B. TECHNOLOGY AND METHODOLOGY

B-1. Survey of ATM Weather Impact Models

B-1.1 En route Convective Weather Avoidance Modeling

In order to determine the impacts of convective weather on en route air traffic operations, it is necessary first to partition airspace into passable and impassable regions. As shown in Figure B-1, en route Convective Weather Avoidance Models (CWAM) calculate Weather Avoidance Fields (WAFs) as a function of observed and/or forecast weather. WAFs are 2D or 3D grids whose grid points are assigned either a probability of deviation or a binary deviation decision value (0 or 1).

Since the pilot is responsible for weather avoidance, CWAM requires both the inference of pilot intent from an analysis of trajectory and weather data and an operational definition of deviation. Two approaches have been taken to model and validate weather-avoiding deviations using trajectory and weather data: trajectory classification [RKP02, DE06, DRP08, CRD07] and spatial cross-correlation [PBB02, K08].

In the trajectory classification approach, planned and actual trajectories of individual flights are compared and each flight is classified as a deviation or non-deviation, based on criteria derived from fair weather operations (e.g., operational route boundaries) or the judgment of a human analyst. Characteristics of the weather encountered along the planned trajectories and the trajectory classification are input to statistical pattern classification algorithms to identify the weather characteristics that best predict deviations.

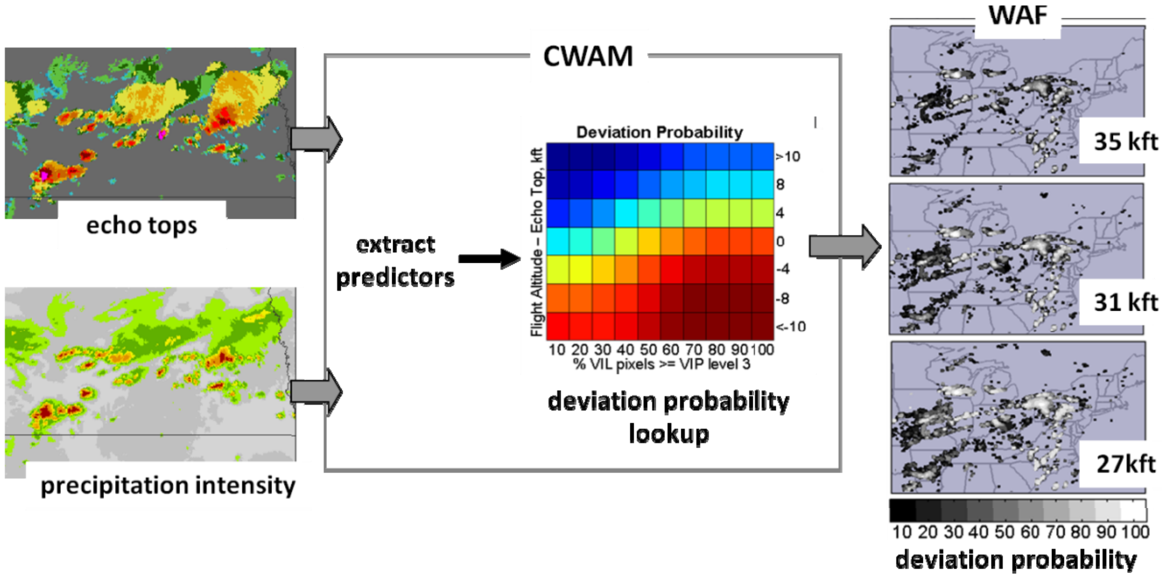


Figure B-1 CWAM implementation to create WAFs.

In the spatial cross-correlation approach, spatial grids of aircraft occupancy are cross-correlated with grids of weather data. Occupancy counts on weather-impacted days are compared to fair-weather counts. Regions where weather-impacted counts are low relative to fair-weather counts are assumed to be areas that pilots are avoiding due to the weather present in the area. The correlation of observed weather with areas of avoidance is used to identify the weather characteristics that best predict the observed weather avoidance.

Both approaches have strengths and weaknesses. Trajectory classification is highly labor intensive, restricting the size of the statistical dataset used in the model, but gives very detailed insights into pilot behavior. Spatial cross-correlation greatly reduces the labor involved in the analysis, vastly increasing the modeling dataset, but does not provide information about individual decisions. Spatial cross-correlation is also subject to errors arising from the displaced weather impacts (e.g., local air traffic counts are abnormally low because airways leading to the region are blocked by weather upstream) or traffic management initiatives that distort demand (e.g., pro-active reroutes to avoid predicted weather that does not materialize as expected).

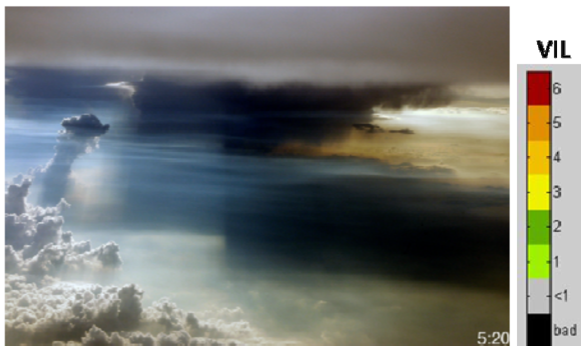
To date, CWAM studies have only considered weather characteristics derived from ground-based weather radar products (precipitation intensity, echo top height). Studies using both methodologies have identified the difference between aircraft altitude and echo top height as the primary predictor of weather-avoiding deviation in en route airspace, with precipitation intensity playing a secondary role. Current CWAM are most prone to error for en route traffic flying at altitudes near the echo top, particularly in regions of moderate precipitation intensity. Since current CWAM are based only on ground-based weather radar, they do not readily discriminate between relatively benign decaying convection and stratiform rain and turbulent downwind from thunderstorms, both of which are often characterized by echo tops in the 30-40 kft. range and moderate precipitation intensities [DCF09]. Further research is needed to examine additional weather information (e.g., satellite, winds, convectively-induced turbulence estimates [CML04]) that may help differentiate between benign and hazardous regions with similar radar signatures. Research is also needed to identify the human factors associated with pilot decision-making, particularly in circumstances where CWAM performs poorly.

B-1.2 Terminal Convective Weather Avoidance Modeling

In order to determine the impacts of convective weather on terminal air traffic operations, it is necessary to partition terminal area airspace into passable and impassable regions. CWAM that take into account the constraints of terminal area flight need to calculate WAFs that apply specifically to terminal area operations. Each WAF grid point is assigned a probability and/or a binary value (0 or 1) that represents that likelihood that pilots will choose to avoid convective weather at a point location in the terminal area.

CWAM for terminal areas are likely to differ from en route CWAM in significant ways. Departures and arrivals are constrained to follow ascending or descending trajectories between the surface and cruise altitude, leaving little flexibility to avoid weather by flying over it. Pilots of aircraft ascending or descending through weather are likely to have few or no visual cues to inform their decision, unlike those in en route airspace who may have clear views of distant thunderstorms as they fly above the clouds. Aircraft flying at low altitudes in the terminal area appear to penetrate weather that en route traffic generally avoids [K08]. The willingness of pilots to penetrate severe weather on arrival increases as they approach the ground [RP98].

CWAM for departures and arrivals are also likely to differ from each other, for example, as illustrated in Figure B-2. The observed difference in behavior is not completely surprising, since arriving and departing flights are characterized by very different constraints and circumstances: arrivals must get down from the sky, while departures can wait on the ground until the weather is more favorable; departures must climb out at full power and hence have little opportunity to deviate to avoid weather in the first few minutes of flight, while arrivals have flexibility to maneuver until final approach; arrivals descending from above the cloud base have less information about the severity of the weather below than departures climbing from the ground.



View of thunderstorm and turbulent rotor (at right of photo), seen from underneath the cloud base. Ascending departures sometimes have a clear view of thunderstorm details that may be hidden from the view of arrivals descending into the airspace from above the cloud base.

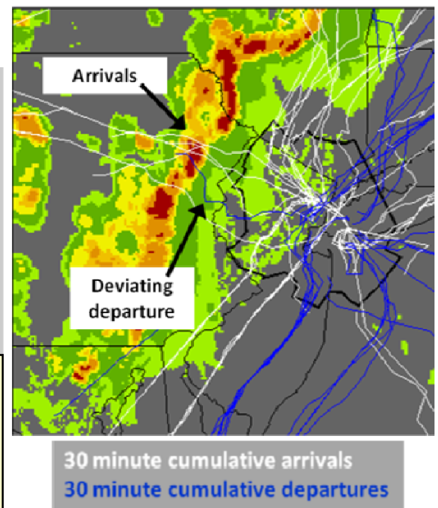


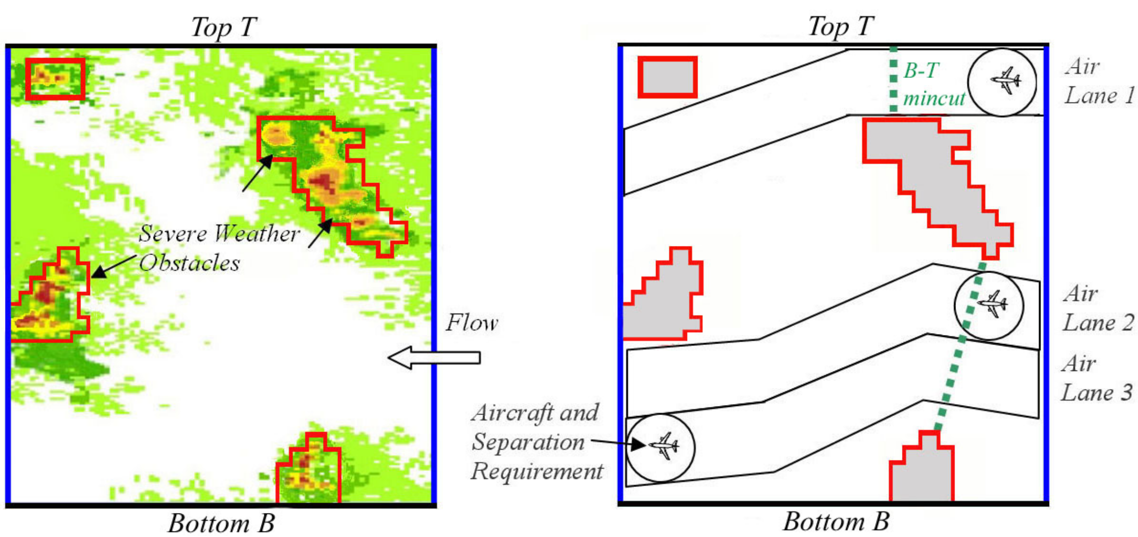
Figure B-2 Arriving pilots penetrate weather that departures seek to avoid.

For NextGen, terminal area CWAM research is needed both to understand the factors that affect pilot decision making in the terminal area during departures and arrivals, to identify the set of weather characteristics that correlate best with observed weather avoidance in the terminal area, and to understand how unstructured routing and Required Navigation Performance (RNP) in NextGen may change the characteristics of terminal area throughputs [KPM08].

B-1.3 Mincut Algorithms to determine Maximum Capacity for an Airspace

For NextGen when jet routes can be dynamically redefined to adjust flows of traffic around weather constraints and when controller workload is not a significant constraint, the maximum capacity of an airspace region may be determined using extensions of MaxFlow/Mincut Theory [AMO93,M90,KMP07]. The network MaxFlow/Mincut Theorem has been extended to a continuous version of the maximum flow problem [M90, I79, St83], which is suitable for estimating the maximum throughput across an en route airspace given a traffic flow pattern [SWG08], a uniform distribution of flow monotonically traversing in a standard direction (e.g., East-to-West), or random, Free Flight conditions [KMP07]. The maximum capacity of transition airspace may also be determined by transforming the problem into an analysis over the ascent or descent cone modeling terminal airspace [KPM08].

The translation is shown in Figure B-3. Given convective weather constraints and a method of defining the weather hazard (e.g., thresholding convective weather at NWS Level 3 or using the CWAM model [CRD07]), a geometric hazard map (or WAF) may be determined. Next, one defines the width of an air lane (equivalently, the required gap size between adjacent hazardous weather cells) that is required for a flow of traffic passing through the airspace, any geometric polygonal shape (such as a sector, FCA, grid cell, or hex cell) in a given period of time. The required gap size between weather constraints may be expressed in terms of RNP requirements for aircraft using the air lane passing through those gaps. In one version of the problem, mixed air lane widths are used to represent a non-uniform RNP equipage and/or set of preferences by aircraft arriving into the airspace [KPM08]. An algorithmic solution identifies the mincut bottleneck line – this mincut line determines the maximum capacity in terms of the maximum number of air lanes that can pass through the gaps in the weather hazards. The maximum number of air lanes can be determined by analyzing weather constraints as a function of time given a weather forecast product.



(a) Weather hazard is defined

(b) Mincut bottleneck determines the maximum number of lanes of traffic that may pass

Figure B-3 The translation of convective weather into maximum ATM throughput.

The described approach is a geometric analysis of the weather constraints transformed into maximum throughput for a given flight level. For NextGen, complexity and human workload (controller and/or pilot) limitations must be taken into account for determining the capacity of an airspace.

B-1.4 Weather-Impacted Sector Capacity considering CWAM and Flow Structure

Sector capacity as an indicator of controllers' workload threshold is not a single value even on clear weather days, since controller workload is not only a function of the number of aircraft, but also a function of traffic complexity. One way to describe traffic complexity is with traffic flow patterns [SWG06]. Traffic flow patterns are described with clustered flow features, which are more predictable and perturbation-resistant than metrics which rely on single-aircraft events or aircraft-to-aircraft interactions. NAS sectors typically exhibit a small set of common traffic flow patterns, and different patterns represent different levels of traffic complexity. In higher-complexity conditions, it takes fewer flights to generate high workload for the controller team, and thus the sector capacity is lower.

As illustrated in Figure B-4, quantifying sector capacity as a function of traffic flow pattern [SWG06] provides a basis for capturing weather impact on sector capacity. In addition to the size of the weather, the shape and the location of the weather in a sector are also captured in a flow-based weather-impacted sector capacity prediction [SWG07]. A Weather Avoidance Altitude Field (WAAF) that most aircraft would deviate is generated based on a CWAM model [DE06, CRD07]. (Note: The WAAF is a 3D version of the WAF of the CWAM.) The future traffic flow pattern in the sector is predicted and described with flows (sector transit triplets) and flow features. The available flow capacity ratio of each flow in the predicted traffic flow pattern is then determined by the MaxFlow/Mincut Theory [AMO93, M90, KMP07]. The available sector capacity ratio is the weighted average of the available flow capacity ratio of all the flows in the predicted traffic flow pattern. The weather-impacted sector capacity is the available sector capacity ratio times the normal sector capacity given the predicted traffic flow pattern. The flow-based available sector capacity ratio has a strong linear correlation with the estimated actual sector capacity for the sectors with dominant flows [SWG08].

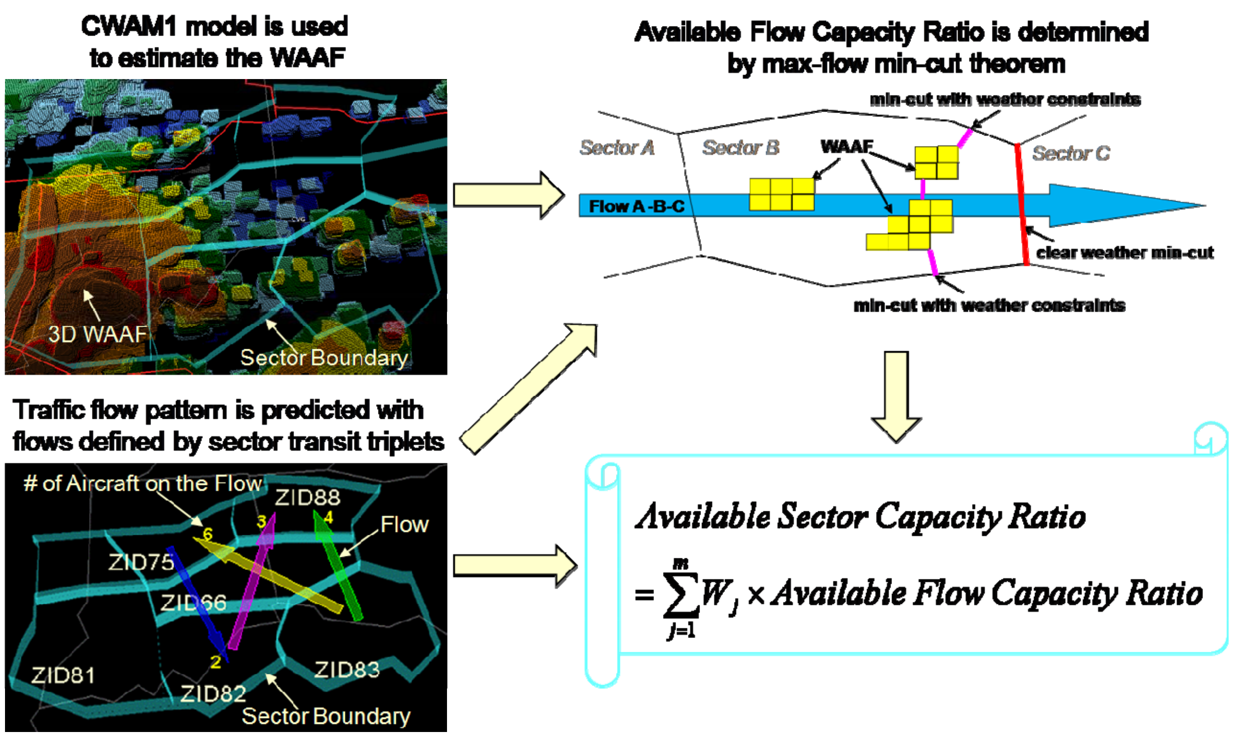


Figure B-4 Weather impacted sector capacity estimation

An alternative approach to quantifying sector capacity given the fair weather traffic flow patterns is to determine to what extent the fair weather routes are blocked and the fraction of the overall sector traffic carried by those routes [M07]. This model estimates the usage of the sector predicted by a route blockage algorithm (which is discussed next).

B-1.5 Route Availability in Convective Weather

Several ATM tasks, including departure and arrival flow management and the planning of weather-avoiding reroutes, require the assessment of the availability and/or capacity of individual traffic routes or flows. Thus, it is natural to extend Mincut/Maxflow, CWAM, and WAF concepts into route availability prediction tools.

A route defines a spatially bounded trajectory. A route is available if there is a way for traffic to generally follow the trajectory and stay within the bounds while avoiding hazardous weather. The route capacity is the rate of traffic flow that an available route can support. Estimating route availability may be achieved by Mincut/Maxflow (MM) [M90, KMP07, SWG07, SWG08] and Route Blockage (RB) techniques [M07]. Both methods identify weather-avoiding paths that traverse a portion of airspace along a route. Capacity estimates based on MM and RB must account for the workload and uncertainty involved in flying the weather-avoiding trajectories that they identify.

MM begins with a deterministic partition of the airspace into passable and impassible regions. MM identifies all paths that traverse the airspace without crossing weather obstacles, and characterizes each path by its minimum width. Route availability and capacity are related to the number, required width (gap between hazardous weather cells), and complexity of paths identified.

RB uses a probabilistic partition of airspace, in which each pixel is assigned a probability of deviation around the pixel. RB finds the best path that traverses the space, defined as the widest path that encounters the minimum probability of deviation in the traversal. The route blockage is a weighted average of all pixels in the space with deviation probabilities ≥ the minimum probability encountered by the best path. RB differs from MM in that it identifies a single path that traverses the airspace, and it takes into account the nature of the weather that trajectories are likely to encounter on their traversal of the airspace (Figure B-5, left).

