# Impact of Arrivals on Departure Taxi Operations at Airports

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**Aircraft taxi operations are a major source of fuel burn and emissions on the ground. Given rising fuel prices and growing concerns about the contributions of aviation to air pollution and greenhouse gas emissions, recent research aims to develop strategies to reduce fuel burn at airports. In order to develop such strategies, an understanding of taxi operations and the factors that affect taxi-out times is required. This paper describes an analysis of taxi-out times at two major U.S. airports in order to identify the primary causal factors affecting the duration of taxi-out operations. Through an analysis of departures out of John F. Kennedy International Airport and Boston Logan International Airport, several variables affecting taxi-out times were identified, including primarily the number of arrivals and number of departures during the taxi-out operation of an aircraft. Previous literature suggests that the number of arrivals on the surface has limited influence on taxi-out times; however, this analysis demonstrates that the number of arrivals is in fact significantly correlated with taxi-out times. Furthermore, we find that arrivals have a greater impact on taxi-out times under runway configurations where there is increased interaction between arrivals and departures.**

## Nomenclature

| | | |
|---|---|---|
| $t_{out}$ | = | gate out / pushback time |
| $t_{off}$ | = | wheels off / takeoff time |
| $T$ | = | taxi-out time ($t_{off}$ - $t_{out}$) |
| $t_{in}$ | = | gate in time |
| $t_{on}$ | = | wheels on / landing time |
| $D$ | = | number of departures that takeoff between $t_{out}$ and $t_{off}$ |
| $A$ | = | number of arrivals on the surface at $t_{out}$ |
| $N$ | = | number of departures and arrivals (D + A) |
| *BOS* | = | Boston Logan International Airport |
| *JFK* | = | John F. Kennedy International Airport |
| *ASPM* | = | Aviation System Performance Metrics |
| *ACARS* | = | Aircraft Communications Addressing and Reporting System |
| *ARINC* | = | Aeronautical Radio, Incorporated |
| *OOOI* | = | Gate Out, Wheels Off, Wheels On, Gate In |
| *IMC* | = | Instrument Meteorological Conditions |
| *VMC* | = | Visual Meteorological Conditions |

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## I. Introduction

AIRCRAFT taxi-out operations are a growing source of fuel burn and emissions at airports. In 2007, an estimated 4,000 tons of hydrocarbons, 8,000 tons of nitrogen oxides and 45,000 tons of carbon monoxide were emitted through taxi-out operations at U.S. airports.[1] These air pollutants represent an endangerment to human health and welfare, and directly impact local nonattainment of air pollution prevention measures (e.g., the Clean Air Act). A number of strategies to reduce these surface emissions through departure planning and surface movement optimization are currently being explored. However, such strategies rely on accurate estimates of taxi-out times and an understanding of the causal factors affecting taxi delays.

Previous literature on the analysis of taxi-out operations suggests that a handful of variables primarily affect departure operations at Boston Logan International Airport (BOS) as well as those at other airports.[2,3] These works include high-level analysis focused on identifying the main flow constraints of the departure process. Established literature suggests that the main bottleneck is the runway system, which manifests itself in the following forms: separation requirements between successive departures, capacity limitations based on runway configurations, allocation of runway occupancy to landing aircraft, and capacity limitations of runway crossings. Additional factors that have been shown to lead to taxi delays include excessive demand, air traffic controller workload, and downstream constraints. Idris at al. analyzed the departure process at BOS in great detail, identifying the following main causal factors affecting taxi-out times: runway configuration, the airline/terminal, weather conditions, downstream restrictions, and the departure queue.[4] By building a regression model, this study determined that the size of the departure queue, measured as the number of takeoffs between pushback time and takeoff time, was highly correlated with observed taxi-out times. Idris et al. also identified runway configuration as a key variable affecting taxi-out times, as well as the distances between terminals and departure runways and the capacities of different runway configurations. However, in this previous study, there was a poor correlation between taxi-out times and the volume of arriving traffic at BOS, in contrast with qualitative observations about interactions between arrivals and departures.[2,3] Other established studies which focus on taxi-out time prediction or departure planning use similar explanatory variables, excluding arriving traffic when modeling or predicting the departure rate and taxi-out times, regardless of the layout of the particular airport examined.[5,6,7,8,9]

This paper describes an analysis of departing flights from John F. Kennedy International Airport (JFK) and Boston Logan International Airport (BOS) in order to re-examine and re-evaluate the factors affecting taxi-out times by making use of more complete datasets, deploying more rigorous statistical tools, and comparing two different major airports.

The taxi-out time of an aircraft is the time between actual pushback (from the gate) and takeoff, including the time that the aircraft spends on the taxiway system and in runway queues. Based on this study, we find that key variables affecting taxi-out times include the number of arriving aircraft, the number of departing aircraft, runway configuration, weather, and originating terminal. The two most critical explanatory factors are the number of arriving aircraft, previously thought to have had little impact on taxi-out times, and the number of departing aircraft. Furthermore, we find that the impact of arrivals on taxi-out times can vary based on the runway configuration, with taxi-out times increasing as the interaction between departure and arrival runways increases.

## II. Overview of Data Analysis

This study includes an analysis of taxi-out times for all departures out of John F. Kennedy International Airport (JFK) and all departures out of Boston Logan International Airport (BOS) for 2007. These two airports are of particular interest because they are major, high-traffic airports at which taxi-out times have increased over the past decade. Furthermore, these airports have fairly different runway layouts, which allowed us to analyze the impact of runway configurations for two cases where departure and arrival traffic have different levels of interaction. The dataset used in our analysis included 202,247 departing flights from Logan, and 221,062 departing flights from JFK.

The two data sources that are used in this study are the Aviation System Performance Metrics (ASPM) database,[10] which is maintained by the FAA, and Flightstats.[11] For the purposes of this study, we make use of the following:

a) The ASPM module providing information about individual flights:
   - Actual pushback time of each departing flight
   - Actual takeoff time of each departing flight
   - Actual taxi-out time of each departing flight
   - Actual landing time of each arriving flight
   - Actual gate arrival time of each arriving flight
   - Actual taxi-in time of each arriving flight

- Flight code (airline and flight number) of each flight

b) The ASPM module providing information about the airport:
   - Runway configuration in use
   - Meteorological conditions

c) Flightstats:
   - Actual pushback time of each departing flight
   - Actual takeoff time of each departing flight
   - Actual taxi-out time of each departing flight
   - Actual landing time of each arriving flight
   - Actual gate arrival time of each arriving flight
   - Actual taxi-in time of each arriving flight
   - Flight code (airline and flight number) of each flight
   - The terminal and gate of each flight

We utilize Flightstats data in addition to the ASPM database for several reasons. First, Flightstats provides terminal and gate information about most flights. Thus, by matching the dates and the flight codes of the two databases we can get the terminal and gate information for the majority of departing and arriving traffic. Second, the ASPM database is organized into two categories: the OOOI flights and the non-OOOI flights. Several airlines provide the following data for most of their flights: gate pushback (gate-out or OUT), takeoff (wheels-off or OFF), landing (wheels-on or ON), and gate arrival (gate-in or IN); these data points are collectively known as the OOOI (i.e. gate Out, wheels Off, wheels On, gate In) data of a flight. OOOI data are automatically recorded by aircraft equipped with Aircraft Communications Addressing and Reporting System (ACARS) sensors and is processed by Aeronautical Radio, Incorporated (ARINC). The airlines that are equipped with ACARS sensors are often called OOOI carriers. The ASPM database estimates OOOI information for flights of non-participating carriers, as well as for OOOI carriers where OOOI data are unavailable.

There is some evidence that ASPM estimation may not be precise.[12] For this reason, we correct the OOOI information of these flights using data from the Flightstats database, when it is available. For the remainder of flights we estimate the OOOI information using the method outlined in Pujet et al.[7] Based on analysis from this same study, we estimate that there is a certain amount of traffic absent from the two databases, primarily general aviation (GA) and military flights. For these flights it is possible to gather runway information from other data sources (e.g. PASSUR Aerospace, Inc.), but not possible to obtain information regarding flight pushback, or gate arrival time, and thus their taxi times; therefore, we omit these flights from our analysis. Finally, the comparison of the two databases can help us detect and correct errors, especially for the non-OOOI carriers, which do not report their OOOI information automatically.

### A. Taxi-Out Time

The dependent variable of primary interest in our analysis is taxi-out time (T), defined as:

$$T = t_{off} - t_{out} \tag{1}$$

In Eq. (1), $t_{off}$ is the "wheels off" or takeoff time, and $t_{out}$ is the "gate out" or pushback time of the departing aircraft.

Our original dataset for JFK included flights with taxi-out times ranging from 1 to 1439 minutes (i.e. roughly 24 hours). Due to the likelihood that departures with greater than 3 hours of recorded taxi-out times were due to inaccurate measurements, false reports of actual taxi-out time, or traffic flow management initiatives, we utilized data within 99% of the observed taxi-out times for both JFK and BOS. Table 1 summarizes the observed taxi-out times for departures from JFK and BOS in 2007 from our final dataset.

