Sensor fault detection and isolation for single, multiples and simultaneous faults: Application to a waste water treatment process

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Abstract: In this paper, sensor fault detection, isolation and identification model-based approach is designed. We introduce a new state variable so that an augmented system can be constructed to treat sensor faults as actuator faults. The approach uses the model of the system and a bank of adaptive observers to generate residuals. Structured residuals are defined in such way to isolate the faulty sensor after detecting the fault occurrence. The advantage of this method is that we can treat single, multiple and simultaneous sensor faults. In this study, we consider that only abrupt faults in the system sensor can occur. The proposed strategy is validated by simulation results of a nonlinear model of a waste water treatment process.

1. INTRODUCTION

In all industrial processes the reliability and the security of the system is a very important task. A fault may occur in all possible location, such as actuators, sensors and system's parameters. Fault detection techniques could prevent from all the undesirable consequences. In order to improve efficiency, the reliability can be achieved by fault-tolerant control, which relies on early fault detection, using fault detection and isolation (FDI) procedures. So FDI is becoming an attractive topic. Model based fault detection and diagnosis systems have found extensive use because of the fast response to abrupt failure and the implementation of the model based FDI in real-time algorithms. A comprehensive review of the different methods for FDI and their applicability to a given physical system has been presented in ([Iserman, 1994] and [Venkatasubramanian *et al.* 2003]). A variety of effective methods can be used to realize FDI, such as differential geometric approach [De Persis and Isidori 2001], sliding mode observer ([Edwards and Spurgeon 1994] and [Xing-Gang and Edwards 2005]), and adaptive control technique ([Frank, 1994] and [Hammouri *et al.* 1999]).

The progressive deterioration of the water resources and the great quantity of polluted water produced in the industrialized companies, give to the waste water treatments (WWT) a great importance in the safeguarding of water quality. The new directives and regulations (the directing 91/271/CEE referring itself to the European countries) impose the adoption of specific indices for the quality of treated waste water. Taking into account the current ecological problems, it is realistic to believe that this tendency will continue. At the same time, the existing factories increase thanks to the growth of the urban sectors and this situation requires more effective treatments of the used water. Consequently, we want that such an industry, almost always, operates with the maximum effectiveness.

Generally, the recent evolution of the legislation of some countries, about the use of surface or subsoil waters, is such that the total reuse of the water used in the processes became a very important issue. So the waste water treatment became a part of the production process, where the quality control of effluent is very important. Since the weak operation of the treatment can carry out to an important loss of production and to ecological problems.

The paper is organized as follows. In Section 2, we present the class of the nonlinear systems that we study, the filter that we apply to form the new extended system and the formulation of the fault problem. Then we give the principle of the fault detection and isolation scheme and the synthesis of the observer. Section 3 describes the waste water treatment process which is used to show the effectiveness of the proposed method. In Section 4, we give simulation results that illustrate the method for single, multiple and simultaneous faults. Conclusion and perspectives end the paper.

2. EXTENTED MODEL AND PROPOSED METHOD

2.1 Filter for the system's output

We consider the following class of nonlinear systems:

$$\begin{cases} \dot{x} = f(x) + g(x)u \\ y = Cx \end{cases} \qquad (1)$$

where $f(x)$ is a nonlinear vector function from $\Re^n$ to $\Re^n$, $g(x) \in \Re^{n \times m}$ is a matrix function whose elements are nonlinear functions, $C \in \Re^{p \times n}$ is a matrix, $u \in \Re^m$ is the input vector and $y \in \Re^p$ is the output vector. Throughout this paper, we assume that only constant sensor faults can occur $y_j^f(t) = y_j(t) + f_{sj}$, that is $y_j^f \equiv \theta_j$ for $t \geq t_f$, $j \in 1, 2, \cdots p$, and $\lim_{t\to\infty} | y_j(t) - \theta_j | \neq 0$, where θ_j is a constant and $y_j^f(t)$ is the actual output of the j^{th} sensor when it is faulty, while $y_j(t)$ is the expected output when it is healthy.

