

## COVER PAGE

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# Analysis of Tarmac Delays Under Decreased Airport Capacity



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## **Executive Summary**

Infrequent, but lengthy, tarmac delays have been of concern in the airline industry for many years. This issue has received particular attention with the recent passing of a Department of Transportation (DOT) ruling. The new rule becomes effective on April 26, 2010 and requires airlines to eliminate tarmac delays that exceed three hours. Many of these three hour tarmac delays are caused by unpredictable circumstances, such as poor weather. The poor weather reduces the number of planes that can take off, which in turn reduces the number of gates available for incoming flights. In light of the new DOT ruling, we analyze the potential severity of tarmac delays under extreme instances of decreased capacity.

To gain insight into the severity of tarmac delays under decreased airport capacity, we built a linear program that minimizes the worst tarmac delay for a given day. We used flight data from the Bureau of Transportation Statistics (BTS) and focused our computations on New York LaGuardia Airport. After computing the worst tarmac delays with hypothetical decreased capacity and historical decreased capacity, we found that, even under ideal conditions, significant tarmac delays are inevitable without significant changes in infrastructure.

In following paper we discuss the cause of tarmac delays and the idea of optimizing gate push-back times according to the 'best worst' tarmac delay. We outline previous work that has been done in flight delay estimation and gate assignments. Our methods in building our model and collecting data are also examined. We provide our mathematical model, including the model variations we used in our computational results. Finally, future work in creating a more sophisticated model that incorporates the effects of considering multiple airlines is discussed.

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## **Problem Statement and Background**

Due to the uncertain and complex environment that the airline industry operates under, airlines must make quick operational decisions that could cost them incredible amounts of time and money. In 2008, airline delays totaling 129 million minutes cost the airline industry close to \$10 billion (Cost of Delays, 2009). The complex environment that the airline industry operates under stems from the fact that flights, aircrafts, crew, and ground resources must be coordinated. A schedule disruption has the potential to affect many aspects of the airline network. The uncertainty of the airline industry can be explained by the unpredictability of weather, security issues, and mechanical failures. Rarely do airlines run according to schedule. Over 25% of flights in 2008 were either delayed or cancelled (On-time performance, 2010).

Capacity is a critical factor in determining whether an airport experiences delays. The capacity of an airport is the rate at which departing flights takeoff. Generally, it is measured as the number of departures per hour. Under normal operating conditions, airports have a maximum capacity that varies from airport to airport. A particular airport's maximum capacity depends on the traffic of the airport, number of runways, and the size of the airport, among other factors. For example, Detroit Wayne County Metro Airport (DTW) has a maximum capacity of 143-146 departures per hour and New York LaGuardia Airport (LGA) has an optimal capacity of 80-81 departures per hour (Airport benchmark capacity, 2001). When flights are scheduled for a particular airport, airlines insure that the airport's maximum capacity can handle the number of scheduled flights. However, due to weather, security measures, and mechanical failures, airports rarely operate under maximum capacity.

When an airport's capacity is decreased, it is often the case that flights will experience either delays or cancellations, in response. This is because more flights are

scheduled to take off than the decreased capacity can accommodate. From a passenger's point of view, the worst type of delay is a tarmac delay. Tarmac delays occur when departing planes push-off from a gate and are in queue for the runway or when inbound flights land and wait for a gate to unload passengers. Figure 1, below, is from the Bureau of Transportation Statistics (BTS, 2010). This chart shows the number of tarmac delays that were over 3 hours long for the past 16 months.

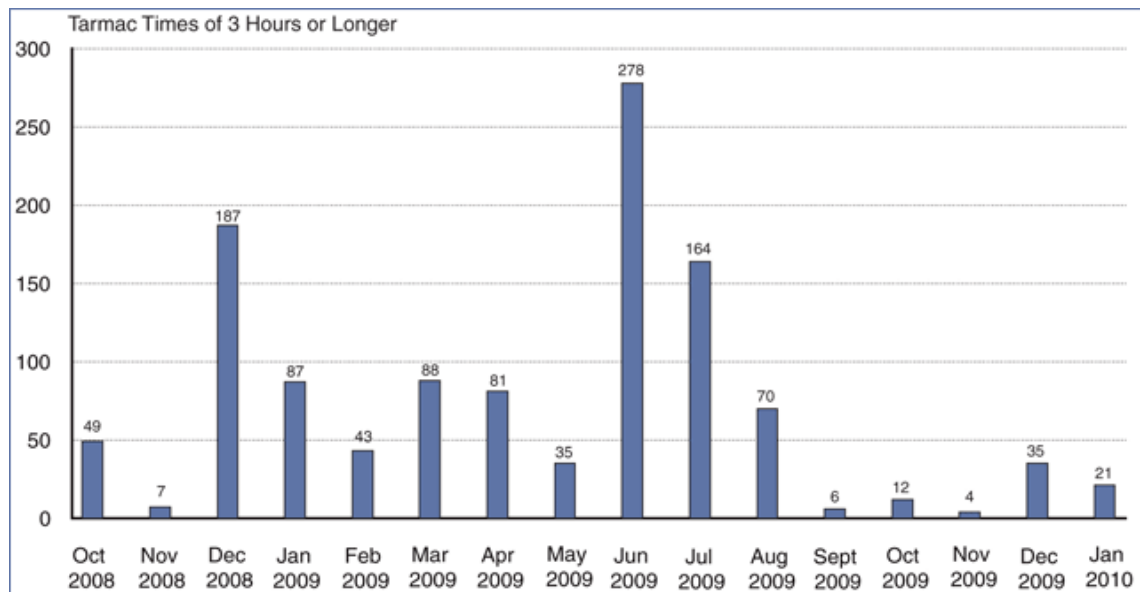


**Figure 1:** Tarmac delays of 3 hours or longer

The recent DOT ruling has raised awareness of long tarmac delays. This paper focuses on a delay trade-off assessment between the arriving and departing flights. We pay special attention to delays that occur during periods of decreased capacity if flights are not cancelled.

To understand the delay trade-off, suppose an airport has reduced capacity resulting in fewer flights to take-off. To avoid passengers having to experience long tarmac delays waiting to take-off, one might argue to delay pushing back from the gate to allow passengers to remain in the terminal. However, this can have a downstream impact on incoming customers. For example, consider the simple case where we have one gate, one outbound aircraft currently scheduled to depart from that gate, and one inbound

aircraft waiting to pull into that gate. If the outbound flight pushes back from the gate, the outbound passengers will experience a long tarmac delay due to the decreased capacity. If the outbound flight waits to push off from the gate until it can take-off, then the inbound passengers will experience a long tarmac delay. A trade-off arises between which aircraft, outbound or inbound, occupies the single gate and which aircraft experiences tarmac delay. Below, Figure 2 illustrates three possible scenarios of when the departing flight might push off from the gate.

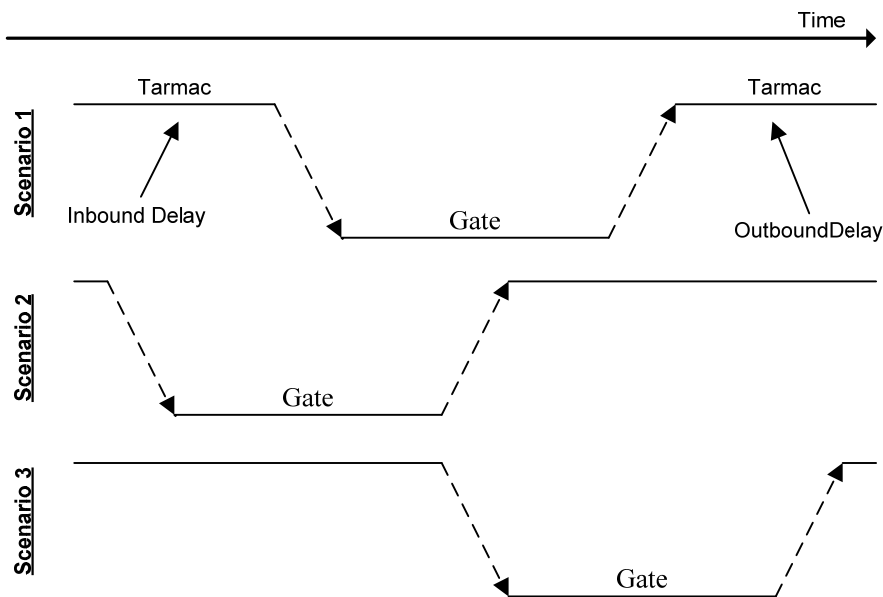


**Figure 2:** Airport Delay Scenarios

As seen in the single gate scenario in Figure 2, the departure time of the outbound aircraft affects the next aircraft that wishes to use the gate. In the first scenario, the inbound aircraft waits on the tarmac until a gate becomes available, then uses the gate and finally departs and has to wait on the tarmac until actual take-off time. In the second scenario, the aircraft is immediately pulled into the gate, but has to move onto the tarmac once its gate time has been exhausted. That is, in this particular case, we move the outbound aircraft to the tarmac to create availability for the next inbound aircraft. Finally, in scenario 3, the aircraft inbound is asked to wait on the tarmac until a gate becomes

available. Notice that the total delay in each scenario is equal. However, spreading the tarmac delay over both the arriving and departing flight, the worst tarmac delay that is experienced is cut in half. This idea was first motivated by Kontoyiannakis et al. (2009). We use this idea of spreading the tarmac delay over all flights, arriving and departing, to formulate a mathematical model that calculates the worst tarmac delay for a given day of scheduled flights.

