Spatial Modeling of Airport Surface Fuel Burn for Environmental Impact Analyses

Sandeep Badrinath, James Abel &
Hamsa Balakrishnan
Department of Aeronautics & Astronautics
Massachusetts Institute of Technology
Cambridge, MA, USA

Emily Joback & Tom Reynolds
Air Traffic Control Systems Group
MIT Lincoln Laboratory
Lexington, MA, USA

Abstract—**The assessment of the fuel burn and emissions impact of airport surface operations is a key part of understanding the environmental impacts of aviation. These assessments are needed at two levels: the analysis of inventories (the total amount of fuel burned and emissions discharged over some period of time), and the analysis of spatial distributions (the amount of emissions experienced at a particular location within or near the airport). While the availability of taxi times for the operations of interest is sufficient for inventory analysis, the analysis of spatial distributions requires estimates of where on the airport surface an aircraft is located as it consumes fuel. In this paper, we show how a data-driven queuing network model can be developed in order to estimate the time that an aircraft spends at different congested locations on the airport surface. These models are useful both for spatial distribution analysis and for predicting taxi times in the absence of measurements (e.g., for projected demand sets). We use measurements of Ultra Fine Particles (UFPs) at Los Angeles International (LAX) airport to demonstrate that the proposed model can help predict the measured emissions at different monitoring sites located in the vicinity of the airport. In the process, we show how one could develop a machine learning model of the spatial distribution of airport surface emissions, given pollutant measurements, air traffic demand, and prevailing weather conditions. Finally, we develop a clustering-based method to evaluate the generalizability of our surface operations modeling framework.**

Keywords—*Airport surface operations; queuing; fuel burn; environment; emissions; AEDT*

I. INTRODUCTION

There is a need for accurate airport surface operations, fuel and emissions modeling to support the objectives of a range of aviation stakeholders. For example, Air Navigation Service Providers such as the Federal Aviation Administration (FAA) or Eurocontrol need airport surface models to help develop safe and efficient procedures and to assess the impacts of new technologies. As environmental impacts of aviation take on increasing importance, such models are needed to support airport fuel burn and emissions (e.g., for air quality and noise) impact studies. Many industry-standard models used for estimating surface fuel burn and emissions make simplifying assumptions which introduce errors into the calculations and decrease their utility. The availability of increased amounts of operational data and modern analysis techniques provides an opportunity to develop enhanced modeling approaches to increase the accuracy and validity of airport surface models for these applications.

Two categories of analyses are important when considering the environmental impacts of airport surface operations:

- *Inventory analysis:* The objective of such an analysis is to determine aggregate total fuel burn or emissions over a period of time for current or potential future scenarios. These analyses often support higher level analysis objectives, for example to assess system-wide fuel and emissions impacts of different procedures or technologies.
- *Spatial distribution analysis:* This type of analysis requires more fine-grained models that reflect *where* on the airport surface fuel and emissions are released and is relevant for assessing spatial and temporal impacts of fuel burn and emissions. Applications of such analyses include the assessments of impacts on communities near to an airport.

In this paper, we present approaches for developing airport surface operations models that can support spatial distribution analysis, which requires the modeling of not just the total fuel burn (or emissions) over some time period, but also a determination of the location on the airport surface at which the fuel burn and emissions occur.

Section II provides background information on current models typically used for these types of analyses. Section III briefly summarizes prior work on improving surface models for inventory analyses. Section IV presents an approach for modeling the location of fuel burn and emissions using queuing models in order to support spatial distribution analysis enhancements and also presents an approach using clustering to guide model validation efforts. In Section V, we demonstrate the proposed approach through a case study of fuel burn and emissions analysis at Los Angeles International Airport (LAX), using monitoring site measurements of Ultra Fine Particles (UFPs) or nanoparticles with an aerodynamic diameter of $0.1\,\mu m$ ($100\,nm$) or less. In doing so, we also a present an approach to integrate pollutant monitoring site measurements, when available, into environmental impact analyses. Finally, Section VI concludes with the key takeaways of this work.

II. CURRENT AIRPORT FUEL BURN & EMISSIONS MODELS

The current software tool used by the U.S. government for assessing fuel burn and emissions is the FAA's Aviation Environmental Design Tool (AEDT) [1]. AEDT was developed as a single tool to replace a suite of existing models for predicting aviation environmental impacts. The previous legacy models included the:

- Integrated Noise Model (INM) [2], used for obtaining noise estimates
- Model for Assessing Global Exposure to the Noise of Transport Aircraft (MAGENTA) [3], used for determining the global impact of aircraft noise
- Noise Integrated Routing System (NIRS) [4], used for comparing the noise impact between different routes and procedures
- Emissions and Dispersion Modeling System (EDMS) [5], used to estimate emissions on the airport surface
- System for Assessing Aviation's Global Emissions (SAGE) [6], which predicted global totals of fuel burn and emissions across all commercial flights, or alternatively the impact from a single aircraft.

A tool similar to AEDT is EUROCONTROL's Advanced Emission Model (AEM), which is used to estimate aircraft fuel burn and emissions [23]. AEM is a part of Fuel Burn and Emission Inventory System (FEIS) used by EUROCONTROL for annual inventory analysis, which helps drive policy decisions for the European Environmental Agency [23]. Another commercial tool that has been used to estimate flight-specific fuel burn and emissions is Piano-X [24]. In addition to these industry tools, researchers have proposed various enhancements and standalone models to improve the estimation accuracy (a recent review can be found in [25]).

The work presented in this paper focuses on recommended enhancements to surface fuel and emissions models, using AEDT as the exemplar case and focusing on impacts of fuel consumption and emissions on air quality impacts.