In [Chee and Edwards 2003] the authors presents a method for the linear system where the output vector passes through two orthogonal matrices $T_{r,1}$ and $T_{r,2}$. At the same time these matrices make the separation of the outputs at $y_1 \in \Re^{p-h}$ and $y_2 \in \Re^h$ where y_1 are the outputs without fault and y_2 are the outputs with a fault. The same manipulation of the outputs for the nonlinear system (1) is impossible but there is a similar method proposed in [Chen and Saif 2006] for the class of the nonlinear systems (1) that we presented above. We will apply to the output vector y a filter of the form:

$$\dot{\xi} = A_f \xi + B_f y \quad (2)$$

Where the state vector is $\xi \in \Re^p$, we select $A_f \in \Re^{p \times p}$ as a Hurwitz matrix and $B_f \in \Re^{p \times p}$ is chosen as an invertible matrix. We form the new input $w = \begin{bmatrix} u \\ y \end{bmatrix}$ and we define the extended system of the form:

$$\dot{z} = \underline{f}(x, \xi) + \underline{g}(x) w \qquad (3)$$

Where the vector $z \in \Re^{n+p}$ is the new state $z = \begin{bmatrix} x \\ \xi \end{bmatrix}$, $\underline{f}(x, \xi) \in \Re^{n+p}$ is a vector with nonlinear and linear elements ($\underline{f}(x, \xi) = \begin{bmatrix} f(x) \\ A_f \xi \end{bmatrix}$). The matrix $\underline{g}(x) \in \Re^{(n+p)\times(m+p)}$ is a matrix with nonlinear and linear elements ($\underline{g}(x) = \begin{bmatrix} g(x) & 0_{n\times p} \\ 0_{p\times m} & B_f \end{bmatrix}$) and finally the vector $w \in \Re^{m+p}$ is the new input vector. So, as we have seen with this transformation we have extended the system and the initial sensor fault problem has become, after the transformation, an actuator fault problem. The output vector y of the system has become a part of the input vector w of the new system. Based on the approach developed in [Blanke *et al.* 2003], it is easy to build the corresponding extended faulty model:

$$\begin{cases} \dot{z} = \underline{f}(x, \xi) + \sum_{j \neq l} \underline{g}_j(x) w_j + \underline{g}_l(x) \theta_l \\ y = \begin{bmatrix} C & 0_{p\times p} \end{bmatrix} z \end{cases} \qquad (4)$$

where we have a fault in the l^{th} actuator and $\underline{g}(x) = [\underline{g}_1(x) \cdots \underline{g}_{m+p}(x)]$.

The new system input as we already mentioned is the vector *w*. This vector includes the inputs and the outputs of the system (1), $w^T = [u_1 \ \cdots \ u_m \ | \ y_1 \ \cdots \ y_p]$. In this paper, we are focusing only in sensors faults. As the method that it will be used is an actuator fault detection and isolation method, the inputs of the new vector *w* that we are interested are from w_{m+1} to w_{m+p}.

2.2 The fault detection and isolation scheme

After this transformation, the problem has become an actuator fault detection and isolation problem where the faults have the same properties with the ones presented in the begin of the subsection *2.1*; only that in the place of the output y we have the input w. For the fault detection and isolation, we will develop a bank of p adaptive observers, where $\hat{\theta}$ is the fault estimation [Chen and Saif 2005]. The form of the adaptive observer that we will use in this bank for the l^{th} actuator is:

$$\begin{cases} \dot{\hat{z}}_l = \underline{f}(x, \xi) + \sum_{j \neq l} \underline{g}_j(x) w_j + \underline{g}_l(x) \hat{\theta}_l + H_l(\hat{z} - z) \\ \dot{\hat{\theta}}_l = -2\gamma (\hat{z}_l - z)^T P_l \underline{g}_l(x) \quad m+1 \leq l \leq m+p \end{cases} \qquad (5)$$

