Downstream Impact of Flight Rerouting

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ABSTRACT

Reroute, as a common Air Traffic Flow Management (ATFM) scheme, is often considered as effective to deal with inclement weather or restricted capacity at destination airport. 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 existing literature; however, the benefit/harm of both kinds of reroutes might be exaggerated without taking its system impact into account. Thus, we propose to develop a framework for evaluating the net benefit of applying a reroute at a system level by analyzing its downstream impact.

For the purposes of our study, we focus on evaluating the downstream impacts of reroutes with en route flight time by five minutes or more. Adopting a similar 'Multiplier' concept that was proposed in previous research and making use of two-year (2013 to 2014) flight level data at the main 34 U.S. airports, we are able to analyze the relationship between reroute time and airport throughput alteration. We find that the downstream impacts of reroutes differ remarkably at different airports, and identify airports with either strong or weak linear correlation between flight rerouting and its downstream impacts. In addition, we compare downstream impacts among different types of reroutes. Lastly, we present two days with top multipliers in detail to demonstrate situations in which a high multiplier reroute would more likely to occur.

Keywords: system impact, downstream impact, airport, reroute, demand, actual, arrival, congestion, evaluation

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. Alternatively, traffic and weather conditions may enable a more direct path that saves the flight time and fuel. The route may be changed prior to departure or after the flight is underway. The main focus of this study is post-departure reroutes. Reroutes can also be categorized into those that lengthen or shorten the flight path. The former are generally necessitated by weather or traffic conditions, while the latter exploit opportunities based on improving weather, low traffic, or reduced uncertainty.

A number of research and development programs have been geared toward employing reroutes to increase efficiency. At NASA, the Direct-to and Dynamic Weather Routes (DWR) programs use software that continually scans for opportunities to shorten flight paths by flying direct between waypoints. DWR, which has been implemented at American Airlines for the Dallas ARTCC, focuses on situations in which the initial planned route is designed to avoid regions where convective weather is forecast. Often in such situations, the realized weather offers opportunities to shorten the planned route while still avoiding convective weather regions. A related program, known as the NAS Constraint Evaluation and Notification Tool (NASCENT) extends the DWR concept to the continental US, and shifts the initiation of reroutes from the flight operator to the service provider.

DWR and NASCENT are intended to mitigate inefficiencies that result because initial pre-departure flights plans, made in the face of considerable uncertainty about the precise regions of convective weather at flight time, are often very conservative. The aim is to take advantage of portions of the airspace that turn out to be flyable. Other programs, such as MITRE's En Route Flow Planning Tool (EFPT) or 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 in the 15-90 minute time frame, devise and rank potential solutions, and execute the chosen reroutes. This would help avoid the high communications workload, traffic complexity, and unpredictability that often results from "just-in-time" route deviations initiated by pilots, which by their nature are concentrated in space and time and must be handled urgently. The AAC includes both a strategic and a tactical weather avoidance capability, as well as tactical conflict resolution. Strategic reroutes are initiated about 20 minutes prior the predicted time of entry into the weather cell and re-evaluated every 15 minutes, while the tactical rerouting algorithm operates on a 1-minute cycle.

To assess the benefits of programs such as the ones above, most previous research has focused on the direct time savings from reroutes to the impacted flights. If, for example, a reroute allows a flight to fly direct from point A to point C in 20 minutes, while the planned route included segments from A to B and from B to C with a flight time of 25 minutes, then the direct time savings is 5 minutes. Using this approach, for example, McNally et al. estimate potential savings at about 10 min. per flight rerouted by 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 (*1*). Others consider the impact on the flight as a whole. For example, Refai et al. use a fast-time simulation, ACES, to find the changes in delay, defined as the difference between actual and scheduled en route flight times, to rerouted flights (*2*).

While simple and straightforward, this approach may not accurately reflect the actual impact of the rerouting either on the rerouted flight itself or to the NAS as a whole. For instance, due to airport congestion, direct time savings 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. This increased delay to other flights may partly or completely offset the time savings to the rerouted flight. It is also possible, as will be explained below, that the direct time savings from a reroute will cause an even greater time savings for the system as a whole. Of course, the converse possibilities exist when a reroute results in a direct time penalty.

This motivates the questions of how to evaluate the net time savings of issuing a reroute from a system perspective, and how the net savings compare to the immediate effect of the reroute. These are the subjects of the current paper. We develop and operationalize a methodology for determining how a change in en route time for a given flight impacts the total amount of flight time for all flights destined for the same airport. We apply this methodology to an extensive data set that summarizes reroutes, in terms of the difference between total planned and flown en route flight distances, for a large set of US flights. This enables us to estimate how each individual distance change affects the aggregate flight time, and hence to study the relationship between the immediate impact of a reroute on the rerouted flight and its overall impact on all flights bound for the same airport.

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

LITERATURE REVIEW

A great deal of research attention, at both local (i.e. individual flight) and systematic (the impact on the NAS) scale, has been devoted to the study of delay propagation. The definitions of downstream impact and multiplier vary in different scopes. Based on actual delay statistic, Boswell et al. developed an analytical model to estimate the delays in successive flight legs when a multi-leg flight encounters an initial delay in a daily itinerary (*3*). A downstream multiplier is defined as the ratio between the seed delay and its total downstream impact. This study provides an omnibus multiplier which can be applied at all sites and in all traffic conditions. It reveals that on average 2.5 downstream legs are impacted by a seed delay, and one minute of seed delay engender 0.8 minute of parallel carryover delay in subsequent flight legs in winter weather.

Kondo has adopted similar ideas by defining a propagated delay in a sequence of flights operated by the same tail-numbered aircraft (*4*) in a study aiming at comparing the difference of propagated delay between point-to-point carriers and network carriers. Rather than using a single, national multiplier, Welman et al. uses an "aircraft-operational day" as the study unit and developed arrival delay propagation multipliers for both individual and groups of airports in airport cost-benefit studies on the basis of mapping original and propagated delay across the NAS (*5*). The authors discovered variation in the multipliers at different sites, reflecting that that delay propagation is a network phenomenon and is influenced by a mixture of factors across the network.

