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## Downstream impact of flight rerouting

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### ABSTRACT

In this paper, we estimate the impacts of post-departure flight rerouting on times of arrival at destination airports. There are mainly two types of post-departure reroutes – opportunistic reroutes (distance-saving reroutes) and reactive reroutes (distance-increasing reroutes). To the best of our knowledge, the downstream impact of rerouting has received little attention in the existing literature; however, the benefit/harm of both kinds of reroutes might be exaggerated if their system impact is not taken into account. Thus, we developed a framework for evaluating the net effect of applying a reroute at the system level by analyzing its impact on arrival times at the destination of the rerouted flight.

We focus on reroutes that affect en route flight time by 5 min or more. Adopting a “multiplier” concept that was proposed in previous research and making use of two-year (2013–2014) flight level data at the 34 main airports in the US, we analyze how the en route time change affects cumulative arrival throughput at the destination airport, and the associated time savings or time costs. We find that these impacts of reroutes differ remarkably at different airports, and identify airports where the arrival time impact is highly correlated with the en route time change as well as those for which this correlation is weak. In addition, we compare downstream impacts among different types of reroutes. Finally, we study cases with very high multipliers in detail in order to identify these circumstances under which they occur.

## 1. Introduction

It is common for flights to deviate from their initial planned routes. Such a change may be necessary if the original route traverses a region that should be avoided for some reason, such as poor weather conditions, sector congestion, or a potential conflict with another flight. Here we refer to such cases as reactive reroutes (RR). Alternatively, lower traffic than expected, improved weather conditions, and reduced uncertainty may enable a more direct path than the one defined in the flight plan, thereby saving flight time and fuel. We term these opportunistic reroutes (OR). The route may be changed prior to departure or after the flight is underway. The focus of this study is post-departure reroutes.

A number of research and development programs have been geared toward employing reroutes to increase efficiency. At NASA, Direct-to and Dynamic Weather Routes (DWR) programs use software that continually scans for opportunities to shorten flight paths by flying directly between waypoints. DWR can benefit flights with an initial planned route designed to avoid regions in which convective weather is forecasted but realized weather offers opportunities to shorten the planned route. As a pilot program, DWR has been implemented at American Airlines for flights going through the Dallas Air Route Traffic Control Center (ARTCC). A related

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program, known as the NAS Constraint Evaluation and Notification Tool (NASCENT), extends the DWR concept to the continental US. In general, DWR and NASCENT are intended to mitigate inefficiencies that result from initial conservative pre-departure flight plans made in the face of considerable uncertainty about convective weather.

Other programs, such as MITRE's En Route Flow Planning Tool (EFPT) and NASA's Advanced Airspace Concept (AAC), are designed to improve decision making when reroutes become necessary to avoid weather or congestion. EFPT is designed to help traffic managers identify flights and flows requiring rerouting within the next 15–90 min, devise and rank potential solutions, and execute the chosen reroutes. This helps avoid the high controller-pilot communications workload, traffic complexity, and unpredictability that often result from “just-in-time” route deviations initiated by pilots, which, by their nature, involve limited options and must be handled promptly. The AAC includes both strategic and tactical weather-avoidance capabilities as well as tactical conflict resolution functions. Strategic reroutes are initiated about 20 min prior to the predicted time of entry into the weather cell and re-evaluated every 15 min, whereas the tactical rerouting algorithm operates on a 1-min cycle.

To assess the benefits of these programs, most previous research has focused on the direct time savings of rerouted flights. Some studies consider only part of a route. For example, if a reroute allows a flight to fly directly from point A to point C in 20 min and the planned route included segments from A to B and from B to C with a total flight time of 25 min, then the direct timesaving would be 5 min. Using this approach, for example, McNally et al. estimated potential savings at about 10 min per flight rerouted using DWR and corrected potential savings, which account for route amendments to the same flights that are made currently without using DWR, of 6.6 min (McNally et al., 2015). Others consider the impact of rerouting on the entire flight route. For example, Refai and Windhorst used a fast-time simulation, Airspace Concept Evaluation System (ACES), to determine changes in delay, defined as the difference between actual and scheduled en route flight times, to rerouted flights (Refai and Windhorst, 2011).

Although simple and straightforward, the direct timesaving approach may not accurately reflect the impact of the rerouting on arrival times at destination airports, since it does not consider how the change en route time may affect when that flight can actually land, or the landing times of other flights bound for the same destination. For instance, due to airport congestion, the direct time-saving of a reroute may result in the flight taking a longer delay when it reaches the destination terminal area if the destination airport is operating at capacity – the so-called “hurry up and wait” phenomenon. In addition, adding one more flight (the rerouted flight) into the arrival queue of the destination airport earlier may delay the flights behind it. Such increased delay due to the rerouted flight may partly or completely offset the direct timesaving. In contrast, it is also possible, as explained below, for the direct timesaving from a reroute to lead to an even greater timesaving if one considers all the arriving flights instead of just the rerouted one. For brevity, we will refer to the impact of a reroute to a given flight bound for airport A on the arrival times of all flights to A as the *system impact* of the reroute. To properly assess the value of the aforementioned programs for guiding and executing rerouting, and guide the development for other rerouting tools in the future, the system impact of reroutes must be taken into account.

In this study, we develop a methodology for estimating the system impact of rerouted flights. We apply this methodology to an extensive data set of US flights and studied the relationship between the direct impact of a reroute – i.e. the change in en route time of the rerouted flight – and the system impact, in the sense defined in the previous paragraph.

After a brief review of relevant literature in the next section, we present our methodology in Section 3. Section 4 introduces the data set and summarizes what it reveals about flight distance changes that result from reroutes. Section 5 presents the results of applying the methodology to the data set, followed by conclusions in Section 6.

