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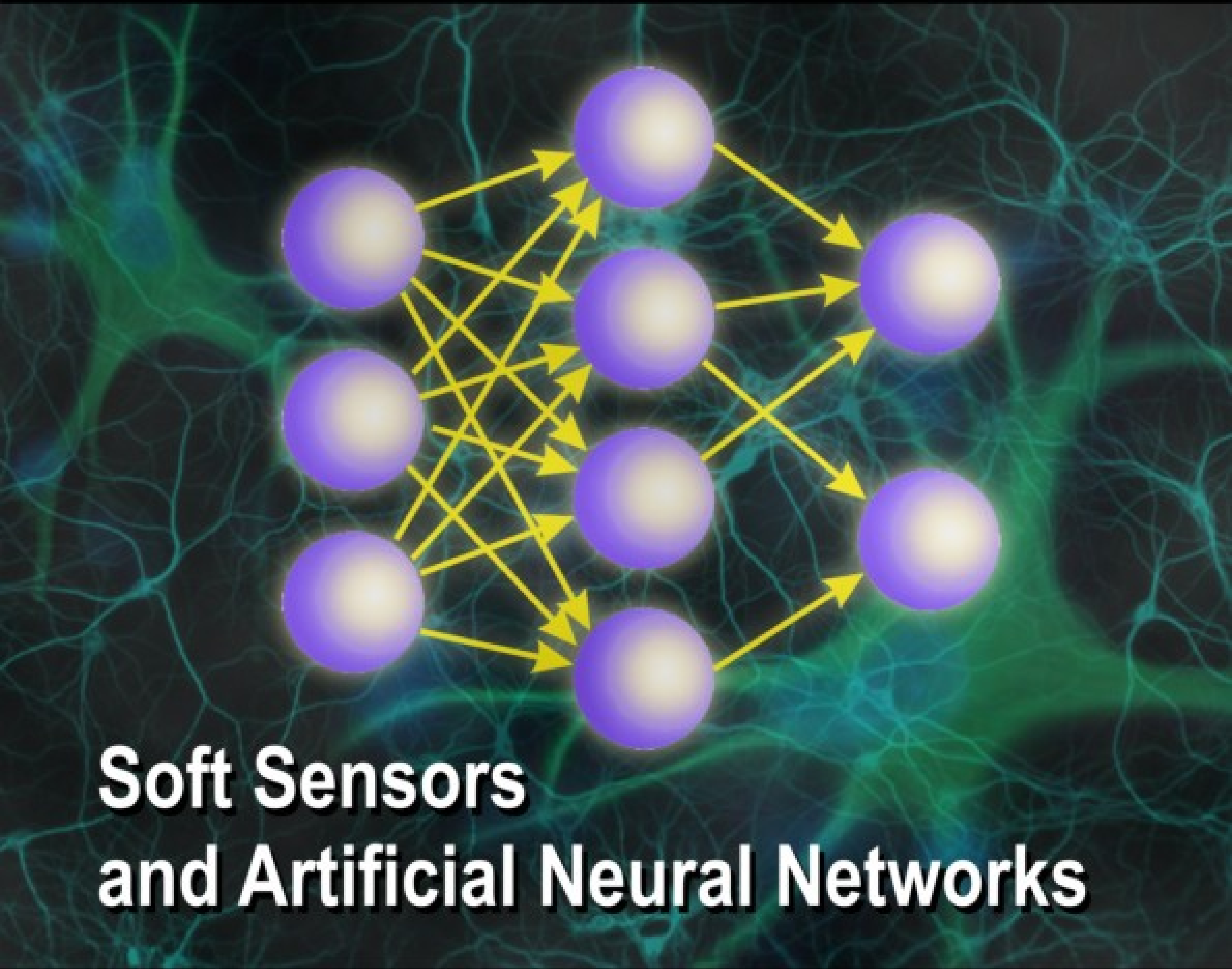

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Integration of Fault Detection and Isolation with Control Using Neuro-fuzzy Scheme

