Control of Interacting Level Process Under Sensor Failure Conditions using Coactive Adaptive Neuro-Fuzzy Observer

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Abstract: **This paper presents the design of Coactive Adaptive Neuro-Fuzzy Observer based sensor fault detection and fault tolerant control under sensor failure conditions for a three-tank interacting level process. Fault detection is performed by estimating the states of the level process and comparing them with measured values. A fault is signaled when the difference between the estimated and measured values crosses a threshold value. Three pairs of observers estimate the three system states. These Observers are designed with Coactive Adaptive Neuro-Fuzzy Inference System (CANFIS) that uses a neural network to fix optimal shape and parameters for the membership functions and effective rule base for the fuzzy system. Decision functions are built from estimation errors to detect the fault. If any failure is identified, the control law is modified accordingly using the estimated value replacing the failed sensor output. In this work, CANFIS observer based fault detection is designed and simulated. The individual failures of three level sensors are considered and the results are discussed. The results show that the system is able to detect any sensor failure and to control the level in interacting tanks perfectly under failure situations.**

Keywords: Adaptive Neuro-Fuzzy Inference System, Fault Detection, Observers, Three Tank Interacting Level Process.

I. INTRODUCTION

The sensor failure detection and identification has been considered as an important issue, particularly when measurements from sensors are used in the feedback loop of a control law. Since the control law uses the sensor feedback to establish the current states of the process, the control with failed sensors can lead to an imperfect control or closed loop instability. Model based fault detection techniques are based on observers [1], state estimating filters [2] or Parameter Estimators [3].

Observers can be designed to estimate the states if some state variables of the system cannot be measured for feedback, in some cases. The estimation error that is the difference between the sensor output and the corresponding state given by the observer, gives information regarding the failed sensor. A dedicated observer scheme [4] can be introduced in which each sensor of interest drives an observer to perform a complete state estimation. In an alternative version, generalized observer scheme [5], an estimator dedicated to a certain sensor is driven by all outputs except that of the respective one. The Fault Detection and Identification system (FDI) detects and identifies the sensor failures that may occur during the process.

With the development of neural networks and fuzzy systems, observers are designed using these techniques since they do not need any mathematical model and can accommodate non-linearities [6]. Observers can be modeled using fuzzy system [7], [8]. The tuning of membership functions becomes an important issue in fuzzy modeling. Since this tuning task can be viewed as an optimization problem, neural networks can be used to solve this problem. The shape of the membership functions that depends on different parameters and a specification of the rules including a preliminary definition of the corresponding membership functions can be learned by a neural network. The Adaptive neuro-fuzzy system, which is a neural network, fixes the optimal shape and parameters for the membership functions and effective rule base for the fuzzy system for observer modeling [9].

In the earlier work of the author, the levels in the three tanks of interacting level process are measured as states and used to control the level in the third tank through state feedback. Six Observers using Multiple Adaptive neuro-fuzzy Inference System (MANFIS) are designed with sensor outputs as inputs to estimate all the states of the process and they can be fedback for control [10]. The fault detection and Identification logic detects any fault that occurs and identifies the failed sensor. This fault detection and identification is followed by accommodation using reconfiguration of the control law that performs the fault tolerant control.

In this work, three observers using Coactive Adaptive Neuro Fuzzy Inference System (CANFIS) following the dedicated Observer scheme are designed and implemented replacing the six observers of the previous work to perform the sensor fault detection and Identification.

II. THREE TANK LEVEL CONTROL SYSTEM

A. Process Description

The three-tank interacting level process is shown in Fig. 1. The non-linear equations describing the open loop dynamics of this process are given by

$$\frac{dh_1(t)}{dt} = -\frac{\beta_{12}a_{12}}{A_1}\sqrt{2g(h_1(t)-h_2(t))} + \frac{k_1}{A_1}u_1$$
$$\frac{dh_2(t)}{dt} = \frac{\beta_{12}a_{12}}{A_2}\sqrt{2g(h_1(t)-h_2(t))} - \frac{\beta_{23}a_{23}}{A_2}\sqrt{2g(h_2(t)-h_3(t))}$$
$$\frac{dh_3(t)}{dt} = \frac{\beta_{23}a_{23}}{A_3}\sqrt{2g(h_2(t)-h_3(t))} - \frac{\beta_3 a_3}{A_3}\sqrt{2gh_3(t)} + \frac{k_2}{A_3}u_2 \quad (1)$$

