

The Value of Reduced Uncertainty in Air Traffic Flow Management

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Given the numerous sources of uncertainty inherent in the National Airspace System, plans to alleviate demand-capacity imbalances are sometimes untrustworthy. In addition, differing solutions to demand-capacity imbalances are difficult to compare in terms of their potential quality in the face of weather and schedule uncertainties. In this work, a method for evaluating the robustness of a traffic scheduling solution to various uncertainties is presented. By converting solutions to predicted demands and capacities of sectors and airports together with measures of uncertainty on those predictions, any given plan can be evaluated based on the number of expected capacity violations along with distributions on their severity. With such measures, the most robust of a set of potential plans might be chosen by a traffic manager. As a side-effect of this approach, the value of reduced uncertainties can be measured in terms of reduced expected violations. The value of reduced uncertainty is demonstrated using a deterministic, minimum-delay approach to managing demand-capacity imbalances. When the deterministic solution is measured in terms of expected violations given models of demand and capacity uncertainty, results indicate that if the calculated uncertainty measures are reduced by 50%, then the number of expected violations will decrease by just over 40%.

I. Introduction

UNCERTAINTY makes traffic flow management difficult. If the trajectories for all flights and the capacity of all resources were known with certainty for some planning horizon, there exist computationally feasible approaches to managing the traffic that minimizes overall delay cost. The difficulty with deterministic solutions to the problem of managing air traffic stems from the inherent uncertainties in the system. On the demand side of the problem, for example, it is known that flights often do not depart at the precise minute they are planned to depart and that flights do not always dwell in a given sector for exactly the amount of time they were expected to do so. From the perspective of capacity, weather is the driving force in determining the number of flights an airport or sector can handle at any given time. Thus, capacity is a function of an inherently uncertain variable. The intersection of uncertain demand and uncertain capacity raises reasonable concerns as to the validity of traffic flow scheduling solutions computed with deterministic data about future demand and capacity. In addition, it is unclear how one would compare (in real- or fast-time) a solution produced via a stochastic method with one (or several) found deterministically.

The problem of managing traffic under uncertainty has been coined “Probabilistic Traffic Flow Management” in the literature. There are several aspects to solving flow management problems, including capacity estimation, demand estimation, and actual methods for modeling and solving the problem of demand-capacity imbalances. This work is concerned with demand and capacity uncertainty and its effects on the National Airspace System, which is explicitly considered by Hunter and Ramamoorthy,¹ Masalonis, et al.,² and Zobell.³ Masalonis’s and Zobell’s works focus on the presentation of uncertain data to traffic flow managers and how they might use such data, which is not a focus on the research presented here. This work differs from Hunter in that we examine the value of increased certainty in terms of the reduction in expected violations and they examine the tradeoff between delay and congestion in the face of uncertainty. This work also

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presents a method for using predicted capacities and occupancies of the resources in the National Airspace System together with distributions describing their respective uncertainties to determine the expected number of capacity violations. For example, given some distribution describing the planned demand of a sector 35 minutes in the future together with a distribution describing the expected capacity at that time, we determine the probability that sector will be over capacity at that time. Doing this for all sectors within the planning horizon will provide a quantification of expected violations throughout the National Airspace System.

The remainder of this paper is organized as follows. First, in Section II an overview of the method presented in this paper is provided. In Section III the models used for capacity and demand estimation (together with uncertainties) are provided. Next, in Section IV, the data used in the experiments described in Section V are given. Finally, in Section VI some analysis and concluding remarks are provided. Included there is a discussion of how this method might be used in an active air traffic management system.

II. Method Overview

This paper proposes and examines a method for measuring the expected number of violations (i.e. demand exceeding capacity) due to pre-quantified uncertainties. The proposed tool, the Robustometer, allows for evaluation of any schedule in the form of time-varying sector and airport capacities together with demand on those resources (in the form of departures and arrivals during a time period for airports and flight counts for sectors). The schedule need not be developed using any particular methodology, it need only be translated into planned demand upon the various resources during the times of interest. The expected demand on any resource at any time may be described by some distribution rather than a single, deterministic value. Likewise, each capacity may be described with some distribution rather than a single value. The uncertainties, like the schedule, may be generated using any methodology.

Figure 1 details the Robustometer. The algorithm is relatively simple. For each sector-time pair (for example, sector ZOB34 at time 12:05), there would be an associated expected demand, expected capacity, and description of the uncertainty (in the case of a normal distribution, via a standard deviation) of each. Those uncertainties might be based on historical data, predicted data, or more likely a combination of the two.

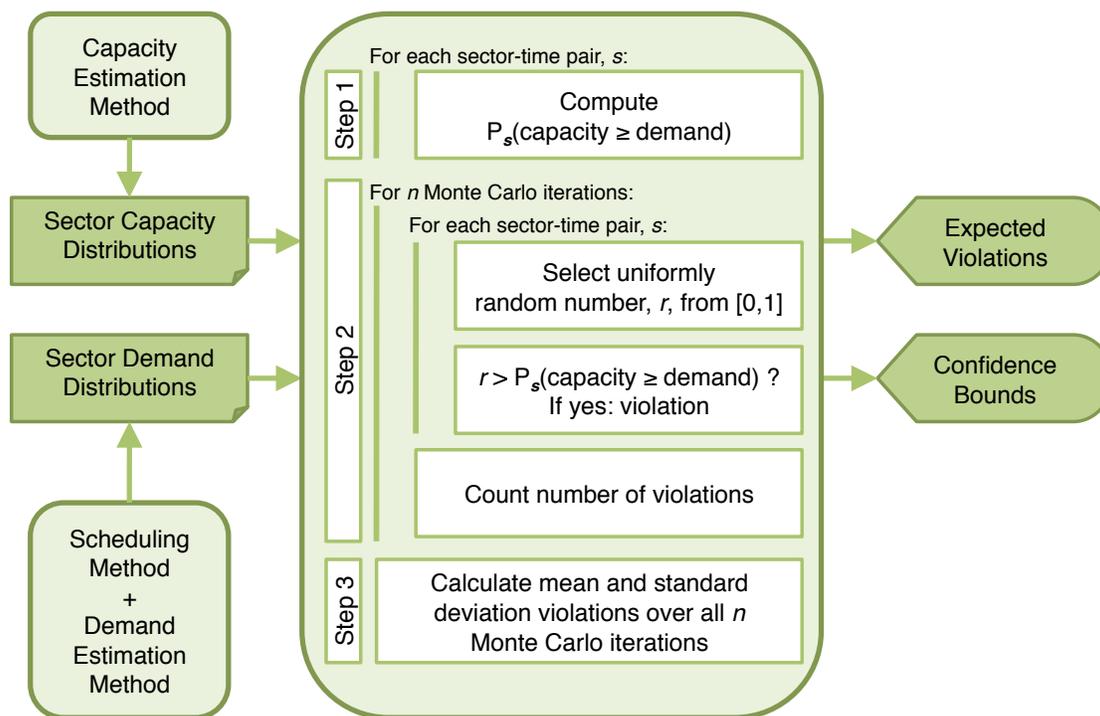


Figure 1. Robustometer with complete algorithm.

