Fault Diagnosis in a Nonlinear Three-Tank System via ANFIS

Kemal UCAK[1], Fikret CALISKAN[1], and Gulay OKE[1]

[1]Istanbul Technical University, Department of Control Engineering, Istanbul, Turkey
kemal.ucak@itu.edu.tr, caliskanf@itu.edu.tr, gulay.oke@itu.edu.tr

Abstract

In this paper, two intelligent methods namely Artificial Neural Network (ANN) and Adaptive Neuro Fuzzy Inference Systems (ANFIS), are implemented to diagnose the leakage faults in a nonlinear three tank system. Two separate structures are utilized for fault diagnosis. One is to identify the dynamics of the plant and the other is to construct the residual logic mechanism. The performance of the proposed methods are evaluated by simulations carried out on a three tank system (TTS). The leakages in tanks are considered as faults in the tank system.

1. Introduction

Fault diagnosis is one of the most important tasks in control systems since the early detection of faults can help to avoid system shut-down, breakdown and also helps to design new controllers to deal with new situations. In case a fault is detected in the system, the necessary actions are taken so that the system safely completes the operation. Hence, the correct detection of the fault is significant for good control performance. Model-based approaches have been utilized in the fault diagnosis research over last 40 years. Since the mathematical model of the system is required in model-based methods, the main disadvantage of this class of methods is being very sensitive to modeling errors, parameter variations, noise and disturbances etc., and the quality of the models affects the fault diagnosis performance directly.

Owing to the nonlinear function approximation ability of the Artificial Intelligence Techniques, they can be utilized in fault diagnosis. Detecting and isolating faults in nonlinear systems via artificial intelligence consist of two stages. The first is to generate residual signals based on a comparison between the actual and estimated states. An intelligent model is trained to predict the future system states based on the current system inputs and states. In the second stage of fault detection and isolation, the characteristics contained in the residuals are classified via classification techniques. Thus, based on the classification given by the network, faults can be detected and isolated.

In the literature, various researches related to model based fault diagnosis have been realized based on neural network and ANFIS approaches. In [1], two different multi-layer neural networks have been used to identify the dynamics of the three tank system and classify the faults. Leakages in the tanks have been considered as faults in the tank system. NARMA (Nonlinear autoregressive recursive moving average) models for fault detection and diagnosis have been proposed in [2] and probability density functions of the residuals have been used for detection and diagnosis. Clogging faults in three tank system have been detected via neural network approach in [3] and the faults have been classified using Kohonen network structure. In [4], the deviation from steady state value of the volume of the CSTR (Continuous Stirred Tank Reactor) has been detected by means of the predefined faults via neural network approach. The classification can be improved and also the computational burden of the classifier is reduced by using dimensionality reduction methods such as independent component analysis as in [7]. Fuzzy models can be trained to model the dynamics of a system utilizing the learning algorithms in NN to employ in fault diagnosis systems as in [14-16].

In this paper, ANN and ANFIS are utilized artificial intelligence based fault diagnosis techniques, and the performance of the proposed methods has been evaluated by the simulations carried out on a three tank system. The leakages in tanks are considered as faults in system.

The rest of the paper is organized as follows. The nonlinear model of the three tank system is summarized in section II. In section III, a brief overview of ANFIS is given. Identification of the plant and residual generator is explained in section IV. Simulation results are presented in section V. The paper ends with a brief conclusion in Section VI.

2. Dynamics of Three-Tank System

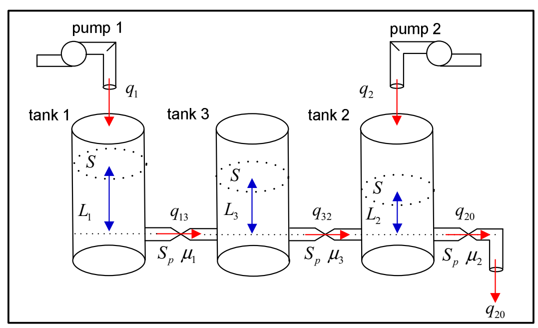

Fig. 1. Three-Tank System

The three tank system illustrated in Fig.1 is frequently used as a benchmark nonlinear system recently. [5, 6]. The system consists of three tanks and two pumps interconnected serially. The liquid levels of the tanks are controlled by the flow rate of the pumps. The differential equations describing the system dynamics are as follows:

$$S\frac{dL_1}{dt} = q_1 - q_{13}\ ,\quad S\frac{dL_2}{dt} = q_2 + q_{32} - q_{20}$$
$$S\frac{dL_3}{dt} = q_{13} - q_{32} \tag{1}$$

where S is the cross sectional area of each tank, and q_{ij} is the water flow rate from tank i to tank j, i,j =1,2,3, given by

$$q_{ij} = \mu_i.S_p.sign(L_i - L_j).\sqrt{2g|L_i - L_j|}$$

where q_{20} represents the outflow rate with $q_{20} = \mu_2.S_p.\sqrt{2gL_2}$. The numerical values in [17] are used as system parameters.