where h_i is the level in tank i (cm), u_i is the control input to the pump i (V), A_i is the cross section area of tank i (cm^2), a_{ij} is the cross section area of the pipe connecting tank i and tank j (cm^2), a_3 is the cross section area of outlet of tank 3 (cm^2), β_{ij} is the valve ratio between tank i and tank j, β_3 is the valve ratio of outlet of tank 3, k_i is the gain of pump i (cm^3/V.s) and g is the gravity (cm /s^2).

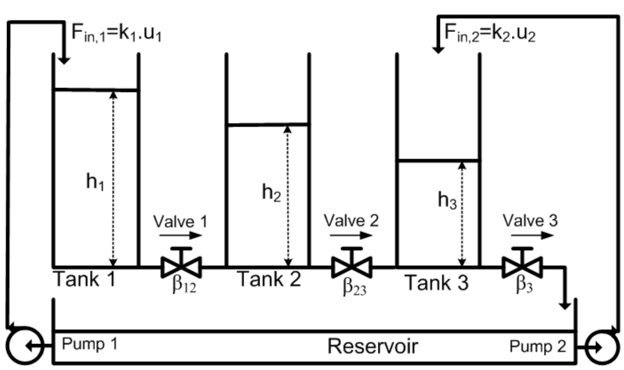


Fig. 1 Three tank interacting level process

This process is linearised about an operating point and the linear state space model can be represented by

$$\frac{dX}{dt} = AX + BU$$
$$Y = CX \tag{2}$$

with state vector X and control input U as

$$X^T = [h_1 \quad h_2 \quad h_3]$$
$$U^T = [u_1 \quad u_2 \quad 1] \tag{3}$$

The matrix C is 3x3 Identity matrix whereas matrices A and B in (2) are given by

$$A = \begin{bmatrix} -\frac{1}{T_{12}} & \frac{1}{T_{12}} & 0 \\ \frac{1}{T'_{12}} & -\left(\frac{1}{T'_{12}} + \frac{1}{T_{23}}\right) & \frac{1}{T_{23}} \\ 0 & \frac{1}{T'_{23}} & -\left(\frac{1}{T'_{23}} + \frac{1}{T_3}\right) \end{bmatrix} \tag{4}$$

$$B = \begin{bmatrix} \frac{k_1}{A_1} & 0 & -\frac{1}{T_{12}}\sqrt[3]{H_1 - H_2} \\ 0 & 0 & \frac{1}{T'_{12}}\sqrt[3]{H_1 - H_2} - \frac{1}{T_{23}}\sqrt[3]{H_2 - H_3} \\ 0 & \frac{k_2}{A_3} & \frac{1}{T'_{23}}\sqrt[3]{H_2 - H_3} - \frac{1}{T_3}\sqrt[3]{H_3} \end{bmatrix} \tag{5}$$

where

$$T_{12} = \frac{A_1}{\beta_{12} a_{12}}\sqrt{\frac{2(H_1 - H_2)}{g}}, T'_{12} = \frac{A_2}{\beta_{12} a_{12}}\sqrt{\frac{2(H_1 - H_2)}{g}},$$
$$T_{23} = \frac{A_2}{\beta_{23} a_{23}}\sqrt{\frac{2(H_2 - H_3)}{g}}, T'_{23} = \frac{A_3}{\beta_{23} a_{23}}\sqrt{\frac{2(H_2 - H_3)}{g}}$$
$$T_3 = \frac{A_3}{\beta_3 a_3}\sqrt{\frac{2H_3}{g}},$$

and H_1, H_2 and H_3 are levels in tank 1, tank 2 and tank 3 respectively at the operating point.

