AIRPORT DELAY PREDICTION USING WEATHER-IMPACTED TRAFFIC INDEX (WITI) MODEL

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Abstract

In this paper, we present a new predictive model for estimating airport delay using data from weather forecast products. We use the well established Weather Impacted Traffic Index (WITI) toolset and metric. The latter quantifies the "front-end" impact of weather and traffic demand on the NAS and is well correlated with NAS delays, which makes WITI a reasonably good high-level model of NAS performance. WITI-FA ("Forecast Accuracy") is the forecast-weather counterpart to WITI: it can use various convective forecast products, as well as Terminal Area Forecast (TAF), and quantify forecast weather impact on the NAS. We show how these models can be refined and re-oriented toward predictive capability. First, instead of using just three WITI components, we break down the weather impacts by type, e.g. wind, snow, low ceilings, en-route thunderstorms, volume, etc – twelve components in total. Second, instead of using a NAS-wide WITI model, we "zoom in" on individual airports. The model is calibrated to minutes of delay for a given airport on an hourly basis. Having trained the model using historical airport performance and actual weather / scheduled traffic data, we then apply it in a predictive mode. The paper contains multiple examples and comparisons of predicted vs. actual delays at major airports under various weather conditions. In addition to predicting delays, the model can be used as a decision support tool. If predicted delays are too high, WITI can be run in what-if mode to gauge demand reduction, guaranteeing sustainable delays in adverse weather conditions. This could also be helpful to airlines when they need to decide on the amount of flight cancellations. Lastly, our airport delay predictor model can be used to compare the efficacy of different weather forecast products.

Introduction

Our objective is to develop a model for airport delay prediction. Modeling airport delay based on forecast data and scheduled flights can lead to improved system performance in the NAS because it enables the comparison of outcomes from different response strategies in weather-impacted scenarios. Specific benefits from this modeling strategy include determining the impact of different levels of airline cancellations and gauging the results of various Traffic Management Initiatives (TMIs). We implement a multiple linear regression model using airport delay minutes as the response. In modeling weather's impact on the NAS, most of the focus has been on convective weather (with some exceptions, e.g., Mosaic ATM's San Francisco marine stratus model). However, convective weather modeling alone is insufficient for developing a complete model of delays, because 60-65% of year-round delays result from non-convective weather, so a model with year-round utility must take into account the impact of both convective and non-convective weather.

Background

Prior Research

Understanding airport delays, their causes and their relationship with inclement weather has been the subject of research for many years, especially since the late 90's, with organizations like MITRE, MIT Lincoln Lab, NASA and academic institutions such as MIT, University of Maryland and George Mason University leading the way. In this paper, we point at a handful of selected publications; additional publications can be found in references [1-6]. The focus has been mostly on convective weather impacts [1-3]; although the initial considerations for terminal weather (first introduced in [1]) have been expanded into a year-round NAS performance model in [4]. The airport delay models were trained using historical traffic and weather data and a variety of regression techniques, and were tested in quasi-prediction mode (post factum) against actual delay data.

Because of the predominant focus on convective weather impacts and the often low granularity of non-convective weather factors' effect on airport performance, we felt that building a more refined model was a worthwhile undertaking. Additionally, new generation of convective forecast products – whose output our software tools and models can ingest and translate into TFM constraints – offer new possibilities in terms of more accurate delay prediction. We have also developed a methodology for comparing airport delay forecasts based on different weather products, which is a novel aspect for this field. Since our Weather Impacted Traffic Index (WITI) technology provides the foundation for this research, we will start with WITI overview.

WITI

WITI is based on actual weather and intended traffic demand [4]. Its twin, WITI-FA, is based on forecast weather and intended traffic demand. WITI is a weighted sum of three components. The en-route component (E-WITI) reflects the impact of convective weather on routes connecting major airports. The terminal component (T-WITI) captures capacity degradation resulting from surface weather impact, proportional to the number of operations at an airport. The queuing delay component (Q-DELAY) measures the cumulative effect of traffic demand in excess of capacity. WITI-FA has analogous components based on forecast weather data.

For its weather inputs, the WITI metric takes National Convective Weather Diagnostic (NCWD) and aviation routine weather (METAR) reports. The E-WITI component processes reports of convective weather from NCWD data on great circle (shortest-path) routes between airports. E-WITI is determined by finding the frequency of convective weather reports in regions that are crossed by flows between major city pairs, weighting this value by the scheduled air traffic between the city pairs, and apportioning the value to the corresponding airports proportionally according to the distance from the convective weather reports to each airport. The T-WITI component processes METAR data; for each airport, it determines the dominant weather at the terminal. The expected capacity degradation resulting from the dominant weather is weighted by the amount of scheduled air traffic to measure the impact of surface weather on air traffic. Q-DELAY measures the cumulative effect of delay over time when traffic demand at a given airport repeatedly exceeds capacity. Airport capacity is determined by finding weather-degraded arrival and departure capacities for the largest-capacity runway configuration that is available for the given wind and surface conditions. Any excess demand over capacity is carried forward to the subsequent time period, establishing a queuing effect.

Forecast Weather (WITI-FA)

By replacing actual en-route and terminal weather data with forecast en-route and terminal weather data, a predictive model in WITI-FA is developed. WITI-FA processes forecast convective weather data from products such as Collaborative Convective Forecast Product (CCFP), Localized Aviation MOS Product (LAMP), Corridor Integrated Weather System (CIWS) and others.

The WITI toolset typically reads 2-, 4- and 6-hour forecasts and converts area-based or gridded probabilistic convective forecast information into gridded quasi-deterministic information (NCWD) [7]. For surface weather conditions, WITI-FA takes as inputs Terminal Aerodrome Forecast (TAF) reports. WITI-FA is constructed similarly to WITI, with E-WITI-FA, T-WITI-FA, and Q-DELAY-FA components. Both WITI and WITI-FA use scheduled air traffic to weight the impact of weather. While WITI is a metric that estimates the impact that actual weather has on scheduled air traffic; WITI-FA is a metric of the impact that forecast weather is expected to have on scheduled air traffic.