The techniques from complex network have also been adopted in studying the structures resulted from delay propagation, yielding a systematic perspective of the propagation procedure, beyond the dynamics of individual flights and airports. Laskey et al. applied Bayesian networks (BN) to model the relationships among different components of aircraft delay, such as local and system level environmental and human-caused factors (*6*). Propagated delay, in this study, is defined as delays 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. Departure delay is identified 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 (*7*). The authors defined 'congested airport' and studied how such airports form connected clusters in the network. Passenger and crew connectivity were identified as the key factor for the rise of congestion in the network. Airport daily schedule was found to affect delay propagation patterns as an airport was not consistently part of the same clusters. It was noted that being in the same cluster was a measure of correlation but not necessarily a sign of a cause and effect relationship.

To the extent that reroute generates distance difference compared with planned route, the widely studied speed adjustment, which causes time difference, is also relevant to our work. For individual flights, both reroute and speed control could lead to deviations from the scheduled arrival times, sometimes such deviations are intended. Jones et al. study the inefficiency in the arrival phase: flights accelerate speed to make the schedule arrival times only to be delayed in the terminal airspace when heavy degree of congestion prevent it from landing (*8*). Such delay could be taken in the descend phase by rerouting mechanisms such as tromboning, vectoring and circular holding pattern to add distance to a flight, or it can be achieved by reducing flight speed in the en route phase. Once given sufficient advance notice, the authors demonstrate that a significant amount of delay could be transferred away from the arrival phase to the en route phase and the efficiency of descent phase will be largely improved.

Deterministic queuing models have been extensively used to evaluate system and individual flight delay. While extremely simple, predictions from these models have been found to closely match those of more complex stochastic queueing models (*9*). Applying this method, Hansen investigates delay impacts of individual flights by comparing the total system delay before and after a particular flight has been eliminated (*10*). The author finds that the delay impact is highly sensitive to when a flight enters the arrival queue. A flight arriving at the beginning of a lengthy period of queuing generates the largest delay, since if were removed many flights arriving behind it in the same queuing period could move up. On the other hand flights that arrive in periods when there is extra capacity cause 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 4-min average queuing delay.

Yin and Hansen apply the deterministic queuing model to estimate system impacts of en route flight delays for flights with different destination airports (*11*). This earlier study draws on a delay multiplier concept to capture the downstream effects of flight's en route delay, finding that the system impact of an en route delay can vary significantly from the immediate impact to the flight incurring delay. 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 (*10*). While this research focuses on differences in flight distance that result from reroutes, which in turn lead to flight time changes, related work examines how control of en route speed can shift delay from the terminal area to the en route phase of flight (*8*). The analyses recognize that when arrival demand exceeds capacity, delaying arrival into the terminal area may not affect the aggregate level of flight delay.

METHODOLOGY

Figure 1 is a diagram showing different flight routes. Line A indicates the great circle distance between origin and destination airports, while line B reveals the great circle distance from 40 nautical mile (nm) radius departure fix (D40) to 100 nm radius arrival fix (A100) of a given flight. Curve C between departure and arrival fixes represents the flight plan en route trajectory, while both D and E illustrate hypothetical en route trajectories. Reroutes considered in this study are based on distances from D40 to A100 rather than distances between origin and destination airports. Reroutes are characterized, very simply, as the aggregate difference in length (based on ground distance) between the planned route (C in Figure 1) and the flown route (for example D or E in Figure 1). While partly a reflection of the limitations in our data set, which will be discussed in more detail below, the aggregate representation also avoids complexities that arise from the fact that reroutes may be issued as a sequence of amendments (see, for example, McNally (*1*), Figure 5).

In reality, many reroutes are local, with the flight trajectory deviating from the planned route sometime after take-off and recapturing the route a short time later. The distance metric does not differentiate between complete reroutes – referring to reroutes deviate from flight plan completely – and such local reroutes shown in Figure 1. A reroute, whether complete or local, may be longer or shorter than the original. We refer to longer reroutes as "reactive" because such reroutes (termed RRs for short) are presumably made in response to some problem such as convective weather or excess traffic. Reroutes that shorten the flight distance are termed "opportunistic" (and abbreviated ORs) because in general they arise from the ability to shorten the route. A given flight may receive a combination of RRs and ORs, but since we consider overall flight distance we represent this combination as a single RR or OR, depending how the combination affects the overall length. We also note that in some situations OR's are motivated by a mixture of problems and opportunities, for example a flight may be cleared to fly direct to its destination in order to resolve a conflict (*7*), while RRs may actually yield time savings as a result of winds, which are not considered in this analysis.

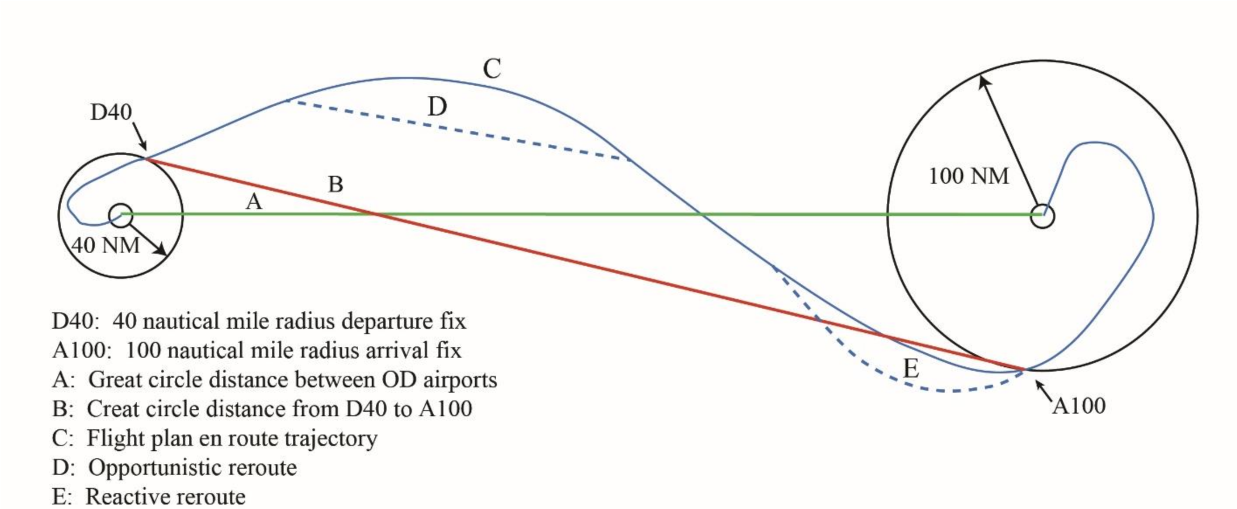

FIGURE 1 Flight route illustration.

