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Robust Diagnosis for Hybrid Dynamical Systems

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***Abstract*— This paper focuses on Fault Detection and Isolation (FDI) of Hybrid Dynamical Systems (HDS) using fault indicator signals, known as residuals. A based method hybrid observer is proposed. It combines two parts one aims to identify the active mode, allowing the discrete faults detection and the other performing the continuous state estimation, allowing the sensors FDI. In the real case, the system operates in a noisy situation. A robust evaluation method based on the residuals norm (errors estimation) is proposed to detect the noisy active mode. The observer based method is designing with pole placement technique.**

***Index Terms*—SDH, FDI, hybrid observer, pole placement, norm-based residual evaluation.**

I. INTRODUCTION

The synthesis of hybrid observers can be divided into two major groups: one that assumes the knowledge of the discrete state (q discrete mode) at every moment [1], [2] and the second overcomes this assumption and estimates the both discrete and continuous state [3], [4], [5], [6].

When the discrete mode is not known, techniques that support the estimation of discrete mode and continuous state must be used. In [1], the authors studied the synthesis of observers for linear switched systems assuming the active mode is known. It remains to estimate the continuous state by using the Lyapunov theory and solving a set of LMI conditions. In the work of Balluchi [3], the current mode detecting a switching system is performed by calculating a bank of residuals and subsequently estimates the continuous state taking into account the dwell time for each switch. In [4], the mode detection is performed using finite state automata (FSA) and a Luenberger observer to estimate the continuous state. The same concept is described in [7] but taking into account the reset state when switching. In [8], to estimate the discrete state, the author uses a logical selection for the continuous state and it uses multiple Lyapunov functions (LMI formulation).

In [8], it adds the concept of dwell time to determine the estimated continuous state. In [9] the authors study the piecewise linear systems in continuous and discrete time assume that the current mode is known and estimate the continuous state with a common Lyapunov function. Similarly, in [6], the authors consider the piecewise linear discrete-time systems. A multiple Lyapunov function is used to prove the convergence of the estimation error on the continuous state.

In [10], the authors use a selection approach for the estimation of the observer mode and moving horizon to estimate the continuous state. The switched system, in [11], is modeled by differential Petri nets and two observers blocks are used to estimate the discrete state and the other to estimate the continuous state.

To correctly identify the current mode and to detect and locate the faults, we propose in this paper a methodology for monitoring using hybrid observer. The proposed diagnosis structure has two observers based modules based on. The first is to generate residuals for identifying the current mode. The second module is synthesized around a DOS Scheme (Dedicated Observer) [12] to generate structured residuals which locate sensor faults. It consists of observer bank for each mode to generate a vector of residuals. In a real case, the systems can be disrupted by noise system. In addition, the model parameters are not perfectly known. We use an evaluation method based on the norm of the residuals which allows us to detect the active mode in the presence of measurement noise and parameter uncertainties.

This paper is organized as follows. In section 2, hybrid observer structure for mode identification and FDI. An illustrative example is treated in section 3 to illustrate the methodology and to show the efficiency of our approach. Finally we conclude by some remarks.

II. HYBRID OBSERVER STRUCTURE FOR MODE IDENTIFICATION AND FDI

The structure of the hybrid observer is composed of two blocks of observation. The first is used to estimate the current discrete mode $\hat{q}$ by generating a bank of residuals. The second block is used to detect and locate sensor faults (figure 1).

A. Mode identification

This module is composed of a bank of M (number of modes) Luenberger observers (Om_i, means the Observer of mode i). We associate with each subsystem (mode) S_i an observer Om_i. Each observer receives all I/O of SDH, the reconstructed outputs $\hat{y}(t)$ by each observer are compared, at any time, to the measured outputs $y(t)$ to generate residuals vectors $r_i(t)$ [13].

