

Fuel Consumption and Operational Performance

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Abstract — Reducing fuel consumption is a major goal for the aviation community due to environmental concern and fuel price uncertainty. The Federal Aviation Administration (FAA) is currently developing and implementing Air Traffic Management (ATM) technologies to ensure reliable operational performance that is robust to delays caused by congestion and weather. These technologies will reduce planned and unexpected airborne delays; as such they will reduce the airline practice of schedule padding, or contingency planning for excess fuel and time consumption on a give route, as well as airborne and departure delay. In this study, we seek to quantify the fuel consumption impact of these technologies on the three operational performance measures: schedule padding, airborne delay, and departure delay. We do so by modeling airline fuel consumption using econometric techniques to isolate the contribution of operational performance. We use fuel consumption reported by a major US-based airline to capture revealed, and not simulated, airspace inefficiencies. For two aircraft types we find that a minute spent in airborne delay burns 50-60 lbs of fuel, compared with 4.5-12 lbs for a minute of schedule padding and 2.3-4.6 lbs for a minute of departure delay. We find additionally that fixed fuel consumed due to congested and complicated airport terminal areas is can be up to 16% greater. When considering specific origin-destination pairs, we find the elimination of the three delay metrics due to technology could reduce airborne fuel consumption up to 10% percent per operation.

Keywords- Aviation, Fuel Consumption, Air Traffic Management, Environmental Impacts

I. INTRODUCTION

Reducing fuel consumption is a major goal for the aviation community. Airlines wish to reduce costs while aviation organizations both national and international in scope seek to assist airlines in managing costs and reducing the environmental impact of aviation. While there are many avenues through which fuel can be reduced, we focus on the impact of airline operational performance on fuel consumption. This perspective is motivated by the introduction of Next Generational Air Transportation (NextGen) technologies which will improve operational performance by reducing flight time variations and enabling more precise operations in the terminal area.

Reducing fuel consumption is a way to manage the risk related to fuel price fluctuations and uncertainty surrounding a future environmental policy. In 2008, jet fuel prices reached

levels more than three times those of 2004. While 2009-2010 fuel prices fell from their 2007-2008 highs, the spike demonstrated uncertainty in the magnitude of future fuel prices. Furthermore, the scope and timeline of a future climate change policy threatens the stability of fuel prices because of the relationship between Greenhouse Gases (GHG) and fuel consumption. The production of most abundant GHG, Carbon Dioxide (CO₂) is directly correlated with fuel consumption. To this end, we consider savings in fuel to be a direct savings of CO₂ emissions. Policies to curtail aviation-related GHG emissions are being considered at many levels, from local airport authorities to the International Civil Aviation Organization (ICAO). While Europe is preparing for the inclusion of aviation in their GHG emissions trading scheme (EU-ETS), the timeline for policy in the US is less clear. Despite the lack of regulation, a desire to protect the environment along with reducing fuel consumption is encouraging aviation organizations to take steps toward reducing fuel.

Much research has focused on fuel reduction possibilities from altering airline business practices. Jamin et al. [1] test the substitution of all connecting flights in the US National Airspace System (NAS) with direct, non-stop flights. Without changing fleet structure, this results in a ten percent decline in fuel burn and CO₂ emissions per year: four percent from decreased travel distances and six percent from fewer landing and take-off cycles. Ryerson and Hansen [2] find that the substitution of turboprops for narrow bodies can reduce fuel consumption by up to 50%, yet this fuel savings would decrease passenger level of service. On the ground, many airlines encourage pilots to taxi on one engine when possible to reduce fuel consumption; however, the percentage of operations in which this procedure is used is limited as a result of safety concerns.

In addition, research on the potential of operational procedures on the ground and in the air show fuel reduction benefits. On the ground, Ohsfeldt et al. [3] find eliminating time spent in taxi beyond an unimpeded taxi time could reduce taxi fuel consumption significantly. In the air, Clarke et al. [4] find that Continuous Descent Approaches (CDA) can reduce fuel consumption on approach by 20%, a finding confirmed by a related study by the Federal Aviation Administration (FAA) Air Traffic Organization [5]. Additionally, harmonizing ground and air operations through Airspace Flow Programs (AFP) could reduce fuel consumption by 10% compared with Ground Delay Programs (GDP) [3].

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Improved operational procedures under investigation are in part enabled by advanced technology in the aviation system. The development and implementation NextGen technologies will and continue to bring improved operational procedures as well as more reliable and improved operational performance. Operational performance as defined by Zou and Hansen [6] includes delay metrics, such that they characterize how closely the air transportation system is adhering to a schedule; they further incorporate how the existing schedule incorporates expected delays. NextGen technologies will improve operational performance by equipping the airspace to handle higher levels of traffic and adverse weather, both of which cause operational inefficiencies in the airspace and variability in travel time.

In this study we investigate the contribution of operational performance on airborne fuel consumption, with the goal of identifying the potential of NextGen technologies to reduce airborne fuel consumption. We identify three areas of operational performance to be improved through NextGen technologies. The first is departure and airborne delay. NextGen capabilities allow for closely spaced parallel approaches and reduced spacing, as well as a reduction of the capacity gap between Visual and Instrument Meteorological Conditions; the result will be a reduction in airborne and departure delays [7]. Furthermore, these technologies should reduce the variance in airborne time, reducing the need for airline schedule padding. The impact of improved operational performance on airline costs is great and measurable. One minute of airborne delay and minute of schedule padding are both found to increase operating costs by 0.6-0.7% at the sample mean level [6]. The extent to which cost savings from improved operational performance is attributed to fuel is the focus of our study.

