2003

Fuel Consumption Modeling of a Transport Category Aircraft: A Flight Operations Quality Assurance (FOQA) Analysis

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Sorenson Best Paper Award Recipient

FUEL CONSUMPTION MODELING OF A TRANSPORT CATEGORY AIRCRAFT: A FLIGHT OPERATIONS QUALITY ASSURANCE (FOQA) ANALYSIS

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ABSTRACT

Flight Operations Quality Assurance (FOQA)-derived data was used to develop parsimonious model(s) for fuel consumption on a Boeing 757 airplane using regression analysis. Using the model(s), it should be possible to identify outliers (specific flights) with respect to fuel consumption, which will enable the air carrier to investigate the cause of excessive fuel consumption and remedy the problem A major air carrier provided the database used for the study. Fuel flow was predicted by calibrated airspeed, gross weight, and n2 (ENG[1 or 2]n2). The models containing these three variables explained approximately 85% of the variation in fuel flow. A reporting routine using these models and FOQA data should be incorporated into the ongoing quality assurance program of the air carrier.

INTRODUCTION

The airline industry, perhaps more than any other, is one that is characterized by large numbers. As example, consider that it costs more than $60 million to purchase and configure one new Boeing 757-200 airplane (Jackson, 2001); that a Boeing 757-200 holds more than 11,000 gallons of jet fuel (Jackson, 2001); that U.S. air carriers consume approximately 14 billion gallons of fuel annually in domestic operations (Fuel, 2002); and that in 2001, U.S. air carriers generated total operating revenues of $375.7 billion in domestic operations and $382.6 billion in operating expenses—a margin of -$6.9 billion (Yearly, 2002).

Given these numbers, it is not surprising that air carriers strive to contain their operating costs. Fuel expenditures represent the industry's second-

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largest operating cost category. To aid in managing this expenditure, extensive fuel-related research is being conducted by a host of organizations, including government, industry, and academia, but the research is primarily focused on engineering-related areas of fuel efficiency. Little exists in the literature on efforts to establish new programs that may improve an air carrier's ability to monitor fuel consumption.

Recent technological advances in hardware and software now enable a wealth of flight performance data to be captured, stored, and retrieved from transport category aircraft. Analysis of this performance data has the potential of revealing problems that may be causing excessive fuel consumption on specific airplanes. These problems may be caused by airframe or engine abnormalities and may result in significantly higher fuel costs to the airline and, ultimately, higher costs to the traveling public. Thus, both the airlines and the public should benefit from the analysis of flight performance data for fuel consumption anomalies.

Many aircraft and component manufacturers, such as The Boeing Aircraft Company, have developed programs for monitoring aircraft performance. These programs range from the relatively simple recording of instrument indications as observed by the flight crew to the digital recording of numerous parameters using airborne sensing and recording devices. Among the apparent deficiencies of some of these programs is that the data is limited to parameters that are strictly performance-related; to wit, parameters that may provide additional insight into the object of concern are sometimes unavailable in the existing performance monitoring programs.

One of several emerging quality assurance programs in the aviation industry, Flight Operations Quality Assurance (FOQA), involves the routine collection and analysis of a full range of data recorded on the airplane for the purpose of improving safety and operational procedures. Since FOQA is not as data-limited as are traditional aircraft performance monitoring programs, FOQA warrants study as a performance monitoring tool. The current study explores the use of FOQA in monitoring the important area of fuel consumption.

Purpose of the Study

The purpose of the study was to develop a parsimonious model(s) for fuel consumption using multiple regression analysis to analyze FOQA-derived data, with the objective of being able to identify outliers (specific flights) with respect to fuel consumption. The identification of outliers will enable the air carrier to investigate the cause of excessive fuel consumption and remedy the problem. While other aircraft manufacturer and airline initiatives may also lead to such identification of anomalies, the availability of FOQA data to use for this purpose offers airlines robust new tools for monitoring fuel consumption. For the study, flight performance data from a Boeing 757-200 model aircraft were collected and analyzed.

