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Modeling and Predicting Taxi Times at Airports

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by

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ACRONYMS

ATA	Air Transportation Association
ATC	Air Traffic Control
APO	Office of Aviation Policy and Plans
ASDE-X	Airport Surface Detection Equipment Model - X
ASQP	Airline Service Quality Performance
BTS	Bureau of Transportation Statistics
CDM	Collaborative Decision Making
ETMS	Enhanced Traffic Management Systems
FAA	Federal Aviation Administration
NAS	National Airspace System
NextGen	Next Generation Air Transportation
SMS	Safety Management Systems

ABSTRACT

This research aims at providing methods in analyzing and estimating the taxi times of aircraft at airports, which are expected to be an important element for reducing taxiing delay and consequent excess fuel consumption and environmental costs. The proposed model involves a set of regression equations to model the taxi-out and taxi-in times at airports. The estimated results can be used to calculate the nominal taxi times, which are essential measures for evaluating the taxiing delays at airports. Given the outcomes of the regression model, an iterative algorithm is developed to predict taxi times. A case study at LGA shows that the proposed algorithm demonstrates higher accuracy in comparison to other algorithms in existing literature.

CHAPTER 1

INTRODUCTION

1.1 Overview

Increasing urbanization has taken its toll on the airline and many others. There has been gradual increase over the years in airline traffic. Today, there are about 7,000 flights in America's skies during the peak hours. This is despite a slump in air traffic recently due to the global market meltdown. Air traffic has still been up when compared to the periods before the recession.

Figure 1-1 shows the trend of passenger enplanements from 1995 to 2009. This rise in air traffic has seen major delays in the National Airspace System (NAS). This trend is expected to continue through the next decade and cause heightened congestion. Expanding the infrastructure of the airport system is one of the options to alleviate congestion and reduce flight delay at airports. These improvements are in the form of increasing the number of runways or adding new airports; however, these come at a large capital cost. As an alternative for these improvements, the Next Generation Air Transportation System (NextGen) calls for improved management of flights at airfields and in airspace to increase the capacity of the NAS.

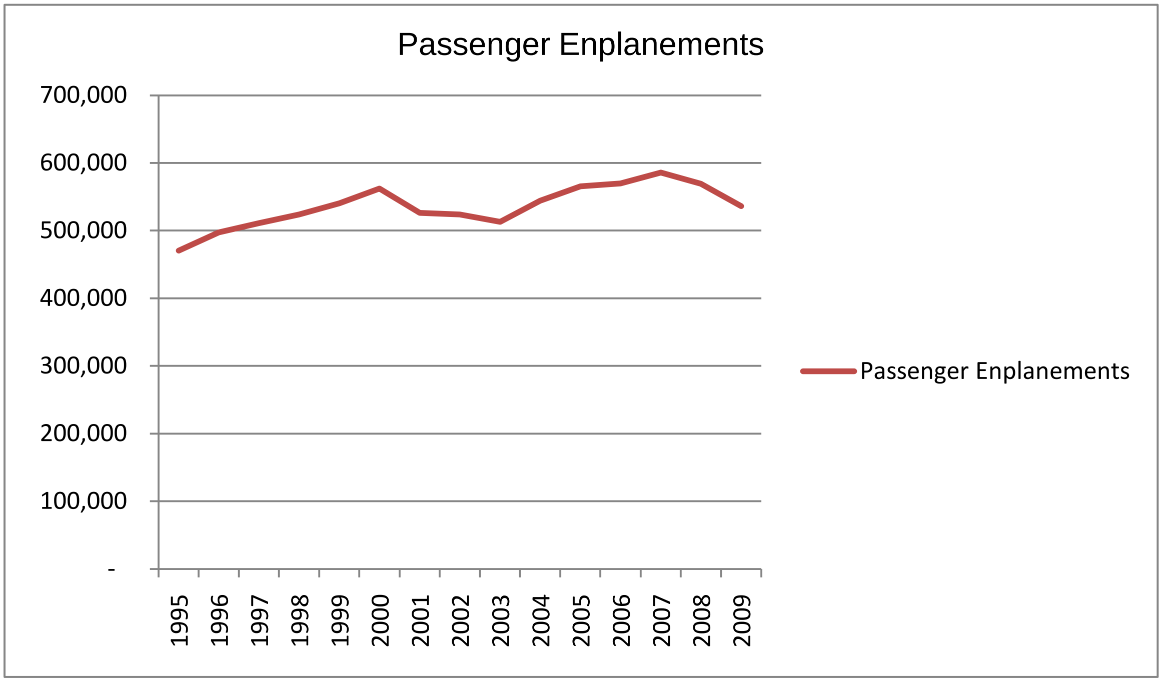

Figure 1-1 Passenger Enplanements 1995 – 2009

A large percentage of flight delay is due to ground holding and ground transit, which includes taxiing delay [1]. In the Aviation System Performance Metric (ASPM) data system, taxi times are defined as the times spent by an aircraft between rolling from a gate to when it takes off or from the entrance of taxiways to a gate after it lands. Figure 1-2 shows a representation of taxi-out time.

According to Figure 1-2, assume that t_0 is the time when the aircraft is at the gate and it takes off at time t_1. Then, the taxi time of the aircraft will be $t_1 - t_0$. In other words, the time taken by the aircraft to leave the gate and enter the taxiway, from the taxiway onto the runway, and then take off is known as taxi time. This figure shows the departure process in brief, so taxi-out time is the time taken by the aircraft from the first step, i.e., leaving the gate, to the last step, i.e., taking off. Similarly, for taxi-in time it would be in reverse, with the time taken from when the aircraft lands onto the runway to the time it reaches the gate.

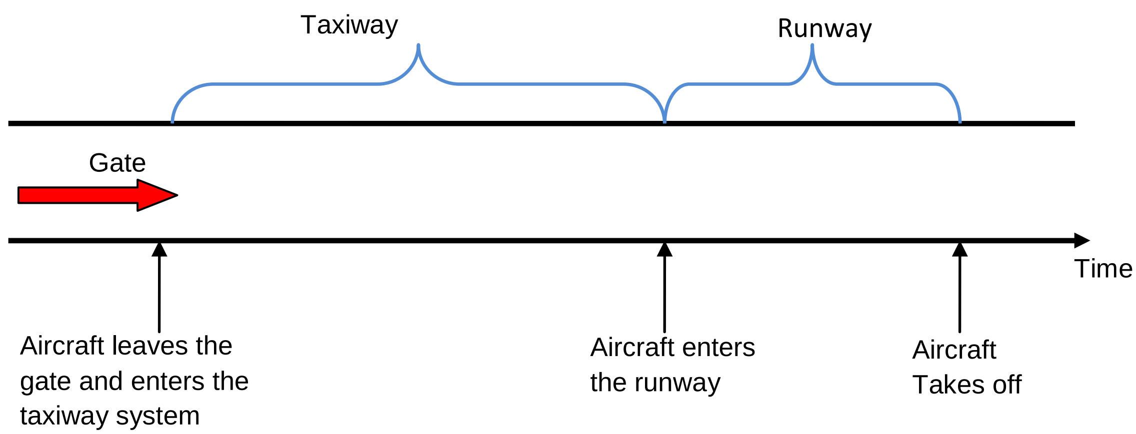

Figure 1-2 Departure Process of an Aircraft

Considering the distribution of delays experienced by a flight, taxi-out delay contributes to 26 percent of the total delay experienced by a departing flight [2].

According to Figure 1-3, for a departing flight, given the actual taxi-out time of a flight, which is the difference between actual wheel-off time and actual push-back time, and the nominal taxi-out time, which is defined on the basis of the airline queue lengths (which are discussed in detail in Chapter 2) of departing and arriving flights, etc., the taxiing delay of an aircraft is determined by computing the difference between the actual and nominal taxi-out times. The nominal time can be defined more precisely by adding new variables that affect the taxi-out time of an aircraft such as the terminal or gate the aircraft uses and its distance from the runway that is in use during that particular quarter hour.

