Chapter

Health Monitoring of an Aircraft Fuel System Using Artificial Intelligence Techniques

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Abstract

Aircraft is a non-linear complex system and is need of regular monitoring. Integrated Vehicle Health Management (IVHM) is a process of health management paradigm, which involves system parameter monitoring, assessment of current, future conditions through diagnostic and prognostic approaches by providing required maintenance activities. Deployment of diagnostic, prognostic and health management processes enable to improve the system reliability and reduces the operating cost of the aircraft. Health monitoring and management plays a vibrant role in safe operation and maintenance of aircraft. Soft computing methodologies such as Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) are used to estimate the health status of fuel system by developing model of a typical pump feed, twin-engine, four-tank small aircraft fuel system using Simulink in the laboratory environment. The controller is designed to generate the signals of the fuel tanks based on the fuel requirement of the engine. The ANFIS based management system helps to detect the faults existing in the fuel system and diagnose those faults using the expert's logical rules. During a fault ailment, the controller's performance is evaluated. The efficacy of this intelligent controller is verified with the present fuel control system and ANN controller.

Keywords: Aircraft fuel system, Fault detection and diagnosis, Prognosis, Integrated Vehicle Health Management, Artificial Intelligence, ANN and ANFIS

1. Introduction

1.1 Health monitoring of an aircraft fuel system

In recent years significant quantity of research work have been done using Artificial Intelligence (AI) and Expert Systems (ES) to predict and estimate the faults in the system in order to investigate the complete health status of the system [1]. Soft computing technique is an intelligent computing approach which integrates the human reasoning ability with learning capability of uncertainty and imprecision of the system. The prime importance of the soft computing technique is the non-requirement of the well-defined mathematical model of the system. Therefore, soft computing is becoming more popular in the fault diagnosis and prognosis applications. The powerful machine learning techniques used for the current work are Artificial Neural Network (ANN) and Adaptive Network-based Fuzzy Inference System (ANFIS). A brief description and implementation of these techniques for fuel system health management is presented in this chapter. The general steps to determine the system health status are described as below:

i. Detecting the symptoms of faults by monitoring and analyzing

ii. Identification of the cause of faults

iii. Manual insertion of faults within the model of the system

iv. Diagnosing the effect of the fault on the system and

v. Predicting the functional behavior of the system.

Figure 1 illustrates the health management architecture of the fuel system and its diagnostic and prognostic functioning process. This architecture comprises three main functions, such as monitoring, diagnosis and prognosis. The operation of the first function is to monitor the fuel flow rate and status of its co-operating components like pumps, the quantity of fuel in each tank, valve functioning, the rate of fuel consumption by the engine. Based on the initial fuel flow rate, the rate of fuel consumed by the engine is estimated by the monitoring function. Further, the required fuel flow rate from each tank is calculated by the prediction model. An

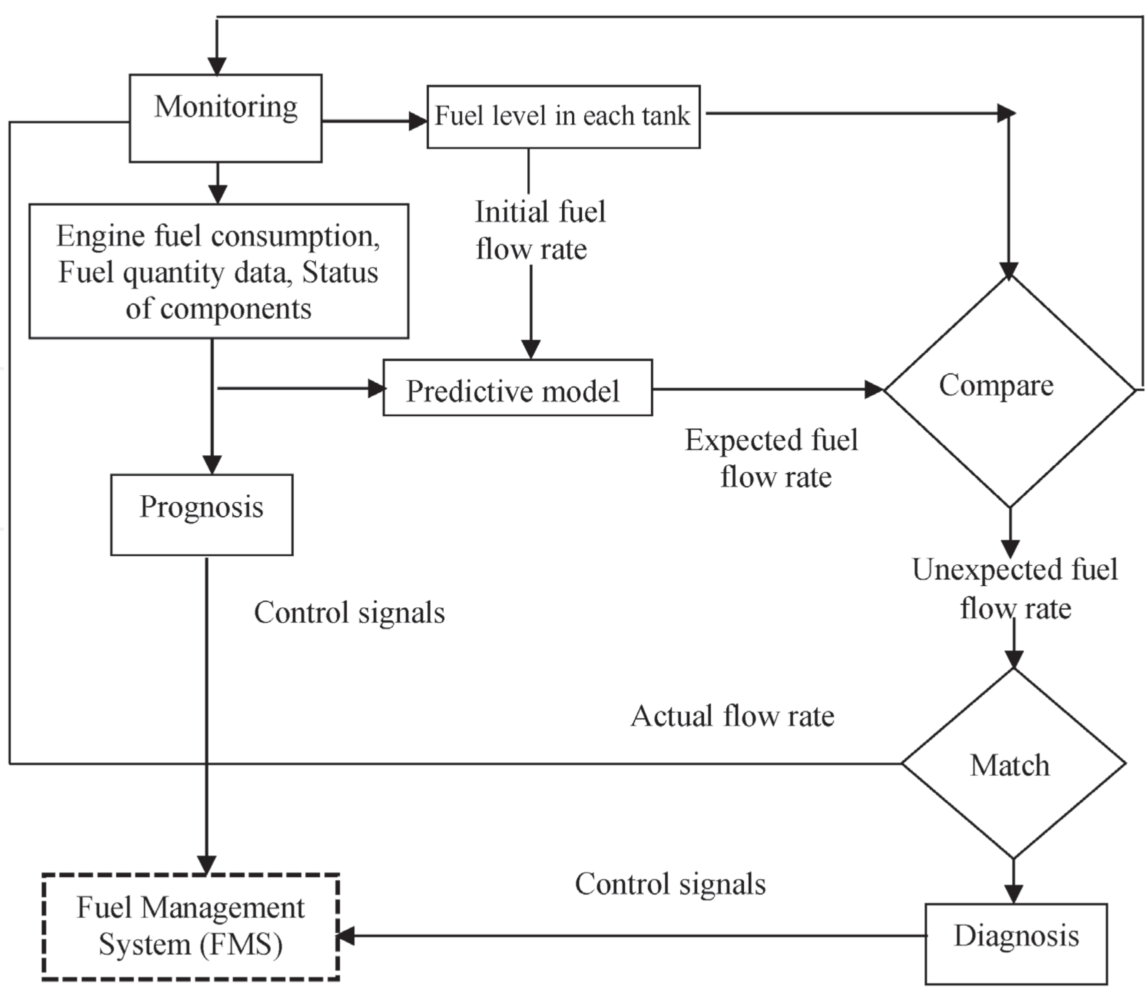

Figure 1.
Fuel system health management architecture.

artificial intelligence approach is implemented for the simulation of a typical small aircraft fuel system for fault analysis.

In the health management process initially, a comparison is done between the actual flow rate and the required fuel flow rate. If the flow rate is not in the desired range, an analysis is conducted to detect and determine the reason for this disagreement, which activates the fault analysis process. Further, it is used as the criterion of failure that leads to the diagnostic function. The prognostic function in the assumed fuel system is to forecast the fuel flow rate from each of the tanks. Thus, the monitoring function helps to predict the variations in the fuel flow rate and helps to assess the overall health status of the fuel system.

2. Literature review

Many different approaches of fault diagnosis and prognosis are demonstrated in the literature with their pros and cons and it is difficult to say which is a better approach. It depends on the type of the complex system considered to model, available expert knowledge and data. AI techniques are very effective in pattern classification, decision making, pattern recognition and problem solving *etc*. The hybrid (Neural Network with Fuzzy Systems) approach developed holds good when modeling the complex systems like aircraft and its subsystems for fault analysis and health management. The advantage of using fuzzy logic is to provide direct interpretation of human knowledge into the fault analysis process using the rules which are simple to comprehend. Further, the process of neuro fuzzy system is distributed parallel processing of data, knowledge inference matching conflict and distributed storage of diagnosis rules which help to overcome the black box limitation of a neural network. This combination provides a healthy solution for fault analysis by detecting the missed faults and decreasing the false alarms even in the presence of disturbance and changing environment of system during operation.

The combination of AI techniques with model-based approaches has excellent efficiency for fault diagnosis. ANFIS takes advantage of the learning ability of ANN and knowledge representation of Fuzzy logic systems. Implementation of ANFIS as fault diagnosis tool was reported by [2, 3]. A method for faults diagnosis of induction motors using ANFIS and regression techniques was described by [4, 5] used recurrent NN and ANFIS to forecast the crack propagation in rotating machine and provided the comparison results of both predictors. Application of prognosis in aerospace industries is an evolving arena with very a smaller number of real-time implementations. Thus, implementation of a model-based methodology with the integration of AI techniques is considered for providing better representation of the complex system like aircraft fuel system.

3. Fuel system health monitoring

The fuel level monitoring function is primarily used to manage and monitor the quantity of fuel in each tank. A platform for the study of the fuel system sequencing, a simulation of fuel management system was modeled by [6]. Fuel level sensors installed in each tank provides the quantity of fuel and also, transfer the signal to the fuel management system. The outer model of a typical small aircraft fuel system is shown in **Figure 2**. The Simulink model developed includes a tank model, tank parameters and fuel pump model as sub-models. The following are some assumptions made during the simulation using Simulink.

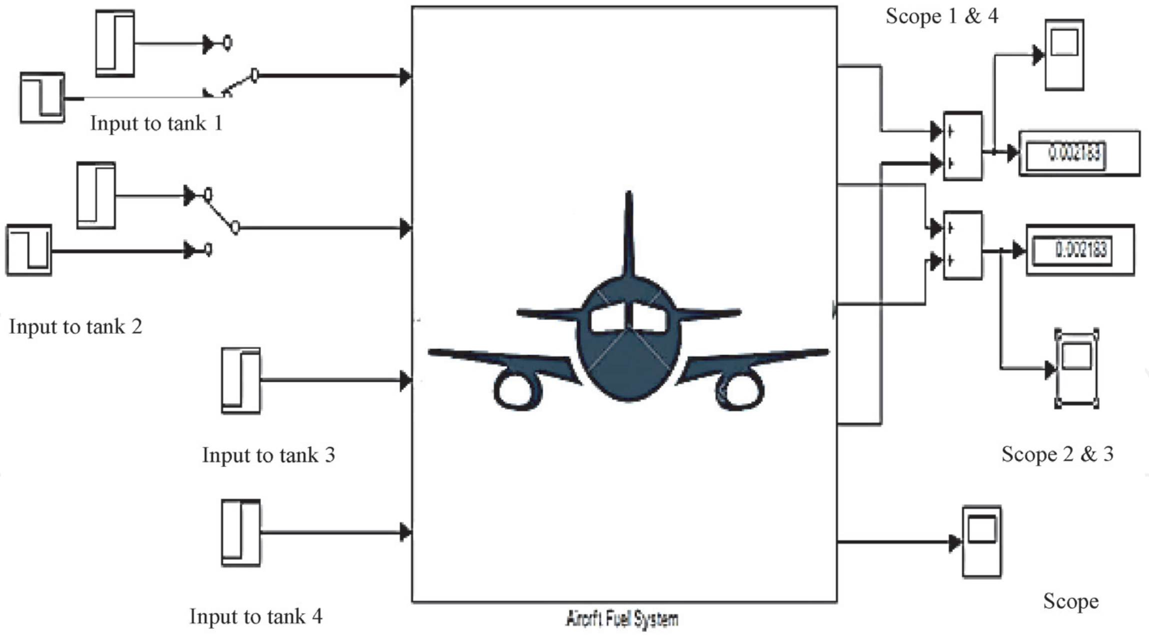

Figure 2.
Snapshot of outer model of the typical aircraft fuel system.

