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Regional Airline Study: The Impact Of Operational Volume On Performance At Capacity Constrained Airports

Brady Bjerke

REGIONAL AIRLINE STUDY: THE IMPACT OF OPERATIONAL VOLUME ON PERFORMANCE AT CAPACITY CONSTRAINED AIRPORTS

by

Brady Todd Bjerke
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This thesis, submitted by Brady Todd Bjerke in partial fulfillment of the requirements for the Degree of Master of Science from the University of North Dakota, has been read by the Faculty Advisory Committee under whom the work has been done and is hereby approved.

Mark Dusenbury, PhD
Associate Professor, University of North Dakota

Jim Higgins, PhD
Associate Professor, University of North Dakota

Shayne Daku
Assistant Professor, University of North Dakota

This thesis is being submitted by the appointed advisory committee as having met all of the requirements of the School of Graduate Studies at the University of North Dakota and is hereby approved.

Grant McGimpsey
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ABSTRACT

New regulation requires mainline carriers to report regional airline on-time performance. Regional airlines have a high operational volume at capacity constrained airports. Studies have indicated that if volume at a capacity constrained airport increases, then flight delays are likely to grow. Regional airline operational data in JFK and LGA is analyzed to determine the relationship between volume and on-time performance over a two-year period. Through reviewing statistical test results, recommendations are made in effort to predict a regional airline's optimal volume while maintaining adequate on-time performance. Operational volume is characterized by three independent variables: block hours, aircraft utilization, and the number of scheduled departures. Three on-time performance metrics are considered: delays, significant delays and completion factor. The results of the output models show that an increase of volume at JFK and LGA led to an increase of delays, significant delays, and cancellations. Volume predicts operational performance but the relationship is sensitive to operational season, fleet type, and hub station.

CHAPTER I

Introduction

In the race between air traffic growth and new airport capacity in the United States, traffic growth is winning, causing further congestion at capacity constrained airports. Delayed flights, cancellations, and air traffic control ground stops have made air travel a burden for the traveling public. Chronic congestion at capacity constrained airports has legislators and economists at odds for a solution; varying from capacity control to congestion pricing methods (Dachis & Poole, 2007; Whalen, Carlton, Heyer, & Richard, 2012). Regardless of the debated congestion management approaches, airlines have been forced for decades to mitigate delays and cancellations at various congested airport environments across the U.S.

Chronic congestion is showcased at two capacity constrained airports in New York: John F. Kennedy (JFK) and LaGuardia (LGA). According to the Bureau of Transportation Statistics (2017), the percentage of departure delays is trending upward, increasing eight percent at JFK and two percent at LGA from July 2015 to July 2017. Not only are delays increasing, but the average delay minute has an upward trend, increasing by 19 minutes at JFK and 15 minutes at LGA from July 2015 to July 2017.

The delay rise in New York is attributed to air travel demand growth in addition to airlines opting to substitute large aircraft for smaller regional aircraft, resulting in an increase of departures. The major airlines push flying to regional affiliates in effort to reduce cost. Smaller aircraft, such as the Bombardier Canadian Regional Jet, feature significant operating cost improvements. Advantageously, the regional jet enables airlines to offer an increased amount of point-to-point flying, which increases destination options for the mainline carrier (Vasigh, Fleming, & Tacker, 2013). Airlines may be offering additional travel options to their customers, yet they are responsible for a dramatic increase in volume at already capacity constrained airports. While New York departure numbers rise, the number of seats per aircraft have declined dramatically, further creating congestion (Whalen, Carlton, Heyer, Richard, 2009). Although the increase of departures give regional airlines the opportunity to grow their presence in the lucrative New York market, performance is paramount to gain acceptance and recognition from their mainline partner.

For regional airlines to be commercially successful, they require a high volume of flying given the high costs associated with aircraft, labor, and fuel. While regional jets offer cost advantages compared to mainline narrow-body jets, the overall cost burden at a regional airline should be considered. To spread these high costs over more units of output, airlines have a strong incentive to use their aircraft as intensive as possible (Vasigh, Fleming, & Tacker, 2013). Since an aircraft is not earning money while sitting on the ground, the more an aircraft is flying, the more passengers the airline carries. This parallels with additional revenue a regional airline can earn from their mainline partner. The overall concept is simple when travel is in high demand: increased flying equals increased revenue available to cover cost.

Economically, a high cost commodity, like aircraft, should be utilized as much *as possible* to gain a return on investment. But how does this concept change in a congested market? The foundation of airline network strategy is to maximize the use of resources without subjecting the operation to significant delays and cancellations. Congested airports, like JFK and LGA, hurt high aircraft utilization as available capacity does not meet demand which creates a logistical burden for all airlines trying to maximize revenues. All in all, the balance of aircraft utilization and on-time performance remains unclear. The challenge faced by regional airlines is sustaining the on-time performance standards of their mainline partner while maximizing volume in capacity constrained airports.

Importance

The study of regional airline volume and on-time performance in congested markets is important for several reasons. First, the On-Time Disclosure Rule, implemented by the U.S. Department of Transportation in 1987, made on-time performance reports of major U.S. airlines available to the public. The goal was to increase delay transparency to the traveling public while incentivizing and promoting airlines that perform best. Since the rule was implemented, on-time performance is a significant factor when airlines make scheduling decisions (Shumsky, 1993). For years, the On-Time Disclosure Rule only required mainline carriers to report their mainline flight performance, excluding their regional affiliates. However, effective January 1, 2018, the U.S. Department of Transportation will require mainline carriers to report their regional affiliates in their overall on-time performance data. This will, undoubtedly, drive more attention to regional airline delay and cancellation rates.

Second, according to IATA's World Air Transport Statistics report (2016), airlines carried seven percent more passengers worldwide than the year before. U.S. passengers lead the way with 810 million enplanements which is one-fifth of all passengers worldwide. Specifically, the Federal Aviation Administration forecasts long-term growth rates per enplanement of five and a half percent for U.S. regional airlines (Vasigh, Fleming, & Tacker, 2013). With travel demand at an all-time high, several U.S. regional airlines will continue to experiment with the balance of volume and on-time performance in congested markets.

This study will focus on one U.S. regional airline that operates Bombardier Canadair Regional Jets (CRJ) in New York. The focus airline is a growing airline with firm plans to increase its fleet by 20 percent in 2018. Operationally, the airline has extended its footprint in JFK and LGA over 65 percent from January 2016 to October 2017, scheduled to amass over 15,000 block hours in New York by the end of 2017. Remarkably, the focus airline has grown to be largest regional airline in JFK and LGA, ranking as the fourth overall airline in both hubs, enplaning more than 8 percent of total passengers from August 2016 to July 2017 (BTS, 2017). Despite finding success in growing a tough market at an extraordinary rate, congestion at JFK and LGA makes maintaining the on-time performance standard mainline carriers expect from a regional airline very challenging, especially during uncontrollable events such as inclement weather or Air Traffic Control ground stop programs.

Literature Review

In an extensive research initiative, Jacquillat (2012) created a predictive simulation model of New York airport congestion using data reported in the Aviation System Performance Metrics maintained by the FAA. The model concluded that if demand at a capacity constrained airport continues to increase, then significant flight delays are likely to grow at an exponential rate (Jacquillat, 2012).

Further research conducted by Jacquillat and Odoni (2015) involved developing original methodology to quantify airport congestion under different capacity scenarios. Their research suggested that delays in JFK and LGA can be extremely sensitive to even the smallest of changes in the volume of flights and the distribution of flights scheduled in a day. Furthermore, cancellations in JFK and LGA can be extremely sensitive to the volume of flights scheduled in a day (Jacquillat & Odoni, 2015).

Research led by Yu (2016) explores alternate methodologies for measuring airline efficiency and productivity. The literature states that geographic environment and factors beyond managerial control, or “exogenous” factors, greatly influence an airline’s ability to be efficient. Yu (2016) controls the effects of exogenous factors by performing identical efficiency analysis on two different data sets, one with the exogenous factors and one without. Furthermore, the study acknowledges that a quality of service measurement (such as on-time performance) is missing from airline productivity literature (Yu, 2016).

Research Questions

The purpose of this study is to analyze regional airline operational data in JFK and LGA, provided by a focus airline, to determine the relationship of volume paired with uncontrollable events to delay and cancellation rates. A two-year sample of operational data is collected to answer these questions:

- How does volume, represented by block hours, aircraft utilization, and departures, impact delays, significant delays and cancellations?
- Does the relationship change between operational season (winter, summer, stable), fleet type (CRJ-200/CRJ-900), or affected hub (JFK/LGA)?
- What is the optimal volume for the focus airline to reach on-time performance goals, accounting for uncontrollable events?

