# COMPARISON OF ANFIS AND ANN TECHNIQUES IN THE SIMULATION OF A TYPICAL AIRCRAFT FUEL SYSTEM HEALTH MANAGEMENT

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***ABSTRACT***

*The performance of an aircraft can be improved by predicting the possible complications associated with the system. Prognostics and Health Management (PHM) methodology includes fault detection, diagnosis, and prognosis. In this paper, a comparison of Adaptive Neuro-Fuzzy Inference System (ANFIS) with Artificial Neural Network (ANN) based fault prognosis tool for a typical aircraft fuel system is proposed. The ANFIS is an expert system which works on logical rules. The inputs of both ANFIS and ANN are trained by considering the same input data and generate the corresponding control signal. These methods identify the presence of faults and mitigate them to maintain a proper fuel flow to the engine. Overlooking the presence of any faults in time could potentially be catastrophic which can lead to possible loss of lives and the aircraft as well. These proposed tools work on the logical rules developed as per the engine's fuel consumption and quantity of fuel flow from the tanks. The results are compared and analyzed which demonstrate the superiority of ANFIS tool compared to ANN.*

***KEYWORDS***

*Aircraft Fuel System, ANFIS, ANN, Fault Analysis, Diagnosis, Prognosis, Health Management*

## 1. INTRODUCTION

Prognostics and Health Management (PHM) is the study of breakdown mechanisms and lifecycle management of a system [1]. It is a method that helps to assess the consistency of a system under its operating conditions to analyse the time of failure and mitigate the system risks [2]. An aircraft is a complex system operating as a group of interrelated systems and subsystems [3]. Every aircraft system is responsible for safe operation.

Prognostics is the process of prediction based on present and prior conditions. Diagnostics pertains to the recognition and separation of faults or failures [4, 5]. The goal of prognostics is to assess the overall future healthiness or condition of a system. It also deals with the prediction of the quality of a system including the Remaining Useful Life (RUL) of the system. In an aircraft, fuel to the engine is made to flow through fuel pipelines. A malfunction in any of the components, like, leakage in tanks, pump breakdown, pipeline leakage, and the valve stuck, *etc.,* may lead to improper functioning of the fuel system that results in the failure of the mission.

In the presnt work, a simulation model is built to monitor and manage the health condition with a rule-based prognostics mechanism thus helping to make such predictions possible. The process of prognostics is a mathematical computation mechanism that predicts the future health of a complex system, fuel system in this context, based on the amount of past and current data

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available. The ultimate predictions made are based on data collected from multiple tanks with warnings, alerts, and safety measures. Continuous availability of useful data facilitates in improving the ability to diagnose and predict the useful functional life of a system. As the complexity of a given system increases, identification and isolation of the fault becomes difficult within the system, thus increases the work of the maintenance engineers [6]. With these increasing demands on the safety of systems and dependability, a broad range of fault detection, diagnostic and prognostic methodologies have been projected in the literature in the recent years [7].

Artificial Intelligence (AI) techniques based on neural networks and fuzzy logic are effective for modeling the health management of an airplane fuel system. An ANN model can imitate a non-linear relationship between the required input and predicted output with good precision [8]. ANN is trained before it is used to model as per our required input-output relationship of the fuel system. Automatic updates of ANN model consider the data for any changes in working conditions of the system [9]. ANFIS is a robust scheme which includes both neural network and fuzzy logic. It is a hybrid technique with two methodologies compensating one drawback with the asset of other. Similar to the ANN based tool [10], ANFIS tool provides fault detection and prediction approach, which helps to investigate the health of an fuel system under consideration. The ANFIS controller [11] is based on the logical rules of the expert system that generates the control signals as per the fuel requirement by the engine. This study focuses on proper management of the flow of fuel to the engine by isolating the faults and mitigating them using these prognosis tools.

## 2. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

ANFIS is a hybrid soft computing technique which incorporates high reasoning capability with high computational power [12]. The rules of ANFIS depends on both input data and expected a result. Fuzzy inference tuning mechanism is combined with the learning capability of the neural network. The layered structure of ANFIS is as shown in figure 1. It consists of five layers, (i) input layer, (ii) Fuzzification layer, (iii) Product layer, (iv) Normalization layer and (v) Defuzzification layer. The inputs to the ANFIS tool considered are fuel consumption of engine and previous instant fuel flow. Further, the control signals generated correct the fuel flow rate and maintain to avoid any malfunctioning of the system tank. Thus, from the considered parameters the ANFIS methodology helps in achieving a proper tuning [13].