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$$S_i : \begin{cases} \dot{x}(t) = A_i x(t) + B_i u(t) \\ y(t) = C_i x(t) + E_{iy} d(t) + F_{iy} \varphi(t) \end{cases} \quad (1)$$

$$\text{Om\_i} : \begin{cases} \dot{\hat{x}}(t) = A_i \hat{x}(t) + B_i u(t) + K_i \left(y(t) - \hat{y}(t) \right), \quad \hat{x}(0) = \hat{x}_0 \\ \hat{y}(t) = C_i \hat{x}(t) \end{cases}$$

(2)

$$\begin{cases} \dot{e}_i(t) = (A_i - K_i C_i) e_i(t) - K_i E_{iy} d(t) - K_i F_{iy} \varphi(t) \\ r_i(t) = C_i e_i(t) + E_{iy} d(t) + F_{iy} \varphi(t) \end{cases}$$

In the presence of noise and measurement system, residuals will be disturbed. The decision becomes more difficult. As in [14], we propose to use the quadratic average residual calculated on a sliding window. The threshold value "*Si*" detection must be set according to the noise and the sensitivity of the residuals to these disturbances. The threshold can be determined to guarantee a certain probability of false alarm (an alarm when the fault is not present). It is to be calculated if the noise characteristics are assumed to be known or determined using experimental data. The norm residual $\|r_i(t)\|_{2,T}$ is calculated on a T window and compared to the threshold "Si".

The norm $\|r_i(t)\|_{2,T}$ is defined as follow:

$$\|r_i(t)\|_{2,T} = \sqrt{\left[\int_{t-T}^{t} r_i^{\,T}(t) r_i(t) dt \right]} \quad (3)$$

The method of norm-based residual evaluation is to compare each element using the following decision logic:

$$S_{ri} = 0 \quad \text{si} \quad \|r_i(t)\|_{2,T} > Si \quad (4)$$

$$S_{ri} = 1 \quad \text{si} \quad \|r_i(t)\|_{2,T} \leq Si$$

Where Si is determined using experimental data and S_{ri} is the experimental signature of mode i. The experimental signature of mode i ($i = 1, \ldots, M$) is:

$$S_{\hat{q}} = \{ S_{r1}, S_{r2}, \ldots, S_{ri}, \ldots, S_{rM} \} \quad (5)$$

The current mode identification is the correspondence between the obtained experimental signature and the theoretical signatures of operating modes.

B. *Sensor fault detection and isolation*

Once, the mode i was identified, we use k observers corresponding to the identified mode as each of these observers is sensitive to a single output. For k sensor faults and for each mode i ($i = 1, \ldots, M$), a DOS-based observer scheme is used to generate residual sensitive to a single sensor fault see Figure 1 (OSF_j which means "Observer for Sensor Fault j").

Each mode i is described by:

$$S^j{}_i : \begin{cases} \dot{x}(t) = A_i x(t) + B_i u(t), \quad x(0) = x_0, \quad i = 1, \ldots, M \text{ et } j = 1, \ldots, k \\ y_j(t) = C_i^{\,j} x(t) + E_{iy}^{\,j} d(t) + F_{iy}^{\,j} \varphi(t) \end{cases} \quad (6)$$

The structure of the sensitive j^{th} component observer of the output vector is given by:

$$\text{OSF\_j} : \begin{cases} \dot{\hat{x}}(t) = A_i \hat{x}(t) + B_i u(t) + L_i^{\,j} \left(y_j(t) - \hat{y}_j(t) \right) \quad , i = 1, \ldots, M \text{ et } j = 1, \ldots, k \\ \hat{y}_j(t) = C_i^{\,j} \hat{x}(t) + D_i^{\,j} u(t) \\ z_i^{\,j}(t) = y_j(t) - \hat{y}_j(t) \end{cases} \quad (7)$$

Where $\hat{x}(t) \in \Re^n$ is the estimated state vector, $\hat{y}_j(t)$ is the j^{th} component of the vector of estimated output and $z_i^j(t)$ is the j^{th} component of the vector of residuals to time t. $L^j{}_i$ is the observer gain calculators and i represents the index of the identified mode at the instant t.

The vector of residuals of the identified mode i is then given by:

$$\left[z_i^1 \cdots z_i^j \cdots z_i^k \right]^T = \left[H_i^1(u, y_1) \cdots H_i^j(u, y_j) \cdots H_i^k(u, y_k) \right]^T$$

(8)

Where $H_i^{\,j}(u, y_j), \quad j = 1, \cdots, k$ et $i = 1, \cdots, M$ represents the function that links the input vector u and the j^{th} element of the output vector y. From (7), the j^{th} component of the residuals z_i^j can only be influenced by the j^{th} component of the sensor faults φ.

