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PASSIVE ROBUST FAULT DETECTION APPROACHES USING INTERVAL MODELS

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Abstract: The problem of robustness in fault detection has been treated basically using two kinds of approaches: actives and passives. Most of the literature in robust fault detection is focused on the problem of active approach based on decoupling the effects of the uncertainty from the effects of the faults on the residual. On the other hand, the passive approach is based of propagating the effect of the uncertainty on the residuals and then using adaptive thresholds. In this paper, the passive approach based on adaptive thresholds produced using a model with uncertain parameters bounded in intervals, also known as an "*interval model*", will be presented in the context of parity equations and observers methodologies, deriving their corresponding interval versions. Finally, an example based on an industrial actuator used as a FDI benchmark in the European project DAMADICS will be used for testing and comparing the proposed approaches. *Copyright © 2002 IFAC*

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

1. INTRODUCTION

Model-based fault detection is based on the use of mathematical models of the monitored system. The better the model used to represent the dynamic behaviour of the system, the better will be the chance of improving the reliability and performance in detecting faults. However, modelling errors and disturbances in complex engineering systems are inevitable, and hence there is a need to develop robust fault detection algorithms. The ***robustness*** of a fault detection system means that it must be only sensitive to faults, even in the presence of model-reality differences (Chen,1999). One of the approaches to robustness is based on generating residuals which are insensitive to uncertainty, while at the same time sensitive to faults. This approach is known as ***active*** and it has been extensively developed these last years for several researchers using different techniques: unknown input observers, robust parity equations, H_∞, etc. In the book of Chen and Patton (1999) there is an excellent survey of the active approach. On the other hand, there is a second approach, called ***passive***, that enhances the robustness of the fault detection system at the decision-making stage, mainly using an adaptive threshold.

According to Gertler (1998), there is no algorithm which is robust under arbitrary model error conditions. To design an algorithm for robustness, some rather detailed information is necessary about the nature of errors and uncertainties, and such information is seldom available. But even if it is, what can be achieved is rather limited. Generally ***perfect decoupling*** of the residuals from uncertainties it is only possible in a limited number of model parameters. Uncertainty can be located in the parameters (***structured*** or ***parametric***) or in the structure of the model (***unstructured***). For the case of structured uncertainty with unlimited number of uncertain parameters, passive robustness based on using models with parameter values bounded in intervals, also known as "***interval models***", will be very suitable as it will be shown. These models can be obtained using identification techniques that provides the nominal value and the confidence interval for every parameter. Actually, several research groups actually are following this approach, also known, as the ***bounding-approach***, because of the use of bounds to describe the uncertainty. To the best of our knowledge these groups are at University of Girona (Spain) (Armengol,2000), at LAAS-Toulouse (France) (Travé,1997), at Technical University of Catalonia (Spain) (Puig,1999) (Puig,2000) (Escobet,2001) and at CRAN-Nancy (France) (Adrot,2000) (Ploix,2000). Interval models have aslo been applied successfully in fault diagnosis of gas turbines in European ESPRIT projects: TIGER and SHEBA (Travé,1997) (Escobet,2001).

2. ROBUST FAULT DETECTION

Considering a MIMO linear dynamic system in discrete-time, the nominal input-output relationship, without faults, disturbances and noise will be

$$\boldsymbol{y}(k) = \boldsymbol{M}(z)\boldsymbol{u}(k) = \frac{\boldsymbol{G}(z)}{\boldsymbol{H}(z)}\boldsymbol{u}(k) \qquad (1)$$

2.1 Faults, Disturbances and Modelling Errors

Introducing now ***additive*** disturbances $\boldsymbol{q}(k)$, noises $\boldsymbol{v}(k)$ and faults $\boldsymbol{p}(k)$, the input-output relationship (1) can be rewritten as

$$\begin{aligned}\boldsymbol{y}(k) &= \boldsymbol{M}(z)\boldsymbol{u}(k) + \boldsymbol{S_F}(z)\boldsymbol{p}(k) + \\ &\boldsymbol{S_D}(z)\boldsymbol{q}(k) + \boldsymbol{S_N}(z)\boldsymbol{v}(k)\end{aligned} \qquad (2)$$

where: $\boldsymbol{S_F}(z)$ is the combined fault transfer function, $\boldsymbol{S_D}(z)$ is the combined disturbance transfer function and $\boldsymbol{S_N}(z)$ is the combined noise transfer function.

