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Wheels-Off Time Prediction Using Surface Traffic Metrics

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This paper is motivated by the need for wheels-off time prediction required for improving departure scheduling. It will be possible to estimate wheels-off time with high precision at major U. S. airports where airport surface automation, such as the Surface Management System, is deployed. At other airports, controllers are expected to estimate wheels-off time for departure scheduling. This paper analyzes Dallas-Fort Worth airport state data metrics derived from the Aviation System Performance Metrics database and Surface Management System logs for use as inputs to a neural network for predicting wheels-off time at airports where the Surface Management System will not be available. At airports without Surface Management System, these metrics will be either directly available to controllers or can be computed using combinations of flight-plan data, taxi clearance data, surface surveillance data, airline provided Out-Off-On-In (OOOI) data and airport surface geometry data. Analysis of metrics derived from Aviation System Performance Metrics database and Surface Management System logs show that there is a high degree of correlation between these metrics and gate to wheels-off time. Correlations of these metrics with gate departure delay were found to be quite low, so no attempt was made to predict gate departure delay using these metrics. This study assumed the gate departure time to be known for estimating wheels-off time. Gate to wheels-off time is predicted using the neural network with chosen metrics as inputs. The neural network is trained with six days of data and tested on one day of data. Results show that the trained neural network performance on the test data is as good as on the training data. The main finding of the study is that a neural network trained on several days of airport state data was able to generate gate to wheels-off time predictions within the Call for Release departure compliance window of two-minutes early to one-minute late 59% of the time. This performance can be improved further by removing outliers in the training and test sets. Next, a linear model was created with the same set of metrics as independent variables and gate to wheels-off time as the dependent variable. Six days of data were used with the least-squares method to compute the coefficients. These coefficients were then used with one day of test data to estimate the gate to wheels-off time. Results were found to be comparable to that generated by the neural network based on the Mahalanobis distance metric. Comparison of predictions generated using the neural network and the linear model to the test data provide evidence that the chosen metrics are suitable for predicting gate to wheels-off time.

I. Introduction

This paper is motivated by the need for improving departure scheduling advisories. A specific application is for Precision Departure Release Capability (PDRC) which has the goal of using surface trajectory based off-time predictions for Call for Release (CFR). Accurate wheels-off time estimation is important to PDRC both for 1) providing an initial estimate to the Traffic Management Advisor (TMA) for inserting a flight into a constrained overhead stream and for scheduling an inbound flight to a TMA-metered airport, and 2) determining when to release the aircraft from the gate so that its actual wheels-off time corresponds to the wheels-off time coordinated with the Air Route Traffic Control Center. Improved wheels-off time prediction would also benefit traffic flow management (TFM). TFM techniques first estimate traffic demand considering both airborne aircraft that are detected by the air traffic control radars and aircraft on the ground that are scheduled to depart within the forecasting interval, and then

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compare demand to available sector and airport capacities to determine controls needed for moderating demand to stay within capacity limits. Accuracy of the wheels-off time estimate of future departures affects the quality of traffic demand estimates. Inaccurate traffic demand estimates result in either inadequate or unneeded flow restrictions.

Wheels-off time uncertainty is caused by uncertainty in gate departure time, ramp area transit time and taxi time. The largest component to this uncertainty is gate departure time. Recently, use of air carrier data messages that indicate completion of pre-departure steps and readiness for departure has been proposed for improving prediction of gate departure time in Ref. 1. While the distance between the gate/spot and the runway entrance is known, taxi time delay is a function of taxi speed, taxi route, surface winds and visibility, congestion caused by other aircraft, and takeoff and landing demand. Statistical characterization of taxi time, which implicitly includes congestion effects, is provided in Ref. 2. This study considered one year of departure, wheels-off, wheels-on and gate arrival times reported by domestic carriers in the Airline Service Quality Performance (ASQP) database for analysis. Mean and standard deviation values of taxi-out and taxi-in times are listed for the 35 major U. S. airports. Differences in taxi time distributions due to choice of arrival/departure runways and airlines are also discussed. The distributions described in Ref. 2 can be used for predicting early and late wheels-off time bounds. The approach, described in Ref. 3, consists of using the unimpeded taxi time along with queues for ramp and taxiway interactions, and departure queue at the runway. The unimpeded taxi time is modeled as a function of gate location, runway configuration and meteorological condition. Taxiway delay is determined as a function of number of departures in the movement area. An analytical queuing model is used for estimating the delay for the runway service process. The study in Ref. 4 presented statistics of ramp spot wait time, taxi routes and associated taxi times, taxiway speed, and delay due to reconfiguration of arrival/departure runways at Detroit Metropolitan Wayne County Airport. This paper points out that several different taxi routes are used for each gate-runway combination. Reference 5 relates arrival, departure, taxi distance, taxi turns, taxi-stop time and taxi traffic metrics to spot to wheels-off time using linear and log-linear models. They found the linear model to be better than the log-linear model. In summary, wheels-off time can be predicted using simple statistical models, queuing models and simulation models. It is quite likely that the wheels-off time uncertainty will be lowered at airports where Surface Management System (SMS) is being considered for deployment because the SMS scheduler will be aware of constraints and delays. A wheels-off time model will be needed at non-SMS airports where the controllers will be expected to estimate wheels-off time for Call for Release.

This paper analyzes Dallas-Fort Worth Airport data derived from the Aviation System Performance Metrics (ASPM) database and surface traffic data from SMS logs to identify metrics that can be functionally related to gate departure delay and gate to wheels-off time. While SMS logs will not be available at airports without SMS, and ASPM data are historical, these data have been used as convenient sources for computing the desired metrics. At non-SMS airports, these metrics will be either directly available to controllers or can be computed using combinations of flight-plan data, taxi clearance data, surface surveillance data, airline provided Out-Off-On-In (OOOI) data and airport surface geometry data. Selected metrics are used as input to a neural network for predicting gate to wheels-off time assuming gate departure time is known. The surface geometry data needed for the analysis are obtained from the Surface Operations Data Analysis and Adaptation (SODAA) database. Surface Management System logs are analyzed with SODAA data for a detailed understanding of the paths taken by departing and arriving aircraft to/from departure/arrival gates, spots, taxiways and runways. Reference 5 also used metrics derived from SMS log data processed within SODAA in a linear model to predict spot to wheels-off time. This paper addresses a more difficult problem of predicting gate to wheels-off time compared to predicting spot to wheels-off time discussed in Ref. 5. Gate to wheels-off time prediction is more difficult because of high gate to spot travel time uncertainty. To compare the neural network results with the approach in Ref. 5, a linear model was constructed with the same set of metrics used in the neural network. Coefficients of the model were obtained using the least-squares procedure.

