

# Generating Representative Weather-Impact Futures for Strategic Traffic Flow Management: Airport Capacity Prediction

Sandip Roy and Rahul Dhal, Washington State University, Pullman, WA

Christine Taylor and Craig Wanke, Mitre Corporation, McLean, VA

Mengran Xue, University of Michigan, Ann Arbor, MI

Yan Wan, University of North Texas, Denton, TX

Please send correspondence to sroy@eecs.wsu.edu

**Abstract**—Motivated by needs in strategic traffic flow management, we study the problem of forecasting airport capacity profiles over a full-day time horizon. Specifically, we present a case study of Atlanta’s Hartsfield-Jackson International Airport (KATL), which explores use of 1) convective weather presence/absence near the terminal, 2) cloud ceiling height, and 3) wind speed as predictors of the total airport capacity. It is shown that terminal-area convective weather is a primary cause of capacity reduction, and also that low ceilings are a sensitive and specific predictor of reduced capacity. Wind speeds are shown to be less specific predictors, but nevertheless modulate capacity. Using these analyses, a preliminary predictive model that stochastically generates capacity profiles is proposed. This model leverages Terminal Aerodrome Forecasts of wind and ceilings, as well as convective-weather scenarios obtained from an ensemble-forecast-derived weather simulator, in generating possible profiles. Model-generated forecast profiles for Atlanta Hartsfield airport are compared with the historical profile for a particular bad-weather day of interest, September 26, 2010.

## I. INTRODUCTION

There is a growing need for effective and robust air traffic management strategies, as airspace congestion grows, airlines are subject to increasing financial pressures, and the airspace system becomes more complex (e.g., due to the integration of unmanned systems), among other reasons. For effective management in the face of uncertain weather, these strategies must

coordinate and adaptively allocate resources (i.e., design traffic management initiatives or TMIs) across the National Airspace System (NAS) at a full-day look-ahead-time (LAT), to efficiently match demand with capacity. Historically, such strategic management of air traffic has largely been done manually. Personnel at the Air Traffic Control Strategic Command Center (ATCSCC), relevant Air Route Traffic Control Centers (ARTCCs), and the airlines develop coordinated plans via an early-morning teleconference, and these plans are revised via further periodic teleconferences in response to developing congestion- and weather-related concerns. However, as congestion and airspace sophistication increases, and financial burdens dictate efficiency, there is a growing need for decision-support tools and/or automation in strategic traffic flow management. One thrust of the *NextGen* initiative to modernize the U.S. air transportation is the development of decision-support tools for strategic traffic management [1,2]. The development of decision-support tools is complicated by the significant uncertainty in weather evolution and its impact on the NAS at 2 to 24 hour LATs.

Several research and development efforts are underway to create decision-support tools for strategic traffic management in the face of weather uncertainty, which involve government, industry, and academic partners. Our team has proposed an operational concept and prototype decision-support tool for strategic traffic flow management, which we call *Flow Contingency Management (FCM)* [1]. FCM permits quantitative evaluation and design of NAS-wide management plans (coordinated TMIs across the NAS), by modeling traffic flow dynamics throughout the NAS for representative weather-impact futures.

A key challenge in implementing FCM is forecasting representative weather-impact futures. Specifically, a tool is needed that leverages weather forecasts and knowledge of airspace-system operations, to generate probabilistic futures or *scenarios* of weather-impacted NAS capacities, including airspace (Sector) capacities and Airport Arrival Rates (AARs) and Airport Departure Rates (ADRs).

The problem of forecasting Sector capacities at 2 to 24 hour LATs has received quite a bit of attention from researchers recently [3-7], with several approaches proposed to exploit ensemble forecasts in predicting weather-impact futures. Our group is using a stochastic-automaton-based methodology as part of the FCM solution [5-7]. This approach generates a large number of Sector-capacity futures with plausible spatial/temporal correlations and fine structure, while statistically matching probabilistic forecasts derived from ensemble forecasts [5,6]. In addition, we have introduced a technique for selecting a small number of representative weather-impact (Sector capacity) scenarios among these potential outcomes [7].

The FCM solution also requires forecasting of AAR and ADR (or total airport capacity, AAR+ADR) trajectories at 2 to 24 hour LATs, at major airports throughout the NAS. Probabilistic forecasting of airport capacities at these longer LATs has received less attention than Sector-capacity forecasting (see e.g. [8] for some initial efforts), and we are still seeking a generic approach for forecasting airport capacity (AAR+ADR) at airports. Our preliminary study in this direction [9] pursued a classification-based approach to AAR+ADR forecasting that leverages wind and cloud-ceiling information in Terminal Aerodrome Forecasts (TAFs). However, this initial study does not account for convective weather, nor does it directly provide a model for simulating AAR+ADR. In this article, we continue the study of airport capacity forecasting, with a particular focus on integrating convective and wind/ceiling impacts on capacity. The focus of the article is on describing a detailed case study of the Hartsfield-Jackson Atlanta International Airport (KATL). In this case study, we explore whether indicators of convective weather as well as high winds and low ceilings are good predictors of significant capacity reductions from the nominal. Using the results of the case studies, we also briefly discuss a preliminary model for AAR+ADR at ATL, and use the model to predict airport capacities on a particular bad-weather day.

