Application of Fuzzy Logic in Aircraft Sensor Fault Diagnosis

E. Kiyak and F. Caliskan

Abstract— Due to the possibility of unexpected situations, the authorities feel the necessity of keeping certain sub systems or components of aircraft under continuous scrutiny. Accordingly, sensors in flight control systems are considered as one of the crucial components of the system. The failure to detect sensor faults is quite likely to cause very serious problems, which makes it vital to carry out effective fault detection and isolation processes. Through the determination of the size of the fault, it might be possible to make use of this information in the realization of the repair. In this study, the detection and isolation of sensor faults are carried out through bank of Unknown Input Observers. Additionally, a structure using fuzzy logic is suggested in order to have an idea about the size of the fault. When this suggested structure is used, it might be possible to choose the most suitable control type to remove the effects of the fault by control reconfiguration following fault detection and isolation. To use some reliability maintenance procedures reduces the number of the catastrophic failures.

Keywords—Fault diagnosis, fuzzy logic, reconfiguration, observers

I. Introduction

The detection, isolation, identification and reconfiguration of a fault involves [1, 2]:

The detection of the fault: Determining the problem when something goes wrong in the system,

Isolating the fault: Determining the exact location and the type of the fault,

Identification of the fault: Determining the size of the fault and its intensity,

System Reconfiguration: The realization of control activities which allow the system to function despite low performance.

A fault can be defined as the deviation of at least one characteristic function from standard, acceptable and usual functioning of a system. Fault occurs within a system and can lead to lower or even no performance of a component of the system responsible for a specific task. There are various types of faults resulting from the following situations; faulty design and production, inappropriate use, maintenance procedures, software, operator, and environmental condition. Some of these faults can also be classified as "errors". In this respect, there is a great human effect in these processes. When no intervention is applied in case of a fault, it can lead to a bigger fault and consequently system disfunctioning (failure).

On the other hand, a failure refers to permanent interruption in the functioning of a system fulfilling a certain task under predetermined working conditions. One or more faults may lead to a system failure.

Any deviation in the system should not be considered as a fault. Deviations can be categorized into three types; temporary, intermittent and permanent. Temporary deviations are due to the effects of external disturbance and last a certain time and turns back to normal functioning with no intervention required. Intermittent deviations are generally due to unstable device and tool functions. Permanent deviations can be caused by component faults, physical damage and design fault. It is quite difficult to detect the cause leading to temporary and intermittent deviations since deviations exist when the cause leading to deviations are present and they end when the cause is not present anymore [3].

The methods used for fault detection can be examined in two groups in general sense; those that are not based on a model and those that are based on a model. The methods which are not based on a model do not require the process to make use of a mathematical model.

The simplest and the most commonly used method in fault detection is to check the limit of measurable variable. In this technique, two limit values are assigned for a measurable variable Y(t). When the value of this variable exceeds the upper limit defined as Y_{max} and is lower than the lower limit Y_{min}, it might be concluded that a problem exists in the system. The disadvantage of this method is the changes in working limits.

Another that might be applied in fault detection method is based on physical redundancy that is the comparison of output values of system components [4].

In addition to the methods that are not based on a model mentioned above, faults can also be detected by making spectrum analyses of system measurements or making use of the structures allowing logical deductions.

The fault detection methods based on modeling involve residual production and decision making processes. They also require the use of a mathematical model as analytical redundancy. The most common model based fault detection

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methods are based on observers in deterministic systems and Kalman Filter in stochastic systems.

Savanur et al. have shown through simulations the sensor fault detection, isolation and reconfiguration in an aircraft model by using fuzzy logic In their studies, the faults are first detected and isolated through Kalman Filter, and then an appropriate control input is established through a rule database formed by means of fuzzy logic [5].

By using simulations, Kiyak et al. have shown how sensor faults for different scenarios of VTOL aircraft were detected [6].

Similarly, the method used by Kulkarni et al. for fault detection in hydraulic systems by using fuzzy logic is shown through simulations. In fuzzy logic controller, residuals and cumulative residuals are used as input, and the intensity of the fault as output. The studies by Kulkarni et al., in short, emphasize not only the detection of the faults but also their size [7].

Kiyak et al. carry out the detection and isolation of aircraft sensor and actuator faults through unknown input observers. The reconfiguration suggests by them allowed the aircraft to function normally again [8].

