Detection of Bias, Drift, Freeze and Abrupt Sensor Failure using Intelligent Dedicated Observer Based Fault Detection and Isolation for Three Interacting Tank Process

[1] C. Amritha, [2] U. Sabura Banu

**[1] Assistant Professor, VelTech Dr SR and Dr RR Technical University
Chennai, Tamil Nadu, India**

**[2] Associate Professor, B. S. Abdur Rehman University
Chennai, Tamil Nadu, India**

Abstract - This paper presents a design of MANFIS (Multiple Adaptive Neuro Fuzzy Inference System) based sensor Fault Detection and Isolation (FDI) scheme for a three interacting tank system. Three pairs of dedicated observers are designed to estimate the three states of the system. The observers designed are fuzzy systems whose optimal membership functions and rule base are determined by neural networks. The difference between the estimated and measured value is called as residuals. Decision functions are determined from the residuals. These functions are compared to a threshold value, when the value of these functions exceed a particular threshold, the presence of fault is indicated. The FDI designed is implemented to detect sensor bias, abrupt sensor failure, sensor drift and sensor freeze types of sensor faults.

Keywords: *Bias fault, Sensor freeze, Sensor drift, Abrupt sensor failure, Fault detection and isolation*

1. Introduction

Three tank interacting system is an application model widely used for teaching automated control. The fact that the system is strongly nonlinear, with different possibilities for disturbances, makes this system as a benchmark problem for study in most laboratories. Since the three tank system represents a multivariable process with three sensors, failure of any one of the sensor or any other component (actuators, tank leaks…etc) can make a total failure of the designed control system. It is therefore essential for the system to monitor its behavior so that faults may be addressed before they result in failures. Fault detection and Isolation (FDI) techniques have been widely used in process industry to detect faults in sensors and actuator. If a fault is detected the structure of the controller can then be changed to get the best possible response from a redundant sensor. In the past, redundancy was mainly in the form of three hardware sensors used for the same measurement and considering two out of three logic. If any one of the sensor is faulty it will be either sent to maintenance for repairing or changed with a new sensor leading to invest more fund and cost. To reduce the financial burden, soft sensors (analytical redundancy) were introduced.

FDI techniques can be either model based or model free. In model based FDI approach, all the information on the system can be used to monitor the behavior of the plant, including the knowledge about dynamics. The presence of faults is detected by means of the so called residuals, i.e., quantities that are over sensitive to the malfunctions. Residual generation can be performed in different ways: parity equations, observer based generation, and the methods based on parameter estimation [1]. Among model-based approaches, a differential geometric method has been successfully applied in [2] for a three interacting tank system. Rather than considering a complex nonlinear model, [3] have estimated the state vector based around various operating points through a bank of decoupled observers to generate residuals for fault detection. A bank of decoupled observers to detect and isolate actuator/sensor faults around multiple operating points applied to the three-tank system was proposed [4]. Koenig et al. [5] have synthesized a decoupled linear observer to detect and to isolate actuator and component faults (pipe, tank, etc.) around an operating point without fault magnitude estimation.

In this paper, a dedicated observer scheme is used, where measurements from perfectly working sensors are used to estimate the output of the failed sensors. The residual generation is based on the estimation error of the observers. In recent years, many researchers have focused on soft computing techniques such as Fuzzy System (FS), Neural Networks (NN) and Genetic Algorithms (GA) for observer design. Some of the FDI methods based on neural models applied to three tank systems have been illustrated in [6]. FDI methods based on fuzzy are illustrated in [7, 8]. Neural networks being black box model, makes it difficult to analyse a system physically, whereas fuzzy, requires a priori knowledge of the system for producing a good model. Combining the learning ability of the neural networks and the use of human expertise of fuzzy, Adaptive Neuro_Fuzzy Inference Systems can be used for designing observers. [9] observer design is done using MANFIS and fault tolerant control is carried out for abrupt failures. A survey on soft computing approaches to fault diagnosis for dynamic systems is dealt with [10].

This paper deals with a model based diagnosis of sensor (bias, drift and abrupt failure) faults using MANFIS based observers for three interacting tank system. The paper is organized as follows: section 2 deals with the non-linear and linearized mathematical model of the three tank system. The state feedback controller and the controller parameters are given in section 3. Section 4 gives a small introduction about ANFIS. In section 5, fault detection and isolation scheme for the process is given. The results of the process is shown in section 6.

2. Three interacting tank system description

The hydraulic system shown in figure 1 consists of three identical cylindrical tanks with equal cross-sectional area (A). These three tanks are connected by two cylindrical pipes of the same cross sectional area (α). The process liquid is pumped to the first interacting tank from the sump by pump-1 through the control valve-1 and the input flow to the first interacting tank is F_{in1}.The liquid is pumped to the third interacting tank from the sump by pump-2 through the control valve-2 and this input flow to the third interacting tank is F_{in2}.

The three levels in the three interacting tanks is measured using differential pressure transmitter. The three tanks are interconnected with manual valves. The objective is to control the level in the third tank by varying the flow F_{in1} of the first tank and keeping the flow input F_{in2} to the third tank constant. The schematic diagram for a three interacting system is shown in Figure1.

