Scenario-based Strategic Flight Reassignment in Multiple Airport Regions

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***Abstract*— Airport congestion and delay are subject to many sources of uncertainty including daily variations of airport capacity and demand. Taking advantage of interconnections among airports serving the same metropolitan region help alleviate airport congestion by utilizing excess resources in other airports. This study proposes to shift flights between airports in the same Multiple Airport Region (MAR) to improve regional operational performance. We consider such flight shifting at strategic level. If one airport is consistently congested and another has excess capacity, flights can be reassigned to less congested airport to reduce delay. We identify US MARs based on temporal distance between airports, and characterize spatial-temporal patterns of airport capacity variation within MAR. Then the stochastic flight shift model is formulated as a Mixed Integer Linear Programming (MILP) model to optimize the average total delay and reassignment cost of the flight schedule in the MAR among all possible capacity scenarios. Since the stochastic flight shift model is computationally expensive with high flight traffic intensity, we solve the model in decomposed flight batches. The proposed methodology is applied to New York MAR. Results show that by reassigning flight landing airport and time, the flight delay in the New York MAR could be significantly reduced.**

Keywords- flight diversion, Multiple Airport Region (MAR), capacity scenarios, scenario-based stochastic programming, flight rescheduling, multimodal scheduling

I. INTRODUCTION

Shortages of airport capacity and traffic demand growth are two major causes of flight delay. Most of flight delay takes place in major metropolitan areas. Metropolitan areas with high demand are often served by a system of two or more airports whose arrival and departure operations are highly interdependent. Though there has been considerable research to address flight arrival delay problem, they focus on scheduling improvements at a single airport to reduce delay [1, 2, 3]. This motivates us to leverage the interconnections among different airports in the same metropolitan region. We refer to such a region as a Multiple Airport Region (MAR) [1].

Airports in the same MAR may face different capacity-demand imbalance situations. It may therefore be possible to take advantage of excess capacities of some airports to reduce the overall airport delay of the MAR. In this research, we investigate the opportunities for reducing delay through adjustments in the schedule that may involve reassigning arrival airports within MAR region.

The flight reassignment was commonly applied in tactical level, especially in disruption management and recovery problem. There are many existing research working on the problem consists in constructing aircraft routes and passenger itineraries for the recovery period that allow the resumption of regular operations and minimize operating costs and impacts on passengers [4, 5, 6]. This research explores the potential benefits of implementing flight reassignment in operational traffic management. Many practical challenges may arise including aircraft type compatibility of reassigned airports, feasibility of passengers with connecting flights, aircrafts and crews dispatch, airline equity problem, etc. Our previous work [7] investigated the tactical implementation of such flight reassignment. The cost of same-day reassignment of flights and passengers is large, perhaps prohibitively so. In this paper, we focus on flight reassignment from a long-term perspective. The arrival airport reassignment may be incorporated in the flight schedule, several months or more in advance. In long-term perspective, airlines have more time to plan the aircraft rotations, crew schedules, multi-leg passenger routings, and so on. The cost of transporting passengers by ground mode and feasibility problem with their connecting flight are eliminated, as the flight reassignment happens before passengers purchase tickets. However, some flexibility is lost by restricting the reassignment to a fixed airport in the strategic level, which could be addressed by integrating strategic flight reassignment in advance with a same-day tactical reassignment.

To explore these possibilities and benefits, we first need to rigorously define MARs and characterize spatial-temporal patterns of airport capacity variation within them. Then, specifically, we propose to shift flights from a congested airport to land at another airport in the same MAR in order to utilize the capacity of the MAR airports more efficiently. Especially when a flight is experiencing a significant delay or causing significant delay to later flights, shifting it to a different airport may ameliorate the problem significantly. As the flight demand increases, flight shifting between airports can be expected to yield increasing delay reduction benefits, enough to offset the substantial cost of shifting a flight to land at a different airport.

Such flight reassignment efficiently schedules flights under different possible airport capacity scenarios. The capacity scenarios are not determined when the flight schedules are revised several months before operation day at strategic level. Therefore, we consider stochastic flight reassignment with alternative MAR capacity scenarios and their associated probabilities. There are considerable existing literatures on flight scheduling for delay optimization with demand and capacity uncertainties [3, 8, 9], but these studies have rarely considered capacity uncertainties in MARs.

