

Takagi Sugeno fuzzy expert model based soft fault diagnosis for two tank interacting system

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The inherent characteristics of fuzzy logic theory make it suitable for fault detection and diagnosis (FDI). Fault detection can benefit from nonlinear fuzzy modeling and fault diagnosis can profit from a transparent reasoning system, which can embed operator experience, but also learn from experimental and/or simulation data. Thus, fuzzy logic-based diagnostic is advantageous since it allows the incorporation of a-priori knowledge and lets the user understand the inference of the system. In this paper, the successful use of a fuzzy FDI based system, based on dynamic fuzzy models for fault detection and diagnosis of an industrial two tank system is presented. The plant data is used for the design and validation of the fuzzy FDI system. The validation results show the effectiveness of this approach.

Key words: extended Kalman filter, fault diagnosis, fuzzy logic, two tank system

1. Introduction

International Federation of Automatic Control (IFAC) defined common terminology of fault is cited to as an unpermitted deviation of at least one characteristics property of variable of the system from acceptable behavior. Faults are classified based on location such as sensor, actuator and component faults. Scaling error, drifts, dead zones in sensors add to sensor faults. State fault and output faults are used to depict the location [3]. According to time behavior, once again faults are classified as abrupt and incipient faults. Depends upon their relation to other parts of the system, faults are again classified as additive and multiplicative faults. Addictive means extra functions are added in system dynamic equations, whereas multiplicative faults are represented by the mathematical product of variable with the faults. Fault diagnosis has the following three jobs, Fault detection tells the decision whether fault occurs or not, Isolation determines the types of fault location and Identification specifies the magnitude of fault. After a fault has been diagnosed, systems are required to be fault tolerant through passive or active controller reconfiguration. This process is said to be Fault Accommodation (FA) system.

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Traditionally limit checking is an above board and easy way for diagnosing the faults. When a sensor signal is out of its normal range, an alarm is generated to signal an abnormal event. Another method is based on hardware redundancy, where duplicate sensors and actuators and components are outfitted to measure the same process variable. But extra components raises the system complexity also cost. Therefore in the last three decades, Fault Diagnosis (FD) using analytical redundancy techniques has received significant interest from industrialist and academies [4]. A systematic way to classify the analytical redundancy proposed in the state of art methods. Where fault diagnosis strategies categorized into following approaches, Quantitative approach, Qualitative approach and Process history based.

In last thirty years quantitative model based fault diagnosis strategies have been significantly looked into and many contribution have been summarized in many work. From this literature [5] [6], residual generation and parameter estimation are two important systematic methods used in quantitative model based fault diagnosis schemes. In residue based FD scheme, a mathematical model of the system being considered is first built, then the residue signals produced from the consistency checking of different variables are assessed to diagnose faults. It equates the available system measurements with their estimation. For different purposes, the generated residual can be quite different. For example, a signal that is null or small in the fault free case and non-zero when fault occurs. This is sufficient for fault detection. But for fault isolation and estimation, more advanced residuals that contain the information of faults have to be developed. The most frequently used residual generation FD strategies are observed based approaches and parity space concepts.

The second class of quantitative model based FD strategies [9], treats fault as deviations in system parameters. Considering a system with a nominated model $M(\theta)$, we use parameter estimation method to obtain an estimate $\hat{\theta}$ of θ . If the deviation of $\hat{\theta}$ from θ is above threshold, then we can conclude that a fault has occurred. However this method is determined by following two aspects are, an assumption that a fault can be modeled as a deviation of system parameters is so limited that is unrealistic for many practical faults and as the number of faults raises, the dimension of the parameter may become so large that calculating the estimation of θ is cumbersome. Therefore compared with parameter estimation methods residue generation methods have received more probes. For control system, this FD scheme has following advantages are no additional hardware components are needed to carry out FD scheme, it can be easily implemented in software on process control and monitoring computers, no extra sensors are needed and it helps to lay down and implement the FA in online.

In this paper, Fuzzy based FD algorithm of sensors faults detection problem is proposed. Before dealing with the problem, were developed the model by using First principle. This algorithm is based on the structure of State Estimation (i.e Extended Kalman Filter) to generate residuals. The residuals results are utilized for Sensor fault detection. A Fuzzy Classifier is built in such a way to isolate and key out the faulty sensor for a Sensor faults after detecting the fault occurrence. The advantages of the innovative Fuzzy based FD algorithm proposed here, is the capacity of single, multiple and simultaneous

faults detection, isolation and identification. Besides, it is readily relevant to both process sensor offset and gain faults. Simulation results are given in order to evidence the effectiveness of the overall proposed algorithm.

2. Mathematical modeling of two tank interacting system

2.1. Description

The system shown in Fig. 1 consists of two interacting tanks connected to each other through connecting pipes of circular cross section provided with a valve. The valves 1 and 2 introduce nonlinearity in the system. For the dynamic model, the incoming mass flows F_{in1} and F_{in2} are defined as inputs, while the two measurements $H_1(t)$ and $H_2(t)$ i.e. the height of fluid in tank are considered as outputs. The dynamic model is derived using the incoming and outgoing mass flows and is described by the following differential equations (1) and (2):

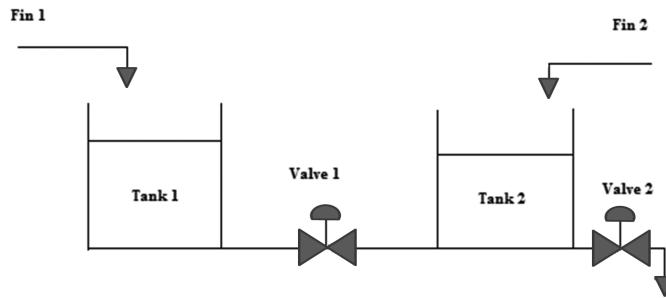


Figure 1. Two tank interacting system.