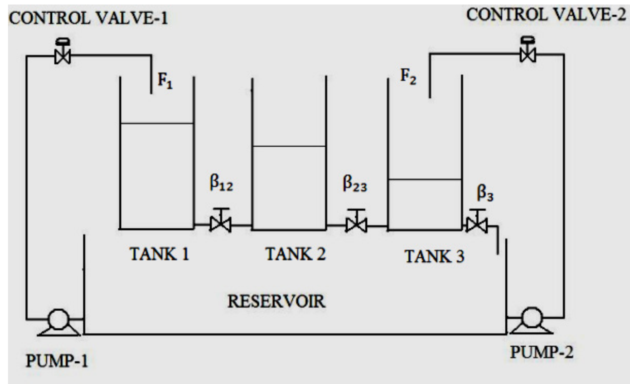

Fig. 1: Three Tank Interacting System

Process Parameters

$A_1 = A_2 = A_3 = 615.75 cm^2$
$\alpha_1 = \alpha_2 = \alpha_3 = 5.0671\ cm^2$
$\beta_{12} = 0.9,\ \beta_{23} = 0.8,\ \beta_3 = 0.3$
$K_1 = K_2 = 75\ cm^3/vs$

Where

h_i	Level of tank i (cm)
u_i	Control input to control valve cv_i (v)
A_i	Area of tank i (cm)
α_i	Cross section area of pipe connecting tank i (cm^2)
β_{ij}	Valve ratio between tank i and tank j.
K_i	Gain of pump(cm^3/vs)
g	Gravity

The process is linearized about an operating point. The table 1 gives the regions and their operating points. The linear state space model can be represented as

$$X' = AX' + BU'$$
$$Y' = CX' + DU'$$
$$X' = X - X_s$$
$$U' = U - U_s$$
$$Y' = Y - Y_s$$

Where

X	State vector $[h_1, h_2, h_3]$
Y	Output vector $[h_1, h_2, h_3]$
U	Input vector $[U_1, U_2]$
X'	State (in terms of deviation variable)
U'	Control input (in terms of deviation variable)
Y'	Output (in terms of deviation variable)
X_s	State variable's steady state operating point
Y_s	Output's operating point
U_s	Input's operating point.

$$A=\begin{bmatrix} -c_1 & c_1 & 0 \\ c_2 & -(c_1+c_3) & c_3 \\ 0 & c_4 & -(c_4+c_5) \end{bmatrix}$$

Where,

$$c_1 = \frac{\beta_{12}\alpha_{12}}{A_1}\sqrt{\frac{g}{2(h_1s-h_2s)}},$$

$$c_2 = \frac{\beta_{12}\alpha_{12}}{A_2}\sqrt{\frac{g}{2(h_1s-h_2s)}}$$

$$c_3 = \frac{\beta_{23}\alpha_{23}}{A_2}\sqrt{\frac{g}{2(h_2s-h_3s)}},$$

$$c_4 = \frac{\beta_{23}\alpha_{23}}{A_3}\sqrt{\frac{g}{2(h_2-h_3)}}$$

$$c_5 = \frac{\beta_3\alpha_3}{A_3}\sqrt{\frac{g}{2h_3s}}$$

$$B = \begin{bmatrix} \frac{K_1}{A_1} & 0 \\ 0 & 0 \\ 0 & \frac{K_2}{A_3} \end{bmatrix}$$

$$C = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

D=0

A and B matrices for the different regions are given in Table 1 and Table 2.

Table 1: Regions and their Operating Points

Region	u_{1s}	h_{1s}	h_{2s}	h_{3s}
0.5 to 2	1.25	4.29	4.08	3.8
2 to 3.5	2.5	13.114	12.268	11.16
3.5 to 4.5	4	30.1304	27.926	25.132
4.5 to 6.5	5.5	54.1084	49.996	44.664

Table 2: State and Input Matrices

Region	A	B
0.5 to 2	$\begin{bmatrix} -0.3579 & 0.3579 & 0 \\ 0.3579 & -0.6335 & 0.2755 \\ 0 & 0.2755 & -0.3036 \end{bmatrix}$	$\begin{bmatrix} 0.1218 & 0 \\ 0 & 0 \\ 0 & 0.1218 \end{bmatrix}$
2 to 3.5	$\begin{bmatrix} -0.1783 & 0.1783 & 0 \\ 0.1783 & -0.3168 & 0.1385 \\ 0 & 0.1385 & -0.1549 \end{bmatrix}$	$\begin{bmatrix} 0.1218 & 0 \\ 0 & 0 \\ 0 & 0.1218 \end{bmatrix}$
3.5 to 4.5	$\begin{bmatrix} -0.1105 & 0.1105 & 0 \\ 0.1105 & -0.1977 & 0.0872 \\ 0 & 0.0872 & -0.0981 \end{bmatrix}$	$\begin{bmatrix} 0.1218 & 0 \\ 0 & 0 \\ 0 & 0.1218 \end{bmatrix}$
4.5 to 6.5	$\begin{bmatrix} -0.0809 & 0.0809 & 0 \\ 0.0809 & -0.1440 & 0.0631 \\ 0 & 0.0631 & -0.0713 \end{bmatrix}$	$\begin{bmatrix} 0.1218 & 0 \\ 0 & 0 \\ 0 & 0.1218 \end{bmatrix}$

3. State Feedback Controller

If a system is completely state controllable, then poles of the closed-loop system can be placed at any desired locations by means of state feedback through an appropriate state feedback gain matrix. The main objective of a state feedback controller is to ensure closed loop stability in the presence of disturbances. In addition to closed-loop stability, the designer is often interested in other characteristics of the closed-loop transient response, such as rise time (tr), peak time (tp), percent overshoot (MO), and settling time (ts) of the step response. Specifying desired closed-loop system behavior via eigenvalue selection is called shaping the dynamic response (or pole placement).