Section II describes the geometry of Dallas-Fort Worth airport and operations based on analysis of ASPM, SMS logs and SODAA data. Correlations between the parameters derived from ASPM and SMS logs and gate to wheels-off time and gate departure delay are discussed in Section III. These provide a measure of importance as inputs for predicting gate to wheels-off time and gate departure delay. A neural network and a linear model for predicting gate to wheels-off time is described in Section IV. Results of training this neural network with six days of data and test on one day of data and comparison with the results obtained with the linear model are also given in Section IV. The paper is concluded in Section V. Parameters for modeling gate to wheels-off time and gate departure delay are discussed in the Appendix.

II. Dallas-Fort Worth Airport Geometry and Operations

Dallas-Fort Worth International Airport (DFW) is the third busiest airport in the United States. According to the March 2011 FAA Administrator's Factbook[7], 652,000 operations were conducted at DFW in 2010 compared to 950,000 operations at Hartsfield-Jackson Atlanta International, the busiest US airport, and 883,000 operations at Chicago O'Hare International, the second busiest US airport. DFW is physically one of the largest airports in the United States and the world with an area spanning five nautical-miles east to west and three nautical-miles north to south. The airport has seven physical runways shown in Fig. A-1 in the Appendix. These runways are operated in the south-flow and north-flow configurations. The runways in south-flow configuration are designated as, 13L, 13R, 17L, 17C, 17R, 18L and 18R. The runways in the north-flow configuration are designated as, 31L, 31R, 35L, 35C, 35R, 36L and 36R. These designations also indicate the runway heading with respect to north; they are physically painted on the two ends of each runway.

To get insight into DFW operations, hourly runway configurations (arrival and departure runways) for each day in 2011 were obtained by generating the "Daily Weather by Hour Report," from the ASPM database. These data were then processed to determine runways that are used for both arrivals and departures, runways that are used only for arrivals and runways that are used solely for departures. Table 1 lists the runways and the time duration of usage during 2011. This table shows that 10 of the 14 runways (considering the same physical runway to be two different runways based on the approach direction) are used both for arrivals and departures. Of these, 18R is used most often. Summing the runway utilization in both directions of the physical runways, it is seen that 17C/35C, 17R/35L, 18L/36R, 18R/36L, 17L/35R and 13R/31L usage is within 20% of each other. Runway 13L/31R usage is 27% of the usage of the most utilized runway, 18R/36L. Data in Table 1 show that runways 17C, 17R, 18L and 18R are utilized more often compared to the other runways; thus, south-flow is the dominant flow direction in DFW operations.

Further analysis of ASPM runway configuration data revealed that 76 arrival-departure runway configurations out of 254 theoretically possible configurations were used in 2011. Number of theoretically possible combinations is obtained using,

$$n = \sum_{1 \le k \le 7} \binom{7}{k} + \sum_{1 \le k \le 7} \binom{7}{k} \quad (1)$$

where $\binom{7}{k}$ means the number of ways in which "k" runways can be chosen out of seven runways. The two summations are for the seven south-flow and seven north-flow runways. Table 2 lists the top ten configurations along with the percentage of time they were used with respect to 8,760 hours in the year. Observe that the ten configurations listed in Table 2 were used 95% of the time. Summing the percentage use of the 76 south-flow and north-flow configurations, it is seen that the south-flow configuration is used 70% of the time and the north-flow configuration is used 30% of the time. Reference 6 also cited the same numbers.

Table 1. 2011 runway usage summary.

Runways Used for both Arrivals and Departures	Usage (hours)	Runways Used only for Arrivals	Usage (hours)	Runways Used only for Departures	Usage (hours)
18R	6,960	17L	5,844	35L	2,556
17R	6,142	13R	5,624	13L	335
17C	6,119				
18L	5,167				
36R	2,569				
35C	2,547				
31L	2,537				
36L	2,526				
35R	2,318				
31R	2,208				

Passenger and cargo traffic in and out of the 233 gates cross 59 spots to exit and enter a network of 96 taxiways to travel to and from the seven physical runways. The taxiways intersect at 215 locations. This includes intersection of taxiways with runways. The taxiways consist of 360 segments partitioned by the intersections. These numbers were obtained by analyzing DFW geometry data derived from SODAA. The DFW airport design is also characterized by multiple runways, high-speed exit taxiways, non-intersecting runways, three towers, and perimeter taxiways near 35L and 35C that permit aircraft to taxi to and from the gates without crossing active runways. These features reduce congestion on the airport surface; delays are mostly weather related and independent of surface operations.[6] This suggests that it might be possible to estimate taxi time with reasonable accuracy for different weather conditions at DFW.

Table 2. 2011top-ten runway configurations.

