

**MODELING PASSENGER REACCOMMODATION TIME
FOR FLIGHT CANCELLATIONS IN AIRLINE NETWORKS**

JUNE 30, 2010

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Modeling Passenger Re-Accommodation Time for Flight Cancellations in Airline Networks

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ABSTRACT

This paper presents the Passenger Displacement Model (“PDM”), an algorithm that estimates the impact of flight cancellations on passengers across a specific network, either generically modeled or fed by real-world airline schedule data for a given airport. This methodology incorporates factors relevant to passenger re-accommodation¹, including the length of time flights are disrupted, airline flight frequencies and schedules, system and route load factors, and the number of passengers who choose to cancel or postpone travel in lieu of immediate rebooking or are rebooked on another airline.

The main conclusion of this paper is that cancellations create significantly more harm to passengers than delays. In addition, we draw three other conclusions. First, prior research based on historical data from years with lower load factors significantly underestimates the passenger inconvenience from cancellations because there are fewer seats available today to re-accommodate passengers on cancelled flights. With summer peak load factors now running 85% or higher, passengers on cancelled flights may wait days for an available seat. For passengers traveling on leisure, with pre-paid hotel rooms or cruises, this may spell disaster for holiday plans.

Second, the time of day that a cancellation event occurs directly correlates to the time required to re-accommodate passengers. Summertime thunderstorms are often an afternoon phenomenon, making rebooking on that same day a challenge. Prior research assumed a 15-hour limit on re-booking time, and this is overly optimistic in today’s load factor environment.

Third, airlines have focused on completing flights (and avoiding cancellations) with the objective of transporting as many passengers as possible to their final destinations, even if that means taking long flight delays. Airlines have therefore focused on “waiting out” weather systems, either at the gate or on the tarmac, with departure as soon as possible when weather or airspace clears. With new limits on tarmac time, airlines have fewer options, likely driving a significant increase in both cancellation rates and passenger trip disruption.²

INTRODUCTION

Every day, certificated airlines carry over 1.7 million passengers within the domestic United States on more than 27,250 scheduled flights. Inclement weather, airspace congestion, resource availability, security, and other factors drove the cancellation of approximately 330 flights daily in 2009, or 1.4% of passenger flights overall.³

Until 1978, airlines were required under the Civil Aeronautics Board Rule 240 to offer passengers on cancelled flights the first available seat on either that airline’s own flight, or on the

¹ Passenger re-accommodation is defined as the time required to transport the customer on an alternative flight itinerary to that passenger’s destination.

² Evidence of flights cancelled due to revisions to 14 CFR Part 259.4 effective April 29, 2010 are numerous, including Delta Air Lines flight 155 on May 8, 2010. The Business Travel Coalition projected the net increase in flight cancellations in the New York area to be 10-15% due to the tarmac delay rules (March 15, 2010).

³ US Department of Transportation, T-100 Data. 618.4 million passengers and 9.96 million revenue flights in 2009. Annual cancellations were 1.87 percent in 2005, 1.71 percent in 2006, 2.16 percent in 2007, 1.96 percent in 2008 and 1.39 percent in 2009.

first available flight of a competing airline. After deregulation in 1978, while most airlines retained this practice, it was no longer a federal requirement. To reduce cost over the past 30 years most airlines have eliminated Part 240 commitments, preferring in the event of cancellations either to transport passengers on their own networks or to issue travel refunds in cash or travel credits (See Table 1). For cancellations within a carrier’s control, including mechanical breakdown of the aircraft, some “legacy” airlines continue to offer re-booking on alternative carriers, but only upon request by the passenger. Other legacy airlines, and most low-fare carriers, do not offer passengers the option of a seat on a competing airline even if requested by the passenger.⁴

Table 1: Contract of Carriage Obligations to Rebook Customers on Cancelled Flights
Source: Airline Contracts of Carriage effective June 28, 2010

<i>Airline Contract of Carriage</i>	<i>Refund Provided Upon Request for Cancelled Flight</i>	<i>Alternative Carrier for Uncontrollable Factors (e.g. weather)</i>	<i>Alternative Carrier for Controllable Factors (e.g. repairs)</i>
United	Yes	Yes	Yes
Delta	Yes	No	Yes
Continental	Yes	No	Yes
JetBlue	Yes	No	No
American ⁵	Yes	No	No
AirTran	Yes	No	No
Southwest	Yes	No	No

There is limited statistical data to explain what percentage of flight cancellations (versus delays) are due to controllable factors for each airline. However, weather-related cancellations account for between 44% and 50% of flight delays each year.⁶ Cancellations peak during the winter months, when major snowstorms can impact large parts of the United States.⁷ With significant notice from weather forecasts, airlines minimize exposure by pre-cancelling flights. They position aircraft for recovery after the snow or rain event passes. As a result, the peak cancellation months are December, January and February (See Table 2).

During the summer, the time and severity of thunderstorm activity (both frontal and pop-up) cannot be accurately predicted days in advance. Unlike winter snowstorms, these summer weather patterns do not give airlines the luxury of planning ahead. Over the past six years, airlines have demonstrated a preference to delay flights during convective activity, although a significant number of flights still cancel during the summer months. Cancellations in June, July and August approximate the annual average. On average, months with relatively little snow or thunderstorm activity have the lowest average delay and cancellation rates.