## 2. Literature review

Much research attention, at both the local (i.e., individual flight) and system (impact on NAS) scales, has been devoted to the study of delay propagation. Many studies define multipliers for quantifying the downstream impact of flight delay or airport-level delay. Based on actual delay statistics, Boswell and Evans developed an analytical model to estimate the delays to successive flight legs when a multi-leg flight encountered an initial delay in a daily itinerary (Boswell and Evans, 1997). In their study, a downstream multiplier is defined as the ratio between seed delay and its total downstream impact. This study provides an omnibus multiplier that can be applied at all sites and in all traffic conditions; however, this multiplier is computed only for the winter season due to data limitations. It reveals that, on average, 2.5 downstream legs are impacted by a seed delay, and 1 min of seed delay engenders 0.8 min of parallel carryover delay in subsequent flight legs in winter weather. Kondo adopted a similar omnibus multiplier idea and compared the difference of flight delay propagation between point-to-point carriers and network carriers (Kondo, 2011). Welman et al. looked into airport delay propagation for other airports in the NAS. They used an “aircraft-operational day” as the study unit and developed arrival delay propagation multipliers for both individual and multiple airports in metroplexes in airport cost-benefit studies by mapping original and propagated delay across the NAS (Welman et al., 2010). The authors discovered the variation of the multipliers at different sites, reflecting that delay propagation is a network phenomenon and is influenced by a mixture of factors across the network. Other tools, such as techniques from complex network and econometrics analysis, also have been adopted in studying delay propagation. Laskey et al. applied Bayesian networks (BN) in a stochastic model to model the relationships among different components of aircraft delay (Laskey et al., 2006). Propagated delay, in the study, is defined as delays resulting from previous flight phases. The study developed regression models to investigate the causal factors contributing to delay in each flight phase and the impact of delay in each phase to the final arrival delay. Using a case study from ORD to ALT during summer 2004, the study identified departure delay as the major factor driving final arrival delay at the destination airport and weather affects delay in all flight phases.

Fleurquin et al. introduced an agent-based model to study observed delay propagation in 305 US airports (Fleurquin et al., 2013). The authors defined the category of “congested airports” and studied how such airports form connected clusters in the network.

Passenger and crew connectivity was identified as key factors for the increase in congestion in the network. However, it was noted that being in the same cluster was a measure of correlation but not necessarily a sign of a causal relationship. Zhang and Nayak introduced a macroscopic framework to examine factors causing flight delays and the interdependency between flight delay at an individual airport and the NAS (Zhang and Nayak, 2010). Using multivariate simultaneous equations, the study investigated delay propagation from a single airport to the system, and vice versa. Hypothetical scenarios were created to study the network effect due to improvement in capacity or demand management strategies at a single airport. The authors suggest using this framework to assist the decision making of resource allocation of nation-wide airport improvement taking the consequent system-wide delay reduction into consideration.

Another stream of recent work has focused on speed control, which, like reroutes, changes the time when flights enter terminal areas, albeit in an intentional manner. Jones et al. studied speed control as a means to prevent the inefficiency that results when flights are expedited to make their scheduled arrival times but are delayed in the terminal airspace when a heavy degree of congestion prevents them from landing (Jones et al., 2013). Such delay could be absorbed in the terminal phase by rerouting mechanisms such as tromboning, vectoring, and holding patterns to add distance to a flight, or it can be achieved by reducing flight speed in the en route phase. The authors demonstrated that with sufficient advance information, a significant amount of delay can be transferred from the arrival phase to the en route phase resulting in reduced fuel burn and controller workload in the terminal area. The analyses also recognize that when arrival demand exceeds capacity, delaying arrivals into the terminal area may not affect the aggregate level of flight delay.

Deterministic queuing models have been used extensively to evaluate flight delay at both the individual flight and system levels. Although extremely simple, predictions from these models have been found to closely match those of more complex stochastic queuing models (Hansen, 2002). Applying this method, Hansen et al. investigated delay impacts of individual flights by comparing total system delay before and after a particular flight was eliminated (Hansen et al., 2009). The author found that the delay impact is highly sensitive to the time when a flight enters the arrival queue. A flight arriving at the beginning of a lengthy period of queuing generates the largest delay, because if it was removed, many flights arriving behind it in the same queuing period could move up. On the other hand, a flight arriving in periods of excess capacity causes no additional delay to the system. Using LAX as a case study, the estimated external delay impacts of individual flights can be as much as three aircraft-hours, even on a moderately-congested day with only 5-min average queuing delay.

Yin and Hansen applied the deterministic queuing model to estimate system impacts of en route flight delays for flights with different destination airports (Yin and Hansen, 2005). This study developed a delay multiplier to capture the downstream effects of flights' en route delay, finding that the system impact of an en route delay can vary significantly from the delay incurred by an individual flight. Sometimes, when downstream effects are accounted for, the system delay impact – including the immediate delay impact as well as the downstream impact – is virtually nothing. In other cases, the system impact may be much greater than the immediate delay increase. As in the LAX study, this range of possibilities reflects the high sensitivity of delay to when a flight enters the arrival queue (Hansen et al., 2009).

### 3. Methodology

The data used in this study include Flight Event data from Enhanced Traffic Management System (ETMS) radar track database, which archives all domestic flights landing at and taking off from the 34 main US airports. These 34 airports are large hub airports in the US according to FAA's classification. Although they are less than 6% of the total number of commercial airports in the US, they serve more than 66% of the controlled flights (Comparison of Air Traffic Management-Related Operational Performance: U.S./Europe, 2014). For each flight, Flight Event data include the following information:

- Great circle distance between origin and destination (OD) pairs
- Great circle distance from D40 (an arc drawn 40 miles from the departure airport) to A100 (an arc drawn 100 miles from the arrival airport)
- Distance from D40 to A100 according to the last filed pre-departure flight plan
- Actual flight trajectory distance from D40 to A100
- Average cruise speed

In addition, Aviation System Performance Metrics (ASPM) quarter-hour data of 34 busiest US airports are used. These data provide quarter-hour counts of demand and actual arrivals at those airports. The demand recorded in ASPM data is the number of flights desiring to land in a particular 15-min period, including unaccommodated demand from prior periods. Thus, a 15-min period is counted as congested when the number of actual arrivals is less than the demand in that period.

Fig. 1 defines the different possible flight routes of a given flight. Line A indicates the great route between origin and destination airports, and line B is the great circle distance route from the point where the flight crosses D40 to where it crosses A100. Curve C between departure and arrival fixes represents the en route trajectory in the flight plan for this flight, and both D and E illustrate possible reroutes. Reroutes are characterized, very simply, as the aggregate difference in length between the D40 to A100 portion of planned route (C in Fig. 1) and the same portion of flown route (for example D or E in Fig. 1). Although partly a reflection of the limitations in our data set, which are discussed in more detail below, the aggregate representation avoids complexities that arise from the fact that reroutes may be issued as a sequence of amendments, i.e., a certain reroute can possibly consist of both opportunistic and reactive reroutes (see, for example, McNally et al. (2015), Fig. 5).