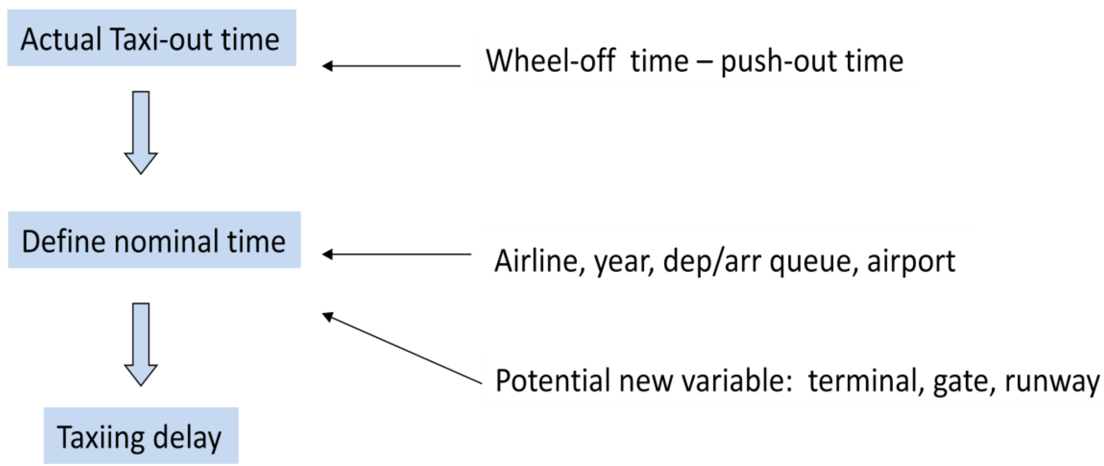

Figure 1-3 Taxiing Delay Definition

According to Bureau of Transportation Statistics (BTS), 2007 has had the highest taxi times recorded, surpassing the previous peak in 2000 [2]. This has also been observed by looking at the average block times between busy city pairs in the U.S., which have increased accordingly. For example, according to Air Transport Association (ATA), in the New York LaGuardia (LGA) – Ronald Reagan Washington National (DCA) route segment, the average block time grew by nine minutes from 1995 to 2005 [3]. Longer taxi times have elevated the direct operating and maintenance costs as well as negative environmental impacts in terms of amplified noise and augmented air pollution on and around the airport.

To mitigate delay problems, the Federal Aviation Authority (FAA) implemented the Collaborative Decision Making (CDM) approach in 1998. The CDM is intended to improve air traffic flow issues in the NAS through the exchange of information among air traffic flow managers, air traffic controllers, and airlines. In the U.S., the initial focus of the CDM was the Ground Delay Program Enhancements (GDP-E), in which the airlines share flight cancellation and reordering information with the Air Traffic Control System Command Center (ATCSCC). Users of the NAS also apply CDM tools to share information on safety and efficiency among themselves. The CDM concept applied to some European Union (EU) airports is known as Airport CDM (A-CDM) [4]. The focal point of A-CDM is to bring together major airport partners such as air traffic controllers, aircraft operators, and ground handlers to share data in a clear manner. This becomes significant for achieving a common situational understanding, consequently leading to better decision-making processes.

Presently, NextGen is under way. Its objective is to improve the NAS to meet future demand, avoid congestion, and make the skies safer. NextGen suggests using various technologies, equipment, and procedures to enhance pilot control over flight paths while the controllers on the ground focus more on traffic flow management [5]. NextGen looks to implement new tools that are being developed to help manage aircraft flow at airports in order to mitigate taxiing delays and reduce engine run times and the consequent environmental impacts. Such new tools require a better understanding of taxiing times and taxiing delays and also call for a way to accurately predict taxiing times. Accurate prediction of departure taxi times are essential to help airlines manage push back times and to obtain and pass on delay information to en-route control centers and destination airports. Accurate prediction is also a key component of the CDM operations and leads to better gate management and reduced arrival and departure delays. Air

Traffic Control will benefit as well via improved demand forecasts for airports and en-route air sectors.

This study contains four parts. In the first part, a literature review is presented. The second part presents an ordered response model that shows the propensity of various factors on taxi-out times. In the third part, an alternative model is proposed that, in addition to offering inputs for the predicting model, is used to calculate the nominal taxi times by adding certain factors that were not considered in the present Aviation Policy and Plans Office (APO) model introduced in the literature review. This model provides us with essential measures that can be used to evaluate the taxiing delays at the airports. In the fourth and final part, an iterative algorithm is proposed to predict the taxi-out time with the outcomes from the regression models and other inputs. In comparison to other existing taxi time predicting models, the outcomes of the case study with our model provide higher accuracy and reliability.

1.2 Scientific Contribution

The primary contribution of this thesis is to better model taxi times and to propose a method to predict taxi-out time effectively. Flight delays cause the government to incur huge losses every year. Figure 1-4 shows the average amount of time a flight needs to take off after it leaves the gate and to reach the gate once it lands. It shows LGA has a high mean taxi time when compared to other airports and, since it is in the busy northeast corridor of the United States, the delay at this airport also affects delay for other flights, due to the ripple effect causing losses [10]. These losses are also environmentally hazardous due to the burning of excess fuel during longer times spent by the aircraft on the tarmac. Therefore, it is important to address these issues. While this thesis does not declare to solve the problem completely, it provides ways to estimate the nominal taxi times more precisely and also proposes a better model to predict the taxi-out times of an aircraft.

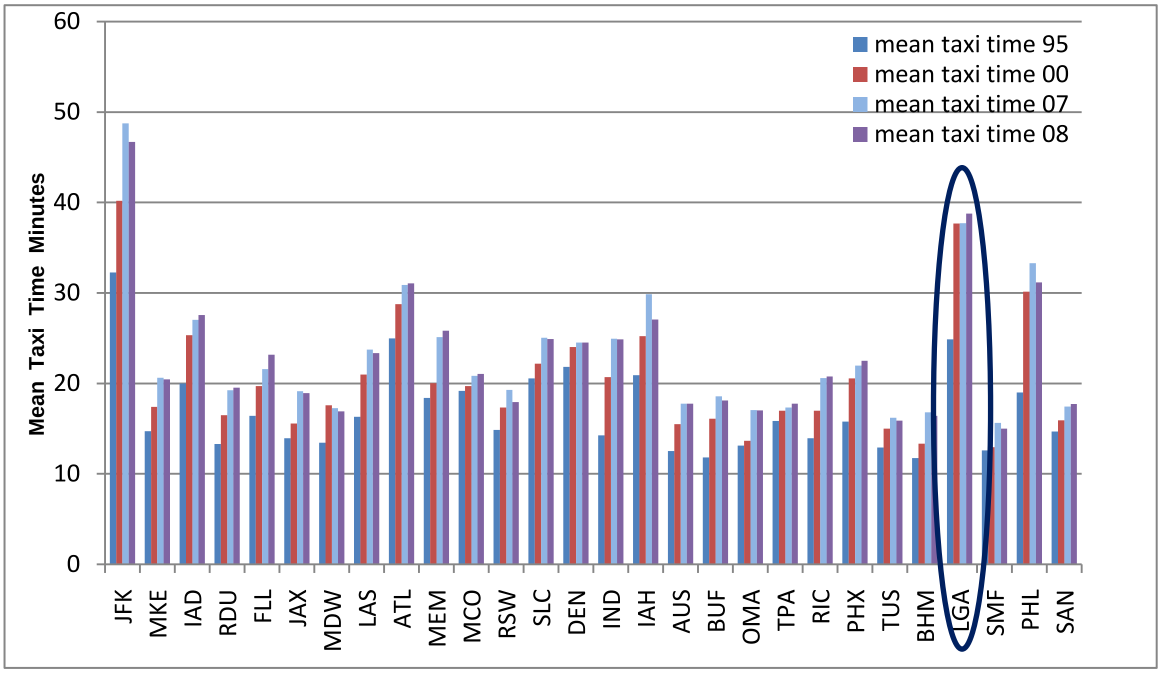

Figure 1-4 Mean Taxi Time for Major U.S. Airports

1.3 Content of the Thesis

Chapter 2 presents the literature review and explains the APO model that is used currently to define the unimpeded (nominal) taxi times recorded in ASPM.

Chapter 3 proposes an ordered response model that looks at the propensity of various factors affecting the taxi-out delay of a departing flight. The model is run in Gauss 9.0, and the results are tabulated to show the effects of the variables on taxi-out delay. These results are discussed in this chapter as well.

Chapter 4 proposes a new model that includes additional factors that have effects on the time taken by flights on the surface of the airport before they wheel off. When compared with the APO model, the proposed model shows higher R-square values.

Chapter 5 introduces an iterative algorithm that applies estimated coefficients from the previous regression models as the inputs along with data from ASPM. The iterative steps in the algorithm find successive approximations, and this process is repeated until the difference between each iteration is lower than a given convergence parameter. The algorithm predicts the taxi times for departing and arriving aircrafts, which are then compared to their respective reported values in the ASPM database. The results show a higher accuracy when compared to a previous study, which is discussed in this chapter.

Chapter 6 includes remarks and recommendations for future work in this area.

CHAPTER 2

LITERATURE REVIEW

The existing model for estimating unimpeded taxi times recorded in the ASPM database developed by Kondo is based on two linear equations, one for taxi-in, the other for taxi-out, while containing both taxi-in and taxi-out queue lengths [6]. Given the actual flight information, such as actual gate-out and wheel-off times, which are available from the ASPM database, Kondo defines departure queue length as the number of aircraft ahead of the flight at the queue entry time and arrival queue length as the number of aircraft ahead of the flight at the wheels-on time.

