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Fault Modeling for Nonlinear Systems Using ANFIS

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Abstract. In this paper we develop a new method to model occurred faults in different parts of nonlinear systems. Using an Adaptive Neuro-Fuzzy Inference System (ANFIS) we build a model for faultless plant which is used in the procedure of fault modeling. The considered model for fault is again an ANFIS system and its parameters are adjusted in an indirect way using difference between actual output and output of plant model. Simulation results on a nonlinear system are shown in this paper and they clearly demonstrate the capability of the proposed method for fault modeling.

1 Introduction

A look at the number of publications in the last decades about fault detection, diagnosis and accommodation methods obviously clears importance of this field from scientific and industrial viewpoints. From the industrial point of view, always there is a request for more reliability and more safety in the case of occurrence of abnormal situations in the system for avoiding terrible collapse or complete failure. From the other hand, it is a real challenge for scientists and researches in control field to find a proper solution in the shortest possible time and to revitalize the system to its normal situation. These two views joint industry and scientific institutes for developing reliable methods achieving those goals.

In literature, this problem has been addressed from different angles. Broadly, hardware and analytical redundancy are two major plans of attack for FDI/FDA [1]. The first one has its particular defects such being heavy and costly and its applications are limited. As one screens further research works in the 80's and 90's related to analytical redundancy, it becomes clear that there are three schools of investigations. One of the most prevalent avenues from scientific viewpoint is quantitative model-based method. Availability of analytical model of the system brings many facilities that some methods such as observer, parity space and (Extended) Kalman Filter (EKF) use them for accomplishing FDI/FDA tasks [2]. Another direction which has been paid enough attention in the recent years is the qualitative model-based method. As mentioned in [3], the difference between quantitative model-based and qualitative model-based methods for FDI/FDA mainly refers to the applied tools for expressing and modeling our understanding from the system. While this knowledge is cast in some mathematical terms for quantitative model-based methods, some qualitative functions contain this information in the latter one. Process history based methods are the last school and are the most involved and committed methods in the industrial applications of FDI/FDA [4]. This is due to this fact that in these methods there is no necessity for availability of any kind of model which properly meets lack of model in huge industrial plants. The interested reader can refer to [2, 3] and [4] for a comprehensive review of different methods and their specifications.

In this paper we design and implement a method which benefits from intelligent techniques for modeling. Plenty of outstanding scientific and industrial applications of those methods can be found in literature [3, 6, 7, 8, 9]. In fact, we attempt to find a way to model any occurred fault in the system using intelligent methods while there is no analytical model of the underlying plant available. The topic of fault modeling is not much new and has been addressed in some papers [5, 6]. In general, it is not possible to obtain an exact model of a real process for using those methods. Even if we can do that, the obtained model for complicated plants is only an approximate one with modeling errors which degrade the performance of fault modeling method. In the other hand, they suffer from the same problems prevailing in the quantitative model-based techniques for FDI/FDA. In contrast with those methods mentioned in [5] and [6], in the proposed method there is no necessity for availability of an accurate or even an approximate quantitative model of plant. Rather, we use an ANFIS system for creating a model for the intact plant which is used in a closed loop for modeling of different occurred faults. This is a considerable benefit which paves the way for using completely intelligent techniques for FDI/FDA in complex systems specifically in industrial applications.

The proposed method in this paper has been developed for discrete time systems. In a case study, we applied it to a NARMAX system with one input and two outputs. Developing and extending the proposed method to the continuous systems is an interesting work and will be addressed in future works.

The rest of the paper is organized as follows: A brief description about problem and different fault types is provided in section 2. Then, section 3 describes different steps of the proposed method for fault detection. Simulation results for triple faults in sensors, actuators, and plant components are displayed in section 4. Section 5 concludes this paper with a brief summary and some suggestions for future works.

2 Problem Description

A typical NARMAX model has a form as follow

$$y(k) = h(y(k-1), y(k-2), \cdots, y(k-n), u(k), u(k-1), \cdots, u(k-m)). \qquad (1)$$

h denotes a nonlinear function which is available perhaps with unknown parameters. n and m respectively determine the number of delayed outputs and inputs which contribute to the model. In building a model using available data, n and m are often determined by try and error in simulations. Oftentimes we start from small integers for both and increase them until the obtained model, h, with those numbers fulfils the required accuracy.

