

Estimating Flow Rates in Convective Weather: A Simulation-Based Approach

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Abstract— A number of approaches have been proposed to estimate and manage airspace and airport capacity in the presence of weather. These tools have the potential to provide the user community with improved situational awareness. Yet, there are few tools that translate strategic level forecasts into airspace capacity and those that do have considerable uncertainty associated with their estimates. This modeling inaccuracy can compromise the effectiveness of prescriptive models in identifying solutions that perform well. In this paper, we assess the use of automated decision support in a fast-time Air Traffic Management simulation as a means of supplementing strategic weather translational models. The concept uses information from weather translational models and compares the performance of flow rates produced through a stochastic integer programming model with random exploration against those generated by an epsilon greedy algorithm. The concept is validated against a historical case day in which the New York region was affected by convective weather. The results suggest that while both methods provide significant improvement over a set of randomly generated rates, the solutions identified with the epsilon greedy algorithm generally outperform those generated with a combination of integer programming and random exploration.

Keywords- Reinforcement Learning, Integer programming, epsilon greedy, Weather, Simulation, Airspace Capacity

I. INTRODUCTION

Managing airspace and airport resources in the presence of weather is a challenging endeavor for traffic managers. By limiting the available capacity of strategic airspace resources, the weather forces airlines and Air Navigation Service Providers (ANSPs) to alter the planned schedule, costing passengers and carriers billions annually. As weather forecasts are often erroneous, these disruptive events are particularly challenging for stakeholders due to the uncertainty associated with the forecasted intensity, location and direction of propagation of the events. To manage these events, traffic managers often adjust the strategic flight demand by imposing Traffic Management Initiatives (TMIs) such as Ground Delay Programs (GDPs), Airspace Flow Programs (AFPs) and the new Collaborative Trajectory Options Programs (CTOPs) with the goal of limiting, in advance, the flow of traffic into the affected resources to a level commensurate with the available capacity.

Over the past decade, a new set of automated decision support tools has enabled traffic managers to implement increasingly complex TMIs. In addition to applying strategic flow management through TMIs, traffic managers can also employ tactical tools, such as time-based metering, to adjust flights over a shorter horizon, when weather forecasts are more certain. As several studies have shown, the cooperative use of speed control and strategic flow management can yield considerable benefits for stakeholders, including reduced fuel cost and improved predictability [1, 2, 3, 4, 5]. In recent years, the NASA Integrated Demand Management (IDM) program studied and demonstrated these concepts through a series of Human-in-the-Loop experiments [6, 7, 8, 9]. The effort seeks to pre-emptively curb the level of mismatch between the demand from flights and the capacity at constrained resources by pre-conditioning traffic demand at the strategic level through the use of the Traffic Flow Management System (TFMS) to facilitate a more manageable arrival stream near the terminal. In the IDM study, demand was conditioned by using a CTOP to control flight arrival times to two boundaries: an inner circle Flow Constrained Area (FCA) immediately surrounding the airport (making the program in some ways similar to a GDP) as well as an outer Flow Evaluation Area at 400 NM, where Time Based Flow Management (TBFM) assumes control of the flights. Demand was also controlled at the tactical level with TBFM via extended metering initiated 400 NM away from the airport. The complementary use of traffic flow management tools revealed many significant benefits, including a reduction in the amount of ground delay assigned by TBFM, a drop in the amount of congestion in en route and terminal airspace following TBFM assignment, and a more equitable distribution of delay across flights. The application of the concept also revealed significant improvements in operational performance for airlines even in the presence of modest CTOP adoption [10], and is shown to reduce the extent of the double-delay penalty imposed by TBFM on short-haul flights previously identified in [11].

The success of such studies suggests that the implementation of coordinated strategic and tactical operations can provide effective system-wide benefits. The ability of the system to realize these benefits, however, may be compromised if the available tools do not provide actionable recommendations on how TMIs should be designed to deal with disruptions. Neither TFMS nor TBFM provide the user with any explicit advice on how resources should be managed over

a strategic horizon in the presence of convective weather. In this paper, we propose a decision support capability designed to issue strategic recommendations to help Traffic Managers select arrival rates for weather induced TMIs.

The subject of resource capacity estimation and management has received considerable treatment in the literature and this line of research can generally be grouped into two areas: (1) descriptive studies that try to predict the capacity at resources and (2) prescriptive studies that recommend decisions for managing the demand in the face of capacity uncertainty. The prescriptive studies commonly use an integer program to assign a number of flights to an airport(s) and/or airspace resource(s) over a fixed time horizon based on the available capacity at the resource(s) [12, 13, 14, 15, 16, 17, 18, 19]. In these problems, the decision-maker assumes either that he/she knows the resource capacity or that he/she has access to a set of scenarios to represent the potential evolution of resource capacities given the weather. When the proposed methods were used, they were shown to yield optimal solutions based on the information provided, despite considerable computational complexity in some cases. The effectiveness of such methods in practice, however, has been compromised to some extent due to the inability of numerical and probabilistic weather models and the weather translational tools to supply the accurate estimates of the resource capacities that these methods require in order to define their problem constraints. In recent years, however, advances in statistical learning methods and the available computational resources have spurred a number of developments in descriptive modeling, particularly in the area of airport acceptance rate prediction [20, 21, 22, 23, 24, 25]. These efforts typically use supervised or unsupervised machine learning methods to issue predictions based on a weather forecast product coupled with historical data on the airport acceptance rate. The success of these efforts has allowed researchers to integrate descriptive models of airport capacity with stochastic integer programming models for GDP planning [24, 25].

