USING FLIGHT SHIFTING TO MITIGATE DELAY IN MULTIPLE AIRPORT REGIONS

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Abstract

This study aims to improve operational performance of a multiple airport region (MAR) by analyzing interdependent capacity scenarios of that MAR airports and redistributing airport traffic to make more efficient use of the available capacity. We propose to shift flights between MAR airports in order to reduce flight delays. Both the deterministic and stochastic versions of a flight shift model are formulated as a mixed-integer linear program (MILP). The proposed methodology is applied to New York MAR, which includes five airports, using data for the year 2015. The deterministic model is applied to short-term flight reassignment where the MAR capacity scenario is known and flights are re-assigned on the day of operations, while the stochastic model is applied to re-assign flights in the original flight schedule based on capacity scenario probabilities. Results of both models show that by rescheduling flight landing airport and landing time, the total flight delay in the New York MAR could be significantly reduced, even when a high airport reassignment cost is assumed.

Keywords- Airport Capacity; Flight Diversion; Disruption Management; Airport Congestion Mitigation; Flight Delay

Introduction

Imbalance between airfield capacity and flight demand, caused by the growth of air traffic demand in a long-term perspective and by airport capacity degradation or demand variation in the short term, leads to congestion and delay. To address this problem, there has been considerable research on scheduling improvements at a single airport to reduce delay [1,2,3] In this research, we investigate the opportunities for reducing delay through adjustments in the schedule that involve multiple airports serving a given region. Specifically, we propose to shift flights from a congested airport to land at another airport in the same multiple airport region (MAR) in order to utilize the capacity of the MAR airports more efficiently. Especially when a flight is experiencing large delays or is causing huge delay to later flights, shifting flights may ameliorate the problem significantly. In this study, therefore, we propose scheduling changes across multiple airports to reduce delay. In order to analyze the benefit of shifting flights, capacity analysis of multiple airports is performed. We formulate a mixed integer linear program to optimize the total delay and re-assignment cost of the flight schedule in the MAR under different capacity scenarios.

Literature Review

When exploring the countermeasures to mitigate congestion and delay in the NAS, the solution space can be considerably expanded if flight shifts between airports serving the same region are allowed. When two or more major commercial airports serve passengers in the same metropolitan region, we refer to it as a MAR [4]. Different airports in the same MAR may face different capacity-demand imbalance situations. It may therefore possible to take the advantage of excess capacities of some of the airports to reduce the overall airport delay of the MAR.

Airport capacities are subject to substantial variability as they depend on weather conditions, selected runway configurations, and other dynamic factors. Capacity scenario analysis identifies the patterns of airport capacity variation and has been used widely for air traffic management and airport planning [5]. Methodologies for generating capacity scenario trees for a single airport from empirical data, and the performance of models to optimize ground delay programs based on scenario trees, are studied in [6]. This builds on earlier research [7], in which capacity uncertainty has been addressed by considering a set of scenarios, each corresponding to a time-varying airport capacity profile. All of these studies focused on capacity analysis of single airport. In this study, we apply clustering analysis to identify capacity scenarios of multiple airports in the same MAR. These scenarios capture the interdependence

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of capacity profiles of different airports and lay the foundation for the flight shift model that we propose to mitigate airport congestion and flight delay, which will be elaborated in later sections.

Flight diversion has been proposed in existing research to reduce delay for airport disruption. [8] proposes "real-time inter-modalism" involving the substitution of flights by surface vehicle trips and, when the hub is part of a regional airport system, the use of inter-airport ground transport to enable diversion of flights to alternate hubs. Zhang and Hansen [9] proposes a Regional Ground Delay Program (R-GDP) concept into the Collaborative Decision Making (CDM) system when a hub airport located in a regional airport system encounters a severe airside capacity reduction. They suggested that if there is excess capacity at other airports in the same region, airlines could utilize the excess capacity by diverting flights originally scheduled to the hub airport to other airports and transport passengers and crew members between original scheduled and diverted airports by incorporating ground transport modes into their disruption management. However, they only applied the modeling to a simple case with two airports, one primary and one alternative airport in the same region. In our study, we propose a general mathematical modeling to explore the potential of flight shifting across all airports in an MAR to alleviate delay. Such model could be a powerful decision tool for air traffic controllers and managers to alleviate airport congestion and delay and would benefit airlines, airports, passengers, as well as local communities suffering the negative impacts of airport congestion and delay.

Existing research works on the stochastic flight scheduling problem to capture uncertainties and variabilities. An integrated approach is developed in [10,11] for airport congestion, capacity utilization and scheduling interventions to jointly optimize the rescheduling of flights through scheduling interventions at the strategic level and the utilization of airport capacity at the tactical level. [12] proposes a model that optimizes scheduling interventions and ground-holding operations across airports networks, under operating uncertainty. In our work, both flight shifting in tactical and strategical levels are considered and proposed using deterministic and stochastic models, respectively.

In the United States, a major source delay throughout the NAS are New York commercial airports. Since approximately a third of the nation's air traffic passes through NY airports, delays in NYC ripple through the system causing delays at other airports [13]. These delays can be attributed to shortfalls in daily airport capacity (often due to weather) and to airline scheduling practices [14]. Therefore, this study takes New York MAR as a case study to perform capacity analysis and demonstrate the flight shift model.

In sum, previous research has introduced the concepts of MAR and methods for identifying MARs. Other studies have introduced the concept of capacity scenario for an individual airport, and studied the possibilities of reducing capacity demand imbalances either by shifting flights from high demand to lower demand periods, or from an airport with a severe capacity demand imbalance to a secondary airport. This research builds on previous contributions by considering the possibility of reducing delay by shifting flights between several different airports in a MAR. Toward this end, we identify capacity scenarios that consider all airports in an MAR, and solve an optimization model that redistributes flights among airports in the MAR in a manner that takes into account both the available capacity and temporal distances between airports.

Capacity Scenarios Clustering

We analyze capacity variation in the New York MAR by identifying capacity scenarios for its five airports: JFK (John F. Kennedy International Airport), EWR (Newark Liberty International Airport), HPN (Westchester County Airport), ISP (Long Island MacArthur Airport), and LGA (LaGuardia Airport). These airports were found to belong to the New York MAR following the algorithm in [15] with 1.5-hour threshold of temporal distance between airports (See Figure 1). A given scenario specifies a daily capacity profile for each of these airports. Combinations of visibility, winds, other factors determine which capacity scenario is realized on a given day.