Arrival	Departure	Usage (%)	Flow
13R,17C,17L,18R	17R,18L	45.4	South
31R,35C,35R,36L	31L,35L,36R	22.7	North
13R,17C,17L,18R	17R,18R	9.7	South
17C,17L,18R	17R,18L	4.7	South
13R,17C,17L,18R	13L,17R,18L	3.1	South
13R,17C,18R	17R,18L	2.9	South
35C,35R,36L	31L,35L,36R	2.9	North
31R,35C,36L	31L,35L,36R	1.5	North
13R,17C,17L	17R,18R	1.2	South
13R,17C,17L	17R,18L	0.8	South

To estimate wheels-off time, estimates of gate departure time and taxi time are needed. Of these two estimates, gate departure time estimate is much more difficult to compute. In the absence of airline provided gate departure time, the choices are limited to the scheduled departure time from the Official Airline Guide (OAG) and the proposed departure time included in the filed flight-plan. These times provide approximate estimates of gate-out time. Reference 1 proposes the use of pre-departure event times to improve estimate of gate-out time. The central idea employed in Ref. 1 is that gate-out time becomes more certain as completion of each step taken by airline and air traffic for preparing the flight for departure are reported via the Aircraft Communication Addressing and Reporting System (ACARS). Taxi time is a function of distance between the gate and the runway, taxi-speed and congestion of the surface. Since a taxi route is specified, distance along the route can be determined. Taxi-speed differences between flights are significant; taxi-speed is a function of pilot preference, stops needed at intersections and congestion along the route to the runway threshold.

To determine gate to runway distances and taxi-out times to the runways at DFW, one week- spanning 7 August 2011 through 13 August 2011 of surface traffic data were obtained by processing SMS logs. The chosen seven days had good weather, and consisted of 6,284 departures. After discarding flights with more than 60 minutes of gate departure delay and 30 minutes of gate to runway entry time, 5,822 departures were considered for further analysis. It was determined that 393 unique gate-runway combinations were used by these aircraft. Figure 1 shows the gate to runway distance distribution and Fig. 2 shows the average taxi speed distribution of 5,822 departures. Average taxi

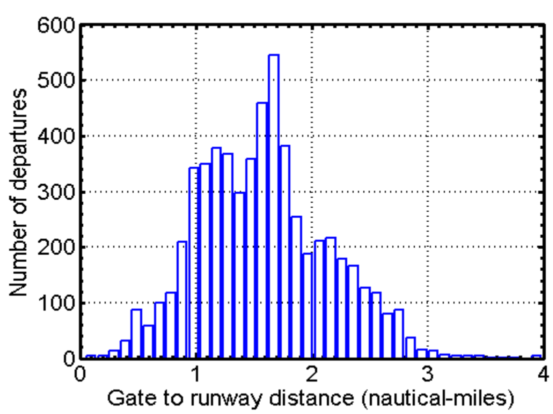

Figure 1. Gate to runway distance distribution.

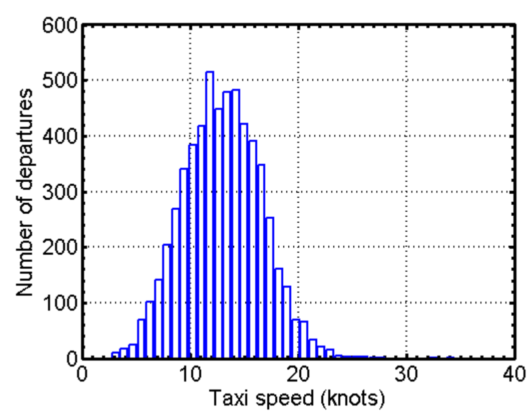

Figure 2. Average taxi speed distribution.

speed is obtained as the ratio of gate to runway distance to taxi-out time. Average, standard deviation and maximum gate to runway distance were found to be 1.6, 0.6 and 4.0 nautical-miles, respectively. The average, standard deviation and maximum of the average taxi-out speed were found to be 13, 3.6 and 34.5 knots, respectively. Average and standard deviation of the taxi-out time were determined to be 7.8 and 3.6 minutes, respectively.

III. Correlation Between Metrics and Gate to Wheels-off Time and Gate Departure Delay

Correlation coefficients between gate to wheels-off time (SMS Log Data Item 4 in the Appendix) and variables selected from the two sets discussed in the SMS Log Data and ASPM Data sections in the Appendix were computed to make an assessment of their suitability as predictors of gate to wheels-off time in a neural network and a linear model framework. The procedure was repeated for correlations with respect to gate departure delay (SMS Log Data Item 15 in the Appendix) to ascertain the ability of these variables to predict gate departure delay.

Prior to computing the correlation coefficients, data were conditioned as follows. SMS Log data for flights with absolute value of the gate departure delay greater than the specified threshold of 60 minutes were discarded. The data were found to contain large negative gate departure delays. Another check was performed for gate to runway taxi time with a threshold value of 30 minutes. Only flights with gate to runway entry time of less than 30 minutes were considered. Total number of samples prior to pruning is 6,284. After pruning 5,822 remain. 462 samples removed represent a 7.4% loss with respect to 6,284 samples.

Table 3 shows the correlation (with 100% being perfect correlation) and p-value of the selected variables with gate to wheels-off time. Here, correlation means the cross-correlation coefficient derived from the covariance matrix of the two variables being compared and the p-value is the probability of obtaining a correlation as large as the observed value by random chance, when the true correlation between the variables is zero. p-value of less than 0.05 is considered to be significant. The gate to runway distance has the highest correlation followed by average taxi-out delay and number of departures on the surface. Wind angle, visibility and temperature were found to be negatively correlated. Weak negative correlation with visibility and temperature is reasonable in that as visibility and temperature decrease, one would expect taxi-time to increase a bit. Wind angle correlation is difficult to interpret without examining wind velocity components relative to the surface trajectory. Few variables that are independent of each other (contain different type of information) with high correlation can be used to develop a linear model or a neural network model for predicting gate to wheels-off time. Such models could be adequate for CFR at DFW because in current operations, CFR is initiated after pushback from the gate. This means that the gate departure time is known. At some other airports, for example at San Jose International airport, airlines are asked to inform air traffic control (ATC) some time (for example, 15 minutes) prior to ready for departure when the flight is impacted by CFR. Gate departure time uncertainty can be expected to be small in this scenario therefore wheels-off time could be predicted with these models.

For predicting gate departure time, the only available information about when an aircraft might leave the gate is the scheduled gate departure time. Improvement beyond the scheduled gate departure time is possible if metrics derived from observed or estimated airport state are found to be good predictors of gate departure delay. This is examined next.