We used data from LaGuardia airport as a case study. The actual layout of LaGuardia can be found in Appendix G. LaGuardia is one of the busiest airports in the country and is known for being congested. Among the top 30 airports in the US, LaGuardia ranked 25th for percentage of on-time departures in 2009 (Airline on-time table, 2010). From August 2008- January 2010, less than 70% of flights were on time. Our analysis can be applied to any airport to gain insight about the severity of tarmac delays given a schedule of flights and airport capacity.

## **Literature Review**

Much work has been done on increasing the smoothness of airport operations. These works can be categorized into different fields such as delay estimation, delay propagation analysis, and gate assignment. Flight delay estimation is crucial for airlines in making operational decision such as flight cancellation and gate assignments.

Tu, Ball, and Jank (2005) developed a statistical model to estimate flight departure delay distributions, which takes into account daily delay propagation, crew connection problems, seasonal demand, and weather impacts. Instead of departure delay, maximum tarmac delay is estimated in our work using linear programming by considering limited runway capacity during poor weather condition. By only focusing on tarmac delay, we were able to eliminate many of the factors that Tu, Ball, and Jank analyzed in their model.

Another paper by Wang, Shortle, Wang, and Sherry (2009) analyzed causes of gate waiting delay and estimates gate waiting delay using historical data. They found that gate waiting delay is correlated with scheduling strategy and schedule disruption. Schedule disruption, caused by flight cancellation and longer turnaround times, cause the airport to have more flights on the ground than it can hold. Flight cancellations are usually the consequence of poor weather condition. We will focus on the effect of poor weather condition on tarmac delay. Also, our work differs in that we are only interested in the maximum tarmac delay instead of the mean gate waiting delay. However, these causes of gate waiting delay are for the most part also eliminated to make the model simpler. These causes are important though or future research when airlines must use these causes to help determine the best decisions to make in their scheduling and cancelling of flights.

Schaffer and Millner (2001) provide an insight on delay propagation due to limited runway capacity caused by poor weather condition. The authors found that the mean flight delay increases with longer period of inclement weather. They also found that delays are not significant during poor weather condition in airports with high capacity to demand ratio. The authors do not take limited number of gates into consideration as presented in our work. This work is crucial in understanding how delays can build up, and can be used in future work to help airlines plan on how to deal with weather forecasts.

Efficient gate assignment is another challenge in airline operations. Haghani and Chen (1998) present an integer model to optimize gate assignments. The presented model minimizes passenger walking distances by taking into account flight schedules. However, the situation where the demand is higher than the number of gates in the airport is not considered.

Lastly, Kontoyiannakis, Serrano, Tse, Lapp, and Cohn (2009) studied gate allocation policies during extreme delays. One important concept of this paper was that inbound flights are given priority to runway usage. This comes into effect in the data preparation for the model, which will be explained later. A second important finding of the paper was that customers will rather wait in the airport than wait on the tarmac. This idea is a motivating force for this study which will analyze the tarmac delays under certain levels of capacity.

### **Problem Solving Approach**

When approaching this problem, optimization modeling and linear programming is used to calculate the optimal solution of minimizing the maximum tarmac delay at an airport under diminished capacity. In creating the mathematical model, several assumptions are made for simplicity. Assumptions are also present for the purpose of creating an ideal environment in order to see how diminished capacity patterns can affect tarmac delay in its simplest form.

Our model, with its assumptions, creates a lower bound on the severity of tarmac delays that can be expected in the real world. The computational results reflect optimistic lengths in tarmac delays because the mathematical model simplifies airport operations to create an ideal operational environment. Although these results would not be experienced in the real world, the results provide insight to the best case scenario that airlines can expect. Realistically, tarmac delays will be *worse* than what our model predicts. Along with providing a lower bound on the worst tarmac delay, the results can be used to understand the relationship between airport capacity and tarmac delay.

To add validity to the model, real data is used from the BTS databases ([www.bts.gov](http://www.bts.gov)) to test actual daily schedules against the diminished capacity patterns.

Also, historical weather is taken from wolfram alpha online weather databases ([www.wolframalpha.com](http://www.wolframalpha.com)) to compare historical weather to the delays that occurred on that day. After all of these aspects are collected and organized for the model, they are run through the model to ultimately minimize the maximum tarmac delay of any flight. This section explains how the above aspects were gathered and their importance for the model.

### **Model Assumptions**

Several assumptions are made in the designing of the model to simplify the scenario and focus on tarmac delay at its most basic form. While the assumptions are used to simplify the model, some of the assumptions are also made due to the method of solving the model, which will be discussed in a later section. Some of the simpler assumptions include that all planes and gates are interchangeable, that timing is instantaneous, that gate assignments are non-specific, and that only scheduled departure time is needed before allowing a plane to depart. Each one of these will now be described in more detail. Then more complex assumptions will be explained later.

#### *Interchangeable Gates and Planes*

First, the concept that all planes and gates are interchangeable is important because it allows us to filter through the historical data and not worry about what type of plane was used for each flight. In reality, certain gates can only service certain types of aircraft. This assumption allows a plane to proceed to any available gate, and therefore makes the model simpler. Another important implication of this assumption is that all gates and all planes are controlled by one airline; or that all airlines share all gates and work together to best utilize those gates. Either interpretation of this assumption is valid, and is important because we can also filter out specific airline from the historical data. Both of these assumptions can be reconsidered in future research to study the implications of factoring them in to delay.

### *Instantaneous Timing*

Second, the assumption of instantaneous timing is important to note when interpreting the results of the tests. The model does not take into account the time it would take a plane to taxi, pull into the gate, unload, go through turn process, reload, pull out of the gate, and then taxi again. Most of these procedures such as pulling into and out of the gate and taxiing would add time to the overall “delay,” but since these times are not considered when calculating tarmac delay, it actually would have no effect on our model. Turn time would affect our model because the time it takes an aircraft to unload, get serviced, and reload takes away from that particular gate’s availability. Since our model does not consider turn time for the sake of simplicity, our value of tarmac delay will be underestimated.

### *Non-Specific Gate Assignments*

Third, the idea of gate assignments being non-specific should have no major effect on the model. Due to the idea that gates and planes are interchangeable, gates and planes have no attributes that make them unique. Therefore, as long as the total number of gates is known in the model, it doesn’t matter to the results which gate is used for which plane. Again, this underestimates the value of tarmac delay because the longest plane waiting will receive the first gate available. In reality, we would need to assign a specific gate number to a specific plane, but in this scenario we do not need to do this. Once again, since we already assume all planes and gates are interchangeable, not specifying gates has no affect on the outcome of the model.

### *Known Scheduled Departure Time*

The final simple assumption is that only scheduled departure time is needed before allowing a plane to depart. This is related to the instantaneous assumption because of the aspects of loading and unloading time as well as turn time. Other considerations

that are not considered are crew availability as well as mandatory procedures before departure. By leaving these considerations out, we can allow a plane to leave the gate as early as the model sees is optimal, constrained only by the scheduled departure time, in order to allow another plane to occupy that gate.

#### *First-In First-Out*

The final assumption, which is based on a combination of the assumptions mentioned thus far, is the assumption of using the First-In First-Out (FIFO) principle. This principle states that the first entity “in” to an area will be the first entity “out” of an area, thus the entity that has been waiting the longest will leave first. The FIFO assumption is used in three aspects of the model. While each aspect where it is used is affecting a different variable, the proof of FIFO holds for each and therefore would only need to be explained once. The importance of using FIFO is that by following its guidelines will always yield the minimum of the maximum tarmac delay of any flight. By not following FIFO, it is shown, in Appendix H, that at least one plane will have a worse delay than if under the FIFO guidelines. The three areas where FIFO is enforced is with the three decision variables of the model (gate-in time, gate-out time, and wheels up time). This is enforced by simply saying that a certain flight cannot do one of the above actions until the flight before it has done that action. This constraint is enforced over all flights in the model. Another implication of FIFO is that the first flight to come into a gate will be the first flight to leave. This becomes important in the constraints of the mathematical model, by saying that the first flight to leave cannot do so until the first flight arrives. This is a simple concept to visualize, but FIFO must be enforced for it to work.

A simple example of FIFO can be seen in Figure 3.

