Predicting Block Time: An Application of Quantile Regression

by Tony Diana

Airlines face three types of delay that make it difficult to build robust schedules and to support block time predictability. Block time is the time elapsed from gate departure to gate arrival and refers to the time when blocks are off the wheels at the departure airport to the time they are back on at the destination airport. These delays can be induced (i.e., ground delays), propagated, or stochastic. With capacity constrained at major airports and regulators facing greater public pressure to alleviate congestion and tarmac delays, aviation practitioners have renewed their interest in the predictability of block time. This study presents a methodology based on the case study of the Seattle/Tacoma International (SEA) and Oakland International airport (OAK) city pair to determine the predictability of block time. The methodology based on quantile regression models is appropriate for a skewed distribution where analysts are interested in the impact of selected operational variables on the conditional mean of block times at given percentiles. Quantile regression provides a measure of on-time performance based on the percentile results that show the most significance and best fit.

INTRODUCTION

Block time refers to the time that an aircraft spends from gate departure to gate arrival. Pilots are usually paid on the basis of "lock time or better," meaning the greater of scheduled or actual gate-to-gate time. Actual block time depends on external factors such as available airport capacity, ground surface congestion, en route delays, weather events, air traffic control delays, and airline operational issues, among others. To minimize the impact of these unanticipated conditions, airlines have some incentive to pad their schedules so as to make on-time performance look better. The padding is all the more important as U.S. airlines schedule for good weather condition (visual meteorological conditions) compared with European airlines that take into account reduced capacity (instrument meteorological conditions) and whose traffic at large hubs is slot-constrained. Airlines often use on-time performance as an important marketing argument to attract passengers. Both on-time performance and the causes of delay are published monthly by the Bureau of Transportation Statistics[1] (BTS) in the Airline Service Performance Quality (ASQP) report. Therefore, scheduled block time is often construed as a measure of passenger experience.

This article proposes a methodology to determine the predictability of block time based on the case study of the Seattle-Oakland city pair. The proposed methodology relies on quantile regression to determine how some selected operational variables are likely to affect actual block times at different percentiles. This is of importance to aviation practitioners and, especially, airline schedulers who have often resorted to schedule padding to make up for ground and en route delays.

Predictability is all the more difficult to achieve as airlines often face three types of delay. First, delays can be induced: The Federal Aviation Administration (FAA) can initiate a ground delay program in case of adverse weather conditions or heavy traffic volume on the ground or en route. These delays are reported by air carriers as National Airspace System (NAS) delay when non-extreme weather conditions or airspace/airport conditions prevent on-time operations. Second, delays can be propagated; in a sequence of legs operated by the same tail-numbered aircraft, a flight may accumulate delays that cannot be recovered by the end of an itinerary. These delays are usually reported as late arriving aircraft delays. Finally, delays can be stochastic because they are the results of random events such as equipment breakdown or crew problems (air carrier-related delays), security, or an extreme weather event.

Predictability represents an important key performance indicator in the aviation industry for several reasons.

- For the International Civil Aviation Organization (ICAO), predictability refers to the "ability of the airspace users and ATM [Air Traffic Management] service providers to provide consistent and dependable levels of performance." [2] Air Traffic Management (ATM) services can be public agencies such as the FAA or a private non-share capital corporation, such as NavCanada. The fundamental mission of ATM is to ensure flight safety by enforcing separation between aircraft.
- One of the goals of the U.S. Next Generation of Air Transportation System (NextGen) is to foster the transition from an air traffic control to more of an air traffic managed system where pilots have more flexibility to select their routes, utilize performance-based navigation (PBN), and make decisions based on automated information sharing. Performance-based navigation refers to either required navigation performance (RNP) when navigation entails on-board performance monitoring and alerting or area navigation (RNAV) when there are no requirements for monitoring and alerting. PBN procedures enable aircraft to fly more efficient arrival and departure trajectories not previously available due to the constraints of ground-based navigation aids such VHF omnidirectional radio range.[3] PBN makes it possible for aircraft to operate at airports that are difficult to access because of surrounding terrain or airspace congestion. Presently, it is very difficult to assess the impact of NextGen-related technologies on flight performance because surveillance data do not account for the difference between the use of required navigational performance and instrument landing systems (ILS) when flight tracks for both types of procedure overlay, for instance. Surveillance data are generated by radar such as the Traffic Flow Management System data.
- According to Rapajic (2009), "cutting five minutes off average of 50% of schedules thanks to higher predictability would be worth some €1,000 million per annum, through savings or better use of airlines and airport resources." Unpredictability imposes considerable costs on airlines in the forms of lost revenues, customer dissatisfaction, and potential loss of market share.

Recently, much discussion has revolved around the validity of using airlines' schedules as a measure of on-time performance and the variance of block delay as an indicator of predictability. Both airlines' limited control over the three types of delay and airport congestion make it difficult to build robust schedules. In this discussion, the predictable block time is located at the percentile where the sign and magnitude of the pseudo coefficient of determination (a measure of goodness of fit) is the highest with all the explanatory variables significant at a given confidence level. Ordinary Least Square (OLS) regression models enable analysts to evaluate the percentage of variation in actual block time explained by changes in selected operational variables. However, quantile regression is more robust to outliers than the traditional OLS regression because the latter does not focus on the conditional mean. The attributes of quantile regression will be addressed later in the discussion.

This article presents a different perspective on the study of predictability with the intent of helping aviation practitioners achieve the following objectives:

- To assess the impact of selected independent variables at different locations of the distribution of block delays in order to anticipate block time based on selected operational variables.
- To derive more predictable block times based on the impact of operational independent variables at various percentiles.
- To test a model without any assumption about the distribution of errors and homoscedasticity.

After a brief background, the discussion will proceed with the methodology, an explanation of the outcomes, and, eventually some final comments.

BACKGROUND

There has been much discussion recently about the impact of schedule buffers and their reliability as a tool to measure airline or even the National Airspace System (NAS) performance. Constructing robust schedules is important for an airline because they support profitability. Lohatepanont and Barnhart (2004) focused on fleet assignment to determine where and when flights should be offered and what type of equipment should be used to maximize profits.