Concurrent with the developments in airport capacity forecasting, similar advances have been made in the area of airspace capacity prediction. The Traffic Flow Impact (TFI) tool developed by Lincoln Laboratory maps convective weather forecasts of up to 8 hours into an estimate of the airspace flow rates and provides a set of uncertainty bounds associated with this estimate [26]. A similar analysis has examined the airspace capacity in the terminal area [27]. The available airspace capacity estimates from the tool, however, can sometimes have considerable uncertainty. The large uncertainty is a product of the high-dimensionality of the problem space, the lack of historical weather days to train the model and the fact that TFI does not provide the ability to evaluate counterfactuals.

Fast-time simulations offer an alternative means of evaluating scenarios in which weather impacts air traffic management operations. Tools such as FACET [28] and ACES [29] provide researchers with a means of studying the effect of various decisions under a set of common air traffic scenarios. This capability is particularly useful in assessing the effectiveness of specific interventions within the National

Airspace System (NAS) in the presence of capacity/demand imbalances. Recently, researchers from MIT Lincoln Laboratory developed another simulation tool known as NASPlay that integrates a fast-time agent-based simulation with strategic en route weather translational models from TFI [30]. The tool provides a training capability for traffic managers and controllers by allowing the user to define strategies through a user interface. Yet, while the model allows the user to evaluate the effect of various TMI strategies against historical weather scenarios, past versions of the product had no automated planning capability. Another approach uses genetic algorithms to design TMI strategies based on forecasts of the demand and capacity [31]. While that approach has demonstrated an end-to-end planning and simulation capability, it depends largely on aggregating a set of ensemble forecasts at the sector level that individually do not perform well over a strategic horizon. While such aggregation may improve the overall quality of the forecast, simulation-based efforts that leverage newer strategic airspace capacity forecasting models may also offer a promising alternative means of improving airspace capacity estimates.

In this paper, we propose two different approaches for deriving flow rates at airspace resources by drawing ideas from both the integer-programming and simulation-based lines of study. In one approach we start by incorporating the strategic airspace permeability estimates derived with the TFI model into a set of constraints on a stochastic integer program. The integer program attempts to control the set of planned flow rates to minimize a weighted objective of ground and airborne delay. The resulting planned flow rates are then used to define the mean value of a distribution that will generate a set of flow rate candidates through pure exploration of the function space vicinity. These selected candidates are then evaluated with a fast-time air traffic simulation to gauge the effectiveness of the proposed TMI. The second method considers a set of solutions that were identified using a reinforcement learning approach that does not use any explicit knowledge of weather forecast parameters but iteratively refines its estimates based on feedback metrics it receives from a fast-time simulation.

In Section II, we describe our modeling framework and the mechanics of the two approaches. In Section III, we discuss our computational experiments and evaluate our two approaches over a case day with significant convective weather impact in the Northeast United States and investigate the extent to which these approaches can be used to better estimate the appropriate airspace flow rates.

II. METHODOLOGY

A. *Traffic Flow Impact*

The lack of weather forecast translational tools in use to support flight operations represents a significant gap in capability within current air traffic management practices. Although there has been some effort to develop weather-aided decision support tools, the scope of their applicability has been limited. Previous efforts to translate weather forecasts into airspace capacity estimates have been focused at the sector level [21, 32, 33]. The TFI tool addresses this shortfall by mapping

an ensemble set of weather forecasts to a metric known as permeability. This permeability score is a measure between 0%-100% that describes the availability of passable corridors through a given volume of airspace. The score is calculated by taking a weighted average of trajectory impacts through a set of notional routes that cross the examined airspace. A score of 100% equates to complete availability while a score of 0% describes complete blockage of the airspace. As these volumes of airspace typically cover large portions of Air Route Traffic Control Centers (ARTCCs) rather than sectors, they are more resilient against small-scale movements of weather relative to forecasts that commonly occur over strategic horizons (6-8 hours). Thus, they are generally applicable for strategic use rather than tactical applications (1-2 hours out). While permeability does not explicitly assess the flow rate within the airspace, the metric can be translated to a flow rate by correlating permeability against historical flight patterns.

Although the translation of a weather forecast is a desirable property to facilitate decision support, as weather forecasts are inherently uncertain, it is also important to consider the role of uncertainty in decision making. To that end, TFI also provides an estimate of the uncertainty associated with the permeability metric. This uncertainty is represented by a prediction interval which describes the likelihood of the potential score range over time that is bounded between the 20th and 80th percentile. An illustration of the tool display is shown in Figure 1. In this example, the uncertainty of the metric grows over time. This phenomenon expresses the lack of trust in the forecast's ability to predict the location and intensity of the weather as the forecast temporal horizon increases. When faced with this information, the decision-maker can incorporate the relative uncertainty of the weather forecast in his/her choice of intervention rather than simply basing a decision on a single estimate.

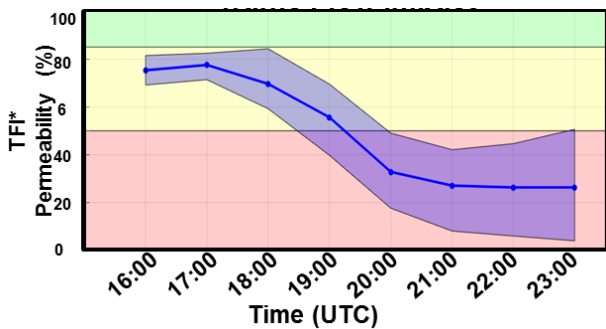


Figure 1. TFI display describing the evolution of airspace permeability over time.

