

Estimating Current & Future System-Wide Benefits of Airport Surface Congestion Management*

Alex H. Nakahara & Tom G. Reynolds
 MIT Lincoln Laboratory
 Lexington, MA, USA

Abstract—Air traffic is expected to continue to grow in the future and improved methods for dealing with the increased demand on the system need to be designed and implemented. One method for reducing airport congestion is surface congestion management. The concept generally involves determining a limit to how many aircraft can efficiently taxi to departure runways, and then holding “excess” aircraft at the gate or in the ramp area with engines off instead of releasing them onto the active movement area during periods of high departure demand. This results in reduced congestion and taxi time, with jet fuel and emissions savings. In order to determine the appropriateness of deploying surface congestion management, estimates of the potential benefits at a wide range of airports into the future are necessary to assist with investment analysis decisions. To overcome challenges associated with the resulting wide spatial and temporal scope, a multi-fidelity modeling approach has been developed where high fidelity models are developed and executed for a small number of key airports, and these are used to inform, validate and extrapolate medium and low fidelity models which are applied to ever-broader sets of airports. Application of these models produce estimates of fuel savings from surface congestion management of 2.2-3.9 billion gallons across the top 35 US airports over the period 2010-2030, with a value of \$5.5-9.5 billion. Additional benefits in the form of reduced climate and air quality-impacting emissions have also been estimated to have similar orders of magnitude to the fuel savings.

Keywords—Surface congestion management; departure metering; benefits assessment; multi-fidelity modeling.

I. INTRODUCTION

Air traffic is expected to continue to grow in the future and methods for dealing with the increased demand on the system are needed. The airport surface is one area where system inefficiencies are especially evident in the form of congestion. At the top 35 airports in the United States in 2010 there were over 48 million minutes of departure taxi delay (i.e., taxi time over the unimpeded time), translating into approximately 200 million gallons of excess fuel burn [1]. One method for improving efficiency at airports is surface congestion management (SCM), also commonly called departure queue management or departure metering. The concept generally involves determining an efficient number of aircraft to allow to taxi to the runways and holding “excess” aircraft at the gate or other pre-designated location during periods of high departure demand, as shown in Figure 1. By restricting the number of aircraft on the surface, taxi-out delay, fuel burn and emissions

can be reduced as aircraft that would otherwise be waiting in taxiway queues with engines on are instead held elsewhere with engines off. There are also potential secondary benefits of gate holds, such as increased passenger and bag connectivity.

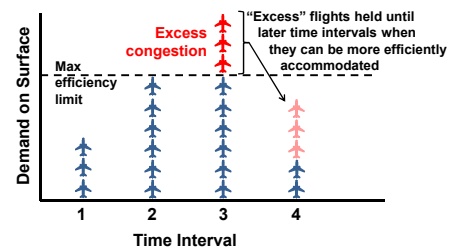


Figure 1. Surface Congestion Management Concept

In order to better understand the role surface congestion management can play in the air transportation system, benefits assessment activities are required across a broad range of airports for many (e.g., twenty) years into the future. However, benefits are difficult to calculate over such a broad spatial and temporal scope because of their sensitivity to site-specific parameters and the high uncertainty in future demand and capacity forecasts. To address these challenges, this paper uses a multi-fidelity modeling approach where high fidelity models are developed and executed for a small number of key airports, and these are used to inform, validate and extrapolate medium and low fidelity models which are applied to ever-broader sets of airports over longer time horizons, as illustrated in Figure 2.

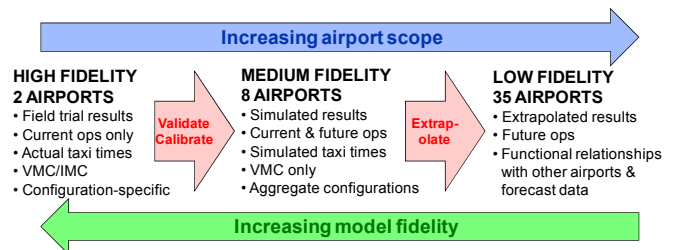


Figure 2. Multi-fidelity Modeling Approach

Multi-fidelity modeling has commonly been used in optimization and design work, as well as other applications [2][3][4]. In addition, there are several estimates of current benefits at various airports, both from field trials [5][6][7] and simulations [8][9][10][11][12]. These will be compared to the estimates presented here. However, little work has been done

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on estimating future benefits in ATC using this approach. The sections that follow present results from each of the fidelity levels and how they were used to build up current and future system-wide benefits estimates for SCM.

II. HIGH FIDELITY MODELING AT FEW AIRPORTS

Operational trials of surface congestion management have been conducted at a number of airports, including JFK [5], BOS [6] and MEM [7]. These studies afford tremendous insights into the application of surface congestion management in actual operations and therefore lend themselves to high fidelity models to determine “current” benefit estimates. The high fidelity analysis of the JFK and BOS field trials was used to support this system-wide SCM benefits assessment, but only the JFK analysis is summarized below.

A. JFK Surface Congestion Management Implementation

A surface congestion management scheme (coordinated by PASSUR Aerospace) was tested operationally at JFK for over a year starting in early 2010. A schematic of the implementation of the specific approach at JFK is shown in Figure 3.