The most common fuzzy rule set used is first order Takagi-Sugeno inference system which is expressed as:

Rule 1: If $X$ is $M_1$ and $Y$ is $N_1$ then $f_1 = p_1 X + r_1 Y + k_1$

Rule 2: If $X$ is $M_2$ and $Y$ is $N_2$ then $f_2 = p_2 X + r_2 Y + k_2$

Where, $p_1, p_2, r_1, r_2, k_1$ *and* $k_2$ are the linear parameters and $M_1, M_2, N_1$ *and* $N_2$ are the non-linear parameters.

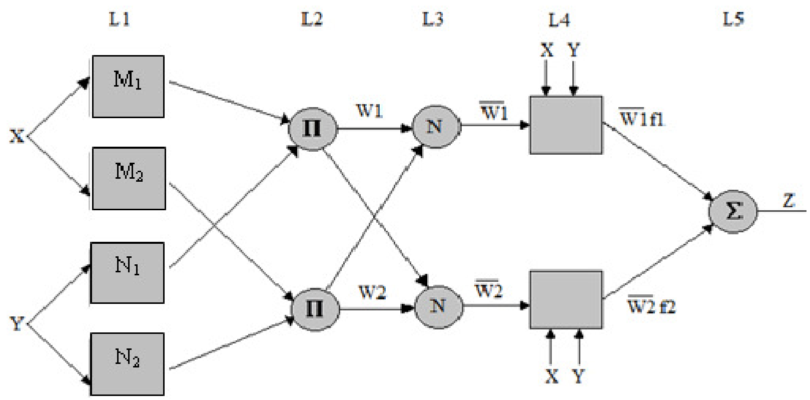


**Figure 1.** Structure of the ANFIS Methodology

### 2.1. Fuzzification layer:

In this layer every node adapts to an input function parameter. Each node output is a membership value that is given by the membership functions. The two inputs, (i) fuel flow at earlier instance (x) and (ii) fuel consumption of the engine (y) are connected to the $M_1, M_2, N_1$ *and* $N_2$ adaptive nodes. The degree of fuzzification is obtained by following equations:

$$S_{L1,i} = \mu M_i(X),\ i = 1,2 \quad (1)$$

$$S_{L1,j} = \mu N_j(Y),\ j = 1,2 \quad (2)$$

Where, $S_{L1,i}$ and $S_{L1,j}$ indicate the outputs of the fuzzy layer: $\mu M_i(X)$ and $\mu N_j(Y)$ are the membership functions of the fuzzy layer.

### 2.2. Product layer:

In this layer, the logical "and" operation that implies the product between the input membership functions is carried out. The outputs from the product layer act as the subsequent node's input weight functions. Equations (3) and (4) represent the outputs of the product layer.

$$W_1 = S_{L2,i} = \mu M_i(X).\mu N_i(Y),\ i = 1,2 \quad (3)$$

$$W_2 = S_{L2,j} = \mu M_j(X).\ \mu N_j(Y),\ j = 1,2 \quad (4)$$

### 2.3. Normalization layer:

This layer forms the third layer in the ANFIS structure. Here, every node is fixed and points to the IF portion in the fuzzy rule. The input weights get normalized in this layer for permitting the execution of fuzzy "and" operation. N is the label of this layer and the outputs from this layer are depicted in equations (5) and (6).

$$\overline{W_1} = S_{L3,i} = \frac{W_i}{W_1 + W_2},\ i = 1,2 \quad (5)$$

$$\overline{W_2} = S_{L3,j} = \frac{W_j}{W_1 + W_2}, \; j = 1,2 \tag{6}$$

### 2.4. Defuzzification layer:

An adaptive action is conducted in this layer. The previously set fuzzy rules help in obtaining the output membership functions from this layer. The outputs of this layer are described by the equations (7) and (8).

$$\overline{W_1} f_i = S_{L4,i} = \frac{W_i}{W_1 + W_2}\left[ p_1 X + r_1 Y + k_1 \right] \tag{7}$$

$$\overline{W_2} f_j = S_{L4,j} = \frac{W_j}{W_1 + W_2}\left[ p_2 X + r_2 Y + k_2 \right] \tag{8}$$

### 2.5. Output layer:

The THEN part of the fuzzy rule is represented using this layer of ANFIS. The outputs are evaluated using the relation:

$$f = S_{L5,i} = \sum \overline{W}_i f_i = \frac{\sum \overline{W}_i f_i}{\sum W_i} \tag{9}$$