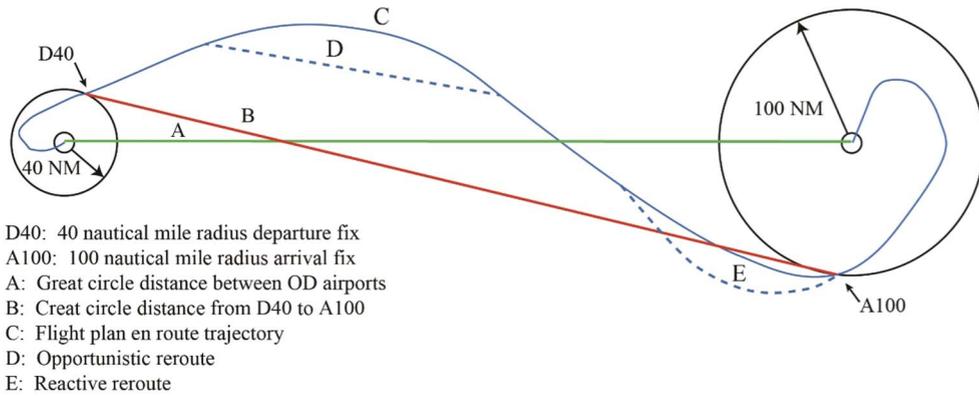


Fig. 1. Flight route illustration.

Many reroutes are local, with the flight trajectory deviating from the planned route sometime after take-off and recapturing the planned route a short time later. The distance metric does not differentiate between complete reroutes (reroutes that deviate from the flight plan completely) and local reroutes shown in Fig. 1. A reroute, whether complete or local, may be longer or shorter than the original. Longer reroutes are referred to as “reactive reroutes” (RRs) because such reroutes presumably are made in response to problems such as convective weather or excess traffic. Reroutes that shorten the flight distance are termed “opportunistic reroutes” (ORs) because, in general, they seize the opportunity of improved weather or available sector capacity and take actions to shorten the route. In some cases, ORs are motivated by a mixture of problems and opportunities; for example, a flight may be cleared to fly directly to its destination to resolve a conflict (Erzberger et al., 2010). A given flight may perform a combination of RRs and ORs throughout the flight process. In our study, given that the research goal was to understand the system impacts of a reroute, we consider only the aggregate difference in distance arising from all of the reroutes received by a given flight.

The following describes the method of computing the system impacts of rerouting. Let  $\Delta t_{rf}$  be the direct time difference resulting from the reroute of flight  $f$ . It is the distance difference divided by an average cruise speed from the Flight Event data.

$$\Delta t_{rf} = \frac{d_f^a - d_f^p}{v_f} \tag{1}$$

where  $d_f^a$  is the actual flown distance from D40 to A100 for flight  $f$ ,  $d_f^p$  is the flight plan distance, and  $v_f$  is the average cruise speed. For RRs,  $\Delta t_{rf}$  is positive, and for ORs it is negative.

Let  $t_{ff}^r$  be the arrival times of flight  $f'$  at the runway of its destination airport, given that the reroute of flight  $f$  to the same destination took place, and  $\tilde{t}_{ff}^r$  be the hypothetical arrival time if this reroute did not occur. The system impact of the reroute of flight  $f$  is defined as:

$$\Delta t_{sf} = \sum_{f'} (t_{ff'}^r - \tilde{t}_{ff'}^r) \tag{2}$$

When the destination airport has excess capacity, we assume that earlier or later arrival of the rerouted flight does not affect the arrival time of other flights, the time savings of the rerouted flight will translate directly into a system impact. That is, in such situations:

$$t_{ff'}^r - \tilde{t}_{ff'}^r = \begin{cases} 0 & f' \neq f \\ \Delta t_{rf} & f' = f \end{cases} \tag{3}$$

$$\Delta t_{sf} = \Delta t_{rf}$$

This is the implicit assumption behind benefit studies for DWR (McNally et al., 2015) and NASCENT (Sheth et al., 2015), among others.

If the destination airport does not have excess capacity, the effects of the reroute may spill over to other flights, so that Eq. (3) does not apply. For example, suppose one flight arrives earlier than the estimated arrival time of its flight plan due to an OR, but it arrives during a congested period. To accommodate this rerouted flight, some flights arriving after it are affected, i.e., they encounter additional delay compared to the scenario in which the reroute did not occur. From a system perspective, the timesaving of the rerouted flight is offset by additional delay to other arrivals at the destination airport. There are other scenarios as well; for example, if the rerouted flight arrives during a non-congested time period but its original arrival could fall into a congested time period, then the rerouting frees up a slot in the congested time period and flights arriving at times after this slot can land sooner. In this case, in addition to the timesaving of the rerouted flight, system impacts should also include the timesaving of flights whose arrival times are advanced. In principle, any flight  $f' \neq f$  with the same destination, and whose arrival time is after the earlier of the arrival times of the rerouted flight with and without the reroute, may be affected by the reroute. However, as detailed below, the set of flights actually affected is much smaller, since any non-congested period after these two arrival times breaks the chain of impact and all

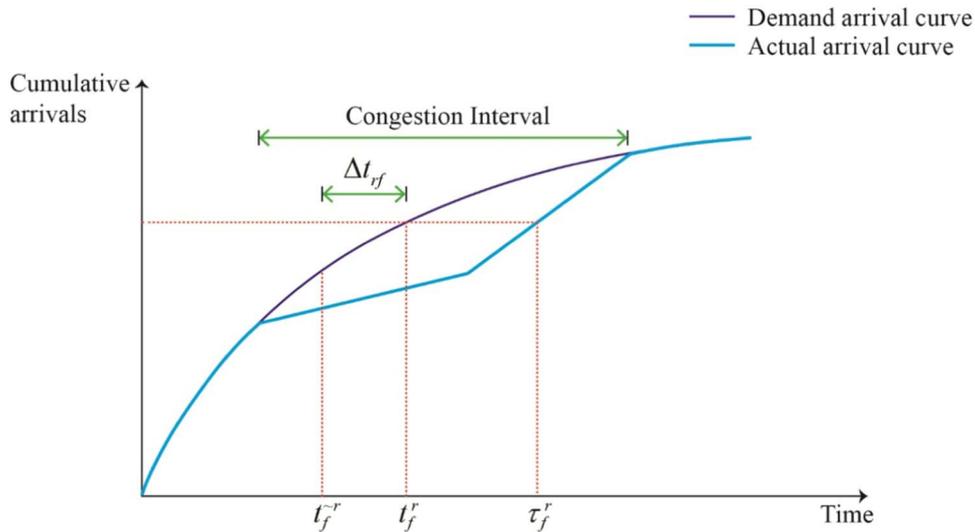


Fig. 2. Illustration of demand arrival time mapping.

subsequent flights are not affected.