The remainder of the article is organized as follows. Section II reviews the literature in airport-capacity prediction and overviews challenges in developing a prediction tool for FCM. In Section III, the case study on prediction of capacity (AAR+ADR) is described. In Section IV, we present a preliminary model of capacity for KATL, and generate AAR+ADR forecast scenarios for a day of interest, September 26, 2010, using the model.

## II. AIRPORT CAPACITY FORECASTING: BACKGROUND AND NEEDS

Airport capacity is defined as the maximum number of operations (arrivals and departures) that can be handled by an airport in a given amount of time (usually, 15mins, 30mins, or 60mins intervals). Loosely the airport capacity can be viewed as the inverse of the permissible inter-operation time [1]. Since airports have been identified as one of the major bottlenecks in air traffic flow [2], predicting airport capacity at strategic LATs is a problem of interest. Several causal factors have been identified with respect to airport capacity. Specifically, traffic demand, runway configuration, and forecast/actual terminal area weather (specifically, ceilings and wind) are some of the key factors that influence an airport's operational capacity. In particular, capacity is primarily influenced by the airport's choice of runway configurations, which in turn are chosen based on terminal area forecasts and predicted demand. Therefore, existing models for airport capacities focus on predicting and/or characterizing the influence of runway configuration on airport capacity.

The existing research on airport capacity can broadly be classified into two categories. One category is geared towards developing models for predicting (or suggesting an optimal choice for) runway configuration given various influencing factors [12,13]. The other category is focused on quantifying trade-offs between arrival and departure capacity given the operating conditions, including the runway configuration [14,15]. The aim of the first category is to understand how managers in an airport choose a particular runway configuration given the data available at the time, while the second category is aimed towards informing managers about how their operating protocols result in the complex tradeoff between arrival and departure capacities. These two categories are clearly inter-dependent, and both need to be considered while developing models for airport capacity. Since our focus here is on the first

direction (modeling airport capacities), we only review the literature in this category.

We stress here that changing runway configurations at an airport is a fairly involved process and is usually done at intervals of 3 hours or more [13]. Predictions of demand and weather are seldom entirely accurate over such time-horizons, and also configuration-selection may not always account for all weather conditions impacting the terminal. Therefore, while forecast-based choices of runway configuration affect airport capacity, the realized capacity of an airport is also influenced, although to a somewhat lesser extent, by the realized weather and demand. Of particular note, possible convective weather at a terminal may significantly modulate airport capacities (e.g., by requiring pauses in airport operations) for a given airport configuration. Thus at a strategic time-horizon, it may be a good idea to develop a simpler direct prediction model for airport capacity using terminal weather forecasts and demand forecasts, rather than predicting runway configuration intermediately. We also believe that convective weather in the terminal airspace is another important factor that should be included in models for airport capacity. We discuss these issues further below.

#### *A. Background: Predicting runway configuration*

As we pointed out earlier, the existing models for predicting runway configuration can be broadly classified into two groups. One of the groups consists of models that predict which runway configurations are most likely to be chosen given the forecasted operating conditions, while the other group consists of decision-support tools to help airports choose an optimal runway configuration. Human factors play an important role in the decision making process that leads a particular runway configuration to be chosen over other feasible configurations. Both prediction and optimization of runway configurations needs to account for the human element.

Much of the literature on runway configuration prediction and design is airport-specific. These studies are not included in our review. However, there are some papers that seek generic solutions. Several of these studies employ machine-learning and estimation theory type approaches to develop models that predict runway configurations from predicted operating conditions (wind direction, ceiling, demand, etc). For example, [13] and [16] explore discrete-choice models to estimate the relationship between influencing factors (like terminal area weather and arrival/departure

demand) and favorability of a particular runway configuration. The authors also compare the discrete-choice models against a Markovian transition process constructed from observed data. The discrete - choice model seems to be a very good model for shorter time horizons (on the order of 3 hours).

A different approach to the problem of predicting runway configuration from forecasted operating conditions (demand, time of day, ceiling, wind speed etc.) is presented in [15]. Specifically, the authors develop a deterministic as well as a probabilistic prediction model for runway configuration that takes forecasts as its input. In their approach, the forecasted winds, ceiling, etc. are classified into discrete levels before being used as an input to the prediction models. The deterministic prediction model, which is simply a classification decision tree created from historical Airspace Systems Performance Metric (ASPM) data, predicts the most likely configuration to be chosen, while assuming that the snapshot forecast of the operating conditions are accurate. The model does not account for uncertainties in the forecasts. The probabilistic prediction model, overcomes this limitation by predicting a Probability Mass Function (PMF) for all possible runway configurations for the given forecast. The PMF for the runway configuration is created from an empirical conditional PMF derived from historical ASPM data and the NOAA LAMP forecasts. The authors of [15] test the two models for 35 Operational Evolution Partnership (OEP) airports and a 2-hour time horizon and assert that the models have reasonable success rates. However, in our opinion this assertion is somewhat debatable. Nevertheless, the approaches discussed in [6], especially the probabilistic prediction model, may prove to be a good starting point for more sophisticated models for longer look-ahead times.

