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ORIGINAL ARTICLE

Evaluation of aircraft engine performance during takeoff phase with machine learning methods

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Abstract

During the takeoff phase, aircraft engines reach maximum speed and temperature to achieve the required thrust. Due to these harsh operating conditions, the performance of aircraft engines may decrease. This decrease in performance increases both fuel consumption and environmental damage. Reducing or eliminating the damages caused by aircraft is among the objectives of ICAO. In order to achieve this goal, aircraft engines are compulsorily tested, evaluated by experts and certified. The data obtained during the test process is recorded and stored in the engine emission databank (EEDB). During the takeoff phase, there is no system that can evaluate aircraft engines without dismantling and without expert knowledge. In this study, EEDB 2019 and 2021 takeoff phase data sets were used. Fuel flow *T/O* parameter is an important parameter used both in the calculation of aircraft emissions and in the evaluation of engine performance. Gaussian process regression (GPR), support vector machine (SVM) and multilayer perceptron (MLP) models were used to estimate the fuel flow *T/O* parameter. The results obtained were compared according to error performance criteria and the best model was selected. In MATLAB® environment, confidence intervals were plotted with the estimated fuel flow *T/O* value at 99% confidence level. This study demonstrates that the performance evaluation of aircraft engines during the takeoff phase can be performed without the need for expert knowledge.

Keywords Machine learning · Performance evaluation · Fuel flow *T/O* · EEDB

Abbreviations

BC	Black carbon
CO	Carbon monoxide
CO_2	Carbon dioxide
HC	Hydrocarbon
H_2O	Water
NO_x	Nitrogen oxides
PM_{10} and $PM_{2.5}$	Particulate matter
SO_2	Sulfur dioxide
SO_x	Oxides of sulfur
TOG	Total organic gases
VOC_s	Volatile organic compounds

1 Introduction

Aviation is an important sector that facilitates the lives of people around the world, stimulates economic growth and increases global connectivity. The International Air Transport Association (IATA) forecasts that passenger numbers will increase to 8.2 billion in 2037 [1]. The growing aviation industry is also causing an increase in significant undesirable problems. Aircraft engines reach their highest speed and temperature during the takeoff phase. Engines operating at high speeds and temperatures may experience performance degradation. Some of the reasons for performance deterioration of gas turbine engines are as follows [2];

- Fouling [3]
- Erosion and abrasion [4]
- Particle fusing [5]
- Corrosion, hot corrosion and oxidation [6]
- Mechanical degradation [7]

Performance degradation in aircraft engines increases aircraft fuel consumption and aircraft engine emissions [8, 9].

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Aviation emissions $SO_2, NO_x, HC, PM_{10}, PM_{2.5}, BC$ and VOC_s negatively affect air quality [10]. Deterioration of air quality causes harm to human health and other living things [11]. In addition, these emissions increase global warming [12].

The International Civil Aviation Organization (ICAO) was established as a result of the Chicago Civil Aviation Agreement signed in Chicago in 1944. With this agreement, ICAO regulates and standardizes international civil aviation. ICAO has set 3 goals to minimize the environmental damage caused by the aviation sector [13].

- To reduce or limit the damage caused by aircraft noise.
- To reduce or limit the impact of emissions that degrade air quality.
- To reduce or limit the impact of global warming caused by the aviation sector.

To achieve its objectives, ICAO certifies turbojet and turbofan aircraft engines with a maximum engine power higher than 26.7 kN under Annex 16 [15]. Aircraft engines that fail to obtain a certificate are overhauled and retested. Aircraft operating within the standards and limits set by ICAO can obtain airworthiness certificate [16]. The certification process for aircraft engines is based on the landing and takeoff (LTO) cycle shown in Fig. 1. Table 1 shows the thrust setting and application time in the certification process of an aircraft engine. The LTO concept proposed by ICAO measures aircraft engines during takeoff, approach, climb and taxi/idle phases. The results of the measured parameters of the aircraft are recorded in the ICAO engine emission data bank (EEDB). The different processes used for aircraft emission calculation are shown in Fig. 2 [13, 14, 17].

Below 3000 feet, the ICAO-recommended LTO cycle is used for fuel consumption calculation. EEDB contains emission indices and fuel flow values for many aircraft engines. The EUROCONTROL Experimental Centre has developed "Base of Aircraft Data (BADA)" for fuel consumption calculations at altitudes above 3000 feet [18]. BADA provides location and altitude-dependent fuel consumption and performance data for more than 100 aircraft types. For emission calculations above 3000 ft, the "Boeing method 2" developed by The Boeing Company is used. The Advanced Emissions Model 3 (AEM3) is the name of a computer model used to study and assess environmental impacts in the aviation industry. Table 2 illustrates the process of calculating fuel consumption and emissions with AEM3.

The ICAO LTO cycle is a common practice used in aviation emission estimation and provides information for phases of flight. Advances in technology have led to new models for the calculation of aircraft fuel consumption and harmful emissions. Different studies have been conducted in the literature using the EEDB data set and operational data. Filippone and Bojdo developed a statistical analysis with the ICAO database to estimate the exhaust emissions of aircraft engines during the landing and takeoff cycle [20]. Yılmaz calculated emissions from passenger aircraft at Kayseri Airport using the EEDB data set [21]. Chati and

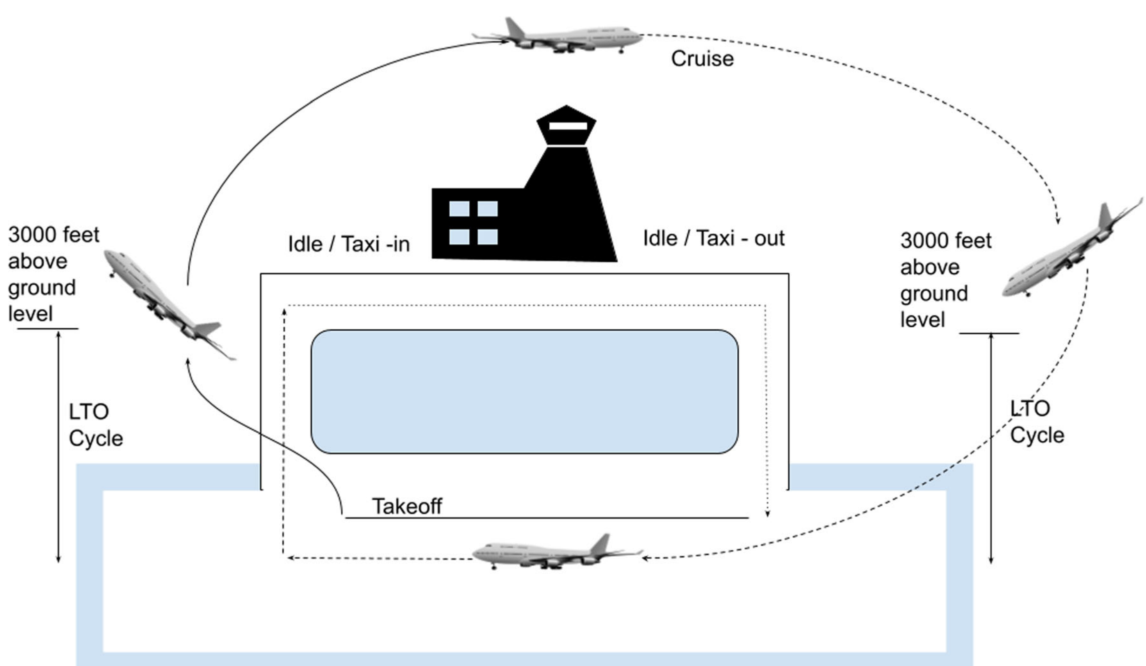


Fig. 1 Illustration of ICAO emissions certification procedure [13]

Table 1 Engine thrust setting and operating times under different operating conditions of the standard LTO cycle specified by ICAO [14]