Airport WITI Model

Need to Enhance WITI Model Granularity

When attempting to identify the weather's impact on individual airports, it was discovered that the 3-component WITI formulation has insufficient granularity. The broad categorizations of VMC/IMC weather conditions captured by the 3-component WITI formulation provide some information about an airport's capacity degradation; however, when incorporating specific weather phenomena into the model, we can create a significantly more comprehensive picture of the weather's impact on an airport's capacity. Our next step is to construct a WITI model that processes specific weather factors (such as thunderstorms, wind, etc) and fine-tunes the impact of these factors, airport-by-airport.

Breakdown into Specific Weather Factors

Incorporating additional individual weather factors further expands our model from the 3-component model previously described to a more airport focused model. We begin by breaking the weather impact down to the following 7 factors:

- En-route convective weather. This shows convective weather impact on an airport's inbound/outbound flows within approx. 600-NM range.
- Local convective weather. This reflects how convective weather in the vicinity or directly over the airport reduces airport's capacity.
- Wind. Any time there is a wind greater than 20 Kt, or there is precipitation *and* wind greater than 15 Kt, the corresponding impact is recorded.
- Snow, freezing rain, ice etc. The corresponding impact is recorded.
- IMC. Ceiling or visibility below airport specific minima; fog; and heavy rain. The corresponding FAA capacity benchmarks for IMC are used.
- Queuing Delay (No Weather) plus Ripple Effects. No particular weather factor recorded locally for the given airport / given hour but WITI software computed that there would be queuing delays. This can be simply due to high traffic demand or in an aftermath of a major weather event when queuing delays linger on (even as the weather has moved out).

  Additionally, Ripple Effects are recorded in this component. For example, if ORD experiences departure queuing delays, its corresponding destination airports will get some additional arrival queuing delay.
- Other. Includes minor impacts due to light/moderate rain or drizzle but ceilings/visibility above VFR minima; also unfavorable RWY configuration usually due to light-to-moderate winds (15-20 Kt or even 10 Kt) that prevent optimum-capacity runway configurations from being used.

The 12-Component Airport WITI

The 7 weather/traffic factors identified above are now translated into a 12-component Airport WITI. The components include an En-route WITI (E-WITI) which does not depend on the airport's terminal weather, as well as a Volume WITI which does not depend on weather at all, only on traffic. The remaining 5 of the 7 factors, namely Local convective, Wind, Snow, IMC, Other, are each converted into two WITI components: T-WITI (linear) and Q-DELAY (nonlinear).

Figure 1 shows the original 3-component WITI. Figure 2 shows the resulting 12-component Airport WITI with weather factor specific weights, whereby instead of a generic T-WITI, we are now talking about a "Snow T-WITI" or "IMC T-WITI" or "Wind T-WITI".

The final step is to use airport specific weather factors and their respective weights, so that "Snow T-WITI" or "IMC T-WITI" becomes "JFK Snow T-WITI" or "ORD IMC T-WITI" or "DFW Wind T-WITI". That is, the 12 components and their weighting coefficients now relate to a specific airport as well as its specific weather factors and how they impact this particular airport (Figure 3).

$$\textbf{Overall WITI} = \text{EWITI} * \mathit{Wght\_Coef\_EWITI} + \text{TWITI} * \mathit{Wght\_Coef\_TWITI} + \text{QDelay} * \mathit{Wght\_Coef\_Qdelay}$$

Figure 1. The Three-Component WITI

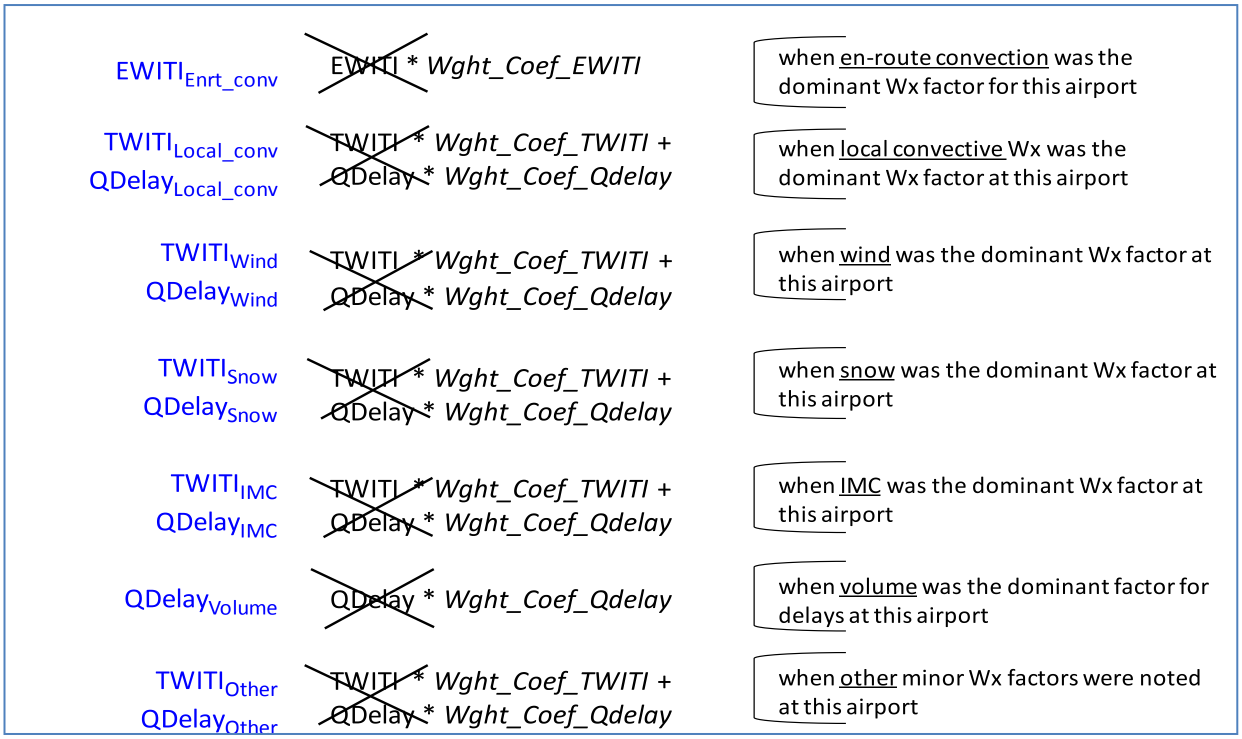

Figure 2. The 12-Component NAS WITI

Every hour [i], for airport [k]:

$$
\begin{aligned}
\text{Airport}_k\ \text{WITI}^i = {} & \text{Airport}_k\text{\_EWITI}^i * \mathit{Wght\_Coef\_EWITI}_k + \\
& \text{Airport}_k\text{\_TWITI}^i{}_{\text{Local\_conv}} * \mathit{Wght\_Coef\_TWITI\_Local\_conv}_k + \\
& \text{Airport}_k\text{\_QDelay}^i{}_{\text{Local\_conv}} * \mathit{Wght\_Coef\_Qdelay\_Local\_conv}_k + \\
& \text{Airport}_k\text{\_TWITI}^i{}_{\text{Wind}} * \mathit{Wght\_Coef\_TWITI\_Wind}_k + \\
& \text{Airport}_k\text{\_QDelay}^i{}_{\text{Wind}} * \mathit{Wght\_Coef\_Qdelay\_Wind}_k + \\
& \text{Airport}_k\text{\_TWITI}^i{}_{\text{Snow}} * \mathit{Wght\_Coef\_TWITI\_Snow}_k + \\
& \text{Airport}_k\text{\_QDelay}^i{}_{\text{Snow}} * \mathit{Wght\_Coef\_Qdelay\_Snow}_k + \\
& \text{Airport}_k\text{\_TWITI}^i{}_{\text{IMC}} * \mathit{Wght\_Coef\_TWITI\_IMC}_k + \\
& \text{Airport}_k\text{\_QDelay}^i{}_{\text{IMC}} * \mathit{Wght\_Coef\_Qdelay\_IMC}_k + \\
& \text{Airport}_k\text{\_QDelay}^i{}_{\text{Volume}} * \mathit{Wght\_Coef\_Qdelay\_Volume}_k + \\
& \text{Airport}_k\text{\_TWITI}^i{}_{\text{Other}} * \mathit{Wght\_Coef\_TWITI\_Other}_k + \\
& \text{Airport}_k\text{\_QDelay}^i{}_{\text{Other}} * \mathit{Wght\_Coef\_Qdelay\_Other}_k
\end{aligned}
$$

Figure 3. Airport specific 12-Component WITI

At each hour, the dominant weather for the hour at the airport is determined from METAR reports (WITI) and TAF reports (WITI-FA). Only the dominant weather is considered; for example, if there are thunderstorms and also rain at the airport, then only the thunderstorms (the more severe weather phenomenon) are considered. Dominant weather at the airport is determined using a predefined hierarchy of weather severity. With the addition of the new components, T-WITI will consist of five weather-specific values which are the products of the weather-related capacity degradation percentage of each airport and the number of scheduled operations at the airport. Q-DELAY will likewise be computed with five separate values for weather-specific capacity reductions in addition to a volume Q-DELAY factor. The Airport WITI model thus built is a 12-component weighted sum of airport specific weather/traffic factors (see Fig. 3). The weights are determined through multiple linear regression of

Airport WITI vs. Delay from historical data (FAA ASPM database [8]).

Model Calibration

In this experiment, since it is aimed at delay prediction, we would typically use recent data for model calibration because we are developing a forward-looking model and we want the most recent full year of airport performance data. Also, for some airports, runway construction has rendered earlier data insufficient. From the data, we determine preferred runway configuration priority for each airport. The model selects the first runway configuration that is available for current surface weather conditions at the airport. Capacities for each configuration are estimated from historical data of actual arrivals and departures. Values near the right-tail of the distribution of actual arrivals and departures are used for each runway configuration's capacity. These capacity degradation estimates are verified against FAA capacity benchmarks where the latter are available. Effectively, we are using actual throughput under near-ideal conditions with high scheduled traffic as a proxy for capacity. Next, capacity degradations under specific weather conditions are estimated, again using historical data. An airport's arrival and departure capacities are reduced by a certain percentage that reflects the degradation associated with the specific dominant weather (e.g., thunderstorms, heavy wind, etc.). Capacity degradations are airport-specific so that the model can account for different operating procedures at different airports.

Next, we implement sensitivity analysis to further refine our airport capacity degradation parameters. Due to fluctuations in scheduled traffic and non-weather related strains on the system, fine-tuning of the parameters obtained by historical data is desirable. Thus, we refine the parameters by running the model using a year's or several years' worth airport data and observe the correlation between WITI and delay for various reasonable adjustments of the original parameters. Again, this correlation results from a multiple regression model with E-WITI, T-WITI, and Q-DELAY. For each airport, we select the parameterized model that produces the highest correlation between WITI and delay for its set of runway configuration capacities and its set of capacity degradations.

