Improving Departure Taxi Time Predictions Using ASDE-X Surveillance Data

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Abstract— **Flights incur a large percentage of delay on the ground during the departure process; however, predicting the taxi-out time is difficult due to uncertainties associated with the factors influencing it, such as airport surface traffic, downstream traffic restrictions, runway configuration, weather, and human causes. Airport Surface Detection Equipment, Model X (ASDE-X) surveillance data provides high resolution coverage of aircraft surface movement which can be leveraged to address this problem. This paper presents a novel approach which builds an adaptive taxi-out prediction model based on a historical traffic flow database generated using the ASDE-X data. The model correlates taxi-out time and taxi-out delay to a set of explanatory variables such as aircraft queue position, distance to the runway, arrival rates, departure rates and weather. Two prediction models are developed. One treats aircraft movement from starting location to the runway threshold uniformly while the other models aircraft time to get to the runway queue different from the wait time experienced by the aircraft while in the runway queue. The models are evaluated using data from New York's John F Kennedy (JFK) airport during the summer of 2010. Results show significant improvement in taxi-out predictions as compared to predictions from FAA's Enhanced Traffic Management System (ETMS).**

Keywords-ATM; Ground Delay; ASDE-X; Taxi-out

I. INTRODUCTION

Traffic flow management (TFM) is focused on balancing demand and capacity to maintain safety while minimizing flight delays. Managing that balance is predicated on predicting both demand and capacity. The greatest source of error in demand prediction comes from error in predicted departure taxi (i.e. taxi-out) time which is defined as the time from the actual pushback to takeoff. Improved departure taxi time prediction will result in more stable trajectory modeling and better en-route sector demand forecasts. It will also help airlines proactively manage pushback times and improve the efficiency of airport surface movement operations.

Taxi-out prediction for a flight is complex due to uncertainties associated with the factors contributing to it. Surface departure traffic, interaction with arriving traffic, runway configuration, downstream traffic restrictions, airport layout, human causes and weather related delays are all potential contributing factors. Real-time prediction for applications such as trajectory modeling is even more challenging, as data values associated with explanatory variables such as queue position are not readily available. Prior work in the area of taxi-out prediction has been limited due to lack of high quality surface movement data. Predictions have been based primarily on pushback and wheels-off data from sources like the Aviation System Performance Metrics (ASPM) system, and have been made on aggregate quantities rather than the individual flight level. The ASDE-X surveillance system fills this gap by providing high quality surface movement data on aircraft on and around the airport.

This study explores using high-resolution position updates from the ASDE-X surveillance system to develop a taxi-out prediction model. It is based on the premise that existing surface traffic conditions and short-term traffic trends (past 15-60 minutes) revealed from analyzing ASDE-X data are better predictors of future taxi-out time than historical averages. The airport surface is digitized into a number of logical areas such as terminals, taxiways, queues, and runways, and ASDE-X traffic flow data is superimposed on this layout to heuristically determine the aircraft's location, status (such as taxiing, queued, taking off, airborne, arriving and landed), runway queue order (number of aircraft which will take off before the flight under consideration) and paths of flights on the airport surface. A historical traffic flow database is created and analyzed to discover correlations of potential explanatory variables such as queue position, runway distance, arrival rates, departure rates and weather to the observed taxi-out time. Two approaches to taxi-out predictions are explored. One treats aircraft movement from the starting location to the runway threshold uniformly (referred to as the "Uniform Flow Model" or UFM) and correlates taxi-out time to a combination of explanatory variables. The other approach, referred to as the "Split Flow Model" (SFM), treats aircraft movement prior to the runway queue (nominal taxi time) differently from when it is in the departure queue (taxi out delay) and predicts taxi-out time as sum of predicted nominal taxi time and predicted taxi-out delay. The models are calibrated for the departure runways of JFK airport and applied to the test data. Predictions from both models are compared to each other and to those obtained from ETMS and historical taxi-out average for a flight. Results show significant improvement in taxi-out prediction compared to the Enhanced Traffic Management System (ETMS) predicted and average taxi-out values. The Split Flow Model (SFM) performs better than Uniform Flow Model (UFM) in

traffic conditions when departure queues are present; however, UFM performs more consistently in all traffic conditions.

The organization of this paper is as follows: related work in the area of prediction of departure taxi times is first explored in the Background section. Section III discusses causal factors affecting departure taxi time and how they are included in the study. Next is a high level description of the methodology adopted. Section V on Data Sources details the data sources, attributes and data validation strategy used. Following this, Section VI on Traffic Situation Discovery details heuristics underpinning the determination of flight information. After that is a section on the prediction models and underlying statistical analysis. The results of applying the models to the test data are presented the Section VIII, along with analysis and comparisons to ETMS predictions and average taxi-out values. Finally, the conclusion points out the strengths and weakness of this approach.

II. BACKGROUND

A number of prior efforts have been made to address prediction of departure taxi times. Shumsky [1] used a linear regression model to predict taxi out time using airline, departure demand and departure runway as explanatory variables. He also developed a queuing model for the runway service process; however the model was based on cumulative behavior and did not account for the stochastic nature of the process. Herbert [2] modeled the queuing service using exponential, Erlang and server absence models, assuming a Markovian system entry process. In another notable work, Idris et el [3] developed a queuing model to predict taxi out time based on factors such as queue size, runway configuration, weather, aircraft type, downstream traffic restrictions and starting terminal. In this study, queue size was estimated based on number of departing aircraft on the airport and estimated number of aircrafts it will pass on its way to the runway. His work concluded that the takeoff queue length is most significant explanatory variable to predict the taxi out time. All these papers identified key factors influencing taxi-out time; however predictions were made at an aggregate level and not on an individual flight basis.

A study on individual flight prediction was done by Pujet [4] who developed a queuing model by predicting the travel time an aircraft will take to reach departure runway and adding that to a runway queue time modeled as a probabilistic service process. Simaiakis and Balakrishnan [5] improved the prediction model by including taxiway interactions as a factor influencing the taxi-out time. In a study based on ASDE-X surveillance data, Legge and Levy [6] modeled taxi-out time based on the relationship with Virtual Departure Queue (VDQ), defined as the number of aircraft which have pushed back before the current one. This study, while using ASDE-X data, did not leverage the detailed traffic situational map that can be constructed using this data. Also, the study limited its scope to using VDQ as the only explanatory variable to taxi-out time.