A fault, represented by $f(\cdot)$, appears in the plant model as follow:

$$\begin{aligned} y(k) &= h(y(k-1), y(k-2), \cdots, y(k-n), u(k), u(k-1), \cdots, u(k-m)) \\ &+ f(y(k-1), y(k-2), \cdots, y(k-n_f), u(k), u(k-1), \cdots, u(k-m_f)) \end{aligned} \qquad (2)$$

where n_f and m_f in $f(\cdot)$ have the same role of n and m in $h(\cdot)$.

Using this kind of presentation for plant and fault, we can describe the triple faults in sensors, actuators, and plant components as follow:

2.1 Sensor Fault

In normal situation, measurements have the same values of corresponding outputs. It means that the sensor outputs are like the actual outputs. From practical angle, sensor fault is a very prevalent phenomenon causing serious problems in the performance of the controlling system. Providing incorrect measurements for controller leads to wrong decisions which are source of abnormal situations in behavior of the system. Two widespread kinds of sensor faults are gain and bias faults. In case of gain fault, the measurement is the actual output multiplied by a value named magnitude of sensor gain fault, $f_g(\cdot)$, as follow:

$$y_s(k) = f_g(k)y(k)\,. \tag{3}$$

The bias fault in sensors is more common than previous one and can be considered as follow:

$$y_s(k) = y(k) + f_b(k) \tag{4}$$

where $f_b(\cdot)$ is bias fault magnitude.

Both $f_g(\cdot)$ and $f_b(\cdot)$ can be constant or even have a nonlinear dynamic depending on previous measurements or other things. Furthermore, in some cases they can occur simultaneously leading a critical situation.

The presence of them in (2) can be presented like this:

$$f(k) = h(\cdot)(f_g - 1) + f_b\,. \tag{5}$$

In this case, the measurement is:

$$y_s(k) = y(k)f_g(k) + f_b(k) \tag{6}$$

where $y_s(\cdot)$ and $y(\cdot)$ are sensor output and actual output respectively.

2.2 Actuator Fault

This fault occurs when an actuator can't deliver the required controlling signal to the plant. For instance, in a manipulator robot, some thing wrong happens for electrical DC motors and the ordered torque by controller can not be actualized. Blockages in pipes or defects in pumps in chemical plants are examples of faults in this category. In all of these cases, actuator generates a percentage of the requested controlling value depending on the severity of the occurred gain fault, $f_a(\cdot)$. We can mathematically show this kind of faults as follow:

$$u_a(k) = u(k)f_a(k) \tag{7}$$

in which $u(\cdot)$ and $u_a(\cdot)$ denote the controlling signal and the actuator output respectively.

From mathematical point of view, this fault changes NARMAX model of the plant from $h(\cdot)$ to $\hat{h}(\cdot)$. To follow this fact, we skillfully consider the mathematical presentation of this kind of fault as follow:

$$f(k) = \hat{h}(\cdot) - h(\cdot) \tag{8}$$

in which $\hat{h}(\cdot)$ stands for faulty plant.

2.3 Plant Component Fault

Any change in nominal values of plant components leads to an abnormal situation which is named plant component fault. Leakages or unknown inflows in a simple chemical tank are two instances for this class of faults. Mathematical presentation of this kind of fault is like former one.

This completes our discussion about diverse faults in different parts threatening the overall performance of the underlying system. In presentation of faults in the form of (6), (7), and (8), there is no restriction on fault magnitude or structure. It can be constant or time-varying with a nonlinear dynamic depending on both inputs and outputs.

3 Fault Modeling Technique

In this section, we describe the proposed method in this paper for the fault modeling. It is a general method which works for three mentioned classes of faults. In comparison with those methods mentioned in [10] and [11], this method has more generality because of covering all fault classes.

For starting the procedure and in the first place, we build an ANFIS model of system using available fault-free data. We can apply backpropagation or hybrid learning techniques to train the ANFIS model. More details about ANFIS and these learning methods can be found in [12]. Inputs and some delayed outputs of the underlying system form ANFIS input bunch. Besides this, we consider another one as input which is always zero. This zero input enters fault to the structure of the built ANFIS model. Since this input is zero in training step, it has no role in adjustment of ANFIS model parameters for faultless plant. Fig. 1 schematically shows presentation of this stage.