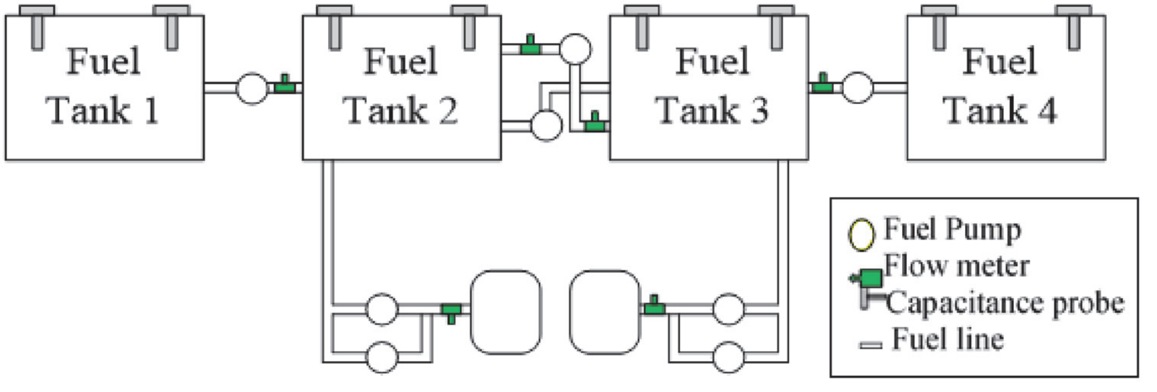

Figure 3.
Structure of a typical small aircraft fuel system.

i. In the aircraft fuel tank, the fuel and gas temperature are homogeneous

ii. The acceleration and deacceleration effect on the fuel is not considered while analyzing. Thus the sloshing is not interpreted for the simulation.

iii. Tank geometry of cubic meter is considered without any fixed reference frame

iv. The fuel properties are not affected by the changing ambient pressure and temperature

The assumed typical small aircraft fuel system contains four fuel tanks and a total of eight fuel pumps as depicted in **Figure 3**. It consists of four main pumps of which two pumps are used for backup and remaining two pumps for delivery of fuel between wings at emergency conditions [7]. The flow of fuel in this aircraft is managed and monitored by the designed adaptive intelligent controller. The primary objective is to manage the fuel flow to the engine without fail and to reach the required engine fuel consumption rate. If any fault arises in any of the fuel tanks,

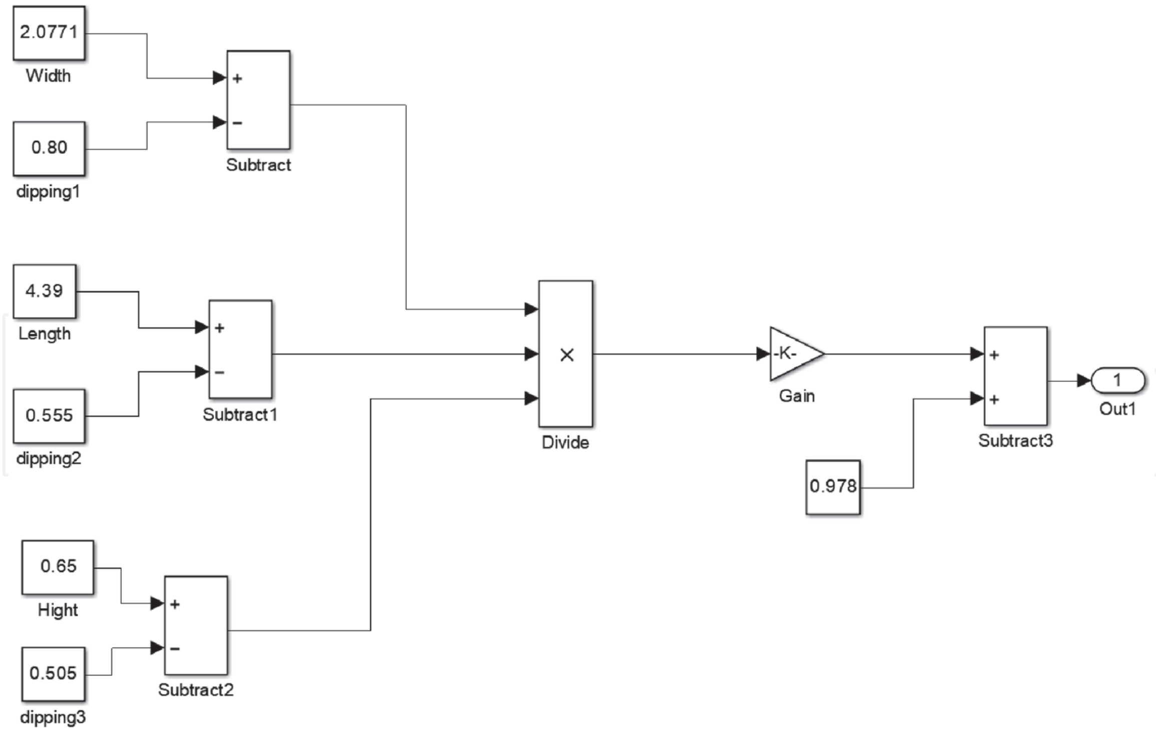

Figure 4.
Geometry of the aircraft fuel tank.

the controller model detects it and reacts as per the fuel requirement of the aircraft's engine. The typical fuel system consists of four tanks with a total fuel capacity of 2800 kg with each tank capacity of 700 kg respectively. The tanks are symmetrically located in both left and right wings.

The model of the aircraft fuel system is simulated based on the fuel system design [8], and the fuel system health management is analyzed using the hybrid fuzzy system. The efficiency ANN based controller is analyzed by comparing with ANFIS based intelligent tool. The total usable capacity of 2800 kg of fuel is sufficient for at least 30 minutes of operation of the assumed aircraft at full continuous power. Simulation of fuel pump is done using the properties of the Hyjet-4A fluid as fuel. The assumed temperature and the viscosity value of fuel are 22.72°C and 1, respectively. The fuel line is built and simulated in the same manner as in the practical fuel systems using the metal pipes that are firm and fixed. A pipe of length 500 mm is assumed which connects the internal wing-tip tanks. The length of pipe between the engines and the integral wing tanks is considered to be of 7200 mm. The pipes have an internal diameter of 10 mm, and the shape of pipes is decided with a geometry factor of 64. **Figure 4** shows the Simulink model of the geometry of the fuel tank. An integral fuel tank of height 0.65 m, length 4.39 m and width of 2.0771 m is modeled. An axial pump containing an electric motor drive is selected, with an angular velocity of 1770 rpm and the correction factor of 0.8. **Figure 5** shows the model of the fuel pump as well as the fuel line for the transfer of fuel between the wing tanks. In other words, the monitoring function helps to provide alert messages to the flight crew and provide data to the prediction model. **Table 1** provides the simulated values assumed at normal operating conditions for linear motion of the aircraft.

The flight range of simulated typical aircraft was calculated based on steady linear motion. Substituting assumed values of **Table 1** into the equation, for each tank the flight ranges are obtained. For a fuel system with four tanks each of 700 kg of fuel capacity, the flight range can be calculated as:

$$s = \left(\frac{V.v}{Q}\right) \tag{1}$$

$$= \frac{700 \times 81.9}{2800} = 20.475\, m/sec \cong 73.71 km/hr$$

Where, V is the quantity of fuel in each fuel tanks, v speed of the aircraft and Q is total quantity of the fuel.

Figures 6 and 7 shows the level of fuel of a healthy tank and a faulty tank. The faults are introduced intentionally in the first tank by decreasing the fuel level which may occur due to leakage in the tanks, pipelines, valve stuck or maybe because of the filters blocks or icing within the fuel system. **Figure** 7 demonstrates the leakage in the fuel system for 5 seconds, which affects the operation of the engine. The decrease in the level of fuel in the first tank is detected and diagnosed effectively by the developed health management methodologies. The level of fuel decreases after 6.5 sec during simulation for a simulation time of 25 seconds as shown in **Figure** 7.

3.1 Fuel system diagnosis and prognosis

This section discusses the diagnostic and prognostic function associated with the assumed fuel system. Prognosis is prediction of remaining useful life time of the system. Based on the available fuel quantity, engine fuel consumption and status of

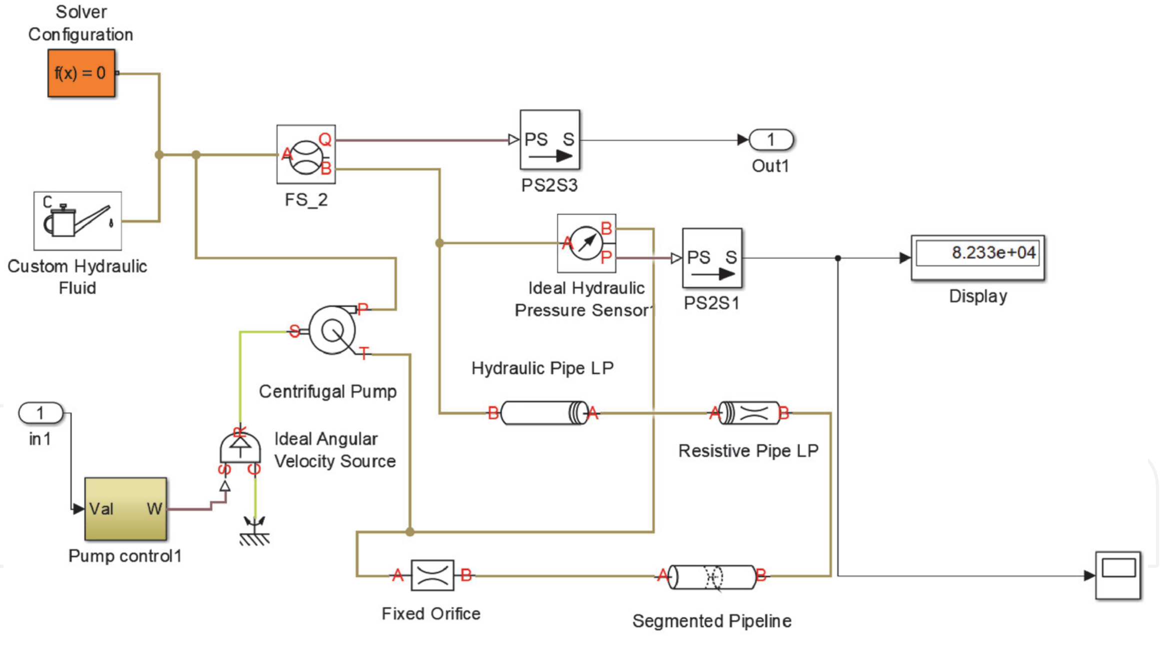

Figure 5.
Fuel pump and fuel line model.

Sl. No.	Parameter	Value
1	Mach number	0.26
2	Temperature of the ambient air	22.72°C
3	Speed of sound	314.8 m/sec
4	Aircraft speed	81.9 m/sec

Table 1.
Assumed simulated values of an aircraft.

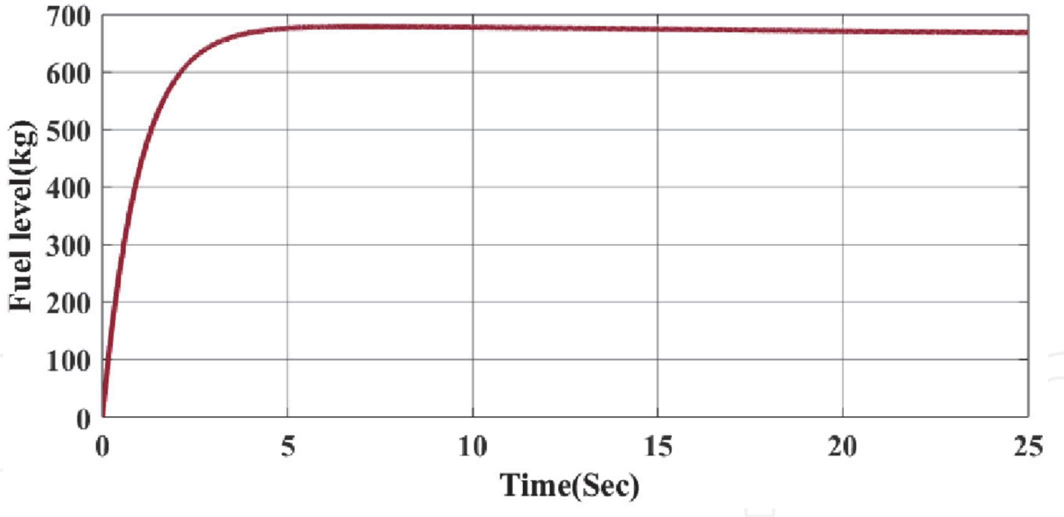

Figure 6.
Level of fuel in healthy tank.