Both ORs and RRs may engender downstream impacts. Formally, let Δt_{rf} be the direct time savings resulting from the reroute of flight *f*. We estimate this using:

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

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 cruise speed. For RRs, Δt_{rf} is positive, while for ORs it is negative. Now let $t_{ff'}^r$ be the arrival time of flight *f's* given that the reroute to flight *f* took place, and $t_{ff'}^{\sim r}$ the arrival time in the counterfactual that this reroute did not take place, i.e. that $\Delta t_{rf} = 0$. We are interested in finding the system impact of the reroute to flight *f*, defined as:

$$\Delta t_{sf} = \sum_{f'} t_{ff'}^r - t_{ff'}^{\sim r}$$

When the destination airport and other downstream resources have excess capacity, the reroute time impact will translate directly into a system time impact. That is, in such situations:

$$t_{ff'}^r - t_{ff'}^{\sim r} = \begin{matrix} 0 & f' \neq f \\ \Delta t_{rf} & f' = f \end{matrix}$$

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

This is the implicit assumption behind benefits studies for DWR (*1*) and NASCENT (*8*), among others.

On the other hand, when there is congestion downstream, the effect of the reroute becomes less straightforward. To take one example, suppose that, with or without the reroute, demand exceeds capacity at the destination airport during the time period surrounding the arrival time of the rerouted flight. In this case the reroute should not affect the total system delay. While the rerouted flight will arrive sooner or later as a result of the reroute, this difference would be offset by changes in delay to other flights that are either pushed back or move up in the queue at the destination airport. In terms of deterministic queuing theory, the reroute shifts the cumulative arrival demand curve but not the cumulative arrival throughput curve.

We extend this idea by constructing, from historical data, daily cumulative arrival demand and arrival throughput curves at the destination airport for a given flight *f* whose reroute is being considered. We will denote these as $Q_f\left(t\right)$ and $A_f\left(t\right)$ respectively, where the subscript *f* matches the flight with its associated destination and day of operation. These curves reflect all reroutes that have actually taken place. Using these curves, we identify congested periods at the destination airport as those times there is a discrepancy between arrival demand and arrival throughput. In other words, defining C_f as the set of times that fall into a congested period at the destination and day of operation of flight *f*, $t \in C_f \quad iff\ Q_f(t) > A_f(t)$.

We want to determine how the queuing diagram would be different if flight *f* had not been given a reroute. We assume that without the reroute, the time when flight *f* joins the arrival queue would be shifted by Δt_{rf}. In other words, if t_f^r and $t_f^{\sim r}$ are respectively the times when flight *f* joins the queue with and without the reroute, then $t_f^{\sim r} = t_f^r - \Delta t_{rf}$. To employ this assumption, we must estimate t_f^r, since this is not directly observable in our data, based on its observed actual arrival time, which we denote τ_f^r. To do so, we employ the following procedure, which is based on the assumption of a first-in first-out (FIFO) queueing discipline. First, we obtain the value of the cumulative arrival throughput curve at the observed arrival time of the rerouted flight, $A_i\left(\tau_f^r\right)$. Next, we identify the corresponding queue arrival time t_f^r for the flight by finding the time when the cumulative arrival demand curve reaches the value $A_f\left(\tau_f^r\right)$: $t_f^r = Q_f^{r^{-1}}\left(A\left(\tau_f^r\right)\right)$. Figure 2 illustrates the procedure in a case in which the observed arrival time is during a congestion interval, i.e. $\tau_f^r \in C_f$, so that $\tau_f^r > t_f^r$. (Conversely, we see that $\tau_f^r = t_f^r\ iff\ \tau_f^r, t_f^r \notin C_f$.)

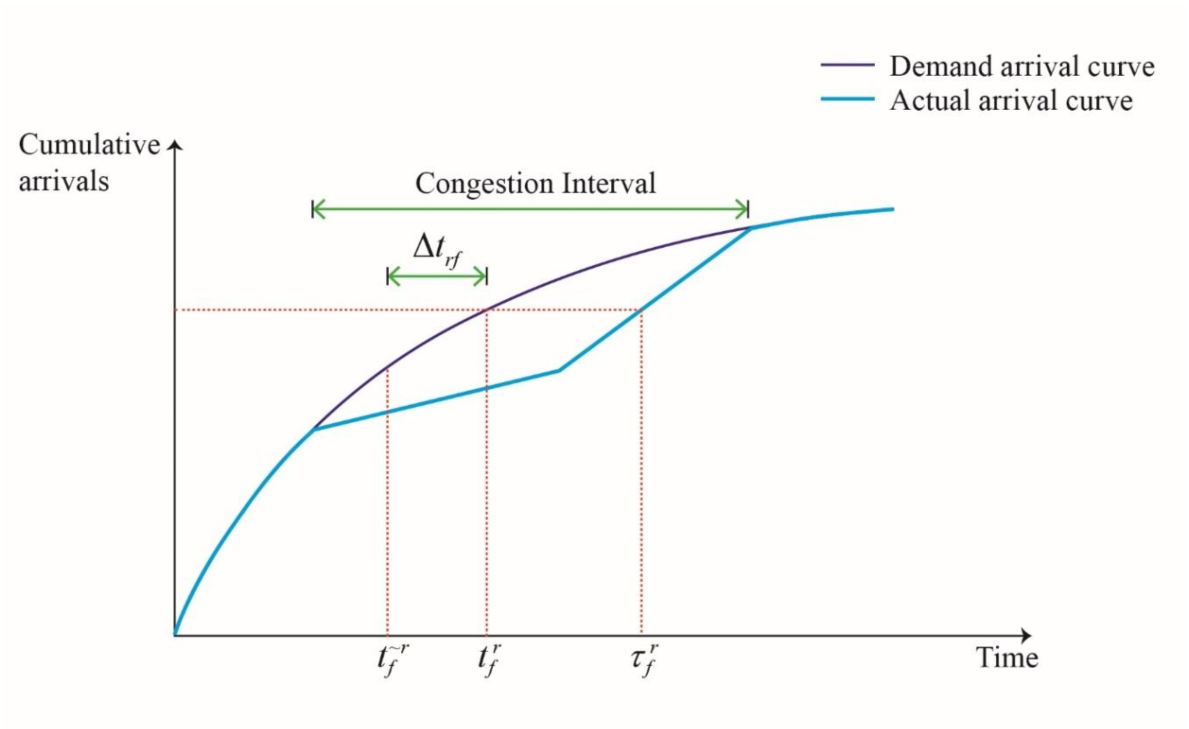

FIGURE 2 Illustration of demand arrival time mapping

Given that the queue arrival time without the reroute shifts from t_f^r to $\tilde{t}_f^r$, how does this affect the total delay in the system? This depends on C_f, i.e. on when the destination airport for flight f is congested on that flight's day of operation. As a simplifying approximation, we assume that the congestion intervals themselves are not affected by the shift of any one flight. Under this assumption, an airport can also serve one more flight if its capacity is able to accommodate the demand at a particular time, and likewise will remain congested if a flight is removed from the demand during a congested period.