3. Adaptive Neuro-Fuzzy Inference System

Adaptive Neuro-Fuzzy Inference Systems (ANFIS) combines the reasoning mechanism of fuzzy systems with learning and adaptation capabilities of ANN. Owing to their powerful generalization performance and robustness against uncertainty, ANFIS based methods can be utilized in identifying complex nonlinear dynamics. The structure of ANFIS is functionally equivalent to a Sugeno fuzzy model is as in Fig. 2[7, 8]. ANFIS distinguishes itself from fuzzy logic systems by the adaptive parameters, i.e., both the premise and consequent parameters are adjustable [12]. The structure consists of 5 layers [8-14]. The links in adaptive networks only indicate the flow directions of the signals between nodes, that is, no weights are associated with the links [9]. The layers and their functions can be summarized as follows:

Layer 1: The membership degree of the inputs is computed in this layer. Since the membership functions have adjustable parameters, this layer is an adaptive layer and the parameters in this layer are referred to as premise parameters.

Layer 2: The firing strengths of each rule is calculated in this layer. This layer is a fixed layer labeled Π.

Layer 3: The firing strengths are normalized in this layer.

Layer 4: The parameters of this node are $\{p_i, q_i, r_i\}$ and referred to as consequent parameters. This layer includes adaptive parameters. f_i's are given by $f_i = p_i x_1 + q_i x_2 + r_i$.

Layer 5: The layer is called as output layer. Outputs of the fourth layer are summed up in this layer.

Layer 1 and layer 4 are called adaptive layers [15, 16]. In order to optimize the parameters in these layers, a hybrid learning algorithm is utilized. The hybrid learning algorithm combines the back propagation algorithm and LMS (Least Mean Square) algorithm. The learning process is carried out in two steps: forward pass and backward pass.

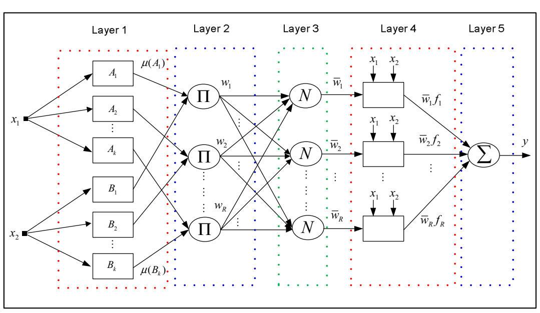

Fig. 2. ANFIS Network Structure

In forward pass, while the premise parameters are held fixed, the network inputs are propagated forward up to layer 4 and the normalized firing strengths are calculated, then the optimal consequent parameters are obtained via LMS for the given normalized firing strengths. In the backward pass, while the consequent parameters are held fixed, the premise parameters are adjusted using back propagation algorithm. This approach increases the convergence speed since LMS reduces the search space dimension of the back propagation algorithm [10, 11]. Owing to this, hybrid learning algorithm is more effective than pure back propagation algorithm. ANFIS and its hybrid learning algorithm are covered in [13] in more detail.

4. Fault Diagnosis via ANFIS

The fault detection and isolation scheme is illustrated in Fig. 3. The diagnostician consists of three parts. The system identifier approximates the future behavior of the plant based on the difference between system states and model output. Depending on the modeling error, residuals are generated and corrected in residual generator if necessary. Fault detection and isolation part that is fault classifier is utilized to detect the faults based on the residuals.

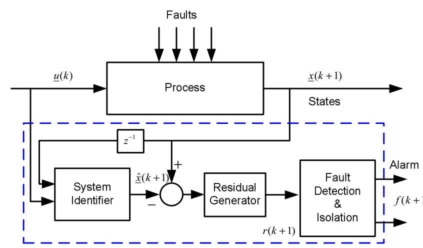

Fig. 3. ANFIS Network Structure

The identifier will behave unusually in the case of faults in the system, and this situation can be detected via system identifier. An inference mechanism is designed to detect the leakage faults depending on residuals. Subsection 4.1 outlines the system identification problem. Fault detection and isolation classifier are explained in subsection 4.2.