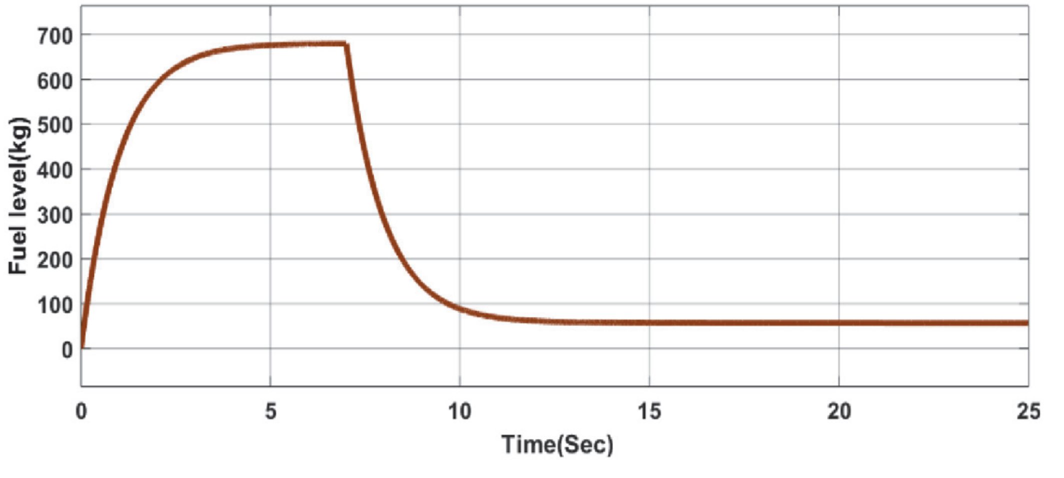

Figure 7.
Level of fuel in fault tank.

the components, the prognosis function generates the control signals to the fuel management system to predict and mitigate the faults within the system. Further, through the diagnosis function the obtained flow rate is matched with the control signals and corrective measures are taken to identify and detect the fault in the fuel system. In this way, using these functions health management of the fuel system can be achieved.

Soft computing techniques such as Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) are used for diagnostic and prognostic analysis of the aircraft fuel system. Health management process using ANN and ANFIS as a controller is illustrated in this chapter.

3.2 Health monitoring of fuel system using ANN

Backpropagation is considered to be the most efficient training algorithm among different artificial neural network algorithms [9]. Learning process in ANN is achieved by collecting the information and training them accordingly. For the assumed fuel system, ANN-based health management tool uses the fuel flow rate as input data and previous engine fuel consumption rate as the historical information. The ANN model has trained accordingly and generates output signals in relation to

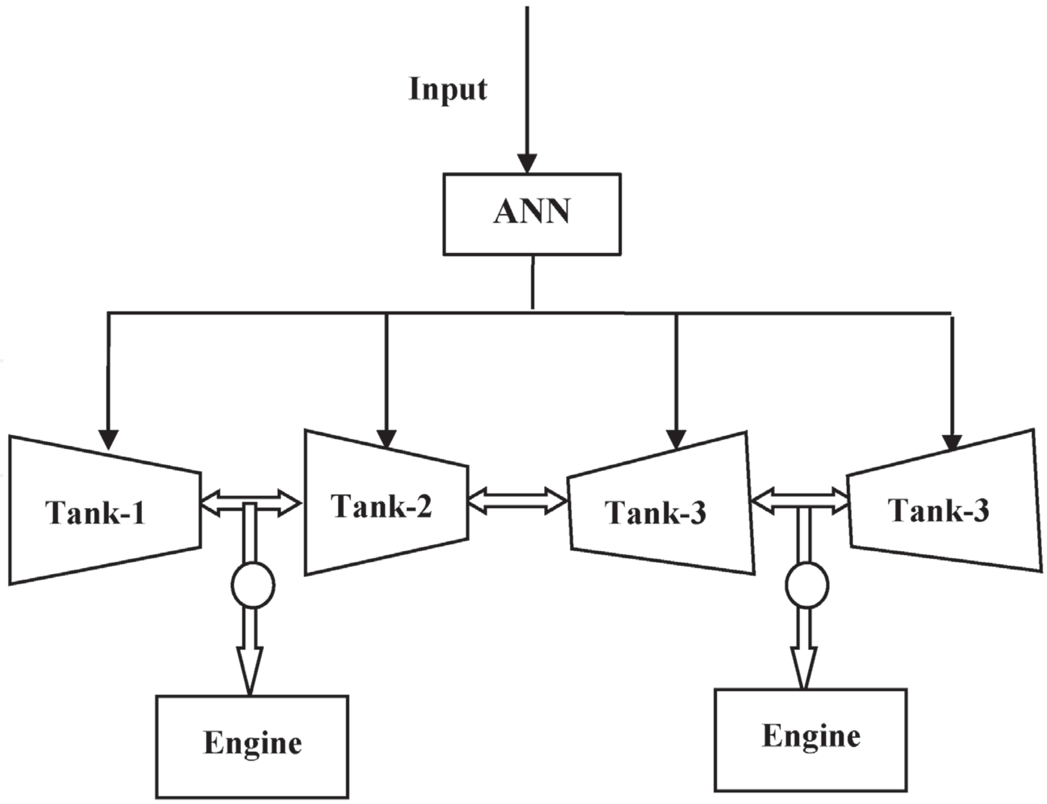

Figure 8.
Structure of the assumed fuel system with ANN as controller.

working condition of the fuel system. **Figure 8** shows the structure of the assumed fuel system with ANN controller. Based on the present and previous instance fuel flow rate, it generates the output signal in the presence of faults. The ANN health management tool continuously monitors the flow rate of fuel to the engines and provides the require d fuel flow to both the engines.

This section exploited the basics of ANN. Proper training of NN helps to perform fault analysis, detection, and diagnosis without the requirement of a complex mathematical model. The interpretation of the NN similar to human thinking and multiple parallel processing features of NN enhances the network performance [10].

4. Simulation of fuel system health monitoring using ANN

Feedforward neural network is implemented which regulates the input parameters of the assumed fuel system to obtain the desired outputs. A simple model of the neural network is shown in **Figure 9**. The ‘n’ number of input signals are denoted as $x'_1, x'_2 \dots, x'_n$, and weights of each signal as $w'_{k1}, w'_{k2} \dots, w'_{kn}$. These weighted input signals are summed and output signal Y' is found through activation function F.

Backpropagation (BP) is a supervised learning algorithm [4]. By gradient descent, the algorithm calculates the error function in relation to the weights of the neural networks. Learning process in ANN is achieved by collecting the information and training accordingly. The following equations describe the implementation of a feed-forward neural network.

$$v_k = \sum_{j=1}^{n} w'_{kj} x'_j \tag{2}$$

$$y'(k) = s(v_k) \tag{3}$$

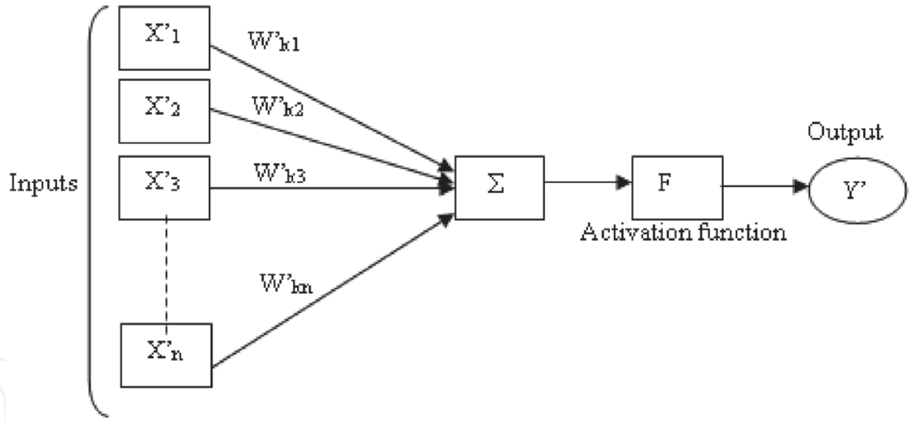

Figure 9.
A neural network model.

$$y = \theta\left(\sum_{k=1}^{n} y'(k)\right) \tag{4}$$

where, $x'_1, x'_2, \dots \dots \dots .. x'_n$ are the inputs and $w'_{k1}, w'_{k2}, \dots \dots \dots .. w'_{kn}$ are the weights with $y'(k)$ is the sigmoid function. $S(.)$ is the sigmoid activation function and $\theta(.)$ is the threshold activation function. y and n are the output of the NN and total number of neurons in the second layer of the network respectively. The output y obtained is the prediction based on the inputs of the NN and weights applied.

For hidden layers according to the BP algorithm, the derivation error of backpropagation is expressed as:

$$\delta_k = \left(1 - y'_k\right)\sum_k w_{kj}.\delta_p \tag{5}$$

$$\delta_p = y_p - t_p \tag{6}$$

Where, δ_p is the error derivation at p^{th} neuron, y_p, p^{th} unit activation output, δ_k derivation of error and t_p corresponding target. Based on the weights of the first layer and the next layer, the gradient of error is calculated. Further, the weights are updated accordingly.

For the assumed fuel system, ANN-based health management tool uses the fuel flow rate as input data and previous engine fuel consumption rate as the historical information. The ANN model has trained accordingly and generate the output signals in relation to the working state of the fuel system. The predictive output signal of the ANN model is obtained as:

$$v_k = f\left(w'_{k1}, w'_{k2}, \dots \dots \dots .. w'_{kn}\right) \tag{7}$$

Where, v_k is the predicted output of the NN.

Training of ANN with backpropagation algorithm calculates the gradient error and regulates the weights by the required flow rate to be consumed by the engines. Continuous updating of ANN model helps to maintain the required flow rate of fuel irrespective of malfunctioning of the any of the component within the fuel system. The disadvantage of the Feed Forward Neural Network with BP algorithm is the necessity of complex mathematical calculation, slow rate of error convergence and more amount of time required for a non-linear system operating condition. A hybrid ANFIS methodology is utilized to overcome this drawback. This methodology provides better performance results for non-linear and changing operating condition for the assumed aircraft fuel system.

ANN controller monitors and manages the flow of fuel without any limitations to meet the required flow rate. Fault occurrence within the fuel tanks are detected, and corrective measures are taken by the ANN. Any change in the data is identified by the unique property of the ANN algorithm that differentiate the data points in noisy conditions. The ANN controller calculates the gradient error, and accordingly the target signals are generated by adjusting the weights of the BP algorithm. **Figure 10** shows the flowchart of the updation process of the ANN. Timely maintenance of the fuel tanks and fuel system helps to improve the performance of the aircraft. Faults in the tanks like leakage, filter blockage or pump failure during flight may degrade the operation of the aircraft. Under such circumstances, ANN algorithm continuously updates with the actual data and maintains the required flow rate.

4.1 Simulation results and discussion using ANN

The two hidden layers of ANN model using Simulink is depicted in **Figure 11**. In this neural network four input samples and four target samples are used. The hidden layer consists of 100 neurons and output layer of four nodes for the assumed four-tank fuel system. The neural network toolbox of Matlab/Simulink utilizes the data points in three stages. In the first stage, the training data points are used for training the neurons and the gradient error is calculated by using the weights of successive layers. The upadated weights of the network reduces the error for the given value. During second stage, validation fail check is done. Testing process of data points is carried out in the third stage. The performance of the developed NN is then analyzed.

The BP algorithm uses the Mean Square Error (MSE) procedure to compute the error in each step or iteration. MSE is the performance index of the BP algorithm. It is the error computed as variance between the network output and target output. The relation given in Eq. (8) computes the MSE in each step for each output,

$$MSE = \frac{1}{N}\sum_{1}^{N}\left[e_{i/p} - e_{o/p}\right]^2 \tag{8}$$

Where, $e_{i/p}$ is the actual input, $e_{o/p}$ is the output of the NN model and N is the number of iterations considered. The required number of iterations for converging the procedure and time taken for training depends on the size and structure of NN, learning methodology adopted, number of layers, and also on the length of data points including input data and output data.

