ROBUST FAULT ISOLATION USING NON-LINEAR INTERVAL OBSERVERS: THE DAMADICS BENCHMARK CASE STUDY

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Abstract: This paper presents a passive robust fault detection and isolation approach using non-linear interval observers. In industrial complex systems there is usually some uncertainty on model parameters that can be bounded using intervals. A model with parameters bounded in interval is known as an "interval model". Intervals observers propagate parameter uncertainty to the residual generating an adaptive threshold that allow to robust detect system faults. In order to isolate faults, a bank of those observers with a specified fault signature is required. Finally, this approach will be applied to detect and isolate some of the faults proposed in an industrial actuator used as an FDI benchmark in the European project DAMADICS.

Keywords: Fault Detection, Fault Diagnosis, Robustness, Envelope Generation, Adaptive Threshold, Optimisation, Sliding Window Principle.

1. INTRODUCTION

The problem of robustness in fault detection using observers has been treated basically using the active approach, based on decoupling the effects of the uncertainty from the effects of the faults on the residual (Chen, 1999). On the other hand, the passive approach is based on propagating the effect of the uncertainty to the residuals and then using adaptive thresholds (Horak, 1988)(Puig, 2002). In this paper, the passive approach based on adaptive thresholds using a model with uncertain parameters bounded in intervals, also known as an "***interval model***", will be presented in the context of observer methodology, deriving their corresponding interval version (Puig, 2003b). Moreover, some non-linearities present in the real system will be included in the structure of the model in order to improve the accuracy of the predicted behaviours. This will lead to the design of non-linear ***interval observers*** that have been already proposed for robust fault detection in Stancu (2003). In this paper, the integration of such algorithms with existent fault isolation algorithms will be presented. Finally, a fault isolation case study based on the industrial actuator used as FDI benchmark in the European project DAMADICS will be used to show the effectiveness of the fault isolation capabilities of the proposed approach.

2. ROBUST FAULT DETECTION USING NON-LINEAR INTERVAL OBSERVERS

2.1 Adaptive thresholding

The problem of adaptive threshold generation in discrete time-domain using non-linear interval observers with a Luenberger-like structure can be formulated mathematically as follows: at every time-instant an interval for the predicted output $\left[\underline{\hat{y}}(k),\overline{\hat{y}}(k)\right]$ (or alternatively, for the residual) should be computed subject to:

$$\begin{aligned}\hat{\boldsymbol{x}}(k+1) &= \boldsymbol{g}(\hat{\boldsymbol{x}}(k),\boldsymbol{u}(k),\boldsymbol{\theta}) + \boldsymbol{K}(\boldsymbol{y}(k)-\hat{\boldsymbol{y}}(k)) \\ \hat{\boldsymbol{y}}(k) &= \boldsymbol{h}(\hat{\boldsymbol{x}}(k),\boldsymbol{u}(k),\boldsymbol{\theta})\end{aligned} \qquad (1)$$

where: $\hat{\boldsymbol{x}} \in \Re^{nx}$ and $\hat{\boldsymbol{y}} \in \Re^{ny}$ are estimated state and output vectors of dimension nx and ny respectively; $\boldsymbol{g}$ and $\boldsymbol{h}$ are the state space and measurement non-linear function ; $\boldsymbol{\theta}$ is the vector of uncertain parameters of dimension p with their values bounded by a compact set $\boldsymbol{\theta} \in \boldsymbol{\Theta}$ of box type, i.e., $\boldsymbol{\Theta} = \{\boldsymbol{\theta} \in \Re^p \mid \underline{\boldsymbol{\theta}} \le \boldsymbol{\theta} \le \overline{\boldsymbol{\theta}}\}$ and $\boldsymbol{K}$ is the gain of the observer designed to guarantee observer stability for all $\boldsymbol{\theta} \in \boldsymbol{\Theta}$. In case that

$$\boldsymbol{y}(k) \in \left[\underline{\hat{\boldsymbol{y}}}(k),\overline{\hat{\boldsymbol{y}}}(k)\right] \qquad (2)$$

holds no fault can be indicated. Otherwise, a fault should be indicated. Fault detection test (2) is equivalent to checking if $0 \in [\boldsymbol{r}(k)] = \boldsymbol{y}(k) - [\hat{\boldsymbol{y}}(k)]$.