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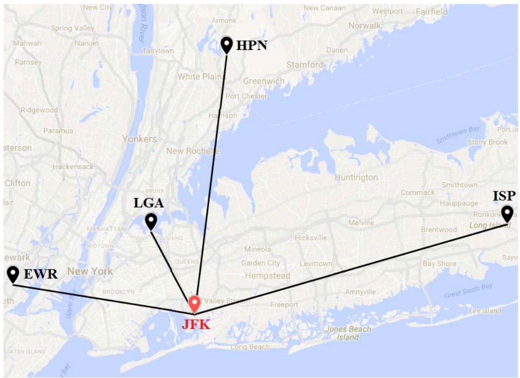

Figure 1. New York MAR

We obtained quarter-hour Airport Arrival Rate (AAR) from the FAA ASPM data base. According to FAA order JO 7210.3W, AAR is "a dynamic parameter specifying the number of arrival aircraft that an airport, in conjunction with terminal airspace, can accept under specific conditions throughout any consecutive sixty (60) minute period." Thus, in our study, AAR is used as the capacity data of New York MAR airports for this analysis. Instead of 60 minutes, we used quarter-hour as the time unit, hoping to capture the airport capacity variation with higher resolution. Developed the combined capacity scenarios for the New York MAR in the year 2015.

The capacity of an airport varies from hour to hour and day to day, due to the variability of weather, fleet mix, availability of airport facilities, operational status of air traffic control equipage, etc. In the case of the New York MAR, there are also significant interactions between airport configurations that also affect capacity. In order to get typical MAR daily capacity scenarios, we perform clustering analysis of daily capacity profiles of five airports in the New York MAR altogether. By analyzing the combined capacity scenarios, we take into account the interdependence in airport capacities that may result from correlated weather, traffic interactions, and other factors. Considering the low traffic during the nighttime hours, which may reduce the reliability of the called rates, we only analyzed the recorded capacity from 7 am to 11 pm in a day.

We apply K-means clustering analysis to study New York MAR capacity profiles. Both elbow method and silhouette analysis are performed with number of capacity scenarios from 1 to 50 to determine the number of clusters. From both analysis, we judged that 11 clusters was the point beyond which increases in explained variance begin to diminish significantly. We thus use 11 clusters in our subsequent analysis.

Table 1 presents the clustering results of the three example (out of 11 total) capacity profiles in New York MAR of the year 2015. Each capacity profile centroid plot on the left side represents a daily capacity scenario of New York MAR in 2015, while the plots on the right-hand side show the original capacity data for the days corresponding to that scenario. The centroid capacity profiles on the left side are simply the mean of individual values for the days included in the cluster. From the top to the bottom, the lines (Orange, blue, dark blue, green and light blue) represent the capacity trends of JFK, EWR, LGA, ISP and HPN airports. The number and the percentage on the left bottom of the picture represent the number and the percentage of the days belonging to the cluster. Plots (a0) and (c0) show a scenario in which capacities of all the airports in New York MAR are relatively stable through the day but with JFK at a higher capacity in (a0) and a lower capacity in (c0). Plot (b0) represents the situation that the capacity of JFK airport is at the low level in the early morning and then increases at noon.

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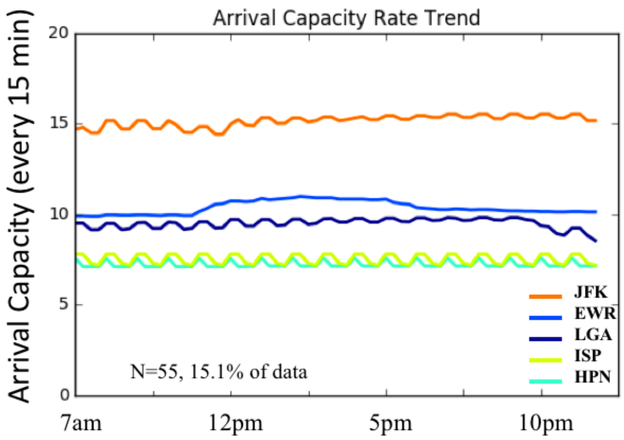
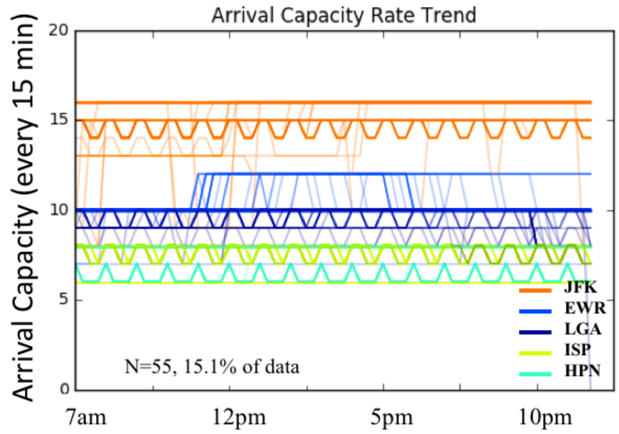
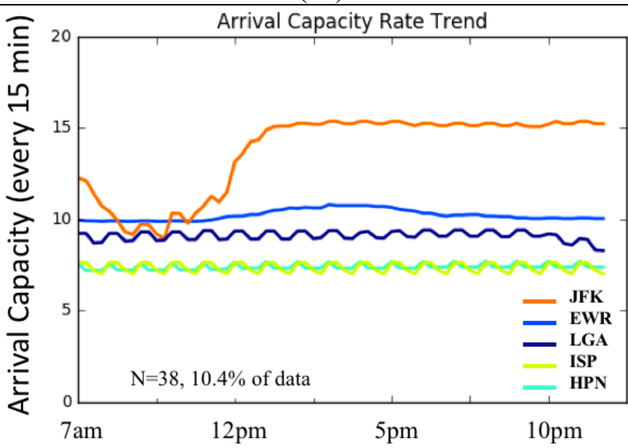
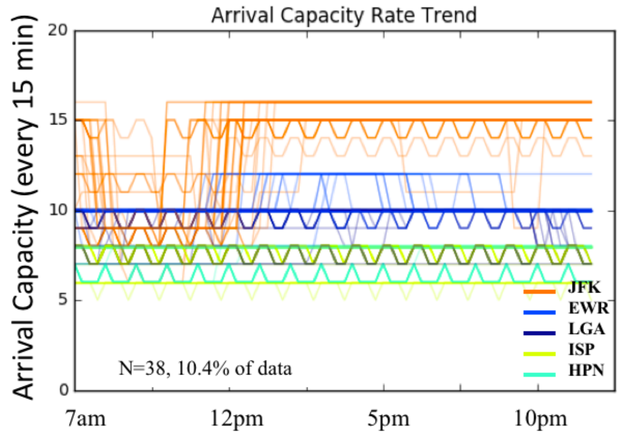
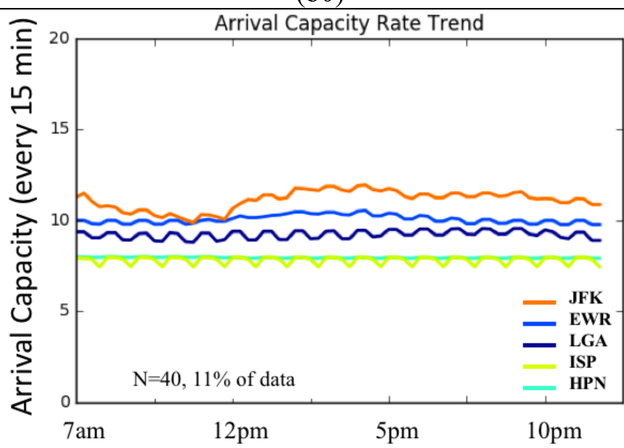
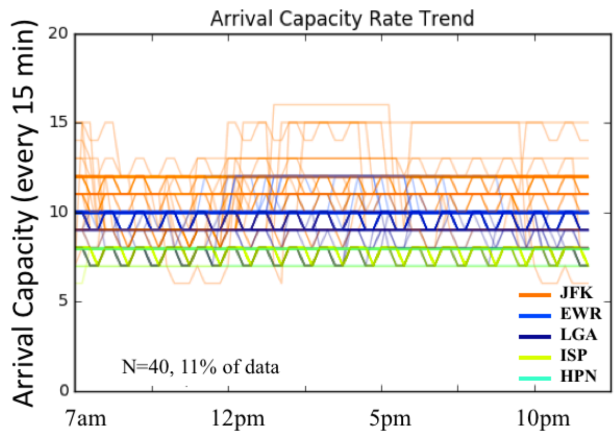
Table 1. Three Capacity Profile Clusters Results