With this assumption, there are five scenarios, illustrated in Figure 3, that govern the relationship between the change in queue arrival time and the change in system delay. In Figure 3, two red points $\tilde{t}_f^r$ and t_f^r, and the cross-hatched areas represents the congested periods C_f associated with $\tilde{t}_f^r$ and t_f^r given they are in queue. If t_f^r (respectively $\tilde{t}_f^r$) falls is in a congested period, Q_e^r (respectively $\tilde{Q}_e^r$) denotes 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. We present the relationship under each scenario, in turn:

- *Scenario 1* – t_f^r and $\tilde{t}_f^r$ fall into the same congested period. In this case the time shift has no impact of system delay. The difference in actual arrival time for flight *f* is offset by differences for other flights in the same queue. Therefore $\Delta t_{sf} = 0$.
- *Scenario 2* – t_f^r and $\tilde{t}_f^r$ are in uncongested periods. In this case the change in system delay is equal to the time shift: $\Delta t_{sf} = \Delta t_{rf}$.

- *Scenario 3* – t_f^r falls into a congested period but $t_f^{\sim r}$ does not. In other words the reroute moves the queue arrival time from an uncongested period to a congested one. The addition of a flight into a congested period cannot affect throughput until the end of that period, which is Q_e^r. Therefore $\Delta t_{sf} = Q_e^r - t_f^{\sim r}$.
- *Scenario 4* – $t_f^{\sim r}$ falls into a congested period but t_f^r does not. In other words the reroute moves the queue arrival time from a congested period to an uncongested one. The loss of a flight from the congested period cannot affect throughput until the end of that period, which is $Q_e^{\sim r}$. Hence $\Delta t_{sf} = t_f^r - Q_e^{\sim r}$.
- *Scenario 5* – $t_f^{\sim r}$ and t_f^r fall into two different congested periods. The throughputs can change only at the end of the respective congested periods. Thus $\Delta t_{sf} = Q_e^r - Q_e^{\sim r}$.

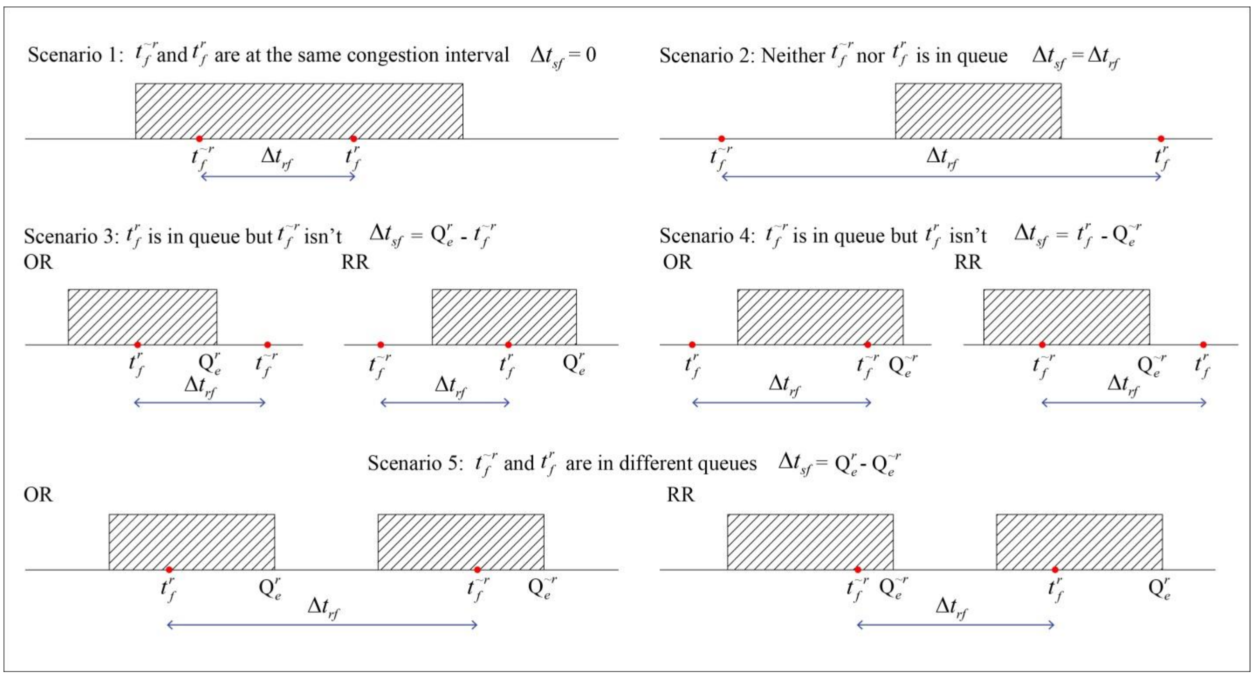

FIGURE 3 Illustration of Multiplier Calculation

The foregoing analysis demonstrates the impact of a reroute on system delay maybe less than, equal to, or greater than the direct impact on when the rerouted flight reaches the terminal area. We define a multiplier M as the ratio of the system delay impact Δt_{sf} to the direct impact Δt_{rf}. In aggregating the multiplier across flights, we can either consider the average M of a flight by flight basis, or first sum the impacts and then take the ratio. Thus we define:

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

$$\overline{M} = \frac{\sum |\Delta t_{sf}|}{\sum |\Delta t_{rf}|}$$

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

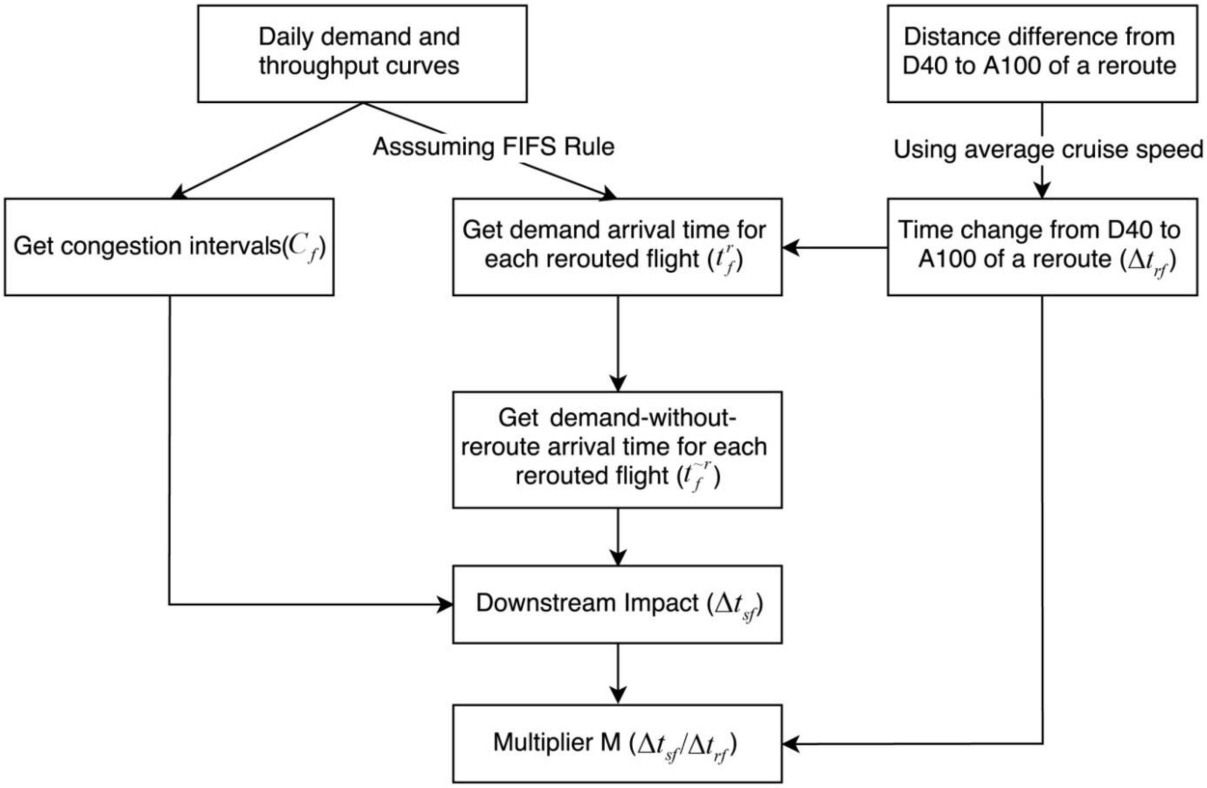

FIGURE 4 Method of Multiplier Calculation

DESCRIPTIVE RESULTS OF REROUTE PATTERNS

To perform our analysis, we used Flight Event data from Enhanced Traffic Management System (ETMS) radar track archives covering all domestic flights over the U.S. from January 2013 to December 2014. It contains data for domestic flights landing at and taking-off from the main 34 airports located in the continental United States, which account for 66% of the controlled flights in the U.S (*9*). For each flight, Flight Event data includes the following information:

1. Great circle distance between origin and destination (OD) pairs;
2. Great circle distance from D40 to A100;
3. Distance from D40 to A100 according to last filed pre-departure flight plan;
4. Actual flight trajectory distance from D40 to A100.

In addition, Aviation System Performance Metrics (ASPM) quarterly hour data is used for this study, which allows us to gain access to the quarter-hourly counts of demand and actual arrivals for all 34 airports. Note that the demand recorded in ASPM data at any time slot *i* is the maximum possible demand for that particular 15-minute period including unaccommodated demand from prior time windows. Thus a 15-minute period is counted as congested when the actual arrivals is less than the demand in that period.

There are a total of 5,362,149 flights in the Flight Event data set. In virtually all of them, the pre-departure flight plan distance is somewhat different from the actual flown distance. In this sense the planned and actual routes are almost never identical. Virtually all of the differences are small, however. For purposes of our analysis, we define minor, moderate, and major reroutes as those cases when the actual flow and flight plan time differ by less than 5 minutes, 5-10 minutes, and more than 10 minutes (Note that minor reroutes would often not be considered reroutes at all in the normal sense of the term). 95.65% of all flights fall into the minor category. Major and moderate reroutes represent 1.6% and 2.75% respectively.

Figure 5 depicts the distribution of flights in different categories between 2013 and 2014. The first grouping is based on reroute category and excludes minor reroutes. The other categories – major OR, moderate OR, major RR and moderate RR – each account for less than 100,000 flights. The second grouping, based on departure time of the day, shows that morning (6:00 am to 12:00 pm) is the most common departure time. From the third grouping, based on season, we see that summer has slightly more traffic than other seasons. The last part of this figure looks at the variation of traffic volume among great circle distance (from D40 to A100) categories. The percentage of flights with great circle distance larger than 1000 nm is the highest while flights with such distance between 100 and 200 nm has the smallest fraction.

