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ORIGINAL ARTICLE

Prediction of performance degradation in aircraft engines with fuel flow parameter

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Abstract

Planned maintenance is required by licensed maintenance organizations to detect and prevent performance degradation in aircraft engines. In the literature, engine performance is evaluated with parameters that show engine performance. Fuel flow parameter is one of the important parameters that shows engine performance. In the models developed earlier, no engine performance evaluation was made with the fuel flow parameter at all stages from the take-off to the landing of the aircraft. In this study, fuel flow parameter is estimated with over 99.9% accuracy by using artificial neural network in MATLAB® software. In order to detect the engine performance deterioration of the aircraft, the fuel flow values obtained from the artificial neural network and confidence intervals with 99% confidence level were established. Each value taken from the fuel flow sensor is evaluated by the model in all flight phases. In the model, engine performance is considered normal if the fuel flow value is within the confidence interval, and abnormal (anomaly) if it is outside the confidence interval. An accuracy of over 99.9% was achieved and results of this study showed that fuel flow rate of the engine of interest was within the confidence interval (no performance deterioration).

Keywords Artificial neural network · Confidence bounds · Performance degradation · Fuel flow rate

Abbreviations

ANN	Artificial neural network
CAS	Calibrated airspeed
DADC	Digital air data computer
EGT	Exhaust gas temperature
EIS	Engine instrument system
EPR	Engine pressure ratio
F/F	Fuel flow
MAE	The mean absolute prediction error
MSE	The mean squared prediction error
MAPE	The mean absolute percent prediction error
RPM	Revolutions per minute
Traincgb	Conjugate gradient backpropagation with Powell-Beale restarts
Traincgp	Conjugate gradient backpropagation with Polak-Ribiére updates
Traingda	Gradient descent with adaptive learning rate backpropagation
Traingdx	Gradient descent with momentum and adaptive learning rate backpropagation
Trainlm	Levenberg–Marquardt backpropagation
Trainoss	One-step secant backpropagation
Trainrp	Resilient backpropagation
Trainscg	Scaled conjugate gradient backpropagation

1 Introduction

The thrust required for aircraft to fly safely is provided by the aircraft's engines. These engines operate at high speeds and at high temperatures. The aviation sector is a sector that grows every year and causes an increase in environmental pollution [1]. There are many different damages caused by the aviation industry to the environment. Carbon dioxide (CO_2), nitrogen dioxide (NO_x) and other greenhouse gases released into the atmosphere during long-haul flights cause global climate change [2]. Exhaust gases from airplanes increase air pollution [3]. Fuel, oils, chemicals and other dangerous substances released during aircraft maintenance leak into the soil and cause pollution [4]. Airplanes create noise pollution around the airport during

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the landing and take-off processes [5]. The aviation authority ICAO aims to reduce the environmental damage caused by aircraft during flight operations [6]. Although aircraft engines consist of parts produced with advanced technology, wear and tear can be seen in these engine parts over time. Engine performance may deteriorate due to wear, breakage or aging of engine parts. Figure 1 shows sample defective engine parts that may cause deterioration of engine performance. In addition to the damage caused by normal airplanes to the environment, the following results may occur in an airplane with poor engine performance;

- It causes an increase in the damage caused by airplanes to the environment.
- The safety of the aircraft is adversely affected.
- It affects the performance of the aircraft in flight stages such as acceleration, climb, cruise and landing.
- It increases fuel consumption.
- Aircraft maintenance costs increase.
- It may cause accident and loss of life.

The aviation authority has made it mandatory to carry out maintenance on aircraft engines by licensed maintenance organizations in order to reduce the damage caused by aircraft engines to the environment. Table 1 shows the maintenance strategies used to increase the safety and reliability of aircraft. Maintenance is done for an engine to perform its functions for a certain period of time. Maintenance planning is required to prevent malfunctions or performance deterioration in engines. Planned maintenance is divided into two groups as predictive maintenance and preventive maintenance. Maintenance organizations check all parts and systems on certain dates. In preventive maintenance, operations such as lubrication, part replacement and control are performed periodically.

Fig. 1 Engine parts of a deteriorated aircraft engine

Monitoring the operation of a system in real operating conditions, recording and evaluating its data is called predictive maintenance [8]. Predictive maintenance is a technology used in aircraft and increases the safety and efficiency of aircraft [9]. Instant data can be collected from aircraft systems and engines by means of sensors. The performance of the aircraft is revealed by evaluating the data obtained by software and experts. For the evaluation of aerodynamic performance in commercial aircraft [10]; EGT [11], EPR [12], fuel flow [13], throttle position [14] and engine RPM [15] are monitored. In order to evaluate the mechanical performance of commercial aircraft, parameters such as oil [16] and vibration [17] are monitored. Predictive maintenance offers a more effective and efficient maintenance approach instead of pre-programmed periodic maintenance on aircraft.