In this study, we used a deterministic queuing model to compute system impacts of reroutes. Fig. 2 presents a queuing diagram that illustrates our approach. The horizontal axis in Fig. 2 is the time of day and the vertical axis is the cumulative arrivals at an airport. The upper curve is the arrival demand curve, and below it is the actual arrival curve. Cumulative actual arrivals could be equal to the cumulative demand, but will never exceed it. Define the congested time period  $C_f$ , with subscript  $f$  indicating the rerouted flight  $f$  that we are studying, as the set of times on the day of operation of flight  $f$  when the destination airport of  $f$  could not accommodate all the demand. Also define  $N_f(t)$  and  $A_f(t)$  as the cumulative arrival demand and actual arrival curves on the day and destination airport associated with flight  $f$ . For  $t \in C_f, N_f(t) > A_f(t)$ , so there would be a discrepancy between the arrival demand and actual arrival curves.

We applied such queuing diagrams to calculate the system impact of any given rerouted flight  $f$  and applied it to a large set of rerouted flights into different airports in the NAS. The observed arrival time of flight  $f$  recorded in ASPM is  $\tau_f^r$ . Assuming first-in-first-out (FIFO) queueing discipline, we employed the following procedure to derive the  $t_f^r$ , estimated arrival time of rerouted flight  $f$  on the demand curve, and  $\tilde{t}_f^r$ , estimated arrival time of flight  $f$  on the demand curve if no reroute occurred. The estimated arrival time of a flight on the demand curve is referred to as queue arrival time. First, we obtained the value of the cumulative arrival throughput curve at the observed arrival time of the rerouted flight,  $A_f(\tau_f^r)$ . Next, we identified the corresponding queue arrival time  $t_f^r$  for the flight by finding the time when the cumulative arrival demand curve reached the value  $A_f(\tau_f^r)$ :  $t_f^r = N_f^{-1}(A_f(\tau_f^r))$ . Third, knowing the rerouted distance of flight  $f$  from the ETMS radar track database, we obtained the time difference  $\Delta t_{rf}$  by dividing that distance by the average cruise speed. Then, given  $t_f^r$  and  $\Delta t_{rf}$ , we obtain  $\tilde{t}_f^r$ . Fig. 2 illustrates the case in which the observed arrival time is during a congestion interval, i.e.,  $\tau_f^r \in C_f$ , so that  $\tau_f^r > t_f^r$ . In this case, the rerouting delayed the arrival time of flight  $f$  but this flight-level impact is offset by other flights in the same congestion period that can move up in the queue, resulting in no system impact from the reroute.

The system impact of a reroute depends on the congestion time period  $C_f$  and the relationship of  $t_f^r$  and  $C_f$ , and  $\tilde{t}_f^r$  and  $C_f$ . For simplification purposes, we assumed that the congestion intervals would not be affected by the shift of any one flight. Under this assumption, an airport can serve one more flight in a time period if it is not congested and, likewise, a congested time interval will remain congested if one flight is removed from the demand during that congested period. Since congested periods typically last an hour or more, and arrival headways under congested conditions are on the order of 1 min, the error introduced by this assumption is negligible.

We categorized the relationships of  $t_f^r$ ,  $\tilde{t}_f^r$  and  $C_f$  into five scenarios, as illustrated in Fig. 3. In the figure, two red points represent  $\tilde{t}_f^r$  and  $t_f^r$ , and the cross-hatched areas represents the congested period  $C_f$ . If  $t_f^r$  (or  $\tilde{t}_f^r$ ) falls into a congested period, let  $Q_f^r$  (or  $\tilde{Q}_f^r$ ) denote the end time of that congested period. The scenarios apply to both ORs and RRs; for the former, the change in system delay is negative or 0, while for the latter it is positive or 0. The scenarios are described as follows:

- **Scenario 1** –  $t_f^r$  and  $\tilde{t}_f^r$  are in the same congested period. The timesaving/postponing of rerouted flight  $f$  is offset by the cumulative effect on other flights. In the event of an OR, other flights are pushed back in the queue, while in the case of an RR, they can be moved up. Thus, in this case, the time shift due to rerouting has no impact on the system delay, i.e.  $\Delta t_{sf} = 0$ .
- **Scenario 2** –  $t_f^r$  and  $\tilde{t}_f^r$  are both in uncongested periods. In this case, the reroute does not affect other flights at the destination airport, so that  $\Delta t_{sf} = \Delta t_{rf}$ .
- **Scenario 3** –  $t_f^r$  is in a congested period, but  $\tilde{t}_f^r$  is not. In other words, the reroute moves the queue arrival time of the flight from an

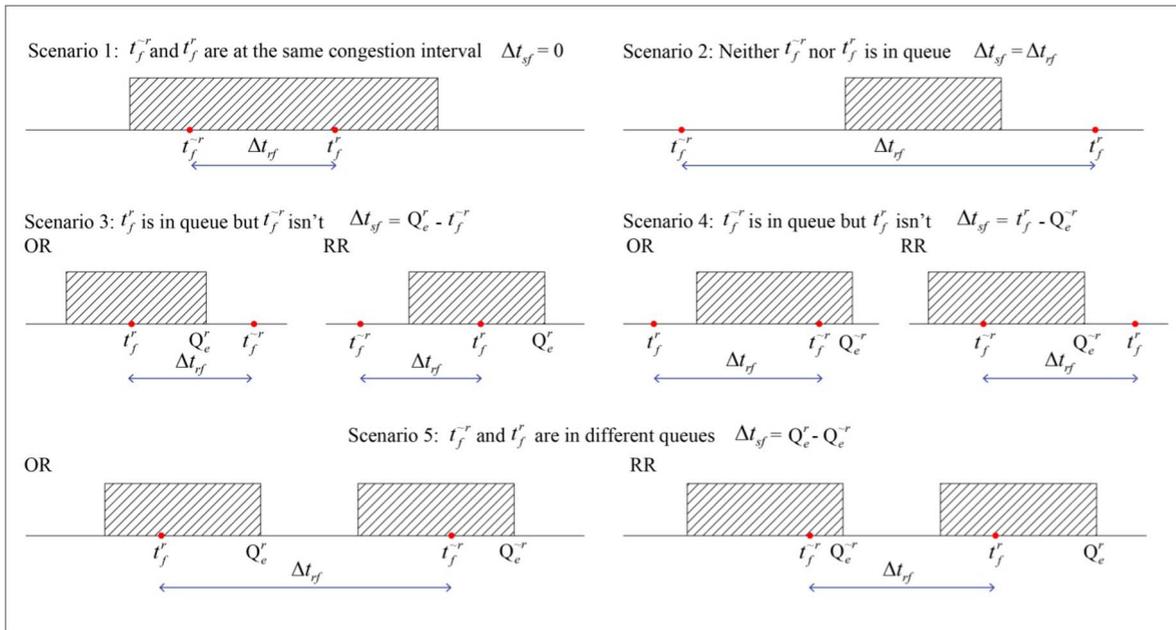


Fig. 3. Illustration of multiplier calculation.

uncongested period to a congested one. For OR, part of the timesaving of the rerouted flight is offset by the delay it imposes on other flights in the congested period. For RR, the system impact should be the additional time encountered by the rerouted flight plus the delay it imposes on the other flights in the congested period. Given the congested period ends at  $Q_e^r$ ,  $\Delta t_{sf} = Q_e^r - \tilde{t}_f^r$ .