Wu (2005) highlighted the difference between the real operating delays, the inherent delays (from simulation) and the zero-delay scenario. The reliability is also affected by delay propagation when an aircraft accumulates delays over a series of legs that cannot be recovered at the end of the total trip. Wu (2005) recommended that airlines integrate buffers in their schedule in a way that strengthens reliability. This article provides a methodology that evaluates the effect of selected operational variables on block time in order to support more reliable schedules.

Lan et al. (2006) proposed two methodologies to minimize passenger disruptions and achieve robust scheduling based on aircraft routing and retiming flight departure times. The purpose of their research was to identify ways to minimize passenger disruption and minimize delay propagation through mixed integer programming. The disadvantage of such methodology is that it does not take into consideration the impact of key operational variables on block time that includes ground movement operations and flight time.

Robust airline scheduling is the outcome of four sequential tasks, including schedule generation, fleet assignment, aircraft routing, and crew pairing/rostering (Wu 2010, Abdelghany and Abdelghany 2009). Fleet assignment models (FAM) are often used to determine how demand for air travel is met by available fleet (see Abara 1989 and Hane et al. 1995). Moreover, the fleet assignment models present two challenges: complexity and size of the problem that the FAM can handle.

Rapajic (2009) identified network structure and fleet composition as sources of flight irregularities. Wu (2010) provided an excellent exposition of issues related to delay management, operating process optimization, and schedule disruption management. Wu (2010) explained that "airline schedule planning is deeply rooted in economic principles and market forces, some of which are imposed and constrained by the operating environment of the [airline] industry." He presented a schedule optimization model to improve the robustness of airline scheduling. However, such a model does not consider how selective operational variables are likely to impact scheduling.

Morrisset and Odoni (2011) compared runway system capacity, air traffic delay, scheduling practices, and flight schedule reliability at 34 major airports in Europe and the United States from 2007 to 2008. The authors explained that European airports limit air traffic delay through slot controls. The other difference is that declared capacity (therefore, the number of available slots) is based mainly on operations under instrument meteorological conditions. In Europe, slot refers to a time window when a flight is scheduled to depart. By not placing restrictions on the number of operations, schedule reliability in the United States is all the more dependent on weather conditions as European airports.

METHODOLOGY

The Sample and the Assumptions

The sample includes daily data for the months of June to August in 2000, 2004, 2010, and 2011 for the Seattle/Tacoma International (SEA)-Oakland International (OAK) city pair. The summer season is usually characterized by low ceiling and visibility that determine instrument meteorological conditions and weather events such as thunderstorms—all likely to skew the distribution of block times.

Figures 1 to 4 show the shape of the distribution for each summer and provides some key statistics. The skewness coefficients are 0.11, -0.44, 0.37, and 0.19 respectively for summer 2011, 2010, 2004, and 2000. A negative skew indicates that the left tail is longer. While the standard deviation is appropriate to measure the spread of a symmetric distribution, interquartile ranges are more indicative of spread changes in skewed distributions. The Jarque-Bera statistic indicates whether the data are from a normal distribution. A normal distribution has an expected skewness and kurtosis of zero. A small probability value implies the rejection of the null hypothesis (H0: the distribution is normal).

Figure 1: Histograms of Block Time
(Counts of Flights by Average Minutes of Block Time, June-August 2011)

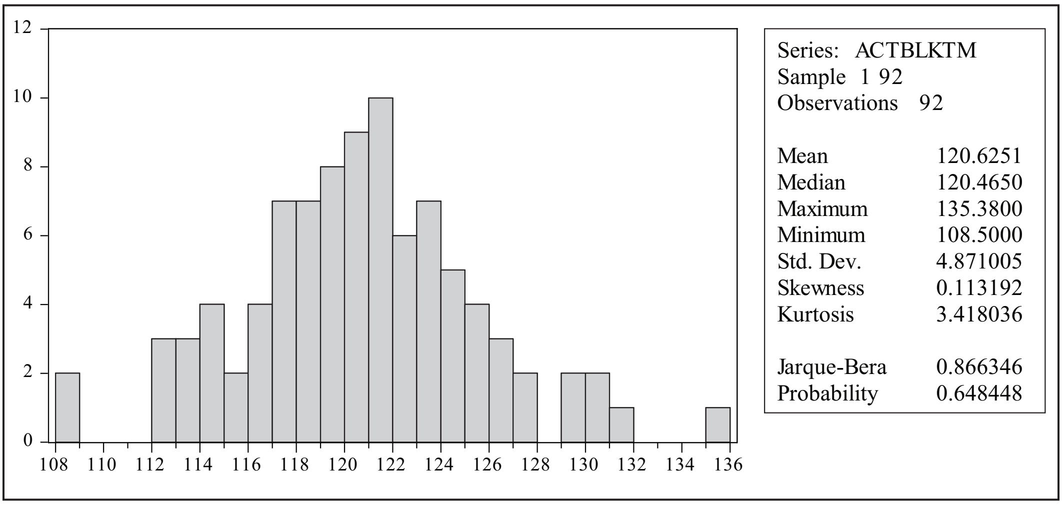


Figure 2: Histograms of Block Time
(Counts of Flights by Average Minutes of Block Time, June-August 2010)

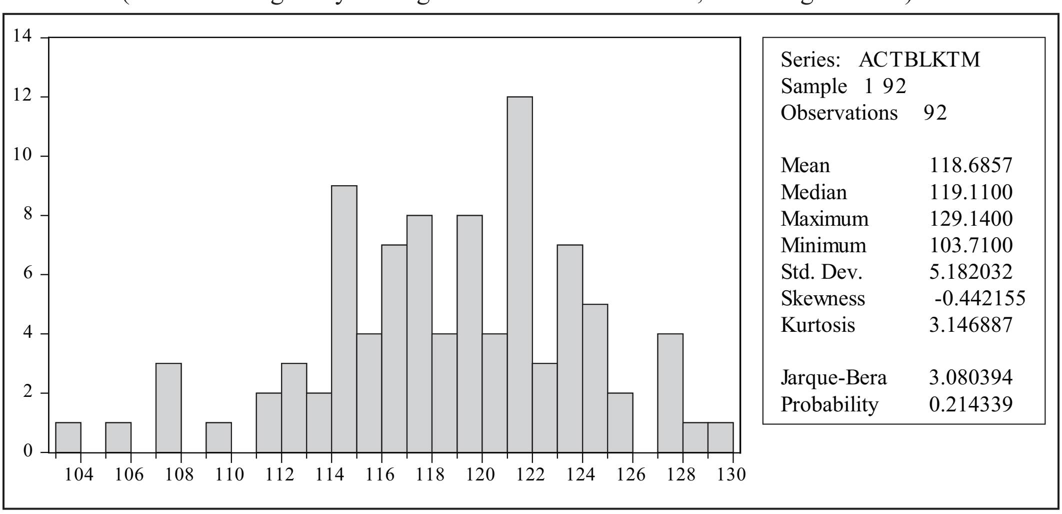


Figure 3: Histograms of Block Time
(Counts of Flights by Average Minutes of Block Time, June-August 2004)