Operating phase	Takeoff	Approach	Climb	Taxi and ground idle
Time in mode (min.)	0.7	4.0	2.2	26(7.0 (in)–19.0 (out))
Thrust setting (%)	100	30	85	7

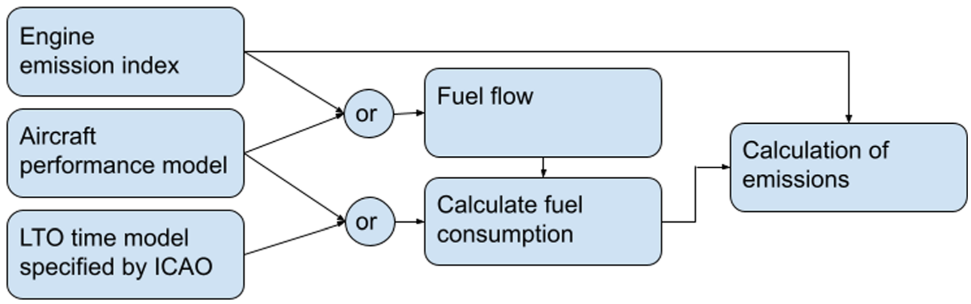


Fig. 2 Calculation of harmful emissions from airplanes [17]

Table 2 Approaches to calculating emissions and fuel consumption [19]

	Fuel burn	HC, CO, NO_x	VOC, TOG	SO_x, H_2O, CO_2
Below 3000 feet	EEDB		Proportional to HC emissions	Proportional to fuel burn
Above 3000 feet	BADA	Boeing method 2	Proportional to HC emissions	Proportional to fuel burn

Balakrishnan calculated fuel and emission values with the aircraft's operational data set values. They compared the statistically obtained results with EEDB [22]. Zhou et al. propose a new approach to estimate aircraft emissions using the LTO cycle [23]. Ge et al. predicted aviation nonvolatile particulate matter emissions with artificial neural networks [15]. Collins used radar data to estimate aircraft fuel consumption [24]. Allaire estimated NOx and CO emissions using combustion models [25]. Patterson et al. calculated fuel flow using flight data recorder (FDR) data [26]. Baklacioglu estimated the fuel flow rate using an optimized neural network model and actual flight data of an aircraft [27]. Huang et al. investigated statistical models for estimating fuel flow rate from piston engine aircraft data [28].

For ICAO, improving the reliability and safety of aircraft is an important problem to be solved. Thanks to advances in technology and new studies, the adversities caused by the aviation industry are being reduced. Systems such as engine test bench (ETB) are used to monitor, analyze and predict performance parameters in aircraft engines [37]. Another source of data used for performance evaluation of aircraft engines is the FDR. Records of important parameters measured during the flight are stored in this device. According to the data recorded in the FDR, the details of the flight can be explained. After aircraft accidents, this data is used to understand the causes of the accident and to improve flight safety. Example studies with different algorithms for fuel consumption estimation are shown in Table 3 [37].

Unlike the studies in the literature, there is no model that can evaluate the performance of the engine during the takeoff phase using EEDB data with machine learning methods. This study aims to develop a model that can evaluate the performance of the aircraft engine using machine learning. In order to develop the model, EEDB data sets for 2019 and 2021 obtained from the aircraft engine certification process were used [16, 38]. When the performance of aircraft engines deteriorates, the value of the fuel flow parameter increases or decreases. Therefore, the fuel flow *T/O* parameter was selected to evaluate the engine performance during the takeoff phase. Regression analysis was performed to select the input parameters that affect the fuel flow *T/O* parameter in the data set. Ambient humidity, engine type, ambient baro, rated output, ambient temp, bypass ratio and press ratio were selected as input parameters. The input parameters were applied to Gaussian process regression, multilayer perception and support vector machine models to predict the fuel flow *T/O* parameter. The results obtained were compared with error performance criteria and the best model was selected. The predicted fuel flow *T/O* value obtained from the best model

Table 3 Example of different algorithms on fuel consumption in aircraft

Authors	Algorithms	Data set
Kurt [29]	ANN with confidence interval	Flight data recorder
Atasoy [18]	DL, GLM, RF and BADA	Flight data recorder
Huang et al. [30]	CART and NN	Vertical speed, barometric altitude and ground speed
Yanto et al. [31]	HDBSCAN	Flight operational data
Srivastava et al. [32]	GLR and PRE	Flight data recorder
Baumann and Klingauf [33]	Decision tree regression and ANN	ADU, control inputs and engine parameters
Huang et al. [28]	SS-ANOVA and CART	Flight altitude, vertical speed and ground speed
Kang and Hansen [34]	QR, GBM and RQF	Takeoff hour, weather, air vehicle types, time and past traffic
Chati and Balakrishnan [35]	LSB and CART	Flight trajectory, altitude, acceleration, time and velocity
Wang and Chen [36]	SVM	Flight data recorder

ADU, Air data unit; ANN, artificial neural network; BADA, Base of Aircraft Data; CART, classification and regression tree; DL, deep learning; GLM, generalized linear model; GBM, gradient boosting machine; GLR, generalized linear rules; HDBSCAN, hierarchical density-based spatial clustering of applications with noise; LSB, least-squares boosting, NN, neural network, PRE, prediction rule ensemble; QR, quantile regression, RF, random forest, RQF, random quantile forests; SS-ANOVA, smoothing spline ANOVA, SVM, support vector method

is used to determine the confidence interval. Each fuel flow value of the aircraft engine during the takeoff phase was compared with the confidence interval. If the measured fuel flow *T/O* parameter value is within the confidence interval (99%), the aircraft engine performance in the takeoff phase is normal. If the measured fuel flow *T/O* parameter value is out of the confidence interval(99%), this indicates that there may be a performance deterioration in the aircraft engine. With the developed model, it is shown that the performance of the engine at takeoff can be evaluated without any mathematical calculations or expert knowledge. The structure chart of the paper is shown in Fig. 3.

The rest of this article is structured as follows. In Sect. 2, the characteristics and statistical information of the EEDB used in the development of the model are given. Then, the machine learning methods used to estimate the fuel flow *T/O* parameter are explained. In Sect. 3, the best model is selected among the models that estimate the fuel flow *T/O* parameter. Error performance results and graphs of the developed models are presented. In addition, confidence intervals are constructed with the fuel flow *T/O* parameter obtained from the output of the best predicting model. In conclusion, the importance and benefits of the study are emphasized.

2 Materials and methods

Aircraft engines reach their highest performance during the takeoff phase. For the safety of aircraft, engine performance must not deteriorate. The value of the fuel flow parameter decreases or increases due to performance deterioration in aircraft engines. Failures such as engine separation, flameout, severe damage, seizure, fuel control problems, fire, surge and fuel leakage cause unexpected changes in the fuel flow value [39]. In addition, fuel flow is

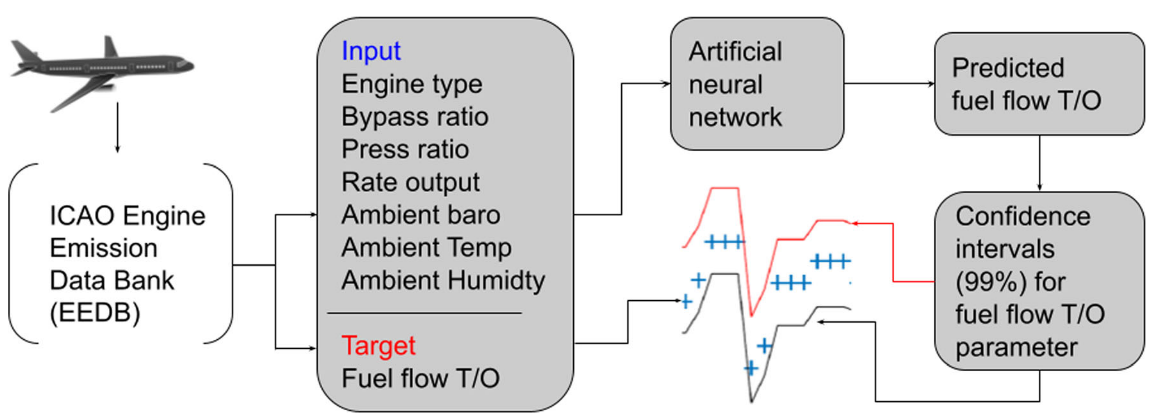


Fig. 3 Flowchart

also a parameter used in the calculation of total emissions (See Fig. 2). The aim of this study is to develop a model, which is not available in the literature, that can evaluate the performance of an aircraft engine during the takeoff phase using the EEDB data set. In order to increase the safety of airplanes, there is a need for such studies with low cost and short time results.