- Scenario 4 –  $\tilde{t}_f^r$  is in a congested period but  $t_f^r$  is not. This is the opposite case of Scenario 3. Given that the end of the congested period is indicated as  $\tilde{Q}_e^r$ ,  $\Delta t_{sf} = t_f^r - \tilde{Q}_e^r$ .
- Scenario 5 –  $t_f^r$  and  $\tilde{t}_f^r$  are in two different congested periods. For the OR case shown on the left, the effect is to shift one flight from the congested period ending at  $Q_e^r$  to the earlier congested period ending at  $\tilde{Q}_e^r$ . The system impact is thus  $\Delta t_{sf} = Q_e^r - \tilde{Q}_e^r$ . By similar reasoning, the system impact of an RR is also  $\Delta t_{sf} = \tilde{Q}_e^r - Q_e^r$ .

The foregoing analysis demonstrates that the system impact of a rerouted flight could be less than, equal to, or greater than the direct impact on the rerouted flight itself. We define a multiplier  $M$  as the ratio of the system impact  $\Delta t_{sf}$  to the direct impact  $\Delta t_{rf}$ .

$$M = \frac{\Delta t_{sf}}{\Delta t_{rf}} \tag{4}$$

We propose two ways to calculate the average multiplier. One method is to simply take average value of all  $M$  values for some set of reroutes of interest, say of flight bound for a given airport. The formula is shown below:

$$\bar{M} = \frac{\sum_{i=1}^n M_i}{n} \tag{5}$$

In aggregating the multiplier across flights, we define a weighted average multiplier as the overall system impact “weighted” by the overall reroute time. The formula is as follows:

$$\bar{\bar{M}} = \frac{\sum |\Delta t_{sf}|}{\sum |\Delta t_{rf}|} \tag{6}$$

Fig. 4 summarizes the methodology that has been detailed in this section.

#### 4. Descriptive results of reroute patterns

We apply our methodology to analyze the downstream impact of rerouting of all rerouted domestic flights with destinations being the 34 main US airports. From January 2013 to December 2014, there are a total of 5,362,149 such flights in the ETMS Flight Event data set. For virtually all flights, the actual flown distance was somewhat different from the pre-departure flight plan distance, but most of the differences were very small. For the purposes of our analysis, we defined minor, moderate, and major reroutes as those cases when the actual flow and flight plan time differ by less than 5 min, 5–10 min, and more than 10 min, respectively. In total, 95.6% of all flights fall into the minor category, while major and moderate reroutes represent 1.6% and 2.8% of total flights,

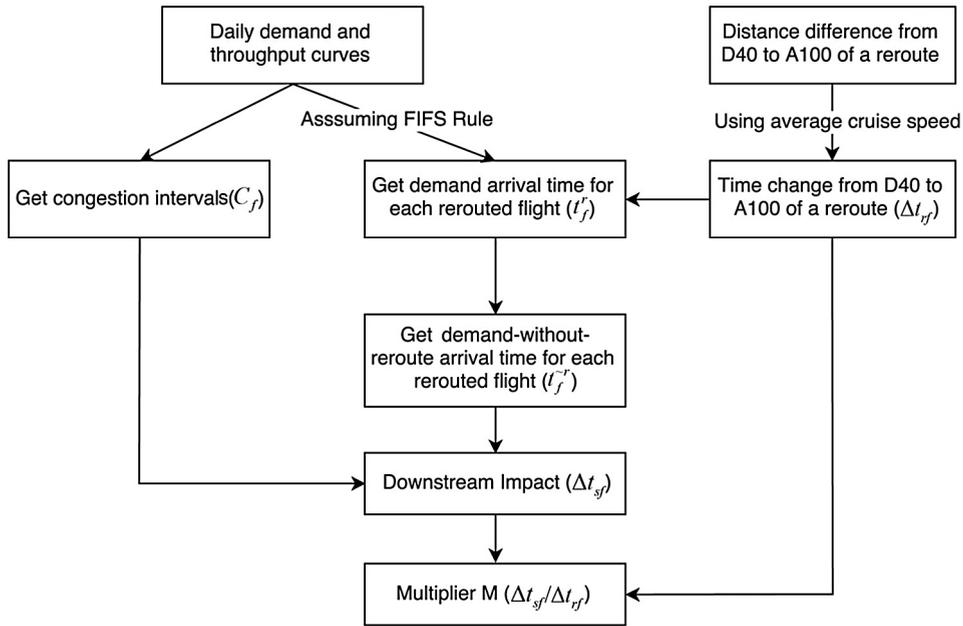


Fig. 4. Method of multiplier calculation.

respectively, for a total of 233,481 flights. Further analysis showed that 67% of minor reroutes have a reroute time of less than 1 min – either positive or negative, and only 5% of minor reroutes had a time change larger than 3 min. Such small-scale time and distance deviations could be due to slight deviations of the flight trajectory from the flight plan, rather than a reroute. Thus, we excluded minor reroutes from the following analysis and focused on evaluating the system impacts of major and moderate reroutes.

In addition to the distance differences of the reroutes, more descriptive statistics are summarized in Fig. 5. The first and second groupings are daily and seasonal patterns of flight departure time. We categorized parts of the day as follows, morning is from 6 to noon, afternoon is from noon to 5 pm, evening is from 5 pm to 9 pm and night is from 9 pm to 4 am. The graph shows that morning is the most common departure time and summer has slightly more traffic than other seasons. The third grouping shows the number of reroutes falling into different distance brackets based on the great circle distance from D40 to A100 of the flights. The largest number of reroutes involve flights with great circle distances larger than 1000 nm; while flights with great circle distances between 100 and 200 nm have the smallest number of reroutes.