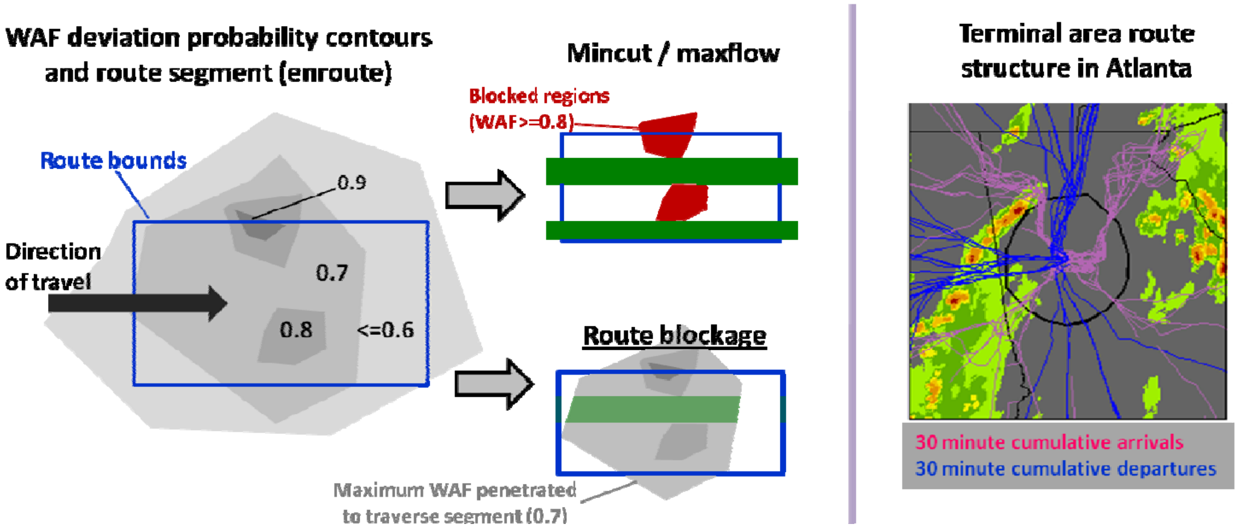


Figure B-5 Mincut/Maxflow and Route Blockage estimate route availability in structured, en route airspace (left) and flexible routing to avoid terminal area convective weather (right).

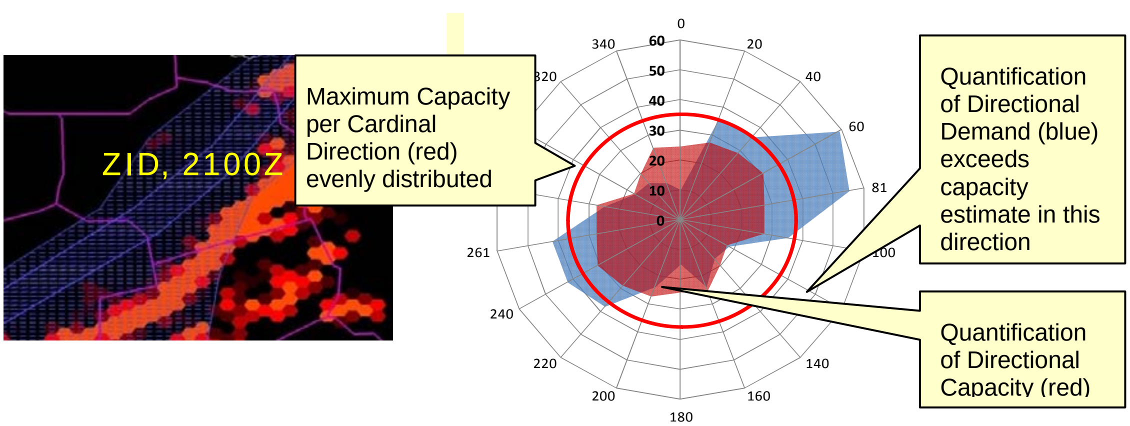
Estimating route availability in terminal areas has additional difficulties. Air traffic controllers have considerable flexibility to route aircraft around weather in terminal areas, and the bounds on traffic flows may be fluid and difficult to define (Figure B-5, right). Route availability in the terminal area may not be accurately determined simply by characterizing the weather impacts on nominal (i.e., fair weather) departure and arrival routes and sector geometry. The constraints on traffic flows at any given time depend on specific details of the flow structure and the nature of the demand (balance between arrivals and departures). Uncertainty in predicting flight time from runway to departure fix (or from metering fix to runway) when aircraft are maneuvering to avoid weather also has an impact on capacity that is difficult to estimate. Significant research is needed to develop terminal area airspace usage models that can be combined with WAFs to provide reliable estimates of route availability and time of flight between the runway and en route airspace.

B-1.6 Directional Capacity and Directional Demand

In addition to capacity being a function of flow pattern for a given airspace unit, airborne separation and RNP requirements, and convective weather impacting the airspace, capacity is also a function of traffic demand, both spatial and temporal. Since traffic flow patterns are directional, capacity is also directional. If the majority of traffic in a given period of time wants to traverse a center in the east-west direction and the center airspace capacity cannot accommodate this demand (e.g. due to weather blocking large portions of the east-west flows), the fact that the center might have, in principle, plenty of capacity to accommodate north-south traffic does not help. Consider for instance, the case of a squall line weather system, and traffic flow trying to pass through gaps in the squall line vs. parallel to it. Queuing delays will ensue when the capacity is limited in a particular direction, and upstream traffic will be forced to deviate around the constraint, be held upstream, and/or back at origin airports.

The capacity of an airspace can be estimated for a series of 'cardinal' directions, e.g., the standard directions of North (N), East (E), South (S), West (W) and the diagonals NE, NW, SE, and SW [ZKK09]. Also, directions can be quantified every □ degrees (e.g., □=20 deg.), spaced around a given NAS resource, for instance, around an airport, metroplex, or fix location, or within a section of airspace [KPM08, KCW08]. For each angular wedge of airspace, the maximum capacity for traffic arriving from or traveling in that direction may be established. MaxFlow/Mincut techniques [ZKK09, KPM08] as well as scan line techniques [KCW08] have been demonstrated for this purpose. The maximum capacity for a particular angular wedge of airspace will quantify the permeability of the weather with respect to traffic arriving from [KPM08] or traveling in [KCW08] this particular direction. The permeability can be calculated using pre-defined permeability thresholds [SSM07] that indicate at what probability or actual intensity of convective weather will most aircraft be likely to deviate (or plan the flight around the weather in the first place).

Directional capacity percent reductions may be used to determine the acceptable number of aircraft that can be accepted from or can travel in a particular direction. This may be expressed in units relative to the maximum capacity for the airspace when no weather is present. Demand can also be calculated in each direction using the primary direction a flight will take within a given unit of airspace (grid cell, hex cell, sector, center, FCA, etc.). By comparing directional capacity vs. demand on a rose chart, for instance as illustrated in Figure B-6, directional demand-capacity imbalances can be identified as well as regions where there may be excess directional capacity to accommodate additional demand. In NextGen, en route traffic flow patterns may be adjusted [ZKK09] or terminal traffic flow patterns may be adjusted (e.g., route structures and metering fix locations around a metroplex [KPM08]) in order to maximize the capacity by restructuring the traffic flow pattern (demand) to best meet the directional capacity.



(a) Forecasted Weather Constraint (b) Directional Impact

Figure B-6 Directional capacity and demand rose chart.

NextGen researchers must still address how directional capacity should consider the complexity of the traffic demand and controller workload issues. Hence, if flow is largely directional, but there are very important traffic merge points within the region of interest [HH02], or if there are occasional crossing traffic constraints, then the directional capacity estimates must address these issues.

B-1.7 ATM Impact based on the Weather Impacted Traffic Index

The Weather Impacted Traffic Index (WITI) measures the number of flights impacted by weather (Figure B-7). Each weather constraint is weighted by the number of flights encountering that weather constraint in order to measure the impact of weather on NAS traffic at a given location. Historically, WITI has focused on en route convective weather, but the approach is now applied to other weather hazard types as well. In WITI's basic form, every grid cell of a weather grid W is assigned a value of 1 if above a severe weather threshold and a value of 0 otherwise. The CWAM model [CRD07] can be used to identify whether a pilot will fly through a weather hazard or will deviate around it at a given altitude. The number of aircraft T in each grid cell of the weather grid W is counted. The WITI can then be computed for any time period (such as 1 minute intervals) as the sum over all grid cells of the product of W and T for each grid cell [CDC01]. A WITI-B variation evaluates the extent to which a flight would have to reroute in order to avoid severe weather [KCWS08]. If a planned trajectory encounters severe weather, the algorithm finds the closest point in a perpendicular direction to the flow where no severe weather is present. The WITI score for that route is then weighted by the number of cells between the original impeded cell and the unimpeded cell found for the re route.

Various methods for determining the traffic count have been explored. WITI can use actual flight tracks from "good weather days" as the traffic data source [CS04], current day flight plan trajectories [PBB02], or great circle tracks between the origin and destination airports as the ideal, shortest-path unimpeded flight trajectories [KJL07]. Actual scheduled flight frequencies on these flows for the day in question are used. The En route WITI (E-WITI) for a flow is the product of its hourly flight frequency and the amount of convective reports in rectangular or hexagonal grid cells. This is then aggregated to the NAS level and to a 24-hour day, as well as by center, sector, or general airspace geometry. Another approach apportions all en route WITI measures to origin and destination airports. Even though en route delays may not be due to any local airport weather, the resulting delays will originate and/or eventuate at the departure or arrival airports. A grid cell's WITI score for a flow is apportioned to each airport proportional to the square root of the distance from the cell to those airports. The closer a weather cell is to an airport, the larger the portion of the WITI will be assigned to that airport. This provides a national WITI score broken out by airport – consistent with how NAS delays are recorded in ASPM today [KJL07].

Given that the WITI is an estimation of NAS performance, WITI has also been used as a measure of NAS delays [S06]. Multiple years of weather, traffic, and delay data have been analyzed, and a strong correlation exists between the WITI metric and NAS delays. Recent research considers other factors in addition to delay, such as the number of cancellations, diversions, and excess miles flown in reroutes [Kl05].

The correlation between the WITI and delays has improved as additional types of weather besides en route convection have been considered. Terminal WITI (T-WITI) considers terminal area weather, ranked by severity of impact, and weights it by the departures and arrivals at an airport. Types of weather include local convection, terminal area winds (direction, severity, and altitude), freezing precipitation, and low ceilings/visibility. The impact of turbulence on en route flows is also being studied as an inclusion to WITI [CKW08].

The National Weather Index (NWX) implements the WITI for the FAA. In addition to calculating E-WITI and T-WITI, it considers the additional delays due to queuing during periods where demand exceeds capacity, both en route and at airports. This 4-component NWX is referred to as the NWX4 [CKW08]. Current research is now exploring the use of the WITI for airline route evaluation, departure and arrival fix evaluation at TRACONs, and principal fix evaluation in ATM centers [KMK09].

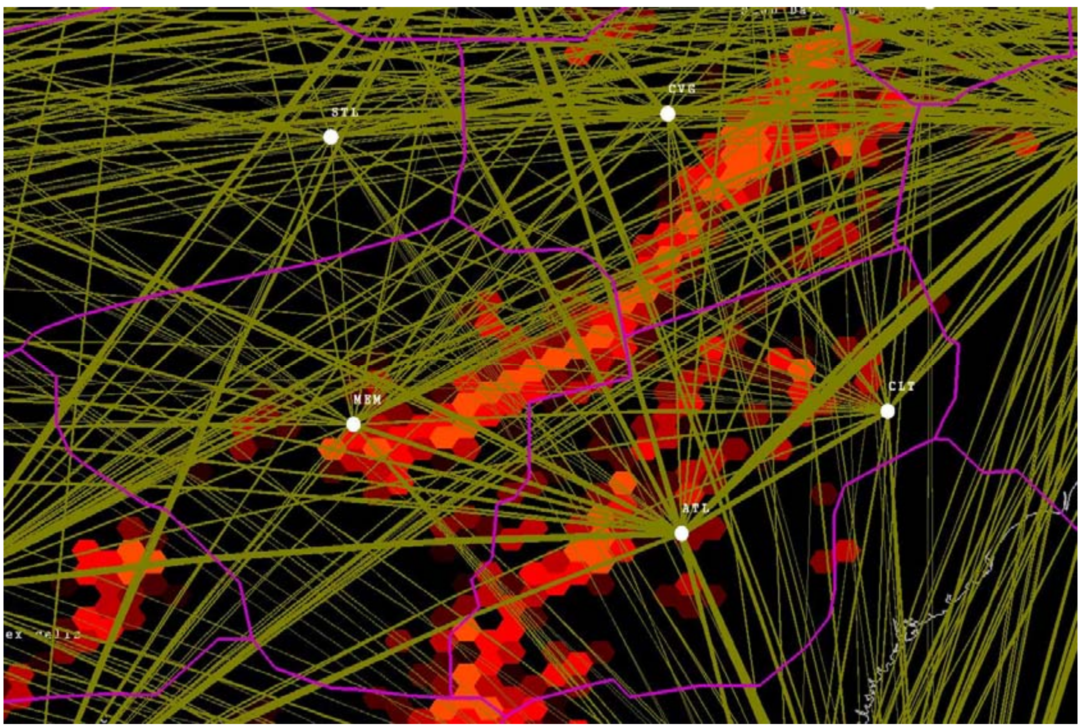


Figure B-7 Factors included in a WITI calculation.

B-1.8 Weather-Weighted Periodic Auto Regressive Models for Sector Demand Prediction

Traditional air traffic flow prediction models track the aircraft count in a region of the airspace based on the trajectories of the proposed flights. Deterministic forecasting of sector demand is routinely done within ETMS, which relies on the computation of each aircraft's entry and exit times at each sector along the path of flight. Since the accuracy of these predictions is impacted by departure time and weather uncertainties [MC02, E01], and since weather forecast uncertainty causes errors in the sector count predictions [KRG02, WCG03], traditional methods can only predict the behavior of NAS for short durations of time – up to 20 minutes. It is difficult to make sound strategic ATM decisions with such a short prediction accuracy. If a severe storm blocks a sector or regions near it, both sector capacity and demand may drop dramatically [SWG07 SWG08]; trajectory predictions must account for this.

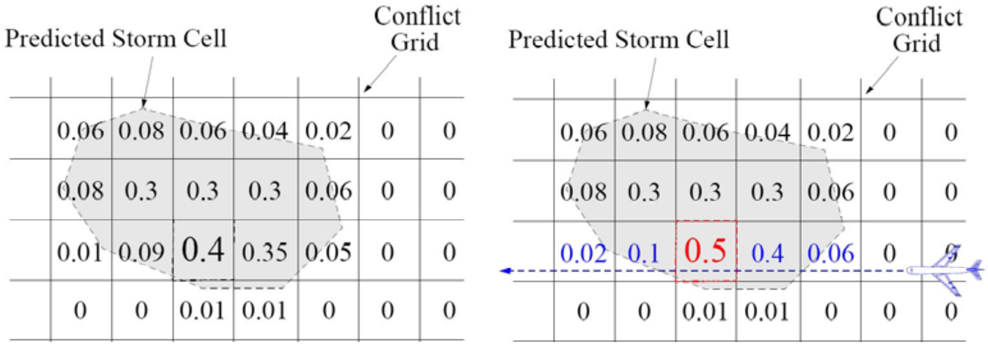
An empirical sector prediction model accounts for weather impact on both short-term (15 minutes) and mid-term (30 minutes to 2 hours) predictions. Different from traditional trajectory-based methods, a Periodic Auto-Regressive (PAR) model and its variants [Lj99, FP03] evaluate the performance of various demand prediction models considering both the historical traffic flows to capture the mid-term trend, and flows in the near past to capture the transient response. A component is embedded in the model to reflect weather impacts on sector demand. In addition, to capture the impact on all low, high, and super high sectors, storm echo tops information is needed. Only the storms with the echo tops above the lower boundary of the sector are considered. Results indicate improvements over the traditional sector demand models [CS09].

B-1.9 ATM Impact in terms of a Stochastic Congestion Grid

The effects of weather (convection, turbulence, or icing) on airspace capacity may be formulated in terms of a Stochastic Congestion Grid (SCG) [J05]. The SCG quantifies congestion (density of aircraft) in a way that accounts for the uncertainty of the aircraft demand and uncertainty of the weather forecast for long look-ahead times, as required by strategic TFM planning processes.

As illustrated in Figure B-8, each grid cell (a horizontal 2D grid is shown) records an estimate of the probability that the expected traffic exceeds a threshold level established by the Air Traffic Service Provider (ATSP). In NextGen, 4D trajectories are submitted for each aircraft flying in the NAS, they are stored in the 4D congestion grid by projecting the 4D trajectory onto the grid with an error model for along track error and cross track error. An increase in probability of congestion occurs where the traffic flow increase coincides with the predicted weather constraint. A probability that a weather constraint will exist is described on a grid cell instead of a binary value for a constraint versus no constraint. If the probability that traffic in any 4D grid cell exceeds tolerable thresholds set by ATSP (dependent on a weather-to-ATM impact model [CRD07, SWG08]), then an airspace resource conflict is monitored and appropriate action is taken by the ATSP.

For strategic look-ahead times, all information is probabilistic for when and where TFM strategies must take action. As an aircraft nears a location of a weather constraint, the probability for when and where the aircraft traverses the grid cell becomes more tightly bounded (that is, more deterministic as the variance goes down). Furthermore, the geometry and severity of the forecasted weather constraints are also more tightly bounded. This congestion management method limits the number of aircraft within a given region of airspace, but at this point it does not need to specifically determine which aircraft are in conflict with one another, nor the specific conflict geometry between two aircraft; the SCG is simply a congestion monitor.



(a) before addition of aircraft demand at time t

(b) congestion prediction after addition of the probability of an aircraft passing at time t

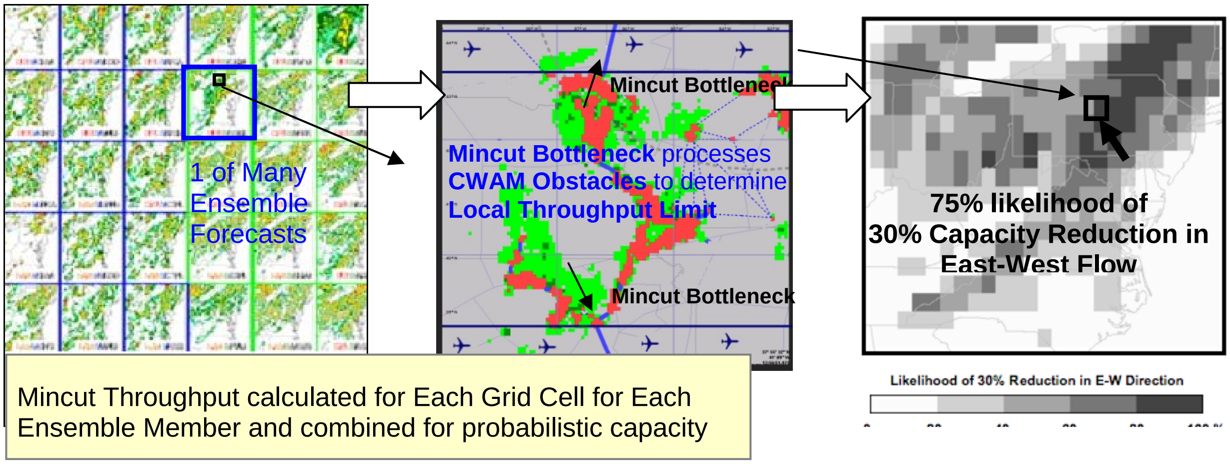
Figure B-8 Stochastic congestion grid with combined traffic and weather constraint probabilities.

The SCG is a prediction of large-scale regions of high aircraft density, including bottleneck regions between weather constraints or airspace regions with high demand. The SCG may be implemented with square or hex cells, and may be applied to sectors, centers, or the entire NAS. The ATSP can use the SCG to help make strategic decisions to identify FCAs and manage the predicted congestion.

B-1.10 Translation of Ensemble Weather Forecasts into Probabilistic ATM Impacts

In NextGen, in order to capture the uncertainties posed by long-term weather forecasting, ATM will rely on utilizing automated Decision Support Tools (DSTs) that will integrate probabilistic ensemble weather forecast information into ATM impacts [SM08, SB09], thus forming the basis for strategic TFM planning. The use of probabilistic forecasts will provide better tools to assist with a risk-based decision making. In the coming years, however, an understanding of the operational use of probabilistic forecasts will need to be developed, where probability may be either a measure of how likely it is that an event will occur (in space and time) or a number expressing the ratio of favorable cases to the whole number of cases possible. The move to probabilistic forecasting has been helped with the continued development of high-resolution Numerical Weather Prediction (NWP) models and ensemble prediction systems, both spurred by increases in computing power and a decrease of equipment cost, which enables NWP models to process more data in a shorter time period.

Figure B-9 illustrates the ensemble-based translation concept. Ensemble forecast systems generate a series of deterministic forecasts of potential weather outcomes (i.e., members of the ensemble). Each ensemble forecast represents a possible weather scenario that may emerge later in the day. These ensemble weather forecasts, in turn, are translated into ATM impacts with relative likelihoods and probability density functions (pdfs) for either use by humans-over-the-loop or computer-to-computer ATM applications [SK09].



(a) Ensemble of Forecasts (b) Local ATM impact per Grid Cell (c) ATM Impact Map

Figure B-9 Procedure for translating an ensemble of weather forecasts into a probabilistic capacity map in terms of likelihood of a given capacity reduction.