The details of the developed model are described in 3 subsections. Section 2.1 describes the features of the data used in the study. In Sect. 2.2, the outputs of the multiple regression model analysis used to determine the input parameters are presented. In Sect. 2.3, information about machine learning methods MLP, SVM and GPR are given.

2.1 Data properties

The ICAO LTO cycle consists of four operating modes representing pollutant emissions near airports as shown in Table 1. Important parameters are measured and recorded during the takeoff, approach, climb, taxi and ground idle phases of the engine certification process, and these data are collected and stored in the publicly available ICAO emissions database. For this study, data sets for 2019 and 2021 were obtained from ICAO's corporate web page. The ICAO aircraft engine emissions databank (EEDB-09/2019) was used to develop the model that evaluates the engine performance during the takeoff phase of the aircraft [16]. The ICAO aircraft engine emissions databank (EEDB-07/2021) was used to test the reliability and performance of the developed model [38]. Statistical information of the two data sets are shown in Tables 4 and 5.

In order for the trained model to learn the relationship between the fuel flow *T/O* parameter and the input parameters, the data set shown in table 4 should be divided into training, test and validation groups. There are different ratios in the literature to determine the distribution of the data set [25, 26]. 15% of EEDB (09/2019) set is allocated for testing, 70% for training and 15% for validation groups. The data in the test and validation groups were not used in the training of the developed models. In order to randomly distribute the data to the groups, "dividerand" command was used in MATLAB® program. Real data were used throughout the study. Randomly selected examples of the data sets used in the study are presented in Table 6.

2.2 Multiple regression model analysis

The purpose of multiple regression analysis is to measure the cause and effect relationship between the target parameter and the input parameters. The arithmetical form of the multiple regression model is shown in Eq. (1). In the equation β_0 is the regression constant and $\beta_1, \beta_1, \ldots\beta_n$ are the coefficient values. Input parameters are $p_1, p_2, \ldots, p_n$. ϵ is the deviation between the true value and the predicted value. The output parameter is called y.

$$y = \beta_0 + \beta_1 p_1 + \beta_2 p_2 + \cdots + \beta_n p_n + \epsilon \quad (1)$$

Different multiple regression model analyses were performed to see the effects of the parameters in the engine emission databank set on the fuel flow *T/O* parameter. Ambient humidity, engine type, ambient baro, rated output, ambient temperature, bypass ratio and press ratio parameters were found to be significantly effective on fuel flow *T/O* parameter. As a result of the analysis, 8 parameters were selected from the engine emission databank. Statistical information of the selected parameters is given in Table 4. The calculations obtained in the multiple regression model analysis are given below.

In Table 7, the *R*-square value is shown as 0.979. The value of *R* = 0.99 indicates the value of multiple correlation. Adjusted *R*-square was found to be 0.979. The predictive power of the model is 97.9%.

ANOVA test was conducted to obtain data on the significance of the developed model. Sig. value in the ANOVA test is a value used to determine the level of statistical significance. Since the Sig. value in Table 8 is $0.000 < 0.001$, it shows that the developed model is highly significant [40].

When the results of the regression coefficients in Table 9 are examined, it is seen that the coefficients $\beta_0 =$

Table 4 Statistical values of aircraft engine emissions databank (EEDB-09/2019)

Parameters	Samples	Min.	Max.	Mean	Std. Deviation
Engine type	565	1.00	2.00	1.2248	0.41781
Bypass ratio	565	0.64	12.72	6.1787	2.39113
Press ratio	565	9.76	49.40	30.4341	8.30142
Rate output	565	9.79	513.90	189.7491	116.31773
Ambient baro	565	0.00	1019394.5	8004.3	85867.3925
Ambient temp	565	144	308.50	286.9116	10.30618
Ambient humidity	565	0.00	0.02	0.0069	0.00366
Fuel flow *T/O*	565	0.15	4.69	1.7095	0.94789
Valid *N* (listwise)	565				

Table 5 Statistical values of aircraft engine emissions databank (EEDB-07/2021)

Parameters	Samples	Min	Max	Mean	Std. Deviation
Engine type	773	1.00	2.00	1.2096	0.40727
Bypass ratio	773	0.00	12.72	6.5978	2.64116
Press ratio	773	9.76	49.60	31.3034	8.52827
Rate output	773	9.79	513.90	186.5325	118.29263
Ambient baro	773	95.15	103.45	99.4889	1.67661
Ambient temp	773	226.50	308.50	287.1879	8.14578
Ambient humidity	773	0.00	0.04	0.0070	0.00377
Fuel flow *T/O*	773	0.15	4.69	1.6410	0.96349
Valid *N* (listwise)	773				

Table 6 Randomly selected sample values from the ICAO aircraft engine emissions databank (EEDB)

UID NO	Parameters	Engine type	Bypass ratio	Press ratio	Rated output (kN)	Ambient baro. (kPa)	Ambient temp. (K)	Ambient humidity (kg/kg)	Fuel flow *T/O* (kg/s)
1AS001	(training)	1	2.64	13.9	15.6	97.4	286.5	0.00765	0.205
4AL002	(validation)	2	4.76	17.81	33.73	101.3	144	0.0063	0.380
1AA001	(test)	2	0.85	18.4	66.64	103	293	0.01048	1.670
2CM012	(2021 set)	1	5.70	30.2	133.45	97.835	288.65	0.00715	1.359

UID no, Unique Identification Number for an EEDB entry

Table 7 Summary results of the multiple regression model

Designed model	*R*	*R*-square	Adjusted *R*-square	Std. Error
1	0.990*	0.979	0.979	0.13733

*Predictors: (constant), ambient humidity, engine type, ambient baro, rated output, ambient temp, bypass ratio, press ratio. Dependent variable: fuel flow *T/O*

Table 8 ANOVA[a] test results

Designed model	Sum of squares	*df*	Mean square	*F*	Sig.
Regression	496.246	7	70.892	3759.001	0.000[b]
Residual	10.505	557	0.019		
Total	506.751	564			

[a]Dependent variable: fuel flow *T/O*

[b]Predictors: (constant), ambient humidity, engine type, ambient baro, rated output, ambient temp, bypass ratio, press ratio

$1.302, \beta_1 = -0.49, \beta_2 = -0.1, \beta_3 = -7.308 * 10^{(-5)}, \beta_4 = 0.009, \beta_5 = 2.242 * 10^{(-7)}, \beta_6 = -0.002,$ and $\beta_7 = -4.612$. The regression equation consisting of the input parameters that affect the prediction of the fuel flow *T/O* parameter at takeoff phase is shown in Eq. (3).

$$\begin{aligned} \text{Fuel Flow}\, T/O &= 1.302 - 0.49 \times \text{engine type} \\ &- 0.1 \times \text{bypass ratio} - \\ &7.308 \times 10^{-5} \times \text{press ratio} + 0.009 \times \text{rated output} + \\ &2.242 \times 10^{-7} \times \text{ambient baro} - 0.002 \times \\ &\text{ambient temp} - 4.612 \times \text{ambient humidity} \end{aligned} \quad (2)$$

Table 9 Coefficients[a]

Designed model	Unstandardized coefficients		Standardized coefficients	t	Sig.
	β	Std. Error	Beta		
(Constant)	1.302	0.194		6.721	0.000
Engine type	− 0.49	0.017	− 0.22	− 2.962	0.003
Bypass ratio	− 0.100	0.004	− 0.252	− 23.782	0.000
Press ratio	− 7.308E−5	0.002	− 0.001	− 0.046	0.963
Rated output	0.009	0.000	1.063	100.231	0.000
Ambient baro	2.242E−7	0.000	0.020	3.234	0.001
Ambient temp	− 0.002	0.001	− 0.020	− 2.646	0.008
Ambient humidity	− 4.612	1.966	− 0.018	− 2.346	0.019

[a]Dependent variable: fuel flow *T/O*

2.3 Machine learning approaches

Machine learning algorithms trained with data obtained from the operating conditions of a system gain the ability to make predictions about that system. This ability is nowadays used in many fields to solve different problems [41]. The training of machine learning models in this study is based on the EEDB (09/2019) was used [16]. Multilayer perceptron neural network, Gaussian processes regression and support vector machine algorithms were used to predict the fuel flow *T/O* parameter during the takeoff phase of the aircraft. The general features of these algorithms are given below.