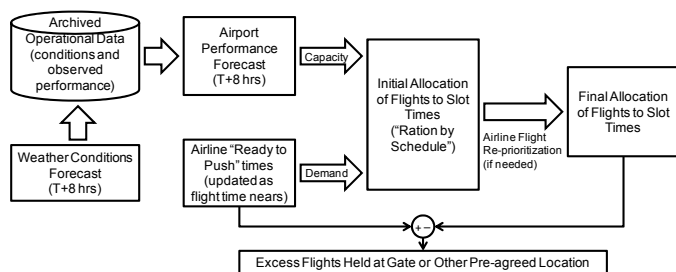


Figure 3. JFK Surface Congestion Management Implementation

Predictive analytics were used to forecast (up to eight hours in advance) the expected departure and arrival capacity (in terms of departure and arrival “slot counts”) of the airport based on the configuration/weather forecast and matching past airport performance under similar predicted conditions. This in turn was used with the demand information of flight-specific requested push-times sourced from (and updated by) the airlines to develop the initial allocation of flights to permitted taxi “slot times” over the forecast period. When the number of aircraft wanting to push-back was below what the airport could efficiently handle in 15 minute time bins, the slot times were the same as the desired push times. But when the number of flights wanting to push exceeded what the airport could efficiently handle, the excess flights were allocated slot times later than their desired push times into bins when the airport could more efficiently handle them, as illustrated in Figure 1. The initial allocation of flights to slot times used the concept of “ration by schedule” [13] in which the number of slots per hour was allocated to each operator based on their normal (unrestricted) percentage of the hourly volume. Slots were issued up to two hours in advance, to accommodate the longer planning horizon of international operations. Once the initial allocation of departure slots had occurred, the users had the opportunity to request swaps and substitutions within their allotment of departure slots, in order to better reflect their internal business priorities. These requests were received and

processed electronically via a web interface managed by the “slot allocation manager”: a neutral third-party established to run the program. All slot assignments could be seen by all program users, ensuring maximum transparency and trust that there was no gaming of the system. The foundation of the process was that users did not push-back and contact the air traffic control tower until they had reached their assigned departure slot time rather than simply pushing back whenever they were ready (as done without SCM). When a flight’s slot time was later than the requested push time, the hold time was absorbed either at the gate or, if the gate was required by another aircraft, at a pre-assigned holding pad with engines off as much as possible.

B. High Fidelity Modeling Approach

Analysis was conducted to develop an estimate of the “current” impacts of SCM at JFK during 2010 by comparing taxi times, fuel burn & emissions pre/post SCM implementation, with all other relevant operational factors being as equal as possible. It was possible to find a few days where the airport was operating under very similar conditions pre/post SCM implementation, allowing example impacts of the technique to be observed. Such example comparison days are shown in Figure 4. Surface congestion management is seen to reduce the number of aircraft on the airport surface between 17:00 and 21:00 (corresponding to the evening departure push) from a peak of 40 on the sample day before SCM, to about 25 after it was implemented, resulting in taxi-out time savings of over 20 minutes for flights at 20:00. The surface traffic snapshot shown in Figure 5 reinforces the effect in terms of reduced departure queue size and taxi-out times, with the “excess” aircraft being held off the active movement area. Airport configuration and demand were similar in both cases.

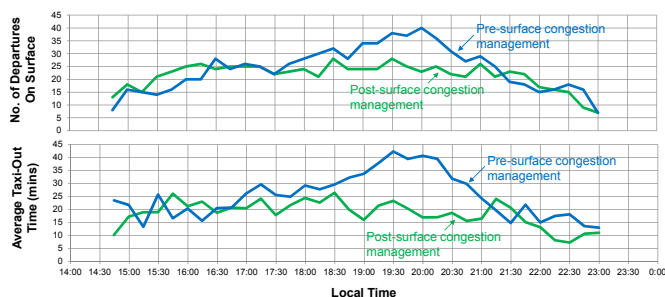


Figure 4. Comparison of JFK Taxi-out Times Pre/Post Surface Congestion Management for Sample Days

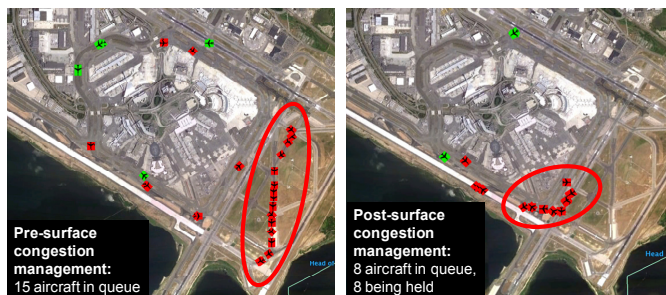


Figure 5. Comparison of JFK Departure Queues Pre/Post Surface Congestion Management (red icons = departures, green icons = arrivals)

Although these observations provide insights into the effect of surface congestion management, data across numerous days was required to estimate annualized impacts. However, the large number of factors that influence airport operations (e.g., demand, capacity, airport configuration, weather, traffic management initiatives, equipment status, etc.) and the complexity of operations at JFK, made finding a large enough sample of comparable days pre/post-SCM implementation very difficult. Therefore, a modeling approach was developed which found relationships between surface congestion management and taxi time impacts in each major airport configuration, and then applied the identified relationships to the full set of data to determine the annualized impacts of the congestion management technique. The resulting high fidelity modeling methodology is presented in Figure 6. The general sequence of steps is presented along the top and more detail on how the steps were executed is provided below.

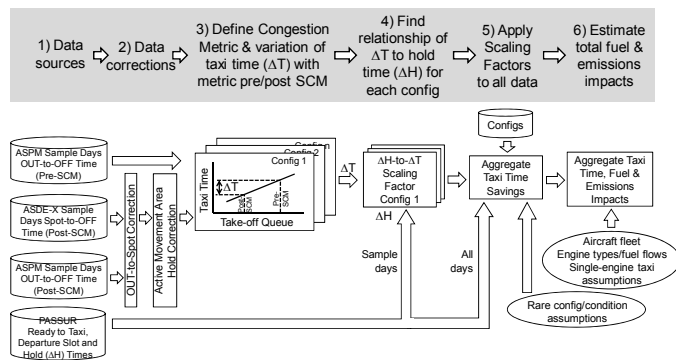


Figure 6. JFK High Fidelity Modeling Approach

1) Data Sources

The analysis used the following data sources:

- FAA Aviation System Performance Metrics (ASPM) database which provided flight-specific OOOI (gate OUT, wheels OFF, wheels ON, gate IN) times & airport throughput in 15 min intervals.
- Airport Surface Detection Equipment-X (ASDE-X) data which provided position in the active movement area (not ramp) at 1 second intervals.
- PASSUR surface congestion management data which provided flight-specific ready to push, allocated departure slot and resulting hold times (if any).