Where H is a Hurwitz matrix that it can be chosen freely, γ is a design constant and P is a positive definite matrix. We can calculate the matrix P and H with the help of the following Lyapunov equation:

$$H^T P + PH = -Q \qquad (6)$$

where Q is a positive definite matrix that it can be chosen freely. The analysis of the method can be found in [Chen and Saif 2005] along with all the proofs and details. An application of this method for an actuator fault detection and isolation to the same system that we studied can be found in [Fragkoulis *et al.* 2007]. The residual r_i that it is proposed in this paper is the difference between the estimation of the fault $\hat{\theta}_i$ determined in (5) and the output of the system so:

$$r_i = \hat{\theta}_{m+i} - y_i, \, i \in [1 \ldots p] \quad (7)$$

The residuals are designed to be sensitive to a fault that comes from a specific sensor and as insensitive as possible to all the others sensor faults. This residual will permit us to treat not only with single faults but also with multiple and simultaneous faults. To facilitate the isolation of the fault the structured residual will be used, and in particular the Boolean method introduced in [Gertler 1998] with simple thresholds δ_{si}.

$$\varepsilon_i(t) = \begin{cases} 1 & if \quad |r_i(t)| \geq \delta_{si} \\ 0 & if \quad |r_i(t)| < \delta_{si} \end{cases} \quad (8)$$

$$\Phi = [\varepsilon_1(t)\ \varepsilon_2(t) \ldots \varepsilon_p(t)] \quad (9)$$

$$r_s \leftarrow \Phi f_s \quad (10)$$

So the five steps for this new FDI scheme are:

1. we determine the filter as in (2) for the augmented space.
2. we form the new faulty model (4) and the new input vector *w*.
3. we build a bank of *p* observers as in (5) for the detection and isolation of the fault.
4. we generate the residuals r_i (7).
5. from the thresholds δ_{si} we elaborate the structural matrix Φ and then
6. from (10) we generate the structured residuals r_s for the fault isolation and identification.

3. WASTE WATER TREATMENT PROCES MODEL

The process of water treatment by activated sludge, invented in Manchester in 1914, industrially reproduced the purifying effect of the rivers, and became the principal current process of purification. It consists of an aerobic biological system in which the biological floc (biofloc) are continuously recycled and given in contact with organic waste water in the presence of oxygen. Oxygen is usually provided by bubbles of air, insufflated in the mixture of liquid and sludge under conditions of turbulence or by units of surface mechanics or by other aeration types.

A plant of water purification with activated sludge generally consists of a system of treatment in two phases (figure 1). The first phase of the treatment consists in eliminating pollutant in suspension, which mainly includes the degreasing, the de-sanding and the de-oiling. Now, we present the second phase which can be described by three reactors placed in cascade. The first reactor called primary decanter receives polluted water coming from the urban or industrial environments. Water penetrates then in a second reactor, called aerated basin, which constitutes the heart of the plant. The treatment is based on setting in contact of a bacterial population (micro-organisms) with organic matter contained in the effluent to treat. In the aerated basin occur initially a fast adsorption and flocculation of the colloidal matters in suspension and of the organic matter soluble by the activated sludge. Then there is a progressive oxidation of a synthesis of the adsorbed organic matter and of the extracted organic matter. Finally, water undergoes a last treatment in the third reactor, called settling tank. This one delivers purified water after the decantation of sludge. A part of this latter is recycled in the aerated basin (recycled sludge) and sludge in excess is evacuated for a suitable external treatment.

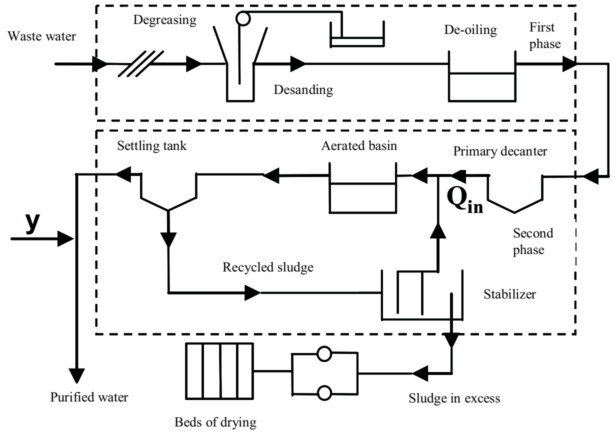

Figure.1 Waste water treatment process

The mathematical model for the activated sludge process (aerated basin and settling tank) is based on the equations, resulting from mass balance considerations, carried out on each of the reactant of the process.

