QUANTIFYING THE BENEFITS OF PRE-EMPTIVE REBOOKING: 
A CASE STUDY FOR A U.S. HUB

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QUANTIFYING THE BENEFITS OF PRE-EMPTIVE REBOOKING:
A CASE STUDY FOR A MIDWEST HUB
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Abstract

Although, on average, only 2.1% of airline flights are cancelled each year, some of these cancellations occur in batches due to events that impact network operations such as snow storms, equipment outages, and labor issues. Batch 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. Since some of these batch flight cancellations can be now be accurately predicted in advance. Along with changes in the National Airspace System (NAS) that allow airlines to plan cancellations in advance (i.e. Collaborative Decision Making programs), and the ubiquity of inexpensive and reliable broadband communication services for communication between airlines and passengers, it is now possible for airlines to migrate from a concept-of-operations of rebooking passengers after the cancellation event, to re-booking passengers before the large scale cancellation event (i.e. pre-emptive rebooking).

This paper describes a method for Monte Carlo analysis of the feasibility and benefits of pre-emptive rebooking of passengers. A case-study of 13 one-day cancellation events for a major U.S. network carrier operating a mid-west hub showed that: (i) pre-emptive rebooking is feasible accommodating more than 70% of the passengers seeking to rebook pre-emptively, (ii) rebooking passengers on the same day before the departure time of the cancelled flight, accommodates a majority of the passengers (i.e. previous day rebooking is not required), (iii) airlines can recoup up to an average of $297K per one-day event in airfare refund obligations, and (iv) corporations sponsoring business travel can save collectively up to an average of $49K on unplanned travel expenses. 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

In a typical year of operations for a large U.S. network carrier only 2.1% of the flights are cancelled. Although this is relatively low number, these flight cancellations can occur in batches at the same time and same location. For example in 2012, a mid-west U.S. network carrier experienced a large scale cancellation event, in which between 20 and 160 or more flights were cancelled on 5.5% of the days of the year (Figure 1). These flight cancellation events impacted a total of 60,669 passengers, and were estimated to cost airlines an average of up to $297K per one cancellation event in airfare refunds, and to cost corporations sponsoring employee travel $49K in unbudgeted travel expenses. Out of 21 days which had more than 20 cancelled flights, 13 of those were once – day cancellation events.

![Figure 1](image.png)

**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 forecast (i.e. snow storms, labor issues, and equipment outages), uncertainty in Air Traffic Control (ATC) and in competing
airline response to these events obliged airline’s to *reactively* rebook passengers *after* the event. However, the advent of Collaborative Decision Making to enable equitable advance planning by the airlines (Wambsganns, 2001), along with the ubiquity of broadband wireless communication between airline and passengers, now enables airlines to *proactively* cancel flights in advance and rebook passengers *before* the cancellation event.

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

This paper describes a method for the analysis of the feasibility and benefits of pre-emptive rebooking of passengers scheduled to fly through a hub airport in advance of forecast large scale flight cancellation events. A Monte Carlo simulation of joint passenger itinerary and historic flight data is described. A case study of the concept of operations for a U.S. network carrier operating a mid-west hub showed that:

- 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. <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 their 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 a case-study for 13 one day cancellation events for a large U.S. network carrier. Section 5 discusses the implications of these results.

1.1 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, 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 (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 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 now enable airlines to contact and coordinate changes in reservations with passengers in a reliable, fast, and low-cost manner.

As a consequence, passengers can now 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 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.
2. METHOD OF ANALYSIS

To analyze the feasibility and benefits of pre-emptive rebooking strategies the Passenger Itinerary Delay Algorithm (PIDA) (Sherry et al, 2011) is embedded in a Monte Carlo Simulation. The PIDA, Monte Carlo Simulation, Metrics, and the Design of Experiment are described in this section.