The approach presented here combines the insights gained from earlier work on causal factors for taxi-out delays with detailed surface traffic situation provided using ASDE-X data to develop a new flight-specific taxi-out prediction model.

III. CAUSAL FACTORS AND THEIR INCLUSION

Consider the airport surface traffic operations depicted schematically in Fig. 1. There is interaction among traffic on different components of the system such as arrival runways, taxiways, terminal gates, ramps and departure runways. As throughput of each component varies, queues are formed in them which add to the taxi-out times. The snapshot of actual airport traffic (JFK on July 9, 2010 at 7:00pm) shown in Fig. 2 reveals complex interactions in play among these components. There is a significant aircraft queue waiting to takeoff from runway 22R. Cross traffic from arrivals on runway 22L and departures from runway 13R impact 22R's departure rates. Taxiing streams of aircraft interact with each other as they merge to enter the runway queue area, causing delays and uncertainty in the aircraft order in the runway queue. Aircraft travel varying distances to the runway, contributing to taxi-out variations. The runway configuration in use alters the traffic pattern and arrival/departure balance and therefore impacts taxi-out times. Downstream traffic restrictions due to weather or high traffic volumes significantly affect departure rates and hence the departure times.

Based on these observations, the following key causal factors are included in this study.

A. Runway Queue Position

It is defined as the number of aircraft which will depart from the assigned runway before the aircraft under consideration. An aircraft with a zero queue position implies that it will depart next. An algorithm to determine the queue position is described in Traffic Situation Discovery section.

B. Runway Configuration

The departing runway has an impact on taxi-out times because of variance in taxiing distance and interaction with arriving and departing traffic from other runways. This study models predictions on a runway basis, using it as a primary differentiating factor. The arrival and departure rates of parallel and crossing runways are also included in the analysis.

C. Airline/Terminal

The distance travelled by an aircraft to the runway varies depending on its starting location, which can potentially impact
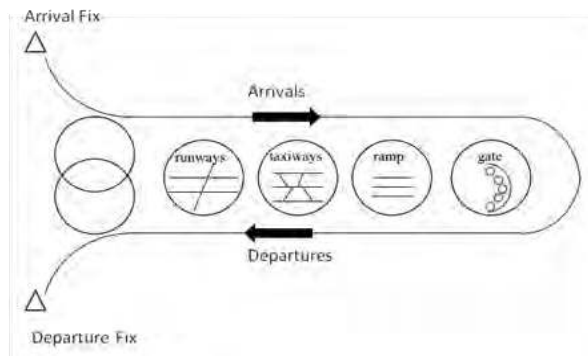

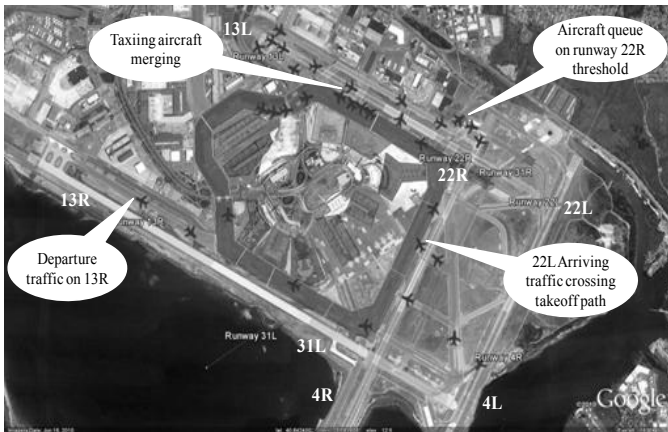Figure 1. Airport surface traffic operations [7]

Figure 2. Airport traffic snap shot (JFK on July 9th at 7:00pm)

the taxi-out time. For this study, the straight line distance from the aircraft to the runway threshold is used as approximation of the actual distance.

D. Weather

The impact of weather on taxi-out is included by using data from Severe Weather Avoidance Programs (SWAP) in the model.

E. Taxiing Traffic Interactions

This is a difficult factor to account for, as there are very complex traffic interactions during busy times. Runway crossing traffic is accounted for by considering arrival and departure rates from crossing and parallel runways; the arrival rate of the current runway is included to model interactions resulting when the same runway is used for both arrivals and departures.

F. Downstream Traffic Restrictions

Moving average taxi-out time for the runway is used as the primary indicator of this factor in this study. It represents the traffic flow rate from the runway and is considered an important predictor of future flow rate. Fifteen, thirty and sixty minute averages are kept.

IV. METHODOLOGY

Raw ASDE-X data is transformed and enriched in a series of steps to derive key metrics and generate a traffic flow database which underpin the taxi-out prediction model. The main steps in this process are:

a. Produce a digitized surface layout map of the airport. In this step, airport surface layout features such as runways and taxiways are digitized at sufficient accuracy and stored in XML data files.

b. Traffic situation discovery. The ASDE-X data is cleansed and superimposed on the digitized airport map to infer aircraft status, location, runway used and queue position. A database of historical traffic patterns with attributes representing explanatory variables is created in this step.

A traffic visualization framework is developed for display and validation purposes.

c. Validate data. In this step ASDE-X data is validated for completeness and accuracy using visual checks and comparisons with other data sources such as Aviation System Performance Metrics (ASPM) and Airline Service Quality Performance System (ASQP).

d. Prediction model development and application. Linear regression analysis is used to model taxi-out relationship to the explanatory variables. Two different models are developed based on regression analysis and applied to the test data.

e. Results analysis and comparison with ETMS predictions.

V. DATA SOURCES

A. Airport Surface Detection Equipment – Model X Data

The ASDE-X surveillance system is primarily a runway safety tool that fuses data from multiple sources such as radars on air traffic control tower or remote tower, multilateration sensors, ADS-B (Automatic Dependent Surveillance-Broadcast) sensors, terminal automation system and aircraft transponder into a single stream. The data covers moving "tracks' which may be aircraft or non-aircraft objects (such as luggage carts) on and around (up to a minimum of five miles from the airport) the airport. There are over hundred data attributes stored for each track. For this study, only the following attributes are used:

- timestamp of the track at one second resolution
- call sign
- latitude, longitude, altitude
- aircraft type
- aircraft heading
- speed

For this study JFK ASDE-X data from July 3, 2010 to August 14, 2010 is used.

