International Journal of Advanced Information Science and Technology (IJAIST) ISSN: 2319:268
Vol.2, No.9, September 2013 DOI:10.15693/ijaist/2013.v2i9.24-27

Sensor Fault Modeling Using ANFIS

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***Abstract*— Fault detection and isolation (FDI) of dynamic systems is necessary to assure system reliability and safety. FDI has obtained more attention in many areas like nuclear systems, aerospace and industrial control. There are many different approaches to fault detection and isolation. To increase the accuracy of fault detection multiple approaches have been combined. In the present paper, a fault diagnosis approach to detection and estimate sensor fault is carried out using Adaptive Network based Fuzzy Inference System(ANFIS). It is a hybrid method with fuzzy inference system implemented in the framework of adaptive networks.**

Key Words—ANFIS, Fault diagnosis, hybrid algorithm, fault modeling.

INTRODUCTION

Fault detection is recognizing that a problem has occurred, without knowing the root cause. Fault Diagnosis is identifying the root causes of problems, to the point where corrective action can be taken and referred as fault isolation. The failures in a system may be caused by malfunctions in a system components, actuators and sensors due to unexpected interference or aging of system components. An effective means to assume reliability and safety is to detect the failures in sensors, actuators and system components, so that proper remedies may be undertaken. Fault diagnostic methods are broadly classified as process model based and process history based. Both are further divided into quantitative and qualitative methods.

The qualitative process model based approach is based on cause-effect reasoning about system behavior. A serious limitation of these methods is the generation of a large number of hypotheses-poor resolutions making the decision process uncertain. Computational efforts with qualitative process model based are high when used online. On the other hand quantitative methods rely on the mathematical relations that exists between variables, generally state space model is used. Robustness is an important issue in quantitative model method because of difficulty in obtaining the accurate models of the process. The qualitative process history based methods include rule based system and are typically made up an antecedent part and a consequent part. In quantitative process history based, Neural network methods for fault diagnosis have received considerable attentions over last few years. A Single method cannot handle all the requirements of a good diagnostic system and therefore hybrid methods are employed[1,2].

ANFIS is a hybrid method which combines both neural network and fuzzy inference system. It uses hybrid learning algorithm elaborated next. First neural network with specific topology is chosen, in the forward pass the consequent parameters are identified by the least square estimate and in the backward pass the error rates propagate backward and the premise parameters are updated by gradient descent method. ANFIS can serve as a basis for constructing a set of fuzzy if then rules with appropriate membership functions to generate the expected input output pairs [3]. This utilizes Takagi and Sugeno fuzzy inference system in which the output of each rule is a linear combination of input variables plus a constant term. The final output is the weighted average of each rule's output. The remainder of the current paper is organized as follows. Section II, highlights the ANFIS architecture. Sensor fault modeling is discussed in section III. Simulation results with and without sensor faults are presented in Section IV. Finally conclusions are given in Section V.

I. ANFIS

Fig. 1 shows the ANFIS architecture with two inputs and each with three membership functions. It consist five layers and the function of each layer as follows.

Layer1: Every node i in this layer is a square node with a node function $\mu_{A_i}(x)$ where x is the input to node i and A_i is the linguistic variable associated with this node. Thus the output of this node i is O_i^1 the membership of x in A_i. Bell shaped or Gaussian membership function is normally considered.

Bell shaped Membership function

$$\mu_{A_i}(x) = \frac{1}{1 + \left(\frac{x - c_i}{a_i}\right)^2 b_i} \quad (1)$$

Gaussian membership function

$$\mu_{A_i}(x) = a_i \exp\left(-\left(\frac{x - c_i}{b_i}\right)^2\right) \quad (2)$$

Where $\{a_i, b_i, c_i\}$ is the parameter set used to define membership function of A_i and also known as premise parameters.