This model is described in this section along with a description of the data sources, selection of the data set, and the steps performed in imitating the model. The data used for this imitation and for all the other models described in this thesis is obtained from ASPM, which are records created by the Federal Aviation Administration (FAA) using data from a variety of sources. Enhanced Traffic Management System (ETMS) supplies next-day operational data, and Innovata provides flight schedule data, while Airline Service Quality Performance (ASQP) provides finalized schedule data, Out Off On In (OOOI) data, and delay causes as reported by the carriers after the close of each month [5]. The data include detailed information on IFR flights to and from ASPM airports (currently 77) and all flights by ASPM carriers (currently 22), including flights by those carriers to international and domestic non-ASPM airports. ASPM also includes airport weather, runway configuration, and arrival and departure rates. This combination of data provides a full-bodied picture of air traffic activity for these airports and air carriers. This data set contains, for every flight, scheduled and actual departure times, actual take-off and landing times, scheduled and actual gate arrival times. ASPM data are available on a next-day basis, and updated records are not available until three or four weeks after the end of each calendar month. These data are Internet accessible.

To select the case study, we studied airport characteristics, and it was observed that airports with the longest taxi-out times are typically those with a higher volume of air traffic. These airports are mostly either hub airports or focus cities for airlines. According to BTS, for 2007, the top three airports with longest ground times waiting for takeoff in 2007 were from the New York area, and LGA was ranked at number three with average taxi-out times of 29 minutes [2]. This was also seen in Figure 4 in Chapter 1. Among the three New York airports, LGA is an ideal airport for our case study because it has only two cross runways, one for arrival and one for departure, and since not only the runway configuration but also the information of specific runways that flights are assigned to affects the taxi times, this works out to be an ideal data set. The imitation of the existing APO model using the data set selected is performed and is then compared with the proposed model that was introduced in Chapter 1. The data are obtained individually for departure and arrival flights. A code is developed using SAS 9.2 to clean the data and keep the required data columns for further analysis. A season parameter is also set up that divides the months of a year into four seasons. The parameter defines winter as all days from December through February, spring as March through May, summer as June through August, and fall as September through November. The departure data contain the date, airport, carrier, season, actual gate-out time, and actual wheels-off time. The arrival data contains the date, airport, carrier, season, actual wheels-on time, and actual gate-in time. Bins are then set up for each minute of a single day that count how many departing aircraft ahead of a reference flight at its queue entry time, i.e., its gate-out time. The number of aircraft ahead is considered as the departure queue length for that flight. Arrival queue length can be obtained in a similar way by considering wheel-on and gate-in times. Figure 2-1 explains the queue length of a departing aircraft.

The X axis is the location on the airport surface and the Y axis is the time. Four aircraft are taxing-out from the gate and taking off from the end of the runway. The reference aircraft leaves the gate at a time t_1 and takes-off at a time t_2. The taxi-out duration of the reference aircraft is t_2 - t_1. There are three aircraft that have a gate-out time before t_1. They have entered onto the airport surface at a time before t_1 and are, therefore, a part of the departure queue of the reference aircraft. Departure queue is defined as the number of flights ahead of the aircraft at queue entry time (gate-out time). In this case, that number is 3. For arrival flights, the queue length estimation method is similar. Arrival queue length is defined as the number of aircraft ahead of the flight at queue entry time, which is wheels-on time.

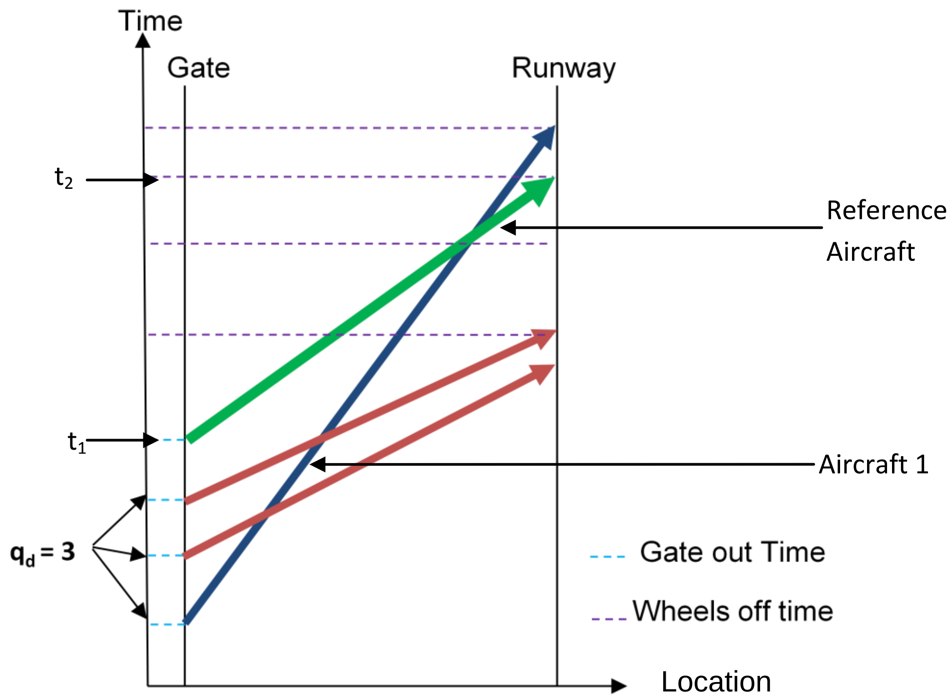

Figure 2-1 Queue Length of APO Model

The arrival queue lengths are merged into the departing flight data set according to date, time, and carrier, and the departure queue length is merged with the arrival data set by the same variables. This is done so that every flight has an arrival and departure queue at a particular time, whether it is an arriving or a departing flight. The upper 25 percent of the data is excluded from further computation. This is done to avoid large values of taxi-out time from having an effect on the estimates. These high values of taxi time maybe due to other reasons such as delay in boarding of passengers onto the plane, baggage issues, or a technical problem with the aircraft. These large values of taxi time do not reflect the real reasons that affect the taxi time and will influence the regression estimates or coefficients; since this model estimates optimal taxi time assuming there is no obstruction in the taxiways, it makes this a valid assumption.

For each group, defined according to carrier and season, the taxi-out time is then modeled as the linear combination of an intercept, weighted taxi-out queue length, and weighted taxi-in queue length, as well as the taxi-in time with a different set of coefficients. These weights (coefficients) can be regressed with the Ordinary Least Squares method. This model captured the major factor contributing to taxi times, the queue lengths of arrival and departure flights. However, it did not consider other factors such as runway configurations, weather impact, and others. These factors also affect the times that airplanes spend on the ground for their taxi time. The regression analysis is then performed for each part separately with taxi-out time (for departing flights) as the dependent variable and the independent variables being departure and arrival queues. For arrival flights, the taxi-in time is the dependent variable, and the queue lengths are the independent variables. For the calculation of unimpeded taxi-out time, the taxi-out equation is substituted by a departure queue length of 1 and arrival queue length is substituted by 0. This is because when we are estimating the unimpeded or nominal taxi time, we consider the aircraft to be the only plane on the airport surface. Similarly, to estimate the nominal taxi-in time, the arrival queue length is considered to be 1 and the departure queue length is taken as 0.

A research paper by Idris et al. [1] identified delay causal factors such as runway configuration, airline/terminal location, departure demand, departure queue size, weather, and downstream restrictions. They stated that the runway configuration determines the flow of aircraft at the airport, presents the level of interaction between the flows, and restricts the capacity of arrivals and departures. Idris et al. also discussed weather and downstream restrictions in view of the fact that adverse weather greatly reduces the capacity of the airport. They suggested another way of calculating the arrival and departure queue length, accounting for the passing of aircraft. This method of calculation of queue length is discussed in detail later.

The queuing model proposed by Idris et al. for taxi-out estimation assumed takeoff queue to be the primary factor affecting the taxi-out time of an aircraft without taking into consideration the arrival queue. They set up different combinations of carriers and runway configurations as subsets. The data of the case study that they presented in the paper contained a total of 56 subsets. The downstream restrictions were not considered as separate variables but were assumed to be a part of the departure queue. Idris et al stated that, aircraft that experienced long taxi-out times due to passing and restrictions would have long take-off queues. For all the subsets, a probability distribution function (PDF) is developed that gives the probability of a queue forming depending on the number of aircraft present on the airport surface at that particular time. An average taxi-out time is calculated over all possible queue sizes, and then a second-order equation is fitted to these values. Their model was compared to the running average model that is used in the ETMS and showed a reduced mean absolute error by approximately twenty percent and an improved accuracy rate by about ten percent. The model predicted 66 percent of taxi-out times within 5 minutes of actual time and is applicable when the number of aircraft present on the airport surface is known.

The Enhanced Traffic Management System (ETMS) model [7] estimates the taxi-out time using the running averages of the last two weeks. The limitation of this model is that it does not take into consideration important factors affecting the taxi-out time of an aircraft such as runway configuration. Shumsky [8] proposed two linear models to predict the taxi-out time of an aircraft. One was a static model and the other was a dynamic one. The static model uses the variables such as carrier, runway configuration, weather, and a measure of airport congestion. To explain airport congestion, Shumsky projected two different measurements, the number of pushbacks in a given time period around the pushback of the aircraft and the number of departing aircrafts present on the runway at the pushback time. The results of this study showed that estimations using the queue size were better than using the number of aircrafts on the runway as a measurement for airport congestion. Shumsky also claimed that the static model was as good as the dynamic model for short time horizon, such as a 15-minute period. Nevertheless, for a longer time horizon, the static model yields superior results.