for tank 1,

$$A_1 \frac{dH_1}{dt} = F_{in1} - b_1 \sqrt{H_1 - H_2} \quad (1)$$

for tank 2,

$$A_2 \frac{dH_2}{dt} = F_{in2} + b_1 \sqrt{H_1 - H_2} - b_2 \sqrt{H_2} \quad (2)$$

where the valve coefficients of tank 1 and tank 2 are $b_1 = s_1 a_1 \sqrt{2g}$ and $b_2 = s_2 a_2 \sqrt{2g}$. The physical parameters of the two tank process are given in Tab. 1.

2.2. Linearization

The nonlinear equations are linearized using the Jacobian matrices to get the *ABCD* parameters. The matrices are given as follows

$$A = \begin{bmatrix} \frac{\partial f_1}{\partial H_1} & \frac{\partial f_1}{\partial H_2} \\ \frac{\partial f_2}{\partial H_1} & \frac{\partial f_2}{\partial H_2} \end{bmatrix}, \quad B = \begin{bmatrix} \frac{\partial f_1}{\partial q_1} & \frac{\partial f_1}{\partial q_2} \\ \frac{\partial f_2}{\partial q_1} & \frac{\partial f_2}{\partial q_2} \end{bmatrix}, \quad C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad D = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

Table 1. Physical parameters of two tank process.

Description	Values
Area of the tanks (A_1, A_2)	0.0154 m ²
Acceleration due to gravity	9.81 m/sec ²
Maximum permissible height of water levels (H_{max})	0.63 m
Cross section of the connecting pipes (a)	0.005 m ²
Coefficient of the connecting pipes (s)	0.45
Nominal operating conditions	Nominal inflow rate
$H_1 = 0.4$ m	$F_{in1} = 0.00315$ m ³ /sec
$H_2 = 0.3$ m	$F_{in2} = 0.00231$ m ³ /sec

where f_1 and f_2 are the differential equations (1) and (2) respectively; q_1 and q_2 are the inflow rates. After substituting and simplifying, the discrete matrices are obtained as

$$A = \begin{bmatrix} 0.9071 & 0.0901 \\ 0.0901 & 0.8551 \end{bmatrix}, \quad B = \begin{bmatrix} 6.1817 & 0.3056 \\ 0.3056 & 6.0052 \end{bmatrix}.$$

3. Problem statement

The problem of model-based fault diagnosis can be expressed as follows: The plant of an automatic control system with the known input vector u and the output vector y . Suppose there may occur faults in the functional devices of the plant that lead intolerable performance of the system. From the fault-detection point of view it is practicable to divide the faults into three categories: actuator faults, component faults (i.e., faults in the framework of the process), and sensor faults, as shown in Fig. 2. The faults can normally be described as additional inputs.

Typical cases of such faults are:

- structural defects, such as cracks, ruptures, fractures, leaks, and loosen parts;
- faults in the drives, deficiencies in force or momentum, such as damage in the bearings, defects in the gears, and ageing effects;
- faults in sensors, such as scaling errors, drift, hysteresis, dead zones, shortcuts, and contact failures;
- abnormal parameter variations.

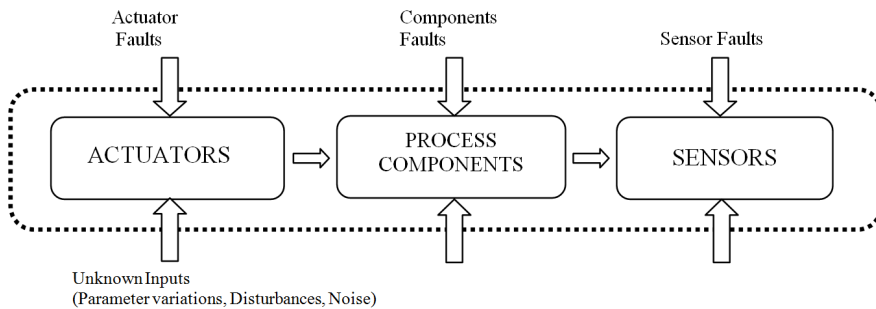


Figure 2. Fault definition.

The goal of fault diagnosis is to detect the faults of concern and their causes early enough so that failure of the overall system can be annulled. In addition there is always modeling uncertainty due to disturbances, noise, and model mismatch. This may not be vital for the process behavior but may blot out fault detection by raising false alarms. The modeling uncertainty is taken into consideration by extra vectors of unknown inputs. The basic tasks of fault diagnosis are to detect and set apart occurring faults and to provide information regarding their size and source. This has to be done on line in the face of the existing unknown inputs and with as few warnings as possible.

For the practical implementation of fault diagnosis the succeeding three steps have to be taken:

1. Residual (symptom) generation, i.e. the generation of signals which echo the faults. In order to set apart different faults, properly structured residuals of directed residual vectors are required.
2. Residual evaluation (fault classification), i.e. logical deciding on the time of occurrence and the location of a fault.
3. Fault analysis, i.e., finding of the type of fault, its size and cause.

The structural diagram of the residual generation and evaluation, which make up the first two steps of fault diagnosis, is given in Fig. 3. The first two steps have antecedently been carried out with methods of system theory, but artificial-intelligence-based methods are now getting more important and are proposed in this contribution. Step 3 requires in general either a human adept or a knowledge-based system ('diagnosis expert system').