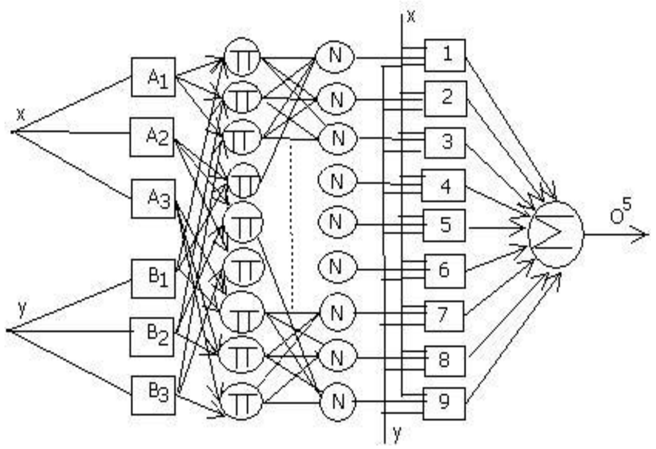

Fig.1 ANFIS structure

Layer2: In this layer the membership function values coming from each input multiplies each other and each node value of these multiplications are defined as the firing strength. Every node in this layer is a circle node labeled with π and the output

$$w_{ij} = \mu_{A_i}(x) \text{ x } \mu_{B_i}(y) \quad (3)$$

where i=1 to 3 and j=1 to 3.

Layer3: Every node in this layer is a circle node labeled with N. Each node output in this layer is the ratio of the corresponding rule's firing strength to the sum of all the rules firing strength. Thus it gives the normalized firing strength.

$$\overline{w_i} = \frac{w_i}{\sum_{i=1}^{9} w_i} \quad (4)$$

Layer4: In this layer, using each input, first order function is generated and multiplied by normalized firing strength and represented by a square node.

$$O_i = \overline{w_i}[p_i x + q_i y + r_i] \quad (5)$$

The parameters of these first order functions are called consequent parameters.

Layer5: Single node that computes the overall output as the summation of all the incoming signals.

$$O^5 = \sum_i \overline{w_i}[p_i x + q_i y + r_i] \quad (6)$$

The structure of ANFIS is a multiple input single output(MISO). But most of the dynamic systems are multiple input multiple output (MIMO). Thus for these systems multiple ANFIS with independent parameters and outputs are used [4].

II. SENSOR FAULT MODELING USING ANFIS

First ANFIS model of a fault free system as shown in Fig. 2 is built with hybrid algorithm through minimizing the difference between measurement and the output of the model. Input and some delayed outputs of the underlying system form the ANFIS inputs along with one more input which is always zero while training the faultless plant.

Assuming the inputs to the ANFIS model as four, namely two delayed outputs, plant input and one fault input which is always zero while training of faultless plant, the mathematical representation of ANFIS model is

$$y(k) = \sum_{i=1}^{N} \overline{w_i}\,[m_i y(k-1) + n_i y(k-2) + p_i u(k) + q_i f(k) + r_i] \quad (7)$$

Where m_i, n_i, p_i, q_i and r_i are consequent parameters of each rule.

After training the ANFIS model, we deliberately put equal to one the coefficient that relate to the fault input $f(k)$ of each rules. With this modification the output of the model remains same as that of fault free system due to $f(k)$ is zero and it enables us to introduce the modeled fault to the plant model without changing the structure of the ANFIS model.

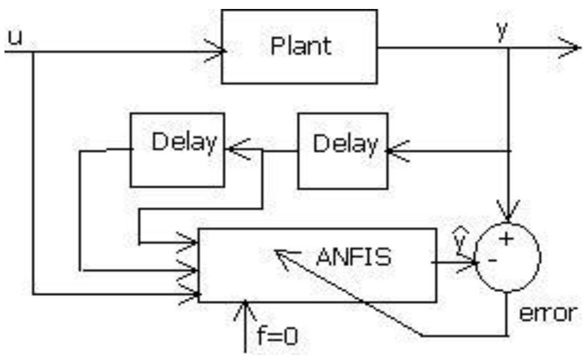

Fig. 2 ANFIS model of fault free system

To model the occurred fault, we use another ANFIS system as shown in Fig. 3 with same number of inputs as that of fault free model. The training of the fault model is by minimizing objective function J(t) [5].

$$J(t) = 0.5(\hat{y}(t) - y(t))^2 \tag{8}$$

Where $y(t)$ and $\hat{y}(t)$ are the actual and model outputs respectively. Using partial derivative rule, one of the parameter say θ of the fault model is tuned as follows

$$\frac{\partial J}{\partial \theta} = \frac{\partial J}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial f} \frac{\partial f}{\partial \theta} = -e \frac{\partial \hat{y}}{\partial f} \frac{\partial f}{\partial \theta} \tag{9}$$