This process will be adapted to the needs of particular ATM applications. It can be performed using tactical 1-hour as well as strategic 2, 4, or 6-hour forecasts, processing anything from 2-member to 30-member (or more) ensemble weather forecasts. The definition of a weather hazard could be for convection, turbulence, icing, or other aviation-relevant hazards and events (e.g., major wind shifts at an airport), and any appropriate weather hazard model can be placed into the ensemble-translation process; for instance, the CWAM WAF [DE06, CRD07] for a given altitude range. The airspace capacity reduction could be directional [KCW08, ZKK09], for instance, in the East-West direction, or in any particular direction where TFM plans to organize and direct traffic.

The resulting probabilistic ATM impact maps, once they become routinely available during the NextGen era (perhaps a decade from now), will be used by many decision makers to assess risks when formulating tactical and strategic plans. Air traffic controllers, traffic flow managers, airline dispatchers, airport operators, and NextGen automated DSTs, for example, will use these results to help reason about the weather forecast uncertainties when making decisions about traffic flows and operational impacts from one to several hours into the future.

B-1.11 Translation of a Deterministic Weather Forecast into Probabilistic ATM Impacts

While the previously mentioned ensemble approach for characterizing uncertainty of forecasts is promising for long term weather forecasts, other methods may be useful in short look ahead times. In NextGen, systems can benefit from understanding how a single deterministic forecast in a grid-based format, and some error bounds associated with the forecast, can be used to create probabilistic ATM impacts for a given region of airspace [KZM09].

Figure B-10 illustrates the concept for convective weather. A single deterministic forecast is input, and variations on this forecast are created by considering error models that account for possible errors in timing, errors in coverage, translational errors, or echo top errors. Given a standard deviation that describes the potential error in each of these dimensions, a synthetic ensemble of forecasts is created that are similar (perturbations) to the input deterministic forecast. The intermediate ensemble of erroneous forecasts is then input into an ATM-impact model, for instance, a Mincut/Maxflow method, route blockage method, or CWAM model, and a set of ATM-impacts is output. The ATM impacts may be quantified in terms of a cumulative distribution function (cdf), probability density function (pdf), a set of scenarios or maps and associated metrics, or some other format. The set of erroneous forecasts represents "what if" cases; "what if the weather system arrives early", "what if it arrives late", "what if it is larger than expected", "what if it is smaller than expected", etc. The underlying assumption is that the weather organization has been correctly forecasted, but the growth or decay of weather cells may be in question. The ATM impact model can determine, say, through a cdf, what is the probability that two lanes of traffic will be available for routing traffic through transition airspace to the North-East quadrant around a metroplex.

This process will be adapted to the needs of the particular ATM application. This process can be performed using tactical 15-minute to 1-hour look ahead. At some point, true ensemble methods (ensembles of NWP forecasts) will perform better than this method of creating synthetic ensembles, so future research is needed to identify at what look ahead time this method should be replaced with the processing of true ensemble forecasts. The benefit of the synthetic ensemble method is that it provides a well-defined sensitivity estimate of the ATM impact given errors in a single deterministic forecast. This method helps the user (or DST) reason about potential weather forecast uncertainties when making decisions about traffic flows and operational impacts.

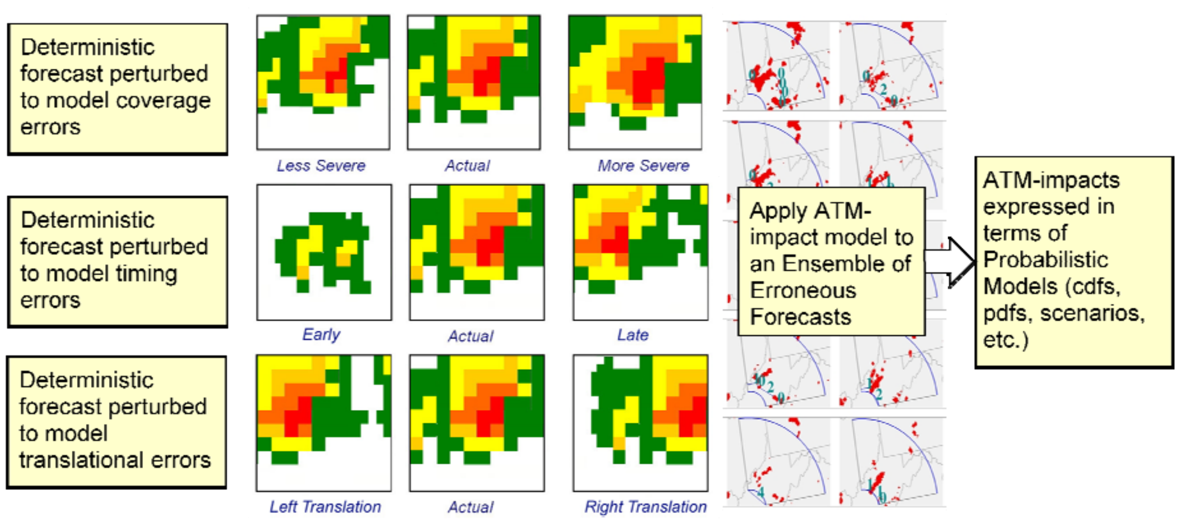


Figure B-10 Weather forecast errors characterized in terms of coverage, timing, and translational errors create an ensemble of weather constraints for a probabilistic ATM-impact assessment.

B-1.12 Sensitivity of NAS-wide ATM Performance to Weather Forecasting Uncertainty

Planners need to understand sensitivity of ATM performance to the weather forecasting uncertainty in order to make research and development decisions. The ATM performance improvement (benefit) is determined by comparing the performance sensitivity and the contemplated forecasting uncertainty reduction.

The ATM performance sensitivity to the weather forecasting uncertainty is difficult to understand for several reasons. First, there are challenges to modeling the ATM response to weather constraints. For instance, ATM performance can be characterized in a variety of ways, and likewise weather includes a variety of phenomena and no two scenarios are exactly alike. Second, not only must the ATM response to weather be modeled, but the ATM response to weather forecasts must also be modeled. Also, weather forecasting improvements may reduce uncertainty in a variety of ways. For instance, the forecasting may be improved for the short-term, but not the long-term. For these and other reasons, ATM performance sensitivity to the weather forecasting uncertainty is difficult to model and evaluate.

ATM performance has several nonlinear dependencies on independent variables such as the weather. Therefore simulation is typically required to model ATM performance. Of course, the simulation must include effects of the weather and its forecast in order to model the sensitivity to the weather forecasting uncertainty. For instance, such effects might include vectoring, rerouting and ground hold decision making models in response to weather forecasts. Such simulations have been constructed at a regional level [HB95,BH98, KPP07] and NAS wide level [RBH06, KD07].

The ATM performance simulations require weather forecasts of varying accuracy in order to evaluate the sensitivity to forecasting uncertainty. This uncertainty variation can be modeled using different approaches. For instance, two broad, and well developed, types of solution to this simulation problem are covariance propagation and Monte Carlo methods [Ge74]. In this problem, covariance propagation varies the forecast uncertainty while Monte Carlo varies the forecast itself. Of course, the covariance propagation requires that the simulation take as input the forecast uncertainty, and not merely the forecast itself. On the other hand, the Monte Carlo method requires a large number of weather forecasts. This can be accomplished with a forecast ensemble, or with forecasts from several different days.

In many problems, simple bounding cases which provide worst and best possible results are quite useful to help guide further research and planning. This is conveniently available for weather forecasts in the form of the persistence (i.e., the current weather is the forecast) and perfect (i.e., the future weather is the forecast) weather forecasts.

For example, in Figure B-11 persistence and perfect convection forecasts were used to compare the effect of the convection forecast with two ATM capabilities: trajectory-based operations traffic flow decision making where the delays and reroutes are assigned to specific flights rather than to flows, and agile decision making where flights can be rerouted or delayed minutes prior to departure [HR07]. For this scenario, these results indicate that NAS performance was most sensitive to the trajectory-based versus flow-based operations. The trajectory-based operations case significantly moved the NAS performance tradeoff curve to lower levels of congestion and delay, compared to the flow-based operations. TFM agility was the next most significant factor influencing ATM performance. The agile TFM moved the NAS performance to lower levels of congestion and delay, compared to the non agile TFM case. Also, the non agile, flow-based operations was the best approximation of the NAS performance as measured by ETMS and ASPM data sources. Finally, the convection forecast uncertainties were the least significant factors influencing ATM performance. Improving these forecasts resulted in second order NAS performance improvement compared to the other factors. These results, however, may not hold for other types of NAS weather or traffic days, which should be explored in future research.

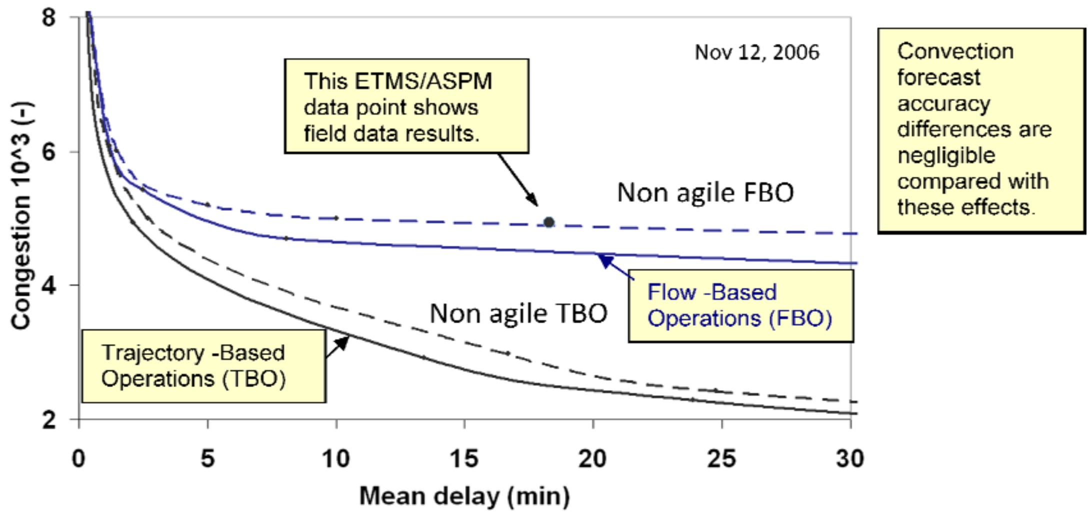


Figure B-11 NAS performance sensitivities of trajectory-based and flow-based operations performance improvements and agile versus non agile decision making.

B-1.13 Use of Probabilistic Convective Weather Forecasts to Assess Pilot Deviation Probability

Probabilistic weather forecasts for convection are being developed today and for NextGen. For instance, the operational 0-6 hour National Convective Weather Forecast (NCWF-6) product provides up to 6-hour forecasts of the probability of convection. Efforts have been made to determine how to use this forecast in ATM automation where probabilities of convective need to be translated to ATM impact. One approach is to determine a correlation between aircraft position and NCWF-6 convective probability values [SSM07]. Using the derived correlation, a decision-maker could assess the NCWF-6 probability that aircraft are willing to traverse, and in turn, the risk associated with traveling in the vicinity of forecasted NCWF-6 probability contours. The Probability Cut-off Parameter (PCP) is the maximum NCWF-6 probability contour which correlates with a majority of aircraft positions based on historical analysis. With a 1-hour NCWF-6 forecast, the 80th percentile value (PCP) for all aircraft flying through the probability field across the continental US is around 35% using four months of flight track and weather data [SSM07]. PCP values differ for longer forecast times. Also, PCP values can be established for a local scope, at center and sector levels [SAG09]. Figure 13 shows the method to create the PCP.

A flight traversed an NCWF-6 forecast and the contours it coincided with are recorded. These data can then be aggregated for many flights. The bottom of Figure B-12 shows an aggregation of many flights of similar aircraft to develop a PCP for aircraft type. Future research must address how storm echo tops can be included in the analysis of probabilistic weather forecasts and PCP analysis.

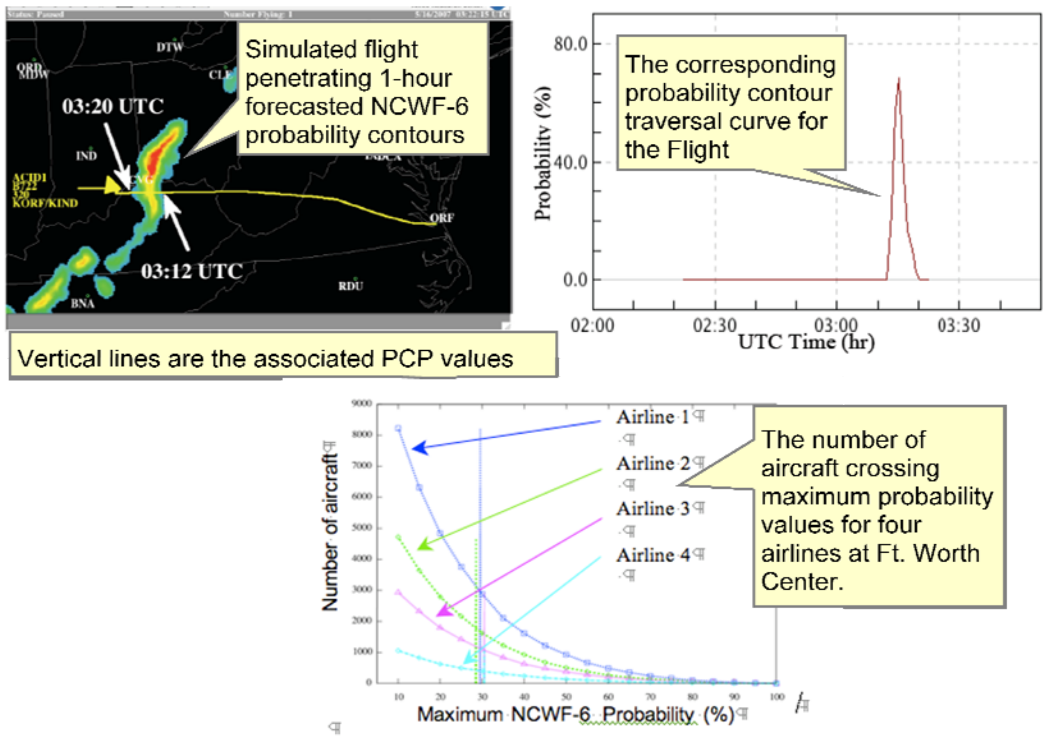


Figure B-12 Transforming a probabilistic NCWF-6 forecast into probability of penetration.

B-1.14 Integrated Forecast Quality Assessment with ATM Impacts for Aviation Operational Applications

The ATM planning process uses specific weather information to develop strategic traffic flow plans. Plans often reroute traffic when hazardous convective weather occurs within the NAS. In order to better understand the application of convective weather forecasts into the ATM planning process, convective forecast products are objectively evaluated at key strategic decision points throughout the day.

An example of how forecasts can be evaluated in the context of ATM strategic planning processes is illustrated in Figure B-13. A sector-based verification approach along with the ATM strategic planning decision points and a measure of weather impact across the NAS [KMM07, MLL08] can be used to evaluate convective weather forecast quality in an operational context. The fundamental unit of measure is applied to super high sectors – the volumes that are used for strategic air traffic planning of en route air traffic. In Figure B-13, a squall line is moving into the

Tennessee Valley. The goal is to correctly transform the forecast into sector impacts quantified by the ATM impact model that applies, for instance CWAM model [CRD07, SWG08]. The ATM-impact model may have a flow plan and decision points as an input in order to determine the demand flow direction and quantity. In this example, the northern polygons were false alarms – areas where events were forecast, but did not occur. Convection occurring over the southeast, ahead of the squall line, was not captured by the forecast, and the sectors were considered missed events.

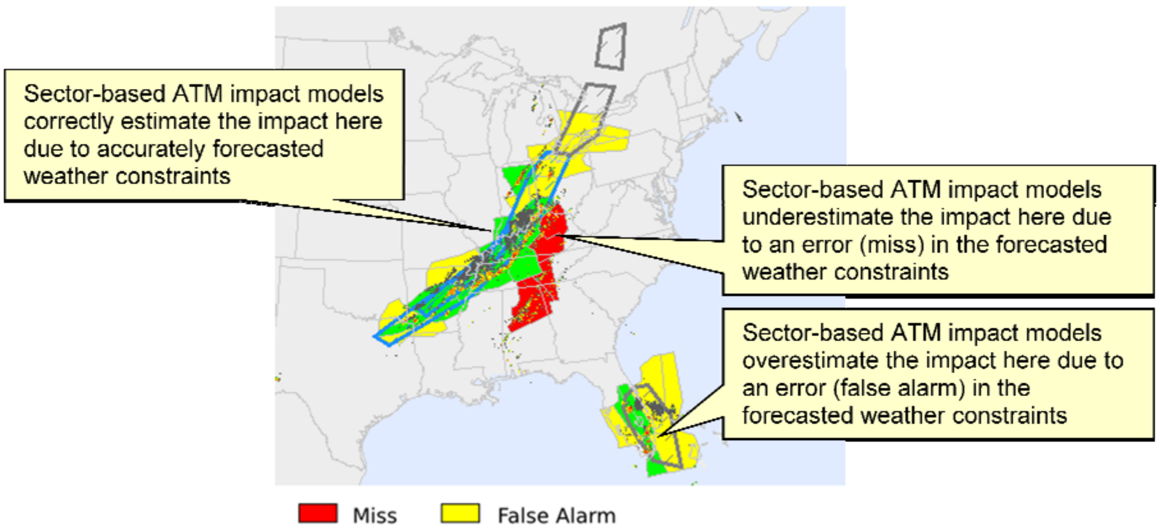
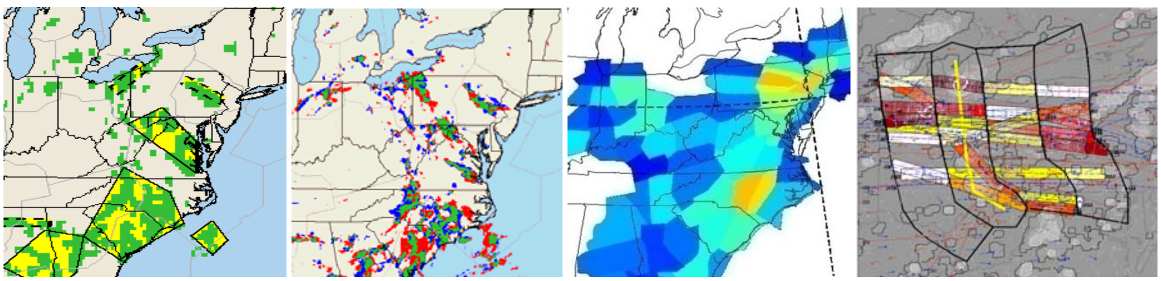


Figure B-13 Sector-based verification of a 2-hour forecast and observations (impacted sectors are color-coded to depict the verification results).

In NextGen, accurate and consistent weather information will be the foundation of the 4D weather Single Authoritative Source (SAS) for ATM operations. User-specific evaluation of weather forecast quality plays a significant role in providing accurate and consistent weather information to the SAS. ATM impact models must be tied into the evaluation of weather forecast quality in a way that the ATM impact is accurately predicted in measures that are meaningful to the ATM application.

B-1.15 Conditioning ATM Impact Models into User-relevant Metrics

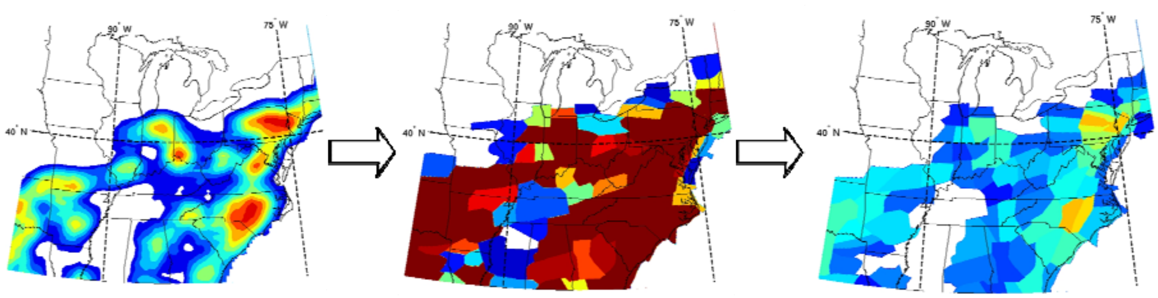
NextGen ATM planners and automated DSTs need useful weather information for efficiently planning, managing, and scheduling the flow of air traffic across the NAS. Significant efforts are currently underway to provide improved forecasts of convective weather for traffic flow managers to help them increase air space usage efficiency during times of convective weather impacts. However, due to the increased workload created by convective weather impacting congested air traffic routes and other factors, increased forecast performance does not always translate directly into more efficient operations. Weather forecasts need to be processed in a way that accounts for the ATM strategic planning procedures making weather information easily digestible for ATM DSTs and their users, in the particular format that is required (e.g., as shown in Figure B-14). In order to translate the weather forecasts into useful information for ATM planners, weather forecasts need to be calibrated, not with respect to meteorological criteria, but with respect to operational planning criteria. Since the airlines participate in the ATM process through Collaborative Decision Making (CDM) processes [BCH08], calibrated ATM-impacts must be expressed in meaningful terms to the airlines (dispatch and ATC coordinators) as well as to the ATSP. When planning and scheduling flows of air traffic to cross the NAS, one must project flight schedules and trajectories and weather forecast information into an ATM impact model to arrive at delay estimates (arrival and airborne delays), cancellation estimates, and cost estimates.