## 3. ARTIFICIAL NEURAL NETWORK (ANN)

Similar to ANFIS, ANN is built by using a feed-forward mechanism by regulating the input parameters to obtain the desired results. A rule-based mechanism does learning and training process of the input-output patterns. This method helps to learn and adapt not only from environmental changes but also from changes in the output, *i.e.,* fuel consumption by the engine. A line connecting to fuel

Different types of sensors are installed in given an aircraft system. As sensors become smaller and smarter, the use of such sensors helps to gather a large volume of data which can be processed for prognostics [14]. Artificial Neural Network models match with the biological neural systems that process parallel information [15]. ANN consists of two layers connected to the peripherals: an input layer to collect the data and an output layer to represent the result of the network. An example of a simple neural network is as shown in figure 2. $A_1, \ldots, A_n$, represent the 'n' number of input signals and $Wk1, \ldots, Wkn$, represent the weights associated with each signal. These weighted inputs are added in a summing junction, and an output $Y$ is obtained through the activation function $F$.

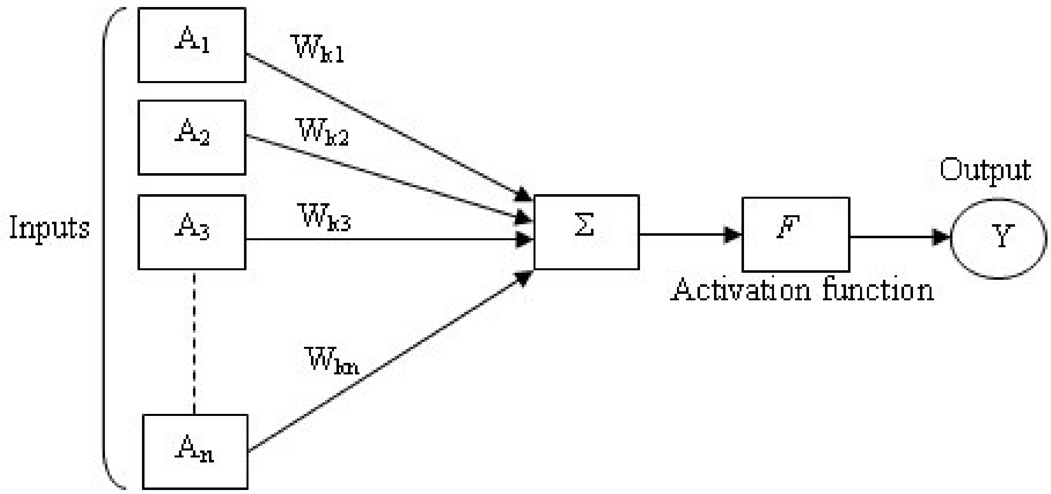


Figure 2. A Neural Network Model

In this neural network model, the summation function aggregates a weighted sum of inputs, and the activation function converts the sum into the final output of the network [16]. Among the different training methods, Back Propagation (BP) is the most efficient one. Learning in this neural network is achieved by collecting the information in the form of training data set. The weights are considered based on the type of training algorithm adopted.

This prognostic model includes four layers; an input layer, two intermediate hidden layers and an output layer as shown in the above figure 2. The feed-forward neural network equations for each step are as shown:

$$\mathrm{V_k} = \sum_{j=1}^{n} Wkj\ Aj \tag{10}$$

$$Y'(k) = S(V_k) \tag{11}$$

$$Y = \theta\left(\sum_{k=1}^{n} Y'(k)\right) \tag{12}$$

Proper training of the neural network model once done can be used for any type of incomplete or new data. The response obtained give predictions based on the inputs and adjusted weights accordingly. The prognostics engine uses input data (the fuel flow rate) and historical information (previous engine consumption rate) to train the ANN model for making predictions. The output function is described as:

$$V_k = f\,(W_{k1},\ W_{k2},\ \dots\ ,\ W_{kn}) \tag{13}$$

The model with the least error level is considered through comparing results by training the model with a different number of layers with multiple iterations.