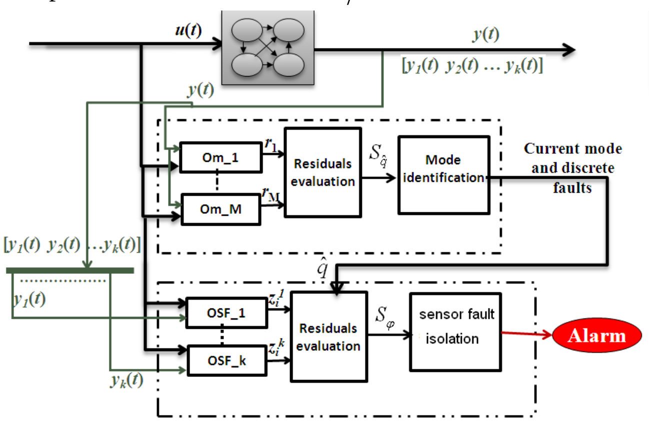

Fig. 1 SDH monitoring scheme

Our objective is to determine the gain matrices $L_i^{\,j}$ that ensure the convergence of each observer (7). So, we study the convergence of estimation errors.

$$\begin{cases} \dot{e}_i(t) = (A_i - L_i^{\,j} C_i^{\,j}) e_i(t) \quad i = 1, \ldots, M \text{ et } j = 1, \ldots, k \\ z_i^j(t) = C_i^{\,j} e_i(t) + E_{iy}^{\,j} d(t) + F_{iy}^{\,j} \varphi(t) \end{cases} \quad (9)$$

To evaluate the structured residuals, we apply the norm based residual evaluation which compares the norm structured residual $\|z_i^j(t)\|_{2,T}$ calculated over the interval T to a threshold S_{ij}. Each element of the actual signature is defined as follows:

$$S_{zi}^j = 1 \quad \text{si} \quad \|z_i^j(t)\|_{2,T} > S_{ij} \quad (10)$$

$$S_{zi}^j = 0 \quad \text{si} \quad \|z_i^j(t)\|_{2,T} \leq S_{ij}$$

Where, S_{zi}^j is the experimental signature.

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The norm $\left\| z_i^{\,j}(t) \right\|_{2,T}$ is defined as follows:

$$\left\| z_i^{\,j}(t) \right\|_{2,T} = \sqrt{\left[\int_{t-T}^{t} z_i^{\,jT}(t) z_i^{\,j}(t) dt \right]} = \left\| C_i^{\,j} e_i(t) + E_{iy}^{\,j} d(t) + F_{iy}^{\,j} \varphi(t) \right\|_{2,T}$$

(11)

The threshold of detection is calculated as follows:

$$S_{ij} = \sup(\left\| z_i^{\,j}(t) \right\|_{2,T} \Big|_{\varphi=0})$$

(12)

III. ILLUSTRATIVE EXAMPLE

To illustrate the use of observation residuals for mode identification and fault detection, we consider the described hybrid system described by figure 2.

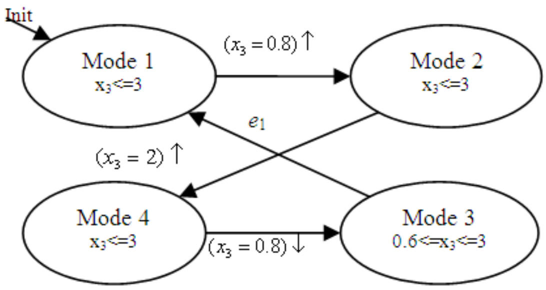

Fig. 2 Hybrid system modeling

Each mode is represented by:

$$S_i : \begin{cases} \dot{x}(t) &= A_i x(t) + B_i u(t) \\ y(t) &= C_i x(t) + E_{iy} d(t) + F_{iy} \varphi(t) = \begin{bmatrix} y_1(t) \\ y_2(t) \end{bmatrix} \end{cases}$$