2.2 Interval observation as an interval simulation

In order to determine $\left[\underline{\hat{\boldsymbol{y}}}(k),\overline{\hat{\boldsymbol{y}}}(k)\right]$, observer equation (1) can be reorganised as a system with one output and two inputs, according to

$$\begin{aligned}\hat{\boldsymbol{x}}(k+1) &= \boldsymbol{g}_o(\hat{\boldsymbol{x}}(k),\boldsymbol{u}_o(k),\boldsymbol{\theta}) \\ \hat{\boldsymbol{y}}(k) &= \boldsymbol{h}(\hat{\boldsymbol{x}}(k),\boldsymbol{u}(k),\boldsymbol{\theta})\end{aligned} \qquad (3)$$

where: $\boldsymbol{u}_o(k) = [\boldsymbol{u}(k) \quad \boldsymbol{y}(k)]^t$. Then, interval observation can be formulated as an ***interval simulation***. Existent algorithms can be classified according to if they compute the output interval using (Puig, 2005): one step-ahead iteration based on previous approximations of the set of estimated states (***region based approaches***) or a set of punctual trajectories generated by selecting particular values of $\boldsymbol{\theta} \in \boldsymbol{\Theta}$ using heuristics or optimisation (***trajectory based approaches***). The first approach assumes implicitly that the uncertain parameters are time-varying. In this paper the second approach is followed since uncertain parameters are considered time-invariant.

3. NON-LINEAR INTERVAL OBSERVATION ALGORITHM

In order to preserve uncertain parameter time-invariance, a functional relation between states and parameters at any time instant k that will relate initial and present state is derived. This is possible through formulating an optimisation problem that considers all the transitions from the initial to the present state as it is usually done in formulating an optimal control problem. Using this idea the following algorithm is proposed (Stancu, 2003):

Algorithm 1. *Let* $\boldsymbol{y} = \{\boldsymbol{y}(0),\boldsymbol{y}(1),\boldsymbol{y}(2),...\boldsymbol{y}(k-1)\}$ *be a measurement trajectory of system (1) and assuming that the uncertainty on the initial state is such that* $\boldsymbol{x}(0) \in \boldsymbol{X}_0$. *At each time step compute* $\square\hat{\boldsymbol{X}}(k) = \left[\underline{\hat{\boldsymbol{x}}}(k),\overline{\hat{\boldsymbol{x}}}(k)\right]$, *solving the following optimisation problem to determine* $\underline{\hat{\boldsymbol{x}}}(k)$:

$$\begin{aligned}&\underline{\hat{\boldsymbol{x}}}(k) = \min\ (globally)\ \hat{\boldsymbol{x}}(k) \\ &\text{subject to :} \\ &\hat{\boldsymbol{x}}(k) = \boldsymbol{g}_0(\hat{\boldsymbol{x}}(k-1),\boldsymbol{u}_0(k-1),\boldsymbol{\theta}) \\ &\ldots \\ &\hat{\boldsymbol{x}}(1) = \boldsymbol{g}_0(\hat{\boldsymbol{x}}(0),\boldsymbol{u}_0(0),\boldsymbol{\theta}) \\ &\hat{\boldsymbol{x}}(j) \in \left[\underline{\hat{\boldsymbol{x}}}(j),\overline{\hat{\boldsymbol{x}}}(j)\right] \quad for \quad j = 0,...,k \\ &\boldsymbol{\theta} \in \left[\underline{\boldsymbol{\theta}},\overline{\boldsymbol{\theta}}\right]\end{aligned} \qquad (4)$$

where: $\boldsymbol{g}_0(\hat{\boldsymbol{x}}(k),\boldsymbol{u}_0(k),\boldsymbol{\theta})$ *is the state space observer function and* $\boldsymbol{u}_o(k) = [\boldsymbol{u}(k) \quad \boldsymbol{y}(k)]^t$ *is the observer input*

And solving again the previous optimisation problem substituting min by max to determine $\overline{\hat{\boldsymbol{x}}}(k)$.

The wrapping effect is avoided since uncertainty is not propagated from step to step but instead always from the initial state. This approach yields the accurate time-invariant interval observation without any conservatism, assuming that the previous optimisation problems could be solved with infinite precision and the global optimum could be determined (Puig, 2003b). However, in practice it only could be solved with a given precision. On the other hand, one of the main drawbacks of this approach is the high computational complexity of the optimisation algorithm since at every iteration an additional restriction is added. So, the amount of computation needed is increasing with time being impossible to operate over a large time interval. The length increase problem in the previous approach can be solved if the observer is asymptotically stable, as it is presented in Stancu (2003). In this case, any transients in the observer settle to negligible values in a finite-time. Therefore, for any time k, it is possible to approximate (6) using a sliding window, starting at time k-L and ending at k, where L is the length of this window. Of course, the parameter time-invariance is only guaranteed inside the sliding window. This is why this approach is referred as ***almost time-invariant***. Finally, if the observer satisfies the isotony property (Gouzé, 2002), the solution of the optimisation problems is located in the vertices of the uncertain initial state and parameter space