The parameters and the operating point of the process are given in Table I and Table II respectively.

TABLE I
PARAMETERS OF THE PROCESS

A_1, A_2, A_3 (cm^2)	a_{12}, a_{23}, a_3 (cm^2)	β_{12}	β_{23}	β_3	k_1, k_2 (cm^3/V.s)
615.7522	5.0671	0.9	0.8	0.3	75

TABLE II
OPERATING POINT OF THE PROCESS

H_1 (cm)	H_2 (cm)	H_3 (cm)	u_1 (V)	u_2 (V)
48.9169	44.4106	39.3580	6.0	0.5

The control system is designed based on this model using the state feedback with the objective to control the level h_3 in tank 3 at the desired value. Thus the control system will require information from all the three sensors directly while they are normal and through fault detection while they fail.

B. State Feedback

In control system design by pole placement technique, the states are used for feedback to achieve desired closed loop poles. The advantage in this system is that the closed loop poles may be placed at any desired locations by means of state feedback through an appropriate state feed back gain matrix K to achieve a perfect and smooth control. The control is done by controlling u_1 only with a fixed u_2 in this work.

Using State feedback,

$$u_1 = -KX \tag{6}$$

Then

$$\frac{dX}{dt} = (A - BK)X \tag{7}$$

The characteristic polynomial of the system with state feedback is given by

$$[SI - (A - BK)] = 0 \tag{8}$$

with $K = [K_1 \quad K_2 \quad K_3]$

(9)

The Coefficient of the polynomial in (9) is a function of K_1, K_2 and K_3. The desired characteristic polynomial is found by choosing desired closed loop poles for best control. By equating the coefficients of actual characteristic polynomial and the desired characteristic polynomial, the state feedback gain K is determined [11]. For this process, the state feedback gain K is determined and the values of K_1, K_2 and K_3 are 0.5995, 17.4876 and 3.1696 respectively.

An integral control in the path in series with the process is provided to achieve zero steady state error for given reference input $h_{3,ref}$. The gain K_I for integral control is 0.215. The block diagram of state feedback with integral control is shown in Fig. 2.

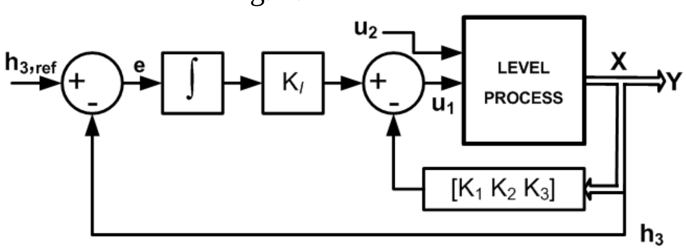


Fig. 2 State feedback with Integral control

III. ADAPTIVE NEUROFUZZY INFERENCE SYSTEM

A neuro-fuzzy system is a combination of an Artificial Neural Network (ANN) and a Fuzzy Inference System (FIS) in such a way that neural network learning algorithms are used to determine the parameters of FIS. Adaptive Neuro-Fuzzy Inference System (ANFIS) [12] implements Sugeno FIS and has a five layered architecture as shown in Fig. 3