**Table 1. Taxi-Out Times at JFK and BOS in 2007.**

| Airport | Taxi-Out Times (in minutes) | | | |
|---|---|---|---|---|
| | Minimum | Maximum | Mean | Median |
| JFK | 1 | 129 | 37 | 32 |
| BOS | 1 | 66 | 20 | 18 |

## B. Number of Departing and Arriving Aircraft

Our analysis indicated that correlation between the number of departures and taxi-out times or the number of arrivals and taxi-out times varies substantially depending on the definition of "departing aircraft" and "arriving aircraft" utilized. Initially, three definitions of departures and arrivals were examined to build the regression model on taxi-out times. Departures (D) were defined in the following three ways:

$$D_I(i) = \sum_j count(j) if[t_{out}(j) < t_{out}(i) < t_{off}(j)] \tag{2}$$

$$D_{II}(i) = \sum_j count(j) if[t_{out}(i) < t_{out}(j) < t_{off}(i)] \tag{3}$$

$$D_{III}(i) = \sum_j count(j) if[t_{out}(i) < t_{out}(j) < t_{off}(i)] \bigcup [t_{out}(j) < t_{out}(i) < t_{off}(j)] \tag{4}$$

In Eq. (2) the number of departures $D_I(i)$ for an aircraft $i$ is defined as the number of departing aircraft having a pushback time earlier than the pushback time of aircraft $i$ and a takeoff time later than the pushback time of aircraft $i$. In other words, it accounts for all departing aircraft on the ground when aircraft $i$ pushes back. In Eq. (3), the number of departures $D_{II}(i)$ comprises the number of takeoffs which take place between the pushback time of aircraft $i$ and its takeoff time. $D_{III}(i)$, as defined in Eq. (4), is the union of $D_I(i)$ and $D_{II}(i)$ .

Based on simple linear regression analysis, the number of departures measured by $D_{II}$, as defined in Eq. (3), had the highest correlation with taxi-out times for both JFK and BOS airport data, in agreement with the results from Idris et al.[4] Table 2 summarizes the results of the $R^2$ values associated with the three regression models for JFK and BOS.

**Table 2. $R^2$ values for Regression Model Based on Departing Aircraft**

| Airport | D: Definition I | D: Definition II | D: Definition III |
|---|---|---|---|
| **JFK** | 0.5188 | 0.7599 | 0.6997 |
| **BOS** | 0.1992 | 0.6380 | 0.5012 |

In contrast to departures, the arrivals have not been extensively quantitatively studied as a factor contributing to higher taxi times. Idris et al. examined the correlation between taxi-out times and arriving traffic.[4] In Idris et al., the number of arrivals is defined as the number of aircraft that landed or parked at the gate in a time window around the pushback time of a taxiing aircraft. This previous study found a very low correlation (i.e., an $R^2$ value of 0.02) between taxi-out times and their definition of arrivals. This finding is contrary to what we might anticipate; it is well understood that the takeoff capacity of an airport depends on the landings capacity (i.e., and the arrivals) according to the concept of the capacity envelope[13]. Since taxi-out times are dependent on the takeoff capacity, one would expect taxi-out times to be related to the arrivals activity in some way. This relation has also qualitatively observed,[2,3] but not quantified. We explore this potential relation, by investigating several alternative definitions of the number of arrivals (A) in our preliminary analysis.

$$A_I(i) = \sum_j count(j) if[t_{on}(j) < t_{out}(i) < t_{in}(j)] \tag{5}$$

$$A_{II}(i) = \sum_j count(j) if[t_{out}(i) < t_{on}(j) < t_{off}(i)] \tag{6}$$

$$A_{III}(i) = \sum_j count(j) if[t_{out}(i) < t_{on}(j) < t_{off}(i)] \bigcup [t_{on}(j) < t_{out}(i) < t_{in}(j)] \tag{7}$$

$$A_{IV}(i) = \sum_j count(j) if[t_{out}(i) < t_{in}(j) < t_{off}(i)] \tag{8}$$

$$A_V(i) = \sum_j count(j) if[t_{out}(i) < t_{on}(j)] \bigcap [t_{in}(j) < t_{off}(i)] \tag{9}$$

Analogous to the departures case, $A_I(i)$, as defined in Eq. (5), accounts for all aircraft $j$ that land before aircraft $i$'s pushback time and have a gate-in time after aircraft $i$'s pushback time; in simple terms, it includes all aircraft that were taxiing in when aircraft $i$ pushed back from its gate. The number of arrivals $A_{II}(i)$, as defined in Eq. (6), measures the number of aircraft that land while aircraft $i$ taxies and $A_{III}(i)$ the union of the two.

$A_{IV}(i)$, as defined in Eq. (8), measures the number of aircraft that arrive at their gate while aircraft *i* is taxiing out. Finally, $A_V(i)$, defined in Eq. (9), measures both the number of aircraft that landed and arrived at their gates while aircraft *i* was taxiing out. In other words, $A_V(i)$ is the intersection of $A_{II}(i)$ and $A_{IV}(i)$.

The number of arrivals based on the definition $A_V$ was most highly correlated with taxi-out times based on a simple linear regression analysis. Table 3 summarizes the results of the $R^2$ values associated with the five arrivals-based regression models for JFK and BOS.

**Table 3. $R^2$ value for Regression Models Based on Arriving Aircraft**

| Airport | A: Definition I | A: Definition II | A: Definition III | A: Definition IV | A: Definition V |
|---|---|---|---|---|---|
| **JFK** | 0.1221 | 0.7118 | 0.6586 | 0.7155 | 0.7470 |
| **BOS** | 0.0199 | 0.5848 | 0.4776 | 0.5618 | 0.6773 |

For one particular definition of arrivals ($A_I$), we find a similar relationship between the number of arrivals and taxi-out times as in Idris et al.,[4] in which a simple regression model yielded an $R^2$ value of 0.02. In Idris et al., the number of arrivals was defined as the number of aircraft that landed or parked at the gate in a time window around the pushback time of a taxiing aircraft for BOS. This definition from Idris et al. is analogous to our definition of arrivals described by $A_I$, and the $R^2$ values of the analyses for BOS are equal. It turns out that the taxi-out time of an aircraft *i* indeed has a very low correlation with the number of aircraft that are taxiing-in ($A_I$) when aircraft *i* pushes back from the gate. However, we find that taxi-out times do in fact have a high correlation with the number of aircraft that landed ($A_{II}$), that arrived at their gate ($A_{IV}$), or that both landed and arrived at their gate ($A_V$) while aircraft *i* taxies out for departure.

In the linear regression models of the next section, Eq. (3) is utilized to calculate the number of departing aircraft in order to predict an aircraft's taxi-out time. The number of departures (*D*) when aircraft *i* is in the taxi-out process includes all aircraft *j* that take off after aircraft *i*'s pushback time and before aircraft *i*'s takeoff time, and can therefore be called the "takeoff queue" of aircraft *i*. The takeoff queue of aircraft *i* is not known at the time of the pushback of an aircraft. However, it has been shown that it can be estimated with good precision.[4,14] Thus, incorporating the takeoff queue in prediction models is both informative, since it has a great correlation with taxi-out times, and practical, since it can be readily estimated.

In contrast, the term $A_V$, which accounts for arriving aircraft that both land and arrive at their gate while an aircraft is taxiing out, is difficult to estimate because it requires estimating the taxiing time of an arriving aircraft. Thus in order to predict the taxi-out time of an aircraft we need to first estimate the taxi-in of the aircraft that land while it taxies out. Calculating the taxi-in times poses a new prediction problem on its own, and is outside the scope of this paper. Furthermore, to the best of our knowledge, there are no validated models predicting taxi-in times that are available.

The term $A_{II}$, which accounts for arriving aircraft that land while an aircraft is taxiing out, is quite straightforward to estimate and use in a predictive model: the expected landing traffic at an airport is known with great accuracy in a 30 minute horizon. This metric can practically be utilized in predictive models. For this reason, in the linear regression models of the next section, the number of arrivals (A) used as an explanatory variable is defined by $A_{II}$, described in Eq. (6).

### C. Runway Configuration

Previous literature suggests that runway configuration is a key causal factor affecting taxi-out times. In this analysis, regression models were developed which examined all runway configurations for JFK and BOS, as discussed in the following sections. An additional categorical variable was developed to analyze the interaction effects of arrivals and departures; specifically, to examine runway configurations in which the primary departure runway and primary arrival runway is shared.

## III. Analysis of Taxi-Out Times at JFK International Airport

Based on extensive analysis of taxi-out times at JFK, the number of departures and the number of arrivals were found to have the greatest correlation with taxi-out times for departing aircraft. Similar to previous research, runway configuration also appeared to influence taxi-out times, though not as significant a factor as the number of departures or number of arrivals.

## A. Departure Queue

The number of other departures is the most significant factor affecting taxi-out times for a departing aircraft. Due to limitations related to runway capacity, taxiway capacity, and separation requirements, the number of additional departing aircraft in the takeoff queue is the primary causal factor affecting taxi-out delays.

Utilizing linear regression analysis, we find that a simple model of taxi-out times based on the size of the departure queue explains much of the variability in taxi-out times. Using a simple regression model defined by Eq. (10), we obtain $R^2$ values of 0.7599, indicating that we can explain 76% of the variability in taxi-out times based on the size of the departure queue.

$$T = 11.618 + 1.182*D \tag{10}$$

## B. Arriving Aircraft

Previous literature suggests that the number of arriving aircraft have a limited affect on taxi-out times, and in particular, a lower significance as compared to the runway configuration.[4] Our analysis of departure times at JFK in 2007 indicates that the number of arriving aircraft, as measured using several of the definitions above, actually do affect the departure process, and are a significant causal factor affecting taxi-out times. Figure 1 illustrates the linear relationship between taxi-out times and the number of arriving aircraft.