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Abstract:-In this paper an algorithms is developed for fault diagnosis and fault tolerant control strategy for nonlinear systems subjected to an unknown time-varying fault. At first, the design of fault diagnosis scheme is performed using model based fault detection technique. The neuro-fuzzy chi-square scheme is applied for fault detection and isolation. The fault magnitude and time of occurrence of fault is obtained through neuro-fuzzy chi-square scheme. The estimated magnitude of the fault magnitude is normalized and used by the feed-forward control algorithm to make appropriate changes in the manipulated variable to keep the controlled variable near its set value. The feed-forward controller acts along with feed-back controller to control the multivariable system. The performance of the proposed scheme is applied to a three- tank process for various types of fault inputs to show the effectiveness of the proposed approach. *Copyright © 2009 IFSA.*

Keywords: Fault detection, Neuro fuzzy scheme, Chi-square test, Integration of fault diagnosis and control

1. Introduction

Increasingly faced with the requirements of safety, reliability and profitability, chemical plant operation is relying extensively on highly automated process control systems. Automation, however, tends to also increase vulnerability of the plant to faults, potentially causing a host of economic, environmental, and safety problems that can seriously degrade the operating efficiency of the plant if not addressed within a time appropriate to the context of the process dynamics. Examples include physical damage to the plant equipment, increase in the wasteful use of raw material and energy resources, increase in the downtime for process operation resulting in significant production losses, and jeopardizing personnel and environmental safety. These considerations provide a strong motivation for the development of methods and strategies for the design of advanced fault-tolerant control structures that ensure an efficient and timely response to enhance fault recovery, prevent faults from propagating or developing into total failures, and reduce the risk of safety hazards.

Recently, fault-tolerant control has gained increasing attention in the context of chemical process control; however, the available results are mostly based on the assumption of a linear process description [1-8] and do not account for complexities such as control constraints or the unavailability of state measurements. In process control, given the complex dynamics of chemical processes (example, nonlinearities, uncertainties and constraints) the success of any fault-tolerant control method requires an integrated approach that brings together several essential elements, including: (1) the design of advanced feedback control algorithms that handle complex dynamics effectively, (2) the quick detection of faults, and (3) the design of supervisory switching schemes that orchestrate the transition from the failed control configuration to available well-functioning fallback configurations to ensure fault-tolerance.

Generally speaking there exist two approaches to Fault Tolerant Control: the passive and the active approach. In the passive approach, robust control techniques are used to ensure that the control loop system remains insensitive to certain faults. The effectiveness of this strategy, that usually assumes very restrictive repertory of faults, depends upon the robustness of the nominal closed-loop system. In the active approach a new control system is re-designed according to the estimation of the fault performed by the FDI technique and according to the specification to be met for the faulty system. In this respect it is possible to identify two possible methods which can be used within an active approach: the projection-based methods and on-line automatic controller redesign methods. The first one rely on the idea of selecting new pre- computed control laws depending on the faults which have been detected and on their severity (in this case hybrid control or switching control structures are commonly encountered in literature). On the other hand, the on-line automatic controller re-design methods involve the calculation of new controller parameters once a failure has been detected following the design paradigm typical of adaptive control.

Survey papers by Patton [9] and Frank [10] provide excellent overviews of recent research work on FTC. Over the last two decades, the design and analysis of fault diagnosis algorithms using the model-based analytical redundancy approach have received significant attention [3], [8], [9]. The fault information generated by detection and isolation procedures can be very useful to FTC. However, links between fault diagnosis and FTC techniques are still lacking [7]. Some recent results on the integration of FDI with FTC can be found in [11-15]. This paper presents a unified design and analysis methodology for detecting, isolating, and accommodating faults in a class of nonlinear dynamic systems.

In this paper the on-line automatic controller re-design method is applied to three tank system. The proposed scheme has two main components: 1) *The online monitoring (fault diagnosis) module* consists of a model of the system and a FDI scheme (, neuro-fuzzy chi-square test) which estimates the time of occurrence of fault and estimated magnitude of fault. 2) *The controller (fault accommodation) module* consists of a feed -forward controller, which is used right after fault detection and isolation. The estimated fault magnitude is used for the feed forward controller to make appropriate changes in the manipulated variable to keep the controlled variable near its set value. The performance of the proposed scheme is applied to a three- tank process for various types of disturbance inputs to show the effectiveness of the proposed approach.