4. FAULT ISOLATION USING A BANK OF INTERVAL OBSERVERS

While a single interval observer (residual) is sufficient to detect faults, a bank (or a vector) of interval observers (residuals) are required for fault isolation. Given a set of residuals $\boldsymbol{r(k)} = [r_1(k), \cdots, r_n(k)]$, the ***theoretical fault signature matrix***, *FSM*, can be defined binary codifying the presence or not of a variable in every residual. This matrix has as many rows as residuals and as many columns as variables appearing in the residuals. The element FSM_{ij} of this matrix is equal to 1 if its j^{th} variable appears in the expression of the i^{th} residual, otherwise is equal to 0. This matrix provides the theoretical influence of faults on the residuals in the following way: the j^{th} column can be associated to fault in the j^{th} variable. If multiple faults are considered then number of columns of signature fault matrix has to be expanded up to all possible combinations that are considered. For each residual derived from the corresponding model, a decision procedure should be implemented in order to check the mismatch between the corresponding model and the real observations, using the fault detection procedure described in *Section 2*. The result of these tests applied to the whole set of models will be the ***experimental*** or ***actual fault signature*** of the system: $\boldsymbol{s(k)} = [s_1(k), \cdots, s_n(k)]$. Then, fault isolation will consist in looking for the theoretical fault signature in fault signature matrix that matches with the experimental signature. However, in practice to make more robust this fault selecting the theoretical fault signature with the least distance from the actual fault signature refines isolation process. This fault vector will indicate the actual fault signature distance to every theoretical fault signature allowing to isolate faults (Fig. 1).

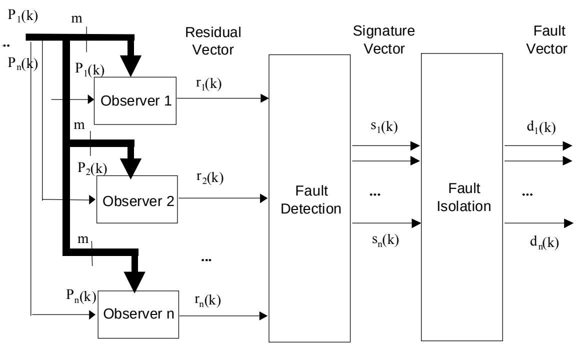

Fig. 1. Fault detection and isolation using a bank of interval observers

5. THE DAMADICS BENCHMARK ISOLATION CASE STUDY

The application example to test the interval observer approach to robust fault isolation, deals with an industrial smart actuator consisting of a flow servo-valve driven by a smart positioner, proposed as an FDI benchmark in the European DAMADICS project. The smart actuator consists of a control valve, a pneumatic servomotor and a smart positioner (Bartys, 2003). The DAMADICS smart actuator can be decoupled in seven components, described by their corresponding elementary relations, listed in Table 1.

Table 1. List of components of DAMADICS servo-actuator

Component	Elementary Relation
Pneumatic Servomotor	$X = e_1(P_s, F_{vc})$ $F_{vc} = e_2(X, P_1, P_2, T_1)$
Control Valve	$F_v = e_3(X, P_1, P_2, T_1)$
Position Controller	$CVP = e_4(SP, PV)$
Electro-Pneumatic Transducer	$P_s = e_5(X, CVP, P_z)$
Positioner Transducer	$PV = e_6(X)$
Chamber Pressure Transducer	$P_{sm} = e_7(P_s)$
Flow Transducer	$F_{vm} = e_8(F_v)$

Considering the following measured variables: rod displacement (X), servomotor chamber pressure (P_s), inlet valve pressure (P_1), outlet valve pressure (P_2), fluid flow controlled by the valve (F_v) and controller output (CVP) and using structural analysis (Staroswiecki, 2001) four analytical redundancy relations can be obtained:

$$\begin{aligned} &r_1(X_m, P_{sm}) = 0 \\ &r_2(P_{sm}, X_m, CVP) = 0 \\ &r_3(P_1, P_2, F_{vm}) = 0 \\ &r_4(CVP, SP, X_m) = 0 \end{aligned} \qquad (5)$$

The parameters and their intervals of uncertainty of such relations are obtained using a set-membership parameter estimation approach similar to that proposed by Ploix (1999), that guarantees that data from free fault scenarios are covered by the interval model.