Chapter II

Methodology

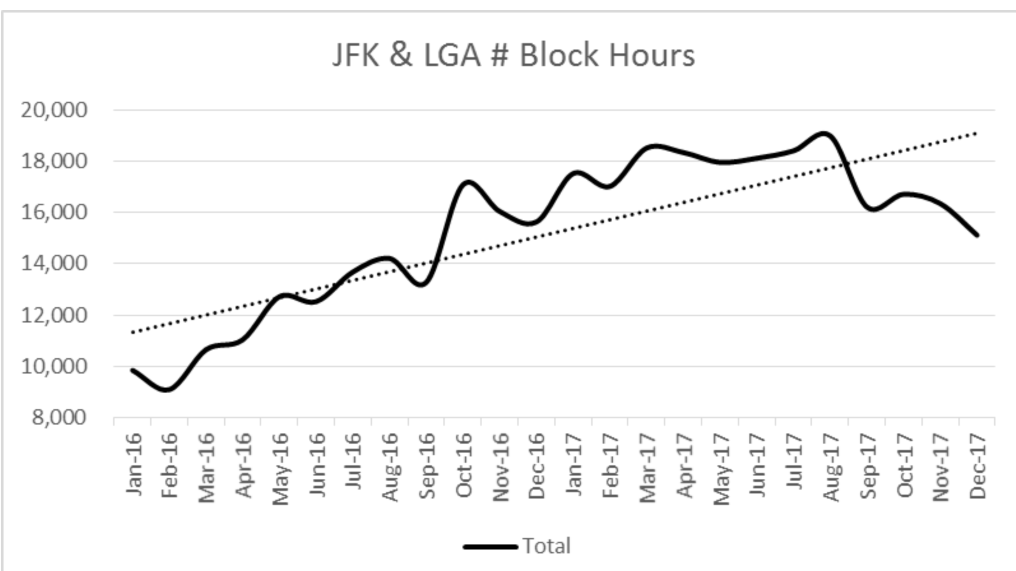
This study will use a purely quantitative approach to analyze the relationship between volume and uncontrollable events to on-time performance. As the study focuses on New York capacity constrained airports, it will use the terms “New York” and “JFK and LGA” interchangeably. The research design will be entirely non-experimental, as the variables will be in their natural state and will not be manipulated in any way. Furthermore, the study analyzes the same variables over the course of the two-year period. Through reviewing the statistical test results, recommendations will be made in effort to predict the focus airline’s optimal volume while maintaining on-time performance goals.

Presentation of Variables

The analysis begins with an overview of the independent variables representing volume in JFK and LGA. Volume is characterized by three independent variables: block hours, aircraft utilization, and the number of departures. First, *block hours* represent the focus airline’s operational capacity in New York. They are the sum of hours, determined by an individual flight’s arrival minus departure time, of total flights scheduled. The block hours distributed to JFK or LGA indicate that a strong majority of those hours directly impact the associated hub. It is important to note that block hours are not tied to the hour value of only departures and arrivals into JFK and LGA, but rather an allocation of hours to each hub. For example, consider two scheduled flights: one departing from JFK and arriving in Boston (BOS), and another departing from Boston (BOS), arriving in Washington-Reagan (DCA). The JFK to BOS flight has a block hour value of one hour and 16 minutes (1:16) and the BOS to DCA flight has a block hour value of one hour and 44 minutes (1:44). Three total hours are allocated to JFK since JFK to BOS is directly impacted from any activity in JFK and BOS to DCA is indirectly impacted from the activity out of JFK. Overall, the allocation of block hours often establishes the size of a hub from a network and crew planning perspective.

Block hours are an important measurement for a regional airline's volume as it reflects the revenue potential of its flights. Regional airlines often get reimbursed from their mainline partner for the commercial flights they operate based on actual block hours flown. Focusing on cost, block hours are the most common measurement metric of crew cost in the airline industry (Vasigh, Fleming, & Tacker, 2013). Expanding on overall operational efficiency, Merkert and Hensher (2011) showed econometrically that the size of an airline in a hub has a positive impact on becoming cost efficient. Block hours also represent the extraordinary growth the focus airline experienced in New York since January 2016. The upward trend in JFK and LGA block hours is shown in Figure 1.

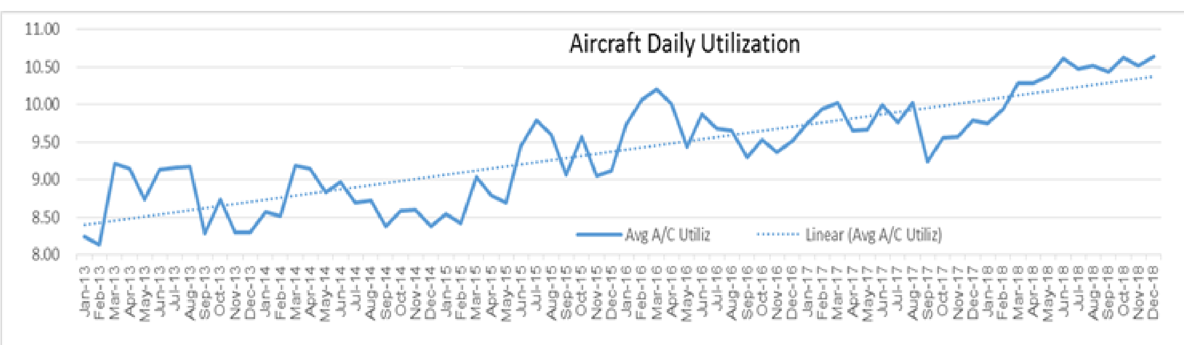
Figure 1. JFK & LGA Number of Block Hours.



The second independent variable associated with volume is *aircraft utilization* which is representative of block hour productivity in relation to number of aircraft assigned to the New York hubs. From a mathematical standpoint, aircraft utilization is derived from number of block hours divided by scheduled aircraft lines. Scheduled line is a common industry term for number of aircraft flying the block hours allocated to a hub. In simplified words, aircraft utilization translates to number of block hours per scheduled aircraft.

A high level of aircraft utilization is without a doubt one of the major network planning desires for regional airlines. There are two principal ways in which an airline can increase its daily average aircraft utilization: turn the aircraft around quicker, or fly longer routes (Vasigh, Fleming, & Tacker, 2013). Compared to the airline industry as a whole, regional airlines predominately operate short haul flights which negatively impact aircraft utilization, generally resulting in lower productivity (Yu, 2016). Since flying longer routes is not always a fundamental option for regional airlines, they must turn aircraft around quicker to increase daily aircraft utilization. Vasigh, Fleming, and Tacker (2013) found a statistically significant strong correlation between high aircraft utilization and reduced operating costs. The focus airline has been successful in increasing its aircraft utilization overall in recent years. A positive trend in aircraft utilization is shown in Figure 2.

Figure 2. Aircraft Daily Utilization.

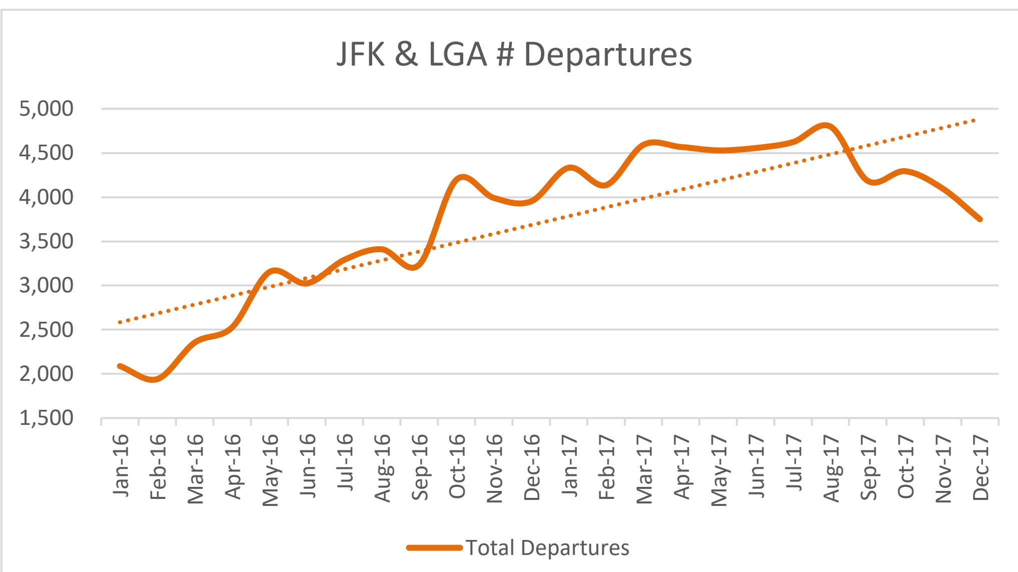


Note: 2018 = projection

The third and final volume variable, *number of departures,* signifies the number of scheduled operations in a hub. Most importantly, number of departures represent the number of flights subject to delays and cancellations in JFK and LGA. Number of departures may embody the strongest connection between volume and on-time performance since the source of on-time performance measures are driven from number of scheduled departures.

On the topic of cost efficiency, the number of aircraft departures per day follows the same trend as Vasigh, Fleming, and Tacker (2013) found for aircraft utilization, although less significant, where more departures per day in a hub equated to lower operating costs. Impressively, the focus airline's number of departures in New York has increased 48 percent in only one year, from June 2016 to June 2017. The growth in JFK and LGA scheduled departures is shown in Figure 3.

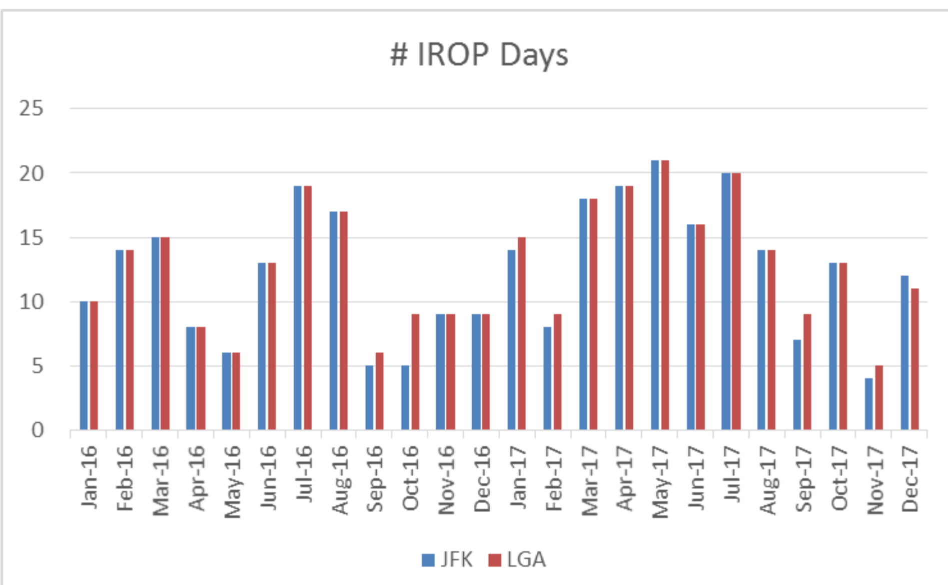
Figure 3. JFK & LGA Number of Departures.



