Quantile Regression Based Estimation of Statistical Contingency Fuel

Lei Kang, Mark Hansen
June 29, 2017
Agenda

- Background
- Industry practice
- Data
- Methodology
- Benefit assessment
- Conclusion
Agenda

- Background
  - Industry practice
  - Data
  - Methodology
  - Benefit assessment
  - Conclusion
Jet Fuel Prices and Consumption

Fuel Consumption (in million gallons) and Cost (in million dollars)

Jet Fuel Price, Fuel Consumption, Fuel Cost

Source:
1. Energy Information Administration, U.S. Gulf Coast Kerosene-Type Jet Fuel Spot Price
2. Bureau of Transportation Statistics, U.S. Carriers Fuel Cost and Consumption
Fuel Costs

Operating Expense 2014

- Fuel: 28%
- Labor: 26%
- Rentals: 6%
- Depreciation & Amortization: 5%
- Landing Fees: 2%
- Maintenance Materials: 2%
- Transport-Related: 13%
- Other: 18%

Operating Expense Quarter 3, 2016

- Fuel: 16%
- Labor: 34%
- Rentals: 6%
- Depreciation & Amortization: 6%
- Transport-Related: 12%
- Maintenance Materials: 2%
- Landing Fees: 2%
- Other: 22%

Source: Bureau of Transportation Statistics
Environmental Impact

• Air transportation contributes
  – **8%** of transportation greenhouse gas (GHG) emissions in the U.S. (EPA, 2016)
  – **11%** of transportation emissions globally (IPCC, 2014)

• The global GHG emissions by 2020 from aviation are projected to be around **70%** higher than in 2005 (ICAO, 2014)
How to Reduce Fuel Consumption?

• Government
  – Enhanced Air Traffic Management (FAA, 2014; European Commission, 2010)
  – Regulation
    • EU Emissions Trading System (European Commission, 2008)
    • EU fuel and environmental taxes (European Commission, 2015)

• Manufactures
  – Aircraft and engine improvement (Irrgang et al., 2011; IPCC, 1999; European Commission, 2015)

• Airlines
  – Operational strategies (Schiefer and Samuel, 2011; Lovegren and Hansman, 2011)
Weight-based Approaches for Reducing Fuel Consumption

• Aircraft fuel burn is directly related to aircraft weight

• Aircraft weight reduction
  – Lightweight materials (Lee et al., 2009; European Commission, 2015)
  – Charge passengers for luggage (Abeyratne, 2009)

• Unnecessary fuel loading is the biggest source of excess weight added to the aircraft (Ryerson et al., 2015; Irrgang, 2011)
Dispatchers Overload Fuel

• Motivating Study 1
  – One U.S. airline fuel burn data analysis (Ryerson et al., 2015)
  – By reducing “unnecessary” fuel loading (assuming $3.2/gallon)
    • ~ $223 million savings per year
    • ~ 661 million kg reduction in CO₂ emission per year
Dispatchers Overload Fuel

- **Motivating Study 2**
  - Six major U.S. airlines in 2012 (Kang et al., 2016)

Cost-to-Carry Unused Fuel

<table>
<thead>
<tr>
<th>Airline</th>
<th>US Dollars (in million)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Airline 1</td>
<td>200</td>
</tr>
<tr>
<td>Airline 2</td>
<td>100</td>
</tr>
<tr>
<td>Airline 3</td>
<td>600</td>
</tr>
<tr>
<td>Airline 4</td>
<td>100</td>
</tr>
<tr>
<td>Airline 5</td>
<td>200</td>
</tr>
<tr>
<td>Airline 6</td>
<td>100</td>
</tr>
</tbody>
</table>

- CTC gate-in Fuel 3$/gallon
- CTC gate-in fuel excluding reserve fuel at 3$/gallon
Agenda

- Background
- Industry practice
- Data
- Methodology
- Benefit assessment
- Conclusion
Agenda

- Background
- **Industry practice**
- Data
- Methodology
- Benefit assessment
- Conclusion
Domestic Flight Planning Basics

- Timeline of **dispatcher duties** for a single flight

- Flight plan is created. Look at weather, choose routing, determine fuel loads.
- Revise flight plan if necessary based on last-minute info.
- Monitor flight while en-route, update pilots with necessary info.