4.1. System Identification

The dynamics of a non-linear system, can be represented by the **N**onlinear **A**uto**R**egressive with e**X**ogenous inputs (NARX) model, as

$$\underline{y}(k) = F([\underline{u}(k),..,\underline{u}(k-k_u), \underline{y}(k-1),.., \underline{y}(k-k_y)]) \quad (2)$$

$\underline{u}(k)$ are the control inputs applied to the plant at time k, $\underline{y}(k)$ are the outputs of the plant , and k_u and k_y stand for the number of past control inputs and the number of past plant outputs involved in the model , respectively. Firstly, random inputs varying between $0-10^{-4}$ have been applied to the plant during $\tau_{\min} = 50$ $\tau_{\max} = 100$ seconds so as to reveal all possible dynamics of the system. Out of the 20000 instances of data generated, 3000 are selected randomly for training and 500 for testing. The selected data has been used to train the ANFIS models, then the test data is used to evaluate the performance of the obtained NARX model. In ANFIS, two Gaussian membership functions for each input have been employed. The validation performance of the ANFIS models are depicted in Fig. 4 for all tanks. The results indicate that the dynamics of the system can be modeled using ANFIS with the proper parameter set.

4.2. Fault Detection and Isolation

The residual signals are generated based on comparison between the actual and predicted state estimates as in (3).

$$\underline{e}(k+1) = \underline{x}(k+1) - \hat{\underline{x}}(k+1) \quad (3)$$

where $\hat{\underline{x}}(k+1)$ is estimated state at k+1. Since the realistic situation may be different due to noise or parameters perturbation or other uncertain factors, a threshold can be utilized for alarm situation.

$$\begin{cases} if\ \ e_i < \varepsilon_i\ \ then\ \ r_i = 0.01\ \ ,\ \ no\ fault\ in\ the\ i^{th}\ \ \tan k \\ if\ \ e_i > \varepsilon_i\ \ then\ \ r_i = 0.1\ ,\ fault\ in\ the\ i^{th}\ \ \tan k \end{cases} \quad (4)$$

Another ANFIS is trained to classify the characteristics contained in the residuals. Thus, the residuals generated by residual generator are examined based on the ANFIS classifier to declare where the fault occurs in the system. The output of ANFIS classifier is the alarm signal $\underline{f} = [f_1\ \ f_2\ \ f_3]$ and f_i denotes the fault in the i^{th} tank. The training data used for the training of the classifier is given in Table 1 for leakage faults based on Generalized Observer Scheme (GOS).

Table 1. Faults isolation for generalized observer scheme

Residuals	Leakage Faults		
	f_1	f_2	f_3
r_1	0	1	1
r_2	1	0	1
r_3	1	1	0

When a leakage fault occurs in the i^{th} tank, i^{th} element of the $\underline{f}$ will be 0, others will be 1 according to GOS. In the case of no alarm, $\underline{f}$ will be $[0\ 0\ 0]$.

5. Simulation Results

5.1. System Identification

The identification performance of the ANFIS models is given in Fig. 4 for all states. 3000 and 500 data are chosen for training and testing processes of the ANFIS identifier. Since the mean square error is smaller than $1.6x10^{-4}$, two curves are seen as a single curve. The identification performances of the ANFIS are compared with ANN models with 20 neuron in hidden layer, but the figures depending on ANN are not given in this section since the performance of the ANFIS is better than ANN. Instead, the comparison results for training, testing and validation performance of ANN and ANFIS are given in Table 2 where e_{tr}, e_{tst} and e_v denote mean absolute average training, testing and validation errors, respectively.

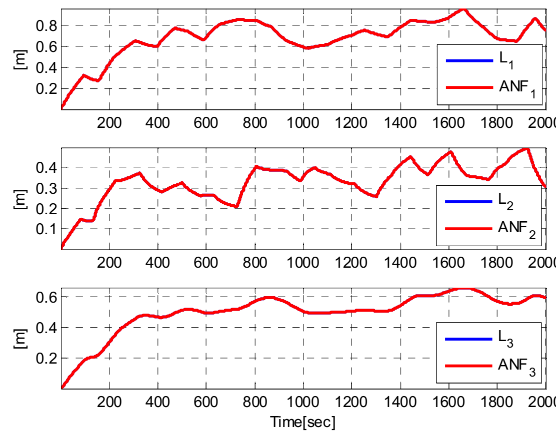

Fig. 4. Identification with ANFIS.