From the distributions on demand and capacity, Equation 1 is used to determine the probability that the capacity will be respected for some sector-time pair s . Equation 1 simply sums the probabilities for each aircraft count from $i = 0$ to $i = b$, that demand will be less than i and capacity is i . A few notes on this equation are warranted. First, Equation 1 is only reasonable given the assumption that demand and capacity are independent. Second, the value of b can be as large as one would like, but should be at least large enough to capture the largest “reasonable” values for capacity. To illustrate with an extreme example, if the nominal capacity for a sector is 15, and the predicted capacity at some time in the future is 13, then setting b to 1000 is mathematically acceptable (the $P_s(\text{capacity} == 1000)$ would essentially be zero and would not add significantly to the summation), however, it would make sense to choose a much smaller value (say, 17). Finally, it should be noted that the uncertainty distributions need not be normal nor even of the same type. They need only be described as Probability Density Functions for the algorithm to work correctly.

$$P_s(\text{capacity} \geq \text{demand}) = \sum_{i=0}^b P_s(\text{demand} \leq i) \times P_s(\text{capacity} == i) \quad (1)$$

If the provided distributions are continuous (even though, in reality, we are dealing with discrete values), the value of $P_s(\text{capacity} == i)$ is approximated as follows:

$$P_s(\text{capacity} == i) \approx P_s(\text{capacity} < i - 0.5) - P_s(\text{capacity} \leq i + 0.5) \quad (2)$$

Once Equation 1 is calculated for every sector-time and airport-time pair, a Monte Carlo simulation is used to determine how many of these capacities are expected to be broken (and by how much) over the course of the planning horizon. Together with that expected value, the standard deviation (σ) and 95% confidence bound ($2 \times \sigma$) on the maximum expected number of capacity violations can be provided.

A natural question with any Monte Carlo experiment is how many iterations to run. While there are methods for determining a precise number of iterations needed to obtain a certain level of confidence in the solution given the number and quality of the uncertain variables, the experiments presented here relied on observation to set the number of Monte Carlo iterations. This was done due to the large number of uncertain variables being examined simultaneously. The number of iterations chosen was 5000. To illustrate the quality of solution obtained using this number of iterations, Figure 2 shows how the bounds on the solutions converge as the number of Monte Carlo iterations increases. Specifically, the illustration shows the spread of expected violations for one scenario (the scenarios are explained in Section V), given a varying number of Monte Carlo iterations (from 500 to 30000 in steps of 500). For each number of Monte Carlo iterations, the experiment was run eleven times. The bars in Figure 2 show the spread of these eleven runs per number of Monte Carlo iterations. Notice how the spread condenses to reasonable ranges (a difference of less than one between the highest expected violations and the lowest) as more iterations are performed and how the quality does not improve dramatically after a certain threshold. It is this observation that led to the conclusion that 5000 iterations is acceptable for all experiments described later. The choice of 5000 may need re-evaluation for future experimentation depending on the number of sectors being considered, the level of uncertainty in the system, or other factors.

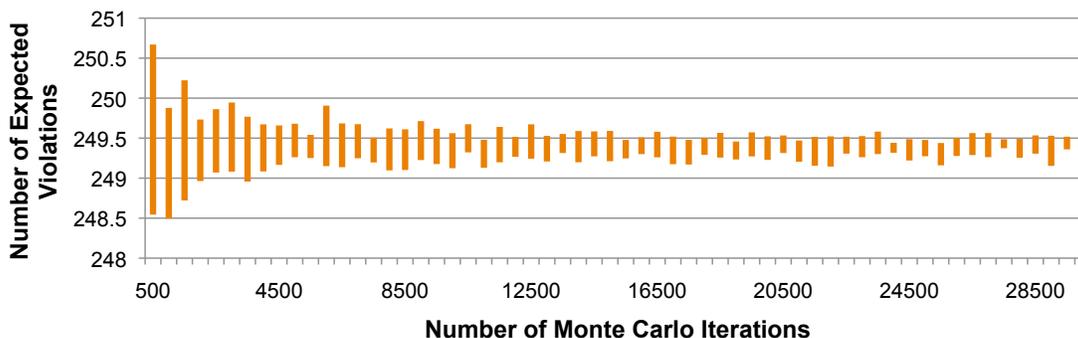


Figure 2. The range of expected violations over the entire NAS for this scenario decreases as the Monte Carlo iterations increase.

III. Models

Three models will be described in this section. The first is for capacity estimation, the second is the demand uncertainty model, and third is for modeling air traffic flow. For each of the models, a high-level overview is provided along with relevant citations for further details as each of the discussed models has been previously published.

III.A. Demand Uncertainty

Currently, the Federal Aviation Administration uses the Traffic Flow Management System to manage air traffic flows. This system provides estimates of demand in the near future based on trajectories of currently airborne flights and the planned trajectories of pre-departure flights. The inclusion of uncertainty in those predictions is minimal. Extending earlier work by Meyn,⁴ Gilbo and Smith^{5,6} and Chatterji, et al.⁷ each produce probabilistic measures of demand by examining individual trajectory uncertainties and then aggregating the results of that analysis. Wanke, et al.⁸ take a similar approach while also determining the factors that effect the uncertainty (look-ahead time, traffic mix, day of the week, etc.). Chen and Sridhar⁹ take a control-theoretic approach to estimating demand that produces quantified uncertainties. For more information on the sources and types of demand uncertainty, Wanke, et al.¹⁰ and Krozel, et al.¹¹ provide good overviews.

For this study, the method presented by Gilbo and Smith⁶ is used to estimate demand uncertainty. Of the published methods examined, their method fit the application most appropriately. They consider the trajectory predictions of all flights together with a normal distribution on sector entry time uncertainty to create a closed-form method for estimating expected sector demand and a standard deviation from that expected demand.

