Clear-Air Turbulence Impact Modeling Based on Flight Route Analysis

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In this study, a Route-Based Turbulent-Weather Avoidance Model (TWAM-R) is presented. TWAM-R improves a previously reported trajectory-based model which was tactical in nature. TWAM-R considers more strategic turbulence-avoidance decisions that are based on turbulence forecasts and pilot reports (PIREPs). TWAM-R identifies areas of reduced capacity and areas of potential hazards due to congestion caused by air traffic avoiding clear-air turbulence. The algorithm is explained and illustrated using real-life turbulence and air traffic demand data. This study is a part of a larger effort aimed at the creation of weather impact translation models which specify the link between the weather hazard causes and their impact on the National Airspace System (NAS).

Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tr>
<td>AIM</td>
<td>Aeronautical Information Manual</td>
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<td>ASL</td>
<td>Above Sea Level</td>
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<td>ATM</td>
<td>Air Traffic Management</td>
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<td>CAT</td>
<td>Clear-Air Turbulence</td>
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<td>CIT</td>
<td>Convection-Induced Turbulence</td>
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<td>edr</td>
<td>eddy dissipation rate</td>
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<td>FCA</td>
<td>Flow Constrained Area</td>
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<td>FL</td>
<td>Flight Level</td>
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<td>ft</td>
<td>feet</td>
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<td>GTG</td>
<td>Graphical Turbulence Guidance</td>
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<td>kts</td>
<td>knots</td>
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<td>MoG</td>
<td>Moderate-or-Greater</td>
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<td>MWT</td>
<td>Mountain-Wave Turbulence</td>
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<td>NAS</td>
<td>National Airspace System</td>
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<td>NextGen</td>
<td>Next Generation Air Transportation System</td>
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<td>nmi</td>
<td>nautical mile</td>
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<td>PIREP</td>
<td>Pilot Report</td>
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<td>RUC</td>
<td>Rapid Update Cycle</td>
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<td>SoG</td>
<td>Severe-or-Greater</td>
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<td>TFM</td>
<td>Traffic Flow Management</td>
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<td>TFMS</td>
<td>Traffic Flow Management System</td>
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<td>TWAM</td>
<td>Turbulence Weather Avoidance Model</td>
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<td>US</td>
<td>United States</td>
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<tr>
<td>WCTO</td>
<td>Worst-Case Turbulence Outlook</td>
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<td>Z</td>
<td>Zulu Time</td>
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I. Introduction

Traffic Flow Management (TFM) in the National Airspace System (NAS) is affected by a wide variety of constraints imposed by weather. Hazardous weather constraints include: fog, haze, smoke, clouds, thunderstorms, hurricanes, lightning, hail, heavy rain, surface icing, in flight icing, wind shifts, wind shears, gusts, jet streams, Convection-Induced Turbulence (CIT), Clear-Air Turbulence (CAT), Mountain-Wave Turbulence (MWT), microbursts, tornadoes, waterspouts, snow, blizzards, volcanic ash, and space weather. Krozel¹ provides additional background documenting this taxonomy of aviation weather hazards and ATM-impact models. Related literature²-⁶ provides pilot guidelines for addressing weather hazards in the NAS – not just turbulence hazards but a wide variety of aviation weather hazards. Additional literature⁷-¹² presents mathematical models for the ATM impact of aviation weather hazards. While the majority of the ATM impact models have been derived for how pilots react to convective weather hazards, we have focused on gathering statistics for turbulence hazard impacts in order to expand the understanding of ATM impacts due to turbulence.

II. Background

We start by providing some background material related to CAT.
A. CAT versus CIT

CAT is typically caused by the wind shear that exists at the boundaries between large air masses and at the boundaries of the jet stream. As the name implies, this turbulence can occur without visual or radar indication. MWT (Figure 1) is a type of CAT, where the wavelike effect is characterized by updrafts and downdrafts that occur above and downwind from a mountain range when rapidly flowing air encounters the mountain range’s steep front. The resulting wave can travel higher than 20,000 ft above the terrain and propagate downstream several hundred miles. These waves frequently produce Moderate-or-Greater (MoG) turbulence. As with other types of CAT, airborne detection of this phenomenon is not possible with current technology onboard modern airliners.