Flight Operations Quality Assurance

According to Yantiss (2001), the role of quality assurance in the U.S. aviation industry involves assessing the effectiveness of the systems, controls, and work processes established for any function for the purpose of identifying the areas in the operation that may lead to a breakdown. Yantiss observed that quality is the means to achieving all quality parameters, including an organization's safety performance parameters. In the past several years, numerous programs have emerged for the purpose of assuring quality, including safety, in the aviation industry, such as the Aviation Safety Action Program, Air Transport Oversight System, Internal Evaluation Program, Advanced Qualification Program, and Flight Operations Quality Assurance. As indicated by this proliferation of quality and safety programs, quality assurance is evolving and expanding in the airline industry.

In 1995, the U.S. Department of Transportation (DOT) sponsored an aviation safety conference in cooperation with representatives from industry and government. The focus of the conference was the development of additional measures that might be implemented to reverse the trend of an increasing number of accidents in the airline industry. One of the significant conclusions of the conference was that the voluntary implementation of FOQA might be the most promising initiative to reduce the number of accidents. Upon the recommendation of the conference attendees, the Federal Aviation Administration (FAA) sponsored an FOQA demonstration project with the following objectives: to develop hands-on experience with FOQA technology in an U.S. environment, document the cost-benefits of voluntary implementation of FOQA programs, and initiate the development of organizational strategies for FOQA information management and use (Federal Aviation Administration, DOT, 1998). The FAA-funded $5.5 million demonstration project was begun in July 1995.

Essentially, "FOQA is a program for obtaining and analyzing data recorded in flight to improve flight crew performance, air carrier training programs and operating procedures, air traffic control procedures, airport maintenance and design, and aircraft operations and design" (U.S. General Accounting Office, 1997). FOQA is a voluntary program that involves the routine downloading and systematic analysis of aircraft parameters that were recorded during flight. The recording unit, which receives data from the flight data acquisition unit(s), is either a crash-protected device or a quick access recorder (QAR). The QAR is a device that allows convenient access to the recording medium and typically records more data than crash-protected devices. Three types of analysis can be performed on the data: (a) exceedance detection, which is the continuous comparison of recorded operational data with predefined parameters to detect occurrences that exceed those parameters; (b) data compilation, which is used to determine the operation and condition of engines and systems; and (c) diagnostics, research, and incident investigation (Holtom, 2000).

Most air carrier aircraft store FOQA data on an optical storage device and then transfer the data to a ground analysis system where it is processed by expert software. Typically, modern digital aircraft capture and store between 200 and 500 parameters per second (U.S. General Accounting Office, 1997), including gauge readings, switch positions, control wheel deflections, control positions, engine performance, hydraulic and electrical system status, and many others.

According to the FAA, ten U.S. airlines have implemented FOQA programs (Federal Aviation Administration, DOT, 2001). The benefits from these programs are beginning to be documented. Several examples of safety and operational problems for which FOQA provided objective information are cited by the U.S. General Accounting Office (1997).

1. An airline discovered through its FOQA program that the number of exceedances was greater during flight in visual conditions than in instrument conditions. This finding caused the airline's training managers to change the training program to emphasize flight in visual conditions. This is a demonstrable quality and safety benefit that was enabled by the FOQA program.

2. Another airline's FOQA analysis determined that the incidence of descent-rate exceedances was unusually high at one particular runway at a specific airport. The cause was determined to be a poorly designed instrument approach procedure that required flight crews to descend steeply during the final approach segment. When these findings were shared with the FAA, the approach was redesigned to correct the problem.

3. FOQA has provided a number of airlines with objective, quantitative information that can be used to evaluate approach procedures that are unusual with respect to rate of descent or excessive maneuvering at low altitude.