5.1 Dynamic redundancy relations: bank of interval observers

Analytical redundancy relations r_1 and r_2 are dynamic relations that will be evaluated through two reduced observers: one for the rod displacement and the other for the servomotor chamber pressure, that correct partially (through observer gain) the estimation using measurements. This implies that estimation will also be affected by the fault.

5.1.1 Analytical redundancy relation r_1

Analytical redundancy relation r_1 is derived using a reduced observer for the rod displacement and can be formulated as

$$\begin{aligned} \hat{x}_1(k+1) &= \hat{x}_1(k) + \Delta t \hat{x}_2(k) \\ &\quad + K_x(x_m(k) - \hat{x}_1(k)) \\ \hat{x}_2(k+1) &= -a_{21}\Delta t\, \hat{x}_1(k) + (1-\Delta t\, a_{22})\hat{x}_2(k) \\ &\quad + \frac{A_e}{m}\Delta t\, P_{sm}(k) + 1580\, \Delta t \\ r_1(k) &= x_m(k) - \hat{x}_1(k) \end{aligned} \tag{6}$$

where: $x_1 = X$ (the rod displacement), $x_2 = \frac{dX}{dt}$ (the rod velocity), K_x is the displacement observer gain, x_m is the rod displacement measurement and Δt is the sampling time being equal to 1 s.

5.1.2 Analytical redundancy relation r_2

Analytical redundancy relation r_2 is derived a reduced observer for the chamber pressure can be formulated as

$$\begin{aligned} \hat{x}_3(k+1) &= \hat{x}_3(k) - A_e \Delta t\, \dot{x}_m(k) \frac{\hat{x}_3(k) + P_a}{V_0 + A_e x_m(k)} \\ &\quad + \frac{\hat{x}_4(k+1) - \hat{x}_4(k)}{\hat{x}_4(k)}(\hat{x}_3(k) + P_a) \\ &\quad + K_{Ps}(P_{sm}(k) - \hat{x}_3(k)) \\ \hat{x}_4(k+1) &= \hat{x}_4(k) \\ &\quad + \Delta t\, k_1 CVP(k)\sqrt{P_z - \hat{x}_3(k)}\, f_{p1} \\ &\quad + \Delta t\, k_1 CVP(k)\sqrt{\hat{x}_3(k)}\, f_{p2} \\ r_2(k) &= P_{sm}(k) - \hat{x}_3(k) \end{aligned} \tag{7}$$

where: $x_3 = P_s$ (the pressure in the servomotor's chamber) and $x_4 = m_a$ (the air mass) K_{Ps} is the observer gain and P_{sm} is the chamber pressure measurement coming from the sensors.

5.2 Static analytical interval redundancy relations

Two additional static residuals (r_3 and r_4) can be generated from fluid mass flow and controller output equations.

5.2.1 Analytical redundancy relation r_3

Analytical redundancy relation r_3 is derived using - fluid mass flow:

$$r_3(k) = P_{2m} - P_{1m} - \frac{\rho_f}{10000}\left(\frac{F_{vm}}{K_v(x_m)}\right)^2 \tag{8}$$

where: P_{1m} is the measurement of the inlet pressure, P_{2m} is the measurement of the outlet pressure and F_{vm} is the measurement of the fluid mass flow

5.2.2 Analytical redundancy relation r_4

Analytical redundancy relation r_4 is derived using controller output:

$$\begin{aligned} r_4(k) &= CVP(k) - K_p(SP(k) \\ &\quad -(\frac{1}{2} + \frac{3}{\pi} arcsin(\frac{x_m(k)}{0.0381} - \frac{1}{2}))) \end{aligned} \tag{9}$$

where: CVP is the measurement of the output of the controller, SP is the set-point and x_m is the measurement of the rod displacement.

5.4 Theoretical fault signature matrix

Considering residuals generated by interval observers (6) and (7), and by the static analytical redundancy relations (8) and (9) the theoretical fault signature matrix presented in Table 2 considering the 19 faults defined in the benchmark can be deduced. Looking at Table 2, it can be noticed that with the considered models and measurements not all fault could be isolated or even detected. For example, f_7, f_{18}, f_{12} and f_{19} will not be detected and f_2 can not be isolated from f_3, among other.