CIT – which is not in the scope of present analysis – is caused by the instability and resulting up and down drafts due to convective activity, typically associated with thunderstorms. CIT can range from light to severe. Airborne radar can indicate the precipitation regions where CIT is likely; however, CIT can also occur outside the boundaries of precipitation, and both the existence and magnitude of CIT is impossible to detect with current avionics technology.

B. CAT Impact

En route turbulence is probably the most common weather factor pilots must deal with on a daily basis. In previous work\textsuperscript{13,20}, we have established a causal relationship between different levels of turbulence and the ATM impact, as illustrated in Figure 2. (The components of the causality diagram that are outlined in bold blue are the ones that are in the primary scope of the present work. They are addressed in detail in subsequent sections.) MoG turbulence tends to close en route airspace given that passenger comfort and safety is a high priority for many airlines. Forecasted or reported Severe-or-Greater (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. Further information about turbulence impacts can be found elsewhere\textsuperscript{13-18, 20, 21}.

This paper focuses on modeling how SoG CAT – anticipated or experienced along a given flight route – affects the usage of airspace that the route goes through.

![Figure 1. Mountain Wave Turbulence](Image courtesy of UCAR).

![Figure 2. Causality Diagram for Turbulence.](Image courtesy of UCAR).
III. Turbulence Impact Modeling

A. Modeling Challenges
Quantifying the impact of severe turbulence on NAS resources is a complex problem with the following difficulties:

- **Accurate Forecasting.** CAT cannot be seen and does not accompany any visible phenomenon (like a thunderstorm in the case of CIT) and thus the stakeholders have to rely on turbulence forecasts (that are imprecise by nature and based on scientific models with known or unknown deficiencies) and/or PIREPs (that are subjective and sporadic).

- **Varying Spatial and Temporal Extent.** A single turbulence event can be contained within a single NAS sector at one or two flight levels or may affect large volumes of airspace – tens of sectors and flight levels at once and to varying degrees (also changing with time). Besides, different sector/altitude levels have different air traffic densities and thus different overall importance to the NAS.

- **Varying Pilot Response.** As previously documented\(^\text{13}\), multiple factors need to be identified, understood, quantified (if possible) and properly taken into account for building a turbulence impact model. These include factors such as: the amount of turbulence currently experienced by the pilot at the current altitude, user class, weight class, aircraft type, turbulence at flight levels above and below the current flight level of the aircraft, and proximity of the aircraft to other aircraft or to the final destination.

- **Generalization of Pilot Responses.** The turbulence impact model built from a limited number of turbulence situations in certain parts of the NAS at certain times of the year may or may not be projected onto the impact on the entire NAS for the entire year. This is an open research question that must be addressed.

B. Sources of Data
In our analysis, we rely on flight route/track data and turbulence data; the data sources are described next.

The Traffic Flow Management System (TFMS) provides real-time aircraft tracking data used operationally by all FAA air traffic control personnel to direct aircraft flow in the NAS. We use TFMS data to identify the flight call sign, aircraft type, user type, departure and arrival times, aircraft location (in 1 minute intervals), filed flight plan, and flight plan amendments.

For turbulence forecast data, we use Graphical Turbulence Guidance (GTG) products\(^\text{19}\). A sample output of the standard deterministic GTG product is depicted in **Figure 3**. GTG uses output from numerical weather prediction model forecasts – based on the Rapid Update Cycle (RUC-2) – to derive a dozen of turbulence diagnostics that are combined as a weighted sum with the relative weights computed to give the best agreement with the most recent available turbulence observations (i.e., PIREPs). The set of diagnostics – currently, 12 – is selected to ensure that the indices appropriately represent the variety of atmospheric processes that may be contributing to the existing turbulence conditions – e.g., wind shear, Richardson’s number, Ellrod Index, eddy dissipation rate (edr), vertical wind speed, etc. These indices are used in forecasting upper level CAT associated with MWT, upper level fronts, and jet streams. GTG reports turbulence data at common flight levels (in increments of 1000 ft) and mapped to a common turbulence intensity edr \([0,1]\) scale (**Table 1**), where 0 is no turbulence and 1 is extreme turbulence.