Brinton et al. [9] described Surface Management System (SMS) architecture and presented results at four major airports. They then proposed enhancements to the algorithms to potentially improve the accuracy of predicting taxi times that are predicted by SMS. According to Brinton, the most significant aspects of surface activity include the number of available runways and their layout, runway occupancy time requirements, surface congestion, and gate availability. The goal of the research was to provide a coordinated motion plan for all vehicles currently using, and those anticipated to be using, the surface resources (runways, taxiways, gates) over a certain time horizon. Based on the inputs from SMS, the routing and de-confliction algorithms approximate the taxi routings and resource utilization (gates/runways) that are most likely to be realized by tower controllers and focused on algorithms defining the Trajectory Synthesis and Flow Modeling capability. They demonstrated each of the algorithms on a simple planning problem involving the simultaneous routing of three arrivals and three departures on a mock symmetric airport layout and found that the Event-Based A* outperformed the Co-Evolution strategy in terms of cumulative time of completion over the set of all vehicles.

CHAPTER 3

ORDERED RESPONSE MODEL

3.1 Introduction

Figure 3-1 is taken from a 2008 report by the Bureau of Transportation Statistics (BTS), “Sitting on the Runway.” Taking 2003 as the base, since this was the year when all certified carriers were required to report the traffic data, this figure compares yearly flight volume, taxi-out time, and taxi-in time from 2003 to 2007 [2]. As the flight volume increased in the first year, so did the taxi times of the aircraft. From 2004 to 2005, there was an increase in flight volume and a decrease in the taxi-out times; the taxi-in times, on the other hand, remained almost the same. The year 2006 saw a decrease of flight volume with an increase in ground transit times of airplanes. The year 2007 showed a more drastic increase in taxi times compared to the flight volume. This shows that flight volume or congestion is not the only factor that effects the taxi times of flights; there are other factors as well that influence the times spent on the ground.

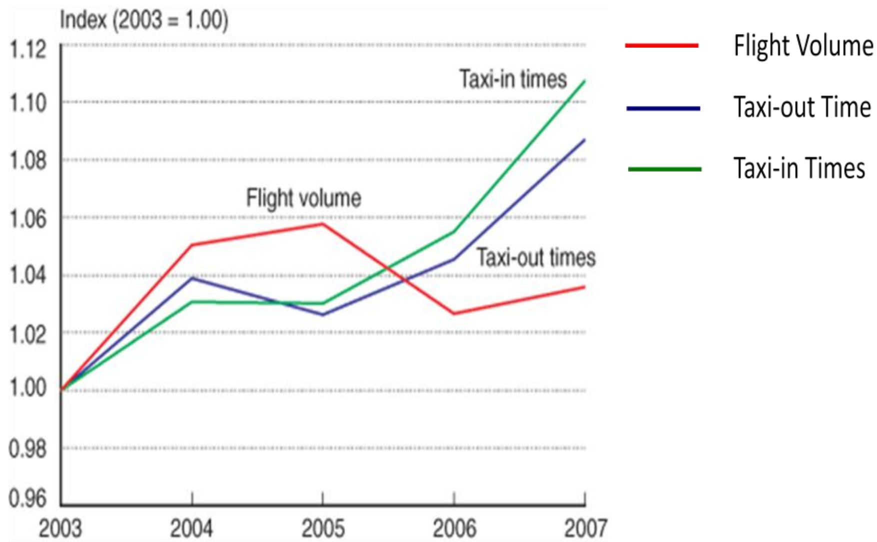

Figure 3-1 Comparison of Trends of Flight Volume and Taxi Time

The ordered response model in this sections aims to look at the propensity of various factors affecting taxi-out delay. Taxi-out delay was explained in Chapter 1 and is defined as the difference in time between actual taxi-out time and nominal or unimpeded taxi-out time. The purpose of using this model is to identify the propensity of various factors that may have an effect on the taxi-out delay.

The data used for this model estimation are taken from the ASPM complete database mentioned in the previous chapter. The data, however, do not reflect the actual on-site circumstances that may cause large differences in gate-out and wheel-off times (taxi-out times). Another data source that allows the analyst to see the movement of the airplanes on the surface of the airport is the Airport Surface Detection Equipment – Model X (ASDE-X) surveillance data. This was developed at the Sensis Corporation and provides seamless coverage and aircraft identification to air traffic controllers. This system is able to determine the position and identification of aircraft and transponder-equipped vehicles on the airport movement data, which will give a detailed understanding of the movement of aircraft. However, these data are not available for all airports; there is a plan to make it available for the OEP-35 airports. The data set considered is of the LaGuardia International Airport (LGA) from January 2007 to December 2007. Some of the variables used in the analysis are not present in the individual flights database and, therefore, have to be obtained from the airport data. These are then merged to form a single data set with all the required variables. These variables are then checked for any missing values or any discrepancy by conducting a descriptive statistic test, so that the model estimation performed in gauss does not alter the desired results. The model used is an ordered response model, and the dependent variable is categorized into different classifications. The dependent variable in this case is the taxi-out delay, and this is classified into four categories, as discussed later.

3.2 Explanation of Variables

3.2.1 Departure and Arrival Queues

These are the departure and arrival queue lengths at that particular time for each departing aircraft. These are calculated separately and are not a part of the data available. The departure queue is one of the most important factors of taxi-out delay. This is because during high departure flows there are longer queues for departure. When an aircraft gates out, it spends some time on the runway in the departure queue waiting to use the runway. This leads to longer taxi-out times as the aircraft have to wait for their turn to depart. There are similar conditions with arrival queues. The arrival queues are longer when the number of arrivals is higher. This has little effect on taxi-out time; however, due to the interactions between arriving and departing aircraft, the arrival queue also affects the taxi-out time.

3.2.2 Expected Departure Clearance Times (EDCT)

Traffic management personnel assess the traffic coming in and going out of the airports and then use strategies to hold the aircraft and give it a new departure time so that the demand and capacity remain balanced. Once the EDCT time is allotted, the aircraft have around 15 minutes to depart or else they will be assigned a new EDCT time and there will be more delay. So the premise is if a new EDCT is assigned, then there will be longer taxi-out time and the aircraft will experience more delay.

3.2.3 Time of Day

This variable is a dummy variable for the time of day. There are peak and off-peak hours of airline traffic, with is a high volume of traffic during the peak hours. During this time, the taxi-out delay is expected to be larger compared to off-peak hours. The dummy variables are divided into four categories: category A is a departure time of between 6:00 hrs and 8:59 hrs, B is a departure time of between 9:00 hrs and 14:00 hrs, C is a departure time of between 14:00 hrs and 21:00 hrs, and D is a departure time greater than 21:00 hrs.

3.2.4 Holidays

This variable is a dummy variable for all federal holidays in the U.S. The premise is that holidays are the times when people travel a lot and, therefore, there will be high volumes of aircraft and an increase in taxi-out delay. Only federal holidays were included; a total of 8 holidays have been considered.

3.2.5 Airport Supplied Departure Rate (ADR)

This is the actual departure rate of the airport during a particular quarter hour. This is important factor in that it reflects the capacity of the airport based on the runway configurations selected at that particular hour.

3.2.6 Season

Dummy variables for season are used in the estimation. Season is divided into four categories: S_1 for March through May, S_2 for June through August, S_3 for September through November, and S_4 for December through February. Season represents, to an extent, the weather conditions at the airports and also the volume of traffic.

3.2.7 Weather

A dummy variable for IMC ratio is used and tested in the model; however, it was not significant since the effect of weather is taken into account by the season variable and the queue lengths.

3.2.8 Runway Configuration

Several different runway configurations that are possible at LGA, and they differ in capacity depending on which type is used and which airlines are using them. Figure 3-2 shows the runway configuration of LGA. For each runway configuration, the dummy variable is set to be 1 if the configuration was operated while one flight taxiing-in or taxiing-out or 0 if it was not.

3.2.9 Arrival and departure runways in use

Arrival and departure runways in use define the distances from gates to the end of runway(s) and the distances from runway exist(s) to the gates. This information can be difficult to obtain. In the ASPM data used to conduct the case study, there were no arrival and departure runways in use recorded. Fortunately, we found some airports (LGA was one of them) that have only one arrival runway and one departure runway. Thus, given the runway configuration, it is easy to know the arrival and departure runways in use. For modeling other airports with a more complex runway configuration, an additional database, such as the Performance Data Analysis and Reporting System (PDARS), needs to be used for obtaining such information.