To evaluate the potential of improved operational performance to reduce fuel, we develop a statistical model based on historical data to estimate fuel consumption and isolate the contribution of operational performance. We merge data from a major US air carrier reporting on airborne fuel consumption and scheduled and actual airborne and departure time with airborne fuel consumption estimated by the FAA’s National Airspace System Performance Analysis Capability (NASPAC) [8]. NASPAC uses a flight plan trajectory interpolator based on Eurocontrol’s Base of Aircraft Data (BADA) to estimate fuel consumption [9].

Section II introduces the methodology and modeling approach, and discusses the data collected. Coefficient estimates are presented and interpreted based on the objective of the study (Section III). Numerical examples are presented in Section IV with a discussion of how operational procedures can impact fuel consumption. Conclusions and future research are discussed in Section V.

II. METHODOLOGY AND MODELING

In this section, we present an overview of the fuel consumption model from which we will isolate the impact of operational performance on fuel consumption. We then explore the definition of the operational performance variables in depth, as well as the additional variables for analysis. Upon

defining the variables for analysis, we explore the data sources for the research.

A. Fuel consumption model overview

We consider the “realized” fuel per operation (f), or the fuel reportedly consumed by a major US airline, for a particular aircraft type to have the following form:

$$f = g(c, \vec{d}, \vec{q}, \vec{y}, \vec{w}) \quad (1)$$

where c is a baseline (simulated) airborne fuel consumption value; \vec{d} is a vector of operational performance variables; \vec{q} is the vector of take-off weights; \vec{w} is a vector of airport weather variables; and \vec{y} is the vector dummy variables indicating origin and destination airports of the flight. The key vectors of interest include \vec{d} , \vec{w} , and \vec{y} , as they capture the impact of operational performance. The additional values and vectors influence fuel consumption and are therefore included in order to isolate the impact of \vec{d} , \vec{w} , and \vec{y} .

The vector \vec{d} captures the three operational performance variables: airborne delay (\mathcal{E}^a), which is the difference between planned and actual airborne time; departure delay (\mathcal{E}^d), the difference between scheduled and actual departure time; and schedule padding (\mathcal{E}^p), the additional scheduled airborne time beyond an unimpeded airborne time. Consider Fig. 1, in which we depict the regions of time possibly incurred on a single operation related to the values in vector \vec{d} .

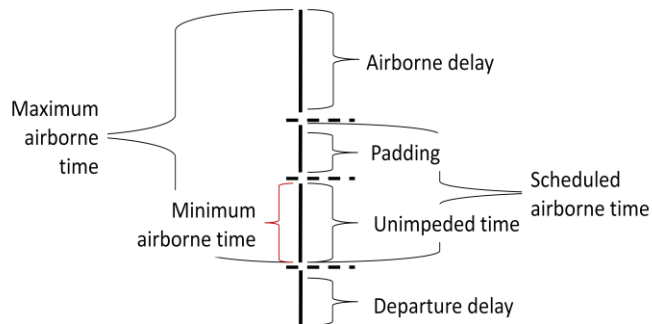


Figure 1. Decomposing delay effects.

Each time region possibly plays a unique role in contributing to aircraft fuel burn, described below.

Good operational performance begins with an on-time departure from the gate; congestion, weather, and other events could cause a delayed departure. While departure delay may not directly impact airborne fuel consumption, we hypothesize that departure delays and airborne fuel consumption are correlated. For example, it is possible that a departure delay could lead to an airline trying to fly at a faster rate to “make-up” time. It is also possible that departure delay is a proxy for airspace congestion which could lead to an aircraft experiencing inefficient climb-out procedures due to controller workload. If a controller is not under a heavy workload, they may be able to provide constant communication with an aircraft during climb leading to an efficient climb absent level-offs. Reynolds [10] states that while standardized departure procedures have system efficiency benefits they may increase flight distance and fuel consumption. The use of the

“departure delay” variable does not isolate the impact of, for example, controller workload, but it does shed light on the possibility of improved operational performance through departure delay reduction to reduce fuel. While the value of departure delay could be positive or negative in practice, we limit our scope to positive departure delays. Therefore, this variable is truncated at zero.

Airborne delay is the difference between planned airborne time and actual airborne time. This quantity represents the time beyond that expected incurred in the air. If this value if positive, it represents any unexpected change in routing, due to holding, vectoring, or a change in speed. Depending on the circumstance, this could increase or decrease fuel burn. If airborne delay is absorbed by slowing down, a minute in airborne delay could have a lower fuel consumption rate than a minute in unimpeded cruise. If the delay takes the form of a more circuitous route, more fuel would be used. If this value is negative, it reflects a shorter than anticipated airborne time, possibly from obtaining a direct routing or an efficient altitude.

Airborne schedule padding is the practice of increasing the scheduled airborne time such that it is greater than the unimpeded airborne time. This practice reflects expected declines in operational performance, caused by weather or congestion, which are so prevalent on a given route that it is more efficient from the airline perspective to operate as if the delay is certain to occur. It would be expected that airborne schedule padding will have an impact on fuel consumption as padding the schedule is a signal of a large variance in airborne time. This leads to contingency planning and higher fuel loads to minimize the need to divert; higher fuel loads lead to greater fuel consumption rates. As schedule padding is a planned-for operational performance issue, it may have a smaller impact on fuel compared with airborne and departure delay.