Through examination of historical air traffic data, it is revealed that there is a strong correlation between the predicted demand in adjacent time periods and the statistics describing the uncertainty in demand. This method, therefore, weights the chance a flight scheduled to enter a sector at some time, t , actually enters the sector at time $t + 1$, $t - 1$, $t + 2$, $t - 2$, etc. The uncertainty in sector entry time is quantified by Gilbo and Smith as a parameter for determining demand uncertainty. They note that a value of 4 for the standard deviation, σ , is reasonable for en route flights, while $\sigma = 15$ is reasonable for flights that have not yet departed. Since the authors were using 1-minute time steps in their work and this work uses 5-minute time steps, values of 0.8 ($4/5$) and 3 ($15/5$) were used for the standard deviation of airborne and pre-departure flights, respectively. Note that these values are simply estimates. If, in the future, better values for σ are discovered, the approach presented here would not change. Rather, the results would simply become more accurate.

Let the predicted demand for a given sector at time i be denoted D_i and declare that to be the mean value for the uncertain, predicted demand for that sector at that time. D_i is the sum of the airborne flights d_i^a and pre-departure flights d_i^g predicted to enter the sector at time i . Let τ be the average time flights dwell within that particular sector. A flight scheduled to enter a sector at time i may actually enter at a different time, therefore denote by β the maximum time from i that should be considered for flights that might enter the sector at time i . For example, if $i = 7$ and $\beta = 3$, then flights scheduled to enter the sector at times 4 through 10 might actually enter at time 7 are considered in the calculation of the standard deviation, $\sigma(D_i)$. Since airborne flights and pre-departure flights have different uncertainty characteristics, define separate β values for each of them (β_a and β_g , respectively). Finally, define $P_{i,k}^a$ to be the probability that an airborne flight scheduled to enter the sector at time k actually enters at time i . Similarly define $P_{i,k}^g$ for pre-departure flights. With that notation, the following formula is defined:

$$\sigma(D_i) = \sqrt{\sum_{k=i-\beta_a-\tau+1}^{i+\beta_a} P_{i,k}^a (1 - P_{i,k}^a) d_k^a + \sum_{k=i-\beta_g-\tau+1}^{i+\beta_g} P_{i,k}^g (1 - P_{i,k}^g) d_k^g} \quad (3)$$

The formulation presented in Equation 3 is a simplification of the one presented by Gilbo and Smith.

Specifically, τ is not an average in their work, it is a set of values such that each flight’s actual dwell time within the sector is considered and Equation 3 includes another summation under the square root to account for the various τ values. In addition, Gilbo and Smith do not use the predicted count as the mean for this standard deviation, rather, they calculate it in a similar way to the standard deviation calculation.

To give the reader a sense for the set of standard deviations that were calculated, Figure 3 is provided. This is a histogram of the various standard deviation values used in the experiments described below. A quick glance reveals that the most frequent range within which any given standard deviation falls is 2.5 to 3.0. Note that only pairs of sectors and look-ahead times where the residual capacity (predicted capacity - predicted demand) was at least 7. This means that there are many low-demand sectors (whose demand standard deviations would be quite low) that are not included in this histogram.

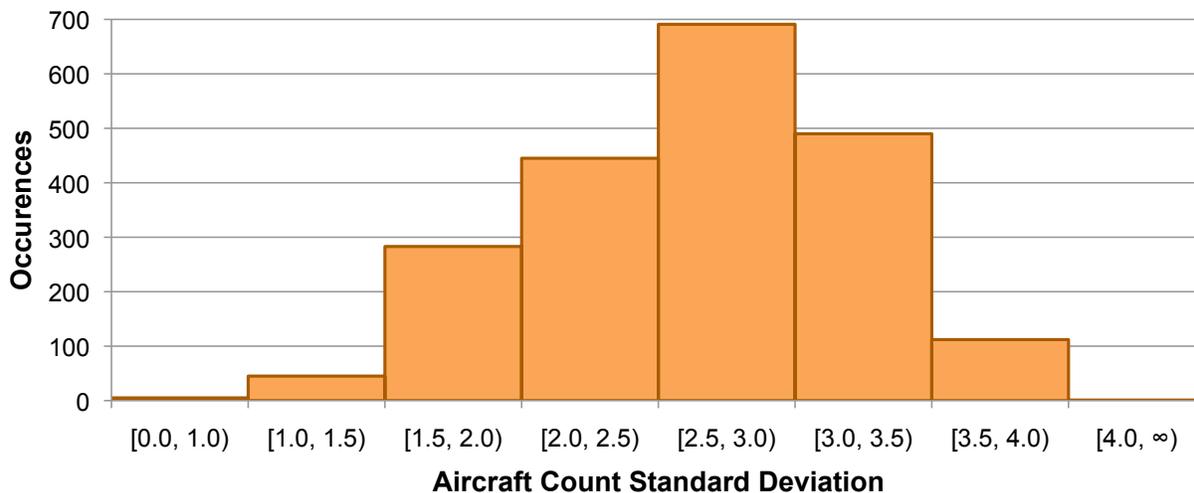


Figure 3. Histogram of demand standard deviation values used in our experiments.

III.B. Capacity Estimation

Several researchers have investigated the problem of capacity estimation. Krozel, Mitchell, et al.^{12–14} estimate capacities by finding the minimum cut across blocked flows and then determining the maximum flow that can be accommodated through those minimum cuts. Klein, Cook, and Wood use a scan line technique, which determines the amount of blockage in various directions through a sector and then translating that into a measure of directional capacity.¹⁵ Another technique for estimating capacity is derived from the workload of the controller of a sector and translating that into a capacity measure.^{16–18} Operationally, the capacity of a sector is called the Monitor Alert Parameter and is roughly $\frac{5}{3}$ times the average historical dwell time for flights in that sector in clear weather situations.¹⁹

The method for capacity estimation used for this study is the “Mincut/Maxflow” method presented by Krozel, Mitchell, et al.^{12–14} This method identifies the narrowest path(s) in each of the important flow directions of a sector and then calculates the maximum flow that could be accommodated through those paths. The overall capacity of the sectors is calibrated by examining historical data to obtain realistic estimates of capacity. For more detailed information on the method, see the papers by the original authors.^{12–14}

To determine the uncertainty in the predicted capacities provided by the mincut/maxflow algorithm, the predicted capacities are compared to the nowcast capacities calculated with the same algorithm. For example, if the mincut/maxflow algorithm calculates the current capacity for a sector to be ten, but one hour ago the prediction for this time was 8, there would be an error of two in that prediction. By examining all of the predictions for 30, 60, 90, and 120 minutes and comparing them to the appropriate nowcast values, a distribution of the errors is determined.