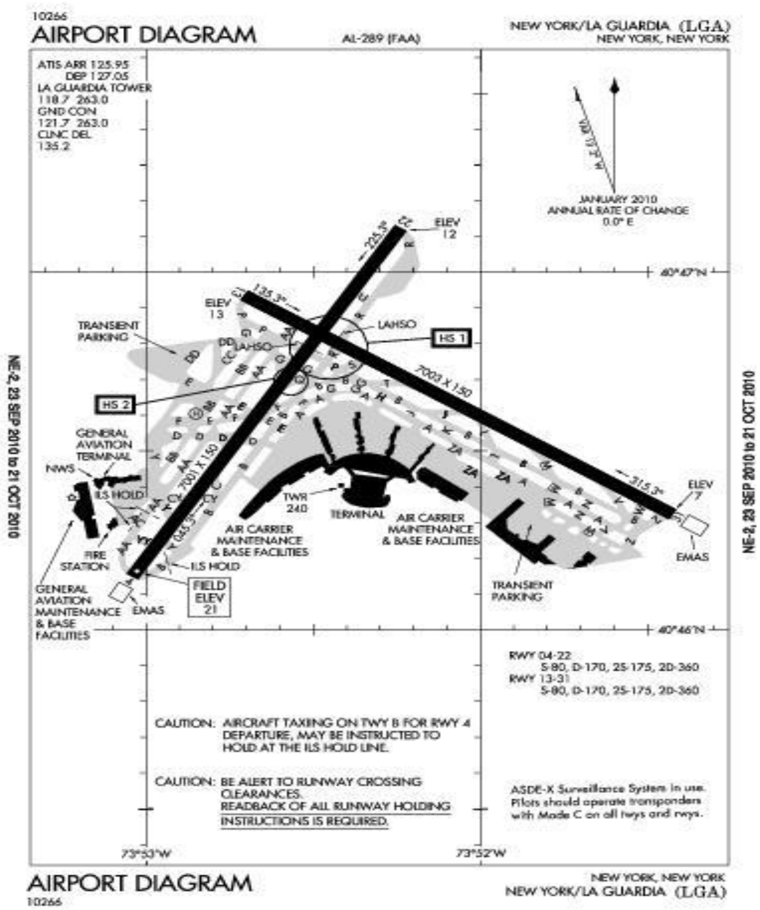

Figure 3-2 Runway Layout at LGA

Runway 04/22 and Runway 13/31 are the runways at LGA. Different combinations of these runways are used for arrivals and departures, and there are different taxi times for these combinations. This is because of the various interactions between the arriving and departure flights and the distance of the runways from the gates.

Descriptive statistics are shown in Table 3-1 and Table 3-2. The statistics in Table 3-2 show the percentage of the dummy variables that are involved in the model.

Table 3-1 Descriptive Statistics

Explanatory Variables	*No. of Cases*	*Mean*	*Standard Deviation*
Actual Departure Demand	13,283	9.425807	1.065949
Actual Arrival Demand	13,283	9.240006	1.130768
Nominal Taxi-out	13,283	12.38345	1.307837
Actual Taxi-Out	13,283	20.67929	6.689501
Departure Queue	13,283	11.45351	5.237472
Arrival Queue	13,283	3.134307	1.879049

Table 3-2 Descriptive Statistics in terms of Percentages

Explanatory Variables	*No. of Cases*	*Percentage*
EDCT	13,283	0.159509
Dummy variable for runway configuration	13,283	0.5947
Dummy variable for runway configuration	13,283	1.4831
Dummy variable for runway configuration	13,283	28.5628
Dummy variable for runway configuration	13,283	00.9862
Dummy variable for runway configuration	13,283	25.6042
Dummy variable for runway configuration	13,283	00.128
Dummy variable for runway configuration	13,283	06.2938
Dummy variable for runway configuration	13,283	19.7019
Dummy variable for runway configuration	13,283	12.5725
Dummy variable for runway configuration	13,283	00.3538
Dummy variable for runway configuration	13,283	03.1318
Dummy variable for hour of day	13,283	14.9063
Dummy variable for hour of day	13,283	36.6182
Dummy variable for hour of day	13,283	38.5003
Dummy variable for hour of day	13,283	07.3477

3.3 Model Estimation

Gauss 9.0 is used to perform the model estimation. Since the dataset is very large, a random sample is taken using SPSS. The random sample is 10 percent of the data set. The data set is reduced to around 13,000 cases. Since a sample is used, the weights need to be calculated. These weights are calculated using a ratio shown below.

Weight of taxi-out delay = (market share / sample share) of taxi-out delay

The dependent variable is taxi-out delay, and it is calculated as the difference between actual taxi-out time and nominal taxi-out time. The dependent variable is classified into four categories, and an ordered probit model is used for estimation. The categories for delay are as follows:

Category 1 = no delay

Category 2 = >0 and <8 minutes of delay

Category 3 = >= 8 minutes and <16 minutes of delay

Category 4 = >= 16 minutes of delay

This was defined using a histogram of the taxi-out delay

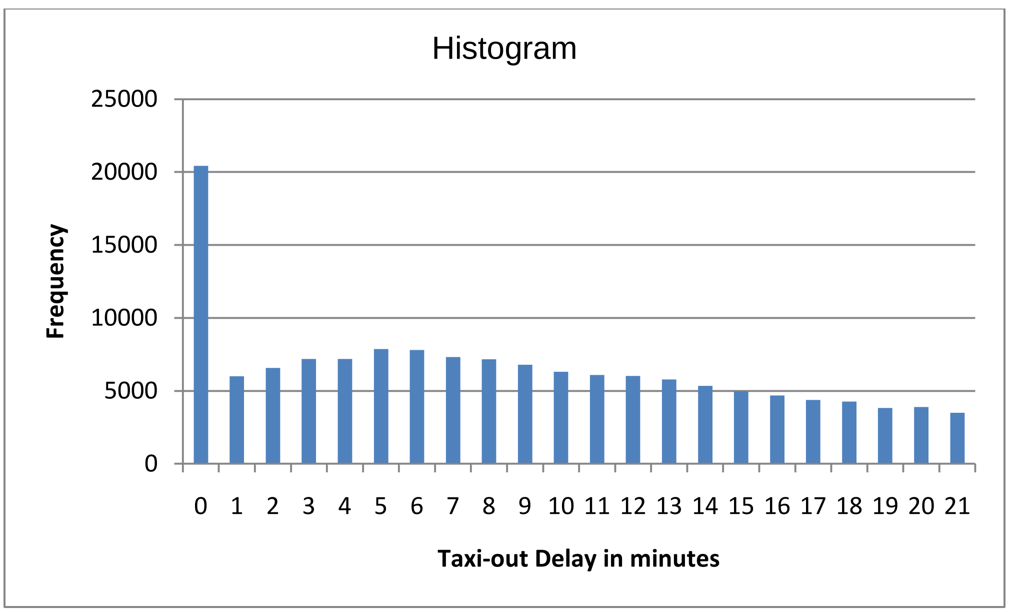

Figure 3-3 Histogram to Define the Categorization of Taxi-out Delay

Ordered probit model is used for estimation, and the resultant equation is:

$$\mathrm{Dlto} = \partial + \mathrm{q_d} * \upbeta_1 + \mathrm{q_a} * \upbeta_2 + \mathrm{E} * \upbeta_3 + \mathrm{A} * \upbeta_4 + \mathrm{C} * \upbeta_5 + \mathrm{D} * \upbeta_6 + \mathrm{H} * \upbeta_7 +$$

$$\mathrm{ADR} * \upbeta_8 + \mathrm{S_1} * \upbeta_9 + \mathrm{S_3} * \upbeta_{10} + \mathrm{S_4} * \upbeta_{11} + \sum_{\mathrm{n}=1}^{\mathrm{t}} \mathrm{R_n} * \upbeta_{12\mathrm{n}}$$

Where,

Dlto = taxi-out delay

Q_d = departure queue

Q_a = arrival queue

E = expected departure clearance times

A = dummy variable for time between 6 am to 8 am

C = dummy variable for time between 2 pm to 9 pm

D = dummy variable for time greater than 9 pm

H = dummy variable for all federal holidays in the US.

S_1 = months between March and May

S_3 = months between September and November

S_4 = months between December and February

R_n = dummy variable for runway configuration in use

The Ordered-Response Model estimated the factors causing delay and determined the propensity of these factors on taxi-out delay. The taxi-out delay is a continuous variable was ordered in the classes mentioned above.

The Ordered-Probit Model has the following form:

$$P_n(y_n = 1) = cdf(\psi_1 - \beta' X_n) - cdf(\psi_0 - \beta' X_n)$$

$$P_n(y_n = k) = cdf(\psi_k - \beta' X_n) - cdf(\psi_{k-1} - \beta' X_n)$$

$$P_n(y_n = 3) = 1 - cdf(\psi_2 - \beta' X_n)$$

P_n is the probability that the subject n belongs to category k.

Once the model is set up the results[1] are tabulated and shown in Table 3-3.