In addition to the operational performance vector \vec{d} , the key vectors of interest include \vec{w} , the vector of airport weather, and \vec{y} , the vector of airport origins and destinations. While not a delay by definition, the impact of airport arrival and departure procedures can impact fuel consumption such that some airports are inherently more fuel efficient than others. As discussed in Reynolds [10], airports may require aircraft to meet certain arrival fixes which may be at non-optimal altitudes or require non-optimal speed profiles. This is in addition to the discussion related to departure delay. To isolate the impact of airport-specific procedures, we include the vector \vec{y} ; to capture airport procedures that are specifically inefficient because of poor weather, we include vector \vec{w} .

To isolate the impact of operational performance and airport specific procedures, we include additional variables in the fuel consumption model. We begin with the variable c , the baseline fuel consumed based on the filed flight plan. By restricting the baseline fuel consumption to cruise, the airport fixed effects are able to better isolate the contribution of airport-specific departure and arrival operations and fuel consumption, and the operational performance variables can capture any deviation from the wind-optimal planned trajectory. We further eliminate concerns related to the ability

of a BADA-based model to capture terminal area fuel consumption [11]. Additionally, we include the vector \vec{q} (departure weights) to capture the influence of aircraft weight over fuel consumption.

Table I describes the variables in the fuel consumption model and the vector to which they belong. In section 2B we explore the data source of each variable as well as their derivation.

TABLE I. VARIABLES OF THE FUEL CONSUMPTION MODEL.

Variable Name (Value/Vector)	Variable Details		
	Var. label	Var. Units	Variable description
Fuel consumed	f	lbs/ operation	Fuel consumed from wheels-off to wheels-on
Departure delay (\vec{d})	ℓ^d	minutes/ operation	Difference between scheduled departure time and actual departure time ($\ell^d \geq 0$)
Airborne delay (\vec{d})	ℓ^r	minutes/ operation	Difference between scheduled and actual airborne time
Padding (\vec{d})	ℓ^p	minutes/ operation	Difference between scheduled airborne time and 20 th percentile of actual airborne time ($\ell^p \geq 0$)
Take-off weight difference (\vec{q})	o^d	lbs/ operation	Difference between actual take-off weight (TOW) and a nominal TOW
Actual take-off weight (\vec{q})	o^a	lbs/ operation	Actual take-off weight
Flight-plan cruise fuel consumed (c)	c	lbs/ operation	Fuel consumed in cruise estimated by NASPAC
Origin airport (\vec{y})	y_o	binary	Origin airport fixed effects
Destination airport (\vec{y})	y_d	binary	Destination airport fixed effects
Origin weather (\vec{w})	w_o	binary	Origin airport weather (0 if VMC, 1 if IMC)
Destination weather (\vec{w})	w_d	binary	Destination airport weather (0 if VMC, 1 if IMC)

B. Fuel Consumption Model Data Sources

The data on which the fuel consumption model in (1) is estimated is collected from three sources: A major United States-based air carrier; the FAA National Airspace System Performance Analysis Capability (NASPAC); and weather data from the FAA’s Aviation System Performance Metrics (ASPM) database.

1) *Data from Major US Air Carrier:* The data provided by the US carrier included all domestic operations between the US Operational Evolution Partnership 35 (OEP) airports, between the dates of 11/12/10 and 11/29/10 inclusive. While the data spans all aircraft types operated by this US carrier, we focus on two aircraft types commonly operated by this carrier between the US OEP 35: Boeing 757-200 (B752) and Boeing 737-800 (B738). These aircraft types are commonly used for short, medium, and long haul routes across the world.

The data collected from the airline includes reported data on airborne fuel consumption, take-off weight, airport origin and destination, scheduled and actual airborne time, and scheduled and actual departure time. Airborne fuel consumption reported by the airline is directly translated to the

dependent variable (f) in (1). This includes the climb-out, cruise, and descent phases of flight. The actual take-off weight (TOW) is reported by the airline (o^a); this value also factors into the calculation of the difference between the actual and nominal take-off weights (o^d). Also reported by the airline are the origin (y_o) and destination (y_d) airports which are represented as fixed effects: $y_o = 1$ if the observation originates at airport o and 0 otherwise; the same holds for y_d .

The three operational performance variables are derived from the collected airline data. This includes departure delay (ℓ^d); airborne delay (ℓ^r); and padding (ℓ^p). We define departure time as dt ; airborne time as at ; and the three possible subscripts s , a , and i to represent scheduled, actual, and unimpeded time. Each of the three defined operational performance variables are a function of the following reported values for every flight: scheduled departure time (dt_s); actual departure time (dt_a); schedule airborne time (at_s); and actual airborne time (at_a).

Departure delay (ℓ^d) is the difference between scheduled departure time and actual departure time.

$$\ell^d = \max(dt_s - dt_a, 0) \quad (2)$$

For airborne delay, we consider the difference between schedule airborne time and actual airborne time, allowing for a negative or positive value:

$$\ell^r = at_s - at_a \quad (3)$$

Following Zou and Hansen [6], we consider padding to be the difference between the schedule airborne time and the unimpeded airborne time (at_i) for a specific origin-destination pair. To calculate an unimpeded time, we find the 20th percentile of actual flying time; we seek a value such that for all actual airborne times at_a , $P(at_a > at_i) = 0.2$.