In this study, the detection and isolation of sensor faults in a flight control system are carried out through observers based on modeling. In addition, a fuzzy logic structure is suggested to have an idea about the size of sensor fault. When this suggested structure is used, it might be possible to choose the most suitable control type to remove the effect of the faults efficiently during the phase of reconfiguration following the detection and isolation of the fault.

II. Maintenance and Fault Diagnosis

Maintenance applications can be classified as planned maintenance and unplanned maintenance [9].

Unscheduled maintenance in aviation is not wanted. To reduce the number of unexpected downtimes, fault diagnosis methods and reliability centered maintenance can be used to address dominant causes of equipment failure. This allows maintenance personnel to fix failures before aircraft damage or crash [10].

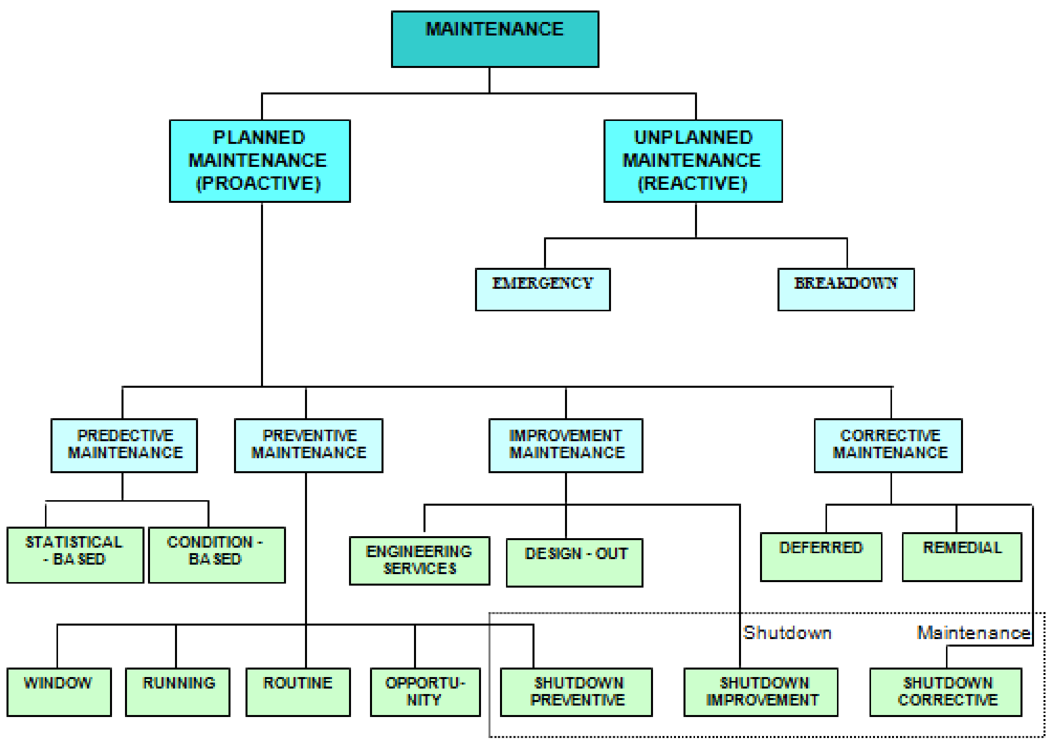

Fig. 1 Types of maintenance

Corrective maintenance activities are conducted by four important steps [11] as shown in detail in Figure 1:

1. Fault detection.
2. Fault isolation.
3. Fault elimination.
4. Verification of fault elimination.

In the fault elimination step several actions could be taken such as adjusting, aligning, calibrating, reworking, removing, replacing or renovation.

Corrective maintenance has several prerequisites in order to be carried out effectively [11]:

1. Accurate identification of incipient problems.
2. Effective planning which depends on the skills of the planners, the availability of well developed

maintenance database about standard time to repair, a complete repair procedures, and the required labour skills, specific tools, parts and equipment.
3. Proper repair procedures.
4. Adequate time to repair.
5. Verification of repair.