III. FUEL & EMISSIONS INVENTORY ANALYSIS

In this section, we present a brief discussion about our proposed enhancements for inventory analysis, and readers can refer to our earlier paper [7] for a more detailed discussion. As mentioned earlier, inventory analysis involves determining the aggregate fuel burn and emissions over a period of time. The current taxi phase model in AEDT calculates fuel burn as the product of a baseline taxi fuel burn rate and a nominal taxi time, as illustrated in the top portion of Figure 1. Emissions are calculated by multiplying the resulting total fuel burn by an emissions index [8] for the emissions species of interest. The estimated baseline taxi fuel burn rate for a given aircraft type is based on a constant engine specific 7% thrust level (and resulting fuel flow rate) during taxi, determined from engine manufacturer certification data. This can be significantly different than the actual fuel burn characteristics during operational conditions for a given aircraft because of factors such as the age of the engine (as the engine gets older the amount of fuel it burns changes), as well as pilot technique (e.g., choosing a slightly higher or lower taxi thrust setting or "riding the brakes" instead of throttling down the engines when coming to a stop on the airport surface). The nominal taxi times are often based on the standard certification Landing and Take-Off (LTO) cycle which assumes 26 minutes of taxi time on the airport surface, typically broken into 19 minutes taxi-out and 7 minutes taxi-in. Different airports may have very different taxi times depending on topology, configuration, congestion levels, etc. which can lead to a large range of different taxi times. In addition, the current AEDT approach uses simplified assumptions regarding emissions (but no explicit modeling of fuel burn) contributions from the pushback and engine start events, including engine and Auxiliary Power Unit (APU) contributions [9]. These events can be significant contributors to the overall surface fuel burn and emissions, and therefore need to be modeled accurately.

New data availability and modeling techniques provide opportunities to make model enhancements to the taxi fuel burn rate, taxi time and pre-taxi (gate and engine start) elements
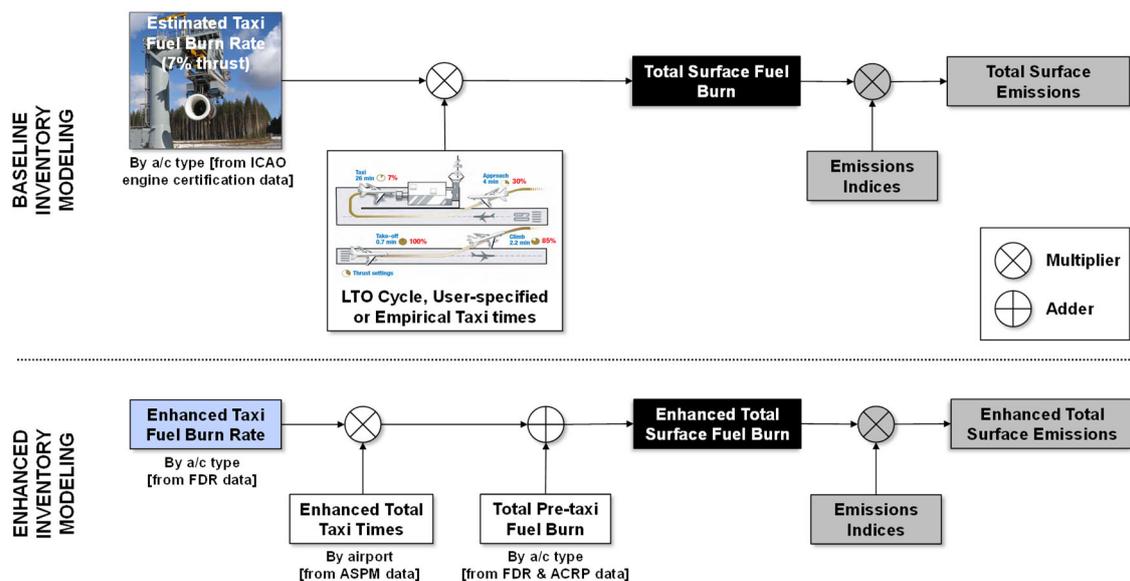
Figure 1. Fuel & Emissions Inventory Analysis Model Baseline & Enhancements

A/C type	Engine type	Proposed model	Mean error (%)		Mean absolute error (%)	
			Proposed model	AEDT	Proposed model	AEDT
A320-214	2 × CFMI CFM56-5B4/2	$0.81\,\dot{m}_f\delta_\infty^{-0.12}\theta_\infty^{-0.48}$	1.0	36.3	13.3	39.4
A321-111	2 × CFMI CFM56-5B1/2	$0.80\,\dot{m}_f\delta_\infty\theta_\infty^{0.21}$	3.8	47.1	14.9	50.1
A330-343	2 × RR Trent 772B-60	$0.78\,\dot{m}_f\delta_\infty\theta_\infty^{0.35}$	-3.0	36.4	5.8	39.1
A340-313	4 × CFMI CFM-56 5C4/P	$1.02\,\dot{m}_f\delta_\infty\theta_\infty^{0.60}$	-0.7	7.8	9.1	12.5
B777-300ER	2 × GE GE90-115BL	$0.75\,\dot{m}_f\delta_\infty^{-6.7}\theta_\infty^{0.72}$	-2.2	42.3	3.1	43.1
C Series-100	2 × PW PW1542G	$0.97\,\dot{m}_f\delta_\infty\theta_\infty^{0.19}$	0.1	17.7	5.5	19.3

Table 1. Proposed Model for Baseline Fuel Flow Rate and Error Statistics

shown in the bottom portion of Figure 1. In our previous work [7], we had proposed enhancements in each of these elements which are summarized below.

A. Enhanced Taxi Fuel Burn Rate

The recent (limited) availability of Flight Data Recorder (FDR) data provides direct observability of engine fuel flow rates during realistic operational conditions in order to address many of the shortcomings identified above with previous baseline fuel flow models. Using FDR data, we have developed models for the mean baseline fuel flow rate as a function of the mean values of the ambient temperature (θ_∞) and pressure (δ_∞) ratios (these input features are used for consistency with the Boeing Fuel Flow Method [9]). Table 1 shows the proposed model equations for different aircraft types in our dataset, where $\dot{m}_f$ represents the ICAO Databank fuel burn index during taxi-out. The table also shows a comparison of the error statistics of the taxi-out fuel burn obtained using our proposed model and the current AEDT model, evaluated over an independent test set. The error statistics indicate that the proposed models are more accurate than the current AEDT model, and the reduction in mean absolute error is up to about 93% for some aircraft types.

B. Enhanced Total Taxi Times

Airport-specific taxi out times are available in current versions of AEDT but these can be outdated. For this part of the study, recent taxi-out data were collected from the FAA's Aviation System Performance Metrics (ASPM) database [10].