With:

$$A_1 = \begin{bmatrix} -2 & 0 & 0 \\ 0 & -5 & 0 \\ 0 & 0 & -1 \end{bmatrix}, A_2 = \begin{bmatrix} -1 & 4 & 0 \\ 0 & -1.5 & 0 \\ 6 & 0 & -2 \end{bmatrix},$$

$$A_3 = \begin{bmatrix} -1 & 0 & 0 \\ 0 & -8 & 0 \\ 0 & 0 & -2 \end{bmatrix}, A_4 = \begin{bmatrix} -1 & 4 & 0 \\ 0 & -1.5 & 0 \\ 0.5 & 0 & -2 \end{bmatrix}$$

$$B_1 = B_2 = B_3 = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, B_4 = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}; C_1 = C_2 = C_3 = C_4 = \begin{bmatrix} 0.8 & 1 & 1 \\ 1 & 0.6 & 1 \end{bmatrix}$$

$$E_{1y} = E_{2y} = E_{3y} = E_{4y} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}; F_{1y} = F_{2y} = F_{3y} = F_{4y} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}; \varphi(t) = \begin{bmatrix} \phi_1 \\ 0 \end{bmatrix}$$

e_1 is a controlled event (controlled by the operator). This event occurs at t = 3s. The transition from one mode to another is due to the presence (or absence) of this external event and the state value of $x_3(t)$ (the third component of $x(t)$).

In this example, the bank of observers dedicated to identify the current mode consists of four observers $O_i \quad ,i \in \{1,2,3,4\}$. Each observer Om_i is associated with a mode i to estimate the current mode.

Using a pole placement technique to observer design for each subsystem (mode), we choose to fixe the dynamics of each observer $O_i \quad ,i \in \{1,2,3,4\}$:

$$P_1 = \begin{bmatrix} -15+15i \\ -15-15i \\ -15 \end{bmatrix}; P_2 = \begin{bmatrix} -17+17i \\ -17-17i \\ -15 \end{bmatrix}; P_3 = \begin{bmatrix} -12+12i \\ -12-12i \\ -12 \end{bmatrix}; P_4 = \begin{bmatrix} -12+12i \\ -12-12i \\ -12 \end{bmatrix}$$

Each observer gain is:

$$K_1 = \begin{bmatrix} -321.33 & 229.8 \\ -118.47 & 76.95 \\ 411.30 & -274.74 \end{bmatrix}, K_2 = \begin{bmatrix} -50.60 & 113.96 \\ 6.12 & 23.67 \\ 34.61 & -83.92 \end{bmatrix}$$

$$K_3 = \begin{bmatrix} -329.76 & 343.70 \\ -120.13 & 125.60 \\ 395.17 & -402.29 \end{bmatrix}, K_4 = \begin{bmatrix} -116.15 & 184.00 \\ -28.90 & 58.28 \\ 128.33 & -193.98 \end{bmatrix}$$

Case 1: Discrete fault detection

Assume that the sensor fault is not present. Consider the case of a fault that produces a discrete transition to a no successor mode. We assume that the discrete fault occurs at the instant 1.82s. The SDH switches to mode 3 instead of mode 4 in normal operation. We suppose that we know the discrete trajectory 12431243.

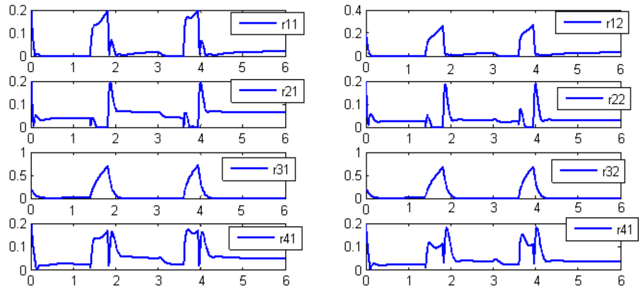

Fig. 3 Residuals for 4 modes in the case of a discrete fault

After the generation of residuals for each mode, then we use decision logic in order to identify the current mode. Same as above, the experimental signature S_{ri} (see Figure 4) are obtained using the logic decision (4).