Maintenance Objectives are [11]:

- Maximising production or increasing facilities availability at the lowest cost and at the highest quality and safety standards.
- Reducing breakdowns and emergency shutdowns.
- Optimising resources utilisation.
- Reducing downtime.
- Improving spares stock control
- Improving equipment efficiency and reducing scrap rate.
- Minimising energy usage.
- Optimising the useful life of equipment.
- Providing reliable cost and budgetary control.
- Identifying and implementing cost reductions

The maintenance can be improved if an efficient procedure for the prediction of failures is implemented. The primary source of information on the health of the engines comes from measurement during flights. Several variables such as the core speed, the oil pressure and quantity, the fan speed, etc. are measured, together with environmental variables such as the outside temperature, altitude, aircraft speed, etc [12].

Teranishi and Stubberud monitored each blade position into an aircraft engine using eddy-current data to detect potential damage to a turbine engine. A hierarchical neural network was used to track changes in the position of the blades [13].

Fuzzy logic or other decision support tools could be used for maintenance by designers and managers [14]. Intelligent computer systems that can solve problems and adapt to new situations [15, 16].

If decision support systems are used, it is useful to identify parts/spares critical to the operation of a training aircraft in terms of both their prices and quantities and application of reliable and robust forecasting method to predict the future demand requirements, thereby optimizing the logistic supply chain and aircrafts operational performance over the life cycle [17].

Because of the dynamic process, aircraft maintenance's work is unpredictable. An electronic based of work in progress system is apparently required [18]. Such system would be to reduce the number of delays and cancellations and the number of unnecessary parts removal, which add significant costs to airline and military airplane maintenance operations [19].

III. Model-Based Fault Detection and Isolation (FDI)

It is quite disadvantageous to have at least two spares to detect one fault. For instance, it is not convenient to have two spares for each component (sensor, actuator and control surfaces) in such a complex system like aircraft since they might cause extra weight and cost as well as space problems. Therefore; this method should be used for simpler systems where above mentioned disadvantages do not cause considerable problems.

As for fault detection, it would be more advantageous to use analytical redundancy (computer, microprocessors or software) in which a mathematical model is used and various computations are made rather than using software excess through special sensors, physical excess and limit control that are not based on modeling.

The basic principle of observers is that the predictions of state variables of a dynamic system are closer to the predictions of state variables of another system called "observer". The same principle is applicable to unknown input observers (UIO), which is insensitive to disturbance (unknown input).

Consider a continuous linear time invariant state space model of the system [20, 21]:

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) + Ed(t) \\ y(t) &= Cx(t) \end{aligned} \tag{1}$$

A, B, C, E, x, u, y, and d represent the system coefficient matrix, the input coefficient matrix, the output coefficient matrix, the unknown input distribution matrix, the state vector, the input vector, the sensor output and the unknown input vector respectively.

The structure of the unknown input observer is described as [22, 23]

$$\begin{aligned} \dot{z}(t) &= Fz(t) + TBu(t) + Ky(t) \\ \hat{x}(t) &= z(t) + Hy(t) \end{aligned} \tag{2}$$

F, z, and $\hat{x}$ represent the observer dynamics matrix, the observation vector, and the estimated state vector respectively. T, K and H are defined below.

The error vector is defined by:

$$e(t) = x(t) - \hat{x}(t) \tag{3}$$

Using Equation (1) and (2), error vector is rewritten as

$$\begin{aligned} e(t) &= x(t) - \hat{x}(t) = x(t) - z(t) - Hy(t) \\ &= x(t) - z(t) - HCx(t) \\ &= (I - HC)x(t) - z(t) \end{aligned} \tag{4}$$

Using Equation (4), the derivative of the error vector is obtained as

$$\begin{aligned} \dot{e}(t) = {} & (A - HCA - K_1C)e(t) - [F - (A - HCA - K_1C)]z(t) \\ & - [K_2 - (A - HCA - K_1C)H]y(t) \\ & - [T - (I - HC)]Bu(t) - (I - HC)Ed(t) \end{aligned} \tag{5}$$

If the following relations hold true and $K = K_1 + K_2$;

$$(HC - I)E = 0 \tag{6}$$

$$T = I - HC \tag{7}$$

$$F = A - HCA - K_1 C \tag{8}$$

$$K_2 = FH \tag{9}$$

derivative of the error vector will be [24]:

$$\dot{e}(t) = Fe(t) \tag{10}$$

and, then the solution of the error vector is $e(t) = e^{Ft} e(0)$. If F is chosen as a Hurwitz matrix, the solution of the error equation goes to zero asymptotically. So, $\hat{x}$ converges to x.