4. Airlines have reported that they have used FOQA information to identify and correct a variety of safety problems through changes or renewed emphasis in standard operating procedures, retraining, and repair of faulty equipment.

The FAA's preliminary estimates of costs versus benefits of FOQA programs are encouraging to advocates of FOQA. In 1991 it was estimated that the annual cost of a FOQA program with 50 aircraft was approximately $760,000 per year. Savings from reduced expenditures for fuel, engine maintenance, and accident costs were estimated at $1.65 million per year, resulting in a net annual savings of $892,000 (U.S. General Accounting Office, 1997).

METHODOLOGY

Statistical Methodologies

Regression analysis is a tool used with proven success in studies dealing with prediction of dependent variables. As such, there are numerous studies in the literature that illustrate the use of regression analysis in the quality field (e.g., Young, 1996), in the field of aviation (e.g., Gibbons & McDonald, 1999; Luxhoj, Williams, & Shyur, 1997), and in fuel consumption analysis (Redsell, Lucas, & Ashford, 1993). Attractive features of regression analysis are its general ease of use, the flexibility of inserting and removing independent variables, and its potential use with existing data. Regression analysis models attempt to describe the extent, direction, and strength of relationships between a single dependent variable and one or more independent variables. The continuous dependent variable represents an expression of events or conditions that researchers desire to explain through existing knowledge of the independent variable(s) (Stammer, 1982).

Several of the variables considered in the analysis were engine specific (e.g., exhaust gas temperature, engine pressure ratio), while most were not directly related to the engines (e.g., flap position, total air temperature, altitude). The presence of engine specific variables necessitated the exploration of two models—one using Engine 1-related variables along with the remaining (non engine-specific) independent variables, and a second model using Engine 2-related variables along with the remaining variables.

Boeing 757-200

The Boeing 757-200 was the aircraft used in the study. The Boeing 757 is a twin-engine, medium- to long-range commercial jetliner that is in widespread use in the air transportation industry. Of the 5,445 Air Transport Association (ATA)-member U.S. air carrier aircraft in service in 2000, 567 (10.4%) are Boeing 757 model aircraft (Air Transport Association, 2000). As of December 2001, Boeing reported total orders of 987 and total deliveries of 965 for the 757-200 model, including domestic and international sales (Commercial, 2001). Basic specifications for the subject aircraft are included in Table 1 (Jackson, 2001).

Table 1. Boeing 757-200 Specifications

Feature	*Specification*
Wingspan	124 feet 10 inches (38.05 meters)
Length	155 feet 3 inches (47.32 meters)
Overall Height	44 feet 6 inches (13.6 meters)
Cruising Speed	Mach 0.80
Range (with 201 passengers)	2,570 (4,759 kilometers)
Passenger Capacity	195 to 231
Maximum Takeoff Weight	220,000 lbs. (99,790 kilograms)
Engines	(2) Pratt & Whitney PW 2037
Engine Thrust (per engine)	36,600 lbs. (162.8 kilonewtons)
Standard Fuel Capacity	11,276 gallons (42,684 liters)

Note. These specifications are generally consistent for the Boeing 757-200 as configured for the air carrier that provided the database.

Data Used for the Study

The data used for the study were provided by a major air carrier. The database consists of 3,480 routine passenger-carrying flights on six Boeing 757-200 aircraft that occurred during a six-month period from October 1999 to March 2000. AVSCAN analysis software was used. In accordance with FOQA procedures, the data were de-identified as they were processed by the FOQA analysis software; that is, information that could connect a specific flight crew with a particular flight was removed from the data.

Data Point Selection

Although data is captured and stored each second during the operation of the aircraft, it is impractical to analyze what is essentially a continuous stream of information. Therefore, a single data point was identified for each flight and used for the analysis. Since the purpose of the study was to develop a regression equation for the purpose of identifying outliers with respect to fuel consumption, the cruise phase of flight was determined to be the most appropriate focus for this investigation. The cruise phase is important for several reasons: (a) on a typical flight, a large proportion of the fuel is consumed during the cruise segment; and (b) more stable performance information can be obtained during cruise compared to other phases of flight.