B. Identifying rates with Reinforcement Learning

TFI provides a significant step towards the automation of weather translational air traffic management decision support. Yet there are a number of areas that the tool does not directly address. While the metric of permeability can be translated into a flow rate, the uncertainty associated with such translation can be considerably large. As a result, it can, in some cases, be difficult to discern the appropriate flow rate for the affected

resource. This large uncertainty is partially the result of the fact that, although TFI represents large areas of airspace, it only considers the activity at isolated ARTCC boundaries rather than accounting for the activity occurring in the adjacent ARTCCs. Fast-time simulations, when paired with methods such as reinforcement learning, offer a means of exploring a wider range of scenarios than what is covered in the limited set of relevant historical days used to train TFI, and potentially evaluating the effect of rerouting additional air traffic from weather-impacted resources on the flow rates of non-weather impacted resources. By combining the two techniques, we may be able to provide a supplementary avenue for refining existing airspace capacity estimates and generating new capacity estimates for areas of airspace that TFI was not trained to predict and identify strategies for better managing the airspace as a whole.

There are a number of algorithms in the reinforcement learning community that allow the decision-making agent to determine the optimal course of action given the information available. For this study, we adapt a reinforcement learning approach designed to facilitate decision-making in which the system under study exhibits behavior that cannot be explicitly described by a mathematical model. Under these conditions, the algorithm attempts to learn the behavior of the system through direct observation. We consider a system that exhibits states, S , where the decision-maker has a set of available actions, A . We would like to find a value-function V that maximizes the quality of the decision made over n states and all actions. The optimal action at step n can be described by the relationship:

$$a^n = \underset{a \in A}{\operatorname{argmax}} V^{n-1}(S^n, a) \quad (1)$$

The task of deriving an optimal policy can be quite challenging, particularly as the decision-maker may know very little about the relative value of each action. Since the performance of the policies is not known *a priori*, at each action the decision-maker is left with the choice of exploring the state space to collect more information about the problem or selecting the decision with the highest certain pay-off given the information available. This dilemma is commonly referred to as the exploitation vs. exploration problem. ϵ -greedy policies are commonly used to deal with this gap in information. Under this approach, the decision-maker samples from a random distribution. If the value of that sample exceeds a threshold, ϵ , then the decision-maker selects an action at random, otherwise the agent selects the optimal action given the information currently available at the time of the decision. If a random action is selected, the agent then learns the value of the action and can update the set of available information accordingly. As more actions are performed the value of acquiring new information often diminishes. As a result, the value of epsilon is often adjusted after each action to reflect an increase relative to the value of exploiting the existing information.

A feature vector describing the action space will represent a single realization in the set of possible decisions. We would like to iteratively use this information to learn the best possible decisions at each time step. Under these conditions, we can adapt an ϵ -greedy policy to our air traffic management use case. In this instance, the action space corresponds to an airspace flow program implemented at an airport of interest. We would

like to control the program to rates that permit high throughput while reducing holding. We evaluate our performance toward these ends by using the NASPlay fast-time simulation [30]. The simulation can ingest airspace capacity estimates from TFI based on either forecast or actual weather. It also processes wind fields from the Rapid Refresh (RAP) numerical model to calculate the four-dimensional trajectories of each flight. Sector workload constraints are enforced using the analytical workload model described in [32] and [34]. By modeling the appropriate traffic management initiatives under realistic weather conditions, we can project the level of performance for each TMI.

We initialize the algorithm by generating a few TMI sample rates to see how our Air Traffic Management (ATM) simulation will respond. After our initialization, we then use a selection method (in this case an ϵ -greedy algorithm) to set a flow rate sequence at each resource of interest over the simulation. We observe the performance of this strategy in the simulation and score the resulting metrics. We then use results from the simulation to fit a value function representing the value of choosing the set of programs at the affected resources of interest. This value function can be fit using a variety of different supervised learning methods (e.g., Random Forests, Gradient Tree Boosting Regression, Support Vector Regression etc.). As this process iterates, we continue our series of air traffic management simulations, choosing a different set of AFP parameters each time. When the simulation is re-run, the values of each set of previous AFP strategies, along with the performance metrics, are stored to enrich the training set available for the next iteration. A description of the adapted algorithm is shown in Table I, while a visual depiction is shown in Figure 2.

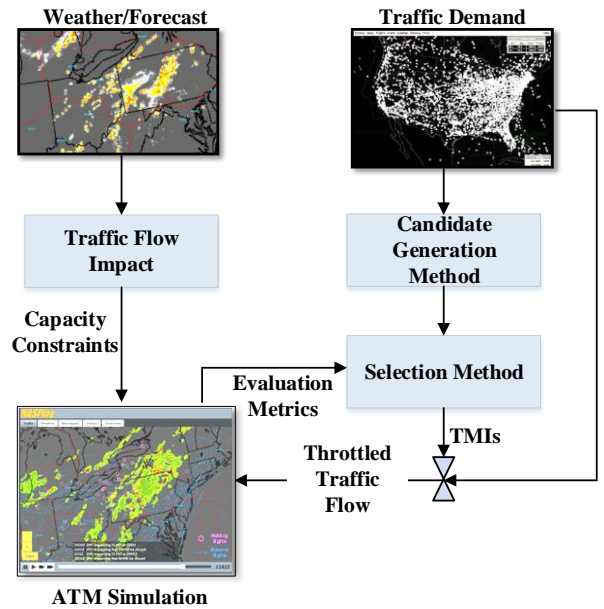


Figure 2. A simulation framework to facilitate exploration of airspace flow rates.