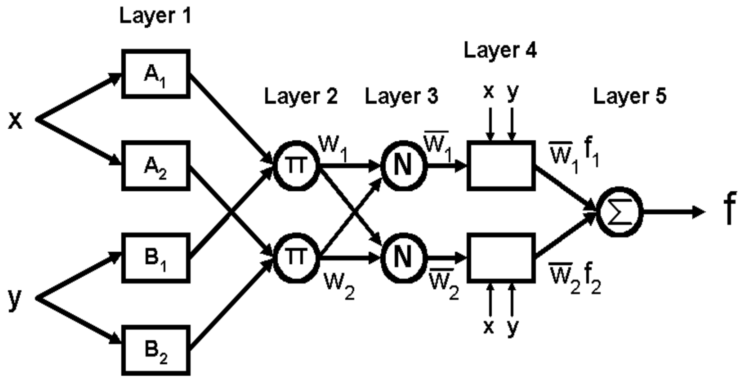


Fig. 3. Architecture of ANFIS

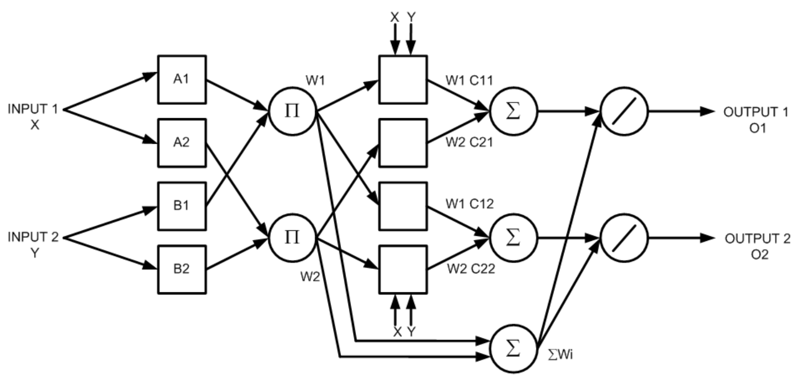


Fig. 4. Architecture of CANFIS

Multiple Neuro-Fuzzy Inference System (MANFIS) can produce multiple outputs. Since it requires a parallel structure with two ANFIS sharing same inputs to produce multiple outputs, Coactive ANFIS structure is tried and implemented. The CANFIS architecture is shown in Fig. 4**.**

The learning procedure is executed in two parts. In the first part, the input patterns are propagated and the optimal consequent parameters are estimated by an iterative least mean squares procedure whereas the premise parameters are assumed to be fixed for the current cycle through the training set. In the second part the patterns are propagated again, and in this epoch, back-propagation is used to modify the premise parameters, whereas the consequent parameters remain fixed. This procedure is then iterated.

IV. STATE ESTIMATION USING CANFIS

State estimations are carried out in Dedicated Observer Scheme on the assumption that only one state variable is measurable and the other two states are immeasurable. An adaptive network with CANFIS structure is constructed as a dedicated observer. The neural networks are trained with the known open loop input-output relationships of level process in all possible ranges.

The optimal shape and parameters for the membership functions of fuzzy inference systems with effective rule base are fixed by neural network. The membership functions are *Gaussian* for inputs and *linear* for outputs. 13696 sets of data are used for training.

Three observers are constructed with each sensor, forming dedicated observer scheme to estimate other two states. Each observer is applied with one sensor output in addition to the control input u_1 to estimate other two states.

V. SENSOR FAULT DETECTION AND IDENTIFICATION

The fault detection scheme is shown in Fig.5. The states of the process x_1, x_2 and x_3 are the outputs h_1, h_2 and h_3 respectively from level sensors. The estimated states by the observers for state x_1 are x^e_{12} and x^e_{13}. The estimated states for x_2 are x^e_{21} and x^e_{23} whereas X^e_{31} and x^e_{32} are the estimated states for x_3.

First set of residuals is generated for fault detection from the three values of state x_3, one from h_3 sensor output and two from estimated values of state x_3, to detect a failed sensor. The estimation errors that are the difference between the three values of state x_3 are calculated as given by

$$f_1 = \left| x_3 - x^e_{32} \right| \quad f_2 = \left| x_3 - x^e_{31} \right| \text{ and } f_3 = \left| x^e_{32} - x^e_{31} \right| \tag{10}$$