In this study, we propose to reassign flights across airports in the same MAR to reduce delay. This idea of multimodal scheduling involves flight diversion and using ground transportation to accommodate shifted passengers. Since the re-assignment cost is large and uncertain, we solve the models for a large range assumed re-assignment costs, and find significant gains from flight shifting even when these costs are assumed to be very high.

II. Literature Review

Multimodal strategies are widely used in disruption management to reduce airport delay considering alternative modes or airports. [10] proposed to use inter-airport ground transport to enable diversion of flights to alternate hubs in regional airport system, when the system encounters a severe airside capacity reduction. Airlines could transport passengers and crew members between original scheduled and diverted airports by incorporating ground transport modes into their disruption management. Multimodal collaboration approach was developed in [11] to reroute passengers and help the recovery process using the case study of Asiana Crash at San Francisco International Airport. Predeparture algorithms was developed in [12] to reroute aircrafts, reassign passengers, and change flight schedules in response to disruptions. [13] investigated the relationship between the choice of diversion airport and the characteristics of an intended destination airport and the individual flights. In disruption management, airlines have contingency plans to divert flights enroute to an airport that experiences a full or partial outage. There are plenty of existing research working on how to efficiently make diversion decision to save substantial diversion cost [14, 15, 16].

Flight diversion could also be applied in strategic flight reassignment and scheduling among multiple airports to reduce delay by taking advantage of excess resources. Limited research has been working on stochastic flight reassignment in MAR for the purpose of reducing delay in regular flight operations other than disruptions. Such flight diversion and scheduling are investigated under varying airport capacities.

Airport capacities are subject to substantial variability as they depend on weather conditions, selected runway configurations, accidents and other uncertainties. Capacity scenario analysis identifies the patterns of airport capacity variation and has been used widely for air traffic management and airport planning [17]. [18] presented the methodologies of generating capacity scenario trees for a single airport from empirical data, and examined the performance of scenario-based single airport ground holding models using scenario trees. Research [19] investigated the real-world applicability of scenario-based approaches to the single airport stochastic ground holding problem. In the model of research [20], capacity uncertainty has been addressed by considering a set of scenarios, each corresponding to a time-varying airport capacity profile. [21] presented a model to determine the optimal strategies for utilization of airport capacity in accordance with the dynamics of traffic demands and weather. Existing studies have focused on capacity analysis of single airport. In this study, we extend clustering analysis to analyze capacity scenarios of multiple airports in the same MARs.

Over the past decades, research has led to the advancement of flight delay control under capacity uncertainties. Most existing models leverage stochastic optimization methods, which use probabilistic representation of airport capacity and how it evolves over time-of-day. [8] proposed an algorithm that assigns departure delays to flights scheduled to arrive at San Francisco International Airport in the presence of airport capacity uncertainty. A multi-stage (dynamic) stochastic optimization model is proposed for assigning ground delays and revising them in response to updated forecasts [3]. [9] designs and evaluates a GDP framework that simultaneously allocates arrival and departure delays, and explicitly accounts for uncertainty in capacity forecasts. This paper extends the individual airport capacity uncertainty to multiple airports, and leverages the capacity interdependence of airports in the same MAR.

