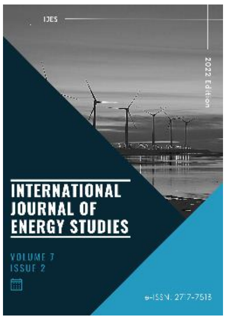
INTERNATIONAL JOURNAL OF ENERGY STUDIES

e-ISSN: 2717-7513 (ONLINE); homepage: https://dergipark.org.tr/en/pub/ijes



Research Article

Int J Energy Studies 2022; 7(2): 179-194

DOI: 10.58559/ijes.1207971

Received: 21 Nov 2022
Revised: 29 Nov 2022
Accepted: 30 Nov 2022

Fuel estimation of commercial aircraft for the climb-out phase using gaussian process regression model

Vehbi Emrah Atasoy [a*],

[a] *Department of Aircraft Maintenance and Repair, Erzincan Binali Yıldırım University, Erzincan, Turkey,*

ORCID Number: 0000-0002-6781-9278

*(*Corresponding Author: veatasoy@erzincan.edu.tr)*

Highlights

- The actual flight data used are obtained from the FDR data sets.
- The Gaussian Process Regression model indicates successful performance to predict fuel consumption during the climb-out phase.
- Different statistical tests are applied to evaluate the performance of the regression model.

You can cite this article as: Atasoy VE. Fuel estimation of commercial aircraft for the climb-out phase using gaussian process regression model. Int J Energy Studies 2022; 7(2): 179-194.

ABSTRACT

In this study, Gaussian Process Regression (GPR) is utilised to accurately estimate fuel consumption. For this purpose, ten randomly determined flights performed by Boeing B737-800 twin-engine medium-haul narrow-bodied commercial aircraft are selected. In this context, actual flight data obtained from the Flight Data Recorder (FDR) is used to estimate fuel consumption during the climb-out phase. Different statistical tests, namely Root Mean Square Error (RMSE), coefficient of determination (R^2), and Mean Absolute Error (MAE), are applied to evaluate the performance of the GPR in this paper. RMSE, R^2, and MAE values for GPR is calculated to be 209.41, 0.99, and 111.38, respectively. As can be seen from the results of all statistical tests, the GPR model indicates successful performance.

Keywords: Climb-out phase, fuel consumption, gaussian process regression

1. INTRODUCTION

While air transportation makes significant contributions to social and economic fields, the increase in fuel prices and environmental problems negatively affect the aviation industry. For these reasons, fuel consumption from aircraft are the main research subjects in many studies. Fuel consumption is the most crucial performance indicator in aviation due to both economic and environmental issues. To give an example, the cost of fuel is one of the biggest direct operating expenses for airlines. Due to these reasons, airlines make considerable efforts to decrease fuel consumption [1]. Moreover, aircraft emissions from fule consumption can have a variety of negative effects on air quality, climate change, and human health [2-4]. Because of the issues mentioned, determining the accurate and precise fuel consumption of an aircraft becomes crucial to minimize negative environmental effects, and also to offer better efficient aircraft operations. Furthermore different approach are being tested and researched to reduce the economic and environmental reasons through each phase of flight [5-7].

Several researchers conduct in-depth research on estimating or calculating the fuel flow of aircraft for various flight phases [8-12]. Luo et al. [13] construct fuel flow regression model based on Recurrent Neural Networks model. They utilize the actual quick access recorder (QAR) dataset while creating the model. According to the experimental findings, the model has a high level of accuracy in cruise phase. Baumann and Klingauf [14] employe Machine Learning Algorithms, which are Neural Networks and Decision Trees, to find the fuel consumption of the aircraft at different phases of flight. When these two models are compared, the Neural Networks model gives better results than the Decision Trees model. Baklacioglu [15] generates a neural network model using a genetic algorithm to estimate the fuel flow rate for different flight phases. It takes altitude and speed values into consideration when creating models.

A significant portion of the fuel is consumed during the climb phase of the flight due to the high thrust applied, especially on short-haul flights. Because of these reasons, one of the flight phases where the aircraft is heaviest is the climb phase.As a result of this condition, increasing fuel use results in both an increase in emissions and economic loss [16]. When the studies for the climb-out phase are examined, it is seen that many studies on the climb-out phase focus on emission values [17]. Chati and Balakrishnan [18] develop the GPR model to predict fuel consumption during the climb-out and approach phases. The authors state that this model provides more accurate fuel consumption and emission values around the airports. Liati et al. [19] examine the soot characteristics of the CFM56-7B26 turbofan engine with different tests, including X-ray micro-spectroscopy and transmission electron microscopy. For these tests, Jet A-1 and a biofuel fuels are used at ground idle and climb-out engine thrust values. The findings show that for all these types of fuel, soot reaction declines from ground idle to climb-out conditions.

In this paper, a regression model is offered to predict fuel consumption during climb-out phase. The GPR model is selected to accurately estimate fuel consumption. In the GPR model, altitude (ALT), gross weight (GW), calibrated airspeed (CAS), total air temperature (TAT), flight path angle (FPA), and wind speed (WS) are independent variables and fuel consumption in the climb-out phase (FFCO) is dependent variable. Thanks to the regression model created using these selected model variables, precise fuel consumption estimation can be made around the airports. Making accurate fuel consumption planning also causes a decrease in emission values. In addition, this paper can provide more correct flight trajectory planning and estimation in air traffic management.