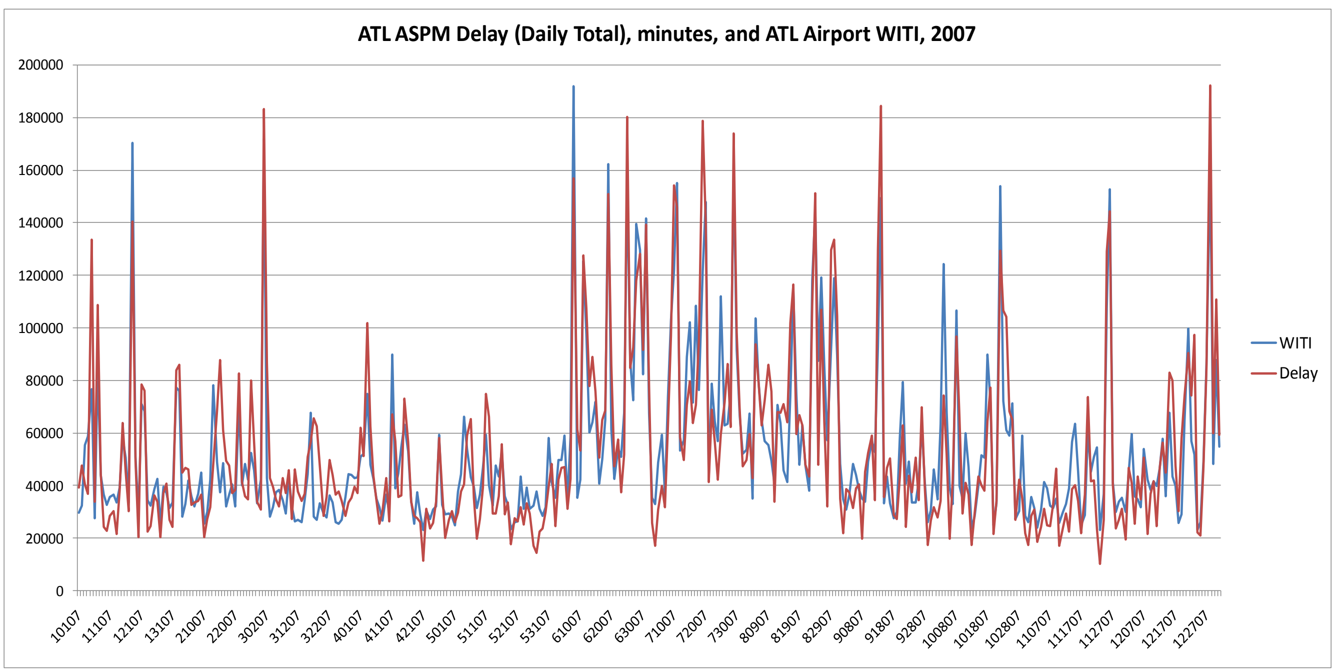

Figure 4. WITI and Delay Correlation for ATL

The correlation between WITI and delay is determined by fitting a multiple linear regression model where each WITI component is an independent variable in the model. Total delay (in minutes) is the dependent variable. Total delay is the sum of arrival and departure delays; we estimate arrival delays by multiplying the number of arrivals at each airport by the average airport arrival delay for each hour, and we estimate departure delays analogously. The coefficients for each explanatory variable in the best-fit model are the weights applied to each WITI model component.

Figure 4 shows the plot of the daily WITI value (computed from the weighted components) and daily delay minutes for Atlanta in 2007 (a year with high traffic demand in the NAS) shows a strong linear relationship. The coefficient of multiple determination (R^2) indicates that more than 70% of the variability in delay is accounted for by WITI. A value for R^2 is this range yields strong predictive power given the quantity of observations (365) and the range of observations (mild to severe weather days over the course of a year). Reasons for outlying values will be discussed in the upcoming section.

Predicting Airport Delays

Concept Outline

In a nutshell, the process is as follows (Fig. 5):

- Use a more refined airport WITI model;
- Train it on historical data (actual weather and scheduled traffic, plus delays);
- Calibrate to minutes of delay;
- "Turn around" and apply the model trained on historical data for delay forward-looking prediction (use forecast weather and scheduled traffic).

After obtaining a refined model with strong correlation between WITI and delay for a specific airport, we can then use this model for delay prediction. Using forecast weather (e.g., CCFP, LAMP, etc.) and scheduled arrivals and departures, WITI-FA component values are generated. We then input the WITI-FA component values into the best-fit regression equation for WITI and delay to predict the minutes of delay that will be experienced.

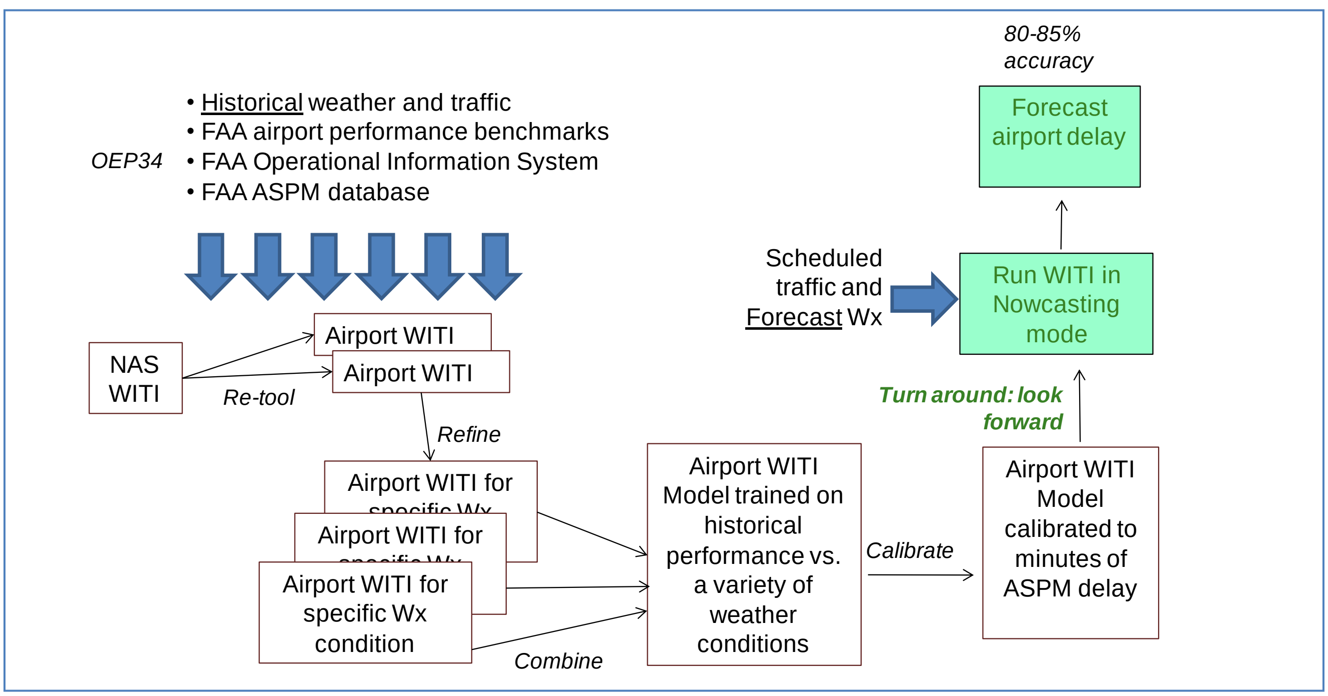

Figure 5. Airport WITI concept derived from NAS WITI and applied to airport delay prediction

Expected delay can be computed NAS-wide, ATC Center-wide, or for individual airports on an hourly, daily, seasonal, or annual basis. Using historical data, WITI-FA projected delay can be compared to actual delay. Non-weather-related effects (such as equipment outages or VIP flights) will cause differences in some cases. Also, large-scale cancellations can result in somewhat low delays while the WITI-FA value is high. Cases in which delay is relatively low but cancellations are high have an inverse relationship between WITI-FA and delay as the latter is an incomplete measure of weather's impact on air traffic. Severe weather forecasts result in high WITI-FA scores (high projected impact on air traffic); we just need to remember that this impact does not manifest itself in delays alone. In future analyses we may consider using a wider metric which may provide higher correlation between operational impact and system response.