Once the fault is detected, locating the component where the fault occurs is called the isolation of the fault.

The fault isolation is to locate the fault. One method is called "Dedicated Observer Scheme" (DOS) in the related literature. Here, each residual signal is designed to be sensitive to one fault but is insensitive to others. These properties make isolation possible. However; it is quite demanding to obtain such a situation. To make maximum design freedom, another method called a generalized observer scheme (GOS) is used. Here, each residual signal is designed to be sensitive to faults in all but one sensor. The relationship between residuals and the fault in this structure is as follows:

$$\begin{aligned} &\left\| r^j(t) \right\| < \varepsilon^j \\ &\left\| r^k(t) \right\| \geq \varepsilon^k \quad k = 1, \dots j-1, \; j+1, \dots n \end{aligned} \tag{11}$$

In this situation, any fault in sensor (j) can be detected and isolated by checking the norms of the residuals as in Equation (11). Here, ε^j and ε^k are defined as threshold values.

During the identification and reconfiguration phase, fuzzy logic is used. The fuzzy process consists of three main units; namely fuzzifier unit; rule processing unit, and defuzzifier unit.

Fuzzifier unit is the first unit in fuzzy system. The data entered into this unit as certain and feedback results are fuzzified through some scale changes. In other words, each piece of information is assigned a membership value, and sent to rule processing unit after they are converted into a linguistic structure. The data that reach the rule processing unit are combined with rule processing data ('if … and … then … else') that are based on a database available as stored in the rule processing unit. The logical propositions mentioned here can be formed with numerical values as well depending on the structure of the problem. In the last step, the results obtained by using appropriate logical decision propositions are sent to defuzzier unit. When Fuzzy set relationships that are sent to defuzzifier unit are considered, fuzzy data are converted into real numerical values following another change of scale [25, 26].

IV. Detection of Aircraft Sensor Fault and Determining Its Size

Figure 2 displays the block diagram of the FDI and reconfiguration scheme.

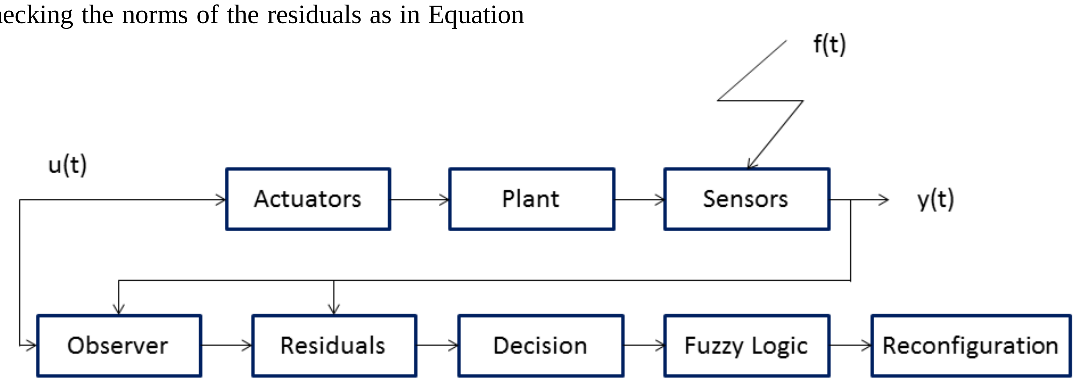

Fig. 2 Block diagram of the FDI and reconfiguration scheme.

As seen in Figure 2, the faults regarding the sensors during the overall process are determined through residuals by using unknown input observer structure. During decision making process, fault detection and isolation are carried out by evaluating the produced residuals. Later, fuzzy logic is used to obtain information concerning the size of the fault. Depending on the result of the evaluation, the generating corrective control signal or the generation of the signal switching on the spare sensor are realized.