Upon investigation, it was discovered that Honeywell had established conditions to be used for determining the best point (i.e., stable conditions) during cruise flight to capture data for airplane and engine performance analysis purposes (Honeywell International, 1997). Further, the program written by Honeywell is designed to capture and use only one data point per flight. The *stability logic* used by Honeywell was replicated as closely as possible in the FOQA system for data point selection purposes. Several steps were accomplished to create such a point within AVSCAN.

First, 46 computed parameters necessary for the logic were created. The creation of these parameters enabled the collection of information such as the test period; stability basic conditions; the highest level flight altitude attained during the flight; the measurement period; and the minimum, maximum and stability values for recorded parameters such as altitude, engine performance, airspeed, altitude, and others, during the test period.

Second, a new AVSCAN event, *stableperiod*, was created to enable a data collection point during stable engine cruise. It is possible for this event to occur only one time during each flight. The data used for the study were the data collected at the time of the *stableperiod* event.

Third, a new template file was created that included the new computed parameters and the new event. The process of creating a template was repeated several times and tested on a small portion of the database for validity. Thirteen templates were designed and rejected due to problems discovered during the validation process.

Selection of Parameters

There are many factors that influence fuel consumption in a transport category aircraft, such as thrust setting, altitude, temperature, weight of the aircraft, and other environmental and flight conditions (Padilla, 1996). The method used to identify the factors that would be included in the regression analysis was to refer to technical information produced by The Boeing Company. Specifically, Boeing produces an Airplane Performance Monitoring (APM) program to assist operators in performance monitoring of Boeing aircraft. The results of the program are used for tracking long-term airframe and engine performance trends. The APM program provides for manually recording cruise performance data using a Manual Standard Interface Record Format (MSIRF), as well as an automated method using a Digital Standard Interface Record Format (DSIRF). MSIRF considers only 7 primary parameters (mach, exhaust pressure ratio, fuel flow, total air temperature, altitude, calibrated airspeed, and gross weight), while DSIRF captures approximately 48 performance related parameters within 181 total field names (The Boeing Company: Flight Operations Engineering, 1999). In the documentation, Boeing states that by analyzing cruise performance data, the APM program will identify airplanes for which performance has deviated from the applicable baseline. Thus, it can be inferred that abnormal or inadequate performance would be reflected in these 48 performance parameters using DSIRF, and perhaps especially in the 7 parameters using MSIRF. Further, it follows that if an abnormal performance condition exists, this will be reflected in the fuel flow rate(s) of the engine(s), as well as in other parameters. For example, if a landing gear door is misrigged and introduces increased parasitic drag to the airplane in cruise flight, the performance of the airplane will deteriorate. This will result in the need for additional engine thrust, and consequently fuel flow, to travel at the same speed; if additional thrust and fuel are not provided, the airspeed will decrease. Since fuel flow is one of the parameters recorded in both MSIRF and DSIRF formats, anomalous airplane performance that is reflected in other performance parameters should be detectable in the fuel flow variable. It is the examination of these variables and their relationship to fuel flow that was the object of this investigation.