$$\ell^p = \max(at_s - at_i, 0) \quad (4)$$

2) *Data from FAA NASPAC Model:* We use the FAA's NASPAC modeling tool to estimate the nominal fuel consumption during the cruise phase of flight. While NASPAC is a system wide modeling tool, it contains a flight by flight trajectory interpolator and fuel burn estimator that is based on the BADA model issued by Eurocontrol [9]. The BADA model consists of flight performance characteristics data for over 100 different aircraft types. A preprocessing step of the NASPAC platform uses the BADA data to calculate a four dimensional trajectory assuming the standard BADA model operating at the aircraft's nominal mass throughout the flight. The assumption of using the nominal mass is necessitated by the lack of actual or estimated TOW on a flight by flight basis. The TOW provided by the US carrier for this study was not available to the FAA for use in estimating the cruise fuel consumption. NASPAC bases the ground track for its interpolated, four dimensional trajectory on the waypoints that come from the flight's last filed flight plan as reported by the Enhanced Traffic Management System (ETMS) [12]. Also, NASPAC uses the filed altitude and filed airspeed at cruise altitude as reported by ETMS. NASPAC uses a world wide, three dimensional wind product in its

simulation of flight times and fuel burn. NASPAC can simulate the fuel burn during the entire flight, however, because of the challenges related to the BADA-based model to capture terminal area fuel consumption, we collect data only from the cruise portion in the FAA NASPAC model [11]. We term this variable c .

3) *Data from FAA ASPM Database:* Data on airport weather were gathered from the FAA's ASPM database. The "Airport Efficiency" portion of this database provides variables on hourly meteorological condition (MC). From this information, we develop two variables: MC at the origin airport at schedule departure time (w_o) and MC at the destination airport at the scheduled arrival time (w_d). These variables are binary, such that the value is 1 if the MC is instrumental meteorological conditions (IMC) and 0 if the conditions are visual meteorological conditions (VMC).

4) *Data Exploration:* Before proceeding with model estimation, we explore the data to understand the relationships between the dependent and operational performance variables.

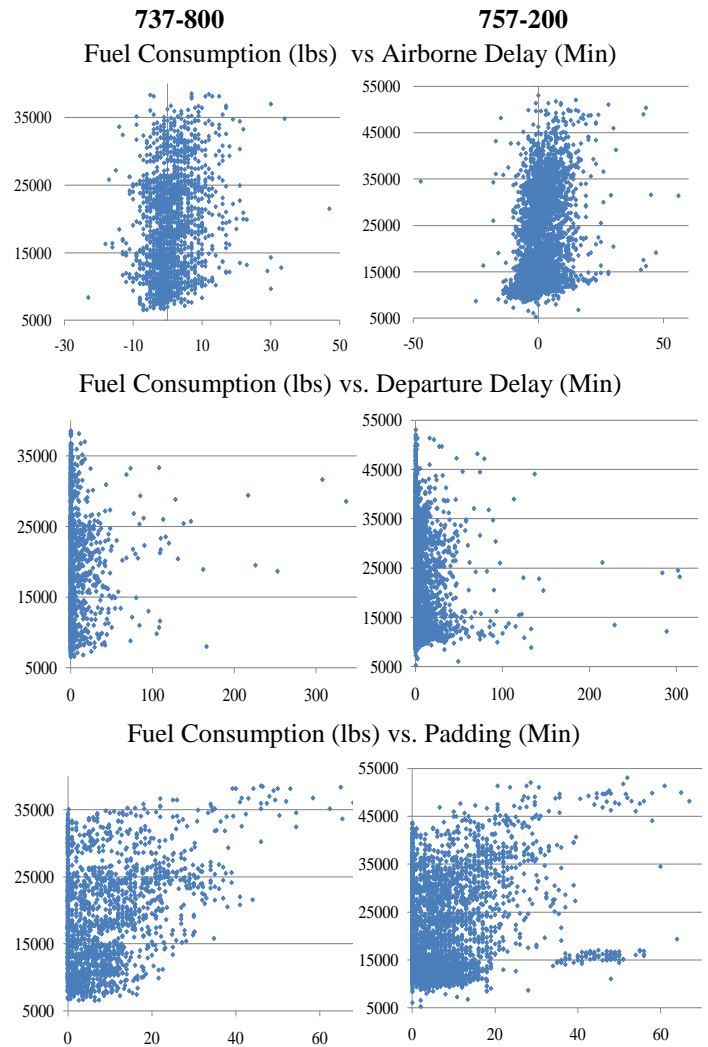


Figure 2. Fuel consumption vs. airborne delay, departure delay and padding for both aircraft types.

Fig. 2 shows the range of fuel consumption values for both vehicle types and the relationship between fuel consumption and the three operational performance variables. There appears to be an upward trend in fuel consumption related to airborne delay for both aircraft, as there is a density of observations in lower left and upper right quadrants of the graph. There appears to be a strong correlation between fuel consumption due and schedule padding for both aircraft types, with the highest values of fuel consumption falling in the region of greatest schedule padding. Related to departure delay, there seems to be a correlation between fuel consumption and departure delay, especially with the 737-800. To formalize these relationships, we define and estimate the fuel consumption model.

III. FUEL CONSUMPTION MODEL ESTIMATION

A. Model Estimation

For each aircraft type, an observation is uniquely defined by an origin, destination, and a date-hour (t).¹ We then identify a new index, i , which represents an origin-destination pair. The data we have is a panel, as in each data set we have i origin-destination pairs with observations over time t ; the data is furthermore an unbalanced panel as not every origin-destination pair has an observation in every time period t .