The pre-implementation analysis period was selected to be January 1, 2009 - December 31, 2009. The initiation of the surface congestion management process coincided with the closure of one of JFK's main runways (13R/31L) but the impacts of SCM during the runway closure were not analyzed because the airport was not in its normal state (i.e., there was no pre-implementation data corresponding to JFK without runway 13R/31L). Therefore, the post-implementation analysis period was selected to be the six month period July 1, 2010 - December 31, 2010 corresponding to the day runway 13R/31L re-opened through the last day for which all of the data sources discussed above were available for this analysis.

2) Data Corrections

The data sources identified above provided the key analysis events illustrated in Figure 7. The difference between the ASPM OUT and OFF times provided a good measure of the taxi-out time in the pre-SCM environment. However, it was not suitable in the post-surface congestion management environment due to the fact that a large number of the flights which were given slot times after their ready to push times were held "off-gate" so the gates could be available for incoming arrivals. In those cases, the ASPM OUT time was not an accurate reflection of when the aircraft actually started taxiing to its departure runway, but rather when it left the gate to be held elsewhere. Therefore, the post-SCM taxi-out times were determined from ASDE-X data. Given that the ASDE-X tracks were generally picked up at the spots (the interface between the ramp and taxiways/active movement area), the tracks needed to be corrected back to an equivalent OUT time so they could be directly compared to the pre-implementation taxi-out times based on the ASPM OUT-to-OFF events. To determine the appropriate "OUT-to-spot" correction factor, distributions of the differences between ASPM OUT times and ASDE-X pickup times were calculated for pre- and post-surface congestion management days [5]. This was found to be well approximated by a Normal distribution with a mean of 7 minutes and a standard deviation of 2 minutes. This defines the distribution of times for flights at JFK to reach the spot once the parking brake was released at the gate, accounting for tug push-back, engine start and checklist completion times.

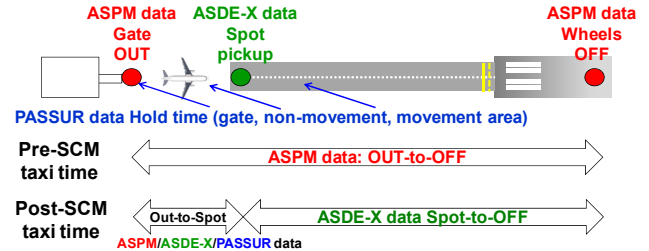


Figure 7. Key Analysis Events

3) Define Congestion Metric & Variation of Taxi Time with Metric Pre/Post SCM

The key congestion metric used in this analysis was the "take-off queue", which for a flight i is defined as the number of other take-offs which occur between the pushback and take-off time of aircraft i . Prior work has shown that the taxi time of a flight is related to the take-off queue it faces [14]. To convert the change in take-off queue into a change in taxi time at JFK with SCM, a regression was calculated using taxi time versus take-off queue as shown in Figure 8. The slope of the regression is the incremental taxi time for every additional aircraft in the take-off queue. The slopes of the regression pre- and post-SCM are very similar, indicating the underlying dynamics of the airport are unaffected by the procedure, but the airport is operating at much lower average take-off queue counts (i.e., more often on the lower end of the regression line) when SCM is in operation.

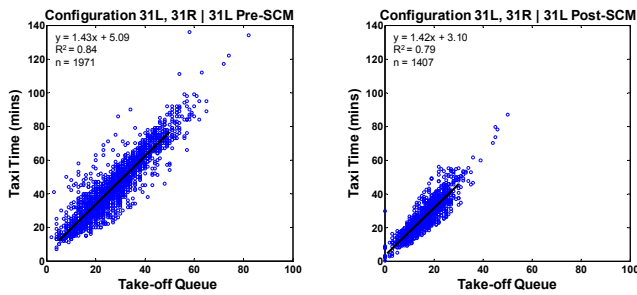


Figure 8. Relationship of Taxi Time to Take-off Queue

Regression lines were calculated for the top six most common configurations that experienced holds at JFK and the regression line slopes of all but one of the configurations were very similar pre- and post-implementation, but did vary between configurations as expected given their different capacities. The average takeoff queue across a group of representative sample days was calculated in 15 minute bins for each configuration pre- and post-surface congestion management implementation. Using the regression lines for each configuration, the taxi time impact of the SCM technique was determined in those 15 minute time bins. This was then summed over all time periods in the sample days to determine a total amount of taxi time saved in each major configuration.

4) Find Relationship of Taxi Time to Hold Time for Each Major Configuration

The difference in taxi time observed from the previous step was compared to the operational hold time due to surface congestion management to determine configuration-specific scaling factors. There were variations between configurations, but the average across all but one was 0.92, indicating 0.92 minutes of taxi time reduction was observed for each minute of hold time. One configuration had a much lower scaling factor indicating loss of benefit when it was used.

5) Apply Scaling Factors to All Data

Once scaling factors for the main configurations were calculated, they were generalized to the others in use at JFK by comparing the number and specifics of runways in use. This full list of scaling factors was then applied to all the gate holds in the SCM analysis period to estimate the aggregate taxi time impacts of surface congestion management at JFK.

6) Estimate Total Fuel & Emissions Impacts

To convert from taxi time savings into fuel and emissions savings, an average fuel burn index was calculated for each month of the study period. The PASSUR data included the tail number of all aircraft. A fleet database was used to match tail numbers to engine types, and then ICAO ground idle fuel flow certification data [15] was used to estimate the taxi fuel flow rate for each aircraft accounting for the number of engines of each type it possessed and APU/single-engine taxi assumptions. Fuel burn savings from surface congestion management were determined by multiplying this fuel flow rate by the taxi time savings determined from the previous

steps and summing over all flights. Fuel burn savings were converted to carbon dioxide emissions savings by using the standard CO₂ emissions index of 3.16 kg CO₂/kg fuel burnt.

C. High Fidelity Modeling Results

Results from using the methodology described above are presented in Table I. Total annualized “engines-on” taxi time reductions of 14,800 hours were calculated. These translate into estimated annual savings of 5.0 million US gallons of jet fuel and 48,000 metric tons of carbon dioxide from surface congestion management at JFK assuming all taxiing is conducted with all engines operating (i.e., no single engine taxi). At the FAA recommended benefits analysis fuel price of \$2.43/gallon [16], this translates into SCM fuel cost savings of \$12.2 million spread across all operators at JFK in 2010. For comparison, annual estimates for JFK benefits in the literature range from 12,500 hours [11] to 19,000 hours of time saved [12], albeit for different years.