Cluster Centroid	Original Data in The Cluster
	
(a0)	(a1)
	
(b0)	(b1)
	
(c0)	(c1)

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Flight Shift Model

Airports in an MAR are relatively close to one another, raising the possibility that flights may be shifted between MAR airports in order to alleviate demand capacity imbalances. Such shifting could occur at either a tactical or strategic level. Tactically, if on a day of operations (or a part thereof), one MAR airport had excess capacity while another had excess demand, flight shifting could reduce the queueing delay at the airport with excess demand. Strategically, if future traffic projections suggest that one airport will be consistently congested while another has excess capacity, flight schedules might be adjusted to shift the demand into the less congested facility. Neither of these options can be exercised easily, since the costs of such flight shifting are substantial. However, it is at least conceivable that when there are substantial differences in congestion at different airports, such reallocation would be appropriate. Therefore, in this section, we leverage our MAR and capacity scenario analyses to develop a simple mathematical model to reassign airports and landing times to flights in order to improve flights operations in an MAR. Both deterministic and stochastic versions of model are presented for short-term and long-term flight reassignment respectively. We again use the New York MAR as a case study. In applying the model, we assume a wide range of flight shift penalties, since the value of this penalty is uncertain, and in order to determine the penalty level that would preclude flight shifting as a desirable strategy.

Deterministic Flight Shift Model

The deterministic model assigns flight shifting under certain capacity scenario, which can be applied to short-term flight reassignment when capacity scenario is known or predictable. We analyze the results with 11 capacity scenarios of New York MAR. Sensitivity analysis is performed with different flight shift fixed costs and demand levels.

Model Description

Let the set F denote the set of flights scheduled to arrive at any of the set of airports, denoted A, in a MAR over a day, which we divide into a set of discrete time intervals T. Our integer decision variables, $X_{a,b,t}$, are defined as the number of flights scheduled to land at airport a and shifted to land at airport b in an updated time period t.

Our optimization problem includes the input parameters defined in Table 2:

Table 2. Description of Model Parameters

Parameter	Definition
$S_{a,t}$	Number of flights scheduled to land at airport a in time period t
$C_{a,t}$	Arrival capacity of airport a in time period t
$l_{a,b} = L_{a,b} + c$	Cost of shifting per flight from scheduled airport a to shifted airport b. The cost includes flight shift fixed cost, and time cost of passengers from shifted airport back to scheduled airport. The cost is in time unit
$L_{a,b}$	Ground travel time from scheduled landing airport a to shifted airport b in the same MAR
c	Penalty, in time units, of shifting any flight from its scheduled airport to some other airport, not including the ground travel time

We see to minimize the total cost of shifting flights to later arrival times and other airports, taking into account airport arrival capacity constraints. This is formulated as:

$$Min \sum_{a,b,t} \Big(\sum_{i=1..t} S_{a,i} - \sum_{i=1..t} X_{a,b,i} + l_{a,b} \cdot X_{a,b,t} \Big)$$

s.t.

$$\textstyle\sum_{b,i} X_{a,b,i} \leq \sum_i S_{a,i} \qquad \forall\, i = 1..t,\ t\ in\ T, a, b\ in\ A \qquad (1)$$

$$\textstyle\sum_a X_{a,b,t} \leq C_{b,t} \qquad \forall\, t\ in\ T, b\ in\ A \qquad (2)$$

$$\textstyle\sum_{b,t} X_{a,b,t} = \sum_t S_{a,t} \qquad \forall\, a\ in\ A \qquad (3)$$

$$X_{a,b,t} \geq 0 \qquad \forall\, t\ in\ T, a, b\ in\ A \qquad (4)$$

The objective function is the total penalty of flight delay as well as shifting flights to other airports in the MAR. $\sum_{a,b,t}(\sum_{i=1..t} S_{a,i} - \sum_{i=1..t} X_{a,b,i})$ represents the delay cost of all the flights and $\sum_{a,b,t}(l_{a,b} \cdot X_{a,b,t})$ represents the shifting cost. Constraint (1) describes the reassigned arrival time at shifted airport cannot be earlier than the scheduled arrival time; Constraint (2) restricts the number of arrival flights landing in each time unit at each airport from exceeding the airport capacity for that time interval in the updated flight schedule with flight

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shifting; Constraint (3) maintains the balance of flight flow between original and updated flight schedules.