**Figure 3.** Deterministic GTG forecast of CAT potential for 1600 UTC, June 26, 2008, at FL390.

**Figure 4.** Probabilistic SoG GTG forecast for 1800 UTC, January 24, 2007, at FL390.
The probabilistic GTG forecast product (e.g., Figure 4) is a prototype product that is being developed, among other reasons, to comply with Next Generation Air Transportation System (NextGen) requirements. Probabilistic GTG maps are derived by computing the percentage of the number of turbulence diagnostics (or indices) that agree for different intensity levels on a grid-point-by-grid-point basis. A four-color code is employed.

For example, if light turbulence is of interest, the probabilistic GTG map will depict as white, green, yellow and red, respectively, the areas where fewer than 25%, at least 25%, at least 50%, or at least 75% (i.e., 9 out of the 12) turbulence indices fall into the “light” category (i.e., between 0.125 and 0.375, according to Table 1). For moderate and severe turbulence, the likelihood of the agreement among the GTG indices is smaller, so the cutoffs for the smoothed GTG index agreement data depicted by green, yellow and red colors are set at 10%, 20% and 30%, respectively (Figure 4).

The probabilistic GTG forecasts are sensitive to the “moderate” and “severe” thresholds chosen for individual indices, and these are likely to be further optimized in future work. This uncertainty – alongside the fact that (a) all forecasts only have a limited accuracy and (b) GTG is a macro-scale forecast of an aircraft-size phenomenon – introduces uncertainty into our results. However, the probabilistic GTG product still provides a useful and intuitive means of quantifying the likelihood of a turbulence encounter in a given NAS resource.

C. Previous Research

Here we briefly describe previously reported sector-based20,21 (TWAM-S) and trajectory-based21 (TWAM-T) turbulence impact models. General geometry for both approaches is shown in Figure 5.

![Geometry of the approaches for sector-based and trajectory-based analysis.](image)

Table 1. Turbulence weather hazard classifications.

<table>
<thead>
<tr>
<th>Intensity (edr)</th>
<th>Color</th>
<th>Terminology</th>
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<tr>
<td>0.000 - 0.125</td>
<td>None</td>
<td>No turbulence</td>
</tr>
<tr>
<td>0.125 - 0.375</td>
<td>Light Green</td>
<td>Light</td>
</tr>
<tr>
<td>0.375 - 0.625</td>
<td>Yellow</td>
<td>Moderate</td>
</tr>
<tr>
<td>0.625 - 0.875</td>
<td>Orange</td>
<td>Severe</td>
</tr>
<tr>
<td>0.875 - 1.000</td>
<td>Red</td>
<td>Extreme</td>
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![Number of agreeing turbulence diagnostics](image)

1. Sector-based TWAM (TWAM-S)

For TWAM-S, the probability of a severe turbulence encounter in a given NAS sector at a given flight level for a given probabilistic GTG cutoff (green, yellow or red) is expressed as the percentage of the sector area covered by the corresponding GTG color and “higher” colors (Figure 5 (a)). Figure 6 shows how the occupancy of a single flight level of an average sector (relative to a “no turbulence” baseline day) changes based on a single probabilistic GTG hourly forecast. Figure 7 shows the distribution of the air traffic responses (no response, altitude adjustment, sector route adjustment (re-route), altitude adjustment and re-route, and other) for a sector with a given relative probability of a severe turbulence encounter of a given threshold (“green-or-greater”, “yellow-or-greater”, or “red-or-greater” in the color language of probabilistic GTG maps).
Figure 7. Distribution of turbulence-avoidance responses for air traffic entering a sector/flight level with a given probability of severe turbulence encounter (colors correspond to GTG agreement threshold).