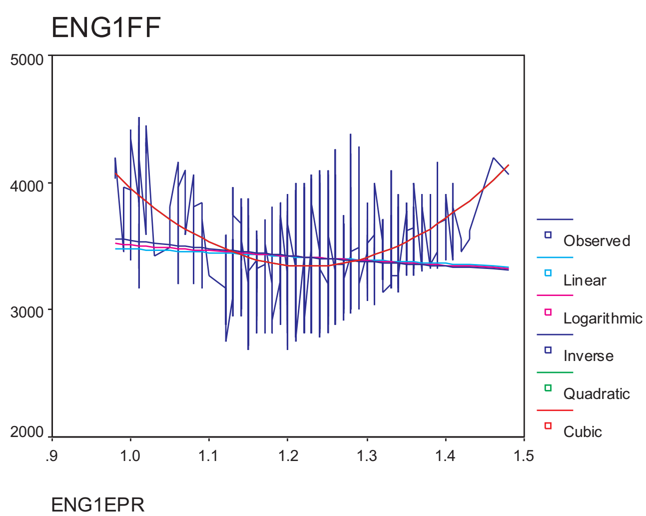
All 7 parameters listed in MSIRF were available in the FOQA database. Of the 48 parameters listed in DSIRF, many were not relevant to the study, many were essentially duplicates (e.g., calibrated airspeed left and calibrated airspeed right), and several of the parameters were not captured by the FOQA system. Hence, the number of parameters available for the study for each engine was 20 (excluding fuel flow which was the predicted variable in the study). These parameters are listed in Table 2.

Table 2. FOQA Parameters

FOQA Parameter Name	*Definition*
Mach	Mach
CAS	Calibrated airspeed
TAT	Total air temperature
ALT	Altitude
GWeight	Gross weight
ENG1epr, ENG2epr	Engine 1 and 2exhaust pressure ratio
ENG1n1, ENG2n1	Engine 1 and 2 n1
ENG1n2, ENG2n2	Engine 1 and 2 n2
ENG1egt, ENG2egt	Engine 1 and 2 exhaust gas temperature
AOA	Angle of attack
ATTroll	Angle of bank
ATTpitch	Pitch attitude
SFCstab	Stabilizer position
CTLspdbrk	Speedbrake control position
SFCalrn	Left aileron position
SFCalrnrt	Right aileron position
SFCrudder	Rudder position
SFCelev	Left elevator position
SFCelevrt	Right elevator position
SFCflap	Flap position

RESULTS

Following the elimination of erroneous data, the flap position parameter for all the remaining flights was zero. Thus, the flap position parameter was removed from further consideration, and the total number of parameters used in the study was reduced to 19. Given that the pool of predictor variables was not excessively large, a standard regression approach was used following reasoned elimination of curvilinear, multicollinear, and non-significant predictors. The predictors with curvilinear indications included total air temperature, exhaust pressure ratio, ENG1n1, ENG2n1, angle of attack, pitch altitude, and stabilizer position. For example, Figure 1 illustrates a clear curvature in the exhaust pressure ratio for Engine 1 data, and indicates that a quadratic function ($R^2 = .201$) provides a better fit to the data than does a linear function ($R^2 = .005$).



Independent: ENG1epr

Dependent	Mth	R^2	d.f.	F	Sigf	b0	b1	b2
ENG1FF	LIN	.005	1846	10.20	.001	3763.80	-286.41	
ENG1FF	LOG	.010	1846	18.84	.000	3508.14	-467.28	
ENG1FF	INV	.016	1846	30.36	.000	2838.07	704.470	
ENG1FF	QUA	.201	1845	232.22	.000	21603.2	-29832	12183.7
9 ENG1FF	CUB	.201	1845	232.22	.000	21603.2	-29832	12183.7

Notes:
9 Tolerance limits reached; some dependent variables were not entered.

Figure 1. Curvature of ENG1epr Data

Since high levels of interactions among predictors can lead to spuriously high R values, particular attention was paid to collinearity analysis. Univariate correlations showed that there was severe collinearity between some of the predictors (e.g., r CAS and ENG1epr = -0.75; r CAS and ATTpitch = 0.76; r ENG1epr and ATTpitch = 0.73). The variables correlating with other predictors higher than 0.70 included calibrated airspeed, altitude, exhaust pressure ratio ENG1n1, ENG2n1, ENG1n2, ENG2n2, exhaust gas temperature for each engine, angle of attack, and pitch altitude. Several transformations were performed on these variables, such as square root, log, and inverse transformations. These transformations had only a marginal effect on the interactions.