Numerical Example of New York MAR

We apply this model to the New York MAR. Thus $A = \{EWR, HPN, ISP, JFK, LGA\}$. We solve the model for 11 different capacity scenarios of five airports in New York MAR. To select a representative flight schedule, we sort the number of flights in JFK airport of the year 2015 in descending order and choose the flight schedule data of the 10th daily enplanement day (July 2nd 2015) as inputs for our model. For that day, there are 1985 flights schedule to land at the New York MAR airports. We use the capacity profiles of the 11 clusters as the capacity input of New York MAR to our model. Thus, we solve the model for 11 different capacity inputs. We consider a set of flight shift fixed costs c ranging from 0.5 to 15 hours, as well as a baseline case in which flight shifting is prohibited (i.e. $c = \infty$).

Table 3 shows, as an example, the results of reassigned schedule when flight shift fixed cost is set as 12 hours, including the amount of delay, the number of shifted flights, and total penalty of reassigned schedule by the shift model and original schedule based on airport capacity without flight shifting. We observe that there is some flight shifting in eight of the 11 scenarios, but it exceeds 1% of flights in just three scenarios. Scenario 10 has by far the greatest amount of flight shifting, with 7.5% of flights arriving at a different airport than originally scheduled. Shifting in this scenario reduces total cost of delay and shifting from 4061 to 3038, about 25%. Note that these savings are realized despite a penalty in excess of 12 hours for shifting any flight.

Table 3. Model Solution

Cluster	Flight Shift Model With 12-hour Flight Shift Fixed Cost			No Shift Model	Cost Savings (hrs)
	Total cost including flight shifting (hrs)	Flight delay cost (hrs)	Fraction of shifted flights	Flight delay cost (hrs)	
1	600	339	0.011	666	66
2	1291	1064	0.009	1330	39
3	85	85	0.000	85	0
4	420	346	0.003	428	8
5	168	131	0.002	171	3
6	184	184	0.000	184	0
7	175	163	0.001	176	0.06
8	123	123	0.000	123	0
9	97	97	0.000	97	0
10	3038	1133	0.075	4061	1023

Given the probability, P_j, of each cluster j from Table 3, we calculated the average cost savings, ACS, which is the estimated cost savings per day from flight shifting. This is found to be 32 flight hours per day assuming 12-hour flight shift fixed cost.

$$ACS = \sum_{j=1}^{11} CS_j \cdot P_j$$

Table 4 presents four typical airport capacity scenarios (on the left) and the details of shifted flights under the given capacity profiles (on the right) with 3-hour and 12-hour flight shift fixed cost. The bar heights on the right-side plots indicate the number of flights shifted between different airport pairs; their colors indicate the times of day of the flight shifts. For capacity scenario 1 with a 3-hour penalty, flights are shifted mainly from LGA and EWR to JFK and HPN, and mainly in the morning and afternoon. With the 12-hour penalty, the only shifts are morning flights from LGA to JFK. For capacity scenario 2, which features a lower capacity at JFK throughout the day, there is considerable shifting from JFK to other airports in the afternoon under the lower shift penalty, but this is largely eliminated with the higher penalty. The shifting that remains with the 12-hour penalty is mostly from LGA in the morning. For capacity scenario 5, small amount of flights will be shifted because most airports are in good capacity situation. The only shifts are flights from LGA to

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JFK with either 3-hour or 12-hour penalty. In the case of cluster 5 with 3-hour shift fixed cost, there are more flights shifted to land at JFK airport in the afternoon than in the morning, taking advantages of the higher capacity at JFK airport in the afternoon. The afternoon shifts disappeared under higher flight shifting penalty. Cluster 10 is an extremely bad case when JFK, EWR, and LGA all have low capacity compared to other case. Thus, a large number of flights are shifted from JFK, EWR, and LGA to other airports. Flights are mainly shifted from LGA and EWR to ISP, JFK, and HPN. Small amount of flights will be shifted from JFK to ISP and HPN in the afternoon. The total number of shifted flights are higher than in the three other capacity scenarios above. Less flights will be shifted with higher penalty according to the scale of vertical axis.

There are fewer shifted flights with higher shift fixed cost, comparing the two graphs on the right (note that these have different vertical scales). Cluster 1 and cluster 5 are experiencing a relatively good day for the MAR because only a few number of flights will be shifted, according to the scale of vertical axis in the graphs on the right. JFK airport has higher capacity in these two capacity scenarios, therefore some flights in other airports are shifted to land at JFK airport when lack of arrival capacity at their originally scheduled arrival airports.

Commenting more generally about Table 4, we observe that many airport pairs are involved in shifts. LGA is a major source of shifted flights, and HPN as JFK are major sinks for these shifts. Flights are never shifted to LGA and EWR under these four scenarios. Temporally, morning and afternoon are the primary times for shifting; which of these time periods has more shifting depends on the capacity scenario and the shift cost. There will be fewer shifted flights with higher shift fixed cost under each scenario.

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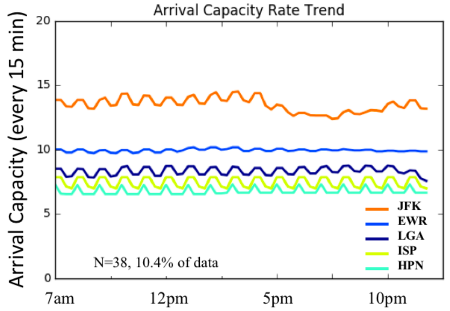
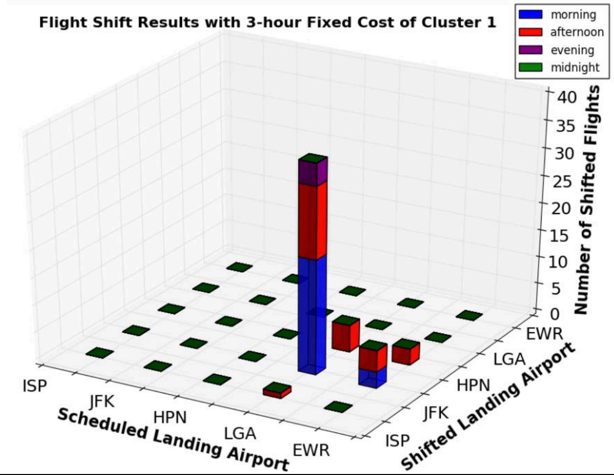
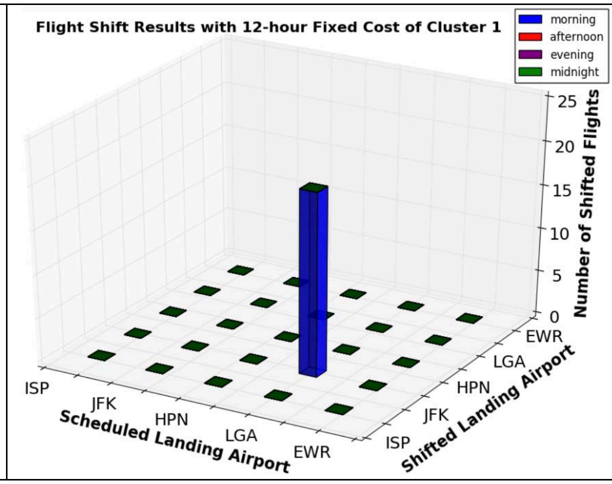
Table 4. MAR Flight Shifting Results