4. Proposed FDI methodology

The proposed FDI system executes the tasks of failure detection and identification by ceaselessly monitoring the outputs of the sensors. Under nominal conditions, these measurements follow predictable patterns, within a tolerance influenced by the amount

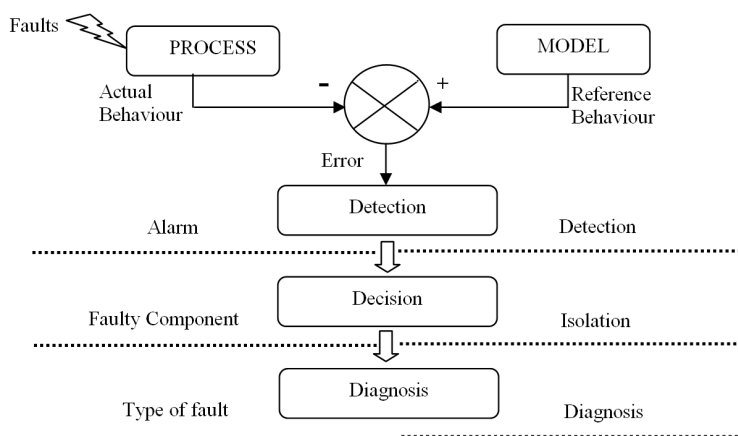


Figure 3. Concept of model based fault detection and isolation.

of uncertainties introduced by random system disturbances and measurement noise in the sensors. Usually, its tasks are fulfilled by state estimator when the output of a failed sensors varies from its predicted pattern. For Plant sensors fault detection, the first job to detect the abnormal system behavior and estimate the order of magnitude of the fault called residues. Then, based on the magnitude of the estimated residues by Kalman Filter, it is being classed by Fuzzy System. The details of this proposed FDI related with the fuzzy classifier are given in the following sections.

4.1. Architecture for fault detection and diagnosis

This paper proposes a simple architecture to detect, isolate and identify faults. The FDI system is based on fuzzy observers (models) identified directly from data. The model-based technique uses a fuzzy model for the process running in normal operation, and state estimator (model) for each of the faults to be detected. Suppose that a process is running, and n possible faults can be detected. The fault detection and isolation system proposed in this paper for these n faults is depicted in Fig. 1. The multi dimensional input \mathbf{u} , of the system enters both the process and a model (state estimator) in normal operation. The vector of residuals $\boldsymbol{\varepsilon}$ is defined as

$$\boldsymbol{\varepsilon} = \mathbf{y} - \hat{\mathbf{y}} \tag{3}$$

Where \mathbf{y} is the output of the system and $\hat{\mathbf{y}}$ is the output of the model in normal operation. When any component of $\boldsymbol{\varepsilon}$ is bigger than a certain threshold δ , the system detects faults. In this case, n estimators (models), one for each fault, are activated, and n vectors of residuals are computed. Each residual i , with $i = 1, \dots, n$ is computed as

$$\boldsymbol{\varepsilon}F_i = \mathbf{y} - \hat{\mathbf{y}}F_i \tag{4}$$

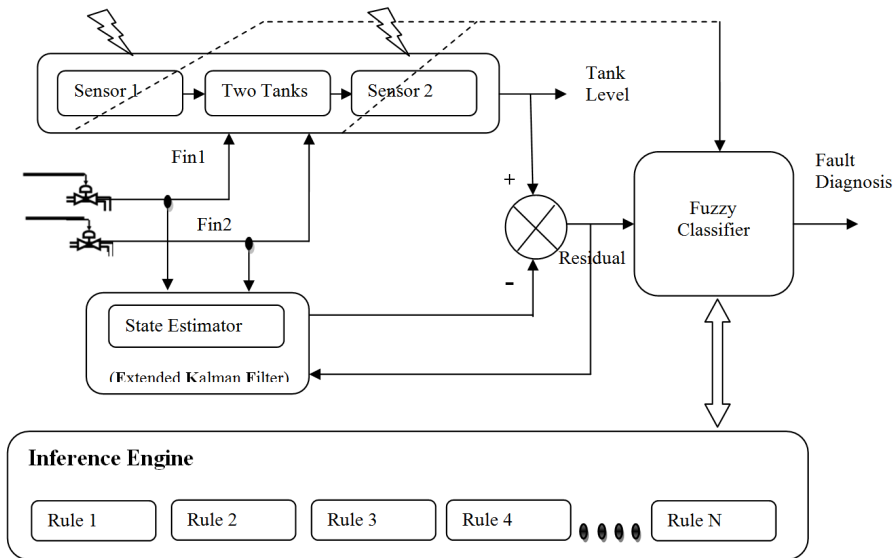


Figure 4. Fuzzy based fault detection procedure.

where \hat{y}_i is the output of the estimator for the fault i . The residuals $\epsilon F_1, \dots, \epsilon F_n$ are evaluated, and the fault or faults detected are the outputs of the FDI system. In this paper, all the models, i.e., the estimator for normal operation and the estimator for the n faults, are fuzzy models reproducing the dynamic behavior of the process, for each condition considered. This technique revealed to be adequate to identify models extracted from the plant.