⁴ See airconsumer.dot.gov/publications/flyrights.htm for more information. Specific Rule 240 language can be found in each airline’s Contract of Carriage.

⁵ American Airlines discontinued alternative carrier provisions during 2007.

⁶ Bureau of Transportation Statistics. During 2009 flight delays were driven by air carrier reasons (including mechanical repairs and crew availability) (28.0%), late arriving aircraft (36.2%), security delays (0.1%), national airspace delays (30.6%) and extreme (non-flyable) weather (5.0%). Of national airspace delays, 65.7% were due to weather events. Aggregating these figures, BTS estimates that weather accounts for between 44% and 50% of flight delays between 2003 and 2009.

⁷ A cancellation is defined by DOT as a cancelled flight that was scheduled to operate as of seven days before departure.

Table 2: 2004-2009 Flight Delays and Cancellations, Average By Month as Percent of Total Flights Scheduled

Source: DOT Bureau of Transportation Statistics
Weighted average calculation per month

<i>2004-2009</i>	<i>On-Time</i>	<i>Delayed</i>	<i>Cancelled</i>
January	78.13%	19.09%	2.78%
February	78.23%	19.24%	2.53%
March	79.05%	19.03%	1.93%
April	82.42%	16.21%	1.37%
May	82.54%	16.31%	1.15%
June	75.87%	22.31%	1.82%
July	76.49%	21.74%	1.77%
August	78.95%	19.41%	1.65%
September	84.97%	13.30%	1.73%
October	82.56%	16.18%	1.26%
November	83.59%	15.35%	1.07%
December	72.44%	24.68%	2.88%
Average	79.60%	18.57%	1.83%

Table 2 indicates that in the calm weather months of early spring and late fall (April, May, October and November), between the snow and thunderstorm seasons, the cancellation rate averages 1.21% over the period between 2004 and 2009. Similarly, during months with active snowstorms and thunderstorms (January, February, June, July and December) the cancellation rate averages 2.36%. Airlines schedules during these periods reflect similar levels of operation, and therefore the incidence of cancellations due to mechanical breakdown and other airline-controllable factors should be similar between periods as well.⁸ The variance in cancellations is weather-driven; between 45% and 50% of total cancellations can be attributed to weather.

In 2009, we estimate that about 11,500 daily passengers on average were stranded due to weather-related cancellations. Another 12,000 were stranded daily due to airline-controllable and non-weather factors.⁹ As Table 1 indicates, passengers on the significant majority of these flights had to wait for an open seat on their booked carrier – or simply requested a refund and sought alternate means of travel.

When flights cancel on short notice (both due to controllable and uncontrollable factors) the business and leisure travel plans of passengers are significantly disrupted. With advance notice, airlines can protect passengers on cancelled flights and notify passengers before they travel to the airport (or begin their trips). With limited advance notice (including flights that cancel at the gate, or cancel after taxi-out) airlines must scramble to protect passengers who are already en route at a connecting hub or trying to return home.

⁸ During the period from 2004 to 2009, the average flight departures scheduled for the months of January, February, June, July and December was 585,328 per month. For the months of April, May, October and November, the average was 584,069 per month, a 0.2% difference (Source: BTS). Mechanical failures on a systemwide basis can be tied to operating hours and cycles (i.e. departures).

⁹ Based on average passengers per departure in 2009 of 70.6; 121,360 total cancelled flights including reporting and non-reporting airlines, and 48% (1.21/2.36) of flights cancelled due to weather events. For more detail, see Table 4.

Estimating the impact of cancellations on passenger travel time has significant implications for network design and public policy. Short-notice cancellations that occur within 24 hours of departure are of particular concern, given that passenger flexibility may be limited by numerous factors, including passengers stranded away from home. Prior research has correlated passenger delays and flight delays during a specific calendar month using proprietary airline data, or reviewed systemic trends across years of operations to measure passenger impact on a large-scale perspective.

This paper presents the Passenger Displacement Model (“PDM”) to estimate the impact of flight cancellations on passengers across a specific network, either generically modeled or fed by real-world airline schedule data for a given airport. The PDM incorporates factors relevant to passenger re-accommodation, modeling how a weather or operational disruption of user-defined duration creates a flood of displaced passengers that must be re-accommodated in next available seats. The PDM is based on user-defined flight frequencies and schedules, system and route load factors, and assumptions about the number of passengers who choose to cancel or postpone travel in lieu of immediate rebooking.

The PDM is designed to model major operating disruptions where several flights are impacted at once. This is usually due to severe weather disruptions and other uncontrollable factors, rather than airline-controlled failures such as mechanical repairs or crew availability. The PDM therefore reflects the dominant airline policy of not permitting re-booking on other carriers, although the benefits from such rebooking are debatable during irregular operations that impact all carriers at a given airport.

This paper applies the PDM in two scenarios. In both scenarios, a two-hour operating disruption is assumed which causes the cancellation of flights within that window. Some passengers are assumed to request refunds in lieu of rebooking, while the majority must be accommodated in available seats on future flights on that carrier. Assuming that a significant number of passengers will request refunds also has the advantage of making PDM output more conservative.

First, a generic nine-node network is presented with between two and ten daily frequencies from the central hub to a set of short, medium and long-haul spoke cities. This generic network is based on a de-peaked scheduling model with relatively even distribution of flights through the day.¹⁰ While the PDM can accommodate any aircraft type, two aircraft types are modeled here, with larger aircraft assigned to routes with higher assumed demand.