2.3.1 Gaussian process regression

Gaussian process regression is a successful machine learning method used to solve nonlinear regression problems. The GPR method has the ability to make successful predictions even for small data sets. Different covariance functions can be used to make the most accurate prediction with GPR [42]. The Gaussian process regression model is shown in Eq. 3 [43].

$$f(x) \sim \mathrm{GPR}(m(x), k(x, x')) \quad (3)$$

Here $f(x)$ is a function of variable x, $k(x, x')$ is a covariance function and $m(x)$ is mean function. In this study, rational quadratic kernel functions, exponential kernel functions and squared exponential kernel functions were used to estimate the fuel flow *T/O* parameter.

2.3.2 Support vector machine

Support vector machines developed by Vapnik and Cortes are a widely used machine learning technique [44]. Support vector machines gives effective results in solving linear and nonlinear problems. Support vector machines based on statistical learning theory. Support vector machines is basically a machine learning technique to best distinguish between two groups of data is used. For this process, hyperplanes or decision boundaries are defined. In a nonlinear data set, support vector machines cannot draw a linear hyperplane. Kernel functions are used to solve the problem. The kernel function greatly improves machine learning on nonlinear problem [45]. The mathematical expression of the kernel method is shown in Eq. 4 [46].

$$y = (K_{xi} * W_{jk}) + b \quad (4)$$

This y is the output predicted value, K_{xi} is a nonlinear function, W_{jk} is the weight vector and b is the bias. The structure of the three-layer support vector machines model used in this study is illustrated in Fig. 4.

2.3.3 Multilayer perceptron neural network

Artificial neural network is used for problem solving in many different fields such as engineering, medicine, social sciences and physical sciences. In 1943, Mcculloch and Pitts first introduced the idea of artificial neural [47]. Until today, different artificial neural networks have been developed for solving different problems. The multilayer perceptron (MLP) model is one of the most basic and widely used types of artificial neural networks (ANN). MLP, a deep learning model based on a multilayer feed-forward neural network, plays a critical role in machine learning to solve complex problems [48].

An artificial neural network cell consists of an input layer, transfer function, variable weight multipliers, sum function and output layer. By applying input data to the input layer, results are obtained from the output layer. Figure 5 shows the general structure of a multilayer perceptron neural network. Estimating the fuel flow *T/O* parameter at takeoff phase is a nonlinear problem. MLP model gives good results in solving nonlinear problems. MLP model can learn, generalize and classify. MLP can make predictions about any operating system or problem.

Fig. 4 Structure of support vector machine

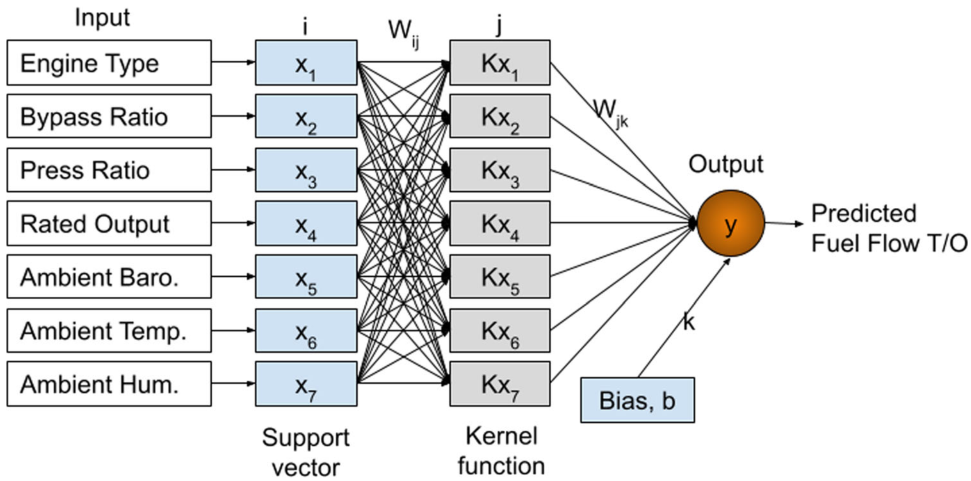
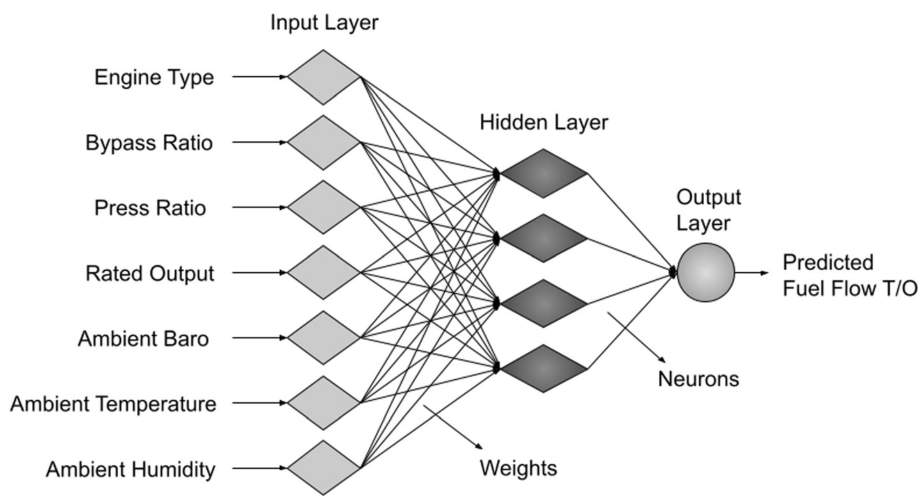


Fig. 5 Structure of a multilayer perceptron



Therefore, MLP model is selected to estimate the fuel flow *T/O* parameter.

3 Results and discussion

The aim of this study is to develop a new model to evaluate the performance of aircraft engines during the takeoff phase. To achieve this objective, the fuel flow *T/O* parameter is estimated by different machine learning models. The following performance criteria were used to evaluate the performance of the developed models. The mathematical expression of the error performance models used is Eq. (5), Eq. (6) and Eq. (7). In the formulas, $FF_{T/O}$ is the actual value received from the EEDB, n is the number of observations and $ff_{T/O}$ is the predicted value.