2. MATERIALS AND METHODOLOGY

2.1. Materials

This study presents ten international and domestic flights performed by Boeing B737-800 twin-engined, medium-haul, narrow-bodied commercial aircraft. The departure airport is the same for all the flights (Istanbul Ataturk International Airport (LTBA)), while the destination airports are ten different international and national airports (denoted as F1 through F10). The flight between these city pairs is shown in Table 1. The same type of aircraft (but not one with the same tail number) carries out these flights. In this paper, it is important to point out that the CFM56-7B26, a high-bypass turbofan engine with a bypass ratio of 5.5, an overall pressure ratio of 32, is used as the turbofan engine.

When it comes to fuel consumption during a flight, there are many factors that can have an effect on it. As observed in many studies, the fuel flow rate during a cruise flight is primarily influenced by the GW, ALT, and CAS. Also FPA influences the fuel consumption during descent and climb phases. In addition to these flight phases, the emissions resulting from the fuels burned during the climb-out and approach phases cause significant environmental impacts at the airports. Climb-out phase, which forms part of climb phase, is especially used in emission calculations and is included in the landing and take-off cycle (LTO cycle). The LTO consists of different operation modes. The

LTO cycle begins when the aircraft lands below 3000 feet. Finally, the LTO cycle ends with the climb-out phase up to 3000 ft above field elevation [20]. In this study, the climb-out phase starts at the end of the take-off phase and ends when the aircraft reaches 3000 feet. Within the scope of this study, the climb-out phase is examined in detail and the parameters affecting fuel consumption in the phase are determined. Therefore, actual FDR data sets are used for a more accurate analysis of the climb-out phase. Parameters affecting fuel consumption in the climb-out phase, which are ALT, GW, CAS, TAT, FPA, and WS, are taken into consideration to estimate fuel flow during climb-out. These performance parameter’s types, physical meanings, symbols, and units are identified in Table 2. Fuel consumption in the climb-out phase is denoted as FFCO.

Table 1. Airports information

Departure Airport	Destination Airports	ID
Istanbul Ataturk International Airport (LTBA)	Amsterdam Airport Schiphol (EHAM)	F1
	Tbilisi International Airport (UGTB)	F2
	Valencia Airport (LEVC)	F3
	Adnan Menderes Airport (LTBJ)	F4
	Koca Seyit Airport (LFTD)	F5
	Manas International Airport (UAFM)	F6
	Tenerife South Airport (GCTS)	F7
	Cardak Airport (LTAY)	F8
	Esenboğa Airport (LTAC)	F9
	Dalaman Airport (LTBS)	F10

Table 2. Flight performance parameters' types, physical meanings, symbols, and units

Physical meaning	Symbol	Unit
Flight time	TIME	s
Gross weight	GW	lbs
Fuel flow of engine-1	FF1	lb/h
Fuel flow of engine-2	FF2	lb/h
Altitude	ALT	feet
Flight path angle	FPA	°
Total air temperature	TAT	˚C
Calibrated airspeed	CAS	knot
Wind speed	WS	knot

Figures 1-6 depict the change of performance parameters versus time during the climb-out phases for all flights. The ALT values for each flight are denoted as ALT-F1 through ALT-F10. For example, the ALT values of the first flight are shown as ALT-F1 in this study. Other flight performance parameters are also presented in the same way. When the altitude values are examined, it is seen that the altitudes values increases roughly linearly in Figure 1. The change in the GW values of the aircraft depends on the fuel consumption. As seen in Figure 2, the minimum and maximum values of the GW-F1, GW-F2, GW-F3, GW-F4, GW-F5, GW-F6, GW-F7, GW-F8, GW-F9, and GW-F10 are found to be 155767 and 156155 lbs; 145333 and 145755 lbs; 153089 and 153434 lbs; 133401 and 133755 lbs; 137163 and 137515 lbs; 169339 and 169755 lbs; 130229 and 130556 lbs; 134089 and 134475 lbs; 129817 and 130155 lbs; 137370 and 137756 lbs, respectively. When it comes to the CAS values in Figure 3, similar fluctuations are observed in CAS values. The mean values of the CAS-F1, CAS-F2, CAS-F3, CAS-F4, CAS-F5, CAS-F6, CAS-F7, CAS-F8, CAS-F9, and CAS-F10 are found to be 186, 190, 202, 187, 189, 206, 184, 192, 186, and 185 knots, respectively. There are significant differences between the TAT values when considering all flights. When a single flight is examined, the TAT values do not show any significant change, except for the TAT-F2 values in Figure 4. The TAT values in all flights range from a low of 1 °C (TAT-F3) to a high of 22 °C (TAT-F1). The FPA values are one of the parameters that has the significant impacts on an aircraft's fuel consumption. The first few seconds following the end of the take-off phase see naturally higher the FPA values. Figure 5 indicate the variation of the FPA values versus times during the climb-out phase in the study. It is observed that mean values of the FPA-F1, FPA-F2, FPA-F3, FPA-F4, FPA-F5, FPA-F6, FPA-F7, FPA-F8, FPA-F9, and FPA-F10 are 6, 5, 7, 6, 7, 5, 7, 6, 7, and 5°, respectively. The WS values, which are one of the atmospheric parameters, fluctuate between a minimum of 3 knots and a maximum of 49 knots among all flights in Figure 6.