### Mission Fuel
- Reserve Fuel
- Alternate Fuel
- Contingency Fuel
- Other Fuel

~ 2 hours

Departure

Arrival
Fueling Categories

• Mission fuel
  – The fuel to complete a planned route
  – Calculated by the Flight Planning System (FPS)

• Reserve fuel
  – The quantity of fuel an aircraft needs to fly for 45 min at normal cruising speed regulated by the FAA
  – Calculated by the FPS
Fueling Categories

• **Contingency Fuel**
  – Reflects the airline dispatcher’s assessment of the “downside” risks that may lead to additional fuel burn beyond what is projected by the flight plan

• **Alternate Fuel**
  – The quantity of fuel that would be needed to fly to an alternate airport at the destination if missed a landing approach
  – One or two alternates may be included
  – 1st alternate is required by weather conditions: visibility < 3 miles or ceiling < 2000 feet or thunderstorm within scheduled Estimated Time of Arrival ± 1 hour
  – Otherwise, alternate is discretionary
Statistical Contingency Fuel (SCF)

• For domestic flights, dispatchers are presented with suggested values for contingency fuel, called Statistical Contingency Fuel (SCF)

• The goal of SCF is to provide dispatchers with consistent and objective contingency fuel loading recommendation

• SCF has been widely used in airline industry
  – Air India, British Midland International, United Airlines, Virgin America, Virgin Atlantic, SAS Group of Airlines, etc. (Schiefer and Samuel, 2011)
Statistical Contingency Fuel (SCF)

- The numbers are based on the historical distribution of over-under burn (actual fuel burn – planned mission fuel) required for similar flights.

- For example, FPS pulls historical data of all flights between the same Origin-Destination (OD) pair that were scheduled to depart in the same “hour bank” or time window specified by the airline.
Current SCF Estimation Procedure

Actual fuel – planned fuel (in lbs)

95% 99%

SCF99
SCF95
Limitations of Current SCF

• Normality assumption might not hold

• The estimate of a 95th or 99th percentile based on the sample mean and standard deviation with small sample size is subject to considerable sampling error
  – Impossible to calculate SCF values in the case of serving a new OD market with no similar historical flights

• Over-simplified grouping criterion (OD-hour)
  – In order to increase the confidence level of dispatchers in SCF values, weather forecast should also be explicitly taken into account
• Dispatchers in general load more discretionary fuel than the SCF95 recommendation
Objectives

• Propose a new SCF estimation procedure so that new SCF can better assist dispatchers in fuel planning
  – Overcome current limitations in estimation
  – More believable to dispatchers so that unnecessary fuel loading could be reduced

• Assess the fuel saving benefit of adopting the new SCF estimation procedure
  – Monetary saving to airlines
  – CO$_2$ reduction
Agenda

- Background
- Industry practice
- Data
- Methodology
- Benefit assessment
- Conclusion
Agenda

- Background
- Industry practice
- Data
- Methodology
- Benefit assessment
- Conclusion
Data Collection

• **Airline Fuel Data**
  – One major U.S.-based airline
  – Domestic operations between April 2012 and July 2013
  – Detailed flight-level information including flight characteristics, all categories of fuel uplift in units of minutes and pounds, SCF, etc.
Data Collection

• Weather Data
  – National Oceanic and Atmospheric Administration (NOAA)
  – Actual weather and weather forecast (TAFs) information for major U.S. airports including ceiling, visibility as well as indicators of the presence of thunderstorms and snow
  – A weather impacted flight is defined as a flight for which the TAF forecasted destination ceiling below 2000 feet, or visibility below 3 miles, or forecasted thunderstorm presence
Data Collection

• Traffic Data
  – Aviation System Performance Metrics (ASPM)
  – Construct historical flight time distribution
  – Same OD pair, scheduled departure hour, and month that occurred in the previous year
  – Mean, standard deviation, different quantiles of historical airborne time distribution
Agenda