Fig. 6 illustrates the incidence of major and moderate reroutes for flights categorized by departure time of day, season, and great circle distance from D40 to A100. RRs and ORs both occur in less than 10% of all flights, with ORs slightly more frequent than RRs and moderate reroutes more common than major ones. RRs are, however, more common than ORs for flight departure times in the afternoon, in the summer season and with great circle distances between 400 and 600 nm. Fig. 6 also shows that ORs are much more common for night flights and more frequent for evening, winter, and long-haul flights. The incidence of both ORs and RRs increases with flight distance; they are about three times as likely for flights over 1000 nm compared to flights of 100–200 nm.

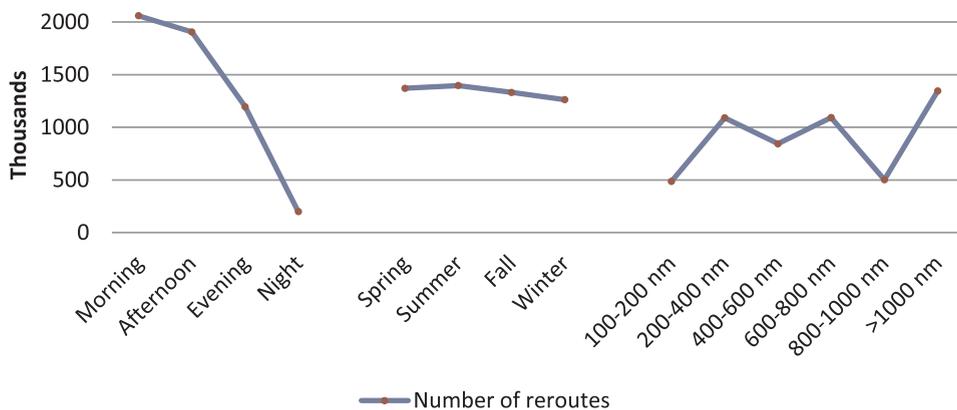


Fig. 5. Number of moderate and major reroutes and daily, seasonal, and distance distributions.

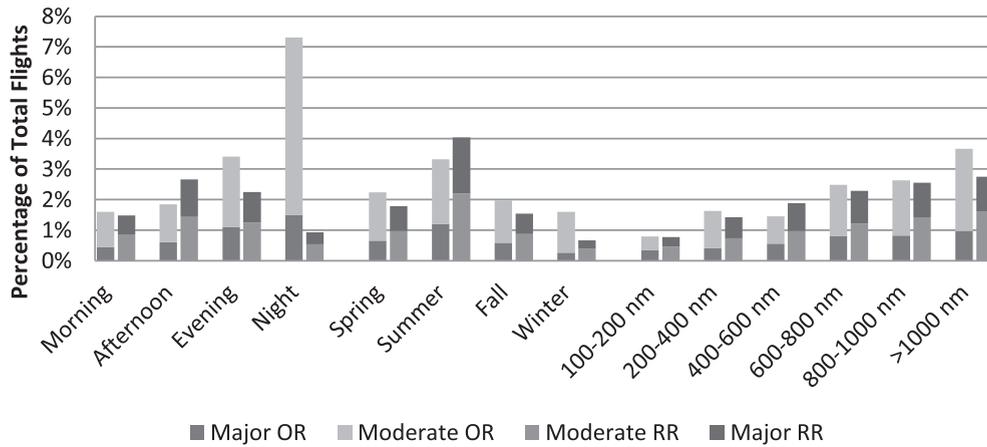


Fig. 6. Daily, seasonal, and distance patterns of moderate and major OR and RR.

5. Downstream impact study of 34 US airports

Applying the methodology described earlier and depicted in Fig. 4, we calculated the downstream impact and resulting  $M$  values of all moderate and major reroutes found in the Flight Event data set. The main findings of our calculations are summarized as follows.

Across all the moderate and major reroutes in our data set are  $M$  values ranging from 0 to 219. In Fig. 7, the distributions of  $M$  values for flights arriving at the 34 airports are summarized. The distributions vary significantly. The most common value for  $M$  is 1, as depicted as Scenario 2 in Fig. 3. Recall that when  $M = 1$ , the system impact of a reroute is equal to the direct impact, as assumed in many assessments of rerouting decision support tools such as DWR. However, the percentage of reroutes with  $M = 1$  varies from airport to airport, with the lowest (18%) at LGA and the highest (85%) at PDX. The second most common value of  $M$  is 0, i.e., the shifted queue arrival time causes a reshuffling of delay in a congested time period, resulting in no net change, as depicted as Scenario 1 in Fig. 3. The third most common case is  $0 < M < 1$ , and the least common is  $M < 1$ . The airports at which reroutes with  $M < 1$  occur the most include MEM (5.8% of total moderate and major reroutes), CLT (5.7%), and LAX (5.6%); the least include LGA (2.2%) and PDX (2.5%).

We further explored the relationship between the direct time impact of the reroute and its system impact – i.e., between  $\Delta t_{rf}$  and  $\Delta t_{sf}$  – using scatter plots. Fig. 8 shows two scatter plots – for LGA and PDX – that reflect the differences among airports. It can easily be seen that the magnitude of the system impact of the rerouted flights at PDX is similar to the direct time impact of the rerouted flight. Nevertheless, for LGA, some rerouted flights cause significant system impacts, and the largest is more than 1100 min. Also, compared to PDX, there is a much larger proportion of moderate and major reroutes – over 70% – with  $M = 0$  at LGA. This is foreseeable because LGA has consistent high demand throughout the day, so the congested time periods are longer. Statistics show that the daily average amount of time in queue is 413 min at LGA and 113 min at PDX. Thus, Scenario 1 in Fig. 3 is more likely to occur at LGA. From a practical standpoint, using the standard assumption that  $M = 1$  to predict the system impact of a reroute – i.e. the 45-degree lines in Fig. 8 – would yield predictions that are often accurate but occasionally quite wrong if PDX is the destination, whereas for LGA such predictions would be rarely accurate and often wildly wrong.

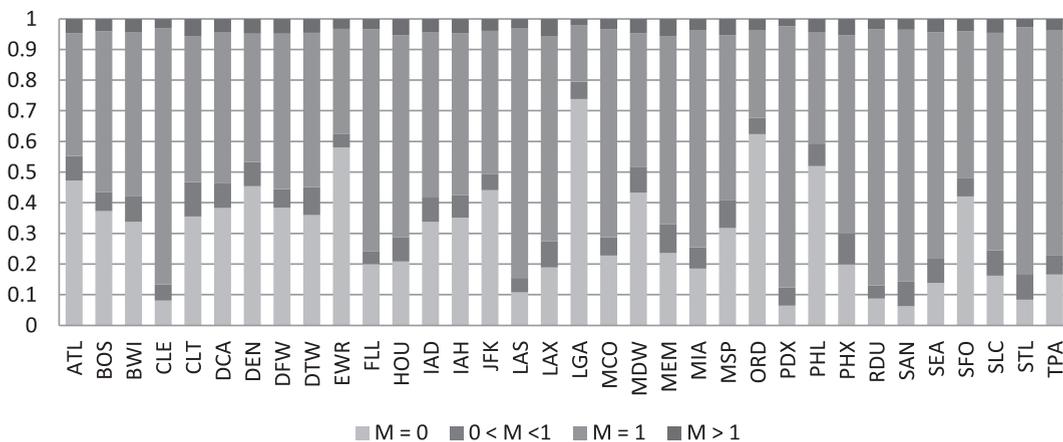


Fig. 7. Multiplier distributions at 34 airports.