<table>
<tr><th>Capacity Trend</th><th>Shifted Flights (3-hour shift fixed cost)</th><th>Shifted Flights (12-hour shift fixed cost)</th></tr>
<tr><th colspan="3">Cluster 1</th></tr>
<tr><td>
</td><td>
</td><td>
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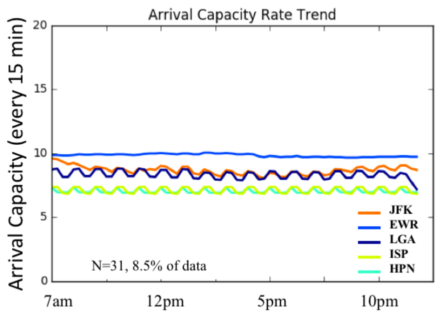
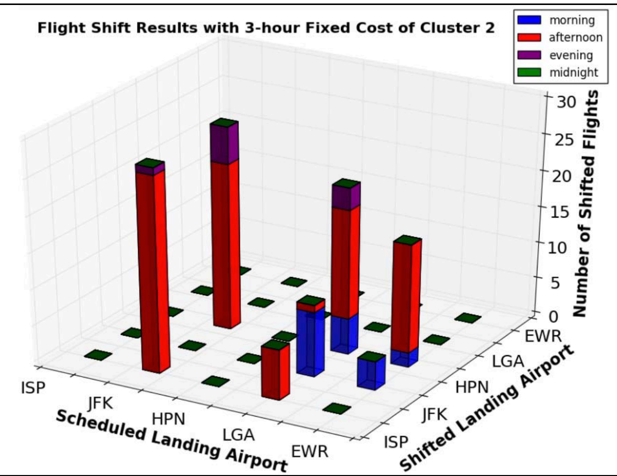
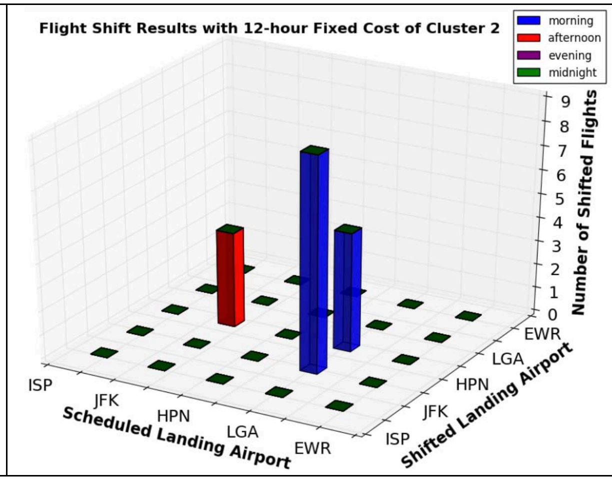
<tr><td>
</td><td>
</td><td>
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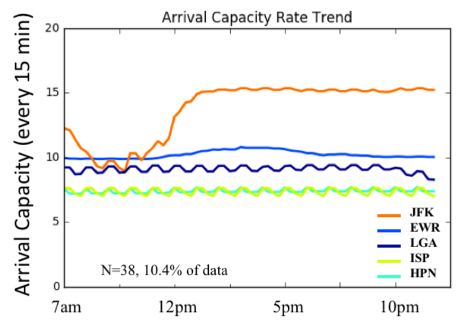
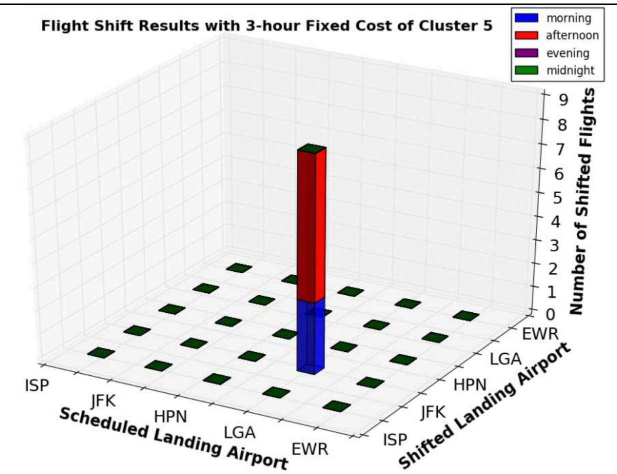
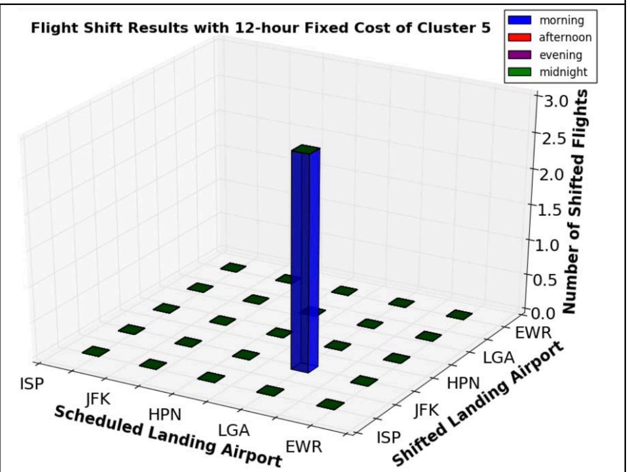
Capacity Trend	Shifted Flights (3-hour shift fixed cost)	Shifted Flights (12-hour shift fixed cost)