Table 3-3 Model Results

Explanatory Variables	***Parameter Estimate***	***T-Stat***
Thresh01	0.1389	1.523
Thresh02	1.6637	18.1
Thresh03	2.9472	31.44
Departure Queue	0.1599	68.54
Arrival Queue	0.0097	1.659
EDCT	0.2607	4.305
Holidays	-0.1176	-2.198
Actual Departure Rate	-0.0366	-3.959
Time of the day		
Dummy for time between 6am and 8 am	-0.0744	-2.456
Dummy for time between 3pm to 9 pm	0.0609	2.751
Dummy for time greater than 9 pm	0.1585	3.974
Season		
Dummy for months from March to May	0.0481	1.75
Dummy for months from Dec to Feb	0.0174	0.634
Dummy for months from Sep to Nov	0.1593	5.655

[1] **The results of the model will yield better estimates of the parameters if the thresholds are provided with start values. In this model the thresholds were estimated and not given.**

Table 3-3 (Continued.)

Runway Configuration		
Dummy for runway conf	0.1965	2.436
Dummy for runway conf	0.2841	2.913
Dummy for runway conf	0.4473	1.599
Dummy for runway conf	0.3222	1.907
Dummy for runway conf	0.2127	1.689
Number of cases	13283	
Log likelihood at convergence	-14016.62	
Log likelihood for constants-only model	-16754.91	
Rho^2	0.1634	
Adjusted Rho^2	0.1625	

3.4 Interpretation of Results

3.4.1 Departure Queue

This estimate is positive and is correct according to the premise of the longer the departure queue, the higher the taxi-out delay. The t-stat of this variable is extremely high, indicating that this may lead to a positive feedback cycle; in other words, as the delay increases, the departure queue increases as well.

3.4.2 Arrival Queue

The parameter estimate of arrival queue is positive as well and, according to the t-stat, the variable is not statistically significant (>=1.96). However, this is an important variable and so it needs to be considered in the estimation. This is because when there is an aircraft taxiing out, there are interactions with arriving aircraft and this increases the taxi time. So, if the arrival queue is longer, there will be more interactions, and the taxi-out delay will increase slightly as well.

3.4.3 EDCT

This variable is positive, and the basic assumption that if EDCT is assigned, then the taxi-out delay will be higher when compared to airlines that have not assigned an EDCT. So, if an aircraft is assigned an EDCT time, the taxi-out time of that aircraft increases as it adds up to the departure queue for a longer time. The t-stat of this variable is also significant.

3.4.4 Time of Day

The peak time of the day is in the afternoons and evenings. The departures are greater in the afternoons and the arrivals are greater later in the day. According to the model estimation, the premise of taxi-out delay being greater during peak hours is true. The first parameter is negative, that is, the taxi-out delay is less if the departure time is between 6 am to 8 am when compared to a departure time of 9 am to 2 pm (which is taken as a base). The other two parameters are positive, indicating higher taxi-out delay when compared to the base, that is, a departure time between 9 am to 2 pm. The t-stat of all the three are significant (>=1.96).

3.4.5 Holidays

The premise that holidays are higher volume days and therefore will have high taxi-out delays has failed here, as the estimate is negative. The could be because, since air traffic has declined the over the past 2-3 years because of the recession, people have started to avoid traveling to far-away destinations and are sticking to the road and going to destinations that are easily accessible and close by. Also, people are tired of paying for things that were once free in the airline industry. Perhaps air travel is now being used more for business than for leisure. The t-stat is significant as well.

3.4.6 ADR

Capacity of the airport is a straightforward variable that should be negative, and is. If the capacity is greater than the demand, then the taxi-out delay reduces and there is smoother travel with fewer delays. The t-stat is significant.

3.4.7 Season

The dummy variable for season reflects the weather and volume delays combined. All the variables are positive, meaning that these months have higher taxi-out delay when compared to June, July, and August when the weather is good and there are very few delays. Even though the t-stats are not significant, these are important variables and are required for model estimation.

3.4.8 Runway Configuration

Runway configuration shows that some types of configurations have higher taxi-out delay than others because of their proximity to the gates of certain airlines. This is an important variable and taxi-out delay is different under different runway configurations.

The results of this model provide an idea of what effect certain factors have on taxi-out delay, which is used as a reference in selecting the variables that are used in the proposed model. All the variables tested by this model cannot be used in the proposed regression model that is discussed in the next chapter, since, although the t-square values are significant, the variables that are actually used in the proposed model take account of the left out variables.

CHAPTER 4

PROPOSED REGRESSION MODEL

4.1 Queue Length Calculation in the Alternate Model

A different approach can be used to calculate the queue lengths in this model. This alternate model uses the concept of aircraft passing and over-passing. Aircraft passing and over-passing occur if the reference aircraft is held up for certain reasons and other aircraft pass it, or if other aircraft are held up and the reference aircraft passes them. Consider this in Figure 4-1. The reference aircraft leaves the gate at a time t_1 and wheels off at time t_2. Aircraft 1 has a gate-out time before t_1, and a wheel-off time after t_2 (wheel-off time of the reference aircraft). This aircraft has been passed by the reference aircraft and will not be counted in the queue length of the reference aircraft. Now consider aircraft 4; this aircraft has a gate-out time after the reference aircraft has left the gate but takes off before the reference aircraft. This aircraft will be a part of the departure queue of the reference aircraft since it has passed the reference aircraft. In other words, the departure queue of an aircraft is defined as the number of flights that have a take-off time during its taxi-out, and the arrival queue is defined as the number of flights that have a gate-in time falling into its taxi-in duration.

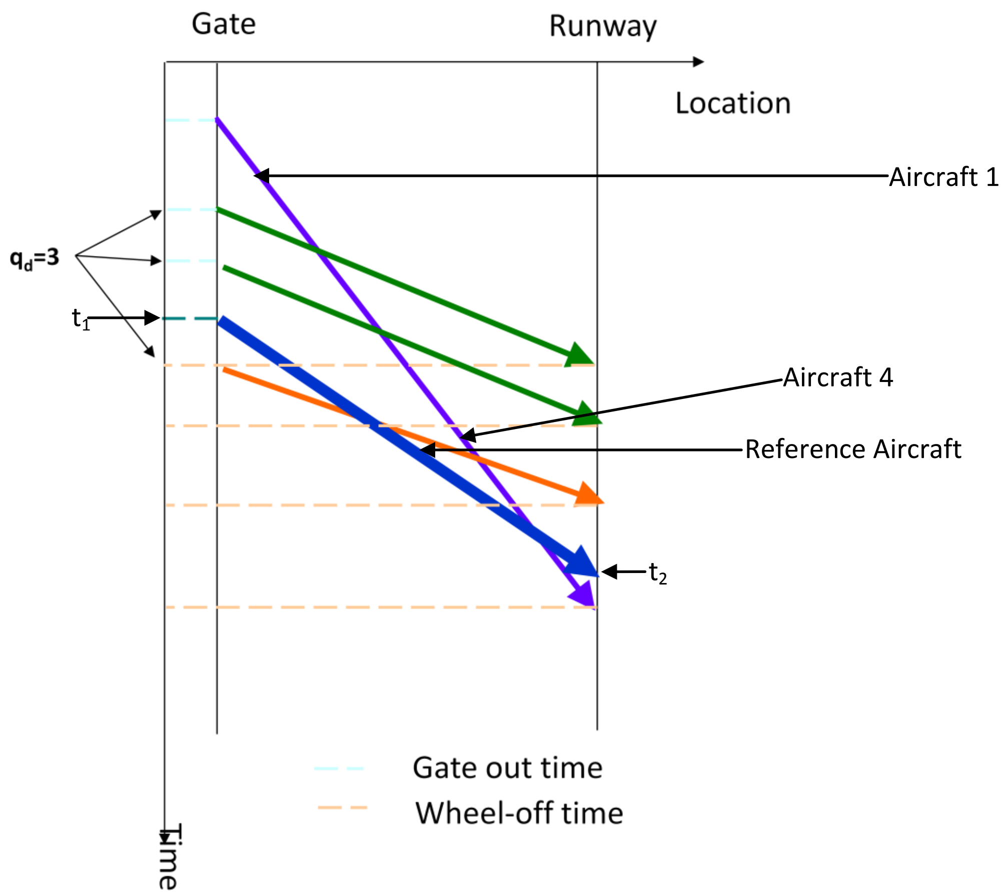

Figure 4-1 Taxi-out Representation

4.2 Comparison of Queue Length

Table 4-1 illustrates the difference in the calculation of queue lengths between the APO model and the proposed model. According to the definition by the FAA APO model, the departure queue for NWA at 7:10 am is 7, which is the number of aircraft on the airport surface at its gate-out time. The departure queue for that flight is 5, according to Idris et al.'s definition, because it has passed the two flights DAL and FLG that had a gate-out time of 7:08 am but took off later than the NWA flight.