The design technique begins with a determination of the desired closed-loop poles based on the transient response and/or frequency response requirements, such as speed, damping ratio, or bandwidth, as well as steady-state requirements. Assuming the closed-loop poles be μ_1,… μ_n, an appropriate gain matrix for state feedback is chosen, so that it is possible to force the system to have closed-loop poles at the desired locations.

Using state feedback,
u= -Kx

Then,
dx/dt=(A-BK)x

Characteristic polynomial of the system with state feedback is given by,

[SI-(A-BK)]

With K = [k_(1) k_(2) k_(3)]

The state feedback controller discussed above, can only influence the transient response and the stability of closed loop system, but there is no control on the steady-state value of the system. Adding an integral term to the control law guarantees obtaining a system that yields zero steady-state tracking error for step reference inputs, as long as closed-loop stability is maintained. A general block diagram is given in Figure 2.

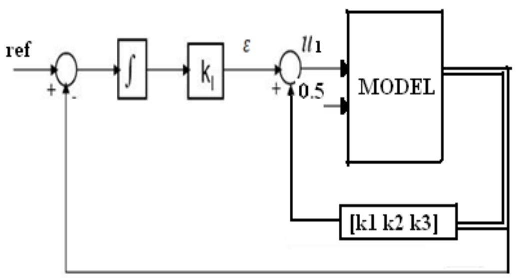

Fig. 2: Block diagram of the closed loop system

The feedback gain matrix for the different regions is given in Table 3. Figure 3 shows the response of the process for set point changes.

Table 3: Feedback Gain Values

REGION	K	Ki
0.5 to 2	[1.8274 1.2993 -2.9883]	0.0026
2 to 3.5	[7.1100 4.4145 -10.654]	0.0120

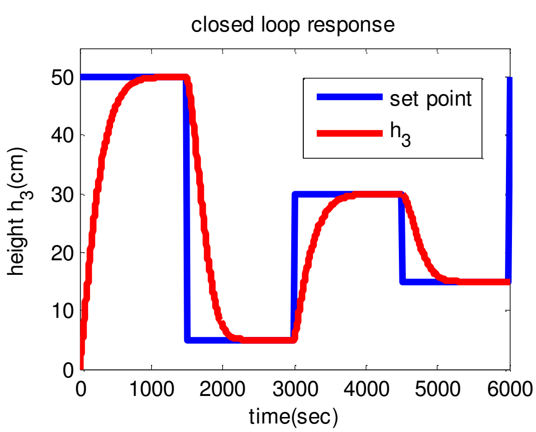

Fig. 3: Response of the closed loop system

4. Adaptive Neuro-Fuzzy Inference System

Figure 4 shows the block diagram of the ANFIS architecture. Fuzzy models are superior to linear models in capability to represent a given unknown system. It is based on "Fuzzy partition" of input space and it can be viewed as the expansion of piecewise linear partition. Consider a first order TSK (Takagi_Sugeno) fuzzy inference system that consists of two rules. Figure shows the ANFIS architecture.

Rule 1: If X is A_1 and Y is B_1 then $f_1 = p_1x+q_1y+r_1$
Rule 2: If X is A_2 and Y is B_2 then $f_{12} = p_2x+q_2y+r_2$

If f_1 and f_2 are constants instead of linear equations.

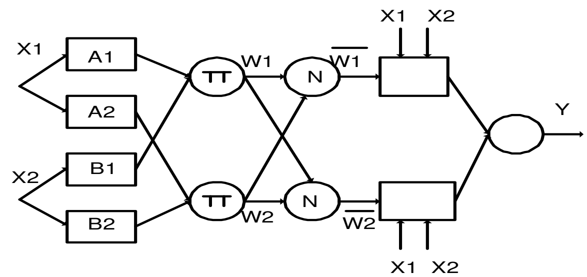

Fig. 4: ANFIS architecture

Layer 1: Each node in this layer generates membership grades of a linguistic label.

For instance, the node function of ith node might be

$$O_i^1 = m_{Ai}(x) = \max\min\left\{\left[\frac{x-a}{b-a},1,\frac{d-x}{d-c}\right],o\right\} \quad (1)$$

where x is the input node I, A_i is the linguistic label (small, large, etc) associated with this node; and {a,b,c,d} is the parameter set that changes the shape of the membership function. Parameters in this layer are referred to as the premise parameter.

Layer 2: Each node in this layer calculates the firing strength of each rule via multiplication

$$O_i^2 = w_i = \mu_{Ai}(x) * \mu_{Bi}(y), i = 1,2 \quad (2)$$

Layer 3: The ith node of this layer calculates the ration of the ith rule's firing strength to the sum of all rules firing strength

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \ i = 1,2 \quad (3)$$

Layer 4: Node i in this layer has the following node function

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i) \quad (4)$$

where w_i is the output of layer 3 and {p_i,q_i,r_i} is the parameter set. Parameters in this layer will be referred to as the consequent parameters.