An airline operates under varying conditions and are subject to many factors beyond their control. Therefore, it is essential to consider the effects of these uncontrollable factors on hub volume and the on-time performance of airlines. This leads to the final independent variable: irregular operation or *IROP* days.

An irregular operation usually is declared when the normal operation is abnormally stressed, mostly due to weather events, Air Traffic Control volume, and ground stops. Declaring an IROP is quite frequent in New York, as weather events and Air Traffic Control volume does not mix well with the negative effects of airport construction. An irregular operation is when fifteen percent or more of flights originating at a hub over the remainder of the day are expected to be canceled due to circumstances beyond the company's control. Such circumstances include, but are not limited to, ATC flow control, ground stops, weather, deicing, airworthiness directives, national emergencies, and acts of God. The number of days in each month that the airline declared an "IROP" in JFK and LGA is shown in Figure 4.

Figure 4. JFK & LGA IROP days.



The analysis continues with an explanation of dependent variables relating to on-time performance. Airlines use on-time performance metrics as a benchmark for improvement and to, ultimately, compare results with their competition. A single late departure can cause negative consequences throughout the remainder of the day which includes postponing future flights, burning more fuel to make up for lost time, and causing customers to miss their connecting flights. In this study, three dependent variables are considered: delays, significant delays and completion factor.

Formerly, the definition of a delay must be established. The U.S. Department of Transportation states that a flight is counted as "on-time" if it operated less than 15 minutes after the scheduled time shown in the carriers' Computerized Reservations Systems (2017). For departures, this is commonly referred to as D14: departed within 14 minutes of scheduled time. For this study, a common industry standard of D0 will be used. A flight achieving D0 is defined as a “departure within zero minutes of scheduled time” or simply, departing at or before scheduled time. Each flight not meeting D0 will be counted as a delay.

There is no dispute that delays negatively impact an airline’s operation. However, it is possible a flight that does not make D0 could have little effect on the overall operation or its passengers arriving to their destinations on-time. For example, consider a flight that departs only two minutes after scheduled time. This flight is categorized as a departure delay, through the accepted definition of D0, even though the flight may still arrive at its destination on-time. Therefore, it is important to understand the significance of the delayed flights on operational performance. The magnitude of delays is extremely sensitive to small changes in number of scheduled flights in a day of operation: the more flights, the larger in average delay time (Jacquillat, 2012).

Through internal research, the focus carrier has identified ninety minute delays as having an adverse impact on customer loyalty, often resulting in negative customer service scores due to late arrivals and the rebooking missed connected passengers. Consequently, the focus carrier has increased attention on ninety minute delays by creating a metric, designated as D90, in recent years. A flight achieving D90 is defined as a "departure within ninety minutes of scheduled time." The D90 metric will be used in this study to symbolize significant delays.

Flight cancellations happen for several reasons: weather, Air Traffic Control, maintenance, and more intriguingly, proactive volume reductions. The most common form of measuring cancellations across the airline industry is Completion Factor (CF). The U.S. Department of Transportation states an airline's Completion Factor measures the percent of scheduled flights that are completed, departure to arrival (2017). This study will use CF to determine the cancellation rate in New York. No consideration will be made to flight cancellation reason.

Explanation of Environment

For volume and on-time performance to be adequately predicted, the operational environment in which the variables are influenced must be considered. Recall that a two-year sample is used as representative of the focus airline's New York operation. The two-year operational sample is mainly based on the availability of data. However, it also allows for an opportunity to limit the impact of anomalies or outliers found in one year that may not have existed in another. Furthermore, specific periods within the two-year sample have a unique environment with its own operational challenges and characteristics. This study concentrates on the importance of categorizing any natural tendency in the operational environment to control the influence on the outcome such as weather, fleet size, and airport. Therefore, three grouping variables have been identified: operational season, fleet type, and affected hub.

The first grouping variable is *operational season* which categorizes scheduled flights into a period where the flights are exposed to similar elements. Current practice followed by most major airlines in developing the flight schedule for a target month starts by adopting a historical schedule that represents that target month. For example, if the airline is developing a schedule for the month of January of next year, the airline may use the schedule of the month of January of the current year as a starting point (Abdelghany, Abdelghany, and Azadian, 2017). This same concept is translated into this study in an effort to predict the optimal volume. The data is organized into three separate operational seasons: Winter, Summer, and Stable. The date ranges of each operational season during the two-year sample data is explained in Table 1.

Table 1. Dates of Operational Seasons.

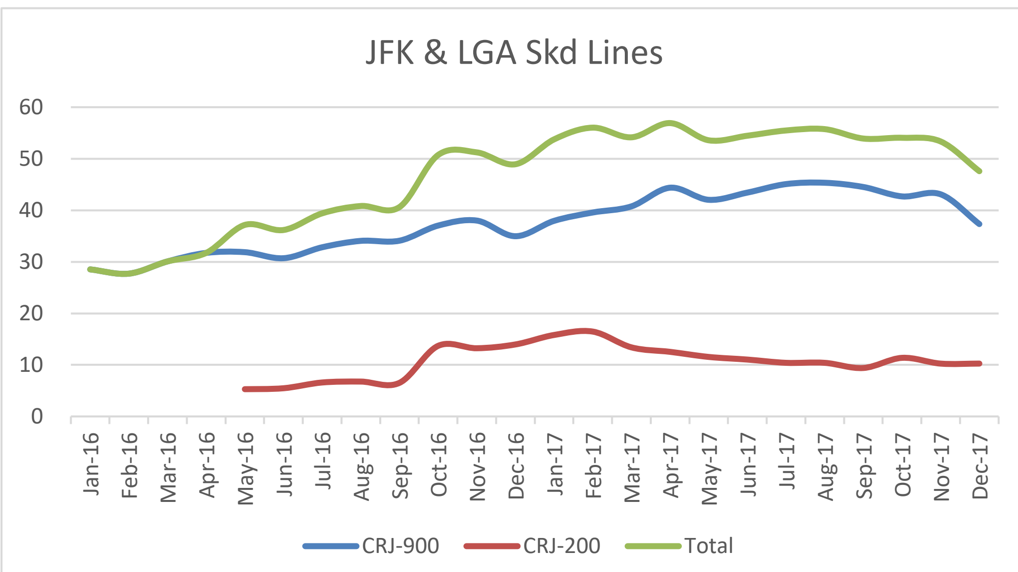
Dates	Season
1/1/2016 – 2/28/2016	Winter
2/29/2016 – 6/2/2016	Stable
6/3/2016 – 9/6/2016	Summer
9/7/2016 – 12/13/2016	Stable
12/14/2016 – 2/26/2017	Winter
2/27/2017 – 6/1/2017	Stable
6/2/2017 – 9/5/2017	Summer
9/6/2017 – 12/3/2017	Stable
12/4/2017 – 12/31/2017	Winter

Operational seasons reflect the diverse elements by which the flight schedule is strained or relieved. During the Winter season, flights are subject to snow storms, de-icing, and high travel demand during the holiday season which runs from late December to early January. The

Summer season includes significant weather activity with thunderstorms, high travel demand, and airport construction. The Stable season represents the patchiness of scheduled flights, variable travel demand, and relatively favorable weather conditions for flight.

Another grouping variable is *fleet type*. There are a few reasons why fleet is a variable considered in the study. First, the duration and timeline of the focus airline's JFK and LGA operations differ. The focus airline operated the two-class CRJ-900 out of both JFK and LGA within the entire two-year data set: January 2016 through December 2017. Comparatively, the focus airline did not open a single-class CRJ-200 base in JFK and LGA until September 2016. The scheduled aircraft line growth in JFK and LGA is shown in Figure 5.

Figure 5. JFK & LGA Scheduled Lines.



Second, the CRJ-900 aircraft utilization is much higher than the CRJ-200 fleet at the focus airline. Aircraft utilization is higher because the airline's CRJ-900 fleet is larger which supports higher network productivity. This concept is reinforced by the findings of Merkert and Hensher (2011) who showed that the number of aircraft in a given fleet has a statistically significant positive relationship in overall efficiency. Additionally, higher demand exists in the overall airline network for two-class aircraft, especially in New York, driving more block hours flown by the CRJ-900 fleet. The difference between fleet aircraft utilization in JFK and LGA is shown in Figure 6 and 7.

Figure 6. JFK CRJ-900 & CRJ-200 Aircraft Utilization.