During the training process of ANN after 4th iteration the performance of 4.33e-33 obtained which indicates the amount of minimized error. Gradient of 3.16e-12 indicates the variance occurred in the error rate, Mu of 1.00e-07 is the threshold value achieved after each iteration and validation check indicates reduced error after current (4th) iteration as compared to previous (3rd) iteration. The graph illustrated in **Figure 12** shows the performance and status of the training process. It is a curve showing the plot of MSE versus four epochs. The blue line plotted represents the training result, green color line denotes the result of validation check and red line indicates the test result. During the ANN training process, as the MSE decreases, consequently the network output reaches to target output. The performance using ANN as fault diagnosis and prognosis process is assessed by computing

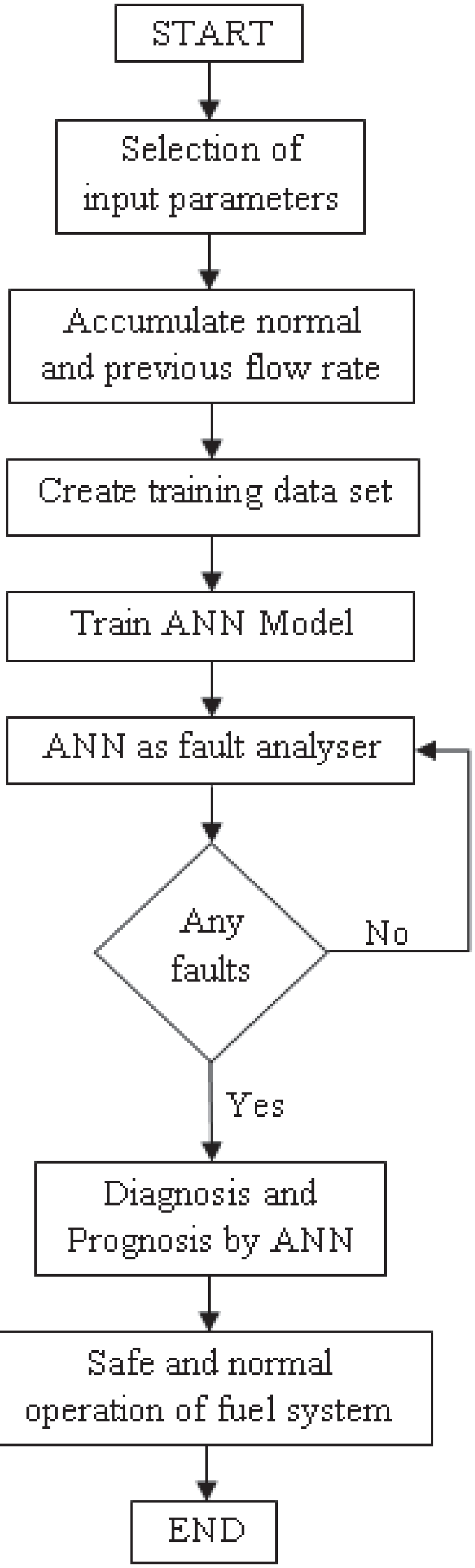

Figure 10.
Flowchart of ANN-based prognostic tool for the fuel system.

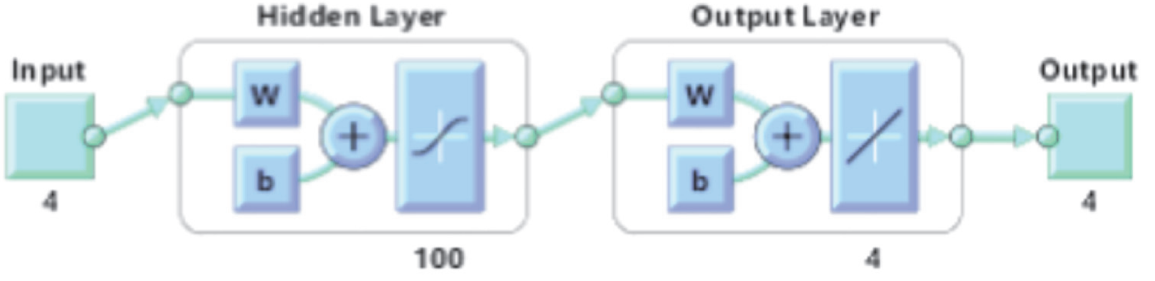

Figure 11.
Developed ANN Simulink model.

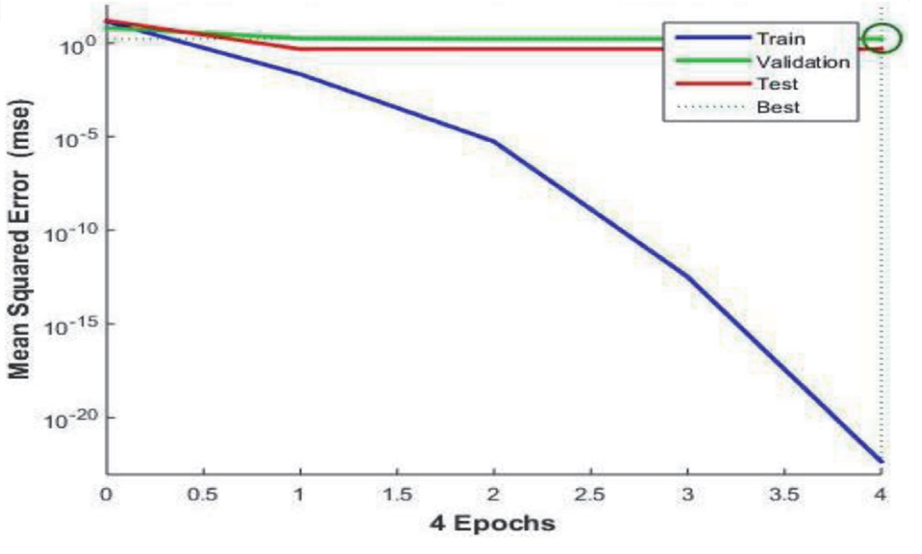

Figure 12.
Training performance of ANN.

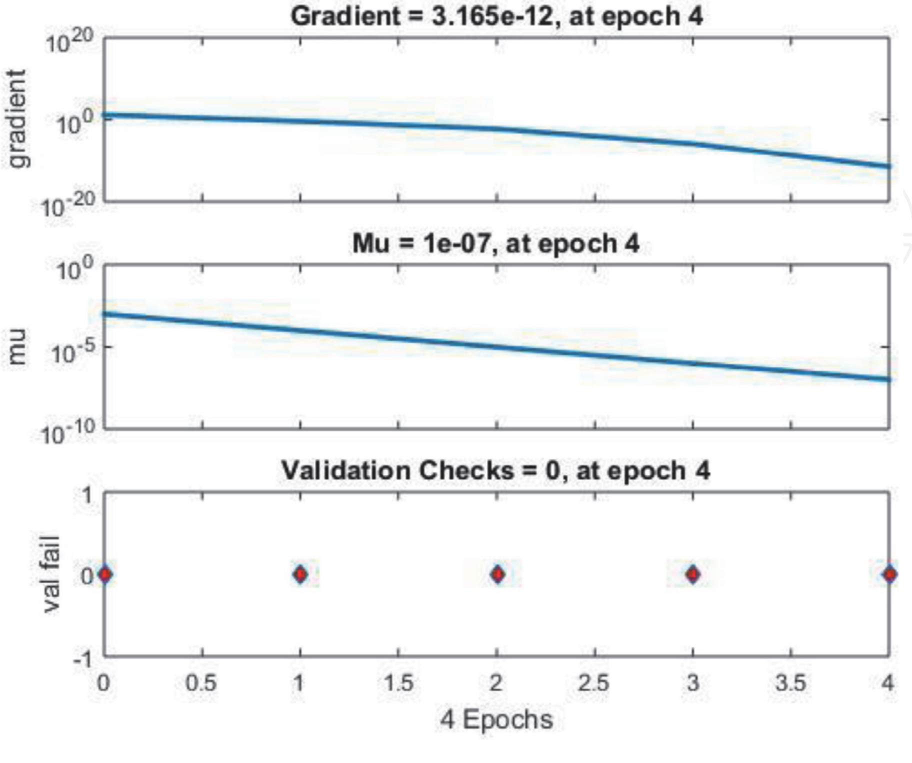

Figure 13.
Gradient and validation performance plot of the ANN model.

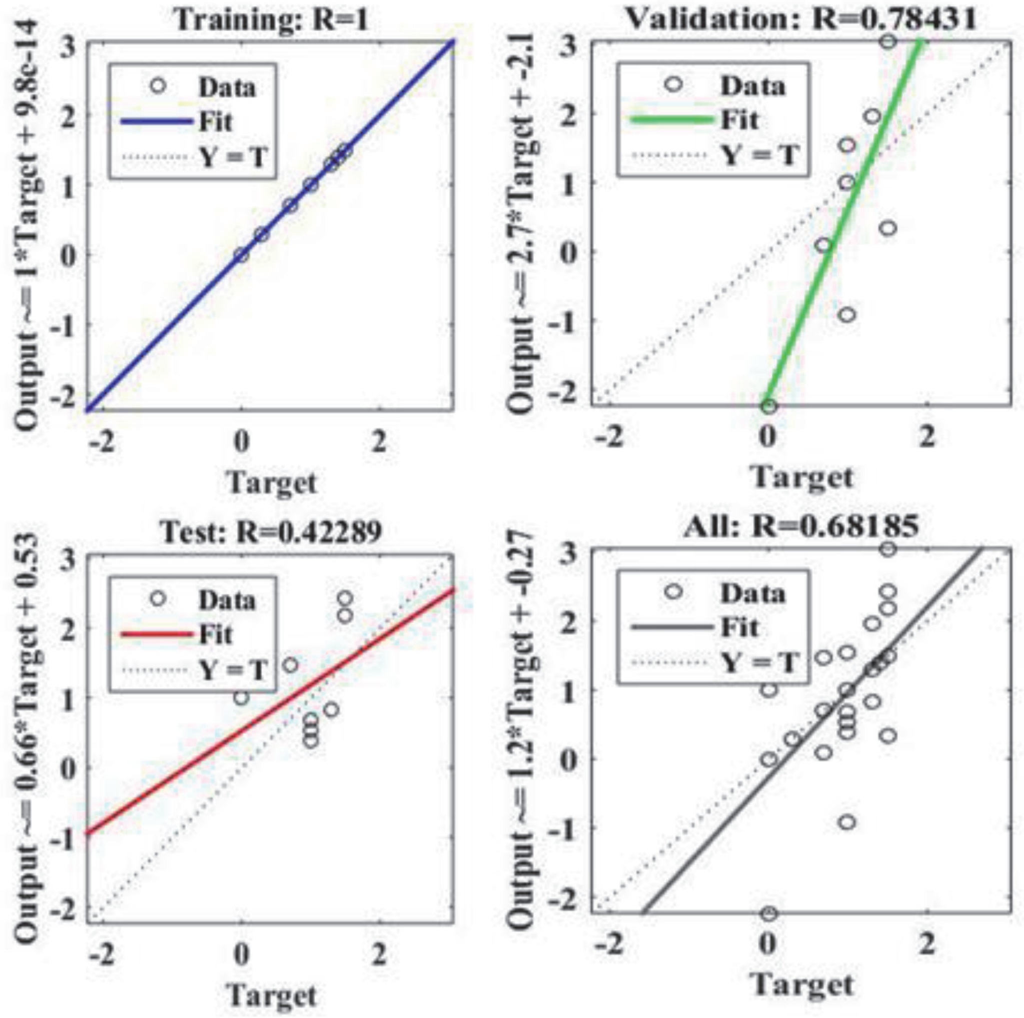

Figure 14.
Training performance plot of the ANN model.

Sl.No	Tank 1	Tank 2	Tank 3	Tank 4
1.	1	1	1	1
2.	0.7000	1	1	1
3.	0.3000	1	1	1
4.	0	1	1	1
5.	1	0.7000	1	1
6.	1	0.3000	1	1
7.	1	0	1	1
8.	1	1	0.7000	1
9.	1	1	0.3000	1
10.	1	1	0	1
11.	1	1	1	1
12.	1	1	1	1
13.	1	1	1	0

Table 2.
ANN training data.

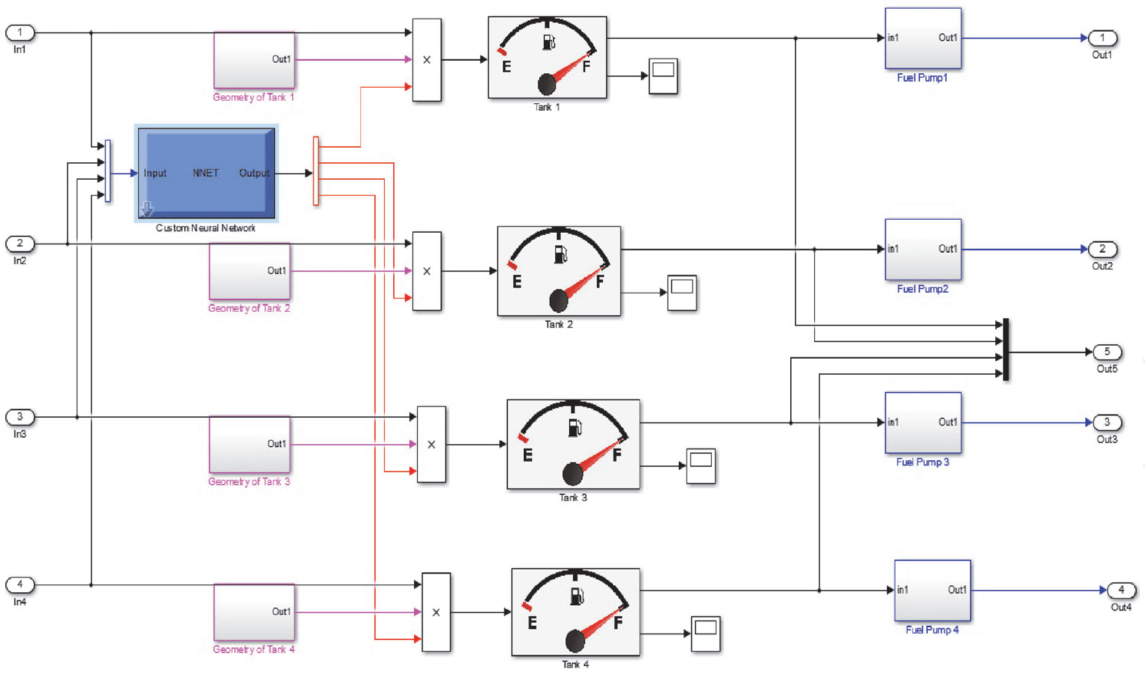

Figure 15.
The Simulink model of the aircraft fuel system with ANN as a controller.