MSE (Mean Squared Error): The mean squared error is the average of the error squares of the model predictions. A lower MSE indicates that the model performs better.

$$\mathrm{MSE} = \frac{1}{n}\sum_{t=1}^{n}\left(FF_{T/O} - ff_{T/O}\right)^2 \tag{5}$$

MAE (Mean Absolute Error): The mean absolute error shows how much the predictions deviate from the true values. A lower MAE indicates that the model is better.

$$\mathrm{MAE} = \frac{1}{n}\sum_{t=1}^{n} | FF_{T/O} - ff_{T/O} | \tag{6}$$

MAPE (Mean Absolute Percentage Error): The mean absolute percentage error shows the average percentage error of the predictions. A lower MAPE indicates that the model is more accurate. In the literature, prediction models with MAPE less than 10% are considered to have a “high accuracy.”

$$\mathrm{MAPE} = \frac{100}{n}\sum_{t=1}^{n} \left| \frac{FF_{T/O} - ff_{T/O}}{FF_{T/O}} \right| \tag{7}$$

3.1 Gaussian process regression prediction results

A total of 565 data shown in Table 4 were used in the GPR model trained to predict the fuel flow *T/O* parameter of aircraft engines during the takeoff phase. Of these data, 395 were used in the training process, 85 in the testing and the remaining 85 in the validation phase. Rational quadratic, squared exponential and exponential kernel functions were used to estimate the fuel flow *T/O* parameter. The same training, test and validation data sets were used for all three models. The prediction results R and MSE of the GPR models were compared. In all GPR models, ambient humidity, engine type, ambient baro, rated output, ambient temperature, bypass ratio and press ratio parameters were used as inputs and fuel flow *T/O* parameter was estimated at the output. The results of the Gaussian processes regression models are illustrated in Table 10.

When Table 10 is examined, it is seen that the exponential GPR model gives the best result with an R value of 1 and 0.9964 in the training and test data set, respectively. The rational quadratic GPR model seems to make the best prediction with 0.98337 in the validation set. In order to select the best model among squared exponential, exponential and rational quadratic GPR models, MSE performance criterion was used for the test data set. When the results are analyzed, the exponential GPR model, which predicts the MSE value with 0.0066 is the best model. The performance graphs of the developed exponential GPR model are shown in Fig. 6. Also, information about the structure of the selected exponential GPR model is presented in Table 11.

3.2 Support vector machine model prediction results

In order to develop the SVM model for predicting the fuel flow *T/O* parameter in the takeoff phase of the aircraft engine, a total of 565 data shown in Table 4 were used. 15% of these data were used in the test process, 15% in the validation and the remaining 70% in the training phase. To estimate the fuel flow *T/O* parameter, linear, quadratic and cubic kernel functions were used.

The same training, validation and test data sets were applied for all three models. The prediction results of the SVM models were compared with R and MSE, error performance criteria. In all SVM models, ambient humidity, engine type, ambient baro, rated output, ambient temperature, bypass ratio and press ratio parameters were used as input and fuel flow *T/O* parameter was predicted at the output. The results of support vector machine models are presented in Table 12.

When Table 12 is examined, it is seen that the R value showing the performance of the quadratic SVM model makes the best prediction with a value of 0.99709 in the test set and 0.99655 in the training set. Linear SVM model made the best prediction with 0.98859 in the validation set. To select the best model among the three models, the MSE performance criterion was used for the test set. When the results are analyzed, it is seen that the quadratic SVM model is the best model since the MSE value of 0.00542 is close to zero. The performance graphs of the developed quadratic SVM model are shown in Fig. 7. Also, information about the structure of the selected quadratic SVM model is presented in Table 13.

3.3 Multilayer perceptron model prediction results

For the MLP model to be used to estimate the fuel flow *T/O* parameter of aircraft engines during takeoff phase, the EEDB shown in Table 4 is used. 15% of this data set was used for testing, 15% for validation and the rest for training. To estimate the fuel flow *T/O* parameter, 9 MLP models trained with "trainlm," "trainrp" and "traincgb" functions were developed. The same data sets were used in the testing, validation and training phases of all models. In all MLP models, ambient humidity, engine type, ambient baro, rated output, ambient temperature, bypass ratio and press ratio parameters were used as input and fuel flow *T/O* parameter was estimated at the output. The results obtained from 9 different MLP models are shown in Table 14. The results are ranked according to the lowest MSE value obtained from the test set.

When the results shown in Table 14 are examined, it is seen that the model 1 developed with R values of 0.9991, 0.9970, 0.9986 and MSE values of 0.00168, 0.00427, 0.0025488, respectively, in the training, validation and test data sets made the best prediction. As a result, the model 1 trained with the training function "trainlm" performed

Table 10 Comparison of GPR models according to MSE values in the test group

Kernel function	*R*			MSE		
	Training	Validation	Test	Training	Validation	Test
Exponential GPR	1	0.98086	0.9964	1.302e−06	0.02783	0.0066
Rational quadratic GPR	0.99997	0.98337	0.9953	5.188e−05	0.02467	0.0090
Squared exponential GPR	0.99996	0.98245	0.9856	6.447e−05	0.02660	0.0272

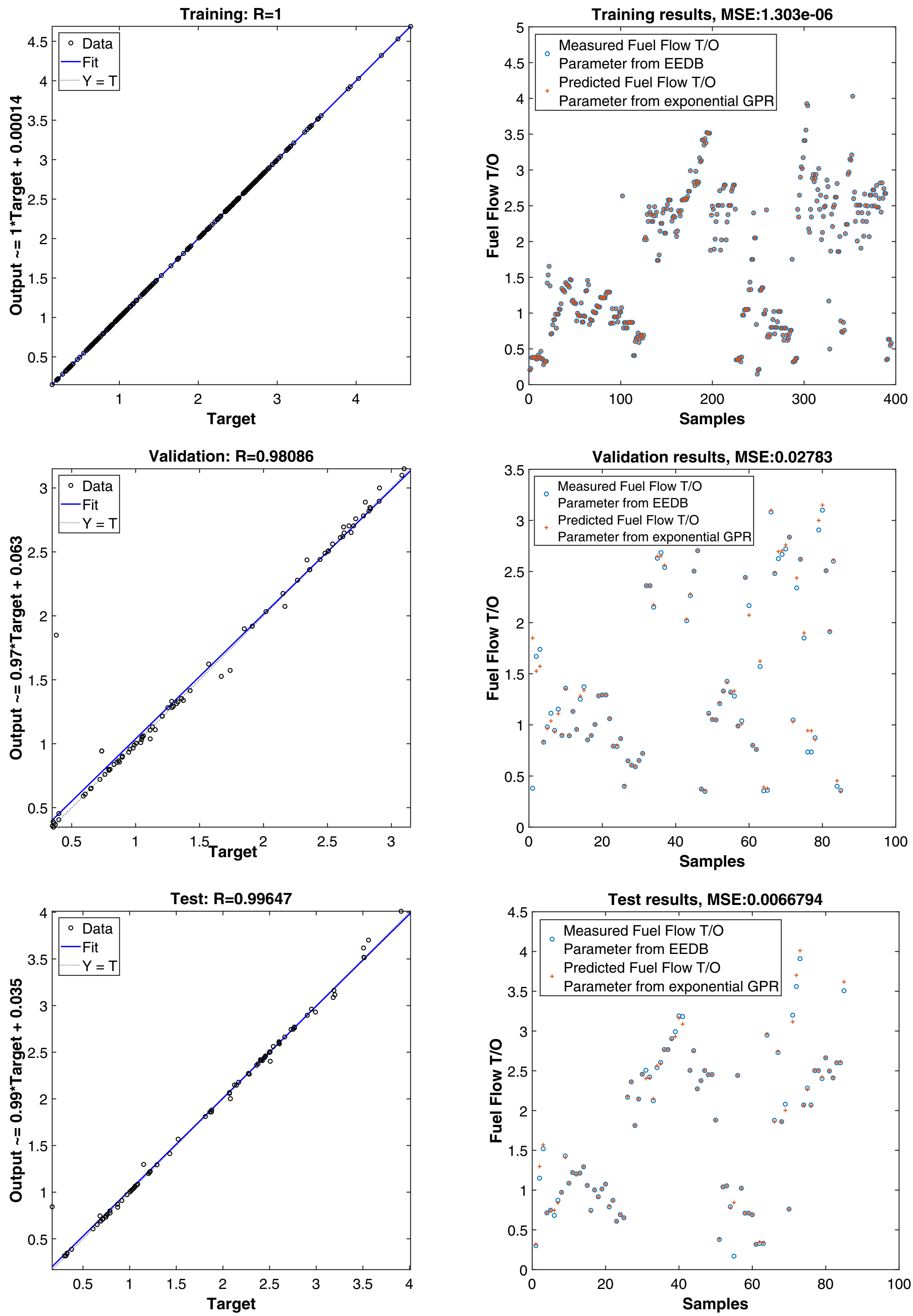


Fig. 6 Regression and MSE plots of the exponential GPR model

Table 11 Structural information of the exponential GPR model

Model type	Exponential GPR				
Property	Basis function	Kernel scale	Sigma	Beta	Optimizer
Value	Constant	Auto	0.0096	1.7404	Quasinewton