This dataset contains flight-specific taxi-out times, available to the nearest minute. ASPM data from flights across 25 major US airports was aggregated for dates between October 2016 and September 2017, to provide a recent model of the distribution of taxi out times at a given airport. The boxplot in Figure 2 gives a side-by-side comparison of all the airport taxi-out distributions across the 25 airports studied (which were clustered into 6 sets of airports with similar taxi characteristics: see [7] for more details). The 19-minute taxi-out simplification is provided as a reference, along with the error between this assumption and median of each of the distributions. The 19-minute default taxi-out time assumption is intended to represent average airport taxi time. This chart shows that the errors in this estimate vary from 0% to 72.7% for these particular airports, which is one reason why users typically do not use the 19 minute default taxi time. By using recent historical data at an airport, the error resulting from predicting the taxi-out time for a given flight can be decreased drastically. This analysis could be updated regularly to reflect evolving taxi time behaviors, and/or extended to taxi-in operations and to other US or international airports as needed.

C. Enhanced Pre-Taxi Fuel Burn

In order to establish a more accurate model of the fuel burn, the fuel consumed by both the engine and APU during the "pre-taxi" phases at the gate, enhanced estimates from push-back and engine startup have been developed. The engine start-up fuel burn was obtained using the FDR data, and the APU fuel burn was determined from [11] and through discussions with an
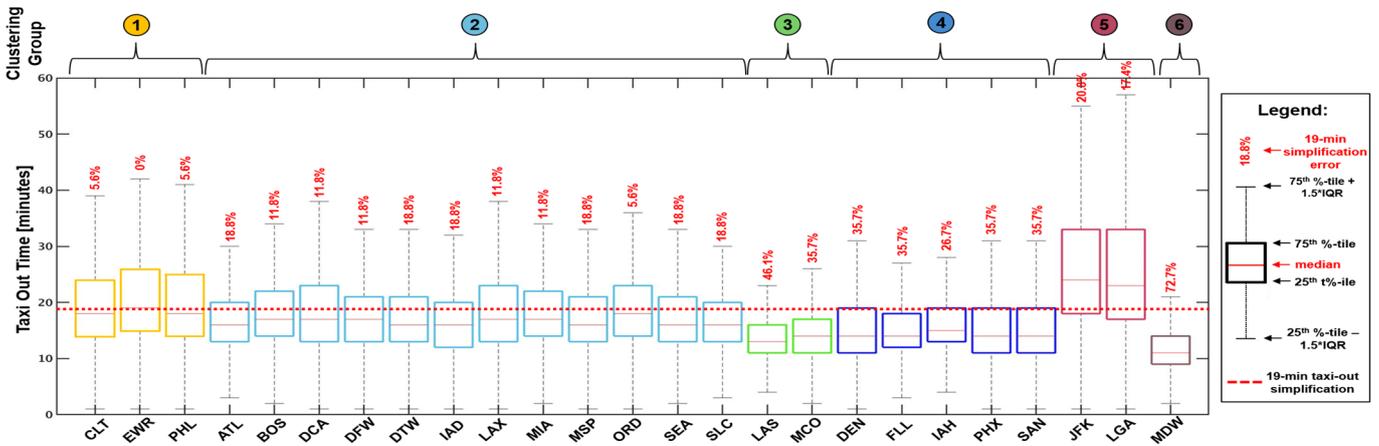
Figure 2. Enhanced Taxi-out Times Based on Recent ASPM Data [7]

experienced commercial pilot. The fuel burn totals for the gate/pushback/engine start processes were aggregated over all the flights of a given aircraft type available in the FDR data as a statistical approach to building the fuel burn histograms from historical data. The resulting pre-taxi fuel burn distributions for the types studied are shown in Figure 3, as the solid curves. The relationship between fuel burn and aircraft weight was then investigated as a means to predict the pre-taxi fuel burn of aircraft types not within the FDR dataset. The total fuel burned during gate/pushback/engine start was seen to be linearly related to the weight of the aircraft type, and this correlation was used to then predict the approximate fuel burn for aircraft types not available in the FDR data set. The result of this process for a number of wide-body aircraft are presented as the dashed lines in Figure 3.
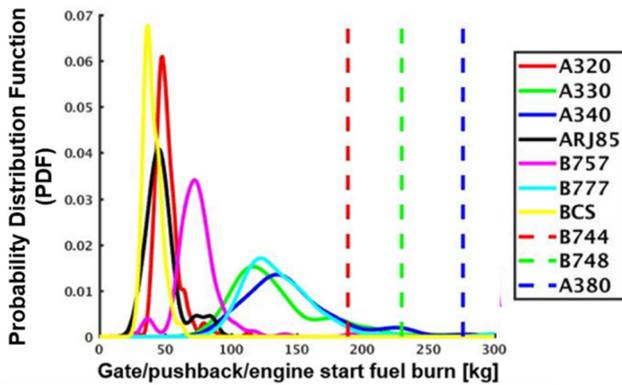
Figure 3. Pre-taxi Fuel Burn Estimates by Aircraft Type [7]

IV.   FUEL & EMISSIONS SPATIAL DISTRIBUTION ANALYSIS

The ideal approach to determining spatial distributions of fuel and emissions from airport surface operations is shown on the top portion of Figure 4. Fuel burn as a function of time and location would be available from FDR data (as used in the previous analysis) given that time, fuel flow for each engine and latitude and longitude locations are then readily available.

Multiplying by emissions indices for the species of interest would then enable emissions as a function of time and location on the airport surface to be easily determined. This is often accomplished by deploying air quality monitors at strategic locations around the airport and its perimeter in order to quantify emissions impacts.

In practice, FDR data is not routinely available and approximations are needed to the different elements outlined above. These are illustrated in the bottom half of Figure 4. The enhanced taxi fuel burn rates from the analysis detailed in the previous Section can be used again here.

The taxi time by airport location is more critical for this type of analysis because of its sensitivity to the accuracy of the amount of time spent (and emissions created) at different airport locations. The updated taxi time analysis from the previous section does not apply for this type of analysis because it only represents *total* taxi time. To determine the amount of time spent by the aircraft at different locations on the airport surface, one can utilize trajectory data from airport surface radar data (e.g., Airport Surface Detection Equipment (ASDE-X)). However, airport surface radar data is insufficient if one is interested in evaluating fuel burn and emissions under infrastructure changes and different airport operating conditions (such as traffic levels, runway usage patterns etc.) not seen in historical operations. Performing such what-if analysis under different operating conditions is the primary use case for airport environmental assessment tools such as AEDT. Therefore, one needs to develop traffic models of the airport surface that are capable of estimating the time spent by the aircraft at different airport locations given the airport operating conditions as the input. Queuing models have been shown to be able to reflect surface traffic congestion at airports.