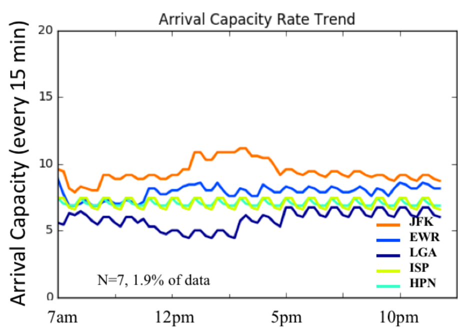
Cluster 5

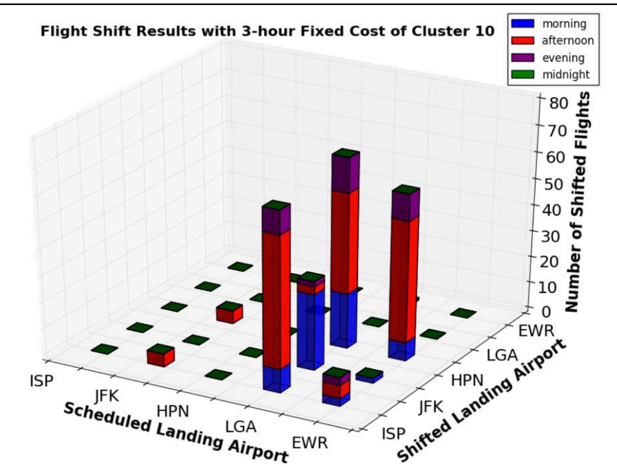


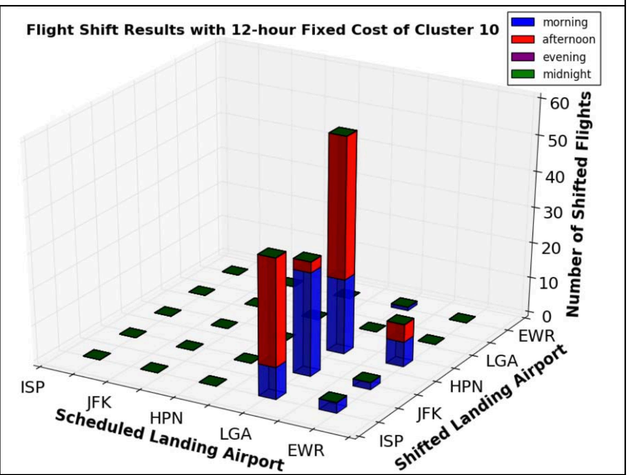




Cluster 10







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Sensitivity Analysis

This section investigates how flight shifting performs differently with different levels of demand and flight shift fixed costs. Taking the 2015 demand as the base, already shown above, we apply the deterministic flight shift model with demand increased by 20% and 50% to explore how the model performs with different demand levels. We also apply the model with flight shift fixed cost changing from 0.5 to 15 hours to test how the flight shift fixed cost influences the reassigned schedule.

- Demand Levels

Sensitivity analysis with different demand levels evaluates the utility of the model in the future with growing demand. Figure 2 describes how flight demand influences the efficiency of the model. Orange, grey and yellow lines represent the saved penalty of 11 capacity scenarios of flight shifting model with 2015 flight demand, 20% increased demand and 50% increased demand, using 12-hour flight shift fixed cost. The saved penalty is calculated by subtracting total cost of model with flight shifting from total cost of model without flight shifting. Saved total penalty increases dramatically when flight demand increases. The average weighted saved costs of shift model with 2015 flight demand, 20% increased demand and 50% increased demand are 32.29, 319.25, and 1828.00 flight hours per day. Compared to the baseline case, in the 20% and 50% increased demand cases, the average weighted saved costs are 9.9 and 56.6 times of the baseline case, respectively. Thus, the flight shift model can save more cost when the flight demand is higher but the MAR airport capacities are not enhanced. In addition, Figure 2 implies the model will save more cost under worse condition, i.e. capacity scenario 4, 8, 10 and 11. The saved penalty for capacity scenario 11 is around 5 times of the saved penalty for capacity scenario 1, 2, 3, 5, 6 and 9, with 50% increased demand. Overall, it is obvious that cost savings for capacity scenarios 4, 8, 10 and 11 are much greater compared to the other scenarios, where capacity is considerably greater.

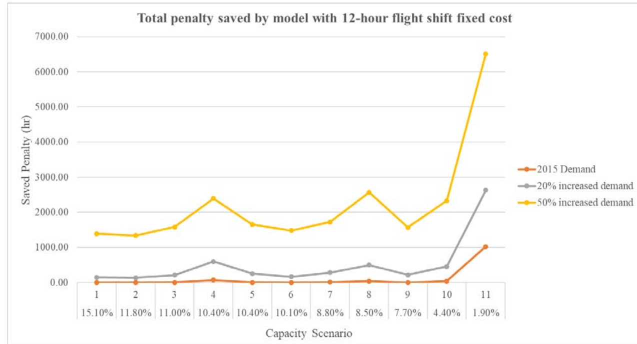

Figure 2. Saved Penalty Under Different Demand Levels

Figure 3 shows the fraction of shifted flights with different flight demand levels for 12-hour fixed cost flight shift model. The fraction of shifted flights increases rapidly when flight demand level increases. There is huge amount of shifted flights under extremely bad capacity scenarios. The fractions of shifted flights under capacity scenario 4, 8, 10 and 11 are much more than that of other capacity scenarios. The fraction of shifted flights for capacity scenario 11 is more than six times higher than that of capacity scenario 1 (with highest probability in 2015) with 20% increased demand. Under extremely bad capacity scenarios, not only the flight will experience huge delay, but also it will cause large amount of delay to its later flights. In addition, the fraction of shifted flights under worse capacity scenarios (i.e. capacity scenario 4, 8, 10, 11) increases slower than that of relatively better scenarios as demand increases. Capacity scenario 1, 2, 3, 5, 6 and 9 have about 4 times more shifted flights with 50% increased demand level than 20% increased demand level, while worse capacity scenarios including 4, 8, 10, and 11 only have less than twice more shifted flights.

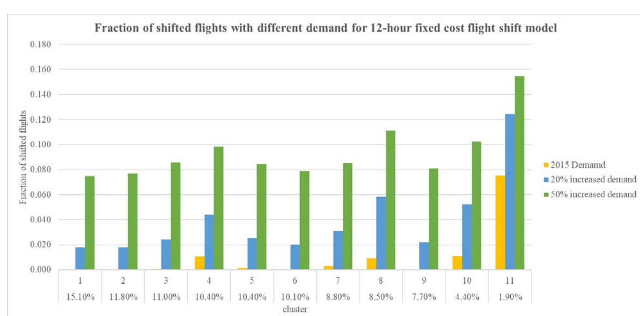

Figure 3. Fraction of Shifted Flights Comparison

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- Flight Shift Fixed Cost

Flight shift fixed cost is the main part of flight shift penalty. Various costs caused by flight shifting needs to be penalized, including aircraft reschedule, passenger reassignment, disruption of connecting itineraries, etc. Determining the value of flight shift fixed cost is difficult. This subsection analyzes the results of the model with different flight shift fixed costs from 0.5 to 15 hours.