In the evaluation of the condition of aircraft engines, the data of the flight of the aircraft are used. In the literature, there are different works on the fuel consumption and fuel flow of aircraft engines. Trani et al. estimated fuel consumption by using the performance data of the Fokker-100 aircraft in the artificial neural network model [18]. Khadilkar and Balakrishnan studied the fuel consumption of the aircraft while taxiing, using the data obtained from the flight data recorder [19]. Turgut et al. investigated the relationship between fuel flow parameter and true air speed, mass and altitude using the data from the cruise phase of the aircraft [20]. Baklacioglu estimated fuel flow rate using real flight data of an aircraft with an optimized neural network model [21]. Oruc et al. developed the first model to estimate the fuel flow rate using the cuckoo search algorithm for the descent phase [22]. Kayaalp et al. modeled the combustion efficiency and exhaust emission index values of the T56-A-15 turboprop engine separately using the long short-term memory method [23]. Işık et al. estimated thrust parameters and fuel flow parameters in unmanned aerial vehicles using artificial neural networks [24]. In the literature, there are various studies for artificial intelligence-based engine condition monitoring, fault prediction and detection [10, 25, 26].

Despite the developments in the aviation industry in recent years, there is no system that can evaluate engine performance by using the fuel flow parameter without expert knowledge at all stages from take-off to landing. The aim of this study is to develop a model that can evaluate engine performance using the fuel flow parameter and display the result graphically. With this model, potential problems can be detected earlier, without aircraft accidents or breakdowns, preventing unplanned maintenance requirements. Also, airplanes stay on the ground less and have more flight time. By detecting engine performance deterioration, the damage caused by the aircraft to the environment, fuel consumption and maintenance costs

Table 1 Most common maintenance strategies [7]

Method	Theory	Data
Corrective maintenance	*Reactive-based *Fail and fix *Unscheduled	No data
Preventive maintenance	*Time-based *Prevent strategy *At regular intervals	Failure user/Event/Time-based data
Predictive maintenance	*Condition-based *Predict and prevent strategy *Just-in-time	Necessary metrics and software to evaluate the performance of the system

are reduced, while the performance, safety and reliability of the aircraft increase.

In this study, real aircraft data including all flight phases from takeoff to landing of an aircraft were used. The aim of the paper is to assess the engine performance of the aircraft in all flight phases using the fuel flow parameter with a new model, which previous studies lack of. The importance of the fuel flow parameter is shown in Table 2. Normalization was not performed on the data set obtained from the aircraft. When the thrust lever angle left, engine N2 left, altitude, thrust lever angle right, total air temperature, engine exhaust gas temperature (EGT) left, engine N1 left, airspeed and engine N1 right parameters in the data set are applied to the developed artificial neural network model, the fuel flow right parameter is predicted with over 99.9 percent accuracy. In order to assess the engine performance of the aircraft, 99% confidence intervals were created with the fuel flow values obtained from the artificial neural network. In all flight phases, engine performance is evaluated by comparing each value taken from the fuel flow sensor with the confidence interval. The structure chart of the article is shown in Fig. 2.

The rest of this paper are organized as follows. In Chapter 2, information is given about the data set, methods and analyzes used in the developed model. Finally, the results are evaluated in Chapter 3.

2 Model development method

Increasing aircraft safety and reliability is one of the most important issues of today and the future. In this study, real data recorded during the flight of airplanes were used. It is aimed to develop a model that can evaluate the performance of the engine without the need for expert knowledge or hardware.

The details of the model developed for the detection of engine performance deterioration are explained in this section. This section consists of 4 subsections. In Sect. 2.1, the data set obtained from the Boeing 737-500 flight was used. Fuel flow parameter and 9 parameters associated with this parameter were selected from the data set. The statistical results of the data sets to be used in the model are presented in Tables 3 and 4 In Sect. 2.2, a brief information about artificial neural networks is given. In Sect. 2.3, the detailed structure of the artificial neural network model that estimates the fuel flow parameter, which allows us to detect the engine performance deterioration, and the estimation results of the model are given. Finally, Sect. 2.4 describes how to obtain confidence intervals to evaluate engine performance.