Finally, Figure 8 presents the magnitude distribution of the climbing/descending maneuvers as a function of the probability of a severe turbulence encounter in an upcoming sector. Data in Figure 8 are labeled according to the probability of a severe turbulence encounter for the “red-or-higher” (≥0.3) threshold for GTG diagnostic agreement.

Figure 8. Magnitude distribution for altitude-changing turbulence-avoidance maneuvers.

2. Trajectory-based TWAM (TWAM-T)
TWAM-T focuses on analyzing CAT forecast data in the immediate vicinity ahead of an aircraft (Figure 5(b)). For a given point along a flight track, we calculate the projected direction of flight and identify the grid cells that overlap with a 5×50 nmi rectangle (light blue cells in Figure 5(b)). For each of these cells, we determine the number of GTG indices that predict SoG turbulence (1/12 if one index indicates SoG turbulence, 2/12 if two, 3/12 if three, etc.), and then average those values over all grid cells inside the rectangle. This gives us an average probabilistic GTG value for turbulent activity in the aircraft’s immediate flight path. Finally, the 50 nmi stretch of the flight track starting from the current position of the aircraft is examined to identify if a pilot initiated a maneuver.

Pilot behavior is classified into the following categories:
- No Response – the aircraft remains in straight and level flight in en route airspace.
- Climbed – the aircraft climbed two or more flight levels.
- Descended – the aircraft descended two or more flight levels.

Figure 9. Maneuver statistics for a potential severe turbulence encounter for all aircraft.
Re-routed – the aircraft re-routes around the sector where turbulence was present, based on the filed flight plan that passes through the sector of interest.

The dependencies of the probability of each maneuver can be established for different user classes, physical classes, weight classes, aircraft types, and airlines. One such relationship – for all aircraft combined – is shown in Figure 9.

Finally, like the sector-based analysis, the trajectory-based data can be further examined to identify the relationship between the magnitude of altitude maneuvers and the probability of severe turbulence present along the upcoming flight trajectory (Figure 10).

III. Route-Based TWAM (TWAM-R)

A. Introduction
TWAM-R calculates the probability of each particular turbulence-avoidance maneuver based on the forecast turbulence from 0 to several hundred nmi along the current flight route (Figure 11).

This model has been developed based on the analysis of about 400 flights that took place between 30 major Western US and 30 major East-coast US airports and crossed the forecast area of high probability of SoG turbulence between 15 Z and 19 Z on Oct. 23, 2007 (the most turbulent day of 2007) (Figure 12).

B. Algorithm
For every minute of the en route portion of each flight the following calculation was made. The remaining portion of the flight route was divided into 20-nmi segments – and the forecast turbulence intensity was evaluated for each segment by setting up a circular area of 20 nmi radius and calculating the portion of the area of this circle that was covered by the probabilistic SoG GTG data corresponding to 1-out-of-12-or-higher, 2-out-of-12-or-higher, etc., GTG index agreements. Flight plan amendment and flight track data were analyzed to see if an altitude maneuver, route change, or both occurred when a flight was facing turbulence coverage of this magnitude along the route. The coverage values for each GTG level and the corresponding distances from the current aircraft location were recorded together with the pilot’s action (No response, Descended, Climbed, or Re-routed). These data were compiled for all flights.
The Worst-Case Turbulence Outlook (WCTO) metric was designed to capture both the severity and the proximity of the worst-case turbulence encounter that a flight faces at its current location along the current flight route. WCTO is a dimensionless variable in the (0,1) range – and represents the product of the average SoG GTG coverage of a circle of 20 nmi radius and a decreasing function of distance to that circle from the current location of the aircraft along the current route (Figure 11). Thus the WCTO metric increases both when the severity of turbulence in the upcoming area becomes higher and/or the distance to that area becomes shorter. The value of zero corresponds to no SoG turbulence present along the current route, and the value of 1, or 100%, represents an aircraft currently at a location (zero distance) where all 12 GTG indices predict SoG turbulence.