Lateral state variables and input vector in an aircraft can be defined as:

$$x=\begin{bmatrix}\beta\\ p\\ r\\ \phi\end{bmatrix},\quad u=\begin{bmatrix}\delta_a\\ \delta_r\end{bmatrix} \tag{12}$$

A and B matrices obtained from stability derivatives are described as: [27, 28]:

$$A=\begin{bmatrix}Y_v & 0 & -1 & g/U_0\\ L'_\beta & L'_p & L'_r & 0\\ N'_\beta & N'_p & N'_r & 0\\ 0 & 1 & 0 & 0\end{bmatrix},\quad B=\begin{bmatrix}0 & Y^*_{\delta_R}\\ L'_{\delta_A} & L'_{\delta_R}\\ N'_{\delta_A} & N'_{\delta_R}\\ 0 & 0\end{bmatrix} \tag{13}$$

β is side-slip angle; p is roll rate; r is yaw rate; ϕ is roll angle; δ_a is aileron deflection; δ_r is rudder deflection; and $Y_v, L'_\beta, L'_p, L'_r, N'_\beta, N'_p, N'_r, Y^*\delta_R, L'_{\delta_A}, L'_{\delta_R}, N'_{\delta_A}, N'_{\delta_R}$ are stability derivatives.

Fault detection, isolation and reconfiguration are evaluated according to sensor fault related scenario. While these scenarios are produced, the values with Gauss distribution are applied in random time intervals within [5 10] closed range as unknown input (d). The system input is $u = [1\ 1]^T$ and the observer dyanamic matrix is F = diag [-10 -10 -10 -10].

Unknown inputs might be non-measurable external disturbances, unknown control effects or unmodelled system dynamics.

The system matrices are as follows:

$$A=\begin{bmatrix}-0.1208 & 0.0022 & -0.9520 & 0.0622\\ -1.6612 & -0.7362 & 0.0644 & -0.0507\\ 1.6127 & -0.1465 & -1.5933 & -0.0123\\ 0 & 1 & 0 & 0\end{bmatrix} \tag{14a}$$

$$B=\begin{bmatrix}0 & 0.014\\ 0.13 & 0.15\\ 0.018 & -0.39\\ 0 & 0\end{bmatrix} \tag{14b}$$

$$E=\begin{bmatrix}0.1\\ 0.1\\ 0.1\\ 0.1\end{bmatrix} \tag{14c}$$

$$C = I\,(4x4) \tag{14d}$$

f_a represents the fault effect due to sensor fault The fault vector used in the simulations is as follows:

$$f_a = [0\ 0\ x\ 0]^T \tag{15}$$

where x is defined as x < 20 degrees/s. The effects under various scenarios are investigated in the simulations.

The output effects in Figure 3 are obtained by using the system matrices given above. As a requirement of the scenario, the fault is generated at any time between the [0, 1000] range. Figure 3 displays the effect of the fault on outputs. 1, 2, 3, and 4 refer to side-slip angle, roll rate, yaw rate and, and roll angle respectively.

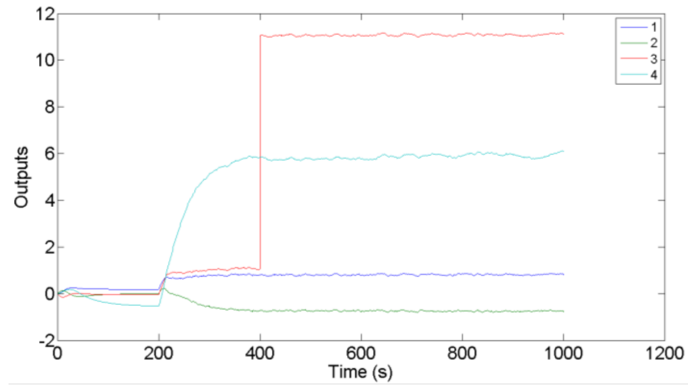

Fig. 3 Outputs

In Figure 3, the effects of unknown inputs are observed after the 200th second. After the 400th second, there is a sharp increase in yaw rate (number 3). Since it is quite difficult to determine whether the sudden change that occurred at 200th seconds, is due to disturbance or a fault, it is more convenient to use GOS for fault detection.

The norms of the residuals to be used in fault detection through UIO are obtained as in Figure 4.