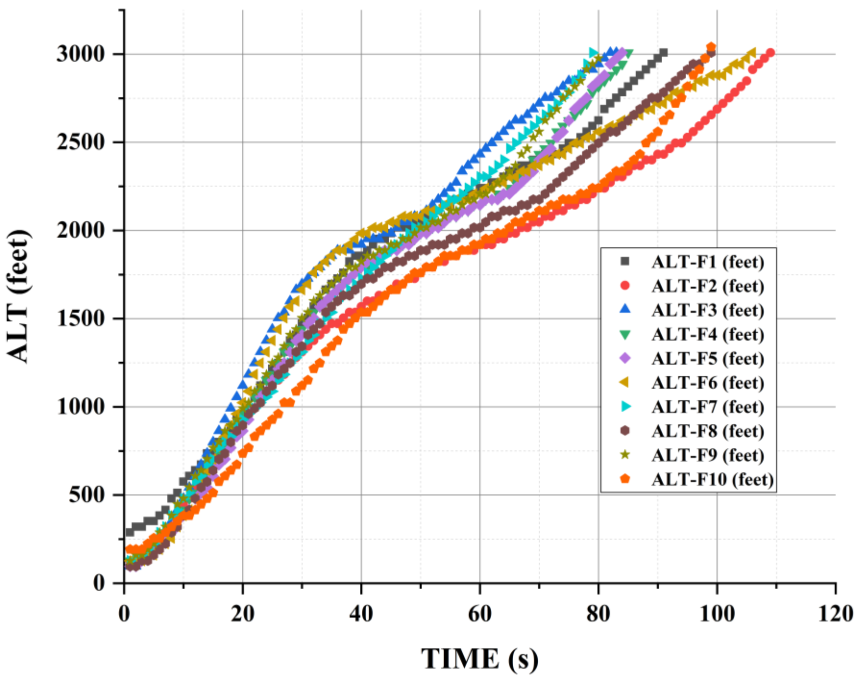


Figure 1. Variation of ALT values during climb-out phases

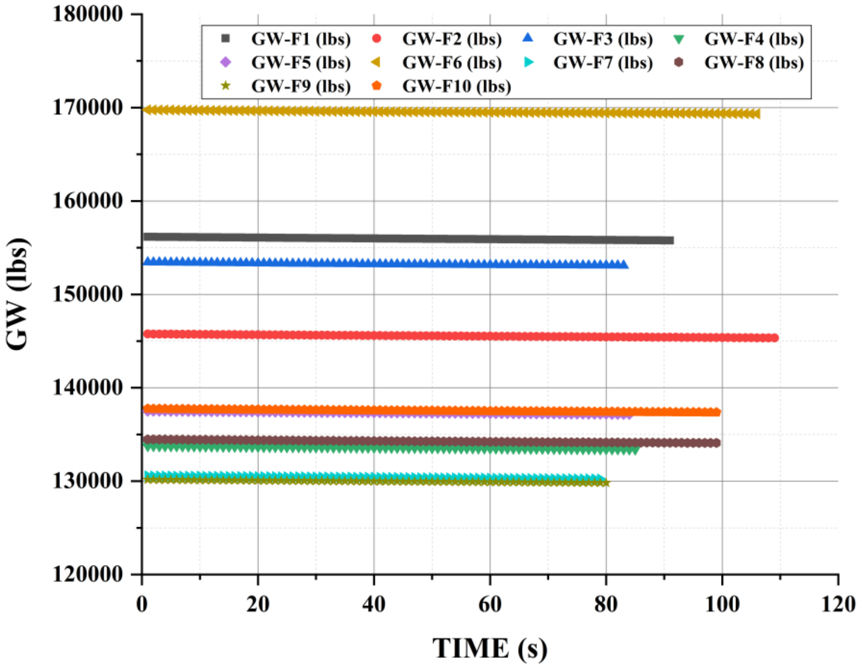


Figure 2. Variation of GW values during climb-out phases

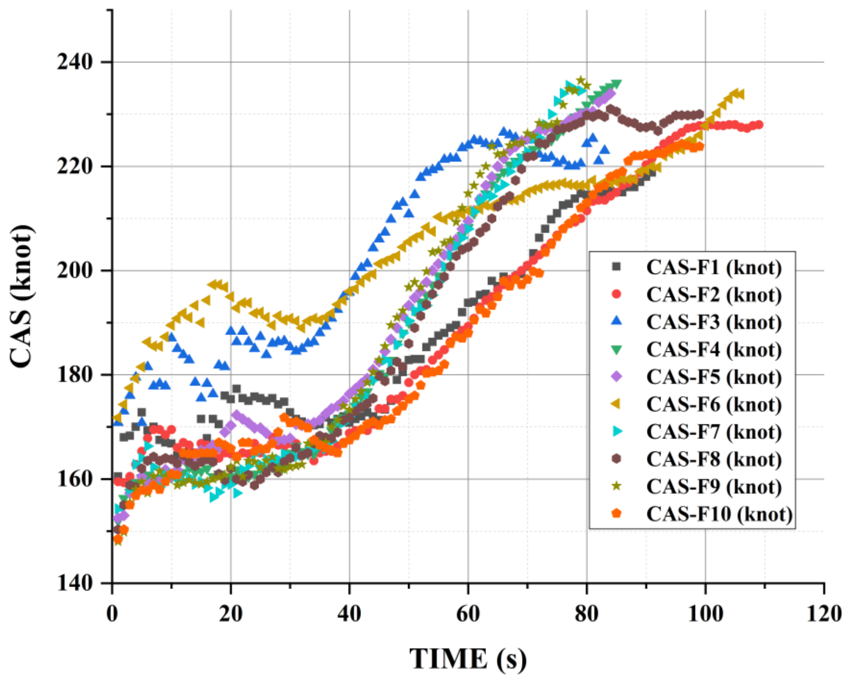


Figure 3. Variation of CAS values during climb-out phases

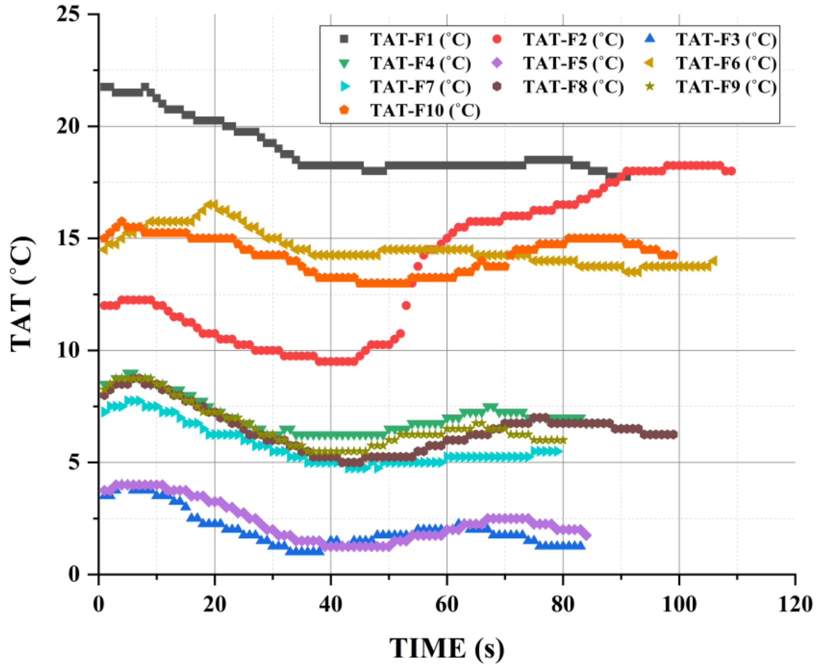


Figure 4. Variation of TAT values during climb-out phases

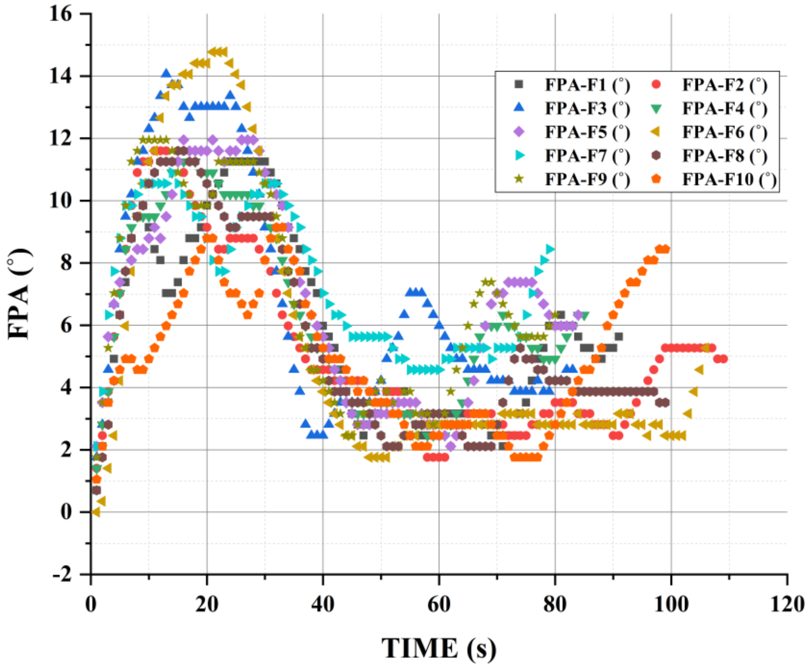


Figure 5. Variation of FPA values during climb-out phases

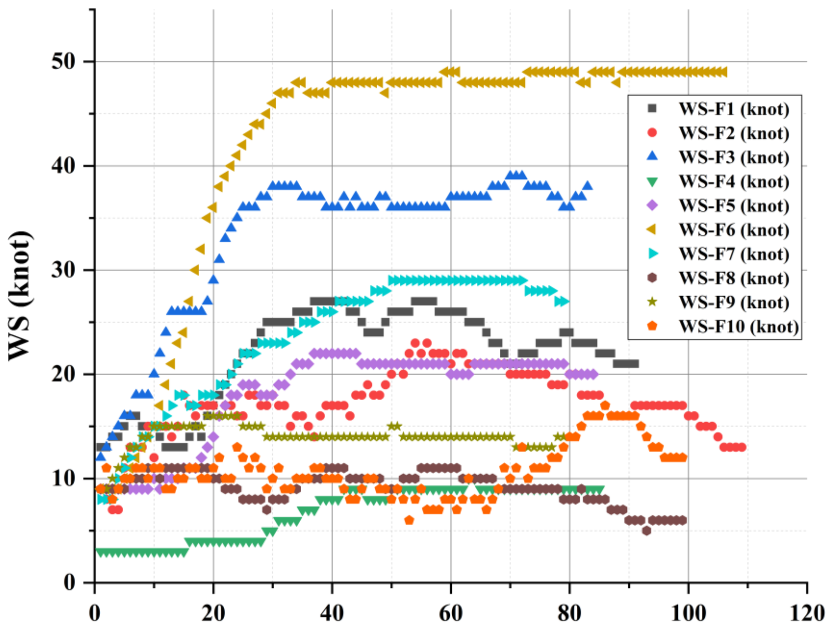


Figure 6. Variation of WS values during climb-out phases

2.2. Methodology

A powerful tool that can be thought of as a general regression model, GPR is used across a wide range of disciplines. In this paper, a Gaussian Process Regression (GPR) model is used for predicting the FFCO values. It is necessary to describe a regression model before explaining the Gaussian Process Regression. In regression, i^{th} observation's (y_i) output is considered to be a function of the variables (x_i) input, plus some noise ($\mathcal{E}_i$),

$$y_i = f(x_i) + \mathcal{E}_i \tag{1}$$

The input parameters and their corresponding given outputs are used to predict the basic regression function $f(x_i)$. After the regression model is created, a new output value is found that corresponds to a new input value. For this reason, regression models are used in many areas[21-23]. For the purposes of GPR, it is assumed that the regression function $f(x)$ is derived from a Gaussian Process (GP) with a zero mean function and the covariance/kernel function $k(x, x')$,