Using the assumption that the errors might vary based on the severity of the capacity reduction, error distributions were created for various levels of predicted capacity reduction (the data presented in Table 1

seem to validate this assumption). Specifically, we obtain different distributions for every 10% step in capacity reduction. These data are calculated from examination of five weather-impacted days in the National Airspace System: August 19th, 2007; September 19th, 2007; October 19th, 2007; December 23rd, 2007; and April 2nd, 2009. The resulting statistics are presented in Table 1 as a look-up table indexed by predicted percentage capacity decrease and look-ahead time. To use the table, the capacity for a given sector is calculated for some time in the future (say, 65 minutes). If the prediction is that there will be a 66% decrease in capacity, the historical standard deviation in capacity is 2.412 (using the 70% column and the 60 minute row). Note the further simplifying assumption that the nowcast calculation provided by the algorithm is the true capacity of the sector (i.e. given deterministic data, the algorithm is able to perfectly calculate the capacity of the sector). If, in the future, this assumption is proven incorrect, any other capacity calculation method could be used within the framework presented in the paper.

Table 1. Standard deviation look-up table for capacity. Generated using mincut/maxflow algorithm over five days of data.

Look-Ahead Time (min.)	Predicted Percentage of Available Capacity									
	10	20	30	40	50	60	70	80	90	100
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
30	6.982	5.147	4.468	3.480	3.012	2.836	2.051	1.510	0.827	0.408
60	6.768	5.493	4.495	4.055	3.129	3.043	2.412	1.623	0.958	0.456
90	6.655	6.031	4.519	4.244	3.630	3.256	2.644	1.733	0.925	0.463
120	7.318	6.035	3.860	5.146	3.467	3.594	2.706	1.732	1.017	0.473

Another interesting and slightly unexpected finding from this generated data was a conservative bias to the predictions. Overall, the mincut/maxflow algorithm underestimates the capacity. It is important to note that *all* of the uncertainty in the algorithm comes directly from the underlying uncertainties in the weather data. Therefore, it would seem that in the weather cases studied here, the actual weather was milder than the predicted weather. An improved weather prediction will immediately lead to better capacity predictions. The bias results are reported in Table 2. They are presented in the same look-up table format as the standard deviations. For all of the experiments described in Section V, these biases are applied to the predictions in order to better estimate demand-capacity imbalances. For illustration, using the example above (66% predicted decrease, 65 minutes ahead), the 70% column and the 60 minute row show that capacity is under predicted by 1.3.

Table 2. Bias look-up table for capacity. Generated using mincut/maxflow algorithm over five days of data.

Look-Ahead Time (min.)	Predicted Percentage of Available Capacity									
	10	20	30	40	50	60	70	80	90	100
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
30	-4.6	-2.4	-2.1	-1.3	-1.3	-1.5	-0.9	-0.7	-0.4	-0.2
60	-4.1	-2.4	-2.5	-1.7	-1.5	-1.5	-1.3	-0.8	-0.5	-0.3
90	-4.2	-3.2	-2.4	-1.8	-2.1	-1.7	-1.7	-1.1	-0.5	-0.3
120	-5.4	-3.3	-1.6	-2.9	-2.0	-2.6	-1.9	-1.0	-0.6	-0.3

To give a sense of the uncertainty used in the experiments presented in Section V, Figure 4 is provided. Notice how different it looks from the demand standard deviations used (Figure 3). A simple, high-level interpretation of these data is that although there are potentially higher levels of uncertainty in capacity estimation, there are fewer sector-time pairs in the planning horizon where weather impacts the capacity estimation. The demand uncertainty might be high even with a few flights going through a sector, however if there is no (or very little) weather in a sector, the capacity uncertainty would be zero (or quite near zero). This leads to low uncertainty across the NAS for capacities, even though some sectors will have high capacity uncertainty.

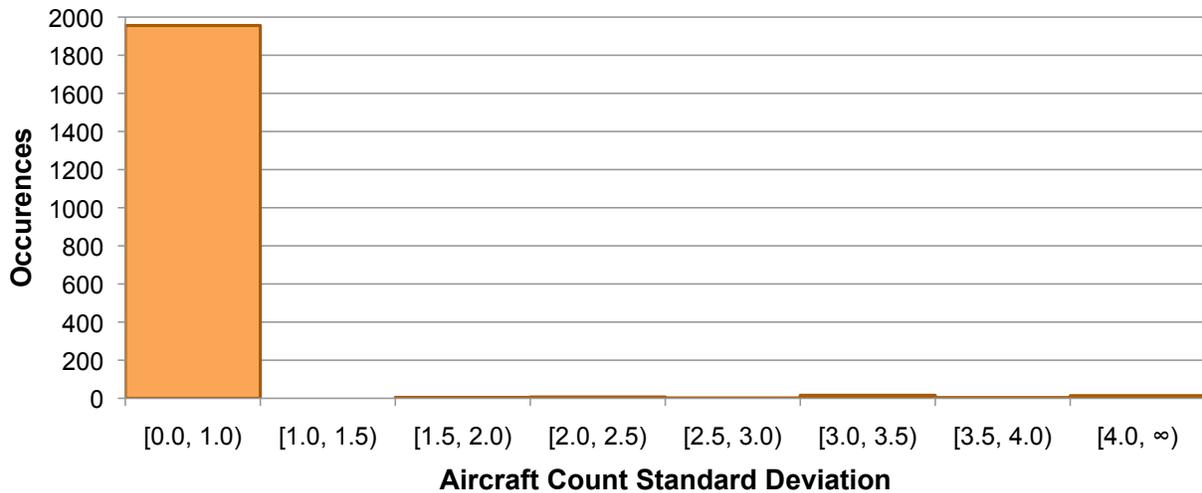


Figure 4. Histogram of capacity standard deviation values used in our experiments.

III.C. Alternate Methods of Uncertainty Data Generation

It is important to re-emphasize that the method for determining demand uncertainty is not vital to the development of the Robustometer. For example, an alternate method tested in the development of this work involved using an established departure uncertainty distribution²⁰ to perturb the departure time of all flights. This perturbation was repetitively simulated using the Computational Appliance for Rapid Prediction of Aircraft Trajectories (CARPAT)²¹ to develop sector demand statistics. This method includes additional, historically-based uncertainties such as aircraft speed uncertainty. These statistics revealed much lower standard deviations. The point being, whatever the method for generating the uncertainties, the Robustometer can easily take the results as input without evaluating the “correctness” of the generating method. When the research community decides the “best” way to develop demand (or capacity) uncertainty, the Robustometer would work the same way as currently described.