(a) Convective Forecast (b) Pixel-based impact (c) Sector-based impact (d) Route-based impact

Figure B-14 Convective forecast transformed into ATM impact in various formats.

TFM planning requires accurate, consistent, and calibrated impacts, as illustrated in Figure B-15. For instance, weather information (un-calibrated and operationally calibrated) must be ingested into ATM impact models that properly account for sector-to-sector queuing in order to measure delay costs associated with the weather forecast and expected demand on sectors. When operationally calibrated weather information is introduced into ATM impact models, costs must be close to those cost associated with ‘perfect’ knowledge of the weather [MKL09]. In NextGen, post-process analysis can be used to adjust the bias on ATM impact models so that future ATM impacts best model actual costs. Ultimately, improving the transformation of weather information into ATM impacts will reduce air traffic delay costs. In NextGen, it will be critical that the impacts of weather information be calibrated with respect to ATM operational decisions for effective planning and automated decision support.



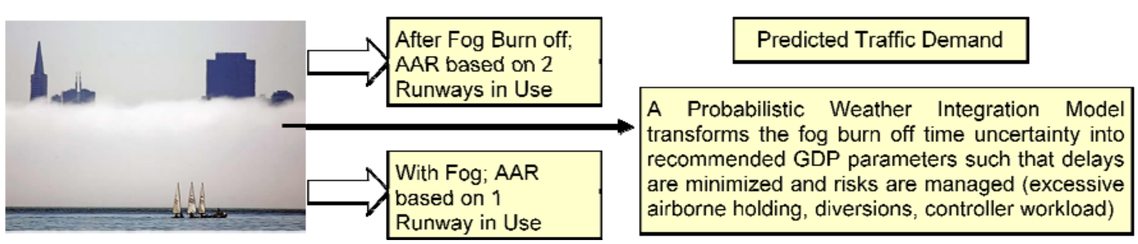
(a) Original Convective Forecast (b) ATM Impact Uncalibrated (c) ATM Impact Calibrated

Figure B-15 Convective forecasts for use by automated ATM planners (impacted sectors are red for high impact and blue no impact).

B-1.16 Integration of the Probabilistic Fog Burn Off Forecast into TFM Decision Making

Convective weather forecasts in the en route environment include uncertainty in multiple dimensions, including time, space, and severity. Attempts at integrating probabilistic weather forecasts into operational decision making in order to address these uncertainties has proven to be challenging – it requires complex models to integrate probabilistic weather forecasts with TFM decision making. The situation at San Francisco (SFO) International Airport provides an opportunity to explore the integration of probabilistic weather forecasts into TFM decision making in a less complex scenario [CW03]. This case involves a forecast of a single weather parameter – the marine stratus (fog) burn off time – at a fixed geographical location (the SFO approach zone). Traffic managers initiate a Ground Delay Program (GDP) to reduce the inflow of aircraft when fog at SFO lingers well into the morning arrival rush, thereby reducing the AAR in half (because only one runway can be used instead of two). One must rate the confidence of each of several forecasts, and use empirical errors of historical forecasts in order to create a probabilistic forecast in terms of a cumulative distribution function (CDF) of clearing time [CIR06].

To address the ATM impact (Figure B-16), a weather translation model must integrate SFO's probabilistic fog burn off forecast in with GDP algorithms [Cl09]. One model uses a Monte-Carlo simulation approach to find the optimal GDP parameters based on objectives of minimizing unnecessary delay and managing the risk of airborne holding [CW09]. The model samples multiple times from the CDF of the forecast of stratus clearing time, calculating the key measures for each possible GDP end time and scope under consideration. The mean value of each metric is calculated over all clearing time samples for each GDP parameters scenario, providing the expected value of each metric given the uncertainty in the clearing time. An objective function uses these key metrics to select the GDP parameters that minimize cost. This model places a high importance on managing the risk of excessive holding if the stratus clears later than anticipated. This is addressed by using an objective function that permits low probabilities of ATM risk, and quickly increases to heavily penalize risky end time decisions.



(a) For Burn off Time Estimate (b) ATM Impact (c) TFM Plan

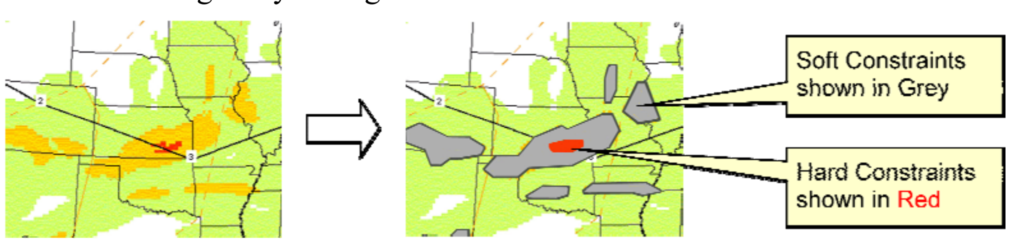
Figure B-16 Integration of a Probabilistic Forecast of Stratus Clearing with TFM.

The planning, implementing, and controlling a GDP under uncertainty in stratus clearance time at SFO is both stochastic and dynamic in nature. Decisions related to airport rates, scope, and flight departure delays require revision in response to updated forecasts. Towards this, a parallel body of research is underway to develop an algorithm for setting AARs and allocating slots to flights, and dynamically revising those decisions based on updated forecasts [MHG09]. The primary input to the algorithm is a set of capacity scenarios and their probabilities, generated from forecasts. Given a distribution of stratus clearing time, one algorithm applies a stochastic optimization model [BHO03] to decide on optimum AARs, following which a slot allocation algorithm is applied to assign landing slots to airlines [HBM07]. After airlines perform substitutions and cancellations, the revised schedule and updated forecasts are fed back to the algorithm, which is re-applied in response to changing conditions.

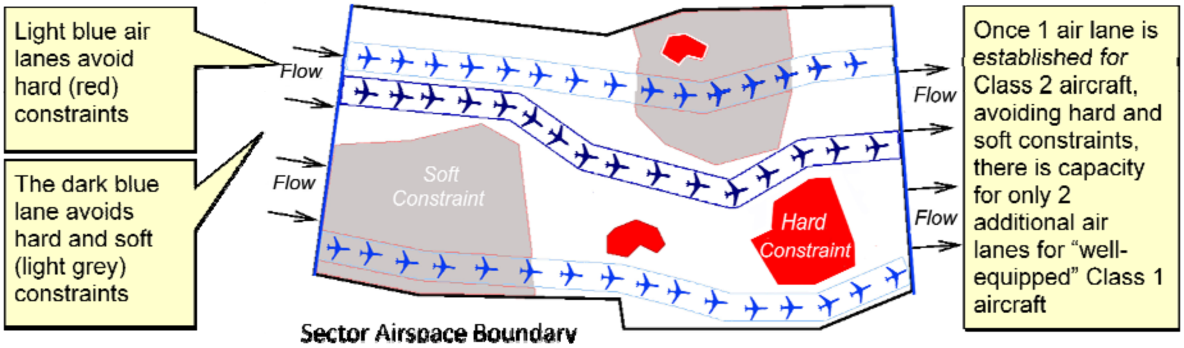
Stochastic dynamic optimization models that simultaneously decide AARs and delays of individual flights require more than just capacity scenarios as input [MH07]. Typically these models apply a wait-and-see policy where certain decisions are delayed until updated information on airport capacity becomes available. Such models could be applied in NextGen if weather forecasts provide a capacity scenario tree whose branching points provide information on when to expect updates in forecasts and the conditional probabilities of scenarios associated with those updates.

B-1.17 Mincut Algorithms given Hard/Soft Constraints to determine Maximum Capacity

While the continuous version of the maximum flow problem [M90, KMP07] is suitable for estimating the maximum throughput across an en route airspace given a traffic flow pattern [SWG08], it assumes that weather hazards are classified in a binary way: traversable or not (hazardous or not). The assumption is that all hazards are hard constraints. However, weather hazards, including the "types" of convection, turbulence, icing, and other weather effects may more generally be classified into hard and soft constraints. Hard constraints are formed by weather hazards that no aircraft can safely fly through (e.g., severe convection, turbulence or in-flight icing). Soft constraints are formed by weather hazards which some pilots or airlines decide to fly through while others do not (e.g., moderate turbulence or icing); these can be characterized as user "business rules". As illustrated in Figure B-17, one can consider two aircraft "classes": Class 1 aircraft that avoid both hard and soft constraints, and Class 2 aircraft that avoid hard constraints but are willing to fly through soft constraints.



(a) Flight Level Turbulence Data (b) Hard and Soft Constraints Model



(c) Some aircraft avoid hard constraints and other aircraft avoid hard and soft constraints.

Figure B-17 Capacity computation for two classes of aircraft among hard and soft constraints.

The problem that arises within this mathematical weather to TFM translation model is that of multi-commodity flow, in which the goal is to determine if there exists a set of air lanes, each with an associated Class of aircraft (the "commodity"), such that each air lane satisfies all constraints from the weather types that impact the Class, and such that the air lanes yield a set of flows that satisfy the demand, or some fraction of the demand. We quantify the capacity of the resulting region of interest in terms of what fraction f of demand is satisfiable, given the multiple types of constraints for various classes of aircraft. The fraction f may be less than 1, indicating that the constraints result in reduced capacity below demand level, or it may be greater than 1, indicating that there is excess capacity available.

B-1.18 ATM Impact of Turbulence

Unexpected turbulence may injure crew and passengers, and potentially can damage aircraft. The hazard results from several different atmospheric phenomena including jet stream interaction, shear, mountain wave generation, and convection. Two distinct types of turbulence are of concern – Clear Air Turbulence (CAT) and Convective Induced Turbulence (CIT). Turbulence within convection is addressed by avoiding convective storms.

The ATM impact (Figure B-18) [KlK09] results from pilots desiring to avoid or exit turbulent conditions for safety reasons. This may happen tactically or strategically. Alerting to potential turbulence is important so that the cabin can be properly secured prior to an encounter. Exiting an unplanned encounter requires information to identify an acceptable exit strategy (that is, climb or descend to airspace clear of turbulence, or avoid by changing horizontal flight path to a region clear of turbulence). The exit strategy can be determined tactically, essentially as an aircraft is experiencing turbulence, or is warned that it is about to enter it, or strategically, with sufficient planning time to enter into a region of potential turbulence or avoid it altogether. Given a turbulence forecast for advanced warning of potential Moderate-or-Greater (MoG) or of Severe-or-Greater (SoG) turbulence, a pilot or dispatcher can decide to enter into a region of potential MoG turbulence if acceptable to the pilot or airlines (a pilot decision or airline policy decision), or in the case of potential SoG, the region should be avoided.

Turbulence is capable of producing both workload and airspace utilization impacts. Tactical information about actual turbulence encounters are conveyed through Pilot Reports (PIREPs or AIREPs). PIREPs are broadcast to controllers and then relayed to other pilots. Today, this occurs by voice communications; in NextGen this process is expected to be automated for many aircraft through electronic PIREPs (e-PIREPs). Processing of PIREPs increases pilot, flight dispatch, and controller workload but does not, strictly speaking, close airspace. MoG turbulence tends to close en route airspace given that passenger comfort and safety is a high priority for many airlines. However, there are some types of aircraft that may fly through MoG turbulence, for instance, cargo aircraft, ferry flights, or some business jets. Forecasted or reported SoG turbulence is an immediate safety hazard which closes airspace and, if encountered, may require diversion due to the likelihood of passenger/pilot injuries and/or required aircraft inspections.

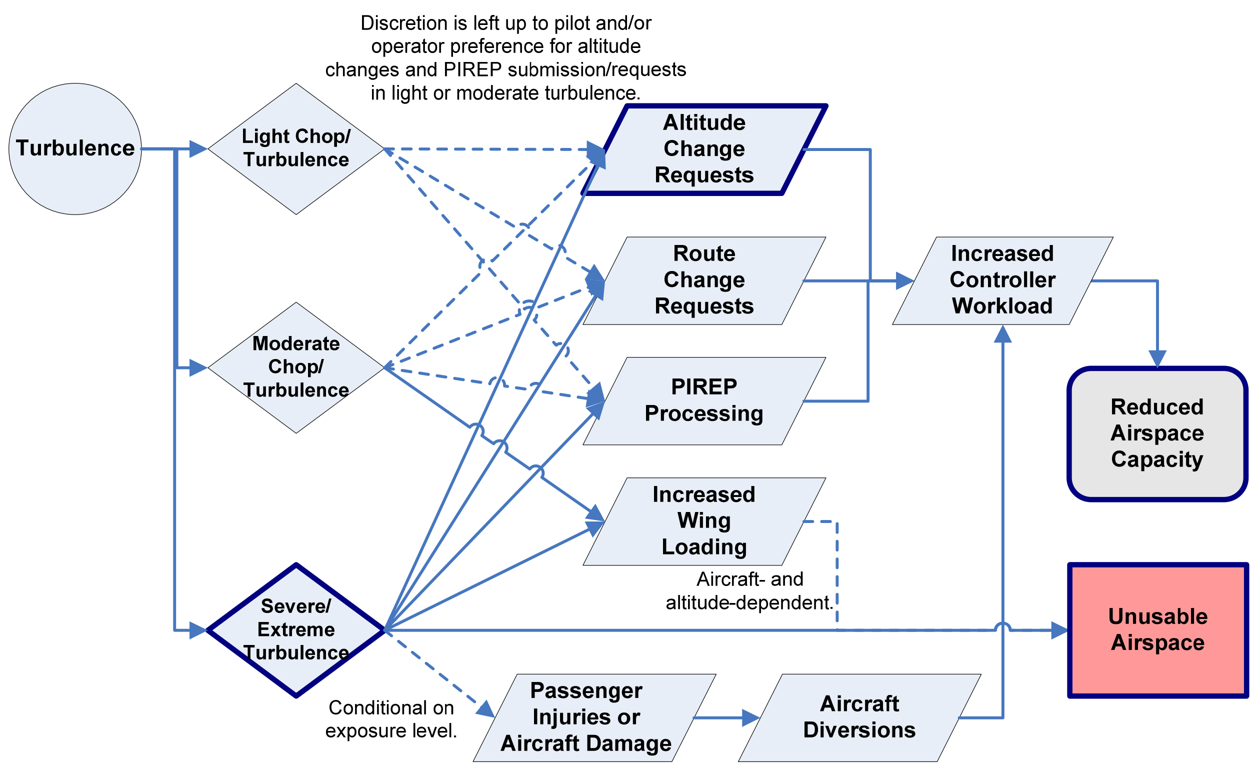


Figure B-18 Causality diagram for turbulence.

Traffic flow impacts are 4D and temporally sensitive because of the dynamic and random nature of turbulence. Current turbulence forecasts predict the potential for turbulence in a given region of airspace, altitude, at a given time in the future. NWP algorithms use coarse grids that cannot directly model and detect the existence of the "subscale" occurrence of turbulence. While fine grids may offer hope for detailed analysis in small airspace studies (e.g., accident investigations), the ability to have a NAS-wide description of exactly where the boundary of the turbulence hazards reside (space and time) is beyond current technology and perhaps may not be achieved in NextGen. Thus, in NextGen, 4D representations of hard constraints for turbulence (SoG level – where no aircraft should enter) and soft constraints for turbulence (MoG level – where some pilots and airlines may choose to go through) will be based on probabilistic information for the potential for where MoG and SoG turbulence may exist. DSTs for dispatchers and controllers must then be designed in NextGen to reason about the risk of entering into turbulence, rather than avoiding a well-defined region of turbulence. It is possible in NextGen that a tactical e-PIREP feedback process of quickly communicating to pilots and controllers where turbulence hazards actually exist will complement long term strategic forecasts of the potential for turbulence to exist.

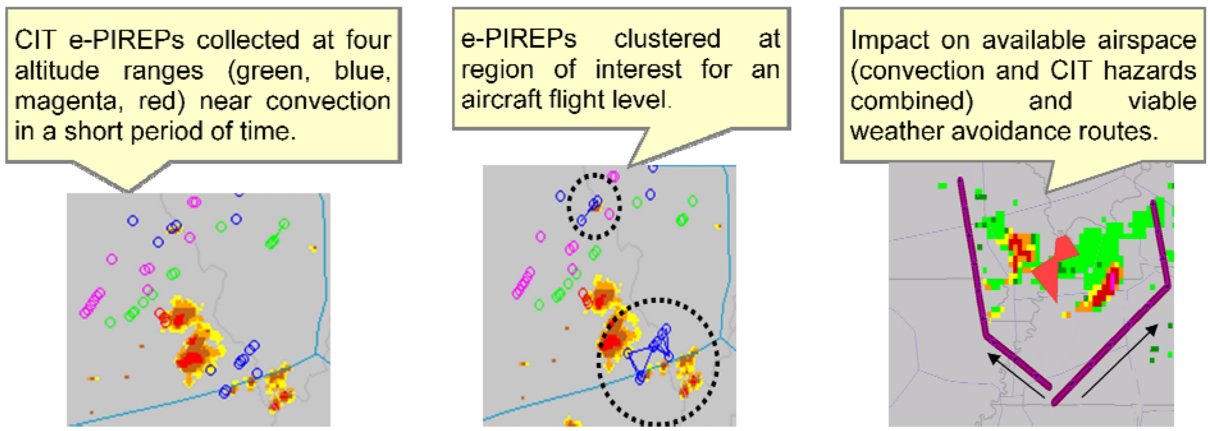
B-1.19 Tactical Feedback of Automated Turbulence electronic Pilot Reports

Currently turbulence encounters are reported from cockpit crews either verbally or by text data link. PIREPs are subjective, late – transmitted only when pilot or controller workload permits, and not easily disseminated to all users. Pilots need to know how turbulence will affect their aircraft in order to make route change decisions. Different aircraft respond to turbulence differently, therefore considerable inference is required on the part of crews to transform turbulence PIREPs from larger or smaller aircraft into the hazard to their own aircraft.

NextGen will likely automate the process of collecting and distributing turbulence (as well as other) PIREP information. Automated e-PIREPs, where human judgment on the magnitude of the turbulence encounter is replaced by an automatic measurement of the turbulence, will automatically and frequently report PIREPs by data link to ATC and to nearby aircraft. Essentially, all e-PIREP equipped aircraft become sensors in the sky for turbulence.

With a collection of e-PIREP information reported at a wide variety of flight levels (null as well as hazard reports), turbulence information can be data linked directly to nearby aircraft or collected and distributed via a centralized database (e.g., NNEW) [KRB09]. Given turbulence data at or above a given threshold (note: the threshold differs based on aircraft type, velocity, altitude, and weight), crews can determine which regions of airspace may be a hazard and which are safe to traverse. Clusters of point e-PIREP data classified as hazardous can be identified (Figure B-19), as well as clusters of clear air data (null or low magnitude reports). Thus, hazardous airspace as well as airspace clear of turbulence can be communicated to nearby aircraft that are soon to pass into such airspace. Since turbulence is a transient hazard, this process needs to be automated, a datalink needs to quickly communicate information to nearby aircraft, and the process must repeat throughout the day for detecting CIT and CAT hazards.

Current turbulence forecasts predict the potential for turbulence in a given region of airspace, altitude, at a given time in the future. NWP algorithms use coarse grids that cannot directly model and detect the existence of the “subscale” occurrence of turbulence. The ability to have a description of exactly where the boundary of the turbulence hazard resides (space and time) is beyond current technology and perhaps may not be achieved in NextGen. However, the tactical feedback process of where turbulence hazards actually exist will complement long term strategic forecasts of the potential for turbulence to exist.



(a) Data Collection (b) Data Clustering (c) Hazard Impact Model

Figure B-19 Feedback of e-PIREP CIT turbulence data transformed into hazard regions.