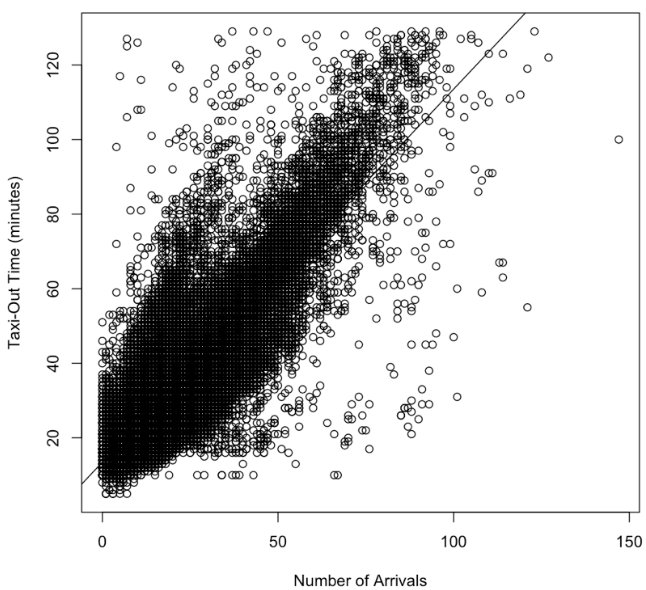


**Figure 1. Taxi-Out Time Correlation with Number of Arrivals (JFK, 2007)**

Arriving aircraft utilize the limited resources on the airport surface, potentially affecting the taxi-out times of departing aircraft. Taxiways are shared between the arrival and departure queue. Furthermore, certain runway configurations can result in more interaction between arrivals and departures.

During peak congestion, there is typically a large volume of both departing and arriving aircraft on the airport surface. In order to determine whether the correlation between taxi-out times and arriving aircraft are due to arriving aircraft, as opposed to congestion caused by departures, we examined taxi-out times at JFK with a set rate of departures and a single runway configuration as shown in Fig. 2. For this analysis, we examine the most frequently used runway configuration at JFK: 31L, 31R | 31L. When departures are fixed at D=0, D=10, D=15, and D=20, and the number of arrivals increases, the average taxi-out times also increase. Given that taxi-out times increase using this analysis, we have additional evidence that arriving aircraft may, in fact, be causal factor affecting taxi-out times.

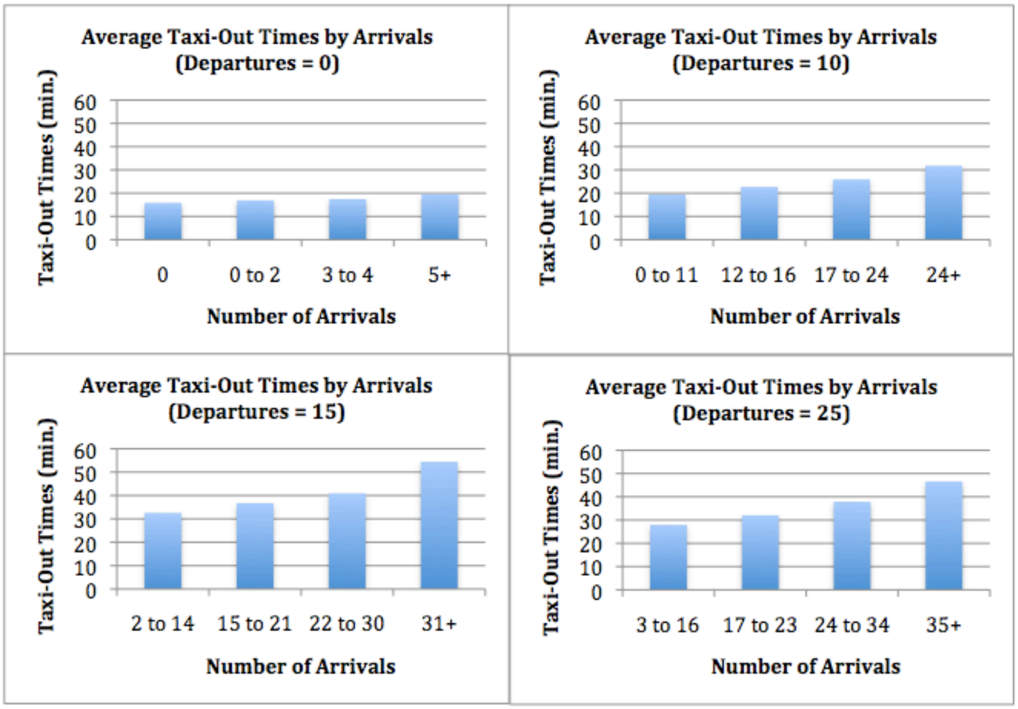


**Figure 2. Average Taxi-Out Times by Number of Arrivals for a Single Runway Configuration**

In order to further examine the affect of arriving aircraft, we conduct regression analysis using the number of arriving aircraft as our primary explanatory variable. Utilizing the second definition of arriving aircraft, given by Eq. (6), we estimate the simple regression model described by Eq. (11). This simple model based on arriving aircraft results in an $R^2$ value of 0.7118, implying that the number of arrivals explains 71% of the variability in taxi-out times, nearly as much of the variability in taxi-out times as explained by the size of the departure queue. Each arrival appears to add roughly 1 minute to the total taxi-out time of a departing aircraft.

$$T = 13.470 + 1.001 * A \tag{11}$$

An improved regression model of taxi-out times would naturally include both the number of departures and the number of arrivals, as given by Eq. (12). The coefficients indicate that additional departures have a greater affect on increasing taxi-out times as compared with arrivals. For each additional departure, taxi-out times increase by 0.77 minutes, whereas for each additional arrival, they increase by 0.52 minutes. This linear model results in an $R^2$ value of 0.8597, indicating that it explains 86% of the variability in taxi-out times, more than either the model based only on the number of departures or the model based only on the number of arrivals. Complete regression model results are provided in Table 4.

$$T = 8.024 + 0.772*D + 0.524*A \tag{12}$$

**Table 4. Results for the Linear Regression Model for JFK**

| Coefficient | Estimate | Std Error | T value | P value |
|---|---|---|---|---|
| Intercept | 8.024 | 0.030 | 266.400 | <2e-16 |
| D | 0.772 | 0.002 | 514.500 | <2e-16 |
| A | 0.524 | 0.001 | 392.400 | <2e-16 |
| RSE | 7.648 on 218861 degrees of freedom | | | |
| $R^2$ | Multiple R-squared: 0.8597, Adjusted R-squared: 0.8597 | | | |
| F Statistic | 6.71E+05 on 2.00E+00 and 218861 DF, p-value: < 2.20E-16 | | | |

In order to further examine how the interaction between departures and arrivals affects taxi-out times, we separately examined those data points when the primary departure runway was shared with the primary arrival runway, and those for which the runways were not shared. We create a dummy variable (RwConflict) that takes the value 1 (i.e., true) if both arrivals and departures utilize the same runway for landing or takeoff, and takes the value 0 (i.e., false) if primary departure and arrival runways are not shared. The linear regression model we construct is given by Eq. (13).

$$T = \beta_1 D + \beta_2 A + \beta_3 RwConflict \quad (13)$$

**Table 5. Results for the Linear Regression Model for JFK including Runway Conflict Variable**

| Coefficient | Estimate | Std Error | T value | P value |
|---|---|---|---|---|
| Intercept | 7.791 | 0.032 | 245.080 | <2e-16 |
| D | 0.773 | 0.002 | 509.010 | <2e-16 |
| A | 0.525 | 0.001 | 390.600 | <2e-16 |
| RwConflict | 0.845 | 0.040 | 21.330 | <2e-16 |
| RSE | 7.625 on 218087 degrees of freedom | | | |
| $R^2$ | Multiple R-squared: 0.8607, Adjusted R-squared: 0.8607 | | | |
| F Statistic | F-statistic: 4.491e+05 on 3 and 218087 DF, p-value: < 2.2e-16 | | | |

In the summary provided in Table 5, we see that the addition of the "runway conflict" variable raises the $R^2$ value of the model, has a positive sign, and has statistical significance, as expected by intuition. All else being equal, when departures and arrivals share the same primary runway, taxi-out times are expected to be higher. The inclusion of this dummy variable also increases the information explained by the model, since the AIC decreases compared to its value at the linear model (1505470 from 1505018).

Given knowledge that the "runway conflict" variable explains some of the variation in taxi-out times, we separate those data points for which the primary departure runway is shared with the primary arrival runway, and then calculate the coefficients of the linear model for the two scenarios separately. In the first scenario, both arrivals and departures utilize the same runway for landing or takeoff, whereas in the second scenario they do not. The results of our regression analysis for the two scenarios are summarized in Tables 6 and 7.