Layer 5: The single node in this layer computes the overall output as the summation of all incoming signals overall output.

$$O_i^5 = overall\ output = \sum_i \overline{w}_i fi = \frac{\sum w_i f_i}{\sum w_i} \quad (5)$$

5. Fault Detection and Isolation Scheme for a Three Interacting Tank System

The standard controller that has been designed, is to maintain satisfactory operations by compensating for the effects of disturbance and changes occurring in the process. While these controllers can compensate for many types of disturbances, there are certain conditions like sensor or actuator failures, equipment fouling, etc. that may affect the controller performance. These conditions are called faults. The purpose of fault detection is to determine that a fault has occurred in the system, whereas fault isolation procedures are used to determine the location of the fault, after detection.

A fault diagnostic (detection and isolation) task can be split in two subtasks:

Residual Generation: Residual signals reflect inconsistencies between the normal and faulty operating conditions, and are computed as the difference between the measured and its corresponding estimated signal from the observer.
Residual Evaluation: The residual is evaluated in order to detect, isolate and identify the fault. It is performed by first calculating the decision functions, and techniques such as norms, threshold testing and likelihood functions.

Design of fault detection and isolation begins with the design of observers to obtain the residues, which are then converted to decision functions. The decision functions are to be compared with threshold values. If the decision function is greater than the threshold, a fault is indicated.

5.1 Residual Generation

A dedicated manfis observer scheme is used for generating the estimates of the process states. A dedicated observer scheme takes the input of the process and one of the states from the process as inputs and estimates all the other states as outputs.

A. Design of dedicated manfis based observer:
Three observers are constructed with each sensor, to estimate the other two states.

Selection of input and output variables: Each observer is given one sensor output, and the control input u_1 to estimate the other two states. The input and output scheme for all the three MANFIS observers are shown in Fig 2.

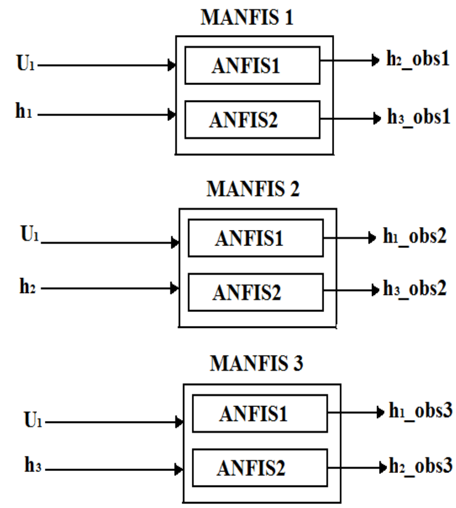

Fig. 5: The input-output scheme for MANFIS observers

Data generation: The data are generated by simulating the process under normal working condition with various set points. A total of 7495 samples are taken as data. Figure 5 shows the input-output for the MANFIS schemes.

Selection of manfis structure: The number of rules, the number and type of membership functions are found using trial and error method and is shown in table.

Table 4: MANFIS Structure details

MANFIS		No of mf	Type of mf	No of rules	output
MANFIS 1	anfis 1	7	gauss	7	h_2_obs1
	anfis 2	6	gauss	6	h_3_obs1
MANFIS 2	anfis 1	5	gauss	5	h_1_obs2
	anfis 2	7	gauss	7	h_3_0bs2
MANFIS 3	anfis 1	7	gauss	7	h_1_obs3
	anfis 2	7	gauss	7	h_2_obs3

Figure 6 shows the comparison of the real process and the observer data.

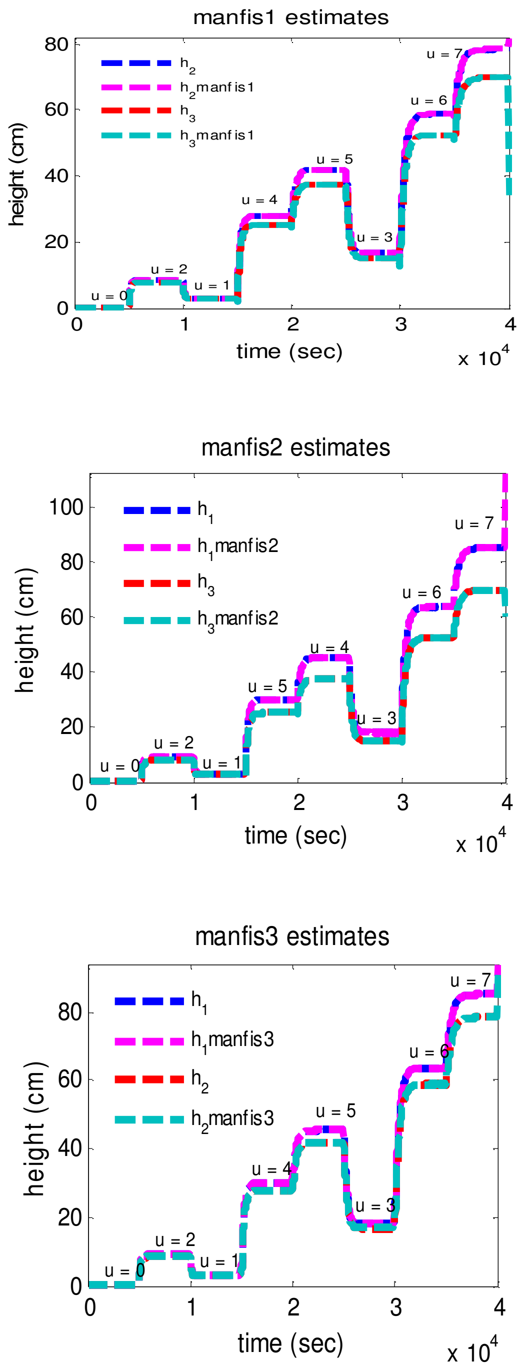

Fig. 6: Comparison of observer data and process data

B. Calculation of residues and decision functions

The residuals are calculated using the estimation error of the observers.