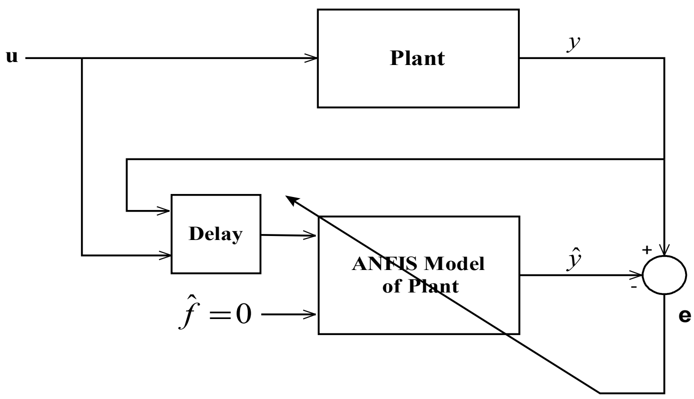

Fig. 1. Schematic of plant modeling using ANFIS

Without any restriction and only for ease in presentation, we suppose that the number of inputs in the ANFIS model is three, namely two delayed outputs and the plant input. Based this supposition, the mathematical presentation of the created ANFIS model will be some thing like this:

$$y(k)=\sum_{i=1}^{N} w_i(a_i y(k-1)+b_i y(k-2)+c_i u(k)+d_i f(k)+e_i) \qquad (9)$$

in which a_i, b_i, c_i, d_i, and e_i are subsequent parameters in the linear part of each rule.

After completing the training stage and meeting the required accuracy for ANFIS model, we deliberately put equal to one all of those coefficients in consequent part of each rule which are related to the fault input, $\hat{f}(\cdot)$. In this way, we directly introduce the modeled fault to the plant model without any change in its value or structure. This is a very important key point which enables us to model the occurred fault using differences between actual output and ANFIS model output using mentioned modification.

In the second place and to model occurred fault, again we choose another ANFIS system and assign it proper inputs. Those inputs can be some delayed measurements or plant inputs. More inputs, more capability for fault modeling. A schematic of the proposed method for fault modeling has been displayed in Fig. 2.

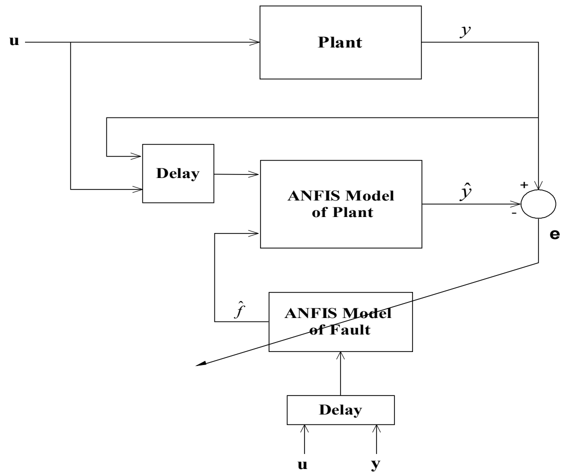

Fig. 2. Schematic of the proposed method for fault modeling

The used technique for training fault model is based on minimization of an objective functional $J(\cdot)$:

$$J(t)=\frac{1}{2}(y(k)-\hat{y}(k))^2 \qquad \textbf{(10)}$$

in which $y(\cdot)$ and $\hat{y}(\cdot)$ are respectively measurement and model output. According Fig. 2 and using partial derivative rule, parameters, θ_f , in the considered model for fault are tuned as follow:

$$\frac{\partial J}{\partial \theta_f}=\frac{\partial J}{\partial \hat{y}}\frac{\partial \hat{y}}{\partial \hat{f}}\frac{\partial \hat{f}}{\partial \theta_f}=-e\left(\frac{\partial \hat{y}}{\partial \hat{f}}\right)\left(\frac{\partial \hat{f}}{\partial \theta_f}\right). \qquad \textbf{(11)}$$

e definition is given by

$$e=y(k)-\hat{y}(k)\,. \qquad \textbf{(12)}$$

$\frac{\partial \hat{y}}{\partial \hat{f}}$ in (11) is sensitivity of the ANFIS model to one of its inputs. Both $\frac{\partial \hat{y}}{\partial \hat{f}}$ and $\frac{\partial \hat{f}}{\partial \theta_f}$ terms can be easily calculated using particular structure of ANFIS model. Actually, benefiting from this property in the computation has been the main motivation for using ANFIS models instead of neural networks or fuzzy systems.

Fault modeling continues until e fulfills the required condition which is oftentimes being less than a predetermined threshold. In case of fulfillment of the considered condition, the trained ANFIS model of fault is approximately an acceptable model of occurred fault in the plant.