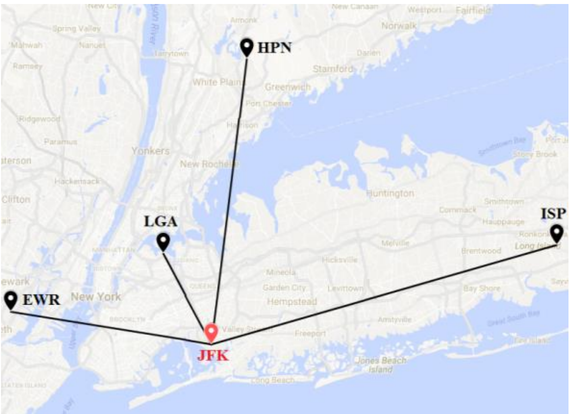

Figure 1. New York MAR

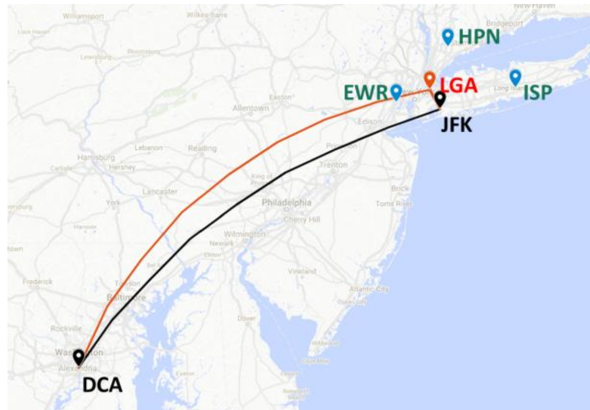

Figure 2. Flight Shifting Example

III. PROBLEM STATEMENT

Airports in a 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. Figure 1 shows an example of a flight scheduled to travel from DCA to JFK is shifted to land at LGA, when the arrival delay in JFK is tremendous. We consider such shifting at a strategic level in this paper. 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. Such flight shifting cannot be exercised easily since the costs of 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.

Strategically, the original flight schedule can be modified and improved by such flight shifting and rescheduling roughly six months in advance. In this case, the MAR capacity is not known, but capacity scenarios probabilities are available. We propose a scenario-based stochastic flight shift model in MAR to reassign flight landing airport and time to improve regional system operations.

IV. METHODOLOGY

We first identify US MARs and characterize spatial-temporal patterns of airport capacity variation within them. The clustering analysis yields a few representative capacity scenarios, each of which specifies capacity time series over a day for all airports in MAR. We then formulate the stochastic flight shift model as a Mixed Integer Linear Programming (MILP) model to optimize the average total delay and re-assignment cost of the flight schedule in the MAR among all possible capacity scenarios. Since the computation time is expensive for solving the stochastic model with high traffic intensity, we propose to solve the MILP in flight batches. This model focuses on the system efficiency view, and is solved with a large range of assumed flight shifting costs. We find significant gains from flight shifting even when these costs are assumed to be very high. We take New York MAR as our case study.

A. US MARs Identification and Capacity Scenarios Clustering

We lay the groundwork for stochastic flight shifting model by generating US MARs and clustering MAR capacity scenarios from previous work [7]. US MARs are identified following the algorithm in [22] with 1.5-hour threshold of temporal distance between airports. Annual Passenger Boarding data from FAA Air Carrier Activity Information System (ACAIS) database is used for MARs generation algorithm. We also use Google Maps Distance Matrix API to query travel time between airport pairs. Figure 2 shows the New York MAR generated from the algorithm.

Then, we generate typical MAR daily capacity scenarios by performing clustering analysis on capacity variation trend of airports in the same MAR. 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. Quarter-hour Airport Arrival Rate (AAR) from the FAA ASPM data base is used for capacity scenario clustering analysis. Specifically, we applied K-means clustering analysis to study MAR capacity profiles. Both elbow method and silhouette analysis are performed to identify the optimal number of clusters. Taking New York MAR as example, we judged that 11 clusters is the point beyond which increases in explained variance begin to diminish significantly. We thus use 11 clusters in our subsequent analysis.

Figure 3 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 in the first row represents a daily capacity scenario of New York MAR in 2015, while the plots in the second row show the original capacity data. The centroid capacity profiles are the mean of individual capacity variation for the days included in the cluster. The number and percentage on the bottom left of each plot represent the number and percentage of the days belonging to the cluster. First column shows the 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. The scenario in the second column represents the situation that the capacity of JFK airport is at the low level in the early morning and then increases at noon. The third scenario is a bad day for most airports in the MAR with much lower capacity, but also with low possibility of occurrence.