## 4. SIMULATION OF THE PROPOSED PROGNOSIS TOOLS

Figure 3, shows the block diagram of the prognosis tool with aircraft fuel tanks, pumps and pipeline routes with ANN and ANFIS methodology. Generally, the fuel tanks in the aircraft are in the aircraft's fuselage and wings [17]. A typical small aircraft fuel system model is simulated in the Simulink, by considering eight centrifugal fuel pumps. Out of eight fuel pumps, two pumps are used for fuel delivery between the left and right wings and two other pumps for backup for any emergency conditions and remaining four main pumps for fuel delivery to the engines.The primary objective of this work is to monitor the fuel flow continuously to the engines without any restrictions to reach the required fuel consumption rate. Any fault occurred in the fuel tanks is detected by ANFIS methodology and mitigated by ANN methodology. In a fuel system, there are various parameters which change due to change in the altitude of the aircraft. For example, ambient temperature variations can cause the water contaminants in the fuel to condense and settle at the bottom of the fuel tanks. Later, ice crystals may form, which block the filter and thus interrupting the flow of fuel to engines.

ANFIS is a machine learning tools which mimics the decision-making capability of the humans. The five-layer structure of ANFIS methodology can learn from the fuzzy theory to estimate the nonlinear functions of the system. Comparing with ANN, ANFIS has faster computational power and it also performs well when compared to the other soft computing tools. In this work, ANFIS acts as a controller and as a diagnostic tool which detects faults and mitigates by generating the desired control signals.

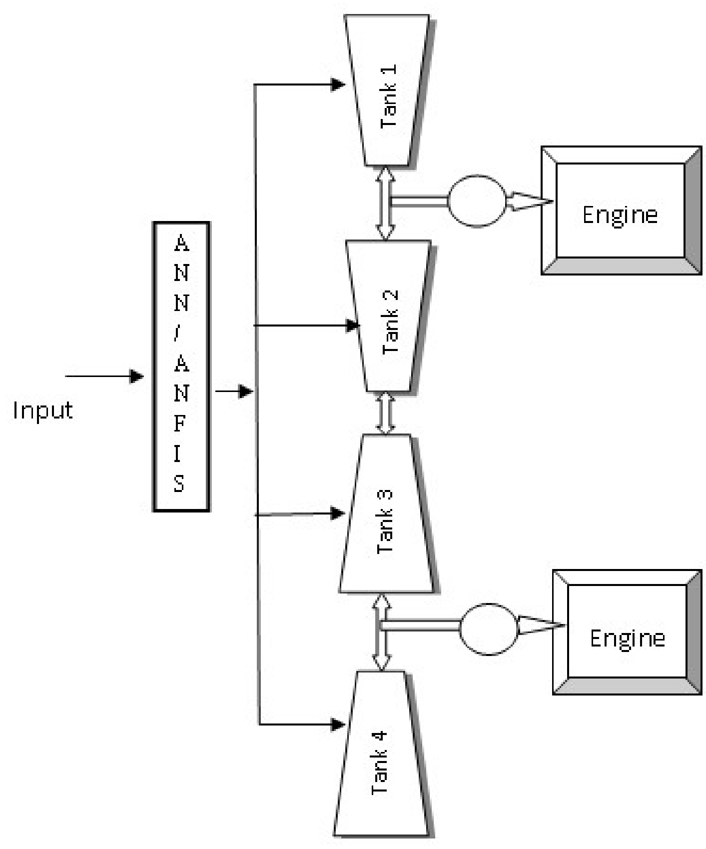


Figure 3. Block diagram of a typical aircraft fuel system with Prognosis tool

Because of these changing features of the fuel system of the aeroplane, both ANN and ANFIS methods are promising for prognostics [18]. These prognosis tools are used to manage and monitor the fuel system and to control the fuel flow as per the fuel consumption rate of the engines. Both perform fault detection and corresponding predictions made to maintain required fuel flow rate to the engine throughout the flight. The input-output relation of the proposed model with two inputs and a single output is as shown in figure 4.

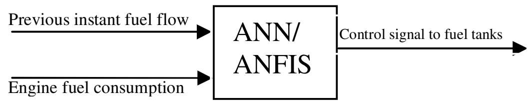


Figure 4. I/P - O/P relation of ANN Model

Back Propagation is an effective training algorithm to minimize the output error. During the process of operation of the fuel system, the BP algorithm measures and calculates the gradient of the error and adjusts the weights of the neural model with respect to the required fuel flow rate. Thus, the ANN prediction model generates the necessary control signals to fetch the required fuel flow rate to the engine. Figure 5 shows an approach for updating process of the ANN model. For maintenance of fuel system, the maintenance engineers generally follow a scheduled maintenance regime. Timely maintenance keeps the working condition of the fuel system within the required range of operation. Any leakage in tanks, pumps failure or other faults can alter the operation or may lead to damage of aircraft. Therefore, it is necessary to continuously update the model with the current data, to maintain the required fuel flow rate.

