

**ENHANCING AIRLINE HANDLING OF LARGE SCALE FLIGHT CANCELTION
EVENTS THROUGH PRE-EMPTIVE REBOOKING**

Sanja Avramovic, Ph.D.

Lance Sherry, Ph.D., lsherry@gmu.edu, 703-993-1711

Center for Air Transportation Systems Research

George Mason University

4400 University Drive MS 4A6

Fairfax, VA 22030

Corresponding Author:

Lance Sherry, lsherry@gmu.edu, 703-993-1711

Permanent Address:

Center for Air Transportation Systems Research

George Mason University

Engineering Building Room 4507

4400 University Drive, Fairfax, VA, 22030

ENHANCING AIRLINE HANDLING OF LARGE SCALE FLIGHT CANCELATION EVENTS THROUGH PRE-EMPTIVE REBOOKING

Abstract

Although, on average, only 2.1% of airline flights are cancelled each year, some of these flight cancellations occur in batches due to events that impact airline network operations such as snow storms, equipment outages, and labor issues. Batch flight cancellations impact a large number of passengers at the same time in the same location and have a negative effect on airline revenue (due to refund obligations), corporate profits (due to unbudgeted costs of employee travel), and overall traveler experience.

Due to technological limitations and air traffic control procedures airlines are obliged to deal with these cancellation events in a reactive manner. The flight cancellation is announced at the last minute and passengers are rebooked after the scheduled flight departure time. Advances in meteorological forecasting, air traffic control procedures for irregular operations (e.g. Collaborative Decision Making), and the ubiquity of inexpensive and reliable broadband communication services for communication between airlines and passengers, have changed the landscape. It is now possible for airlines to migrate to a pro-active approach whereby the cancellation event would be announced in advance and passengers would have the option to re-book *before* the large scale cancellation event (i.e. pre-emptive rebooking).

If an airline were to adopt this pre-emptive approach: (1) could the available seat capacity accommodate the passengers, and (2) would this approach be economically beneficial to the airlines and the passengers?

This paper describes a method for Monte Carlo simulation of passenger re-booking using historic flight schedules, load factors, and passenger itineraries to assess the feasibility and economic benefits. Case-studies of 13 large flight cancellation events for a major U.S. network carrier were analyzed. The results indicate that pre-emptive rebooking is feasible. More than 70% of the passengers choosing to rebook pre-emptively can be accommodated. Further, pre-emptive rebooking is economically beneficial, yielding savings for airlines, and corporate employers of travelers. The implications of these results for airlines, corporations, and travelers are discussed.

Keywords

Airline reliability, Passenger itinerary delays, Passenger disruption, Pre-emptive rebooking

1. INTRODUCTION

On average 2.1% of the flights for a large U.S. network carrier are cancelled. Although this is a relatively low number, these flight cancellations can occur in batches at the same time and same location due to weather (e.g. snow storm, labor action, equipment issues). For example in 2012, the large U.S. network carrier experienced large scale flight cancellation events in which more than 20 flights were cancelled at the same location, on 21 days (Figure 1). These flight cancellation events impacted an estimated total of 60,669 passengers, and required the airlines to refund an estimated \$297K per cancellation event in airfare refunds (see Section 4), and cost corporations sponsoring employee travel an estimated \$49K in unbudgeted travel expenses per event (see Section 4). Out of the 21 days which had more than 20 cancelled flights, 13 of those were one-day cancellation events (i.e. not spread-out over two days or more).

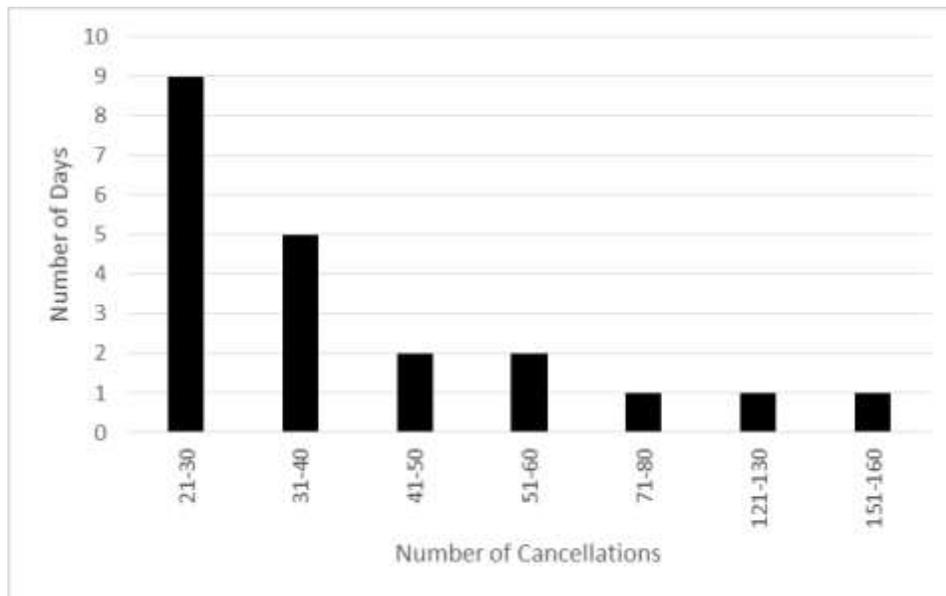


FIGURE 1: Histogram of number of days in which a hub for a U.S. network carrier experienced 20 or more cancelled flights in 2012.

Although many of these large scale cancellation events can be forecasted (i.e. snow storms, labor issues, and equipment outages), uncertainty in Air Traffic Control (ATC) and in the flight operations of competing airline in response to these events, obliges airlines to *reactively* announce flight cancellations close to the scheduled departure time and then rebook passengers *after* the cancellation event.

However, significant procedural changes in air traffic control such as Collaborative Decision Making (Wambsganns, 2001) in which airlines share operational information and coordinate use of limited resources (e.g. departure slots), enable airlines to take advantage of improved forecasting and announce flight cancellations in advance without losing airport arrival and departure slots to competing airlines. In addition, the rapid advances in technology that enable ubiquitous broadband wireless communication between the airlines and passengers, provides a mechanism for passengers to evaluate their options and choose whether to rebook in advance, after, or simply cancel, and if they do choose to rebook, which flight to choose. This allows passengers to make decisions that are best for them.