4.2. Knowledge state estimator

It seems obvious that a fault diagnosis concept using a qualitative knowledge-based model can be coordinated in a configuration similar to that of the analytical estimation. It may consequently be termed a knowledge estimator. The key part of this conception is the qualitative model. Features of all kinds of qualitative modeling is that the dynamic behavior of the process is characterized by a (small) number of symbols or qualitative values such as on, off, or limits values. One may also use inaccurate intermediary values specified by fuzzy sets such as high, small, or little. In the last few years much work has been done in the field of recognition of fuzzy relational systems and qualitative simulation with fuzzy sets [3]. This has become a practicable tool for the qualitative modeling share of the Kalman filters.

Kalman filters allow the prediction of the values of unmeasurable states of a process. These prefigured state values can be used for process monitoring. However, the statistics of the estimated states are dissimilar from the statistics of the actual states as measurement noise, model accuracy, and the soft sensor design/tuning alter the statisti-

cal properties of the estimated states. It is the purpose of this work to formulate a process monitoring technique which can take these factors into consideration.

4.2.1. Extended Kalman filter (EKF)

The well-known Kalman filter figures out the state estimation problem in a stochastic linear system. The EKF is likely the most widely used nonlinear filter. For nonlinear problems, the Kalman Filter is not strictly relevant since linearity plays an significant role in its derivation and performance as an optimal filter. The EKF attempts to surmount this difficulty by using a linearized approximation where the linearization is performed about the current state estimate. The basic model for the EKF involves the estimation of the states of a nonlinear dynamic system given by (1) and (2).

$$x(k) = x(k-1) + \int_{t_{k-1}}^{t_k} F[x(\tau), u(k)] d\tau + w(k) \quad (5)$$

$$y(k) = H[x(k)] + v(k). \quad (6)$$

In the above equations, $x(k)$ represents the unobserved state of the system, $u(k)$ is a known exogenic input and $y(k)$ is the only observed signal. We have presumed $w(k)$ and $v(k)$ as zero mean Gaussian white noise sequences with covariance matrices Q and R respectively. The symbols F and H be an n -dimensional function vector and are presumed known. EKF involves the recursive estimation of the mean and covariance of the state under maximum likeliness condition. The function F can is used to compute the predicted state from the previous estimate and likewise the function H can be used to compute the predicted measurement from the predicted state. However, F and H cannot be utilized to the covariance directly. Instead a matrix of partial derivatives (Jacobian) is calculated at each time step with current predicted state and evaluated. This process basically linearizes the non-linear function around the current estimate.

The predicted state estimates are incurred as

$$\hat{x}(k|k-1) = \hat{x}(k-1|k-1) + \int_{t_{k-1}}^{t_k} F[x(\tau), u(k-1)] d\tau. \quad (7)$$

The covariance matrix of estimation errors in the predicted estimates is incurred as

$$P(k|k-1) = \emptyset(k) P(k-1|k-1) \emptyset(k)^T + Q \quad (8)$$

where $\emptyset(k)$ is the Jacobian matrix of partial derivatives of F with respect to x

$$\emptyset(k) = \left[\frac{\partial F}{\partial x} \right]_{[\hat{x}(k-1|k-1), u(k-1)]} \quad (9)$$

Note that the EKF calculates covariances using the linear propagation. The measurement prediction, calculation of innovation and covariance matrix of innovation are as follows

$$\hat{y}(k|k-1) = H[\hat{x}(k|k-1)] \quad (10)$$

$$\gamma(k|k-1) = y(k) - \hat{y}(k|k-1) \quad (11)$$

$$V(k) = C(k)P(k|k-1)C(k)^T + R \quad (12)$$

where $C(k)$ is the Jacobian matrix of partial derivatives of H with respect to x

$$C(k) = \left[\frac{\partial H}{\partial x} \right]_{[\hat{x}(k-1|k-1), u(k-1)]} \quad (13)$$

The Kalman gain is calculated using the following equation

$$K(k) = P(k|k-1)C(k)^T V^{-1}(k). \quad (14)$$

The updated state estimates are incurred using the following equation

$$\hat{x}(k|k) = \hat{x}(k|k-1) + K(k)\gamma(K|k-1). \quad (15)$$

The covariance matrix of estimation errors in the updated state estimates is incurred as

$$P(k|k) = [I - K(k)C(k)]P(k|k-1). \quad (16)$$

Independent residuals are built for each different sensors failure. Residuals are designed which enhance fault isolation for an individual failure and not to the others. Generally, residuals are functions of the difference between real and estimated state outputs. As a matter of fact, for two tank sensors fault detection and isolation, the following residuals are built given by,

$$e_1(kT) = \mathbf{x}_1(kT) - \hat{\mathbf{x}}_1(kT) \quad (17)$$

$$e_2(kT) = \mathbf{x}_2(kT) - \hat{\mathbf{x}}_2(kT) \quad (18)$$

During practical applications, substantial high frequency noise may exist, which may affect the above residuals. To overcome this problem, it necessitates an additional block for robust residuals generation. In fact, the residuals are fed onto this additional block to develop respectively robust low pass filtered residuals. After this additional filtering unit, the filtered residuals are sent out to the fuzzy classifier where they compared thresholds to generate an error signature and to find the presence of faults. But Kalman filter uses a stochastic framework, no need to use an additional filter unit. It is model based filter, suppress the noises in high and low frequency ranges automatically. Fig. 4 shows the residual plot for different fault models.

5. Fuzzy modeling

Fuzzy modeling often follows the approach of encoding expert knowledge expressed in a verbal form in a collection of if-then rules, creating a model structure. Parameters

in this structure can be adapted using input-output data. When no prior knowledge about the system is available, a fuzzy model can be constructed entirely on the basis of system measurements. Note that the fuzzy estimators used in the architecture for fault detection and diagnoses proposed in this paper are fuzzy models. In the following, we consider data-driven modeling based on fuzzy clustering [1, 8]. This approach avoids the well-known bottle neck of knowledge acquisition. The fuzzy model is acquired from sampled process data, utilizing the functional approximation capabilities of fuzzy systems. Assume that data from an unknown system $y = F(\mathbf{x})$ is observed.