The model to estimate is:

$$f_{it} = \alpha + \beta_{\rho^d} \rho_{it}^d + \beta_{\rho^r} \rho_{it}^r + \beta_{\rho^p} \rho_{it}^p + \beta_o o_{it}^d + \beta_c c_{it} + \beta_{co} c_{it} o_{it}^d + \sum_{\gamma_o} \gamma_o \phi_{\gamma_o} + \sum_{\gamma_d} \gamma_d \phi_{\gamma_d} + \sum_{w_o} w_o \gamma_o \phi_{w_o} + \sum_d w_d \gamma_d \phi_{w_d} + \varepsilon_{it} \quad (5)$$

Where $\alpha, \beta_{\rho^d}, \beta_{\rho^r}, \beta_{\rho^p}, \beta_o, \beta_c, \beta_{co}, \phi_{\gamma_o}, \phi_{\gamma_d}, \phi_{w_o}, \phi_{w_d}$ are coefficients to be estimated

To properly estimate the model in equation (5), we must take into account the data form an unbalanced panel. The data is a panel of origin-destination pairs, and it is possible that different origin-destination pairs have different error variances. We test for the presence of heteroskedasticity using the Breusch-Pagan Cook-Weisberg test for and find that heteroskedasticity is indeed present. Furthermore, we expect to see autocorrelation; because the data is in a time series, we expect the error terms of a particular origin-destination pair to be correlated over time. Using the Wooldridge test for autocorrelation, we reject the null hypothesis that it is not present and therefore must include a correction in the model for autocorrelation. To estimate the model, we use ordinary least squares with panel-corrected standard error estimates and assuming first-order autocorrelation within panels.

The coefficient values are in units of fuel per minute; to help interpret their magnitudes we use the airline data to estimate the B738 and B752 fuel. Fig. 3 presents a box plot of the average fuel consumed on a flight per minute for both aircraft types. Note that the tops and bottoms of the box are the 25th and 75th percentiles of the samples, respectively and the middle line of each box is the sample median. The whiskers extending above and below each box extend the length of 1.5 times the interquartile range (IQR) (the distance between the 25th and 75th percentile). Any observations

beyond the whiskers are more extreme cases, representing the variability of fuel consumption. Along with the box plots we can consider the BADA cruise numbers for these two aircraft types. According to the BADA tables, a nominal cruise fuel consumption rate is 133.6 lbs/minute for the B752 and 93.9 lbs/minute for the B738 [9]; these values are very close to the median fuel consumption per minute.

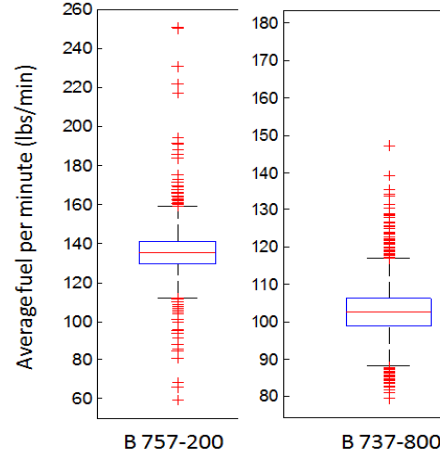


Figure 3. Airborne delay, departure delay and padding vs. fuel consumption for both aircraft types.

B. Coefficient Analysis

Table II contains select estimation results (because of the large number of fixed effects, we present the main variables of interest and discuss key fixed effects in this section). We first notice that across aircraft types all coefficient estimates are statistically significant. We also notice all coefficient estimates have the expected sign (positive), such that all variables influence fuel consumption in the positive direction.

TABLE II. VARIABLES OF THE FUEL CONSUMPTION MODEL.

Coeff. estimate (Std. error)	B757-200	B737-800
α	7898.955 (123.362)	5442.603 (78.378)
β_{ρ^d}	4.565 (1.036)	2.332 (0.857)
β_{ρ^r}	60.085 (3.318)	50.080 (3.017)
β_{ρ^p}	11.900 (3.085)	4.508** (2.059)
β_{o^d}	0.007** (0.003)	0.032 (0.004)
β_c	0.133 (0.047)	0.483 (0.054)
β_{co}	$3.58 \cdot 10^{-6}$ ($2.19 \cdot 10^{-7}$)	$3.060 \cdot 10^{-6}$ ($3.40 \cdot 10^{-7}$)
R^2	0.9898	0.9930
N (Number of observations)	4000	1827

All coefficients are significant at the 1% level unless noted
 **Variables are significant at the 5% level
 *Variables are significant at the 10% level

¹ The time identifier is date-hour-quarter for the Boeing 757-200.

1) *Operational Performance Variables:* Table II shows the coefficient estimates for departure delay (β_{pd}), airborne delay (β_{pr}), and schedule padding (β_{pp}).

We find that a minute of airborne delay leads to about 60 lbs of fuel consumption for the B752 and 50 lbs for the B738. These values are about 50% of the median fuel per minute for both aircraft types, and of a similar magnitude to the lower whisker seen in the box plot. These coefficients should be seen as averages since the fuel burn impact of an airborne delay varies according to how and where the delay is absorbed. The fact that the coefficients are well below median average fuel burn and the BADA cruise value suggests that in many cases the aircraft are burning less fuel to absorb delay than they do in nominal cruise mode.