Previous research describes methods for addressing the general class of airline irregular operations including: robust flight scheduling (Clarke, 1998; Bratu, Barnhart, 2006; AhmadBeygi, Cohn, Guan, Belobaba, 2008; Chiraphadhanakul, Barnhart 2013), and aircraft assignment during irregular operations (Eggenberg, Salani, Bierlaire, 2010; Jafari, Zegordi, 2011). The effects of passenger rebooking have been analyzed by Yan et.al. (submitted 2015). Pre-emptive passenger rebooking for a possible missed connection for a single delayed flight was discussed in McCarty (2012).

This paper describes a method for the analysis of the feasibility and benefits to airlines and passengers of pre-emptive rebooking of passengers scheduled to fly to, from, or through a hub

airport in advance of forecast large scale flight cancellation event. A Monte Carlo simulation of passenger itinerary rebooking based on historic flight and passenger data is described. A case study of the concept-of-operations for a U.S. network carrier operating a Midwest hub showed that the concept is feasible and economically beneficial:

- the pre-emptive rebooking concept-of-operations is feasible for any given combination of passengers seeking pre-emptive rebooking by accommodating more than 70% of the passengers.
- Rebooking earlier on the same day is sufficient to accommodate passengers. Previous day rebooking is not required as it did not change the percentage of passengers rebooked pre-emptively (i.e. less than 7%).
- Airlines can recoup up to an average of \$297K per one-day cancellation event in airfare refund obligations. Corporations can collectively save approximately up to an average of \$49K per one-day cancellation event in unexpected (i.e. unbudgeted) travel costs.

This paper is organized as follows: Section 2 describes the Pre-emptive Rebooking concept-of-operations. Section 3 describes the method of analysis. Section 4 describes the results of case-studies for 13 one day cancellation events for a large U.S. network carrier. Section 5 discusses the implications of these results.

2 PRE-EMPTIVE REBOOKING CONCEPT-OF-OPERATIONS

In response to irregular operations (e.g. snow storms, labor actions, equipment shortage or outages, or construction) the traditional concept-of-operations is for the airline to wait until a few hours before departure time to cancel the flight. Cancelling as late as possible keeps the airlines' options open and provides the means to maximize airline revenue and/or minimize costs. This

modus-operandi is in place largely due to the combination of the first-come/first-served rules used by Air Traffic Control (ATC) for airspace operations, the uncertainty in the occurrence of the cancellation events, the uncertainty in competitors' response to the events with regards to flight operations, and the absence of collaboration between stakeholders in allocating available airspace and runway resources. The options for re-accommodating passengers is also limited as passengers could not be reliably contacted in a quick and affordable manner.

As a consequence of the late flight cancellation announcement, passengers are then rebooked *after* their ticketed flight departure time resulting in missed travel objectives (e.g. wedding, sporting event, business meeting). Passengers that cannot be rebooked on flights on the same day overflow into rebooked flights on the next day and even the next-next day (see Figure 2).

Under this concept-of-operations, airlines stand to lose revenue due to refund obligations. Corporations sponsoring employee travel must absorb non-billable expenses in unplanned and unbudgeted expenses.

Several factors that have emerged over the last decade provide an opportunity to change the paradigm and facilitate a more cost effective and passenger friendly response to these flight cancellation events. First, Collaborative Decision-Making (CDM) has changed the way flight operations in the National Airspace System (NAS) are managed from a reactive to a pro-active *modus-operandi*. Capacity shortfalls at airports or airspace are forecast and identified in advance. Available slots are allocated in advance allowing airlines to coordinate aircraft and crew assignment, and plan for delays and cancellations.

Second, interactive airline reservation systems and broadband/wireless communication enable airlines to contact and coordinate changes in reservations with passengers in a reliable, fast, and low-cost manner.

As a consequence, passengers can be rebooked *pre-emptively*, in advance of a large scale flight cancellation event (i.e. earlier on the day of the cancelled flight or on the previous day). Passengers that cannot be accommodated are still have to be rebooked on the next day (see Figure 2). In this way passengers can make decisions consistent with their travel objectives, airline’s refund obligations are reduced, and corporations’ experience less unplanned travel expenses.

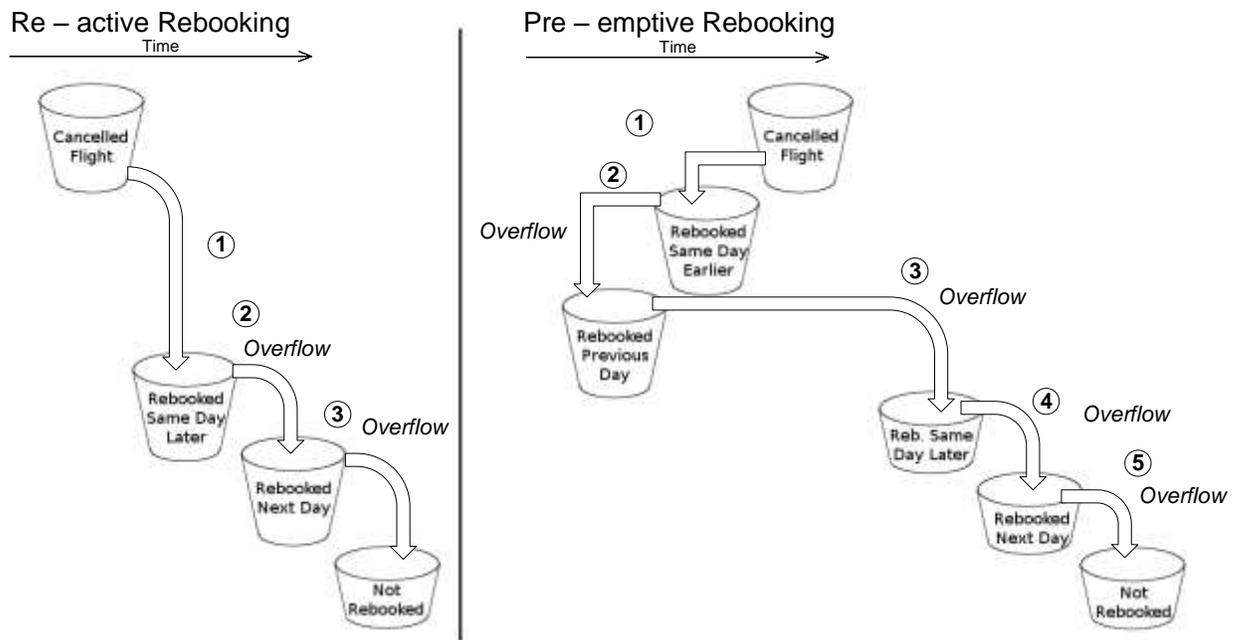


Figure 2: Sequence of passengers rebooking: reactive rebooking (left), pre-emptive rebooking (right).