Data Validation

The ASDE-X data is evaluated for positional accuracy, reliability, coverage and completeness. Positional accuracy of data is assessed visually by observing how well tracks of aircraft line up with center-line of taxiways and runways and observing inter-aircraft distances. Fig. 3 shows that tracks of two aircraft line up well with the center of the taxiway. Reliability of data was very high as no missing updates were observed in data processing.

Coverage analysis shows that most tracks (95%) start from the taxiway area, just outside the ramp (the "spot"). This implies that the actual pushback event is missed in the available ASDE-X data. Fig. 4 shows that ASDE-X spotted the aircraft on average 10.9 minutes after the actual pushback for aircraft headed to runway 22R.
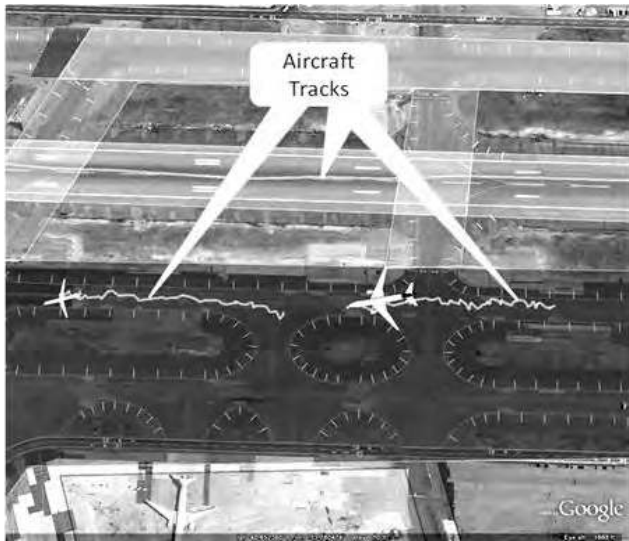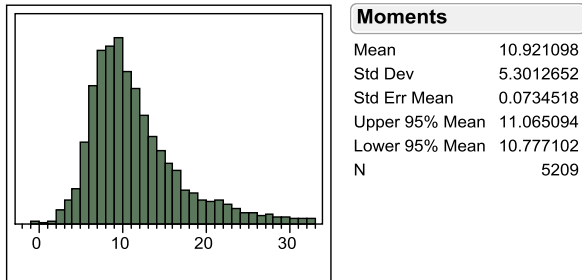
Figure 3. Aircraft tracks

Moments	
Mean	10.921098
Std Dev	5.3012652
Std Err Mean	0.0734518
Upper 95% Mean	11.065094
Lower 95% Mean	10.777102
N	5209

Figure 4. ASDE-X start time variance with actual pushback
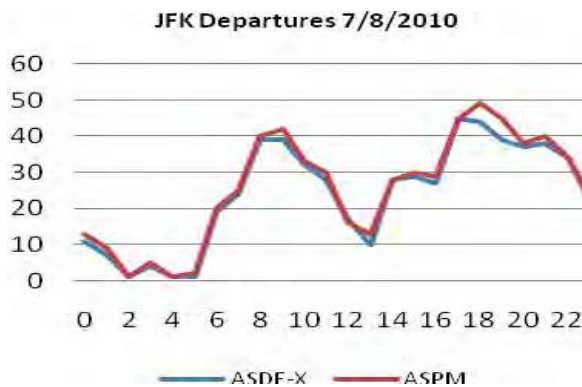
Figure 5. Hourly departure counts ASDE-X versus ASPM data

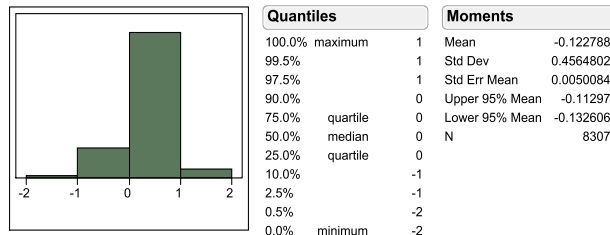| Quantiles			Moments	
100.0%	maximum	1	Mean	-0.122788
99.5%		1	Std Dev	0.4564802
97.5%		1	Std Err Mean	0.0050084
90.0%		0	Upper 95% Mean	-0.11297
75.0%	quartile	0	Lower 95% Mean	-0.132606
50.0%	median	0	N	8307
25.0%	quartile	0		
10.0%		-1		
2.5%		-1		
0.5%		-2		
0.0%	minimum	-2		

Figure 6. ASDE-X wheels-off variance in minutes from ASQP

The completeness of data was checked by comparing hourly departure figures computed using ASDE-X data with those from ETMS. For JFK during July 2010, ASDE-X reported 94% of flights reported in ETMS. Fig. 5 compares ASDE-X and ETMS hourly departures, showing a close match in trends.

Accuracy of ASDE-X-derived wheels-off time is assessed based on its comparison with Airline Service Quality Performance (ASQP) data. Fig. 6 shows the two matched well, confirming accuracy of ASDE-X data.

Overall, ASDE-X data is found to have sufficient accuracy to form the basis of a taxi-out prediction algorithm.

B. Airport Layout & Metadata

To trace an aircraft's surface path, the airport layout is segregated into logical areas. Google Earth is used to digitize the airport layout information as it is sufficiently accurate and provides flexibility to create named polygon areas which can be saved as files (KML format). The accuracy of this tool is established by visually validating the projected ASDE-X traffic on JFK, EWR, IAD, CLT and ORD airports. Empirical traffic flow patterns are studied to determine the number and layout of "airport areas" needed to capture the traffic flow at adequate granularity. The following area types are identified and digitized: runways, terminals, taxiways and queues. Queues are the areas where aircraft tend to line up and wait before taking off from a runway, other areas correspond to their physical equivalents.

Fig. 8 shows the airport areas of JFK airport.