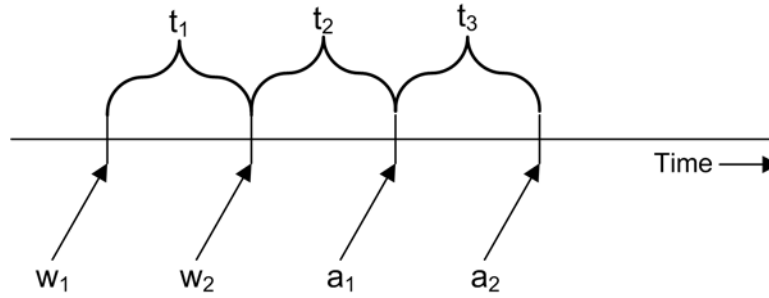


**Figure 3:** Simple Example of FIFO

As seen in Figure 3, if the  $w$ 's are viewed as arrival time, the  $a$ 's are viewed as gate-in time, and the  $t$ 's are viewed as time intervals, it is clear that assigning  $w_1$  to  $a_1$  would yield a lower delay than assigning  $w_1$  to  $a_2$ . More simply, the delay of the first example ( $t_1+t_2$ ) is less than that delay of the other example ( $t_1+t_2+t_3$ ). This reasoning can be repeated for the other instances where FIFO is used.

### Model Data

The data for the model is gathered through BTS databases of historical flights and schedules. To sort through the data to only get relevant flight information, the unchanged schedule for LaGuardia on the chosen day is put into an excel spreadsheet.

We filter and alter the data in the following ways.

- Eliminate International flights
- Categorize between wheels down time and departure time
- Sort each category chronologically

The first idea of eliminating international flights is used for simplicity and also because international flights follow different guidelines from domestic flights. The second concept of using those two categories is used because they are the necessary values for arrival time and departure time to make our model work. We need values for arrival and departure because we are considering both arriving and departing flights at LaGuardia. The other variables are based on these values. Aircraft are then sorted chronologically to enforce and support FIFO.

After ordering the flights chronologically by category, flights are also ordered chronologically in one category. This list of flights is used for determining the number of gates to use. By ordering flights chronologically, a count can be made of how many planes are on the ground at any specific time. The maximum of those numbers is used as the number of gates at the airport for two reasons. The first reason is the number of domestic gates at LaGuardia is an unknown because some gates could be used for both domestic and international flights, while some gates are strictly for international flights. Since the number is unknown, an estimate must be made on how many gates there are. This leads to the second reason this number was used, which is for the purpose of determining what the needed number of gates would be so that there was no delay built into the schedule. This allows the results to be interpreted that if there is a delay; it is not inherent to the schedule so it must be coming from another reason.

Lastly, the flight schedule data for several days are graphed to show throughout the course of a day how many planes were leaving per hour (airport capacity). These graphs are used to determine an optimal inter-departure time. Inter-departure time is the time that is necessary in between take-offs, and is an inverse of capacity. The optimal inter-departure time would be related to the optimal capacity, and we use the optimal capacity as the normal day capacity of LaGuardia. These values are used so that the initial results could be found using the optimal inter-departure time. One of these graphs can be seen in Figure 6 in the Computational Results section below.

The only other data that is needed is weather data from the historical flights days that are used. The weather data is important for two reasons. It confirmed that days with close to optimal capacity are days with close to optimal weather, and vice versa for days that had diminished capacity. This data also gives a good starting point for what is a reasonable value for inter-departure times for diminished capacity and how patterns of

diminished capacity usually affect the airport. The weather data for the chosen days can be seen in Appendix I.

### **Model Concepts**

The primary concept behind the model is minimizing the **maximum** tarmac delay of any flight. Simply, if viewing what each flight's tarmac delay was, the objective is to take the largest value of delay and minimize it. By doing this, the model outputs the best value of the worst possible delay. A simple example of minimizing the maximum was shown in Figure 1.

This is an important value to observe because if the worst value is not a significant delay, then it shows that all aircraft do not have a significant delay. On the flip side, if the worst value is a lengthy delay, it shows that at least one, if not more flights, has a lengthy delay. As discussed above, the idea of FIFO is enforced to have a simple method to determine a lower bound on tarmac delay. As discussed above, using FIFO will have a lower delay than not using FIFO. Furthermore, we discussed how some of the other assumptions will underestimate delay, leaving our solution as a lower bound, making the actual delay worse than the calculated one.

The other aspect of the model that is restricting is that the model was made using linear programming. For this reason, many of the above assumption had to be made in order for the problem to be modeled in a linear way. By making the model more complicated, it would no longer be linear. Since our objective was to analyze how diminished capacity affects delay, we could still see trends in our results. Furthermore, we could still find a lower bound on delay that is pretty accurate and useful.

Lastly, it is important to note that even though in this example we use inbound and outbound flights from LaGuardia, this model can be applied to any airport. By

following the procedures for sorting the raw data and making appropriate data files, any airport can be used.

### Mathematical Model – Proposal 1

This is our first iteration of the mathematical model. It models departures with a departure rate ( $r$ ) for the entire day.

#### Sets:

|     |                              |
|-----|------------------------------|
| $A$ | the set of arriving flights  |
| $D$ | the set of departing flights |

#### Parameters:

|       |                                                                              |
|-------|------------------------------------------------------------------------------|
| $g$   | the number of gates at the airport                                           |
| $a_f$ | the time flight $f$ is scheduled to arrive at the airport, $\forall f \in A$ |
| $d_f$ | the time flight $f$ is scheduled to depart the airport, $\forall f \in D$    |
| $r$   | the rate of departure for flight                                             |

#### Variables (Decision):

|       |                                                                             |
|-------|-----------------------------------------------------------------------------|
| $x_f$ | we define $x_f$ as the time flight $f$ enters the gate, $\forall f \in A$ . |
| $y_f$ | we define $y_f$ as the time flight $f$ leaves the gate, $\forall f \in D$ . |
| $z_f$ | we define $z_f$ as the time flight $f$ 's wheels go up, $\forall f \in D$ . |
| $W$   | we define $W$ as the maximum delay incurred during the day                  |

#### Objective (Goal):

The goal of the optimization is to minimize the maximum delay.

$$\text{Min } W$$

#### Constraints (Rules):

|                            |                          |     |
|----------------------------|--------------------------|-----|
| $x_f \geq a_f$             | $\forall f \in A$        | (1) |
| $y_f \geq x_f$             | $\forall f \in D$        | (2) |
| $y_f \geq d_f$             | $\forall f \in D$        | (3) |
| $x_j \geq y_{(j-g)}$       | $\forall j \in A, j > g$ | (4) |
| $W \geq x_f - a_f$         | $\forall f \in A$        | (5) |
| $W \geq z_f - y_f$         | $\forall f \in D$        | (6) |
| $z_f \geq y_f$             | $\forall f \in D$        | (7) |
| $z_f \geq z_{(f-1)} + r_f$ | $\forall f \in D, f > 1$ | (8) |

Constraint (1) ensures a plane does not go to a gate until it has arrived. Constraint (2) ensures a plane does not leave the gate until it has entered the gate. Constraint (3)

ensures a plane does not leave the gate until the scheduled departure time. Constraint (4) ensures a plane does not enter a gate when all the gates are full. To further explain constraint (4), consider if there were only 3 gates available and 3 planes have arrived, therefore all gates currently being occupied. Assuming the first plane into a gate is the first plane out, the fourth plane to arrive must wait until the first plane has left for a gate to be available. Constraint (5) defines the maximum delay as the difference between arrival time and the entrance to a gate. Constraint (6) defines the maximum delay as the difference between gate push back time and actual wheels off the ground. Constraint (7) ensures that a plane does not take off from the ground until it has pushed back from the gate. Constraint (8) defines wheels up time as a function of the airport departure rate and the previous flights wheels up time.

### Variable Restrictions

In our formulation, our decision variables are positive integers.

$$\begin{aligned} x_f &\in Z^+ \quad \forall f \in F \\ y_f &\in Z^+ \quad \forall f \in F \\ z_f &\in Z^+ \quad \forall f \in F \end{aligned}$$

### Mathematical Model – Proposal 2

The second iteration of our model takes the departure rate ( $r$ ) and turns it into a function of each flight. Therefore, each flight has an associated departure rate, meaning each flight will have a specific amount of time to wait before it can take off once the flight before it takes off. This model change was done to incorporate the fact that the departure rate varies over time and is not a static variable for the entire day. This was done by changing the parameter  $r$  and constraint (8).

### Parameter Change:

$$r_f \quad \text{the rate of departure for flight } f, \forall f \in F$$

### Constraint Change:

$$z_f \geq z_{(f-1)} + r_f \quad \forall f \in F, 1 < f \leq \text{departures} \quad (9)$$

Constraint (9) replaces constraint (8) from iteration 1, defining the wheels up time as a function of the airport departure rate and the previous flights wheels up time. The constraint utilizes a departure rate in terms of the flight about to leave, not a departure rate for the entire day. This changes our model to represent the departure rate as a function of time, not for the entire day.