Table .I Threshold detection of current mode

MODE	Mode 1	Mode 2	Mode 3	Mode 4
Threshol	S_{11}=0.00	S_{21}=0.00	S_{31}=0.000	S_{41}=0.0001
d	7	6	1	S_{42}=0.0001
Selector	S_{12}=0.00	S_{22}=0.00	S_{32}=0.000	
T=0.1s	4	5	1	

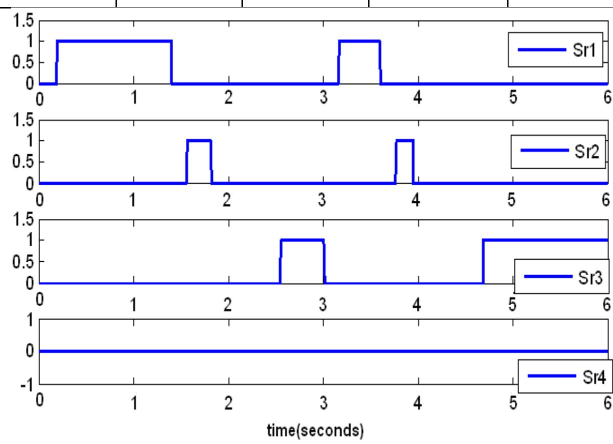

Fig. 4 Experimental signature for the detection of discrete fault

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Table .II. Identification of current mode in the presence of a discreet fault

Time Interval	$S_{\hat{q}}$				current mode
	Sr1	Sr2	Sr3	Sr4	
0.20s<t<1.39s	1	0	0	0	Mode1
1.55s<t<1.81s	0	1	0	0	Mode2
2.50s<t<3.00s	0	0	0	1	Mode3
3.06s <t<3.60s	0	0	1	0	Mode1
3.73s<t<3.95s	1	0	0	0	Mode2
4.17s <t<6.00s	0	1	0	0	Mode3

When the discrete fault occurs at time 1.82s, the discrete path changes its normal evolution see Table II.

Case 2: Continuous fault detection (sensor faults) in the presence of measurement noise

Now let us consider a failure (sensor fault) ϕ_1 which occurs on the time interval [5.20s, 5.31s] with amplitude of 0.2. This sensor fault ϕ_1 occurs when the system is in mode 3. In order to illustrate the problem of identification, detection and isolation of the faults in a noisy context, a Gaussian noise of null average and variance equal to 10^{-4} is added to the measurement y_1. The residuals in the presence of disturbance and fault are given by figure 5.

Let us start by identifying the current mode using the first module (see figure 1).

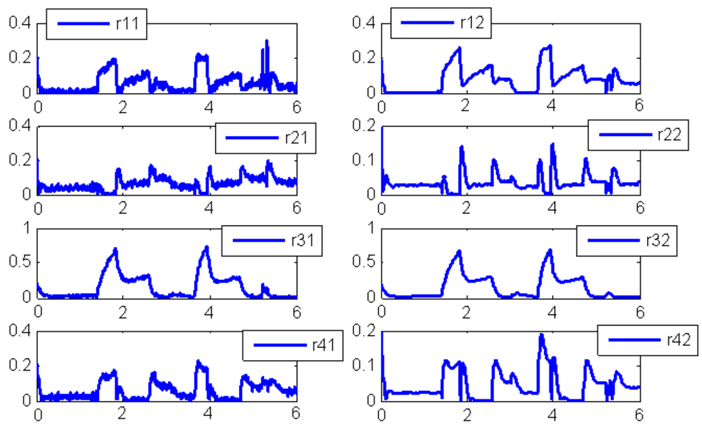

Fig. 5 Residuals for 4 modes in the presence of sensor fault and disturbances (measurement noise)

The values of the thresholds and norm 2 of residuals are presented respectively in table III and figure 6. We note that each component of the vectors of residuals $r_i(t)$ converges towards zero only when the SDH evolves in mode *i*, if not it moves away notably from zero.

The convergence of the observers is not instantaneous. We can observe that the influence of convergence time is not negligible on the recognition of current mode.

The binary experimental signatures generated by the evaluation of the L2 Norm of residuals (see expression 4) are presented in figure 7.