Table 2. Errors

e_v	Errors		
	ANN	*ANFIS*	*ANFIS vs ANN*
e_{tr1}	4.5134e-4	1.1704e-5	97.4068
e_{tr2}	5.6569e-4	1.0499e-5	98.1440
e_{tr3}	6.0353e-4	2.8974e-6	99.5199
e_{tst1}	4.7838e-4	1.2353e-5	97.4177
e_{tst2}	6.4341e-4	9.8523e-6	98.4687
e_{tst3}	5.9652e-4	3.0929e-6	99.4815
e_{v1}	6.4535e-4	8.1657e-5	87.3469
e_{v2}	9.4120e-4	1.5126e-4	83.9291
e_{v3}	8.2236e-4	8.8265e-6	98.9267

The third column is calculated using the following equation:

$$J = 100\,\frac{|e_{ANN}| - |e_{ANFIS}|}{|e_{ANN}|} \quad (5)$$

As can be seen from Table 2, the ANN and ANFIS have small modeling errors. The third column of the table indicates the performance difference between ANFIS and ANN. For all cases ANFIS has better performance than ANN.

5.2. Fault Detection and Isolation Classifier

In order to construct the fault detection and isolation logic via Table 1, 2000 training and 500 validation data pairs are generated for each residual to train ANFIS. The validation performance of the classifier is depicted in Fig. 5. The results indicate that the ANFIS based fault and isolation logic has ideal inference logic. The performances of ANN and ANFIS are compared in Table 3.

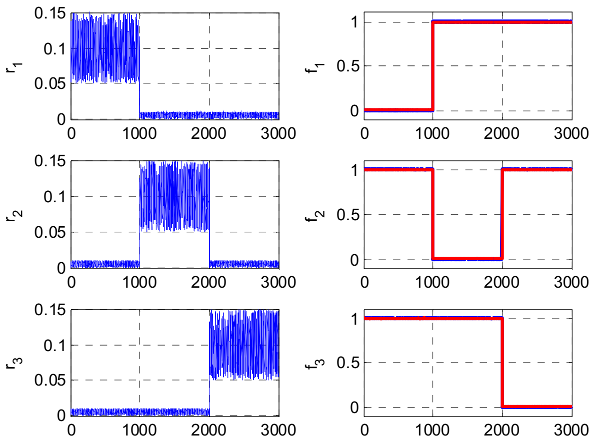

Fig. 5. Validation performance of the FDI classifier, blue(actual), red(ANFIS)

As can be seen from Table 3, whereas the performance of the ANFIS is better than ANN in training phase, the performance of the ANFIS is very close to the ANN in validation phase.

Table 3. Errors

e_v	Errors		
	ANN	*ANFIS*	*ANFIS vs ANN*
e_{tr1}	0.0034	4.9974e-10	100
e_{tr2}	0.0025	5.1124e-10	100
e_{tr3}	0.0025	3.9921e-10	100
e_{v1}	0.0360	0.0334	7.2222
e_{v2}	0.0350	0.0333	4.8571
e_{v3}	0.0351	0.0333	5.1282

5.3. Fault Diagnosis

To evaluate the performance of the ANFIS, leakage faults are assumed to occur in 500-600th seconds in tank 1, in 700-800th seconds in tank 2, and in 850-870th seconds in tank 3 respectively. The time instants and durations of the leakage faults are chosen arbitrarily. The second fault occurs after the first one is repaired. The fault diagnosis and isolation system is sensitive to the effects of the fault in the case that a new fault occurs before the end of the previous one. The fault in a tank affects others. Fig. 6-7 illustrate the system behavior, observer output and estimation errors. It is observed that the estimation error comprises due to leakage in tanks. The residual signals are normalized using a threshold value compared with errors given in fig. 7. Then, the modified residual signals are applied to determine the location of the faults. As can be seen from Fig. 8, the fault vector $f = [0\ 1\ 1]$ is between 400-600 seconds. According to the given values in Table 1, the leakage fault in tank 1 has been detected since $f = [0\ 1\ 1]$ is between 400-600th seconds. Similarly, the faults in tank 2 and tank 3 are isolated at 700-800th and 850-870th seconds respectively.