A Fuel Management System (FMS) gives fuel measurements based on distance to travel, wind and time. When an aeroplane is programmed for a flight route, the fuel monitoring and management system have a capability of displaying the total flight endurance, amount of fuel available and estimation of remaining fuel. The fuel display in the cockpit can be unreliable if there are tank leaks, pipeline leaks, components failure or plumbing malfunctions [19]. The main task of the fuel management system is to provide the estimation of fuel for the complete flight. This estimation in the FMS is obtained by actual rate of fuel consumption and amount of fuel available in the fuel tanks. In the current FMS, maintenance cost is high and need to check the proper functioning of all subsystems to maintain actual fuel flow rate. Any anomaly in the process leads to catastrophic damage to the system.

Some of the general factors faced during the process of fuel management are fuel exhaustion, fuel starvation, and fuel contamination. Fuel starvation is an onboard condition wherein the engines will not receive any information regarding the availability of fuel. Fuel exhaustion is another condition where the airplane's engines are running out of fuel because of some malfunction in the fuel system. Presence of foreign particles like water, surfactants, dirt in the fuel cause fuel contamination which may lead to engine breakdown through damaging or the blocking fuel system subcomponents [20]. Hence, ANN and ANFIS prognosis tools help to detect and diagnose the occurrence of any faults, which is not possible with the programmed fuel management system. Also, with these proposed tools, redundant components in the fuel system can be reduced.

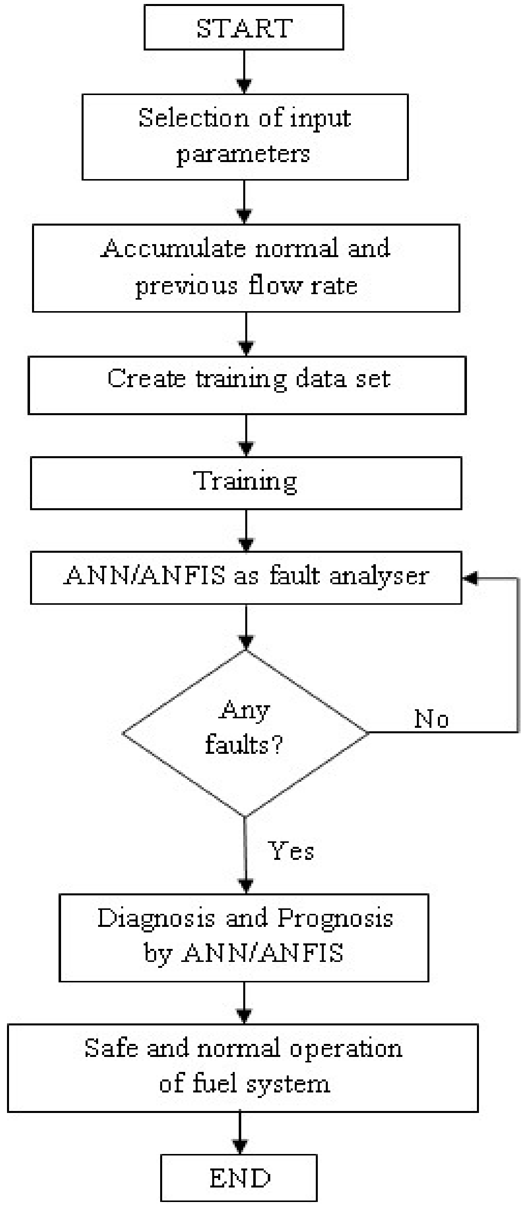


Figure 5. Flowchart of ANN/ANFIS-based prognostic tool for fuel system

## 5. SIMULATION RESULTS AND DISCUSSION

Both the ANN and ANFIS based prognostic tools are implemented in MATLab/Simulink. In this work, the model of the aircraft fuel system is simulated similar to the methodology of the paper [21]. A typical small aircraft fuel system model is interfaced with both ANN and ANFIS controllers, which detect the fault occurrences, diagnose and predict the required rate of fuel flow. The fuel management process is visualized using these prognostic tools. The simulated model of a typical aircraft fuel system is as shown in Figure 6. Simulink model of the fuel tank, fuel pump, fuel line and geometry of the aircraft fuel tank are simulated, and details of the same are available in the authors paper [11]. For simulation, the fuel assumed is the liquid Hyjet-4A and the characteristics are available in the simulink toolbox. The fuel temperature of 22.72°C and the viscosity of 1 are assumed respectively. The Simulink model of aircraft fuel pipeline with an internal diameter of 10mm geometry factor of 64 is built similar to the actual pipelines with metal pipes. An axial-centrifugal pump with electric driven motor is modeled and opted in the place of the actual fuel pump. During simulation of the fuel pump, the angular velocity of 1770 rpm and the correction factor of 0.8 are set.