Table. III. Détection threshold current mode

MODE	Mode 1	Mode 2	Mode 3	Mode 4
Thresholds Selector T=0.1s	S_{11}=0.007 S_{12}=0.004	S_{21}=0.006 S_{22}=0.005	S_{31}=0.0001 S_{32}=0.0001	S_{41}=0.0001 S_{42}=0.0001

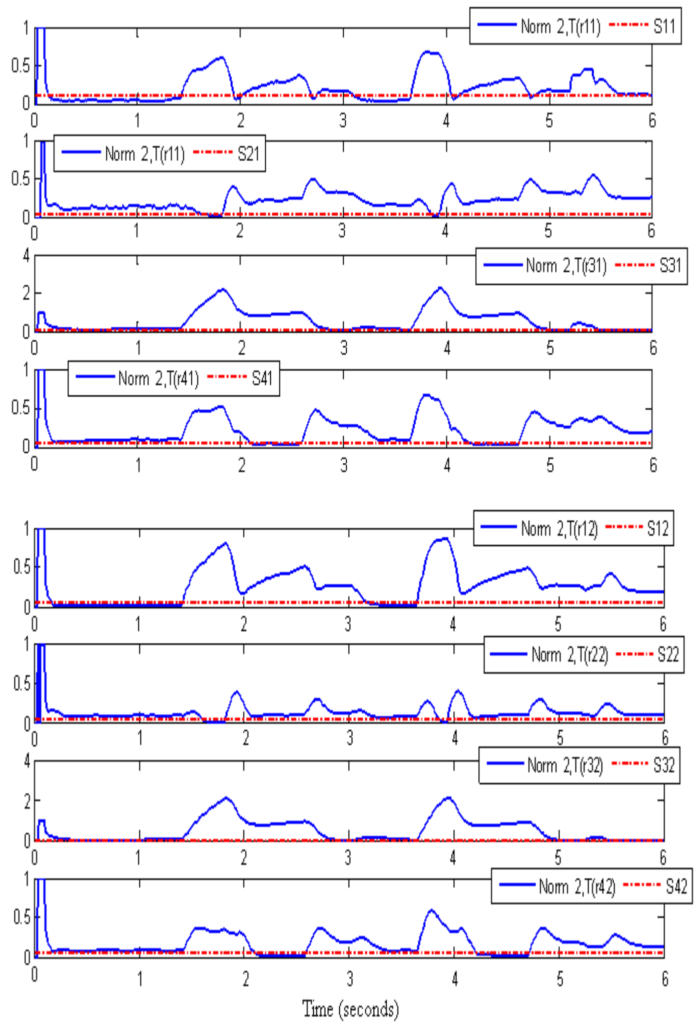

Fig. 6 Norm 2 of Residuals for each mode in the presence of sensor fault and noisy case

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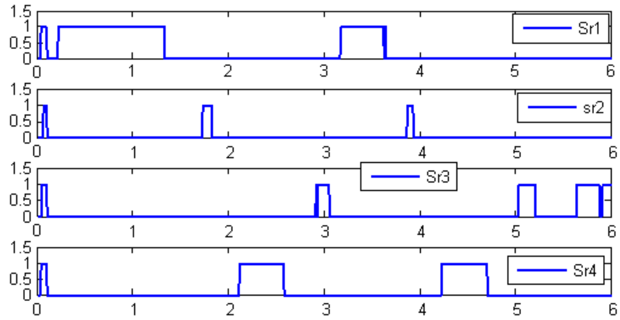

Fig. 7 Modes signatures in the presence of sensor fault and noisy case

In order to isolate the sensor faults, a bank of observers (DOS) is used. It consists of two Luenberger observers for each mode *i*, each observer is sensitive to an output.

Let us use the pole placement technique to determine the gains of observers of each mode. We choose,

$$P_{11} = P_{12} = P_{21} = P_{22} = P_{31} = P_{32} = P_{41} = P_{42} = \begin{bmatrix} -30+30i \\ -30-30i \\ -20 \end{bmatrix};$$

The gains $L_i^j \quad i \in \{1,2,3,4\}\ et\ j \in \{1,2\}$ of each observer O_i^j are:

$L_1^1 = 10^4 \times [\ \text{-1.26} \quad 0.19 \quad 0.82]$

$L_1^2 = 10^4 \times [\ \text{-1.01} \quad 0.31 \quad 0.82]$

$L_2^1 = 10^3 \times [\ \text{-0.26} \quad 1.24 \quad \text{-0.96}]$

$L_2^2 = 10^3 \times [\ \text{-0.35} \quad 1.22 \quad \text{-0.30}]$

$L_3^1 = 10^4 \times [\ 1.03 \quad 0.19 \quad \text{-1.01}]$

$L_3^2 = 10^4 \times [\ 1.26 \quad 0.52 \quad \text{-1.57}]$

$L_4^1 = 10^4 \times [\ \text{-2.47} \quad 0.94 \quad 1.04]$

$L_4^2 = 10^4 \times [\text{-2.17} \quad 0.82 \quad 1.68]$

The structured residuals are presented in figure 8.