At the time of writing this paper, although airlines routinely allow no-fee pre-emptive rebooking for multi-day flight cancellations events for snow storms. This paper evaluates the feasibility and benefits of no-fee pre-emptive rebooking for one-day flight cancellation events.

The questions are: (1) is pre-emptive no-fee rebooking with passenger flight options feasible given an airlines flight schedule and seat availability? and (2) is it economically beneficial for airlines and passengers?

3. METHOD OF ANALYSIS

To analyze the feasibility and economics of pre-emptive rebooking strategies the Passenger Itinerary Delay Algorithm (PIDA) (Sherry et al, 2010) is embedded in a Monte Carlo Simulation. The PIDA, Monte Carlo Simulation, and the Metrics are described in this section.

3.1 *Passenger Itinerary Delay Algorithm (PIDA)*

The PIDA is used to generate statistics for trip delays for each ticketed passenger itinerary (Sherry, 2011). The PIDA algorithm takes as an input individual passenger itineraries (i.e. origin, destination, connection, scheduled departure and arrival time). These itineraries are reverse engineered from publicly available data (Sherry, 2011). The itineraries are processed using actual performance of the flights associated with the itinerary. As is standard industry practice, flights that arrive within 15 minutes of their scheduled arrival time are considered on-time. If the flight is delayed more than 15 minutes, the PIDA assigns the delay to each passenger. If a flight is cancelled, or a passenger experiences a missed connection, the PIDA rebooks the passengers on alternate flights and calculates trip delays based on when the passengers arrives at their destination.

The PIDA rebooks passengers according to a set of rules that take into account airline policies, subsidiary airlines, and re-accommodation contracts with other airlines. Under standard rebooking rules, passengers are rebooked on the first available flight *after* the original cancelled scheduled departure time. If there is no available flight with available seats between the

cancelled flight and the end of the day, then the passenger is rebooked on the first available flight the next day (see Figure 3). The PIDA does not take into account frequent flyer status and ticket class in the order of the rebooking the passengers. The order does no effect the aggregate results.

For the purpose of pre-emptive rebooking, the PIDA rebooking algorithm rebooks in advance of the cancelled flight (Figure 4). For example, after a 11:36 a.m. cancellation, flights with available seats are used from 11:36 a.m. working back to 6 a.m. (i.e. start of day). If there are no itineraries or available seats, the passenger will be rebooked on the previous day (starting from the last flight of the day working back to the start of the day). If there are no itineraries or available seats on the previous day, the passenger will be rebooked on the first available flight after the original (cancelled) scheduled departure time (same day or next day), as with the traditional rebooking method.

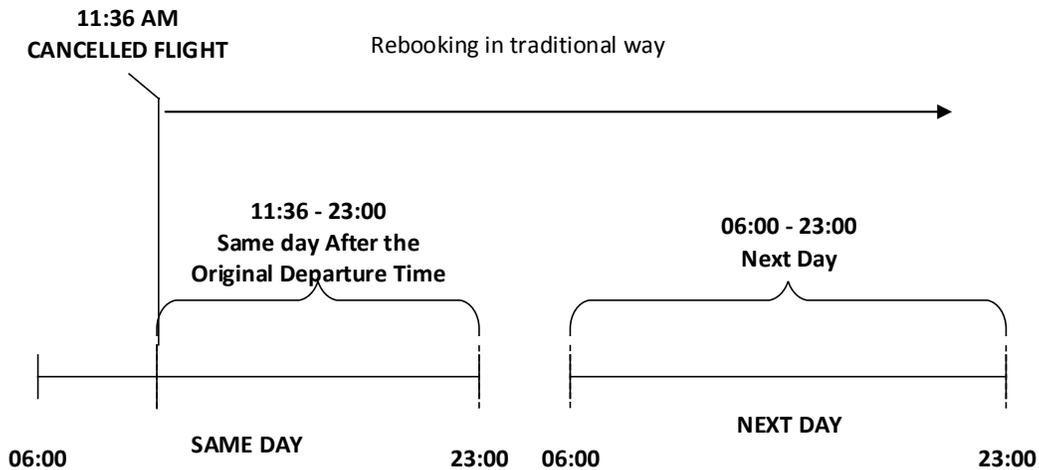


Figure 3 Traditional rebooking. Passenger is rebooked on the same day after the cancelled flight or the next day.

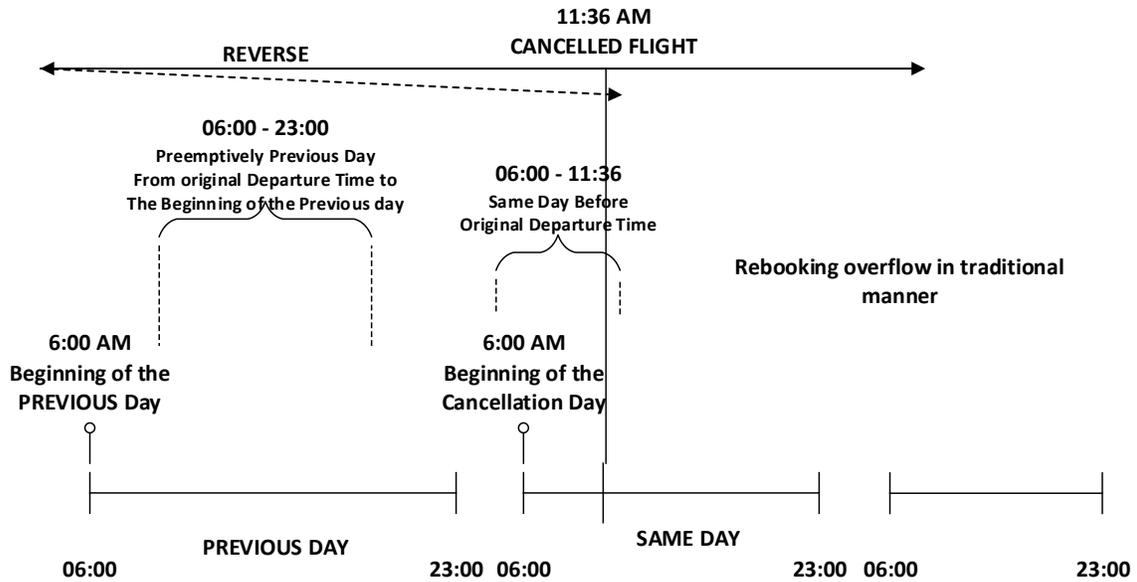


Figure 4 Preemptive rebooking. Passenger is rebooked prior to the cancelled flight if possible, otherwise after the flight.