Predicting Airport Delays: Examples

The following series of charts (Fig. 6 and 7) illustrates results of post-factum airport delay prediction for several major airports and for two different seasons (summer, winter).

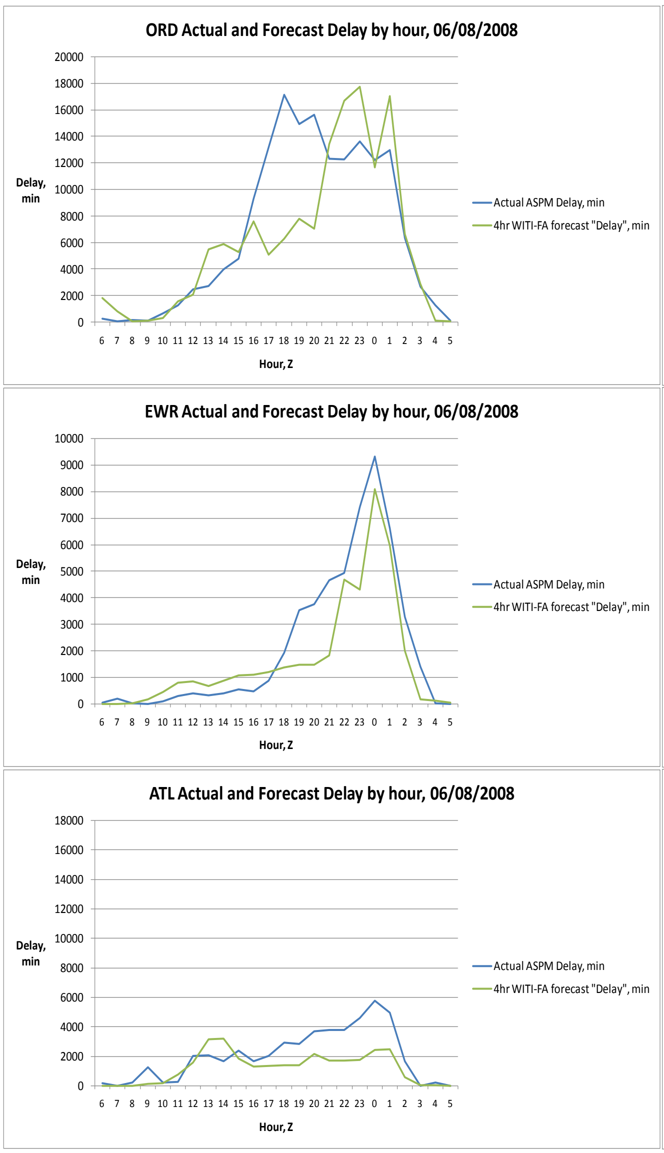

Figure 6. Predicted and actual delays, summer

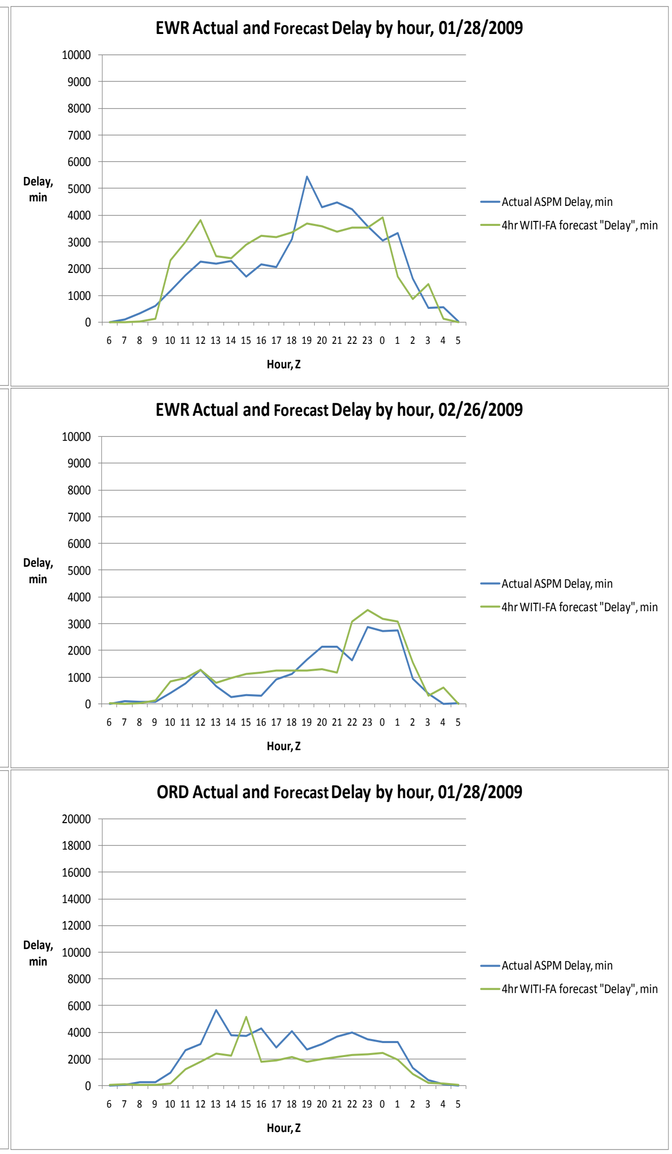

Figure 7. Predicted and actual delays, winter

Applications

Assessing Possible Cancellation Levels

Predicting the amount of delay using forecast weather can provide airlines with information to determine the amount of cancellations required to achieve sustainable delay levels. A model that is built only on forecast accuracy is of little help in this regard. A predictive model of delays that uses traffic demand and weather's geographic impact on this demand enables the user to assess the impact that different levels of cancellations are expected to have on delay. With our model, this means adjusting the scheduled traffic data to account for different proportions of cancellations. For each level of cancellations, the projected minutes of delay are computed according to our multiple-regression model. Comparing the projected minutes of delay that will be encountered for various levels of cancellations, the latter can be set to level that prevents delays from increasing exponentially while satisfying as much traffic demand as possible.