The PDM predicts, based on this generic network design, the average time required to re-accommodate passengers who elect to continue their journeys. The PDM allows users to test the effect of operational disruptions that impact only a portion of overall flights during the event. This reflects real-world airline strategies of prioritizing lower-frequency, longer-haul flights during disruptions over more frequent, short-haul flights where alternative transportation (i.e. train service) may be available.

Second, this paper applies the PDM to a real-world flight operation. JetBlue Airways’ June 21, 2010 domestic flight schedule for New York John F. Kennedy (JFK) Airport provides the network frequencies and departure times for the model. The JetBlue schedule includes 125 daily domestic departures to 37 destinations from JFK, and the model reflects the actual assignments of JetBlue’s 150-seat Airbus A320 and 100-seat Embraer 190 aircraft to those

¹⁰ This is a significant assumption and is designed to test a pure-play de-peaked hub scheduling strategy. The second example provided later in this paper presents a more traditional network design oriented around local business and leisure demand.

flights.¹¹ As with the generic network design, the user can vary the length of the operational disruption, the types of flights impacted and variations in aircraft size for each route frequency.

Model outputs for both the generic and real-world application are similar. Faster passenger re-accommodation correlates primarily to aircraft size, daily frequencies and route load factor, and secondarily to the distribution of frequencies through the day, and the percentage of passengers who choose to receive a refund or postpone trips in lieu of rebooking. Low-frequency markets have the highest re-accommodation time, while short-haul markets with higher frequencies offer the most significant opportunities to rebook passengers quickly. Since JetBlue's network does not offer significant connecting opportunities through other key cities, passenger re-accommodation is assumed only on New York-originating flights.

BACKGROUND

Over the past ten years, changes in airline pricing, inventory management tools, and direct distribution have driven a significant increase in airline load factors, on a year-round basis as well as during both winter and summer months.¹²

Table 3: Changes in Airline Domestic Load Factors, with Min and Max Months

Source: U.S. Department of Transportation Bureau of Transportation Statistics

<i>Calendar Year</i>	<i>Domestic Load Factor</i>	<i>Operated Dom. Flights</i>	<i>Minimum Load Factor</i>	<i>Month of Minimum LF</i>	<i>Maximum Load Factor</i>	<i>Month of Maximum LF</i>
2000	71.22%	7,905,617	61.97%	January	78.60%	June
2001	69.15%	7,626,312	62.14%	January	75.72%	July
2002	70.37%	8,089,140	62.83%	January	75.66%	August
2003	72.68%	9,458,818	64.40%	January	80.98%	July
2004	74.46%	9,968,049	65.28%	January	82.20%	July
2005	77.16%	10,038,373	69.77%	January	83.94%	July
2006	79.11%	9,712,720	72.68%	January	84.95%	July
2007	79.74%	9,839,578	72.30%	January	86.24%	July
2008	79.74%	9,376,219	72.93%	January	84.24%	June
2009	81.05%	8,760,405	72.82%	January	87.09%	July

For the full calendar year 2001, airline load factors in the United States for domestic flights were 69.15%, increasing to 81.05% in 2009. There have been significant increases in load factors both during summer and winter months. July, which historically has the highest average domestic load factors, has increased from 75.72% in 2001 to 87.09% in 2009. Even January, when leisure traffic is light, has increased from 62.14% in 2001 to 72.82% in 2009. While the number of flights operated peaked in 2004 and 2005, the total flights operated in 2009 remained 14.9% higher than in 2001. During that same period from 2001 to 2009, total passengers carried increased 18.9%. More passengers are now chasing fewer seats, and airlines have fewer seats available at departure to accommodate displaced passengers.¹³

¹¹ Schedule data collected from KVS Availability Tool, June 21, 2010. Includes San Juan, PR.

¹² Load factor is traditionally defined in the industry on a unit basis, as the ratio of Revenue Passenger Miles over Available Seat Miles. The ratio of enplaned revenue passengers to available seats on a given flight or airline system is technically defined as Seat Factor, although commonly referred to as Load Factor. This paper follows common convention and uses Load Factor as a measure of filled seats on a given flight or route.

¹³ US Department of Transportation, BTS Transtats Web Site

Table 4: Cancelled Domestic Flights & Impacted Passengers

Source: U.S. Department of Transportation Bureau of Transportation Statistics

YEAR	<i>Flights by Reporting Airlines</i> ¹⁴	<i>Cancelled Flights by Reporting Airlines</i>	<i>% Flights Cancelled (Reporting Airlines)</i>	<i>Total Flights, All Airlines</i>	<i>Est, Total Flights Cancelled</i>	<i>Average Passengers per Flight</i> ¹⁵	<i>Estimated Passengers Impacted</i>
2004	7,129,270	127,757	1.79%	9,962,391	178,527	63.2	11,285,485
2005	7,140,595	133,730	1.87%	10,033,140	187,902	65.5	12,309,270
2006	7,141,922	121,934	1.71%	9,707,992	165,745	67.8	11,240,228
2007	7,455,458	160,809	2.16%	9,835,733	212,150	69.1	14,649,177
2008	7,009,726	137,432	1.96%	9,373,752	183,781	69.5	12,777,205
2009	6,450,285	89,377	1.39%	8,758,486	121,360	70.6	8,568,659

While flight cancellations in aggregate have decreased significantly, from 1.87% of flights scheduled in 2005 to 1.39% of flights scheduled in 2009, the increase in passenger load factor has increased misery for passengers on cancelled flights.¹⁶ Between 2005 and 2009, total domestic flights operated decreased from 10.0 million to 8.76 million, a decrease of 12.7%. During this same period, total passengers declined from 657.3 million to 618.4 million, a decrease of 5.9%. Average aircraft capacity per departure was consistent through the period.¹⁷ Available capacity on a systemwide basis therefore shrank faster than the number of passengers decreased. On a unit basis, load factor increased.