Table 4 shows the correlation of the selected metrics with gate departure delay. The table shows that time of day at the scheduled gate departure time has the highest correlation followed by average gate departure delay in the previous 15-minutes. Average taxi-in delay in previous 15-minutes is similarly correlated with gate departure delay. While unexpected, temperature was found to be mathematically correlated to gate departure delay. It turns out that temperature increase from morning to afternoon and then decrease in the evening is somewhat correlated to the schedule of the departure pushes. The degree of correlation can be expected to change with different weather conditions. Comparing Tables 3 and 4, it is seen that the degree of correlation of the selected metrics with gate departure delay is much lower compared to with gate to wheels-off time. This suggests that constructing a model for reliable prediction of gate departure delay based on these metrics might be difficult. Furthermore, wheels-off time prediction at the scheduled gate departure time requires that the metrics computed based on airport state data at scheduled departure time be correlated to gate to wheels-off time at actual gate departure time. These correlations are likely to be worse compared to the correlations in Table 3 which are based on airport state data at or close to the actual gate departure time and not at an earlier time. These issues have not been examined further in this paper. The rest of the paper assumes that gate departure time is known and a prediction of gate to wheels-off time is needed for wheels-off time estimate.

Table 3. Gate to wheels-off correlations.

#	Metric	Correlation (%)	p-value
1	Gate to runway distance	66.3	0.00
2	Average taxi-out delay in previous 15-minutes	36.7	0.00
3	Number of departures on surface at actual gate departure time	36.2	0.00
4	Average taxi-out delay of departures on same runway in previous 15-minutes	23.5	0.00
5	Average taxi-out delay of departures to same fix in previous 15-minutes	22.9	0.00
6	Gate departure count previous 15-minutes	13.2	0.00
7	Number of departures to same fix in previous 15-minutes	12.6	0.00
8	Wind angle	-12.0	0.00
9	ATC set airport arrival rate	9.7	0.00
10	Number of departures on same runway in previous 15-minutes	9.4	0.00
11	Average taxi-in delay in previous 15-minutes	8.3	0.00
12	Wind speed on surface	7.5	0.00
13	Average taxi-out delay of departures to same destination in previous 15-minutes	6.9	0.00
14	ATC set airport departure rate	6.0	0.00
15	Number of departures to same destination in previous 15-minutes	5.5	0.00
16	Number of arrivals on surface at actual gate departure time	5.3	0.00
17	Visibility	-4.4	0.00
18	Average gate departure delay in previous 15-minutes	3.8	0.00
19	Takeoff count previous 15-minutes	3.6	0.00
20	Time of day at gate departure	3.0	0.02
21	Landing count previous 15-minutes	2.5	0.05
22	Temperature	-2.2	0.09
23	Gate arrival count previous 15-minutes	2.0	0.13
24	Average gate arrival delay in previous 15-minutes	1.6	0.23
25	Meteorological condition (VMC or IMC)	1.3	0.33

IV. Neural Network Model and Results

A three-layer neural network with seven nodes in the input layer, 20 nodes in the hidden layer and one node in the output layer was designed to predict gate to wheels-off time. Such a neural network is shown in Fig. 3. The seven selected inputs are, 1) gate to runway distance, 2) average taxi-out delay in previous 15-minutes, 3) number of departures on surface at actual gate departure time, 4) average taxi-out delay of departures on same runway in previous 15-minutes, 5) average taxi-out delay of departures to same fix in previous 15-minutes, 6) wind angle and 7) ATC set airport arrival rate. Gate departure count in previous 15 minutes (#6 in Table 3) and number of departures to same fix in previous 15 minutes (#7 in Table 3) were not considered as inputs for the neural network because they were found to be significantly correlated to the other inputs. For example, correlation between metric #6 and #3 is 53.5% and between #7 and #5 is 43.5%. The single output is the gate to wheels-off time. Maximum absolute value of each input was determined for the entire seven day

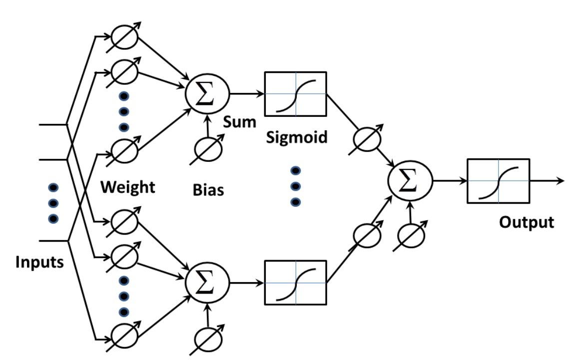

Figure 3. Neural network.

Table 4. Gate departure delay correlations.

#	Metric	Correlation (%)	p-value
1	Time of day at scheduled gate departure	13.8	0.00
2	Average gate departure delay in previous 15-minutes	11.0	0.00
3	Temperature	10.1	0.00
4	Average taxi-in delay in previous 15-minutes	9.6	0.00
5	Landing count previous 15-minutes	8.9	0.00
6	Gate arrival count previous 15-minutes	7.7	0.00
7	Number of arrivals on surface at scheduled gate departure time	6.5	0.00
8	Wind angle	-5.3	0.00
9	Average gate arrival delay in previous 15-minutes	5.1	0.00
10	Average taxi-out delay of departures to same destination in previous 15-minutes	4.9	0.00
11	Takeoff count previous 15-minutes	4.8	0.00
12	ATC set airport departure rate	4.2	0.00
13	Average taxi-out delay in previous 15-minutes	3.5	0.01
14	Number of departures on surface at scheduled gate departure time	3.1	0.03
15	Gate departure count previous 15-minutes	3.0	0.04
16	Wind speed on surface	-1.2	0.40
17	Visibility	1.1	0.43
18	Average taxi-out delay of departures on same runway in previous 15-minutes	0.6	0.66
19	ATC set airport arrival rate	0.6	0.69
20	Gate to runway distance	0.5	0.73
21	Average taxi-out delay of departures to same fix in previous 15-minutes	-0.4	0.80
22	Meteorological condition (VMC or IMC)	-0.1	0.93