B-1.20 ATM Impact of Winter Weather at Airports

The accumulation of ice on aircraft prior to take off is a significant safety hazard affecting aircraft. Research [RCM00] indicates that the icing hazard for aircraft directly corresponds to the amount of water in the snow, rather than visibility – the traditional metric used to determine de-icing and take off decisions. Results from field tests of de-icing fluids have identified the liquid-equivalent snowfall rate as the most important factor determining the holdover time (time until a fluid fails to protect against further ice build-up) [RVC99].

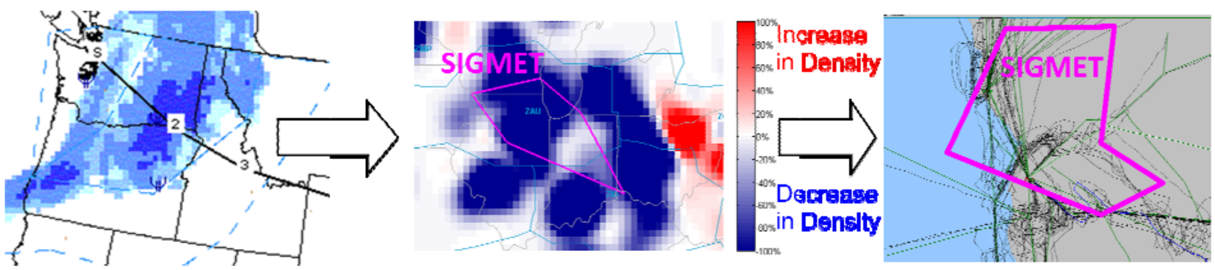
Furthermore, winter weather also impacts other areas of the airport, e.g. roads into and out of the airport, parking areas and transportation to the terminals. This adds to the difficulty of loading passengers and cargo for travel.

The ATM impact of decisions made regarding aircraft de-icing holdover times, de-icing fluid types, and application procedures have yet to be defined and integrated into a NextGen gate-to-gate concept of operations. From initial field evaluations using stand-alone DSTs, significant impacts to an airport occur from de-icing operations [RCM00], including airport ground congestion, decreased arrival rates, and decreased departure rates. Metrics affecting severity of impacts include precise timing of the snow event start and stop times, characterization of snowfall in terms of Liquid Water Equivalent (LWE), optimal deicer mix and temperature to maximize holdover times, and precise timing of the sequence of events from pushback, to de-icing, taxi, and takeoff to prevent additional de-icing. NextGen integration needs further decision support requirements for winter weather impact in order to optimize gate-to-gate performance.

B-1.21 ATM Impact of In-Flight Icing

In-flight icing impacts air traffic flow in complex ways. For aircraft not certified for icing conditions, all known or forecast icing is prohibited airspace and considered a "hard" constraint – these aircraft are not allowed to fly into such an airspace. A SIGMET issued by the National Weather Service (NWS) is considered a hard constraint for all aircraft. Today, SIGMETs are typically valid for up to 4 hours and usually affect a large volume of airspace. Some situations have icing severity and aircraft equipage combined to define a “soft” constraint – some aircraft may penetrate the icing volume for limited exposure times.

In-flight icing is typically a low altitude hazard, generally less than FL200. Major ATM impacts, therefore, are seen for low-end General Aviation (GA) and for all aircraft in the arrival/departure and terminal phases of flight. National ATM impact can be significant when icing affects large airport metroplexes. Figure B-20 illustrates some of the air traffic responses due to SIGMETs issued for severe icing [KrK09]. The traffic density is significantly decreased by a SIGMET when compared to the same day a week before and a week after – the effect is strongest if the SIGMET has a lower altitude that reaches ground level. Holding patterns are established outside of the SIGMET volume to allow aircraft to descend below the SIGMET prior to arrival if the SIGMET does not extend to ground level. Other impacts include increased ground delays until the SIGMET is released, cancellations of flights scheduled to take of when the SIGMET is active, and aircraft forced to fly above or below the SIGMET altitude ranges, thus increasing densities above and below the SIGMET volume and increasing controller workload for those altitudes.



(a) Icing Forecast (b) Decrease in density of Traffic (c) Holding and Delays Impact

Figure B-20 In-flight icing causes significant ATM impacts.

NextGen traffic flow impacts will be 4D and temporally sensitive. In NextGen, flight data objects representing aircraft and traffic flows will integrate with 4D representations of hard and soft constraints due to current and forecast icing conditions. NextGen icing forecasts will be automatically generated. The SIGMET for NextGen will likely be a 4D airspace that is shaped by the 4D forecasted icing volumetric icing phenomenon. Icing decision support can then be provided to flight crews, air traffic managers and controllers, dispatchers, and automated DSTs in the same spatial and temporal context. A 4D gridded format will be highly consistent with planned NNEW formats. Future products needed to fully address ATM impacts include calibrated icing probability and icing severity. Further, a better understanding and mathematical model of the in-flight icing ATM impact in both the terminal and en route environments is needed.

B-1.22 Probabilistic Forecasts for Ceiling and Visibility and Obstructions to Visibility

The Ceiling and Visibility (C&V), and Obstructions to Visibility (OTV) impacts differ depending on the flight regime (terminal, en route, ground operations) and type of aircraft operation (Part 91 vs. Part 135 or Part 121). For the en route NAS, ATM impact for IFR-equipped aircraft results from reduced AARs and Miles-in-Trail (MIT) restrictions that originate from the impacts of OTV on terminal airspace and airport ground areas. This impact can greatly reduce air route capacity and may propagate from sector to sector as passback MIT restrictions. OTV impact on terminal arrival and departure operations (see Figure B-21) include restrictions on VFR operations, increased MIT requirements on final approach, increased missed approach potential, higher workload for pilots and controllers (e.g., Pilot Report (PIREP) communications), and restrictions on use of Land And Hold Short Operations (LAHSO). Impacts result from ground fog, low ceiling, low visibility due to precipitation, and smoke and haze. These conditions are further influenced by day/night effects and by viewing angle relative to solar angle. For ground operations, the OTV impacts come from ground fog, low visibility due to precipitation, blowing snow, plus day/night and viewing angle effects as above. For non-IFR equipped GA aircraft, the OTV impact to ATM is minimal; however, the safety impact to inadvertent penetration into IMC during VFR operations is significant.

The core OTV forecast technology, plus translation to ATM impact and decision support dealing with uncertainty, are NextGen technology gaps. NAS systems need realistic system-wide impact assessment models that use current and forecast probabilistic OTV-impacted AARs at individual terminals to forecast resulting composite air route MIT restrictions. The assessment models must represent the system-wide impacts of propagating passback MIT restrictions, which result in impacts on air route capacity as well as reduced AARs, ground holds and departure delays at remote airports where OTV conditions are not present.

B-1.23 Improved Wind Forecasts to predict Runway Configuration Changes

The airport configuration is a primary factor in various airport characteristics such as arrival and departure capacities (AARs) and ADRs) and terminal area traffic patterns. Since the airport configuration is largely dependent on airport wind conditions, an ATM-impact model must translate the wind conditions (and other factors) into AAR, ADR, and other impacts. Today there is poor dissemination throughout the NAS of the airport configurations in use at each airport at

The airport configuration is a primary factor in various airport characteristics such as arrival and departure capacities (AARs) and ADRs) and terminal area traffic patterns. Since the airport configuration is largely dependent on airport wind conditions, an ATM-impact model must translate the wind conditions (and other factors) into AAR, ADR, and other impacts. Today there is poor dissemination throughout the NAS of the airport configurations in use at each airport at any given time, with very little known about expected future configuration changes. AARs, ADRs, and terminal traffic patterns are central to a variety of ATM decisions, such as setting arrival restrictions to avoid airborne holding as well as the effects certain airport configurations have on nearby airport traffic flows and configurations. Consequently, as uncertainty from wind conditions translates into uncertainty about the current or future airport configuration, this results in traffic management decisions that underutilize or overload airports, resulting in unnecessary or inefficient delays.

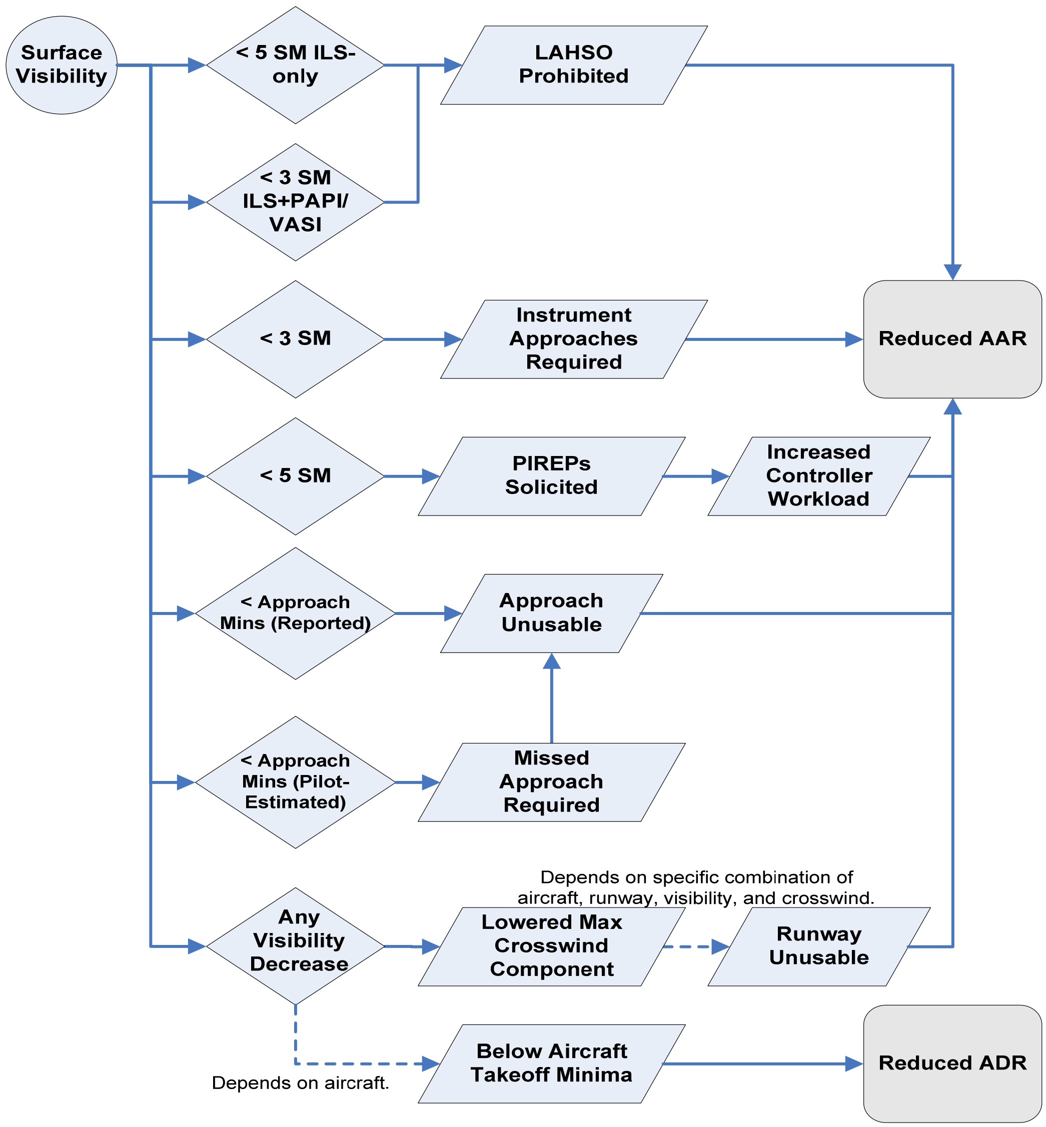


Figure B-21 Causality Diagram for Terminal C&V.

In order to build a model for translating wind conditions into ATM impacts, both meteorological and ATM modeling need to be addressed. The wind speed and direction is essential in determining which runways are feasible. Terminal Aerodrome Forecasts (TAFs) do not currently predict wind conditions precisely enough or accurately enough to enable airport configuration prediction. NextGen weather forecast systems must correct this in order to assimilate weather into DSTs for airport surface operations as well as TFM decision making. Accurately predicting wind conditions at an airport is difficult, and viable automated methods are only now emerging due to recent scientific advances and gains in computer performance. Furthermore, TAFs are intended primarily to provide information for filing flight plans, so they are not required to include certain changes in wind speed or direction that may cause a change in airport configuration.

As for modeling the ATM impact, there is also research needed to establish the relationship between how controllers choose between viable configurations to meet the arrival and departure demands of an airport. Controllers usually have 30 minutes or more leeway in the time at which runway usage can be changed while maintaining safety. This leeway is generally used to choose a time at which to implement a runway configuration change so as to minimize inefficiencies associated with making the change. The timing of the arrival and departure traffic demand, weather (winds as well as possibly convective weather constraints), and other factors need to be modeled. Furthermore, there is generally a preferred configuration that will be used if it is feasible for a sufficiently long period of time. There is a need to build a mathematical model that relates these factors to the forecasted weather (and traffic) conditions.

B-1.24 Improved Wind Forecasts to facilitate Wake Vortex Decision Support

Turbulence associated with aircraft wake vortices pose a potential hazard to other aircraft, especially lighter aircraft following at low altitude. This risk is mitigated by increased separation standards when wake turbulence avoidance is a concern. Historically, these separation standards were established under the assumption that little or no information is available in near real time with regard to the location, severity, or movement of wake vortices. As a result, they are designed conservatively, presuming the existence of a significant wake threat following each Heavy aircraft, and atmospheric conditions that would allow the wake turbulence to persist at a severe intensity for a relatively long duration (several minutes) in a location that encroaches on the flight path of the trailing aircraft.

Knowledge of wake vortex characteristics and behavior in near real time allows the opportunity to safely reduce existing separation standards to increase throughput, particularly within the terminal airspace [LMC03]. Early attempts to develop operational systems to mitigate wake impact focused on detection of vortices, with concurrent meteorological sensing to anticipate wake behavior, particularly wake dissipation rate and vertical displacement [HCB00]. Ground-based systems (e.g. Lidar) have proven extremely effective in local (on-airport) detection; their primary weakness is limited detection range in inclement weather, and they are relatively expensive. Furthermore, prediction of wake behavior based on meteorological measurements of atmospheric stability produced mixed results.

More recent efforts have focused on wind dependent solutions [LTL05, LTD07, RC08]. A very short term wind forecast (20 minutes) is sufficient to determine when persistent transport crosswinds protect specific Closely Spaced Parallel Runways (CSPR) from the threat of a wake vortex moving into the departure flight path, thereby safely allowing reduced separations. Analogous wind dependent solutions currently under investigation for arrival operations have more substantial implications for TFM. Unlike departures, for which a ground queue of aircraft may be immediately available to exploit available capacity, reduced separations for arrivals implies TFM planning to ensure aircraft availability to fill available slots. This puts more rigorous demands on wind forecast performance. First, it requires sufficient forecast lead time to allow for positioning of en route aircraft, which requires additional release of ground held aircraft. Furthermore, the burden of managing the flow of airborne planes (as opposed to a ground queue) requires that the forecast window of opportunity be of sufficient length to provide commensurate benefits, and that the end time of favorable crosswinds be forecast with high reliability to avoid an oversupply of airborne arrivals.

These concepts are illustrated in Figure B-22. (1) The initial forecast of future arrival capacity increase will likely require at least a 1-hour lead time to indicate the potential for increased capacity. (2) When winds are verified as favorable, and the current forecast indicates an expected duration of at least 3 hours of favorable crosswind, ATM can increase upstream throughput, presumably involving the release of additional ground-held aircraft. (3) Additional arrival demand becomes available locally to fully utilize arrival slots made available by reduced separations. Typically this would be expected 60-90 minutes after release of additional aircraft. (4) At some point during the increased capacity window, the wind forecast would indicate an expected end to favorable winds. This would require at least 1 hour lead time to reduce flow of upstream arrivals and absorb existing en route arrivals. (5) Crosswinds no longer favorable for reduced separations. Note that this example represents a minimum acceptable benefits scenario, i.e. a 3-hour wind of favorable crosswinds, during which at least 1.5-2.0 hours could be exploited with a sufficiently increased supply of incoming arrivals. A more aggressive approach to further exploit capacity would be to increase the upstream flow rate immediately upon the initial forecast of favorable conditions occurring within 1 hour. This, of course, adds additional risk of oversupply in the event of an incorrect forecast.

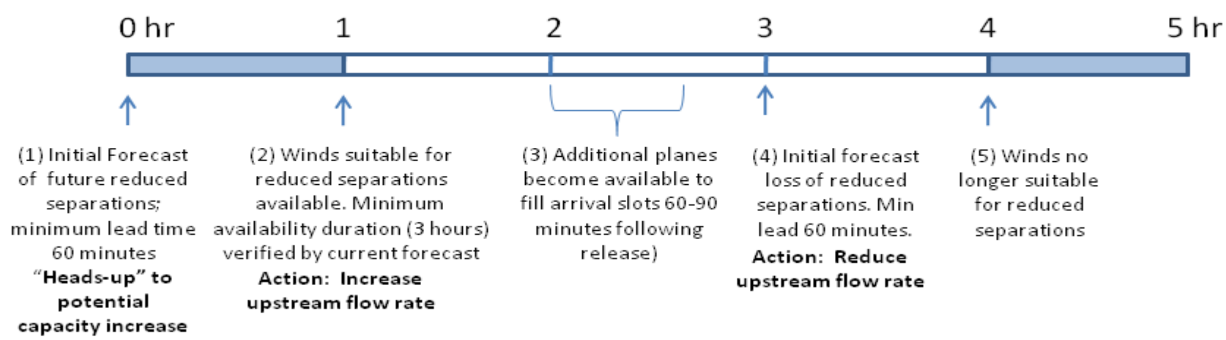


Figure B-22 Conceptual timeline showing traffic flow management in response to reduced wake vortex separations for arrival aircraft.

In NextGen, an increased availability of aircraft meteorological data (e.g. via the Meteorological Data Collection and Reporting System (MDCRS)) and aircraft surveillance technology (e.g. ADS-B) may provide the necessary near real time information for wind dependent solutions without the high cost of more sophisticated ground-based sensors. In particular, flight path observations could be used to validate favorable conditions aloft (nominally up to a few thousand feet) to support the concept. Additionally, continuing advancement in NWP modeling performance and resolution is expected to be of central importance for meeting the wind forecast lead time and precision requirements. Since the capacity impact of wake separation restrictions is highly dependent upon aircraft mix, solutions must also integrate sequence optimization schemes to fully exploit available capacity.

B-1.25 Impact of Winds Aloft on the Compression of Terminal Area Traffic Flows

Strong winds aloft impact an airspace by causing aircraft spacing problems. Generally, when strong winds aloft are present, the wind speed will vary considerably with altitude. This will cause large variations in groundspeeds between aircraft at different altitudes and in trail spacing becomes difficult to maintain. The effect on one flow direction may be very different from the effect in the opposite flow direction, for instance, traffic flying East with the wind will have different effects from traffic flying West into the wind. From an ATM perspective, greater MIT restrictions will be issued to deal with this effect, which controllers refer to as compression. Generally when winds aloft impact the airspace, MIT restrictions have to be increased, and there is also the possibility of impacting performance with a lower AARs with the potential of GDPs and Ground Stops (GS).

Vertical wind information, both observed and forecasted, can be used to manage the impact of compression. Current hourly updated vertical profiles of forecast winds will need to be more frequent in NextGen to facilitate better wind forecasts for this ATM application. The outstanding issue is how to translate this information to determine compression effects on ATM, specifically predicting MIT and any reduced AAR or the need for GDPs or GSs. In NextGen, a larger percentage of traffic will be following Continuous Descent Approaches (CDAs) and tracking Area Navigation (RNAV) routes within a required RNP level, and these procedures will also drive wind forecast accuracy requirements. How the requirements relate to the weather forecast accuracy is an open research question.

B-1.26 Oceanic/Remote Weather Integration

The NextGen Concept of Operations envisions a seamless transition between CONUS, terminal, and oceanic domains. Weather information for oceanic and remote areas will be integrated with ATM at the same level as for CONUS operations. A number of oceanic procedures are already being implemented as wide-spread use of Automatic Dependent Surveillance – Broadcast (ADS-B) expands. For example, airlines are already exploiting the benefits from Dynamic Airborne Reroute Procedures (DARP) which allow airborne aircraft to take advantage of updated atmospheric conditions and cruise-climb more efficiently for better fuel consumption. Oceanic routes integrate with CDAs into gateway terminals to permit idle thrust descents from cruise to short final approach. All of these capabilities depend on timely weather updates on hazards (convection, turbulence, volcanic ash, in-flight icing), winds, and Outside Air Temperature (OAT).