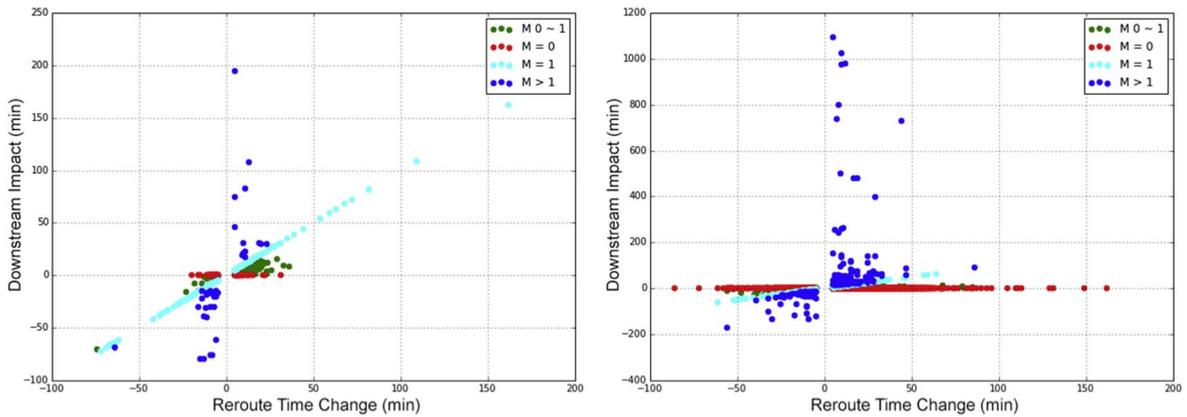


Fig. 8. Scatter plots of reroute time and downstream impact of two representative airports: PDX (left) and LGA (right).

While the above results show that  $M$  values vary considerably even for a specific airport, it is still useful to summarize them by reporting average  $M$  values. As explained above, the average value for  $M$  can be obtained in two ways, one of which gives equal weight to each reroute event and one which weights reroutes with greater flight time impacts proportionally higher. Fig. 9 presents the two values at each airport. For about half the airports, the multipliers are above 0.8. The lowest values are at LGA, between 0.2 and 0.4. The unweighted average value of  $\bar{M}$  is larger than the weighted average multiplier  $\bar{M}$  for all airports, implying that small values of  $\Delta t_{rf}$  are more likely to have larger  $M$  values. SEA has the least difference (0.017) between the two, and EWR has the largest difference, with an  $\bar{M}$  of 0.47 compared an  $\bar{M}$  of 0.62. Fig. 9 again clearly shows that assuming system impact  $\Delta t_{sf}$  is equal to immediate impact  $\Delta t_{rf}$  will likely lead to erroneous conclusions. Not surprisingly, this is especially true for the nation’s busiest and most congested airports, including the New York metropolis, ATL, BOS, PHL, ORD, and SFO. On the other hand, there is not, in general, a large difference between the two averages of  $M$ .

While the multiplier averages discussed above include both RRs and ORs, there is a reason to believe that the multipliers for these different types of reroutes may also be different. For example, one reason for an RR is to meter flow into a congested airport, which would often result in a multiplier of 0. On the other hand, a well-informed decision maker would be less likely to initiate or approve an OR into a congested airport precisely because this would not yield benefits from a system perspective. This suggests the hypothesis that RRs will on average have lower multipliers than ORs. To test this hypothesis, we compared the  $\bar{M}$  value for RRs and ORs for major and moderate reroutes at each airport and also conducted both one- and two-tailed hypothesis tests to examine whether the average  $\bar{M}$  value of one kind of reroute is different from another.

For the majority of airports (30 of 34), the mean multipliers of RRs and ORs were significantly different at the 0.05 level with a two-tailed  $t$  test. In all of these cases, ORs had higher average multipliers than RRs. This result supports the argument that RRs with low multipliers and ORs with high ones are more likely. The four airports that do not possess the difference between OR and RR are BWI, CLE, MDW, and PDX. We also found that the  $\bar{M}$  value of moderate reroutes was significantly larger than that for major reroutes at the 0.05 level, except at CLE, MDW, and PDX.

The multipliers of the four types of reroutes—moderate RR, moderate OR, major RR, and major OR – were compared based on the whole dataset (see Table 1). Moderate ORs had the largest  $\bar{M}$  and  $\bar{M}$  values (0.988 and 0.984, respectively), and major RRs had the lowest values (0.470 and 0.421, respectively). The average  $\bar{M}$  values for major ORs and moderate RRs were 0.855 and 0.742, respectively, and the  $\bar{M}$  s for the two were 0.835 and 0.737, respectively. The results suggest that the technologies or innovations that lead to moderate ORs can be assessed fairly accurately by considering the direct impact only, whereas major RRs have considerably less system impacts than the direct impact would imply. The impacts of major ORs and moderate RRs lie somewhere in between.

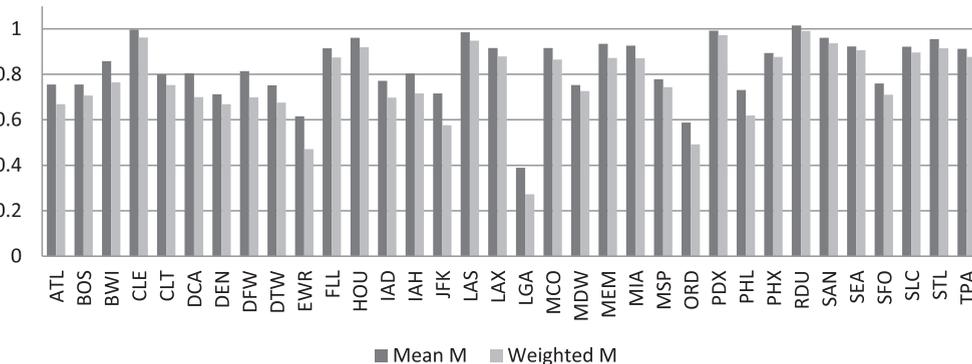


Fig. 9. Comparison of  $\bar{M}$  (Mean M) and  $\bar{M}$  (Weighted M) at 34 airports.