$$f(x) \sim GP\big(0, k(x, x')\big) \tag{2}$$

It is also considered that the noise $\mathcal{E}_i$ has a Gaussian distribution. The function $k(x, x')$ is known as a kernel function. The covariance between the regression model values $f(x)$ and $f(x')$ at the two inputs x and x' is represented by this function.

3. STATISTICAL PERFORMANCE METRICS

The predicted values should be compared to the actual flight data in order to assess the performance of the GPR model. For the assessment, this paper applies three different statistical performance metrics[24-25]. Mean Absolute Error (MAE) indicator is generally employed to show the actual situations of the estimated errors.

$$MAE = \frac{1}{S}\sum_{i=1}^{S} |z_i - \hat{z}_i| \tag{3}$$

where **S** represents the total number of estimations. The predicted values from the GPR model are denoted by $\boldsymbol{\hat{z}_i}$, and $\boldsymbol{z_i}$ stands for the actual values. The following indicators can also be described using these terms.

Another widely used indicator to show the difference between estimated and actual values is the Root Mean Square Error (RMSE).

$$RMSE = \sqrt{\frac{1}{S}\sum_{i=1}^{S}(z_i - \hat{z}_i)^2} \tag{4}$$

Last important indicator used to predict actual values is Coefficient of Determination (R^2).

$$R^2 = 1 - \frac{\sum_{i=1}^{S}(z_i - \hat{z}_i)^2}{\sum_{i=1}^{S}(z_i - \bar{z})^2} \tag{5}$$

where $\bar{\boldsymbol{z}}$ is the mean of the actual values.

4. RESULTS AND DISCUSSION