## **Computational Results**

To gain insight on the potential severity of tarmac delays under decreased capacity, we focus our computations on the effects of various durations and intensities of decreased capacity on tarmac delay length. The first part of our computations is based on hypothetical durations and intensities of decreased capacity. The computational data ranges from short durations with high capacity, to long durations with low capacity. Although our scenarios of decreased capacity are hypothetical, the data used in our computations are based on historical flight schedules. For this reason, we can make valid conclusions about the potential severity of tarmac delays with the given flight schedule.

To provide a cohesive and complete interpretation of the results, computed values of tarmac delays on the same day, February 4, 2010, are used. To obtain more realistic results, rather than hypothetical, we compute tarmac delays based on the historical for a specific day capacity at LaGuardia. To understand the effect of historical decreased capacity on tarmac delays, we use data from days that had actually experienced decreased capacity. With hypothetical and historical computations, related conclusions can be made from the results.

## **Hypothetical Decreased Capacity**

For the hypothetical diminished capacity, two parameters are varied to study the effects on delay. The first parameter is the value of  $r$ . By varying the inter-departure time, we

can try to find a relationship between diminished capacity and delay. The other parameter that is observed is the length of the diminished capacity. By changing the length that  $r$  affects the model, we can try to find a relationship between length of diminished capacity and delay.

To complete this analysis, we use  $r$  values ranging between 2 and 12 minutes incrementing by 1 minute. The length of times we use range from 2 to 12 hours incrementing by 2 hours. To alter the input data file, we have to determine how many flights to enforce this decreased capacity, and how many flights to remain at normal capacity. Since we know that the  $r$  value for a normal day is 2 minutes, any unchanged flights would have to have an  $r$  value of 2. Where the logic becomes less clear is when determining how many flights to effect with the new  $r$ . For any bad  $r$  value, enforced over a specific length, the number of flights that would be affected would be the greater of two flight numbers. The first flight number would be equal to a flight that has a scheduled departure exactly the length of time after the diminished capacity starts. The other number would be the number of flights that would be affected should the diminished capacity be a tight constraint for the entire period. By taking the higher of these two numbers this ensures that the diminished capacity affects the correct number of flights.

A table with the changed  $r$  values on the vertical axis and the length of diminished capacity on the horizontal axis can be seen below. The value of the maximum delay as calculated by our model under these circumstances is shown in Table 1.

| r \ Length | 2    | 4    | 6     | 8     | 10    | 12    |
|------------|------|------|-------|-------|-------|-------|
| 2          | 0    | 0    | 0     | 0     | 0     | 0     |
| 3          | 0.5  | 4    | 4     | 4     | 4     | 4     |
| 4          | 10.5 | 30   | 38.5  | 51    | 68    | 78.5  |
| 5          | 19   | 45.5 | 67.5  | 86.5  | 110.5 | 138   |
| 6          | 25   | 57   | 89    | 115.5 | 138.5 | 170   |
| 7          | 30   | 66.5 | 97.5  | 125   | 152   | 174.5 |
| 8          | 32.5 | 73.5 | 111   | 150   | 181.5 | 215   |
| 9          | 33.5 | 77   | 119.5 | 162   | 199   | 237.5 |
| 10         | 32   | 76.5 | 119   | 163   | 207   | 243.5 |
| 11         | 33   | 80.5 | 124.5 | 169.5 | 216   | 260   |
| 12         | 33   | 82   | 126.5 | 174   | 220   | 266   |

**Table 1:** Maximum Tarmac Delay for Various Capacity and Duration

Figure 5 below of the graph plots the values of the above table. In this graph  $r$  values are plotted on the horizontal axis, length of diminished capacity values are plotted on the diagonal axis, and  $W$ , the length of delay, is plotted on the vertical axis. The colors represent different ranges of delay, as indicated by the key on the right. The area of each color represents the approximate amount of time that the corresponding delay occurs.

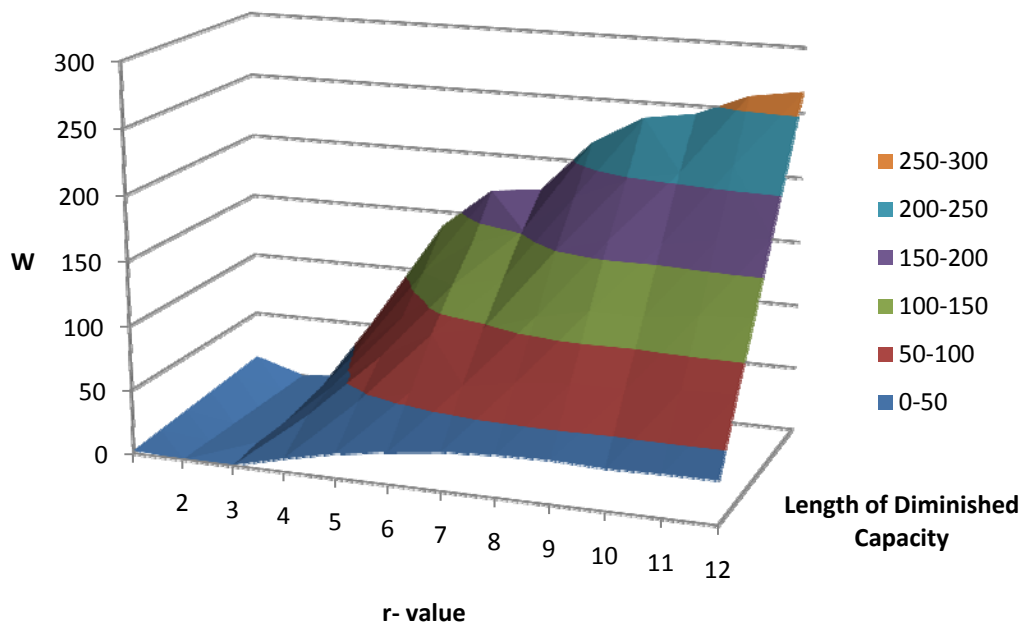


**Figure 5:** Worst Tarmac Delay for Various Capacity and Duration

To see the relationships more clearly, Figure 5 can be broken down to hold one variable constant and vary the other. Figure 6 shows an example of holding the length of diminished capacity constant at 4 hours.

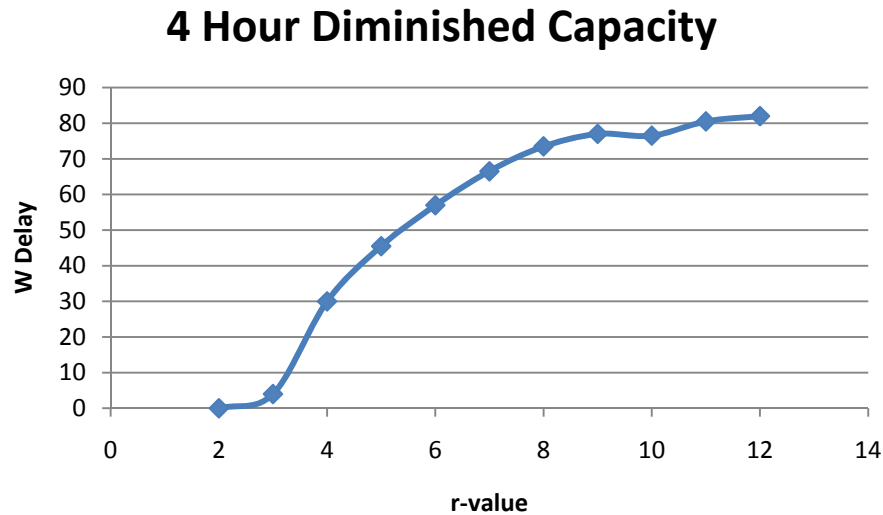


**Figure 6:** Worst Tarmac Delay for 4 Hours Diminished Capacity

From the graph above, the effect of the change of  $r$  value can be seen as duration remains constant. These parameters can be changes so that  $r$  value is held constant and duration is varied. Figure 7 shows an example of holding the  $r$  value constant at 5 minutes.