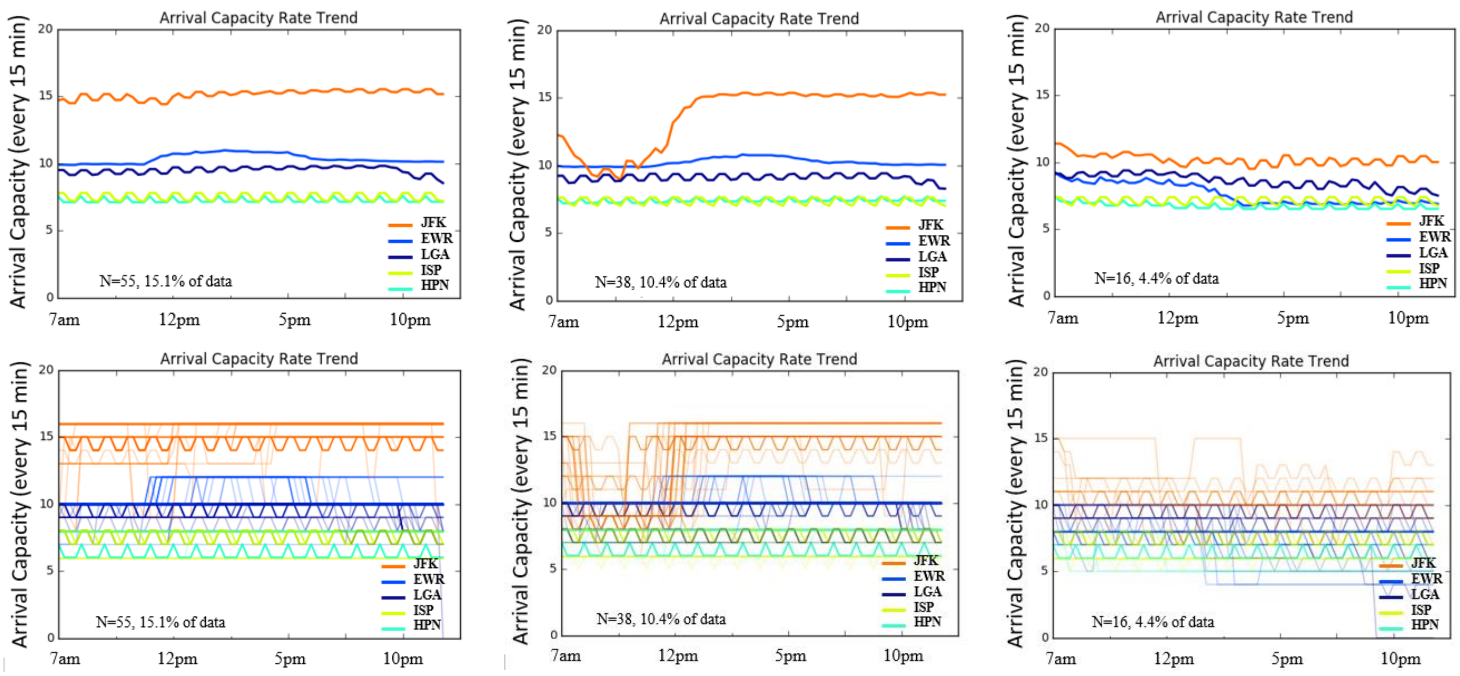

Figure 3. New York MAR Capacity Profiles Examples

B. Stochastic Flight Shifting Approach

Our stochastic flight shift approach leverages the interdependence of airports in the same MAR. It efficiently assigns flights with large delay to airports with excess resources. If daily airport capacity profile is given, one may find the optimal solution by using the deterministic flight shift model in [7]. At strategic level, only the probability of MAR daily capacity profile is available. The stochastic flight shift model is formulated as a Mixed Integer Linear Programming (MILP) model. The model provides with a rescheduling solution of which airport in the same MAR a flight is shifted to. Table 1 presents the definition of sets, variables and parameters in our model.