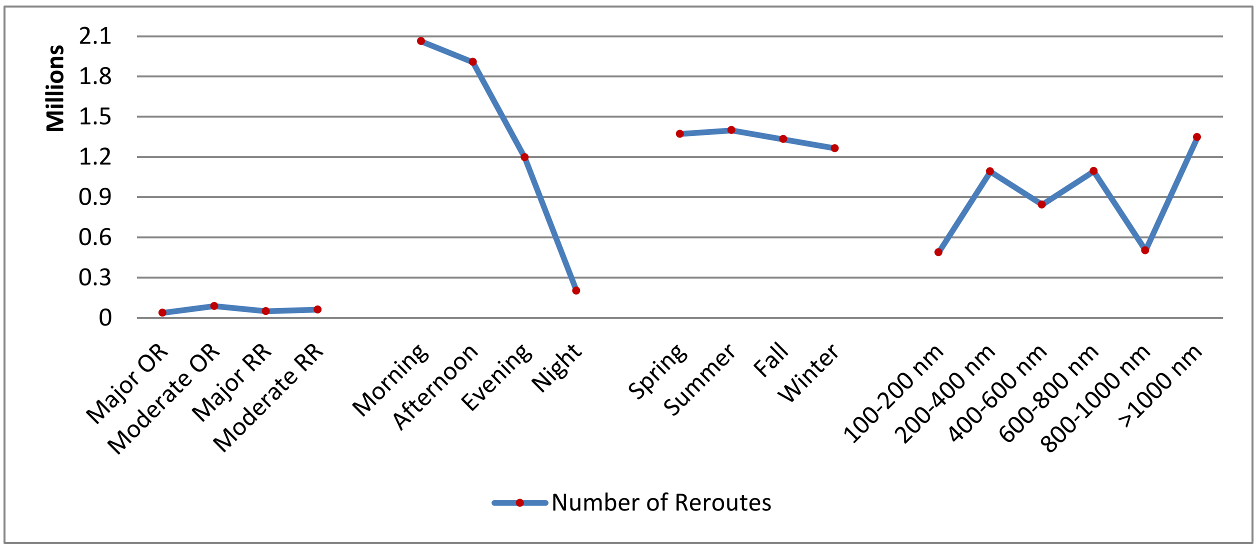

FIGURE 5 Number of flights in each category

Figure 6 illustrates the incidence of major and moderate reroutes for flights categorized by departure time of the day, season and great circle distance from D40 to A100. RRs and ORs both occur less than 10% for 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 certain flight categories, including afternoon departure flights, summer season flights and flights with great circle distance between 400 to 600 nm. Figure 6 also shows that ORs are much more common for night flights, and somewhat more frequent for evening, winter and long-haul flights. The incidence of both ORs and RRs increases with flight distance; they are more than twice as likely for flights over 1000 nm compared to flights of 100-200 nm.

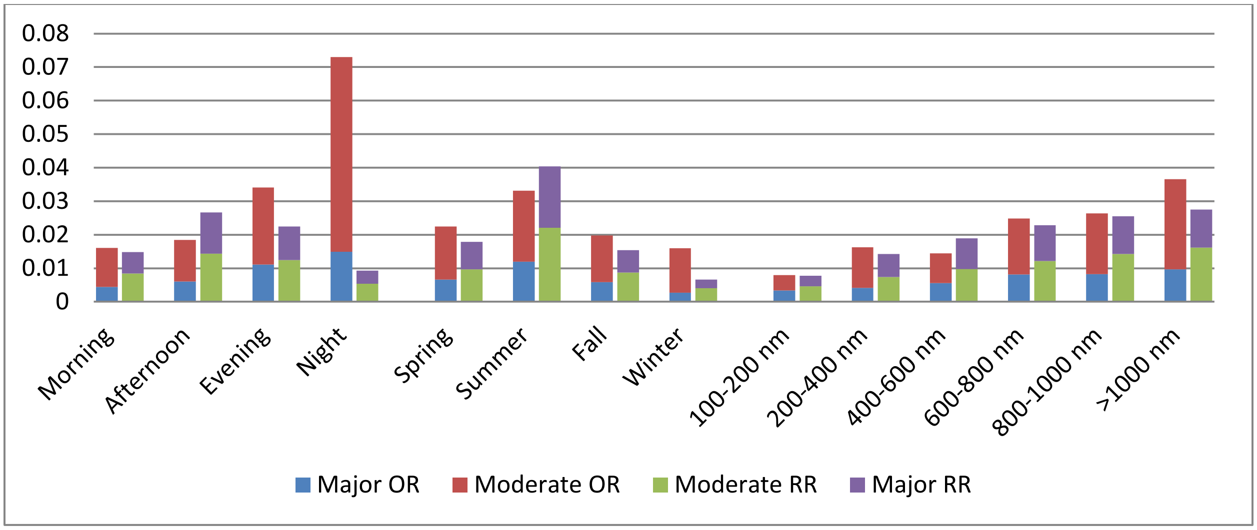

FIGURE 6 Proportion of different types of reroutes

Despite the fact that the majority of reroutes are minor ones, the statistics of minor reroutes reveals that only 5% of minor reroutes has a time change – either positive or negative – larger than 3 minutes, while 67.4% of them has reroute time less than one minute. Such small scale of deviation between actual distance and flight plan distance could due to recording errors in the data or approximation errors of speed in deriving time difference of reroute. It is then highly possible that there is no reroute has taken place for such flights. Thus, we exclude minor reroutes from the following analysis and focus on evaluating system impacts of major and moderate reroutes, with a total of 233,481 flights.

DOWNSTREAM IMPACT STUDY OF 34 AIRPORTS

Using the methodology described earlier and depicted in Figure 4, we calculated the downstream impact and resulting M value of all moderate and major reroutes found in the Flight Event data set. We did not consider minor reroutes, since they have little impact on the arrival time into the terminal area – usually less than one minute and almost always less than three minutes. In this section we summarize the main findings of our calculations. Across all the moderate and major reroutes in our data set, we find M values ranging from 0 to 219. In Figure 7, we summarize the distributions of M values for flights arriving at the 34 airports. The distributions vary significantly. The first notable finding is that at most airports the most common value for M is 1, indicating Scenario 2 in Figure 3. More specifically, the percentage of such reroutes ranges from 18% at LGA to 85% at PDX. On the other hand, it is by no means unusual for M to deviate from 1. Of these cases, by far the most common is $M = 0$ – i.e. Scenario 1 in which the shift queue arrival time causes a reshuffling of delay with no net change. The third most common case is $0 < M < 1$, while the least common is $M > 1$. The airports where reroutes with $M > 1$ occur the most include MEM (5.8% of total moderate and major reroutes), CLT (5.7%), and LAX (5.6%). Reroutes with $M > 1$ are least common at LGA (2.2%) and PDX (2.5%).