The aim is to use this data to construct a deterministic function $y = f(\mathbf{x})$ that can approximate $F(\mathbf{x})$. The function f is represented as a collection of fuzzy if-then rules. Depending on the form of the propositions and on the structure of the rule base, different types of rule-based fuzzy models can be distinguished. The system to be identified can be represented as a MIMO nonlinear auto-regressive (NARX) model. This MIMO system can be decomposed into several MISO models, without loss of generality [1]:

$$\hat{y}(k+1) = F(\mathbf{x}(k)) \quad (19)$$

Where $\mathbf{x}(k) \subset \mathfrak{R}^n$ is the state of the system and are represented by previous inputs and outputs. Only MIMO models are considered in the following for evaluation of proposed method.

5.1. Takagi-Sugeno fuzzy model

We consider rule-based models of the Takagi-Sugeno (TS) type [9]. It consists of fuzzy rules which each describe a local input output relation, typically in an affine form. The representation of (3) as a TS model is given by

$$R_i : \text{If } x_1 \text{ is } A_{i_1} \text{ and } \dots \text{ and } x_n \text{ is } A_{i_n} \text{ then } y_i = \mathbf{a}_i \mathbf{x} + b_i$$

with $i = 1, 2, \dots, K$. Here, R_i is the i th rule, A_{i_1}, \dots, A_{i_n} are fuzzy sets defined in the antecedent space, $\mathbf{x} = [x_1, \dots, x_n]^T$ is the antecedent vector, and y_i is the rule output variable. K denotes the number of rules in the rule base, and the aggregated output of the model, \hat{y} , is calculated by taking the weighted average of the rule consequents:

$$\hat{y} = \frac{\sum_{i=1}^K \beta_i y_i}{\sum_{i=1}^K \beta_i} \quad (20)$$

where β_i is the degree of activation of the i th rule:

$$\beta_i = \prod_{j=1}^n \mu_{A_{ij}}(x_j), i = 1, 2, \dots, K \quad (21)$$

and $\mu_{A_{ij}}(x_j) : \mathfrak{R} \rightarrow [0, 1]$ is the membership function of the fuzzy set A_{ij} in the antecedent of R_i .

5.2. Identification by fuzzy clustering

The nonlinear identification problem is solved in two steps: structure identification, and parameter estimation.

5.2.1. Structure identification

The designer must choose first the order of the model, and the significant state variables \mathbf{x} of the model. This step is crucial in the identification of fuzzy estimators for FDI, since the smaller the vector \mathbf{x} the faster the model. Note that fuzzy estimators for FDI must be both simple and accurate models in order to detect the faults as fast as possible. To identify the model (4), the regression matrix X and an output vector \mathbf{y} are constructed from the available data:

$$X^T = [x_1, \dots, x_N], \quad Y^T = [y_1, \dots, y_N]. \quad (22)$$

Here $N \gg n$ is the number of samples used for identification. The objective of identification is to construct the unknown nonlinear function $\mathbf{y} = f(\mathbf{x})$ from the data, where f is the TS model in (3).

5.2.2. Parameter estimation

The number of rules, K , the antecedent fuzzy sets, A_{ij} , and the consequent parameters, \mathbf{a}_i , b_i are determined in this step, by means of fuzzy clustering in the product space of $X \times Y$ [10, 11, 1]. Hence, the data set Z to be clustered is composed from X and \mathbf{y} :

$$Z = [X, \mathbf{y}]. \quad (23)$$

Given Z and an estimated number of clusters K , the Gustafson-Kessel fuzzy clustering algorithm [6] is applied to compute the fuzzy partition matrix U . This provides a description of the system in terms of its local characteristic behavior in regions of the data identified by the clustering algorithm, and each cluster defines a rule. Unlike the popular fuzzy c-means algorithm [3], the Gustafson-Kessel algorithm applies an adaptive distance measure. As such, it can find hyper-ellipsoid regions in the data that can be efficiently approximated by the hyper-planes described by the consequents in the TS model. The fuzzy sets in the antecedent of the rules are obtained from the partition matrix U , whose i_k th element $\mu_{ik} \in [0, 1]$ is the membership degree of the data object \mathbf{z}_k in the cluster i . One dimensional fuzzy set A_{ij} are obtained from the multi dimensional fuzzy sets defined point-wise in the i th row of the partition matrix by projections onto the space of the input variables x_j :

$$\mu_{A_{ij}}(x_{jk}) = \text{proj}_j^{N_{n+1}}(\mu_{ik}) \quad (24)$$

where, proj is the point-wise projection operator [7].

The point wise defined fuzzy sets A_{ij} are approximated by suitable parametric functions in order to compute $\mu_{A_{ij}}(x_j)$ for any value of x_j . In this paper like [1] after clustering the consequent parameters for each rule are obtained as a weighted ordinary least-square estimate. Let $\theta^T_i = [a^T_i; b_i]$; let X_e denote the matrix $[X; \mathbf{1}]$ and let W_i denote a

diagonal matrix in $\mathfrak{R}^{n \times n}$ having the degree of activation, $\beta_i(\mathbf{x}_k)$, as its k th diagonal elements defined in (21). Assuming that the columns of X_e are linearly independent and $\beta_i(\mathbf{x}_k) > 0$ for $1 \leq k \leq N$, the weighted least-squares solution of $y = X_e \theta + \varepsilon$ becomes

$$\theta_i = [X_e^T W_i X_e]^{-1} X_e^T W_i y. \quad (25)$$

Rule bases constructed from clusters are often unnecessary redundant due to the fact that the rules defined in the multi dimensional premise are overlapping in one or more dimensions. The rules were framed based on the fault dictionary given in Tab. 2.