III.D. Optimal Traffic Flow Scheduling

The Bertsimas-Stock Patterson (BSP) model²² is used to perform scheduling that minimizes delay costs (weighted sum of air and ground delays). The constraints consist of sector capacities, arrival rates, and departure rates at each time step as well as physical constraints on each flight in the system ensuring that flights visit the required sectors in their flight paths in the correct order and dwell in each sector for the required minimum amount of time. The decision variables are binary and indexed by flight, time, and sector (airports are considered special cases of sectors). These variables indicate whether a flight has entered a sector by some time. It is a linear, deterministic model that has been used as the basis for several Traffic Flow Management research projects.^{23–25} To solve the problem quickly, a decomposition approach is employed. The approach provides a relaxed solution (i.e. the integer nature of the variables is ignored). To obtain an integer solution from this relaxation, the non-integer variables are rounded. Clearly, this heuristic can (and often does) break some of the constraints in the system, but experimental evidence suggests that the breakages are likely operationally acceptable.²⁵ For more details on the model, the interested reader is directed to the original paper by Bertsimas and Stock Patterson²² and for more information on other models and algorithms for Traffic Flow Management, the survey by Sridhar, Grabbe, and Mukherjee²⁶ is informative.

IV. Data

Historical traffic and weather from various days are used as inputs for the experiments. The traffic data is from Wednesday, the 24th of August, 2005 beginning at 9 A.M. Eastern Daylight Time. This time period is a busy time as many East Coast departures are in the air and West Coast departures are slowly ramping up. This date was chosen due to its representative traffic pattern (i.e. weekday without a nearby holiday), and the distinct lack of weather activity. The lack of weather activity is important in order to discount major Traffic Management Initiatives on that date, which would significantly alter the flow of traffic. The two-hour window starting at 9 A.M. on this date include 11,168 flights.

CWAM (Convective Weather Avoidance Model) data²⁷ is used for the mincut capacity estimation. CWAM is a derivative of CIWS (Corridor Integrated Weather System).²⁸ CIWS measures the convective weather activity in a volume of airspace and CWAM translates that measure into a probability of deviation by pilots entering that volume. The CIWS data for these experiments is from the 19th of June, 2007 starting at 0120 UTC (18th of June, 2007 at 9:20 P.M. EDT). The weather system at that time would be significant enough to disrupt several East-West flows (see Figure 5) if it occurred at a high-traffic time. Since the CIWS forecasts are provided with a two-hour look-ahead time, all scenarios presented here are two hours in length. The forecasts are provided in five-minute time steps, thus the traffic and weather are both captured at this resolution.

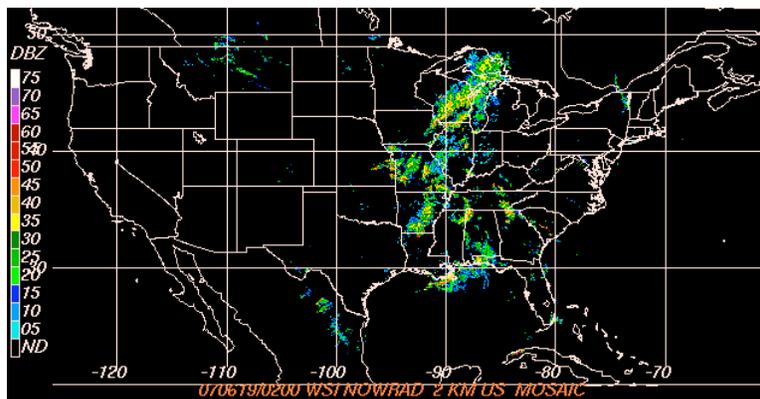


Figure 5. Radar image of weather scenario used for experiments (18 June, 2007 at 10 P.M. EDT).

V. Experiments

Each experiment consisted of a series of 5000 Monte Carlo iterations. There were just over 2000 sector-time pairs included in each experiment (varying slightly depending on capacity estimation method). As mentioned in Section IV time size of the time step was 5-minutes and the planning horizon was two hours. The experiments varied over three parameters: capacity estimation method, flight control state, and uncertainty variation. To ease the discussion, Table 3 shows the experimental matrix for the first two parameters.

Table 3. Base experimental matrix.

Nominal Capacity, Uncontrolled Traffic	Nominal Capacity, Controlled Traffic
Mincut Capacity, Uncontrolled Traffic	Mincut Capacity, Controlled Traffic

The term *controlled traffic* implies that the optimization approach described in Section III.D was used to determine ground and air holding times to satisfy the specified capacities (or nearly satisfy due to rounding), while *uncontrolled traffic* implies that all traffic was allowed to fly its filed flight plan regardless of capacity violations. The term *nominal capacity* refers to the FAA-declared Monitor Alert Parameters for en route sectors while *mincut capacity* refers to the weather-impacted capacity calculations as described in Section III.B.

The base experimental matrix (Table 3) was run in conjunction with four different methods of varying

uncertainty, resulting in a total of sixteen different experimental runs. Demand uncertainty, capacity uncertainty, both demand and capacity uncertainty, or neither (deterministic predictions) was varied giving the four modes of uncertainty variation. The first runs were to determine the value of controlling traffic in an “optimal” or at least “near-optimal” way versus not controlling the demand at all. Figure 6 presents results for demand uncertainty (calculated as described in Section III.A) and indicate that the gains of a schedule generated to satisfy nominal, deterministic capacities are not very significant. As a contrast, if demand and capacity are both completely deterministic (the left set of bars), the value of providing a controlled schedule over an uncontrolled one (in terms of capacity violations) is evident.

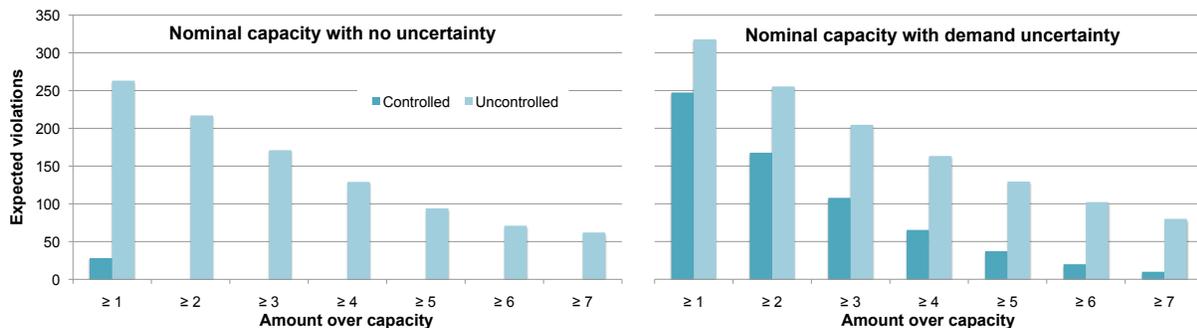


Figure 6. Results for the nominal capacity scenarios with deterministic (left) and uncertain (right) demand.