Where $e = y(t) - \hat{y}(t)$, $\frac{\partial \hat{y}}{\partial f}$ is the sensitivity of fault free model to the fault input f and $\frac{\partial f}{\partial \theta}$ is the sensitivity of fault model to one of its parameter. When ever $f = 0$, the training of fault model do not start. Any difference between actual and model out starts training the fault model until error reaches predetermined threshold level. The output from the fault model is approximately same as that of fault. The closed loop configuration of both the ANFIS is to model the fault online and indirectly [5].

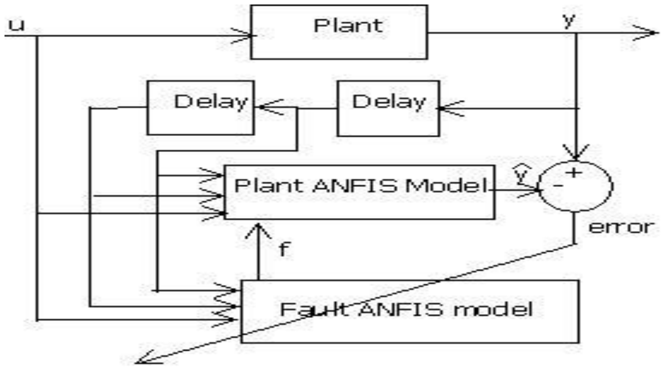

Fig. 3. Structure of fault model

IV RESULTS

A nonlinear system with single input of periodic signal as given by the equation (10) and two outputs whose input output relation as given by the expressions (11) and (12) is considered. The sensor fault of magnitude as specified by the equation (13) is generated and introduced to the second output.The Simulated results of input and second output of the system with and without sensor fault as shown in Fig. 4

$$u(k) = \sin(\sin(\pi k/100)\cos(\pi k/20))^2 \tag{10}$$

$$y_1(k) = \frac{y_2(k-1)}{1 + (y_1(k-1))^2} \tag{11}$$

$$y_2(k) = 0.1 y_1(k-1) \times y_2(k-1) + u(k) \tag{12}$$

$$f(k) = 0.3\, y_2(k) \tag{13}$$

Fig. 5 shows the output of the ANFIS model of a plant after training the ANFIS under no sensor fault. From this figure we can say that the output y_2 of the system and the ANFIS output are acceptabaly same which clearly indicates that the ANFIS is well trained. Fig. 6 shows the same ANFIS out with changing the consequence parameter q_i from 0 to 1of all the rules and with the fault input $f = 0$. It is observed that, under this condition ANFIS still provides same output.Thus under no fault, ANFIS output is same as that of system output y_2 and the change in the ANFIS parameter is to accomadate the fault.