Apart from the layout coordinates of the areas, additional information is collected to aid processing. Each area has one or more adjoining areas; centers of the dividing edges are captured as exit-points for that area. Fig. 7 shows four exit points from Taxiway 7. Depending on the number of exit-points, an area may contain multiple flows of aircraft. Note that there can be multiple queues for a runway, for example Queue1 22R and Queue2 22R serve runway 22R (see Fig. 8). The layout information along with additional metadata is captured in an airport-specific configuration file

Figure 7. Exit points for taxiway 7

Figure 8. JFK airport areas

VI. TRAFFIC SITUATION DISCOVERY

A. Flight Status and Location

Positional attributes of ASDE-X data are mapped to areas configured in the digitized airport layout to locate it on or around the airport. Aircraft spotted first while on the airport surface are considered to be departing, while those in the air (altitude above ground level is greater than zero) are considered arriving. An aircraft is marked as being queued when it is in the queue area and its speed drops below a threshold. A flight is marked as taking off when it is on the runway and its speed exceeds a takeoff speed threshold; once its altitude exceeds zero it is marked as having taken off and is airborne. Similarly, an arriving flight is marked as landed when its altitude drops to zero. Aircraft location and status feed into the process of queue assignment and ordering.

B. Queue Assignment and Order

Each departing flight is assigned to one of the currently active runways. If there is only one active departure runway, all departing flights are assigned to its queue. In the case of multiple active runways, the algorithm assigns an aircraft to the runway X queue as follows:

- aircraft on the runway X are assigned first
- aircraft on the queue area to runway X are assigned next
- aircraft on area adjacent to the queue area are assigned to runway X next.
- aircraft heading to the runway X queue are assigned next depending on the number of airport areas they have to traverse to get to the queue area.

In Fig. 9, white aircraft icons are assigned to runway 22R and black to runway 13R. Note that an aircraft's proximity and heading are both considered for queue assignment; for example, the aircraft at queue position three is assigned to runway 13R even though it is close to the queue for 22R.

Queue order is determined as follows:
- aircraft on the runway are ordered based on their distance to the departing runway end.
- aircraft on queue are ordered next, based on their distance to runway entrance point
- aircraft on other surfaces are ordered next based on their distance to runway entrance point
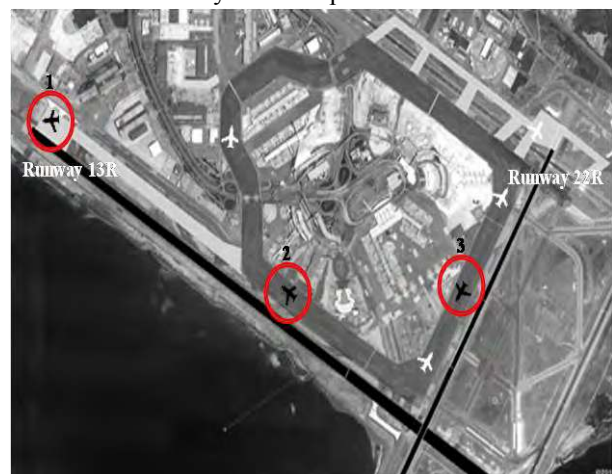

Figure 9. Queue ordering for runways 22R and 13R

C. Runway Activity Data

Runway activity is recorded every minute to compute arrival rate, departure rate and average taxi-out time over the last fifteen, thirty and sixty minutes.

Traffic situation discovery results are captured in a database table. Key attributes collected are: call sign, starting area, start time, surface path, taxi-out time, departing runway, initial runway assignment, initial queue position and initial distance to the runway. For SFM, queue entry time, queue position and distance to runway on queue entry are also captured.

VII. TAXI-OUT PREDICTION MODELS

The taxi-out prediction model is based on modeling the relationship of taxi-out time to the explanatory variables described previously. Historical traffic data from 3 July 2010 to 23 July 2010 is processed to create the database used to calibrate the models.

Fig. 10 shows a typical aircraft taxi-out track. Using traffic situation discovery rules, the following data points are collected for each flight:

- time when the aircraft is first spotted
- runway assignment
- queue time when the aircraft stops in queue area indicating it is waiting in queue
- wheels off time
- initial queue position in the runway queue
- queue position in the runway queue when the aircraft gets queued
- straight line distance of aircraft to the runway threshold

The following runway activity data is collected every minute:

- active arrival and departure runways
- moving taxi-out average for each departure runway in fifteen, thirty and sixty minute bins
- arrival and departure rates for each runway in fifteen, thirty and sixty minute bins

Taxi-out time is modeled using two approaches.

A. Uniform Flow Model (UFM)

This approach assumes uniform aircraft movement behavior during the entire taxi-out process and models the taxi-out time in a single segment. Taxi-out time is modeled as function of explanatory variables as discovered using linear regression analysis. The model can be applied to all flight departures.

B. Split Flow Model (SFM)

This approach assumes that aircraft movement behavior when it is travelling to the queue is different from when it is waiting in the queue. This model calculates taxi-out time as sum of time to get to the queue (nominal time) and queue time.
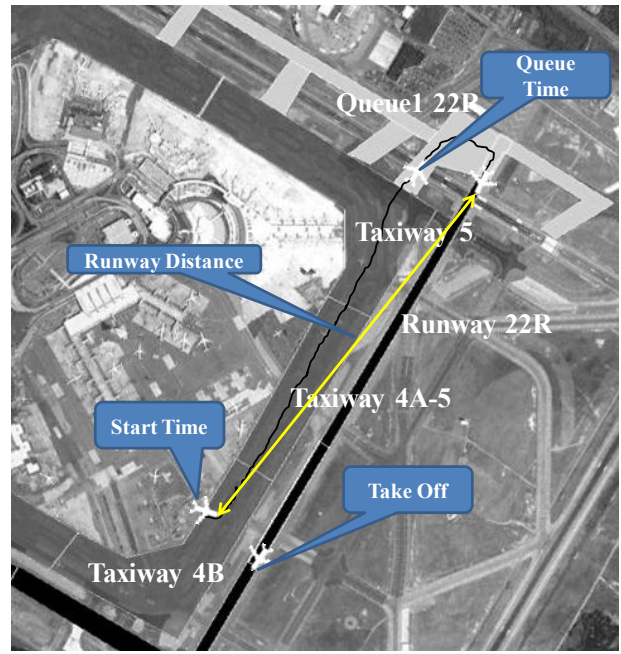
Taxi-out time = Nominal time + Queue time