Table 2. Fault diagnosis for two tank system.

Fault dictionary						
Type		Residue diagnosis		Process output		Fault index
		Tank 1	Tank 2	Tank 1	Tank 2	
		[Min,Max]	[Min,Max]	[Min,Max]	[Min,Max]	
No fault	Fault free	[0, 0]	[0, 0]	[744,767]	[498,520]	0
	Sensor 1	[0, -34]	[0, -86]	[751,797]	[654,762]	1
Multiplic.	Sensor 2	[0, -42]	[0, -145]	[722,913]	[553,613]	2
	Both	[0, -175]	[0, -130]	[724,988]	[562,728]	3
Additive	Sensor 1	[0, 35]	[0, 88]	[695,738]	[395,515]	4
	Sensor 2	[0, 140]	[0, 53]	[576,757]	[491,564]	5

6. Conclusion

A fuzzy based expert system is proposed for fault diagnosis for two tank system to sensors with the help of dedicated Kalman filter. The FD is designed based on model with coolant flow and feed water flow as inputs. Concentration, temperature are the outputs. The deviation in the output is very low as the estimators are very accurate. The estimator state and the actual state variable is compared to form the residuals which are evaluated for the fault detection and Identification. The proposed expert scheme isolate the fault at the very same instant of its occurrence showing its capability of instantaneous handling of sensors fault in addictive and multiplicative nature.

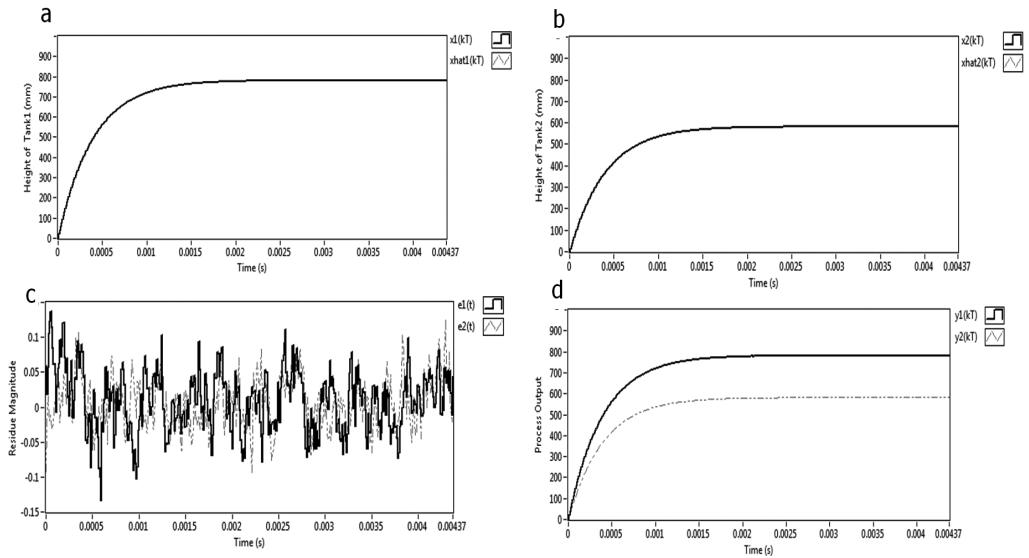


Figure 5. Responses for fault free condition: (a) Actual and estimated height of tank 1. (b) Actual and estimated height of tank 2. (c) Residues plot. (d) Process output.

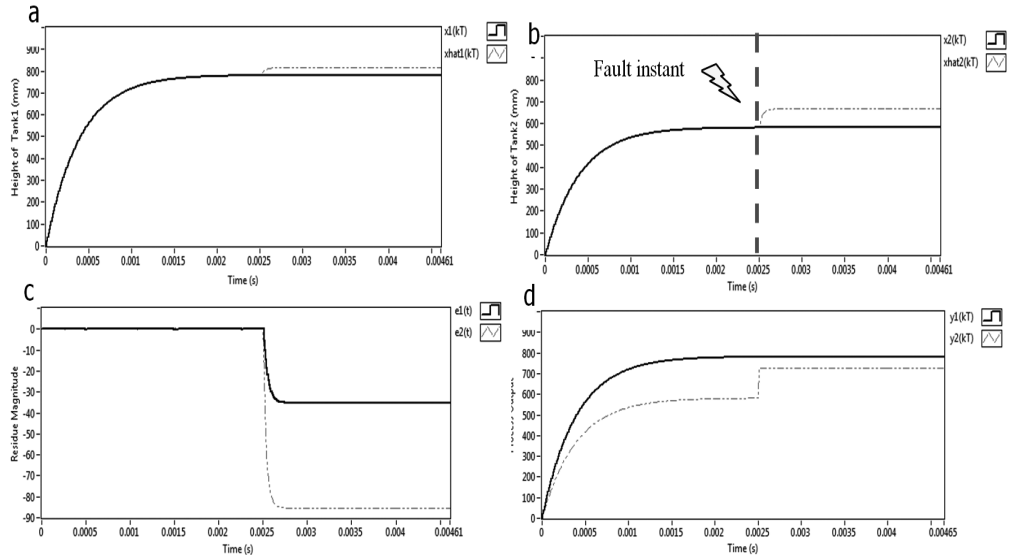


Figure 6. Responses of Sensor 1- Fault free and Sensor 2 – 20% Fault / [Additive in nature]: (a) Actual and estimated height of tank 1. (b) Actual and estimated height of tank 2. (c) Residues plot. (d) Process output.