The decision functions η_1, η_2 and η_3 are formed as

$$\eta_1 = f_2 f_3,\ \eta_2 = f_1 f_3 \text{ and } \eta_3 = f_1 f_2 \tag{11}$$

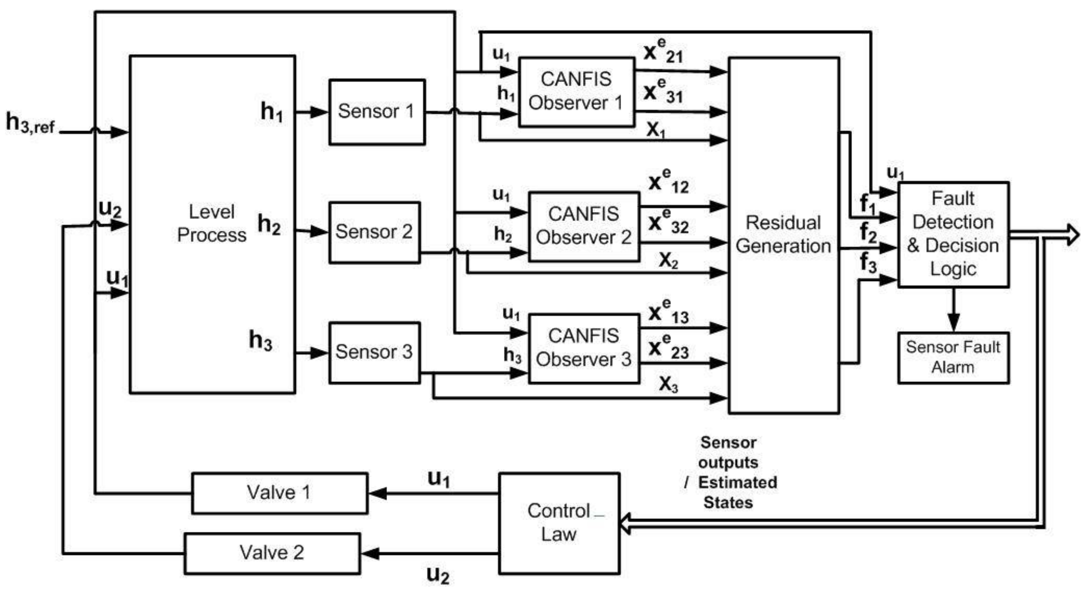


Fig.5 Fault Detection and Identification Scheme

The values of the decision functions will be zero if no sensor fails. If any sensor fails, the decision function formed from the product of estimation errors will show great deviation. This deviation is used to identify the failure of h_3 level sensor and to make the fault alarm to do the reconfiguration of the control law. The threshold values of decision functions η_1, η_2 and η_3 are 300, 250 and 200 respectively. η_1, η_2 and η_3 make fault alarm indicating failure of h_1 sensor, h_2 sensor and h_3 sensor respectively when crossing these threshold values. Similarly second and third sets of residuals are generated from x_1 and x_2 state estimations respectively.

Decisions functions are formed from these residuals also and threshold values are fixed for these decision functions. To avoid false alarm, Fault confirmation logic is proposed. This fault confirmation logic will inspect all the decision functions. A Sensor fault will be declared only if all the decision functions relevant to the sensor under inspection have crossed their threshold values. Since a failure decision is made on results from different sources, this confirmation logic ensures accuracy and no false alarms.

If any sensor failure is identified by the fault detection and identification logic, the best estimated state will come into action and gives the value of the state of the system for state feedback. Hence perfect and smooth control is possible even under sensor failure conditions.

The system under no failure condition will work with the basic control law given by

$$u_1 = -K_1 h_1 - K_2 h_2 - K_3 h_3 - K_{IN}\left(h_{3,ref} - h_3\right) \tag{12}$$

If any failure is detected by the fault detection logic, the control law will be modified and the alternative control laws for h_1 level sensor failure, h_2 level sensor failure and h_3 level sensor failure are, respectively,

$$u_1 = -K_1 x^e{}_{12} - K_2 h_2 - K_3 h_3 - K_{IN}\left(h_{3,ref} - h_3\right) \tag{13}$$

$$u_1 = -K_1 h_1 - K_2 x^e{}_{23} - K_3 h_3 - K_{IN}\left(h_{3,ref} - h_3\right) \tag{14}$$

$$u_1 = -K_1 h_1 - K_2 h_2 - K_3 x^e{}_{32} - K_{IN}\left(h_{3,ref} - x^e{}_{32}\right) \tag{15}$$

Estimated states x^e_{12}, x^e_{23} and x^e_{32} are used as redundant states in alternative control laws since they are more accurate than estimated states x^e_{13}, x^e_{21} and x^e_{31} respectively.