Variation = ±Conversion + Feeding − Drawing off

All the details about the system and the values of the model parameters can be found in ([Nejjari 2001] and [Fragkoulis *et al.* 2007]). The FDI scheme will monitor the sensors S_I, S_S, X_I, X_S, X_H and S_O, measuring the output vector *y* of the settling tank (cf. figure 1), by using a bank of adaptive observers. The algorithm for this model is constituted by a bank of six adaptive observers for the fault detection, isolation and identification. More details about the observer synthesis can be found in [Fragkoulis *et al.* 2008].

4. SIMULATION RESULTS

In this section, we will give the results obtained from the developed method for one or more sensor faults. We have to mention that in the case of multiple and simultaneous faults, while the second fault occurs the first fault still acts in the system. The banks of adaptive observers run simultaneously with the system. The considered installation is a closed loop system. So the presence of the controller makes the sensor fault problem more complex. In this case, the fault affects not only the faulty sensors but also the system's dynamic (the other outputs of the system). The sampling period is one sample per hour, the value of all the constant thresholds are $\delta_{si} = 0.5$. Finally we have to mention that all the outputs and so all the faults are in *mg/l*.

4.1 Single fault

We have applied a fault with magnitude $f_{s5} = -2.2\, mg/l$ at time $t = 50$ days in the fifth sensor X_H. In Figure 2, we present the six residuals r_i associated to the six observers. The six residuals in the begin needs a short time period to converge. This time depends on the initialisation time of the observer's bank, so as to be ready for a fault detection and isolation. After, they reach a constant value and stays there until the fault occurrence.