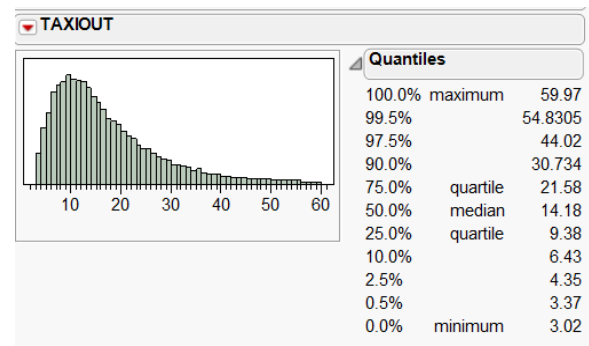Figure 10. Data points collected for each flight

Figure 11. Actual taxi-out distribution for runway 22R

A nominal taxi-out time value for each runway is established as the ten percentile point of the actual taxi-out time distribution. Fig. 11 shows the distribution for runway 22R, 6.43 minutes is used as nominal time for this runway.

C. Exception Situations

At times, an aircraft takes inordinately large taxi-out time due to exception conditions such as mechanical issues or human causes. Taxi-out values lying outside 2σ from the mean are ignored to account for these situations. In some cases the taxi-out predictions can be impacted due to anomalies in traffic pattern, such as aircrafts cutting through the queue. To account for that, five percent of outlying predictions are ignored when considering the performance of all prediction methods.

D. Model Equation

The regression analysis on historical database fits the data to an optimal linear solution, which outputs predicted taxi-out time (taxi-out delay for SFM) as a function of the explanatory variables. This is represented as a linear equation for each departure runway considered. For UFM, the equation produces

the final predicted taxi-out time; for example, equation for the runway 4L is:

$$T_{taxiout} = 151 + 64.1*QP + 0.10*RD + 0.03*FA + \qquad (1)$$
$$38.05*4LA + 13.64*4RA$$

$T_{taxiout}$	Predicted taxi-out time (seconds)
QP	Queue position
RD	Distance to runway threshold (meters)
FA	Taxi-out mean (15 minutes bin, in seconds)
4LA	4L Arrivals last fifteen minutes
4RA	4R Arrivals last fifteen minutes

For SFM, taxi-out time is computed as sum of queue time (or taxi-out delay) and nominal time to get to the queue. The queue time is predicted using linear equation derived from regression analysis, such as equation (1) and nominal time is taken as ten percentile value of taxi-out distribution for the runway.

VIII. MODEL PREDICTION RESULTS & ANALYSIS

UFM and SFM models were applied to JFK ASDE-X data from 24th July 2010 to 13th August 2010 to assess the following:

- Impact of explanatory variables on taxi-out time
- Comparison between the two ASDE-X prediction models
- Stability of ASDE-X model predictions
- Comparison between ASDE-X and ETMS predictions and average taxi-out values

Table 1 shows mean, standard deviation and coefficient of determination (R^2 or square of correlation coefficient) of taxi-out prediction error (predicted-actual taxi-out) in minutes for the two models broken down by explanatory variable for each departure runway. Variables taxi-out mean and all arrival rates are for fifteen minute bins; thirty and sixty minute bins are ignored as they are less significant. The last row of each set (All) is based on a multi-linear regression of all the explanatory variables in the set.

A. Impact of Explanatory Variables

Queue position emerges as the most significant determinant of taxi-out time as indicated by highest value of R^2 for both the models. For UFM, average taxi-out time is next, followed by arrival rates on parallel runway. For SFM, runway distance is the next most significant factor, followed by average taxi-out time; other factors are insignificant. Fig. 12 shows a scatter plot of UFM predicted taxi-out times against queue positions for runway 4L; linear and quadratic fits are plotted. The two plots are almost identical, indicating that a linear relationship can be assumed for this most significant explanatory variable. Fig. 13 and Fig. 14 show the scatter plot of average taxi-out time (15 minutes) and 4R arrival rates versus the taxi-out times,

indicating a less well-defined relationship compared to queue position.

TABLE 1. RUNWAY WISE MODEL PERFORMANCE

Runway 4L						
Independent Variables	**Uniform Flow model**			**Split Flow Model**		
	Mean	*Stdev*	*R^2*	*Mean*	*Stdev*	*R^2*
Queue Position	0.31	3.91	0.47677	0.50	3.61	0.73614
Taxi-out Mean	0.05	5.19	0.15158	0.28	5.18	0.14630
Runway Distance	0.59	5.12	0.04641	0.65	4.78	0.40552
Severe Weather	n/a	n/a	n/a	0.67	5.38	0.00321
4L Arrival rate	0.68	5.05	0.03327	0.80	5.21	0.01992
4R Arrival rate	0.68	5.37	0.15504	0.80	5.30	0.16971
All (multi-linear)	**0.37**	**3.53**	**0.54233**	**0.50**	**3.51**	**0.79027**

N=1525 Nominal Time=7.57 minutes

Runway 22R						
Independent Variables	**Uniform Flow model**			**Split Flow Model**		
	Mean	*Stdev*	*R^2*	*Mean*	*Stdev*	*R^2*
Queue Position	1.77	5.11	0.56709	0.51	5.56	0.69177
Taxi-out Mean	1.56	6.11	0.49451	0.67	7.28	0.14867
Runway Distance	4.24	7.64	0.04069	0.54	6.23	0.31834
Severe Weather	3.50	7.86	0.14864	1.13	7.85	0.06540
22R Arrival rate	4.31	8.22	0.01464	0.90	8.20	0.02882
22L Arrival rate	3.92	7.82	0.03145	1.20	7.91	0.04412
All (multi-linear)	**1.15**	**4.89**	**0.64471**	**0.51**	**5.55**	**0.72092**

N=2206 Nominal time= 6.43 minutes

Runway 13R						
Independent Variables	**Uniform Flow model**			**Split Flow Model**		
	Mean	*Stdev*	*R^2*	*Mean*	*Stdev*	*R^2*
Queue Position	-0.32	5.79	0.51725	1.20	6.63	0.72164
Taxi-out Mean	-1.75	7.18	0.23378	-0.27	7.83	0.28394
Runway Distance	-4.68	9.50	0.00653	-2.07	9.0	0.33786
Severe Weather	-3.73	9.05	0.02046	-1.4	9.4	0.00126
13R Arrival rate	-4.67	9.46	0.00656	-1.49	9.5	0.03479
13L Arrival rate	4.72	9.54	0.00250	-2.45	9.78	0.03109
All (multi-linear)	**-0.40**	**5.82**	**0.52795**	**0.10**	**7.35**	**0.77754**