**Table 1**  
Statistics of average and weighted multipliers at 34 airports.

Average multiplier	Major OR	Moderate OR	Major RR	Moderate RR
Mean	0.855	0.988	0.470	0.742
Minimum	0.000	0.000	0.000	0.000
Maximum	102.000	188.333	109.600	219.000
Std	1.892	2.913	1.725	2.748
Weighted multiplier	Major OR	Moderate OR	Major RR	Moderate RR
Value	0.835	0.984	0.421	0.737

Finally, we investigated two specific reroutes with very high  $M$  values to identify the conditions under which these could occur. One case was a flight destined for LGA on June 13, 2013, with a moderate RR, and the other was a flight to SFO on July 30, 2013, with a moderate OR. Table 2 provides detailed information for these two events. On June 13, 2013, LGA became congested a few seconds after 7:44 am, and the queue did not dissipate until 1:59 am the next day. Flight 1, whose planned queue arrival time was 7:44 am, had an actual queue arrival time of 7:49 am due to a 5-min RR. Because Flight 1's adjusted queue arrival time fell into a congested time period, it negatively affected many subsequent flights by delaying their landings. The multiplier of this RR was very large, as a 5-min RR rerouting yielded more than 1000 min of system delay and the  $M$  value was 219. In the other case at SFO, Flight 2's queue planned arrival time was 7:45 am but it joined the arrival queue at 7:39 am due to an OR reroute that saved 6 min. SFO suffered from continuous congestion from 7:44 am to the next day at 2:29 am; therefore, if Flight 2 had not been issued a reroute, its queue arrival time would have fallen into a congested time period and it would delay all flights arriving after it. The system-level timesaving from this OR reroute was significant, with a multiplier of 188. It can be seen from these two high  $M$  cases that large multipliers occur when flight  $f$ 's  $\tilde{t}_f^q$  ( $t_f^q$ ) falls into a long congested period while its  $t_f^d$  ( $\tilde{t}_f^d$ ) is in an earlier non-congested period for OR (RR).

**6. Conclusions and recommendations**

Downstream or system impacts of rerouting have not been systematically considered in previous literature or in air traffic management operations. In this study, we developed an analytical framework for evaluating the downstream impacts of rerouting by identifying five representative cases and developing a method of calculating multipliers. We have defined major, moderate, and minor reroutes based on the estimated time difference of the reroute, and ORs and RRs based on whether the reroute increased or decreased the path length. We also defined the multiplier  $M$  as the ratio of the direct and system time savings (positive or negative) associated with a reroute, and two average multipliers – one, the arithmetic average and the other the weighted average – to quantify different levels of impacts. The empirical results showed that moderate and major reroutes have widely varying downstream impacts as a result of the interaction between reroute time change and airport operational conditions. Additionally, the multipliers vary across airports. We also find that, as hypothesized, at most US airports, the average multipliers of ORs are, on average, larger than those of RRs. Moderate reroutes also have higher average multipliers than major reroutes.

DWR and NASCENT are being developed to support and improve reroute planning and execution for flights in en route airspace. In the future, air traffic managers and airline operation centers may rely on these tools to find shortcuts on pre-selected weather avoidance routes and identify rerouting opportunities that may lead to time and fuel savings. Given that the downstream impacts could be less than, equal to, or more than the direct impact of rerouting, we recommend enhancing these tools to include a downstream impact analysis tool that gives priority to opportunistic reroutes (OR) that would generate the greatest positive downstream impacts and avoid those that would simply hasten the arrival of a flight into a congested airport. Similarly, it may be useful to anticipate the system impacts of reroutes when resolving conflicts or considering pilot requests. Our study has developed a simple reroute performance measurement, the multiplier  $M$ , which could be incorporated into reroute decision-support tools to facilitate the rerouting decisions and improve the efficiency of air traffic operations. Unlike the current retrospective analysis, such a tool would need to work prospectively, anticipating how a given reroute would affect delays to other flights that have yet to reach a given airport. To do this one must be able to anticipate congested and uncongested time periods at the destination airport. There is a substantial infrastructure for doing this already in place. For example, airport demand lists, predicting when flights will arrive at given airport and being updated every 5 min, could provide basis for these predictions.

**Table 2**  
Summary of two reroutes with high  $M$  values.

ID	Type	Des.	$\tilde{t}_f^q$	$t_f^q$	$C_f$	$\Delta t_{rf}$	$\Delta t_{sf}$	Multiplier
1	Moderate RR	LGA	06/13/2013 07:44	06/13/2013 07:49	06/13/2013 07:44–06/14/2013 01:59	5	1095	219
2	Moderate OR	SFO	07/30/2013 07:45	07/30/2013 07:39	07/30/2013 07:44–07/31/2013 02:29	–6	–1130	188

Our analysis is limited to queueing delay, which is not the same as delay against schedule. The latter is affected by other sources of delay as well as the amount of buffer built into the scheduled block times. The delay impacts estimated in this paper could change either the earliness or lateness of a flight relative to the schedule, as well as make an early flight late or vice versa. Changes in the delay relative to schedule can also propagate to subsequent flights, either because they use the same airframe or crew members, or in order to accommodate connecting passengers. In these ways a reroute can change arrival times not just at the destination of the rerouted flight but at other airports as well. While there is considerable research on flight delay propagation in general, it would be useful in future research to consider these effects specifically in the context of reroutes.

One limitation of this study is that flight phases from departure airport to D40 and A100 to the arrival airport were not considered. Congestion could occur due to not only runway capacity but also to arrival fix capacity. The present study, by relying on a simple queueing model and relationship between distance saving and time saving, yields only rough estimates of the downstream impacts on any particulate reroute. Its virtue is simplicity and accordingly the ability to apply it to a large set of flights. In future research, with more complete information from the ETMS radar track database, we could study the downstream impacts more precisely. Another future research direction would be to understand the decision of whether to accept DWR reroute suggestions from the airlines' perspective, which may be influenced by route characteristics, environmental factors, and internal business objectives. For example, airline internal business interest could distinguish flights according to the number of passengers, connecting passengers, and crews on board, which are not available in the data used in this study and thus are not considered in our analysis. Such follow-on work will allow ATCs to better understand and predict reroutes in the NAS, increase the predictability of the NAS, and, ultimately, improve system performance.

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