3.2 Metrics for Evaluating Pre-emptive Rebooking

The metric for evaluating the feasibility of pre-emptive rebooking is: Percentage of Passengers Accommodated (PPA) by rebooking.

The metrics for evaluating the economic benefits of pre-emptive rebooking for airlines are: Airfare Not Refunded (ANR) and Percentage of Airfare Not Refunded (%ANR). The metrics for evaluating the economic benefits of pre-emptive rebooking for passengers and their employers are: Corporate Travel Expense Savings (CTES) and Percentage of Corporate Travel Expense Savings (%CTES)

Percentage of Passengers Accommodated (PPA) is the percentage of passengers that chose to rebook pre-emptively and could be accommodated given the airline schedule and the availability of seats.

Airfare Not Refunded (ANR) is the difference in Airfare refunded by the airline without pre-emptive rebooking and with pre-emptive rebooking.

$$ANR = AR_{base} - AR$$

Where:

$$AR_{base} = (PAX_{RebNDBase} + PAX_{RemBase}) \cdot \$377$$

$$AR = (PAX_{RebND} + PAX_{Rem}) \cdot \$377$$

$PAX_{RebNDBase}$: Number of passengers rebooked next day, with no pre-emptive rebooking.

PAX_{RebND} : Number of passengers rebooked next day with pre-emptive rebooking.

$PAX_{RemBase}$: Number of unbooked passengers remaining, with no pre-emptive rebooking.

PAX_{Rem} : Number of unbooked passengers remaining for pre-emptive rebooking.

AR_{base} : Airfare refund for the baseline case (i.e. without pre-emptive rebooking)

AR : Airfare refund for the case for the % of passengers that choose pre-emptive rebooking

\$377 is the average U.S. domestic airfare for this time period (Bureau of Transportation Statistics, 2015).

Percentage of Airfare Not Refunded (%ANR) is calculated as follows.

$$\%ANR = 100\% \cdot ANR / AR_{base}$$

For the purpose of modeling the change in %ANR with regards to the %PSPR a linear regression model can be estimated as follows.

$$\%ANR = (m_{ANR} * \%PSPR) + b_{ANR}$$

where:

$\%PAX_{Rebooked}$: the percentage rate at which passengers accept a preemptive rebooking offer.

m_{ANR} : the slope of the line relating the rate of the % of passengers choosing preemptive rebooking to the ANR value.

b_{ANR} : the y-intercept of the line relating the rate of the % of passengers choosing preemptive rebooking to the ANR value, thus $b_{ANR} = 0$.

Corporate Travel Expense Savings (CTES) is the additional travel expenses accrued by corporate travelers that are required to overnight due to rebooking the next day (Sherry, 2014). The additional costs for overnight stays is estimated at \$250 (\$160 for hotel accommodation and \$90 for food and transportation expenses) per government per-diem rates (U.S. GSA, 2012). It is assumed that 50% of the passengers are not at their hometown airport and would require overnight hotel accommodation (Li, Baik, Trani, 2010). Further 50% of these passengers are estimated to travel on corporate expense accounts (DoT, 2015).

$$CTES = CTE_{Base} - CTE$$

Where:

$$CTE_{Base} = \$250 \cdot (PAX_{RebNDBase} + PAX_{RemBase} + PAX_{RebPDBase}) \cdot 0.5 \cdot 0.5$$

$$CTE = \$250 \cdot (PAX_{RebND} + PAX_{Rem} + PAX_{RebPD}) \cdot 0.5 \cdot 0.5$$

$PAX_{RebPDBase}$: Number of passengers rebooked Previous Day, with no pre-emptive rebooking.

PAX_{RebPD} : Number of passengers rebooked Previous Day, using the % of passengers that choose of pre-emptive rebooking.

Percentage of Corporate Travel Expense Savings (%CTES) is calculated as follows.

$$\%CTES = 100\% \cdot CTES / CTE_{Base}$$

For the purpose of modeling the change in %CTES with regards to the %PSPR a linear regression model can be estimated as follows:

$$\% CTES = (m_{CTES} * \%PSPR) + b_{CTES}$$

where:

m_{CTES} : the slope of the line relating the rate of preemptive acceptance to the *CTES* value.

b_{CTES} : the y-intercept of the line relating the rate of preemptive acceptance to the *CTES* value, thus $b_{CTES} = 0$.

3.3 Monte Carlo Simulation

To achieve the objectives of the analysis, inputs to the PIDA are modified over multiple runs of a Monte Carlo simulation. The passengers that choose to participate in the pre-emptive rebooking are chosen randomly using a uniform distribution (i.e. on each run of the Monte Carlo simulation, each passenger has equal likelihood of choosing to participate in pre-emptive rebooking). The random selection of passengers is one way of accounting for groups of passengers (e.g. families, corporate teams) and preferential treatment due to seating class (business class, and frequent flyer miles).

To achieve a 95% confidence interval in the results of the Monte Carlo simulation it is required to be executed 25 repetitions for each replication. The number of repetitions was determined by a review of the standard deviation from 500 repetitions for a randomly selected day and verified by simulation for 5 randomly selected days. There were diminishing returns beyond 25 repetitions.

The Monte Carlo simulation is run for 10 treatments defined by the combination of:

1. Percentage of passengers that choose to participate in pre-emptive rebooking from 0% (baseline) to 10%, 30%, 50% and 70%.

2. The time in advance that the pre-emptive rebooking option is made available to passengers (i.e. Same Day Before the scheduled departure time of the cancelled flight, or Previous Day and Same Day Earlier Before the scheduled departure time of the cancelled flight).

4. CASE-STUDY RESULTS AND DISCUSSION

A case-study was conducted for the scheduled domestic flights for a major U.S. network carrier operating from a Midwest hub for all one-day cancellation events in 2012. There were a total of 21 days with more than 20 cancelled flights in that year, out of which 13 days were one-day cancellation events (Table 1).

Table 1 Days and Number of Cancelled Flights per day for One Day Cancellation Events for a Network Carrier in 2012

Month	Day	Number of Cancelled Flights	Arrival Flights Cancelled	Departure Flights Cancelled
1	12	56	31	26
1	20	77	33	44
1	23	38	23	15
2	23	28	11	17
5	6	26	8	18
5	29	30	15	15
6	22	28	12	16
6	29	22	10	12
7	13	34	16	18
7	15	25	12	13
7	18	37	14	23
11	7	37	31	24
12	20	37	20	17

In 2012 at the Midwest hub the airline experienced 4 days with between 20 and 30 flight cancellations. There were 5 days with 30 and 40 cancelled flight, 4 days with between 40 and 60 cancelled flights, and 2 days with more than 100 cancelled flights.