**Table 6. Results for the Linear Regression Model for JFK including Arrivals when RwConflict=True**

| Coefficient | Estimate | Std Error | T value | P value |
|---|---|---|---|---|
| Intercept | 7.391 | 0.058 | 127.900 | <2e-16 |
| D | 0.836 | 0.003 | 282.400 | <2e-16 |
| A | 0.527 | 0.002 | 212.700 | <2e-16 |
| RSE | 6.836 on 48680 degrees of freedom | | | |
| $R^2$ | Multiple R-squared: 0.8761, Adjusted R-squared: 0.8761 | | | |
| F Statistic | 172100.000 on 2.000 and 48680 DF, p-value: <2.20E-16 | | | |

**Table 7. Results for the Linear Regression Model for JFK including Arrivals when RwConflict=False**

| Coefficient | Estimate | Std Error | T value | P value |
|---|---|---|---|---|
| Intercept | 8.122 | 0.035 | 232.100 | <2e-16 |
| D | 0.758 | 0.002 | 431.200 | <2e-16 |
| A | 0.525 | 0.002 | 332.800 | <2e-16 |
| RSE | 7.820 on 169405 degrees of freedom | | | |
| $R^2$ | Multiple R-squared: 0.8571, Adjusted R-squared: 0.8571 | | | |
| F Statistic | 274700.000 on 2.000 and 169405 DF, p-value: < 2.20E-16 | | | |

Our analysis of the two datasets revealed that the number of departures and the number of arrivals explain more of the variability in taxi-out times when there is a runway conflict; that is, when departure and arrival interaction is increased. The coefficient of the arriving aircraft variable (A) increases only marginally (1%) whereas the coefficient of the departing aircraft variable (D) increases from 0.758 to 0.834.

One would expect the coefficient of the variable (A) to change significantly, because the marginal cost of an additional arrival should be higher when the runway is shared. However, Tables 6 and 7 suggest that the marginal cost of an additional departure is higher when the runways are shared. This suggests a different interpretation: The fact that the primary departures runway is shared, introduces a higher delay per departure. However, arrivals seem to have the same impact. The fact that the impact of arrivals cannot be readily analyzed by just comparing the coefficients of Tables 6 and 7 is a typical problem in a multiple regression model: the independent variables could obscure each other's effects. This seems to be the case here.

In order to further investigate the effect of arrivals when the runway is shared and when not, we isolate and compare two major runway configurations at JFK: 31L, 31R | 31L and 31R | 31L. For the former configuration, runway 31L is used for both takeoffs and landings, whereas for the latter it is used exclusively for takeoffs. The results of our regression analysis for these two runway configurations are summarized in Tables 8 and 9. Here we can see that the coefficient of the variable (D) is higher for the runway configuration 31R | 31L, whereas the coefficient of the variable (A) is higher for the runway configuration 31L, 31R | 31L. These results seem to agree with our intuitive theory:[15] When the departure runway is shared, the arrivals impact to a greater extent the taxi-out times since several of them will be served by the shared runway, thereby decreasing its takeoff capacity. On the other hand, landings and takeoffs are usually alternated on a shared runway. Thus, part of the separation requirement between two departing aircraft is absorbed by the landing aircraft and the delay introduced by an additional departure is shorter than the one introduced by an additional departure in the case where a runway used exclusively for takeoffs. The overall delay introduced by an additional departure and an additional arrival is naturally higher for runway configuration 31L, 31R | 31L than for runway configuration 31R | 31L.

It is hard to draw more detailed or quantitative conclusions because currently we do not have information on the extent that runway 31L is shared by arrivals and departures at runway configuration 31L, 31R | 31L, the traffic mix and the sequencing techniques used.

**Table 8. Results for the Linear Regression Model for JFK Runway Configuration 31L, 31R | 31L**

| Coefficient | Estimate | Std Error | T value | P value |
|---|---|---|---|---|
| Intercept | 7.699 | 0.055 | 140.200 | <2e-16 |
| D | 0.824 | 0.003 | 290.200 | <2e-16 |
| A | 0.494 | 0.002 | 206.400 | <2e-16 |
| RSE | 5.676 on 38021 degrees of freedom | | | |
| $R^2$ | Multiple R-squared: 0.8995, Adjusted R-squared: 0.8995 | | | |
| F Statistic | 1.701e+05 on 2 and 38021 DF, p-value: < 2.2e-16 | | | |

**Table 9. Results for the Linear Regression Model for JFK Runway Configuration 31R | 31L**

| Coefficient | Estimate | Std Error | T value | P value |
|---|---|---|---|---|
| Intercept | 9.841 | 0.065 | 151.8 | <2e-16 |
| D | 0.848 | 0.003 | 250.8 | <2e-16 |
| A | 0.434 | 0.003 | 136.2 | <2e-16 |
| RSE | 6.506 on 31944 degrees of freedom | | | |
| $R^2$ | Multiple R-squared: 0.8892, Adjusted R-squared: 0.8892 | | | |
| F Statistic | 128200 on 2 and 31944 DF, p-value: < 2.2e-16 | | | |

### C. An Improved Model of Taxi-Out Times

We can improve our model of taxi-out times by developing a polynomial regression model, as outlined in Eq. (14), utilizing the number of departing aircraft and the number of arriving aircraft as our primary explanatory variables.

$$T = \beta_1 D + \beta_2 D^2 + \beta_3 A + \beta_4 A^2 \tag{14}$$

The main reason we add the quadratic term is to account for the queuing dynamics that relate taxi-out times with the number of departures and arrivals. It is well understood and observed that these queuing dynamics lead to non-linear increase of taxi times with the growth of traffic.[15]

We first investigate the performance of a polynomial model for the most frequently used runway configuration and compare it with the linear model. The results of the polynomial regression model are provided in Table 10, and the simpler model in Table 8 above.

**Table 10. Results for the Polynomial Regression Model for RwConfig : 31L, 31R | 31L**

| Coefficient | Estimate | Std Error | T value | P value |
|---|---|---|---|---|
| Intercept | 10.020 | 0.085 | 117.840 | <2e-16 |
| D | 0.666 | 0.007 | 92.140 | <2e-16 |
| $D^2$ | 0.003 | 0.000 | 23.570 | <2e-16 |
| A | 0.415 | 0.006 | 71.280 | <2e-16 |
| $A^2$ | 0.001 | 0.000 | 14.720 | <2e-16 |
| RSE | 5.582 on 38019 degrees of freedom | | | |
| $R^2$ | Multiple R-squared: 0.9028, Adjusted R-squared: 0.9028 | | | |
| F Statistic | 8.826e+04 on 4 and 38019 DF, p-value: < 2.2e-16 | | | |

Comparing the model output from Tables 8 and 10, we find that the non-linear model results in increased $R^2$ values (i.e., 0.9028) for this runway configuration, indicating that it explains more of the variation in taxi-out times than the linear model. An ANOVA test shows that the model including non-linear terms is a significant improvement over the linear model. We repeat the coefficients estimation for the polynomial model, including data for all runway configurations utilized at JFK in 2007. The results of the complete model are summarized in Table 11.

**Table 11. Results for the Polynomial Regression Model for JFK**

| Coefficient | Estimate | Std Error | T value | P value |
|---|---|---|---|---|
| Intercept | 11.200 | 0.045 | 247.470 | <2e-16 |
| D | 0.632 | 0.004 | 172.480 | <2e-16 |
| $D^2$ | 0.003 | 0.000 | 43.880 | <2e-16 |
| A | 0.367 | 0.003 | 117.420 | <2e-16 |
| $A^2$ | 0.002 | 0.000 | 52.320 | <2e-16 |
| RSE | 7.501 on 218859 degrees of freedom | | | |
| $R^2$ | Multiple R-squared: 0.8651, Adjusted R-squared: 0.8651 | | | |
| F Statistic | 350800.000 on 4.000 and 218859 DF, p-value: < 2.20E-16 | | | |

The above model results in increased $R^2$ values (i.e., 0.8655) for our complete JFK data set, indicating that it explains more of the variation in taxi-out times than our simpler model.

### D. Other Causal Factors

*1. Weather*

It is well understood that Instrumental Meteorological Conditions (IMC) have a negative impact on the operational efficiency of an airport. In order to build a simple model for the taxi-out time cost of IMC, we apply the following model described by Eq. (15).

$$T = \beta_1 D + \beta_2 D^2 + \beta_3 A + \beta_4 A^2 + \beta_5 \text{Weather} \tag{15}$$

We include *weather* as a categorical variable taking values VMC and IMC. In our regression model we develop a dummy variable "Weather VMC" that takes the value 1 when the reported conditions are VMC and 0 when they are IMC. The results from this analysis are summarized in Table 12.

**Table 12. Results of the Improved Regression Model, including Weather**

| Coefficient | Estimate | Std Error | T value | P value |
|---|---|---|---|---|
| Intercept | 15.740 | 0.062 | 254.080 | <2e-16 |
| D | 0.634 | 0.004 | 177.210 | <2e-16 |
| $D^2$ | 0.002 | 0.000 | 43.130 | <2e-16 |
| A | 0.366 | 0.003 | 120.090 | <2e-16 |
| $A^2$ | 0.002 | 0.000 | 52.190 | <2e-16 |
| Weather VMC | -5.051 | 0.048 | -104.580 | <2e-16 |
| RSE | 7.320 on 218858 degrees of freedom | | | |
| $R^2$ | Multiple R-squared: 0.8715, Adjusted R-squared: 0.8715 | | | |
| F Statistic | 296900.000 on 5.000 and 218858 DF, p-value: <2.2e-16 | | | |

Including the weather information improves the performance of the model both in terms of explained variance and residual errors and the results follow our intuition: we can see that on average VMC leads to approximately 5 minutes shorter taxi times, which implies that all else being equal, IMC leads to 5 more minutes of taxi-out time for a departing aircraft. This extra taxi time is a result of three effects: 1) under IMC the departure rate for a runway drops because of larger separation requirements; 2) airplanes travel slower on the surface because of limited visibility; and 3) the airport cannot use its runways as efficiently as under VMC.