Generally, the fuel system is exposed to inertia, vibration, fluid, and load of aircraft during operation which has to be considered without breakdown. The content of fuel tank(s) should provide at least 30 minutes of continuous engine operation with full power. The Simulink model of a simple four tank fuel system is designed along with fuel pumps, pipelines, and fuel indications. As controllers, both the prognostic tools are connected and analyzed successively.

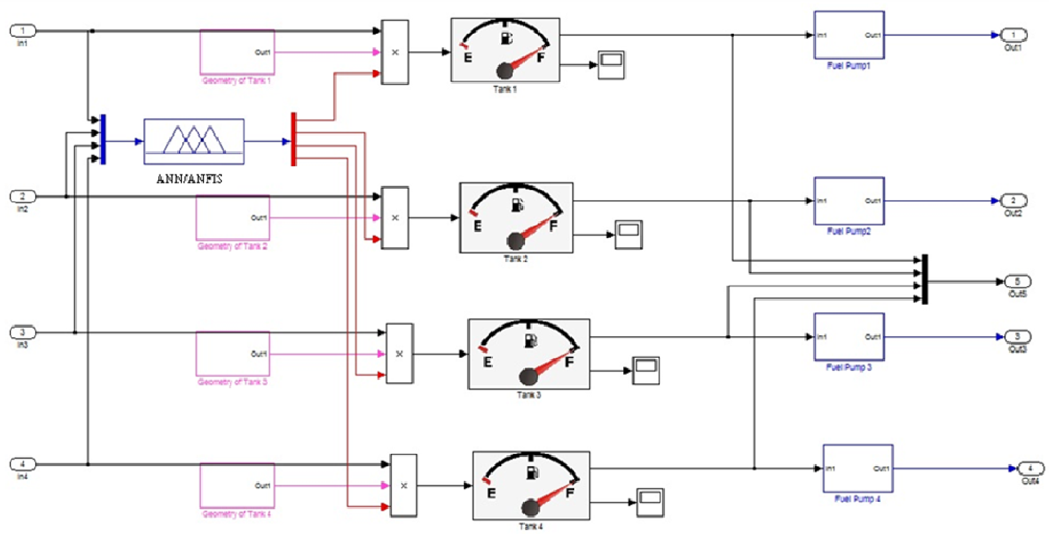


Figure 6. The Simulink model of the aircraft fuel system with ANN/ANFIS as a controller

They detect the fault occurrences and take necessary action to correct by training according to the input parameters. The output generated from both the models are the desired control signals obtained based on the previous instant flow rate of fuel and rate of fuel consumed by the engines. Thus, the control signal fetches the required rate of fuel to the engine(s) without any change, irrespective of any anomalies during operation. It takes few minutes and/or hours to visualize the fuel leaks because fuel has a slow evaporation rate. Hence, it becomes difficult to identify fuel leaks immediately. The effectiveness of this method is evaluated by results with the ANN prognostic technique. The fuel management test result without a controller is depicted in figure 7a, and the fuel consumption requirement is illustrated in figure 7b.