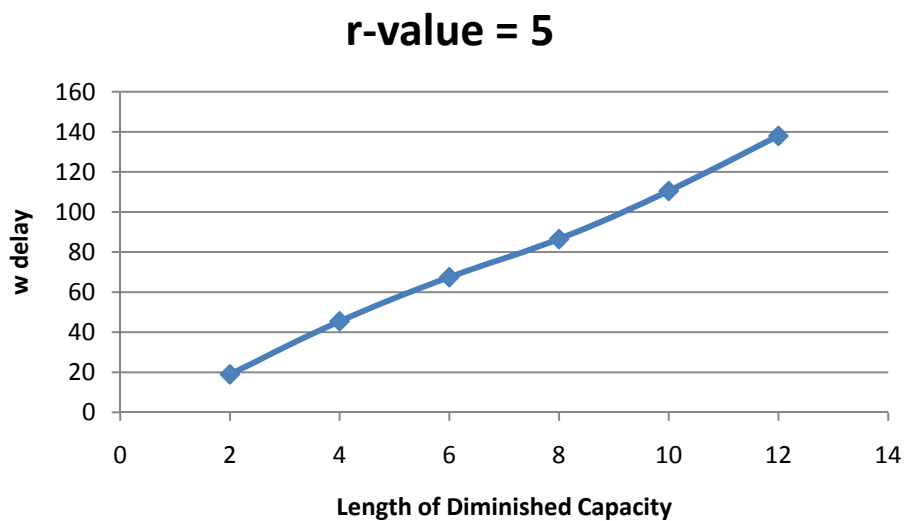


**Figure 7:** Worst Tarmac Delay for 5 Minute Inter Departure Time

From this graph above, the effect of the change of duration can be seen while holding the  $r$  value constant. Both of the above graphs show the same concept. The first graph shows that while the  $r$  value gets worse, so does the delay. This makes sense because as  $r$  value gets worse, less flights can take-off, leaving more flights on the ground waiting to take-off. The second graph shows that while the duration of diminished capacity gets great, so does the delay. This also makes sense because as the duration gets greater, more flights are affected by the  $r$  value, so again fewer flights can take-off and more flights are waiting to take-off. These graphs only show two examples of holding one variable constant, more examples of these graphs can be seen in Appendix J for constant duration and Appendix K for constant  $r$  value.

### **Historical Decreased Capacity Computations**

To observe the effects of experienced decreased capacity on the severity of tarmac delays, we look at several days for two different reasons. First, we use a number of days at LaGuardia, under normal operating capacity, to compile a typical flight schedule for a weekday. The flight schedule is used for the wheels on and departure times in our computations. Second, we use two days with decreased capacity to gather instances of poor airport operations due to bad weather conditions. By computing the frequency of flight departures, we are able to map the airports decreased capacity throughout the day. All days are weekdays and roughly have the same flight schedule. However, the sample days that experienced bad weather also experienced cancellations. Cancellations are the reason we use separate two days for the historical computation. Since cancellations were experienced during bad weather, we have to gather the anticipated schedule from a different day. Using the decreased capacity throughout the day with the anticipated flight schedule, we are able to analyze the impact of decreased capacity under a normal flight schedule.

### Schedules of Days with Normal and Decreased Capacity

To obtain a schedule of anticipated flights, we use weekdays from January 26, 2009 to February 20, 2009. In our historical computations, we use the wheels down and departure times from February 17, 2009 because it closely follows the anticipated schedule that we compiled. Below, Figure 8 shows the frequency of departures for the anticipated schedule, January 17, January 28, and February 3.

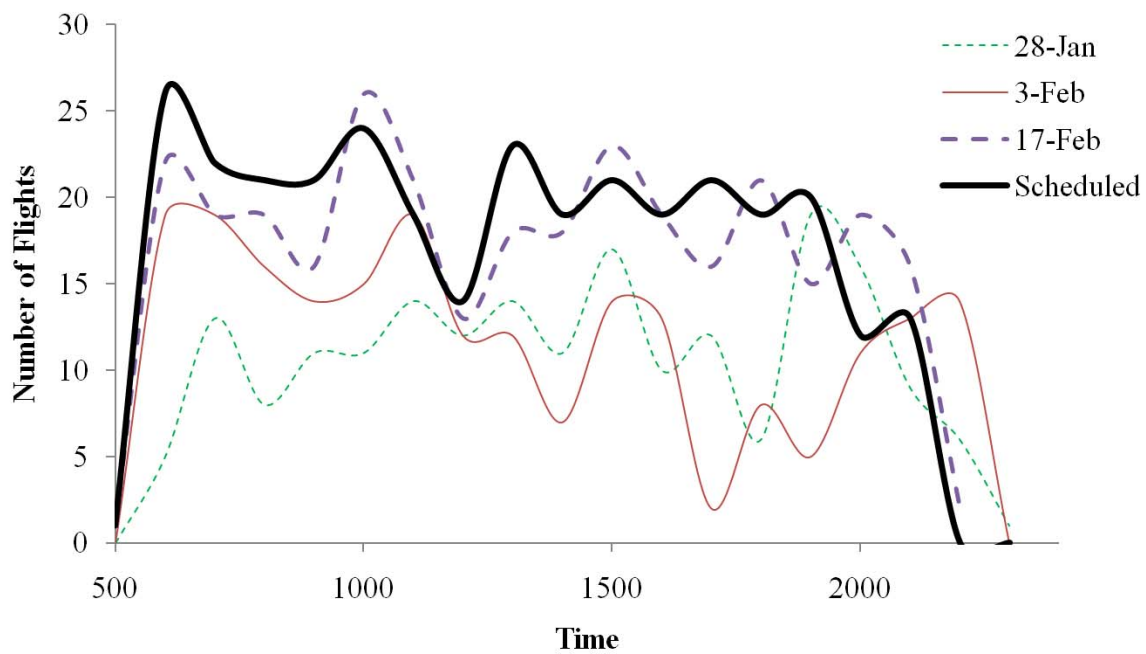


**Figure 8:** Departure Frequencies for Historical Computations

Both January 28, 2009 and February 3, 2009 experienced heavy precipitation and cloud cover, which greatly reduced LaGuardia's capacity. In Appendix I the precipitation, cloud coverage, and wind speed are shown.

### **Tarmac Delays From Decreased Capacity Under Normal Schedule**

The severity of the worst tarmac delay for January 28, 2009 and February 3, 2009 are shown below in Table 2.

| <b>Date</b>      | <b>Tarmac Delay (min.)</b> |
|------------------|----------------------------|
| January 28, 2009 | 138.06                     |
| February 3, 2009 | 177.93                     |

**Table 2:** Worst Tarmac Delays Experienced Under Decreased Capacity

As seen in Table 2, the worst tarmac delay for January 28, 2009 is over two hours and for February 3, 2009 is nearly three hours.

### **Conclusions and Future Research**

Flight delay estimation is essential in developing effective airport operations. This paper developed a mathematical model to estimate the worst tarmac delay in an airport with reduced capacity. The worst tarmac delay is estimated under the best case scenario, where we assume zero taxi time and interchangeable gates and planes in the model. Thus, the real worst tarmac delay is expected to be higher than the one our model estimates. Our model distributes the delays evenly to every flight affected by the reduced capacity, so there will not be a flight sitting on the tarmac for a long time while other flights are taking off on time.

By using a linear program, we found that the worst tarmac delay increases when the runway capacity is lower or the reduced capacity period is longer. These results are obtained by using hypothetical reduced capacity. We also used historical data to compute the worst tarmac delay by applying an anticipated flight schedule on a day with reduced capacity, caused by poor weather condition. The worst tarmac delays computed by using this approach turn out to be around 2 – 3 hours. Again, we expect the worst tarmac delay in the real world to be higher since the estimation is done under best case scenario.

Two solutions can be applied to avoid long tarmac delay. 1) Carriers should cancel flights because the reduced capacity runway will not be able to fly as many flights as in a normal operation day. 2) Carriers should push off flights only when the runway is back to normal capacity. We believe that it is always better to have passengers waiting in the terminal rather than on the flight since passengers can at least surf the internet, eat in the restaurants, or walk around in the terminal. These activities are impossible if they are on the flights. However, by pushing off the flights later than they schedules, the arrival flights will have no gate to go to since the gates are occupied by these delayed flights. This leads to several extensions of possible future research.

First, we could extend our model to determine the number of gates needed so that the airport will have enough capacity to accommodate both incoming and delayed flights. We could also incorporate the fact that gates are airline specific, where flights can only go to gates assigned to the carriers. The model has been developed and the results are yet to be computed.

In our model, we assume that gates and flights are interchangeable. The accuracy of worst tarmac delay estimation could be improved by eliminating the assumption above. In this case, the facts that flights must get to gates before their next connections, and aircraft types that could not be parked near to each other will be taken into account. Finally, we would also like to extend the model so that it can determine which flights to cancel in order to make sure the worst tarmac delay would not exceed a certain level.

### **Future Research**

The next step in our work should begin to incorporate airline specific gates. This detail is very important to the realism of a model, because the competitive nature between airlines can be a source of delay. We have begun to formulate a model to represent airline

specific gates. Please find below the additions and changes to our current model to incorporate this detail.

This future model for analysis incorporates the fact that gates are airline specific. We have done this by making each flight attached to a select group of gates to choose from, instead of all the gates at the airport.

**Sets Addition:**

N: the set of outbound flights {1,2,3...departures}

**Variables Change/Addition:**

$z_{f,n}$  we define  $z_{f,n}$  as the time flight  $f$  takes off from the ground if it is the  $n$ th outbound flight,  $\forall f \in F, \forall n \in N$

$B_{f,n}$  we define  $B_{f,n}$  as a binary variable, where  $B_{f,n} = 1$ , if flight  $f$  is the the  $n$ th outbound flight and 0, otherwise.