5.5 Isolation results

Four fault scenarios are considered: a servomotor's diaphragm perforation (f_{10}), unexpected pressure change across valve (f_{17}), pressure sensor fault (f_{14}) and positioner supply pressure drop (f_{16}). Looking at Table 2, fault f_{10} and f_{14} present the same fault signature f_1 and f_4 . So, in practice they could not be isolated. Fault f_{16} presents the same fault signature with the considered residuals than f_9. And, finally, fault f_{17} can be isolated since it presents a unique fault signature. In the following fault scenarios only those residuals that are affected by the corresponding fault will be presented because of the lack of space.

5.5.1 Fault f_{10} (servomotor's diaphragm perforation)

From theoretical fault signature matrix presented in Table 2, fault f_{10} should only affect residual r_1 and r_2. Fault f_{10} is introduced at time instant 150 s. From Figure 2 and 3, it can be observed that this fault is detected by residuals r_1 and r_2. However, residual r_1 is not as persistent as residual r_2 since it only indicates the fault presence between 150 and 170 s. So, fault f_{10} only could be isolated in this time interval.

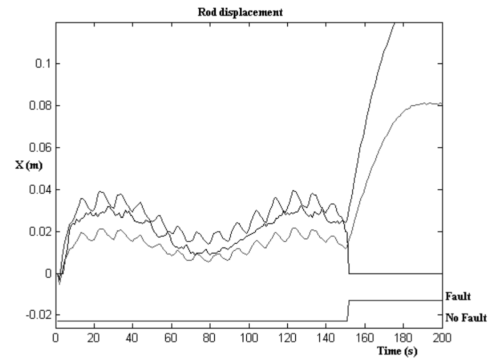

Fig.2 Residual r_1 evaluation under fault f_{10}

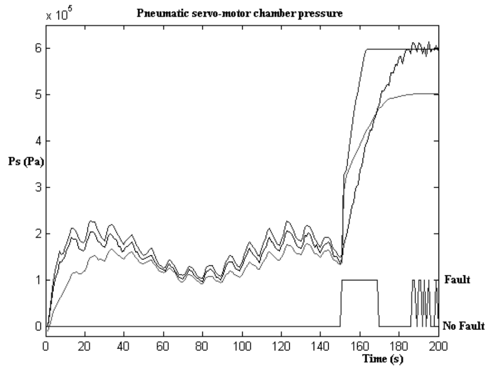

Fig. 3 Residual r_2 evaluation under fault f_{10}

5.5.2 Fault f_{17} (unexpected pressure change across valve)

Fault f_{17} should only affect residuals r_1, r_2 and r_3 according to theoretical fault signature matrix presented in Table 2. It is introduced at time instant 150 s. From Figure 4, 5 and 6, it can be observed that this fault is detected by residuals r_1, r_2 and r_3. However, residual r_2 is not as persistent as residuals r_2 and r_3 since it only indicate the fault presence between 150 and 180 s. Therefore, fault f_{17} only could be isolated in this time interval.