2.1 Data

Flight data recorder (FDR) is an important tool used in aviation industry to investigate accidents and incidents, to

Table 2 Faults that cause the fuel flow parameter to change in gas turbine engines [27]

	Surge	Engine separation	Seizure	Severe damage	Flame out	Fire	Fuel control problems	Fuel leak
Fuel flow change	–	+	–	–	+	–	–	+

–: Symptom possible

+: Symptom very likely

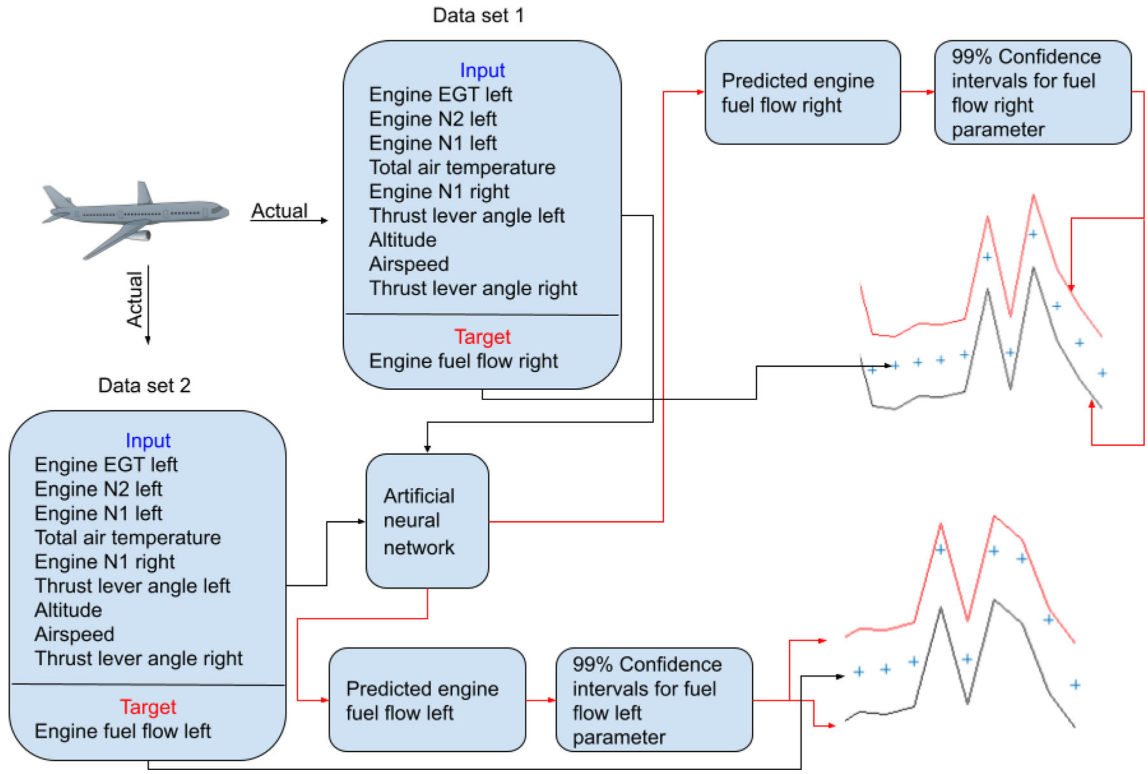

Fig. 2 The structure flow chart of the article

Table 3 Data set 1 for fuel flow right parameter

Parameters	Descriptive statistics			
	Sample	Min	Max	Mean
ENGINE EGT LEFT (EIS)	63	3800.00	7910.00	5475.0000
ENGINE N2 LEFT (EIS)	63	365.00	956.00	803.4603
ENGINE N1 LEFT (EIS)	63	103.00	921.00	599.6984
TOTAL AIR TEMPERATURE	63	− 313.00	548.00	− 88.8413
ENGINE N1 RIGHT (EIS)	63	210.00	920.00	598.0159
THRUST LEVER ANGLE LEFT	63	0.00	464.00	202.4127
ALTITUDE	63	− 328.00	31,968.00	17,275.9365
AIRSPEED (CAS) (DADC)	63	45.00	284.00	218.0635
THRUST LEVER ANGLE RIGHT	63	7.00	471.00	210.4127
ENGINE FUEL FLOW RIGHT (EIS)	63	496.00	7376.00	2286.6032

increase flight safety and to perform error analysis [28]. Recorded data includes aircraft speed, altitude, heading, engine parameters, location of control surfaces, flight system data, and other important parameters. In this study, real data of a flight obtained from the flight data recorder of Boeing 737-500 aircraft were used. The fuel flow parameter value is measured every 60 s during flight. In airplanes, fuel flow right and fuel flow left parameters are recorded with 2 different names. Two separate data sets were created without changing the values of these data. Statistical values of 9 parameters affecting fuel flow right parameter in Table 3, and fuel flow left parameter in Table 4 are shown. The data set shown in Table 3 was used to training, test, and validate the neural network. It was used to show the accuracy of the model developed with the data set shown in Table 4.