Denoting the actual transfer function of the physical system, $\boldsymbol{M}^o(z)$, then

$$\begin{aligned}\boldsymbol{y}(k) &= \boldsymbol{M}^o(z)\boldsymbol{u}(k) \\ &= \boldsymbol{M}(z)\boldsymbol{u}(k) + \Delta\boldsymbol{M}(z)\boldsymbol{u}(k)\end{aligned} \qquad (3)$$

where: $\Delta\boldsymbol{M}(z)$ is the discrepancy between the model and the true system. It represents two conceptually different situations: a ***parametric (or multiplicative) fault*** and a ***modelling error***. The ***underlying parameters approximation*** allows the appropriate decomposition between parametric faults and modelling errors (***multiplicative disturbances***) (Gertler,1998):

$$\begin{aligned}\Delta\boldsymbol{M}(z)\boldsymbol{u}(k) &= \Delta\boldsymbol{M}_F(z)\boldsymbol{u}(k) + \Delta\boldsymbol{M}_D(z)\boldsymbol{u}(k) \\ &= \boldsymbol{N}_F(z)\Delta\boldsymbol{\theta}_F + \boldsymbol{N}_D(z)\Delta\boldsymbol{\theta}_D\end{aligned} \qquad (4)$$

where: $\Delta\theta_F$ is a parametric fault and $\Delta\theta_D$ is a parametric modelling error. Then, the input-output relationship (2) can be rewritten as

$$\begin{aligned}&\boldsymbol{y}(k) = \boldsymbol{M}(z)\boldsymbol{u}(k) + \boldsymbol{S}_F(z)\boldsymbol{p}(k) \\ &+ \boldsymbol{N}_F(k)\Delta\boldsymbol{\theta}_F + \boldsymbol{S}_D(z)\boldsymbol{q}(k) \\ &+ \boldsymbol{N}_D(k)\Delta\boldsymbol{\theta}_D + \boldsymbol{S}_N(z)\boldsymbol{v}(k)\end{aligned} \qquad (5)$$

2.2 Residual generation

The generic form of a ***residual generator*** is

$$\boldsymbol{r}(k) = \boldsymbol{V}(z)\boldsymbol{u}(k) + \boldsymbol{W}(z)\boldsymbol{y}(k) \qquad (6)$$

where: $\boldsymbol{r}(k)$ is the vector of residuals, $\boldsymbol{V}(z)$ and $\boldsymbol{W}(z)$ are transfer functions. However, (6) is not necessarily a residual generator. To be a residual generator to has to return zero when all unknown inputs are zero, that is, when (1) holds. Then,

$$\boldsymbol{r}(k) = \boldsymbol{W}(z)[\boldsymbol{y}(k) - \boldsymbol{M}(z)\boldsymbol{u}(k)] \qquad (7)$$

This form is also known as the ***computational form***. Now, substituting $\boldsymbol{y}(k) - \boldsymbol{M}(z)\boldsymbol{u}(k)$ by (5) yields

$$\begin{aligned}&\boldsymbol{r}(k) = \boldsymbol{W}(z)[\,\boldsymbol{S}_F(z)\boldsymbol{p}(k) + \boldsymbol{N}_F(k)\Delta\boldsymbol{\theta}_F \\ &+ \boldsymbol{S}_D(z)\boldsymbol{q}(k) + \boldsymbol{N}_D(k)\Delta\boldsymbol{\theta}_D + \boldsymbol{S}_N(z)\boldsymbol{v}(k)]\end{aligned} \qquad (8)$$

This form is known as the ***internal*** or ***unknown-input-effect*** form of the generic residual generator, showing how the residuals depend on faults, disturbances, modelling errors and noise.

2.3 Robustness Issues

Ideally, the residuals should only be affected by the faults. However, the presence of disturbances, noise and modelling errors causes the residuals to become nonzero and thus interferes with the detection of faults. Therefore, the fault detection procedure must be ***robust*** in the face of these undesired effects. Robustness can be achieved in the residual generation (***active robustness***) or in the decision making stage (***passive robustness***), as it has been introduced in Section 1. The passive approach rest on the fact that the uncertainty caused by model errors depends on the operating conditions. If it may be possible to model this dependence, theoretically or empirically, then the test thresholds could be changed accordingly. Adaptive thresholding techniques were first proposed by Clark (1989), who suggests an empirical relation between the operation point and the corresponding detection threshold. Further approaches are due to Emami-Naemi (1988), who develops a theoretical relation between the operation point, the model uncertainty and the detection threshold. This approach is based in H_∞ techniques and it was further explored by Ding and Frank (1991). Another approach for adaptive threshold generation was proposed by Horak (1988) and it is based on a dynamical optimisation assuming parametric uncertainty.