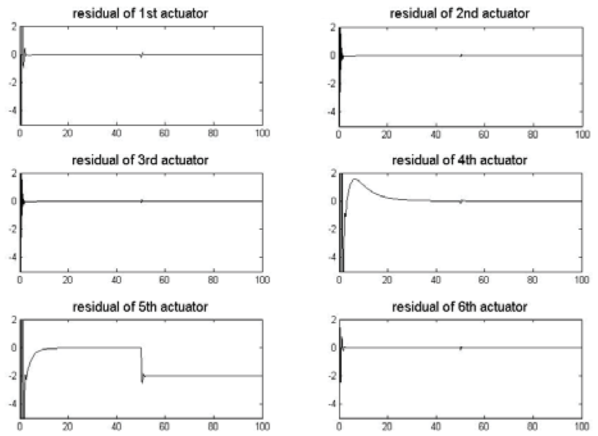

Figure.2 Residuals r_i for a single fault

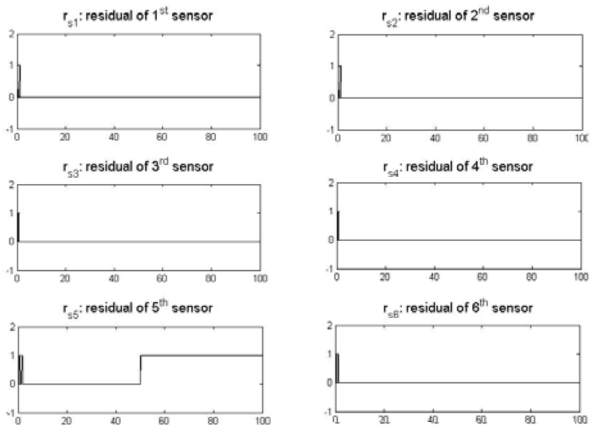

Figure.3 Structured residuals r_{si} for a single fault

At time $t = 50$ days, we can see that the residual of all the six observers leave zero but after a very short period (one day maximum), all of them return to their initial values, except from the residual associated to the fifth observer that corresponds to the output X_H that it takes a new constant value and remains there. In figure 3 we present the structured residuals for this fault. As expected all the residuals stay at zero except from the residual r_{s5} associated to the fifth sensor that at time $t = 51$ days takes and stays at the value "1". Thus, this fact indicates that this is the faulty sensor. Therefore, we isolate the faulty sensor correctly and rapidly enough. As we already mention, this method not only isolates the fault but also identify its value, which can be used for the system reconfiguration. In this case, the actual value of the fault is $f_{s5} = -2.2\, mg/l$ and the estimated value is $\hat{f}_{s5} = -2.1\, mg/l$, so we had identified the fault very accurately.

4.2 Multiple faults

We have applied a constant fault with magnitude $f_{s3} = -5\, mg/l$ at time $t = 50$ days in the third sensor X_I and one with magnitude $f_{s1} = -3\, mg/l$ in the first sensor S_I at time $t = 60$ days. The fault at the third sensor is still occurred when the fault at first sensor has been introduced. Figure 4 shows, the six residuals associated to the observers, where after the initialisation, they have a constant value until $t = 50$ days. There, all the residuals leave their initial values and only the residual associated to the third observer that corresponds at the third sensor stays to the new value. The other five residuals return to their initial values.

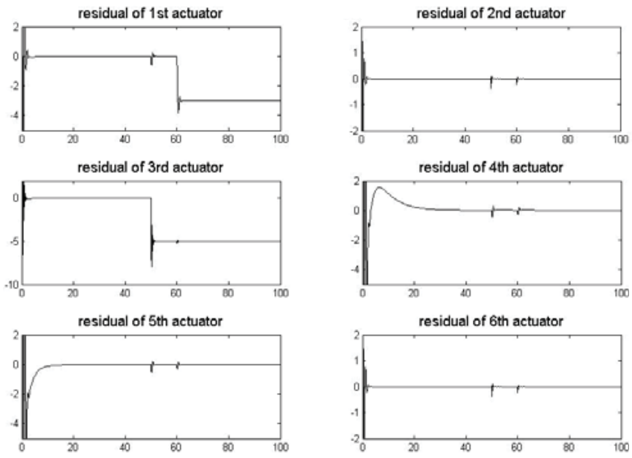

Figure.4 Residuals r_i for multiple faults

At time $t = 60$ days, where the second fault has been entered, the residual that corresponds to the first sensor S_I change from his initial value. It stays at the new value but the other five residuals leave their value and returns to them after a short time period. The third residual, which corresponds to the third sensor where the first fault still occurs, has not been affected by the new fault.

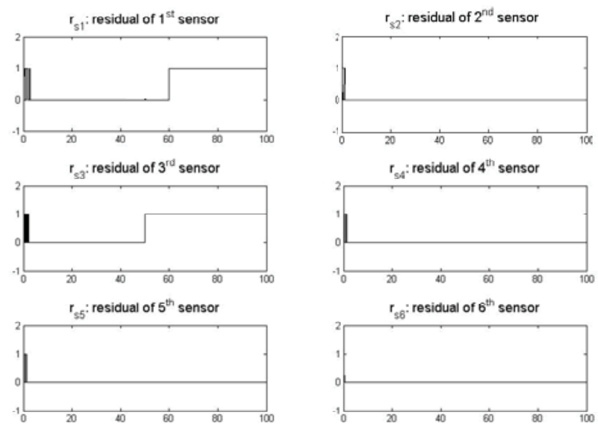

Figure.5 Structured residuals r_{si} for multiple faults

In figure 5, we can see the structured residuals where only the residuals r_{s3} and r_{s1} at time $t = 51$ days and $t = 61$ days respectively leave zero and stay at their new value “1”. More generally each fault affects only the corresponding residual and the isolation of the multiple faults has been done. For the fault identification we have: the estimation of the first fault is $\hat{f}_{s3} = -4.5\, mg/l$ and the actual value is $f_{s3} = -5\, mg/l$; the estimation of the second fault is $\hat{f}_{s1} = -2.85\, mg/l$ and the actual value is $f_{s1} = -3\, mg/l$. So we have a good estimation of the fault, not only for the first one where we have a single fault but also for the second one, the multiple fault case.