2.2 Artificial neural network

Artificial neural networks are used today as an information processing technology developed by being influenced by the working system of the human brain [29, 30]. With the data collected from the physical field, real-time results can

Table 4 Data set 2 for fuel flow left parameter

Parameters	Descriptive statistics			
	Sample	Min	Max	Mean
ENGINE EGT LEFT (EIS)	63	3800.00	7910.00	5484.5238
ENGINE N2 LEFT (EIS)	63	428.00	956.00	803.7302
ENGINE N1 LEFT (EIS)	63	135.00	921.00	598.1905
TOTAL AIR TEMPERATURE	63	− 315.00	585,00	− 88.0159
ENGINE N1 RIGHT (EIS)	63	211.00	921.00	596.2857
THRUST LEVER ANGLE LEFT	63	0.00	464.00	204.5397
ALTITUDE	63	− 328.00	31,968.00	17,278.2222
AIRSPEED (CAS) (DADC)	63	45.00	284.00	217.8730
THRUST LEVER ANGLE RIGHT	63	7.00	471.00	212.6508
ENGINE FUEL FLOW LEFT (EIS)	63	504.00	7144.00	2256.3810

be obtained by using artificial neural network models [31]. The ANN generally consist of 3 layers as input, hidden and output. The structure of the multilayer ANN is shown in Fig. 3. In ANN, changes are made in the form of the model and training functions in order to obtain the requested results. It is operated and controlled by different sensors in order for the aircraft to fly safely. Large amounts of data can be obtained with sensors. These obtained data are used for condition monitoring and fault prediction. In ANN models, data are applied to the input layer. The data represent weights for w_{k1}, w_{k2},..., w_{kn}. The inputs are summed with the aggregation function. It is transmitted to the last layer via the activation function. The result is obtained from the ANN.

2.3 Estimating the fuel flow parameter with the ANN model

In order to evaluate the engine performance, the fuel flow parameter value must be estimated with high accuracy in all phases of the aircraft from takeoff to landing. Real flight data records of Boeing 737-500 aircraft are used to develop the ANN model that estimates the fuel flow parameter. Statistical information about the data used in the paper is given in Table 3. In this data set, thrust lever angle right, thrust lever angle left, total air temperature, engine exhaust gas temperature (EGT) left, engine N1 left, airspeed, engine N2 left, altitude and engine N1 right parameters were determined as input parameters. When data are applied to the input of the ANN, the engine fuel flow right parameter is estimated at the output. ANN model will be used to estimate the fuel flow parameter. In the MATLAB® software, the data shown in Table 3 were randomly divided into 3 groups with the "dividerand" command. 45 samples were used for training the ANN model, 9 samples were used for testing the ANN model and 9 samples were used for the validity of the ANN model. To estimate the fuel flow parameter with high accuracy, many models with different architectures and training functions have been developed in the MATLAB® software. The results of 8 training functions, which are among the models that best predict the fuel flow right parameter, are shown in Table 5.

Fig. 3 Diagram of a multilayer neural network

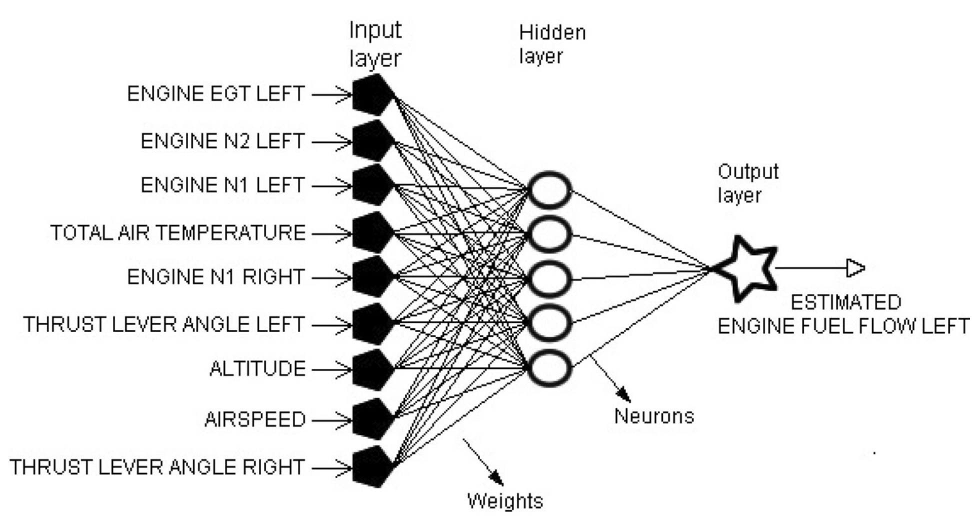

Table 5 Comparison of the ANN training algorithms

Training function	R		
	Training	Validation	Test
Trainlm	0.999	0.999	0.999
Traingdx	0.992	0.996	0.996
Trainoss	0.996	0.997	0.995
Traincgp	0.992	0.972	0.991
Traingda	0.942	0.948	0.988
Trainrp	0.919	0.977	0.971
Traincgb	0.992	0.933	0.970
Trainscg	0.917	0.957	0.959

When Table 5 is analyzed, it is seen that the ANN model trained with the training function "trainlm" gives the best results.