TABLE I. JFK HIGH FIDELITY MODELING RESULTS

Configuration	Proportion of Hold Mins	Hold Time (hours)	Scaling Factor	Taxi-out Time Reduction (hours)	Fuel Reduction (US gallons)	Carbon Dioxide Reduction (metric tons)
31L, 31R 31L	20%	1970	1.17 & 1.02	2160	730,000	6,990
13L 13R	18%	1730	0.67	1160	391,000	3,750
22L 22R, 31L	13%	1250	0.16	200	66,200	630
4R 4L, 31L	9%	870	0.66	570	191,000	1,830
31R 31L	7%	720	0.79	570	187,000	1,790
13L, 22L 13R	6%	580	1.2	700	239,000	2,290
Others	27%	2580	0.79	2040	690,000	6,600
Totals (6 months)		9700	0.76	7400	2,490,000	23,900
Totals (annual)				14,800	4,980,000	47,800

III. MEDIUM FIDELITY MODELING AT MULTIPLE AIRPORTS

High fidelity analyses based on operational data allow detailed insights to be gained on the impacts of SCM at specific airports in current day operations. However, to estimate current and future system-wide benefits at more airports, generalized models are also needed which are informed by the high fidelity analysis results. Hence, a medium fidelity modeling approach was also developed to estimate SCM benefits at eight key US airports for twenty years into the future. Full details of this analysis can be found in [17], but a summary is given below.

A. Medium Fidelity Modeling Approach

The medium fidelity modeling approach is illustrated in Figure 9. Each major element is discussed in turn next, starting with the fundamental throughput saturation curves.

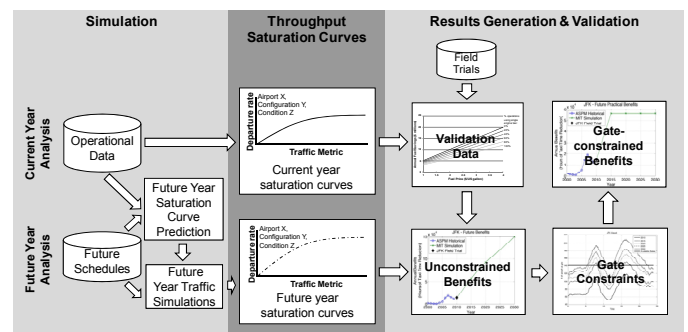


Figure 9. Medium Fidelity Modeling Approach

1) Throughput Saturation Curves

At the core of the methodology is the concept of throughput saturation curves, which relate departure throughput to an appropriate traffic metric (e.g., number of departing aircraft on the airport surface or in a departure queue). The concept is illustrated in Figure 10.

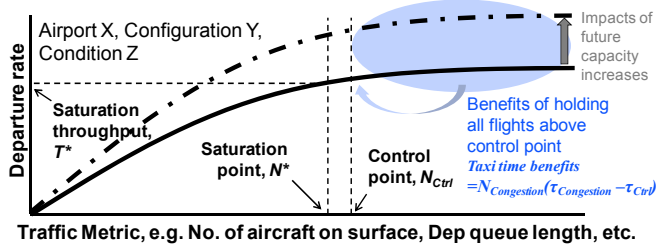


Figure 10. Throughput Saturation Curve

As more aircraft push back from their gates onto the taxiway system, the throughput of the departure runway(s) initially increases because more aircraft are available in the departure queue(s). But as the number of aircraft continues to increase, the airport eventually reaches a saturation departure throughput. The saturation value depends on the airport configuration (due to different capacities); arrival demand (due to departure/arrival interactions); meteorological conditions (visual vs. instrument conditions); and controller technique. When the airport is operating beyond its saturation point, any additional aircraft that push back simply increase the time they are taxiing out with engines on without any gain in departure throughput. The objective of surface congestion management is to maintain the number of aircraft pushed back at a certain control level (N_{Ctrl}) just above the saturation point (N^*). In this way, high departure throughput can be achieved without unnecessary surface congestion by moving the operating point at congested times from above the control point back along the curve to the control point, as illustrated by the blue oval in Figure 10. Prior MIT work has automated the estimation of benefits for *current day* operations by quantifying the reduction in active taxi time from moving the operating point from the congested regime to the control point [18]. The potential benefits of SCM are then calculated by:

$$\text{Taxi Time Reduction Benefits} = N_{Congestion}(\tau_{Congestion} - \tau_{Control}) \quad (1)$$

where $N_{Congestion}$ is the number of aircraft held by SCM, $\tau_{Congestion}$ is the average taxi time those flights would have had in the absence of SCM, and $\tau_{Control}$ is the average taxi time those flights had with SCM. This taxi time reduction leads to fuel burn and emissions reductions (because engines are on for less time): these reductions are the primary benefit mechanism of SCM which can be monetized. Note that overall passenger delay is not typically reduced through SCM as delay is being moved from being accommodated on the taxiways (with engines on) to the gate or other hold location (with engines off).

2) Simulation

The data inputs identified in Figure 9 allowed current-day throughput saturation curves and the operating points along those curves to be determined for the study airports using archived operational data such as ASPM and ASDE-X surveillance data. This study used ASPM for historical data, which provided OOOI times for individual flights as well as airport configuration in 15 minute intervals, while the OFF times were used to calculate the airport throughput in the same 15 minute intervals. Active taxi time reductions by employing surface congestion management techniques were calculated as described by Eqn. (1) and converted to fuel burn savings by multiplying by ICAO-standard fuel flow and emissions rates for different aircraft types consistent with the fleet mix at the different study airports (also obtained from ASPM). The “current year” benefits results using this analysis methodology were compared to the high fidelity analysis results for JFK (and BOS) discussed in the previous section.