Among the tools that aim at finding the optimal runway configuration is NASA's System Oriented Runway Management (SORM) initiative ([17-19]). SORM is a high-level management tool that takes a holistic approach towards developing runway management procedures for strategic and tactical time-frames. The article [20] discusses some other aspects of planning various runway operations, including runway configuration selection, at a high level. Some examples of other approaches that try to provide implementable runway configurations are [12] and [21]. The general theme of these works is to define and maximize a throughput function for feasible runway configurations, while taking into account forecast uncertainty. We stress

the decision-support tools based on these approaches may not work well at strategic time horizon because of the level of uncertainty.

### *B. Strategic Airport Capacity Forecasting*

Airport capacity forecasts at shorter time-horizons are largely based on runway-configuration forecasting [13,15]. At longer time horizons, however, uncertainties in weather forecasts may be large enough that accurate runway-configuration forecasts are hard to obtain. At the same time, for strategic decision making, specifics about the runway configuration are often unimportant: a rough estimate of airport capacity is all that is needed for predicting congestion and planning management. Further, translating runway configuration to airport capacity is a non-trivial task. Therefore, we propose to develop a model that predicts capacity directly from forecasts of the various influencing factors of airport capacity. Some of the most influential factors of airport capacity are: meteorological conditions (ceiling cover, wind condition, visibility, convective weather, etc.), demand, and time-of-day. At a strategic time-horizon, the amount of uncertainty in the forecasts for meteorological conditions far exceeds those in other factors. Therefore our focus is on generating capacity trajectories based only on the forecasts for meteorological conditions.

The authors of [8] adopt a similar philosophy in developing a model for AAR trajectories using the Terminal Aerodrome Forecast (TAF). Specifically, for each day the TAF is converted into a time-series at 15-min intervals. Then, using statistical and data mining techniques, the authors classify the TAF time-series for the day-of-operation as one of some finite number of classifications, based on some metric of similarity between TAFs time-series for two different days. Once classified, a probabilistic AAR trajectory is proposed for the day-of-operation. To the best of our knowledge, [8] is the only study that attempts to develop a predictive model for AAR trajectories from weather forecasts at strategic time horizons. However, we believe that this effort has some shortcomings. First, the approach assumes that historical TAFs adequately reflect the possible outcomes of weather on the day of interest, and that no further information can be gleaned from the TAFs other than by comparison with historical days; we believe that this is a restrictive assumption. Second, convective weather is not considered.

Our initial study of total capacity (AAR+ADR) forecasting using the TAF [9] suggests that

classification-based prediction may be a promising alternative. Specifically, this study suggests that the AAR+ADR during each hour can be classified into bins (e.g., nominal, reduced, or highly reduced) in terms of categorizations of the concurrent cloud ceiling heights, wind speed, and wind direction. The data analyses pursued in [9] show that these classifications are predictive of capacity. However, the initial study [9] does not posit a model for the capacity, nor does it evaluate tradeoffs in selecting categories. Also, the possibility of convective weather is ignored entirely. Our work here aims to resolve these deficiencies.

### III. PREDICTING AIRPORT CAPACITY: CASE STUDY

We describe a detailed case study of AAR+ADR prediction from concurrent observed weather, for KATL. We note that convective weather and wind/ceilings all affect capacity at KATL with significant frequency, and hence a predictor that integrates these factors is needed. The aim of this case study is 1) to determine whether indicators of convective weather, low ceilings, and high winds are good predictors of airport capacity reduction; and 2) understand the fine structure of the dependence between these indicators and capacity reduction. Using the case study, we expect to develop a generic modeling methodology for airport-capacity prediction at the strategic horizon. See Section IV for a preliminary modeling effort.

We used data from the Airspace System Performance Metrics (ASPM) database to develop the KATL case study. Specifically, historical hourly AAR+ADR counts, hourly observed cloud-ceiling heights, wind speeds, and wind directions between April 1st, 2011, and September 30, 2011 were obtained from the “Analysis” GUI of the ASPM database and used in our study. We note that the ceiling and wind data originate from METARs taken at the terminals, which are tabulated in ASPM. For the case study, we also required information on convective weather in the vicinity of the terminal. This information is also contained in METAR reports, at hourly or higher frequencies (with higher-frequency reporting when weather conditions are changing or may impact air traffic, such as during convective-weather events). Unfortunately, we were not able to extract this information from ASPM; instead, we used public archived METARs, which are available on several web sites (see e.g. [22]).

We conducted four data analyses using the weather and capacity data for KATL:

A) A basic evaluation of capacity reduction events for KATL and the role of convective weather in causing these reductions;

B) An evaluation of ceiling heights as a predictor of concurrent capacity reduction due to low-ceiling conditions.

C) An evaluation of wind speed and direction as a predictor of concurrent capacity reduction due to wind impact.