2.1 Passenger Itinerary Delay Algorithm (PIDA)

PIDA is used to generate statistics for trip delays for each ticketed passenger itinerary (Sherry, 2011). PIDA takes as an input each individual passenger itinerary (direct and connecting). The itineraries are compared with actual performance of the flights associated with the itinerary. If the flight is delayed more than 15 minutes, PIDA assigns the delay to each
passenger. If a flight is cancelled, or a passenger misses a connection, the PIDA rebooks the passengers on alternate flights and calculates trip delays based on when the passengers arrives at their destination.

Passengers are rebooked according to a set of rules that take into account airline policies, subsidiary airlines, and re-accommodation contracts with other airlines. Under traditional rebooking rules, passengers are rebooked on the first available flight after the original cancelled scheduled departure time. If there is no available flight with empty 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).

For the purpose of pre-emptive rebooking, the passenger is rebooked in advance of the cancelled flight (Figure 4). For example, after a 11:36 a.m. cancellation, flights with available seats are sought 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.

2.2 Metrics for Pre-emptive Rebooking

The metrics for evaluating the feasibility and benefits of pre-emptive rebooking are described.
**Percentage of Passenger Accommodated (PPA)** is the percentage of passengers that were seeking pre-emptive rebooking (PSPR) that were accommodated by pre-emptive rebooking.

**Airfares 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:

\[ AR_{base} = (PAX_{RebNDbase} + PAX_{RemBase}) \times 377 \]

\[ AR = (PAX_{RebND} + PAX_{Rem}) \times 377 \]

Where:

- \( PAX_{RebNDbase} \): Number of passengers rebooked Next Day, with no pre-emptive rebooking.
- \( PAX_{RebND} \): Number of passengers rebooked Next Day for 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 without pre-emptive rebooking
- \( AR \): Airfare refund for the case for the chosen level of pre-emptive rebooking

$377$ is for average airfare (Bureau of Transportation Statistics, 2015).

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

\[ \%ANR = 100\% \times \frac{ANR}{AR_{base}} \]

Using a linear regression model, the \( \%ANR \) per \( \%PSPR \) can also be estimated as follows.

\[ \%ANR = (m_{ANR} \times \%PAX_{Rebooked}) + b_{ANR} \]
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 preemptive acceptance to the ANR value.

\( b_{ANR} \): the y-intercept of the line relating the rate of preemptive acceptance to the ANR value, thus \( b_{ANR} = 0 \).

**Corporate Travel Expense Savings (CTES)** is the difference in additional travel expenses accrued by corporate travelers without pre-emptive rebooking and with each of the pre-emptive rebooking percentages 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 home town 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:

\[
CTE_{Base} = \$250 \times (PAX_{RebND} + PAX_{Rem} + PAX_{RebPD}) \times 0.5 \times 0.5
\]

\[
CTE = \$250 \times (PAX_{RebND} + PAX_{Rem} + PAX_{RebPD}) \times 0.5 \times 0.5
\]

\( PAX_{RebPD} \): Number of passengers rebooked Previous Day, with no pre-emptive rebooking.

\( PAX_{RebPD} \): Number of passengers rebooked Previous Day, using the chosen level of pre-emptive rebooking.

**Percentage of Corporate Travel Expense Savings (\( \%CTES \))** is calculated as follows.
Using a linear regression model, the % \textit{CTES per PSPR} can be estimated as follows.

\[
%\text{CTES} = (m_{\text{CTES}} \times \%\text{PAX}_{\text{Rebooked}}) + b_{\text{CTES}}
\]

where:

\(m_{\text{CTES}}\): the slope of the line relating the rate of preemptive acceptance to the \textit{CTES} value.

\(b_{\text{CTES}}\): the \(y\)-intercept of the line relating the rate of preemptive acceptance to the \textit{CTES} value, thus \(b_{\text{CTES}} = 0\).

\textit{2.3 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 selected for 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 being selected for 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 the Monte Carlo simulation is executed 25 times for each replication. This result was calculated based on the standard deviation from 500 runs for a randomly selected day and verified by simulation for 5 randomly selected days.