The evidence provided by these preliminary results led to uncertainty variation experiments. The subsequent runs allowed the value of the standard deviation of the demand (again, as calculated in Section III.A) to vary between 0% and 100% of its calculated value. Note that Figure 6 illustrates the two extremes (0% on the left and 100% on the right). The percentage was varied in 5% steps and the expected number of violations of various sizes were captured. The results for the nominal case are presented first in Figure 7. The results for the mincut weather scenarios follow in Figure 8.

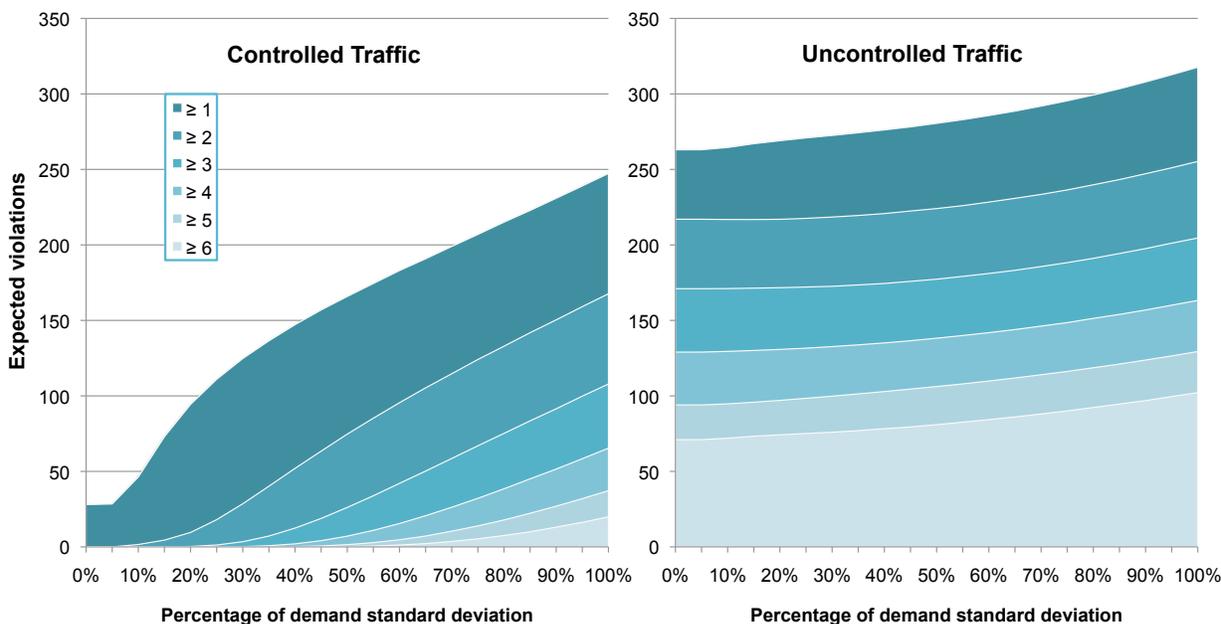


Figure 7. Nominal, deterministic capacity scenarios: demand standard deviations vary 0%-100% of predicted values.

The remainder of the presented results relate to just the mincut scenarios. A similar chart to the demand variation provided in Figure 8 is provided for capacity uncertainty (and deterministic demand) in Figure 9. Finally, the plots for varying *both* demand and capacity standard deviations (by the same factor in each run) are provided in Figure 10.

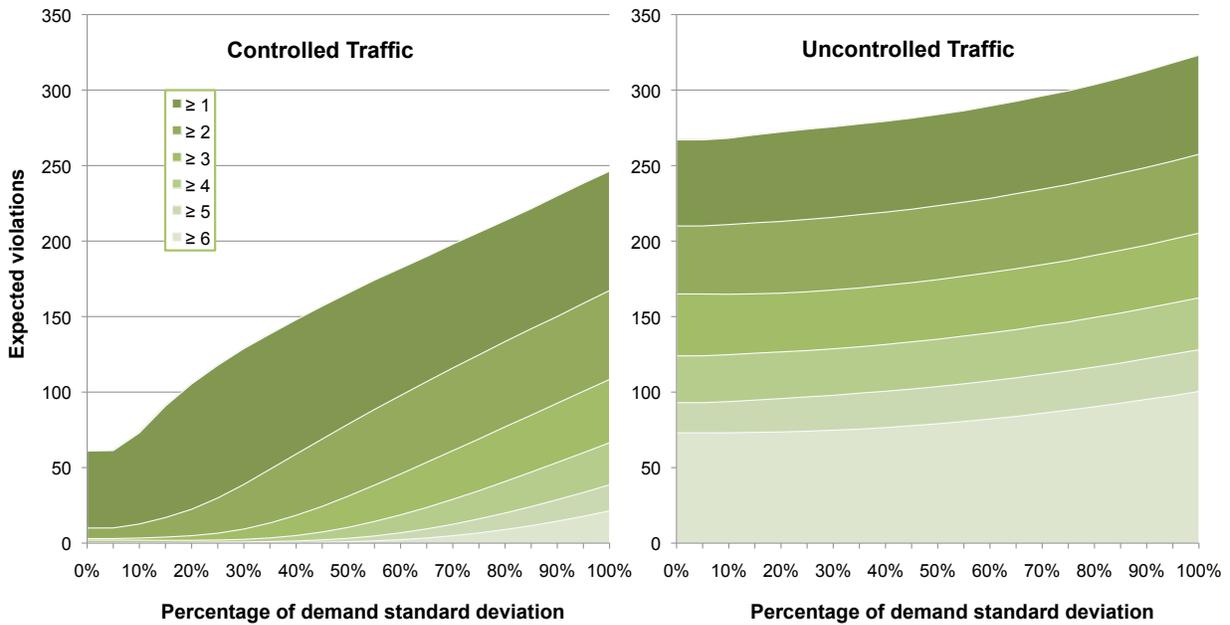


Figure 8. Mincut, deterministic capacity scenarios: demand standard deviations vary 0%-100% of predicted values.