But with fewer available seats to transport displaced passengers, the time spent waiting for an open seat when a flight cancels has increased. The traveling public has demanded transparency from DOT and the airlines, and recent consumer protection initiatives by the industry and regulators have improved disclosure of cancellations, particularly for flights that are chronically impacted by weather, airspace capacity and airline-specific factors.¹⁸

Literature Review

There has been considerable work calculating the cost of airline delays. For example, Bratu and Barnhart (2006) and Kohl *et al.* (2007) provided substantial reviews of airline responses to irregular operations and scheduled disruptions. Other authors including Cramer and Irrgang (2007), Cook *et al.* (2004), Hansen *et al.* (2009), Cook *et al.* (2009), and Cook *et al.* (2009a) examine the cost of airline disruptions for airlines, airports and consumers.

In this paper, we focus narrowly on the cost of cancellations on passenger travel time. In contrast to prior work based on systemwide analysis, we do not estimate the monetary cost of passenger delay time. We solely focus on passenger time lost due to re-accommodation on alternative flights. With ongoing trends toward higher systemwide load factors, the need for such an algorithm to model generically the impact on passenger travel time has increased. Prior research has established the correlation between passenger trip time and airline cancellations, and

¹⁴ Includes AirTran, Alaska, American and American Eagle, Comair, Continental, Delta, Expressjet, Frontier, Hawaiian, JetBlue, Mesa, Northwest, Pinnacle, SkyWest, Southwest, US Airways and United.

¹⁵ For 2009, total 618.4 million passengers boarded 9.96 million flights. (DOT BTS T-100)

¹⁶ DOT BTS T-100 Database

¹⁷ Average seats per departure ranged from 122.5 in 2005 to 122.8 in 2009. Source: DOT BTS T-100 Database.

¹⁸ For revisions to tarmac delay limits, see 14 CFR 259.4, Contingency Plan for Lengthy Tarmac Delays. For Customer Service Plan see 14 CFR 259.5. For reporting and disclosure requirements see 14 CFR 244.3.

illustrated using data from 2000-2005 the systemwide trends towards longer passenger re-accommodation time.¹⁹

Airline-specific research conducted by Bratu and Barnhart (2005) based on August 2000 operating data provides a snapshot to establish passenger re-accommodation time for a specific network at a specific point in time, without control for the impact of load factor. The Bratu results are outdated due to material changes in several factors, including (1) material changes in airline policy of rebooking displaced passengers on other airlines, as only one major airline now offers the equivalent of Part 240 protection to consumers for both controllable and uncontrollable cancellation events, forcing passengers to wait for available seats on their booked carrier; and (2) a significant increase in overall passenger load factors, including a 9.5 percentage point increase in August load factors between 2000 and 2009.²⁰ Together, these changes drive a significant increase in the time passengers must wait for alternative routings on their booked carriers.

More recent work by Ball, Lovell, Mukherjee and Subramanian (2006) provides an analytical model and decision tree that estimates the impact of irregular operations on a large-scale, systemwide basis. Their methodology assumes a fixed passenger delay not reflective of real-world airline networks, scheduling and passenger rebooking strategies.

Wang and Sherry (2006) introduced a segment-based trend analysis that estimated passenger trip time based on national airspace data from 2004 and 2005. Wang's methodology correlated flight operations, cancellations and load factors based on systemwide data to estimate the increase in passenger travel time from cancellations. Wang's approach provides a useful methodology for retrospective analysis of large-scale national systems, but is based on historical data that does not align with today's environment. Since 2005, load factors are significantly higher (for both peak month and annual average), total flight departures have declined, and fewer airlines offer Part 240 provisions for passengers. Wang's approach is limited by upper-bound delay assumptions and limited capacity to model passenger re-accommodation delays extending for more than one day.

A new methodology is required with controls for systemwide and route load factors, lengthy operating delays and passenger preferences in requesting refunds in lieu of rebooked travel.

METHODOLOGY

The PDM can be driven both by hypothetical network models and real-world airline schedules. The PDM is driven by a set of user-defined controls to set the time of day that the cancellation event occurs, the percentage of passengers who choose to re-book travel or travel on alternative dates, carriers or modes of transportation, assumed route load factors, flight schedules and aircraft assignments. The PDM then models the time to re-accommodate passengers and outputs the average time by system-wide load factor.

User-controllable factors include:

- Time that the cancellation event starts
- Duration of the cancellation event

²⁰ In August 2000, the domestic systemwide load factor was 75.5%. In August 2009, the domestic systemwide load factor was 84.97%, an increase of 9.47 percentage points.