dataset. Inputs were then normalized with these values. The gate to wheels-off time data used for training the neural network were also normalized by the maximum absolute value obtained from seven days of gate to wheels-off time data. Figure 3 shows that the inputs are multiplied by weights and summed together with a bias at each hidden layer node and input to the sigmoid function, which is real-valued and differentiable. This means that the neural network had 140 weights and 20 biases for seven inputs and 20 nodes in the hidden layer. The output of the sigmoid functions in the hidden layer are multiplied with another set of weights and summed together with a bias and input to sigmoid functions in the output layer. Since this neural network has 20 nodes in the hidden layer and one node in the output layer, there are 20 weights and one bias between the hidden and output layers. The 160 neural network weights and 21 biases were initialized with values between -1 and 1 using a uniform random number generator. These weights were then adjusted using the standard gradient-based back-propagation algorithm in the neural network training step. Four-hundred iterations resulted in reduced error between the gate to wheels-off time predicted by the neural network and the gate to wheels-off time used for training the network as shown in Fig. 4. Note that the error is dimensionless because the training and neural network outputs are normalized. Six days, 7 August 2011 through 12 August 2011, of data were used for training the neural network and one day, 13 August 2011, of data were used for evaluating the gate to wheels-off time estimation ability of the neural network.

Correlation between the gate to wheels-off time used for training and that generated by the neural network after training on the same set of neural network input data was found to be 72.4%. This is an improvement over gate to

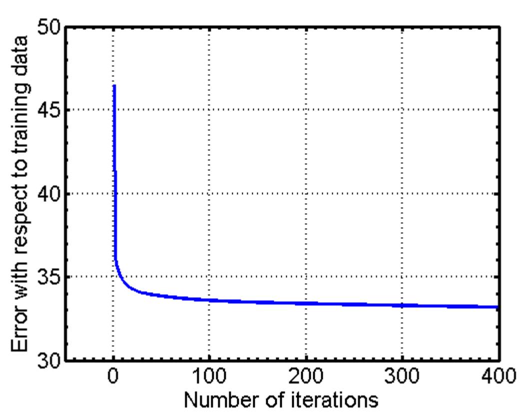

Figure 4. Neural network convergence.

runway distance correlation with gate to wheels-off time of 66.3%. Average and standard deviation of the error with respect to the gate to wheels-off time training data turned out to be 23 seconds and 2.6 minutes, respectively. The average and standard deviation of gate to wheels-off time in the six day training set is 8.9 and 3.8 minutes, respectively. A histogram of the training error is shown in Fig. 5.

Reference 8 notes that while the compliance window for CFR varies by facility and that a nationwide standard does not exist, information from traffic managers and inter-facility agreements ask for flights to depart within a three-minute window, two-minutes early to one-minute late, with respect to the coordinated departure time. The reason for allowing departures to be two-minutes early compared to one-minute late is because it is easier to slow down the flight compared to accelerating it for merging into the constrained flow. Considering the neural network predicted gate to wheels-off time to be the coordinated departure time and the difference of the actual gate to wheels-off time with respect to this predicted time to be delay, 53.5% of the flights were found to be in compliance with the CFR window based on the error distribution in Fig. 5. This increased to 61.2% when the window was expanded to allow two-minute early to two-minute late departures.

For the 13 August gate to wheels-off time test data, the correlation with the neural network generated gate to wheels-off time estimate is 74%. Average and standard deviation of the error with respect to the test data are 35 seconds and 2.3 minutes. These values can be compared to the average and standard deviation of gate to wheels-off

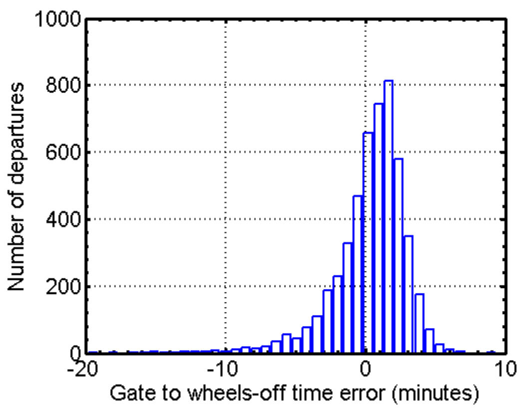

Figure 5. Training error distribution.

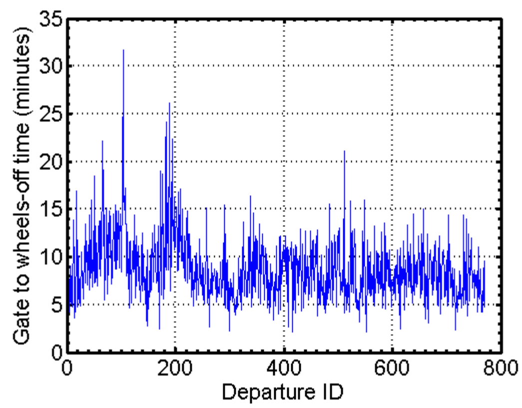

Figure 6. Test set data.

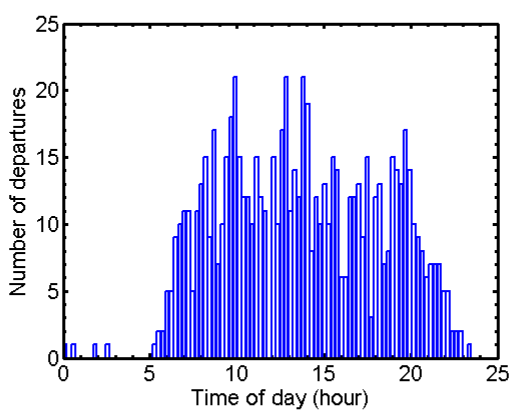

Figure 7. Test set departure distribution.