4.3 Simultaneous faults

We illustrate the case where more than one faults occur at the same time on the system or briefly the simultaneous faults. We have applied two faults: one on the fourth sensor X_S with magnitude $f_{s4} = -13\, mg/l$ and one on the sixth sensor S_O with magnitude $f_{s6} = -2\, mg/l$ at the same time $t = 50$ days.

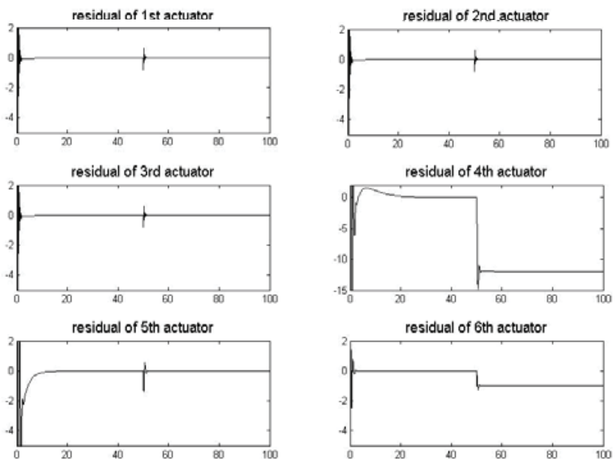

Figure.6 Residuals r_i for simultaneous faults

In Figure 6, we give the residuals associated to the observers and we can see that their values are equal to a constant value until $t = 50$ days where the two faults occur on the system. At that time, all the residuals leaves their initial values and only the residual associated to the fourth observer that correspond to the fourth sensor and the residual associated to the sixth observer that correspond to the sixth sensor stays to their new value; the other four residuals returns to their initials values. Figure 7 presents the structured residuals where only the residuals r_{s4} and r_{s6} leaves zero at time $t = 51$ days, therefore we isolate the two faulty sensors. The identification of the two faults is quite accurate, so for the fourth sensor the estimation is $\hat{f}_{s4} = -12.5\, mg/l$ and for the other one the estimation is $\hat{f}_{s6} = -1.8\, mg/l$.

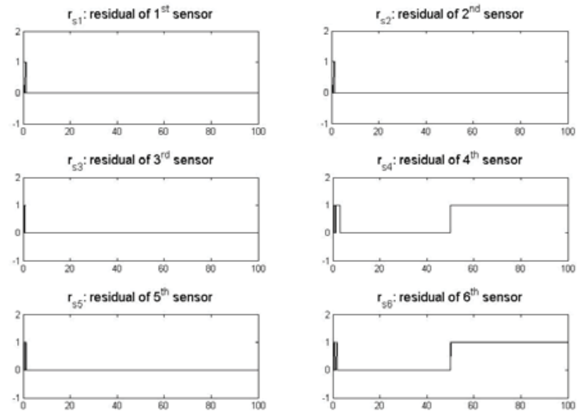

Figure.7 Structured residuals r_{si} for simultaneous faults

4.4 Single fault with real data

We will present the case where the input Q_{in} which is the flow rate input of the aerated basin (cf. figure 1) take his values from a file with real data. These data are collected from a benchmark installed in Terrassa Spain [Nejjari 2001], while the other three inputs have a constant value as in reality. Thus a single fault occurs in one of the six sensors and the method’s validity will be presented. In figure 6 we present the input Q_{in}.