In the remainder of this section, we discuss (1) the development of an airport queuing model built on FDR or radar data, or even data on the pushback, takeoff, landing and gate-in times when available, and (2) a method based on clustering analysis to evaluate the generalizability of queuing models of surface operations.
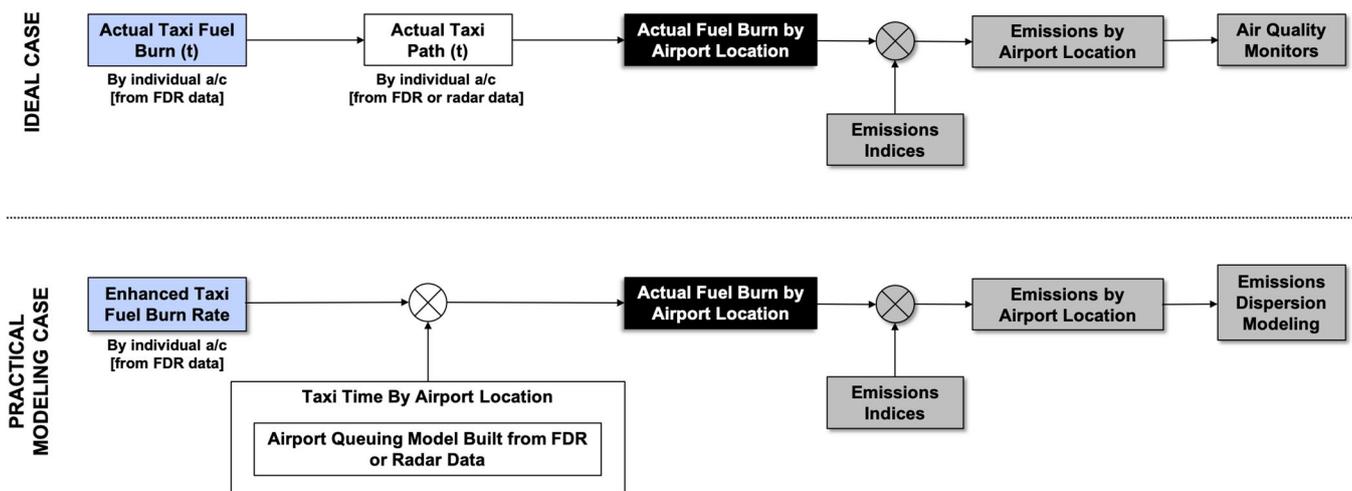
Figure 4. Fuel & Emissions Spatial Distribution Analysis Ideal & Practical Models

A. Development of Airport Queuing Model

When developing a queuing model for an airport, the queuing locations on the surface must first be known. To this end, we use airport traffic density from surface radar data (e.g., ASDE-X) to create heat maps, where hot spots within the image correspond to locations of airport surface congestion. To illustrate this, ASDE-X flight track data from Los Angeles International Airport (LAX) was analyzed. This data contained details on aircraft trajectories such as latitude, longitude, and time, recorded at 1 second intervals. In order to identify airport dynamics during congested periods, we considered data only from the time periods when the taxi-out time was greater than 99th percentile of the taxi-out time calculated from ASPM data. For all time windows containing a mean taxi-out time greater than the 99th percentile, the ASDE-X data was aggregated and interpolated to a 500-by-500 cell grid laid on top of the airport, where the value of a grid point represented the number of flight track points at that spot. A flight in a queue at a particular grid point increased that grid point's count every second. The count at each grid point was then normalized by the number of flights which passed over that location. Therefore, when plotting the point density of the grid as a heat map image, bright spots represent locations where aircraft were queued over a given period of time. The heat map for sample data at LAX from February-April 2012 (see later for why this period was selected) is shown in Figure 5. Queuing spots are seen as bright yellow in the image, where markups have been added to the image to highlight what different queuing spots represent from an operational perspective. For example, queues are seen for flights departing on both runway 24L and runway 25R, as well as for flights arriving on the remaining two runways which then must cross an additional runway to reach the terminal regions. Such details inform what queue spots need to be considered when developing a queueing model for LAX. A similar approach could be applied at any other airport of interest to determine what queuing model elements are appropriate.
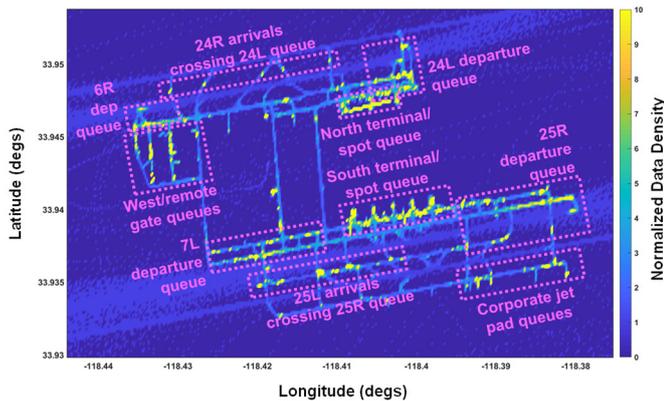
Figure 5. Data Density Heat Map for LAX Airport (Analysis Period 2/1/2012 – 4/30/2012)

The objective of the queuing model is to determine macroscopic quantities of interest such as queue length and taxi-out time as a function of demand (pushback-time) and other parameters such as meteorological conditions. We next focus on developing the queuing model for West-flow runway configuration (24L, 25R|24R, 25L) at LAX, that represents the most frequently used configuration with around 90% of the operations during the period considered in our analysis (Feb 1 – Mar 15, 2012).