The model is formulated as follows:

$$\text{Min} \quad \sum_{f,b,t,q} P_q \cdot (I_{f,b,t,q} \cdot (t - S_f) + l_{f,b} \cdot I_{f,b,t,q})$$

s.t.

$$I_{f,b,t,q} \cdot t \geq S_f \cdot I_{f,b,t,q} \qquad \forall\ f \ in\ F, t\ in\ T, b\ in\ A, q\ in\ Q \qquad (1)$$

$$\sum_f I_{f,b,t,q} \leq C_{b,t,q} \qquad \forall\ t\ in\ T, b\ in\ A, q\ in\ Q \qquad (2)$$

$$\sum_{bt} I_{f,b,t,q} = 1 \qquad \forall\ f\ in\ F, q\ in\ Q \qquad (3)$$

$$\sum_t I_{f,b,t,1} = \sum_t I_{f,b,t,2} = \cdots = \sum_t I_{f,b,t,11} \quad \forall\ f\ in\ F, b\ in\ A \qquad (4)$$

The objective function calculates the expected total daily cost of flight delay and shifting across all MAR capacity scenarios. The flight shifting cost $l_{f,b}$ is composed of a shifting fixed cost and ground travel time from new landing airport to the original one. The ground travel time between airports in MAR is queried from Google Maps Distance Matrix API. In addition, we assume a wide range of flight shift penalties, since the value of this penalty is uncertain, and in order to determine the range of penalty levels under which flight shifting would be beneficial. Constraint (1) requires that the reassigned arrival time at shifted airport under each capacity scenario cannot be earlier than the scheduled arrival time; Constraint (2) restricts the number of arrival flights landing in each time slot at each airport under each capacity scenario from exceeding the airport capacity; Constraint (3) specifies that each flight under each capacity scenario is assigned to one and only one airport and time period. Constraint (4) is a coupling constraint incorporated in the stochastic model [21]. It maintains that the reassigned landing airport of a flight stays the same under each capacity scenario, but the reassigned arrival time can be different. In long-term prospective of flight reassignment, the shifted landing airports will be determined in advance, but the reassigned arrival time, which includes arrival delay, is flexible.

TABLE I. DEFINITION OF SETS, VARIABLES AND PARAMETERS

Set	**Definition**
F	Set of scheduled flights
T	Set of quarter-hour time intervals
A	Set of airports in the MAR
Q	Set of daily MAR capcacity senarios
Decision Variable	**Definition**
$I_{f,b,t,q}$	Binary decision variable equal to 1 if flight f is assigned to land at airport b at time t under scenario q
Parameters	**Definition**
$C_{b,t,q}$	Capacity of airport b at time t under scenario q
S_f	Scehduled landing time of flight f
P_q	Probability of scenario q happening in 2015
$l_{f,b}$	The cost of shifting flight f from its scheduled landing airport to airport b. The shifting cost is composed of a fixed cost plus ground travel time from new landing airport to original landing airport.

C. Flight-batch Optimzation Solution

The stochastic flight shift model is computationally expensive with high flight traffic intensity in large-size MAR. The computation time increases dramatically with larger number of flights, airports in MAR, time slots and capacity scenarios. This motivates the approach of solving the stochastic optimization model in decomposed flight groups. Figure 4 presents the workflow of solving flight-batch optimization problem. We divide the flights in order of scheduled landing time to batches with the same size. Then, the stochastic optimization model is solved in individual batch iteratively. For each batch, we add an extended period to the capacity to accommodate flights delayed beyond the batch time period. The length of extended period is determined by the maximum flight delay without flight shifting across all capacity scenarios. In other words, the extended time period is calculated by maximizing assigned flight delay from results of solving the following model individually under each of 11 capacity scenarios with shift cost infinitely large.

$$\text{Min} \quad \sum_{f,b,t}(I_{f,b,t} \cdot (t - S_f) + l^{\infty}_{f,b} \cdot I_{f,b,t})$$

s.t.

$$I_{f,b,t} \cdot t \geq S_f \cdot I_{f,b,t} \qquad \forall\ f\ in\ F, t\ in\ T, b\ in\ A \qquad (5)$$