Tank 1	Tank 2	Tank 3	Tank 4
1	1	1	1
0.7000	1.3000	1	1
0.3000	1.4000	1.3000	1
0	1.5000	1.5000	1
1	0.7000	1.3000	1
1.4000	0.3000	1.3000	1
1.5000	0	1.5000	1
1	1.3000	0.7000	1
1.3000	1.4000	0.3000	1
1.5000	1.5000	0	1
1	1	1.3000	0.7000
1	1.4000	1.3000	0.3000
1.3000	1.3000	1.4000	0

Table 3.
Target data of ANN.

the MSE based on the Eq. (8). The best validation performance achieved is of 1.6835 at four epochs. The graph with all the three results of training, testing and validation coincide is considered to be the best performance.

The gradient and validation plot determine a process of assessing the performance of the training and testing of ANN technique. The gradient of error and validation plot for four epochs obtained is as shown in **Figure 13**. It is observed that a smooth decrease in the gradient error at four epochs and maximum measures of validation check at four iteration fails to zero.

Another important factor considered while evaluating the performance of the ANN is the correlation coefficient obtained for training, testing and validation.

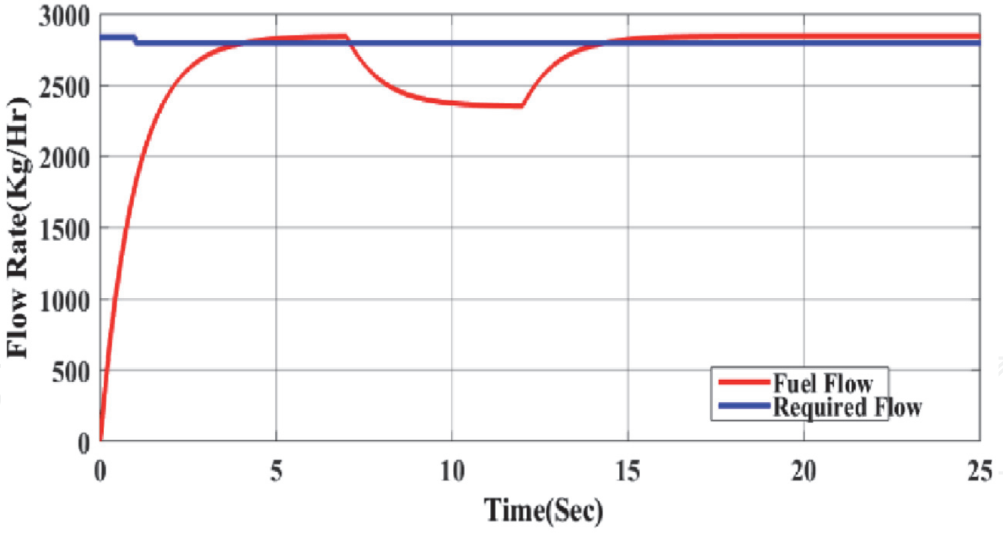

Figure 16.
Fuel consumption by the engine of the aircraft fuel system without a controller.

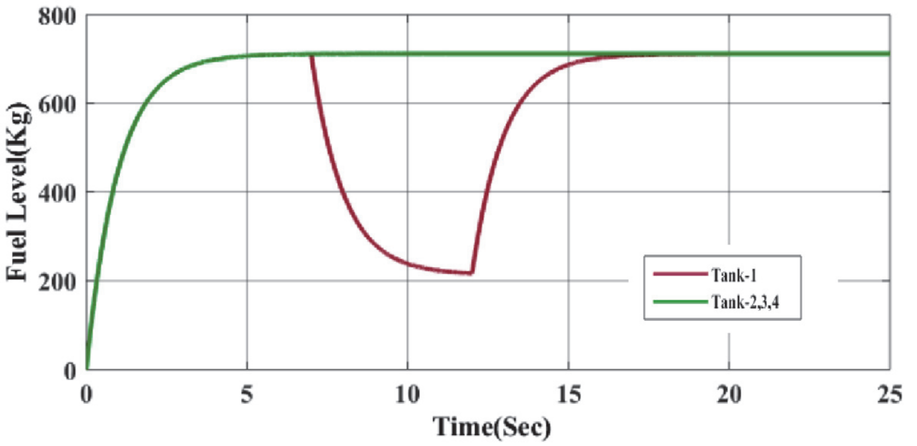

Figure 17.
Fuel management test without a controller.

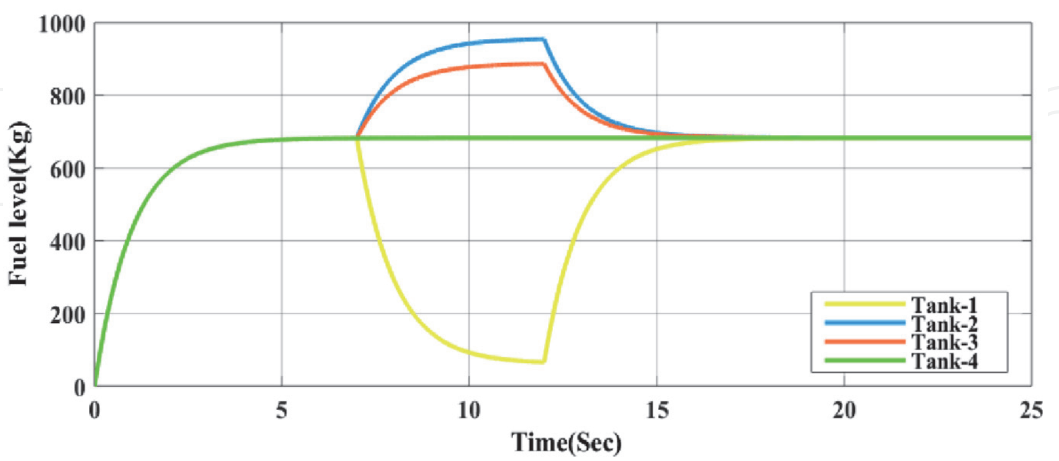

Figure 18.
Fuel management test with the ANN model as a controller.

From the **Figure 14**, it is seen that the overall correlation coefficient is 0.6818. **Table 2** provides the details of the ANN training data where intentional faults are inserted into the tanks and trained accordingly. **Figure 15** shows the Simulink model of four tank fuel system with ANN as a controller. Due to faults, the input

Tank-1	70 kg	Required Fuel
Tank-2	960 kg	2800 kg
Tank-3	870 kg	
Tank-4	700 kg	
Total	2600 kg	

Table 4.
Fuel fetched from each tank using ANN as controller.

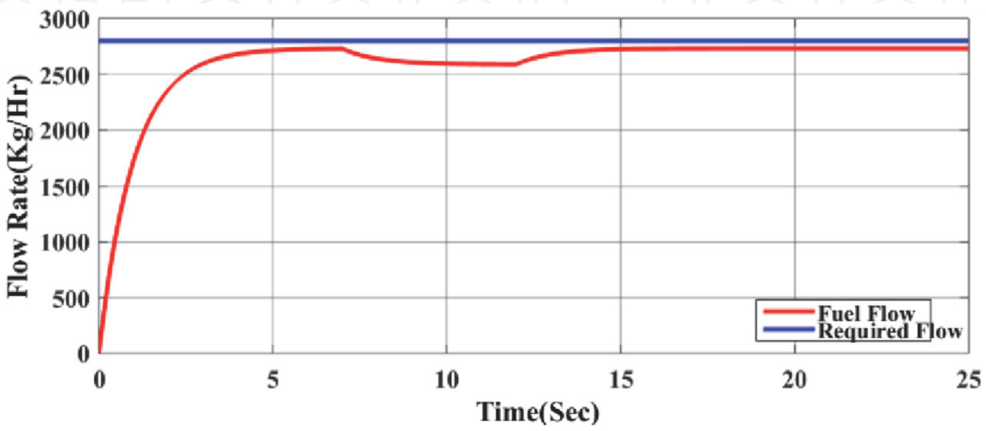

Figure 19.
Fuel consumption by the engine using ANN as a controller.

data points vary and such variations are trained consequently by updating the weights of the neural network. The ANN-based health management process is implemented by taking corrective measures in the presence of faults (**Table 3**).

The simulated model of the fuel system can operate continuously for 30 minutes with full control and power. Fuel consumption test and fuel management test performed on the fuel system without a controller is shown in **Figures 16** and **17** respectively. In the plot blue line indicates the required fuel flow rate and red line indicates the obtained flow rate without controller within the fuel system.

As observed in **Figure 17** for a simulation time of 20 seconds, within four seconds engine(s) get the required amount of fuel. The blue line indicates the required flow rate of 2800 kg/hr., which is fulfilled by delivering the fuel from all the four tanks with capacity of 700 kg per tank. It was obseverd that after a time period of 4 seconds, the level of the fuel in the first tank decreases indicating the presence of faults in the fuel tank. Because of faults the level of fuel in first tank decerases. Thus, when the quantity of fuel and level of fuel in the tank varies, it affects the flow rate of fuel to the engine. This may lead to the fuel starvation that causes the failure of the aircraft engine because of insufficient fuel supply to the engine. The existing aircrafts fuel system with automatic and programmed fuel management system may not identify sudden decrease in the level of fuel properly due to which the performance of the system gets degraded.

Figure 18 shows the fuel management test using ANN as a controller which identifies, detects the change in the fuel quantity and level of fuel in the first tank and correct it by fetching the required fuel from the second and third tanks. The ANN as controller predicts the required fuel by fetching the fuel quantity from the other tanks as per the **Table 4**.

The weight updating process of the BP algorithm during training process classifies the fault data, and testing process identifies the fault occurrence and mitigate it by predicting and fetching the required fuel from other tanks. Compared to the existing fuel management system, ANN as a controller in the presence of faults manages the fuel quantity and flow rate more efficiently. It detects the time of the fault, diagnoses it and mitigates it providing the complete health management of the fuel system. Minimizing the gradient of error for four iterations, the ANN model could be able to fetch the fuel flow rate of 2600 kg/hr. as shown in **Figure 19**. Using ANN as contorller during fuel managemnt test able to fetch 2600 kg/hr. of fuel where as the required flow rate by the engine is 2800 kg/hr. This variation in the flow rate is because of the drawbacks such as slow rate of error convergence and necessity of intensive calculation of BP algorithm for assumed operating conditions. Thus, an intelligent control model ANFIS as a health management tool is used to fulfill the engine fuel consumption requirement.

5. Health monitoring of fuel system using ANFIS

5.1 Adaptive neural fuzzy inference system

ANFIS is a supervised gradient descent algorithm. In this, fuzzy rules configured upon the NN structure provide a qualitative description for the fault analysis of aircraft fuel system. In the resultant hybrid model, the NN recognize the fault pattern and adapt to the changing atmosphere. On the contrary, the FIS integrates the data and performs inferencing and decision making. The dynamic performance of the system can be represented by modeling the neuro-fuzzy method by extracting the numerical data from the model. Based on this approach, the system modeling serves two purposes. They are: the functional behavior of the assumed system can be predicted from the derived model, and the design of a controller is done using the resultant model. The ANFIS model is built first by initializing the input variables with the rules extracted from the input–output data of the assumed system. Later, the NN is utilized to fine tune the rules of the fuzzy model. The flow chart for ANFIS training procedure is as shown in **Figure 20**. In this work, ANFIS is used to detect and identify the presence of faults in the aircraft fuel system.