VI. RESULTS AND DISCUSSION

A. No Failure Condition

The simulation is conducted under no failure condition. The reference input $h_{3,ref}$ is 30 cm. The time histories of actual level (x_1), level sensor output (h_1), estimated state of level h_1 from observer driven by h_2 level sensor ($x^e{}_{12}$) and estimated state of level h_1 from observer driven by h_3 level sensor ($x^e{}_{13}$) are shown in Fig. 6 (a). Similar trends are shown for level h_2 and level h_3 in Fig. 6 (b) and (c) respectively. All trends are found to be overlapping since the estimations are very accurate. All state estimation errors for states x_1, x_2 and x_3 are shown in Fig. 6 (d), (e) and (f) respectively. The estimation errors are negligible in all the cases. The level h_3 in tank 3 is maintained at the set point nearly after 420 seconds. Fig. 7 (a), (b) and (c) show the error functions f_1, f_2 and f_3 respectively. The decision functions η_1 η_2 and η_3 are shown in Fig. 7 (d), (e) and (f) respectively. No fault alarm is reported since all decision functions are within the threshold values.

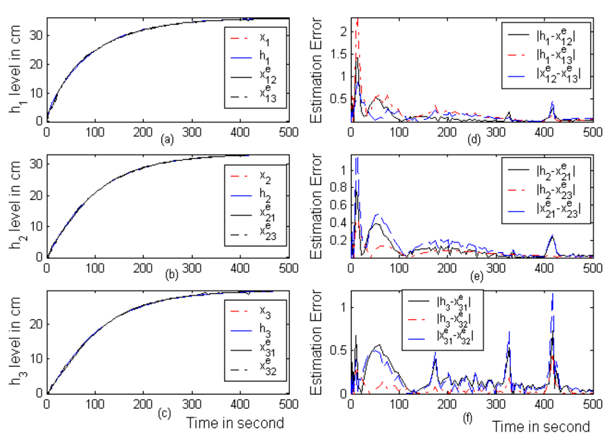


Fig. 6 Time histories under no failure condition

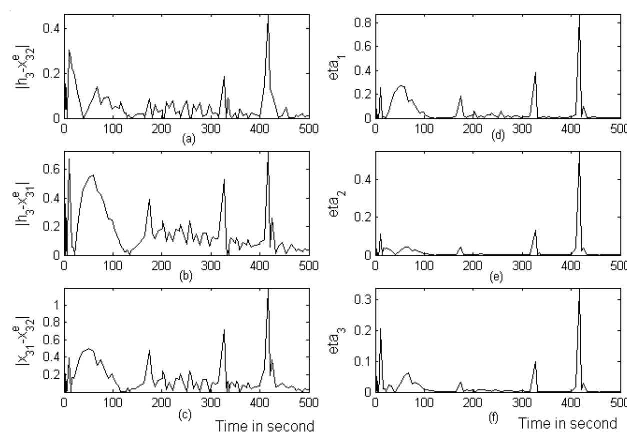


Fig.7 Decision functions under no failure condition

B. Tank 3 Level Sensor Failure Condition

A failure is introduced in h_3 level sensor at 300 second. Time histories for tank 1, tank 2 and tank 3 are shown in Fig. 8 (a), (b) and (c) respectively that include the trends of levels, sensor outputs and estimated states. The states $x^e{}_{13}$ and $x^e{}_{23}$ show greater deviations in the estimation since one of the inputs to these observers is the output from faulty h_3 level sensor. The states $x^e{}_{31}$ and $x^e{}_{32}$ show no significant estimation error since these states are outputs of observers driven by other sensors.

The error functions and decision functions under h_3 sensor failure condition are shown in Fig. 9. The large deviation in sensor h_3 output results in large value of error functions f_1 and f_2 as shown in Fig. 9 (a) and (b) respectively. This in turn results in very large value of η_3 as shown in Fig. 9 (f). The h_3 sensor fault is detected at 300 seconds exactly at the time of failure since the decision function η_3 exceeds the threshold value at 300 second whereas η_1 and η_2 are within their threshold limits. This makes a fault alarm for h_3 level sensor. The output of the failed sensor h_3 is then replaced by its estimated value x^e_{32} for state feedback as in (15) and h_3 is controlled at the set point perfectly even under this failure condition.