Table 12 Comparison of SVM models according to MSE values in the test group

Kernel function	*R*			MSE		
	Training	Validation	Test	Training	Validation	Test
Quadratic SVM	0.99655	0.97499	0.99709	0.00646	0.04503	0.00542
Cubic SVM	0.99624	0.48859	0.99459	0.00717	1.46345	0.01016
Linear SVM	0.98939	0.98859	0.98906	0.02005	0.01735	0.02062

better than the other models. The performance graphs of model 1 are shown in Fig. 9. Also, information about the structure of the selected multilayer perceptron model is shown in Table 15 and Fig. 8.

3.4 Comparison of the three models

In order to estimate the fuel flow *T*/*O* parameter during the takeoff phase of aircraft engines using the EEDB (09/2019) data set, 565 data consisting of 7 input parameters were used. 15% of this data is allocated for validation, 15% for testing and 70% for training. In order to obtain the best result, different models were developed with machine learning methods MLP, SVM and GPR. Among the 3 learning models, the best developed model was selected. The comparison between the models was made according to the MSE error performance criterion. According to these results, the best SVM model is Quadratic SVM, the best GPR model is Exponential GPR and the best MLP model is model 1 trained with "trainlm." The same data sets were used for the modeling.

In order to select the model that best predicts the fuel flow *T*/*O* parameter, it is necessary to compare the different machine learning models developed. The results obtained from all three models are compared according to MSE, MAE and MAPE criteria. In all models, ambient humidity, engine type, ambient baro, rated output, ambient temperature, bypass ratio and press ratio parameters were used as inputs and fuel flow *T*/*O* parameter was estimated at the output. The error performance values of the developed models are presented in Table 16.

In Table 16, the exponential GPR model performs the best with the lowest values of MSE (1.3029736e−06), MAE (5.33330e−04) and MAPE (0.035374%) for the training set. The MLP model also performs well, but has higher error rates than the Exponential GPR model (MSE: 0.0016894, MAE: 0.00260, MAPE: 2.113601%). Quadratic SVM has higher error rates compared to the other two models (MSE: 0,0064694, MAE: 0,06229, MAPE: 5,385750%).

For the validation set, the MLP model performs the best with the lowest values of MSE (0.0042769), MAE (0.0427) and MAPE (3.524579%). Exponential GPR model ranks second (MSE: 0.0278303, MAE: 0.042242, MAPE: 6.688691%). Quadratic SVM has the highest error rates (MSE: 0.0450386, MAE: 0.084739, MAPE: 10.415391%).

For the test set, the best performing model is the multilayer perceptron model. This model predicted with the lowest error with MSE (0.0025488), MAE (0.0314) and MAPE (2.215001%). Exponential GPR model is in second place (MSE: 0.0066794, MAE: 0.025113, MAPE: 5.725879%). Quadratic SVM model again has the highest error rates (MSE: 0.0054221, MAE: 0.059196, MAPE: 4.909031%).

As a result, the MLP model performs best on the validation and test data sets, while the Exponential GPR model performs best on the training data set. Quadratic SVM model has the highest error rates in all data sets and performs lower than the other two models. When the results are evaluated, it appears that the multilayer perceptron model can estimate the fuel flow *T*/*O* parameter with low error with a MAPE value below 5% in all data sets.

In the training, testing and validation phases of the best predicting MLP model, 565 engine data from 2019 (EEDB-09/2019) were used. It is necessary to test the reliability and performance of the developed MLP model. For this purpose, 773 aircraft engine data for 2021 (EEDB-07/2021) were applied to the developed multilayer perceptron model. The error performance results obtained when the EEDB data sets of 2019 and 2021 are applied to the developed MLP model are presented in Table 17. When the results are evaluated, it appears that the MAPE value is less than 3% for both data sets. According to Lewis, models with MAPE values below 10% are classified as "very good" [49].

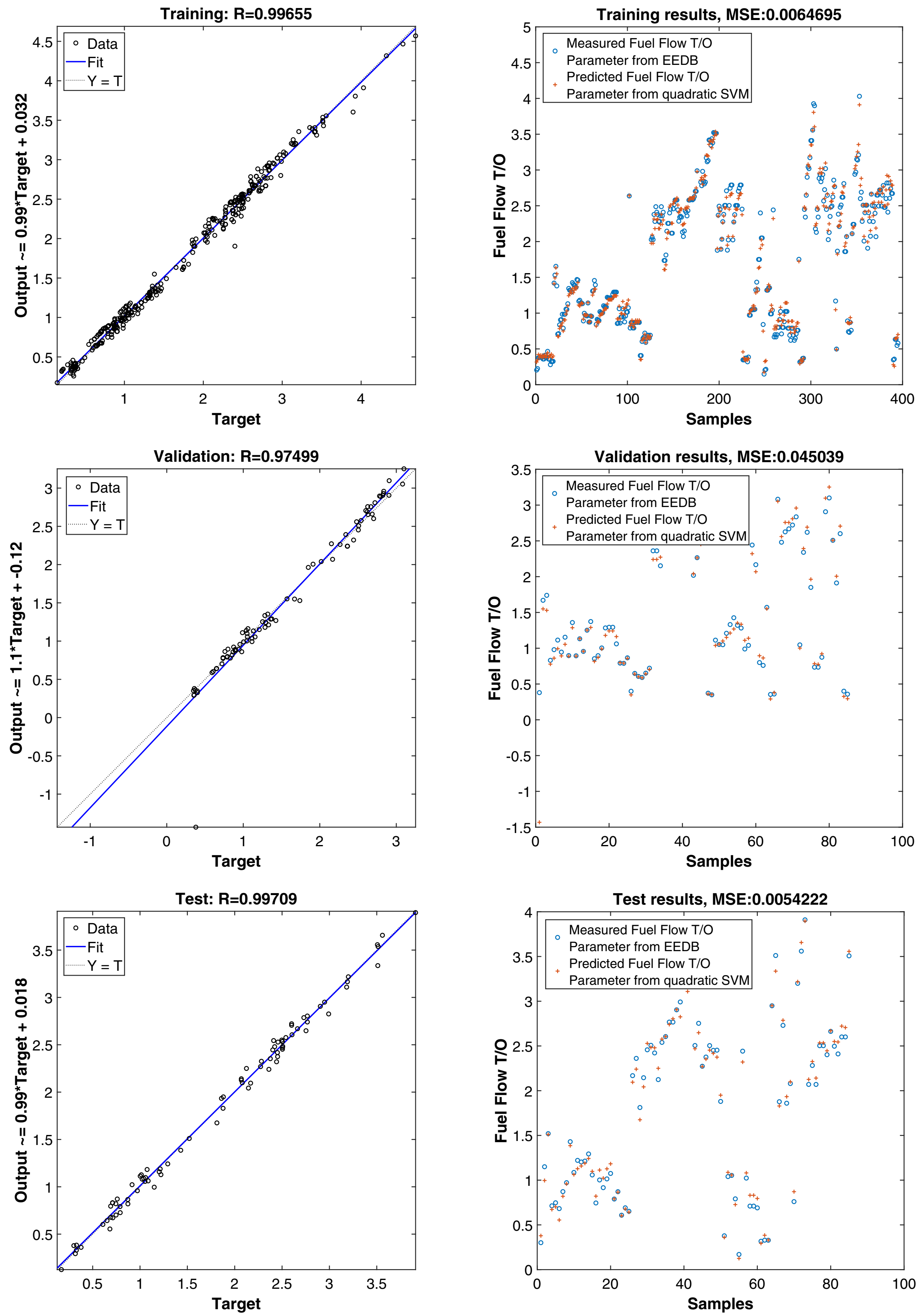


Fig. 7 Regression and MSE plots of quadratic SVM model

Table 13 Structural information of the quadratic SVM model

Model type	Quadratic SVM				
Property	Function	Kernel scale	Box constraint	Bias	Epsilon
Value	Polynomial	Auto	1.2076	1.7458	0.1208