Observer1: error functions

$$\Psi_1\_h_1 = |h_1 - h_1obs2|$$
$$\Psi_2\_h_1 = |h_1 - h_1obs3|$$
$$\Psi_3\_h_1 = |h_1obs2 - h_1obs3|$$

Observer1: decision functions

$$\eta_1\_h_1 = \Psi_1\_h_1 \times \Psi_2\_h_1$$
$$\eta_2\_h_1 = \Psi_1\_h_1 \times \Psi_3\_h_1$$
$$\eta_3\_h_1 = \Psi_2\_h_1 \times \Psi_3\_h_1$$

Observer2: error functions

$$\Psi_1\_h_2 = |h_2 - h_2obs1|$$
$$\Psi_2\_h_2 = |h_2 - h_2obs3|$$
$$\Psi_3\_h_2 = |h_2obs1 - h_2obs3|$$

Observer2: decision functions

$$\eta_1\_h_2 = \Psi_1\_h_2 \times \Psi_2\_h_2$$
$$\eta_2\_h_2 = \Psi_1\_h_2 \times \Psi_3\_h_2$$
$$\eta_3\_h_2 = \Psi_2\_h_2 \times \Psi_3\_h_2$$

Observer3: error functions

$$\Psi_1\_h_3 = |h_3 - h_3obs1|$$
$$\Psi_2\_h_3 = |h_3 - h_3obs2|$$
$$\Psi_3\_h_3 = |h_3obs1 - h_3obs2|$$

Observer2: decision functions

$$\eta_1\_h_3 = \Psi_1\_h_3 \times \Psi_2\_h_3$$
$$\eta_2\_h_3 = \Psi_1\_h_3 \times \Psi_3\_h_3$$
$$\eta_3\_h_3 = \Psi_2\_h_3 \times \Psi_3\_h_3$$

Where,
h_1 – height of tank 1
$h_1$obs2 – Estimate from observer 2
$h_1$obs3 – Estimate from observer 3
h_2 – height of tank 2
$h_2$obs1 – Estimate from observer 1
$h_2$obs3 – Estimate from observer 3
h_3 – height of tank 3
$h_3$obs1 – Estimate from observer 1
$h_3$obs2 – Estimate from observer 2

5.2 Evaluation of decision function

The decision function evaluation method that is used is the threshold testing. The obtained decision functions are compared to a small threshold value, to determine the presence or absence of faults.

A. Threshold Calculation:

Threshold values based on which the presence of a fault can be detected, is calculated by simulating various faults and obtaining the decision functions. The maximum non-zero value of the decision function in the absence of fault is taken as the threshold value.

All the three faults considered can be modelled as additive faults. The sensor bias fault is simulated as a step change, the drift fault is given as a time varying ramp signal, the abrupt failure fault is given in such a way that the output signal becomes zero no matter what the input is and sensor freezing is done such that the sensor output remains frozen at a particular value, no matter the amount of input given. The values of the decision function is noted for all faults, and the least value is taken as the threshold, thereby any fault under any set point when present in a system, their residual will go above the threshold, indicating a presence of a fault.

The least value obtained is 1.2, and it is taken as the threshold value for detecting and isolating all faults.

5.3 Fault detection and Isolation

The decision function value for all the three observers are compared to the threshold, if sensor 1 is faulty,

$\Psi_1\_h_1 = |h_1 - h_1obs2|$ = non_zero value
$\Psi_2\_h_1 = |h_1 - h_1obs3|$ = non_zero value
$\Psi_3\_h_1 = |h_1obs2 - h_1obs3|$=approx zero
There by,
$\eta_1\_h_1 = \Psi_1\_h_1 \times \Psi_2\_h_1$=value greater than threshold.
$\eta_2\_h_1 = \Psi_1\_h_1 \times \Psi_3\_h_1$ = very small value
$\eta_3\_h_1 = \Psi_2\_h_1 \times \Psi_3\_h_1$=very small value
If sensor 2 is faulty,
$\Psi_1\_h_2 = |h_2 - h_2obs1|$ = non_zero value
$\Psi_2\_h_2 = |h_2 - h_2obs3|$ = non_zero value
$\Psi_3\_h_2 = |h_2obs2 - h_2obs3|$=approx zero
There by,
$\eta_1\_h_2 = \Psi_1\_h_2 \times \Psi_2\_h_2$=value greater than threshold.
$\eta_2\_h_2 = \Psi_1\_h_2 \times \Psi_3\_h_2$ = very small value
$\eta_3\_h_2 = \Psi_2\_h_2 \times \Psi_3\_h_2$=very small value
If sensor 3 is faulty,
$\Psi_1\_h_3 = |h_3 - h_3obs1|$ = non_zero value
$\Psi_2\_h_3 = |h_3 - h_3obs2|$ = non_zero value
$\Psi_3\_h_3 = |h_3obs1 - h_3obs2|$=approx zero
There by,
$\eta_1\_h_3 = \Psi_1\_h_3 \times \Psi_2\_h_3$=value greater than threshold.
$\eta_2\_h_3 = \Psi_1\_h_3 \times \Psi_3\_h_3$ = very small value
$\eta_3\_h_3 = \Psi_2\_h_3 \times \Psi_3\_h_3$=very small value

Once the faulty sensor is identified, the data from that sensor is replaced by an estimate from any one of the two observers.