For these one-day cancellation events, the average load factor on *all* flights was 83% with a minimum of 25% and maximum of 100%. The average load factor on the cancelled flights was 80% with a minimum of 32% and maximum of 97%.

The metrics for pre-emptive rebooking for these 13 one-day cancellation events were calculated from the Monte Carlo simulation are shown in Figures 5 – 10 and summarized in Tables 2 and 3. The treatments are: (1) Pre-emptive rebooking on the Same Day, Before the Scheduled Departure Time of the Cancelled Flight for randomly selected passengers that choose the pre-emptive rebooking option 10%, 30%, 50%, 70%, and (2) Pre-emptive rebooking on the Same Day, Before the Scheduled Departure Time of the Cancelled Flight and the Previous Day for randomly selected passengers that choose the pre-emptive rebooking option 10%, 30%, 50%, 70%.

The results for the pre-emptive rebooking on the same day before the scheduled flight, and the results for previous day plus the same day before the scheduled flight are described in the next two sections.

4.1 Pre-emptive Rebooking Same Day Before

The results of the Monte Carlo simulation of randomly selected passengers choosing to take advantage of pre-emptive rebooking (PSPR) for cancelled flights on the same day before the scheduled departure of the cancelled flight are shown in Figure 5, 6 and 7. Each figure shows percentage of passengers that choose pre-emptive rebooking: 0% (baseline) 10%, 30% 50% and 70% of the passengers.

Feasibility of Pre-emptive Rebooking

For each percentage of passengers choosing the pre-emptive option (%PSPR), on average 70% of the passengers can be accommodated (PPA) for each of the 13 one-day cancellation

events are shown in Figure 5. The average slope of PPA as a function of PSPR (m_μ) is 70% with a slope standard deviation (m_σ) of 6.6% (see Table 2). The ratio of average slope to standard deviation (m_μ/m_σ) indicates the consistent behavior across all the 13 one-day cancellation events.

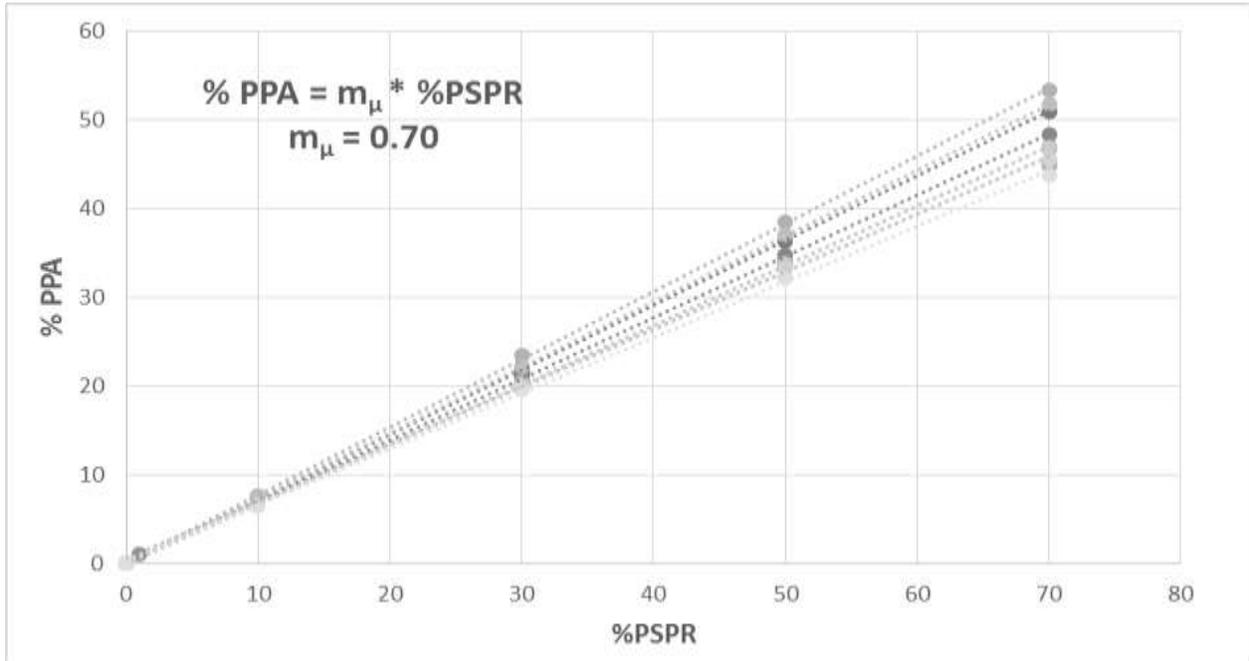


Figure 5: Percentage of Passenger Accomodated (%PPA) for each level of randomly selected passengers opting for pre-meptive rebooking (%PSPR).

Economic Benefits

The Airfare Not Refunded (ANR) by the airlines, and the Corporate Travel Expense Savings (CTES) not paid by traveler’s employers for each of the 13 one-day cancellation events are shown in Figure 6. As the percentage of passengers choosing to take advantage of pre-emptive rebooking (%PSPR) increases, the ANR and CTES increase linearly.

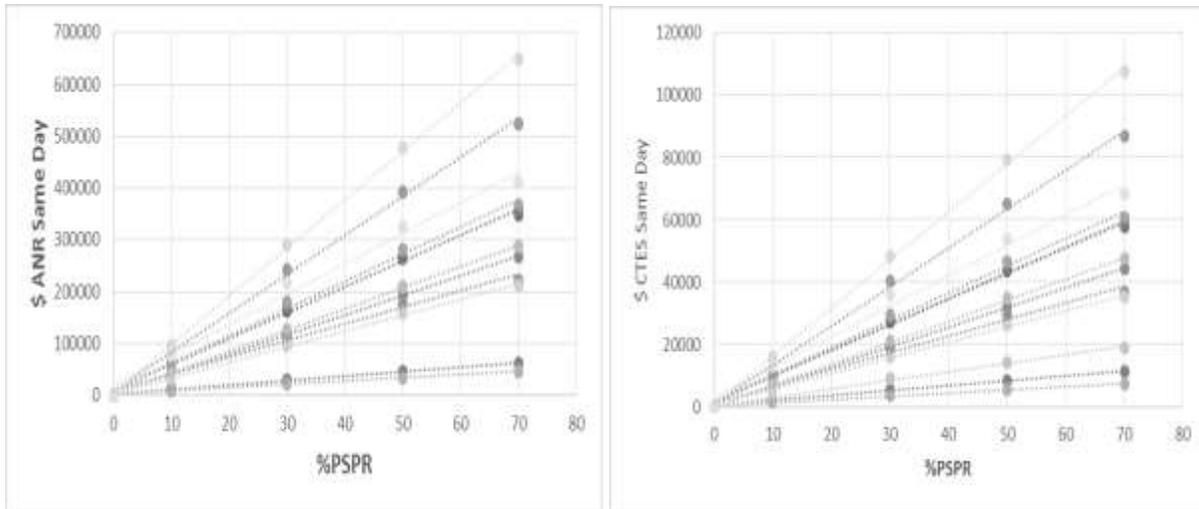


Figure 6: Airfare Not Refunded (ANR) and Corporate Travel Expense Savings (CTES) increase linearly with the percentage of passengers choosing pre-emptive rebooking (%PSPR)