Weather information for remote and oceanic regions is more difficult to create than for the CONUS because data is sparse. This requires creative use of available data from satellites and other limited sources, and is an area of active research. Prototype algorithms have been developed for regional use, but not integrated with ATM procedures.

Studies in the Central East Pacific [GSC06], for instance, demonstrate how wind data can be used to generate wind optimal routes, transitioning away from the fixed Central East Pacific routes to user-preferred routes. While such routing takes advantage of the jet stream, it also must take into account turbulence that can be found near the jet stream, which is an area of future research.

Direct integration of winds and temperature into flight planning systems on the ground, and via data link into flight management systems (FMSs) while airborne, is occurring. Flight plans are optimized prior to departure, and changed as needed en route to take advantage of updated winds and OAT (for cruise-climb). 4D, flight path specific, descriptions of weather hazards (convection, turbulence, volcanic ash, in-flight icing) are needed to complete the NextGen seamless transition to CONUS and terminal operations. 4D hazard information needs to be integrated with winds and temperature effects on flight profiles. Airline dispatchers, oceanic air traffic managers, and pilots can then strategically plan flight profiles and, most importantly, pilots can prepare to react to real-time hazard information prior to an encounter.

B-1.27 Translation of Volcanic Ash Plume Hazards onto Airspace and Airport Impacts

Advanced techniques are needed in NextGen that will detect, forecast, and disseminate information on volcanic ash plume hazards and how the hazards will affect ATM resources to aviation operators and users. Airborne volcanic ash constitutes a recognized threat to aviation that can severely damage jet aircraft engines through erosion, corrosion and congestion. Volcanic ash contamination may render large volumes of airspace unavailable, necessitating costly rerouting contingencies, degrades breaking action at affected airports, as well as completely closes contaminated airports [KMP08]. Problematic ash-related aircraft encounters have been reported days after an eruption and thousands of miles from the source. There are a number of technical issues that need to be addressed to identify volumes of airspace that should be avoided.

The weather translation model for volcanic ash plume hazards (Figure B-23) requires further advancement of both science and operational modeling. Science issues for NextGen include:

- Timely detection of eruption and resulting ash cloud
- Discrimination of ash from water/ice and sulfur clouds
- Missed detections and false alarms
- Sensor response function, measurement precision, calibration
- Dispersion models
- What concentration and ash particle size constitute a hazard
- How the concentration and ash particle size determined
- Operational issues for NextGen include:
- Timely advice of the mathematical model for eruption / ash cloud
- Dispersion model development and validation, and

- More automation needed for integration of ATM impact with NextGen systems.

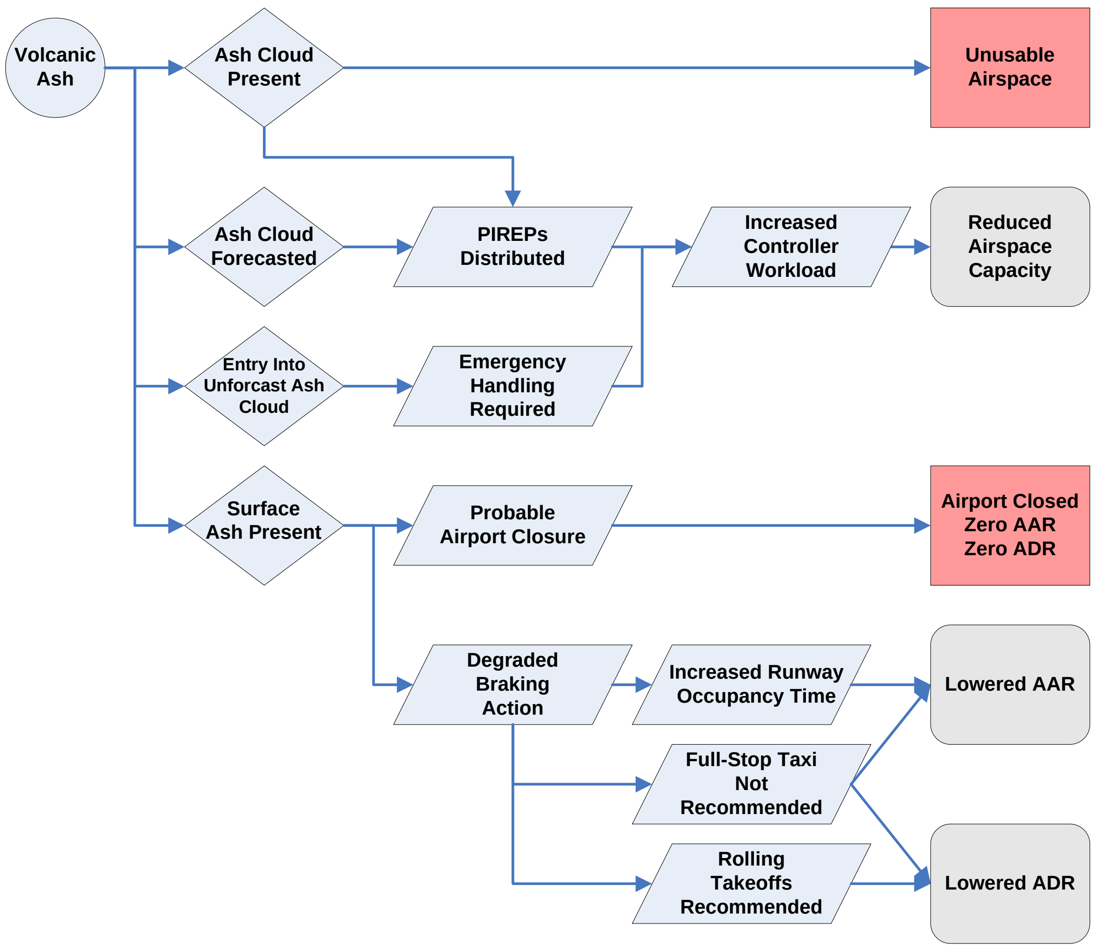


Figure B-23 Causality diagram ATM impacts of volcanic ash.

The ATM impact is so severe that any forecast or actual volcanic ash above a threshold concentration and particle size is considered a hard constraint. A 4D airspace volume defining the hard constraint is required for NextGen. Application of the constraint would be the same as for any 4D weather hazard. It represents a no-fly volume that most likely is deterministic versus probabilistic (pending further research on the above technical issues).

B-1.28 Translation of Atmospheric Effects into Environmental and ATM Impacts

The large increase in air traffic associated with NextGen will have a growing impact on the environment. Environmental impacts will be significant constraints on the capacity and flexibility of NextGen unless these impacts are managed and mitigated [GTA09]. The major environmental effects of aviation are:

- Emission of pollutants affecting local air quality, such as NOx, SOx, CO, and particulate matter;
- Emission of greenhouse gases such as CO_2;
- Aircraft noise; and
- Water pollution via de-icing agents, spilled fuel, etc.

Note that the discussion of fuel consumption in the NextGen Concept of Operations is not an environmental impact but is a surrogate for greenhouse-gas and air-pollution impacts. All of the weather-integration applications discussed here, of course, have an impact on fuel consumption as related to ATM efficiency.

Most of the above environmental impacts are affected by the atmosphere and will require the integration of probabilistic weather forecast elements for proper risk management. The weather elements include, but are not limited to: wind and temperature profiles; probabilistic model output of Atmospheric Impact Variables (AIVs); translation of atmospheric conditions to environmental impact; and translation of environmental impact to ATM impact.

Examples of the translation mechanisms coupling atmospheric conditions to environmental impact include:

- Noise intensity on the ground is affected by wind and temperature via their influence on the strength and directionality of acoustic propagation, and also via their influence on aircraft performance (e.g., climb rates).
- Dispersion and mixing of air pollutants is affected by wind, temperature, and humidity via their impacts on atmospheric mixing and chemistry.
- Generation of greenhouse gases is affected by wind, temperature, and humidity via their impacts on engine performance and fuel consumption.
- Environmental impacts are translated into ATM impacts via several mechanisms, including:
- Mitigation measures such as specialized departure and arrival procedures and routings, as well as restricted periods of operation;
- Routing and altitude assignments that seek to minimize fuel consumption (and possibly contrail formation); and
- Surface and system management that seeks to minimize taxi times and delays on the ground with engines running.

To the degree that the above change the capacity or throughput of airspace or airport elements, then environmental considerations will impact NAS operations.

B-1.29 ATM Impact of Space Weather

There is a growing threat from space weather as aviation's dependence on space and terrestrial networks vulnerable to space weather continues to grow. The threat also exists within the aircraft, affecting communication and navigation abilities for long-haul polar flights. In addition, there is an increasing need to characterize the radiation environment that changes as a consequence of space weather eruptions. Even relatively minor solar storms can affect communications, navigation, and radiation exposure, and this can cause flights to divert or not even dispatch over polar regions. We can expect an as-yet undefined impact to the net-centric NextGen infrastructure in the CONUS as well. Moreover, the human exposure to space radiation is significantly higher on polar routes, which poses a potential health risk.

Information on space weather is currently sparse and not well applied to aviation applications. Recent popularity of polar routes has driven the requirement to include adding appropriate space weather information into the normal operating procedures of commercial aviation. This requirement also extends all over the globe, as communication and navigation issues in particular reach far beyond the polar regions. The physical units describing these events are not translatable to aviation and net-centric impact. First, impact thresholds for both net-centric operations and communications/navigation systems need to be established in terms of the physical units describing solar events. This is an area of active research. Once thresholds are better understood, solar events can be translated into such ATM impacts as alternative communications and navigation methods required for flight; backup net-centric systems for flights through affected regions; support for airline dispatch and air traffic control decisions to close routes and airspace; and restrictions to human exposure to radiation. Forecasts of solar eruptions and their impact time-of-arrival for the Earth's atmosphere are necessary to mitigate these impacts to aviation in NextGen.

B-1.30 ATM Impact of Weather Constraints on General Aviation Access to the NAS

Although GA aircraft operations make up approximately half of all flight hours in the NAS, quantification of the impact of weather upon their operations in the NAS is complicated due to a number of factors. At one extreme, these GA flights are non-scheduled, and thus cancellation and delay data are not available. When these fights do enter into controlled airspace, then ETMS and other trajectory data sources can be mined to yield statistical models of pilot behavior [DE06] however, it is expected that the results will vary considerably compared to the models that have been emerging to characterize commercial airline pilot behavior. Further, GA aircraft cover a wide spectrum from day VFR-only to extremely weather-capable aircraft matching those in scheduled Part 121 service. This diversity in aircraft capability is matched by that of the pilot qualifications and the airports from which the aircraft operate. This variability will be reflected in the response of these aircraft to weather constraints. These constraints include convective activity, turbulence/wind, flight icing, ground icing, and Ceiling and Visibility (C&V).

One example of this variability is in the behavior of pilots when using datalinked reflectivity data to avoid thunderstorm cells. Some pilots interpret the data tactically and penetrate the convective areas while others interpret it strategically, avoiding the entire region of convective activity [B08]. There is considerable variability in pilot behavior near convective areas, making it difficult to model the diversion probability. Pilot experience and training, as well as aircraft equipment, vary considerably, and these will strongly affect weather avoidance strategies. The evolving nature of onboard weather detection can reasonably be expected to ensure that GA pilot deviation behavior will continue to be nonuniform. Existing simulation methodologies can be rapidly configured to explore pilot response to cockpit weather and traffic displays [HMB06].

Terminal area winds and turbulence will also have varied impacts. The decision of whether or not an aircraft will accept an approach to a given runway can depend more upon pilot skill, runway width, and flow field complexity than upon aircraft type and may be difficult to quantify. This is because most GA aircraft do not have well-defined crosswind limits, although some have a maximum demonstrated crosswind.

En route turbulence will usually result in a request for a higher altitude, although pilots with headwinds may choose to sacrifice ride quality for a higher groundspeed, as headwinds will have a lesser impact at lower altitudes. Orogenic turbulence over major mountain ridges can render some altitudes unusable if downdrafts approach or equal climb rate. Clear air turbulence in the vicinity of jet streams will have similar impacts upon GA jets and air carrier aircraft.

Both in-flight icing and ground icing show high variability in their NAS impacts for GA flights. In addition to having less effective anti-icing provisions, smaller GA aircraft typically operate at altitudes where icing is more frequent, so it is likely that GA aircraft will be more affected by in-flight icing than studies show for larger commercial aircraft [KrK09]. Larger, particularly jet, aircraft will experience icing primarily during ascent or decent from or into terminal areas.

Aircraft are classified as approved or not approved for flight into known icing conditions. This classification does not capture the degree of ice protection possessed by the aircraft. Furthermore, not all aircraft sharing a single type certificate have the same status with regard to icing. This wide spectrum of ice protection is matched by a large variability in pilot strategies to avoid ice. However, regardless of the level of ice protection, pilots will avoid areas of potential or reported icing as much as possible. This can make some altitudes unavailable for holding traffic, resulting in aircraft being spread out over large areas. Most GA airports have limited de-icing services, with hangaring being the most common option. A thin layer of overnight frost can cause cancellation or lengthy delay for all unprotected aircraft, particularly impacting early morning departures.

As for C&V, under Part 91, aircraft may begin an instrument approach even if there are no official visibility measurements or if such measurements are below minimums for the approach. This may lead to a greater probability of missed approach procedures being flown compared to Part 135 and Part 121 operations. Pilots of en route VFR GA aircraft may request IFR clearances in the event of sudden reduction in C&V. Others may require special assistance. Either action adds to ATC workload. New cockpit displays, such as moving map and synthetic vision, have the potential to improve VFR into Instrument Meteorological Conditions (IMC) accident rates but may also increase the proportion of VFR pilots who choose to continue toward the destination rather than diverting or changing to IFR, [JWW06] potentially increasing complexity for controllers managing low altitude IFR operations. Non-towered, non-radar airports are typically "one in – one out" for IFR operations, creating significant delays for both arrivals and departures.

While the number of studies that have been performed to build ATM impact translation models has been increasing over the years, few and possibly none of these have focused on the particular parameters that model GA aircraft in particular, or have quantified the overall impacts to GA pilots in the aggregate.

B-2. Methodologies for ATM Weather Integration

Many of the ATM-impact models will eventually be integrated into DSTs in order to help users reason about the impacts of weather while solving ATM problems. The survey includes approaches for addressing weather-related uncertainty in ATM decision making for strategic look ahead times – risk management processes – as well as approaches that wait until the tactical look ahead times to address deterministic forecasts after the uncertainties diminish. The ATM-weather integration techniques make reference to ATM-impact models as appropriate.

B-2.1 Sequential, Probabilistic Congestion Management for addressing Weather Impacts

Flexibility and adaptability in the presence of severe weather is an essential NextGen characteristic. But even at tactical flow management planning times (0 to 2 hours), weather and traffic forecasts contain significant uncertainties. Sequential, probabilistic congestion management [WG08] describes how to incrementally manage en route airspace congestion in the presence of these uncertainties.

The concept is illustrated in Figure B-24 as a control loop, where congestion management decisions are made continually at regular intervals (e.g., every 15 minutes). The distribution of traffic demand in en route sectors is predicted based on flight plans (or downlinked Flight Management System (FMS) data), track data, wind forecasts, aircraft performance data, and other adapted elements. Several methods of predicting traffic demand distributions have been developed. [WZS05, GS07, WSZ05] Convective weather forecasts, which will include measures of forecast uncertainty, are used to predict the probabilistic capacity of en route sectors. This calculation may include the predicted traffic demand, since the true capacity of sectors is sensitive to the traffic flow patterns and how they interact with the weather. Methods for estimating weather impact on sector capacity have been proposed [KMP07, SWG07, M07], however, none have been developed for estimating the distribution of possible sector capacities based on a probabilistic weather forecast product. The distributions of demand and capacity are convolved to produce a probabilistic congestion forecast, where congestion is simply defined as when demand exceeds capacity.

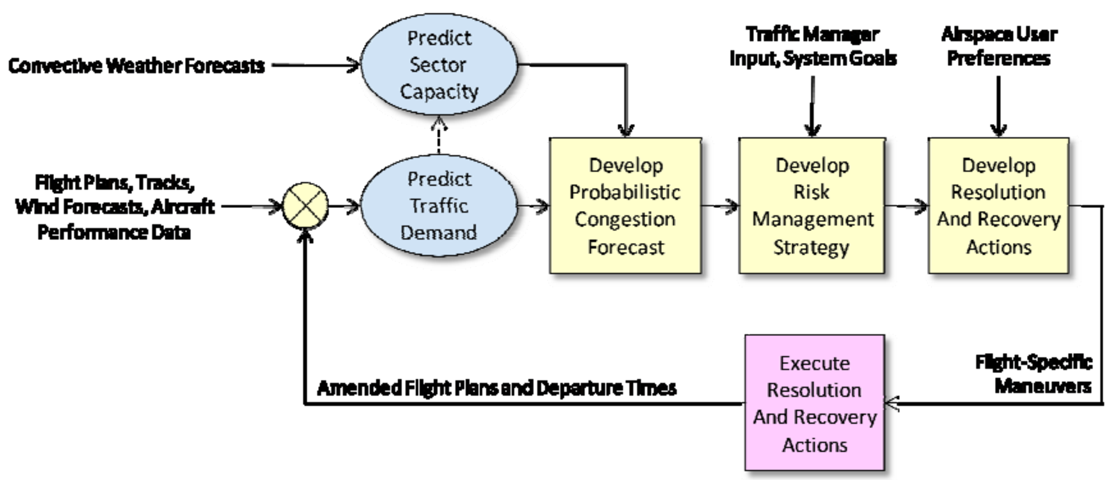


Figure B-24 The sequential, probabilistic congestion management concept as a control loop.

Given a probabilistic congestion forecast, a decision needs to be made. How much control is needed to ensure that the congestion has an acceptable level of risk? This decision is made knowing that the strategy will be modified at the next decision time, and thus it need not be a complete solution to the problem. If too-aggressive action is taken, then some flights will be affected unnecessarily. If insufficient action is taken, then more intrusive maneuvers, such as airborne rerouting, may be required to manage congestion. This is a classic decision-theoretic tradeoff between acting early on uncertain information and waiting for better information. Note that the system goal (congestion risk) and desired types of flight maneuvers can be modified by traffic management personnel at this stage.

Once a congestion management goal has been chosen, specific actions must be developed. If congestion resolution is required, flight-specific maneuvers can be developed in a variety of ways [WG08, TW08, RH06, BS98, SMW07]. If the weather turns out to be less disruptive than predicted, delay recovery actions to undo previous maneuvers may be needed. In both cases, it is anticipated that relatively few aircraft would be maneuvered at any single decision time, as compared to the large-scale traffic flow initiatives commonly used today. At this step, airspace users can collaborate with the ATSP to coordinate resolution or recovery actions with their business needs. This may be via user preferences, or eventually via a 4D trajectory negotiation process. The final step is to execute the actions such that departure times and cleared flight plans, or the agreed-upon 4D trajectory, are updated.

Sequential, probabilistic congestion management can take advantage of probabilistic weather forecasts to reduce weather impact on en route airspace. It would also provide an effective "inner loop" to be used in conjunction with strategic flow management initiatives, based on longer-range weather forecasts [HKD07]. Note that an alternate, multiple-timescale sequential congestion management approach has also been proposed [GSM08]. This method does not employ probabilistic forecasts, but rather relies on adapting to observed weather development.

B-2.2 Sequential Traffic Flow Optimization with Tactical Flight Control Heuristics

A deterministic sequential optimization approach integrates a strategic departure control model with a fast-time simulation environment to reactively control flights subject to system uncertainties, such as imperfect weather and flight intent information [GSM08]. To reduce the computational complexity of the strategic model, only departure delays are assigned, while tactical en route flight control is accomplished through heuristic techniques. These heuristics rely on a shortest path routing algorithm and an airborne holding model that is used only as a control strategy of last resort.

This closed-loop, integrated optimization-simulation system is illustrated in Figure B-25. System inputs consist of user schedules and flight plans, weather data, and airspace adaptation data. The weather forecast inputs are suitable for establishing CWAM WAFs [DE06].