Also of concern was the skewness of several of the variables. Predictors mach, altitude, angle of bank, and stabilizer position all had skewness factors of over 2.5. Given the ranges and variances of these variables, transformations did little to correct the problem of skewness and, in some cases, adversely affected the data. For example, mach (MACH) had a skewness value of –3.996. The skewness factor of MACH square root was –4.205, MACH inverse was 4.881, MACH square was –3.601, and MACH log was –4.422.

Altitude (ALT) had a skewness factor of –2.876. The quadratic function of ALT [3244.39 + .0778 (ALT) – .000002 $(\text{ALT})^2$], improved the skewness factor to 1.372 (and fit the data slightly better than the linear function –.357 R^2 linear; .385 R^2 quadratic). However, the quadratic function did little to improve multicollinearity problems (i.e., r ALT quadratic and CAS = .958; r ALT quadratic and ENG1epr = –.775; r ALT quadratic and ENG2epr = –.774).

Variables that were both curvilinear and exhibited multicollinearity were eliminated from further consideration. These included exhaust pressure ratio for each engine, ENG1n1, ENG2n1, angle of attack, and pitch attitude. Predictor stabilizer position, which was both curvilinear and highly skewed, was eliminated. Predictor altitude, which was both multicollinear and highly skewed, was eliminated. Finally, predictors mach and angle of bank, which were highly skewed and did not respond to transformations, were eliminated. The remaining variables were regressed against the dependent variable(s) [i.e., fuel flow for each engine (ENG1ff and ENG2ff)].

Engine 1 Model Building

The remaining variables pertaining to Engine 1 (calibrated airspeed, gross weight, ENG1n2, exhaust gas temperature, speedbrake control position, left and right aileron positions, rudder position, and left and right elevator positions) were entered into a standard, non-stepwise regression. Variables that did not predict well ($p > 0.05$), had extremely small effect sizes (|beta| < 0.10), or low tolerance/high Variance Inflation Factor (VIF) values (VIF > 10.0) were removed and a new regression computed. The non-predictive variables included speedbrake control position, left and right aileron positions, and left and right elevator position. The variables with small effect sizes included speedbrake control position, left and right aileron position, rudder position, and left and right elevator positions. No variable had VIF values significant to warrant removal of the variable.

Four predictors remained for the Engine 1 model: calibrated airspeed, gross weight, ENG1n2, and exhaust gas temperature. These predictors produced a model with an R^2 of .888. Since the objective was to obtain the most parsimonious model possible while retaining good predictive capabilities, the regression was re-performed with each variable deleted in turn. The removal of either calibrated airspeed or gross weight seriously degraded the model; the R^2 of the model excluding calibrated airspeed was .470, and the model excluding gross weight had an R^2 of .732. However, the removal of either ENG1n2 or exhaust gas temperature did not significantly affect the model. The model that included the three predictors calibrated airspeed, gross weight, and ENG1n2 had an R^2 of .850. The model with only calibrated airspeed, gross weight, and exhaust gas temperature had an R^2 of .879. Either of these models compared favorably to the four variable model R^2 of .888; thus, it was determined that a three-predictor model was the best compromise of performance and model size. Since a common model for both engines was desired, it was decided to examine Engine 2 data before selecting the third predictor (i.e., either ENG1n2 or exhaust gas temperature) for the model.

Engine 2 Model Building

Steps consistent with those followed for fitting the Engine 1 model were followed for Engine 2. Predictors calibrated airspeed, gross weight, ENG2n2, exhaust gas temperature, speedbrake control position, left and right aileron positions, rudder position, and left and right elevator positions were entered into a standard regression. Variables that did not predict well, had extremely small effect sizes, or low tolerance/high VIF values were removed and a new regression computed. The non-predictive variable was left aileron position. The variables with small effect sizes included speedbrake control position, left and right aileron positions, rudder position, and left and right elevator positions. No variables had significant VIF values.