The percentage of Airfare Not Refunded (%ANR) and percentage of Corporate Travel Expense Savings (%CTES) for each of the 13 one-day cancellation events are shown in Figure 7. %ANR and %CTES increase linearly with the percentage of passengers seeing pre-emptive rebooking.

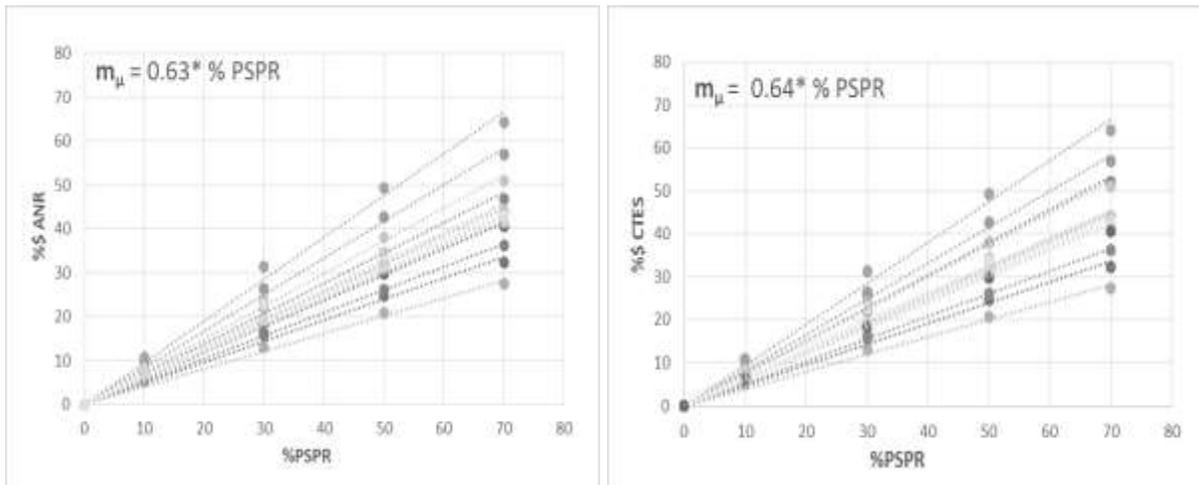


Figure 7: Same day Pre-emptively Rebooked passengers: % savings in ANR, % savings in CTES, as a function of the percentage of passengers seeking rebooking (PPSR) for 13 one day cancellation events.

The average slope of %ANR as function of %PSPR (m_μ) is 63% with a slope standard deviation (m_σ) of 14%. The ratio of average slope to standard deviation (m_μ/m_σ) indicates relatively consistent behavior across all the 13 one-day cancellation events (see Table 2). The average slope of %CTES as a function of %PSPR (m_μ) is 64% with a slope standard deviation (m_σ) of 14%. The ratio of average slope to standard deviation (m_μ/m_σ) indicates relatively consistent behavior across all the 13 one-day cancellation events (Table 2).

Table 2 provides a summary of the “slope” statistics for the Same Day Before pre-emptive rebooking scenario.

Table 2 The statistics for pre-emptive rebooking for 2012

Analysis	Same Day Preemptive		
	m_μ	m_σ	m_μ/m_σ
Slope for % Pax Rebooked	0.70	0.066	11
Slope for ANR	0.63	0.14	4.6
Slope for CTES	0.64	0.14	4.6

4.2 Pre-emptive Rebooking Same Day Before Plus Previous Day

The results of the Monte Carlo simulation of randomly selected passengers seeking pre-emptive rebooking (PSPR) for cancelled flights for 0% 10%, 30% 50% and 70%. The results for PPA, ANR, and CTES are shown in Figure 8, 9, and 10. Each figure shows percentage of passengers that choose pre-emptive rebooking: 0% (baseline) 10%, 30% 50% and 70% of the passengers.

Feasibility of Pre-emptive Rebooking

For each percentage of passengers choosing the pre-emptive option (%PSPR), on average 70% of the passengers can be accommodated (PPA) for each of the 13 one-day cancellation

events are shown in Figure 8. The average slope of PPA as a function of PSPR (m_μ) is 77% with a slope standard deviation (m_σ) of 4.9% (see Table 3). The ratio of average slope to standard deviation (m_μ/m_σ) indicates the consistent behavior across all the 13 one – day cancellation events.