There are two primary metrics of interest in our experiments: (1) the number of arrivals at the airport and (2) the number of aircraft that accrue at least 15 minutes of holding. As AFPs are inherently designed to reduce holding by trading delay in the air for delay on the ground, we chose to focus our objective on generating programs that maximize the number of arrivals at the airport. Thus, the predicted arrivals were used to generate an initial value function for the action space of AFP rates. This action space was pruned by issuing predictions on levels of holding for each program and limiting the action space to programs with predicted holding levels below a user-defined threshold. Additionally, a predefined autocorrelation level was imposed on the random sequences of AFPs to limit the action space further and to avoid unrealistic AFPs that change significantly faster than the airspace permeability.

C. Selecting Rates with Stochastic Integer Programming

There are a number of alternative approaches to the ϵ -greedy method that could be used to identify the appropriate TMI rates. One common approach is to estimate the demand and capacity of a resource or set of resources and solve an integer program. If the information used to define our integer programming model is reasonably accurate, then we would expect the solution to provide a high-quality estimate of the achievable flow rate. Since we know that the information used in the stochastic integer programming (IP) model, however, does not fully describe the complex dynamics within the airspace, this approach may not offer the best solution. One potential way to address this is to use the IP as a baseline solution and perturb the solution with random sampling and simulate to determine whether the perturbations offer better-performing TMI rates.

As an initial step, we generate sequences using a 1st-order Gaussian auto-regressive random process that produces time difference values that are parameterized by the required mean,

TABLE I. AN ϵ -GREEDY APPROACH FOR ASSIGNING FLOW RATES

<p>Define the set of all possible programs P</p> <p>Initialize the probability of selecting an action at random ϵ to 1</p> <p>for $n=1, \dots, N$ do</p> <p style="padding-left: 2em;">With probability ϵ select a random program $a^n \in P$</p> <p style="padding-left: 2em;">Otherwise, with probability $1-\epsilon$, choose an action for such that:</p> <p style="padding-left: 4em;">$a^n = \underset{a \in P}{\operatorname{argmax}} V^{n-1}(S^n, a)$ (1a)</p> <p style="padding-left: 2em;">Run simulation and compute metrics</p> <p style="padding-left: 2em;">Use a supervised learning model to score the value of the each action after simulation by training the model with a set of sample points that have been simulated</p> <p style="padding-left: 2em;">Randomly sample points over the action space and use the trained supervised learning model to generate predictions of the values of each sample</p> <p style="padding-left: 2em;">Update the value of $\epsilon = \alpha / (\alpha + n + 1)$</p> <p>end for</p>
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standard deviation and auto-correlation. The generator creates a time sequence by incrementing each previously created value via a generated time difference value. We further enforce a lower limit on the auto-correlation by requiring repeated values; a positivity constraint on the series is also in place, as AFP values cannot be negative. For the study undertaken in this paper, we generate 3 such sequences for the defined resources, and then normalize the sequences to a predefined total maximum throughput via residuals, such that at every hour, the AFP values sum to a fixed number of aircraft per hour.

As the TFI model provides us with some estimate of how the weather in the immediate vicinity of the airspace resources of interest affects its capacity, one can also use this information to arrive at a set of reasonable candidates by solving a stochastic integer program. The notion that the planned arrival rate can be paired with a weather forecast has been studied with non-convective weather for GDPs [24, 25]. Recently a model for managing CTOP resources has also been proposed [18], though not explicitly paired with a weather forecast. Using a similar idea, one could envision a model for defining a planned flow rate for an AFP consisting of a set of FCAs around an airport that explicitly incorporates the relative costs of throughput and holding into the resulting candidates. This model is shown below:

Parameters:

T ≡ The set of all time periods

Q ≡ The set of all scenarios

R ≡ The set of all resources

X_t ≡ The planned airport acceptance rate at time period t

G_t ≡ The number of flights held on the ground during time period t

X_{jt} ≡ The planned flow rate for resource j at time period t

W_{jq} ≡ The number of flights held in the air traveling through resource j during time period t under scenario q

D_t ≡ The demand at time period t

c_a ≡ The cost of holding in the air

c_g ≡ The cost of holding on the ground

p_q ≡ The probability of scenario q

V_j ≡ The capacity of resource j at time period t

n_{jq} ≡ The additional flights imposed on resource j at time period t in scenario q

Demand-Based Scenario Model

$$\min \left[\sum_{t \in T} c_g G_t + \sum_{\substack{j \in R, t \in T \\ q \in Q}} p_q c_a W_{jq} \right] \quad (2)$$

$$s. t. \quad X_t + G_t - G_{t-1} = D_t \quad \forall t \in \{1..[T]\} \quad (3)$$

$$X_{jt} - W_{jq} + W_{j,t-1} + n_{jq} \leq V_j \quad \forall j \in R, \\ t \in \{1..[T]\}, \forall q \in Q \quad (4)$$

$$G_0 = 0 \quad (5)$$

$$W_{j0} = 0 \quad \forall j \in R, \forall q \in Q \quad (6)$$

$$\sum_{j \in R} X_{jt} = X_t \quad \forall t \in T \quad (7)$$

$$X_t, G_t \in \mathbb{Z}_+, \forall t \in T, X_{jt} \in \mathbb{Z}_+, \forall j \in R, \forall t \in T \quad (8a)$$

$$W_{jq} \in \mathbb{Z}_+ \quad \forall j \in R, \forall t \in T, \forall q \in Q \quad (8b)$$