Fig.1 shows the implementation procedure of the proposed scheme. When there is a fault in the process, the process output differs with model output. This difference is called residual. By simply monitoring the residuals one can say that something is going wrong. But it is not possible to identify the location and magnitude of the fault. So the residual has to be processed to enhance isolation. After processing by neuro-fuzzy chi-square test the fault magnitude is found and it is used to reconfigure the controller.

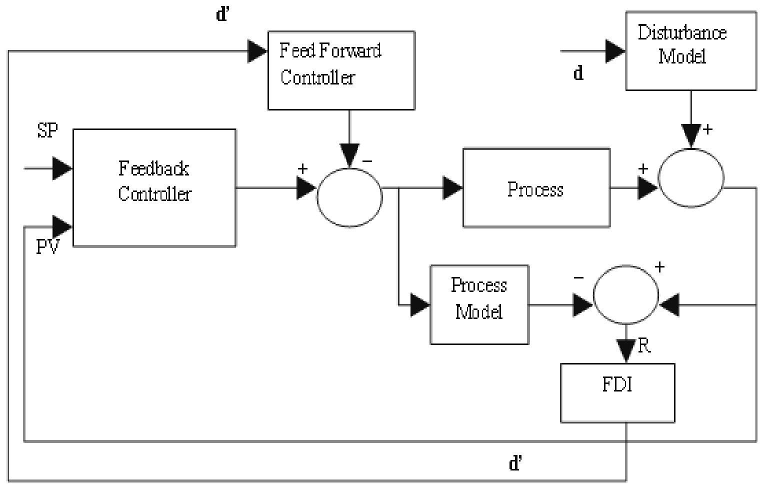

Fig. 1. Implementation of Proposed Scheme.

This paper is organized as follows. In section 2 the system under study i.e. three-tank system is described. In section 3, the identification of un-measured disturbance variables (faults) using chi-square test as reported in literature is explained. The proposed scheme to control in the presence of unmeasured disturbance acting on the process is presented in section 4. In section 5 the integration of FDI with control scheme is discussed. In section 6 the simulation results are discussed. Finally the conclusions are drawn and scope of further work is provided in section 7.

2. System Descriptions

The three-tank system considered for study [6] is shown in Fig. 2. The controlled variables are the level of the tank1 (h1) and level of the tank3 (h3). In flow of tank1 (fin_1) and in flow of tank3 (fin_3) are chosen as manipulated variables to control the level of the tank1 and tank3. The unmeasured outflow of that is leak of tank1; tank2 and tank3 have been considered as fault variables.

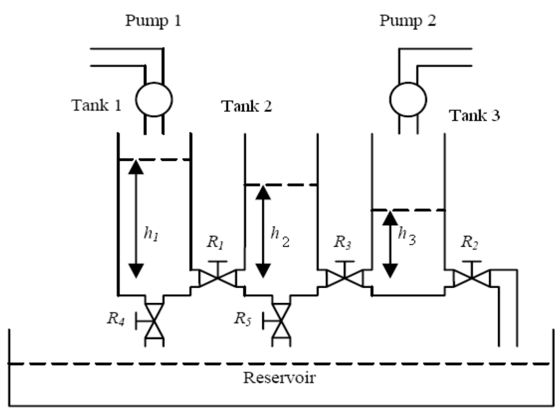

Fig. 2. Three Tanks System.

The material balance equation for the above three-tank system is given by

$$\frac{dh1}{dt}=\frac{fin_1}{S1}-\frac{Az1}{S1}\sqrt{2g(h1-h2)}\ \text{-}L_1$$
$$\frac{dh2}{dt}=\frac{Az1}{S2}\sqrt{2g(h1-h2)}\ \text{-}\frac{Az3}{S2}\sqrt{2g(h1-h3)}\ \text{-}L_2$$
$$\frac{dh3}{dt}=\frac{fin_3}{S3}+\frac{Az3}{S3}\sqrt{2g(h2-h3)}-\frac{Az2}{S3}\sqrt{2gh3}\ \text{-}L_3$$

The steady state operating data of the Three-tank system is given in Table 1.