$$\sum_f I_{f,b,t} \leq C_{b,t} \qquad \forall\ t\ in\ T, b\ in\ A \qquad (6)$$

$$\sum_{bt} I_{f,b,t} = 1 \qquad \forall\ f\ in\ F \qquad (7)$$

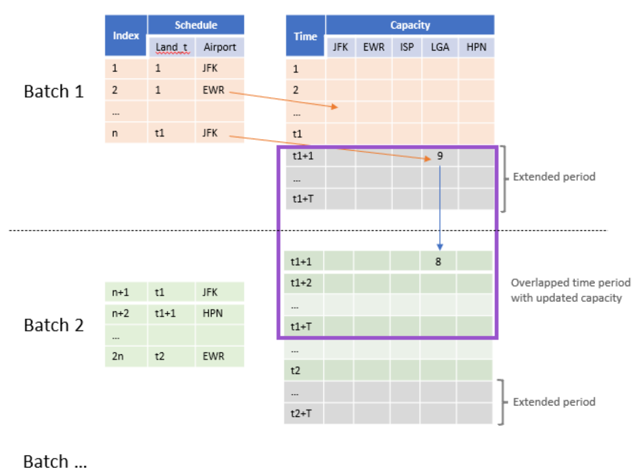

Figure 4. Batch Optimization Steps

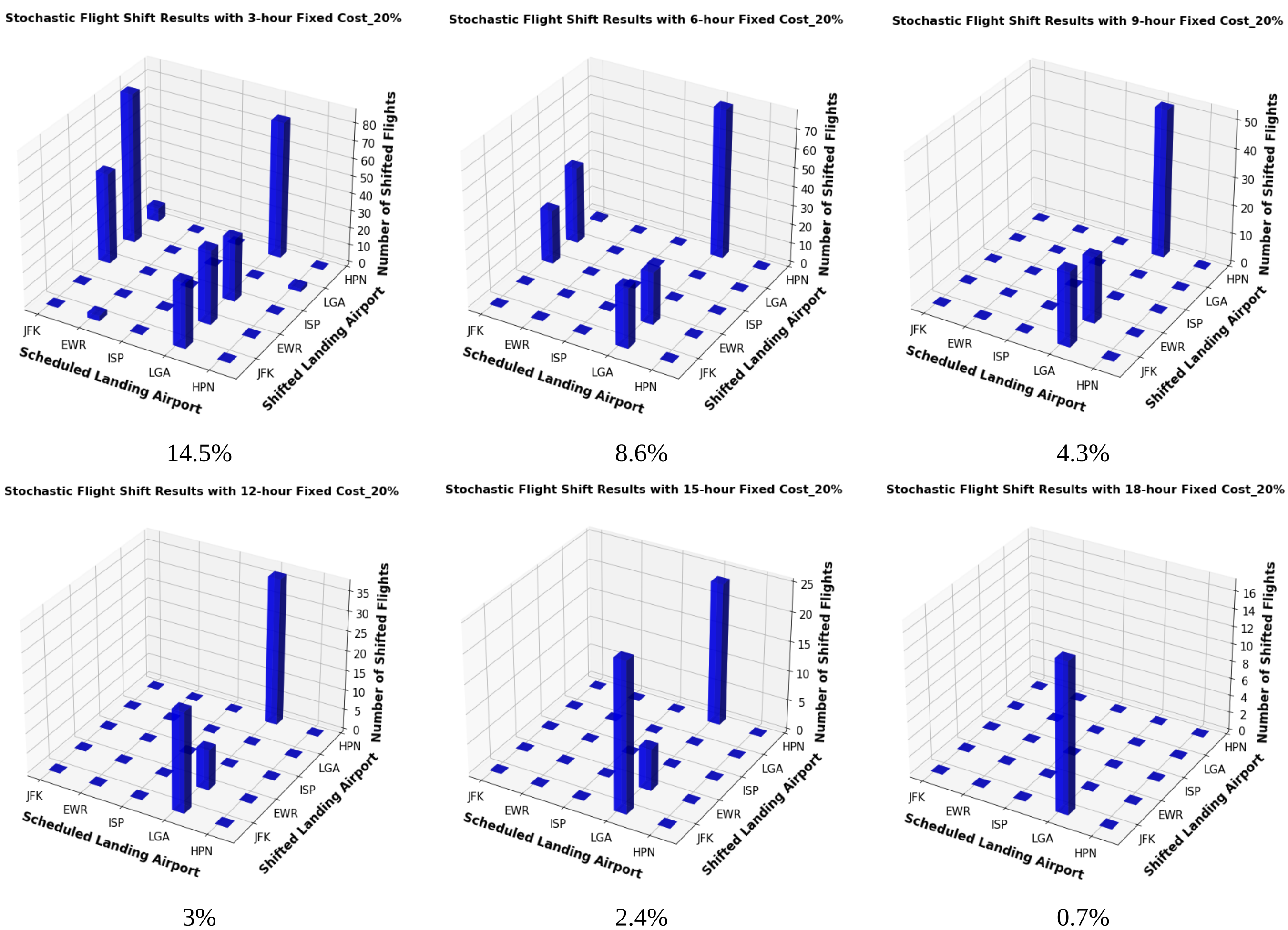

Figure 5. Flight Shifting Results of 20% Increased Demand with Different Shift Fixed costs

If any flight is delayed to the extended period at the current batch, the airport capacity in the next batch at the same time slot will be subtracted with number of delayed flights.

V. EXPERIMENTS ANALYSIS

We apply the stochastic flight shift model to New York MAR and solve the model with 11 capacity profiles of five airports. To select a representative flight schedule, we sort the daily enplanements of JFK airport of the year 2015 in descending order and choose the 10th busiest day (July 2nd) as inputs for our model. For that day, there are 1985 flights scheduled to land at New York MAR airports. To evaluate the benefit of flight shifting in high traffic intensity, we applied the model to 20% and 50% increased demand level. We also consider a set of flight shift fixed costs ranging from 0.5 to 27 hours, as well as a baseline case in which flight shifting is prohibited (i.e. $l_{f,b} = \infty$ if flight is shifted to a different airport).