A minute of schedule padding added to the schedule leads to 11.9 lbs of fuel consumed for the B752 and 4.5 lbs for the B738. The contribution of a minute of schedule padding is significantly less than a minute of airborne delay, leading to an interesting trade-off between planned and un-planned delays. A minute of padding adding to the schedule is incurred regardless of airspace conditions – said another way, if an airline adds 10 minutes of padding to the schedule, they are increasing their per-trip fuel consumption by 119 lbs of fuel on a B752. If the actual trip time is less than the scheduled, this fuel is expended in vain; it was unnecessary because the planned-for delays did not materialize. However, if the 10 minutes of padding were not added and 10 minutes of delay were incurred, the fuel consumed in airborne delay would be 601 lbs instead of 119.

We additionally find that departure delay does add to fuel consumption at a very small scale: 4.6 lbs for a minute of departure delay on a B752 and 2.3 lbs for a minute of departure delay on a B738. This is consistent with our expectation that departure delay is a proxy for congestion in the terminal area: as the time spent in the terminal airspace is limited compared with the time spent in cruise, it follows that these coefficients are significantly smaller than those for airborne delay. Furthermore, if departure delay impacts are persistent they may be captured by airport fixed effects.

2) *Airport and Weather Fixed Effects:* For model estimation purposes, we must choose a base origin and a base destination airport; for this airport, we eliminate their fixed effect from the model. The base airport chosen in this study is Hartsfield-Jackson Atlanta International Airport (ATL). We choose ATL as the base origin and destination airport because it is a hub airport with a diverse fleet mix, and in 2009, it had the largest number of operations worldwide [13]. Furthermore, ATL is dominated by a single carrier. Because of the nature of hub airports, departures and arrivals occur in banks, such that aircraft arrive, passenger deplane and board their connecting flights, and aircraft depart. This practice of peaking causes inefficient terminal area operations – vectoring, holding at inefficient altitudes, and long arrival paths. As such, we would imagine ATL as a base airport would be relatively inefficient, especially as a destination airport compared with other airports. However, even compared to ATL, some airports may

have greater inefficiencies; we examine the fixed effects to shed light on this possibility.

For origin airports, we examine Salt Lake City International Airport (SLC), LaGuardia Airport (LGA), and Ronald Reagan Washington National Airport (DCA). For destination airports, we examine DCA, LGA, Dallas Fort Worth International Airport (DFW), John F. Kennedy International Airport (JFK). Experts consulted by the research team shared that these airports have unique terminal areas compared with ATL and could illustrate the terminal area impact on fuel.

As an origin airport, SLC is reported as an airport that often grants an unrestricted climb. We see this reflected in the airport fixed effects: -549.1 for the 737-800 and -954.7 for the 757-200 (both significant at the 1% level). Two airports known for their conflicted airspace, LGA and DCA, are shown to have positive fixed effects as origin airports for the B738: 520.1 and 546.4 (both significant at the 1% level). These two airports are known for consistently being congested, which leads to the same inefficiency as discussed related to the departure delay. Both are in regions with congested and conflicted airspace.

As a destination airport, ATL is known for a long arrival path at low altitudes, and a practice called “tromboning” – such that aircraft make a large U-shape around the airport at low altitude before landing – which is highly inefficient. The purpose is to handle a high level of demand; when controllers must deal with many arrivals at the same time, they must space out the flights and sequence them so they get as many arrivals on the ground as possible, and not necessarily maximize fuel consumption [10]. This practice is reflected in the fixed effects, as many destination airport fixed effects are negative and statistically significant (including Fort Lauderdale – Hollywood International Airport (FLL) -1078.8 and Louis Armstrong New Orleans International Airport (MSY) -423.0 for the B752 and Boston Logan International Airport (BOS) -571.0 and Seattle-Tacoma International Airport (SEA) -523.9 for the B738) or statistically insignificant.

However, despite Atlanta’s noted inefficiency as a destination airport, there are a few airports that the model shows have even greater inefficiency at the terminal area. Focusing on the B738, these include DCA (567.0); DFW (777.4); JFK (724.1); and LGA (820.5) (all significant at the 1% level). The New York airports along with DCA are well known for their conflicted and complicated airspace, which leads to a great deal of inefficiency as confirmed by [14]. DFW is also a large hub airport, and the results are showing that their approach procedures can lead to greater inefficiencies than those experienced in ATL.

We find most weather-airport interaction fixed effects to be statistically insignificant, as the airport did either not experience IMC or the fuel consumption was not impacted in a statistically significant manner. We do see some statistically significant effects, of the expected sign, including an increase in fuel consumption in IMC of 959.4 lbs for a B752 destined for DFW and an increased in fuel consumption in IMC of

353.7 for a B738 destined for Minneapolis St. Paul International Airport (MSP).

IV. NUMERICAL EXAMPLES

In this section, we utilize the coefficient estimates to determine fuel consumption under different scenarios of operational performance. Using the realized airline data, we generate scenarios of operational performance and predict fuel consumption due padding, departure delay, and airborne delay, along with a baseline fuel consumption assuming zero delays.

We begin by identifying specific origin-destination pairs for each aircraft type, and examine the specific observations. We choose the observation with the maximum sum of padding, departure delay, and airborne delay across all observations, and term this the “Maximum overall flight.” We also identify the maximum value of padding, the maximum value of departure delay, and the maximum value of airborne delay; these values are not necessarily incurred in the same flight observation. We consider the set of these three values to be the “Maximum flight.” We finally, over all observations for a specific origin-destination pair and aircraft type, determine the average padding, departure delay, and airborne delay. The set of these three values is termed the “Average flight.” We then develop four datasets: a baseline (zero padding and airborne and departure delay); an overall maximum flight dataset (with the three delay variables equal to those of the overall maximum flight); a maximum flight dataset (with the three delay variables equal to those of the maximum flight); and an average flight (with the three delay variables equal to the averages). These data sets are based on the original airline data. In developing these datasets, we include all observations between a given airport pair on a particular aircraft type, and simply replace the values of padding, airborne delay and departure delay with either zero; the averages; the maximum overall flights; or the maximum flight. We then predict fuel consumption for each observation using the coefficient estimates, and then finally average the fuel across all observations.