*2. Runway Configurations*

In order to investigate the effect of the runway configuration, we focus on data from the six most frequently used runway configurations at JFK: "31L, 31R | 31L", "13L, 22L | 13R", "31R | 31L", "22L | 22R, 31L", "4R | 4L, 31L", and "13L | 13R". This simplifies analysis of the impact of runway configuration. We modify our most recent regression model to include the runway configuration information as shown in Eq. (16).

$$T = \beta_1 D + \beta_2 D^2 + \beta_3 A + \beta_4 A^2 + \beta_5 Weather + \beta_6 RwConfig \quad (16)$$

We include "runway configuration" as a categorical variable by adding five binary variables, each of which takes the value 1 when the runway configuration is "31L, 31R | 31L", "13L, 22L | 13R", "31R | 31L", "22L | 22R, 31L", and "4R | 4L, 31L" respectively. When the runway configuration is "13L | 13R" they are all equal to 0. In this representation the configuration "13L | 13R" is the baseline for comparisons.

**Table 13. Results of the Improved Regression Model, including Runway Configuration**

| Coefficient | Estimate | Std Error | T value | P value |
|---|---|---|---|---|
| Intercept | 13.980 | 0.085 | 164.020 | <2e-16 |
| D | 0.677 | 0.004 | 188.540 | <2e-16 |
| $D^2$ | 0.002 | 0.000 | 32.950 | <2e-16 |
| A | 0.309 | 0.003 | 98.700 | <2e-16 |
| $A^2$ | 0.002 | 0.000 | 53.880 | <2e-16 |
| WeatherVMC | -2.718 | 0.060 | -45.270 | <2e-16 |
| RwConfig 13L, 22L \| 13R | -1.123 | 0.060 | -18.580 | <2e-16 |
| RwConfig 22L \| 22R, 31L | -2.679 | 0.064 | -42.120 | <2e-16 |
| RwConfig 31L, 31R \| 31L | 0.681 | 0.059 | 11.470 | <2e-16 |
| RwConfig 31R \| 31L | 1.833 | 0.061 | 30.200 | <2e-16 |
| RwConfig 4R \| 4L, 31L | -1.347 | 0.071 | -19.030 | <2e-16 |
| RSE | 6.257 on 170526 degrees of freedom | | | |
| $R^2$ | Multiple R-squared: 0.888, Adjusted R-squared: 0.888 | | | |
| F Statistic | 135200.000 on 10 and 170526 DF, p-value: < 2.20E-16 | | | |

As different runway configurations have different capacities and different level of iteractions with arrivals, neighboring airspace and en-route traffic, they have a significant effect on departure throughput and taxi times. We note that runway configuration 22L | 22R, 31L is conducive to shorter taxi out times. This was expected as this runway configuration has two runways devoted to departures and a separate one to arrivals. It is also consistent with earlier work which estimated that the configuration 22L | 22R, 31L has the highest departure throughput.[7] Runway configuration 31R | 31L introduces the highest delay compared to the baseline 13L | 13R . This is consistent with our earlier study which estimated that 31R | 31L has the lowest departure capacity of these six runway configurations.[7] One would expect these two runway configurations to have similar departure throughputs (since they are symmetric). The reasons for the discrepancy may be differences in the airspace constraints of the two runway configurations, and the fact that they tend to be operated at different times of the day.

*3. Time of Day*

Previous research has indicated that time of day might play a role as well in determining taxi times, since longer taxi times are usually observed at certain hours of the day (particularly in the evening).[16] In our analysis we introduce the "time of day" as a categorical variable that is represented as three binary variables:

- Night=1 when the departure time of the flight was between midnight and 6 am, 0 otherwise
- Evening=1 when the departure time of the flight was between 6pm and 6 midnight, 0 otherwise
- Morning=1 when the departure time of the flight was between 6am and noon, 0 otherwise

When the time of departure was in the afternoon (between noon and 6pm) all of the three binary variables are 0.

$$T = \beta_1 D + \beta_2 D^2 + \beta_3 A + \beta_4 A^2 + \beta_5 Weather + \beta_6 RwConfig + \beta_7 TimeOfDay \tag{17}$$

Our improved regression model, including a TimeOfDay variable, is outlined in Eq. (17). The results of the model are summarized in Table 14.

**Table 14. Results of the Improved Regression Model, including Time of Day**

| Coefficient | Estimate | Std Error | T value | P value |
|---|---|---|---|---|
| Intercept | 10.330 | 0.093 | 111.150 | <2e-16 |
| D | 0.666 | 0.004 | 176.150 | <2e-16 |
| $D^2$ | 0.002 | 0.000 | 32.780 | <2e-16 |
| A | 0.451 | 0.003 | 129.170 | <2e-16 |
| $A^2$ | 0.001 | 0.000 | 18.980 | <2e-16 |
| WeatherVMC | -2.532 | 0.059 | -43.260 | <2e-16 |
| RwConfig 13L, 22L \| 13R | -0.767 | 0.059 | -12.920 | <2e-16 |
| RwConfig 22L \| 22R, 31L | -2.417 | 0.062 | -38.940 | <2e-16 |
| RwConfig 31L, 31R \| 31L | 0.928 | 0.059 | 15.730 | <2e-16 |
| RwConfig 31R \| 31L | 1.807 | 0.059 | 30.430 | <2e-16 |
| RwConfig 4R \| 4L, 31L | -1.322 | 0.069 | -19.070 | <2e-16 |
| TimeOfDay night | 6.380 | 0.077 | 83.300 | <2e-16 |
| TimeOfDay evening | 0.516 | 0.044 | 11.740 | <2e-16 |
| TimeOfDay morning | 2.905 | 0.048 | 60.980 | <2e-16 |
| RSE | 6.094 on 170523 degrees of freedom | | | |
| $R^2$ | Multiple R-squared: 0.8938,Adjusted R-squared: 0.8938 | | | |
| F Statistic | F-statistic: 1.104e+05 on 13 and 170523 DF, p-value: < 2.2e-16 | | | |

We observe that the performance of the model improves and that the time of the day explains some of the variation of the taxi out times. The RSE decreases, R-squared increases and the AIC is lower than the ones of the previous models. It is noteworthy that the coefficients of the runway configurations are reduced. This could result because certain runway configurations tend to be utilized more early in the day and certain configuration later in the day. Thus, time of day might be correlated with the utilization pattern of runway configurations.

We note that according to the regression results, the morning times (6 am to noon) increase the taxi times for 2.9 minutes compared to the afternoon (noon to 6 pm). This might be counterintuitive because in general JFK achieves greater departure throughput in the morning hours. This result can be explained by examining the number of arrivals during the different times of the day (see Table 15).

**Table 15. Average Number of Arrivals by Time of Day.**

| Time of Day | Average Number of Arrivals |
|---|---|
| Night: Midnight – 6 am | 12.828 |
| Morning: 6 am - Noon | 17.110 |
| Afternoon: Noon – 6 pm | 31.719 |
| Evening: 6 pm - Midnight | 25.541 |

In the morning hours, the average number of arriving aircraft is much smaller at the time of pushback of a departing aircraft than in the afternoon and in the evening. That leads us to hypothesize that the time of day is correlated with the arrivals and that the time of day does not really explain the variability of the taxi time, but the regression model uses the added degree of freedom to correct for errors in the polynomial modeling of the interaction of runway configuration, arrivals and taxi out times. If we remove the arrivals terms from the model, the results of the linear regression model are shown in Table 16.

**Table 16. Results of the Regression Model, Absent of Arrivals.**

| Coefficient | Estimate | Std Error | T value | P value |
|---|---|---|---|---|
| Intercept | 16.890 | 0.112 | 150.836 | <2e-16 |
| D | 0.981 | 0.004 | 234.388 | <2e-16 |
| $D^2$ | 0.003 | 0.000 | 49.250 | <2e-16 |
| WeatherVMC | -2.927 | 0.076 | -38.606 | <2e-16 |
| RwConfig 13L, 22L \| 13R | 0.526 | 0.077 | 6.848 | 7.53E-12 |
| RwConfig 22L \| 22R, 31L | -3.912 | 0.080 | -48.840 | <2e-16 |
| RwConfig 31L, 31R \| 31L | 2.369 | 0.076 | 31.088 | <2e-16 |
| RwConfig 31R \| 31L | 2.312 | 0.077 | 30.050 | <2e-16 |
| RwConfig 4R \| 4L, 31L | -2.190 | 0.090 | -24.423 | <2e-16 |
| TimeOfDay night | 4.997 | 0.096 | 52.189 | <2e-16 |
| TimeOfDay evening | -1.656 | 0.056 | -29.440 | <2e-16 |
| TimeOfDay morning | -4.054 | 0.053 | -76.873 | <2e-16 |
| RSE | 7.897 on 170525 degrees of freedom | | | |
| $R^2$ | Multiple R-squared: 0.8216,Adjusted R-squared: 0.8216 | | | |
| F Statistic | F-statistic: 7.141e+04 on 11 and 170525 DF, p-value: < 2.2e-16 | | | |

We note that after omitting the arriving traffic, the model still performs fairly well. We observe though that the coefficients of the TimeOfDay binary variable "morning" changes algebraic sign: taxi-out times are smaller in the morning for equal number of departures and this is most probably because the arriving traffic is less in the mornings. The TimeOfDay binary variable "evening" changes algebraic sign as well. Therefore, we conclude that the time of day does not inherently impact taxi times and is highly correlated with the arriving traffic, and we do not include it in future regression models. Our final model is described in Eq. (18).

$$T = \beta_1 D + \beta_2 D^2 + \beta_3 A + \beta_4 A^2 + \beta_5 Weather + \beta_6 RwConfig \quad (18)$$

### E. Investigation of the Multi Regression Model

*1. Regression Tree Analysis*

In order to investigate complex interactions between the primary explanatory variables, we fit a regression tree model. We examine the following causal factors identified in our initial analysis: departures, arrivals, runway configuration, and weather.