D) A discussion of additional causes of capacity reduction, and the role of capacity classifications in predictor accuracy/specificity.

#### A. Overview of Capacity-Reduction Events

We are concerned with reductions in capacity (AAR+ADR) that may significantly impact traffic flow to the airport. Noting that the maximum hourly operations (arrivals+departures) at KATL are typically about 185, we label hourly AAR+ADR as significantly reduced if it is less than 185. During the six month study window,  $117/4392=2.7\%$  of the hours had significantly reduced AAR+ADR. For these significantly-reduced hours, AAR+ADR ranged from 94 to 185, with a mean of 170 and a standard deviation of 16. We see that most significantly-reduced hours were only slightly below the maximum traffic threshold, but these typical cases are interspersed with some exceptional hours with drastically reduced AAR+ADR.

Among the 117 significant reductions, 52 events or 44% of events are directly attributable to convective weather observed at ATL, as specified in terminal METARs. Incidentally, a block of 5 further events, while not directly connected to convection, were caused by high winds following convective weather associated with a cold-front passage. The high percentage of capacity reductions due to convective weather highlights the importance of modeling terminal-area convection in forecasting AAR+ADR.

#### B. Ceiling Heights and Capacity Reduction

Low cloud ceilings limit usable runway configurations and require extra spacing between aircraft. As such, low ceilings are a primary cause of airport capacity reduction. Recent efforts to forecast AAR+ADR at strategic LATs have verified that cloud ceilings are predictive of capacity reduction, and have proposed using forecast ceiling profiles from TAFs as predictors of capacity. Here, we study further the correlation between low

ceilings and concurrent AAR+ADR, with a particular focus on understanding the sensitivity and specificity of low ceilings as a predictor. To do so, we consider hours during which the ceiling (as specified in METARs) is below a threshold  $q$ , for  $q=200, 500$ , and  $1000$  ft. We determine the numbers/fractions of these low-ceiling hours that do and do not correspond to significant capacity reduction. The results are shown in Table 1.

	Ceil<200 ft	Ceil<500 ft	Ceil<1000 ft
Cap. Reduction Events	15/117=13%	22/117=19%	35/117=30%
False Positives	0/4275=0%	21/4275=0.5%	116/4275=2.7%

Table 1: Sensitivity and Specificity of Ceilings as a Predictor of AAR+ADR Reduction.

Table 1 indicates that low ceilings are indeed a sensitive and specific predictor of low AAR+ADR. A ceiling threshold of 200ft is perfectly specific, and identifies 13% percent of the capacity-reduction events. A threshold of 500ft captures a larger fraction of capacity-reduction events, but yield false positives at a rate of 0.5%. A 1000ft ceiling identifies almost 30% of the capacity-reduction events, but does produce false positives at a higher rate: This analysis highlights that low ceiling heights, as specified by a threshold between 200 and 500 ft, are relatively sensitive and specific predictors of capacity reduction. A higher threshold of 1000ft is more sensitive, but does yield a more significant probability of error.

#### C. Wind and Capacity Reduction

Wind speed and direction are recognized to modulate arrival/departure capacity, since they modulate runway configurations and required spacing among aircraft. In particular, high winds often require use of unfavorable (lower-capacity) runway configurations, and also require larger inter-aircraft separation. Noting these dependences, several recent studies have considered forecast wind-speed and direction profiles as regressors for airport capacity. Here, we also study whether and how AAR+ADR depends on wind speeds and direction, with a focus on understanding sensitivity/specificity of prediction. In analogy with the cloud-ceiling studies, we study whether wind speed above a threshold is predictive of capacity reduction. Specifically, for thresholds of 15 and 20 knots, we determine the number of corresponding hours that

do and do not have significant capacity reduction. The results are shown in Table 2 below.

	Wind Speed>20	Wind Speed>15
Cap. Reduction Events	4/117=3.4%	17/117=14.5%
False Positives	60/4275=1.4%	268/4275=6.2%

Table 2:

Clearly, wind speed is also predictive of airport capacity, in the sense that a higher fraction of the capacity-reduced hours as compared to non-reduced hours correspond to high winds. For instance, for a threshold of 15 kts, 14.5% of the significant capacity-reduction hours are identified, while only 6.2% of the non-reduced hours are identified. However, in absolute terms, wind speeds are not very specific predictors of capacity reduction. Specifically, for the hours with wind speeds above 15mph, only 17 of these hours had capacity reduction, while 268 such hours do not. That is, a wind speed above the threshold only has odds of 17:268=1:16 of corresponding to a capacity-reduction period rather than a non-reduced period.

Tailwinds and cross-winds significantly impact aircraft landing, and hence runway configuration selection also depends closely on the wind direction. As such, we might hypothesize that capacity reductions also depend on wind direction. To test whether there is a dependence, we determine the odds of a significant capacity reduction compared to no significant capacity reduction, for significant-wind hours (>15kts) with wind direction in each quadrant (NE, SE, SW, NW). Here are the odds in each case:

- NE Winds – 1 : 10
- SE Winds – 1 : 10
- SW Winds – 1 : 25
- NW Winds – 1 : 14

The comparison shows that KATL is especially well suited to handle higher winds from the Southwest, which is unsurprising since this is the predominant wind direction (not only at KATL but throughout most of the contiguous United States), and high-capacity runway configurations are planned for the predominant wind direction. However, even with direction-based classification, wind is not a high-specificity predictor of significant capacity reduction: even for wind directions for which capacity is most frequently reduced, the odds of a capacity reduction during high-wind periods is only 1:10. These studies indicate that a capacity-

reduction prediction which uses forecast wind direction/speed classification will either have low sensitivity or specificity.