The correlation coefficient (R) shown in Table 5 reveals the degree of relationship between the mathematically predicted fuel flow parameter and the actual fuel flow parameter. In the performance evaluation with the correlation coefficient (R), it is desired that the result be close to the value of "1". In the performance evaluation with the correlation coefficient, the model whose result is the closest to one is the best. The validation, test and training graphs of the best model estimating the fuel flow right parameter are shown in Figs. 4, 5, and 6.

Information on the architectural structure of the developed ANN is shown in Table 6. The screenshot of the ANN model in MATLAB® software is shown in Fig. 7. When the graphics of the model estimating the fuel flow parameter are examined, it is seen that it has a high accuracy in the training, testing and validation stages.

Error performance models used in the literature were applied to evaluate the performance of the ANN model [32]. Table 7 shows the error results between the measured fuel flow right parameter and the estimated fuel flow parameter values for the validation, testing and training phases. In order to test the validity of our model, the data set of the fuel flow left parameter, which was never used in the training of the developed model, was used. Statistical information about these data is given in Table 4. The results of the ANN model for the fuel flow left parameter are shown in Table 7. When the performance results are examined, it is seen that the developed ANN model can predict the fuel flow parameter with an accuracy of over 99.9%. According to Lewis, prediction models with a mean absolute percent prediction error (MAPE) value below 10% are classified as very good [33]. When the results of the developed model are examined, it is seen that it can predict very well. The mathematical expressions of the error performance methods used are mean absolute prediction error (MAE), mean squared prediction error (MSE) and mean absolute percent prediction error (MAPE). In Eqs. (1), (2), and (3), the estimated value is called FF, the number of samples is called n and the actual value is called ff.

$$\mathrm{MAE} = \frac{1}{n}\sum_{k=1}^{n} |\, ff - FF \,| \tag{1}$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{k=1}^{n} (ff - FF)^2 \tag{2}$$

$$\mathrm{MAPE} = \frac{100}{n}\sum_{k=1}^{n} \left| \frac{ff - FF}{ff} \right| \tag{3}$$