In Figure 5, we see that departing flights are queued up predominantly near the departure runways. Therefore, the taxi-out process was represented using a single queue, one for each departure runway as shown in Figure 6. After pushback, the taxi-out flights enter the departure runway queue after spending an unimpeded gate-to-runway time. Note that we use airline-specific unimpeded taxi-out time (terminal-to-runway) as a surrogate for the unimpeded gate-to-runway travel time in this paper due to the lack of gate information in the ASPM data. However, this assumption serves as a good approximation as will be shown later in the model validation. Additionally, the unimpeded times are determined as the 10th percentile of the taxi-out time distribution for each airline-runway pair.
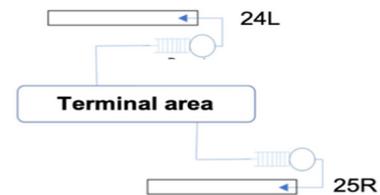
Figure 6. LAX Taxi-out Queuing Network Representation (West-Flow Configuration)

The dynamics for the evolution of the queuing process is obtained using a fluid-flow model, which is a continuum approximation to the discrete queuing process. Such a fluid-flow model for the queuing process has been used earlier to accurately predict the queue lengths and taxi-times for major airports [12]. The dynamics governing the evolution of the departure runway queue is as follows:

$$\dot{x}_i = -\mu_i(t)\frac{C_i(t)x_i(t)}{C_i(t)x_i(t) + 1} + u_i(t - \tau_i), \;\; i = 1, 2$$

where, x_i represents the queue length of the ith departure runway, and τ_i is the average unimpeded travel time from the gate to the ith departure runway, u_i represents the pushback rate to the ith departure runway, C_i is a positive parameter that depends on the coefficient of variation of the service time distribution of the server [12] and μ_i be the mean service rate of the departure runway server. The parameters of the service time distribution of the runway server are determined from operational data [13]. The pushback rate is computed as the number of aircraft pushing back from the gate in a given time interval (5 min in this paper). The time delay in the dynamics accounts for the travel time from the gate to the departure runway. The queue length can be predicted by integrating the dynamics forward in time with appropriate server parameters and pushback rate. The wait times of aircraft entering the queue are determined using the predictions of queue length and time-varying mean service rates [12]. The taxi-out time is then

determined as the sum of the unimpeded gate-to-runway time plus the waiting time in the queue.

Figure 7 shows a comparison of the predicted and observed LAX departure runway 24L queue length for a typical good weather day (March 7, 2012) in the test data set. The data corresponds to a time-based definition of queue length, in which an aircraft is said to be in the runway queue if it has spent unimpeded gate-to-runway time after pushback but is yet to take-off. The time-based definition of queue length is validated by comparing against the physical queues seen at the airport using trajectory data. The deviation was found to be small, with a mean absolute error of 0.6.
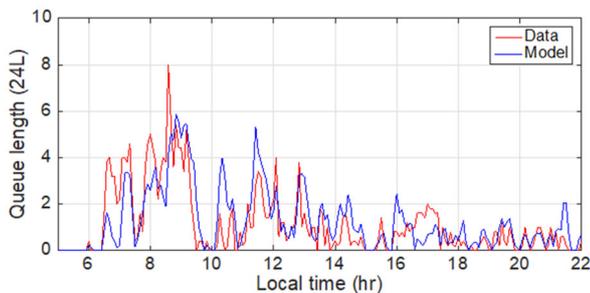
Figure 7. Queue Length Comparison Between Model Predictions and Data for LAX (March 7, 2012)

The taxi-out times for this particular day, averaged over 15-min windows, are shown in Figure 8. These figures show a good match between the model predictions and observed values. Aggregate error statistics of the taxi-out time prediction for individual flights were computed for an independent test set of 6,536 departures over a 9-day period. Here, the errors are computed as the predicted taxi-out time minus the actual value. The mean error was found to be 0.9 min and mean absolute errors was found to be 3.9 min, which are small relative to the mean taxi-out time of 14.2 min. These results indicate that we can predict the congestion level and locations on the airport surface to a good degree of accuracy. Although the focus of the discussion above was departure movements, a similar approach can be adopted for arriving aircraft as well.
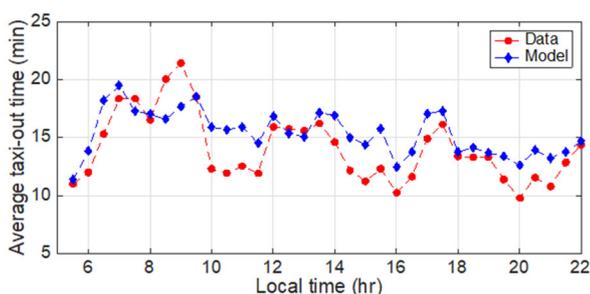
Figure 8. Taxi-out Time Comparison between Model Predictions and Data for LAX (March 7, 2012)

B. Generalization of Queuing Models to Other Airports

There are many major airports around the world where surface operations assessments could be needed, and tailoring the fuel burn and emissions model to each airport individually would be infeasible. Rather than developing a queuing model and validating the framework for every major airport, we use clustering to determine groupings of airports with similar features. We then note that validated queuing models exist in the literature for representative airports in each group, suggesting that the approach generalizes well to a large number of airports.

For this approach, we used k-means clustering algorithm [14]. The features used for the clustering algorithm were chosen with the intent to capture major differences between airports:

- *Mean, standard deviation & skew of taxi-out delay:* The taxi-out time delay was calculated as the difference between the unimpeded taxi-out time (the 10th percentile of the taxi-out time for that year, for that airport), and the actual taxi-out time, for each flight. The mean value of the taxi-out time delay is useful in determining if an airport typically has a lot of delayed flights, but the standard deviation and skew of this distribution yield additional insight. For example, an airport may not experience high delay on average, and thus have a "normal" mean taxi-out time delay, but the delay distribution could be skewed indicating periods still exist where departing flights experience high delay.
- *Mean taxi-out time*: While the previous three features consider the level of congestion on the airport surface, this serves as a metric for measuring the size of the airport.
- *Number of runway configurations:* The number of runway configurations can vary greatly between airports. For example, at LAX the majority of annual air traffic operations are performed in the same configuration. In contrast, Boston Logan International Airport (BOS) has multiple configurations that are commonly utilized, with seasonal traffic patterns from weather effects. This feature measures how many configurations account for the top 75% of annual operations, each of which could have very different queue dynamics and locations.
- *Percentage of operations in Visual Meteorological Conditions (VMC):* This accounts for weather impacts.