\textit{Design of Experiment}

The Monte Carlo simulation is run for 10 treatments defined by:
1. Percentage of passengers that seek a pre-emptive rebooking option 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 Earlier, or Previous Say and Same Day Earlier).

3. CASE-STUDY RESULTS AND DISCUSSION

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

<table>
<thead>
<tr>
<th>Month</th>
<th>Day</th>
<th>Number of Cancelled Flights</th>
<th>Arrival Flights Cancelled</th>
<th>Departure Flights Cancelled</th>
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<tbody>
<tr>
<td>1</td>
<td>12</td>
<td>56</td>
<td>31</td>
<td>26</td>
</tr>
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<td>1</td>
<td>20</td>
<td>77</td>
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<td>1</td>
<td>23</td>
<td>38</td>
<td>23</td>
<td>15</td>
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<td>2</td>
<td>23</td>
<td>28</td>
<td>11</td>
<td>17</td>
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<td>5</td>
<td>6</td>
<td>26</td>
<td>8</td>
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<tr>
<td>12</td>
<td>20</td>
<td>37</td>
<td>20</td>
<td>17</td>
</tr>
</tbody>
</table>

In 2012 at the mid-west hub the airline experienced 4 days (2.5%) with between 20 and 30 flight cancellations. There were 5 days (1.4% of the year) with 30 and 40 cancelled flight, 4 days
(1.1% of the year) with between 40 and 60 cancelled flights, and 2 days (0.54% of the year) with more than 100 cancelled flights.

For the day of the 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 statistics for pre-emptive rebooking for 2012 calculated from the Monte Carlo simulation for (1) PPA, (2) ANR, and (3) CTES for each level of PSPR (baseline 0% to 70%) for each of the 13 days are shown in Figures 5 – 10 and Tables 2 and 3.

3.1 Pre-emptive Rebooking Same Day Before

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% of the passengers. The results for PPA, ANR, and CTES are shown in Figure 5, 6 and 7.

The percentage of passengers accommodated (PPA) is proportional 70% for each percentage of passengers seeking pre-emptive rebooking (PSPR) (Figure 5). The average slope of PPA as a function of PSPR ($m_\mu$) is 70% with a slope standard deviation ($m_\sigma$) of 6.6% (see Table 2). The ratio of average slope to standard deviation ($m_\mu / m_\sigma$) indicates the consistent behavior across all the 13 once – day cancellation events.
Figure 5: Percentage of Passenger Accomodated (%PPA) for each level of passengers seeking pre-emptive rebooking (%PSPR).

The Airfare Not Refunded (ANR) and Corporate Travel Expense Savings (CTES) increase proportionally with the percentage of passengers seeing pre-emptive rebooking (See Figure 6).

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

The percentage of Airfare Not Refunded (%ANR) and percentage of Corporate Travel Expense Savings (%CTES) increase proportionally with the percentage of passengers seeing pre-emptive rebooking (See Figure 7). The average slope of %ANR as function of PSPR ($m_\mu$) is 63% with a slope standard deviation ($m_\sigma$) of 14%. The ratio of average slope to standard deviation
\( m_{\mu} / m_{\sigma} \) indicates relatively consistent behavior across all the 13 once-day cancellation events (see Table 2).

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

The function of PPSR to Corporate Travel Expense Savings (CTES) is also linear. Average slope of this function \( m_{\mu} \) is 64\% with a slope standard deviation \( m_{\sigma} \) of 14\%. The ratio of average slope to standard deviation \( m_{\mu} / m_{\sigma} \) indicates relatively consistent behavior across all the 13 once-day cancellation events (Table 2).

Table 2 provides a summary of the “slope” statistics for the Same Day Before pre-emptive rebooking scenario.
3.2 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.