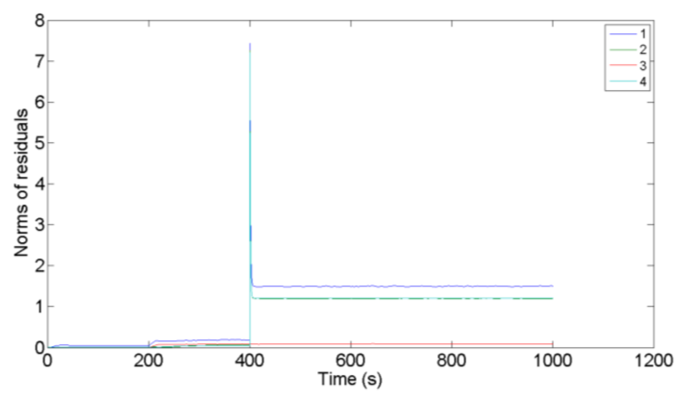

Fig. 4 The detection and isolation of sensor fault through the norms of residuals

In the GOS scheme, a total of four residual norms are obtained. It is observed that a small increase occurs due to the disturbance in residual norms after the 200th second. After the 400th second, on the other hand, there is a considerable increase in every residual norm except the residual norm that belongs to the yaw angle; the 3rd state variable. In our case, the fault in the sensor that belongs to yaw angle state has been detected and isolated. For the purpose of not evaluating the small increases due to unknown inputs as faults by mistake, faulty sensor has been detected by determining a threshold value.

After the detection and isolation of the faulty sensor, the size of the fault is identified by using a fuzzy logic approach, which has one input and one output. In order to determine the size of the fault, the multiplication of residual norms might be considered as a function of the residual norms, and is evaluated as an input parameter. Based on the GOS scheme, fault detection is carried out due to the increase in a total of three residuals. Naturally, these increases in residual norms make it possible to use residual norms multiplication in a clearer way.

The output and input functions of the fuzzy logic are chosen as very small, small, medium, big and very big. The functions that belong to controller are formed as shown in Figure 5 and 6 with the help of expert knowledge and observing the relationships between fault size and the multiplication of residue norms.

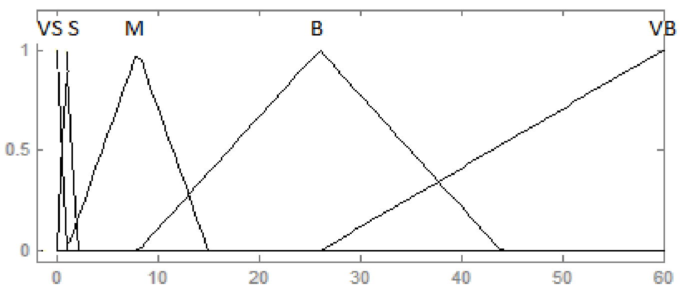

Fig. 5 Membership functions belonging to residual norms multiplication (Input)

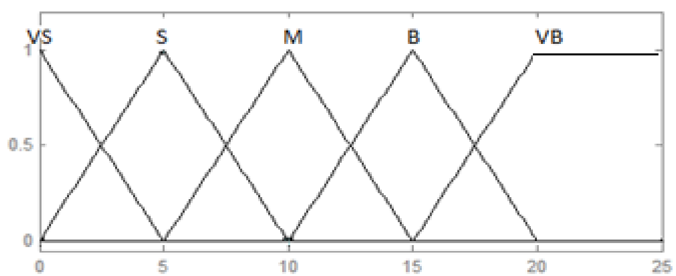

Fig. 6 Fault Size (Output)

The Truth table for the determination of the fault size is in Table 1.

Table 1 Truth Table

I	VS	S	M	B	VB
O	VS	S	M	B	VB

Based on the suggested fuzzy controller and centroid method, the fault sizes given in Equation (15) are successfully detected as shown in Figure 7 and Figure 8.