For all of these features, the data was obtained from ASPM. This database contains flight level information such as taxi-out time, and airport information such as the weather operating condition which is updated hourly. The full 2018 dataset was pulled for the ASPM Core 30 airports [15], and used to calculate the six features identified above. Each feature was normalized across all 30 airports, by subtracting out the mean value and dividing by the standard deviation. This step prevents improper weighting between features which have differing magnitudes (e.g., the mean taxi-out time delay will always be a much larger number than the percentage of operations in VMC, but is not a necessarily more important feature). To determine k, the sum of the squared error was plotted against chosen k values, and the knee in this curve was seen to be at 7 clusters. Repeated use of k-means can sometimes yield varying results on the same set of data due to randomized initial centroids used at the start of the algorithm. To account for this, the k-means algorithm was

repeatedly applied to our dataset for one million iterations, to ensure the final clustering result was consistent. To further verify the fit of the final clustering result, we used the Silhouette coefficient [16], where a larger value for the Silhouette coefficient corresponds to clusters which better fit the data. The silhouette coefficient plot for our final clustering results are shown in Figure 9, which show the final clustering is a good fit given the all positive scores.
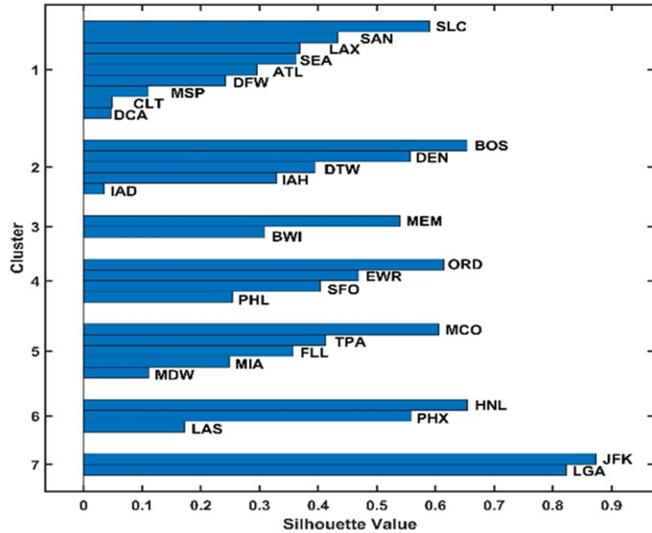
Figure 9. Core 30 Airport Clusters

Additional insight into why certain airports were paired together can be gleaned from looking at the mean feature values across the airports in each cluster: Figure 10. Features with values close to zero are within the normal range when compared against all 30 airports, while a largely negative or positive feature indicates that the feature is significant for the airports in that cluster, and one of the drivers for why those airports were paired. For example, airports in cluster 2 contain features that are relatively normal, but the number of commonly used configurations is high, and the percentage of operations in VMC condition is a bit low. The airports in this cluster, such as

BOS and DEN, are airports that often switch configuration due to weather effects. For such airports, the model would need to consider the current airport configuration, and potentially the season of the year, when making taxi-time, fuel burn, and emissions predictions. In contrast, cluster 6 contains airports with lower than average taxi-out time and delays, and the highest percentage of operations in VMC condition. The three airports in this cluster are HNL, PHX, and LAS – all airports in locations with consistently good weather throughout the year, and minimal surface congestion.

The cluster results presented here provide a way to categorize the airports in a way that differentiates their operational characteristics. We note that queuing models have been developed and validated at airports in many of the clusters, especially ones where the driving features are related to congestion and delays (Figure 10): Cluster 1 (LAX in this paper, CLT [12], DFW [12]), Cluster 2 (BOS [17]), Cluster 4 (EWR [12], PHL [17]), and Cluster 7 (JFK [17], LGA [17]). Consequently, it is reasonable to believe that such queuing models are effective in representing surface operations for airports with different layouts, levels of congestion, and operating environments and that airports in a given cluster have similar characteristics.

V. VALIDATION: MODELING EMISSIONS DISPERSIONS AT LAX

The airport traffic models (such as the queuing model presented earlier) provide the total taxi-time as well as the wait time in the congested regions on the airport surface. Using such models or flight trajectories (if available), one can obtain a spatial distribution of fuel burn on the airport surface by multiplying the residence time of flights at a particular location with the engine-specific fuel flow rate (as detailed earlier). Further, the spatial distribution of fuel burn can be used to compute the spatial sources of emissions by multiplying the fuel burn with the corresponding engine-specific emissions index for each pollutant [8].

To illustrate that one could develop a model to estimate the pollutant concentrations around an airport, we develop an emissions dispersion model for LAX. Note that this exercise
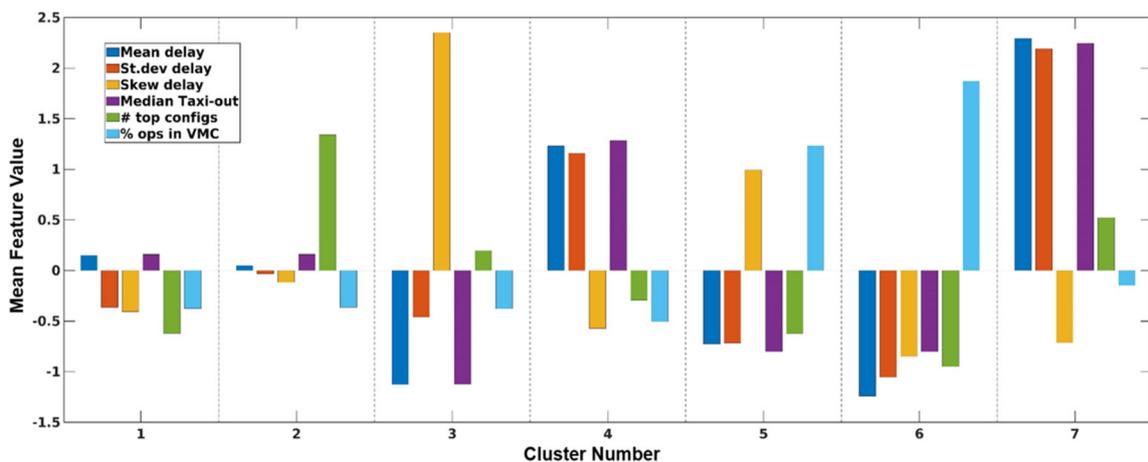
Figure 10. Core 30 Airport Cluster Feature Values

was carried out to check if one could correlate the airport surface traffic with the pollutant concentrations recorded at the monitoring sites around the airport and we do not follow the typical methodology for dispersion computation as done in industry toolboxes (as shown earlier in Figure 4). Figure 11 shows the locations of the four emissions monitoring sites (called AQ, CN, CE, CS) around LAX that was considered in the analysis. The monitoring sites are located 500-5000ft from the airport boundary. The emissions data consists of pollutant concentrations of CO, NOx, SO₂, PM2.5 and ultrafine particles (UFP, i.e., PM with diameter less than 100nm) sampled every minute for the period Feb 01 – Mar 16, 2012.