- Background
- Industry practice
- Data
- Methodology
- Benefit assessment
- Conclusion
Agenda

- Background
- Industry practice
- Data
- **Methodology**
- Benefit assessment
- Conclusion
Quantile Regression Method

• The dependent variable: under-over burn value (in minutes)

• Covariates: weather forests, historical traffic conditions, aircraft types, departure hour window, departure month, and dummies for major airports
Advantages

• It models a given quantile of under-over burn value directly rather than employing simplified grouping criterion and assuming a normal distribution

• It allows covariates to be added into the estimation function so that characteristics such as weather and traffic can be explicitly controlled for

• This method also allows us to estimate SCF values for flights where the old method cannot be used because there is not an adequate sample of similar flights
Basic Formulation

• Quantile regression estimator for \( q \)-th quantile minimizes the following loss function

\[
J_q(\beta) = \sum_{i=1}^{N} \rho_q(y_i - f(x_i, \beta))
\]

• where \( \rho_q(t) = t(q - I(t<0)) \)

• In our case, we choose \( q \) to be 0.95 which corresponds to SCF95

• How to estimate \( f(x_i, \beta) \) ?
Machine Learning Methods of Estimating $f(x)$

- Method 1: parametric quantile regression
  \[ f(x_i, \beta) = x_i' \beta \]

- Method 2: gradient boosting
  \[ \hat{f}_t \leftarrow \hat{f}_{t-1} + \alpha h_t(x^k) \]

- Method 3: random quantile forests
  - report $q$-th empirical quantiles of $Y$ in a leaf and then average the obtained quantiles across all trees
Model Training

• Sample size: 368,607 flights

• Training set (60%), validation set (20%), and test set (20%)

• Tuning parameters selection based on validation set performance

• Final models are evaluated on test set
Model Assessment

• Goodness-of-fit measure:

\[ R(\beta) = 1 - \frac{J_q(f(\beta))}{J_q(\tilde{f}(\beta))} \]

• where \( J_q(f(\beta)) \) is the value of loss function on test set using SCF95 estimation function \( f(\beta) \)
• \( \tilde{f}(\beta) \) is used to denote a model with the constant term only
## Model Training Results

<table>
<thead>
<tr>
<th></th>
<th>Test set</th>
</tr>
</thead>
<tbody>
<tr>
<td>Goodness-of-fit measure</td>
<td>Percentage of flights landing with reserve fuel being used*</td>
</tr>
<tr>
<td><strong>Quantile Regression</strong></td>
<td>0.231 3.4%</td>
</tr>
<tr>
<td><strong>Gradient Boosting Machine</strong></td>
<td>0.237 3.4%</td>
</tr>
<tr>
<td><strong>Random Quantile Forests</strong></td>
<td>0.250 3.2%</td>
</tr>
<tr>
<td><strong>Airline FPS SCF95</strong></td>
<td>0.076 5.1%</td>
</tr>
</tbody>
</table>

* for comparison purpose, the percentages in this table are computed based on flights with FPS SCF95.
Random Quantile Forests Results

Weather impacted flights in the test set

Non-weather impacted flights in the test set
Agenda

- Background
- Industry practice
- Data
- Methodology
- Benefit assessment
- Conclusion
Agenda

- Background
- Industry practice
- Data
- Methodology
- Benefit assessment
- Conclusion
Cost-to-Carry Analysis

• The difference between discretionary fuel loading and new SCF95 value defines our opportunity in fuel saving

• By assuming dispatchers follow new SCF95 recommendation perfectly in loading discretionary fuel, we can compute fuel saving in terms of cost-to-carry (CTC) discretionary fuel reduction

• CTC is defined as the pounds of fuel consumed per pound of fuel carried per mile and it varies across aircraft types and flight distance (Ryerson et al., 2015)
Cost-to-Carry Factor Estimates in lbs/lbs

Source: Ryerson et al. (2015)
Safety Check

- Safety is a dispatcher’s major consideration in discretionary fuel loading

- If we load discretionary fuel exactly as the proposed SCF95 values, we would still encounter a small proportion of flights using reserve fuel which is undesirable to airlines

- To address this safety concern, we propose to add a safe buffer on top of proposed SCF95 which can help achieve a same safety performance as the current practice for our study airline
Safety Check

• We estimate a scaling factor $\eta$ and the new discretionary fuel quantity for flight $j$ becomes $\eta \times SCF_{95 \ j}$.