Figure 4 shows the total cost comparison of models with flight shift fixed cost from 0.5 to 15 hours and without flight shift, given 2015 demand. The total cost increases as flight shift fixed cost increases. The total cost of flight shift model with 15-hour flight shift fixed cost approaches the total cost without flight shifting for most capacity scenarios. Although in many of the cases, the increase of flight shift fixed cost does not affect the total cost too much, in relatively low capacity scenarios, such as 8, 10 and 11, the total cost varies significantly with the change of flight shift fixed cost.

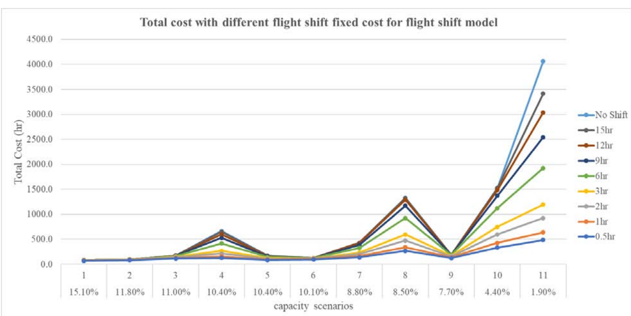

Figure 4. Total Cost Comparison

Figure 5 and Figure 6 show the amount of delay of 11 capacity scenarios and average fraction of shifted flights with different flight shift fixed costs and 2015 flight demand. The amount of delay increases and the fraction of shifted flights decreases as the fixed cost increases. Figure 5 reveals that in most capacity scenarios, fractional cost savings from flight shifting diminish rapidly when the shifting penalty exceeds 9 hours. However, in scenarios 4 and 11 there is substantial savings even when the shifting penalty is 15 hours. In Figure 6, the average percentage of shifted flight is less than 3% no matter the flight shift fixed cost. There is no flight shifting with a 27-hour flight shift fixed cost. There is a steady reduction in shifted flights as the shifting penalty increases through 6 hrs; for shifting penalties greater than 6 hrs the sensitivity becomes more pronounced.

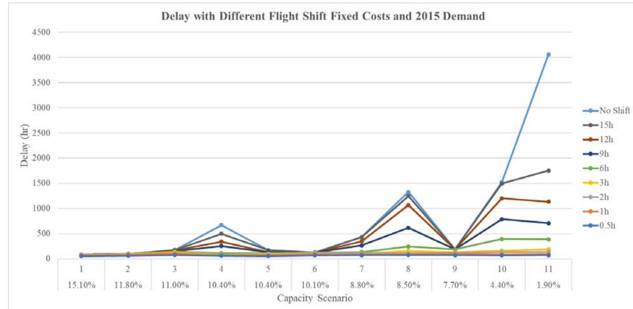

Figure 5. Delay With Different Flight Shift Fixed Cost

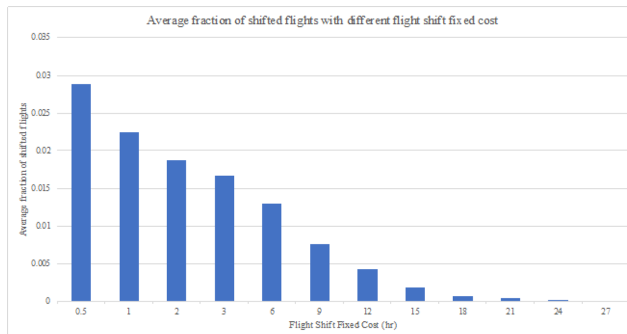

Figure 6. Fraction of Shifted Flights Comparison

Stochastic Flight Shift Model

The deterministic flight shift model in the previous section provides the flight schedule that can save the most cost under a given MAR capacity scenario. These results can guide flight rescheduling on a day of operations. A stochastic version of the model can be used to modify the original flight schedule, which is determined roughly 6 months in advance. In this version of the model, the capacity scenario is not known, but capacity scenario probabilities are available.

Model Description

We keep most of the variables and input parameters from the deterministic flight shift model. Probabilities of each capacity scenario are incorporated into the stochastic flight shift model.

Let set Q denote all possible capacity scenarios of a MAR. (i.e. $Q = \{1, 2, 3, \ldots, 11\}$ for New York MAR in 2015). The only new parameter in the

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stochastic model, P_q, denotes the probability of capacity scenario q. The decision variable, $X_{a,b,t,q}$, is defined as the number of flights scheduled to land at airport a and shifted to land at airport b in an updated time period t under capacity scenario q. The stochastic model is formulated as:

$$Min \sum_{a,b,t,q} P_q \cdot \left(\sum_{i=1..t} S_{a,i} - \sum_{i=1..t} X_{a,b,i,q} + l_{a,b} \cdot X_{a,b,t,q}\right)$$

$$s.t.$$

$$\sum_{b,i} X_{a,b,i,q} \le \sum_i S_{a,i} \quad \forall\, i = 1..t, t \text{ in } T, a, b \text{ in } A, q \text{ in } Q \tag{5}$$

$$\sum_a X_{a,b,t,q} \le C_{b,t,q} \quad \forall\, t \text{ in } T, b \text{ in } A, q \text{ in } Q \tag{6}$$

$$\sum_{b,t} X_{a,b,t,q} = \sum_t S_{a,t} \quad \forall\, a \text{ in } A, q \text{ in } Q \tag{7}$$

$$\sum_t X_{a,b,t,1} = \sum_t X_{a,b,t,2} = \cdots = \sum_t X_{a,b,t,11} \quad \forall\; a, b \text{ in } A, q \text{ in } Q \tag{8}$$

$$X_{a,b,t,q} \ge 0 \quad \forall\, t \text{ in } T, a, b \text{ in } A, q \text{ in } Q \tag{9}$$

The objective function calculates average total cost of flight delay and shift cost of all possible capacity scenarios within a MAR in a day under operation. Constraint (5) describes the reassigned arrival time at shifted airport under each capacity scenario cannot be earlier than the scheduled arrival time; Constraint (6) restricts the number of arrival flights landing in each time unit at each airport under each capacity scenario from exceeding the airport capacity for that time interval and that capacity scenario; Constraint (7) represents that each flight under each capacity scenario is assigned to one and only one airport and time period. Constraint (8) is a coupling constraint [3] incorporated in the stochastic model. It maintains that the reassigned landing airport is the same for different capacity scenarios for each flight f, but the reassigned arrival time can be different under different capacity scenarios. The shifted landing airports of flights in daily schedule will be determined in advance, so only reassigned arrival time is flexible.