**Constraints Change/Addition:**

$$\sum_f^{\infty} z_{f,n} \geq z_{f,(n-1)} + r_f, \quad \forall n \in N \quad (10)$$

$$\sum_n^{\infty} B_{f,n} = 1, \quad \forall f \in F \quad (11)$$

$$\sum_f^n B_{f,n} = 1, \quad \forall n \in N \quad (12)$$

Constraint (10) serves as the same function as constraint (8) and constraint (9) from iteration 1 and 2, defining the wheels up time as a function of the airport departure rate and the previous flights wheels up time. This constraint, however, utilizes our set of outbound flights to ensure ordering as flights depart. Constraint (11) ensures each flight receives a departure slot. Constraint (12) ensures each departure slot receives a flight.

The mathematical model above is just one of the possible avenues that lead a more realistic estimation of tarmac delays under decreased airport capacity. Nevertheless, with a model that assumes the absolute best case scenario, tarmac delays of 2-3 hours are

observed. Under rare, but realistic, decreased capacity, lengthy tarmac delays are inevitable with anticipated flight schedules. These tarmac delays are large enough to cause concern, and solutions should be explored by airlines, especially in the wake of the 3-hour DOT ruling. For many airlines, solutions are limited and it will time before a sustainable solution is conjured.

## Appendix A - Contact Information

**AMY COHN** is an Associate Professor in the Industrial and Operations Engineering Department at the University of Michigan. She holds the Ph.D. in Operations Research from MIT. Her primary research interest is in applied discrete optimization problems, particularly in the airline industry.

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**KYLE GILSON** is an undergraduate student in the Industrial and Operations Engineering Department at the University of Michigan. His academic interests lie in operations research, economics, and finance. He will be graduating in May 2011 with a Bachelors degree in Industrial and Operations Engineering and a Minor in Mathematics.

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**BRIAN HARRIS** is an undergraduate student in the Industrial and Operations Engineering Department at the University of Michigan. His studies have been focused on linear programming and simulation for transportation and manufacturing scenarios. He is working towards getting a Bachelors degree in Industrial and Operations Engineering and a minor in Mathematics from the University of Michigan. He made Deans List for the 2008 Winter Semester and was the Food and Finance Chair in the Phi chapter of the Psi Upsilon Fraternity in the Winter of 2009.

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**MARCIAL LAPP** is a graduate student in the Industrial and Operations Engineering Department at the University of Michigan. His research interests lie in modeling and solving large-scale optimization problems focused on the transportation and logistics industries. He holds a Masters and a Bachelors degree in Computer Science from the University of Michigan.

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**ANDREW SCHLESINGER** is an undergraduate student in the Industrial and Operations Engineering Department at the University of Michigan. His academic interests lie in mathematical modeling and operations research. He will be graduating in May 2011 with a Bachelors degree in Industrial and Operations Engineering. He made Dean's list for the Fall 2009 and is the director for A World in Motion (AWIM) sponsored by the Society of Automotive Engineers (SAE).

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**SHENG HONG TAN** is an undergraduate student from Malaysia in the Industrial and Operations Engineering Department at the University of Michigan. His research interests lie in optimization modeling and finance. His email is <hongtan@umich.edu>; address: Industrial & Operations Engineering, 1205 Beal Ave, Ann Arbor, MI 48109

## **Appendix B - University Description**

### **University Overview**

The University of Michigan is a public research university located in Ann Arbor, Michigan. As the state's oldest university, it provides a distinctive combination of premier scholars, international reach and multidisciplinary achievement. Spanning over 600 acres and 500 buildings, the university manages one of the largest collegiate research budgets in the United States. The University of Michigan is comprised of thirteen undergraduate and eighteen graduate schools and colleges, including the College of Literature, Science, and the Arts, the Ross School of Business and of course the College of Engineering.

In particular, The University of Michigan College of Engineering is a one of the premier engineering schools in the United States, and a global leader in engineering education and research. The college was founded in 1854, with a focus on civil engineering, but has since been a frontrunner in establishing programs in fields including aeronautical engineering, computer science, materials science, and nuclear engineering. Some of its more current highlights include the development of the Robert H. Lurie Nanofabrication Facility, the establishment of the Center for Entrepreneurship, and the creation of the Michigan Memorial Phoenix Energy Institute.

### **Department Overview**

Within the College of Engineering lies the Industrial and Operations Department, created in 1956. The department holds an average enrollment of 500 undergraduate and 260 graduate students, with a faculty of approximately 30. The faculty are involved in a broad range of research projects that span engineering management, operations research, human factors and ergonomics, production and manufacturing systems, statistical decision-making, logistics, financial engineering and enterprise systems. Faculty and students work together to create new and relevant knowledge and extend the frontiers in these areas. Many of these activities are interdisciplinary and link with other highly rated departments and colleges at the University. All of this provides an intellectually stimulating and rewarding environment for faculty, staff and students.

Source: <http://ioe.engin.umich.edu>

## **Appendix C - Non-University Partners**

Daniel Citrenbaum  
Operations Research Analysis  
FAA  
800 Independence Ave. SW  
Portals Bldg., Attn: ASD-430  
Washington, DC 2059  
P: 202-385-7302  
[Daniel.Citrenbaum@faa.gov](mailto:Daniel.Citrenbaum@faa.gov)

## Appendix D - Design Submission Form

Note: This form should be included as Appendix D in the submitted PDF of the design package. The original with signatures must be sent along with the required print copy of the design.

### University of Michigan

List other partnering universities if appropriate\_\_\_\_\_

Design Developed by: ☐ Individual      Student ☒ Student Team

If Individual Student

Name \_\_\_\_\_

Permanent Mailing Address \_\_\_\_\_

Permanent Phone Number \_\_\_\_\_ Email \_\_\_\_\_

If Student Team:

Student Team Lead: **Prof. Amy Cohn**

Permanent Mailing Address: **Industrial & Operations Engineering, 1205 Beal Ave.,  
Ann Arbor, MI 48109**

Permanent Phone Number: **734-615-7258**

Email: **amycohn@umich.edu**

Competition Design Challenge Addressed:  
**Airport Management and Planning Design**

I certify that I served as the Faculty Advisor for the work presented in this Design submission and that the work was done by the student participant(s).

Signed \_\_\_\_\_

Date \_\_\_\_\_

Name: **Amy Cohn**

University/College: **University of Michigan**

Department(s): **Industrial & Operations Engineering**

Street Address: **1205 Beal Ave.**

City: **Ann Arbor**

State: **MI**

Zip Code: **48109**

Telephone: **734-764-6473**

Fax: **734-764-3451**

## **Appendix E - Evaluation of Educational Experience**

### **Student Evaluation**

1. Did the FAA Design Competition provide a meaningful learning experience for you? Why or why not?

The FAA design competition provided a very meaningful experience for us. In most of our classes we are presented with questions that require specific answers. For the competition we had to figure out what the problem was that we wanted to solve before even trying to figure out how to approach solving it. This gave us great insight into real world scenarios where the problem is not specifically defined and it is not known immediately how to interpret the results.

2. What challenges did you and/or your team encounter in undertaking the Competition? How did you overcome them?

One of the major problems that we ran into was the difficulty of realistically modeling the problem. Also when we did model the problem, it was hard to draw meaningful conclusions from the results. We overcame these problems by adjusting the modeling approach and by finding valuable information in the results.

3. Describe the process you or your team used for developing your hypothesis.

We began our research with the motivation to explore tarmac delay in light of the new DOT ruling that is going into effect. We then simply modeled a small, 2 plane 1 gate system to gain an overall understanding of how the logistics of the system work. We then expanded this model to work with any number of planes and any number of gates.

4. Was participation by industry in the project appropriate, meaningful and useful? Why or why not?

We spoke with quite a few experts in the airlines industry and gained great insight as to how the industry works and as to how good the assumptions that we were making were. They also gave us ideas as to how we should present the project so that it would be more meaningful for the industry.

5. What did you learn? Did this project help you with skills and knowledge you need to be successful for entry in the workforce or to pursue further study? Why or why not?

We learned a lot about the airlines industry, how research is done, how to write technical papers and how to pull a big project like this together as a team. All of these are great tools to have in the workforce as well as pursue further studies. We feel that all in all this was a very beneficial experience for us and has prepared us well for future projects in industry and academia.

## **Faculty Evaluation**

1. Describe the value of the educational experience for your student(s) participating in this Competition submission.

The students did excellent work – I am amazed by how much they were able to accomplish in less than a semester! In particular, they made great strides in so many areas: Learning about the airline industry, learning how to tackle open-ended problems, learning to develop sophisticated mathematical models of complex systems well outside the range of a classroom experience. They also had to work together as a team, sometimes collaborating but sometimes dividing-and-conquering the work, and had to pull together a lengthy technical document in a very short time frame.

2. Was the learning experience appropriate to the course level or context in which the competition was undertaken?

All of the undergraduates on the project were juniors who had taken my course in mathematical programming techniques the previous semester, so the timing was ideal – they had enough experience and academic maturity to make excellent progress on the project, but still have another year at the university in which to pursue further research, develop more skills, and use what they've learned in deciding whether to enter the work force or stay on for graduate studies.