N=2994 Nominal Time=9.83 minutes

Runway 31L						
Independent Variables	**Uniform Flow model**			**Split Flow Model**		
	Mean	*Stdev*	*R^2*	*Mean*	*Stdev*	*R^2*
Queue Position	0.83	6.53	0.53557	-7.11	10.80	0.16208
Taxi-out Mean	-0.10	7.33	0.35036	-7.12	10.83	0.02374
Runway Distance	0.20	8.96	0.19952	-7.12	10.88	0.10658
Severe Weather	-0.12	9.25	0.00240	-7.11	10.83	0.00957
31L Arrival rate	0.84	8.51	0.22952	-7.11	10.85	0.00028
31R Arrival rate	1.18	8.75	0.15538	-7.12	10.85	0.01327
All (multi-linear)	**0.83**	**6.05**	**0.61775**	**-7.11**	**10.83**	**0.35403**

N=1685 Nominal time=5.83 minutes

Row header : Mean: taxi-out error (predicted-actual times) in minutes, σ: Taxi-out error standard deviations in minutes, column Tax-out mean and all arrivals are for 15 minutes time-bucket
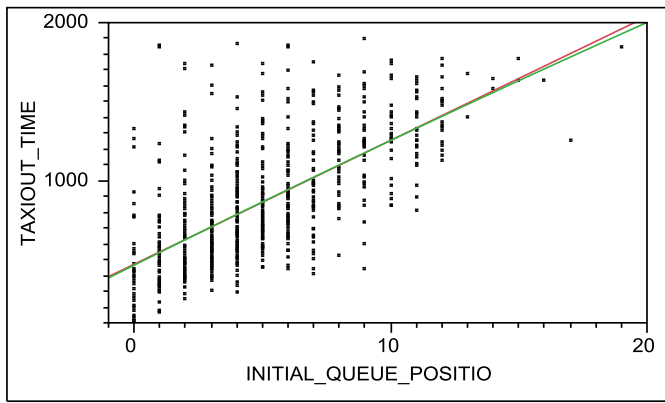
Figure 12. Scatter plot of taxi-out time versus queue position along with linear and quadratic fit curve.
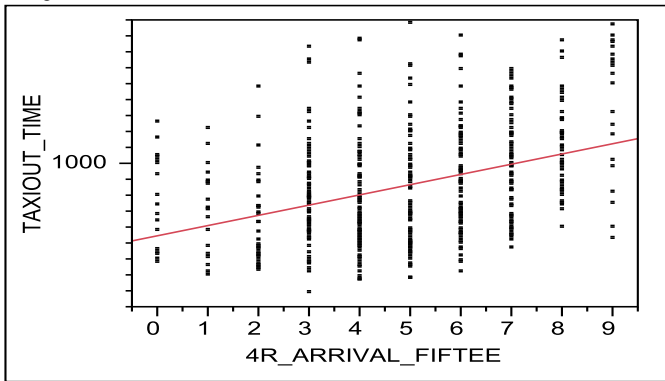

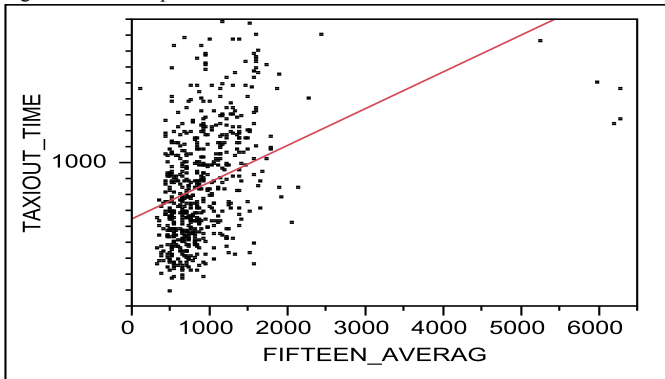Figure 13. Scatter plot of taxi-out time versus 4R arrival rates

Figure 14. Scatter plot of taxi-out time versus taxi-out average last 15 minutes

Arrivals on parallel runways are more significant for runways 4L and 31L than other runways. Since the models consider already taxiing flights and make short-term predictions, weather did not emerge as a significant factor in this study.

B. Models Comparision

The Split Flow Model provides better prediction than Uniform Flow Model for runways 4L, 22R and 13R as indicated by a higher coefficient of determination. This is supported by empirical observations on aircraft movement behavior when they are queued during departure. For runway 31L, the Split Flow Model performs significantly worse as shown by lower coefficient of determination and higher spread and mean error values. This is
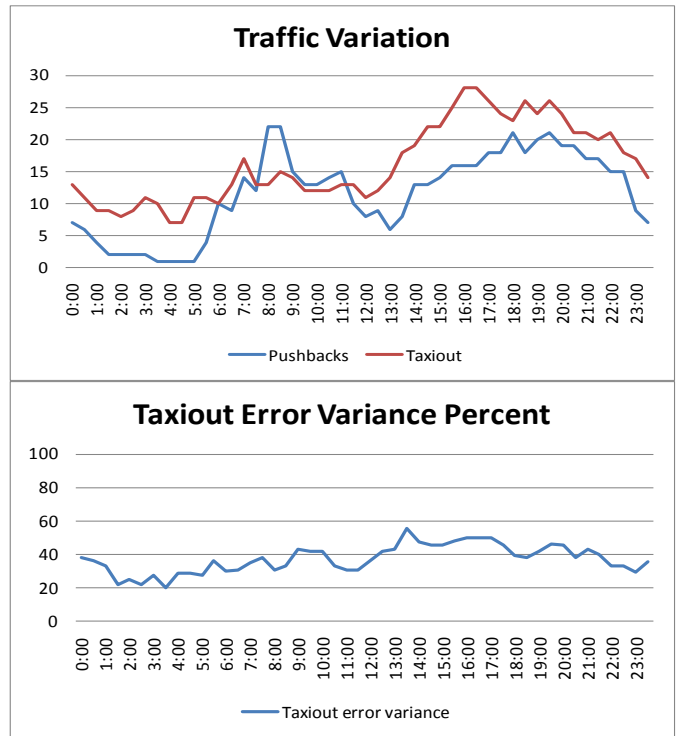

Figure 15. Average daily traffic trend vs taxi-out variance

due to significantly less time the flights were queued for runway 31L (~ 15 percent) compared to other runways (~ 50 percent) as shown in Table 2. UFM performs more consistently than SFM; however SFM performs better in traffic conditions where queues develop during the departure process.