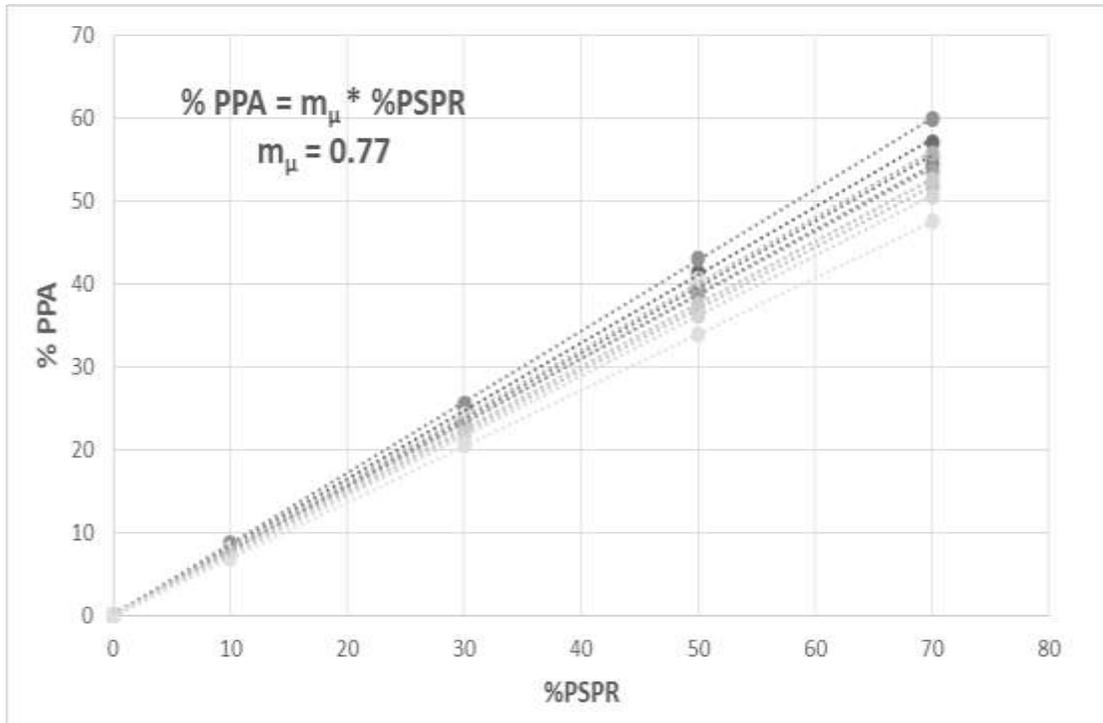


Figure 8: Percentage of Passenger Accomodated (PPA) for each level of randmly selected passengers opting for pre-meptive rebooking (PSPR) for the Same Dat early scenario.

Economic Benefits

The Airfare Not Refunded (ANR) by the airlines, and the Corporate Travel Expense Savings (CTES) not paid by traveler’s employers for each of the 13 one-day cancellation events are shown in Figure 8. As the percentage of passengers choosing to take advantage of pre-emptive rebooking (%PSPR) increases, the ANR and CTES increase linearly.

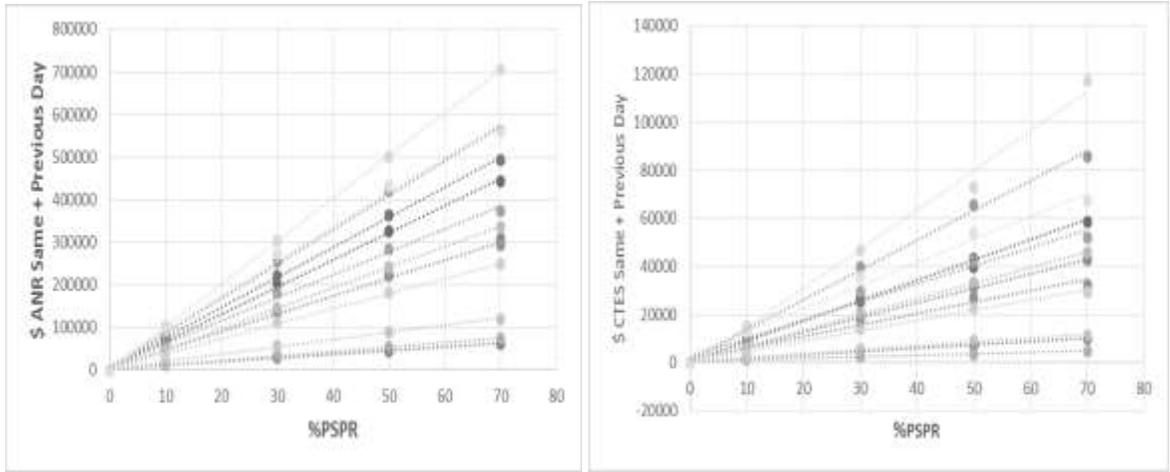


Figure 9: Airfare Not Refunded (ANR) and Corporate Travel Expense Savings (CTES) increase linearly with the percentage of passengers seeing pre-emptive rebooking with Previous and Same Day early Rebooking.

The percentage of Airfare Not Refunded (%ANR) and percentage of Corporate Travel Expense Savings (%CTES) for each of the 13 one-day cancellation events are shown in Figure 10. %ANR and %CTES increase linearly with the percentage of passengers seeing pre-emptive rebooking.

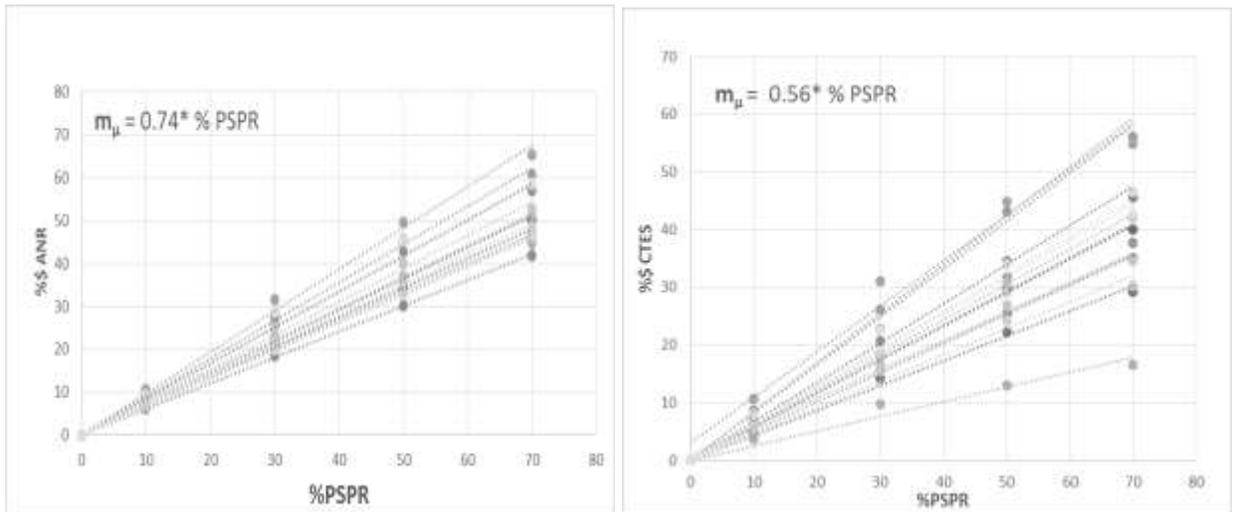


Figure 10: Same +Previous Day Preemptively Rebooked Passengers: % savings in ANR, % savings in CTES, as a function of the percentage of passengers seeking rebooking (PPSR) for 13 one day cancellation events.