TWAM-R predicts what percentage of air traffic will resort to each type of response to turbulence within a given interval of time (from 1 to 20 minutes) once the WTCO metric reached a given value. A few examples of these dependencies are shown in Figure 13. This model was designed for strategic use: for a given filed flight route, it gives us the projected turbulence outlook for every point along the route (up to several hours ahead), along with the probability of the pilot response within a certain interval of time after reaching that point on the route.

TWAM-R also computes the probabilities of an altitude-changing maneuver of each magnitude for a given WCTO value. The probability versus WCTO dependencies for each magnitude were fit with exponential functions, the probability values were calculated for WCTO values with a 5% interval and stored in a lookup table (Figure 14) (note that the percentages along the Y axis are of all maneuvers, while the percentages in Figure 8 and Figure 10 are of all altitude-changing maneuvers).

Figure 12. Probabilistic SoG GTG map for 15 Z, Oct. 23, 2007, FL300.

Figure 13. Turbulence-avoidance maneuver probabilities according to TWAM-R.

Figure 14. Magnitude distribution for TWAM-R altitude-changing turbulence-avoidance maneuvers.
C. Sector Impact (Hazard Prediction)

An algorithm has been developed to predict in which flight levels (or sector overall) congestion may occur – caused by air traffic climbing/descending to avoid turbulence. The algorithm gathers filed flight route information for all flights that are projected to fly through a given NAS sector – or a “stack” of NAS sectors (same LAT/LONs but different altitude bands) – within a given timeframe and calculates the projected flight level occupancies for this sector, first without turbulence and then with turbulence, applying TWAM-R to model the likely turbulence-avoidance flight level changes before and within the sector.

To demonstrate the key concepts, we establish some data sets from various sources and dates to make a simulated example. We considered a “stack” of three en route high-/super-high-altitude sectors in the Southwestern US – sectors ZDV68 (0–26,900 ft), ZDV23 (27,000–35,900 ft), and ZDV24 (36,000–99,999 ft) – that contains a number of major air traffic flows, such as to/from LAS, PHX, DEN, DFW and the East Coast airports (Figure 15).

Figure 15. Typical daily air traffic through the ZDV68/23/24 sectors (sector boundaries are in red and the busiest flow through the ZDV24 sector – LAS-DEN – highlighted in blue).

Figure 16. Probabilistic SoG GTG snapshots for 38,000 ft and 39,000 ft, 17Z, Jan.24, 2007.

Figure 17. Projected ZDV68/23/24 flight level occupancies for 15Z – 19Z (no turbulence).
A busy day – Sunday after Thanksgiving Day, Nov. 29, 2009 – was chosen to demonstrate a potential impact of turbulence on a busy sector. We queried the TFMS database for filed routes for all flights scheduled to enter the selected three sectors between 17 Z and 21 Z – a total of 160 flights. To model the hourly turbulence “nowcast,” we used the available probabilistic SoG GTG data for 15 Z – 19 Z, Jan. 24, 2007 (this date does not match the date of the traffic given above, however, we chose it to force a high traffic count to enter into a high turbulence encounter in our simulated example). Figure 16 shows two of the hourly GTG snapshots for 17 Z. (One can see how quickly turbulence forecast changes with altitude both in terms of location and intensity.) To analyze (in simulation) the impact of severe turbulence on ZDV68/23/24 sectors, we first calculated the projected flight level occupancies without turbulence – that is, if every flight flew according to its projected departure time, route, and altitude. The results are shown in Figure 17. Then, for all 160 flights, we used TWAM-R to calculate the probabilities for each flight to be found in a given flight level when it enters the sectors. These individual-flight probabilities were used, in
turn, to calculate the probabilities for 0, 1-or-more, 2-or-more, etc. aircraft to be found in a given flight level at a given time. Figure 18 shows several examples. In this example, we notice two effects of turbulence:
(a) Upper flight levels of ZDV68 – with no projected air traffic without turbulence – get substantial probabilities of finding 1 or 2 aircraft in them
(b) For FL370, the maximum projected number of aircraft is seven, while turbulence introduces the 23% probability of finding 8-9 aircraft in that level, creating potential congestion.