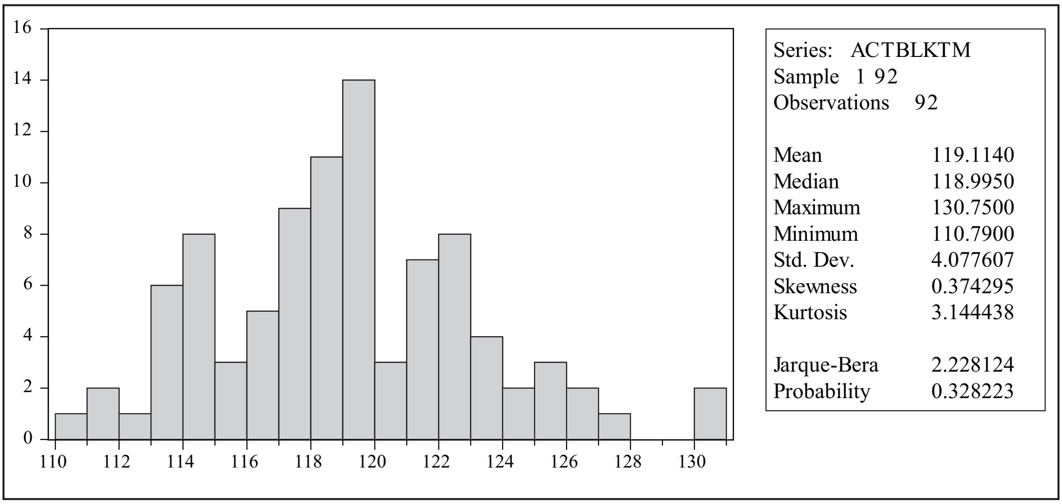


Figure 4: Histograms of Block Time
(Counts of Flights by Average Minutes of Block Time, June-August 2000)

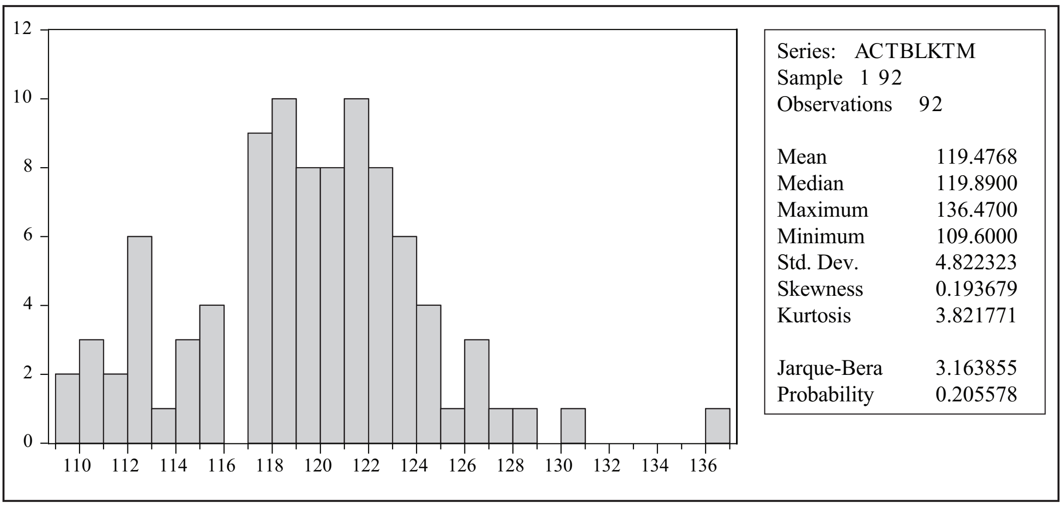
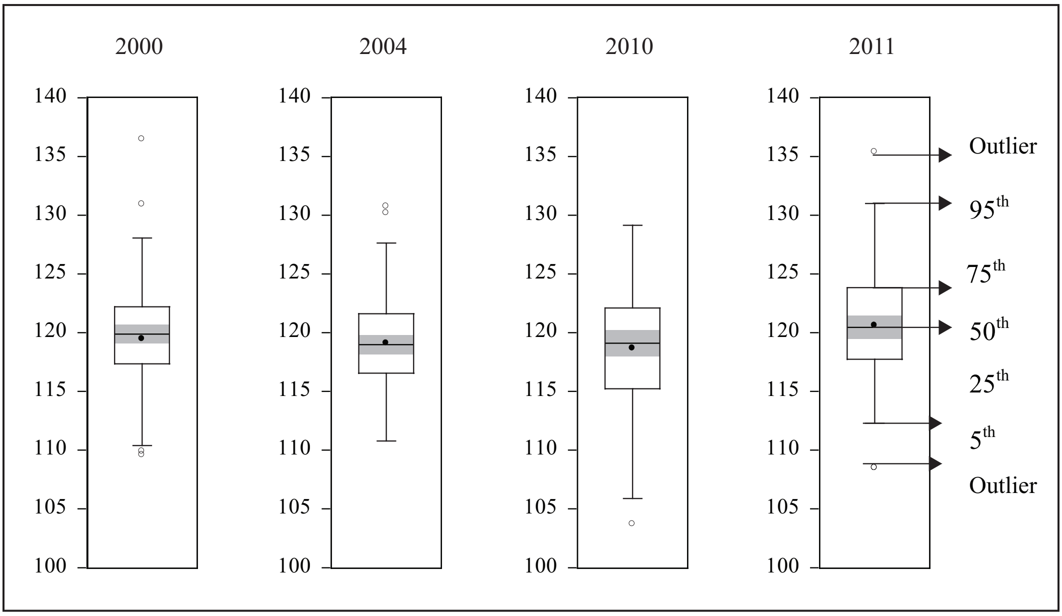


Figure 5 compares the boxplots of actual block times in minutes for the four summers under investigation. The boxplot shows the spread of the distribution, the selected quantile values, the position of the mean and median block times, and the presence of outliers that make it important to consider a regression model at different quantiles. The boxplots reveal an increase in the actual block times between summer 2004 and 2011. Summer 2010 features the largest range as well as the lowest block times at the 5th percentile among the four samples. It is also characterized by the highest proportion of operations in instrument meteorological conditions compared with the other three samples (Table 1).