We present the results in Figs. 4 and 5 for the B752 and Figs. 6 and 7 for the B738; both present two chosen airport pairs. The figures show baseline, departure delay, padding, and airborne delay as a percentage of total fuel consumption.

A. Numerical Examples for the Boeing 757-200

We evaluate a medium-haul and a long-haul airport origin-destination pair for the B752: the 1345 mile route of Los Angeles International Airport (LAX) to MSP and 2300 mile route of JFK to San Francisco International Airport (SFO). LAX and JFK are interesting airports because they are certainly congested with a very diverse fleet mix yet neither is dominated by a single carrier. This is reflected in the airport fixed effects: as an origin the fixed effects are negative and statistically significant, yet as a destination the fixed effects are statistically insignificant meaning that the impact of the terminal area is not statistically different from that of congested ATL. While MSP and SFO are both hubs for a major US carrier like ATL, they have fewer operations and may be less prone to the peaks present at ATL; this is reflected in the origin and destination fixed effects for both airports,

which are both negative and statistically significant at the 1% level. Additionally, both routes experienced large peaks in departure delay and padding, and as such present a strong opportunity to evaluate the impact of these two operational performance variables. Table III presents values for the three operational performance variables for the maximum overall, maximum, and average flight.

TABLE III. BOEING 757-200 FLIGHT SCENARIOS.

Variable name	Flight scenario					
	Maximum overall flight		Maximum flight		Average flight	
	JFK-SFO	LAX-MSP	JFK-SFO	LAX-MSP	JFK-SFO	LAX-MSP
Departure delay	79	14	79	147	3.7	10.1
Airborne delay	23	18	43	29	7.5	4.2
Padding	24.6	24	51.6	37	17.7	10.5

Using these values and the coefficients presented in Table II, we predict fuel consumption and quantify the percentage attributed to each operational performance variable. Fig. 4 presents the results for LAX-MSP and Fig. 5 presents the results for JFK-SFO (note that the x-axis begins with 85% for the purposes of zooming in on the operational performance variables).

We see for the long-haul route the overwhelming percent (95% or higher) of fuel consumed during the flight is not related to operational performance. The medium route is more significantly impacted by operational performance metrics; as it is a shorter flight, the operational performance variables account for a larger percentage of the fuel consumed. We also note the relative impact of the operational performance variables. Table III shows that the departure delay incurred on the maximum flight for both routes is significantly higher than the airborne delay, however the percentage of fuel attributed to departure delay is minimal compared with airborne delay. Both flights experience larger levels of padding for all scenarios, yet Figs. 4 and 5 show that the magnitude of the fuel consumed in airborne is significantly greater than that consumed in padding.

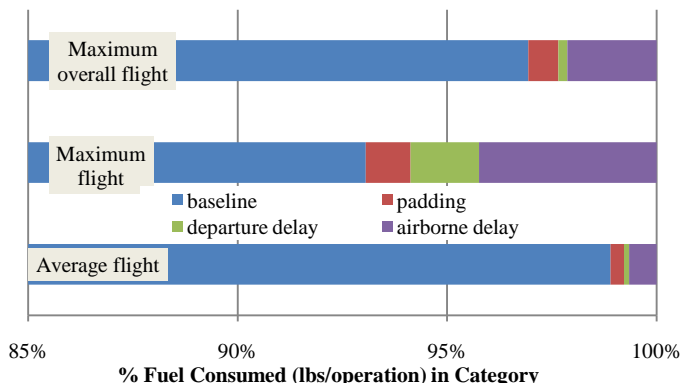


Figure 4. Fuel consumption on a 757-200, LAX-MSP.

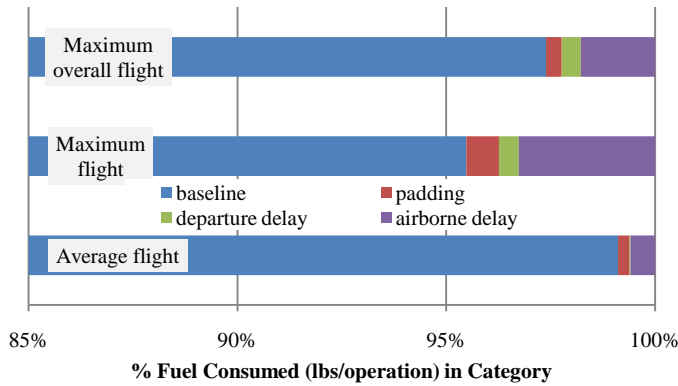


Figure 5. Fuel consumption on a 757-200, JFK-SFO.

B. Numerical Examples for the Boeing 737-800

We evaluate a short-haul and a medium-haul airport origin-destination pair for the B738: the 569 mile route of BOS to Detroit Metro Airport (DTW) and 1700 mile route of ATL to John Wayne Airport (SNA). Unlike the airports chosen for the B752 numerical example, these airports are not statistically different from ATL; as such the fixed fuel consumption may play a larger role in the overall fuel consumption. Additionally, both routes experienced consistent levels of operational delay, except in the maximum overall flight. The maximum overall flight allows us to investigate a n operation with high departure delay and schedule padding (ATL-SNA) with a flight with high airborne delay (BOS-DTW). Table IV presents values for the three operational performance variables for the maximum overall, maximum, and average flight.