- Types of flight operations impacted (all flights, only short-haul flights, medium-haul or long-haul operations)
- Percentage of passengers who choose to receive refund (thereby traveling by other means, including other airline, rail, bus or car) or postpone trip in lieu of being rebooked on next available flight
- Assumed average increase in travel time for passengers that cannot be re-accommodated on next available flights by end of the third day after disruption
- Flight schedules, including destinations, distance of flight, departure times, and capacity

The process flow for the model is below. After the user inputs cancellation parameters, including the mix of short, medium and long-haul flights to be cancelled, the model calculates passenger re-accommodation time based on next-seat availability for the given flight schedule.

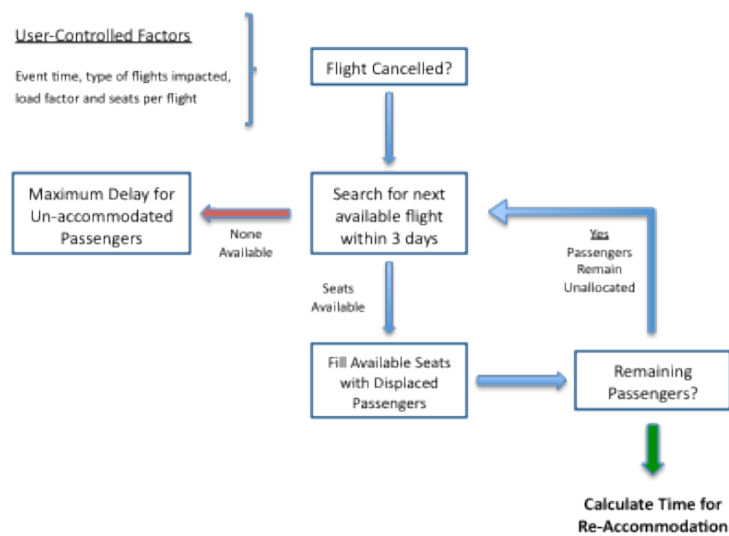


Chart 1: PDM Logic Flow

The formula for calculating total displacement time for all passengers during the event is based on the following variables that are defined as PDM controls.

Passenger-Related Variables

- P_b = Booked passengers
- P_a = Reaccommodated Passengers
- P_o = Passengers unable to be re-accommodated
- P_p = Passengers who elect refund or postponed
- n = Number of cancelled flights

System-Related Variables

- D_o = Original (cancelled) departure time
- D_n = Dep. time of available seat for passenger
- T_d = Displacement Time (Total)
- T_a = Average Displacement per Passenger
- D_m = Delay time for unaccom. pax

The methodology is then:

$$P_a = P_b - P_p - P_o$$
$$T_d = \sum_1^n \left(\sum_1^{P_a} (D_n - D_o) \right) + P_o * D_m$$
$$T_a = \frac{T_d}{(P_b - P_p)}$$

The algorithm can be summarized as follows:

1. Operating assumptions are input for the flight schedule, equipment assignments and seating capacity, event start time and duration, and categories of flights (short, medium and long-haul) impacted by the event. In real-world applications airlines may express a preference to protect long-haul or lower-frequency operations at the cost of short-haul operations.²¹
2. Passenger assumptions are input for the percentage of passengers who choose to receive voluntary refunds or postpone trips beyond three days, and for the assumed delay for passengers who (1) are unable to be accommodated on the cancelling airline's subsequent flights and (2) must be transported on other airlines or travel by road, train or other modes.
3. The model calculates which flights are impacted and the passenger loads on each flight. Subtracting those passengers who elect for immediate postponement or refund, the model calculates the number of passenger who will require re-protection on subsequent flights after the end of the disruption.
4. The model calculates, based on route load factor inputs, the available seats on each subsequent flight. All available seats on subsequent flights are utilized for stranded passengers. The model continues to assign stranded passengers to available seats until the earlier of (a) all remaining stranded passengers are accommodated or (b) the end of the second full day after the disruption.
5. The model assumes that:
 - a. *Forward load visibility.* The cancelling airline will have visibility into forward load factors on a given route and will issue available inventory to stranded passengers soon after the cancellation occurs.
 - b. *Flights after the disruption operate as scheduled.* There are no roll-on or subsequent delays after the disruption that impact passenger travel time.
 - c. *No further sale of seats is permitted until all displaced passengers are accommodated.* The airline will block available inventory exclusively for the use of stranded passengers.

²¹ In addition to prior academic work to demonstrate the advantages of long-haul flight protection (Hoffman, Ball and Mukherjee, 2007) we have conducted interviews with SOC personnel at major and low-fare airlines. Since long-haul flights usually operate at lower frequency than short-haul operations, focusing resources on long-haul departures best accommodates those passengers while allowing short-haul passengers to re-book on future flights, or seek alternate means of transportation including car, bus or rail.

- d. *Passengers who cannot be accommodated within two full days will immediately be offered alternatives.* The airline is assumed to identify those passengers who cannot be accommodated due to loads, and will offer those passengers transportation by alternative means. A fixed delay time is input for passengers in this category.
6. The model calculates the time difference for each displaced passenger between the departure time of the new flight and the departure time of the cancelled flight. No delay time is assumed for passengers who elect for refund or trip postponement beyond three days.
7. The model repeats these calculations for different system-wide load factors to determine the relationship between load factor and passenger re-accommodation time for the given network design.