Table 1. Steady state operating data.

h1, h2,h3 in m	0.7,0.5,0.3
fin_1 and fin_3 in ml/sec	100
Outflow coefficient (Az1, Az2, Az3)	2.251e-5, 3.0571e-5, 2.307e-5
Area of tank (S1-S3)in m^2	0.0154
L_1,L_2,L_3 in ml/sec	0
Acceleration due to gravity in m/sec^2	9.81

3. FDI Using Chi-square Test

An algorithm is presented for detection and isolating additive faults in linear Gaussian dynamic plants, when the statistics and model are known [1].Assuming the no fault as H_o and fault hypothesis as H_l the following equations are derived Under H_o

$$X(k+1) = \Phi x(K) + \Gamma_u u(k) + \Gamma_w w(k) \tag{1}$$

$$Y(k) = Hx(k) + v(k) \tag{2}$$

Under H_l

$$x(k+l) = \Phi x(K) + \Gamma_u u(k) + \Gamma_w w(k) + \Gamma_l S_{k-l.} b \tag{3}$$

$$y(k) = Hx(k) + v(k) \tag{4}$$

When x(k) represents states variable, u(k) represents manipulated variable, y(k) represents measured output, w(k) and v(k) represents state and measurement noise. It is further assumed that w (k) and v (k) are zero mean normally distributed and mutually uncorrelated white noise sequences with known covariance matrix Q and R. The ratio of the hypothesis text is given by

$$L\ (t^*,b) = \frac{p(y(k-1),........y(k)\big|H_{1,t^*b}}{P(y(k-1),.......y(k)\big|H_0} \tag{5}$$

Because both the failure time, t*, and its magnitude *b* are unknown in equation (5), the likelihood ratio is replaced by the generalized likelihood ratio (GLR)

$$L = \max_{t^* \in (k-1,k)} \max_{b} L(t^*,b)$$

The GLR is compared to a threshold at each time k.

The test procedure is carried out as follows:

If $\alpha < L^* < \beta$, the experiment is continued by making an additional observation. If $L^* \geq \beta$ the process is terminated with the acceptance of H_1. If $L^* \leq \alpha$, the process is terminated with the acceptance of Ho. α and β are upper and lower threshold limits. The upper and lower threshold selection is a tradeoff between false alarm rate and the detection time. Lower the threshold, higher is the false alarm rate, but detection will be quicker and vice-versa. The false alarm rate is a function of the window length as well, while the detection speed is also a function of the window length *l* and fault magnitude *b*.

To implement the above test, there is a need to compute L* at each step, and compare it to a threshold. Three difficulties accompany this implementation. Firstly, the test requires two maximizations at each step. The maximization over t* is computationally prohibitive. Specifically, there is need to compute the ratio for each possible t* ε(k-l, k) at each time step k. second, even if t* is fixed, the ratio cannot be computed recursively as the observations y(k-l),…y(k) are not statistically independent. Third, it is not possible to obtain an analytical expression for the threshold as a function of the false alarm and detection speed.

Since the observations y(k-l)……y(k) are not independent, they are to be replaced by their corresponding innovation γ(k).

$$\gamma(k) = y(k) - \hat{y}\ (k/k-1)$$

Innovation under H_o and H_l is

$$H_o: \gamma(k) = \gamma(k)$$

$$H_l: \gamma(k) = \gamma_o(k) + G(k).b,$$

where G(k) is the additive fault signature, which can be recursively computed as the output of linear system.

$$\psi(k+l) = (\phi - KH)\ \psi(k) + \Gamma_l$$

$$G(k) = H\psi(k)$$

In the likelihood ratio approach, for each of the hypothesized fault, the maximum likelihood ratio is computed as follows

$$l(k) = \sum_{j=t}^{k} in \frac{P\left(\gamma(j)/H_1, \hat{v}(k)\right)}{P(\gamma(k)/H_0)} \tag{6}$$

$$l(k) = d^T(k)\ C^{-1}(k)\ d(k),$$

where

$$C(k) = \sum_{j=0}^{k} G^{T}(j;t^{*})V((j)^{-1} G(j;t^{*}) \tag{7}$$

And the linear combination of residuals

$$d(k) = \sum_{j=0}^{k} G^{T}(j;t^{*})V(j)^{-1}\gamma(j)$$

The maximum likelihood estimate of the faults is obtained as

$$b = d(k)/C(k)$$

This method essentially determines the fault model that best fits with the pattern of measurements, in order to identify the fault that has occurred in the three-tank system.