Secondly, summer is part of the high travel season when demand is usually at its peak. This, in turn, is likely to increase airport and en route congestion and subsequently impact block time. Finally, the years were selected to account for the following conditions: (1) pre- and post-September 11, 2001, traffic, (2) lower traffic demand resulting from the 2008-2009 economic recession, and

Figure 5: Boxplots of Actual Block Time (June - August, in Minutes)



Note: The black dot represents the mean

(3) the introduction of the Green Skies over Seattle after 2010. It is an airline industry-wide initiative (i.e. airline, airport, aircraft manufacturer and FAA) designed to maximize performance-based navigation through the use of satellite navigation in order to ensure more direct and optimized landing approaches.

In Table 1, although the number of flights decreased between 2000 and 2011 and the average minutes of expected departure clearance times (EDCT) were higher in 2011 than in 2000, the percentage of on-time gate departures and arrivals and other key delay indicators such as taxi-out delay (a measure of ground congestion) improved in 2011. It is interesting to point out that the percentage of flights in IMC did not change significantly at OAK among the four selected summers. IMC operations were, however, much higher in 2010 and 2011 than in 2000 at SEA, which may explain the existence of average minutes of EDCT in 2010 and 2011.

The sample does not include a variable that measures performance-based navigation. The available surveillance data such as Traffic Flow Management System (TFMS) do not capture whether a pilot had requested a required navigation performance procedure, whether air traffic control had granted the request, and whether the procedure had actually been implemented. Surveillance data refer to information generated by radars. Moreover, it is presently difficult to differentiate flown performance-based navigation procedures from instrument landing system (ILS) approaches in the case of flight track overlay.

Secondly, the availability of Q-routes makes it possible for RNAV/RNP capable aircraft to reduce mileage, to minimize conflicts between routes (especially in a congested airspace such as the San-Francisco/Oakland area), and to maximize high-altitude airspace. The Q-routes are en route high altitude RNAV airways identified by a Q number. For instance, the great circle route between OAK and SEA is 584 nautical miles. The Q5 between the two airports is 523 nautical miles. Q-routes are designed to reduce flight distance and travel time between a city pair. They are available for use by RNAV/RNP capable aircraft between 18,000 feet MSL (mean sea level) and FL 450 inclusive (flight level 45,000 feet). Q-routes help minimize mileage and reduce conflicts between routes.

Table 1: Performance Metrics for the SEA-OAK City Pair

SEA-OAK	**Flight Count**	**% On-Time Gate Departures**	**% On-Time Airport Departures**	**% On-Time Gate Arrivals**	**Arrivals With EDCT***	
2000	1,411	76.26	67.54	77.18	0	
2004	1,473	73.52	68.30	79.16	0	
2010	1,147	91.63	85.27	92.85	1	
2011	1,196	93.73	90.64	94.90	1	
SEA-OAK	**Average EDCT Where EDCT>0**	**Gate Departure Delay (min)**	**Taxi Out Delay (min)**	**Average Taxi Out Time (min)**	**Airport Departure Delay (min)**	
2000	0	9.07	4.48	14.29	12.83	
2004	0	11.03	3.49	12.80	13.84	
2010	94	4.48	3.01	13.34	6.97	
2011	104	3.83	2.79	13.03	5.92	
SEA-OAK	**Airborne Delay (min)**	**Taxi In Delay (min)**	**Block Delay (min)**	**Gate Arrival Delay (min)**	**Percent IMC** SEA**	**Percent IMC** OAK**
2000	4.33	0.95	2.61	9.23	10.58	29.49
2004	6.93	1.22	1.44	9.26	8.33	29.71
2010	5.05	0.50	1.67	3.76	30.29	29.86
2011	3.92	0.70	1.90	3.24	22.83	29.78

* In the event of a ground delay, airlines are issued an expected departure clearance time (EDCT).
Flights held by FAA at the departure airport due to problems at the arrival airport.
EDCT hold delay is computed by comparing EDCT wheels-off time to the flight plan's wheels-off time.
** Instrument Meteorological Conditions
Performance is compared with the last flight plan filed before take-off.

Source: FAA, Aviation System Performance Metrics

Thirdly, block time as a measure of gate-to-gate performance is sensitive to delays on the ground and en route. To account for this, airborne delay represents a surrogate for en route congestion, while increases in taxi times imply surface movement congestion.

Sources and Definition of the Variables

The sources for the variables are ARINC's[4] Out-Off-On-In times and the FAA's Traffic Flow Management System (TFMS). The directional city pair data originated from the "En Route" and "Individual Flights" sections of FAA's Aviation System Performance Metrics data warehouse.[5]

The choice of variables reflects operational and statistical considerations. On the one hand, some model variables represent core factors in airport congestion (taxi times) and en route performance (airborne delays). On the other hand, the model with the highest values for the Akaike Information Criterion (AIC)[6] and Bayesian Information Criterion (BIC)[7] was selected in order to prevent overfitting and to reduce the number of explanatory variables.

The dependent (response variable) and independent variables (also called covariates in the literature on quantile regression) are defined as follows:

- ***Actual Block Time*** (ACTBLKTM) is the dependent variable. It refers to the time from *actual* gate departure to *actual* gate arrival.
- ***Block Buffer*** (BLKBUFFER) represents the difference between planned and optimal block time.[8] The latter is the sum of unimpeded taxi-out times and filed estimated time en route. Block buffer is the additional minutes included in planned block time in order to take into account potential induced, propagated, and stochastic delays. According to Cook (2007), the block buffer is "the additional time built into the schedule specifically to absorb delay whilst the aircraft is on the ground and to allow recovery between the rotations of aircraft." Donohue et al. (2001) explained that "to obtain their desired on-time performance, airlines will add padding into a schedule to reflect an amount above average block times to allow for delay and seasonally experienced variations in block times."
- ***Departure Delay*** (DEPDEL) corresponds to difference between the actual and planned gate departure time at the departure airport in a city pair.
- ***Arrival Delay*** (ARRDEL) refers to the difference between the actual and planned gate arrival time at the arrival airport in a city pair.
- ***Airborne Delay*** (AIRBNDEL) accounts for the total minutes of airborne delay. It is the difference between the actual airborne times (landing minus take-off times) minus the filed estimated time en route.
- ***Taxi-Out Time*** (TXOUTTM) refers to the duration in minutes from gate departure to wheels-off times.