C. *Tank 1 Level Sensor Failure Condition*

A similar failure is introduced in h_1 level sensor at 300 second and the trends are shown in Fig. 10. The states x^e_{21} and x^e_{31} show greater deviations in the estimation whereas the states x^e_{12} and x^e_{13} show no significant estimation error. Fig. 11 shows the time histories of error functions and decision functions. The large deviation of estimated state x^e_{31} results in large value of error functions f_2 and f_3 as shown in Fig. 11 (b) and (c) respectively.

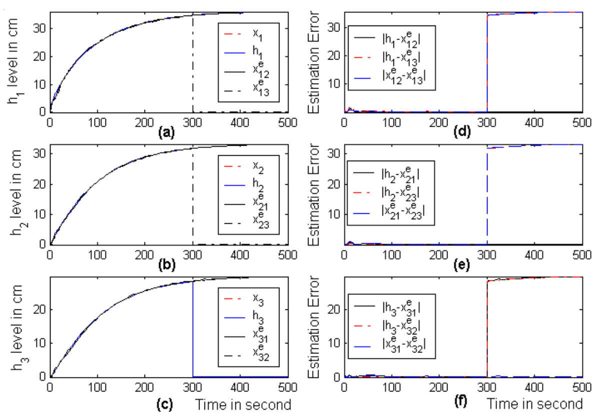


Fig. 8. Time histories under h_3 sensor failure condition

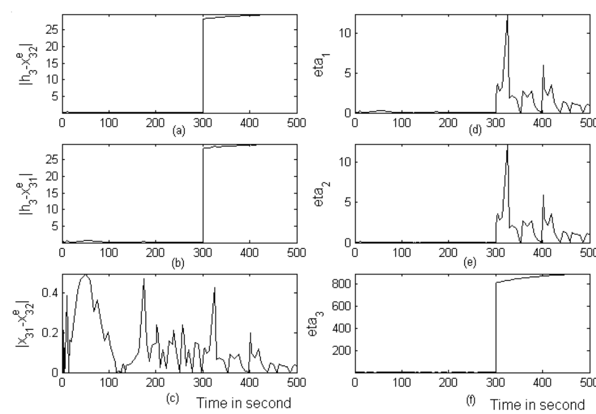
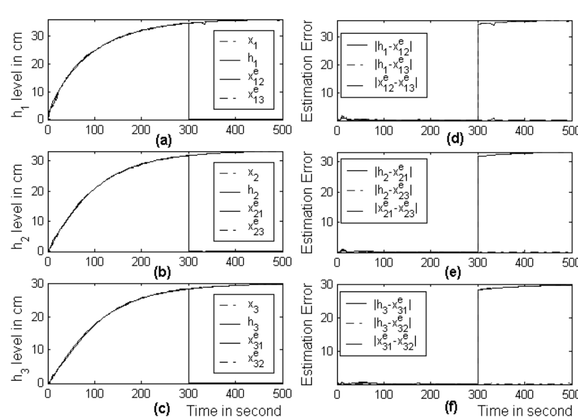


Fig. 9. Decision functions under h_3 sensor failure condition

The value of η_1 grows larger exceeding its threshold value as shown in Fig. 11 (a) whereas η_2 and η_3 are within their threshold values. This makes a fault alarm for the failure of h_1 sensor and fault is detected correctly at 300 second. The control law takes the value of estimated state x^e_{13} instead of h_1 as in (13). The level h_3 in tank 3 is controlled at the desired value, $h_{3,ref}$ perfectly even under this failure condition as seen in Fig. 11 (c).