From another point of view, we establish a closed loop to model the detected fault online and indirectly. In usual modeling methods, like Fig. 1, the training method minimizes the difference between the measurement and output of a model which is under training. In contrast with those methods, the proposed method minimizes that difference for training another model. The cost we pay is a little more computational mass which is negligible in comparison with what we gain.

In summary, when there is no fault, $\hat{f}(\cdot)$ is equal to zero and training of fault model doesn't start. Any mismatch between the actual output and the output of plant model runs the training procedure. It stops whenever we meet the required condition. The identified model of fault can be easily used for fault accommodation which completes FDI/FDA task.

4 Simulation

In this section, three kinds of fault are intentionally generated in an unknown nonlinear system and then are modeled using the proposed method.

The underlying system for simulation has the following form:

$$\begin{aligned} y_1(k) &= \frac{y_2(k-1)}{1+y_1(k-1)^2} \\ y_1(k) &= 0.1y_1(k-1)y_2(k-1)+\sin(u(k))+[f(k)=0] \end{aligned} \quad . \tag{13}$$

$f(k)$ is fault term and $u(k)$ is

$$u(k)=\left(\sin\frac{\pi k}{75}\cos\frac{\pi k}{25}\right)^2 . \tag{14}$$

ANFIS model for this system has four inputs in which one of the inputs, $\hat{f}(k)$, is always zero in training stage. Developing two Gaussian membership functions for each input leads to an ANFIS model with 16 rules. Fig. 3 shows actual output and ANFIS model output for fault free situation.

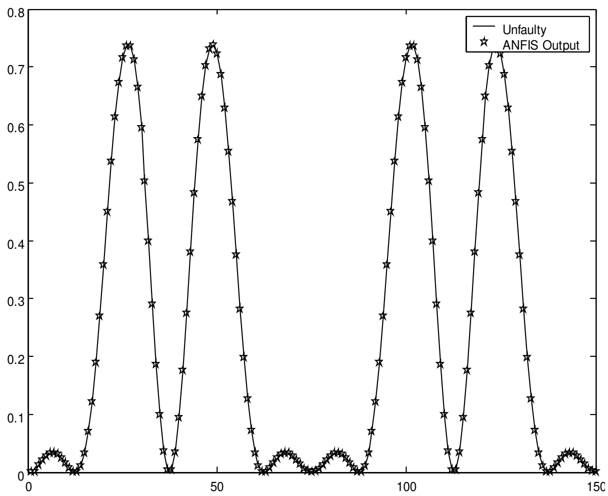

Fig. 3. Actual output and ANFIS model output

In all simulations, fault occurrence time is 50 sec and training starts at 100 sec. This approximately big time interval has been chosen for presentation of fault effects on system. The last but not the least, in the considered ANFIS model for fault, we only tune consequent parameters during fault modeling stage and we ignore training of premise parameters. This is due to this fact that ANFIS model output is highly sensitive to small changes in consequent parameters. The considered criterion to stop model training is fitness of the plant model output on the measurement.

4.1 Sensor Fault

To simulate sensor gain fault for second output, we define $f(k)$ in (13) like this

$$f(k)=0.3y_2(k) . \tag{15}$$

Consequently, the measurement will be $1.3y_2(k)$ instead of $y_2(k)$. In Fig. 4, actual and identified fault have been shown. From this figure, we can obviously see that the plant model output acceptably follows the real output a few seconds after start of training. This fitting means that ANFIS model of fault has been trained well and it contains basic behaviors of the occurred fault.

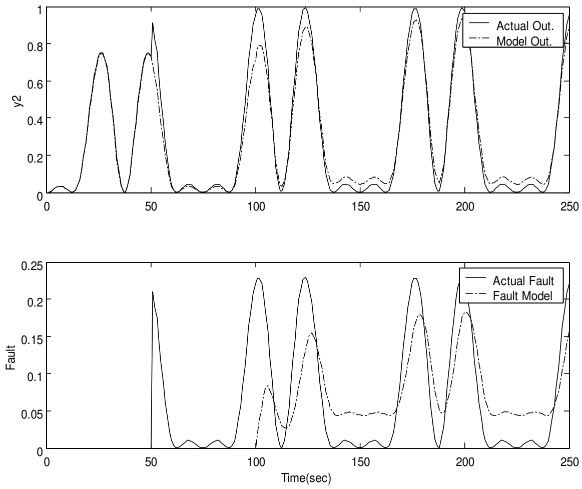

Fig. 4. Actual and modeled fault in case of sensor fault

4.2 Actuator Fault

We substitute $f(\cdot)$ in 13 by term given below as an actuator fault:

$$f(k)=\sin(1.5u(k))-\sin(u(k))$$ f(k)= sin (1.5 u(k))-sin(u(k)). (**16**)