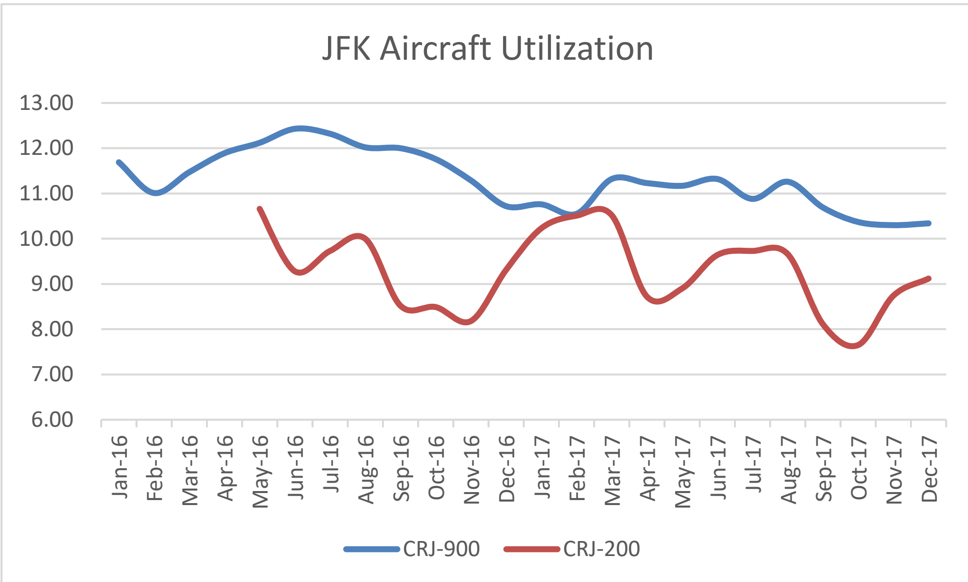
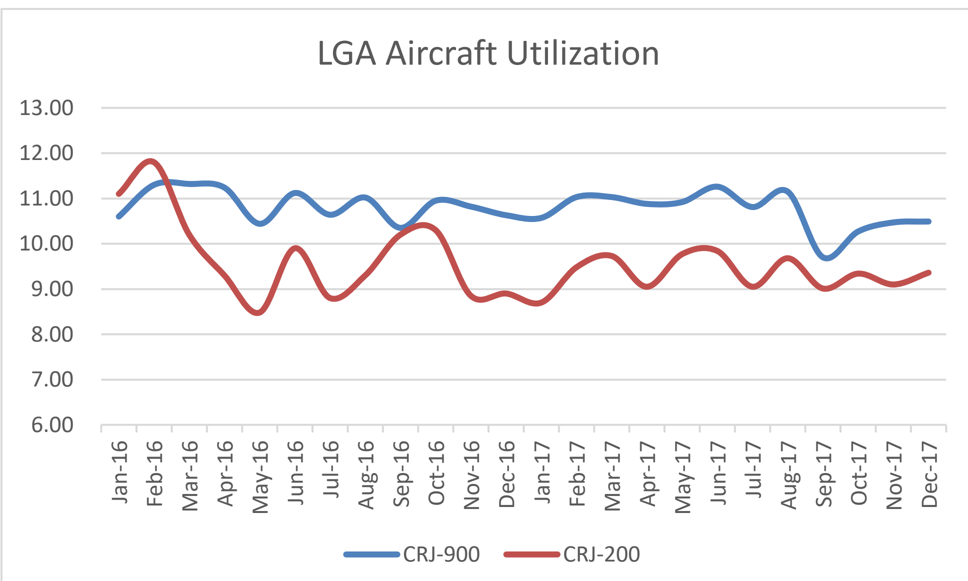


Figure 7. LGA CRJ-900 & CRJ-200 Aircraft Utilization.



The last grouping variable is *affected hub* which breaks out the differences between hub operations on impacting the outcome. Not surprisingly, JFK and LGA hubs have varied operational challenges. JFK is much larger than LGA and is an international hub for mainline partners. On the other hand, LGA is smaller and operates as a domestic hub for mainline partners. For example, during the two-year sample, LGA has experienced significant improvements to terminals and taxiways, resulting in heavy construction. Likewise, one of four runways at JFK was closed for construction in the 2017 summer operational season having tremendous impact on delays and cancellations for all airlines. The varied construction periods at each New York airport may skew the on-time performance outcome. Concentrating on the focus airline, their volume is similar proportionally to the overall volume at each hub. However, the amount of departures and block hours at each hub differs with LGA being a slightly larger operation. The independent volume variables at JFK and LGA are compared in Figures 8 and 9.

Figure 8. JFK Volume Variables: block hours, a/c utilization, and departures.

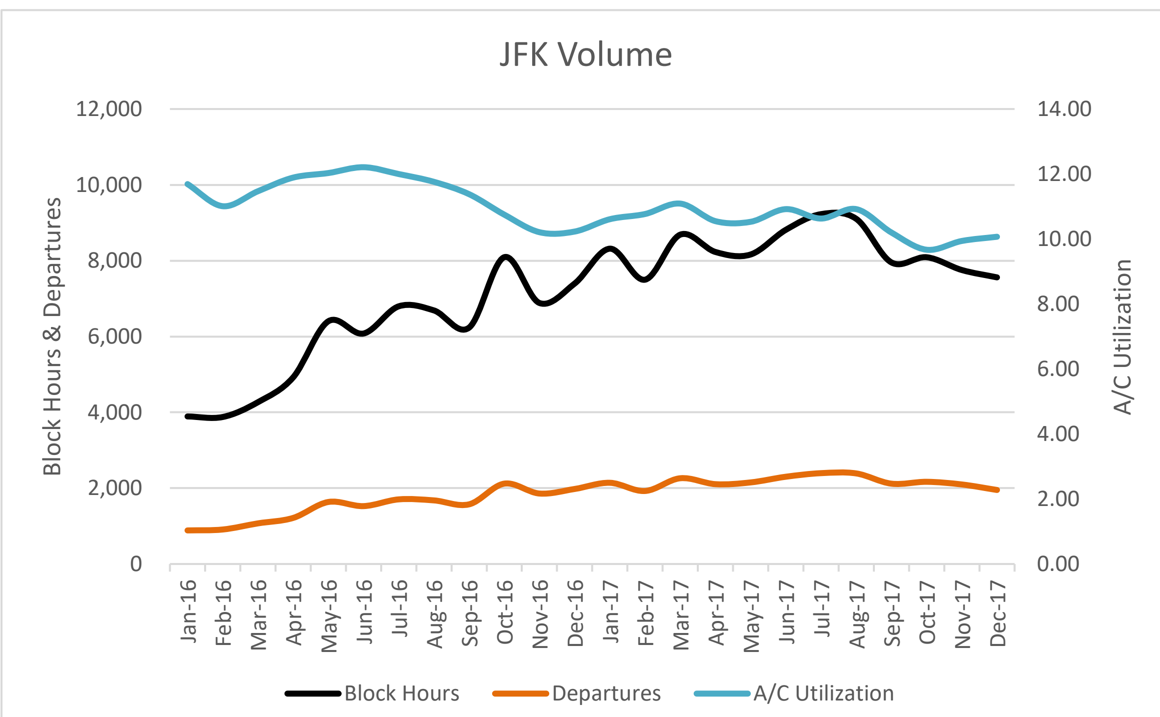
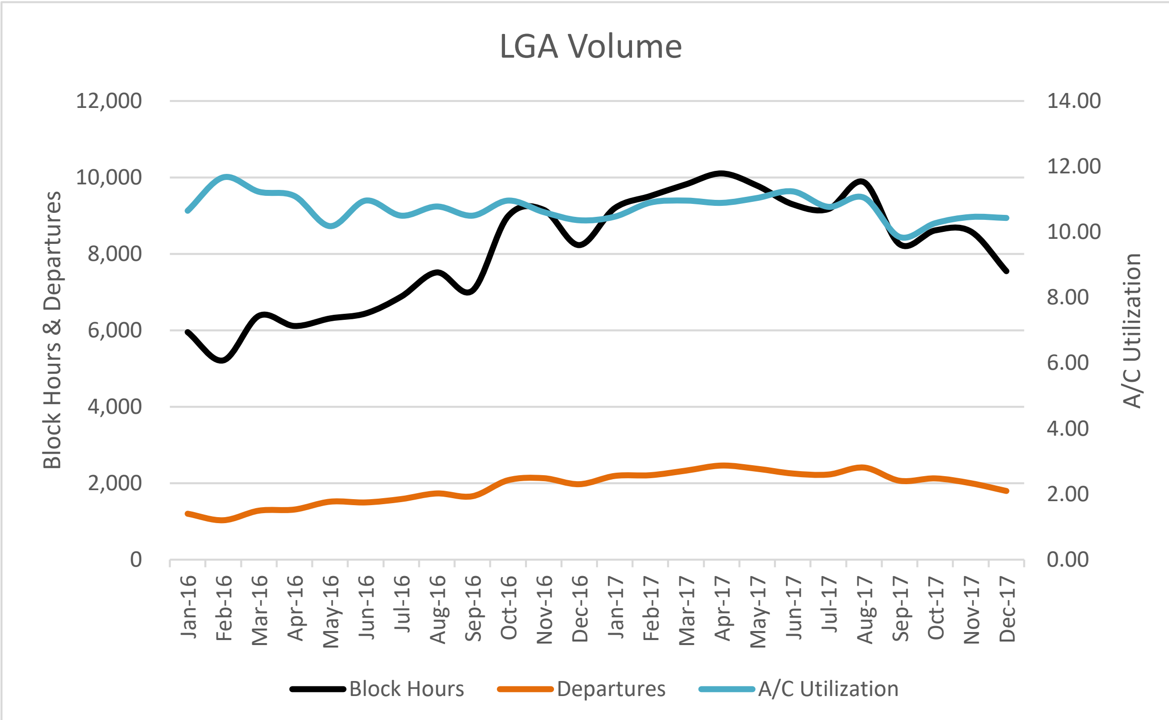


Figure 9. LGA Volume Variables: block hours, a/c utilization, and departures.



Data Collection

Collecting the data for this study required the help of the focus airline. The independent volume variables were gathered using an airline network scheduling tool called Sabre AirVision. This tool allows the user to segregate JFK and LGA scheduled departures and block hours from the rest of the fleet. To calculate aircraft utilization, the number of scheduled aircraft lines is essential. Currently, the focus airline only calculates aircraft utilization at the fleet level, not at the hub level. Fortunately, AirVision provides enough transparency in aircraft schedules that the development of schedule aircraft lines specific to a hub was possible by manually counting the lines associated with the JFK and LGA networks. This took considerable time given the two-year sample.