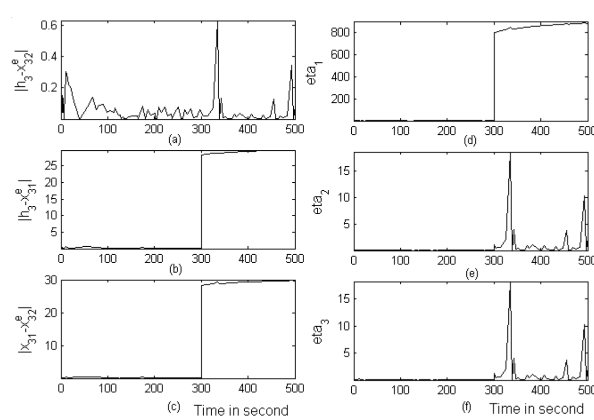


Fig. 10. Time histories under h_1 sensor failure condition

Fig. 11. Decision functions under h_1 sensor failure condition

D. Tank 2 Level Sensor Failure Condition

A failure in h_2 sensor is introduced at 300 seconds and the trends are shown in Fig. 12 (a), (b) and (c) respectively. The estimated states x^e_{12} and x^e_{32} alone, which are output of the observer driven by h_2 sensor, experience large estimation errors. Other estimated states x^e_{21} and x^e_{23} are not disturbed by this failure since they are outputs of observers driven by other sensors and hence they show only negligible errors.

The errors and decision functions under this condition is shown in Fig. 13. The large deviation of estimated state x^e_{32} makes larger values for error functions f_1 and f_3 as shown in Fig. 13 (a) and (c) respectively. Fig. 13 (d) shows the growth in η_2 exceeding the threshold value. This results in a fault alarm for h_2 level sensor failure. The control law is modified accordingly as in (14) and the level h_3 is controlled perfectly under this failure condition as well.

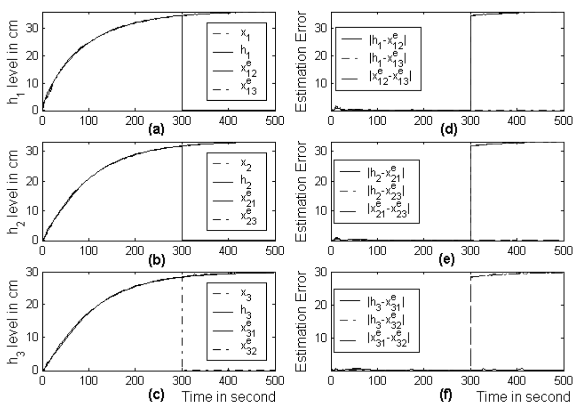


Fig. 12. Time histories under h_2 sensor failure condition

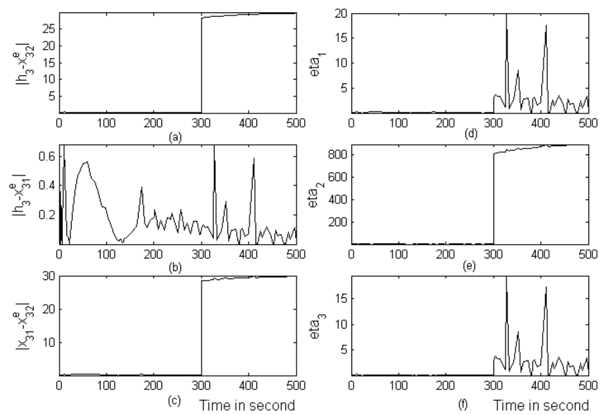


Fig. 13. Decision functions under h_2 sensor failure condition

VII. CONCLUSION

Three observers using Coactive Adaptive Neuro-Fuzzy Inference system are designed by fixing the optimal shape and parameters of the membership functions and effective rule base by neural networks to estimate the levels in three-tank interacting level process. Sensor Fault Detection and Identification System using these three CANFIS observers has been implemented. All level sensor failure conditions are simulated. From the study performed it has been noticed that the system has detected failures successfully at the time of failure itself in any sensor if it occurs. The sensor that has failed is correctly identified. The control law is modified accordingly and the level in tank 3 is maintained at the desired value even under the failure conditions.

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