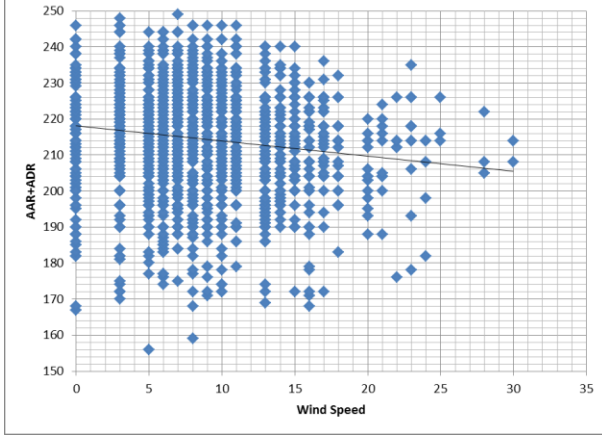
The weak dependence of capacity reduction on wind speed/direction is rather surprising. Winds are well-known to influence runway configurations and hence capacities, but do not appear to be predictive of reduction. In fact, a closer look at the METAR data shows that significant capacity reductions often occur during periods with moderate winds (say 10-15 kts) but high wind gusts (e.g., greater than 25 or 30 kts), while other periods with similar wind speeds but no gusts enjoy full or nearly full capacity. We note that TAFs do predict wind gusts, and hence a capacity model that uses gust information is appropriate. However, both TAFs and METARs present gust information at irregular intervals (i.e., when needed), and hence some processing of the data is needed to permit regression and forecasting. We have not done this processing in an initial study, but expect to do so in future work. We also note that more work on validating TAF gust forecasts is need. A visual inspection of the significant capacity-reduction events suggests that lowered capacity also often corresponds to periods with changing wind directions, which may correspond to intervals where runway configurations need to be changed or low-level wind-shear is present.

The initial studies on predicting capacity levels from wind-speed data indicate that building a classifier using only speed/direction data is infeasible. An alternative is to use a regression of wind speed for prediction. Unlike a classification-based approach which will entirely mis-predict the capacity with some probability, a regression can capture weaker dependencies between the regressor (speed) and output (capacity level), albeit with some error. Figure 1 plots the capacity vs. wind speed using the full six-month data set, and determines a linear regression for the relationship. The regression demonstrates a weak negative correlation between the wind speed and capacity. The regression can be used to predict capacity from wind speed absent other causes of capacity reduction, albeit with significant error.

#### *D. Other Causes of Capacity Reduction*

Of the 117 hours with significant capacity reduction, 82/117=70% are periods with convective weather in the terminal area, high winds (>15mph), or low ceilings (<500ft). Of these 82 hours, it is worth noting that 9 correspond to both high winds

and convective weather. Meanwhile, if we use ceilings of <1000ft as a predictor of capacity reduction, then  $95/117=81\%$  of the capacity-reduction events are captured, again with 9 overlap events with high wind and convective weather.



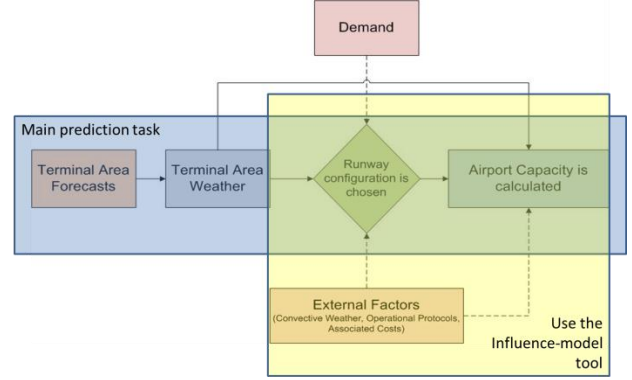
**Figure 1: Linear regression of capacity (AAR+ADR) in terms of concurrent wind speed. A weak negative dependence is indicated.**

We posit that the remaining significant capacity-reduction hours largely correlate with two conditions. First, they may stem from persistence of runway configurations, wherein a lower-capacity runway configuration is maintained even after a weather-impact event has cleared. In particular, the operators may decide to maintain the configuration because there is no need for a higher capacity, or because the configuration change may cause some disruption to traffic at a time of interest. Second, these unpredicted cases may correspond to hidden weather conditions, including especially convective weather near but not at the terminal, and possibly high/gusty winds above the surface. Several other, less common, reasons that a significant capacity reduction is unpredictable can also be imagined, including runway maintenance, failure or maintenance of radar systems, debris on the runway, etc.