4. Neural Inference System

A Neuro-fuzzy system is basically a fuzzy system that uses a learning algorithm derived from or inspired by neural network theory to determine its parameters by processing data samples. Fuzzy systems are generally used in cases when it is impossible or too difficult to define crisp rules that would describe the considered process or system, which is being controlled by a fuzzy control system. Thus, one of the advantages of fuzzy systems is that they allow to describe fuzzy rules, which fit the description of real-world processes to a greater extent. Another advantage of fuzzy systems is their interpretability; it means that it is possible to explain why a particular value appeared at the output of a fuzzy system.

In turn, some of the main disadvantages of fuzzy systems are that expert input or instructions are needed in order to define fuzzy rules, and that the process of tuning of the fuzzy system parameters (e.g., parameters of the membership functions) often requires a relatively long time, especially if there is a high number of fuzzy rules in the system. Both these advantages are related to the fact that it is not possible to train fuzzy systems. A diametrically opposite situation can be observed in the field of neural networks. User can train neural networks, but it is extremely difficult to use a priori knowledge about the considered system and it is almost impossible to explain the behavior of the neural system in a particular situation. In order to compensate the disadvantages of one system with the advantages of another system, several researchers tried to combine fuzzy systems with neural networks. A hybrid system named ANFIS (Adaptive-Network-Based Fuzzy Inference System or Adaptive Neuro-Fuzzy Inference System) has been proposed by [5].ANFIS is the fuzzy-logic based paradigm that grasps the learning abilities of ANN to enhance the intelligent system's performance using a priori knowledge.

Fig. 3 shows the basic structure of the ANFIS algorithm for a first order Sugeno-style fuzzy system. It is worth noting that the Layer-1 consists of membership functions described by the generalized Bell function

$$\mu(x) = (1+((x-c)/a)^{2b})^{-1}, \tag{8}$$

where a, b and c are adaptable parameters. Layer-2 implements the fuzzy AND operator, while Layer-3 acts to scale the firing strengths. The output of the Layer-4 is comprised of a linear combination of the inputs multiplied by the normalized firing strength w

$$Y = w(px + r) , \quad (9)$$

where *p* and *r* are adaptable parameters. Layer-5 is a simple summation of the outputs of Layer-4.

ANFIS applies two techniques in updating parameters. For parameters that define membership functions, ANFIS employs gradient descent to fine-tune them. For consequent parameters that define the coefficients of each output equations, ANFIS uses the least-squares method to identify them. This approach is thus called hybrid learning method because it combines gradient descent and the least-squares method. These techniques provide a method for the fuzzy modeling procedure to learn information about a data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. This learning method works similarly to that of neural networks.

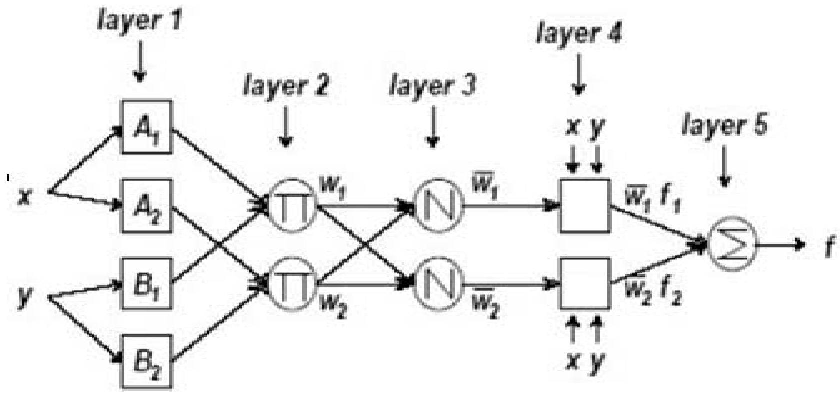

Fig. 3. Basic Structure of the ANFIS Algorithm for a First Order Sugeno-style Fuzzy System.