In a tree model, the lower the branches, the greater the deviance explained. The value at the end leaf of each branch is the conditional mean of the taxi out time under the conditions that the branches dictate. Figure 3 indicates that the take-off queue (i.e., the number of departures) is by far the most important factor affecting taxi-out times. The most critical factor affecting taxi times is if the take-off queue is larger than 17 aircraft.

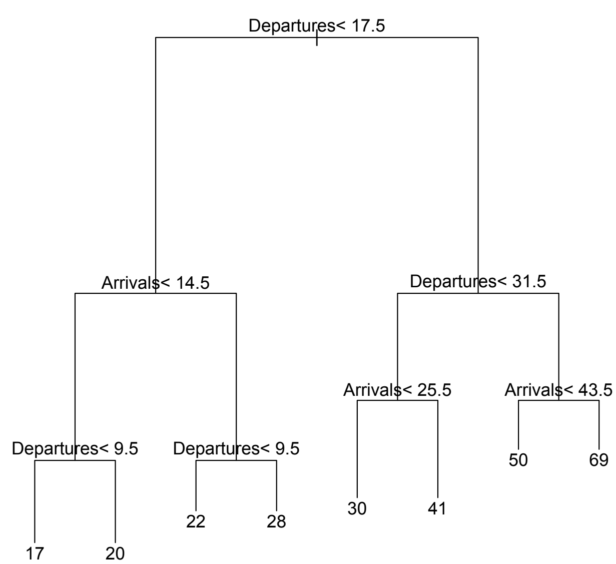


**Figure 3. Regression tree for the taxi out time prediction in JFK**

*2. Potential Dependencies Between Variables*

The final form of the model that we develop is susceptible to potential dependencies between the explanatory variables. We showed previously that the arriving traffic is highly correlated with the time of day. There could be further multicollinearity present in the model: if the arriving traffic affects taxi times, then may also affect the number or departures on the ground (also an explanatory variable). Runway configuration could also be correlated with the arriving traffic. The weather conditions could also be correlated with the runway configuration in use.

We have ensured that the explanatory variables of the final model pass basic informal diagnostics:[17]

- There are no large changes in the estimated regression coefficients when a predictor variable is added or deleted.
- The regressions coefficients have the algebraic sign expected from the theory, observations and previous studies.
- None of the individual tests on the regression coefficients for the predictor variables shows non-significance.
- The confidence intervals of the regression coefficients are not wide.

A more formal test involves using the variance inflation factor. We calculate the generalized variance inflation factors (GVIFs) for the linear version of the final model given by Eq. (19).

$$T = \beta_1 D + \beta_3 A + \beta_5 \text{Weather} + \beta_6 \text{RwConfig} \qquad (19)$$

We do not incorporate the quadratic terms of the Departures and the Arrivals because they are clearly related to the linear terms. The generalized inflation factors are summarized in Table 17.

**Table 17. Generalized Variance Inflation Factors**

| Variable | GVIF |
|---|---|
| Departures | 2.046847 |
| Arrivals | 2.081906 |
| RwConfig | 1.140214 |
| Weather | 1.012443 |

The very low GVIF values (e.g. less than 10) reassure us of the appropriateness of the selection of the explanatory variables.

*3. Appropriateness of the linear regression model*

The linear regression model rests on principal assumptions about the relationship of the dependent and independent variables:[17]

- Linearity of the relationship
- Independence of the errors
- Homoscedasticity of the errors
- Normality of the error distribution

Any violation of these assumptions will lead to inefficient, or misleading predictions. A basic test of these assumptions is the plot of the residuals against fitted values, as illustrated in Fig. 4. This plot shows that the residuals do not increase when the fitted values increase. The scatter, however, is not evenly distributed for positive and negative residuals. There are also many more outliers on the positive side. Taxi times can be very large because of factors that are not included in the model. Examples could be mechanical failures, extreme weather conditions, a safety or security incident at the airport, or a traffic management initiative. All these factors are not included in the model and can cause the taxi times to take very high values. On the other hand, the taxi times can only be shorter than predicted only to a small extent.

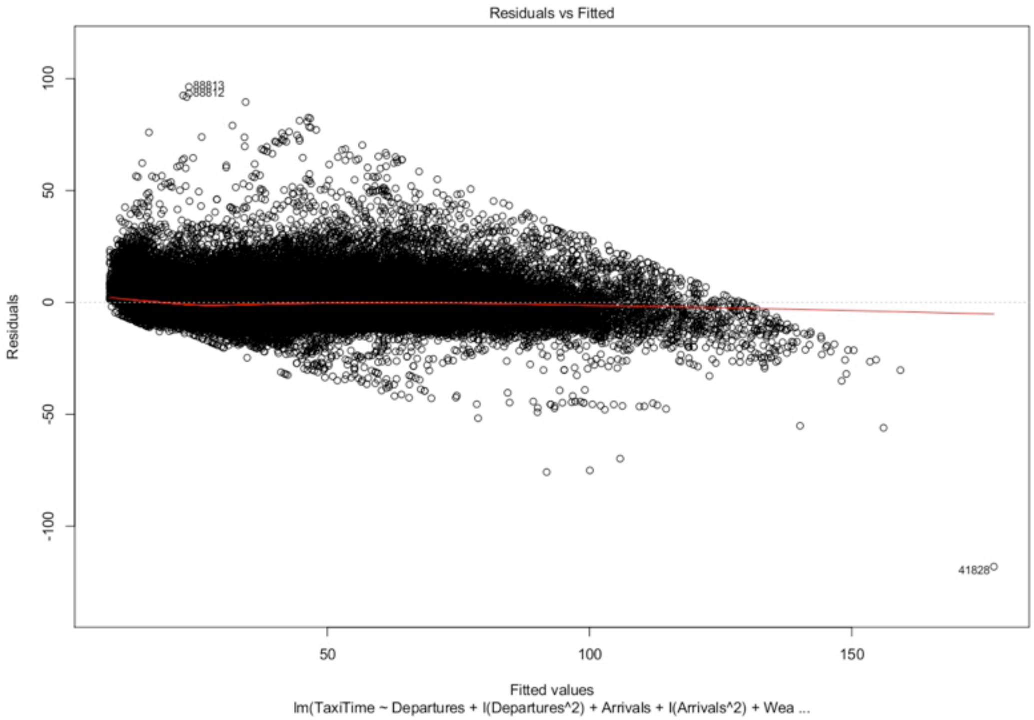


**Figure 4. Residual Plot for JFK Model**

The QQ plot in Fig. 5 illustrates that the errors are not normally distributed.

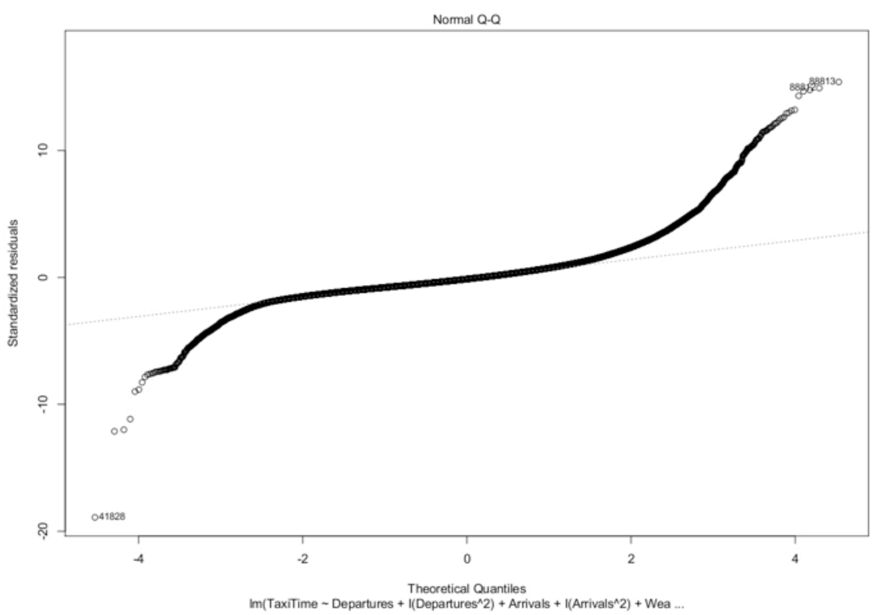


**Figure 5. QQ Plot for JFK Regression Model**

In order to assess the bias that the outliers introduce, we perform a simple form of robust regression, namely least absolute deviations regression for the final model. The coefficients from our robust regression are summarized in Table 18.