The following case illustrates the model's sensitivity to reduced demand. Consider convective impact on Chicago O'Hare (ORD) airport on June 23, 2010 (Fig. 8). Convective weather (NCWD) is shown in red and forecast (CCFP) is shown as blue and gray areas. The corresponding predicted and actual delay (prediction uses CCFP in this case) is shown in Fig. 9. Note the two distinct peaks of weather impact at 1300Z and 2200Z. The under-forecast by CCFP is clearly seen (Fig. 9, green line, vs. NCWD, red line).

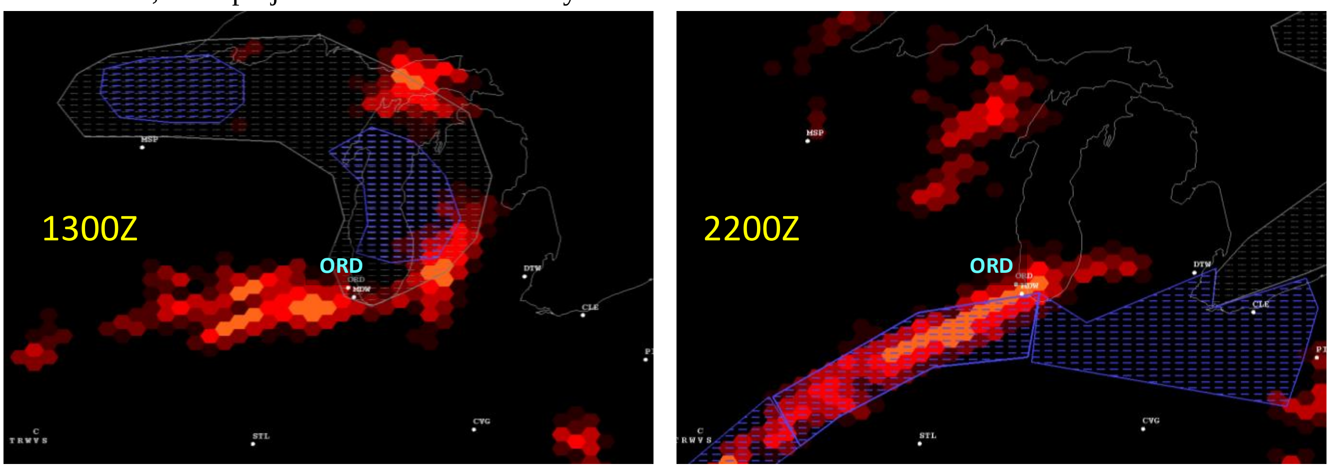

Figure 8. Convective situation around ORD, June 23, 2010, morning and evening

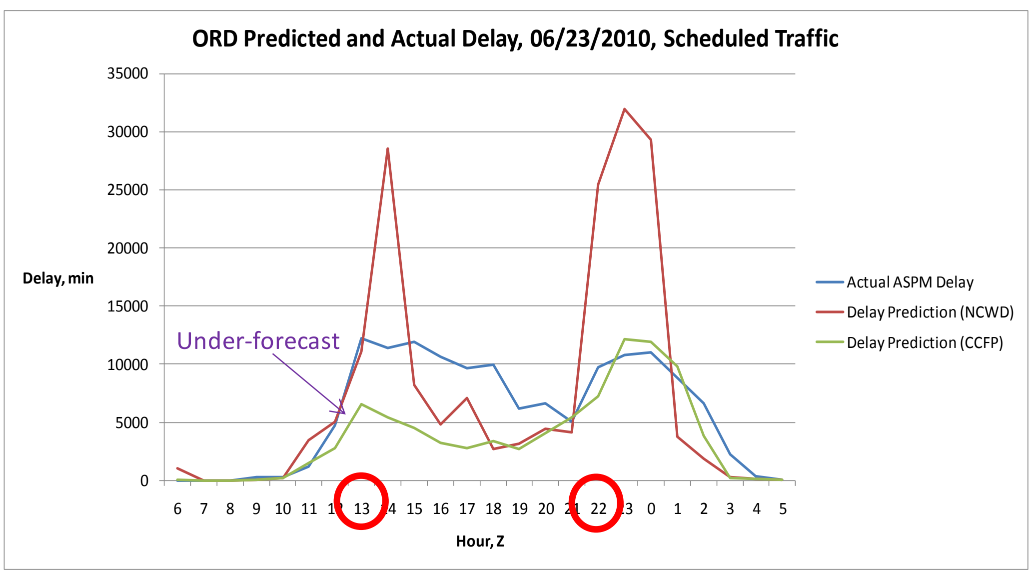

Figure 9. Predicted and actual delays, ORD, June 23, 2010

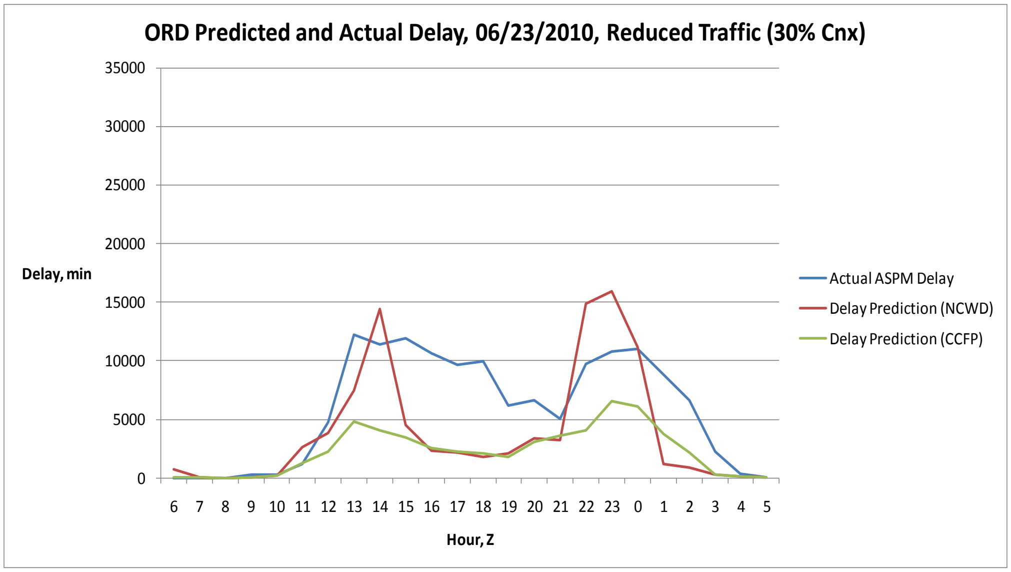

Figure 10. Predicted and actual delays, ORD, June 23, 2010, 30% reduced traffic

The difference between predicted delay based on NCWD (Fig. 9, red line) vs. actual delay on that day (blue line) is striking. To understand this difference, consider that the FAA ATC Report for June 23 showed 1859 operations at ORD, compared to 2622 operations on the same weekday (Wednesday) a week earlier. This means a 30% reduction – due to massive cancellations. Therefore, our next experiment was to compute predicted delay for the same day using a 30% reduced traffic demand for ORD. The result is shown in Figure 10. One can see that the predicted delay matches actual delay much better in terms of magnitude and timing; however the actual delays were more spread out, even in periods when the weather in ORD vicinity was relatively good. This is likely due to ORD ground congestion, multiple aircraft receiving their re-clearances late, and the impact of other airports in the NAS.

The conclusion is that our WITI-FA based Airport Delay Model will show true impact of the weather, even if delays are low because of the widespread cancellations.

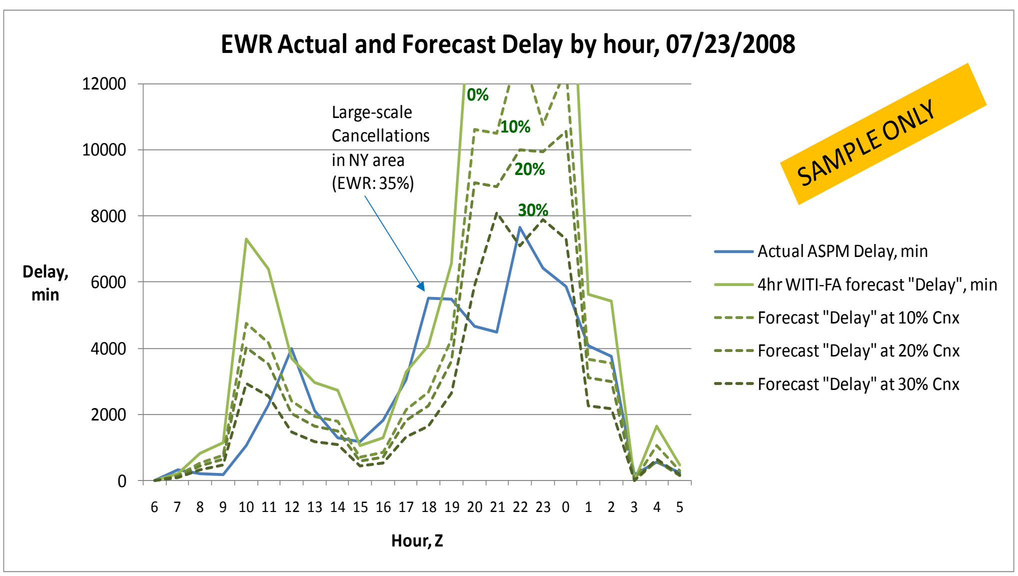

Figure 11. Notional illustration of delay gauging as traffic demand is progressively reduced

Gauging the Traffic Management Initiative (TMI) Scope

Predicting the amount of delay using forecast weather could provide traffic managers with data that can be used in setting traffic management initiatives (TMIs). TMI levels and scopes can be set with improved knowledge of the impact these decisions will have on air traffic. The magnitude or scope of a TMI can be set to levels that will result in sustainable amounts of expected delay. This entails finding multiple WITI-FA values with scheduled traffic adjusted to account for various optional airport arrival rates that could be set