C. Model Stability

Model stability is assessed by plotting the impact of varying traffic conditions on prediction quality, measured as the absolute difference between predicted and actual taxi-out times as percentage of taxi-out time. Average number of push backs and average taxi-out time are used as measure of departure traffic load and delay. Fig. 15 shows traffic variation and taxi-out error variance percent slotted on identical times of the day; all the values are averaged in thirty minute bins. UFM model predictions on JFK data from 24th July 2010 to 13th August 2010 are used for this analysis. The charts show that predictions remain fairly stable in varying traffic conditions.

D. Model Comparison with ETMS and Averages

ETMS generates a series of predictions for a flight starting from the time it is filed to when it takes off. For this analysis, UFM predictions are compared to the ETMS predictions active

TABLE 2. RELATIVE QUEUE TIMES FOR RUNWAYS

Runway	Taxi-out time		Queue time	
	Mean	*Std Dev*	*Mean*	*Std Dev*
4L	15.38	8.17	8.61	5.38
22R	22.11	13.31	10.95	9.39
13R	20.34	10.77	11.34	7.91
31L	16.39	16.38	2.38	2.29

at that time. The runway-wise taxi-out error in minutes (predicted minus actual taxi-out time) distribution is depicted in Fig. 16. The ASDE-X-based model significantly improves predictions for all runways for both taxi-out error mean value and reduced error spread (σ values). In another comparison, taxi-out prediction for a flight is calculated as average of ten or more taxi-out times for the same flight during the period from 3 July 2010 to 23 July 2010 (Averages model). Fig. 17 shows taxi-out error distributions for ETMS, Averages and ASDE-X model for all the runways. The ASDE-X-based model significantly improved predictions over other models in both mean error and error spread as measured by σ values.
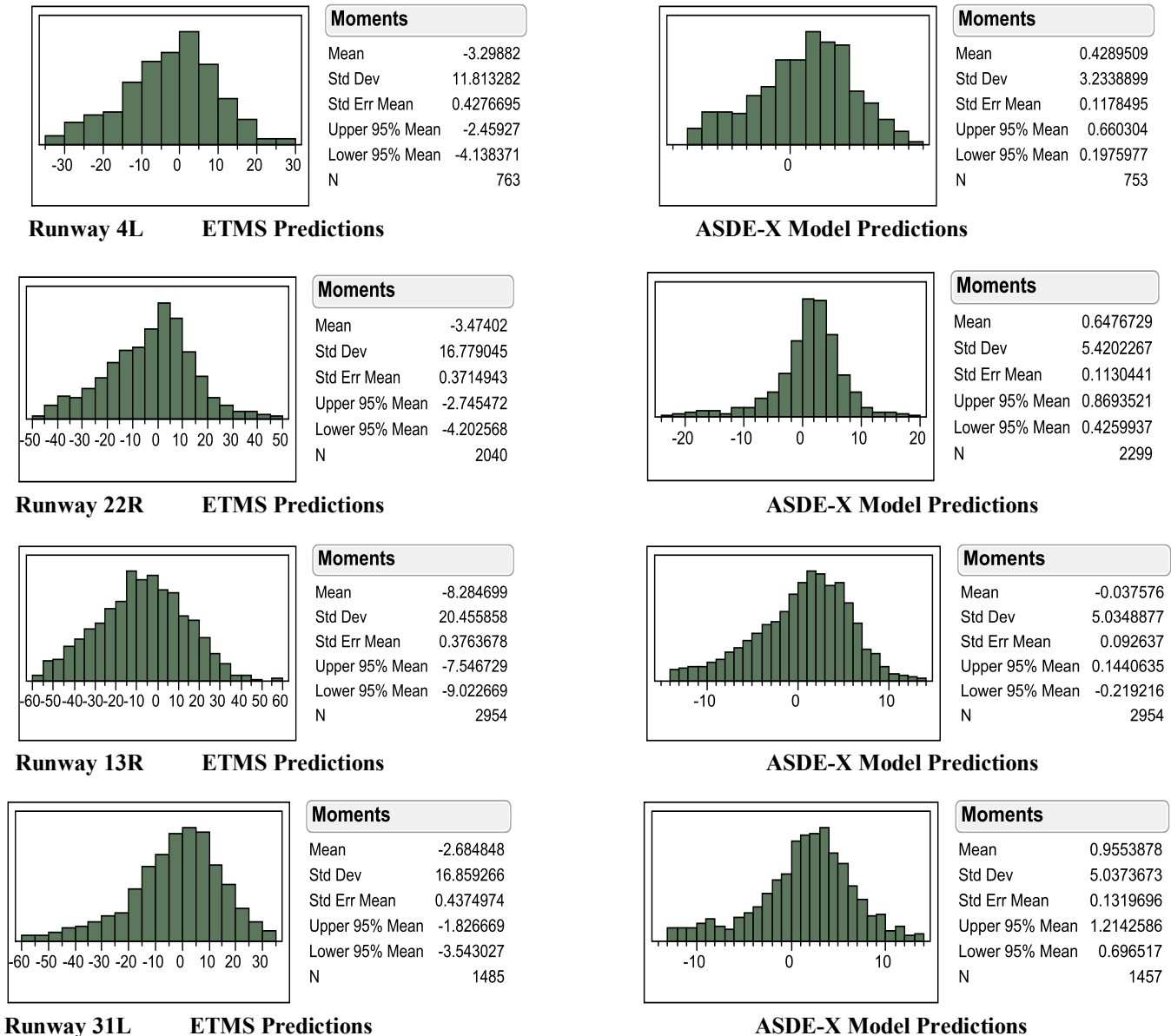
Moments	
Mean	-3.29882
Std Dev	11.813282
Std Err Mean	0.4276695
Upper 95% Mean	-2.45927
Lower 95% Mean	-4.138371
N	763