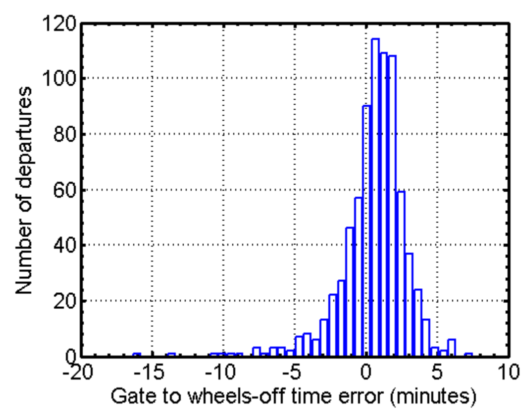

Figure 8. Test error distribution.

time of 8.7 minutes and 3.4 minutes. Gate to wheels-off time test data are shown in Fig. 6 and the departure distribution of the flights whose gate to wheels-off time are in Fig. 6 are shown in Fig. 7 in 15-minute bins. The error distribution is given in Fig. 8. Actual gate to wheels-off times for 59.2% of the flights in the test set were found to be within the two-minute early and one-minute late CFR window with respect to the neural network predicted gate to wheels-off times. This result compares favorably with the observation in Ref. 8, which is based on one-month of data, that 69.2% of aircraft subject to CFRs in which TMA automation was utilized were compliant with the CFR window. Compliance of the test set improved to 66.5% when the window was expanded to allow two-minute early to two-minute late departures. These results confirm that the neural network performance on the test data is as good as it is on the training data. Results discussed in this section show that the selected metrics can be used as inputs to a neural network for generating gate to wheels-off time predictions for CFR after gate pushback. The performance of the neural network can be improved further by removing outliers from the training and test sets. This would require flights with unusual delay to be identified and removed from the training and test sets based on detailed analysis of surface trajectory of each flight.

To compare the results obtained with the neural network with the earlier study reported in Ref. 5, a linear model was set up as follows:

$$y = \sum_{1 \le k \le 7} c_k x_k \tag{2}$$

with x_1 through x_7 representing the seven non-normalized neural network inputs, c_1 through c_7 representing the corresponding coefficients and y representing the non-normalized gate to wheels-off time. These seven coefficients were computed using the least-squares method with the left and the right hand sides of Eq. (2) derived from six days of data that had been used earlier to train the neural network. The numerical values of the coefficients are given in Table 5. Inputs derived from one day of data used for testing the neural network were then multiplied with these coefficients and summed to generate gate to wheels-off time predictions for comparison with the actual gate to wheels-off time.

Table 5. Linear model coefficients.

Coefficient	Value
c_1	241.1828
c_2	10.0057
c_3	10.1521
c_4	0.1049
c_5	0.0369
c_6	-0.2491
c_7	2.4563

Results obtained with the linear model matched the distributions shown in Fig. 5 and 8 based on the Mahalanobis distance metric, which is the ratio of the Euclidean Norm of the error (data in Figs. 5 and 8) and the standard deviation of the gate to wheels-off time distributions used for training and testing. Mahalanobis distance metric values were determined to be 49.55 and 49.02 with neural network and linear model outputs with respect to training data, respectively. With respect to test data, the values were found to be 19.42 and 19.29 with neural network and linear model outputs, respectively. Actual gate to wheels-off times of 62.1% of the flights in the test set were found to be within the two-minute early and one-minute late CFR window with the linear model. CFR compliance is a bit better than 59.2% obtained with the neural network. These results do not show a benefit of using the neural network over a simple linear model for DFW traffic. It remains to be seen if the neural network would perform better on surface data from other airports. Results obtained with both the neural network and linear model validate the suitability of the chosen metrics for predicting gate to wheels-off time. For follow on work, these metrics will be computed using data from airports where SMS will not be available and used with the neural network and linear model to assess the accuracy of gate to wheels-off time predictions.

V. Conclusions

Correlation of airport state metrics derived from the Aviation System Performance Metrics database and Surface Management System logs with gate to wheels-off time and gate departure delay were examined to identify metrics with significant correlation as inputs for a neural network. Gate to runway distance was found to have the highest correlation of 66.3% with gate to wheels-off time. Scheduled departure time of day was found to have the highest correlation of 13.8% with gate departure delay. Given low correlation with gate departure delay, this study did not attempt to develop a model for predicting gate departure time. Instead, gate departure time was assumed to be known. The neural network was trained with six days of data to predict gate to wheels-off time. After training, the correlation with gate to wheels-off time predicted by the neural network and that used for training increased by 6% to 72.4% compared to 66.3% correlation with gate to runway distance. Average and standard deviation of the error with respect to the gate to wheels-off time training data were found to be 23 seconds and 2.6 minutes. One day of data were used for testing the neural network. A 74% correlation was found between these test set data and the neural network generated gate to wheels-off time estimate. Average and standard deviation of the error with respect to the test data were determined to be 35 seconds and 2.3 minutes. These results show that the neural network performance on the test data is comparable to its performance on the training data. Actual wheels-off times for 59% of the departures in the test set were found to be within the two-minute early to one-minute late Call for Release window with respect to the trained neural network predicted wheels-off times. This result is comparable to 69% compliance within the Call for Release window reported in an earlier study. Results based on analysis of Dallas-Fort Worth data show that it is feasible to use the selected metrics as inputs to a neural network for generating gate to wheels-off time predictions for Call for Release after gate pushback. Results obtained with a linear model, with coefficients obtained using the least-squares method, were found to be as good as those obtained with the neural network based on the Mahalanobis distance metric. While a clear benefit of using a neural network over the simple linear model was not found for Dallas-Fort Worth traffic, it remains to be seen if it would perform better on surface data from other airports. Both the approaches suggest that the selected metrics can be used for predicting gate to wheels off time. These metrics will be computed using data from airports where the Surface Management System will be unavailable and used with the neural network and the linear model to determine the accuracy with which gate to wheels-off time can be predicted.

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Appendix

Dallas-Fort Worth airport diagram with the seven runways is shown in Fig. A-1.