The IROP variable data was collected using the focus airline's Crew Scheduling historical tracking system. Each day an IROP is declared for a given hub, Crew Scheduling simply adds a brief report to a monthly calendar. Therefore, the hub where an IROP is declared is specified on each calendar day. Operational performance data was collected using a mainline driven database that tracks individual flight times and delay information. The data was mined using Hyperion Brio and organized using Microsoft Excel.

Data Organization

Organization of the collected data is important in building the statistical tests required for any potential predictive model. Normally, the aircraft utilization and block hour variables are measured and analyzed by month. The number of departures and IROPs variables are usually measured by day. To produce needed detail, and to accommodate specific dates in the operational season grouping variable, all variables have been translated and organized by day. The organization and calculation of variables is presented in Table 2. *A/C Util* shows the number of block hours divided by scheduled lines of aircraft. *CF* indicates the number of scheduled departures completed. *D0* and *D90* indicate the number of completed departures that make the associated metric. The focus airline communicates their on-time performance standards as a percentage, indicated in gray.

Table 2. Variable Organization Example. Grouping Variables: Airport: **JFK**. Fleet: **CRJ-900**. Operational Season: **Winter**.

Day	Skd Lines	Departures	Blk Hours	A/C Util	IROP	D0	D90	CF	%D0	%D90	%CF
1-Jan-16	X	Y	Z	Z/X	Y or N	A	B	C	A/C	B/C	C/Y
2-Jan-16	X	Y	Z	Z/X	Y or N	A	B	C	A/C	B/C	C/Y
3-Jan-16	X	Y	Z	Z/X	Y or N	A	B	C	A/C	B/C	C/Y
4-Jan-16	X	Y	Z	Z/X	Y or N	A	B	C	A/C	B/C	C/Y
EXAMPLE	***20***	***80***	***200***	***10.00***	***Y***	***50***	***75***	***78***	***64%***	***96%***	***98%***

Note: White = Dependent variables; Gray = Independent variables

Using the *EXAMPLE* line found in Table 2, 78 out of the 80 scheduled departures were completed (98 percent CF). Additionally, 50 out of the 78 completed flights departed within zero minutes of scheduled departure (64 percent D0). And, 75 out of the 78 completed flights were less than 90 minutes delayed (96 percent D90).

Actual data for the first 11 days of the CRJ-900 operation in JFK is demonstrated in Table 3. For example, on *1-Jan-16,* the focus airline completed all scheduled departures (100 percent CF). All flights departed within 90 minutes of scheduled departure (100 percent D90). However, only 12 out of the 23 flights departed within zero minutes of scheduled departure (52 percent D0). It is important to note that an IROP was not declared on *1-Jan-16*. This designation is commonly referred to as a "Blue Sky" day in the airline industry; where the operation isn't subject to a significant uncontrollable event such as weather or ground stops.

Table 3. Variable Organization. Grouping Variables: Airport: **JFK**. Fleet: **CRJ-900**. Operational Season: **Winter**.

Day	Skd Lines	Departures	Blk Hours	A/C Util	IROP	D0	D90	CF	%D0	%D90	%CF
1-Jan-16	9	23	102:26	11.38	N	12	23	23	52%	100%	100%
2-Jan-16	9	22	103:24	11.49	N	19	22	22	86%	100%	100%
3-Jan-16	9	23	95:05	10.56	N	19	22	23	83%	96%	100%
4-Jan-16	9	22	98:32	10.95	N	15	21	22	68%	95%	100%
5-Jan-16	11	29	124:29	11.32	N	23	29	29	79%	100%	100%
6-Jan-16	11	30	121:31	11.05	N	26	30	30	87%	100%	100%
7-Jan-16	11	31	130:32	11.87	N	23	31	31	74%	100%	100%
8-Jan-16	11	31	134:11	12.20	N	24	31	31	77%	100%	100%
9-Jan-16	11	27	121:37	11.06	N	21	26	27	78%	96%	100%
10-Jan-16	11	33	140:20	12.76	Y	9	24	26	35%	92%	79%
11-Jan-16	11	29	128:44	11.70	N	22	29	29	76%	100%	100%

Note: White = Dependent variables; Gray = Independent variables

The data shows a dramatic shift in operational performance with the declaration of an IROP on *10-Jan-16* where 26 out of the 33 scheduled departures were completed (79 percent CF). Additionally, 24 out of the 26 completed flights were less than 90 minutes delayed (92 percent D90) and nine (9) out of the 26 completed flights departed within zero minutes of scheduled departure (35 percent D0). The comparison of Blue Sky versus IROP days will determine the impact of IROP days on the operation as well as understanding optimal volume levels in New York hubs.

Statistical Tests

The operational data organized by day will drive a series of inferential statistical testing using SPSS software. Correlation tests will determine which of the independent volume variables can be used. Based on the results of the correlation tests, multiple regression will be performed to predict the maximum volume while upholding the on-time performance standards required by mainline partners.

The initial statistical testing design will be bi-variate, testing the independent volume variables to one dependent variable at a time. A single dependent variable, rather than testing all on-time performance variables at once, is preferred as on-time performance initiatives change often at an airline. For example, airline management would like to focus on improving JFK CRJ-900 D0 performance in the next summer season. The associated JFK, CRJ-900, Summer, D0 predictive model would be attentive to their needs. The bi-variate approach also permits investigative granularity between on-time performance metrics as the optimal volume for D0 may differ from D90 and CF. The independent volume variables will be continuous. Each statistical test scenario is presented in Table 4.

Table 4. Statistical Test Scenarios.

Grouping Variable Set	Independent Variables	Dependent Variable
JFK, CRJ-900, Summer	Aircraft Utilization, #depts, #block hours	D0
JFK, CRJ-900, Summer	Aircraft Utilization, #depts, #block hours	D90
JFK, CRJ-900, Summer	Aircraft Utilization, #depts, #block hours	CF
JFK, CRJ-900, Winter	Aircraft Utilization, #depts, #block hours	D0
JFK, CRJ-900, Winter	Aircraft Utilization, #depts, #block hours	D90

Grouping Variable Set	Independent Variables	Dependent Variable
JFK, CRJ-900, Winter	Aircraft Utilization, #depts, #block hours	CF
JFK, CRJ-900, Stable	Aircraft Utilization, #depts, #block hours	D0
JFK, CRJ-900, Stable	Aircraft Utilization, #depts, #block hours	D90
JFK, CRJ-900, Stable	Aircraft Utilization, #depts, #block hours	CF
JFK, CRJ-200, Summer	Aircraft Utilization, #depts, #block hours	D0
JFK, CRJ-200, Summer	Aircraft Utilization, #depts, #block hours	D90
JFK, CRJ-200, Summer	Aircraft Utilization, #depts, #block hours	CF
JFK, CRJ-200, Winter	Aircraft Utilization, #depts, #block hours	D0
JFK, CRJ-200, Winter	Aircraft Utilization, #depts, #block hours	D90
JFK, CRJ-200, Winter	Aircraft Utilization, #depts, #block hours	CF
JFK, CRJ-200, Stable	Aircraft Utilization, #depts, #block hours	D0
JFK, CRJ-200, Stable	Aircraft Utilization, #depts, #block hours	D90
JFK, CRJ-200, Stable	Aircraft Utilization, #depts, #block hours	CF
LGA, CRJ-900, Summer	Aircraft Utilization, #depts, #block hours	D0
LGA, CRJ-900, Summer	Aircraft Utilization, #depts, #block hours	D90
LGA, CRJ-900, Summer	Aircraft Utilization, #depts, #block hours	CF
LGA, CRJ-900, Winter	Aircraft Utilization, #depts, #block hours	D0
LGA, CRJ-900, Winter	Aircraft Utilization, #depts, #block hours	D90
LGA, CRJ-900, Winter	Aircraft Utilization, #depts, #block hours	CF
LGA, CRJ-900, Stable	Aircraft Utilization, #depts, #block hours	D0
LGA, CRJ-900, Stable	Aircraft Utilization, #depts, #block hours	D90
LGA, CRJ-900, Stable	Aircraft Utilization, #depts, #block hours	CF
LGA, CRJ-200, Summer	Aircraft Utilization, #depts, #block hours	D0
LGA, CRJ-200, Summer	Aircraft Utilization, #depts, #block hours	D90
LGA, CRJ-200, Summer	Aircraft Utilization, #depts, #block hours	CF

Grouping Variable Set	Independent Variables	Dependent Variable
LGA, CRJ-200, Winter	Aircraft Utilization, #depts, #block hours	D0
LGA, CRJ-200, Winter	Aircraft Utilization, #depts, #block hours	D90
LGA, CRJ-200, Winter	Aircraft Utilization, #depts, #block hours	CF
LGA, CRJ-200, Stable	Aircraft Utilization, #depts, #block hours	D0
LGA, CRJ-200, Stable	Aircraft Utilization, #depts, #block hours	D90
LGA, CRJ-200, Stable	Aircraft Utilization, #depts, #block hours	CF

Note: Thirteen days that did not have LGA CRJ-200 scheduled departures were removed from the data set.

The last step in variable organization is to address the IROP day variable. Instead of utilizing a categorical variable during statistical testing, the IROP variable will be controlled through three different data sets. The days that will be included in the three data sets is represented in Table 5.

Table 5. Data Sets.