The fault detection and isolation algorithm keeps checking the decision functions. If,

$\eta_1\_h_1 >$ Threshold

Sensor 1 is faulty. The faulty sensor value (h_1) is replaced by its estimate from the observer2 (h_1obs2). If,

$\eta_2\_h_2 >$ Threshold

Sensor 2 is faulty. The faulty sensor value (h_2) is replaced by its estimate from observer1 (h_2obs3). If,

$\eta_3\_h_3 >$ Threshold

Sensor 3 is faulty. The faulty sensor value (h_3) is replaced by its estimate from observer1 (h_3obs2).

6. Results

The designed MANFIS observers are placed in the closed loop , and a set point of 30 is given as reference. Different fault scenarios are considered and the results are shown.

No Fault scenario: the designed fault detection and isolation scheme is implemented. When no fault is introduced, the decision function generated by all the observers is a very small value. The decision functions for the three observers are shown in Fig 7.

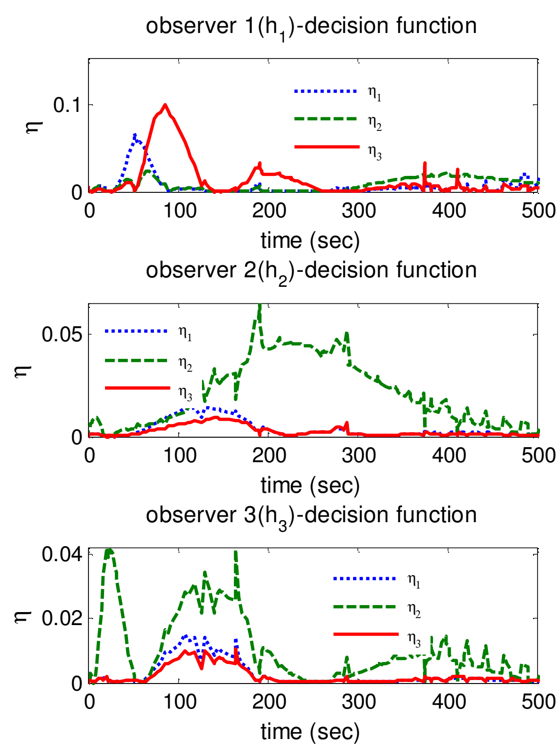

Fig. 7: Decision functions of observers under no fault.

Sensor1 bias fault: A 5% bias fault is introduced in sensor 3 at 760sec. Based on the magnitude, the residual value and therefore the decision function value changes. The plot showing the decision function values after introduction of the fault is shown in Fig 8.

When the decision function increases above the threshold value, the fault detection and isolation algorithm, detects the presence of fault and instead of the faulty signal gives the estimated signal from one of the designed MANFIS observers. This is shown in Fig 9.

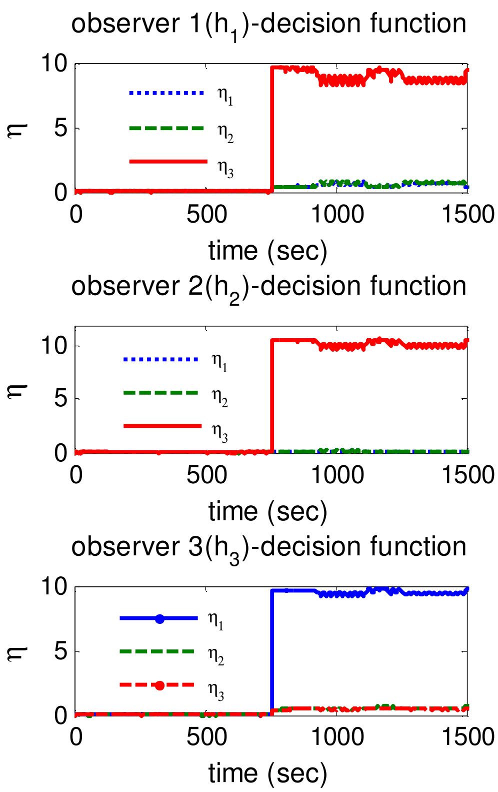

Fig. 8: Decision function of observers under h3 5% sensor bias fault

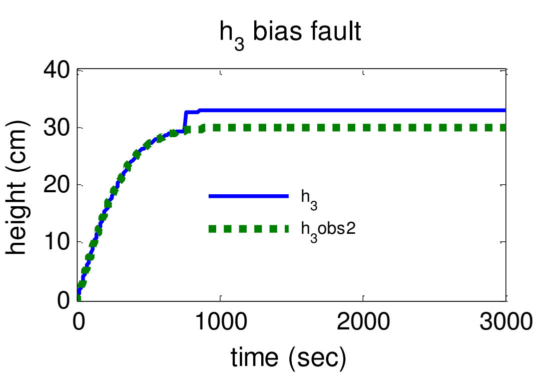

Fig. 9: h_3 sensor with bias fault and its estimated output

Sensor2 drift fault: A 3% drift fault is introduced in sensor 2 at 500sec. Based on the magnitude, the residual value and therefore the decision function value changes. The plot showing the residuals and decision function value after introduction of the fault is shown in Fig 10.