5. Integration of Fault Detection and Isolation with Control

The synthesis method [8] is used for the design of feedback PI controllers. The PI controllers are designed so that the closed loop process behaves like a first order system with unity gain and time constant same as the open loop time constant. The resulting parameter for controlling the height of tank1 using the inflow of tank1 is given by K_c = 2.54e-04 (ml/sec/m) and T_i=222 seconds and that of tank3 using the inflow of tank3 is given by K_c = 7.69e-04 (ml/sec/m) and T_i=200 seconds. The process is simulated using the non-linear first principles model, whereas the FDI is based on the time invariant linearized model (Transfer function model).

The proposed feed-forward –feedback control scheme is shown in Fig. 1. The proposed scheme makes use of structured residual based fault detection and identification proposed by Gertler [1] for detection, isolation and estimation of unmeasured disturbances acting on the process. The estimated magnitude of the disturbance variable is given to the feed-forward control algorithm, which makes appropriate changes in the manipulated variable to keep the controlled variable near its set value. The feed-forward controller is used along with feed-back controller to control the multivariable system. Hence, the feedback controller has much less work to do to compensate for disturbance. It should be noted that the disturbance is detected as it enters the process and immediate corrective action is taken to compensate for its effect on the process. It is well known that design of feed-forward controller depend on the models for the disturbance and the process (Marlin, 1995) and is given by

$$G_{ff}(s) = \{G_d(s) / G (s)\} \quad (10)$$

The disturbance ($G_d(s)$) and process model ($G(s)$) in equation (7) is obtained by linearising the non-linear differential equations of the given system around the nominal operating point and taking Laplace transform. It is assumed that the given system under study can be modeled using first principles approach. However, identified models can also be used. Using the closed loop control u1, u2 and the residual estimation, define a fault-tolerant control by

$$u_1^{[FTC]} = u_1 + u_{a1}$$
$$u_2^{[FTC]} = u_2 + u_{a2},$$

where
- u1, u2 are output of feedback controller;
- The additive control variables ua1, ua2 are defined by
  ua1 = estimated fault magnitude in tank1,
  ua2 = estimated fault magnitude in tank3

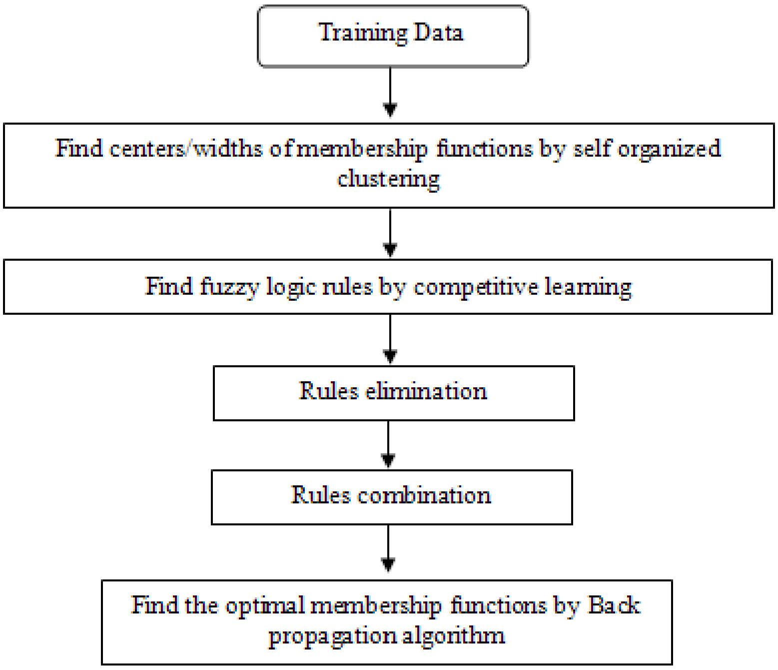

Fig. 4. Flowchart of Hybrid Learning Procedure.

6. Simulation Results

First simulation run is performed in which the outflow of tank1 (L1) is simulated as a step value at t= 3000 seconds of 50 ml/sec. Also, the set point of the tank1 and tank3 has been maintained at their nominal values. The proposed FDI technique able to identify the location of the fault and as well as magnitude of the fault. Then the performance of the proposed scheme is tested by introducing various leak magnitude in all the three tanks. The performance of the proposed scheme is presented in Table 2.