Equation (3) is a network flow queueing constraint that states that the demand at time t should be satisfied such that flights scheduled for take-off during that period either take-off or be delayed on the ground. Equation (4) states that flights in the air should either be allowed to land or be delayed in the air at the assigned resource until the next time period based on the available capacity. Equations (5) and (6) state that, initially, there are no flights held on the ground or in the air. Equation (7) states that the number of flights assigned to each resource at each time slot must sum to the total number of flights assigned to arrive at the airport for that time slot. Equations (8a) and (8b) say that all variables are positive integers. The uncertainty is captured in equation (4) by using the parameter n_{jq} to define the additional imposed flight schedule drift or pop-up flights in each period. Note that n_{jq} is always a non-negative value. The objective of the problem is to minimize the expected total cost of air and ground delay using the capacity profile of the specified quantile, while controlling for the tactical perturbations to demand for each FCA. As the TFI forecasts produce a range of quantiles, one can vary the type of profile that defines the capacity constraints based upon the risk tolerance levels of the decision-makers. A more risk-averse decision-maker may opt for a profile that assigned more flights to the ground in response to a given weather pattern, while more risk-tolerant individuals can elect to use profiles that will result in candidates that naturally assign more flights to the air. Once a solution is generated, we can use random exploration to obtain a new alternative rate by perturbing the planned flow rates with a set of samples from the 1st-order Gaussian auto-regressive sequence and superposing them with the solutions from the stochastic integer program.

III. RESULTS AND DISCUSSION

A set of experiments was performed to assess the relative performance of each method described in the previous section. These experiments were performed using an 8-hour TFI profile from the 50th percentile over one case day to simulate the *a priori* forecasted behavior. The subset of the selected AFP rates were then tested with the simulation using the TFI projections from the actual weather. In this section, we describe the results of these experiments.

A. Experiment Description

A computational experiment was performed using the analytical framework described in the previous section. To test our approach, we selected a scenario based on the weather patterns that occurred on May 15, 2018. The evolving weather patterns were quite severe on that day and greatly affected traffic behavior in the New York metro region. The convective blockage limited the inflow of traffic and forced traffic

managers to impose a number of AFPs and GDPs throughout the Northeast. A snapshot of the weather is shown in Figure 3.

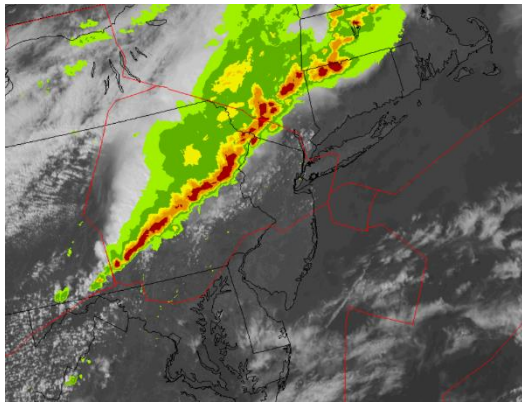


Figure 3. An image of the affecting convective weather at 20:00 GMT.

A sample of the NAS-wide traffic was selected by limiting traffic to flights arriving at Newark Liberty International Airport over a time window of 11:00-00:45 GMT. The resulting capacity can be observed when the rate of flight arrivals is high enough to force the arriving aircraft to hold within the terminal area. The airport was configured to operate with a single runway (22L) at all times. At each arrival fix, we created an arrival route and established a holding area. The holding conditions for each area were triggered, enforcing a set of en route (5 NM) and runway separation standards dictated by the aircraft wake vortex separation guidelines. Any aircraft that violated these conditions was forced into the appropriate holding area. Once an aircraft entered a holding area, it was allowed to exit when it was no longer in jeopardy of violating the separation constraints. As a small amount of aircraft holding is generally operationally acceptable, we restricted our aircraft holding count to flights that accrued more than 15 minutes of holding delay. A plot of the observed holding and arrival values in 1-hour intervals under these conditions is shown in Figure 4. In this figure, the aircraft arrival rate starts out at a relatively modest level and reaches peak levels after 17:00 GMT. We attribute this lag to both lower demand levels in the initial stages and the fact that all flights start on the ground so there is some lag between the start of the simulation and the time the arrivals reach their destination airport. Likewise, the initial holding levels remain low and increase noticeably after 18:00 GMT. This is not surprising, as the traffic demand had increased and the convective weather was moving closer to the terminal. Based on the conditions observed, during the hours in which the arrival rate plateaus, the airport can sustain a rate of around 34-40 aircraft per hour under saturated conditions. For a simulation of the airspace where no TMIs were imposed, a total of 388 arrivals were observed over the simulation. The throughput level resulted in 161 flights accruing at least 15 minutes of holding each.