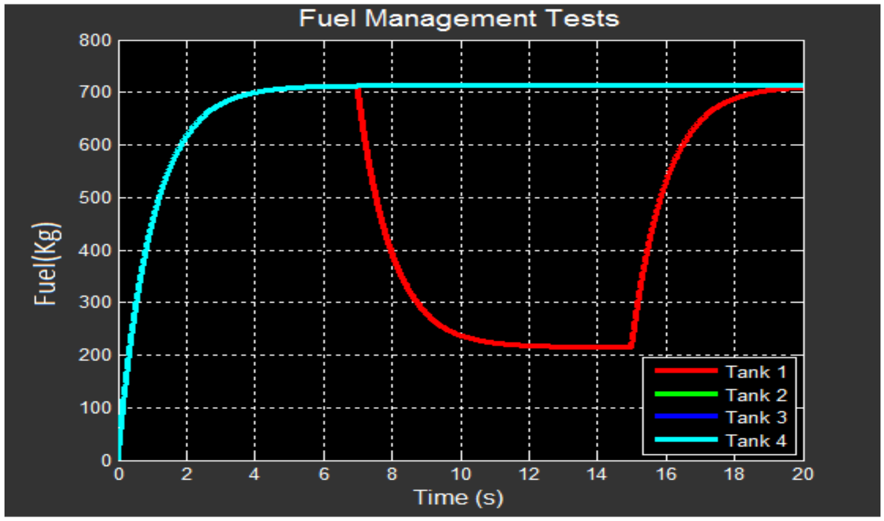


Figure 7a. Fuel management in the aircraft fuel system without a controller

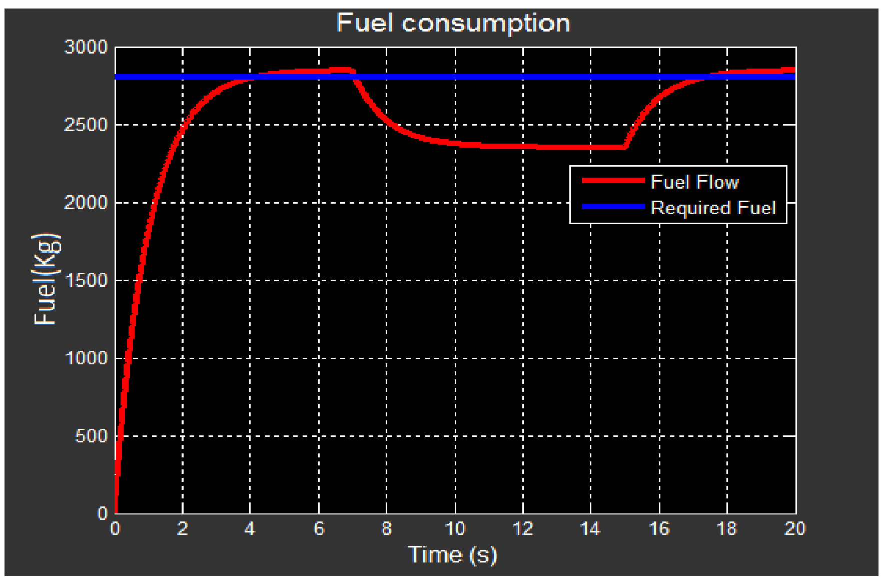


Figure 7b. Fuel consumption in the engine of the aircraft fuel system without a controller

In this paper, the fuel system is connected with ANFIS and ANN controllers. Efficiency of both the methods is assessed by comparing with and without these controllers. Twenty seconds of simulation time is used. From figure 7b, it is clear that the required fuel for a small aircraft fuel system considered is about 2800 kg/hr, which is fulfilled by four fuel tanks with each of 700 kg/hr within 4 to 6.5 seconds. After 4 seconds, the level of fuel in one of the tanks is reduced due to the faults. The current automatic or programmed fuel management system may not identify these faults correctly in the aircraft fuel system. Hence, the performance of the aircraft gets affected. Figure 8 shows the fault condition analysis using ANFIS. Similarly figure 9 shows the fuel management test and consumption of fuel by engine using ANN. Both the techniques identify fault condition and diagnose the issue by injecting additional fuel from other tanks. During simulation faults in the first tank are introduced intentionally which decrease level of fuel in the tank. Since the ANN methodology is a traditional one weight upadation procedure is based on previous input data which is 2600kg/hr. However, it is not the actual requirement of the engine.