3. What challenges did the students face and overcome?

A key challenge was figuring out which assumptions were okay to make and which weren't. Recognizing and accepting the fact that the system can't be modeled perfectly is a difficult adjustment. The students also had substantial time pressures to overcome and needed to work very efficiently to meet all their deadlines. Finally, the mathematical modeling was a level above what they had experienced in class and really forced them to take their understanding to a higher level.

4. Would you use this Competition as an educational vehicle in the future? Why or why not?

Definitely! This is a great opportunity for students to gain many new skills and it is easy to attract students to work on a topic that so many find quite fascinating.

5. Are there changes to the Competition that you would suggest for future years?

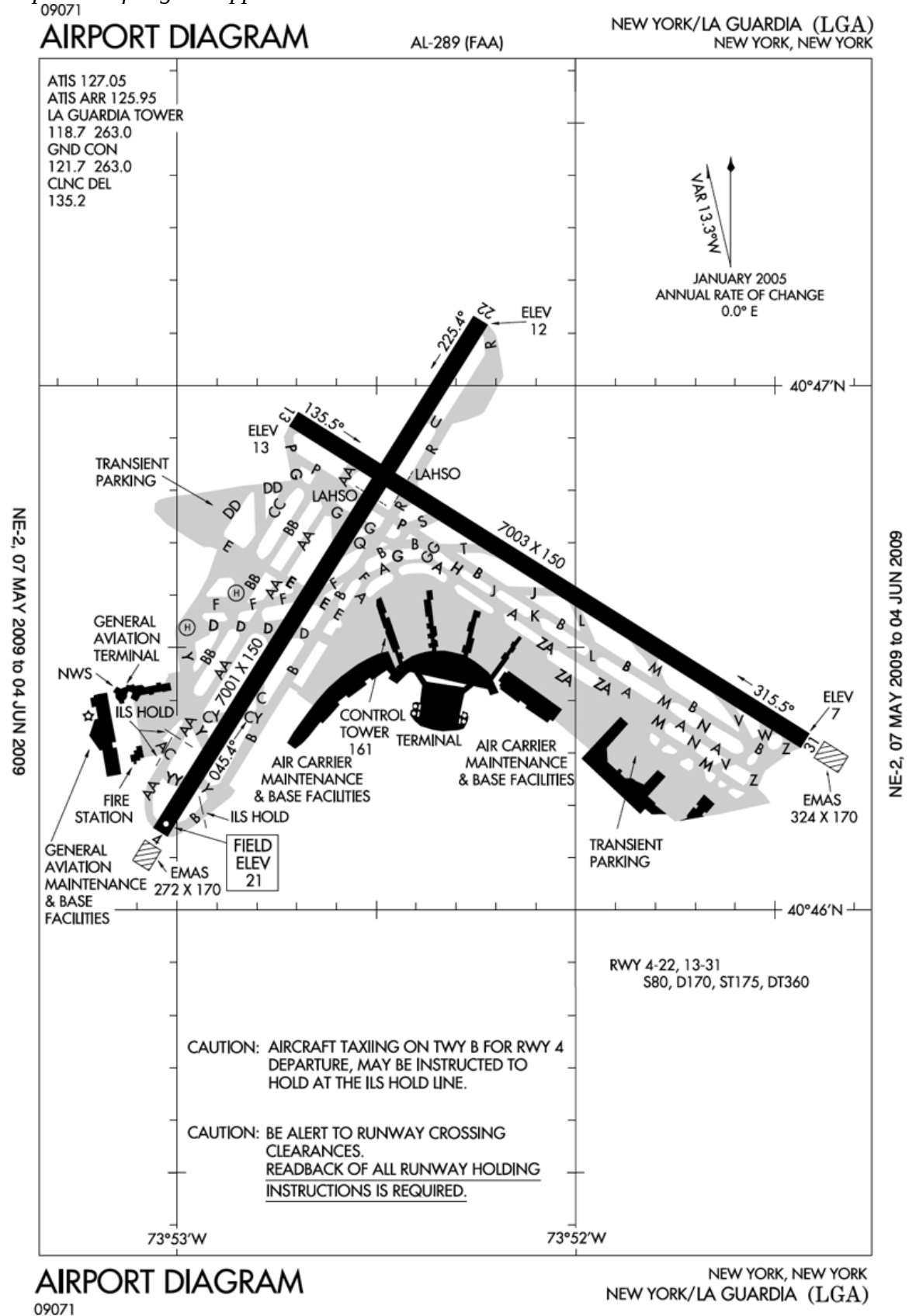
We have always started in January and would benefit from starting in September. In doing so, we'd probably be better able to take advantage of FAA mentoring. Having access to FAA controllers at DTW, our local airport, would be of particular benefit, I think.

## Appendix F - References

- Airport capacity benchmark report 2001.* (n.d.). Retrieved from [http://www.faa.gov/about/office\\_org/headquarters\\_offices/ato/publications/bench/download.htm](http://www.faa.gov/about/office_org/headquarters_offices/ato/publications/bench/download.htm)
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- Kontoyiannakis, K. Serrano, E. Tse, K. Lapp, M. Cohn, A. A Simulation Framework to Evaluate Airport Gate Allocation Policies Under Extreme Delay Conditions. Winter Simulation Conference.

## Appendix G - Layout of LaGuardia Airport

<http://naco.faa.gov/d-tpp/1004/00289AD.PDF>



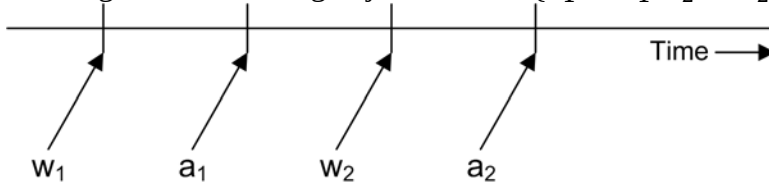
## Appendix H - Proof of FIFO

The following is a proof by contradiction to show that the first-in, first-out gate assignment policy minimizes the maximum inbound tarmac delay. We use the following notation:

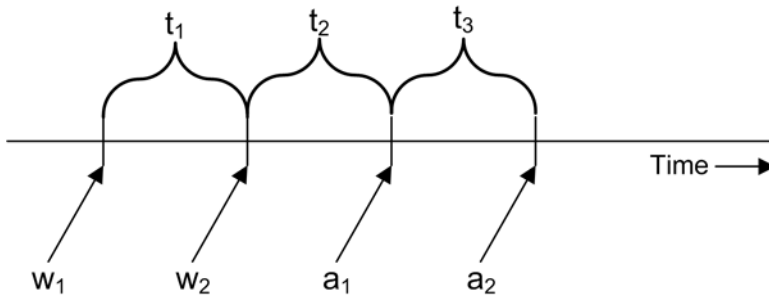
$a_i$  Indicates the time of the availability of a gate

$w_i$  Indicates the time of the arrival of an aircraft (wheels down time)

**Case 1:** In one case, aircraft arrive in between gate availability. As seen in the diagram below, it is trivially true that each aircraft should be assigned to the first available gate resulting in the following objective:  $\max\{a_1 - w_1, a_2 - w_2\}$



**Case 2:** In the case where aircraft and gate available are interspersed, as seen in the diagram below, we can still show that FIFO is the optimal allocation policy.

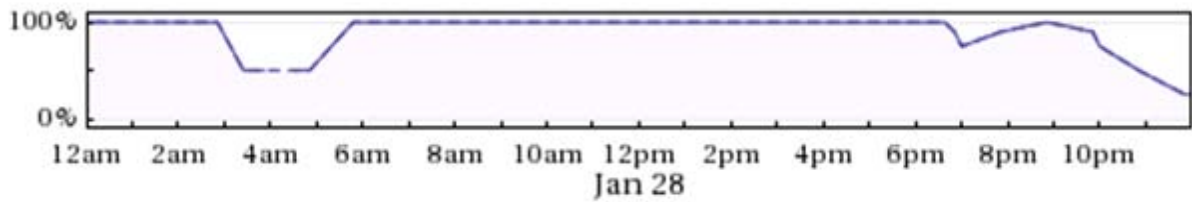


We can show this through the following contradiction. The maximum tarmac delay is minimized if we use the FIFO assignment policy.