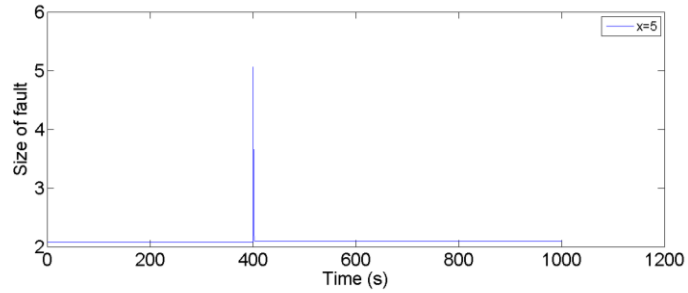

Fig. 7 The determination of the fault size, x=5 through fuzzy logic

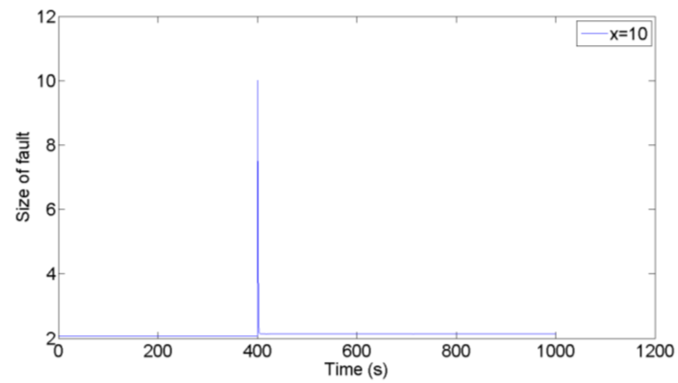

Fig. 8 The determination of the fault size, x=10 through fuzzy logic

After the detection, isolation of the fault, and the determination of the size, the outputs displayed in Figures 9 and 10 are obtained through reconfiguration phase for two different scenarios.

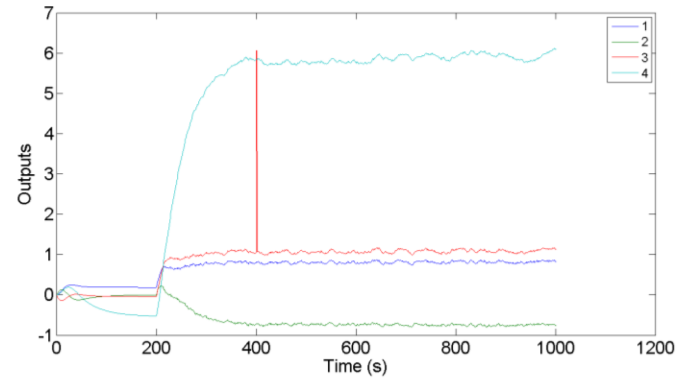

Fig. 9 The reconfiguration for the size, x=5

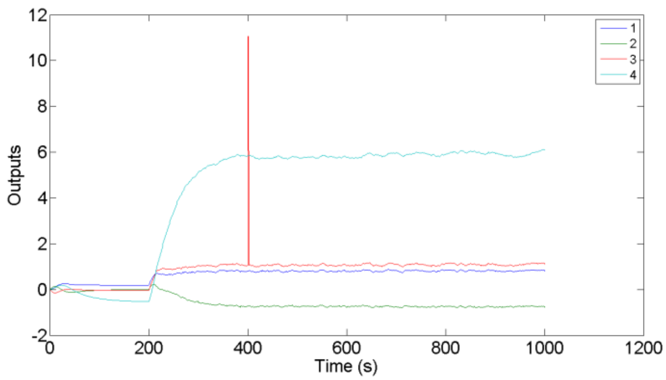

Fig. 10 The reconfiguration for the size, x=10

After the 200th second, a sharp increase is observed due to unknown input into the system. The FDI scheme is insensitive to the disturbance. On the other hand, a fault occurred at the 400th second can be detected as soon as it occurs. During the reconfiguration phase, a corrective control signal is generated according to the fault size. The corrective control signal is the negative value of the identified fault size. Instead of forming a corrective control signal, different methods can be used for reconfiguration when relatively larger scale faults occur.

V. Conclusion

In this study, the detection and the isolation of sensor faults in an aircraft model have been carried out through the use of unknown input observers to detect the fault despite the presence of unknown inputs.

The suggested method has been successful in detecting and isolating sensor faults occurred randomly at any time. At this point, in order to have an opinion about the upcoming system reconfiguration process, a structure with the rules based on fuzzy logic has been designed to identify the sensor fault size. The objective of these attempts has been to provide the choice and implementation of an appropriate control structure on a certain basis. It has been found that fuzzy logic mechanism determines different fault sizes, which have been presented through simulations under different scenarios. System reconfiguration process has been established by forming a corrective control signal and the desired performance has been obtained.

Acknowledgment

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