The performance of the proposed scheme has been demonstrated on a three-tank system. The controlled variables are the level of tank1 (h1) and tank3 (h3). Inflow of tank1 (fin_1) and tank3 (fin_3) are chosen as manipulated inputs. Outflow of tank1 that is leak in tank1 (L_1), leak in tank2 (L_2) and leak in tank3 (L_3) are considered disturbance variables.

Table 2. Performance analysis of neuro-fuzzy chi-square test technique.

Fault magnitude (ml/sec)	Type of fault	False alarm index	Estimated fault magnitude (ml/sec)in neuro chi-square test
50	Leak in tank 1	-	49.67
10	Leak in tank 1	-	10.9
5	Leak in tank 1	-	4.9
1	Leak in tank 1	-	1.139
0.5	Leak in tank 1	-	0.46
0.1	Leak in tank 1	-	0.07
0.05	Leak in tank 1	-	0.04
50	Leak in tank 3	-	49.9
10	Leak in tank 3	-	11
5	Leak in tank 3	-	4.9
1	Leak in tank 3	-	1.8
0.5	Leak in tank 3	-	0.54
0.1	Leak in tank 3	-	0.04
50	Leak in tank 2	-	49.7
10	Leak in tank 2	-	10.6
5	Leak in tank 2	-	4.9
1	Leak in tank 2	-	1.6
0.5	Leak in tank 2	-	0.54
0.1	Leak in tank 2	-	0.06
0.05	Leak in tank 2	-	0.032

The closed loop behavior of the process with proposed scheme when a leak of magnitude 50 ml/sec introduced at time t= 3000 seconds in tank1 is obtained and compared with the conventional method is shown in Fig. 5.

Closed loop response of the system with proposed scheme when leak occurs simultaneously in all the three-tanks i.e., a leak of magnitude 50 ml/sec given in tank1 at t=3000sec, leak of magnitude 50 ml/sec given in tank2 at t=5000 sec and leak of magnitude 100 ml/sec given in tank3 at t=7000 sec is obtained and compared with the conventional method is shown in Fig. 6.

The proposed method is tested for modeling errors in FDI module that is 10% deviation in time constant is considered. The closed loop behavior of the process when a leak of magnitude 50 ml/sec introduced at time t= 6000 seconds in tank3 is shown in Fig. 7.

7. Conclusions

The performance of the proposed scheme has been evaluated on a three- tank process for disturbance in the tanks. The proposed scheme can provide disturbance information even when there is simultaneous change in more than one disturbance. It should be noted that the proposed method is independent of the controller design. From the simulation study, it can be concluded that if the estimated magnitude of the disturbance variable (fault) is close to the true value. The proposed method is found to be robust to plant model mismatch. From the results it is also found that the proposed method can identify and isolate the disturbance quickly. From the simulation results, when compared to conventional scheme the proposed scheme is always gives better performance for various types of disturbance inputs.

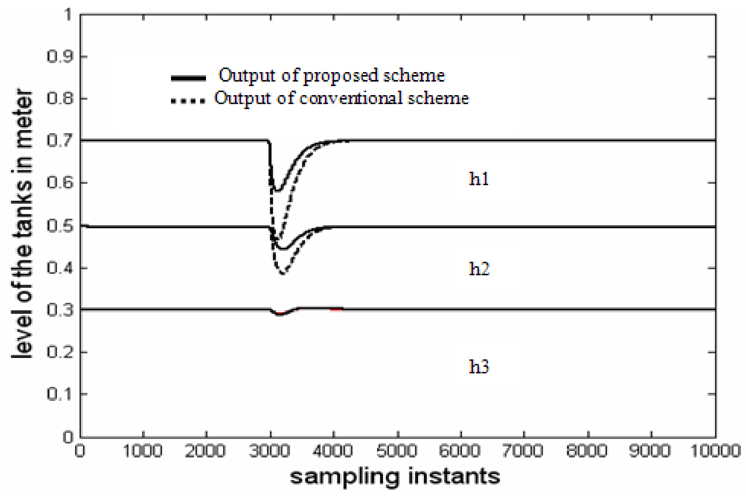

Fig. 5. Comparison of Closed loop response of the proposed scheme with conventional control when a leak of magnitude 100 ml/sec occurs in tank1 at t=3000 sec.