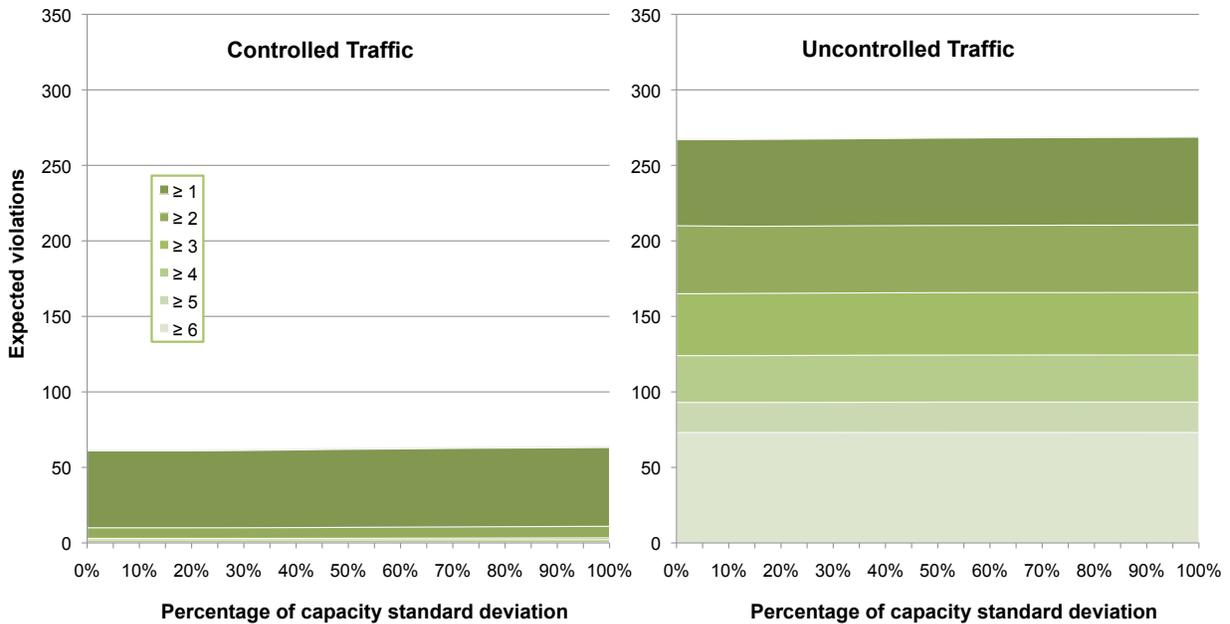


Figure 9. Mincut, deterministic demand scenarios: capacity standard deviations vary 0%-100% of predicted values.

The reason for the “flat” appearance of Figure 9 is due to the description of the underlying capacity uncertainty described in Section III.B. Compared to the method for demand estimation, the standard deviations produced by the weather underlying mincut capacity calculations are small (see Figures 3 and 4 for a clear illustrative comparison). Coupling the smaller standard deviations with the inherent conservative bias (reference Table 2) of the mincut method (or the underlying weather predictions, as the case may be), the resulting expected violations are much lower than for the demand uncertainty cases (Figure 8). There is little surprise, then, that Figures 8 and 10 are so similar since the uncertainty in these experiments is driven primarily by the demand uncertainty.

For the controlled, mincut scenarios it is clear that demand uncertainty virtually guarantees increased num-

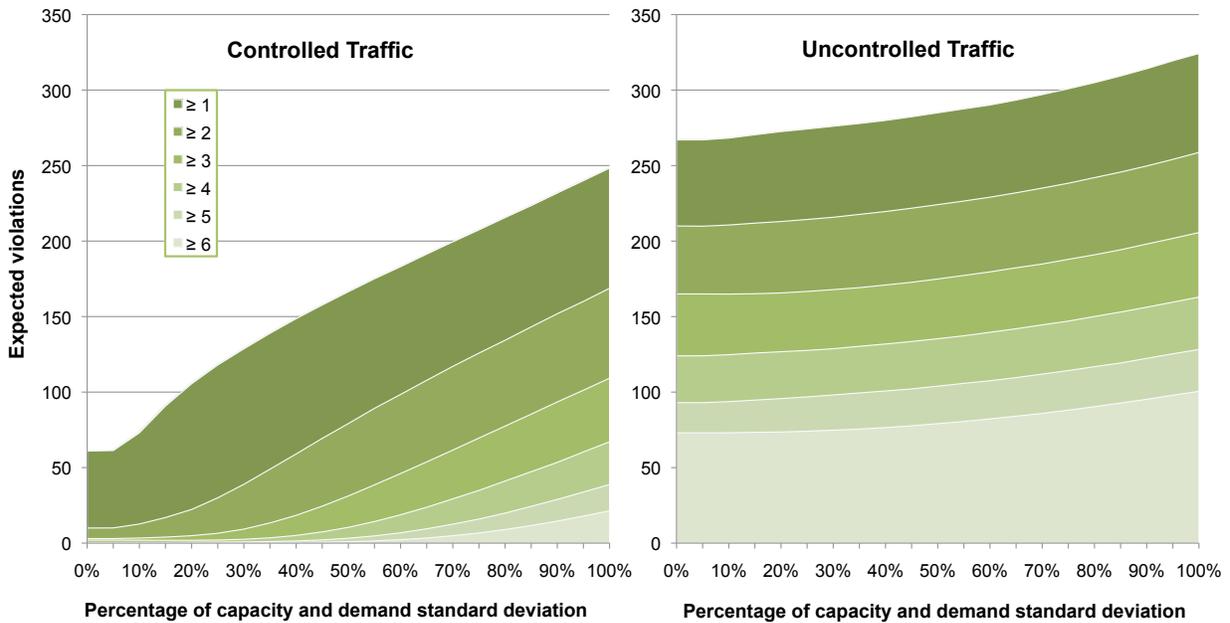


Figure 10. Mincut scenarios: demand and capacity standard deviations vary 0%-100% of predicted values.

bers of capacity violations given the deterministic control method (Bertsimas-Stock Patterson as described in Section III.D) used here. However, an unresolved question that can be answered by the Robustometer is how the uncertainty in that prediction of expected violations increases as demand uncertainty increases. The answer to that question (at least for the scenarios studied) lies within Figure 11. Even though the number of expected violations is increasing as the input uncertainty increases, the uncertainty in the expected violations shows a decrease relative to the number of expected violations. Put another way, while the standard deviation in the number of expected violations increases, it does so at a slower rate than the number of expected violations.