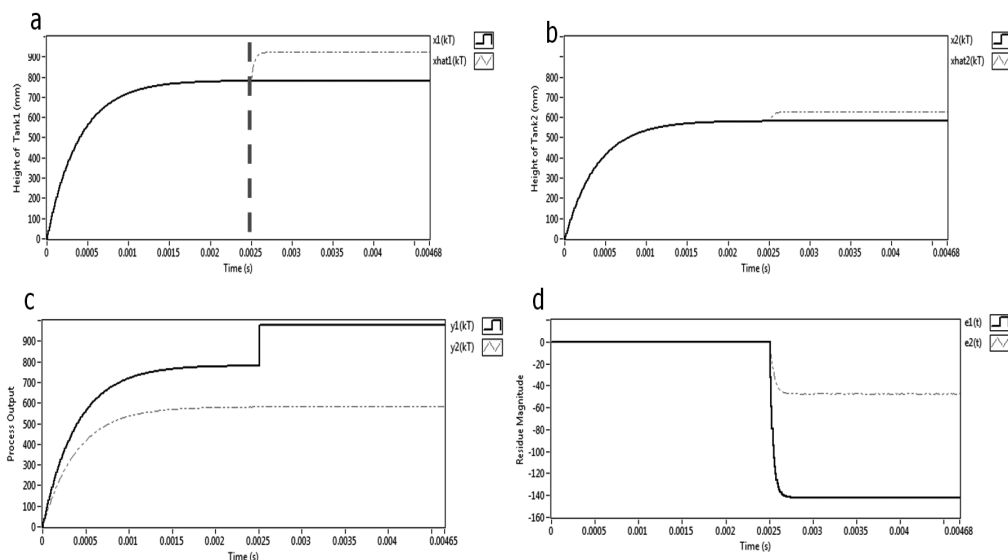


Figure 7. Responses of Sensor 1 – 20% Fault and Sensor 2 – Fault free / [Additive in nature]: (a) Actual and estimated height of tank 1. (b) Actual and estimated height of tank 2. (c) Residues plot. (d) Process output.

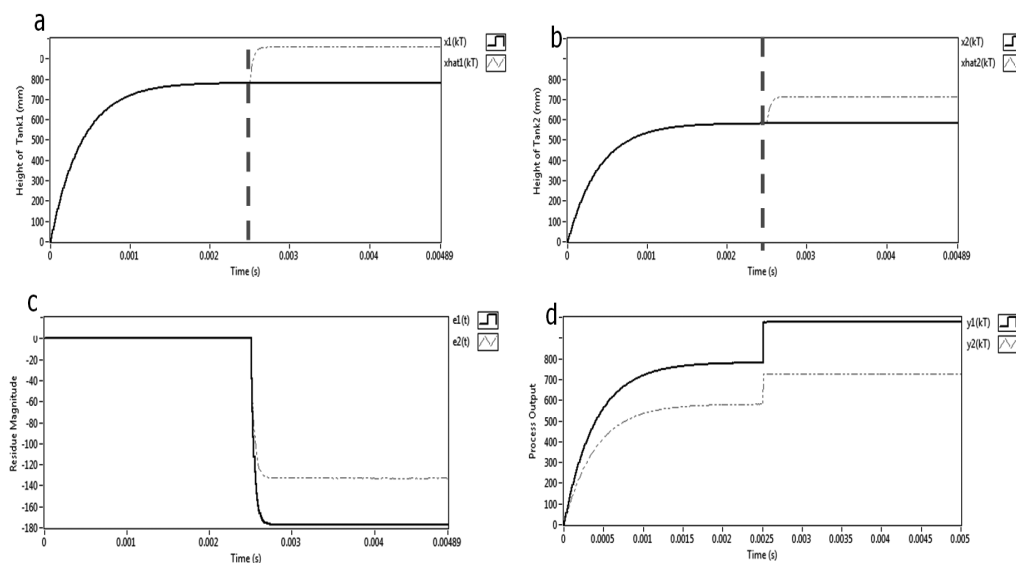


Figure 8. Responses of Sensor 1 – 20% Fault and Sensor 2 – 20% Fault / [Additive in nature]: (a) Actual and estimated height of tank 1. (b) Actual and estimated height of tank 2. (c) Residues plot. (d) Process output.