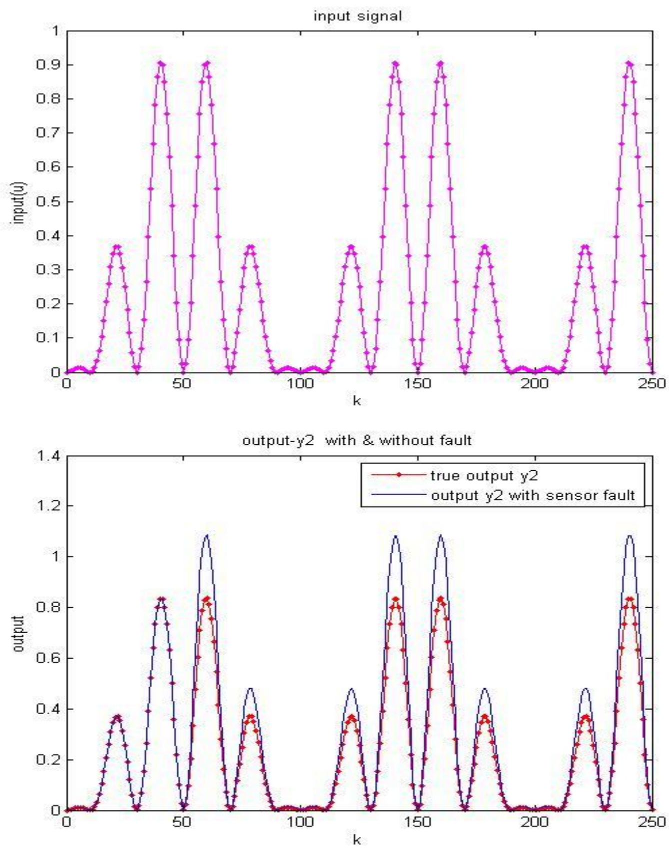

Fig. 4. input and output of the system

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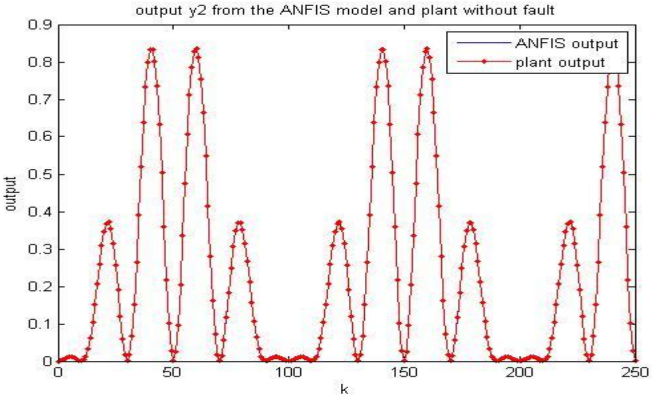

Fig. 5.

Fig. 7 and 8 show the ANFIS output and fault model output respectively, under the sensor fault of magnitude as specifier earlier. In this simulation till 50 samples the fault is considered as zero and the training of fault model starts at 100^{th} samples, as clearly seen from Fig. 7, in order to see the effect of fault on the system.

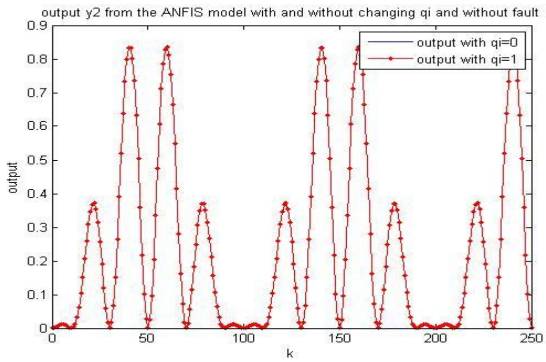

Fig. 6.

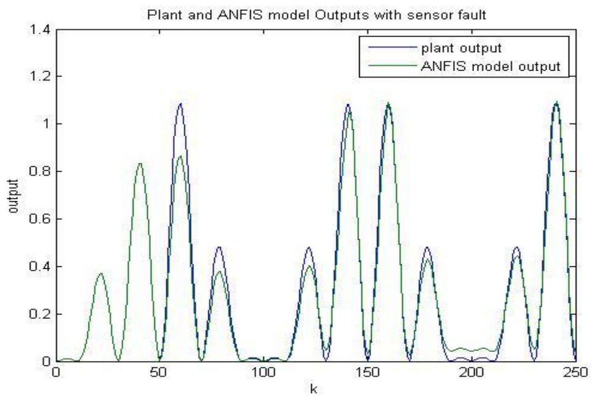

Fig. 7.

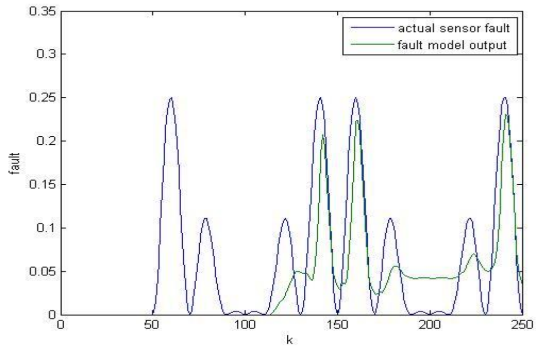

Fig. 8.

V CONCLUSION

The method presented in this paper is used to model the sensor fault. The same method can also be extended to model the actuator and plant component fault occuring individually or combined fault. Fault accomodation need to be addressed once the fault is identified by using the method described.

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