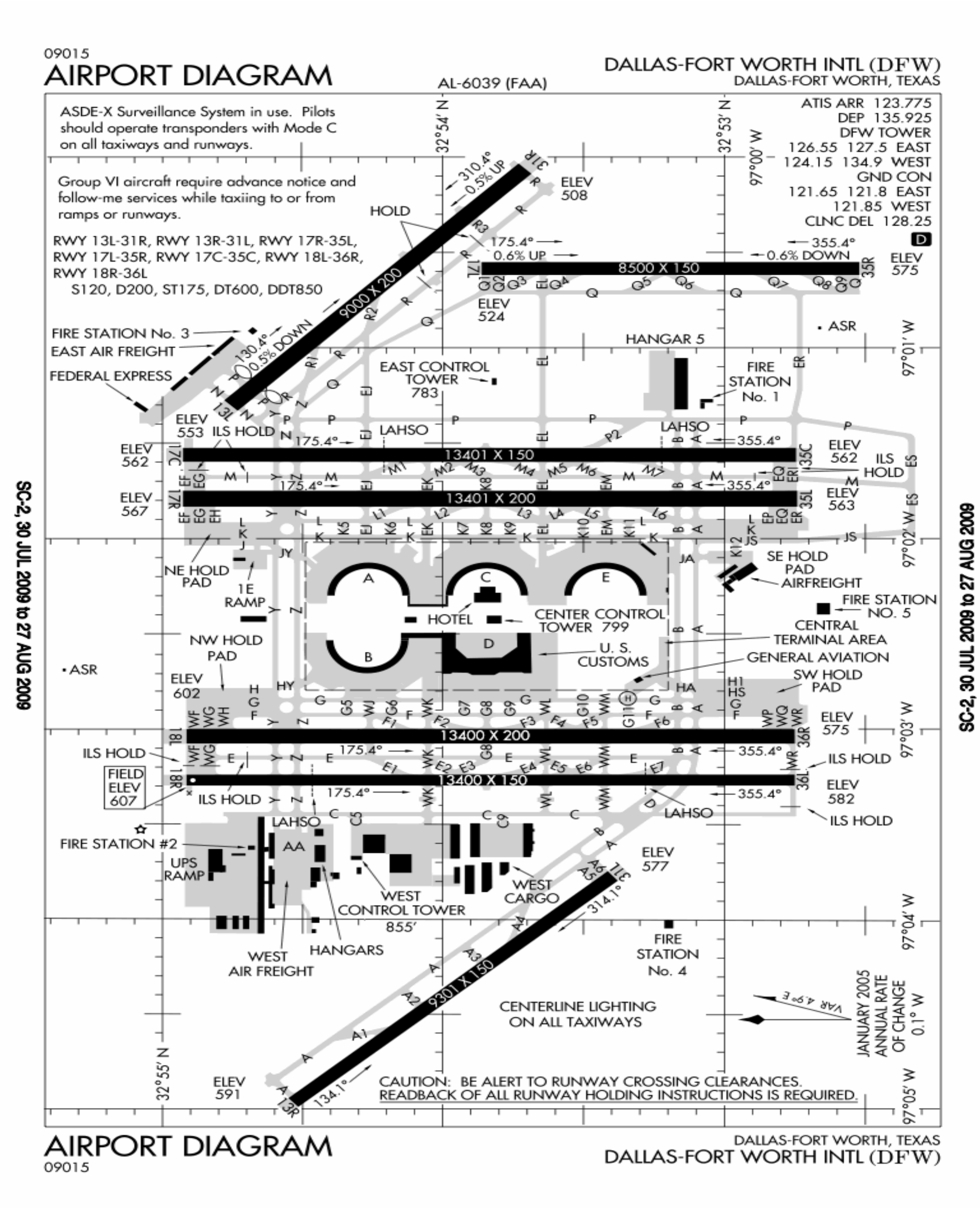

Figure A-1. Dallas-Fort Worth airport layout.

Parameters for Modeling Gate to Wheels-off Time and Gate Departure Delay

The variables chosen for predicting gate to wheels-off time and gate departure delay are discussed in this section. These input variables were obtained by processing seven days, 7 August 2011 through 13 August 2011, of SMS logs and ASPM data.

SMS Log Data

Surface trajectory data, consisting of a sequence of latitudes and longitudes as a function of time, of every flight departing DFW were analyzed to determine the following:

1. Actual gate-out time in hours, minutes and seconds.
2. Time of day in 15-minute interval. For example, 02:45 means 2 hours and 45 minutes past 00:00 local time. Actual gate-out time is within this 15-minute bin.
3. Actual wheels-off time in hours, minutes and seconds.
4. Actual wheels-off time minus actual gate-out time. This is the sum of time spent in the ramp area, time taken to taxi to the runway and time spent on runway till the wheels are off the ground.
5. Flight ID.
6. Departure gate ID.
7. Departure runway ID.
8. Name of the departure fix.
9. Name of the destination airport.
10. Actual gate to runway distance in nautical-miles based on surface trajectory.
11. Actual taxi-out time of the flight in seconds. This is the gate to runway entrance time; sum of time spent in ramp area and taxi time to the runway entry.
12. Aircraft type. For example, Boeing 747-400.
13. Airline name.
14. Scheduled gate departure time in hours, minutes and seconds.
15. Gate departure delay. This is the difference between the actual gate departure time and the scheduled departure time.
16. Number of departures on the surface at the actual gate departure time. These flights are out of the gate and moving towards departure runways.
17. Number of arrivals on the surface at the actual gate departure time. These flights have landed and are moving towards arrival gates.
18. Number of takeoffs from the same runway as this flight in the previous 15-minute interval with respect to the time of day.
19. Average taxi-out delay of departures in seconds using the same runway as this flight in the previous 15-minute interval with respect to the time of day. Taxi-out delay of each departure is computed as the difference of the actual taxi-out time and the unimpeded taxi-out time, where the unimpeded taxi-out time is computed as the ratio of the actual taxi-out distance to the average speed of 13 knots.
20. Number of takeoffs that used the same departure fix as this flight in the previous 15-minute interval with respect to the time of day.
21. Average taxi-out delay of departures in seconds using the same fix in the previous 15-minute interval with respect to the time of day. Taxi-out delay is computed in the same manner as in Item 19.
22. Number of departures to the same destination airport in the previous 15-minute interval with respect to time of day.
23. Average taxi-out delay of departures in seconds to the same destination airport in the previous 15-minute interval with respect to time of day. Taxi-out delay is computed in the same way as in Item 19.
24. Number of departures from all gates in the previous15-minute interval with respect to the time of day.
25. Number of takeoffs from all runways in the previous15-minute interval with respect to the time of day.
26. Number of arrivals at all gates in the previous15-minute interval with respect to the time of day.
27. Number of landings on all runways in the previous15-minute interval with respect to the time of day.
28. Time of day in 15-minute interval such that the scheduled gate-out time is within this time interval. Time is given in the same format as Item 2 of this list. Observe that Item 2 is with reference to actual gate-out time while Item 28 is with respect to scheduled gate-out time.
29. Number of departures on the surface at the scheduled gate departure time. Similar to Item 16 except at scheduled, not actual, gate departure time.
30. Number of arrivals on the surface at the scheduled gate departure time. Similar to Item 17.