The dependent variables except block buffer represent some key flight operations likely to impact block time adversely as they increase. As taxi time increases, take-off is delayed; the airport may experience congestion, and block times may increase.

Quantile Regression

Quantile regression is a type of regression that makes it possible to study the relationship between an independent and dependent variables at different percentiles of the dependent variable distribution. This is all the more important as the distribution is skewed. Quantile regression features several advantages compared with the traditional ordinary-least-square (OLS) regression in assessing the influence of selected operational factors on the variations of block time at various locations of its distribution:

- Quantile regression specifies the conditional quantile function. It permits the analysis of the full conditional distributional properties of block delays as opposed to OLS regression models that focus on the mean.
- It defines functional relations between variables for all portions of a probability distribution. Quantile regression can improve the predictive relationship between block times and selected variables by focusing on quantiles instead of the mean. As Hao and Naiman (2007) pointed out, "While the linear regression model specifies the changes in the conditional mean of the dependent variable associated with a change in the covariates, the quantile regression model specifies changes in the conditional quantile."
- It determines the effect of explanatory variables on the central or non-central location, scale, and shape of the distribution of block times.
- It is distribution-free, which allows the study of extreme quantiles. Outliers influence the length of the right tail and make average block time irrelevant as a standard for identifying the best-possible block time. A single rate of change characterized by the slope of the OLS regression line cannot be representative of the relationship between an independent variable and the entire distribution of block time. In the quantile regression, the estimates represent the rates of change

conditional on adjusting for the effects of the other model variables at a specified percentile. Therefore, the skewed distribution of block times calls for a more robust regression method that takes into account outliers or the lack of sufficient data at a particular percentile (especially at the extremes of the distribution) and generates different slopes for different quantiles.

OUTCOMES AND IMPLICATIONS

The estimates as well as the key regression outputs at the 5th, 25th, median, 75th, and 95th percentile are summarized in Table 2. The 50th quantile estimates can be used to track changes in the location of the median from the lowest to highest observed values of block times. According to Hao and Naiman (2007), the 5th and 95th percentiles "can be used to assess how a covariate predicts the conditional off-central locations as well as shape shifts of the response." The shape shift refers to a movement of the mean (location on the X-axis) due to the presence of outliers. Based on the graphs in Appendix 1, the coefficient estimates show a positive relationship between the quantile value and the estimated coefficients at higher percentiles for scheduled block times, taxi out times, and airborne delay.

If we take the example of the 50th percentile in summer 2011, the quantile regression model for at $\tau = 0.50$ (50th percentile) is as follows:

(1) $\text{Block Time}_{\tau = 0.50} = -0.9105{*}X_{BLKBUFFER} + 0.8888{*}X_{SCHEDBLKTM} - 0.3090{*}X_{DEPDEL}$

$+ 0.2702{*}X_{ARRDEL} + 1.1015{*}X_{AIRBNDEL} + 1.1372{*}X_{TXOUTTM} + \varepsilon$

In equation (1), 1.1372 represents the change in the median of block time between SEA and OAK corresponding to a one minute change in taxi-out time at SEA. Since the p value is zero, we reject the null hypothesis, at a 95% confidence level, that taxi-out times at SEA have no effect on the median block time between SEA and OAK in summer 2011. The pseudo coefficient of determination is a goodness-of-fit measure.[9]

Overall, summer 2011 is the only period when all the independent variables have a significant effect on block times at all the considered percentiles. Remarkably, block buffer, scheduled block time, departure, arrival and airborne delays, as well as taxi-out times are significant at the 95th percentile, at a 95% confidence level, in summer 2011, 2010, 2004, and 2000. This suggests that the difference between actual and planned departure and arrival times are more likely to have an incidence on the conditional mean of block times at the highest percentile as a result of taxi-out delays and surface area movement congestion. Moreover, the magnitude of block buffer and departure delays have a negative impact on the conditional mean of block time for all samples at all selected percentiles. This calls for airline schedulers to understand the reasons for the gap between planned and actual block time and for airport analysts to evaluate the times and conditions when departure operations are delayed.

The results imply that arrival and departure delays have a significant impact on block times at the 95th percentile for all years and at all the percentiles in 2011. Arrival and departure delay imply that an aircraft departed or arrived later than the time filed by the pilot in the last flight plan before take-off. This may be due to ground stops when traffic volume or weather requires departures to be delayed. While the average minutes of EDCT were zero in 2000 and 2004, they increased from 94 in 2010 to 104 in 2011 (Table 1). However, the magnitude of the sparsity value is important to evaluate the relevance of the impact of the independent variables on block time. Sparsity refers to the density of data at a given percentile level. A low value indicates that there are many observations near the quantile. For instance, there were few observations around the 5th percentile (12.64) in summer 2011 than at the other percentiles: The sparsity values were 2.40, 2.27, 2.69, and 4.88 respectively for the 25th, 50th, 75th, and 95th percentiles.

Table 2 shows that 95% of the distribution of block times between SEA and OAK was below 129.14 minutes in the June-to-August time period based across the samples. While the standard distribution is appropriate to measure the spread of a symmetric distribution, interquartile ranges are more indicative of spread changes in skewed distributions. One benefit of quantile regression is that it facilitates the evaluation of scale and magnitude changes across samples and percentiles.

In a comparison of summer 2000 with summer 2011, there has been an increase of 2.21 minutes in block times at the 95th percentile. The SEA-OAK city pair has been mainly operated by Southwest Airlines (SWA) and Alaska Airlines (ASA) with a fleet of Boeing 737s. It was not possible to separate the types of aircraft in the ASPM block en route city pair data that were used for this study. However, based on scheduled data in the Official Airline Guide (OAG) and Innovata, the total number of ASA operations declined to 356 in summer 2011 from 693 in summer 2000, while 91 flights were operated by Horizon's Bombardier Q400 (capable of RNAV/RNP-capable) on behalf of ASA. Nevertheless, ASA operated larger capacity aircraft such as the dash 400, 800, and 900 series, while SWA utilized a combination of dash 300, 500, and 700 aircraft.