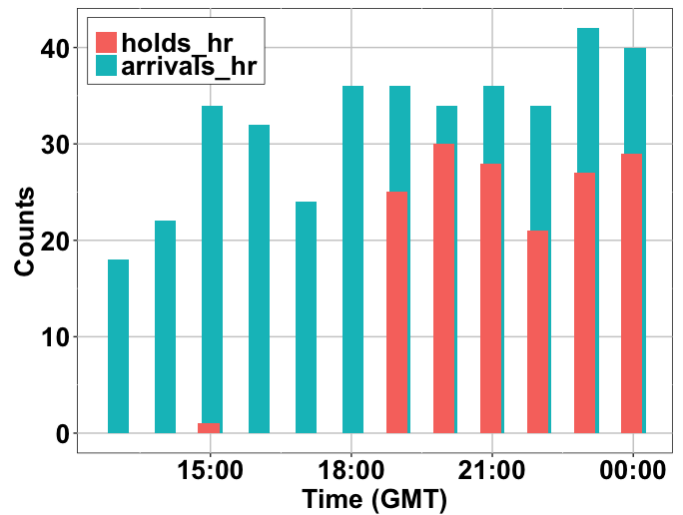


Figure 4. Arrival throughput and holding in 1-hour intervals at Newark Liberty International Airport with no strategic intervention.

B. Results

The results of the previous section suggest that Newark Liberty International airport is capable of achieving a throughput level of approximately 34-40 aircraft per hour when we ignore the en route and network effects from other airports. In practice, however, forcing flights into such holding conditions is operationally undesirable. As such, we would like to determine if imposing airspace arrival constraints near the airport can be used to limit the accrued holding level without significantly sacrificing throughput. To that end, we developed an additional simulation configuration in which we set three FCAs around the airport. These FCAs corresponded to the flows through the North, South and West arrival gates. The map of the FCA locations is shown in Figure 5.



Figure 5. The selected FCA locations and holding areas for the scenario under test.

As it was unlikely that we would consistently find the appropriate flow rates by chance, we applied the ϵ -greedy and integer programming with random exploration methodologies described in sections II. B. and C. to the problem. For the ϵ -greedy approach, the AFP rates were selected using a normal distribution with fixed mean values for each FCA over the entire program and a standard deviation of 4 flights at each

hour. These distributions were normalized at each hourly draw such that the total number of aircraft at all three gates summed to the targeted hourly rate acceptance rate for the airport.

The algorithm began by selecting a random sample and reducing the value of ϵ . As described previously, the value of ϵ was updated at each iteration based on the expression $\epsilon = \alpha / (\alpha + n - 1)$. In this expression, the value of alpha, commonly referred to as the learning rate, dictates the speed at which the algorithm moves from favoring exploration to exploitation. The ϵ -greedy algorithm was tuned to a learning rate of $\alpha = 5$, forcing the model to learn gradually and favor exploiting the information available at later iterations.

The Gradient Tree Boosting Regression method was selected to fit a value function for the ϵ -greedy algorithm from the available data. The algorithm builds a set of decision trees iteratively by fitting the error estimates for the predictions with respect to the true values. At each iteration, an error (or residual) is computed based upon a set of predictions [35]. In the initial stage of the problem, a least-squared error loss function is selected to quantify the effectiveness of the predictions made. A residual is then computed by taking the gradient of the loss function and fitting it to a set of trees. The fitted residual trees are then weighted by a multiplier that minimizes the new loss function when the residual is added to the previous estimate.

Two gradient tree boosting models were created, one to predict the number of arrivals and the other to predict the number of flights with greater than 15 minutes of holding. Each model was trained with an initial sample set of 5 random samples. These trained models were then used to predict the performance of an additional 100,000 samples. As described in section II. B., the model attempted to select the sample point within the pool of 100,000 sample values that maximized the number of arrivals while limiting the predicted number of holds greater than 15 minutes to less than 100. When a maximum value was found, the associated set of AFP rates for the North, South and West flows was selected as our next sample point. This process iterated by increasing the size of the sample set by one after each iteration by including the newly selected sample in the training pool.

As we did not have direct estimates of the airspace permeability at the areas immediately surrounding the airport, the integer programming method was implemented by mapping the forecasted permeability of the nearest en route resource immediately upstream of the FCA of interest, and multiplying the permeability score by a targeted FCA rate for the resource. The resulting rates formed the capacity constraints on the integer program. A set of expressions for the rates are shown below in equations (9) and (10):

$$R_{jt} = Perm * C_{jt} \quad \forall j, t \quad (9)$$

$$s.t. \sum_j C_{jt} = C \quad \forall t \quad (10)$$

Where C is the target acceptance rate for the airport, C_{jt} is target rate for FCA j at time t and R_{jt} is the assumed capacity of resource j at time t .

As we sought to prioritize throughput, the stochastic integer programming model was solved using an objective function with a ground-to-airborne delay cost ratio of 2:1. The resulting rates were then perturbed using a normal distribution $Y \sim N(\mu=0, \sigma=4)$. Since the predictions for each method were made using the forecast and not the actual weather, a subset of the samples were evaluated against the actual weather. As we wanted to evaluate the samples with the highest throughput that had a reasonably low number of flight holdings of at least 15 minutes, we limited our selected samples to the 10 samples with highest throughput and holding levels below the 60-flight threshold for the ϵ -greedy and IP with random exploration (IPRE) approaches. As a point of comparison, we also examined the performance of the AFP rate solutions produced by the IP model as-is without any random exploration. We also generated a set of TMIs with randomly selected rates to gauge performance in the absence of any coherent selection strategy. Neither the IP without random selection nor the random selection strategies were filtered using the 60-flight holding threshold. The performance of each method in terms of the number of arrivals and flights held for at least 15 minutes is shown in Figure 6 for target airport acceptance rates between 35-37 flights per hour. It should be noted that an attempt was made to set the rates beyond the 37 flights per hour for the IPRE, IP and ϵ -greedy approaches, however, it was not possible to generate a substantial percentage of cases with holding values below 60 (or any in the case of the IP). A set of summary statistics is shown in Table II.