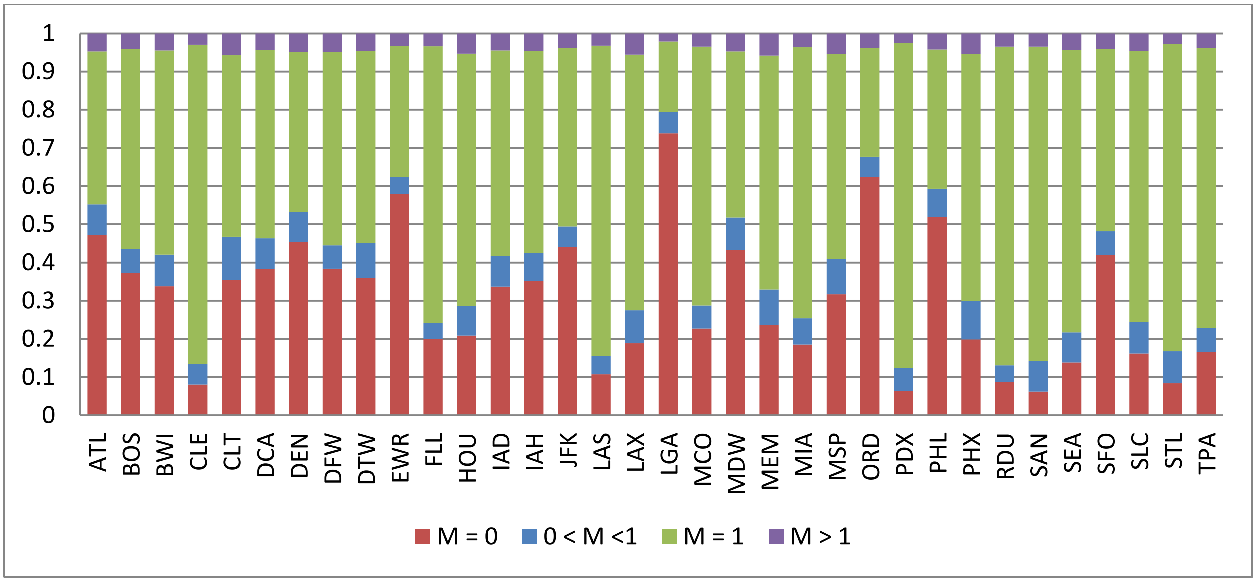

FIGURE 7 Multiplier distributions at 34 airports

We further explore the relation between direct time impact of the reroute and its system impact – i.e. between Δt_{rf} and Δt_{sf} – using scatter plots. We present in Figure 8 two such scatter plots – for LGA and PDX – that reflect the differences among airports. Both plots show that the variation of Δt_{sf} is greater than that of Δt_{rf}, reflecting the presence of cases where $M > 1$. Moreover, it is evident that at PDX, the correlation between Δt_{rf} and Δt_{sf} is stronger, since in most of the cases $M = 1$. In contrast, at LGA, more than 70% of reroutes have $M = 0$, which substantially reduces the correlation between Δt_{rf} and Δt_{sf}. The reason leads for this difference is that LGA is congested more of the time than PDX – the daily average amount of time in queue is 412.73 minutes at LGA, compared to 113.24 minutes at PDX.

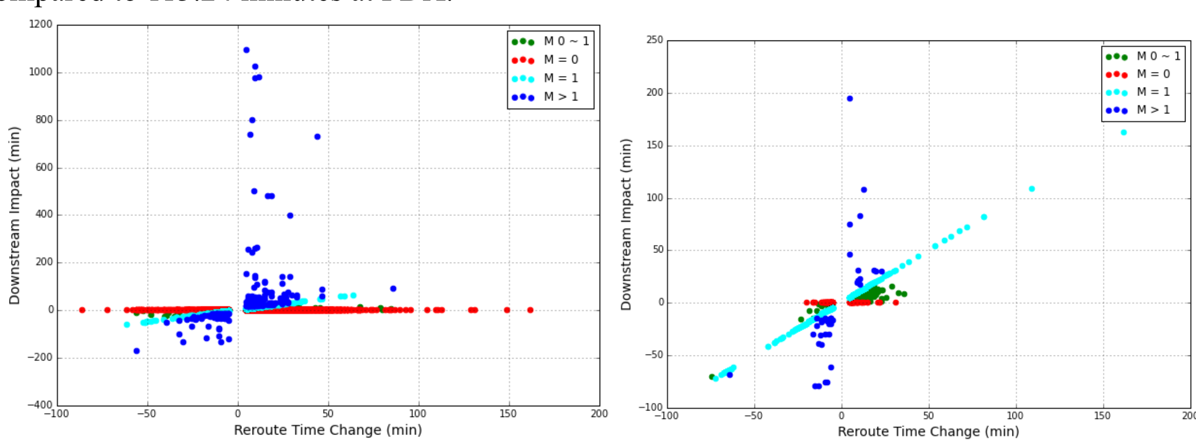

FIGURE 8 Scatter plot of reroute time and downstream impact of 2 representative airports: LGA (left) and PDX (right)

It is also useful to compare the average multipliers – either the simple average multiplier M or weighted average multiplier $\bar{M}$ across airports. Figure 9 shows the two values at each airport. For about half the airports the multipliers are above 0.8, with the lowest values around 0.4. The unweighted average value of M is larger than $\bar{M}$ or all airports, implying that small values for Δt_{rf} are likely to have larger M values. SEA has the least difference – 0.017 – between the two while EWR has the largest difference with an $\bar{M}$ of 0.47 as compared 0.62 for the average value of M. Figure 9 clearly shows airports in which assuming that the system impact Δt_{sf} is equal to the immediate impact Δt_{rf} is most likely to lead to erroneous conclusions. Not surprisingly these include the nation's busiest and most congested airports, including the New York metroplex, ATL, BOS, PHL, ORD, and SFO.