Flight shifting results are presented in Figure 5 with flight shift fixed cost ranging from 3 to 18 hours at 20% increased demand level. No flight shifting occurs with flight shift fixed cost greater than or equal to 21 hours. In general, LGA and JFK are major sources of shifted flights, while all airports used as sinks. There are fewer shifted flights with higher shift fixed cost (note that these plots have different vertical scales). Though JFK airport is the busiest among five airports, it also has higher capacity in most cases. Therefore some flights in other airports are shifted to JFK when there is insufficient arrival capacity at these airports.

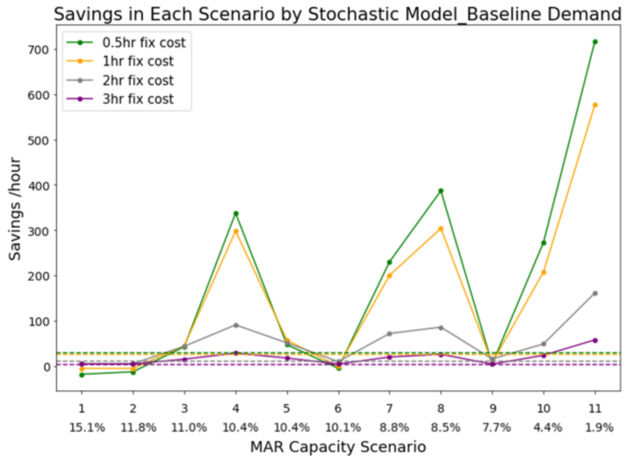

Figure 6. Total Cost Savings by Flight Shifting at 2015 Demand

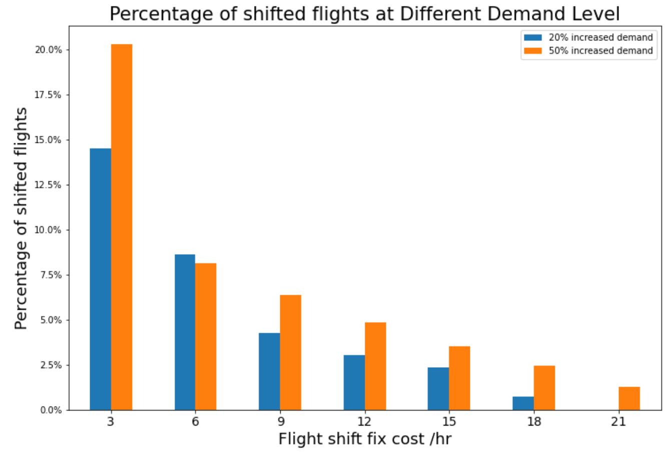

Figure 8. Percentage of Flight Shifting

Figure 6 shows the average savings from flight shifting across all scenarios (see dashed lines) and the scenario-specific savings (see solid lines) obtained from the stochastic model. With 4-hour or greater flight shift cost, there's no flight shifting at 2015 demand level. The model saves more cost under worse scenario cases. The less favorable capacity scenarios (capacity scenario 4, 8, 10 and 11) have larger scenario-based cost savings (solid lines) than average stochastic cost savings (dashed lines). Those low-capacity scenarios also have low probability, and most other scenarios have cost savings lower than the average savings.