For future year benefits estimates, the key challenges were determining the characteristics of the saturation curves and specific operating points along them for future year operations. As illustrated in Figure 10, saturation curves can vary substantially due to changing demand levels and infrastructure additions, but other parameters such as operating procedure enhancements and fleet mix changes can also be important. A method for deriving future saturation curves was developed which accounted for a wide range of relevant characteristics. The approach was based on the Random Forest (RF) method [19] which makes no assumptions about the functional relationship between the input/predictor variables and the output, and avoids biases by not assuming a particular function is the correct form to describe airport behavior. It uses groups of decision trees that test the importance of different parameters in order to predict values by calculating the average over all predictions from the individual trees. The saturation point (N^*) and saturation throughput (T^*) shown in Figure 10 were the target RF prediction variables that defined the airport throughput saturation curves to first order. The saturation point was defined for the purposes of calculation as the first point at which the throughput reached 95% of its maximum value. The input parameters to the RF model to predict these saturation curve parameters were chosen using engineering judgment as well as the input of subject matter experts and included the mean and peak hourly demand and capacity; configuration usage frequency; the physical size of the airport; and the number of gates. The decision trees were trained, or “grown”, on data from 2000 to 2010, those being the years for which ASPM data existed. Data based on the capacity growth forecasts and future schedules (discussed next), supplemented with parametric variation of the curves as appropriate for representative days/conditions for the future study years, were input into the model to obtain future year saturation curves for 2015-2030 in five year increments.

It was then necessary to determine operating points relative to the saturation curves for the future years. A simulation capability previously developed and validated at MIT for

current year operations [18] was modified to use the following future year inputs:

- Forecast annual demand by airport: FAA Terminal Area Forecast (TAF) 2010-2030 [20].
- Forecast capacity by airport: MITRE FACT2 [21].
- Future year “NextGen schedules” supplied by FAA for 12 representative days in the years 2010, 2015, 2020, 2025 and 2030. These were “untrimmed” schedules which did not take into account all physical constraints.
- Physical airport data (Terminals, gates, runways, etc.) forecasts from airport websites.

Using this input data, the simulation calculated taxi times for every flight over the course of a year in a given configuration by modeling the aircraft departure process as a queuing system. It took the future year schedules as its main input and assumed that the scheduled departure times were the pushback times for each flight. Taxi time, τ is related to the size of the departure queue by:

$$\tau = \tau_{Unimpeded} + \alpha R(t) + W_q(t) \quad (2)$$

where $\tau_{Unimpeded}$ is the average unimpeded time (by airline or overall), α is a taxiway congestion factor, $R(t)$ is the number of aircraft on ramps and taxiways at time t , and $W_q(t)$ is the expected waiting time at time t . The simulation calculated the time for three different segments of taxiing: unimpeded time, taxiway congestion time and time in departure queue [22]. In Figure 11, α represents the ramp and taxiway interactions, $W_q(t)$ is the time spent in the departure queue (which depends on the runway server), and $\tau_{Unimpeded}$ is the base time it would take if the ramp interactions and departure queue were 0.

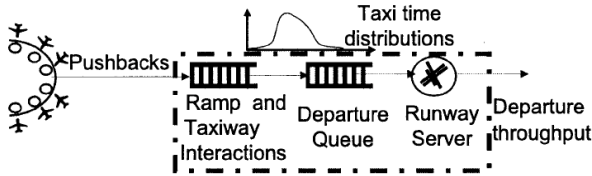


Figure 11. Simulation Departure Processes

These three segments have tunable parameters: $\tau_{unimpeded}$, α and capacity (which affects W_q). The average unimpeded time used was the average across all airlines in a specific configuration from 2010. There were no changes to the unimpeded time for future operations because of the uncertainty in completion times and effectiveness of infrastructure additions at the study airports. The taxiway congestion factor was calibrated from the present day training data by matching the amount of congestion predicted with the congestion actually seen.

The future year saturation throughput from the RF model was used to determine the service rate for the departure queue for different levels of arrivals to reflect the interdependence of the arrival and departure rates. The saturation throughput calculated by the RF model was an average value, so to translate that to different levels of arrivals, the difference

between the average service rate and the rate implied by the saturation throughput was calculated. This difference was added to the rates for each level of arrival to determine the new service rates. The service rates were modeled as Erlang distributions, where the arrivals at the runway threshold were assumed to be random. Each runway configuration at each study airport was modeled as a single server with infinite space for the queue, and aircraft were taken first-come, first-served.

With the resulting estimates of taxi time, the operating point on the future year saturation curve could be determined over the course of the future year day. Note $N(t)$ for the saturation curve is not the same as $R(t)$ from the simulation because $N(t)$ includes aircraft in the departure queue at the end of the runway. Benefits of surface congestion management relative to the baseline case for future years were then calculated using Eqn. (1) as for the current year.

After the future year saturation curves and operating points against them were calculated, the benefits were summed across the 5 most common configurations at each study airport. A scaling factor was calculated for the “current year” results based on the difference between the sum of the benefits for the top 5 configurations and the results with one aggregate saturation curve that included all configurations and weather conditions. This factor was then used to scale up the future year benefits to estimate benefits for all the airport configurations. Configuration-specific calculations were performed because of the insights from the high fidelity method and the requirements of the taxi simulation.

3) Results Generation & Validation

The future year estimates resulting from the approaches discussed above were “unconstrained benefits” because they did not account for the physical constraints to the number of flights that can be held by an SCM approach, e.g., limited number of gates or off-gate hold locations. The “gate-constrained benefits” shown in Figure 9 consider airport gates as the primary limiting resource: if there are too few gates, SCM might need to be scaled back. For each study airport, the approximate number of aircraft on the ground at a gate over the course of a day was calculated for the current year using ASPM data. The gate use count was calculated by adding one when an aircraft arrived at a gate (from the IN time) and subtracting one when an aircraft departed (from the OUT time). The count was calculated at each minute from midnight to midnight of one day and is airline-specific. The ability for an airport to conduct on-gate holds from SCM was then estimated by taking the difference between the total number of gates in use at any given time and the total number of gates at the airport. When the number of required aircraft holds from SCM exceeded the number of free gates, it was assumed additional holds could not take place. The use of total free gates as the metric for how many aircraft could be held by an SCM approach makes several simplifying assumptions: it neglects gate ownership issues (gates at US airports are typically “owned” by a specific airline and are not a shared resource), the size of gates and their ability to handle different types of aircraft and whether or not an aircraft was moved off

a gate after arrival. It also does not explicitly show space available for off-gate holds.