Figure 11. Location of LAX Emissions Monitoring Sites

Figure 12 shows the median pollutant concentrations of CO and NOx at the four emissions monitoring sites around the airport evaluated over the period considered in our analysis.
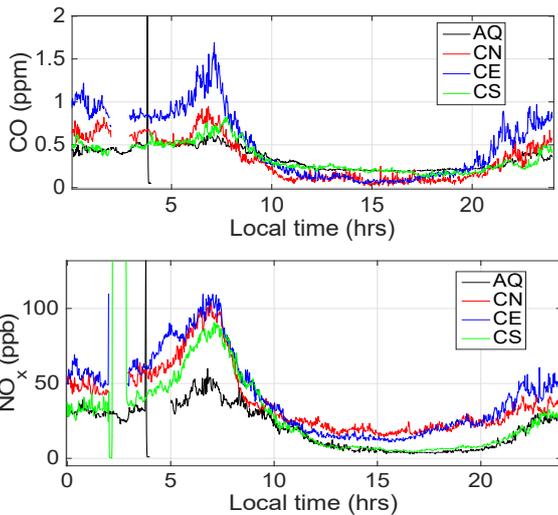
Figure 12. Pollutant Concentrations of CO and NOx at the Four Emissions Monitoring Sites

We notice that the pollutant concentrations are higher during the night compared to the day, which does not follow the trend in air traffic movements. The unexpected discrepancy between the day-time and night-time pollutant concentrations is because of various factors including changes in mixing height and smog formation in the Los Angeles region [18]. Therefore, the variations in the pollutant concentrations in Los Angeles region are largely influenced by other external factors such as photochemical reactions, but not by the airport traffic. This makes these pollutants a bad signal to analyze the environmental impact of airport operations. One needs to note

that the impact of smog formation or other background sources is not specific to LAX but could impact other airports as well [19]. Therefore, there is a need to consider other pollutants that correlate well with airport traffic to better understand the impact of airport operations.

Figure 13 shows the median of the counts (normalized by the sum of the counts over the entire period) of aircraft movements (arrivals and departures) on the airport surface and UFP particle number concentrations corresponding to particle diameter of 10nm at CE site for the period Feb 01 – Mar 16, 2012. We notice a good correlation between the traffic counts and the UFP concentrations. This shows that UFP concentrations are a good signature for studying the influence of airport traffic. The particle size diameter from aircraft emissions are much lower than vehicular emissions or other sources, and are thus an excellent candidate for analyzing the impact of airport operations [20]. Additionally, the particulate matter diameter depends on the aircraft thrust setting, which helps us isolate taxi emissions from other phases of flight [21]. In our analysis, we considered 10nm UFP concentrations because it corresponds to a diameter lower than the particulate matter from vehicular sources (which tend to be greater than 30nm) [20]. Unlike PM2.5 or other pollutants, currently there is no regulation on UFP, but recent studies indicate UFP can have serious health consequences given their smaller size [22].
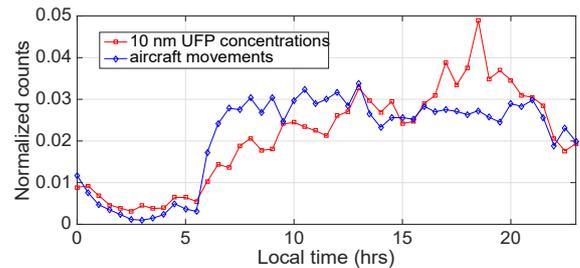
Figure 13. Normalized Counts of Aircraft Movements and 10nm UFP Concentrations

We develop a model for 10nm UFP concentrations as a function of airport traffic and the meteorological data to illustrate an emissions dispersion model. In particular, we develop a *temporal model* and a *spatial model*.

A. Temporal Model

In the temporal model, we estimate the 10nm UFP concentrations at one of the monitoring sites using historical data from the same monitoring site, and a set of inputs that depend on the airport traffic and meteorological conditions. For illustration, we present a model that was trained using data from the CE site that is located to the east of departure runway 25R (see Figure 11). We consider a regression model of the following form:

$$Y = f(C_{k,m}, W_{EW}, W_{NS}, T_{amb}, S_{rad})$$

Here, Y denotes the normalized 10nm UFP concentrations sampled at every 15-min interval. $C_{k,m}$ represents the traffic counts weighted by the baseline aircraft fuel flow rate for arrivals ($k = a$) or departures ($k = d$) in the queue ($m = q$) or actively taxiing aircraft ($m = t$), that have been assigned one of

the southern runways (25R, 25L). W_{EW} and W_{NS} represent the wind speed along East-West and North-South directions, respectively. T_{amb} and S_{rad} denote the ambient temperature and solar irradiance, respectively. The regression function, $f()$, is determined using Gaussian Process Regression (GPR) with 70% of the data (1657 samples) used for training the model and the rest being used for testing the model. The input features were selected based on careful feature engineering, and we skip the details here for conciseness. For example, we found that the magnitude and direction of wind play a significant role in emissions dispersion as one might expect. Additionally, we found that departure and arrival traffic using runway 25R have a significant influence on the pollutant concentrations at the CE site, and including other traffic did not improve the model performance. Figure 14 shows the model predictions along with 95% confidence intervals, and the actual data from an independent test set. We see a good match between the model predictions and actual data. The mean error and mean absolute error evaluated using the test set was found to be 0.009 and 0.038, respectively. Here the errors are computed as the difference between the estimated normalized UFP concentrations from the model and the data.
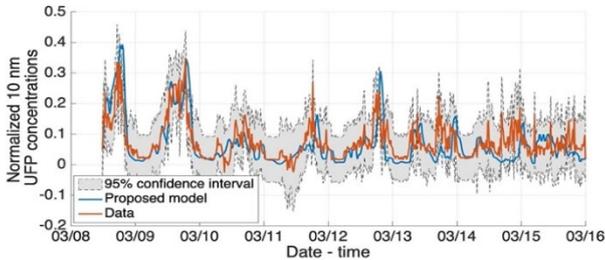
Figure 14. Predictions of the Normalized UFP Concentrations Using Temporal Model