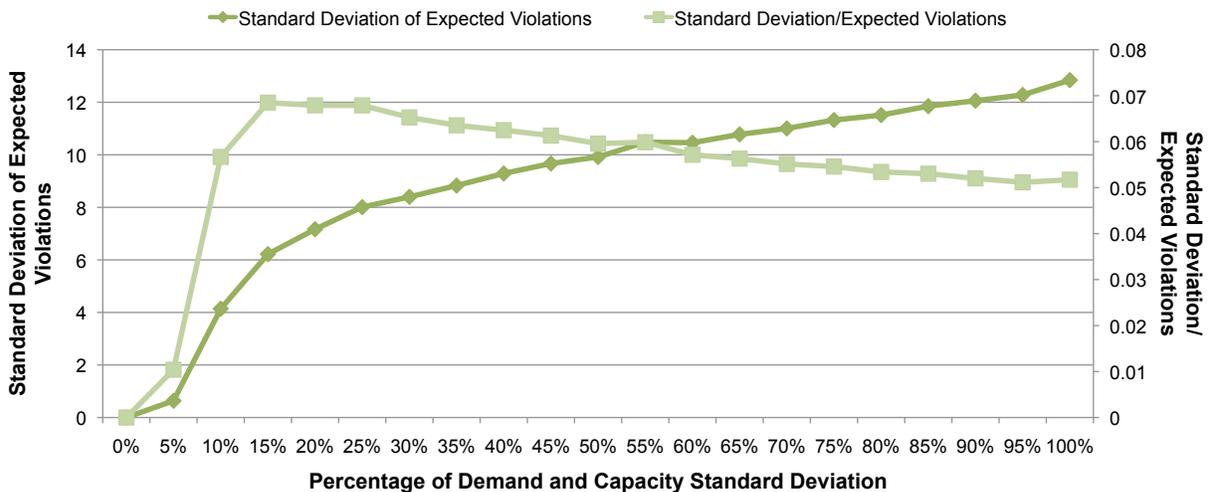


Figure 11. Relating standard deviation in the expected violations to the number of violations and input uncertainty.

It is interesting to investigate how much improvement in expected violations is to be gained by controlling traffic in uncertain conditions. Figure 12 shows this relationship for both the mincut scenarios. An interpretation of the graph is as follows. Assuming the uncertainties used in the experiments are valid and represent the state-of-the-art, the improvement in overall performance of the NAS in terms of capacity violations would be only 18% if traffic was controlled with the optimization approach described earlier over not controlling

the traffic at all. If one wanted to improve this performance to, say, a 50% improvement of controlled versus uncontrolled traffic, one would need to improve the standard deviation of the demand and capacity forecasts to roughly 20% of their current values.

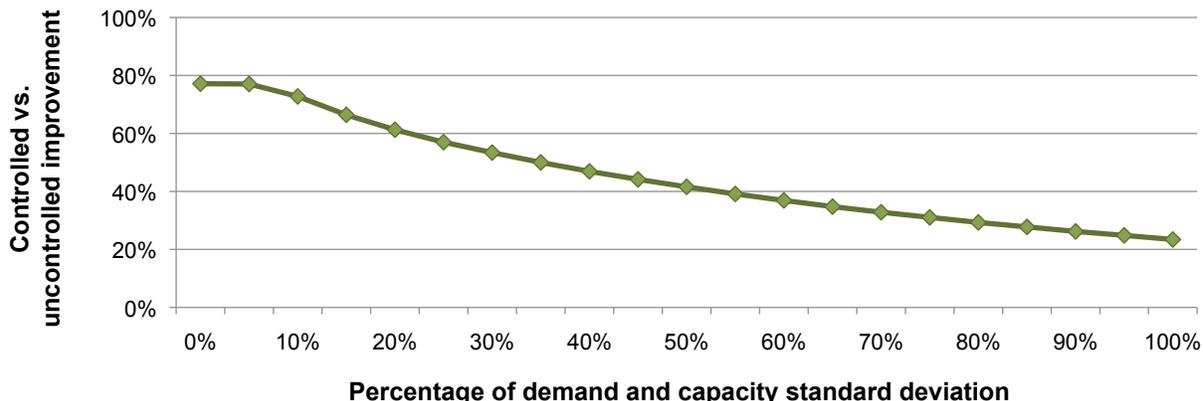


Figure 12. Comparing expected improvement in controlled traffic versus uncontrolled traffic as uncertainty increases.

Further discussion on Figure 12 is warranted. It is important to remember that these are the results given the optimal approach to managing demand-capacity imbalances described in Section III.D. This line would likely look much different if a different approach were used. For example, if a series of Miles-in-Trail restrictions together with Airspace Flow Programs and Reroutes were simulated and the resulting demand was used as input into The Robustometer, one might expect a much greater improvement in sector violations for controlled versus uncontrolled scenarios. This is due to the inherent (and often undiscussed) aggressiveness of optimization approaches versus relatively more conservative, traditional approaches to managing capacity in the National Airspace System. This tension between the approaches could be viewed as a trade-off between congestion and delay (more aggressive techniques like the optimization approach tested here reduce delay at the risk of increased congestion). The interested reader is again directed to Hunter and Ramamoorthy¹ for a more detailed discussion on this trade-off.

Furthermore, there are several other TFM considerations not reported directly by the Robustometer. For instance, airline preferences are not explicitly modeled. However, if through collaboration between the airlines and the FAA,²⁹ a set of potential schedules are developed, the Robustometer could provide traffic managers with a method to choose the best congestion-reducing schedule from among that set. In a similar manner, any set of schedules generated in any manner whatsoever, could be compared in terms of expected violations, thus providing a type of secondary objective to “break ties” among a set of otherwise similar-looking schedules.

VI. Conclusion

This paper presents a method for measuring the robustness of a given schedule to demand and capacity uncertainties with a tool deemed The Robustometer. Assuming the uncertainties are quantified correctly, the described method will provide the expected number of capacity violations given a traffic schedule consisting of departure and arrival times along with dwell times within the sectors of each flight’s path. The method for producing the schedule is not important to the tool. In fact, the original, uncontrolled schedule could be used as input to The Robustometer to determine the number of violation to expect in the absence of any traffic flow controls.

Results indicate that a deterministic, nearly optimal schedule in the face of today’s level of uncertainty will not perform much better than uncontrolled traffic in terms of expected violations. However, the results show marked improvement in performance as the standard deviations of the uncertainties decrease.

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