Table 14 Comparison of MLP models according to MSE values in the test group

Training algorithm	*R*			MSE		
	Training	Validation	Test	Training	Validation	Test
Model 1 “trainlm”	**0.9991**	**0.9970**	**0.9986**	**0.00168**	**0.00427**	**0.0025488**
Model 2 “trainlm”	0.9972	0.9949	0.9973	0.00486	0.00980	0.0054989
Model 3 “trainlm”	0,9970	0.9952	0.9972	0.00822	0.01097	0.0056239
Model 4 “trainrp”	0,9964	0.9945	0.9961	0.00682	0.00839	0.0057155
Model 7 “traincgb”	0,9973	0.9629	0.9967	0.00454	0.08982	0.0064497
Model 5 “trainrp”	0.9971	0.9961	0.9952	0.00538	0.00591	0.0079494
Model 6 “trainrp”	0.9930	0.9928	0.9956	0.01277	0.01067	0.0085341
Model 8 “traincgb”	0.99179	0.99458	0.99469	0.01406	0.01494	0.01059
Model 9 “traincgb”	0.99367	0.99462	0.99115	0.01101	0.00969	0.017282

Traincgb: Conjugate gradient backpropagation with Powell–Beale restarts; Trainlm: Levenberg–Marquardt backpropagation; Trainrp: resilient backpropagation

MAPE: 2.113601%, MAPE: 3.524579%, MAPE: 2.215001%

Table 15 Structural information of the multilayer perceptron model

ANN	Details		
Layers	Input	Hidden	Output
	7	10-8-4-3	1
The ICAO Aircraft Engine Emission Databank	Training set (70%)	Validation (15%)	Test (15%)
	395 sample	85 sample	85 sample
Activation	’tansig’ - ’logsig’ - ’tansig’ - ’purelin’		
	Hidden layer (10-8-4-3)		
Function	Linear		
	Output layer		
Training algorithm	’trainlm’		

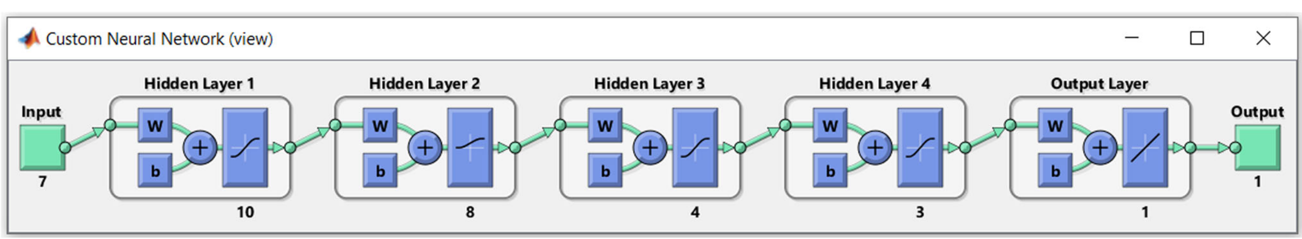


Fig. 8 Screenshot of the MLP model in MATLAB environment

Table 16 Comparison of error performance values of the developed models

Data sets	Models	MSE	MAE	MAPE
	Exponential GPR	**1.3029736e−06**	**5.33330e−04**	**0.035374%**
Training	MLP	0.0016894	0.00260	2.113601%
	Quadratic SVM	0.0064694	0.06229	5.385750%
	MLP	**0.0042769**	**0.0427**	**3.524579%**
Validation	Exponential GPR	0.0278303	0.042242	6.688691%
	Quadratic SVM	0.0450386	0.084739	10.415931%
	MLP	**0.0025488**	**0.0314**	**2.215001%**
Test	Quadratic SVM	0.0054221	0.059196	4.909031%
	Exponential GPR	0.0066794	0.025113	5.725879%

MAPE: 2.113601%, MAPE: 3.524579%, MAPE: 2.215001%

Table 17 Error performance values of the MLP model in two data sets

Data group	Size	MAE	MSE	R	MAPE (%)
EEDB (09/2019) (gaseous emissions and smoke)	565 × 8	0.0294	0.0022	0.99878	2.341126
EEDB (07/2021) (gaseous emissions and smoke)	773 × 8	0.0298	0.0219	0.98839	2.897489

Table 18 Confidence interval values

Levels (%)	$z_{\frac{\alpha}{2}}$	$1-\alpha$
99	2.58	0.99
95	1.96	0.95
90	1.645	0.90

3.5 Determination of confidence interval values for engine performance degradation detection

For a parameter, a single number can be estimated as well as a range estimate. With the confidence levels specified in Table 18, the determination of the smallest numerical value and the maximum numerical values that the parameter can take is called interval estimation. The higher the confidence levels, the more reliable the estimate. The formula used to determine the minimum and maximum numerical values in confidence intervals is Eq. 8 is shown in [50]. The fuel flow *T/O* parameter value of the aircraft is expressed as $FF_{T/O}$. The fuel flow *T/O* parameter got from the MLP model is expressed as $ff_{T/O}$, nth sample size, $z_{\frac{\alpha}{2}}$ critical value and σ standard deviation.

$$ff_{T/O} - z_{\frac{\alpha}{2}}\frac{\sigma}{\sqrt{n}} < FF_{T/O} < ff_{T/O} + z_{\frac{\alpha}{2}}\frac{\sigma}{\sqrt{n}} \quad (8)$$

To interpret the performance of the aircraft engine, if the fuel flow *T/O* parameter value taken from the engine emission databank is within the confidence intervals, it means that the aircraft engine performance is good. If it falls outside this confidence interval, it is considered as an anomaly. In this model, the confidence level is calculated as 99%. With the algorithm made in MATLAB® software, the performance of all engines in the takeoff phase was evaluated for all engines in 2 data sets [16, 38]. The evaluation results are shown in Figs. 10 and 11.

4 Conclusions

In this study, EEDB data sets for 2019 and 2021 were used to estimate the fuel flow *T/O* parameter. Ambient humidity, engine type, ambient baro, rated output, ambient temperature, bypass ratio and press ratio are selected as input parameters. When the input parameters are applied to the developed MLP, SVM and GPR models, the fuel flow *T/O* parameter is estimated. The prediction results are compared with the actual results and the relationship between the models is analyzed. EEDB (09/2019) set was used to train, validate and test all models.

Quadratic SVM model was found to predict with less error than cubic SVM and linear SVM (see Table 12). Also, the exponential GPR model gave better results than the rational quadratic GPR and squared exponential GPR (see Table 10). Finally, model 1 trained with "trainlm" was found to be the best MLP model (see Table 14).

When we compare the best of SVM, GPR and MLP models, the MLP model outperformed the other models in fuel flow *T/O* prediction (see Table 17). MLP model predicted with high (R) value and low MSE, MAE and MAPE values. When 773 EEDB(07/2021) data were applied to the developed MLP model, it was seen that it was in the "very good" model class with a MAPE value of 2.89%. The confidence intervals have been created to represent the aircraft engine's performance during takeoff graphically.