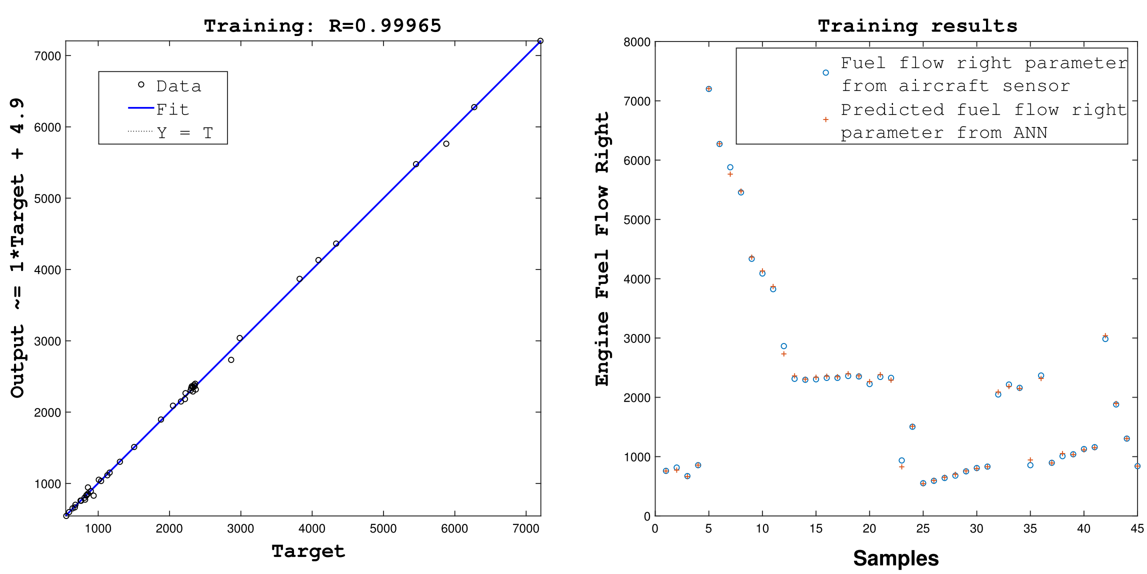

Fig. 4 Performance of the ANN results in the training phase

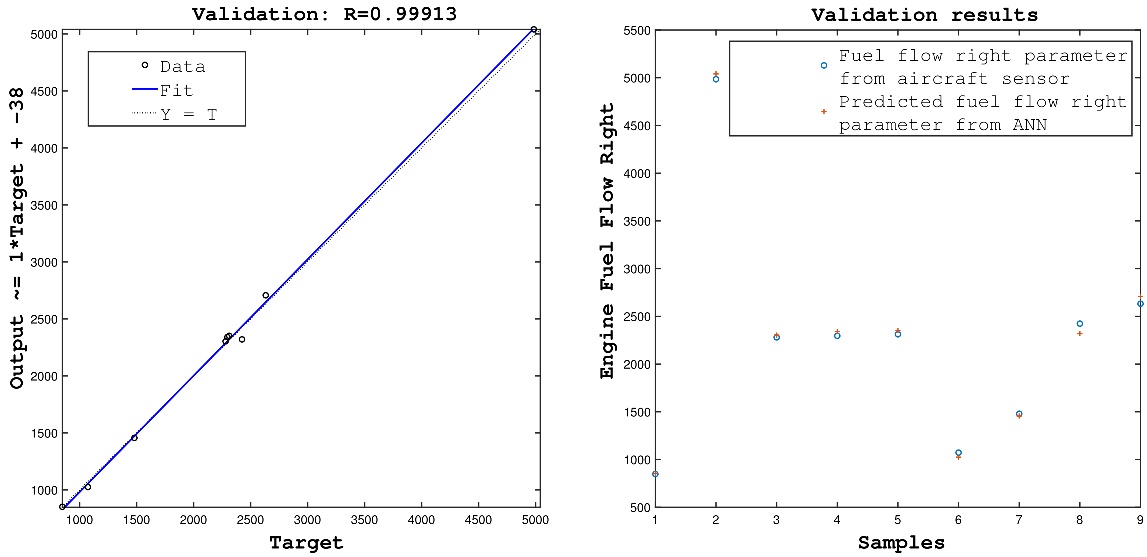

Fig. 5 Performance of the ANN results in the validation phase

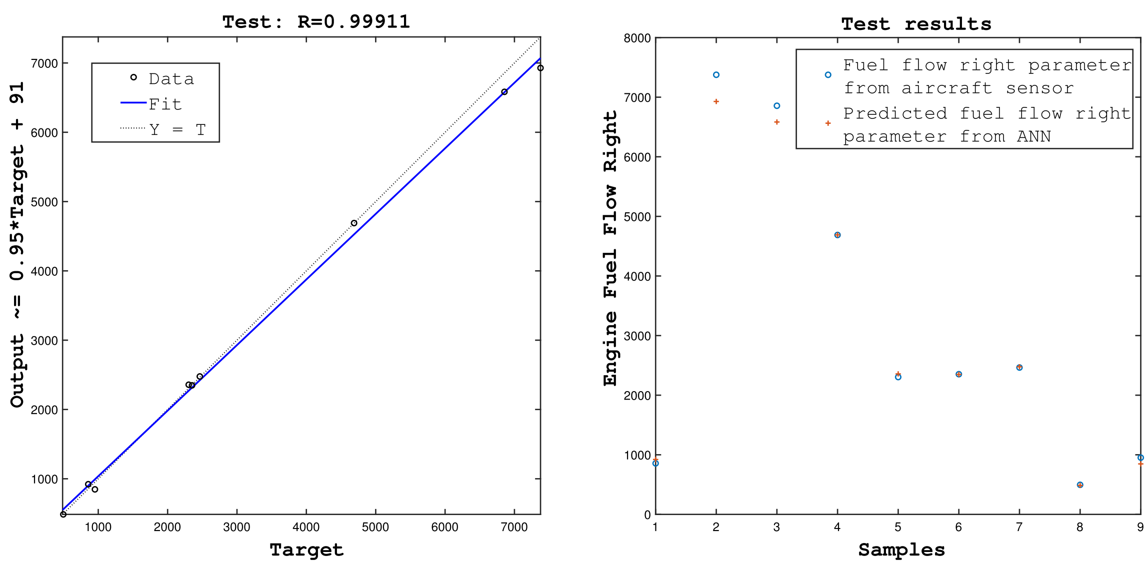

Fig. 6 Performance of the ANN results in the test phase

Table 6 Details of the trained neural network model

ANN model	Details		
Architecture	Input	Hidden layer	Output layer
	7	8 11 7 5	1
Set	Training (70%)	Validation (15%)	Test (15%)
	45	9	9
Activation	Hidden layer		
	‘tansig’, ‘logsig’, ‘tansig’, ‘purelin’		
Function	Output layer		
	Linear		
Training algorithm	Levenberg–Marquardt ‘trainlm’		