This replacement leads elimination of $\sin(u(k))$ term from (13) and emerging $\sin(1.5u(k))$ term as an occurred fault in the faulty actuator. Simulation results for this case have been shown in Fig. 5. Shape and magnitude of the generated fault in this scenario is approximately similar to the previous one. No matter what's happened, the important point is goodness of modeling work which has done well as shown in Fig. 5.

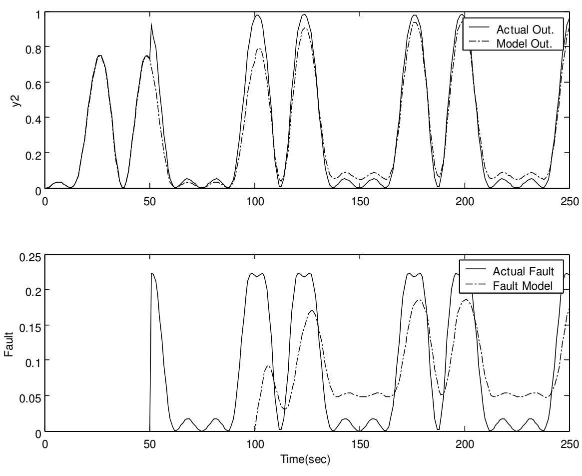

Fig. 5. Actual and modeled fault in case of actuator fault

4.3 Plant Component Fault

Considering $f(k)$ in (13) as follow denotes a plant component fault:

$$f(k) = \frac{y_2(k-1)}{1 + y_2(k-1)^2}\,. \qquad \textbf{(17)}$$

As it is apparent from Fig. 6, performance of the proposal method is acceptable and plant model output takes the same values of actual output which indicates well-done task of fault modeling.

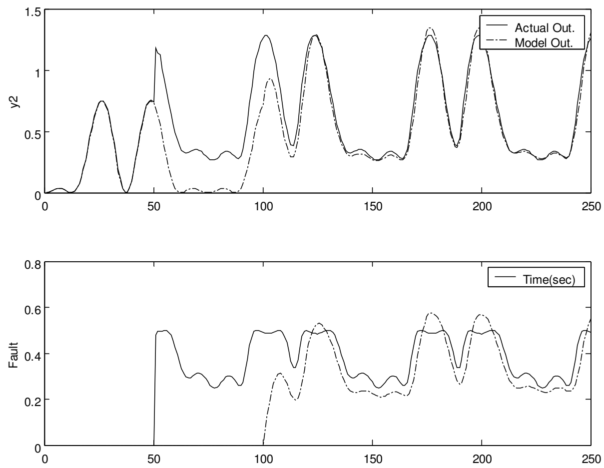

Fig. 6. Actual and modeled fault in case of plant component fault

In all simulation, the identified model is very similar to the actual occurred fault. This similarity thanks that modification skilfully done on the ANFIS model of plant in its creation stage. In online application, fault modeling can be started as soon as a fault is detected.

As mentioned earlier, generality of the proposed method for modeling of triple faults is a noticeable aspect which is demonstrated well through simulations. Moreover, there is no need for availability of analytical model of plant which makes this method more practical. For implementation of this method in practice, we only need fault-free data for building an ANFIS model which is used for training the considered model for the fault.

6 Conclusion

A new method for fault modeling was presented in this paper. It models occurred faults in sensor, actuators and plant components in a short time after their occurrences. From one hand, the proposed method relies on the strength of ANFIS technique for modeling nonlinear systems. From the other hand, the specific structure of ANFIS model in consequent part brings many facilities for doing some mathematical calculations for fault modeling. Its generality for modeling different occurred faults without any limitation related to either kind or structure of faults is another considerable aspect of the proposed method. Capability of this method for modeling triple faults was demonstrated through a case study. Fault accommodation using identified model should be paid enough attention for completing FDI/FDA task in next researches. Furthermore, extending this method to those cases that we have more than one fault or developing it to continuous systems can be addressed in future works.

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