Table 4-1 Comparison of Queue Length Calculation

Carrier	Gate-Out	Wheels-Off	Dep_Queue (Kondo)	Dep_Queue (Idris)
USA	6:57:00	7:13:00		
NKS	7:00:00	7:15:00		
NWA	7:00:00	7:18:00		
UAL	7:02:00	7:19:00		
UAL	7:04:00	7:22:00		
DAL	7:08:00	7:29:00		
FLG	7:08:00	7:26:00		
NWA	7:10:00	7:24:00	7	5
AAL	7:14:00	7:27:00		

4.3 Proposed Model

4.3.1 Model Description

The imitation of the existing APO model shows that there is very little variance of the observed data captured by this model. Although the existing model has included major contributors, such as arrival and departure queue lengths, it did not include other factors that may influence the taxi time, as discussed earlier. To make the estimation more accurate, this study proposes another set of linear equations to model the taxi-in and taxi-out times. Explanatory variables include arrival and departure queue lengths, runway configuration, arrival and departure runways, and dummy variables indicating time of day and EDCT that reflect air traffic flow management activities. Arrival and departure queue lengths and runway configuration have been discussed extensively in the previous section and are widely accepted as major causal factors of taxi-in and taxi-out delay. Nevertheless, the way of counting the queue lengths in proposed model follows what have been defined in the paper of Idris et al., which is different from those in APO model. There are dummy variables created for runway configuration as well. The information on arrival and departure runways in use are also important because it gives the distance from gates to the end of the runway and the distance from runway exits to gates. If the gates are farther away from the ends of the runways, the aircraft will have a longer ground transit time. This kind of information is not available in ASPM. Fortunately, for LGA, the selected case study, only one departure runway and one arrival runway are usually used in daily operation. So runway configuration virtually contains the information of runway usage. Peak and non-peak hours in the day could cause contrasting performance of taxi-in and taxi-out delay due to different gate constraints. In addition, flights experiencing EDCT could perform differently from others. Dummy variables are set up for the time of the day and EDCT to account for these effects. Considering the physical interaction between aircraft in the taxiway systems, quadratic terms of the queue lengths are introduced in this regression model. Similar as the APO model, flights are grouped according to carriers and seasons, and the flights with taxi times in the upper 25th percentile are filtered from the data. The case study of this model with 2007 data at LGA shows higher R square values when compared to the outcomes of the APO model. The regression equation is of the form:

$$\mathrm{T_o} = \partial + \mathrm{q_d} * \beta_1 + \mathrm{q_a} * \beta_2 + \mathrm{q_d}^2 * \beta_3 + \mathrm{q_a}^2 * \beta_4 + \mathrm{q_d} * \mathrm{q_a} * \beta_5 + \mathrm{E} * \beta_6 + \mathrm{A} * \beta_7 + \mathrm{C} * \beta_8 + \mathrm{D} * \beta_9 + \sum_{n=1}^{13} \mathrm{R_n} * \beta_{10n}$$

Where,

Q_d = departure queue length

Q_a = arrival queue length

E = dummy variable for EDCT, 1 if EDCT is assigned, else 0

D = dummy variable for time of the day, 1 if the time is between 6am and 8 am, else 0

C = dummy variable for time of the day, 1 if the time is between 3pm and 9pm, else 0

T = dummy variable for time of the day, 1 if the time is greater than 9pm, else 0

R = dummy variable for runway configuration, 1 if the one in question is in use, else 0

The equation for taxi-in time has similar explanatory variables taken from the arriving flights data. The equation is given below:

$$\mathrm{T_i} = \partial + \mathrm{q_d} * \beta_1{}^* + \mathrm{q_a} * \beta_2{}^* + \mathrm{q_d}^2 * \beta_3{}^* + \mathrm{q_a}^2 * \beta_4{}^* + \mathrm{q_d} * \mathrm{q_a} * \beta_5{}^* + \mathrm{E} * \beta_6{}^* + \mathrm{D} * \beta_7{}^* + \mathrm{C} * \beta_8{}^* + \mathrm{T} * \beta_9{}^* + \sum_{n=1}^{13} \mathrm{R_n} * \beta_{10n}{}^*$$

For unimpeded taxi-out times, such as in the previous model, consider the departure queue length to be equal to 1 and arrival queue length to be equal to 0 and vice-versa for the taxi-in time of an aircraft. The arrival queue length is taken to be 1 and the departing queue length is taken as 0.

4.3.2 Regression Results and Comparison

With the same data, we conducted the regressions of our proposed model and the existing model used to calculate the nominal taxi times recorded in ASPM database. Table 4-2 shows a sample group of the regression results.

Table 4-2 Regression Results

YEAR	DAY	CARRIER	Arr_locid	NOMTO	Tm	season	Intercept	Queue_D	Queue_D2
200703	15	AAL	STL	11.6	8.9	1	11.95	0.93151	0.01111
200706	10	EGF	BGR	11.1	23.02	2	8.78716	1.26215	0
200707	23	EGF	BOS	11.1	18.15	2	8.78716	1.26215	0
200711	2	EGF	CVG	10.8	22.45	3	6.63839	1.27988	0
200708	28	FFT	DEN	13.7	8.38	2	13.06356	0.36974	0.03663
200711	2	FFT	DEN	11.2	6.92	3	8.97368	0.79762	0.01902
200707	30	MEP	MCI	12.4	7.28	2	11.07828	0.47851	0.02719
200703	6	NKS	FLL	12.4	8.63	1	16.26751	0.33255	0.03649

rwyconf4c	rwyconf7c	rwyconf8c	rwyconf9c	rwyconf10c	EDCTc	Bc	Cc	Dc	CALNOMTO
0.32419	-0.93117	-1.67999	-1.552	-0.22996	0.66876	-1.3393	-0.9733	1.06031	11.87742
2.0454	-0.30627	-0.86094	0.42271	0	2.04619	-1.4349	-0.7435	-0.0024	10.46962
2.0454	-0.30627	-0.86094	0.42271	0	2.04619	-1.4349	-0.7435	-0.0024	11.77462
4.07483	1.9921	1.12718	2.26146	2.21779	0.97062	-0.8929	-0.6164	0.46266	10.59872
-0.80952	0.15225	-1.18024	0.27664	0	-3.0128	-0.4509	-0.3580	0	13.2956
-2.20914	0.21465	1.23372	2.59556	-2.40829	0	0.19207	-0.2593	0.96412	11.02404
1.64769	-0.28301	-0.91466	0.5142	0	0	0.15634	0.8448	2.81792	12.09818
-3.97864	-3.33951	-4.27865	-3.26161	0.13974	1.67606	-0.8902	-0.240	0.95519	12.4068

The comparison of the performance of the two models is shown in Table 4-3. The proposed model has an average R^2 value of 0.758 for taxi-out estimation across all groups while the average R^2 value of the APO model is only 0.429. In addition, the standard error of the R^2 values for the proposed model is smaller.

Table 4-3 Comparison of R^2 Values

R^2 Statistics	***Alternate Model***	***Existing Model***
Mean	0.758	0.429
Standard Error	0.004	0.008
Median	0.753	0.434
Mode	0.738	0.455
Standard Deviation	0.044	0.084
Sample Variance	0.002	0.007
Kurtosis	0.814	-0.120
Skewness	0.627	-0.303

CHAPTER 5

PREDICTING TAXI TIMES

5.1 Iterative Algorithm

Given the regression results and other inputs from flight scheduling, we propose an iterative algorithm to predict taxi-out times. The basic idea is to revise arrival and departure queue lengths and update the taxi-out times of the flights in each iteration until the difference between two iterations becomes less than the convergence parameter set up at the beginning, i.e.,

$$\frac{\sum_{f_a}\left(t_i{}^{(n+1)} - t_i{}^{(n)}\right)}{F_a} < \ \varepsilon \text{ for arrival flights}$$

$$\frac{\sum_{f_d}\left(t_o{}^{(n+1)} - t_o{}^{(n)}\right)}{F_d} < \ \varepsilon \text{ for departures flights}$$

Initially, the arrival and departure queue lengths are set as 0. The iteration count variable n is set as 1 and the convergence parameter is defined as 0.005. Given the estimated coefficients and other input variables, the taxi-in time and taxi-out times can be calculated. Given gate-out times and arrival times, we can calculate departure times for departure flights and gate-in times for arrival flights. Assuming there are no gate constraints holding arrival flights from getting a gate, we check the extra taxi-out times that could cause by departure capacity. The 15-minute airport departure rate (ADR) is used as departure capacity of the airport. With the previous calculation, we can determine if the 15-minute ADR is exceeded or not. If exceeded, affected flights are postponed to the next 15-minute time window. The same procedure is repeated until no demand exceeds supply in all 15-minute time windows in the day. Assuming there is no over-passing, we can calculate the arrival or departure queue lengths and then the taxi-in or taxi-out time for each flight. Compare the two sets of taxi-in and taxi-out times mentioned so far, if the differences are smaller than the convergence parameter, the iterative algorithm stops; otherwise, the iteration counts increase one unit and the iteration continues from calculating the departure times for departure flights and gate in times for arrival flights. The iterative steps of the algorithm are now summarized in the form of a pseudo-code.