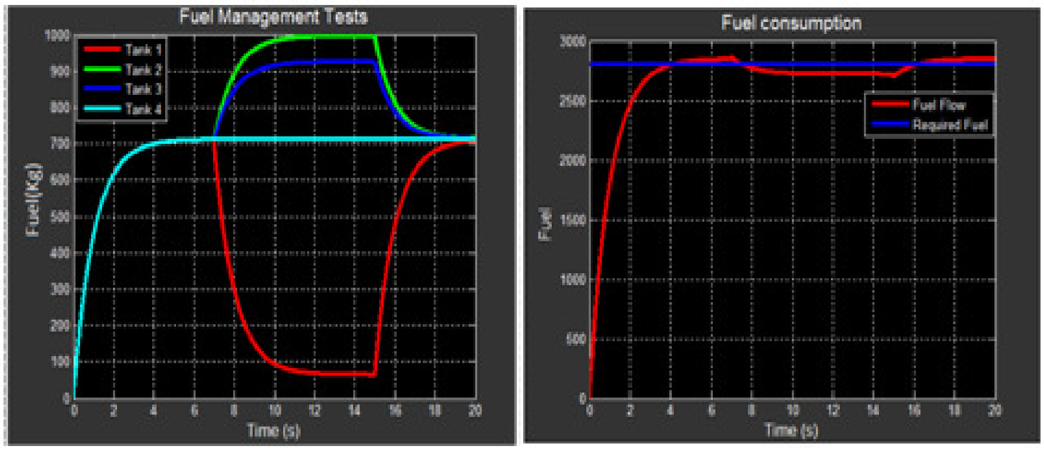


Figure 8. Fuel management and fuel consumption using the controller (ANFIS)

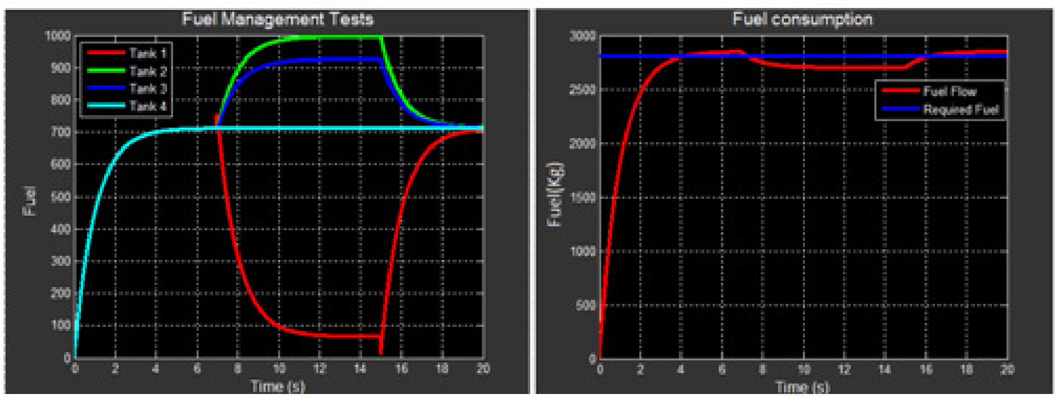


Figure 9. Fuel management and fuel consumption using ANN controller

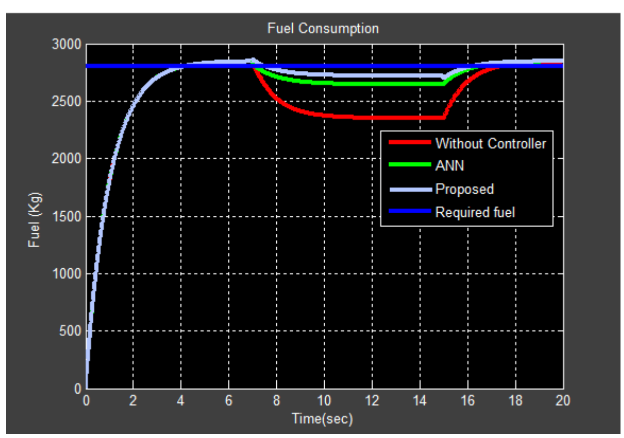


Figure 10. Comparison of fuel consumption using ANFIS AND ANN METHODOLOGY

From the comparison, as shown in figure 10, the ANFIS method effectively detects the fault in the fuel tank and manages the fuel requirement of the aircraft engine. compared with management tests performed without any controller and with ANN. As seen from the results, using ANFIS as a controller the fuel requirement at the required fuel flow rate by the engine is fulfilled even in the presence of anomalies.

## 6. CONCLUSION

Prognostics is a process of failure analysis followed by the health prediction of the system. ANN and ANFIS-based fault prognosis tools for a typical four tank aircraft fuel subsystem is developed and its comparison is presented in this paper. Both the methods used promise to deliver and manage the fuel flow and help to monitor the fuel level in each tank of the fuel system. The proposed prognosis models identify the presence of faults, mitigate them and maintain the proper fuel flow to the engine at the required fuel consumption rate by generating the proper output signal. Through the comparison, the efficiency is verified. It shows that the ANFIS method is a unique and effective methodology to detect, diagnose and mitigate the fault conditions. The tool is simulated in MATLab and Simulink for a laboratory environment.

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Short Biography

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