TABLE IV. BOEING 737-800 FLIGHT SCENARIOS.

Variable name	Flight scenario					
	Maximum overall flight		Maximum flight		Average flight	
	ATL-SNA	BOS-DTW	ATL-SNA	BOS-DTW	ATL-SNA	BOS-DTW
Departure delay	28	0	28	21	1.4	1.3
Airborne delay	2	23	21	29	2.0	8.4
Padding	22	6.6	35	14.6	9.7	3.2

Using the values presented in Table IV and the coefficients presented in Table II, we predict fuel consumption and quantify the percentage attributed to each operational performance variable. Fig. 6 presents the results for ATL-SNA and Fig. 7 presents the results for BOS-DTW.

We first see that for a short-haul flight, BOS-DTW, reduced operational performance greatly impacts the overall fuel consumption of a flight. For this route, we see that for the maximum overall flight, 10% of the fuel consumption is attributed to operational performance variables. If the maximum observable padding, departure delay, and airborne delay are experienced on the same flight, about 13% of the fuel consumed is attributed to operational performance.

We also see that a flight with high airborne delay (BOS-DTW, Maximum overall flight) attributes a much higher percentage of the overall fuel consumption to operational

performance variables compared with a flight with high padding and departure delay (ATL-SNA, Maximum overall flight).

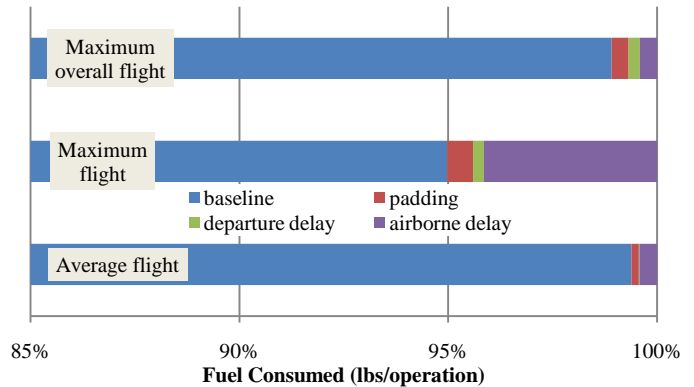


Figure 6. Fuel consumption on a B738, ATL-SNA.

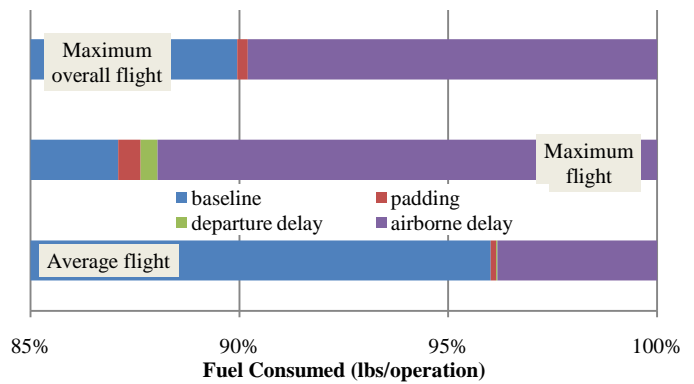


Figure 7. Fuel consumption on a B738, BOS-DTW.

These findings support the literature related to the potential of ATM to reduce fuel consumption and related CO₂ emissions. Reducing airspace delay through the use of AFPs was found to reduce delay by 10% by Ohsfeldt et al.; in this study we find airborne delay can contribute up to 10% of overall fuel consumption [3]. Furthermore, Clarke et al. [4] find that fuel consumption can be reduced by about 20% on approach using CDAs. Our findings support this work: we find that the sum of airport destination fixed effects and the intercept to be up to 13% less than the intercept alone, suggesting that efficient terminal areas, potentially granting unrestricted decent, can reduce fuel consumption by a significant amount.

These findings also shed light on the importance of focusing fuel reduction efforts on airborne operational performance, as the magnitude of the potential savings is much larger than potential savings from taxi fuel reduction. For example, the average B738 flight from BOS-DTW expends 421 lbs of fuel in airborne delay (which translates into about 3.5% of total airborne fuel consumption in Fig. 7); this is compared to the average 118 lbs of fuel consumed in taxi-out and 271 lbs of fuel consumed in taxi-in reported in the data. Cutting the average airborne delay by 35% is equivalent to eliminating taxi-out fuel consumption completely. While much focus is on reducing fuel consumption from surface operations,

the potential of fuel reduction is significantly less than that from airborne operational performance.

V. CONCLUSION

This analysis shows the possibility to reduce fuel consumption through an improvement in operational performance. We find that operational performance is responsible for up to 10% of airborne fuel consumption; these findings are supported by related literature on the potential of ATM to reduce fuel consumption. We further put the magnitude of fuel savings into context by comparing it to taxi fuel reduction potential. We confirm that planning for operational performance degradation incurs a fuel cost; however, this fuel cost is significantly less than the fuel consumed if the delay were not anticipated. The findings of this study help further our understanding of the relationship between schedule padding and airborne delay from a fuel consumption perspective. The findings of this work could be coupled with additional research to determine the likelihood of experiencing delays of a certain length; from these findings an optimal level of schedule padding from a fuel perspective could be encouraged.

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