31. Average taxi-out delay of departures from the same runway as this flight in the previous 15-minute interval with respect to time of day. Taxi-out delay is computed in the same way as in Item 19.
32. Average taxi-out delay of departures through the same departure fix in the previous 15-minute interval with respect to time of day. Taxi-out delay is computed in the same way as in Item 19.
33. Average taxi-out delay of departures to the same destination airport in the previous 15-minute interval with respect to time of day. Taxi-out delay is computed in the same way as in Item 19.

Note that the variables 29 through 33 are with reference to time of day related to the scheduled gate departure time. The other variables are with respect to the actual gate departure time. While some variables, such as 16 and 17, are with respect to the actual gate departure time, most variables are with respect to a broader interval of the time of day. Many variables, such as 1 and 3-15 are flight specific. Other variables like 16-23 and 29-33 are aggregate metrics based on other flights. Additionally, variables like 18-27 and 31-33 are based on aggregate metrics in the 15-minute time interval just prior to either the actual gate departure time or the scheduled gate departure time. It is assumed that these variables can be computed with flight plan data and Out-Off-On-In (OOOI) data provided by airlines available in the current air traffic system. Aggregate metrics 24-27 consider traffic to and from all gates and runways. Thus, they represent general state of airport operations. Time of day variables 2 and 28 are used for relating variables derived from the SMS logs and ASPM data. Variables based on ASPM data are discussed next.

ASPM Data

Federal Aviation Administration's (FAA) Aviation System Performance Metrics (ASPM) database, which is accessible on the web for authorized users, provides detailed data on flights to and from the 77 major U. S. airports (ASPM 77 airports) and flights operated by 29 major carriers (ASPM 29 carriers). Flights operated by ASPM carriers to international and domestic non-ASPM airports are also included. ASPM database also contains information on airport weather, runway configuration, and arrival and departure rates. Data in ASPM provide insight into air traffic and air carrier activity. FAA uses these data for monitoring airport efficiency, aspects of system performance, and retrospective trend analysis studies.

Two different reports were extracted from the ASPM database for Dallas-Fort Worth airport operations spanning the period of 7 August 2011 through 13 August 2011. The first report, "Daily Weather by Quarter Hour Report," provided weather (visual meteorological condition or instrument meteorological condition), ceiling in feet, visibility in statute miles, temperature in degrees Fahrenheit, wind angle in degrees, wind speed in knots, arrival/departure runway configuration, airport departure rate and airport arrival rate in fifteen minute intervals as a function of local time. The second report, "Analysis By Airport By Quarter Hour Report (compared to flight plan)," includes numbers of scheduled departures/arrivals and departures/arrivals used for metric computation, percentages of on-time gate departures, airport departures and gate arrivals, average gate departure delay, average taxi-out time, average taxi-out delay, average airport departure delay, average taxi-in delay, and average gate arrival delay. Times and delays are in minutes. Numbers of scheduled arrivals and departures are based on carrier published schedules. Numbers of arrivals and departures for metric computation are based on itinerant flights to/from the ASPM 77 airports or operated by one of the ASPM 29 carriers. General aviation and military flights are excluded. Percent on-time gate departures is computed as the ratio of the number of flights that departed within 15-minutes past the flight plan gate-out time to the number of departures for metric computation. Percent on-time airport departures is given as the ratio of the number of flights that departed within 15-minutes past the flight plan wheels-off time to the number of departures for metric computation. Percent on-time gate arrivals is determined as the ratio of the number of flights that arrive at the gate less than 15-minutes late compared to the flight plan gate-out time plus the scheduled block time to the total number of arrivals for metric computation. Taxi-out/taxi-in delay is the difference between taxi-out/taxi-in time and unimpeded taxi-out/taxi-in time. Airport departure delay is computed as the difference between the actual wheels-off time and the sum of flight plan gate-out time and unimpeded taxi-out time. Average gate arrival delay is determined by adding minutes of gate arrival delay of one-minute or more, and dividing it by number of arrivals for metric computation. Gate arrival delay is defined as the difference between the actual gate-in time and the flight plan gate-in time. ASPM data from the two reports were processed to determine the following:

1. Time of day in 15-minute intervals in hours and minutes format with respect to 00:00 local time.
2. Meteorological condition- Visual Meteorological condition (VMC) or Instrument Meteorological Condition (IMC).
3. Visibility in statute miles.
4. Temperature in degrees Fahrenheit.
5. Wind angle in degrees.
6. Wind speed in knots.
7. Runway configuration indicating runways used for arrivals and runways used for departures.

8. 15-minute airport departure rate set by air traffic control.
9. 15-minute airport arrival rate set by air traffic control.
10. Average gate departure delay in the previous 15-minute interval with respect to the time of day.
11. Average taxi-out delay in the previous 15-minute interval with respect to the time of day.
12. Average taxi-in delay in the previous 15-minute interval with respect to the time of day.
13. Average gate arrival delay in the previous 15-minute interval with respect to the time of day.

The first 9 items are measured and directly available at the tower. The remaining four items can be calculated based on flight plan and OOOI data.