#### IV. PRELIMINARY AIRPORT CAPACITY MODEL

The data analyses for KATL highlight that convective weather, low ceilings, and wind events all cause reduction in the airport's capacity with relatively high frequency. We believe that these data analyses provide insight into developing an abstract predictive model for the capacity (AAR+ADR) of KATL at 2-24 hr LATs, in a manner that is naturally extensible to other major airports.

Here, we put forth an extremely preliminary predictive model for KATL's capacity, and illustrate the model's performance for one historical day (September 26, 2010).



**Figure 2: Overview of the airport capacity forecasting approach: TAFs are used to predict wind/ceiling effects, while the influence model (which uses SREF-based probabilistic forecasts)**

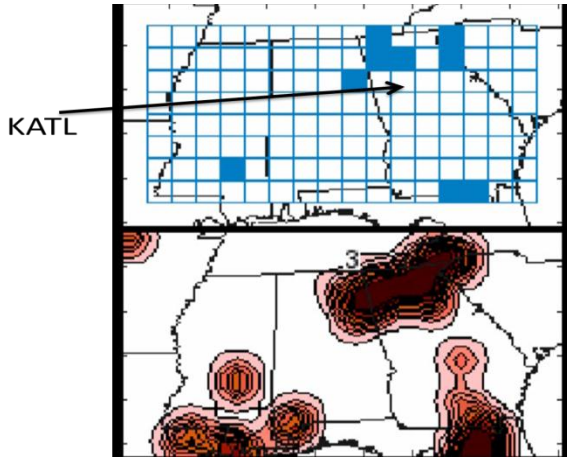
The model that we propose generates hourly forecasts of the capacity based on forecasts of the three regressors considered here: presence/absence of convective weather near the airport, low ceilings, and high winds. The model is stochastic: multiple possible capacity profiles or scenarios are generated, depending on possible (uncertain) futures of weather conditions. The structure of the model is outlined in Figure 2. In our preliminary effort, the wind and ceiling forecasts in the TAF are directly used as regressors of capacity. Meanwhile, our proposed forecasts for absence/presence of convective weather in the terminal area leverage ensemble forecast products --- in this work, specifically the post-processed convection probability guidance product originating from the Short Range Ensemble Forecast (SREF). Rather than using the probabilistic forecast directly, however, we advocate for using an influence-model simulation engine that is parameterized (learned) from the probabilistic forecasts (see [5-7]). This approach allows us to rapidly generate many possible spatio-temporal scenarios of convective weather presence/absence in grid squares across a large geographic region, with 15-minute resolutions. This ensemble of scenarios statistically matches probabilistic forecasts at hourly snapshot times, while *also capturing spatial and temporal correlations in the weather*. In our previous work, we have used the influence model simulator to forecast Sector capacities over LATs of up to 24 hours. Here, we propose to use the simulator-generated trajectories for the grid square (or a few



grid squares) over the airport of interest, to indicate the presence or absence of convective weather. Specifically, each local convective weather trajectory (scenario) is combined with the TAF wind and ceiling forecasts to construct an airport capacity scenario or trajectory.

Now that we have described the components and logic flow, let us present the preliminary airport-capacity model in detail. We focus specifically on developing the model for Atlanta, so as to give an explicit numerical presentation of the model. In particular, we propose to generate airport-capacity (AAR+ADR) scenarios over a 20 hour LAT according to the following algorithm:

1) Generate one regional scenario of convective-weather using the influence model simulator. Recall that the scenario captures presence/absence of convection in grid squares across the region, during 15 minute intervals over the 20 hr LAT. Track the scenario status for the grid square over KATL (see Figure 3), over the 20-hour time horizon.



**Figure 3: The influence model simulator produces stochastic spatiotemporal scenarios of convective weather presence/absence in grid squares across a region of interest (upper plot), which are statistically matched to SREF probabilistic forecasts (lower plot). The weather in the grid square over KATL is tracked for the airport-capacity computation.**

2) For each simulation hour, count the number  $q$  of 15-minute intervals (0,1,2,3, or 4) with convective weather in the KATL grid square. If the number is 0, progress on to Step 3. If not, compute the capacity as  $C = 162(q/4) + 212(1 - q/4)$ , where we recall 162 is the mean capacity under convective weather conditions and 212 is the mean capacity in good-weather conditions. That is, based on the fraction of time with bad weather,

a linear average of the nominal and reduced capacity is used to determine the capacity prediction. As a slightly more sophisticated alternative, the capacity prediction can be chosen stochastically, to match the standard deviation in the historically-measured capacity in addition to the mean; we omit the details. If some convective weather has been predicted ( $q = 1,2,3,4$ ) and hence the capacity has been set, progress directly to Step 5.