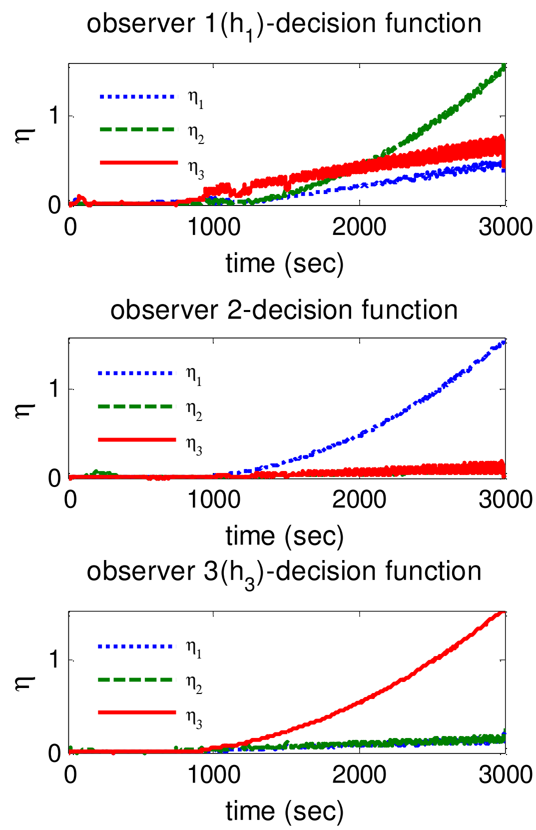

Figure 10: Decision function of observers under drift fault in h_2

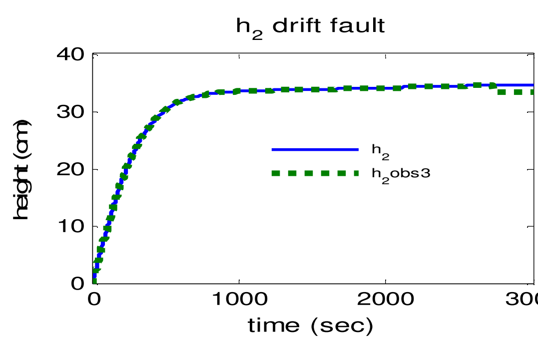

Figure 11: h_2 sensor drift fault and its estimated output

When the decision function increases above the threshold value, the fault detection and isolation algorithm detects the presence of fault and instead of the faulty signal gives the estimated signal from one of the designed MANFIS observers. This is shown in Fig 11.

Sensor3 abrupt failure: Sensor 3 is abruptly failed at 750sec. The residual value and therefore the decision function value changes. The plots showing the decision function and estimated response after introduction of the fault are shown in Fig 12 and 13.

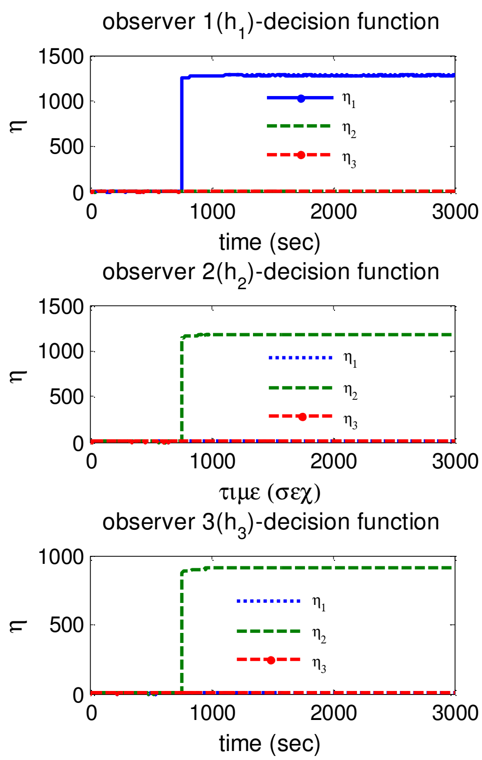

Figure 12: Decision function of observers under abrupt failure in h_1

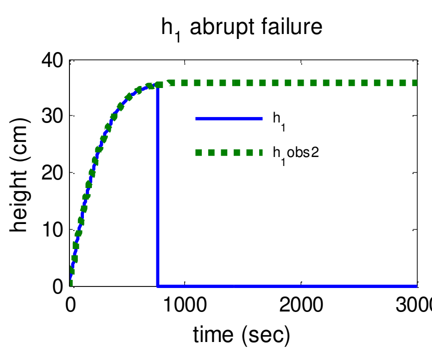

Figure 13: h_1 sensor abrupt failure and its estimated output.

Sensor2 freeze: A fault is introduced such that the sensor 2 freezes at 20. In that case, the decision function and estimated response of all the three observer are shown in figure 14 & 15.