B. Spatial Model

The spatial model allows us to estimate the UFP concentration at any location around the airport. The model is trained using data from multiple monitoring sites, and we consider the spatial component (location) of emission sources by accounting for the distance between the various sources and the location where the pollutant concentration needs to be estimated. Here the sources represent the queuing traffic and actively taxiing traffic for each runway. The input features include traffic at different sources weighted by the baseline fuel flow rate, distance between source and monitor, bearing between wind vector and position vector of monitors, temperature and solar irradiance. Additionally, we include time-delay terms of the input features (previous two 15-min intervals) to account for advection of pollutants from the source to the monitor. For illustration, we present a model that was trained using data from two monitoring locations (CE and CS sites) and test the performance of the model using data from a different location (CN site) that is located to the east of runway 24L. The model was determined using GPR. Figure 15 shows the model predictions along with 95% confidence intervals, and the actual data from an independent test set. We see a good match between the model predictions and actual data. The mean error and mean absolute error evaluated using the test set was

found to be 0.013 and 0.039, respectively. However, the temporal model performs better than the spatial model because it is trained on data from the same monitor, but the advantage of the spatial model is that it can estimate the UFP concentrations at any location around the airport. Overall, these results indicate that queuing models that estimate the airport traffic can be used to predict the UFP concentrations around the airport. Therefore, this framework shows us that we can estimate the environmental impact of taxi operations, without the interference from other background sources of emissions.
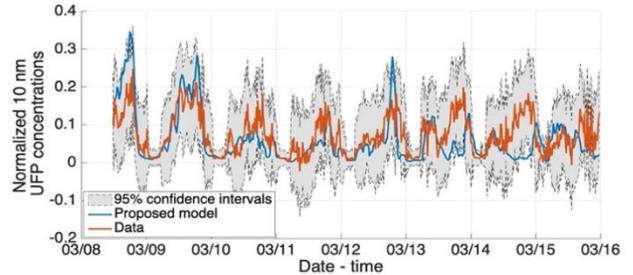
Figure 15. Predictions of the Normalized UFP Concentrations Using Spatial Model

VI. CONCLUSIONS

This paper has discussed characteristics of airport surface models suitable for environmental impact analyses. Models suitable for inventory and spatial distribution analyses have been presented. For inventory analyses, a set of enhancements to currently used industry standard models have been presented in terms of baseline taxi fuel burn rate, taxi time and pre-taxi fuel burn elements. For spatial distribution analyses, a queuing model to estimate the spatial distribution of the airport traffic has been presented, which in turn can be used as inputs to an emissions dispersion model. The queuing model is helpful to analyze airport operations for different demand sets or in cases where granular trajectory data is unavailable. A machine learning approach has been presented to estimate the spatial distribution of UFP concentrations around an airport given the airport traffic and meteorological conditions. UFP concentrations were found to exhibit good correlations with the airport traffic, and they served as an excellent signature to assess the environmental impact of airport operations, unlike other standard pollutants (such as CO and NOx) that are significantly influenced by other background sources. To demonstrate the practical applicability of our framework, we developed and validated the models using actual operational data from LAX. We also presented a clustering approach to categorize the different airports and show the general applicability of the modeling approach. The analysis presented in this paper is intended to provide insights to improve toolkits for environmental impact assessment such as AEDT in the future. Finally, key limitations and future research directions are outlined below.

A. Key Limitations of the Modeling Approach

- *Limited availability of FDR data:* Due to privacy concerns, airlines typically do not share FDR data. As a result, there is a limited availability of FDR data across aircraft and engine

types, thereby making it challenging to develop fuel burn models that covers all the operational aircraft types.

- *Airports with multi-region traffic congestion:* In this paper, we considered departure runways to be the primary bottlenecks that cause taxi-out delays. However, at certain airports, additional taxi-out delays might arise from congestion in the ramp areas (or deicing pads). The queuing model presented in this paper could be extended to accommodate such multi-region congestion [12].

- *Airport infrastructure changes:* Airport air-side infrastructures such as runways and taxiways can undergo changes. Therefore, one needs to keep track of the infrastructure changes, and appropriately update model parameters. Further, infrastructure changes could lead to different traffic hot-spots on the airport surface, which might need a detailed traffic analysis using flight trajectory data as shown earlier in Figure 5.

- *Limited availability of aviation emissions sensor data:* There is limited openly available emissions sensor data recorded at locations close to the airports. To develop accurate emissions dispersion model, one needs access to pollutant concentrations at multiple locations around the airport with reasonable data resolution.

B. Future Research Directions

In this paper, we considered UFP concentrations instead of the other commonly reported pollutant species because UFP concentrations were found to be well correlated with airport surface traffic even in the presence of other background sources (unlike other pollutants). An interesting research direction is to develop models to infer concentrations of standard pollutant species (such as CO, NOx) emitted from aviation-related sources using UFP concentrations. Further, one could integrate the queuing model and emissions model presented in this paper to obtain an emissions inventory and dispersion model for airport environmental impact assessment.

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AUTHOR BIOGRAPHIES

Sandeep Badrinath and **James Abel** are graduate students in the Department of Aeronautics and Astronautics at MIT.
Hamsa Balakrishnan is the William E. Leonhard (1940) Professor of Aeronautics and Astronautics at MIT.
Emily Joback is Associate Staff in the Air Traffic Control Systems Group at MIT Lincoln Laboratory. She has a BS in Applied Mathematics from the University of New Hampshire.
Tom G. Reynolds is Leader of the Air Traffic Control Systems Group at MIT Lincoln Laboratory. He has a Ph.D. in Aerospace Systems from MIT.