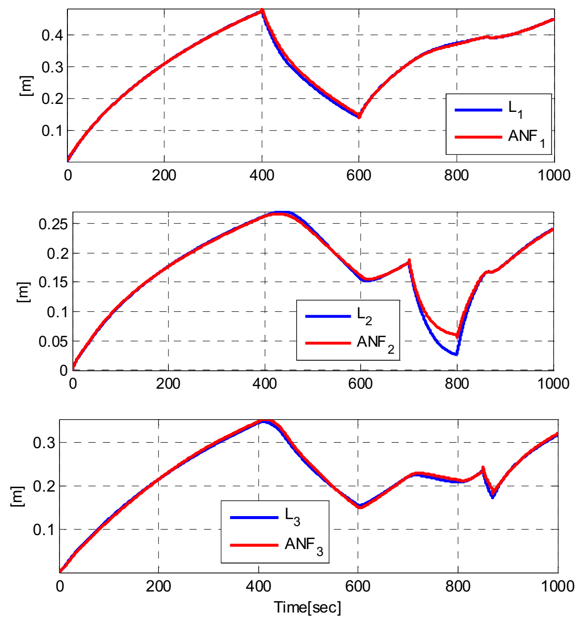

Fig. 6. Observer and system outputs in faulty case

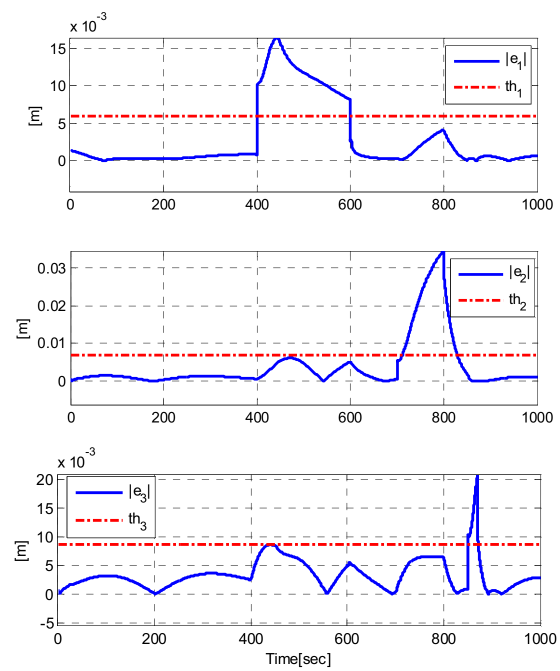

Fig. 7. Error Signals

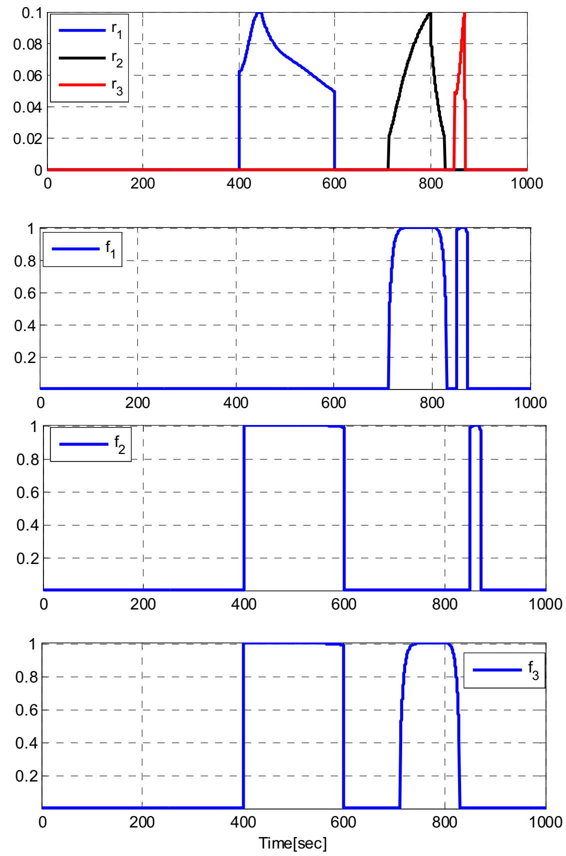

Fig. 8. Residuals and outputs of the classifier

6. Conclusions

In this paper, ANN and ANFIS based models are utilized for fault diagnosis of the three tank system. Two separate AI models are used: one is for system identification and the other is for FDI logic. The simulation results indicate that AI model of the system and FDI logic have been successfully constructed and ANFIS has better performance than ANN.

In future works, other types of faults such as clogging, actuator and measurement faults can be studied and EKF and UKF based estimators can be utilized for prediction of the system states.

7. References

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