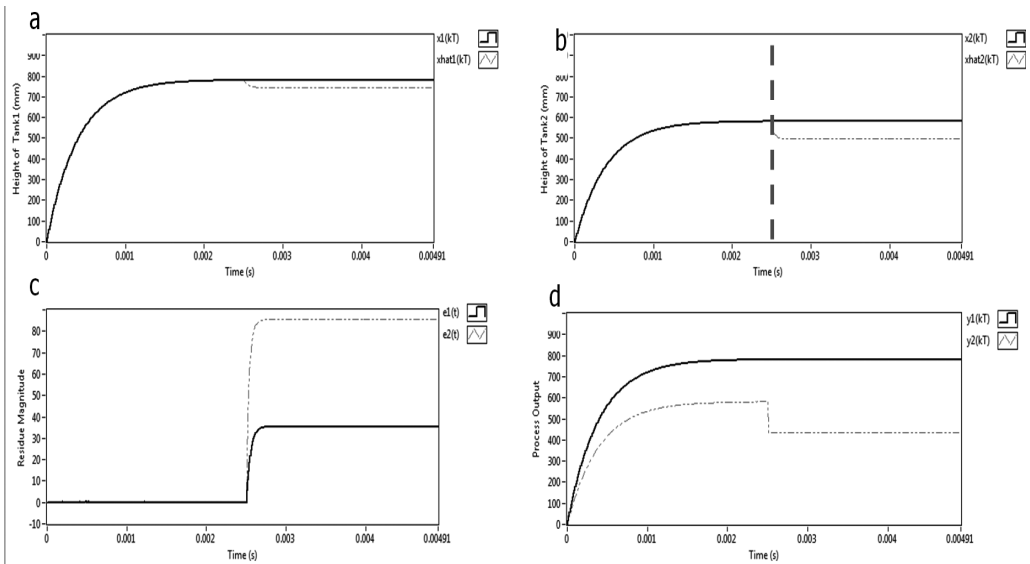


Figure 9. Responses of Sensor 1 – Fault free and Sensor 2 – 20% Fault / [Mutiplicative in nature]: (a) Actual and estimated height of tank 1. (b) Actual and estimated height of tank 2. (c) Residues plot. (d) Process output.

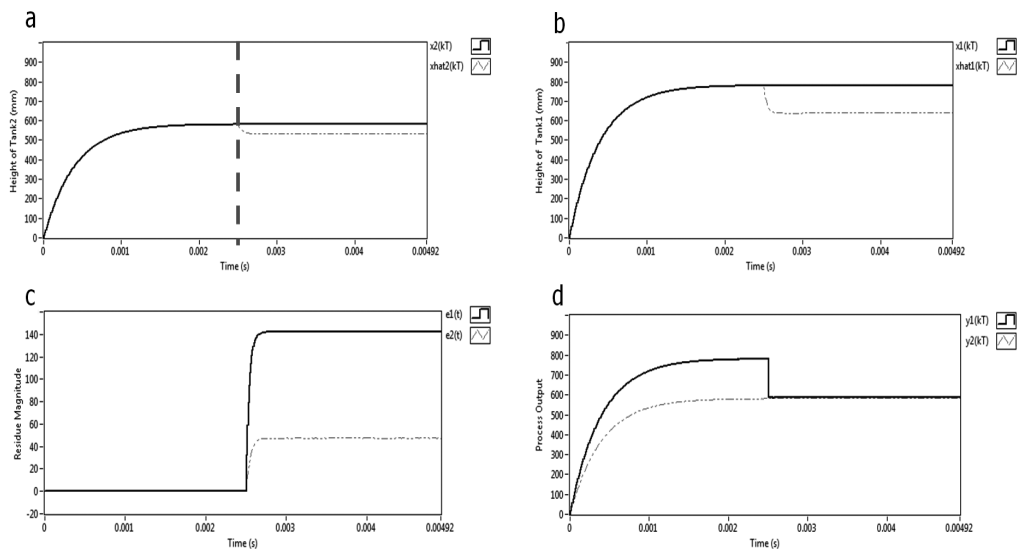


Figure 10. Responses of Sensor 1 – 20% Fault and Sensor 2 – Fault free / [Mutiplicative in nature]: (a) Actual and estimated height of tank 1. (b) Actual and estimated height of tank 2. (c) Residues plot. (d) Process output.

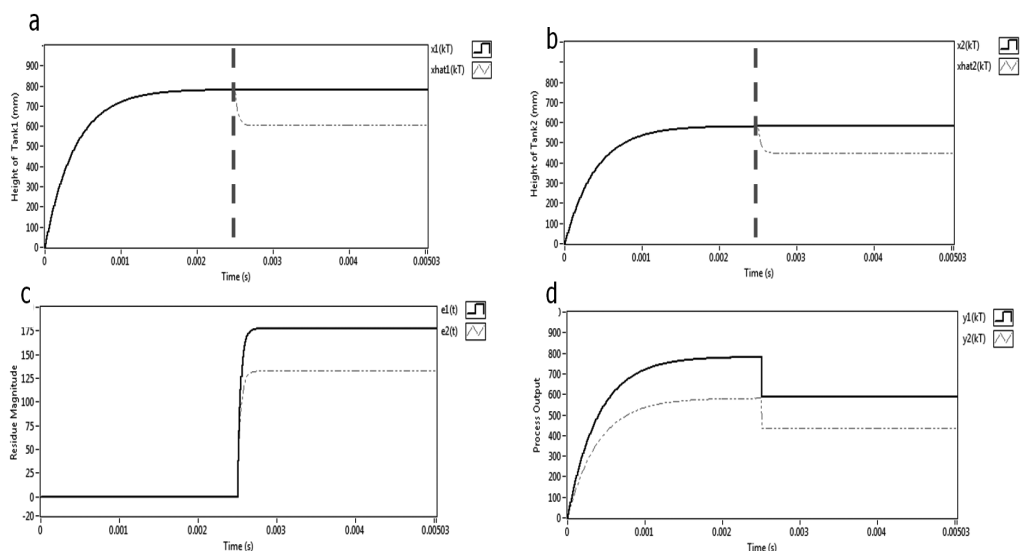


Figure 11. Responses of Sensor 1 – 20% Fault and Sensor 2 – 20% Fault / [Mutiplicative in nature]: (a) Actual and estimated height of tank 1. (b) Actual and estimated height of tank 2. (c) Residues plot. (d) Process output.

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