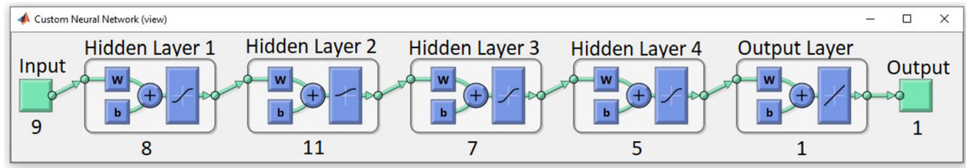

Fig. 7 View of the trained ANN in MATLAB® software

Table 7 Error performance results of the developed ANN model

Trained neural network	Sample	R	MAE	MSE	MAPE %
Fuel flow right (Data set 1)					
Train	45	0.999	29.074	1787.2	1.74
Validation	9	0.999	46.502	2948.7	2.16
Test	9	0.999	107.909	32,564	3.74
Fuel flow left (Data set 2)	63	0.998	78.554	11,502	4.09

Table 8 Confidence interval values

Confidence interval	$1-\sigma$	$z_{\frac{\alpha}{2}}$
90%	0.90	1.645
95%	0.95	1.96
99%	0.99	2.58

2.4 Detection of abnormal conditions with confidence interval estimation for fuel flow parameter

By using statistical methods, point estimation and interval estimation can be made with the data of a system. In the range estimation, the lower and upper limits number values should be determined. The interval determined using the confidence level is called the confidence interval. Confidence intervals used in the literature are displayed in Table 8 [34]. The higher the confidence interval value, the higher the reliability of the estimate. The formula used for the confidence interval is shown in Eq. 4. In the equation, fuel flow parameter obtained from artificial neural network is expressed as FF, standard deviation as σ, critical value as $z_{\frac{\alpha}{2}}$, and number of samples as n. The fuel flow value taken from the aircraft's sensor is called ff.

$$FF - z_{\frac{\alpha}{2}}\frac{\sigma}{\sqrt{n}} < ff < FF + z_{\frac{\alpha}{2}}\frac{\sigma}{\sqrt{n}} \tag{4}$$

The performance of aircraft engines can be evaluated by measurements and observations made by experts.