for time periods when demand exceeds capacity due to weather. A notional display of the results of running WITI-FA for different levels of reduced traffic demand resulting from different TMIs is shown in Figure 11. The blue line (actual delay) is close to the predicted delay at 30% lower traffic demand, and indeed, almost 35% of flights in New York area were cancelled on July 23, 2008 which was one of the worst convective weather days of the season.

Traffic managers and air carrier operators would have the ability to see the projected delay minutes resulting from various TMI implementations. Again, the purpose is for the user to select the TMI that achieves the maximum possible airport throughput while maintaining a manageable amount of delay.

Nowcasting Mode

As part of our NASA funded research, we have developed a prototype Dynamic Airspace Rerouting Tool (DART) which computes economical reroutes and/or ground delays using a blend of actual and forecast weather. A key feature of this tool is the Nowcasting mode: the tool can be launched at any time, and upon startup it reads the current weather and traffic information, as well as the latest forecast information. It can then be fast-forwarded, say up to 6 hours ahead, and using the WITI-based airport departure and arrival rate calculation and delay prediction model, it will show the forecast rates and delays. The latter can be shown as expected total delay per operation or as the expected weather impact on the airport, e.g. on a scale between 0 and 5, where 0 is no impact, 1 is very light impact, 2 is light, 3 is moderate, 4 is severe and 5 is extremely high weather impact. Additionally, the causes of such impact will be shown: if a particular weather factor contributes to > 50% of the overall impact, that factor (e.g. low ceilings) will be listed for the given hour; if there are several major factors at play (e.g. low ceilings and wind), they will all be listed.

The arrival and departure rates computed by the model may change rather quickly as the weather deteriorates or improves. In reality, airports have "inertia" and are not able to adjust their declared capacity too quickly. Risk mitigation factors need to be considered also: in this regard, an excellent methodology has been proposed in [9].

Evaluation of Weather Forecast Products

Airport delays produced using different forecast products can be compared to actual delays. If Forecast Product/Model A produces consistently better airport delay prediction than Forecast Product/Model B, then some conclusions can be made as to which product has more utility for traffic flow management.