5.2 Implementation of ANFIS algorithm

The ANFIS structure developed is based on the model developed by [11]. The ANFIS network is mapping of input and output variables in a multi-layer network with a single target output [12]. The operating model of the ANFIS controller is depicted in **Figure 21**. The ANFIS methodology as a fault diagnosis and prognosis process for aircraft fuel system is briefly described in the following sub-sections. ANFIS is a structural plan that links expert's knowledge and the knowledge capability of the neural networks. ANFIS builds a FIS whose membership function parameters are obtained by training appropriately. Consider FIS with two inputs 'x' and 'y', two connected Membership Functions (MFs) and one output 'z'. The fuzzy if-then rules for the present work based on the model [13] are framed as follows. If 'x' is A_1 and 'y' is A_2, then the target 'z' is $f(x,y)$, where A_1 and A_2 are the sets in the antecedents, and $z = f(x,y)$ is a crisp function in the consequent. $f(x,y)$ is a polynomial for x and y input variables. A zero-order Sugeno fuzzy model is formed when $f(x,y)$ is zero or constant which is a Mamdani FIS [14]. A first-order Sugeno fuzzy system model is formed if $f(x,y)$ is first order polynomial. **Figure 22** shows a five-layer ANFIS architecture.

ANFIS is a five-layered feed-forward neural network, *viz* the input layer, product layer, defuzzy layer, normalized layer, and an output layer. The nodes may be

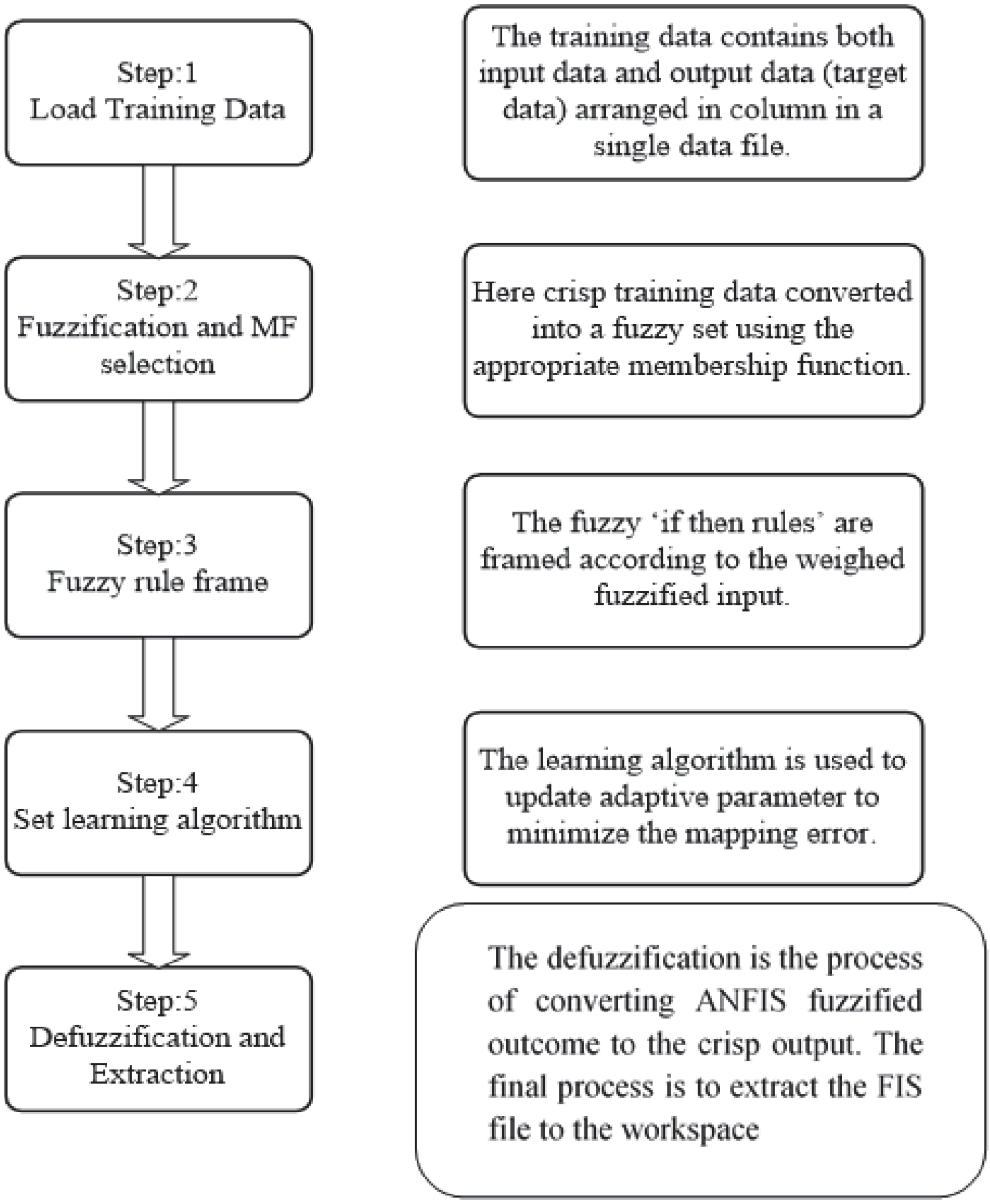

Figure 20.
Flowchart for ANFIS training procedure.

adaptive or fixed. The nodes in a square shape are adaptive and the nodes in the form of a circle are fixed. In this case, the inputs to the ANFIS considered are the flow of fuel at prior instant 'x' and engine's fuel consumption 'y'. The output signals of the fuel tank 'z' are measured as the target output. These parameters aid the ANFIS in formulating the rules as well as realizing a better tuning performance. Every rule covers the unity weight, and the learning procedure of ANFIS is achived on the classified signals. In the ANFIS architecture, two if then rules based on first order Takagi and Sugeno [14] are considered as below:

Rule 1: If x_i is A_1^1 and y_i is A_2^1 then $f_1 = P_1x + Q_1y + C_1$.

Rule 2: If x_i is A_1^2 and y_i is A_2^2 then $f_2 = P_2x + Q_2y + C_2$.

where, $P_1, P_2, Q_1, Q_2, C_1\ and\ C_2$ are the linear parameters, $A_1^1, A_2^1, A_1^2\ and\ A_2^2$ are the nonlinear parameters. Activation levels of the fuzzy rules are considered using the realtion of Eq. (9),

$$W_i = P_i(x) * Q_i(y),\ \ i = 1, 2, \ldots n \tag{9}$$

where the logical operator "and" is modeled as continuous term an in this case it is stated as a product. The individual o/p of all rules is obtained as a linear combination among parameters of the antecedents of every rule as signified by Eq. (10).

$$Z_i = P_i * x + Q_i * y + C_i,\ i = 1, 2, \ldots n \tag{10}$$

The output of the model Z_0 is found by multiplying the standardized activation degree of the rules by the individual output of all rule, and it is stated by subsequent Eq. (11).

$$Z_0 = \frac{W_1 Z_1 + W_2 Z_2}{W_1 + W_2} \Rightarrow Z_0 = \overline{W}_1 \overline{Z}_1 + \overline{W}_2 \overline{Z}_2 \tag{11}$$

where, $\overline{W}_1$ and $\overline{W}_2$ are the normalized values of W_1 and W_2.

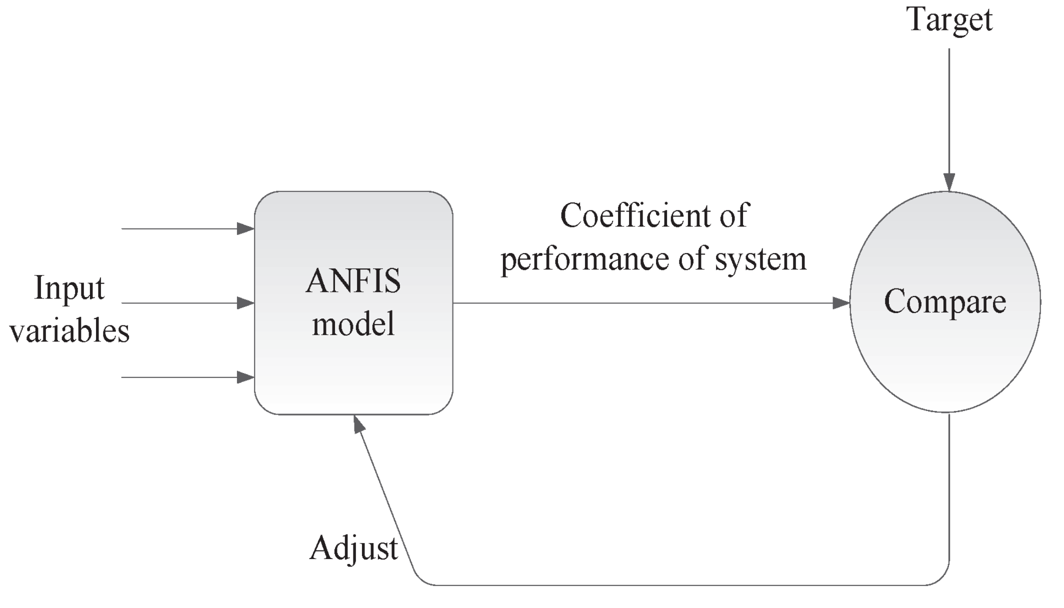

Figure 21.
Working model of the ANFIS controller.

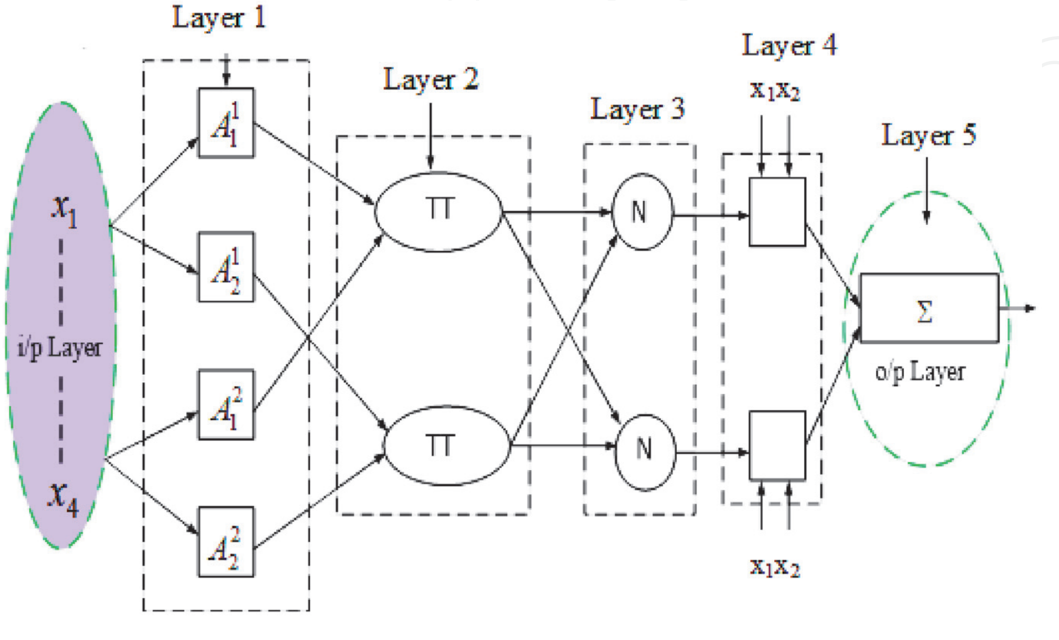

Figure 22.
The equivalent ANFIS architecture.

The hybrid ANN signifying this inference is an adaptable network with five layers. All layers indicating the operation of the Fuzzy Inference System of the ANFIS is examined as follows.

5.2.1 Fuzzification layer

In this method, every input layer is represented as an input variable, and it refers to the fuzzification layer. The input parameters x_i and y_i have the nodes A_1^1, A_2^1, A_1^2 *and* A_2^2 which are the linguistic labels of fuzzy system for isolating the membership performances. The output of the fuzzy layer is given by,

$$F_{L1,i} = \mu {A^1}_i(x) \ \ , i = 1, 2; \tag{12}$$

$$F_{L1,j} = \mu {A^2}_j(y) \ \ , j = 1, 2; \tag{13}$$

where, $F_{L1,i}$ and $F_{L1,j}$ are the outputs of the fuzzy layer, 'x' and 'y' are the input to nodes i and j. $\mu {A^1}_i(x)$ and $\mu {A^2}_j(y)$ are the membership performance of the fuzzy layer.