MODEL OUTPUTS

Two scenarios are analyzed using the PDM algorithm. The first scenario involves a simple nine-spoke network with short-, medium- and long-haul flights in the United States. The hypothetical airline operates between two and seven daily flights on each route. This is reflective of a medium-sized focus city with flights to key business and leisure destinations. The second scenario involves the JetBlue Airways flight schedule (publicly available through online scheduling tools such as KVS Availability) and planned aircraft assignment for domestic departures from New York JFK during the week of June 21, 2010. This is reflective of a major hub operation.

Scenario 1: Nine-Spoke Network

The following flight schedule (Table 5) is input into the model, with even distributions of frequencies in each market between the first and last flights each day. Since the time between departures impacts average passenger delay time, this is a user-controllable field.

The model uses an operational disruption that starts at 2:00pm on the first day and lasts for two hours. During this operational disruption, some or all of the flights operated are assumed to cancel based on user input.

Ten percent of passengers on cancelled flights are assumed to request refunds, postpone their trips or travel by alternate modes (train, bus, etc.). The contracts of carriage for each airline allow passengers to request a refund if the carrier cancels the flight. In most cases, the refund is made in cash (versus a credit for future travel) allowing the passenger to seek other means of transportation to his destination. Business passengers on short trips may elect to cancel and refund, as cancellations may prevent attendance at time-specific events. Leisure passengers connecting onto cruises or otherwise attending time-specific events may also choose to cancel and refund. In aggregate, the model defaults to 10% of passengers requesting refunds in lieu of travel. If the refund percentage is higher, fewer passengers remain to be re-accommodated, reducing the average time increase per passenger.

Table 5: Assumed Flight Schedule for Nine-Spoke Network from New York

<i>Destination from Hub</i>	<i>Daily Frequencies</i>	<i>Distance (mi)</i>	<i>Length of Haul</i>	<i>First Departure</i>	<i>Last Departure</i>
Los Angeles	4	2475	Long-Haul	6:00	20:00
San Francisco	4	2586	Long	7:00	21:00
Seattle	2	2421	Long	10:00	18:00
Dallas	3	1391	Medium	10:30	20:00
Miami	7	1089	Medium	6:30	21:30
Denver	3	1626	Medium	8:00	16:00
Chicago	7	740	Medium	6:30	20:30
Washington	7	213	Short	7:00	20:00
Boston	7	187	Short	7:00	20:00

Base Case Delay. If all flights are assumed to cancel within the 2pm-4pm impact window, the model computes that passenger re-accommodation time will range between 7.5 hours (at a 50% system load factor) to 28 hours (at a 95% system load factor).

Table 6: Base Case (Nine-Node) Average Delay Time by Load Factor 2pm-4pm Disruption

<i>System Load Factor</i>	<i>Average Pax Delay (Hours)</i>	<i>Average Pax Delay (Minutes)</i>	<i>Percent of Passengers Accommodated</i>	<i>Percent of Passengers not Accommodated</i>
50%	7.5	451	100%	0%
55%	7.9	474	100%	0%
60%	8.6	517	100%	0%
65%	9.2	552	100%	0%
70%	10.1	607	100%	0%
75%	12.4	745	100%	0%
80%	15.5	929	100%	0%
85%	18.6	1,119	96%	4%
90%	22.1	1,329	88%	12%
95%	28.4	1,706	68%	32%

At load factors of 85% and higher, some passengers will not be re-accommodated within two full days of the operational disruption. The maximum delay of 24 hours is assumed for those passengers.

Varying Time of Operational Event. Based on this assumed network design, varying the time of the operational disruption has a varying impact on passenger displacement time. At the operational disruption occurs later in the day, accommodation that day becomes challenging, and more passengers must wait until the second or third day to travel. At 2009 average load factors of

81%, disruptions in the morning are better for passengers, because more opportunities exist later in the day to re-accommodate. But the ability for airlines to re-accommodate later in the day is highly dependent on that airline's flight schedule.

Table 7: Varying Event Times for Base Case
Passenger Delay Time, Average (hours)

<i>Load Factor</i>	<i>Average Time (hrs)</i>	<i>8a-10a</i>	<i>10a-12p</i>	<i>12p-2p</i>	<i>2p-4p</i>	<i>4p-6p</i>	<i>6p-8p</i>
50%	5.7	3.7	4.1	2.7	7.5	7.9	8.5
55%	6.3	4.2	4.8	3.2	7.9	8.6	9.1
60%	7.3	5.1	6.2	4.1	8.6	9.8	10.2
65%	8.2	5.8	7.4	4.9	9.2	10.9	11.1
70%	9.2	6.7	8.6	5.7	10.1	12.0	12.1
75%	11.1	8.5	10.6	6.9	12.4	14.3	14.0
80%	13.8	11.0	13.5	9.3	15.5	17.4	16.3
85%	17.4	14.5	18.5	13.7	18.6	20.4	18.4
90%	21.6	20.0	22.9	18.9	22.1	23.6	22.0
95%	28.3	27.9	28.4	29.5	28.4	27.9	27.7

Varying Distribution of Flights. The PDM calculates passenger disruption based on the elapsed time between the original (cancelled) departure time and the departure time of the flight to which the passenger is ultimately assigned. If more frequencies exist through the day, passenger rebooking time declines as more seats are available. The following chart shows average passenger rebooking time (in hours) based on two factors: system load factor and the distribution of frequencies through the day. For this chart, flights are assumed to begin at 7am and end at 9pm each day. At a four-hour average time between frequencies (i.e. average 3.5 frequencies per spoke per day) the passenger rebooking time ranges from 3.5 hours (for a 50% load factor) to 29.0 hours (for 95% loads). As frequencies are added, the time until the next available flight decreases, and passenger rebooking times for all system load factors decline.