The reason for the increase in block time may be attributed to airlines' corporate policy to slow down aircraft speed in order to save on fuel costs and not to large differences in aircraft type (turboprop versus jet aircraft). Based on schedule data, Horizon's Q400's represented a small proportion of the overall traffic between SEA and OAK. Weather conditions characterized by the percentage of operations in instrument meteorological conditions (IMC) did not vary substantially at OAK: It was, respectively, 29.78, 29.86, 29.71, and 29.49% in summer 2011, 2010, 2004, and 2000. At SEA, the percentages were, respectively, 22.83, 30.29, 8.33, and 10.58% during the same time periods (Table 1). Finally, although the use of RNAV/RNP may lengthen the path to the runway, it plays an instrumental role in de-conflicting approaches and departures at neighboring airports, thus minimizing their mutual impact on block times.

CONCLUSION

Predictability is a key performance area identified by the International Civil Aviation Organization. Moreover, it is a cornerstone of the Next Generation of Air Transport System (NextGen) initiatives in the U.S. to ensure the transition from an air traffic controlled to a more air traffic managed environment. As air transportation regulators are under public pressure to crack down on tarmac and other types of delays, it has become imperative for airline schedulers to evaluate models that reflect the influence of key operational variables on actual performance. The complexity of the air traffic system, the inability of airline schedulers to fully anticipate both airport and en route congestion, and the imbalance between travel demand and capacity that results in delay all make it more significant for aviation practitioners to assess the impact of operational variables at different locations of the distribution of block times.

Based on the analysis of the SEA-OAK city pair case study, this article showed how quantile regression can help aviation practitioners develop more robust schedules. First, it enables aviation analysts to consider the impact of explanatory variables at different locations of the distribution of block times. Secondly, the significance of the selected variables and the strength of the impact of selected independent variables on block times make it possible to assess the probability that gate-to-gate operations are likely to reach a specific duration. This is made possible by looking at the conditional mean in the case of quantile regression as opposed to the mean of the distribution of block times in the case of OLS models. Thirdly, quantile regression makes it easier to evaluate the scale and magnitude of changes across specific percentiles over a sample. Finally, quantile regression can help analysts study the impact of explanatory variables from different perspectives. In the present case, the quantile regression models focused on constraining factors such as airborne, departure, and arrival delays on the conditional means of block times, which explains the identification of the 95th

Table 2: The Quantile Regression Outputs

Alpha = .95	2011		2010		2004		2000	
	Coefficient	Probability	Coefficient	Probability	Coefficient	Probability	Coefficient	Probability
5th Percentile								
BLKBUFFER	-0.7594	0.0000	-1.0083	0.0000	-0.9693	0.0000	-0.9904	0.0000
SCHEDBLKTM	0.9263	0.0000	0.9006	0.0000	0.9316	0.0000	0.9051	0.0000
DEPDEL	-0.7318	0.0000	-0.0404	0.3929	-0.0448	0.5115	-0.0616	0.5885
ARRDEL	0.7623	0.0001	0.0788	0.1598	0.0621	0.4139	-0.0131	0.9229
AIRBNDEL	0.7751	0.0000	1.0951	0.0000	0.8766	0.0000	1.2568	0.0000
TXOUTTM	0.5935	0.0127	1.0119	0.0000	0.9374	0.0000	1.0042	0.0000
Pseudo R-squared	**0.7014**		**0.8893**		**0.8878**		**0.8758**	
Adjusted R-squared	0.6841		0.8829		0.8813		0.8686	
S.E. of regression	2.4713		1.0580		1.0013		1.3161	
Quantile dependent var	112.8600		107.5600		113.0000		110.9400	
Sparsity	12.6438		3.4399		2.8121		4.0616	
25th Percentile								
BLKBUFFER	-0.8525	0.0000	-1.0084	0.0000	-0.9134	0.0000	-0.8522	0.0000
SCHEDBLKTM	0.8916	0.0000	0.9066	0.0000	0.9253	0.0000	0.9230	0.0000
DEPDEL	-0.4393	0.0000	-0.0439	0.4714	-0.1207	0.1369	-0.1860	0.0400
ARRDEL	0.3976	0.0000	0.0411	0.6096	0.1134	0.1995	0.1727	0.0665
AIRBNDEL	1.1222	0.0000	1.0805	0.0000	0.9252	0.0000	0.9989	0.0000
TXOUTTM	1.0369	0.0000	1.0048	0.0000	0.9607	0.0000	0.8326	0.0000
Pseudo R-squared	**0.7694**		**0.8952**		**0.8753**		**0.8843**	
Adjusted R-squared	0.7560		0.8891		0.8680		0.8776	
S.E. of regression	1.2083		0.7264		0.7354		0.7577	
Quantile dependent var	117.7100		115.0000		116.5300		117.2100	
Sparsity	2.4094		1.8315		1.5958		1.8171	
50th Percentile								
BLKBUFFER	-0.9105	0.0000	-0.9907	0.0000	-0.9152	0.0000	-0.7903	0.0000
SCHEDBLKTM	0.8888	0.0000	0.9074	0.0000	0.9383	0.0000	0.9285	0.0000
DEPDEL	-0.3090	0.0275	-0.0187	0.8068	-0.1183	0.1299	-0.2783	0.0260
ARRDEL	0.2702	0.0398	-0.0170	0.8388	0.1205	0.1602	0.2709	0.0433
AIRBNDEL	1.1015	0.0000	0.9973	0.0000	0.7753	0.0000	0.9507	0.0000
TXOUTTM	1.1372	0.0000	1.0547	0.0000	0.9383	0.0000	0.7760	0.0000
Pseudo R-squared	**0.7994**		**0.8922**		**0.8631**		**0.8689**	
Adjusted R-squared	0.7877		0.8859		0.8551		0.8613	
S.E. of regression	1.1793		0.6220		0.6015		0.6263	
Quantile dependent var	120.4300		119.0000		118.9300		119.8600	
Sparsity	2.2739		1.4886		1.5010		1.7504	
75th Percentile								
BLKBUFFER	-0.8864	0.0000	-0.9900	0.0000	-0.9185	0.0000	-0.7780	0.0000
SCHEDBLKTM	0.9255	0.0000	0.9140	0.0000	0.9344	0.0000	0.9385	0.0000
DEPDEL	-0.3590	0.0340	-0.0885	0.3238	-0.0900	0.2008	-0.2509	0.0089
ARRDEL	0.3720	0.0402	0.0561	0.5520	0.1094	0.1546	0.2650	0.0144
AIRBNDEL	0.9501	0.0000	0.9861	0.0000	0.8565	0.0000	0.8778	0.0000
TXOUTTM	0.8492	0.0000	1.0249	0.0000	0.9496	0.0000	0.7251	0.0000
Pseudo R-squared	**0.8138**		**0.8954**		**0.8548**		**0.8695**	
Adjusted R-squared	0.8030		0.8893		0.8464		0.8619	
S.E. of regression	1.4336		0.7203		0.6748		0.7868	
Quantile dependent var	123.8000		121.9200		121.6000		122.1500	
Sparsity	2.6969		1.6380		1.9727		2.0322	
95th Percentile								
BLKBUFFER	-0.8970	0.0000	-0.9377	0.0000	-0.7299	0.0000	-0.6846	0.0000
SCHEDBLKTM	0.9308	0.0000	0.9097	0.0000	0.9750	0.0000	0.9456	0.0000
DEPDEL	-0.3469	0.0108	-0.2347	0.0023	-0.3725	0.0002	-0.3753	0.0000
ARRDEL	0.4219	0.0047	0.2056	0.0127	0.3844	0.0001	0.4111	0.0000
AIRBNDEL	0.6948	0.0000	1.0246	0.0000	0.6003	0.0000	0.7797	0.0000
TXOUTTM	0.9168	0.0000	1.0483	0.0000	0.5678	0.0000	0.6431	0.0000
Pseudo R-squared	**0.8430**		**0.8986**		**0.8761**		**0.9103**	
Adjusted R-squared	0.8339		0.8927		0.8689		0.9051	
S.E. of regression	1.9295		1.0992		1.2589		1.1371	
Quantile dependent var	129.1400		127.4300		126.0600		126.9300	
Sparsity	4.8819		3.2418		3.6042		3.4603	