Calculations similar to those presented in Figure 17 and Figure 18 are done for the occupancies of entire sectors. The results are shown in Figure 19 and Figure 20.

Figure 19. Projected ZDV68/23/24 sector occupancies (no turbulence).

Figure 20. Probabilities of finding ≥2, ≥7, ≥11, ≥13, ≥15, and ≥18 aircraft in the ZDV68/23/24 sectors, with turbulence-avoidance maneuvering taken into account.

The calculated probabilities presented in Figure 17 through Figure 20 can be used to forecast the lowest and highest flight level/sector occupancies for a chosen probability threshold. This is important because it can reveal if a given sector/flight level is likely to be significantly under-used or, on the opposite, used at/beyond its capacity.
Figure 21. Highest forecast flight level use for 10% and 40% probability thresholds.

Figure 22. Highest forecast sector occupancy for 3% and 30% probability thresholds.

Figure 23. Historic (4th quarter 2009) ZDV23/24 flight level occupancies for 17Z-21Z.

Figure 24. Historic (4th quarter 2009) ZDV23/24 sector occupancies for 17Z-21Z.

Figure 21 shows the highest flight level use for 10% and 40% probability thresholds for four busiest flight levels. It follows from Figure 21, for example, that one can say with 40% certainty that the occupancy of FL370 of the ZDV24 sector between 18:00 Z and 18:30 Z will be 7-or-higher – but only with 10% certainty that it will be 8-or-higher. The same calculations can be done for the entire sector. Sample results are shown in Figure 22.

The results presented in Figure 21 and Figure 22 can be converted into the language of flight level/sector capacities – which may reveal if a TFM initiative, such as a Flow Constrained Area (FCA) or miles-in-trail (MIT), may be needed to reduce the likelihood of congestion in a given flight level/sector due to turbulence.

There may be various ways to define the capacity of a NAS resource. For illustrative purposes, here we use the 99th percentile of historic flight level/sector occupancies during the time interval of interest (that is 17Z -21Z) to define the resource capacities. For every day of the 4th quarter of 2009 and for every minute between 17Z and 21Z on each of those days we calculated the occupancies of each flight level of the ZDV23 and ZDV24 sectors, as well as for each sector overall. The occupancy distribution for the busiest levels of these sectors is shown in Figure 23, and for the entire sectors in Figure 24.

Thus the capacity of the FL340 of ZDV23 can be defined as 5 aircraft, FL370 as 7 aircraft, and FL390 ft as 5 aircraft (Figure 23). Likewise, we define the capacity of ZDV23 sector overall as 13 aircraft, and ZDV24 as 18 aircraft (Figure 24). With these numbers in mind, we can re-visit Figure 21 and Figure 22 and re-plot them relative to flight level/sector capacities. The results are shown in Figure 25 and Figure 26.
As one can see from Figure 25, there is a 40% chance that the use of all three flight levels shown will be pushed at least to their capacities, and there is a 10% chance that two of those three flight levels will be operating beyond their capacities. The overall situation with the sectors is better, as there is only a 3% chance that the ZDV24 sector will be pushed to its capacity (Figure 26).

![Figure 25. ZDV23/24 forecast flight level use increase/reduction for 10% and 40% probability thresholds.](image)

![Figure 26. ZDV23/24 forecast sector use increase/reduction for 3% and 30% probability thresholds.](image)

**IV. Conclusion**

We have presented a route-based turbulence impact model and used it to demonstrate how the presence of severe turbulence in a busy area of the National Airspace System may lead to reduction of capacity of a number of flight levels – which, in turn, may force other flight levels (of that sector or a neighboring sector) or an entire sector to operate at or beyond its capacity. We suggest through examples how such a model can be used to estimate the capacity of a sector of airspace given a turbulence forecast. This weather translation model is useful for use in traffic flow management planning and decision support.

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**References**