Data Set	Days Included
Blue Sky only	IROP day = N
IROP only	IROP day = Y
Blue Sky + IROP	All days

The Blue Sky only data set will allow a statistical review of the output under normalized operational conditions. Secondly, the Blue Sky only data set provides a base of maximum volume, if uncontrollable events are removed from the environment altogether. Conversely, the IROP only data set will determine how sensitive the volume variables are during uncontrollable events. A combination of the Blue Sky and IROP days would insinuate a degradation of volume as uncontrollable events are introduced to normalized operational conditions. Reviewing the three data sets separately allows for a more refined analysis of how a New York hub's volume influences operational performance.

Chapter III

Multiple Regression Results

Ensuring the independent variables (IV) do not correlate with each other is the first step in determining whether a multiple regression model is possible. Correlation between independent variables means that the independent variables explain too much of each other and; therefore, do not add a meaningful predictive component to the dependent variable. In a correlation test using the entire data set, which includes Blue Sky and IROP days and all grouping variable sets, significant multicollinearity was found of all independent volume variables. Simply put, departures, block hours, and daily utilization are too similar and; therefore, cannot be used to jointly predict the relationship of operational performance. Since multicollinearity was found, using more than one independent variable and; consequently, multiple regression is ruled out as a predictive option. A large significant positive correlation between all independent volume variables (IV) is shown in Table 6.

Table 6. IV Correlations – Entire Data Set

		#depts	#block hours	A/C Util
#depts	Pearson Correlation	1	.988	.645
	Sig. (2-tailed)		.000	.000
#block hours	Pearson Correlation	.988	1	.627
	Sig. (2-tailed)	.000		.000
A/C Util	Pearson Correlation	.645	.627	1
	Sig. (2-tailed)	.000	.000	

A near perfect correlation exists for departures and block hours (r = .988, p = .000). For example, as departures increase, block hours also increase. The collinearity is large and significant for departures and aircraft utilization (r = .645, p = .000) as well as block hours and aircraft utilization (r = .627, p = .000).

This study reviewed if independent variable correlation exists with every grouping variable set. Independent variable correlation tests of each grouping set revealed only two groupings had a Pearson's r value small enough to validate multiple regression eligibility. A small, significant positive correlation of independent volume variables for the JFK CRJ-900 Summer and JFK CRJ-200 Stable grouping variable sets is shown in Table 7 and 8.

Table 7. **JFK CRJ-900 Summer** IV Correlation

IV1	IV2	Pearson's r	Sig.
#depts	#block hours	.990	.000
#depts	A/C Util	**.181**	.012
#block hours	A/C Util	**.203**	.005

Table 8. **JFK CRJ-200 Stable** IV Correlation

IV1	IV2	Pearson's r	Sig.
#depts	#block hours	.996	.000
#depts	A/C Util	**.115**	.041
#block hours	A/C Util	**.141**	.012

For JFK CRJ-900 Summer, a small correlation exists for departures and aircraft utilization (r = .181, p = .012) as well as block hours and aircraft utilization (r = .203, p = .005). For JFK CRJ-200 Stable, the collinearity is small and significant for departures and aircraft utilization (r = .115, p = .041) as well as block hours and aircraft utilization (r = .141, p = .012). Keeping this slight collinearity in mind, multiple regression is performed with the three operational performance variables: departures within zero minutes (D0), departures within 90 minutes (D90), and completion factor (CF). The significant multiple regression result of the JFK-900 Summer grouping (number of departures and D0) is shown in Table 9.

Table 9. **JFK CRJ-900 Summer** Model Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate
.263[a]	.069	.059	16.39859%

a. Predictors: (Constant), A/C Util, #depts

ANOVA[a]	Sum of Squares	df	Mean Square	F	Sig.
Regression	3765.957	2	1882.979	7.002	.001[b]
Residual	50824.726	189	268.914		
Total	54590.683	191			

a. Dependent Variable: %D0
b. Predictors: (Constant), A/C Util, #depts

Coefficients[a]	B	Coefficients Std. Error	Standardized Coefficients	t	Sig.
(Constant)	84.955	13.026		6.522	.000
#depts	-.631	.169	-.267	-3.738	.000
A/C Util	.487	.967	.036	.504	.615

a. Dependent Variable: %D0

The multiple regression model for JFK-900 Summer season is significant; therefore, number of departures and aircraft utilization predict D0 performance. An increase of departures and decrease in aircraft utilization have a negative impact on D0. The Variance Inflation Factor (VIF) score was 1.034 which indicates that number of departures and aircraft utilization slightly correlate. The regression model is significant, explaining 6.9 percent of the variance (R^2 = .069, F (2, 189) = 7.00, p = .001). The regression equation is $Y = -.631X + .487Z + 84.955$ where X is the number of departures, Z is aircraft utilization, and Y is D0 performance.

Only the multiple regression tests that were significant are included in Tables 10 and 11:

Table 10. **JFK CRJ-900 Summer** Multiple Regression Results

IV1	IV2	DV	Result	Linear Equation
#depts	A/C Util	D0	R^2 = .069, *F* (2, 189) = 7.00, *p* = .001	Y = -.631X + .487Z + 84.955
#depts	A/C Util	D90	R^2 = .043, *F* (2, 189) = 4.22, *p* = .016	Y = -.248X + .216Z + 102.94
#block hours	A/C Util	D0	R^2 = .077, *F* (2, 189) = 7.93, *p* = .000	Y = -.158X + .611Z + 84.475
#block hours	A/C Util	D90	R^2 = .047, F (2, 189) = 4.7, p = .010	Y = -.062X + .263Z + 102.69

In the JFK-900 Summer multiple regression results, volume predicted operational performance in four isolated tests where departures and block hours predicted D0 and D90. CF did not generate a significant result; therefore, volume did not predict CF performance.

Table 11. **JFK CRJ-200 Stable** Multiple Regression Results

IV1	IV2	DV	Result	Linear Equation
#depts	A/C Util	D0	R^2 = .044, *F* (2, 311) = 7.22, *p* = .001	Y = -.518X + 1.325Z + 92.58
#depts	A/C Util	CF	R^2 = .026, *F* (2, 312) = 4.12, *p* = .017	Y = -.254X + .352Z + 103.80
#block hours	A/C Util	D0	R^2 = .052, *F* (2, 311) = 8.56, *p* = .000	Y = -.186X + 1.231Z + 92.59
#block hours	A/C Util	CF	R^2 = .029, *F* (2, 312) = 4.64, *p* = .010	Y = -.087X + .313Z + 103.64

In the JFK-200 Stable multiple regression results, volume predicted operational performance in four isolated tests where departures and block hours predicted D0 and CF. D90 did not generate a significant result; therefore, volume did not predict D90 performance. It is important to note that a small correlation exists between each independent volume variable in the above tests. The VIF score was between 1.013 and 1.034 for the multiple regression tests performed which support that the volume variables in each test do slightly correlate.

Linear Regression Results

Due to the multicollinearity of the volume variables, and to avoid collinearity moving forward, the rest of the study uses linear regression to test the relationships. A linear regression practice will include only entering one independent variable into the model at a time. Although, linear models have been criticized for being simplistic, the primary benefit of using a linear model is that the results are straightforward as much of the density is removed in determining the relationship between variables. The linear models will allow a clear characterization of volume variable predictive capabilities on operational performance. First, the entire data set is reviewed, which includes Blue Sky and IROP days and all grouping variable sets. Only the significant results for the entire data set are shown in Table 12.

Table 12. **Blue Sky + IROP day** Linear Regression Results

IV	DV	Result	Linear Equation
#depts	D0	$R^2 = .018$, F (1, 2655) = 43.32, $p = .000$	Y = -.15X + 72.857
#block hours	D0	$R^2 = .014$, F (1, 2655) = 38.91, $p = .000$	Y = -.028X + 71.650
A/C Util	D0	$R^2 = .030$, F (1, 2655) = 81.76, $p = .000$	Y = -1.939X + 87.742

The results show that only D0 performance can be predicted using all volume variables independently. An increase in volume has a negative impact on D0. Volume does not predict D90 or CF in the entire data set.

To determine the sensitivity of the model during uncontrollable events, Blue Sky only and IROP only data sets must be compared. The difference between Blue Sky days and IROP days are compared in Tables 13 and 14.

Table 13. **Blue Sky day only** Linear Regression Results

IV	DV	Result	Linear Equation
#depts	D0	R^2 = .019, F (1, 1564) = 30.731, p = .000	Y = -.111X + 81.591
#depts	CF	R^2 = .014, F (1, 1564) = 22.88, p = .000	Y = .019X + 98.963
#block hours	D0	R^2 = .014, F (1, 1564) = 22.52, p = .000	Y = -.02X + 80.633
#block hours	CF	R^2 = .015, F (1, 1564) = 23.47, p = .000	Y = .004X + 99.045
A/C Util	D0	R^2 = .019, F (1, 1564) = 29.56, p = .000	Y = -1.02X + 88.269
A/C Util	CF	R^2 = .003, F (1, 1564) = 4.11, p = .043	Y = .076X + 98.816

The Blue Sky day only results show D0 and CF performance can be predicted using all volume variables independently. An increase in volume has a negative impact on D0; however, an increase of volume has a slight positive impact on CF. Volume does not predict D90 during Blue Sky days.

Table 14. **IROP day only** Linear Regression Results

IV	DV	Result	Linear Equation
#depts	D0	R^2 = .013, F (1, 1091) = 14.59, p = .000	Y = -.118X + 57.415
#block hours	D0	R^2 = .011, F (1, 1091) = 12.43, p = .000	Y = -.023X + 56.531
A/C Util	D0	R^2 = .020, F (1, 1091) = 22.26, p = .000	Y = -1.677X + 70.929

The IROP day only results show D0 performance can be predicted using all volume variables independently. An increase of volume has a negative impact on D0, the same result as the entire data set. In comparing Blue Sky with IROP days, the clear variance is that volume predicts CF during Blue Sky days, once IROP days are removed from the entire data set.