**Table 18. Robust Regression Results for JFK**

| Coefficient | Estimate | Std Error | T value | P value |
|---|---|---|---|---|
| Intercept | 12.536 | 0.089 | 140.282 | <2e-16 |
| D | 0.676 | 0.004 | 158.612 | <2e-16 |
| $D^2$ | 0.002 | 0.000 | 19.209 | <2e-16 |
| A | 0.269 | 0.004 | 68.616 | <2e-16 |
| $A^2$ | 0.003 | 0.000 | 49.582 | <2e-16 |
| WeatherVMC | -1.792 | 0.066 | -27.102 | <2e-16 |
| RwConfig 13L, 22L \| 13R | -1.025 | 0.057 | -17.879 | <2e-16 |
| RwConfig 22L \| 22R, 31L | -2.336 | 0.059 | -39.548 | <2e-16 |
| RwConfig 31L, 31R \| 31L | 0.699 | 0.056 | 12.500 | <2e-16 |
| RwConfig 31R \| 31L | 1.824 | 0.059 | 31.080 | <2e-16 |
| RwConfig 4R \| 4L, 31L | -0.946 | 0.067 | -14.127 | <2e-16 |

From the comparison of the Tables 13 and 18, we observe that the coefficients of the various explanatory variables do not change significantly in the two models: They keep the same algebraic sign and several of them differ by less than 1%. We conclude that although linear regression may be not the best tool for predicting taxi-out times, the results it yields seem reasonable and robust.

### G. Prediction Model for JFK

Given previous studies of taxi-out times, we know that the originating terminal of an aircraft and its distance to the departure runway can impact taxi-out times.

To develop a prediction model for JFK, we examine a single runway configuration and single airline, in order to control for the impact of originating terminal. Figure 6 illustrates the fit for taxi-out times versus the number of aircraft (N) on the surface for a specific runway configuration (e.g., 22L | 22R, 31L) at JFK and for a specific airline, Jet Blue (JBU). We obtain $R^2$ values of 0.93, indicating that this model explains 93% of the variability in taxi-out times.

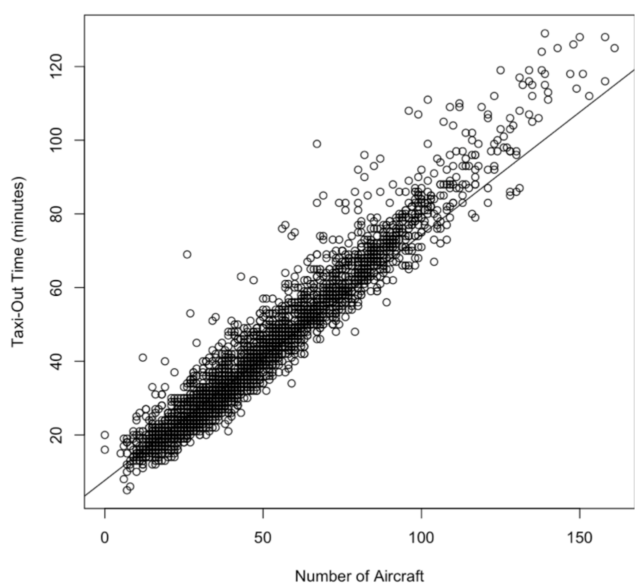


**Figure 6. Taxi-Out Times vs. N for Jet Blue and Runway Configuration "22L | 22R, 31L"**

## IV. Analysis of Taxi-Out Times at Boston Logan Airport

We start developing a model for BOS utilizing the same methods as for the model for JFK. Based on our previous analysis in Section II, the arrival traffic ($A_I$) appears to have positive correlation with the taxi-out times. In addition, our analysis indicates that the number of arriving aircraft explain almost as much variability in taxi-out times as the number of departing aircraft for this airport. The results below imply that 58% of the variability in taxi-out times can be explained by the arrivals only, and that each arriving aircraft on the ground adds more than 1 minute to the total taxi-out time of a departing aircraft.

$$T = 9.187569 + 1.126316 * A \quad (20)$$
$R^2 = 0.5848$

As the simplest starting point, we assume that the taxi times are linearly related to the number of departures (D) and the number of arrivals (A):

$$T = \beta_1 D + \beta_2 A \quad (21)$$

**Table 19. Results for the Linear Regression Model for BOS**

| Coefficient | Estimate | Std Error | T value | P value |
|---|---|---|---|---|
| Intercept | 6.793 | 0.021 | 328.700 | <2e-16 |
| D | 0.719 | 0.002 | 314.100 | <2e-16 |
| A | 0.606 | 0.002 | 249.600 | <2e-16 |
| RSE | 4.285 on 182508 degrees of freedom | | | |
| $R^2$ | Multiple R-squared: 0.7328, Adjusted R-squared: 0.7328 | | | |
| F Statistic | F2.50E+05 on 2.00E+00 and 182508 DF, p-value: < 2.20E-16 | | | |

The estimates for this model are presented in Table 19. There are a few noteworthy differences between the results of the JFK and BOS models (Tables 4 and 19). First off, the residual standard error (RSE) is much higher for JFK (7.648) than for BOS (4.285). This is to be expected, as JFK experiences excessive delays and abnormal operations, which are not entirely dependent on the queuing dynamics on the airport's surface. The simple linear queuing model achieves very low errors in BOS, where congestion and taxi times are much smaller than those in JFK. On the other hand, the R-squared value is higher in JFK (0.860) than in BOS (0.733). Although it is difficult to make comparisons between R-squared values of different datasets, we can roughly say that departures and arrivals explain the variability of taxi times to a greater extent in JFK than in BOS. Thus, although there are many outliers in JFK (which result in a higher RSE), the amount of traffic on the ground is usually high, and so a great proportion of variability of taxi-out times can be attributed to the linear combination of arriving and departing traffic. Surface queues explain taxi times to a greater extent in JFK than in BOS where a much greater fraction of the traffic gets served without experiencing long delays due to queuing. This is consistent with our earlier study comparing surface congestion in BOS and JFK and its impact on taxi times.[12]

**Table 20. Results for the Polynomial Regression Model for BOS**

| Coefficient | Estimate | Std Error | T value | P value |
|---|---|---|---|---|
| Intercept | 9.547 | 0.031 | 304.820 | <2e-16 |
| D | 0.460 | 0.005 | 89.010 | <2e-16 |
| $D^2$ | 0.010 | 0.000 | 53.300 | <2e-16 |
| A | 0.295 | 0.005 | 54.810 | <2e-16 |
| $A^2$ | 0.012 | 0.000 | 60.670 | <2e-16 |
| RSE | 4.14 on 182506 degrees of freedom | | | |
| $R^2$ | Multiple R-squared: 0.7507, Adjusted R-squared: 0.7506 | | | |
| F Statistic | 1.37E+05 on 4 and 182506 DF, p-value: < 2.20E-16 | | | |

Similar to JFK, including second order terms improves the performance of the linear regression model significantly. In order to visualize the contribution of the quadratic terms, we plot the following two linear regressions in Fig. 7:

- $T = \beta_1 D + \beta$ (red line) (22)
- $T = \beta_1 D + \beta_2 D^2$ (blue line) (23)

For simplicity we reduce the model by removing the arrivals term. As shown in Fig. 7, with the addition of the quadratic term, the line is a better fit for low and high values of D. Since the majority of the data points are in the midrange between five and twenty, these points heavily influence the slope and the intercept. This results in divergence for low and high values of D; in both regions, the majority of the data points lie above the red line. The non-linear trends can be explained by queuing theory intuition: for low values of D (less than 5), the take off queue introduces a very small delay and the taxi time observed is fairly constant (close to the unimpeded or nominal taxi time). At very large values of D, queuing stochasticity introduces non-linear delays that the polynomial model can approximate with better precision.

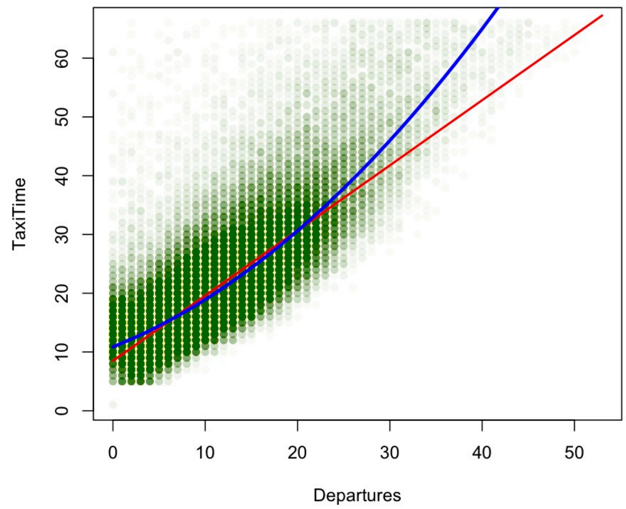

**Figure 7. Scatterplot of the Taxi-Out Times vs. Departures**

### A. Impact of Weather

We investigate the impact of weather in the same way as we did in the JFK model, by introducing a dummy variable that takes the value 1 when the weather conditions are reported to be visual. Including weather information improves the performance of the model by reducing the RSE, increasing the R-square value and achieving a lower value for the AIC. The coefficient of the weather is negative, indicating that visual meteorological conditions lead to reduced taxi out times, as expected from operational practice.