The average slope of %ANR as function of %PSPR (m_μ) is 56% with a slope standard deviation (m_σ) of 15%. The ratio of average slope to standard deviation (m_μ/m_σ) indicates relatively consistent behavior across all the 13 one-day cancellation events (see Table 3). The average slope of %CTES as a function of %PSPR (m_μ) is 56% with a slope standard deviation (m_σ) of 15%. The ratio of average slope to standard deviation (m_μ/m_σ) indicates relatively consistent behavior across all the 13 one-day cancellation events (Table 3).

Table 3 provides a summary of the “slope” statistics for the Same Day Before pre-emptive rebooking scenario.

Table 3 The statistics for pre-emptive rebooking for 2012

Analysis	Same Day+Previous Day Preemptively		
	m_μ	m_σ	m_μ/m_σ
Slope for % Pax Rebooked	0.77	0.049	16
Slope for ANR	0.74	0.10	7.4
Slope for CTES	0.56	0.15	3.7

5. CONCLUSIONS

This paper performed an analysis of the feasibility and economic benefits of Pre-emptive Rebooking for large scale one-day cancelled flight events (i.e. more than 20 flights cancelled on a day). A method was described using a Monte Carlo simulation for alternative rebooking for historic passenger itineraries, flight performance, and seat availability. Metrics were developed for the feasibility, airline economic benefits, and passenger economic benefits.

Case-studies for 13 one-day cancellation events showed that pre-emptive rebooking in advance of forecast large-scale cancellation events is feasible. At least 70% of the passengers choosing to take advantage of pre-emptive rebooking can be accommodated before their original

scheduled flight time. The remaining passengers seeking pre-emptive rebooking cannot be re-accommodated due to insufficient seats (not insufficient flights).

Pre-emptive rebooking on the previous day was not required as it did not significantly change the percentage of passengers re-accommodated.

Pre-emptive rebooking is economically beneficial to both airlines and passengers. The Percentage of Passengers Accommodated (PPA), Airfare Not Refunded (ANR), and Corporate Travel Expense Savings (CTES) for each event are positive. Further these metrics exhibit a linear function with respect to the Percentage of Passengers Seeking Rebooking (PPSR). Approximately 70% of the PPSR were accommodated. On average \$297K of the obligated refunds could be saved (ANR) and \$49K of the unplanned travel expenses could be saved (CTES). Further, the 13 days analyzed across the seasons exhibited similar behavior and this behavior increased linearly with increasing percentage of passengers opting for pre-emptive rebooking.

In addition to the savings, there is the opportunity for the airlines to return some degree of control to the passengers for their travel plans during these irregular operations events and to eliminate uncertainty in travel. There is also an opportunity for airlines to generate additional revenue by offering a for-fee option that would move passengers to the front of the preemptive rebooking queue in the event of a large scale event (Raiteri, 2015).

Future work includes analysis of alternate cancellation policies, load factors and route structures. Monte Carlo analysis could also be done for random variables for airfare distributions between city-pairs and for per-diem distributions for overnight costs. The ANR calculation represents an upper-bound and could take into account passengers choice to accept credit and for

breakage. Analysis could also be done to account for airfare revenue lost by using seats for rebooking that otherwise may have been sold to last minute travelers in flight.

Acknowledgements

Kevin Lai, John Shortle, George Donohue, Anvardh Nanduri (GMU), Ashley Raiteri (The Answer Group), Terry Thompson (LMI), and anonymous reviewers from two major airlines. This work was funded by George Mason University Center for Air Transportation Systems Research Foundation.

References

AhmadBeygi, S., Cohn, A., Guan, Y., & Belobaba, P. (2008). Analysis of the potential for delay propagation in passenger airline networks. *Journal of air transport management*, 14(5), 221-236.

Bratu, S., & Barnhart, C. (2006). Flight operations recovery: New approaches considering passenger recovery. *Journal of Scheduling*, 9(3), 279-298.

Bureau of Transportation and Statistics (2015), Air Fares, Available: <http://www.rita.dot.gov/bts/airfares>

Chiraphadhanakul, V., & Barnhart, C. (2013). Robust flight schedules through slack re-allocation. *EURO Journal on Transportation and Logistics*, 2(4), 277-306.

Clarke, M. D. D. (1998). Irregular airline operations: a review of the state-of-the-practice in airline operations control centers. *Journal of Air Transport Management*, 4(2), 67-76.

DoT (2015). Percentage of Air Travel for Business vs Other Purposes, Available: https://ntl.custhelp.com/app/answers/detail/a_id/252/~/%2Fpercentage-of-air-travel-for-business-vs-other-purposes

Eggenberg, N., Salani, M., & Bierlaire, M. (2010). Constraint-specific recovery network for solving airline recovery problems. *Computers & operations research*, 37(6), 1014-1026.

Jafari, N., & Zegordi, S. H. (2011). Simultaneous recovery model for aircraft and passengers. *Journal of the Franklin Institute*, 348(7), 1638-1655.

Li, Tao, H. Baik, A.A. Trani (2013) A method to estimate the historical US air travel demand. *Journal of Advanced Transportation*. Special Issue: Special Issue: Public Transport Systems. Volume 47, Issue 3, pages 249–265, April 2013

McCarty, L. (2012) Preemptive Rerouting of Airline Passengers Under Uncertain Delays" (2012). Dissertation. Chairs: Amy E. Cohn, Divakar Viswanath. Paper 40. http://digitalcommons.cedarville.edu/faculty_dissertations/40

Raiteri, A (2015) personal conversation

Sherry, L., G. Calderon-Meza, A. Samant (2010) Trends in Airline Passenger Trip Delays (2007 – 2009). In Proceedings 2010 Integrated Communications Navigation and Surveillance (ICNS) Conference May 11-13, 2010

Sherry, L. (2014) A Method for Quantifying Travel Productivity for Corporate Travel Managers. *Journal of Air Transport Management*, Volume 42, January 2015, Pages 118–124

U.S. General Services Administration (2012), GSA: Per Diem Rates, Available: <http://www.gsa.gov/portal/category/104711>

Wambsganss, M.C. (2001) New Concepts and Methods in Air Traffic Management. In Transportation Analysis: Collaborative Decision Making in Air Traffic Management. Editors: Lucio Bianco, Paolo Dell'Olmo, Amedeo R. Odoni. Springer Berlin Heidelberg: Germany. pp 1-15

Yan, C. V. Vaze , A. Vanderboll, C. Barnhart (2015) Tarmac Delay Policies: A Passenger-Centric Analysis. Transportation Research Part A: Policy and Practice. Volume 83, January 2016, Pages 42–62 Elsevier B.V.