Until recently, numerical comparisons of the accuracy of different forecast products did not take into account the impact on air traffic; this latter methodology was introduced in our work (see [7], for example). If a convective weather forecast is correct in timing and severity, but incorrect in location, the assessment of the forecast's value from an air traffic perspective needs to take all these factors into account. So, for example, if the convective weather forecast is somewhat incorrect geographically but the actual weather blocks the same air traffic routes as the projected weather location, then the forecast is accurate enough as it relates to air traffic impact. Likewise, if a weather forecast inaccuracy occurs that only impacts a small amount of air traffic due to its location or its timing then the forecast, while inaccurate, would not be as heavily penalized as a missed forecast that affects an area with a large volume of air traffic.

Our Airport WITI model is trained using actual weather and scheduled traffic to follow actual ASPM delays as closely as possible. Therefore, when applied to forward look (forecast weather and scheduled traffic), the model will translate any major weather forecast inaccuracies into noticeable difference in predicted vs. actual delay, in terms of timing and/or magnitude of delay.

Moreover, if we use two different forecast products (e.g. LAMP vs. CCFP), if one of them is noticeably less accurate, this will translate into noticeably less accurate delay prediction for several major airports affected by the weather in question.

There are caveats to be mindful of:

- Airports cannot always adapt quickly enough to rapidly changing weather conditions and ATM/ATC needs lead time to implement or cancel traffic management initiatives ("inertia");
- Airport delays can be caused by factors other than weather;
- ATM/ATC/Airlines act using both current and forecast weather information;

That is, we capture main trends of airport behavior under different weather conditions (and achieve 80-85% accuracy), but may not capture "white noise".

Even so, airport delays predicted by WITI based on CCFP or LCH or other products are compared to actual ASPM delays as "truth" (which is a good thing). Moderate and major weather forecast inaccuracies (timing and magnitude of predicted vs. actual delay) will be captured. This should give us a reasonable basis for convective forecast product comparisons.

As an example, consider the delay predicted for EWR on August 7, 2008 by two different forecast products, CCFP and LAMP (Figure 12).

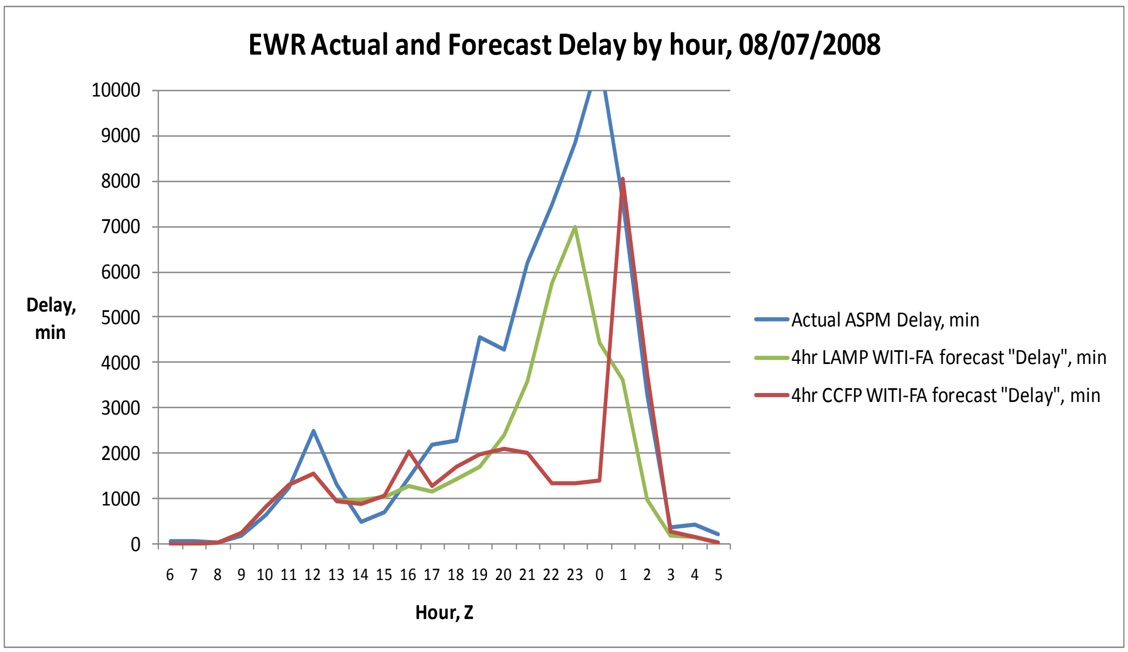

Figure 12. Airport delay predicted using LAMP and CCFP vs. actual delay

While both predicted delays (green and red lines) are somewhat below actual (blue line), this could simply be a reflection of some system inefficiencies and "inertia" mentioned earlier. However, it is clear from Fig. 12 that LAMP based delay prediction is more accurate and realistic in terms of timing. The "under-forecast first, then catching up and shifting into over-forecast" trend seen in Fig. 12 (red line) is not unusual for CCFP.

Conclusions

We have developed an Airport Delay Predictor model that successfully predicts timing and magnitude of weather impacts and resulting delays – for both convective and non-convective weather, year round.

The Predictor shows true weather impact; predicted delays may seem to exceed actual, but if cancellations are factored in, predicted delays show same magnitude as actual.

Actual delays may linger for a longer period after convective weather impact. This is partially due to the inflexibility of airspace design and the long time needed to re-issue clearances to aircraft. But some NAS "inertia" is to be expected as the NAS cannot recover quickly enough and fill gaps in weather. Inaccuracy of convective forecast can also be a factor. Lastly, we do reflect first-order network delays but not all of them.

Differences between Airport Delay Predictor results based on different weather products, e.g. NCWD and CCFP, show that the model is sufficiently sensitive to weather forecast inaccuracies. Therefore, this methodology can be used for convective and non-convective forecast product evaluation. We can also compare different releases of the same forecast product (e.g. CCFP in 2007 vs. CCFP in 2010).

A first step was also made toward operational use of this Airport weather impact and delay (and departure/arrival rate) predictor as we have built a Nowcasting mode prototype.

The model also shows promise for use in TFM decision support tools in that it can help gauge feasible traffic demand reduction levels (through ground delay programs or cancellations) that keep delays at a sustainable level while at the same time pointing at possible-under-the-circumstances airport departure/arrival rates.

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