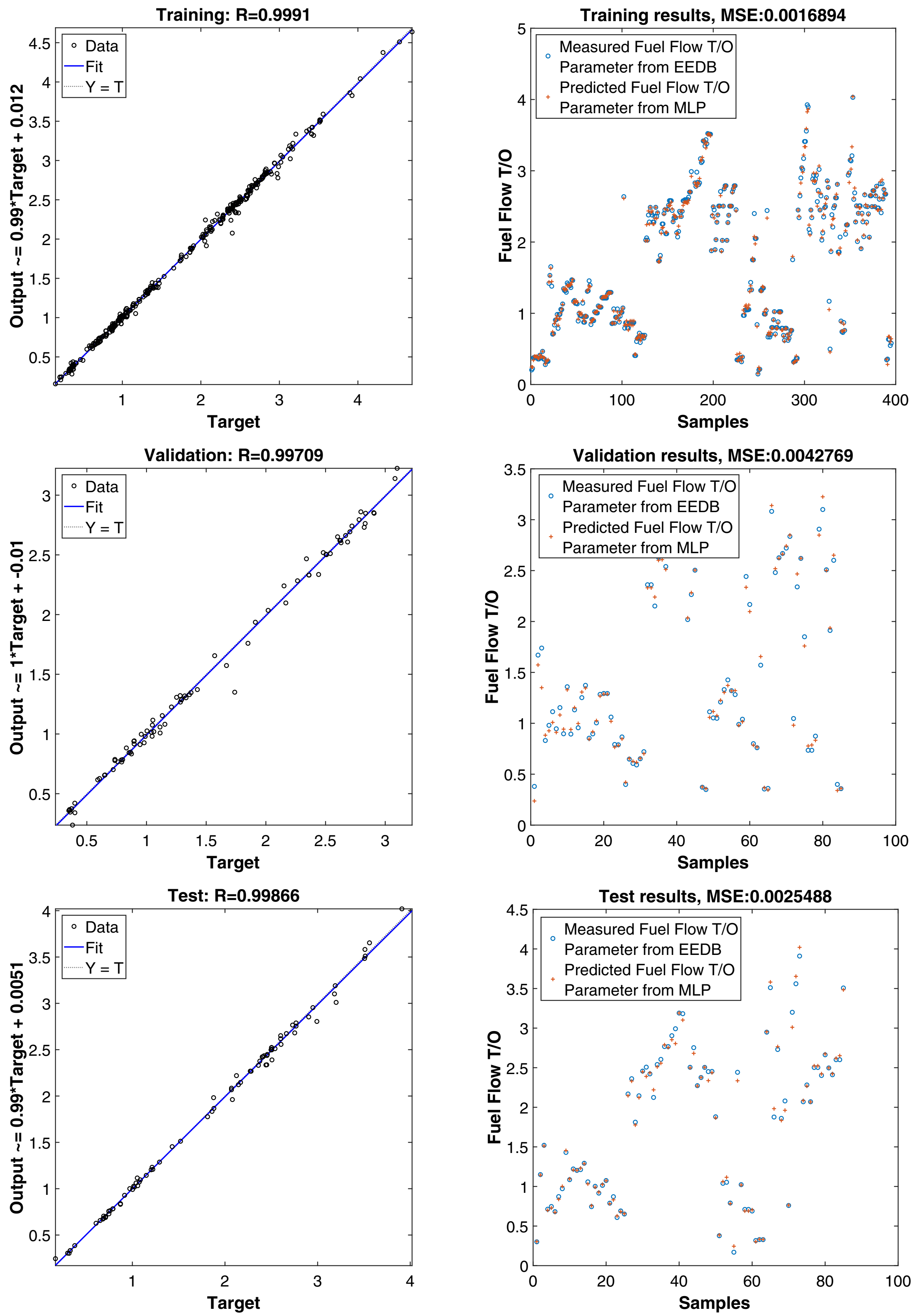


Fig. 9 Regression and MSE plots of MLP model

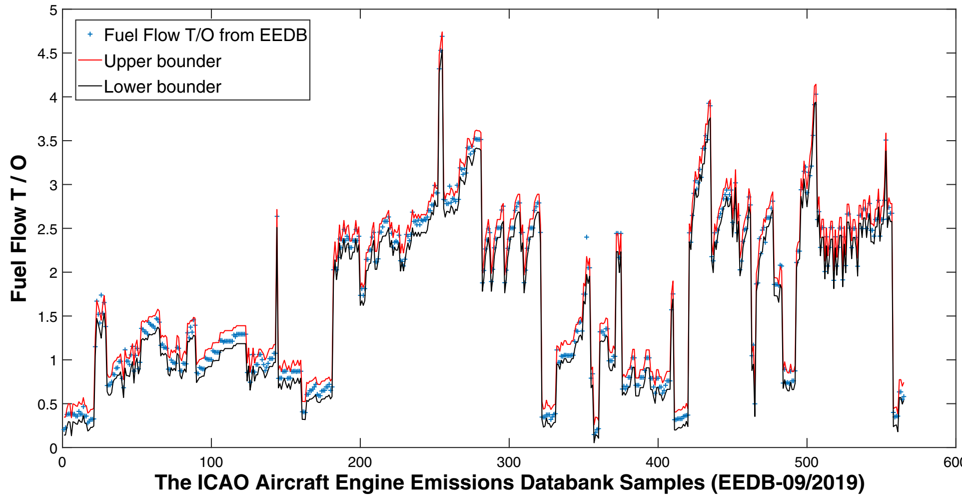


Fig. 10 Fuel flow *T/O* parameters with confidence intervals 99% (EEDB-09/2019)

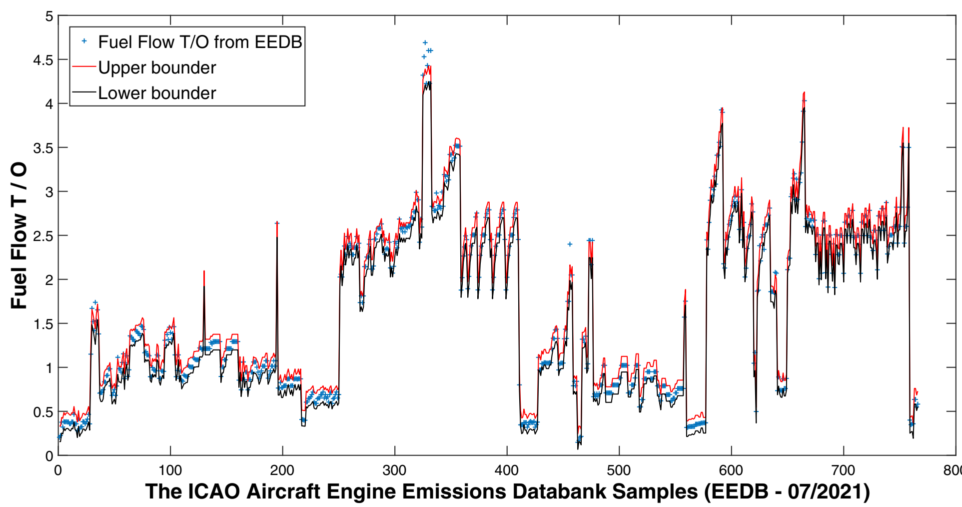


Fig. 11 Fuel flow *T/O* parameters with confidence intervals 99% (EEDB-07/2021)

Data from a total of 1338 engines were applied to the input of the developed model to evaluate engine performance. Figures 10 and 11 show the results obtained. Engine performance is thought usual if the fuel flow *T/O* parameter quantity is within the confidence interval. If the fuel flow *T/O* parameter quantity is external the confidence interval, the engine performance is considered as degraded. The performance degradation that has occurred or may occur during the takeoff phase of the engine can be detected without the need for expert knowledge. With the detection of performance deterioration, malfunctions that have occurred or may occur in the aircraft engine can be prevented. With the implementation of the developed model, the following problems can be reduced;

- Fuel consumption,
- Maintenance cost,
- Cost of flight,
- Accident risk,
- Harmful emissions.

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Data availability The data sets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors declare that they have no conflict of interest

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