If frequencies are not evenly grouped through the day, rebooking time is dependent upon (1) the time of day at which the cancellation event occurs and (2) the relative number of morning and afternoon flights operated. If the disruption occurs prior to a batch of available flights, rebooking time will be lower. If the disruption occurs after the majority of flights, the passenger will be forced to wait for long periods until re-booking can occur.

Table 8: Passenger Delay Time by Load Factor (hours) based on Average Time Between Frequencies for 9-Node Network
Frequency distribution normalized

<i>Passenger Load Factor</i>	<i>Average Hours between Frequencies for 9 Node Network</i>			
	<i>4.0</i>	<i>3.5</i>	<i>3.0</i>	<i>2.5</i>
50%	3.5	3.5	3.1	2.5
55%	3.8	3.8	3.3	2.7
60%	4.4	4.4	3.8	3.1
65%	4.9	4.9	4.3	3.5
70%	5.8	5.8	5.1	4.0
75%	8.3	8.3	7.6	5.2
80%	11.0	11.0	10.2	7.5
85%	14.7	14.7	13.6	11.0
90%	21.5	21.4	19.2	16.1
95%	29.0	29.0	29.2	29.9

Conclusions for Generic Network Design. For a generic system, therefore, the model suggests the following:

- That the passenger delay projection of Wang and Sherry (2006) from system-wide, annual data sources are similar but lower than the PDM suggests for 2010 system loads and current operating practice.
 - o Wang and Sherry estimate an average passenger trip delay of 519 minutes (8.6 hours vs. 11.1 from PDM output) at a 74% system load factor and a delay of 549 minutes (9.15 hours vs. 13.8 hours) at a 78% load factor. As a systemwide analysis, the Wang data set contained an average of 7.7 daily flights per route, higher than the single-airline network assumed in the model.
 - o Wang’s algorithm is based on systemwide data and total frequencies on a given route, regardless of operating airline. The Wang conclusions are based on a “Part 240” environment where displaced passengers are booked on the first available seat, regardless of operating carrier. As noted in Table 1, only one major airline provides inter-carrier transfers during weather-related events. The available pool of seats to rebook passengers is therefore not a function of systemwide capacity, as assumed in Wang, but rather only the booking carrier’s pool of seats.
- The model illustrates why stranded passengers are an acute problem for airlines and airports during the busy summer travel season. With summer load factors at 85% or higher, there are few (if any) seats available to transport stranded passengers. Given that a blended 85% load factor reflects a mix of routes with higher and lower loads – and many departures operating at 100% loads – passengers face few, if any, reasonable options for reaching their destinations on a timely basis.

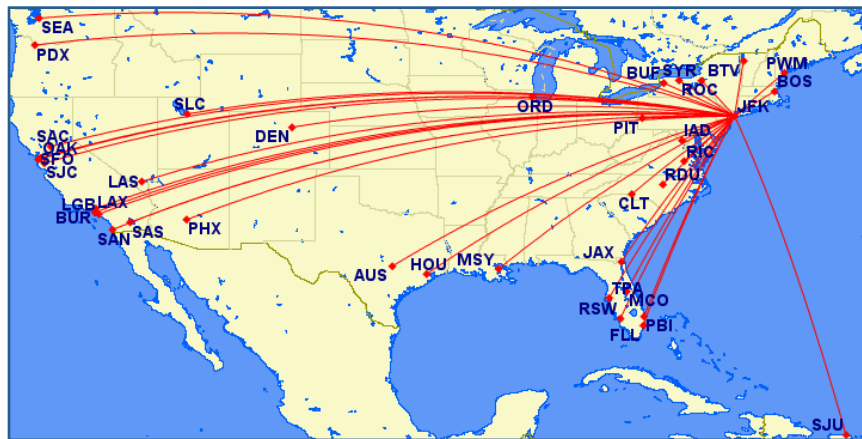
Scenario 2: JetBlue Domestic Summer Schedule at JFK

The model is now run for a real-world airline operation that reflects an actual flight and equipment schedule. The model is programmed with JetBlue's flight schedule (domestic flights during the week of June 21, 2010) for New York JFK.

The JetBlue flight schedule reflects a real-world assignment of flight departure times based on passenger demand, airport and crew availability, scheduled rotations, and airport capacity. The Summer 2010 JetBlue flight schedule contains 125 daily departures to 37 spoke cities. Of those spoke markets, 10 markets are short-haul flights less than 500 miles, 15 are medium-haul less than 2,000 miles, and 12 are long-haul flights greater than 2,000 miles. All flights are operated with a mix of 150-seat Airbus A320 aircraft and 100-seat Embraer 190 aircraft. Long-haul flights are exclusively operated by the A320, while short- and medium-haul markets have one or both aircraft types assigned.

Chart 2: Modeled Flights in JetBlue JFK Network

Map from gcmmap.com



The same operational assumptions are made for the JetBlue network as the standard “base” case. Ten percent of passengers are assumed to request refunds or postpone travel when cancelled; the assumed increase in travel time for passengers who cannot be re-accommodated within two full days is 24 hours.