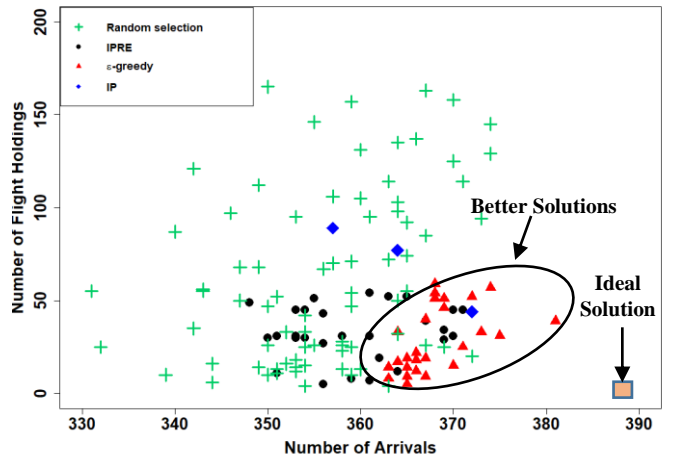


Figure 6. Arrival throughput and number of flight holdings for each test case.

TABLE II. AGGREGATED PERFORMANCE OF EACH SELECTION METHOD

Selection Method	Number of Arrivals Mean (STD)	Number of Holds Mean (STD)	Maximum Arrivals Case Arrivals/Holds
Random	356.27 (9.50)	62.75 (46.96)	374 / 145
IPRE	359.14 (6.80)	33.34 (14.74)	371 / 45
ϵ -greedy	367.70 (4.90)	27.10 (16.92)	381 / 39

Under ideal circumstances, we would like each method to produce samples with high throughput and low holding levels that group in the lower right-hand corner of Figure 6. By that standard, both the IPRE and the ϵ -greedy approaches outperform random selection. The ϵ -greedy approach, however, significantly outperforms the IPRE, on aggregate achieving higher mean throughput and fewer flights held beyond 15 minutes with less variance in both metrics. This strong mean performance and increased consistency with the ϵ -greedy approach suggests that the method is able to produce strong TMI performance despite a potential misalignment of AFP target rates. On the other hand, the larger variance of the IPRE suggests that the method is somewhat sensitive to the assumed capacity constraints used to generate its solutions.

The information presented in Figure 6 and Table II describe the aggregate performance of each approach but it does not directly speak to the performance of any particular method when the method is tuned to a specific rate. While the results show that the ϵ -greedy approach outperforms the IPRE on aggregate, given the high variance associated with the IPRE approach it is conceivable that the IPRE performance approaches that of ϵ -greedy when tuned to the appropriate target level. To understand the performance variation with respect to arrival throughput and holding levels, kernel density estimation was applied to fit a probability density function for the number of arrivals for each method. The estimation used a normal distribution with the bandwidth of 2. The resulting probability density functions are shown in Figures 7 and 8, while a set of summary statistics is shown in Table III.

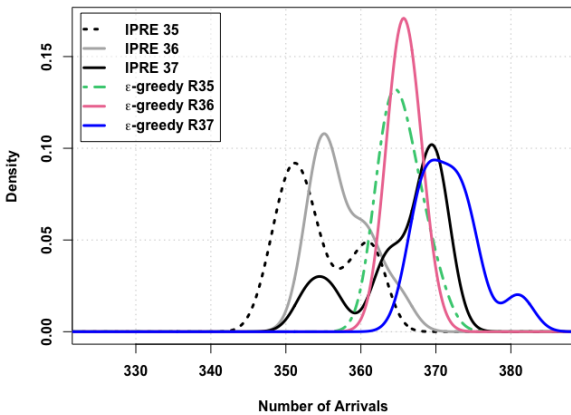


Figure 7. Distributions of the number of arrivals for each method.

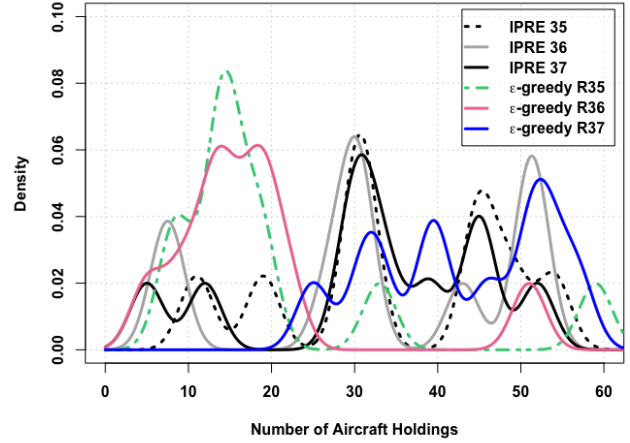


Figure 8. Distributions of the number of aircraft holding for at least 15 minutes for each method.