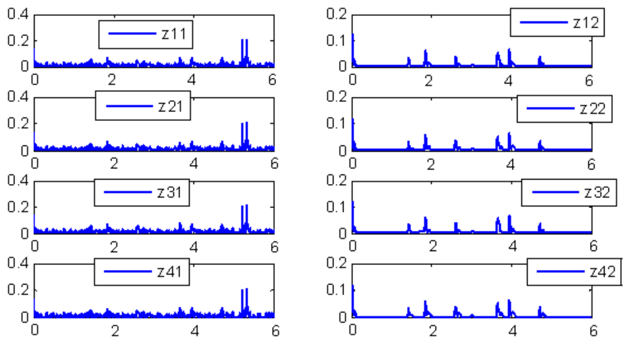

Fig. 8 Structured Residuals for 4 modes in the presence of sensor fault and noisy case

The detection thresholds of sensor fault are given in absence of faults (see (12)), for T =0.1s. We choose a threshold for each mode S_{11}=0.15, S_{12}=0.17.

We have introduced a fault in sensor 1 at the time 5.20s. The structured residuals L_2 Norm evolution and selected thresholds are showed in figure 9. In figure 10, we present the experimental signatures mode for the sensor fault detection.

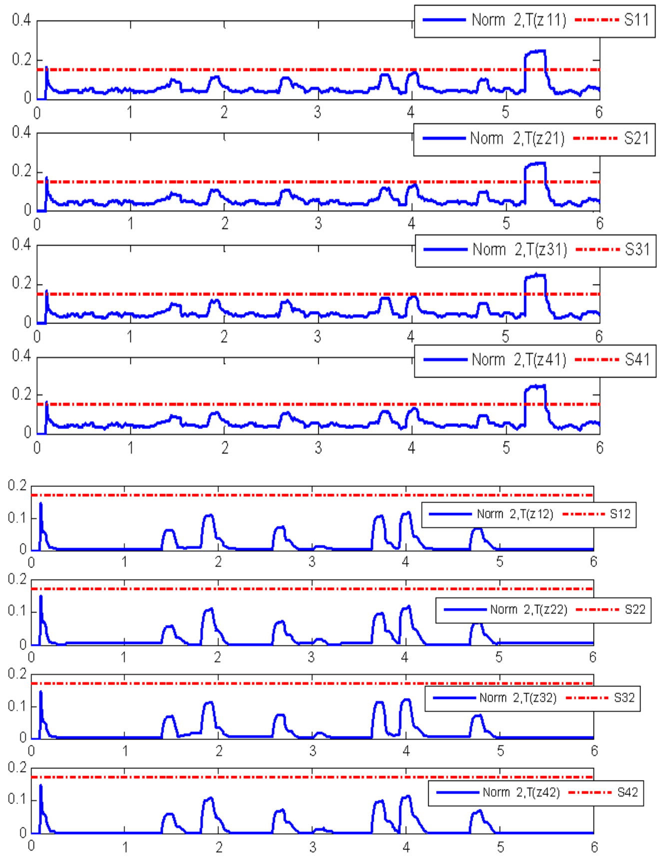

Fig. 9 L2 Norm evolution of the structured residuals and detection thresholds of sensor faults for each mode