Not significant at $\alpha = .95$

percentile optimal values as the expected block time given the impact of the explanatory variables and the strength of the pseudo R-square.

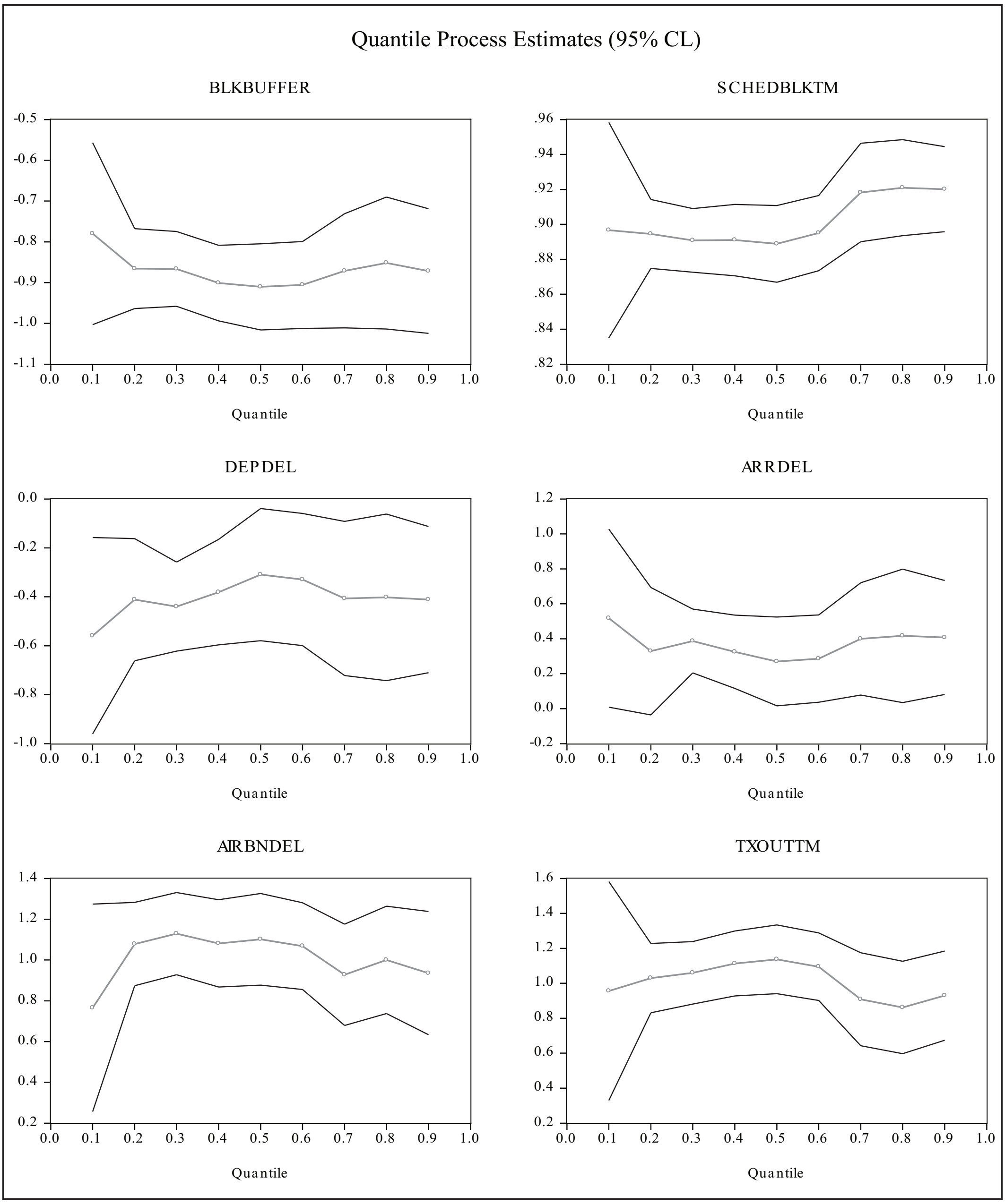
The results suggest that the impact of the dependent variables on block time is holding more consistently at the higher percentile. As a measure of gate-to-gate performance, block time depends on the variability of taxi times. Traffic volume and weather events that can trigger ground delay programs make it more difficult for airlines to predict block times. In fact, the average Expected Departure Clearance Time (EDCT) for the arrivals having an EDCT delay increased from 94 to 104 minutes between summer 2010 and 2011. As the percentage of operations in instrument meteorological conditions did not vary at OAK, it was more variable at SEA. Moreover, while the use of precision approach to OAK has made it possible for RNAV/RNP capable aircraft to avoid airspace congestion around San Francisco, it is likely to increase flight time as aircraft must follow a specific path into OAK.