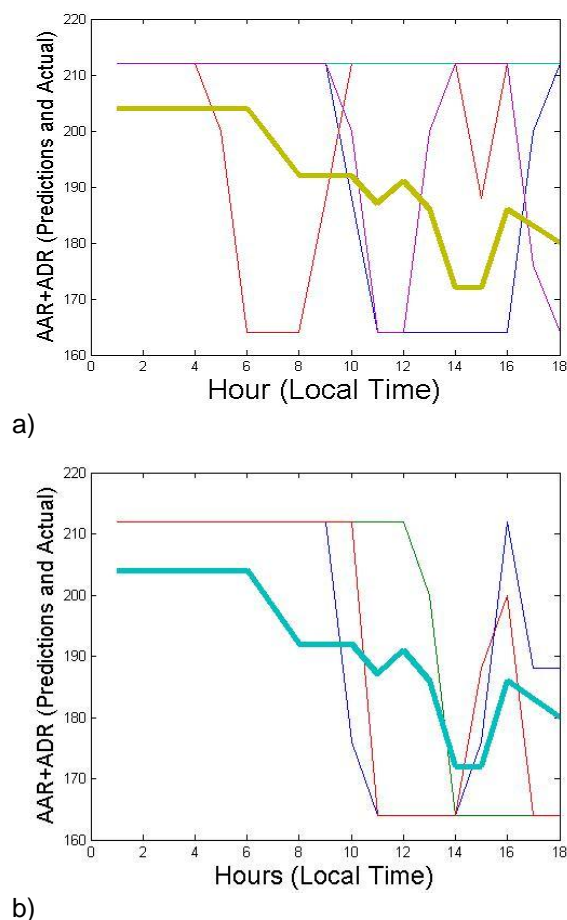
3) From the TAF, determine whether or not the forecast ceiling is below 500ft. If yes, set the predicted capacity to  $C=175$ , which is the mean capacity when ceiling are below 500ft; then progress directly to Step 5. If no, progress to Step 4. Again, we note that a stochastic generator of capacity can be used instead, which matches historical variability under low-ceiling conditions.

4) From the TAF, determine the forecast wind speed. Use the regression in Figure 1 to determine the capacity  $C$ . Progress to Step 5. Again, a stochastic model that reflects the regression error can be used as an alternative.

5) Repeat the capacity computation for a number of influence-model-generated convective weather scenarios, to generate an ensemble of capacity profiles.

We have applied the developed model to generate forecast airport-capacity (AAR+ADR) scenarios for September 26, 2010. On this day, a long-duration tropically-driven convective weather event impacted the Southeastern United States, significantly impacting traffic to and from Atlanta ARTCC airspace including KATL. Using the 3Z SREF, we have built the influence model-based simulator for convective weather from 5Z to 22Z on September 26<sup>th</sup> (1AM-6PM EST). In addition, the TAF for the period of interest has been obtained from a public archive [22]. The TAF does not indicate low ceilings, and indicates wind speeds of around 8 knots throughout the day. The above-described algorithm has been used to generate 100 possible capacity profiles or scenarios for KATL. Three randomly-generated scenarios are shown along with the historical capacity profile (as recorded in the ASPM database) in Figure 4a. Also, we have found the 10 scenarios that are closest to the historical capacity profile, in a mean-square-error sense. Three of these scenarios (chosen randomly from the 10) are shown in Figure 4b.





**Figure 4: Comparison of the historical capacity profile and model simulations of capacity for KATL on September 26, 2010. a) The historical capacity profile is compared with three randomly-selected profiles out of 100 profiles generated by the model. b) The historical profile is compared with three of the 10 closest profiles (in a mean square sense). In both figures, we note that the historical capacity is indicated with a heavier line than the model simulations.**

We see that the scenarios generated by the model capture some salient features of the historical capacity profile. In particular, all of the scenarios predict nominal capacities in the early part of the day, followed by significant probability of capacity reduction later in the day. The predicted nominal and reduced capacities are relatively close to those achieved in the historical profile, and many of the predictions exhibit temporal persistence in capacity reduction as in actuality. The scenarios that are closest to the real profile also exhibit transitions from high to low capacity, as well as capacity minima, at similar times as the historical profile. These similarities suggest that the

modeling approach may be promising for predicting capacity profiles at strategic horizons, though far more study/refinement of the model is needed. We note that the model scenarios do exhibit more drastic capacity changes than the historical case, perhaps suggesting that the fine structure of capacity evolution has not been captured in this initial modeling effort.

Several extensions of the proposed model are important to explore. Perhaps most critically, better models for wind impact on capacity, including ones that use gust and wind-shear information, are needed. Also, models that capture persistence in runway-configuration choices may be desirable, but must be developed with care to ensure that significant capacity reductions are not excluded or delayed. One more important need is to account for uncertainties in the TAFs. In its current conception, the model uses the TAF directly as a wind and ceiling predictor. A model that reflects uncertainty in the TAF would instead generate possible wind and ceiling profiles from the TAF, as a step toward determining the capacity profile.

#### NOTICE

This work was produced for the U.S. Government under Contract DTFAWA-10-C-00080 and is subject to Federal Aviation Administration Acquisition Management System Clause 3.5-13, Rights In Data-General, Alt. III and Alt. IV (Oct. 1996).

The contents of this document reflect the views of the author and The MITRE Corporation and do not necessarily reflect the views of the FAA or the DOT. Neither the Federal Aviation Administration nor the Department of Transportation makes any warranty or guarantee, expressed or implied, concerning the content or accuracy of these views.