Sensitivity analysis

This section analyzed how flight shifting in stochastic model performs differently with different levels of demand and flight shift fixed costs. We apply the model with flight shift fixed cost changing from 0.5 to 15 hours and with demand increased by 20% and 50%.

Figure 7 shows the total cost of the stochastic flight shift model including delay and flight shifting cost with different demand levels and different flight shift fixed costs. At 2015 delay levels, flight shifting can result in considerable cost savings if the fixed flight shifting cost is 2 hrs or less. This threshold increases to around 6 hrs for a 20% demand increase and 12 hrs for a 50% demand increase. Note that in the stochastic model shifting cost reflects the cost of changing the original schedule, which is likely to be substantially less than the "on-the-fly" changes envisioned in the deterministic model.

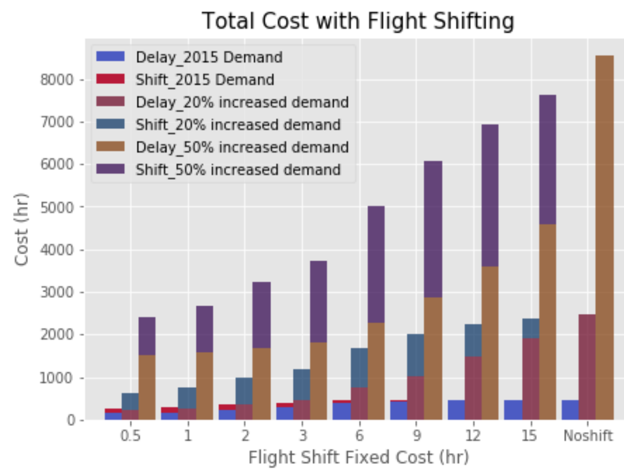

Figure 7. Total Cost Comparison

Figure 8 shows both the saved penalty by stochastic model (dashed lines) and saved penalty for each scenario using respective flight schedule generated by stochastic model (see solid lines). The model saves more cost under worse scenario cases. Some extremely bad scenarios (capacity scenario 4, 8, 10 and 11) have larger scenario-based cost savings (solid lines) than stochastic cost savings (dashed lines). Those extremely bad scenarios have low probability, and most other scenarios have cost savings lower than stochastic total cost savings. Figure 9 shows that larger proportion of flights are shifted with higher demand level or lower flight shift fixed costs. Compared to deterministic model with 2015 demand where no flight shifting with 27-hour or larger flight shift fixed cost, the stochastic model stops assigning flight shifting when flight shift fixed cost is greater than or equal to 12 hours.

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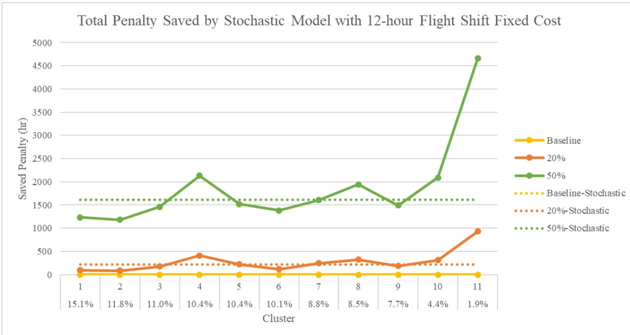

Figure 8. Total Saved Penalty Comparison

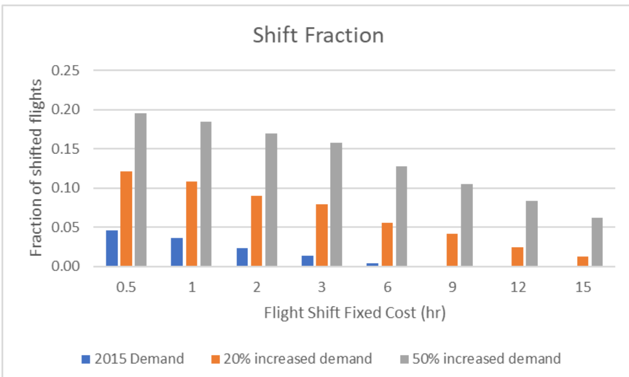

Figure 9. Fraction of Shifted Flights Comparison

Both the deterministic and stochastic flight shift models and their analysis were presented in this section. Deterministic model can be applied to generate flight shift schedules on a day of operations when the capacity scenario is known. The stochastic model provides the flight shift schedules long time before the studied date of operation, by considering the probabilities of different capacity scenarios instead. This section provides models for generation of both short-term and long-term flight shift schedules. The results analyses show that both deterministic and stochastic models can save significant cost even when the shifting penalties are fairly high.

Conclusion

Demand and supply imbalance at airports lead to airport congestion, flight delays, and consequent environment impacts. For multiple airports in MARs, the supply-demand relations could vary, both at tactical and strategic levels. Thus, it is desirable to utilize the excess capacities in MARs to mitigate airport congestion and reduce flight delays. In this study, we found that shifting flights among airports in New York MAR, especially for low capacity scenarios, can reduce the system delay significantly. The determination of flight shifting is dependent on the fixed cost of shifting flights, including passenger transfer, aircraft dispatching, airport changing fee, connection to next flight, etc. Under low capacity scenarios, even with large flight shift fixed cost, e.g. 15 hours, there are still some flights shifted among airports to reduce the systemwide flight delay cost. Both deterministic and stochastic flight shift models bring more benefits at higher demand levels. It will be a useful tool for MARs with growing demand and restrictions of expanding airport capacities in the future.

In this paper, we extended capacity scenarios analysis on multiple airports in MAR and proposed the idea of flight shifting within MAR under different capacity scenarios. Both deterministic and stochastic models are proposed in this study, where deterministic model is for generation of short-term flight shifting and the stochastic model is flight shifting in the original schedule. Stochasticity is considered based on the probability of each capacity scenario.

One future research direction is to apply the capacity analysis and flight shift model at other MARs and understand the nationwide potential benefits of flight shifting. New York MAR is taken as the case study in our study given its well-known important role in national airspace system. The same analysis could be applied to other identified MARs as well. Another direction is to explore the way of determining the flight shift fixed cost. Lastly, we may incorporate airline equity considerations into the flight shift model. For example, we could impose an upper limit of the flight shifting for each airline. We may also construct an inequality penalty term and add that in the objective function.

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