Although the quantile regression models could provide some indication as to the scale and magnitude of change, they would have benefited by measuring the impact of technical changes introduced by NextGen programs and initiatives between summer 2000 and summer 2011. However, the assessment of such changes requires that available surveillance data keep track of the use of procedures such as RNAV/RNP, optimal profile descents, among others.

Abbreviations

ARINC	Aeronautical Radio, Inc.
ASA	Alaska Airlines
AIC	Akaike Information Criterion
ASPM	Aviation System Performance Metrics
ASQP	Airline Service Quality Performance
ATM	Air Traffic Management
BIC	Bayesian Information Criterion
BTS	Bureau of Transportation Statistics
ICAO	International Civil Aviation Organization
ILS	Instrument Landing System
IMC	Instrument Meteorological Conditions
EDCT	Expected Departure Clearance Time
FAA	Federal Aviation Administration
FAM	Fleet Assignment Models
FL	Flight Level
MSL	Mean Sea Level
NAS	National Airspace System
NextGen	U.S. Generation Air Transportation System
OAG	Official Airline Guide
OLS	Ordinary Least Squares
PBN	Performance-Based Navigation
RNAV	Area Navigation
RNP	Required Navigation Performance
SWA	Southwest Airlines
TFMS	Traffic Flow Management System
VMC	Visual Meteorological Conditions

APPENDIX 1: QUANTILE PROCESS ESTIMATE GRAPHS (95% CONFIDENCE LEVEL)



The graphs show the 95% confidence intervals around the regression coefficients listed in Table 2 on the Y-axis and the different quantiles on the X-axis in the case of the June to August 2000 sample.

Endnotes

1. On-time performance and the causes of delay are reported by major carriers in the Airline Service Quality Performance report. There are five categories of delay: air carrier, extreme weather, National Airspace System, late arriving aircraft, and security. The information is available at http://www.bts.gov.

2. Hof, J. "Development of a Performance Framework in Support of the Operational Concept," *ICAO Mid Region Global ATM Operational Concept Training Seminar*, Cairo, Egypt, November 28–December 1, (2005): 36.

3. VHF Omni directional radio range (VOR) is a short-range radio navigation system that allows an aircraft to determine its position.

4. AIRINC stands for Aeronautical Radio, Inc. (http://www.arinc.com).

5. The TFMS (formerly ETMS) and ARINC data, as well as the ASPM delay metrics, are available at http://aspm.faa.gov.

6. The Akaike Information Criterion is defined as 2k – 2 ln(L) where k is the number of parameters and L the maximized value of the likelihood function for the estimated model.

7. The Bayesian Information Criterion is -2 ln(L) + k*ln(n) where n is the number of observations.

8. Block buffer in this paper is determined by the difference between block time based on the last flight plan before takeoff and optimal block time. Therefore, the relationship between block buffer and arrival delay is not as strong as if schedules were used as a benchmark.

9. See Koenker and Machado (1999) for further explanations.

References

Abara, J. "Applying Integer Linear Programming to the Fleet Assignment Problem." *Interfaces* 19 (4), (1989): 20-28.

Abdelghany, F. and K. Abdelghany. *Modeling Applications in the Airline Industry*. Ashgate Publishing Company, Burlington, Vermont, 2009.

Cook, A. *European Air Traffic Management: Principles, Practices, and Research*. Ashgate Publishing Company, Burlington, Vermont, 2007.

Donohue, G.L., A. Zellweger, H. Rediess, and C. Pusch. *Air Transportation System Engineering: Progress in Astronautics and Aeronautics*. American Institute of Aeronautics and Astronautics, Danvers, Massachusetts, 2001.

Federal Aviation Administration, *Aviation System Performance Metrics*, http://aspm.faa.gov.

Federal Aviation Administration, *Traffic Flow Management System*, https://aspm.faa.gov/tfms/sys/main.asp.

Hane, C.A., C. Barnhart, E.L. Johnson, R.E. Marsten, G.L. Nemhauser, and G. Sigismondi. "The Fleet Assignment Problem: Solving a Large Scale Integer Programming." *Mathematical Programming* 70 (2), (1995): 211-232.

Hao, L. and D. Q. Naiman. *Quantile Regression*. Sage Publications, Thousand Oaks, California, 2007.

Koenker, R. and J. Machado. "Goodness of Fit and Related Inference Processes for Quantile Regression." *Journal of the American Statistical Association* 94 (448), (1999): 1296-1310.

Lan, S., J.P. Clarke, and C. Barnhart. "Planning for Robust Airline Operations: Optimizing Aircraft Routing and Flight Departure Times to Minimize Passenger Disruptions." *Transportation Science* 40 (1), (2006): 15-28.

Lohatepanont, M. and C. Barnhart. "Airline Schedule Planning: Integrated Models and Algorithms for Schedule Design and Fleet Assignment." *Transportation Science* 38 (1), (2004): 19–32.

Morissett, T. and A. Odoni. "Capacity, Delay, and Schedule Reliability at Major Airports in Europe and the United States." *Transportation Research Record: Journal of the Transportation Research Board* 2214, (2011): 85-93.

Rapajic, J. *Beyond Airline Disruptions*. Ashgate Publishing Company, Burlington, Vermont, 2009.

Wu, C.L. *Airline Operations and Delay Management: Insights from Airline Economics, Networks and Strategic Schedule Planning*. Ashgate Publishing Company, Burlington, Vermont, 2010.

Wu, C.L. "Inherent Delays and Operational Reliability of Airline Schedules." *Journal of Air Transport Management* 11 (4), (2005): 273-282.

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