The Boeing 737-800, a twin-engine, narrow body commercial airliner that is extensively used in the aviation sector, is chosen for this research. The actual flight data used in the study are obtained from the FDR data set. The GPR model is used to estimate the fuel consumption, which is only taken into account during the climb-out phase. In order to make an effective analysis and comparison, GW, ALT, FF, TAT, CAS, FPA and WS parameters are selected. As seen in Figure 7, the values of FFCO are examined, and it is found that the minimum and maximum values of the of FFCO-F1, FFCO-F2, FFCO-F3, FFCO-F4, FFCO-F5, FFCO-F6, FFCO-F7, FFCO-F8, FFCO-F9, and FFCO-F10 are 14688 and 16672 lb/h; 13120 and 15904 lb/h; 7680 and 20416 lb/h; 14336 and 16800 lb/h; 14528 and 16512 lb/h; 10688 and 18176 lb/h; 13440 and 16224 lb/h; 9984 and 16800lb/h; 14464 and16960 lb/h; 13248 and 15616 lb/h, respectively. The flight with the highest mean FFCO value is F1 flight. The mean value for FFCO-F1 is calculated to be 15472 lb/h. For all flights, variation values of FFCO versus time are given in Figure 8. When the Figure 8 is examined, it is seen that the fuel consumption approximately is high in the first 30 seconds, and this fuel consumption decreases rapidly in the other time intervals. The change in FFCO values of flights F3, F6, and F8 is greater than that of other flights. The main reason for these differences is the change in the throttle resolver angle. The flight with the highest mean FFCO value is F1 flight. The mean value for FFCO-F1 is calculated to be 15472 lb/h.