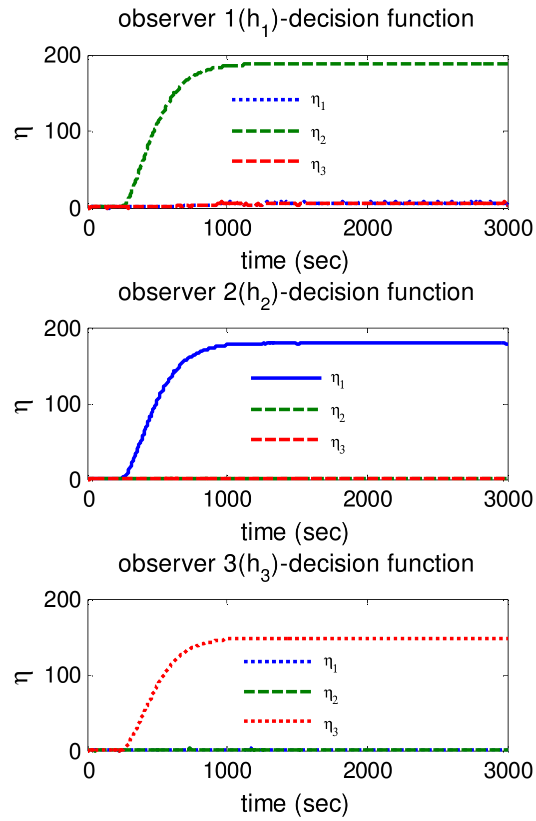

Fig. 14: Decision function of observers under sensor freeze fault

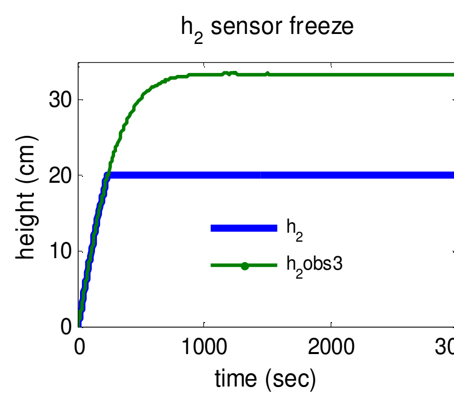

Fig. 15: h_2 sensor frozen at 20 and its estimated output.

7. Conclusion

The designed fault detection and isolation scheme for the three interacting tank system is able to detect all the four types of sensor faults (sensor bias, sensor drift, sensor failure and sensor freeze). The observers designed using adaptive neuro-fuzzy inference systems, were able to give a correct estimate of the system states. Of the three faults considered, sensor drift is the only fault which takes a few seconds (based on the amount of drift and the threshold value) to be detected, as it is a time varying.

References

[1] Isermann, R., 1984. "Process Fault Detection based on Modeling and Estimation methods – A survey" ,Automatica,20(4): 387-404.

[2] C. Join, J.-C. Ponsart, D. Sauter, and D. Theilliol." Nonlinear filter design for fault diagnosis: application to the three-tank system". IEE Proceedings Control Theory and Applications, 152(1):55–64, 2005.

[3] Akhenak, M. Chadli, D. Maquin, and J. Ragot." State estimation via multiple observer the three-tank system". In 5th IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes, pages 1227–1232, Washington DC, USA, 2003.

[4] M. Rodrigues, D. Theilliol, M.A. Medina, and D. Sauter." A fault detection and isolation scheme for industrial systems based on multiple operating models". Control Engineering Practice, 16(2):225–239, 2008.

[5] D. Koenig, S. Nowakowski, and T. Cecchin. "An original approach for actuator and component fault detection and isolation". In 3rd IFAC Symposium on Fault Detection Supervision and Safety for Technical Processes, pages 95–105, Hull, UK, 1997.

[6] T. Marcu, M.H. Matcovschi, and P.M. Frank. "Neural observer-based approach to fault-tolerant control of a three-tank system". In Proceedings of the European Control Conference, Karlsruhe, Germany, 1999. CD-Rom.

[7] J.M. Koscielny. "Application of fuzzy logic for fault isolation in a three-tank system". In 14th IFAC World Congress, pages 73–78, Beijing, R.P. China, 1999.

[8] C.J. Lopez and R.J. Patton. "Takagi-sugeno fuzzy fault-tolerant control for a non-linear system". In Proceedings of the IEEE Conference on Decision and Control, pages 4368–4373, Phoenix, Arizona, USA, 1999.

[9] S.Nagarajan,J.Shanmugam,T.R.Rangaswamy,"MANFIS Observer Based Sensor Fault Detection and Identification in Interacting Level Process with NN Based Threshold Generator", International Journal of Soft computing 3(5):344-354,2008.

[10] Patton, R.J., Uppal F.J., and Lopez-Toribio C.J.(2000)."Soft computing approaches to fault diagnosis for dynamic systems: a survey." Proceedings of IFAC Symposium on Fault Detection,Supervision and Safety for Technical Processes 2000, Budapest, Hungary,vol. 1,303-315.

C. Amritha Bachelor of Engineering(Electronics and Instrumentation), Masters (Electronics and Instrumentation). Currently working as Assistant professor in VelTech Technical University .Research interest includes nano_sensors and control engineering.

U. Sabura Banu Masters,PhD. Currently working as an associate professor in B. S. Abdur Rehman University. Cuurent area of research includes fractional order controllers and biomedical instruments.