Four predictors remained for the Engine 2 model: calibrated airspeed, gross weight, ENG2n2, and exhaust gas temperature. These predictors produced a model with an R^2 of .935. As was the case with Engine 1, the removal of either calibrated airspeed or gross weight seriously degraded the model. The removal of ENG2n2 or exhaust gas temperature adversely affected this model more than the removal of the corresponding variables in the Engine 1 model, but the degradation was not serious. The model that included calibrated airspeed, gross weight and ENG2n2 had an R^2 of .863, and the model with calibrated airspeed, gross weight and exhaust gas temperature had an R^2 of .852.

There is a very slight preference for inclusion of the ENG[1 or 2]n2 variable rather than using exhaust gas temperature as the third predictor in the models. The exhaust gas temperature variable was slightly preferred over the ENG[1 or 2]n2 variable in the Engine 1 model (0.879 R^2 versus 0.850 R^2, respectively), while the Engine 2 model performed slightly better with the ENG[1 or 2]n2 variable (0.863 R^2 versus 0.852 R^2 for the exhaust gas temperature variable). Nevertheless, the ENG[1 or 2]n2 predictor seemed to perform slightly better overall.

Engine 1 Regression

The parameters of calibrated airspeed, gross weight and ENG1n2 predicted the fuel flow of Engine 1. The initial regression equation had an R^2 of .850, and was expressed as: – 9213.354 + 11.008 CAS + 0.008542 GWeight + 94.257 ENG1n2. This model worked for all but four observations in which the standardized residual exceeded 3.0. Removing these outliers redefined the equation only slightly. The final equation is: – 9170.077 + 10.943 CAS + 0.008657 GWeight + 93.701 ENG1n2, with an R^2 of .853. The equation is significant, the tolerances are very high indicating little or no multicollinearity among predictors and the betas are large and uniform.

Engine 2 Regression

The fuel flow of Engine 2 was predicted by calibrated airspeed, gross weight and ENG2n2. The initial regression equation had an R^2 of .863, and was expressed as: – 9388.823 + 10.894 CAS + 0.008622 GWeight + 96.166 ENG2n2. This model worked for all but twelve observations in which the standardized residual exceeded 3.0. After removing these observations, the final equation is: – 9347.178 + 10.835 CAS + 0.008726 GWeight + 95.616 ENG2n2, with an R^2 of .872. The equation is significant, the tolerances are very high indicating little or no multicollinearity among predictors and the betas are large and uniform.

Model Adequacy

The models formulated were checked for adequacy through the examination of residuals and testing for a linear fit of the predictors to the dependent variable. Based on an analysis of residuals and tests for linear fit, there does not appear to be any correlation between random errors, the variables appear to be linearly related, and there appears to be reasonably consistent variances in the data for both models.

Model Validation

The most desirable method of validating a regression model with respect to its prediction performance is to use new data and directly compare the model predictions against them (e.g., Montgomery, Peck, & Vining, 2001). FOQA data on 179 additional flights on Boeing 757-200 aircraft were obtained from the same major air carrier that provided the initial database. Fifty of these flights were selected at random using a random number generator utility, and these fifty data files were processed using the template file created for the study. Table 3 contains the results of the analysis.

Table 3. Model Validation Data for Engine 1 and Engine 2

Factor	*Engine 1*	*Engine 2*
No. of Observations	50	50
Avg. Fuel Consumption—Observed (Pounds Per Hour)	3278	3249
Avg. Fuel Consumption—Predicted (Pounds Per Hour)	3278	3214
Avg. Prediction Error (Pounds Per Hour)	0	35
Sum of Squared Prediction Error	379567	364818
Avg. Squared Prediction Error	7591	7296
Sum of Actual Minus Avg. Fuel Consumption	2920296	2920296
Percentage of Variability Explained by Model	87.0	87.5