TABLE III. SUMMARY PERFORMANCE OF EACH SELECTION METHOD PARTITIONED BY TARGETED DEMAND RATE

Selection Method	Number of Arrivals Mean (STD)	Number of Holds Mean (STD)	Maximum Arrivals Case Arrivals/Holds	IP Solution
IPRE 35	354.1 (4.99)	35.0 (14.34)	362 / 19	357 / 89
IPRE 36	357.5 (4.66)	33.0 (15.16)	365 / 52	364 / 77
IPRE 37	365.2 (6.25)	32.3 (14.64)	371 / 45	372 / 44
ϵ -greedy 35	365.4 (2.37)	20.3 (15.25)	371 / 15	N/A
ϵ -greedy 36	365.8 (1.22)	18.2 (12.59)	368 / 51	N/A
ϵ -greedy 37	371.9 (14.15)	42.8 (10.87)	381 / 39	N/A

The resulting performance suggests that arrival throughput generally improves with increasing demand for each method. This trend is not particularly surprising as we have increased the volume of traffic on the airport. More interestingly, the ϵ -greedy approach outperforms the IPRE method even when the AFP rate is set to lower levels. The performance of the IPRE approach is not comparable to the lowest rate ϵ -greedy method until the AFP target rate reaches 37 flights per hour. The IPRE method experiences its most significant increase in throughput when the AFP targeted rate increases from 36 to 37 flights per hour. This trend is also present in the IP model when no exploration is present. The ϵ -greedy approach also experiences substantial improvement when the AFP target rate transitions to 37 flights per hour. This agreement in rates across the approaches suggests that the available airspace capacity is best aligned with a target rate of 37 flights per hour.

As Table III indicates, the IPRE method sometimes manages to identify better-performing solutions relative to the IP without exploration but only at the lower rates where the IP constraints are poorly calibrated with the actual constraints imposed by the simulation. When the target rate reached 37 flights per hour, the method could not identify any solutions that both increased throughput and reduced holding levels relative

to the IP baseline. Thus, the IPRE method may only offer a means of hedging against the unknown system dynamic effects within the simulation modeling environment. On the other hand, the mean performance of the ϵ -greedy method is essentially comparable to that of the IP without exploration, and its better performing solutions provide a relative increase in performance. This improvement is likely attributable to the ability of the ϵ -greedy approach to learn from the data it receives. By fitting the observations, it is able to achieve an improved understanding of the system response behaviors of the simulation relative to the IP, despite not having any direct knowledge of the weather through a forecast product.

As we began these investigations, we sought to understand how the proposed methods could be used to provide estimates of the sustainable terminal airspace flow rates. Thus far, we have looked at the performance improvement when the method is applied to an aggregate set of cases. By selecting from among the best cases, however, we can see how performance translates to hourly holding and airport acceptance levels. This corresponds to a case with 381 arrivals and 39 aircraft with holding greater than 15 minutes. The associated time series plot of the hourly arrivals and holding levels is shown in Figure 9.

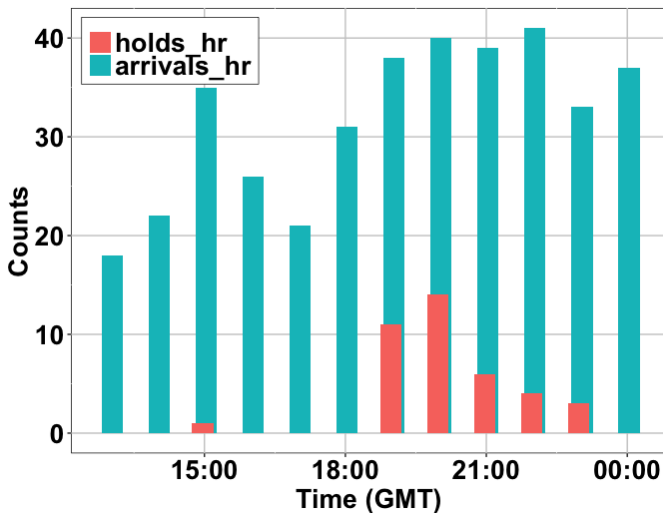


Figure 9. Arrival throughput and holding in 1-hour intervals at Newark Liberty International Airport with best selected program.

The plot suggests that over the period of peak demand starting at 18:00 GMT that the terminal airspace is capable of supporting a throughput of between 33-41 aircraft while controlling the demand at a mean level of 37 aircraft per hour. These results compare quite favorably relative to the case in which no TMI was imposed. When this best-performing TMI is imposed, we are able to achieve 98.2% of the throughput with a 76% reduction in aircraft holding beyond 15 minutes. Under this interpretation, by demonstrating that we can achieve comparable throughput to the case in which no TMI was implemented, we may view the TMI solution that produced these results as an upper bound on the terminal airspace flow rate.

IV. CONCLUSIONS AND FUTURE WORK

In this paper, we presented two methods for estimating the traffic impact of en route convective weather on terminal airspace based on integer programming and reinforcement learning methods. Both methods leverage a strategic forecast of airspace capacity and use simulation as a means of evaluating the hourly flow rate at the appropriate terminal airspace resources. While they both offer an improvement relative to random sampling, the ϵ -greedy approach significantly outperforms the integer programming with random exploration method in each case. The strong relative performance of the ϵ -greedy approach suggests that the method may provide a promising means of assessing airspace flow rates given the information available to decision makers.

There are a number of potential areas of exploration that could build upon the proposed concepts. Our study only considered the effect of convective weather at a single airport. Future investigations could examine how the methodology translates to a regional scenario with multiple airports. The study also focused on deriving airspace flow rates to maximize throughput but the proposed models could be applied to a broader range of metrics and objectives including identifying TMIs that produce fewer airline cancellations, achieve greater system predictability, or impact airlines more equitably. Finally, once the concept has been validated over a wider set of scenarios, the methodology may be formally adapted into a decision support tool that provides TMI recommendations and airspace capacity forecasts for traffic managers over a range of weather-impacted resources.

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