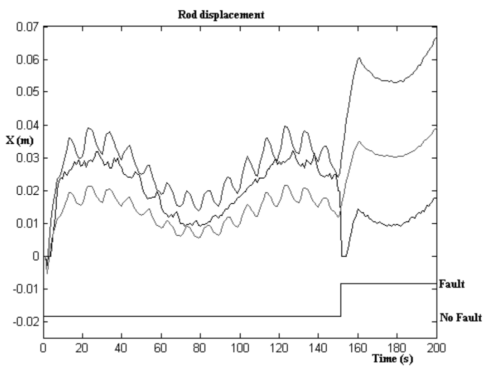

Fig.4 Residual r_1 evaluation under fault f_{17}

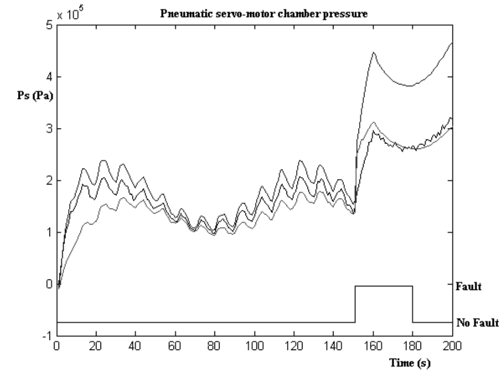

Fig.5 Residual r_2 evaluation under fault f_{17}

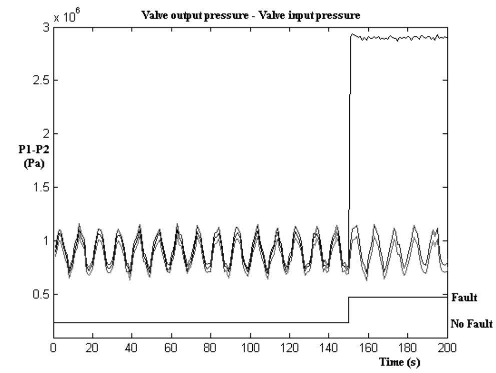

Fig.6 Residual r_3 evaluation under fault f_{17}

5.5.3 Fault f_{14} (pressure sensor fault)

Fault f_{14} should only affect residuals r_1 and r_2 according to theoretical fault signature matrix presented in Table 2. Fault f_{14} is introduced at time instant 150 s. From Figure 7 and 8, it can be observed that this fault is clearly detected by residuals r_1 and r_2. As conclusion, fault f_{14} only could be isolated.

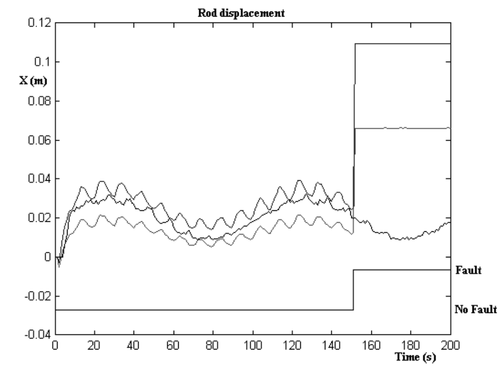

Fig.7 Residual r_1 evaluation under fault f_{14}

5.5.4 Fault f_{16} (Positioner supply pressure drop)

Finally, fault f_{16} should affect only residuals r_2 according to theoretical fault signature matrix presented in Table 2. Residuals r_1, r_3 and r_4 do not detect the fault and for the lack of space are not included. Fault f_{16} is introduced at time instant 150 s. From Figure 9, it can be observed that is detected by residual r_2. So fault f_{16} only could be isolated.

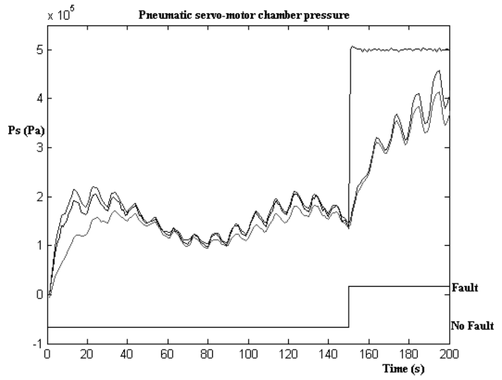

Fig.8 Residual r_2 evaluation under fault f_{14}

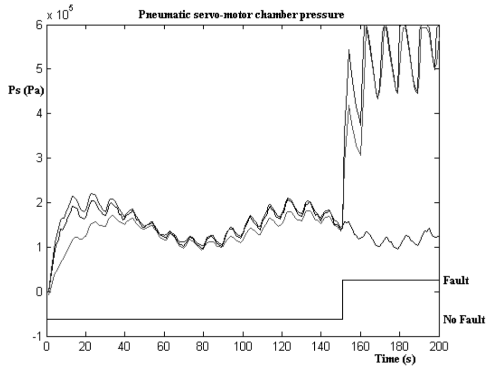

Fig.9 Residual r_2 evaluation under fault f_{16}

6. CONCLUSIONS

In this paper, non-linear interval observers have been presented as an approach to passive robust fault detection and isolation when the monitored process is modelled using a non-linear interval model. Interval observation has been translated to a couple of optimisation problem that provide the interval for the observed output (one for the maximum and another one for the minimum). Then, the detection test consists in checking if the measured output is or not inside this interval. A bank of such of observers is necessary with a given fault signature matrix in order to isolate faults. Interval observers have been applied to detect and isolate some of the faults proposed in the DAMADICS benchmark providing good results.

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Table 2. Fault signature matrix

	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}	f_{12}	f_{13}	f_{14}	f_{15}	f_{16}	f_{17}	f_{18}	f_{19}
r_1	1	1	1	1	0	1	0	1	0	1	1	0	1	1	1	0	1	0	0
r_2	1	1	1	1	0	0	0	1	1	1	0	0	1	1	1	1	1	0	0
r_3	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	1	0	0
r_4	0	1	1	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0