Gate utilization was calculated for each study airport and year and compared to the number of gates at (or planned at) the airport. If the analysis showed that there would not be enough gates to accommodate SCM, “gate-constrained” benefits were restricted to the last year in which there were enough gates for the majority of the day. Estimated gate utilization at DFW and JFK for future years is shown in Figure 12. While DFW is forecast to have little growth in demand for gates in the future, JFK is estimated to face increasing gate competition which could constrain SCM benefits by 2015.

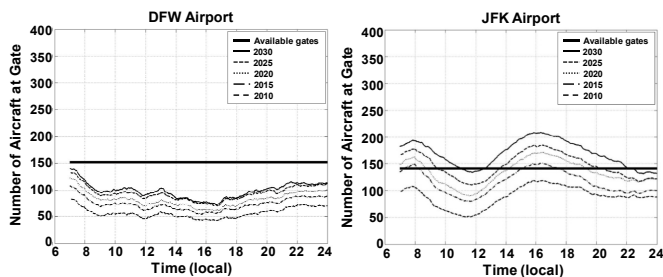


Figure 12. Estimated DFW and JFK Gate Utilization

Several other airports were also estimated to exceed their gate capacity in future years. This illustrates a fundamental problem with the generation of future demand schedules: the only constraining capacity was the runway capacity, when in fact there are several others that can restrict SCM at an airport, such as gate capacity, security, and noise abatement. Because these factors are not considered in FAA NextGen future schedules, using them without modification can lead to overestimates of benefits because demand levels are higher than realistic levels at affected airports. While this work attempts to correct for this by restricting growth of benefits at airports with gate constraints, a better method would be to regenerate the future schedules with these additional constraints included.

B. Medium Fidelity Modeling Results

Eight airports were studied using the methodology outlined in the previous section: ATL, BOS, DFW, IAD, JFK, LGA, ORD and PHL. JFK and BOS were chosen because of their recent field trials of SCM permitting validation of the “current year” medium fidelity results with the high fidelity analyses at these airports. The other airports were chosen to represent different types of airports in terms of size, layout, traffic and congestion level. Detailed results for JFK from the medium fidelity work are presented below. Results for the other airports can be found in [23]. JFK was chosen to present in detail here because of the validation potential with the results presented in Section II and because it displays many of the important trends and traits in the study. Aggregate results in terms of taxi time and fuel burn benefits estimates are then presented for all the study airports.

1) Detailed JFK Results

Results for JFK are shown in Figure 13. Panel a) shows how demand has differed between 2000 and 2010, along with forecasts of how it will evolve through 2030, and changes in capacity and taxi times. The historical demand is obtained from ASPM aggregate operations counts, while the future demand is from the future schedules [20]. The ASPM historical capacity is the average Airport Departure Rate (ADR) seen, and the future capacities are from [21].

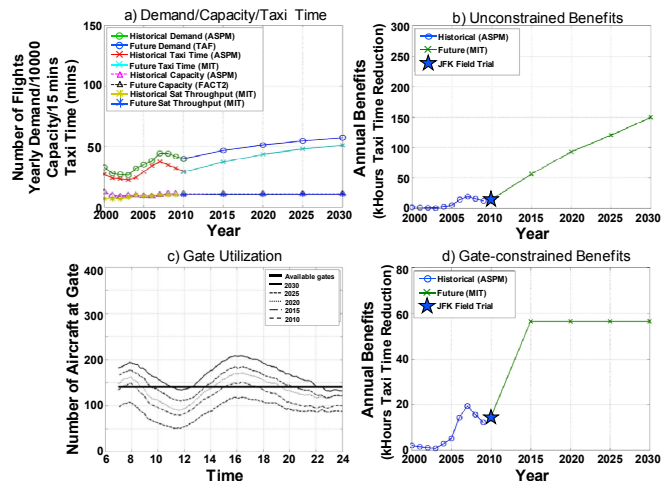


Figure 13. JFK Medium Fidelity Modeling Results

As the demand increases into the future with no change in capacity, the unconstrained benefits from SCM drastically increase, as seen in Panel b). The rise in benefits is due to the simulated rise in taxi time, which indicates more congestion. The taxi time can be seen to closely mirror the demand, as might be expected when JFK is operating close to its capacity and with no major changes in capacity. Two benefits curves are presented in Panel b) representing the historical and future benefits. Historical benefits (benefits that could have been realized if SCM had been in place) between 2000 and 2009 were calculated with ASPM data and are seen to generally validate the MIT methodology because the 2009 (ASPM) and 2010 (MIT simulation) points are very close. The high fidelity analysis of the JFK field trials allows further validation of the approach: the 15,000 hours of taxi time reduction in 2010 from that analysis compare well with the medium fidelity results. Panel c) presents the gate utilization for future years. There is no change in the pattern of usage; each successive year simply moves the curve up, and gate utilization demand is seen to exceed the current number of gates after 2015. Panel d) shows the resulting gate-constrained SCM benefits which are capped at 2015 levels for the years beyond.

2) Aggregate Results at Study Airports

The estimated unconstrained and gate-constrained benefits in terms of gallons of fuel saving across the 8 study airports are presented in Figure 14. Note the use of the JFK high fidelity analysis results to validate the 2010 medium fidelity benefits estimate for JFK.

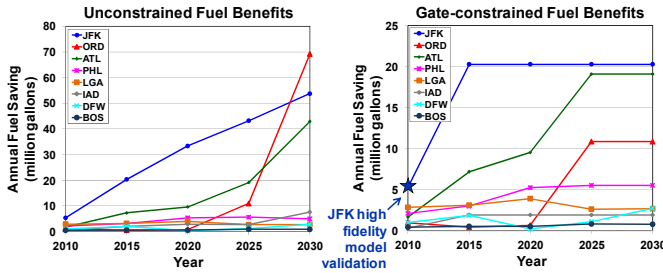


Figure 14. SCM Benefits Estimates for 8 Medium Fidelity Study Airports

The airports with major contributions to the unconstrained benefits are JFK, ORD and ATL. The other five airports are all at about the same lower level of benefits. When the practical benefits are examined, JFK, ORD and ATL have significantly reduced benefits due to gate constraints, but they remain the top three airports in terms of SCM benefits.