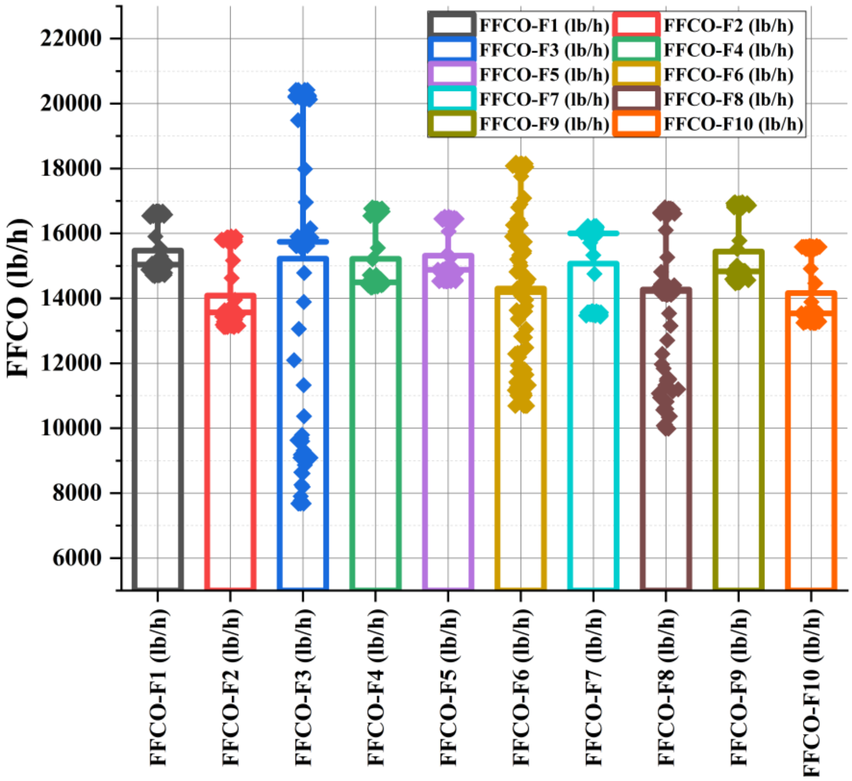


Figure 7. The variation of the actual FFCO values during climb-out phases

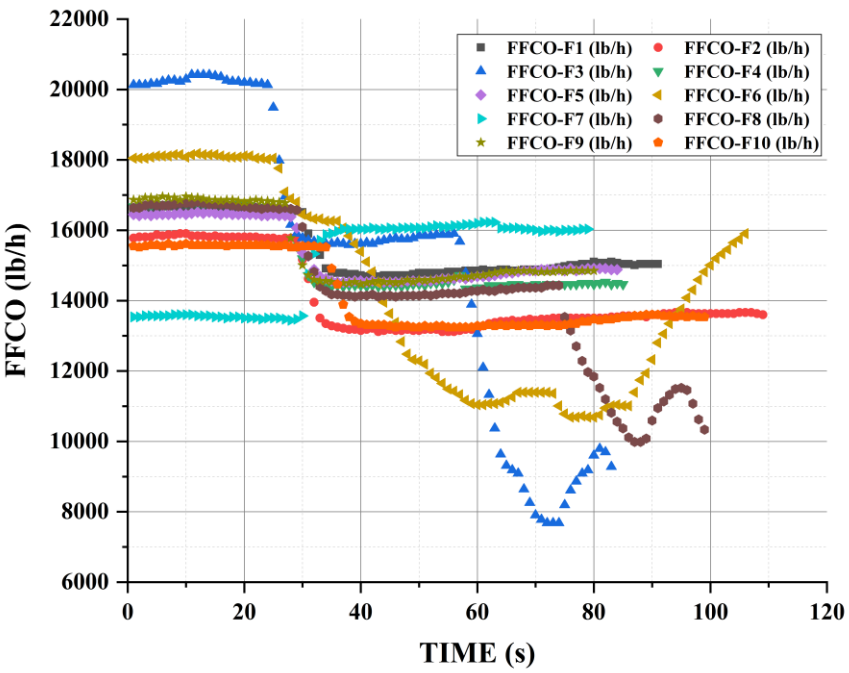


Figure 8. Variation of FFCO values during climb-out phases

The climb-out phase determined within the scope of this study is the phase up to 3000 feet above the altitude where the take-off phase ends. When the FDR dataset is examined, it is seen that FFCO values change depending on many parameters. In the GPR model, GW, ALT, TAT, CAS, FPA and WS are the independent variables, and FFCO is the dependent variable. For the climb-out phase, the variation between the estimated FFCO values and actual FFCO values is shown in Figure 9. The predicted response for the GPR model produces successful results. The residual values for the GPR model are demonstrated in Figure 10. The residuals values for the GPR model fluctuate between a minimum of -1952 lb/h to a maximum of 1567 lb/h.