Goal: Stop when the convergence parameter is met to find the taxi-out time.

1. *Initialization:* $x_o^{(0)} = 0$ and $x_i^{(0)} = 0$ (queue lengths), Iteration count n = 1 Convergence parameter is set, $\varepsilon = 0.005$

2. *Calculate taxi times:* Using the estimated coefficients from the model as input, calculate $t_o^{(n)}$ and $t_i^{(n)}$.

3. *Calculate departure and gate-in times:* Using gate out (g_o) and arrival times (a_i) as inputs, departure time $d_o^{(n)} = g_o + t_o^{(n)}$ and gate in time $g_i^{(n)} = a_i + t_i^{(n)}$.

4. *Check for 15-minute total departures:* If the capacity (ADR) is exceeded, affected flights are moved to the next time window. This stops when all ADR constraints are satisfied.

5. *Calculate queue lengths:* $x_o^{(n)}$ and $x_i^{(n)}$ the departure and arrival queue lengths that are calculated.

6. *Calculate taxi times:* Given the estimated coefficients from the regression model, $t_o^{(n+1)}$ and $t_i^{(n+1)}$.

7. *Convergence Test:* If $\sum_{F_a} \frac{t_i^{(n+1)} - t_i^{(n)}}{F_a} < \varepsilon \text{ and } \sum_{F_d} \frac{t_o^{(n+1)} - t_o^{(n)}}{F_d} < \varepsilon$,

   Stop,

   Else n = n+1 and go to step 3.

5.2 Case Study and Performance of the Algorithm

One day in 2007 was selected, July 13, at LGA to test the performance of the algorithm. More experiments should be conducted later to get a more general idea about the performance. It shows that the model is able to predict 74 percent of taxi-out times within five minutes of the actual times. With a different date set, the model proposed by Idris et al. predicted 66 percent of taxi-out times within five minutes of actual times. Table 5-1 lists the descriptive statistics when comparing the predicted taxi-out times (CALTO) and actual taxi-out (ACTTO) times recorded in ASPM data.

Table 5-1 Comparison of CALTO vs. ACTTO Statistics

Statistics	***ACTTO***	***CALTO***
Mean	18.55	18.95
Standard Error	0.23	0.22
Median	18.00	18.38
Mode	12.00	19.32
Standard Deviation	5.48	5.25
Sample Variance	29.98	27.56
Kurtosis	0.00	0.72
Skewness	0.63	0.47

Figure 5-1 demonstrates the comparison of average taxi-out times for different hours of the day. It is observed that in the evening, there are larger discrepancies between predicted taxi-out times and actual taxi-out times. This could be caused by the gate constraints that we have ignored in our iterative algorithm or other factors. To predict taxi times more accurately, it is worth more investigation to look into surface movement data, observing the real-time operations at airports and evaluating the impact of gate constraints on arrival queues.

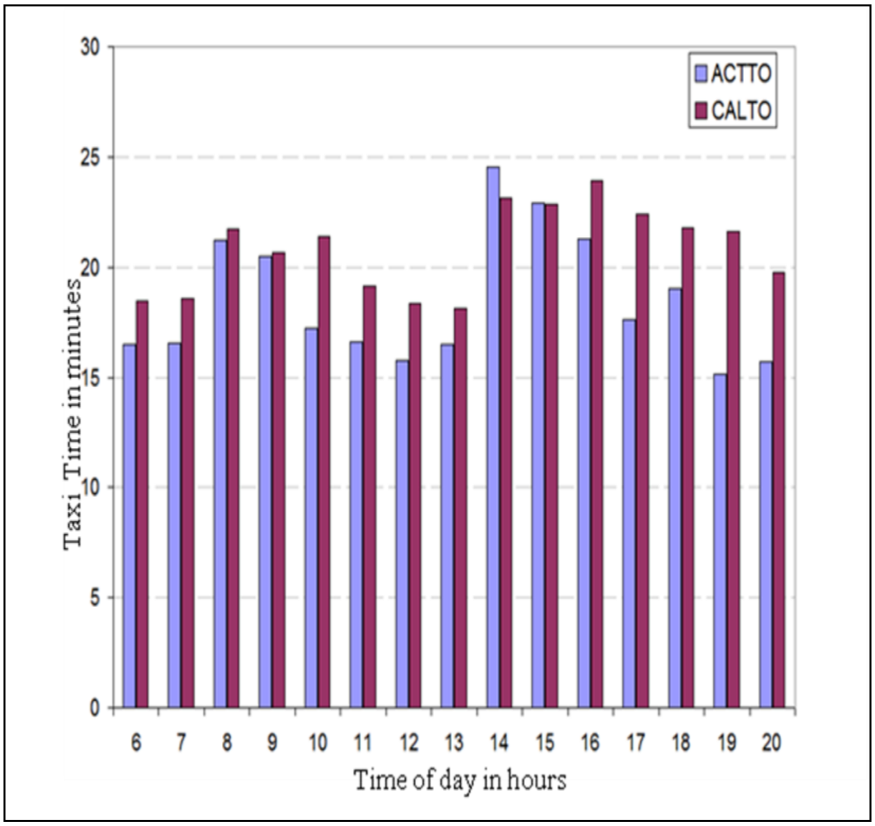

Figure 5-1 Comparison of Actual and Calculated Taxi-out Times during Different Hours of the Day

CHAPTER 6

CONCLUSION

Taxiing delay has always been a major problem for most major airports. In general, there are huge losses associated with taxiing delay due to gas emissions, fuel wastage, ground-holding, etc. This research illustrates the utility of the ordered-probit model to study the taxi-time delay at LaGuardia Airport, one the most congested airports in the U.S. The model developed takes into account all the delay-causing factors previously discussed and estimates the significance of each of them. The dependent variable in this model is taxi-out delay, which is the delay experienced by the aircraft once it departs from the gate to the runway for take-off. The taxi-out delay at LGA airport significantly depends upon departure queue, arrival queue, runway configuration, season, EDCT, and time of day. It was observed that the delay is less during morning period and increases as the day passes, reaching its peak in the evening. It was also seen that the delay generally is reduced during holiday periods due to fewer aircraft using the airport.

This research proposes a set of regression equations to model the taxi times at airports by considering the queuing effect, runway configuration and runways in use, EDCT effect, time of day, and others. The comparison of the proposed model and the model used to calculate the nominal times recorded in ASPM database show that with the expansion of independent variables, the proposed model explains double of the variation of the taxi times. The iterative algorithm for predicting taxi times proposes an alternate method of predicting the taxi times. The inputs for the algorithm include the estimated coefficients from aforementioned regression model, flight gate-out times or arrival times. ADR is taken as the airport departure capacity. Procedures are taken to ensure the departure capacity is not exceeded in each iteration. The algorithm is tested with the data of one day's operations in 2007 at LGA. The predicted results are compared with the actual taxi-out times recorded in ASPM. Overall, 74 percent of predicted value falls into the range within five minutes of the actual times. This is higher than the 66 percent claimed by one of the existing models, although with data from a different airport.

REFERENCES

[1] H. Idris, J.P. Clarke, R. Bhuva and L. Kang. “Queuing Model for Taxi-Out Time Estimation”. *Air Traffic Control Quarterly*, September 11, 2001.

[2] B. Goldberg and D. Chesser. ”Sitting on the Runway: Current Aircraft Taxi Times Now Exceed Pre-9/11 Experience”. Bureau of Transportation Statistics Special Report, May 2008.

[3] J.P. Heimlich. “Commercial Jet Fuel Supply: Impact on U.S. Airlines.” Aviation Subcommittee of the Committee on Transportation and Infrastructure of the U.S. House of Representatives, February 2006.

[4] European Organization for the Safety of Air Navigation. http://www.eurocontrol.int.

[5] Website of FAA program and initiatives, http://www.faa.gov/about/initiatives/nextgen.

[6] N. Pujet, B. Delcairey, and E. Feronz. “Input-Output Modeling and Control of the Departure Process.” Air Traffic Control Quarterly, 2000.

[7] J. Legge and B. Levy. “Departure Taxi Time Predictions using ASDE-X Surveillance Data.” 8th AIAA/ATIO, Anchorage, AK.

[8] E.R. Mueller and G. B. Chatterji. “Analysis of Aircraft Arrival and Departure Delay Characteristics.” Proceedings of AIAA Aircraft Technology, Integration, and Operations Forum at Aviation Week’s Aerospace Expo, Los Angeles, CA, October 1-3, 2002.

[9] Brinton, C., J. Krozel, B. Capozzi, and S. Atkins, “Improved Taxi Prediction Algorithms for the Surface Management System,” Proceedings of the AIAA Guidance, Navigation, and Control Conference, Monterey, CA, August 5–8, 2002,

[10] Yu Zhang and Nagesh Nayak, A Macroscopic Tool for Measuring Delay Performance in the National Airspace System, The Journal of Transportation Research Record, pending, 2010