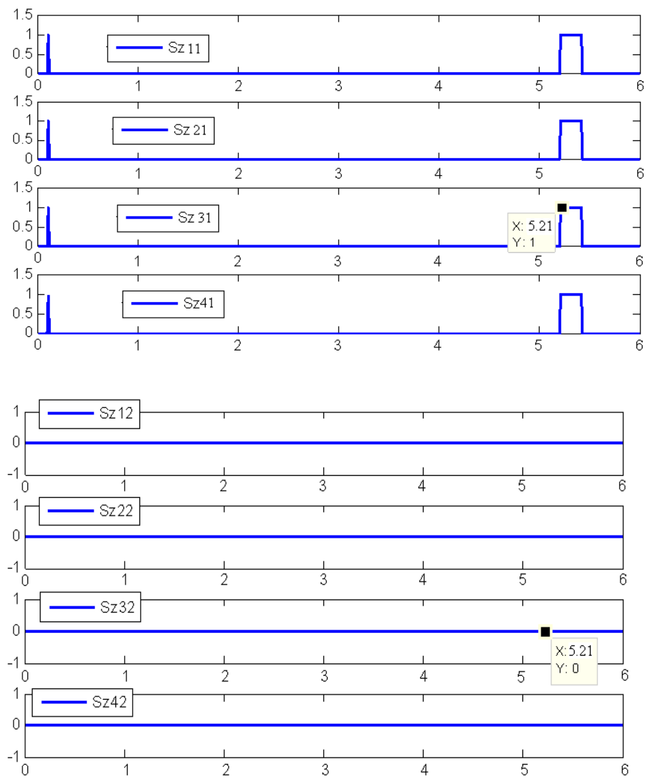

Fig. 10 Structured experimental Signature of residuals for the detection of the sensor faults

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Table .IV.Recognition Mode and fault sensor detection and isolation

Time	mode signature $S_{\hat{q}}$				current mode	Faults signatures S_{φ}				current mode and faults detection
	sr1	sr2	sr3	sr4		sz11 sz12	sz21 sz22	sz31 sz32	sz41 sz42	
0.25≤t≤1.39	1	0	0	0	Mode1	0 0				Mode1 n
1.40≤t≤1.72	0	0	0	0	????	00	00	00	00	?????
1.73≤t≤1.81	0	1	0	0	Mode 2		0 0			Mode2 n
1.82≤t≤2.17	0	0	0	0	????	00	00	00	00	?????
2.18≤t≤2.57	0	0	0	1	Mode4				00	Mode4 n
2.58≤t≤2.90	0	0	0	0	????	00	00	00	00	?????
2.91≤t≤3.05	0	0	1	0	Mode3			00		Mode3 n
3.06≤t≤3.17	0	0	0	0	????	00	00	00	00	?????
3.18≤t≤3.63	1	0	0	0	Mode1	00				Mode1 n
3.64≤t≤3.87	0	0	0	0	????	00	00	00	00	?????
3.88≤t≤3.92	0	1	0	0	Mode2		00			Mode2 n
3.93≤t≤4.28	0	0	0	0	????	00	00	00	00	?????
4.29≤t≤4.69	0	0	0	1	Mode4				00	Mode4 n
4.70≤t≤5.02	0	0	0	0	????	00	00	00	00	?????
5.03≤t≤5.20s	0	0	1	0	Mode3			00		Mode3 n
5.21≤t≤5.45	0	0	0	0	????	10	10	1 0	10	Mode 3 faulty
5.46≤t≤5.66	0	0	0	0	????	00	00	00	00	?????
5.67≤t≤6.00	0	0	1	0	Mode3			00		Mode3 n

Table VI presents the results of identification modes and faults detection and isolation. The time intervals in which we can't identify the correct mode are introduced by "????". This uncertainty decision is due to the time delay of convergence of the observer or to the switching time (change of mode). In this case we should execute in parallel the second module in order to calculate the whole of structured residuals (if Szij=1 then the sensor fault affects the mode previously identified).

We notice according to the table VI that fault is detected at the time 5.21s indicating the presence of a sensor fault in output 1 (Sz_1^1=1, Sz_2^1=1, Sz_3^1=1 and Sz_4^1=1), with detection delay of 0.01s.

IV. Conclusion

In this paper, we proposed a methodology of HDS monitoring by hybrid observer. The proposed approach combines two modules based observers one generates the mode signature in order to identify the current mode and to detect discrete fault. The other module is used to detect and isolate the sensor fault. The first module is composed of bank of observers for each mode in order to generate the residuals. In a real case, the systems can be disturbed by measurement noises. Moreover, the parameters of the models are not perfectly known. Thus, we use an evaluation method based on the L2 Norm of residuals which detect the active mode in the presence of the measurements noises and uncertainties parametric. The second module is synthesized using a DOS scheme in order to generate a vector of the structured residuals for the sensor fault detection and isolation.

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