Figures 7 shows the amount of total delay under the 11 capacity scenarios with different flight shift fixed costs at 2015 demand level. The total delay includes the amount of delay of all flights no matter shifted or not, but not including the flight shift cost.

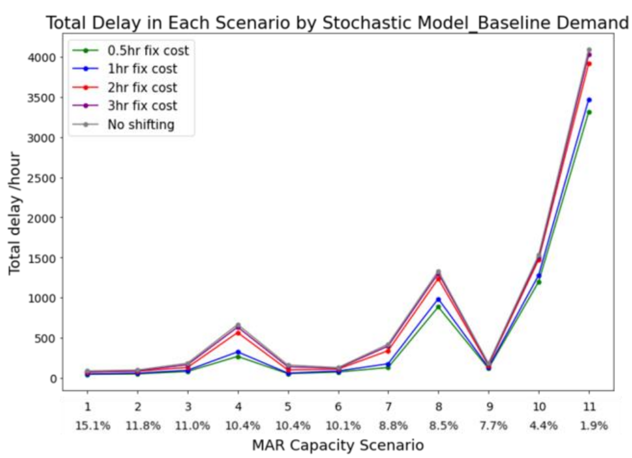

Figure 7. Total Delay of Each Scenario

Flight shifting would largely eliminate delay if the shifting cost is 1 hr or less. Increases in shifting costs above 2 hrs result in more delay as shifting becomes more cost prohibitive. Scenarios 10 and 11 are extreme cases with low capacity in all airports. The probability of these two scenarios is low, but delay is much higher than other scenarios.

Percentages of shifted flights with various flight shift fixed cost are presented in Figure 8. Since no flight shifting occurs at 2015 baseline demand when shift fixed cost is greater than 3 hours, only results at 20% and 50% increased demand levels are plotted. Larger proportion of flights are shifted with higher demand level or lower flight shift fixed costs. The stochastic model stops assigning flight shifting when flight shift fixed cost is greater than or equal to 21 hours at 20% increased demand level, and 27 hours at 50%. This demonstrates that there are still flights shifted even when shift cost is very large. It can be expected that the penalty for shifting flights in the original schedule is substantially less than that for shifting flights "on the fly" once the conditions of the day are known. The results reveal the potential benefit of applying flight shifting in regular flight operations.

VI. CONCLUSIONS

This work proposes a stochastic flight shift model within MAR considering uncertainty of MAR capacity variation profiles. It aims to utilize the excess capacities in MARs to mitigate airport congestion and reduce flight delays. In the results, 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 cost of shifting, including passenger transfer, aircraft dispatching, airport changing fee, connection to next flight, etc. Even with large flight shift fixed cost, e.g. 18 hours at 20% increased demand level, there are still some flights shifted among airports to reduce the systemwide flight delay cost. The 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.

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 NAS. 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. It requires comprehensive datasets, and the result could vary from one MAR to another. Limitations of aircraft type compatibility in reassigned airport should also be considered by adding related constraints in the model. In addition, we may integrate the strategic model in the current work with the tactical model in our previous study to improve the system efficiency while maintaining the flight shifting flexibility. Lastly, we may incorporate airline equity considerations into the flight shift model. Flight slot allocation has been studied to balance system efficiency and equity [23], as well as exchanging flight arrival slots between airlines[24]. Similarly, we could impose an upper limit of the flight shifting for each airline, or construct an inequality penalty term and add that in the objective function. These are important issues, but the results of our current research suggest that the potential benefits of strategic flight shifting are significant enough to warrant a more detailed analysis that addresses them.

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