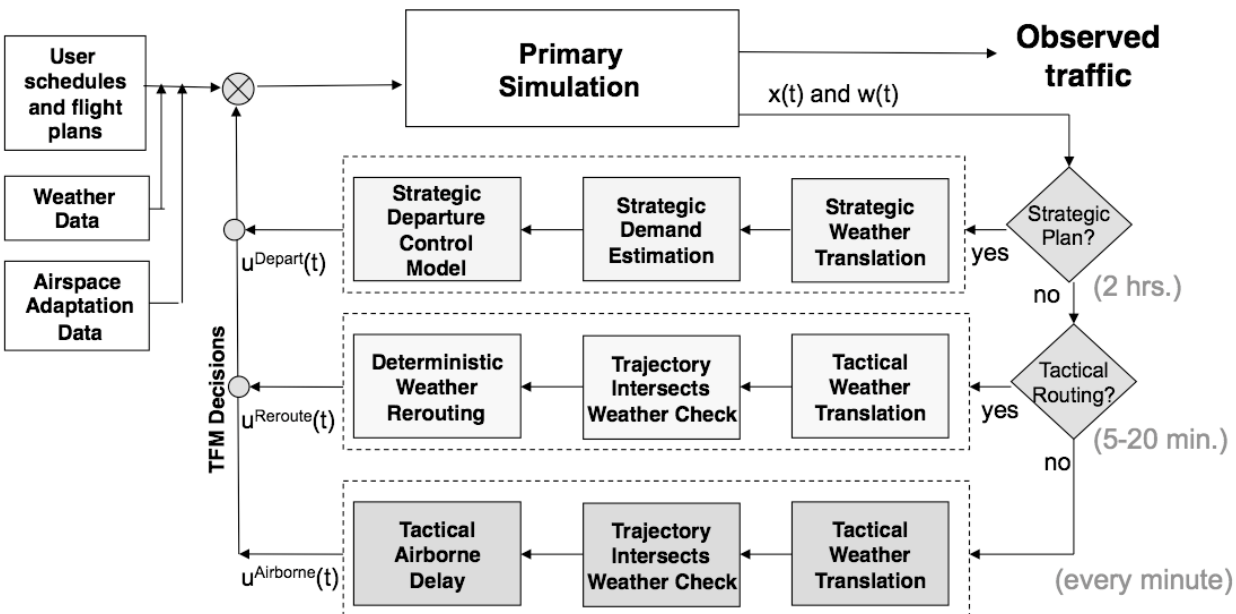


Figure B-25 Sequential optimization with strategic and tactical weather translation.

A Primary Simulation updates state information (e.g., latitude, longitude, speed, altitude, and heading) for all aircraft in the simulation every minute, while updates to the weather forecasts are provided every five minutes. This updated state information is used every two hours to develop and refine deterministic, strategiB-level flow control initiatives, assigning pre-departure delays to flights subject to airport and airspace capacity constraints. The first step in developing these strategiB-level controls is to translate the weather data into reduced sector capacity estimates

[KMP07, M07, SWG08]. Subsequently, the predicted positions of all airborne and scheduled flights over a user defined planning horizon is calculated. The forecasted system demand and capacity estimates are used as inputs for strategic departure control, assigning flight specific pre-departure delays.

Refinements to the strategiB-level traffic flow management plan to account for uncertainties in the demand and capacity estimates are accomplished through two tactical control loops. The first is called at a frequency that ranges between 5 and 30 minutes, and assigns tactical reroutes to flights to ensure that aircraft do not venture into regions of significant convective weather. The variable calling frequency is allowed here to account for the confidence in the weather forecast accuracy. Regions of significant convective weather are defined by CWAM WAFs. The trajectories of all flights over a 100 nmi to 400 nmi look-ahead horizon are checked to determine if any flight intersects a WAF. Flights found to intersect these regions are rerouted. The lowest level control loop that is called every minute is a strategy of last resort to immediately assign airborne delay to any flight that will encounter an en route weather hazard within the next minute.

B-2.3 Airspace Flow Programs to address 4D Probabilistic Weather Constraints

An AFP [Br07, KJP06] is a particular type of Traffic Management Innitiative (TMI) that controls traffic flowing into an airspace where demand is predicted to exceed capacity, as illustrated by Figure B-26. A FCA is defined to be the boundary of the region of airspace where demand exceeds capacity – most typically, due to convective weather constraints. Today's AFPs use fixed locations for FCA boundaries used for AFPs, typically a line segment connecting sector boundaries that aircraft cross at they travel toward eastward destinations, and these regions are defined by air traffic control sector boundaries, not the location of the weather constraint itself.

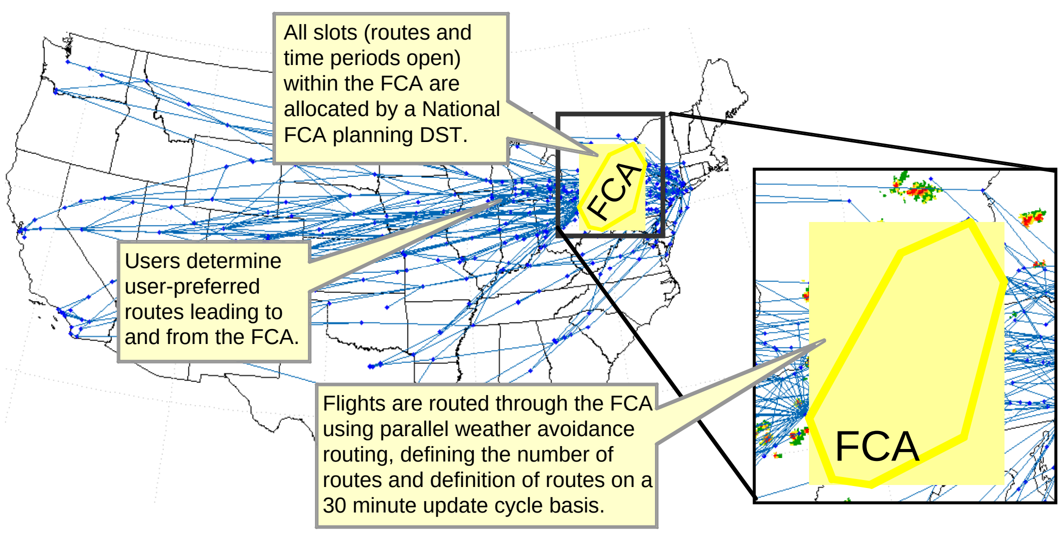


Figure B-26 In an AFP, routes within the FCA are defined by an FCA planning DST to maximize throughput given weather constraints; routes outside the FCA are determined by routing preferences of the user.

In NextGen, the FCA is likely to be a 4D volume that describes the space-time region where weather constraints (not only convection, but severe turbulence and icing regions as well) cause significant ATM impacts. This 4D volume is likely to be derived from weather forecast data from the NextGen 4D data cube and from information about the expected demand at a given time and location that reflects user preferences. The FCA is thus a product of the translation of weather into ATM impact; it requires a capacity estimation technique to define the capacity reduction due to the forecasted weather [CRD07, KMP07, SWG06, SWG07, SWG08]. The AFP is a TMI that responds to the ATM impact in terms of a TFM plan that adjusts periodically (e.g., every 30 minutes) as long as the scheduled demand continues to exceed the FCA capacity.

The AFP for NextGen is able to control a number of factors. Strategically, the AFP controls the takeoff time (ground delay) for aircraft heading to the FCA in order to control the flow rate of traffic entering the FCA. Tactically, the AFP defines the entry points into the FCA as a function of time. As aircraft approach the FCA boundary, the AFP defines safe routes (routes that avoid hazardous convection, turbulence, or icing constriants) across the FCA in order to maximize capacity usage within the FCA region subject to the dynamic 4D weather constraints. One algorithmic solution to the AFP minimizes the sum of all delays experienced by all flights in the AFP [KJP06].

Because the AFP must reason about the effects of weather on airspace capacity for long lookahead times, it is necessary for the AFP to reason about a probabilistic estimate of capacity [MPK06, SB09]. Thus, the FCA boundary is not known precisely, but it represents the general vicinity in 4D where the constrained airspace is likely to occur. As the time horizon shortens (when most aircraft are en route), the exact boundaries of where the FCA must control traffic flow is known more precisely based on deterministic estimates of capacity. Because the routes across the FCA may not be synthesized until flights are within about 1 hour from entry into the FCA, a datalink is required in NextGen to inform air crews of the routing needed for safe and efficient travel across the FCA. Thus, the AFP is an implementation of strategic TFM plans to continuously adjust the flow rate of traffic entering the FCA in order to match demand with the capacity estimates that were initially set using probabilistic techniques and later refined through deterministic means.

B-2.4 Ground Delay Program Planning under Capacity Uncertainty

Uncertainty in capacity forecasts poses significant challenge in planning and controlling a GDP. There are two main decisions associated with any GDP: (1) setting the AAR, and (2) allocating landing slots to flights, and hence, to the airlines who operate those flights.

The AAR is dependent on uncertain weather conditions; it is not known in advance with certainty. Therefore, when a GDP is implemented, a planned AAR (PAAR) must be set based on stochastic information. A “static” stochastic optimization model for deciding optimum PAAR was presented in [BHO03]. There are other variants of such models [KR06, RO93]. The models require an input arrival schedule, a finite set of capacity scenarios, and their probabilities. A scenario represents time-varying profile of airport capacity. A cost-ratio between ground and airborne delay can be adjusted to penalize excessive airborne delays. Given these inputs, the static optimization model [BHO03] generates the optimum PAAR.

Uncertainty in airport capacity is represented by a set of scenarios in stochastic optimization models. Probabilistic weather forecasts are needed. Past research has addressed this issue for specific airports [Wi04]. Research is currently underway to generate probabilistic weather forecasts at airports and en route airspaces. One methodology generates capacity scenarios by analyzing historical observations of AAR [LHM08]. In the future, a combination of probabilistic weather forecasts and empirical data analysis could be used to generate capacity scenarios for airports.

After setting the PAAR, the next step in a GDP is to assign slots to airlines. In today’s system, this is done by executing a Ration-by-Schedule (RBS) algorithm, which is based on first-scheduled-first-served principle. Before RBS is applied, certain flights are exempted from the GDP. The primary reason for exempting flights is to mitigate capacity uncertainty. The RBS algorithm, which lexicographically minimizes the maximum delay of included flights [Vo06], has been accepted as the standard for equitable slot allocation. In a recent study, a new algorithm – Equity-based Ration-by-Distance (E-RBD) – was proposed that considers both equity and efficiency factors in slot allocation [HBM07].

A GDP is a stochastic and a dynamic process. Changing conditions at an airport, for instance due to weather constraints, requires revision of GDP parameters and flight delays. In static optimization models [BHO03, KR06, RO93] decisions are made once and are not revised later based on updated information. This deficiency is overcome by dynamic optimization models [MH07, RO94]. However, it is possible to re-apply static models, and revise decisions, whenever updated forecast becomes available. Figure B-27 presents an algorithm for planning a GDP under uncertainty, and dynamically revising decisions in response to updates in the information on demand and capacity. The steps within the algorithm are similar to how GDPs are planned in today’s system under the Collaborative Decision Making (CDM) paradigm

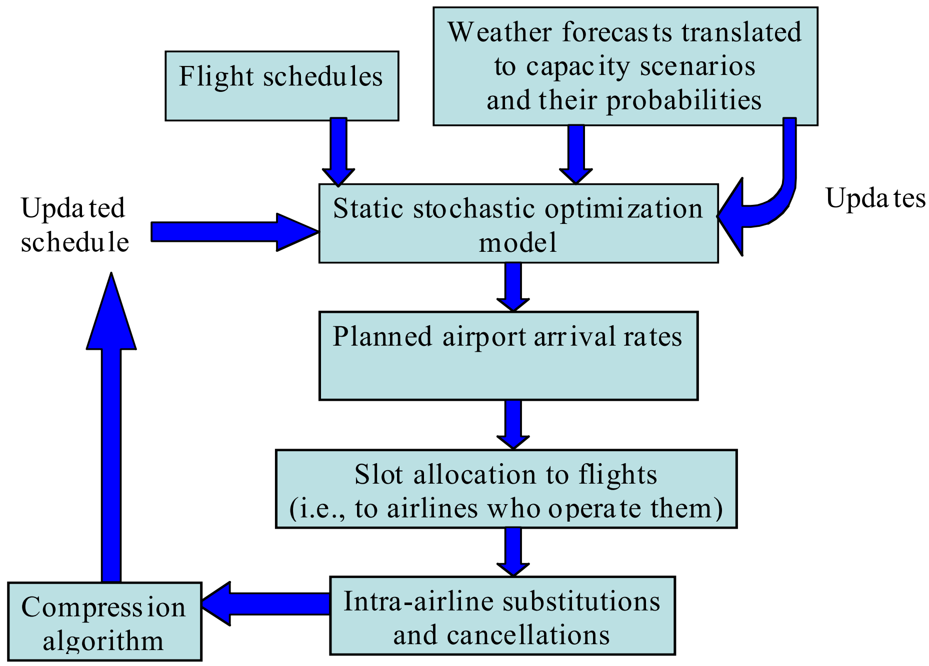


Figure B-27 A dynamic stochastic algorithm for planning and controlling a GDP.

Dynamic stochastic optimization models simultaneously decide PAAR and slot allocation to flights [MH07, RO94]. The dynamic models typically assign scenario-contingent slots to individual flights. These models allow revision of delays based on updated forecasts. Along with a set of capacity scenarios, these models require as input a scenario tree, whose branching points reflect changing AARs. What complicates the applicability of dynamic models is the fact that the branching points in time must be predicted in advance and provided as input to the models. Techniques for generating scenario trees from empirical data were explored in [LHM08]. Performance-wise, however, dynamic models outperform the static models. Application of the dynamic models for GDP planning would require a change in the intra-airline flight substitution process. Unlike in today's system where each flight receives one slot, the dynamic models would assign a portfolio of scenario-specific slots to a single flight. Thus the flight substitutions would also become scenario-specific, and hence, more complex.

Along with capacity uncertainty, there could be uncertainty in flight arrival demand [BVH01]. This could result from flight cancellations, deviation from scheduled or controlled arrival times, and arrivals of un-scheduled flights. Developing models that account for both demand and capacity uncertainty is a potential research topic.

B-2.5 Contingency Planning with Ensemble Weather Forecasts and Probabalistic Decision Trees

Management of the complex interaction between potential weather outcomes and TMIs can be modeled using a collection of potential weather scenarios. These would be retained in an ensemble forecast, which would serve as input to a Probabilistic Decision Tree [DKG04]. Flow planners would make use of this to form a primary plan and contingency flow plans (one for each possible weather scenario) (for instance, strategic two to four hours in the future). This assists in the strategic planning of GDPs, AFPs across FCAs as well as tactical GSs, holding, MIT restrictions, reroutes, and other plans.

Ensemble weather forecasts aim to represent the spread of possible outcomes of the weather. Since there could be hundreds of different weather scenarios, the secret to this techinque is to group the scenarios by general natural and impact on air traffic. Weather organization (e.g. squall line versus popcorn storms) is one such way to group scenarios into a more managable number. Each representative scenario would have associated with it a likelihood (probability) of occurrence. This technique allows for automated routines to propose hedging strategies. Hedging strategies are a proven way to take a wide range of possible outcomes into account without falling back on an overly conservative (worst-case scenario) strategy. Some weight is given to dire outcomes, but other more optimistic outcomes are considered as well. This leads to a more balanced strategy that peforms well on average; cost savings are incurred with repeated use [HKD07]. Probabilistic forecasts and the use of probabilistic decision trees will have failures on a daily review, but over the long-term will show improvement in operations.

The probabilistic decision tree manages the ATM impacts and probabilities of occurance. As illustrated in Figure B-28, the decision tree is set up to reason about the general dimensions of forecast error that are possible in the future, and how these should be linked to strategic and tactical TMIs that will address those scenarios. The tree is mainly for benefit of the human users. It provides a map of key TMI and flow planning decisions that need to be made. Decision makers and other stakeholders can follow along to see which critical decisions must be made, when, and ATM-impact costs associated with the course of action.

First, the ensemble captures potential variations in weather types that may emerge, and associated probabilities. Errors in timing, coverage, echo tops, and translational errors may be considered in the tree. In order to process such errors, the appropriate weather to ATM impact models must be invoked, requiring potentially a wide range of ATM impact models from capacity estimates, route blockage probabilities, affects of weather on AARs, or other impacts. Associated with each branch of the tree is a set of TMIs that would be used if the future evolves to that state.

For NextGen, the use of probabilistic decision trees to manage traffic in the NAS requires both ATM impact models to mature as well as the understanding of how to best assemble TMIs into a probabilistic decision tree that meet the objectives of a strategic plan of operations. Given that the amount of weather forecasts in an ensemble is likely to be large, and the space-time dimensions of potential uncertainty further expand the number of scenarios, NextGen will require research on how to best manage probabilistic decision trees using computers as the number of possible futures is far larger than humans could cognitively grasp

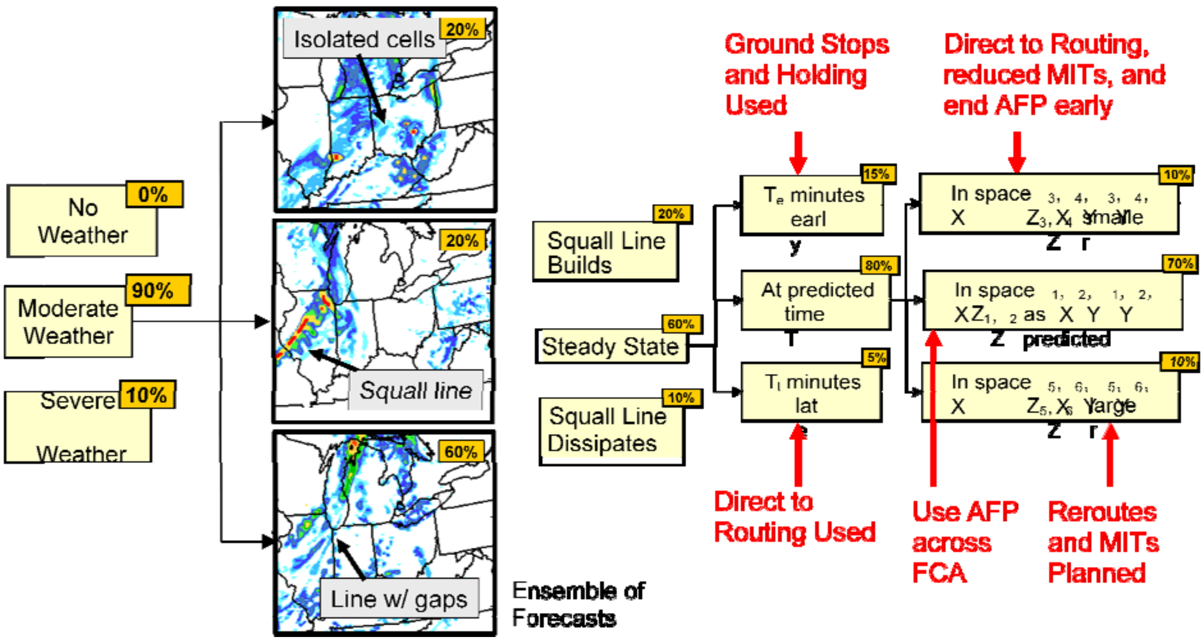


Figure B-28 Probabilistic decision tree reasoning with an ensemble of weather forecasts.

B-2.6 Probabilistic Traffic Flow Management

An important goal of TFM is to ensure that traffic loadings do not exceed system capacities. TFM problems often involve time horizons extending to one or more hours into the future. This strategic TFM problem is inherently stochastic since both the traffic loadings and system capacities are difficult to forecast precisely over such long time horizons [WSZ05]. Strategic TFM solutions need to account for forecasting uncertainties.

The strategic TFM problem is difficult even in the absence of forecasting uncertainties [BS98]. This difficult problem is solved mainly by human operators in today's NAS. A strength of human decision making is its intuitive ability to rapidly assess and approximately account for uncertainties. Such powerful intuition will be a challenge to replace in automated strategic TFM solutions in NextGen. These future TFM solutions hold the promise of significantly improving NAS performance and repeatability, but first they must match the robustness inherent in human decision making.

Any strategic planning activity within the NAS requires forecasts which contain uncertainties since all forecasted quantities are random variables. For instance, surveillance reports, navigation data, communications, user intent and conformance, weather, and the possibility of anomalous events all introduce uncertainty into NAS forecasted quantities. These processes could be modeled and their random variables estimated in a classic covariance propagation [Ge74]. But this is difficult due to the magnitude of the problem and the substantial modeling effort required. Perhaps the biggest drawback to the approach, however, is the difficulty in accounting for the substantial human-in-the-loop decision making that critically affects these processes. In fact, in the absence of such an accounting, the variances of many random variables (e.g., aircraft position) can rapidly grow. In this case distributions flatten and the strategic TFM problem reduces to a non problem due to an absence of information.