5.2.2 Product layer

This layer may be identified as the π that performs logical "AND" operation, *i.e.*, the multiplication of the input membership functions. In this process, the output is the weighted input function of the next node which is symbolized by W_1 and W_2. The output is described by,

$$Z_1 = F_{L2,i} = \mu {A^1}_i(x).\mu {A^2}_i(y), \ \ i = 1, 2 \tag{14}$$

$$Z_2 = F_{L2,j} = \mu {A^1}_j(x).\mu {A^2}_j(y), \ \ j = 1, 2 \tag{15}$$

5.2.3 Normalization layer

In this layer each node of this layer is fixed which represents the "if" part of a fuzzy rule. It is process of normalization of the input weights that can complete the fuzzy "and" operation. In this layer, each node computes the ratio of the i^{th} rule firing strength to the total firing strength of all rules. The normalized firing strength of the i^{th} node is given by,

$$\overline{Z_1} = F_{L3,i} = \frac{Z_i}{Z_1 + Z_2}, \quad i = 1, 2 \tag{16}$$

$$\overline{Z_2} = F_{L3,j} = \frac{Z_j}{Z_1 + Z_2}, \quad j = 1, 2 \tag{17}$$

where, $\overline{Z_1}$ *and* $\overline{Z_2}$ are the outputs of this layer.

5.2.4 Defuzzification layer

This is an adaptive layer that gives output membership function based on predetermined fuzzy rules. The node function is given by Eqs. (18) and (19).

$$\overline{Z_1} f_i = F_{L4,i} = \frac{Z_i}{Z_1 + Z_2} \left[A_1^1(x) + A_2^1(y) + C_1 \right] \tag{18}$$

$$\overline{Z_2}f_j = F_{L4,j} = \frac{Z_j}{Z_1 + Z_2}\left[A_1^2(x) + A_2^2(y) + C_2\right] \tag{19}$$

where, $\overline{Z_i}$ is the o/p of the third layer and $\{P_i, Q_i, C_i\}$ is the consequent parameters set.

5.2.5 Output layer

The output layer is symbolizing the THEN part of the fuzzy rule. This consists of one fixed node that computes the total output which is the summation of the input signals given by the following Eq. (20).

$$f = F_{L5,i} = \sum \overline{Z_l}f_i = \frac{\sum \overline{Z_i}f_i}{\sum Z_i} \tag{20}$$

Where, f is the total output and the function of ANFIS is verified by considering a higher number of signals. Training the ANFIS model for the given inputs generate the control signals which help to maintain the fuel flow rate within the aircraft fuel system.

The important benefits of ANFIS are improved learning capacity, the ability to incorporate the non-linear structure of the system and rapid adaption capability. ANFIS can achieve exceptionally nonlinear mapping, far better than other techniques. Some of the drawbacks of this technique are: there are no standard methodologies to incorporate the changing human learning or experience into the base of a FIS and also there is a need for agent techniques used for tuning the membership functions to diminish or minimize the error during execution.

5.3 Simulation of fuel system using ANFIS methodology

This section defines the simulation procedure of health management of aircraft fuel system using ANFIS as a controller. **Figure 23** shows the model of aircraft fuel system with ANFIS as controller. It includes fuel tanks, pumps, pipelines that connects the tanks and pumps with the engines. The fuel system function is to distribute clean fuel at the required pressure and fuel flow rate to the engines in different operating conditions. The diagnostic and prognostic process of small aircraft fuel system is regulated by the ANFIS intelligent control model, that provides better fuel flow rate compared to ANN methodology. That is because of ANFIS's significant features of significant reasoning ability and the low level of computational power during training process. The main purpose of the ANFIS control model is to direct the fuel flow to the engine and to access the essential engine fuel consumption rate. If a fault arises in any of the fuel tanks, the controller model detects the fault and activates the necessary actions as per the fuel requirement of fuel engine.

The ANFIS controller is concentrated on the optimization of parameters of the aircraft fuel system. Similar to the ANN controller, the ANFIS controller is assessed with the previous instance fuel flow and the engine fuel consumption value of the fuel system.

5.4 Simulation results and discussions using ANFIS

ANFIS's learning ability carried out through the five-layer structure of the Fuzzy Logic system helps to approximate the non-linear functions which depends on the

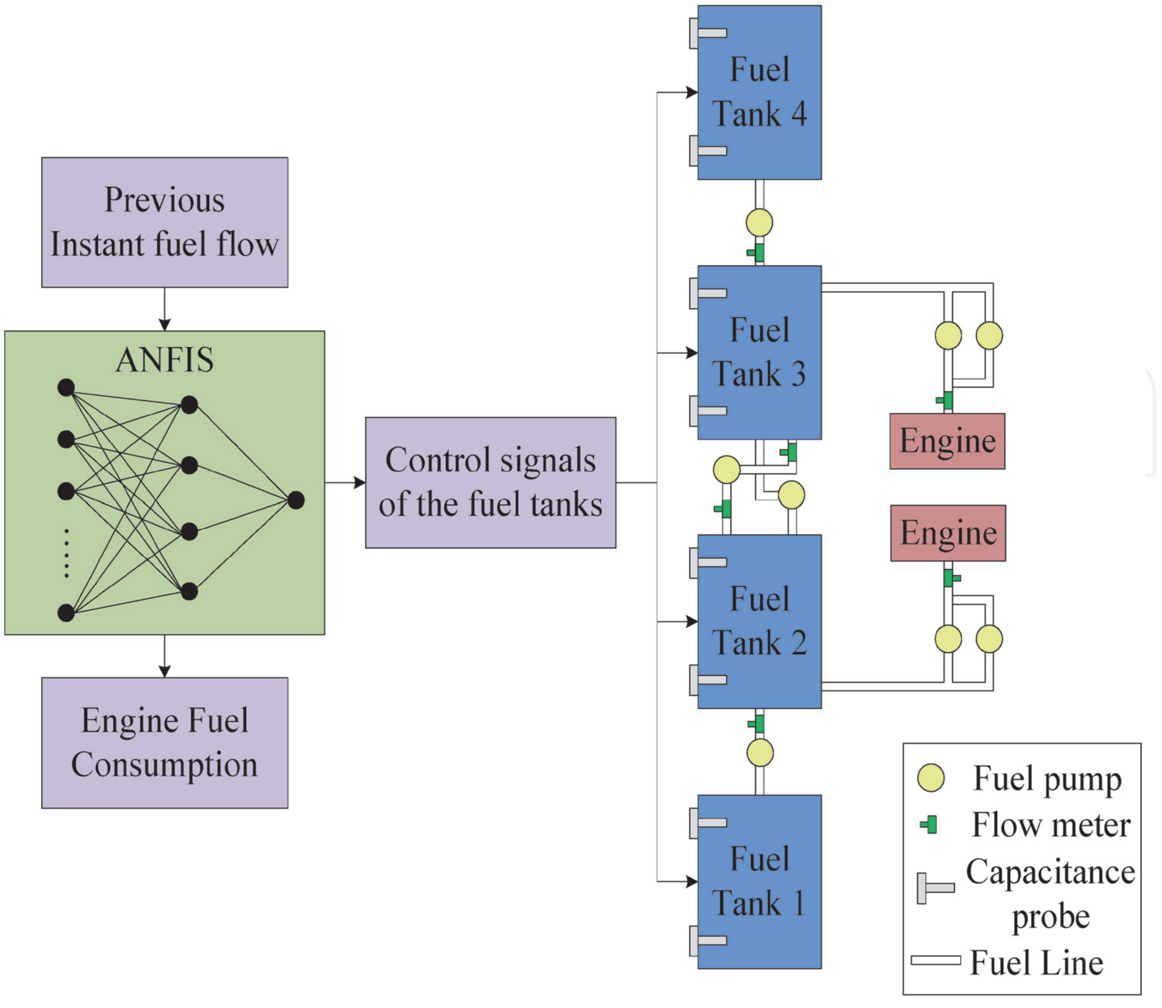

Figure 23.
Structure of the aircraft fuel system with ANFIS as controller.

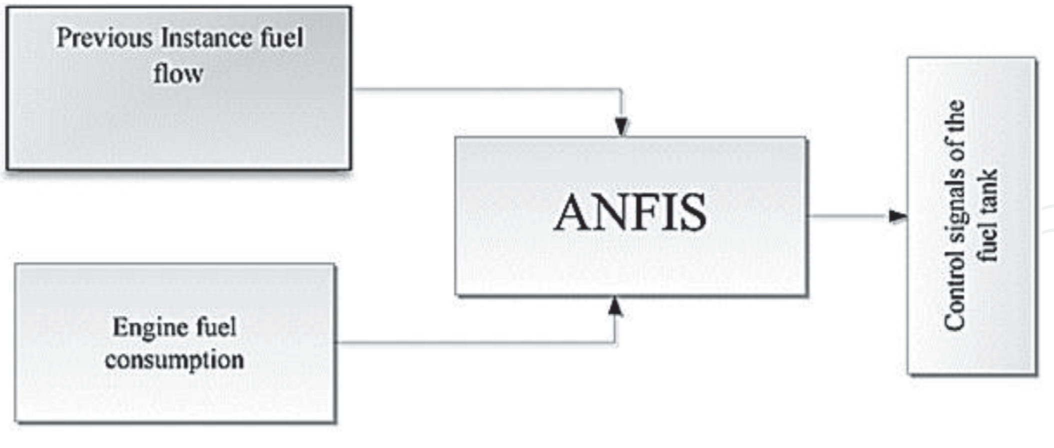

Figure 24.
The structure of the proposed controller.

antecedent and consequent parameters. ANFIS is more robust and has better performance compared to conventional computing methods. These unique properties of the ANFIS such as improved computational power and high reasoning ability, permit it to be used in the fault diagnosis and prognosis of the fuel system to manage fuel flow rate as per engine consumption. The structure of the ANFIS process implemented for the health management of the fuel system is as depicted in **Figure 24**. The control signals generated are decided based upon the input parameters such as engine fuel consumption and previous instance fuel flow to the engine.

The rule structure of ANFIS is determined by the interpretation of the features of the variables of the fuel system model. ANFIS learn details of the input data points, calculate the membership function that best suits to track the input data and output data. The parameters related to the membership functions varies with the learning process of the fuzzy system which depends on the gradient vector. This gradient provides the measure to check the ability of the FIS for the given set of system parameters. The performance is evaluated by considering the error the difference between the actual and desired outputs. **Table 5** shows the fuzzy inference rules framed for the four-tank fuel system. Based on these seven logical rules the learning of the system parameters related to the fuel system with the fault data is carried out. The training data points of input data and output data sets applied to the ANFIS scheme is configured similarly as applied to the ANN.

During the evaluation, the ANFIS structure enables the change in the rules of the FIS. This property of ANFIS helps to optimize itself for the given number of iterations by changing the shape of the membership function, rules and also removes the unnecessary rules during training. A suitable ANFIS Simulink model is designed and developed for the health management purpose of the aircraft fuel system. ANFIS as a controller is designed for the aircraft fuel system with two input

	Input				**Output**			
Rules	**Tank 1**	**Tank 2**	**Tank 3**	**Tank4**	**Tank 1**	**Tank 2**	**Tank 3**	**Tank4**
1	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal
2	Medium	Normal	Normal	Normal	Medium	High	Normal	Normal
3	Low	Normal	Normal	Normal	Low	High	High	Normal
4	Very low	Normal	Normal	Normal	Very low	Very high	Very high	Normal
5	Normal	Medium	Normal	Normal	Medium	High	Normal	Normal
6	Normal	Low	Normal	Normal	High	Low	High	Normal
7	Normal	Very low	Normal	Normal	Very High	Very low	Very high	Normal

Table 5.
Fuzzy inference rules.

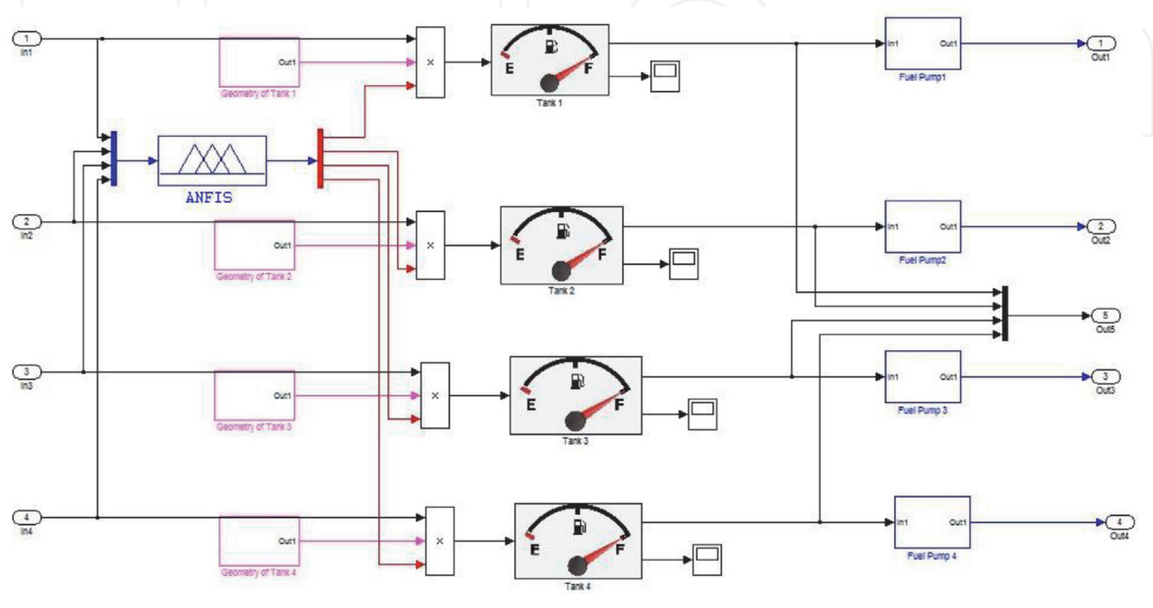

Figure 25.
Snapshot of the Simulink model of a fuel system with ANFIS as a controller.