$$T = \beta_1 D + \beta_2 D^2 + \beta_3 A + \beta_4 A^2 + \beta_5 \text{Weather} \quad (24)$$

**Table 21. Results for the Polynomial Regression Model for BOS including Weather**

| Coefficient | Estimate | Std Error | T value | P value |
|---|---|---|---|---|
| Intercept | 10.941 | 0.038 | 287.350 | <2e-16 |
| D | 0.468 | 0.005 | 91.600 | <2e-16 |
| $D^2$ | 0.009 | 0.000 | 52.120 | <2e-16 |
| A | 0.294 | 0.005 | 55.240 | <2e-16 |
| $A^2$ | 0.012 | 0.000 | 62.020 | <2e-16 |
| WeatherVMC | -1.697 | 0.027 | -62.980 | <2e-16 |
| RSE | 4.096 on 182505 degrees of freedom | | | |
| $R^2$ | Multiple R-squared: 0.756, Adjusted R-squared: 0.756 | | | |
| F Statistic | 1.131e+05 on 5 and 182505 DF, p-value: < 2.2e-16 | | | |

### B. Impact of Runway Configuration

When analyzing the runway configurations in BOS we have to take a different approach than in JFK. Because of the airport layout, the runway configurations that are used the majority of the time under VMC, become unavailable under IMC. In other words, the meteorological conditions define the set of available runway configurations. Under VMC, the most frequently used runway configurations are "22L, 27 | 22L, 22R", "4L, 4R | 4L, 4R, 9", "27, 32 | 33L".

The linear regression model is modified in the following way:

$$T = \beta_1 D + \beta_2 D^2 + \beta_3 A + \beta_4 A^2 + \beta_6 \text{RwConfig} \quad (25)$$

The "Runway Configuration" variable is a categorical variable modeled as two binary variables which take the value 1 when the runway configuration is 4L, 4R | 4L, 4R, 9 and 27, 32 | 33L respectively. When the runway configuration is 22L, 27 | 22L, 22R, both of them are 0. In this representation the configuration 22L, 27 | 22L, 22R is the baseline for comparisons. All data points correspond to departures under one of these runway configurations and VMC.

**Table 22. Results for the Polynomial Regression Model for BOS including Runway Configuration**

| Coefficient | Estimate | Std Error | T value | P value |
|---|---|---|---|---|
| (Intercept) | 9.535 | 0.039 | 247.489 | <2e-16 |
| D | 0.417 | 0.006 | 69.519 | <2e-16 |
| $D^2$ | 0.010 | 0.000 | 48.065 | <2e-16 |
| A | 0.300 | 0.006 | 48.960 | <2e-16 |
| $A^2$ | 0.011 | 0.000 | 50.167 | <2e-16 |
| RwConfig 27, 32 \| 33L | 0.208 | 0.028 | 7.373 | <2e-16 |
| RwConfig 4L, 4R \| 4L, 4R, 9 | -0.902 | 0.026 | -35.020 | 1.68E-13 |
| RSE | 3.482 on 99977 degrees of freedom | | | |
| $R^2$ | Multiple R-squared: 0.8073, Adjusted R-squared: 0.8073 | | | |
| F Statistic | 6.982e+04 on 6 and 99977 DF, p-value: < 2.2e-16 | | | |

If we apply the polynomial model for these three runway configurations without including the runway configuration information, we achieve $R^2$ of 0.8041 and RSE of 3.511. Including the runway configuration improves the predictions, and also reduces the AIC. The runway configuration 4L, 4R | 4L, 4R, 9 is known to achieve the highest departure rates in BOS.[15] Our analysis consistently shows that all else being equal, it leads to 0.9 min lower taxi times in BOS. The runway configuration 27, 32 | 33 is associated with the highest taxi times among the three runway configurations. One potential explanation is that this runway configuration has only one runway used for departures and that the departure runway (33L) crosses the arrival runway (27).

## C. Interactions between the Explanatory Variables

Similar to JFK we find out that the arrival traffic is strongly correlated with the time of day and the time alone does not explain variations in taxi times. Therefore, it is not included in the model.

In order to better understand the interactions between the different explanatory variables, we fit an optimal regression tree as shown in Fig. (8). As in JFK, the take-off queue (i.e., the number of departures) has the highest impact on taxi-out times. For 75% of the flights in BOS the take-off queue is less than 13.5 aircraft and of 70% of these flights, the number of arrivals at push back was less than 10. Thus, approximately 50% of the taxi times correspond to the first two nodes of the tree, and for these flights the majority of their taxi times is due to the number of departures. When the surface of the airport is more congested, the number of arrivals plays a more critical role.

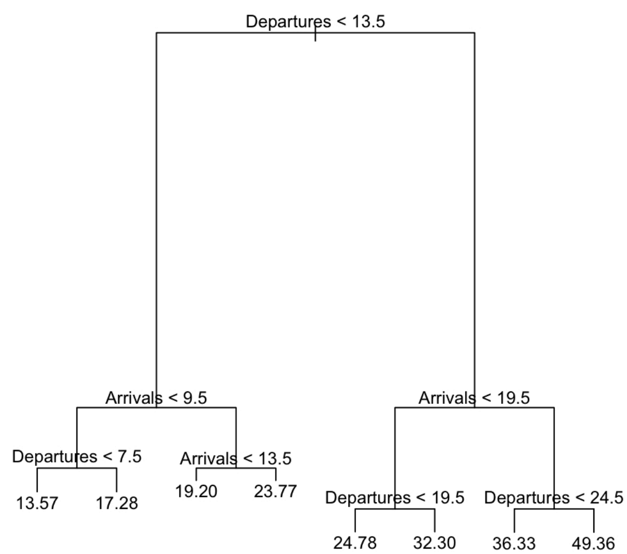


**Figure 8. Regression Tree for BOS**

## D. Impact of Terminal of Origin

Previous research has shown that terminal location affects taxi-out times. It is intuitive that different starting locations at the airport would result in a different travel time to the runway queue. BOS is a good point of study because of its simple landside layout: all the terminals are built next to each other forming a horseshoe. In order to examine the role of terminals, we create a new dummy variable to indicate which terminal the aircraft pushed back from A, B, C, or E). We keep the runway configuration as a control variable, because we want to understand the role of the starting location. In this way we make sure that all aircraft head to the same runways.

$$T = \beta_1 D + \beta_2 D^2 + \beta_3 A + \beta_4 A^2 + \beta_7 \text{Terminal} \quad (26)$$

**Table 23. Results for the Polynomial Regression Model for BOS, 22L, 27 | 22L, 22R including Terminal of Origin Information**

| Coefficient | Estimate | Std Error | T value | P value |
|---|---|---|---|---|
| (Intercept) | 10.424 | 0.077 | 135.560 | <2e-16 |
| D | 0.512 | 0.010 | 52.230 | <2e-16 |
| $D^2$ | 0.008 | 0.000 | 23.150 | <2e-16 |
| A | 0.229 | 0.010 | 23.380 | <2e-16 |
| $A^2$ | 0.012 | 0.000 | 35.660 | <2e-16 |
| TerminalB | -1.360 | 0.049 | -27.550 | <2e-16 |
| TerminalC | -1.600 | 0.054 | -29.880 | <2e-16 |
| TerminalE | -0.826 | 0.081 | -10.190 | <2e-16 |
| RSE | 3.461 on 36020 degrees of freedom | | | |
| $R^2$ | Multiple R-squared: 0.8195, Adjusted R-squared: 0.8195 | | | |
| F Statistic | 2.044e+04 on 8 and 36020 DF, p-value: < 2.2e-16 | | | |

We observe that the terminal information influences the variability of taxi-out times. If we apply the same regression model to this particular runway configuration without the terminal of origin information, we get a lower R-square value (0.8063), lower RSE (3.487), and higher AIC. The coefficients of the different terminals are quite intuitive: Terminal C is the closest to the 22s runways and the aircraft that originate from it have on average 1.6 min lower taxi times than the ones originating from Terminal A. Terminal B is right next to Terminal C and so aircraft originating from it have marginally higher taxi times than the ones from terminal C. Terminal E is also further from the thresholds of the runways 22 than terminal B and that results in a penalty of almost a minute. Terminals B, C and E are all closer to the runways 22 than terminal A, and therefore the aircraft originating from these terminals have on average lower taxi times all else being equal. We therefore conclude that the terminal of origin can be used as an explanatory variable for predicting taxi-out times.

## V. Conclusion and Future Work

Based on extensive analysis of departing aircraft from two U.S. airports, we find that the number of arriving aircraft does, in fact, affect taxi-out times. This impact increases as interaction between departures and arrivals increases, as one might expect. These results imply that strategies to reduce excessive taxi-out times at airports should take into account the effect of arrivals on taxi-out times. Further analysis of various airport layouts, configurations, and levels of congestion could yield additional insights as to the causal factors affecting taxi-out operations at airports, and will help inform strategies to reduce taxi-out times and aircraft ground emissions.

The analysis above demonstrates how taxi-out times might be predicted by various explanatory variables (for example, departures and arrivals). Future work will include how the values of these explanatory variables can be estimated in order to accurately predict taxi times. Other models that concurrently predict taxi-in times and taxi-out times are also being developed. Of further interest is also an analysis of flights that are part of traffic flow management initiatives, and how these programs impact ground operations and emissions.

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