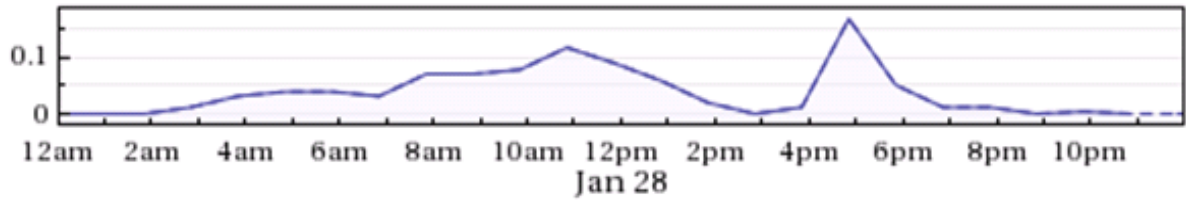
**Proof:** Assume that the maximum tarmac delay is minimized by not using FIFO. We can write objective as:  $\max\{a_1 - w_2, a_2 - w_1\}$ . We can rewrite this in terms of  $w_1$  and  $t_i$  as follows:  $\max\{t_1, t_1 + t_2 + t_3\} = t_1 + t_2 + t_3$ . Using FIFO, our objective becomes  $\max\{a_1 - w_1, a_2 - w_2\} = \max\{t_1 + t_2, t_2 + t_3\}$ . In either case, the objective is clearly smaller using FIFO proving our assumption to be false. Therefore it must be the case that FIFO indeed minimizes the maximum tarmac delay.

## Appendix I - Historical Weather Data

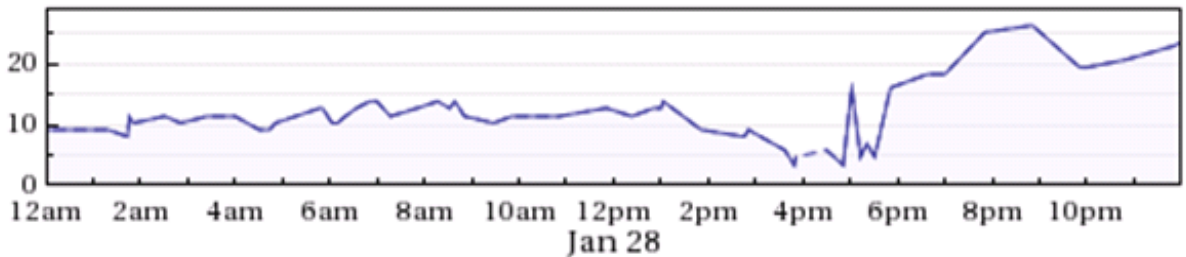
Cloud Cover (Jan 28)



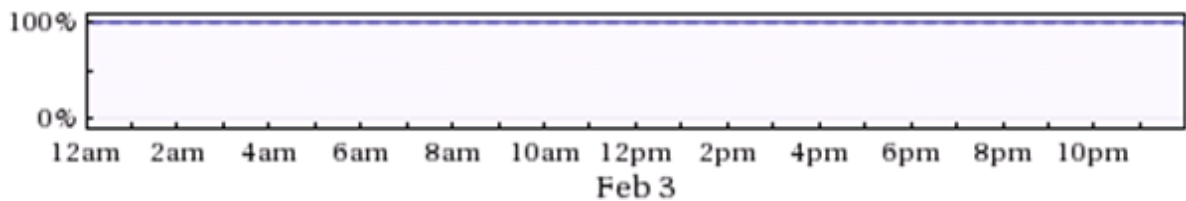
Precipitation rate (in/h) (Jan 28)



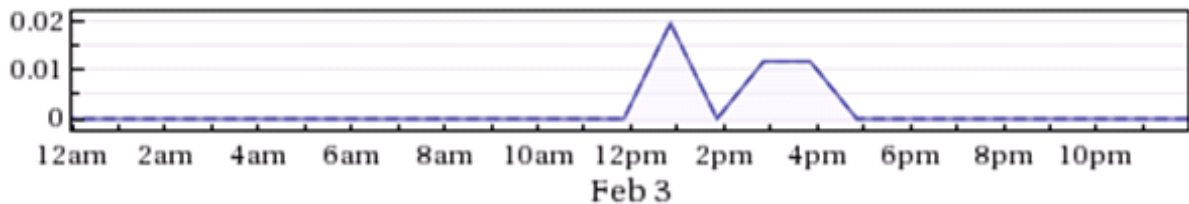
Wind Speed (mph) (Jan 28)



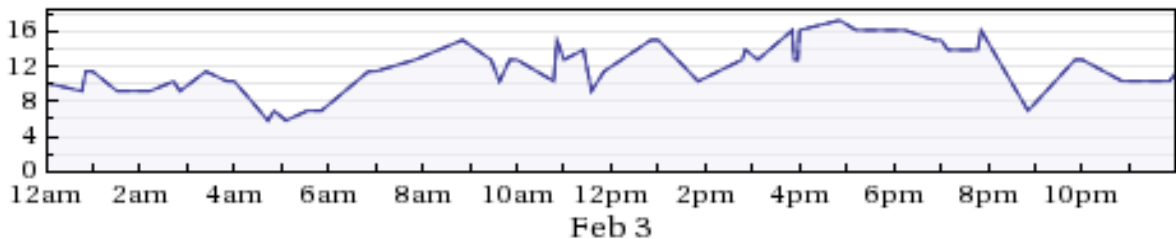
Cloud Cover (Feb 3)



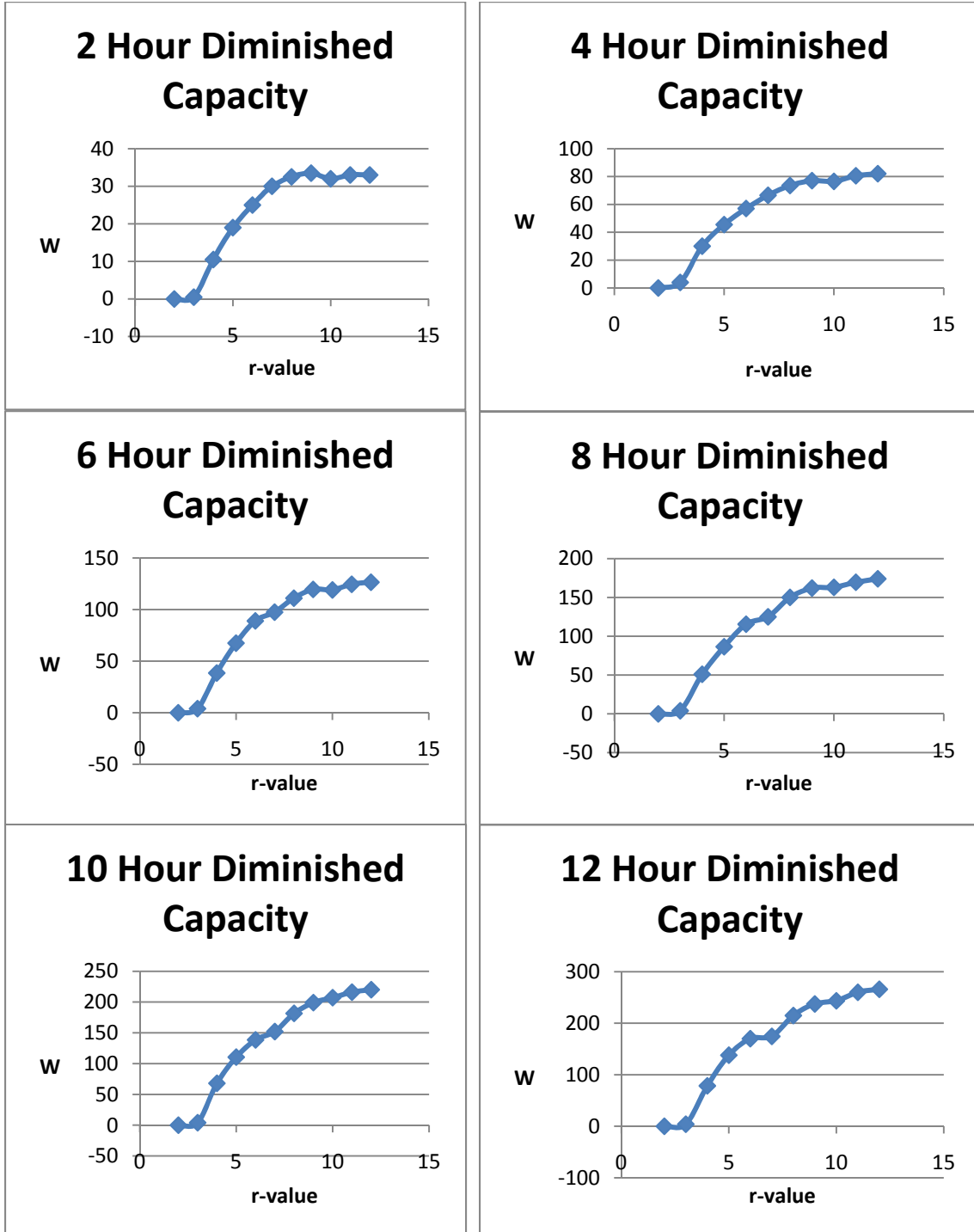
Precipitation rate (in/h) (Feb 3)



Wind Speed (mph) (Feb 3)



## Appendix J – Constant Duration Time Graphs



## Appendix K – Constant $r$ Value Graphs