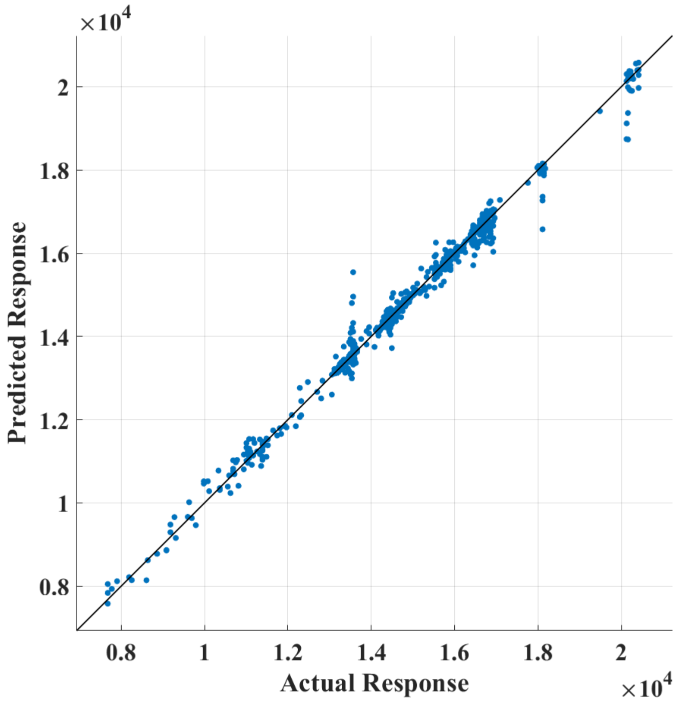


Figure 9. The predicted FFCO values against actual FFCO values

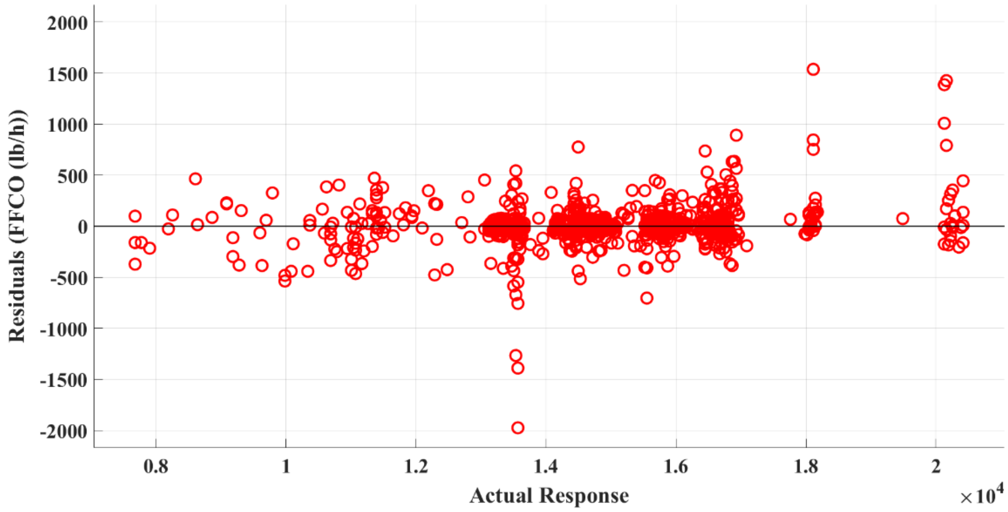


Figure 10. The distribution of prediction errors for GPR model

Table 3. The results of the statistical tests and kernel function type.

	Statistical Test		Kernel Function
	RMSE	209.41	
Gaussian Process Regression	R^2	0.99	Squared Exponential
	MAE	111.38	

Finally, the regression model is evaluated using statistical tests in this study. For this purpose, different statistical tests, which have RMSE, MAE, and R^2, are employed to show the performance of the GPR model. The performance and accuracy of the model increase as the RMSE and MAE values approach zero. In other words, these statistical tests values are asked to be low value in studies. Table 3 presents the results of the statistical tests and kernel function type. Considering the RMSE test for validation, it is seen that the RMSE value for the GPR is 209.41. MAE value for GPR is calculated to be 111.38. The R^2 value of a model is close to one, which means that the model has a high performance. As can be seen from Table 3, R^2 value of the GPR is 0.99. As apparent from the outcome of the statistical tests given in Table 3, GPR model exhibits great performance for the estimation of FFCO.

5. CONCLUSIONS

This research focuses on ten different flights performed by Boeing B737-800 twin-engined, medium-haul, narrow-bodied commercial aircraft. The FDR data sets from these flights are used to investigate fuel consumption during the climb-out phase. By utilizing these actual data sets, the

Gaussian Process Regression model is performed to estimate FFCO during climb-out phase. As a result of reviewing the literature, FFCO, GW, ALT, TAT, CAS, FPA, and WS are selected as model parameters. Within the scope of this study, the climb-out is phase examined. The main reason for choosing the climb-out phase is the high fuel consumption and the resulting increased emission values. Many statistical tests, that are RMSE, MAE, and R^2, are utilized to illustrate the performance of the GPR model. When all statistical tests are examined, it is seen that the GPR model gives successful result. Thanks to this regression model created, the fuel consumption around the airports and the resulting emission values can be calculated accurately. This research has some limitations. Choosing the climb-out phase for the regression model is one of the limitations. Another important limitation is that six different independent variables are determined for the regression model. A few recommendations for the literature can be made in light of the limitations of the present study. Using different aircraft types and more real flight data, the fuel consumption in the climb-out phase can be estimated.