The average prediction error is zero pounds per hour of fuel consumption for Engine 1 data and 35 pounds per hour for Engine 2 data. These errors are at or nearly zero, so it may be concluded that the models seem to produce reasonably unbiased predictions. For Engine 1 data, a comparison of the residual mean square from the fitted model, $MS_{Res} = 11640$, to the average squared prediction error, 7591, indicates that the regression model predicted new data slightly better than it fit the existing data. For Engine 2 data, the residual mean square is 9917, and the average squared prediction error is 7296. The performance of both models suggests that they are likely to be successful as predictors.

It is also useful to compare R^2 from the regression models to the percentage of variability in the new data explained by the model. In the case of the Engine 1 model, R^2 is 86.3% and the variability explained by the model is 87.0%. The Engine 2 model indicated an R^2 of 87.2% and the variability explained is 87.5%. As with the analysis of residual mean squares, the prediction of new observations by both models was approximately equivalent to the fit of the original data.

Comparison of Actual and Projected Fuel Flow

It was also hypothesized that the actual total fuel flow (engines 1 and 2 combined) was greater than that projected by the manufacturer. Based on statistics literature for selection of sample sizes for hypothesis testing, a sample size of 66 flights was determined to be appropriate given a database of 1,848 flights containing the *stableperiod* event, a 10% maximum acceptable margin of error, and a 90% confidence level. A random number generator utility was used to randomly select these 66 flights from the database. The projected total fuel flow for each of these flights was determined by consulting the following charts and graphs in the Boeing 757 Performance Engineers Manual: Generalized Thrust; Fuel Flow/Engine Standard Day; Standard Atmosphere; and Fuel Flow Factor to Be Applied for Non Standard Day Temperatures (The Boeing Commercial Airplane Company, 1996). For these 66 flights, the mean actual total fuel flow was 6,813 pounds per hour and the mean projected total fuel flow was 6,429 pounds per hour; thus, the mean difference was 384 pounds per hour fuel flow. At the 99% confidence level, the value of the test statistic, t, is 13.16, and the p-value is 0.000. The 99% confidence interval of the difference has a lower limit of 306 and an upper limit of 461; thus, the limit does not contain the value zero. Based on the p-value and the confidence interval of the difference, the null hypothesis was rejected and it was concluded that the actual total fuel flow was significantly greater than that projected by the manufacturer.

CONCLUSIONS

Multiple linear regression analysis was accepted as an appropriate technique for modeling fuel consumption on the Boeing 757 transport category aircraft using FOQA data. Using regression methods consistent with those used in other studies (e.g., Irish, Barrett, Malina, & Charbeneau, 1998; Young, 1996), models were developed that predicted fuel flow on new FOQA data to a degree comparable to the original data. Parameters specified by Boeing to monitor airplane performance were useful in identifying the FOQA parameters to be used in the modeling process. Criteria used by Honeywell to establish stable cruise flight for data selection purposes appeared to work well for the study, though the percentage of flights containing the *stableperiod* event was only 53%.

It can be concluded that a parsimonious model can be developed for predicting fuel flow using FOQA data. The model(s) developed can be incorporated by the airline into regular reporting routines to enhance its quality assurance program. This reporting and analysis will enable the investigation of abnormal fuel consumption for the source of the problem and the remedy, and may ultimately result in a financial savings to the airline.

Analysis also revealed that actual fuel flow was significantly greater than the fuel flow projected by the manufacturer. This conclusion adds additional support to existing literature (e.g., Lukins, 1984) that suggests that flight performance deteriorates as airplanes age and accumulate flight time. Airframe and engine time information on the subject airplanes was not made available to the researcher for this study, so it was not possible to compare the degree of degradation with the age of the aircraft. Nevertheless, the analysis performed has implications to air carriers for fuel planning based strictly on manufacturer's data, and demonstrates that further study is needed to quantify the degradation.

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