The total fuel savings across the eight study airports from 2010 through 2030 are estimated at 1.5 billion gallons in the unconstrained case, and 950 million gallons in the gate-constrained case. Using the FAA-recommended future fuel price of \$2.43/gallon, the monetized fuel savings benefits are \$3.6 billion in the unconstrained case and \$2.3 for the gate-constrained case. These estimates assume 3.1 kg per gallon of jet fuel and airport-specific fuel burn rates (using ICAO taxi fuel rates) for the current aircraft fleet mix at each airport. Note the difference between the unconstrained and constrained benefits indicates the incremental benefits achievable through increasing gate capacity at appropriate airports.

IV. LOW FIDELITY MODELING AT SYSTEM-WIDE AIRPORTS

In order to extrapolate the findings from the medium fidelity analysis at eight airports to a broader set of system-wide airports, various low fidelity modeling approaches were developed. The broader set of airports considered in this analysis were the “OEP35” airport set: the top 35 airports in the US which account for more than 70% of total passenger traffic.

A. Low Fidelity Modeling Approaches

Three low fidelity modeling approaches were developed in order to produce a range of scaling factors for the extrapolation of the medium fidelity analysis results:

- Taxi delay scaling factor model.
- Multi-parameter linear regression model.
- Clustering model.

Each of these approaches is discussed in turn below.

1) Taxi Delay Scaling Factor Model

This method determined a scaling factor of 2.45 between the amount of delay observed in the 2010 ASPM operational data at the OEP35 airports relative to the eight medium fidelity analysis airports, and assumed that the benefits at the OEP35 scaled by the same factor relative to the benefits at the 8 medium fidelity study airports. This method has the advantage of being simple to calculate but implies a number of key

assumptions. The first is that taxi delay is linearly proportional to benefits. A comparison of the delay and SCM benefits from the medium fidelity airports for 2010 is presented in Figure 15. There is a relationship to first order, but on closer inspection it is seen that the relationship is not well-behaved, with the differences caused by airport-specific characteristics.

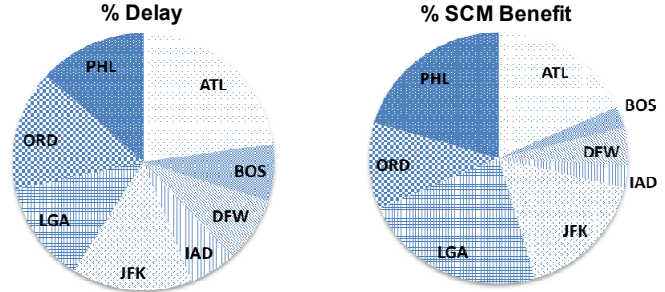


Figure 15. 2010 Delay vs. SCM Benefits Comparison

Another implied assumption is that the ratio of benefits at the OEP35 relative to the eight study airport remains the same into the future. This is difficult to assess without simulation at all the OEP35 airports, which the low fidelity approaches are specifically being designed to avoid. The shortcomings of these assumptions drove the need for additional low fidelity modeling approaches to account for some of the relevant differences between airports and to help bound possible OEP35 SCM benefits, as discussed next.

2) Multi-Parameter Linear Regression Model

These models expanded upon the taxi delay scaling factor approach by adding other explanatory variables that could be estimated relatively easily for the full set of airports into the future. Four regression variables were tested: total annual departure demand (# of pushbacks); total annual departure demand when an airport is operating at demand levels at or above capacity (# of pushbacks in congestion); the number of 15 minute periods in a year when the airport is operating at that point (periods with 100% usage); and the yearly average percentage of capacity used (% capacity used). These four variables were chosen to represent different aspects of congestion and SCM. The total demand indicated the overall size of the airport, because large airports would receive more benefits from an SCM system than a smaller airport with a similar delay per flight. The Pushbacks in Congestion variable represented how much of the total demand is operating when the airport is congested. This is different from the 100% Usage periods, which measures how often the airport is congested. Two airports that are congested for the same amount of time would have different benefits if the capacity is low at one airport (making the threshold for 100% usage low) often and the other airport is congested while in its highest capacity configuration. The % Capacity used variable gives an idea of the overall congestion at an airport.

To build the regression, data from the 8 medium fidelity study airports from 2000 to 2010 was used. The benefits served as the dependent variable, and the four stated inputs

were the independent variables. It was found that the percentage of capacity used did not significantly improve the quality of the model, so it was discarded. Several other statistical tests were performed to test the validity of the regression. The resulting modified regression model was:

$$\sqrt{\text{Benefits}} = a_1X_1 + a_2X_2 + a_3X_3 + a_4 \quad (3)$$

where X_1 is # of pushbacks, X_2 is periods of 100% usage, X_3 is # of pushbacks in congestion, and the a_i parameters are the regression coefficients established from the training data. This multi-parameter linear regression (linear here means that the model is linear in the parameters, even if the dependent variable is transformed) was then used to establish a scaling factor of 1.67 between the benefits of SCM at the OEP35 airports relative to the eight medium fidelity study airports. Full details of the development of this regression, its validation and other non-linear regressions which were tested but discarded, can be found in [23].