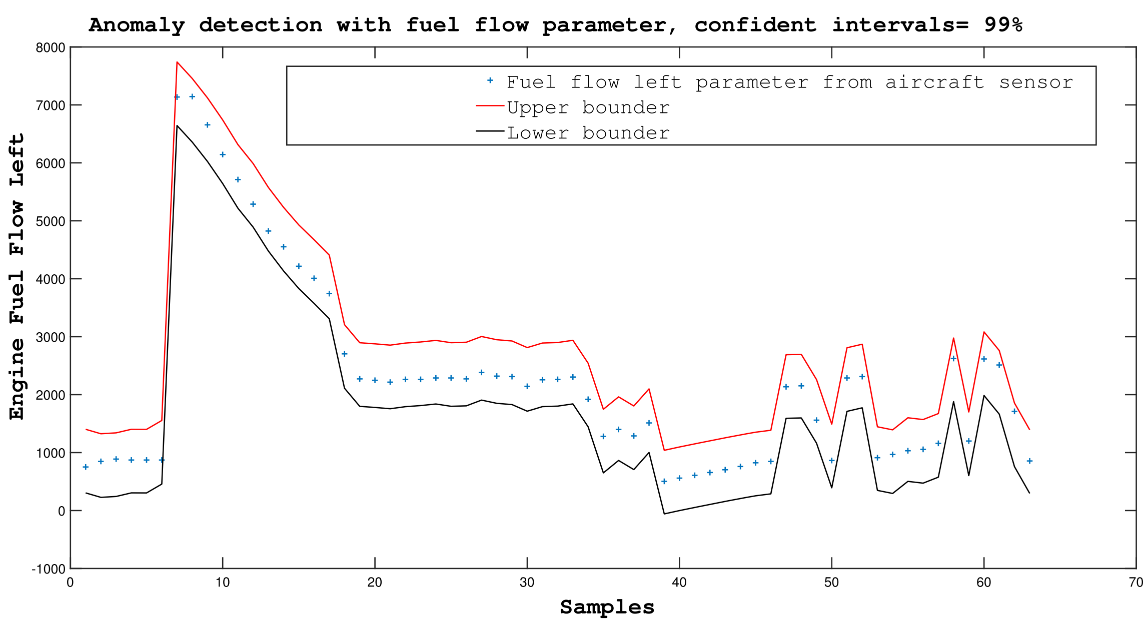

Fig. 8 Fuel Flow left parameters with confidence interval for anomaly detection

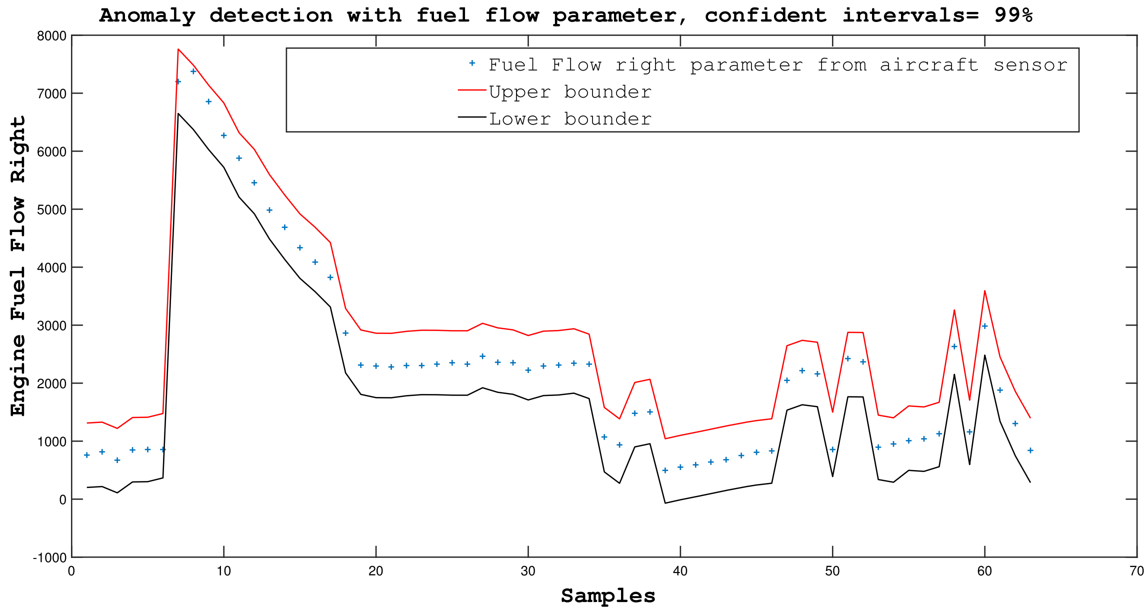

Fig. 9 Fuel Flow right parameters with confidence interval for anomaly detection

Evaluating the performance of aircraft engines with a confidence interval is a commonly used method [34]. In this paper, an ANN model was developed that predicts the fuel flow parameter with high accuracy from take-off to landing of a real airplane.

Confidence intervals were created with Eq. 4 for the fuel flow parameter in the MATLAB® software. Statistical information about the actual data used is given in Table 4. Confidence interval was calculated as 99% in the MATLAB® software. The results obtained are shown in Figs. 8 and 9. With the developed model, each fuel flow parameter recorded from the aircraft's sensor has been evaluated.

3 Conclusions

Engine performance may also deteriorate due to environmental effects and harsh operating conditions in airplanes. Performance degradation in aircraft engines has a variety of consequences. One of these consequences is that the fuel flow parameter reaches unexpected values. The deterioration in the fuel flow parameter may cause the malfunctions in Table 1. In this study, data from the flight of Boeing 737-500 aircraft were used. An artificial neural network model developed in MATLAB® software has been developed. When the input data shown in Table 2 is applied to the developed model, the fuel flow right parameter can be estimated with an accuracy of over 99.9%. When the input data shown in Table 3 was applied to test the validity of the model, the fuel flow left parameter of the engine was estimated with an accuracy of over 99.8%. In the MATLAB® software, 99% confidence intervals were created with the fuel flow parameter obtained from the artificial neural network model. In the graph shown in Figs. 8 and 9, the fuel flow value obtained from sensor is between the confidence intervals, indicating that the engine performance is normal. If the fuel flow value is outside the confidence interval, it is called anomaly. Anomaly indicates that the engine performance is deteriorated. The reason for the increase in fuel consumption, maintenance costs, flight costs and fuel emissions in aircraft is the deterioration of engine performance. It has been shown that the engine performance can be easily determined with the developed model.

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Data availability The datasets 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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