Runway 4L   ETMS Predictions

Moments	
Mean	0.4289509
Std Dev	3.2338899
Std Err Mean	0.1178495
Upper 95% Mean	0.660304
Lower 95% Mean	0.1975977
N	753

ASDE-X Model Predictions

Moments	
Mean	-3.47402
Std Dev	16.779045
Std Err Mean	0.3714943
Upper 95% Mean	-2.745472
Lower 95% Mean	-4.202568
N	2040

Runway 22R   ETMS Predictions

Moments	
Mean	0.6476729
Std Dev	5.4202267
Std Err Mean	0.1130441
Upper 95% Mean	0.8693521
Lower 95% Mean	0.4259937
N	2299

ASDE-X Model Predictions

Moments	
Mean	-8.284699
Std Dev	20.455858
Std Err Mean	0.3763678
Upper 95% Mean	-7.546729
Lower 95% Mean	-9.022669
N	2954

Runway 13R   ETMS Predictions

Moments	
Mean	-0.037576
Std Dev	5.0348877
Std Err Mean	0.092637
Upper 95% Mean	0.1440635
Lower 95% Mean	-0.219216
N	2954

ASDE-X Model Predictions

Moments	
Mean	-2.684848
Std Dev	16.859266
Std Err Mean	0.4374974
Upper 95% Mean	-1.826669
Lower 95% Mean	-3.543027
N	1485

Runway 31L   ETMS Predictions

Moments	
Mean	0.9553878
Std Dev	5.0373673
Std Err Mean	0.1319696
Upper 95% Mean	1.2142586
Lower 95% Mean	0.696517
N	1457

ASDE-X Model Predictions

Figure 16. Runway wise comparison between ETMS & ASDE-X model

Moments	
Mean	-5.134056
Std Dev	18.349047
Std Err Mean	0.2149361
Upper 95% Mean	-4.712719
Lower 95% Mean	-5.555393
N	7288

All   ETMS Predictions

Moments	
Mean	2.2966184
Std Dev	8.1313211
Std Err Mean	0.0955305
Upper 95% Mean	2.4838859
Lower 95% Mean	2.1093508
N	7245

Averages Predictions

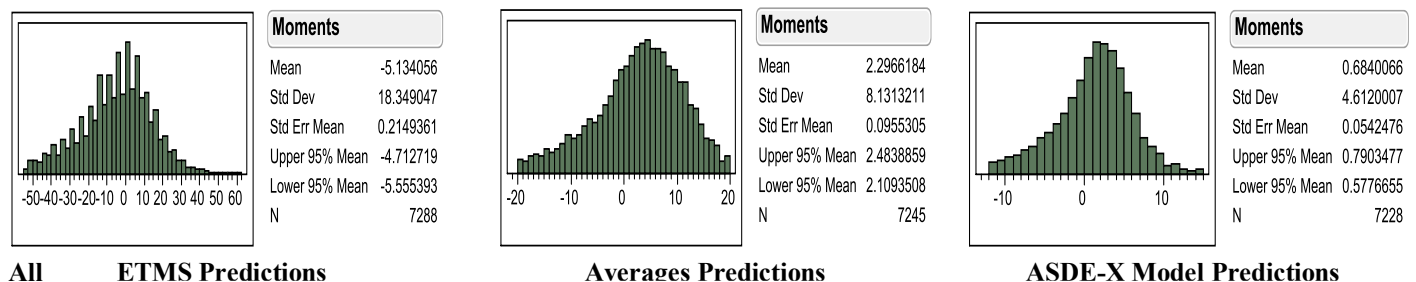| Moments	
Mean	0.6840066
Std Dev	4.6120007
Std Err Mean	0.0542476
Upper 95% Mean	0.7903477
Lower 95% Mean	0.5776655
N	7228

ASDE-X Model Predictions

Figure 17. All runways comparison among ETMS, ASDE-X & Averages prediction models
All numbers are taxi-out error (predicted-actual) in minutes

IX. CONCLUSION

This paper introduces two taxi-out prediction models based on high resolution airport surface movement data available from ASDE-X surveillance system. Uniform Flow Model (UFM) assumes uniform aircraft movement from the starting location to the runway threshold and models taxi-out time in a single segment. Split Flow Model (SFM), on the other hand, models taxi-out time as sum of predicted time to reach the runway queue and taxi-out delay while the aircraft is in the queue. Linear regression analysis on traffic flow database generated using ASDE-X data is used to model taxi-out time (in case of UFM) or taxi-out delay (in case of SFM) as a variable dependent on explanatory variables such as queue position, runway distance, arrival rates, departure rates and weather. Results from applying the models show a significant improvement in quality of predictions when compared with predictions currently available from ETMS or using average taxi-out times (Averages model) for a flight. ASDE-X model (UFM) reduced mean prediction error (predicted-actual taxi-out time) from -8.07 (ETMS) and 2.29 (Averages) to 0.68 minutes. Error spread (standard deviation) was reduced from 21.78 (ETMS) and 8.13 (Averages) to 4.61 minutes. Comparison between the two models shows that SFM performs better in traffic conditions when queues develop at runways, while UFM performs more consistently in all traffic conditions. This study also shows that queue position is most significant determinant of taxi-out times.

Since ASDE-X updates traffic data every second, the model can update predictions as aircraft approach runway, making it suitable for deployment in a real-time environment.

One weakness of this model is that the predictions are for a short-term horizon (thirty minutes or so into the future), as they can only be made when the aircrafts come into the ASDE-X view. The ASDE-X data used in the study starts tracking flights when they leave the ramp area. If the ASDE-X data within the ramp area were available, modeling can start at pushback, thus extending the look ahead time. Also, the model needs to be recalibrated if traffic pattern changes significantly, such as due to closing of a runway, or during winter when aircraft wait for de-icing. The model should constantly adapt to changing traffic pattern by monitoring the error rates and recalibrating if needed.

This model can be further improved by considering other factors such as departure separation rules and fleet mix, flight's departure clearance time when an Expected Departure Clearance Time (EDCT) has been assigned, and the first departure fix in the flight's filed route to fine tune the queue ordering and wait times.

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