3) Clustering Model

The third low fidelity extrapolation method formed clusters of airports with similar characteristics that were assigned the mean benefit level of the medium-fidelity study airports in that set. The clustering parameters chosen were variables that were identified as important based on the experience gained from the high and medium fidelity methods and were: total demand; current % capacity used; growth of demand from 2010 to 2030; and growth of capacity from 2010 to 2030. The first two variables are the same as in the multi-parameter linear regression and are present for the same reasons as given previously. Clustering differs from the regression in that the evolution over time of the variables is not considered. As a result, a variable is needed to represent the expected growth of congestion, which is determined from the demand and capacity growths. Clustering could be performed on these raw variables. However, given the insights from the high and medium fidelity methods, a new variable was created in order to create clusters that corresponded to historical levels of benefits. Several different equations were tested but the following form both grouped the 8 study airports from the medium fidelity method into levels close to the estimated benefits levels and also was relatively simple and meaningful:

$$\text{ClusterVariable} = \left(\frac{\text{DemandGrowth}}{\text{CapacityGrowth}} \right) \times \text{CapacityUsed}^2 \times \sqrt{\text{DemandLevel}} \quad (4)$$

The clustering was performed using the k-means algorithm [24]. This algorithm iteratively divides n observations into k clusters, where an observation belongs to the cluster whose mean it is closest to (Euclidean distance). k was chosen to be four for this analysis corresponding to high, medium, low and negligible SCM benefits potential to both ensure multiple study airports be assigned to each cluster and to sufficiently stratify the results. Three clusters (the low, medium and high levels) had at least one of the 8 study airports from the medium fidelity method, while the fourth cluster (negligible)

was estimated to have half of the benefits of BOS, the airport with the lowest level of benefit from the medium fidelity study set. The remaining 27 airports from the OEP 35 were assigned to clusters based on their value of the clustering variable, and assigned the average value of the benefits at the study airports in that cluster. The resulting clusters are shown in Figure 16. From this, an average scaling factor of 2.14 was established between the OEP35 and 8 medium fidelity airport benefits.

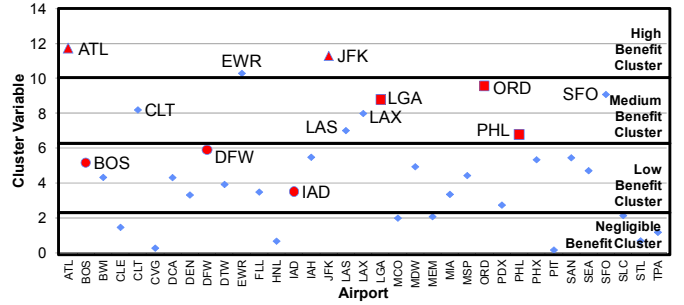


Figure 16. Clustering Results

B. Low Fidelity Modeling Results

The range of scaling factors resulting from the low fidelity modeling approaches outlined above were used to extrapolate the medium fidelity results, as shown in Figure 17.

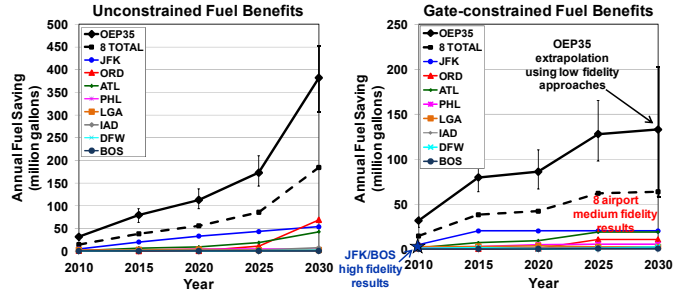


Figure 17. SCM Benefits Estimates for OEP35 Airports

The dashed black line is the sum of the benefits estimates from the medium fidelity results at the 8 study airport, while the solid black line gives the impact of extrapolating this total to the OEP35 airports using the average of the scaling factors from the three low fidelity modeling approaches. The whiskers show the high and low ranges from the individual scaling factors from the different approaches. The base year (2010) estimates can be compared to other studies. Using the various low fidelity methods, the estimate for 2010 taxi time savings ranges from 97,000-142,000 hours, compared to estimates of 107,000 hours in [8] and 194,000 hours in [7].

Summing across the twenty year period at the OEP35 airports, the unconstrained fuel savings 2010-2030 were estimated at 3.9 billion gallons with cost saving to the airlines of \$9.5 billion at \$2.43/gallon, compared to 2.2 billion gallons and \$5.5 billion fuel savings when the gate-constraints were taken into account. These 20 year aggregate estimates can be compared to the total airline industry fuel cost of \$40 billion in 2011 [25], i.e. the 20 year savings from surface congestion

management are equivalent to approximately 14-24% of the 2011 total fuel cost. By calculating total fuel burn during taxi and in-flight [26], it was also possible to estimate that the gate-constrained savings from SCM equated to approximately 18% of taxi-out fuel burn and 1.0% of total block fuel burn averaged across all airports. These fuel burn savings were also converted into carbon dioxide (CO₂) emissions savings of 37 million metric tons in the unconstrained case and 22 million metric tons in the gate-constrained case. Using newly emerging environmental costing parameters [27], additional climate benefits of \$0.2-14.4 billion (at \$29-1226/metric ton fuel) and air quality benefits of \$0.1-2.4 billion (at \$5-65/metric ton CO₂) from system-wide deployment of SCM over the period 2010-2030 were also estimated. The large ranges reflect the high uncertainty in the monetization, but show the environmental benefits can be of similar magnitudes to the fuel cost savings.

V. CONCLUSIONS

This paper has presented a multi-fidelity modeling approach for estimating the current and future US system-wide benefits potential from surface congestion management. High, medium and low fidelity approaches with ever-broader airport and time applications have been used to estimate fuel burn reductions of 2.2-3.9 billion gallons across 35 major US airports over the period 2010-2030, with a value of \$5.5-9.5 billion at FAA-recommended fuel prices. Additional benefits in the form of reduced climate and air quality-impacting emissions have been estimated to have similar orders of magnitude to the fuel savings. These estimates should be of high value to policymakers as they determine the priorities for deploying surface congestion management relative to other enhancements.

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AUTHOR BIOGRAPHIES

Alex H. Nakahara is a systems engineer at Northrop Grumman in the Future Technical Leaders program. He has an MS in Aeronautics and Astronautics from MIT and was a research assistant at MIT Lincoln Laboratory.

Tom G. Reynolds is technical staff in the Air Traffic Control Division of MIT Lincoln Laboratory. He has a Ph.D. in Aerospace Systems from MIT and has worked on the research staff at MIT and the University of Cambridge.