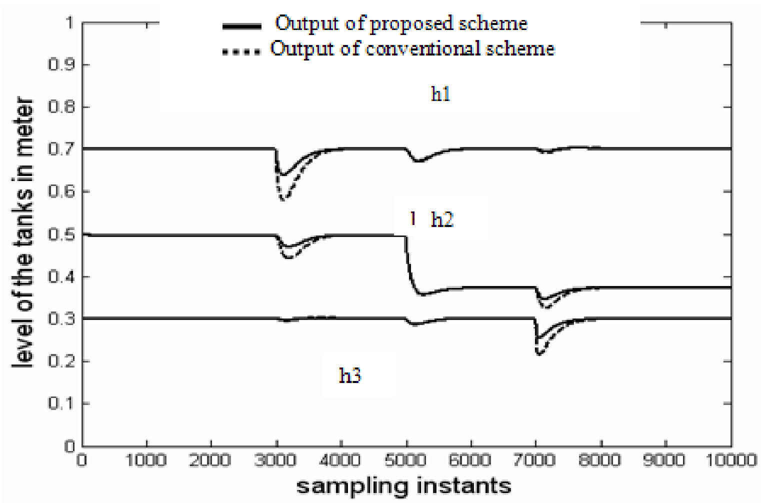

Fig. 6. Comparison of Closed loop response of the proposed scheme with conventional control when a leak of magnitude 100 ml/sec occurs in tank1 at t=3000 sec a leak of magnitude 50 ml/sec occurs in tank2 at t=5000 sec and a leak of magnitude 50 ml/sec occurs in tank3 at t=7000 sec.

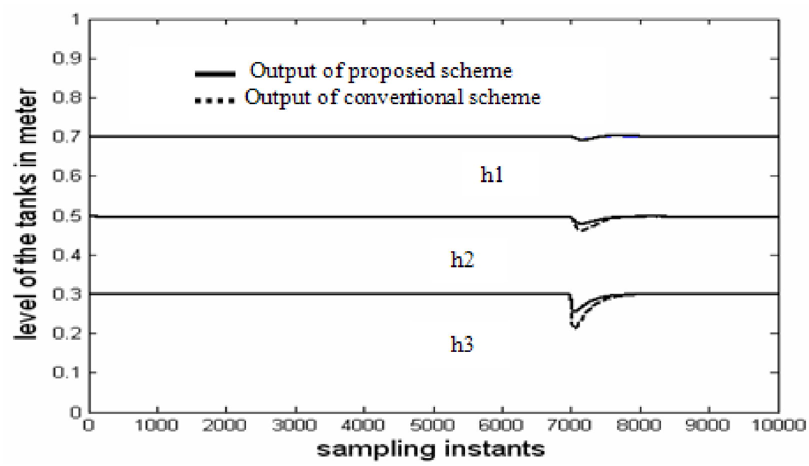

Fig. 7. Comparison of Closed loop response of the proposed scheme with conventional control when a leak of magnitude 50 ml/sec occurs in tank3 at t=7000 sec.

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Guide for Contributors

Aims and Scope

Sensors & Transducers Journal (ISSN 1726-5479) provides an advanced forum for the science and technology of physical, chemical sensors and biosensors. It publishes state-of-the-art reviews, regular research and application specific papers, short notes, letters to Editor and sensors related books reviews as well as academic, practical and commercial information of interest to its readership. Because it is an open access, peer review international journal, papers rapidly published in *Sensors & Transducers Journal* will receive a very high publicity. The journal is published monthly as twelve issues per annual by International Frequency Association (IFSA). In additional, some special sponsored and conference issues published annually. *Sensors & Transducers Journal* is indexed and abstracted very quickly by Chemical Abstracts, IndexCopernicus Journals Master List, Open J-Gate, Google Scholar, etc.

Topics Covered

Contributions are invited on all aspects of research, development and application of the science and technology of sensors, transducers and sensor instrumentations. Topics include, but are not restricted to:

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- Theory, principles, effects, design, standardization and modeling;
- Smart sensors and systems;
- Sensor instrumentation;
- Virtual instruments;
- Sensors interfaces, buses and networks;
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