An alternative to the classic covariance propagation approach is to identify the key random variables in the strategic TFM problem and model them with aggregate uncertainty models, based on system domain knowledge and historical data. In this rational-empirical approach, one (i) constructs mathematical models describing the random variable uncertainty as a function of the relevant independent variables and (ii) fits these models to the historical data [WSZ05, H07a, HR08, HW08]. This approach also has the advantage that many random variables can be ignored as irrelevant. For instance, though surveillance error should be accounted for in a classic covariance propagation approach, it becomes irrelevant in the aggregate model of traffic loading uncertainty [WSZ05].

In the strategic TFM problem, forecasted traffic loadings and system capacities are the most important random variables that need to be estimated. Since loading and capacity are typically expressed as integers, these random variables can be expressed as discrete distributions, known as probability mass functions (PMFs). Properly constructed, these PMFs faithfully represent the forecast accuracy. They are neither less accurate (wider) nor more accurate (thinner) than the forecast accuracy. Given PMFs that faithfully represent the forecast accuracy, the probabilistic TFM solution can then use them to account for the uncertainties that are unavoidable at the planning stage.

A misconception is that a probabilistic TFM solution is limited to probabilistic, or multiple, solutions. Such solutions would be difficult to implement but are easily avoided. Probabilistic TFM solutions can use probabilistic forecasts to produce a deterministic solution. An obvious approach is to compare the traffic loading and system capacity PMFs to evaluate a congestion cost (e.g., by convolving the PMFs). Such a metric can be forecasted for NAS elements, such as airports and regions of airspace, and for flights. Figure 30 shows an example of the distribution of flight costs in a day [H07a].

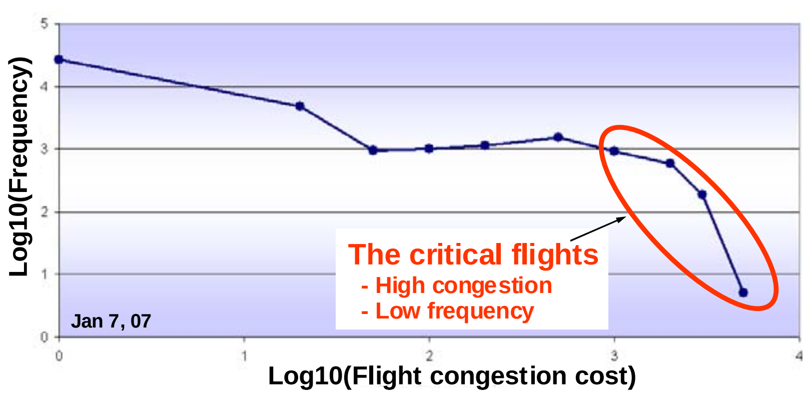


Figure B-29 Example histogram of flight congestion costs.

Such congestion forecasts, by flight or by airspace / airport, are crucial in the probabilistic TFM solution. They can be used to guide flight selection, for delaying or rerouting. And they can be used to manage system congestion to acceptable levels. And this approach is well-suited to the NextGen principles of trajectory-based operations and user involvement.

The specific solution method can take several forms. One is a resource allocation solution involving a combination of rerouting and ground delay. This probabilistic TFM concept has a high maturity level, as it has been defined, analyzed and verified at various levels. Also, it has been simulated for several different types of traffic and weather days, and has been tested in a real-time system testbed [H07a, H07b, H08].

B-2.7 A Heuristic Search for Resolution Actions in Response to Weather Impacts

Uncertainties present in demand, weather, and capacity, create a need to resolve congestion in an efficient and flexible manner. In both the strategic and tactical time frames, the methods utilized to resolve congestion should provide metrics to measure the quality of the proposed solutions. As it is desirable to have flight-specific resolution actions, there are many potential solutions and the challenge is to find a good solution quickly. A Generalized Random Adaptive Search Procedure (GRASP) can address this problem through a computationally-efficient heuristic optimization approach. GRASP finds feasible solutions quickly and evaluates proposed solutions against defined metrics to determine the set of resolution maneuvers that best satisfies the objectives.

Figure B-30 illustrates the decision loop. The process creates an ordered list of flights and then examines each flight individually to determine if it can remain on its original path or if it must be delayed and/or rerouted. Weather information is used to predict sector capacities in and around the congested area, and flight options that violate the congestion resolution goal are less desirable. The flight list is ordered probabilistically, using specified priority criteria such as first-come first-served (FCFS), to determine the likelihood of placement in the sort order. This is useful because it exploits the fact that the chosen prioritization criteria may not fully capture the best situation and therefore minor modification in the ordering may be beneficial [FR95].

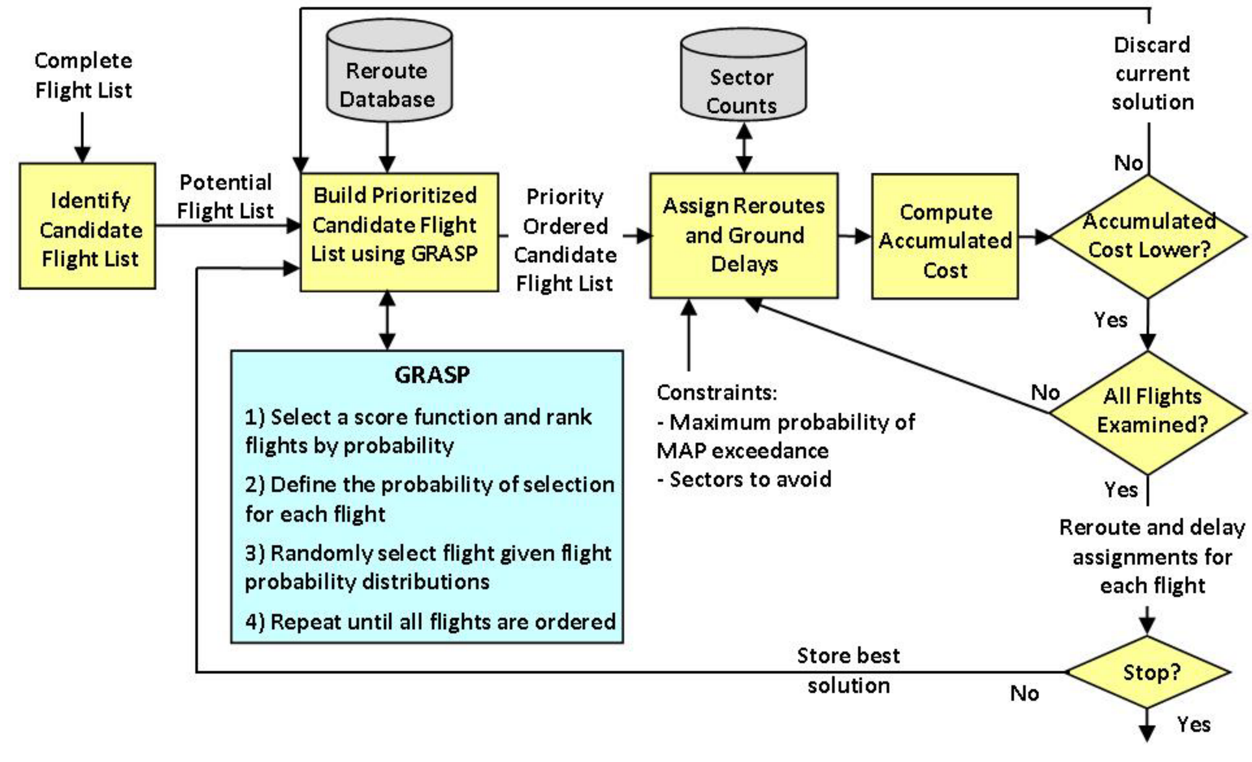


Figure B-30 Congestion management algorithm flow diagram.

Once all flights are examined, an objective function is used to measure solution quality against a variety of goals. Objective functions are formulated to evaluate the quality of the solution as a whole, such as congestion resolution effectiveness, total delay, or the equitable distribution of resolution actions among users. After iterating, the algorithm returns the best solution found.

This process for air traffic congestion provides a flexible and computationally efficient alternative to more traditional heuristic optimization algorithms [MWG06, SMW07]. Given its computational efficiency, GRASP could be employed within a larger decision making process, such as sequential probabilistic congestion management [WG08], to optimize the resolution maneuvers at each stage of the decision process.

Another useful application is to evaluate quantitative measures of the impact on a policy objective that result from implementing a given prioritization criteria. For example, by choosing a FCFS prioritization, the impact on delay and equitable distribution can be compared to the results obtained from the choice of an alternative prioritization (e.g., sort flights by the number of congested sectors they currently are planned to traverse). This type of analysis can provide feedback as to which choice of prioritization criteria is desirable, based on the trade-offs obtained in the policy objectives considered.

B-2.8 Integrated Departure Route Planning with Weather Constraints

NextGen will require an Integrated Departure Route Planning (IDRP) capability in order to handle departure traffic efficiently and safely. The IDRP capability must integrate departure route and en route sector congestion information, especially when weather constraints are present and traffic demand must dynamically adjust to predicted downstream capacity fluctuations. This concept also applies to downstream weather constraints such as convection, turbulence, or icing. The IDRP capability reduces the time needed to coordinate and implement TMIs and supporting departure management plans.

A variety of TMIs such as reroutes, MIT restrictions, and GDPs are generated to control the NAS when air traffic demand on specific resources – sectors, routes, and fixes – is predicted to exceed capacity. This is especially crucial when system capacity is reduced by severe weather. In current operations, with limited automation support, traffic managers must mentally integrate the traffic, weather, and airspace resource information and project that information into the future. This process is difficult, time consuming, and inaccurate. In NextGen, in order to maximize airspace capacity while maintaining safety, it is desirable to minimize the impact of TMIs on operations and to implement only those TMIs necessary to maintain system integrity.

Route availability [DRT08] feedback helps traffic managers determine the specific departure routes, altitudes, and departure times that will be affected by significant convective weather, turbulence, or icing. NextGen DSTs will assist users in deciding when departure routes or fixes should be opened or closed and to identify alternative departure routes that are free of weather constraints. DSTs need to help traffic managers answer the questions:

- If a route is impacted by the weather constraint during a particular time window, which and how many aircraft are affected?
- What alternative departure routes are free of weather constraints during a particular time window, and how many aircraft can the route handle?

The IDRP concept (Figure B-31) translates weather constraints into ATM impacts, and thus helps decision makers evaluate and implement different TMIs [MBD08] in response to the projected ATM impacts. The concept takes into account multiple factors that can have significant effects on departure management when weather constraints are present. In evaluating the impact of congestion and downstream weather constraints on departure operations and potential actions to mitigate those impacts, traffic managers must consider filed flight plans and acceptable alternatives, surface departure queues, predicted weather impacts (route availability) along both departure and arrival routes in the terminal area and nearby en route airspace, the current state of departure routes (open, closed, MIT, etc.), predicted congestion and flight times along weather-avoiding reroutes, and the weather forecast uncertainty. By bringing all of these factors into an integrated environment, IDRP can reduce the time needed to make departure management decisions and coordinate their implementation. If it is integrated with surface and arrival management systems, IDRP can improve efficiency over the NAS considerably.

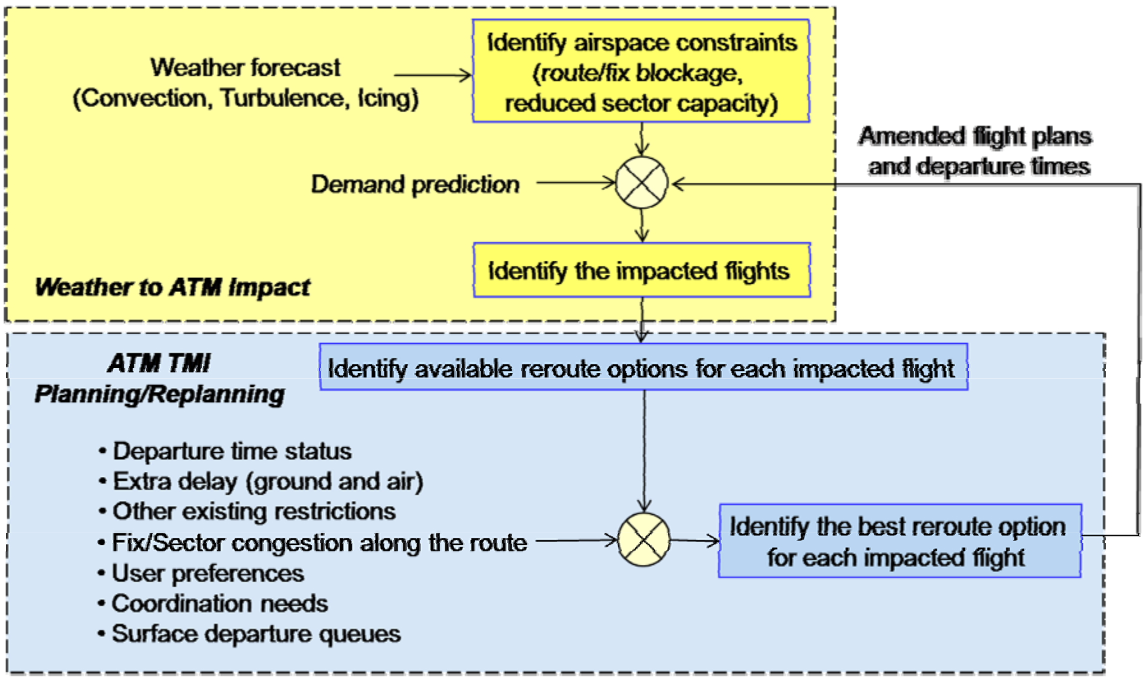


Figure B-31 Integrated Departure Route Planning Concept.

B-2.9 Tactical Flow-based Rerouting

This concept for rerouting air traffic flows around severe weather is for a tactical timeframe (0 to 2 hours out) and requires an ATM-impact model for route blockage, as illustrated by Figure B-32. In this timeframe, weather predictions are relatively good, so the reroutes can be closer to the weather than strategic reroutes and thread through smaller gaps between weather cells. Automated solutions makes tactical rerouting easier, increasing the ability of traffic managers to implement them. Moving this activity from controllers to traffic managers will reduce controller workload, thereby safely increasing airspace capacity during severe weather.

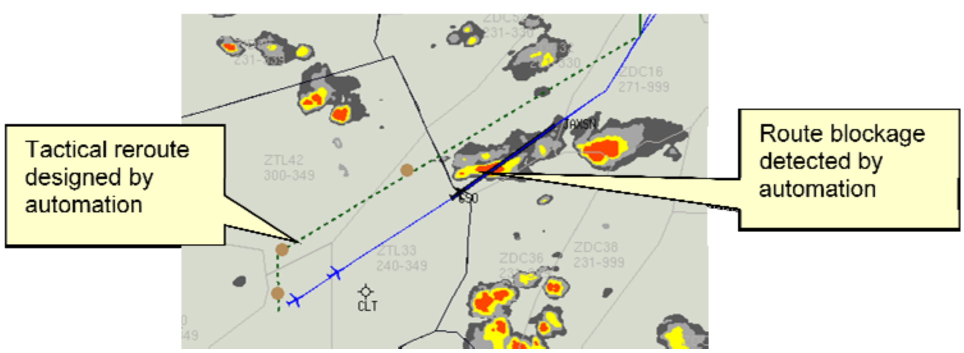


Figure B-32 Example flow reroute.

A Flow-based Tactical Rerouting DST identifies flights that are likely to need deviations from their current routes to avoid severe weather. The flights considered can be limited to the flights in a Flow Evaluation Area (FEA) flight list [CDM04] to narrow the focus to particular flows or areas. To determine severe weather encounters, predicted 4D trajectories are probed against a WAF [DRP08] that is based on a dynamic 4D weather forecast, including echo tops. Parameters are provided to allow the traffic manager to adjust the sensitivity of the probe.

The DST groups the flights identified with WAF encounters into flows according to weather impacted route segment, arrival airport, sectors traversed, or some other manner, and presents those to the traffic manager. The traffic manager can select one or more flows to examine in more detail in a flight list or on a map display, and advance time to view the predicted future situation. The traffic manager can select one or more of the impacted flows and request reroutes from the DST. The DST can then generate reroutes that avoid the WAF. It may achieve this based on historical routes, a network algorithm, or both. A ground delay can also be used with the current route to allow the weather to move off of the route. The resulting clear routes are ranked and filtered based on a number of criteria such as delay, required coordination, consistency with existing traffic flows, sector congestion, and closeness to weather.

Traffic managers determine the best reroutes for each flow. The reroutes go into a list with all the information necessary to implement them, including identification of air traffic managers (external facility or internal area) that need to approve them. After coordination, an air traffic manager in a rerouted flight’s controlling facility can accept and implement the reroute.

B-2.10 Tactical On-Demand Coded Departure Routes (CDRs)

This concept for rerouting air traffic flows around severe weather is based on moving today’s static, fixed Coded Departure Route (CDR) framework for rerouting traffic on jet routes during severe weather events into a dynamically defined “On Demand” CDR framework [KPM06] for NextGen for routing 4D trajectories in a tactical timeframe (0 to 2 hours out). The method requires an ATM-impact model for route blockage to identify ahead of time when On-Demand CDRs are needed, as previously illustrated by Figure B-32, and the ability to design space-time reroutes between city pairs with a 1-2 hour look ahead time (Figure B-33). The purpose of On-Demand CDRs is to move the rerouting decision as close to the tactical time horizon as possible to eliminate the uncertainty in rerouting – eliminating the potential for several weather outcomes, as is the case in ensemble weather forecasts, and focusing in on one projected weather outcome in the tactical time frame.

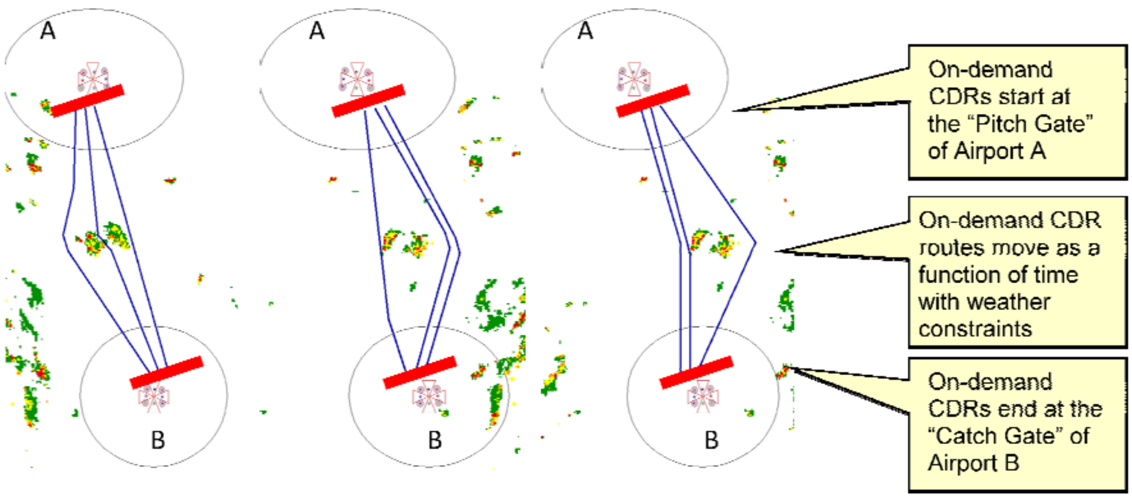


Figure B-33 On-Demand CDRs between pitch and catch gates from Airport A to B.

Today, CDRs are generated far in advance of the day that they are implemented. The routes are maintained in a database and distributed between the ATSP and the users (airlines). If the weather forecast is highly predictable, the ATSP selects the CDR that best solves a weather avoidance problem, given other TFM constraints. For less predictable weather, the ATSP identifies CDRs that could be used to avoid multiple weather constraint scenarios, asks the NAS users to prepare for this full set of contingencies (alternative CDRs), and then assigns the actual route to the flight as it departs. However, today's CDRs often take aircraft far out of the way as they do not shape the weather avoidance route to the actual movement of the weather constraint.

The On-Demand CDR concept dynamically generates CDRs approximately 1-2 hours in advance of take off time based on the latest deterministic weather forecast. The benefit of generating CDRs as needed to meet the constraints imposed by the weather forecast is that the routing solution adapts and best fits both the emergent weather pattern and latest traffic flow requirements. Such weather avoidance routes can be generated with a space-time weather avoidance algorithm [P07] that takes into consideration the weather forecast, CWAM WAF [DE06, CRD07] or other weather avoidance constraints, and relevant human factors and domain knowledge requirements [KPM06]. The weather avoidance routes do not have to be based on today's jet routes and Naviads, since in NextGen, RNAV routing and RNP performance will allow routes to be defined anywhere in the sky

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