• Scaling factor can be learned based on validation set

$$
\min \eta \\
\text{s.t.} \quad \frac{1}{N} \sum_{j=1}^{N} I\{AF_j - PF_j - \eta SCF_{95 \ j} < 45\} < \gamma
$$

• The safety benchmark $\gamma$ is the percentage of flights landing with some reserve fuel being used based on actual discretionary fuel loading.
## Fuel Saving Estimates

<table>
<thead>
<tr>
<th></th>
<th>Test set</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuel Saving per flight</td>
<td>Fuel Saving per flight based on RQF (in lbs)</td>
</tr>
<tr>
<td>based on RQF (in lbs)</td>
<td>Fuel Saving per flight based on RQF after applying scaling factor (in lbs)</td>
</tr>
<tr>
<td>Weather impacted flights</td>
<td>246</td>
</tr>
<tr>
<td>Non-weather impacted flights</td>
<td>229</td>
</tr>
</tbody>
</table>
Fuel Saving Estimates

• The estimated benefit pool for our study airline is in the magnitude of $64 million fuel saving and 446 million kilogram CO$_2$ emission reduction per year

• Even after multiplying scaling factor on our proposed SCF95 estimates, the estimated annual benefits are still significant: $14 million fuel saving and 98 million kilogram CO$_2$ emission reduction
Agenda

- Background
- Industry practice
- Data
- Methodology
- Benefit assessment
- Conclusion
Agenda

- Background
- Industry practice
- Data
- Methodology
- Benefit assessment
- Conclusion
Conclusions

• This analysis shows the possibility to reduce fuel consumption through an improved SCF95 estimation procedure
• A quantile regression based SCF95 estimation procedure has been proposed
• Three estimation models including parametric quantile regression, gradient boosting, and random quantile forests are found to substantially outperform airline’s FPS in SCF95 estimation. RQF is also found to perform slightly better than the other two proposed models
• Using our proposed SCF95, our study airline can achieve $14 million fuel saving and 98 million kilogram CO\textsubscript{2} emission reduction per year with the same safety performance
Thanks for your attention!
## Backup 1-Parametric Quantile