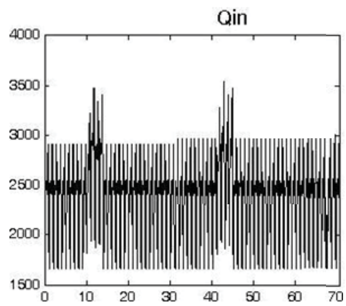

Figure.8 Input Q_{in} with real data

The duration of these data is 70 days and during this time we have two intermittent perturbations, one at the 9th day until the 13th day and another one at the 40th day until the 45th day, caused by the rain. A single fault with magnitude $f_{s4} = -15$ has been occurred at time $t = 50$ days in the fourth sensor X_S.

In figure 9, we show the six residuals associated to the six sensors. As we can see the two perturbations that occurred on the system have a little influence on them. Mainly the first, fourth and fifth residuals have been a little bit affected by them, but the effect can not be misjudged as a fault as long as the residuals remain in the zone defined by the two thresholds δ_{si}. The structured residuals, figure 10, stay at zero during the perturbations.

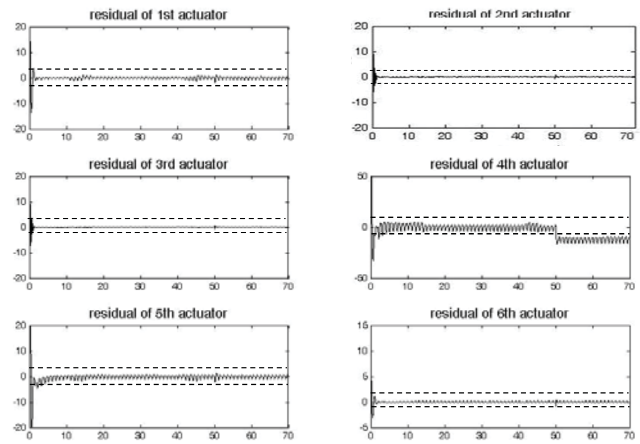

Figure.9 Residuals r_i for single fault with real data

Then at time $t = 50$ days the fourth residual, in both figures, indicates us that there is a fault in the fourth sensor. The simple residual leaves his initial value and gives us the estimation of the fault and the structured residual takes the value "1", so we can easily conclude the source of the fault. For the estimation of the fault we have to use the mean value on a sliding window due to the fact that we have a small oscillation of the value; this mean value is $\hat{f}_{s4} = -16\, mg/l$. In this case the thresholds value is $\delta_{si} = 2$ and they are chosen empirically, also we have to mention that the use of structured residuals facilitates the automatic isolation.

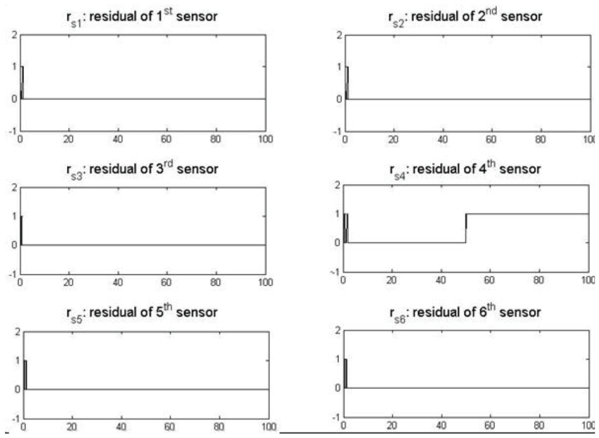

Figure.10 Structured residuals r_{si} for single fault with real data

5. CONCLUSIONS

In this paper, a new method, for sensor fault detection isolation and identification, based on nonlinear observers has been developed. We have reformulated the initial sensor fault problem, by using a transformation filter, to an actuator fault problem. We have designed a known bank of adaptive observers to treat the FDI procedure. Simulation results illustrate the effectiveness of the method for the isolation of single faults, multiple and simultaneous faults. Finally we have validated the proposed method with real data collected from a waste water treatment process benchmark. Our future considerations are to improve the fault estimation in the case of measurement noise by using a better filtering method of the residual. Finally the comparison with the simple method of adaptive observers and mainly the comparison between the isolation time and the fault identification is one of our highly concerns.

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