DECLARATION OF ETHICAL STANDARDS

The author of the paper submitted declares that nothing which is necessary for achieving the paper requires ethical committee and legal-special permissions.

CONTRIBUTION OF THE AUTHOR

Vehbi Emrah Atasoy: Performed the computations, analyzed the results, and wrote the manuscript.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

REFERENCES

[1] Stolzer AJ. Fuel consumption modeling of a transport category aircraft using flight operations quality assurance data: a literature review. Journal of Air Transportation 2002; 7(1): 93.

[2] Lee DS, Pitari G, Grewe V, Gierens K, Penner JE, Petzold A, Prather MJ, Schumann U, Bais A, Berntsen T, Iachetti D, Lim LL, Sausen R. Transport impacts on atmosphere and climate: aviation, Atmospheric Environment 2010; 44(37): 4678-4734.

[3] Larsson J, Elofsson A, Sterner T, Åkerman J. International and national climate policies for aviation: a review. Climate Policy 2019; 19(6): 787-799.

[4] Brzozowski K. Kotlarz W. Modelling of air pollution on a military airfield. Atmospheric Environment 2005; 39(33): 6130-6139.

[5] Senzig DA, Fleming GG, Iovinelli RJ. Modeling of terminal-area airplane fuel consumption. Journal of Aircraft 2009; 46(4): 1089-1093.

[6] Collins B. Estimation of aircraft fuel consumption, Journal of Aircraft 1982; 19(11): 969–975.

[7] Patterson J, Noel GJ, Senzig DA, Roof CJ, Fleming GG. Analysis of departure and arrival profiles using real-time aircraft data. Journal of Aircraft 2009; 46(4): 1094-1103.

[8] Kim HJ, Baik H. Empirical method for estimating aircraft fuel consumption in ground operations. Transportation Research Record 2020; 2674(12): 385-394.

[9] Turgut ET, Rosen MA. Relationship between fuel consumption and altitude for commercial aircraft during descent: preliminary assessment with a genetic algorithm. Aerospace Science and Technology 2012; 17(1): 65-73.

[10] Zhu Q, Pei J, Liu X, Zhou Z. Analyzing commercial aircraft fuel consumption during descent: A case study using an improved K-means clustering algorithm. Journal of Cleaner Production 2019; 223: 869-882.

[11] Oruc R., Baklacioglu T. Modelling of fuel flow-rate of commercial aircraft for the climbing flight using cuckoo search algorithm. Aircraft Engineering and Aerospace Technology 2020; 92(3): 495-501

[12] Seymour K, Held M, Georges G, Boulouchos K. Fuel Estimation in Air Transportation: Modeling global fuel consumption for commercial aviation. Transportation Research Part D: Transport and Environment 2020; 88: 102528.

[13] Luo W, Wu Z, Chen C. An Aircraft Fuel Flow Model of Cruise Phase Based on LSTM and QAR Data. In 2020 13th International Symposium on Computational Intelligence and Design (ISCID) (pp. 118-121). IEEE. 2020.

[14] Baumann S, Klingauf U. Modeling of aircraft fuel consumption using machine learning algorithms. CEAS Aeronautical Journal 2020; 11(1): 277-287.

[15] Baklacioglu T. Modeling the fuel flow-rate of transport aircraft during flight phases using genetic algorithm-optimized neural networks. Aerospace Science and Technology 2016; 49:52-62

[16] Elbir T. Estimation of engine emissions from commercial aircraft at a midsized Turkish airport. Journal of Environmental Engineering 2008; 134(3): 210-215.

[17] Rice CC. Validation of approach and climb-out times-in-mode for aircraft emissions computation. Transportation research record 2003; 1850(1): 79-82.

[18] Chati YS, Balakrishnan H. Data-driven modeling of aircraft engine fuel burn in climb out and approach. Transportation Research Record 2018; 2672(29): 1-11.
[19] Liati A, Schreiber D, Alpert PA, Liao Y, Brem BT, Arroyo PC, Eggenschwiler, PD. Aircraft soot from conventional fuels and biofuels during ground idle and climb-out conditions: Electron microscopy and X-ray micro-spectroscopy. Environmental Pollution 2019; 247: 658-667.
[20] Chilongola FD, Ahyudanari E. Aviation and aircraft engine emissions at Juanda International Airport. Materials Science and Engineering 2019; 645(1): 012022.
[21] Raposo F, Borja R, Ibelli-Bianco C. Predictive regression models for biochemical methane potential tests of biomass samples: Pitfalls and challenges of laboratory measurements. Renewable and Sustainable Energy Reviews 2020; 127: 109890.
[22] Liu K, Hu X, Wei Z, Li Y, Jiang Y. Modified Gaussian process regression models for cyclic capacity prediction of lithium-ion batteries. IEEE Transactions on Transportation Electrification 2019; 5(4): 1225-1236.
[23] Chen X, Huang J, Yi M. Cost estimation for general aviation aircrafts using regression models and variable importance in projection analysis. Journal of Cleaner Production, 2020; 256: 120648.
[24] D'Agostino R. Goodness-of-fit-techniques. Routledge. 2017.
[25] Hagquist C, Stenbeck M. Goodness of fit in regression analysis–R 2 and G 2 reconsidered. Quality and Quantity 1998; 32(3): 229-245.