Next, linear regression is performed for all 36 grouping variable sets, including the three volume and three operational variables, for a total of 108 tests. This will distinguish if the same relationships are found within the groupings, explained in Table 4, as the entire data set. Out of the linear regression results, 49 out of 108 (45 percent) of the tests were significant which means that operational performance can be predicted using the prescribed volume variable. The significant linear regression result of the LGA CRJ-900 Summer group (block hours and D0) is shown in Table 15.

Table 15. **LGA CRJ-900 Summer** Model Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate
.280[a]	.079	.074	18.04394%

a. Predictors: (Constant), #block hours

ANOVA[a]	Sum of Squares	df	Mean Square	F	Sig.
Regression	5282.015	1	5282.015	16.223	.000[b]
Residual	61860.933	190	325.584		
Total	67142.948	191			

a. Dependent Variable: %D0
b. Predictors: (Constant), #block hours

Coefficients[a]	B	Coefficients Std. Error	Standardized Coefficients	t	Sig.
(Constant)	82.142	4.548		18.061	.000
#block hours	-.079	.020	-.280	-4.028	.000

a. Dependent Variable: %D0

The linear regression model for LGA-900 Summer season is significant; therefore, block hours predict D0 performance. An increase of departures has a negative impact on D0. The regression model is significant, explaining 7.9 percent of the variance (R^2 = .079, F (1, 190) = 16.223, p = .00). The regression equation is $Y = -.079X + 82.142$ where X is the number of block hours and Y is D0 performance.

Only the 49 linear regression tests that were significant are included in Tables 16 – 19:

Table 16. **JFK CRJ-900** Linear Regression Results

Op. Season	IV	DV	Result	Linear Equation
Summer	#depts	D0	R^2 = .068, F (1, 190) = 13.81, p = .000	Y = -.616X + 89.827
Summer	#depts	D90	R^2 = .042, F (1, 190) = 8.27, p = .004	Y = -.241X + 105.098
Summer	#block hours	D0	R^2 = .075, F (1, 190) = 15.51, p = .000	Y = -.153X + 90.5
Summer	#block hours	D90	R^2 = .046, F (1, 190) = 9.15, p = .003	Y = -.059X + 105.283
Winter	#depts	D0	R^2 = .024, F (1, 157) = 3.918, p = .050	Y = -.39X + 81.282
Stable	#depts	D0	R^2 = .039, F (1, 374) = 15.33, p = .000	Y = -.469X + 90.9
Stable	#depts	D90	R^2 = .031, F (1, 374) = 12.15, p = .001	Y = -.183X + 103.930
Stable	#depts	CF	R^2 = .011, F (1, 374) = 4.00, p = .046	Y = -.146X + 103.603
Stable	#block hours	D0	R^2 = .051, F (1, 374) = 19.98, p = .000	Y = -.132X + 94.155
Stable	#block hours	D90	R^2 = .036, F (1, 374) = 14.08, p = .000	Y = -.049X + 104.672
Stable	#block hours	CF	R^2 = .015, F (1, 374) = 5.53, p = .019	Y = -.043X + 104.887
Stable	A/C Util	D0	R^2 = .014, F (1, 374) = 5.30, p = .022	Y = -1.686X + 87.9

On the JFK-900, volume predicted operational performance in 44 percent of the statistical tests. In four isolated tests, departures and block hours predicted D0 and D90 in the summer season. The relationship of departures and D0 was the only significant test result in the winter season. Volume predicted operational performance in the stable season for all tests except the relationships between aircraft utilization and D90/CF.

Table 17. **JFK CRJ-200** Linear Regression Results

Op. Season	IV	DV	Result	Linear Equation
Stable	#depts	D0	R^2 = .033, F (1, 312) = 10.72, p = .001	Y = -.554X + 81.331
Stable	#depts	D90	R^2 = .013, F (1, 312) = 4.16, p = .042	Y = -.147X + 98.218

Op. Season	IV	DV	Result	Linear Equation
Stable	#depts	CF	R^2 = .023, *F* (1, 312) = 7.46, *p* = .007	Y = -.264X + 100.823
Stable	#block hours	D0	R^2 = .043, *F* (1, 132) = 13.88, *p* = .000	Y = -.199X + 82.252
Stable	#block hours	D90	R^2 = .017, *F* (1, 132) = 5.29, *p* = .022	Y = -.053X + 98.446
Stable	#block hours	CF	R^2 = .027, *F* (1, 312) = 8.68, *p* = .003	Y = -.09X + 101.015
Stable	A/C Util	D0	R^2 = .016, *F* (1, 312) = 4.98, *p* = .026	Y = -1.561X + 85.802

On the JFK-200, volume predicted operational performance on 26 percent of the statistical tests. In the stable season, volume predicted operational performance for all tests except the relationships between aircraft utilization and D90/CF. The summer and winter seasons did not generate a significant result; therefore, volume did not predict operational performance.

Table 18. **LGA CRJ-900** Linear Regression Results

Op. Season	IV	DV	Result	Linear Equation
Summer	#depts	D0	R^2 = .081, *F* (1, 190) = 16.69, *p* = .000	Y = -.347X + 81.876
Summer	#depts	D90	R^2 = .023, *F* (1, 190) = 4.55, *p* = .034	Y = -.087X + 97.646
Summer	#depts	CF	R^2 = .023, *F* (1, 190) = 4.40, *p* = .037	Y = -.103X + 99.578
Summer	#block hours	D0	R^2 = .079, *F* (1, 190) = 16.22, *p* = .000	Y = -.079X + 82.142
Summer	#block hours	D90	R^2 = .022, *F* (1, 190) = 4.34, *p* = .039	Y = -.02X + 97.672
Summer	#block hours	CF	R^2 = .025, *F* (1, 190) = 4.94, *p* = .027	Y = -.025X + 100.027
Summer	A/C Util	D0	R^2 = .064, *F* (1, 190) = 13.08, *p* = .000	Y = -2.63X + 93.193
Summer	A/C Util	D90	R^2 = .021, *F* (1, 190) = 4.00, *p* = .047	Y = -.694X + 100.861
Summer	A/C Util	CF	R^2 = .035, *F* (1, 190) = 6.85, *p* = .010	Y = -1.08X + 106.207
Winter	#depts	D0	R^2 = .037, *F* (1, 157) = 5.96, *p* = .016	Y = -.275X + 81.078
Winter	#block hours	D0	R^2 = .036, *F* (1, 157) = 5.92, *p* = .016	Y = -.057X + 80.794
Winter	A/C Util	D0	R^2 = .055, *F* (1, 157) = 9.12, *p* = .003	Y = -2.568X + 96.648

Op. Season	IV	DV	Result	Linear Equation
Stable	#depts	D0	R^2 = .142, F (1, 374) = 62.113, p = .000	Y = -.493X + 96.212
Stable	#depts	D90	R^2 = .045, F (1, 374) = 17.76, p = .000	Y = -.098X + 100.935
Stable	#depts	CF	R^2 = .017, F (1, 374) = 6.326, p = .012	Y = -.062X + 101.245
Stable	#block hours	D0	R^2 = .146, F (1, 374) = 64.003, p = .000	Y = -.113X + 97.172
Stable	#block hours	D90	R^2 = .047, F (1, 374) = 18.602, p = .000	Y = -.023X + 101.175
Stable	#block hours	CF	R^2 = .016, F (1, 374) = 6.188, p = .013	Y = -.014X + 101.288
Stable	A/C Util	D0	R^2 = .118, F (1, 374) = 50.044, p = .000	Y = -3.61X + 109.637
Stable	A/C Util	D90	R^2 = .04, F (1, 374) = 15.391, p = .000	Y = -.736X + 103.802

On the LGA-900, volume predicted operational performance on 74 percent of the statistical tests. In the summer season, volume predicted operational performance in all tests. D0 can be predicted in the winter season for each volume variable. Volume predicted operational performance in the stable season for all tests except for one, the relationship between aircraft utilization and CF.

Table 19. **LGA CRJ-200** Linear Regression Results

Op. Season	IV	DV	Result	Linear Equation
Summer	#block hours	D0	R^2 = .021, F (1, 184) = 3.995, p = .047	Y = -.252X + 74.826
Summer	A/C Util	D0	R^2 = .035, F (1, 184) = 6.772, p = .010	Y = -2.45X + 86.725
Stable	#depts	D0	R^2 = .078, F (1, 305) = 8.871, p = .003	Y = -.701X + 82.345
Stable	#depts	D90	R^2 = .018, F (1, 305) = 5.437, p = .020	Y = -.239X + 98.158
Stable	#depts	CF	R^2 = .013, F (1, 305) = 4.153, p = .042	Y = -.223X + 99.695
Stable	#block hours	D0	R^2 = .023, F (1, 305) = 7.142, p = .008	Y = -.189X + 80.55
Stable	#block hours	D90	R^2 = .013, F (1, 305) = 3.984, p = .047	Y = -.061X + 97.397
Stable	A/C Util	D0	R^2 = .02, F (1, 305) = 6.332, p = .012	Y = -1.78X + 87.93

Op. Season	IV	DV	Result	Linear Equation
Stable	A/C Util	D90	$R^2 = .014$, $F\ (1, 305) = 4.42$, $p = .036$	Y = -.647X + 100.433
Stable	A/C Util	CF	$R^2 = .013$, $F\ (1, 305) = 4.161$, $p = .042$	Y = -.668X + 102.428

On the LGA-200, volume predicted operational performance on 37 percent of the statistical tests. In the stable season, volume predicted operational performance for all tests except the relationship between block hours and CF. D0 can be predicted in the summer season using block hours and aircraft utilization independently. The winter season did not generate a significant result; therefore, volume did not predict operational performance.