<table>
<thead>
<tr>
<th>Category</th>
<th>Variable</th>
<th>Estimates</th>
<th>T-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>---</strong></td>
<td><strong>Intercept</strong></td>
<td>-7.829 *</td>
<td>-19.29</td>
</tr>
<tr>
<td><strong>Aircraft type</strong></td>
<td><strong>A320</strong></td>
<td>2.238 *</td>
<td>10.99</td>
</tr>
<tr>
<td>(Baseline is A319)</td>
<td><strong>B737-800</strong></td>
<td>2.042 *</td>
<td>8.58</td>
</tr>
<tr>
<td></td>
<td><strong>B757-300</strong></td>
<td>11.310 *</td>
<td>42.59</td>
</tr>
<tr>
<td></td>
<td><strong>B757-200</strong></td>
<td>13.359 *</td>
<td>65.39</td>
</tr>
<tr>
<td></td>
<td><strong>DC9</strong></td>
<td>15.869 *</td>
<td>59.19</td>
</tr>
<tr>
<td></td>
<td><strong>MD88</strong></td>
<td>16.547 *</td>
<td>85.59</td>
</tr>
<tr>
<td></td>
<td><strong>MD90</strong></td>
<td>9.322 *</td>
<td>45.15</td>
</tr>
<tr>
<td><strong>Distance</strong></td>
<td><strong>Flight distance (in nautical miles)</strong></td>
<td>0.003 *</td>
<td>2.94</td>
</tr>
<tr>
<td></td>
<td><strong>Median of historical airborne time</strong></td>
<td>0.026 *</td>
<td>3.84</td>
</tr>
<tr>
<td><strong>Historical traffic condition</strong></td>
<td><strong>Standard deviation of historical airborne time</strong></td>
<td>-0.027</td>
<td>-1.05</td>
</tr>
<tr>
<td></td>
<td><strong>Median of difference between historical actual and planned airborne time</strong></td>
<td>0.137 *</td>
<td>10.85</td>
</tr>
<tr>
<td></td>
<td><strong>Standard deviation of difference between historical actual and planned airborne time</strong></td>
<td>0.211 *</td>
<td>8.59</td>
</tr>
<tr>
<td><strong>TAF weather forecast for destination airports</strong></td>
<td><strong>Low visibility indicator (1-if lower than 3 miles, 0-otherwise)</strong></td>
<td>2.444 *</td>
<td>7.62</td>
</tr>
<tr>
<td></td>
<td><strong>Low ceiling indicator (1-if lower than 2000 feet, 0-otherwise)</strong></td>
<td>5.052 *</td>
<td>34.60</td>
</tr>
<tr>
<td></td>
<td><strong>Thunderstorm indicator (1-if thunderstorm presents, 0-otherwise)</strong></td>
<td>6.485 *</td>
<td>17.46</td>
</tr>
<tr>
<td></td>
<td><strong>Snow indicator (1-if snow presents, 0-otherwise)</strong></td>
<td>3.147 *</td>
<td>6.27</td>
</tr>
<tr>
<td><strong>TAF weather forecast for origin airports</strong></td>
<td><strong>Low visibility indicator (1-if lower than 3 miles, 0-otherwise)</strong></td>
<td>0.151</td>
<td>0.93</td>
</tr>
<tr>
<td></td>
<td><strong>Low ceiling indicator (1-if lower than 2000 feet, 0-otherwise)</strong></td>
<td>0.058</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td><strong>Thunderstorm indicator (1-if thunderstorm presents, 0-otherwise)</strong></td>
<td>0.963 *</td>
<td>4.18</td>
</tr>
<tr>
<td></td>
<td><strong>Snow indicator (1-if snow presents, 0-otherwise)</strong></td>
<td>-0.217</td>
<td>-0.85</td>
</tr>
<tr>
<td><strong>Month</strong></td>
<td><strong>February</strong></td>
<td>0.221</td>
<td>1.04</td>
</tr>
<tr>
<td>(Baseline is January)</td>
<td><strong>March</strong></td>
<td>-1.328 *</td>
<td>-6.96</td>
</tr>
<tr>
<td></td>
<td><strong>April</strong></td>
<td>-0.493 *</td>
<td>-2.75</td>
</tr>
<tr>
<td></td>
<td><strong>May</strong></td>
<td>0.006</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td><strong>June</strong></td>
<td>-1.034 *</td>
<td>-4.89</td>
</tr>
<tr>
<td></td>
<td><strong>July</strong></td>
<td>-0.781 *</td>
<td>-3.77</td>
</tr>
<tr>
<td></td>
<td><strong>August</strong></td>
<td>-0.672 *</td>
<td>-3.12</td>
</tr>
<tr>
<td></td>
<td><strong>September</strong></td>
<td>-1.290 *</td>
<td>-6.64</td>
</tr>
<tr>
<td></td>
<td><strong>October</strong></td>
<td>-0.981 *</td>
<td>-5.02</td>
</tr>
<tr>
<td></td>
<td><strong>November</strong></td>
<td>-1.284 *</td>
<td>-6.59</td>
</tr>
<tr>
<td></td>
<td><strong>December</strong></td>
<td>-0.261</td>
<td>-1.18</td>
</tr>
<tr>
<td></td>
<td><strong>Number of observations</strong></td>
<td>221,163</td>
<td></td>
</tr>
</tbody>
</table>
Backup 2-Parametric Quantile

Weather impacted flights in the test set  Non-weather impacted flights in the test set
Backup 2-Gradient Boosting

Weather impacted flights in the test set

Non-weather impacted flights in the test set