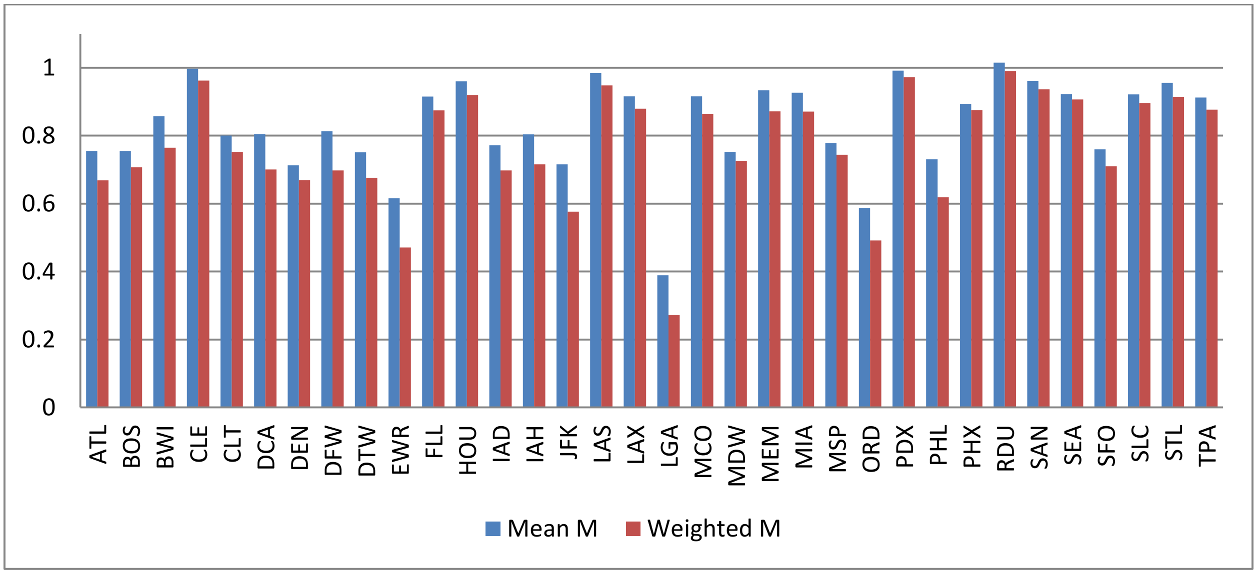

FIGURE 9 Comparison of M and $\bar{\mathbf{M}}$ at 34 airports.

In the following section, we explore the difference of downstream impact between different types of reroutes. To achieve this goal, we compare the unweighted average M value for RRs (distance increasing reroutes) and ORs (distance saving reroutes), as well major and moderate reroutes, at each airport and also perform both one- and two-tailed hypothesis tests to examine whether the average M value of one kind of reroute is different from that of the other.

For the majority of airports (30 out of 34), the mean multiplier of the two values is significantly different (at the 95% confidence level). In all of these cases ORs have higher average multipliers than RRs. This is to be expected since, while RR's are generally non-discretionary, OR's are based on flight operator and controller judgement. These decision makers might be expected to favor reroutes that will have an impact of system delay, as opposed to those would result in earlier arrival into the terminal area of a congested airport. The four airports that do not possess this difference between OR and RR are BWI, CLE, MDW, and PDX. We also find that the mean M value for moderate reroutes is significantly larger than that for major reroutes (at the 95% confidence level), except at CLE, MDW and PDX. This reflects that moderate reroutes have lower Δt_{rf} in the denominator of the expression for M.

Furthermore, we compare the system effects of four types of reroutes – minor RR, minor OR, major RR and major OR based on the whole dataset. Moderate ORs have the largest average M and

$\bar{M}$ values – 0.988 and 0.984 respectively – while major RRs have the lowest values – 0.470 and 0.421. The average *M* values for major ORs and moderate RRs are 0.855 and 0.742 respectively, while the $\bar{M}$'s for the two are 0.835 and 0.737. The results suggest that the technologies or innovations that lead to moderate ORs can be assessed fairly accurately by considering the direct impact only, while reductions in major RR's have considerable less system benefit than the direct impact would imply. Changes in major OR's and moderate RR's lie somewhere in between.

Finally, we investigate two specific reroutes with very high *M* values. In one case a flight destined for LGA on June 13, 2013 had a moderate RR, while the other was a flight to SFO on July 30, 2013 that had a moderate OR. Table 1 provides detailed information for these two events. On Jun. 13th, 2013, a flight arrived at 7:49 am on LGA with a five-minute RR. The system became over capacity a few seconds after 7:44 am, and the queue was not dissipated until 1:59 am the next day, implying that this reroute negatively affects many subsequent flights by delaying their landings. The multiplier of this RR is very large as a five-minute rerouting yields more than 1000 minutes system delay for an *M* value of 219. In the SFO case, flight's queue arrival time was 7:39 am as the result of a reroute that saved six minutes. SFO suffered from continuous congestion from 7:44 am to the next day at 2:29 am, therefore, if this flight were not issued a reroute, it would delayed all flights arriving after 7:45 am. Fortunately, this flight could be accommodated at its shifted queue arrival time when the airport was not yet congested. The multiplier is as large as 188.

Type	Destination	$t_f^{\sim r}$	t_f^r	C_f	Δt_{rf}	Δt_{sf}	Multiplier
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
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

Table 1 Summary of two reroutes with highest M values

These two high *M* cases are similar since in both the destination airport has congestion throughout the day. More precisely, large multiplier occurs when either flight *f*'s $t_f^{\sim r}$ or t_f^r is in queue while the other is not and a long congestion period starts right before or after the time in queue. The resulting changes in total system delay, which are demonstrated as Scenario 3 or 4 in Figure 3, are very great compare to the direct impact of the reroute on terminal arrival time.

CONCLUSIONS AND RECOMMENDATIONS

The purpose of our work is to evaluate downstream impacts of flight rerouting to more fully address the system impact of issuing reroutes. We develop a framework and identify five scenarios, each with a different relationship between the direct impact of the reroute and the system impact. We operationalize this approach and apply to flights arriving into 34 major U.S. airports. For flights whose reroutes are estimated to affect en route flight time by five minutes or more, we estimate the differences in reroute time and system delay that result from the reroute, as well as the delay multiplier value *M*, defined as the ratio of system delay change to flight time change.

The results show that reroutes have widely varying system impacts as determined by the interaction between flight rerouting and terminal queuing condition. While in the plurality of cases the system impact is the same as the direct impact, there are also many cases in which the system impact is zero because the reroute merely changes when a given flight joins the same queue. Other cases, in which the delay multiplier is less than one but greater than zero, or exceeds one, also occur, albeit somewhat less frequently. We also find considerable variation among airports, reroute type, and reroute magnitude in terms of the average delay multiplier value.

The estimates of downstream impacts of individual flights are clearly approximations due to a number of factors, such as inaccuracy in the raw data, speed approximation error in our method, the first-in first-out assumption for estimating queue arrival time, failure to consider winds, exclusive focus on the arrival airport as the only bottleneck, and so on. However, since a very large number of flights have been analyzed, errors at the individual flight level are unlikely to greatly distort aggregate results. The main conclusion of our study is that researchers and managers should pay attention to system impacts from reroutes both in assessing the benefits of tools to improve or encourage reroutes, and in making reroute decisions on a given day of operation. Such attention should include more sophisticated and thus more accurate methods for determining the system impacts of specific reroutes that have been roughly approximated in this research. On the day of operation, these more refined methods should be incorporated into existing and future decision tools for supporting reroute decision making for both flight operators and air traffic control.

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