The function of Passengers Seeking Rebooking to Percentage of Passengers Accommodated is linear. Average slope of this function ($m_{\mu}$) is 77% with a slope standard deviation ($m_{\sigma}$) of 4.9% (see Table 3). The ratio of average slope to standard deviation ($m_{\mu}/m_{\sigma}$) indicates the consistent behavior across all the 13 once-day cancellation events.

<table>
<thead>
<tr>
<th>Analysis</th>
<th>Same Day Preemptive</th>
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</thead>
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<tr>
<td></td>
<td>$m_{\mu}$</td>
</tr>
<tr>
<td>Slope for % Pax Rebooked</td>
<td>0.70</td>
</tr>
<tr>
<td>Slope for ANR</td>
<td>0.63</td>
</tr>
<tr>
<td>Slope for CTES</td>
<td>0.64</td>
</tr>
</tbody>
</table>

Table 2 The statistics for pre-emptive rebooking for 2012

Figure 8: Percentage of Passenger Accomodated (PPA) for each level of passengers seeking pre-emptive rebooking (PSPR) for the Same Dat early scenario.
The function of Passengers Seeking Rebooking to Airfare Not Refunded (ANR) is linear (Figure 9).

**Figure 9:** Airfare Not Refunded (ANR) and Corporate Travel Expense Savings (CTES) increase proportionally 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) increase proportionally with the percentage of passengers seeing pre-emptive rebooking (See Figure 10). The average slope of %ANR as function of PSPR ($m_\mu$) is 74% with a slope standard deviation ($m_\sigma$) of 10%. The ratio of average slope to standard deviation ($m_\mu / m_\sigma$) indicates relatively consistent behavior across all the 13 once-day cancellation events (see Table 3).
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 function of Passengers Seeking Rebooking to Corporate Travel Expense Savings (CTES) is also linear. Average slope of this function ($m_\mu$) is 56% with a slope standard deviation ($m_\sigma$) of 15%. The ratio of average slope to standard deviation ($m_\mu / m_\sigma$) indicates relatively consistent behavior across all the 13 once-day cancellation events.

For each of the 13 days, the slope ($m$) of the function was computed. The average of these slopes ($m_\mu$) and the standard deviation of the slopes ($m_\sigma$) was computed and shown in Table 3 along with the signal-to-noise ratio ($m_\mu / m_\sigma$). These metrics were computed for pre-emptive rebooking on the same day and pre-emptive rebooking on the same day and previous day.

### Table 3 The statistics for pre-emptive rebooking for 2012

<table>
<thead>
<tr>
<th>Analysis</th>
<th>Same Day+Previous Day Preemptively</th>
<th>$m_\mu$</th>
<th>$m_\sigma$</th>
<th>$m_\mu / m_\sigma$</th>
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<tr>
<td>Slope for % Pax Rebooked</td>
<td></td>
<td>0.77</td>
<td>0.049</td>
<td>16</td>
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<tr>
<td>Slope for ANR</td>
<td></td>
<td>0.74</td>
<td>0.10</td>
<td>7.4</td>
</tr>
<tr>
<td>Slope for CTES</td>
<td></td>
<td>0.56</td>
<td>0.15</td>
<td>3.7</td>
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</table>
4. CONCLUSIONS

This paper performed an analysis of the feasibility and benefits of Pre-emptive Rebooking for large scale one-day cancelled flight events (i.e. more than 20 flights cancelled on a day). The analysis showed that pre-emptive rebooking in advance of forecast large-scale cancellation events is feasible. At least 70% of the passengers seeking 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.

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

The Percentage of Passengers Accommodated (PPA), Airfare Not Refunded (ANR), and Corporate Travel Expense Savings (CTES) for each event exhibit a linear function with respect to the Percentage of Passengers Seeking Rebooking (PPSR). Approximately 70% of the PPSR were accommodated. On an 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.

In addition to the savings, there is the opportunity for the airlines to return some degree of control of their travel plans to 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. 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.

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