Tank 1	Tank 2	Tank 3	Tank 4
1	1	1	1
0.7500	1.3300	1	1
0.3500	1.4200	1.3300	1
0	1.5500	1.5500	1
1	0.7500	1.3500	1
1.4000	0.3500	1.3500	1
1.5500	0	1.5500	1
1	1.3500	0.7500	1
1.3000	1.4500	0.3500	1
1.5500	1.5500	0	1
1	1	1.3500	0.7000

Table 6.
ANFIS target data.

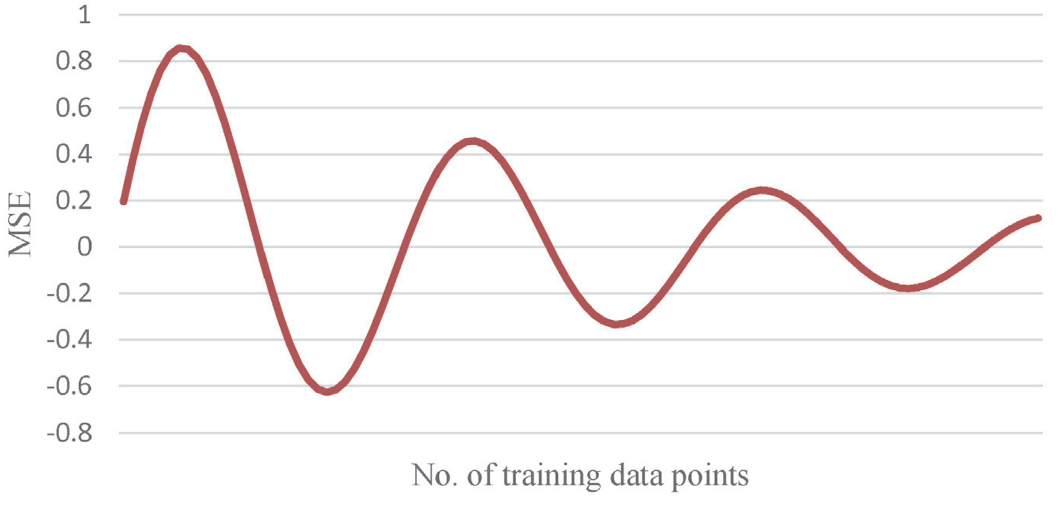

Figure 26.
Training process of ANFIS.

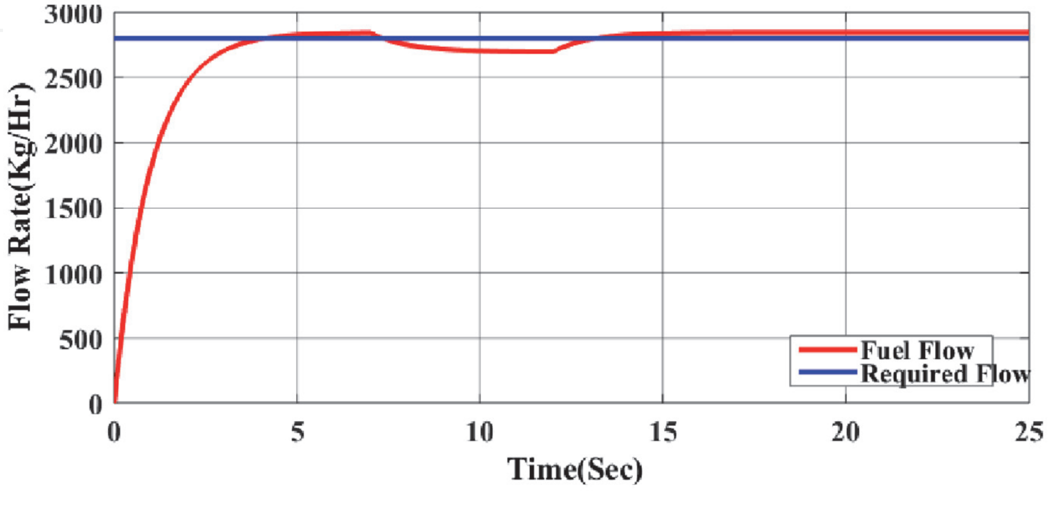

Figure 27.
Fuel consumption by the engine using ANFIS as a controller.

parameters and five bell membership functions for each input unit. **Figure 25** shows Simulink model of aircraft fuel system with ANFIS controller.

Table 6 gives the details of the target output generated by the ANFIS. Similar to the ANN, ANFIS performance is evaluated based on the MSE value. **Figure 26** depicts the curve of convergence of the training data with ANFIS target data indicated as reduction of MSE error. As the number of iterations are increased the MSE reduces indicating the fulfillment of desired target data from the training process of the ANFIS.

Figures 27 and **28** shows the rate of fuel consumption and management test using ANFIS as a controller. The target output generated as control signal identifies the presence of a fault and provide 2700 kg/hr. of fuel flow rate which is almost

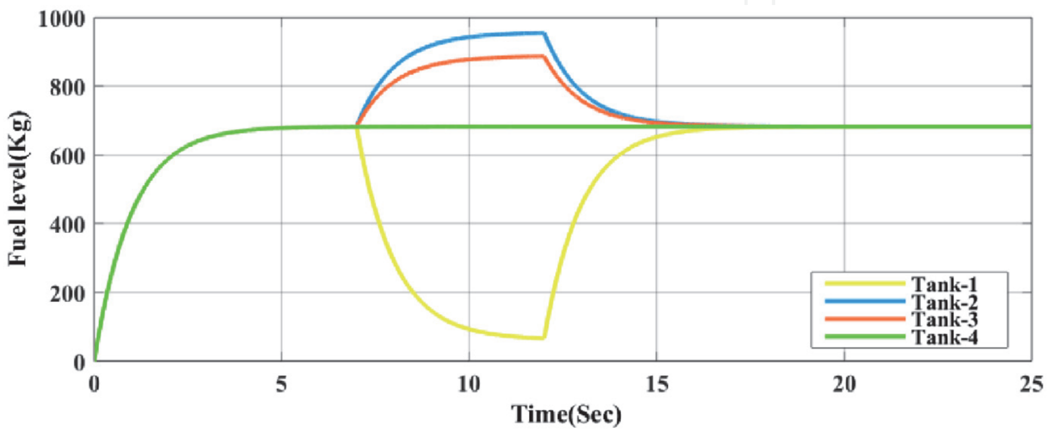

Figure 28.
Fuel management test with the ANFIS controller.

Tank-1	70 kg	Required Fuel
Tank-2	990 kg	2800 kg
Tank-3	940 kg	
Tank-4	700 kg	
Total	2700 kg	

Table 7.
Fuel fetched from each tank using ANFIS as controller.

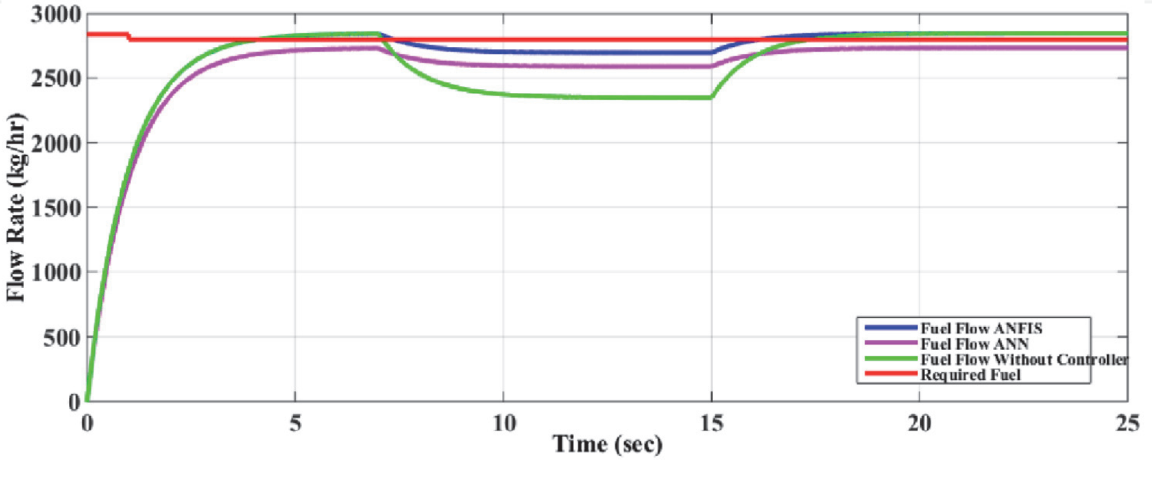

Figure 29.
Comparisons of fuel consumption.

near to the engine requirement 2800 kg/hr. **Figure 27** also illustrates that the learning ability of the ANFIS reproduces accurately the desired output as compared to the ANN process. Thus, the error difference between the actual output value and the obtained output value is very small which is of 100 kg/hr. of flow rate. The ANFIS controller predicts the required fuel by fetching the fuel from the other tanks as per the **Table 7**.

The effectiveness of the ANFIS health management scheme is evaluated by comparing with ANN and fuel system without a controller. The details of the ANFIS based fault diagnosis process is presented in work of [15]. Both techniques uses similar fault conditions. In terms of comparison of training process using ANFIS and ANN techniques, it is clear from the **Figure 29** that ANFIS provides better results. ANN and ANFIS methods detect the time of the fault, diagnose and predict the required flow rate by injecting the additional fuel from other tanks. However, the weight updation process of ANN is based on the historical dataset, which gives the mismatching results during the testing time. Due to this reason, the fuel flow rate obtained by the ANN method is 2600 kg/hr. and is not the desired requirement of fuel by the engine. Hence, it shows that ANFIS technique manage the health status of the aircraft fuel system by monitoring and managing the accurate fuel flow to the engine.

6. Conclusion

Soft computing methodologies like ANN and ANFIS are described in this chapter. A comparison study is made in [16]. All the simulation done is considered for the laboratory conditions only. Based on the theory of NN and FIS, the concept of hybrid five-layer ANFIS structure is implemented and simulated for the health management of the fuel system. Both the techniques help to monitor and manage the rate of fuel flow as required by the aircraft's engine by generating the control signals. Further, based on an adaptive algorithm fault analysis is carried by the author in paper [17]. Diagnostic and prognostic process are carried out through managing the previous fuel flow and fuel consumption by the aircraft engine using ANFIS. ANFIS is a hybrid computational tool, which helps to tune and explain past data and predict future behavior of the system. The fuzzy inference rules that are created in ANFIS rely on both the input and the target output. Tuning can be accomplished with the learning ability of NN. To achieve flawless performance possible faults in the fuel system are detected and corrected by generating the appropriate control signals before the occurrence of massive damages in terms of economy and human life. In this scenario, health management tools have been encouraged.

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Nomenclature

$S(.)$	Sigmoid activation function
$y'(k)$	Sigmoid function
$\theta(.)$	Threshold activation function
δ_p	Error derivation
δ_k	Derivation of error
t_p	Corresponding target
v_k	Predicted outputs
$e_{i/p}$	Actual input
$e_{o/p}$	Output of the NN model
N	Number of iterations
$F_{L1,i}$ and $F_{L1,j}$	Outputs of the fuzzy layer
$\mu A^1{}_i(x)$ and $\mu A^2{}_j(y)$	Membership functions
$\overline{Z_i}$	Output of the third layer
$\{P_i, Q_i, C_i\}$	Consequent parameters set
f	Total output
W	Regular hyperplane
R	Highest distance value
$\|\|w\|\|$	Geometry distance
Φ	Kernel function
$f_T^1(t)$	Time taken by the fuel tank
$f_T^{fuzz}(t)$	Time taken by the fuel tank after fuzzification
$T_{ar}{}^{fuzz}(t)$	Target time of fuel tank

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