© 2013 The MITRE Corporation. All Rights Reserved.

Approved for Public Release; Distribution Unlimited. Case Number: 13-0803.

[1] C. Taylor, C. Wanke, Y. Wan, and S. Roy "A framework for flow contingency management," *Proceedings of the AIAA Aviation Technologies Integration and Operations Conference*, Virginia Beach, Sep. 2011.

[2] *Concept of Operations for the Next-Generation Air Transportation System*, Joint Planning and

Development Office (JPDO) Report Version 3.0, Washington DC, Oct. 2009.

[3] Steiner, M., Mueller, C., Davidson, G., and Krozel, J. 2008. "Integration of probabilistic weather information with air traffic management decision support tools: A conceptual vision for the future," 13th Conference on Aviation, Range, and Aerospace Meteorology, January 21-24. American Meteorological Society, New Orleans, LA.

[4] A. Tafazzoli, A. Yousefi, T. Myers, and B. Khorammi, "An ensemble-based approach for representing weather uncertainty in air traffic management," 12th AIAA Aviation Technology, Integration, and Operations (ATIO) Conference, Indianapolis, IN, Sep. 2012.

[5] Roy, S., Wan, Y., Taylor, C. P., and Wanke, C. R., "A stochastic network model for uncertain spatiotemporal weather impact at the strategic time horizon," in *Proceedings of the 10th Aviation Technology, Integration, and Operations Conference*, Fort Worth, TX, Sep. 2010.

[6] Xue, M., Zobell, S. M., Roy, S., Taylor, C. P., Wan, Y., Wanke, C. R., "Using Stochastic, Dynamic Weather-Impact Models in Strategic Traffic Flow Management," in *Proceedings of 91st American Meteorological Society Annual Meeting*, Seattle, WA, January 2011.

[7] Xue, M., Roy, S., Zobell, S. M., Wan, Y., Taylor, C. P., Wanke, C. R., "A Stochastic Spatiotemporal Weather-Impact Simulator: Representative Scenario Selection," in *Proceedings of the 11th AIAA Aviation Technology, Integration, and Operations Conference*, Virginia Beach, VA, 20-22 Sep. 2011.

[8] G. Buxi and M. Hansen, "Generating probabilistic capacity profiles from weather forecast: a design-of-experiment approach," in *2011 USA/Europe Air Traffic Management Research and Development Seminar (ATM2011)*, Berlin, Germany, 2011.

[9] Dhal\_Roy\_old

[10] E. Gilbo, "Airport capacity: Representation, estimation, optimization," *IEEE Transactions on Control Systems Technology*, 1993.

[11] B. Sridhar, S. Grabbe and A. Mukherjee, "Modeling and Optimization in Traffic Flow Management," *Proceedings of the IEEE*, vol. 96, no. 12, pp. 2060-2080, 2008.

[12] D. Bertsimas, M. Frankovich and A. Odoni, "Optimal Selection of Airport Runway Configurations," *Operations Research*, vol. 59, no. 6, pp. 1407-1419, 2011.

[13] V. Ramanujam and H. Balakrishnan, "Estimation of maximum-likelihood discrete-choice models of the runway configuration selection

process," in *American Control Conference (ACC)*, 2011.

[14] V. Ramanujam and H. Balakrishnan, "Estimation of Arrival-Departure Capacity Tradeoffs in Multi-Airport Systems," in *48th IEEE Conference on Decision and Control*, 2009.

[15] K. Ramamoorthy and G. Hunter, "An Empirical Airport Configuration Prediction Model," in *AIAA Modeling and Simulation Technologies Conference*, Minneapolis, Minnesota, 2012.

[16] K. Ramamoorthy and G. Hunter, "An Empirical Airport Configuration Prediction Model," in *AIAA Modeling and Simulation Technologies Conference*, Minneapolis, Minnesota, 2012.

[17] V. Ramanujam, "Estimation and tactical allocation of airport capacity in the presence of uncertainty," *Massachusetts Institute of Technology*, 2012.

[18] G. W. Lohr, S. A. Brown, S. Atkins, S. W. Eisenhower, T. F. Bott, D. Long and S. Hasan, "Progress Toward Future Runway Management," in *11th AIAA Aviation Technology, Integration, and Operations (ATIO) Conference*, Virginia Beach, VA; United States, 2011.

[19] S. Atkins, "Toward System Oriented Runway Management," in *2010 IEEE/AIAA 29th Digital Avionics Systems Conference (DASC)*, , 2010.

[20] G. Lohr and D. M. Williams, "Current Practices in Runway Configuration Management (RCM) and Arrival/Departure Runway Balancing (ADRB)," *NASA Langley Research Center*, Hampton, VA, 2008.

[21] I. Anagnostakis, J.-P. Clarke, D. Bohme and U. Volckers, "Runway operations planning and control sequencing and scheduling," in *34th Annual Hawaii International Conference on System Sciences*, 2001.

[22] <http://www.navlost.eu/aero/metar/>