JetBlue operates a flight schedule oriented towards leisure traffic. Some markets operate with as many as ten daily frequencies, but the majority of markets have three or fewer daily departures. As a result, average passenger re-accommodation times for the JetBlue network are higher than the base-case scenario above, where frequencies are assumed to have even distribution through the day. JetBlue's flight schedule at JFK must necessarily adapt to the busy evening bank of international flights that congest the facility between 3pm and 8pm. Flights that cancel in the early afternoon therefore displace passengers into the late evening or the next day.

Not surprisingly, morning cancellations can be absorbed faster than afternoon or evening events by the JetBlue network, unless load factors are high thus restricting available seats. The base case (9-node hypothetical network) and JetBlue perform similarly for morning disruptions. Evening disruptions, however, create significant disruption, particularly for long-haul flights where re-accommodation may take 24 hours or greater.

Table 9: JetBlue JFK Average Delay Time by Load Factor
June 21, 2010 Flight Schedule, 2pm-4pm Disruption

<i>System Load Factor</i>	<i>Average Pax Delay (Hours)</i>	<i>Average Pax Delay (Minutes)</i>	<i>Percent of Passengers Accommodated</i>	<i>Percent of Passengers not Accommodated</i>
50%	8.9	532.6	100%	0%
55%	9.9	592.8	100%	0%
60%	11.5	689.6	100%	0%
65%	12.9	774.4	100%	0%
70%	14.7	883.1	100%	0%
75%	16.9	1,011.9	98%	2%
80%	19.7	1,180.7	96%	4%
85%	23.3	1,395.9	90%	10%
90%	26.9	1,615.7	78%	22%
95%	27.2	1,634.2	46%	54%

Table 10: Cancellation Window in Morning, Afternoon and Evening
Base Case (9-Node Network) versus JetBlue JFK (June 21, 2010) Domestic

<i>Assumed Load Factor</i>	<i>Morning Base Case</i>	<i>Morning JetBlue JFK</i>	<i>Afternoon Base Case</i>	<i>Afternoon JetBlue JFK</i>	<i>Evening Base Case</i>	<i>Evening JetBlue</i>
50%	4.1	4.4	7.5	8.9	5.5	10.9
55%	4.8	5.1	7.9	9.9	6.4	11.6
60%	6.2	6.4	8.6	11.5	8.0	12.8
65%	7.4	7.5	9.2	12.9	9.4	13.8
70%	8.6	8.8	10.1	14.7	10.8	14.8
75%	10.6	10.9	12.4	16.9	13.0	16.1
80%	13.5	14.1	15.5	19.7	15.5	18.3
85%	18.5	18.7	18.6	23.3	17.3	20.8
90%	22.9	22.7	22.1	26.9	19.8	23.8
95%	28.4	27.8	28.4	27.2	28.2	24.6

The model therefore suggests the following:

- That in real-world networks, cancellations in the afternoon or early evening during the summer – when load factors are already high – have a significant impact on passenger travel time. The model suggests that average re-accommodation time may exceed 18 hours during the summer, and be greater than 24 hours on average at peak load factors.
- In high load factor environments, delaying flights is significantly preferable both for the passenger and for the airline operation. A flight that ultimately arrives at the destination saves on-board passengers a full day or more of travel time. Historically, airlines would have freed gate resources during extended disruptions by loading passengers, departing the gate and waiting on the tarmac for weather or airspace constraints to clear. With a fixed cap on tarmac delays effective April 2010, airlines no longer can “push and hold” for two or more hours as they would have before. Cancellations are more likely.

CONCLUSIONS

The Passenger Displacement Model provides insight into the time required to accommodate passengers from cancelled flights on available frequencies to a destination, controlling for network design, frequency distribution, assigned equipment, and other airline operations factors. The PDM illustrates the exponential relationship between system and route load factor and the time required to re-accommodate passengers. The PDM also demonstrates the correlation between frequency distribution, departure time and passenger preferences and the time required to re-book.

There are three key conclusions from this model, both using a hypothetical nine-node network (the “Base Case”) and a real-world flight schedule for JetBlue Airways at JFK.

1. Prior research based on years with lower load factors significantly underestimates the passenger inconvenience from cancellations. Most airlines today do not transfer passengers on cancelled flights to other airlines, so only seats on the booking carrier can be used to absorb cancelled passengers. The number of seats available has declined since the last studies were compiled, measured both in aggregate based on system load factors and on a per-departure basis. Load factors have risen dramatically. With summer peak load factors now running 85%, passengers on cancelled flights may wait days for an available seat. For passengers traveling on leisure, with pre-paid hotel rooms or cruises, this may spell disaster for holiday plans.
2. The time of day that a cancellation event occurs has direct correlation to the time required to re-accommodate passengers. Summertime thunderstorms are often an afternoon phenomenon, making rebooking on that same day a challenge. Prior research that assumed a 15-hour limit on re-booking time is overly optimistic given today’s load factor environment.
3. Given the objective of transporting as many passengers as possible to their final destinations, airlines have taken a historical interest in “waiting out” weather systems on the tarmac, with departure as soon as possible when weather or airspace clears. With new limits on tarmac time, airlines have fewer options and cancellation rates are likely to increase.

There is a significant opportunity for further research in these areas. Topics for further analysis could include estimating the dollar cost to passengers of delays of cancellations based on average projected re-booking time, and reviewing the impact of tarmac delay rules on flight cancellations and passengers during peak and off-peak months.

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