Chapter IV

Discussion

How does volume impact delays, significant delays and cancellations?

Although the statistical output did not allow for the independent volume variables to be in the same model, the results of the linear models show that an increase of volume led to an increase in delays, significant delays, and cancellations. Overall, the linear regression results show that volume can be used to predict D0 in the entire data set but not necessarily for each grouping variable set. The truth in the results is that the focus regional airline cannot reasonably expect to grow in a capacity constrained airport, like JFK and LGA, without a degradation of D0 performance. The results show an emphasis on D0 because it naturally differs from D90 and CF. Each and every flight is pushing to achieve D0, which makes it an extremely sensitive metric. Comparatively to D0, delays longer than ninety minutes and cancellations happen infrequently. For a single flight to go out on-time, achieving D0, everything must synchronize. There are a number of aspects that can go awry: maintenance, customer service, baggage handling, flight service, inflight, catering, the Operations Control Center, customs – many dynamic components and groups have to come together. Also, some flights are faced with the impossibility of reaching D0 based on performance faced earlier in the day. All in all, there is no doubt that D0 is the toughest metric to manage. Its sensitivity to volume is shown throughout the data set.

Once IROP days were removed from the data, an increase in volume led to an increase in completion factor. This indicates that with an increase in volume, the number of cancelled flights decreases on Blue Sky days. Additionally, studying only the IROP days, completion factor could not be predicted based on volume. This is because each IROP differs in overall impact and the percentage of cancelled flights varies, making prediction difficult.

Previous research stated that if more flights are scheduled, average delay time grew. This study showed that volume can sometimes predict D90, although it depended on the grouping variable set. For the grouping variable sets that provided a significant result, an increase volume had a negative impact on D90, supporting previous research conducted.

The significant results, based on which variable was involved, is outlined in Table 20.

Table 20. Significant Results by Variable

Variable	% sig. results
Departures	53%
Block Hours	50%
Aircraft Utilization	33%
D0	64%
D90	42%
CF	31%

Number of departures was an acceptable predictor variable in over half (53 percent) of its statistical tests. This significance is important for model integrity, considering departures represent the strongest connection between volume and on-time performance. In applying the model results, using departures feels natural as the source of on-time performance measures derive from number of scheduled departures.

Departures and block hours predicted too much of each other which was not unexpected given the nature of hub structure. As departures grow in a hub, more block hours get allocated to a given hub. Not anticipated in this study was that aircraft utilization correlated with departures and block hours. Once more, aircraft utilization takes into consideration block hours per scheduled aircraft and is not a reflection of how many block hours in any given day. An increase in departures and block hours does not always translate to aircraft efficiency as high aircraft utilization is a common business concept for regional airlines to control cost. Realized is that the focus airline's growth in New York affects all volume variables: departures, time spent in the air, and the efficiency of the aircraft itself.

In the grouping variable sets, departures tended to be predictive when block hours were predictive, which was not a surprise, given their strong positive correlation. The exception to this rule, was on the LGA CRJ-200. Aircraft utilization predicted performance in the stable operational season and very infrequently in the summer season. A high aircraft utilization had a negative influence on on-time performance during the stable season. During this season of generally favorable weather conditions, the focus airline may want to consider tailoring its aircraft utilization in an effort to improve on-time performance. Likewise, since aircraft utilization and performance relationship cannot be assumed during summer and winter, the high aircraft efficiency concept can sensibly be applied.

Does the relationship change between operational season, fleet type, or affected hub?

The relationship between volume and operational performance changed between operational season, fleet type, and affected hub. The significant results, based on the grouping variable, is outlined Table 21.

Table 21. Significant Results by Grouping

Grouping	% sig. results
Stable	83%
Summer	42%
Winter	11%
CRJ-900	59%

Grouping	% sig. results
CRJ-200	31%
LGA	56%
JFK	35%

The stable operational season results, categorized by the patchiness of scheduled flight, variable travel demand, and relatively favorable weather conditions, had a tendency to be meaningful in 83 percent of tests conducted in this season returning a negative significant relationship. Conceivably, the variable relationship is measurable due to the volume of days in the data set or ‘N’ in the statistical tests. The number of days analyzed in the stable season was more than the summer and winter seasons combined. Another inclination is that favorable weather conditions played a part in the predictive value of the regression models.

The summer operational season results were inconstant with 42 percent of the tests conducted returning a negative significant relationship, likely due to overall increased volume within the airline’s network. At JFK and LGA, volume drastically increases in the summer due to a busy travel season. During summer, JFK and LGA heavily utilize ground delay programs (GDP) to manage a high volume of traffic. Compounding with GDPs is growth in uncontrollable events due to significant thunderstorm activity and airport construction. These factors work against the volume increase, but it would appear that the summer environment in New York is as inconstant as the summer results.

During the winter season, volume tended to have little to no significance on operational performance. Only 11 percent of the winter statistical tests showed a significant result meaning a volume and performance relationship was rarely determined. The focus airline has more planned block time into flights in the winter to account for winter weather operational conditions such as de-icing. Many airlines add from five to ten percent additional block time during the winter season. Adding more scheduled block time per flight simply means additional padding, in effort to improve operational performance. Conceptually, the more an airline “pads” its flight schedule, the more flexibility it has during the daily operation. This is important because additional block padding influences the overall volume of flights at a hub.

The CRJ-900 fleet tended to be more predictive (59 percent) than the CRJ-200 fleet (31 percent). One striking difference between fleets is that the volume and performance relationship in the summer season determined a significant negative result on the CRJ-900 and was inconclusive on the CRJ-200. The CRJ-900 variable relationship is more measurable due to sheer volume as the CRJ-900 is a much larger fleet than the CRJ-200. Also, the rapid growth in LGA on the CRJ-200 may have influenced the relationship of the variables. The focus airline did not open a CRJ-200 base in New York until September 2016 but, when it did, the growth in volume was significant. Second, the CRJ-900 aircraft utilization is much higher than the CRJ-200 fleet at the focus airline.

The LGA hub tended to be more predictive (56 percent) than the JFK hub (35 percent). In comparing the hub volume, LGA is a slightly larger operation in terms of departures and block hours. A considerable difference between hubs is that the CRJ-900 volume and completion factor relationship in the summer and winter seasons determined a significant negative result in LGA and were inconclusive in JFK. The varied construction periods at each New York airport did not seem to skew the outcome. On the JFK CRJ-900 Summer volume negatively impacted D0 due to one of four runways being closed for construction in the 2017 summer season, having tremendous impact on delays for airlines. Through varied construction periods at LGA, all volume variables for both fleets had a significant negative relationship with each performance metric, with the exception of LGA CRJ-200 D0.

Conclusion

What is the optimal volume for the focus airline to reach on-time performance goals, accounting for uncontrollable events?

The study aimed to identify the optimal volume for the focus airline to reach on-time performance goals while accounting for uncontrollable events. The initial model sheds some light on the impact of uncontrollable events, or IROPS days, present in the data set. Once IROP days, were removed from data set, D0 improved by ten percent. The D0 disparity between Blue Sky days and IROP days showed an eye-opening 25 percent. Once IROP days are removed from the data set, the relationship between volume and completion factor is meaningful; where an increase of volume has a slight positive impact on CF.

The significant results of the multiple regression tests provide a benefit of studying two independent variables in the same model. This is important in planning growth and managing aircraft efficiency while balancing the performance goals set by a regional airline. For example, airline management would like to focus on improving JFK CRJ-900 D0 performance in the next summer season. Specifically, the focus airline would like to increase their D0 performance by five percent at JFK, which yields to a goal of 62 percent. Using the multiple regression equation shown in Table 8, a model suggestion of 45 departures and an aircraft utilization of 11.17 will achieve the goal in JFK:

$$62.00 = -.631(\mathbf{45}) + .487(\mathbf{11.17}) + 84.955$$

Furthermore, block hours required to achieve this goal can be calculated while keeping one other volume variable constant, in this case, an aircraft utilization of 11.17:

$62.07 = -.158(185) + .611(\mathit{11.17}) + 84.475$

In summary, for the focus airline to reach its D0 goal for LGA CRJ-900 in July, the volume needs to begin with 45 departures and 185 block hours per day, along with an 11.17 aircraft utilization, based on historical, two-year performance. This concept can be applied to the JFK-200 Stable grouping set as well.

Additionally, the linear regression models provide individual review of operational performance measures, accounting for uncontrollable events. For example, the focus airline expects to increase its CRJ-900 LGA departures in July of 2019. Since the linear equations were all significant, the volume variables can be used as predictive indicators. For example, the focus airline's number scheduled departures on July 15th is 60. The airline can estimate that the operational performance to be: 61.06 percent D0, 92.43 percent D90, and 93.40 percent CF.

D0: $61.06 = -.347(\mathbf{60}) + 81.876$

D90: $92.43 = -.087(\mathbf{60}) + 97.646$

CF: $93.40 = -.103(\mathbf{60}) + 99.578$

With new regulation requiring mainline carriers to report regional airline operational performance, the balance between volume and operational performance is more relevant for a regional airline than ever. Travel demand is at an all-time high and volume is organically increasing at capacity constrained airports like JFK and LGA. Not only is travel demand propelling volume but regional airlines, like the focus airline, need a high volume of flying to operate at a lower cost.

The anticipation of the relationship between volume and operational performance is greatly important to an airline. It drives the decision-making process as management must factor the ability to grow while maintaining operational performance based on their current network structure. It also allows an airline to benchmark its performance to focus on improving results. Airlines are constantly pushing the envelope, developing programs in effort to improve on-time performance, especially at capacity constrained airports. For the focus airline, the models presented can help determine if those performance programs are successful.

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