shows how the NAS delay varies with the airport congestion, when the airspace congestion is fixed at the observed, ETMS level.

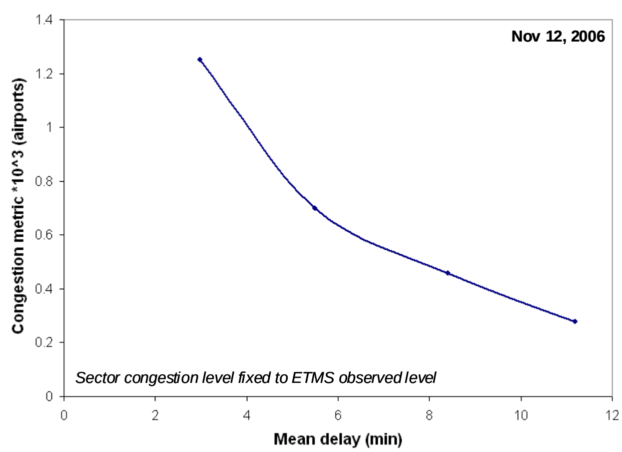

Figure 10. NAS Congestion-delay tradeoff

As with the sector congestion versus delay tradeoff, the airport congestion is also inversely proportional to system delay.

Not surprisingly these results confirm analytical models that predict a tradeoff between system congestion and delay. But these are preliminary results and there is substantial future work. In particular, our next steps include (i) adding wind direction to our surface wind impact model, (ii) validating of our airport capacity impact models using data sources such as ASPM, (iii) including airport specific models for the impact of C&V and surface winds, (iv) adding models for other terminal area weather effects, and (v) calibrating ProbTFM to empirical airport congestion data.

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