The passive approach has the advantage over the corresponding active approach that it can achieve robustness in the detection procedure in spite of the number of uncertain parameters in the model, and without using any approximation based on the simplification of the underlying parameter representation (Gertler, 1998). The passive approach based on adaptive thresholding is based not in avoiding the effect of uncertainty in the residual through perfect decoupling, but in propagating the parameter uncertainty to the residual, and then bounding the residual uncertainty using an interval. Then, while the residual

$$\boldsymbol{r}(k) = \boldsymbol{y}(k) - \hat{\boldsymbol{y}}(k) \in \left[\boldsymbol{r}_k^-, \boldsymbol{r}_k^+\right] \quad (9)$$

no fault can be signalled, because the residual value can be due to the parameter uncertainty. Of course, this approach has the drawback that faults producing a residual deviation smaller than the residual uncertainty due to parameter uncertainty will be missed.

3. PASSIVE ROBUSTNESS BASED ON INTERVAL PARITY EQUATIONS

3.1 ARMA interval parity equations

Considering equations (7) and (8) with $\boldsymbol{W}(z)$=1:

$$\begin{aligned}&\boldsymbol{r}(k) = \boldsymbol{y}(k) - \boldsymbol{M}(z)\boldsymbol{u}(k) = \\ &\boldsymbol{S}_F(z)\boldsymbol{p}(k) + \boldsymbol{N}_F(k)\Delta\boldsymbol{\theta}_F + \boldsymbol{S}_D\boldsymbol{q}(k) + \\ &\boldsymbol{N}_D(k)\Delta\boldsymbol{\theta}_D + \boldsymbol{S}_N(z)\boldsymbol{v}(k)\end{aligned} \quad (10)$$

a vector of residuals which are computationally autoregressive-moving average (ARMA) is obtained. This vector is known as ***ARMA parity equations*** or ***residuals***. This approach is also known as the ***simulation approach*** because the state estimation is based only in the inputs and in the model, i.e., it is a open-loop approach.

Considering now ARMA parity equations given by (10), without noise, faults and disturbances, only with modelling errors

$$\begin{aligned}&\boldsymbol{r}(k) = \boldsymbol{y}(k) - \boldsymbol{M}(z)\boldsymbol{u}(k) = \\ &\Delta\boldsymbol{M}(z)\boldsymbol{u}(k) = \boldsymbol{N}_D(k)\Delta\boldsymbol{\theta}_D\end{aligned} \quad (11)$$

Then, while:

$$\left|\boldsymbol{r}(k)\right| < \left|\Delta\boldsymbol{M}(z)\boldsymbol{u}(k)\right| = \left|\boldsymbol{N}_D(k)\Delta\boldsymbol{\theta}_D\right| \quad (12)$$

no fault can be signalled. The evaluation of (12) can be done by performing a ***worst-case simulation*** using the system nominal model $\boldsymbol{M}(z)$ and the modelling errors $\Delta\boldsymbol{M}(z)$. The problem of worst-case simulation has been studied extensively and from different fields of research: ***Qualitative Reasoning***, ***Validated Solution of Differential Equations*** and ***Automatic Control***. Here, the approach proposed by Puig (1999) will be presented for a SISO system. Considering a SISO system model described by a discrete-time transfer function:

$$\hat{y}(k) = \frac{g_1 z^{-1} + ... + g_n z^{-n}}{1 + h_1 z^{-1} + ... + h_m z^{-m}} u(k) \quad (13)$$

with $g_i \in \left[g_i^-, g_i^+\right]$ for i=1,...,n and $h_j \in \left[h_j^-, h_j^+\right]$ for j=1,...,m. Then, using the canonical observer form in state-space of (13), at every time instant k the interval for the predicted measure, $[\hat{\boldsymbol{y}}_k^-, \hat{\boldsymbol{y}}_k^+]$, can be computed solving the following optimisation problems:

$$\hat{y}_k^+ = max\left(\boldsymbol{C}[\boldsymbol{A}^L\boldsymbol{x}_{k-L} + \boldsymbol{A}^{L-1}\boldsymbol{B}\boldsymbol{u}_{k-L} + \cdots + \boldsymbol{B}\boldsymbol{u}_{k-1}]\right)$$

subject to: (14)

$$\boldsymbol{x}_{k-L} \in \left[\boldsymbol{x}_{k-L}^-, \boldsymbol{x}_{k-L}^+\right], \; g_i \in \left[g_i^-, g_i^+\right], \; h_j \in \left[h_j^-, h_j^+\right]$$

with $i=1,...,n$ and $j=1,...,m$. And analogously for $\hat{y}_k^-$ substituting *max* for *min* in (14).

3.2 MA interval parity equations

On the other hand, considering equations (8) and (9) with $\boldsymbol{W}(z)$=1, the following vector of residuals can be obtained:

$$\begin{aligned}&\boldsymbol{r}(k) = \boldsymbol{H}(z)\boldsymbol{y}(k) - \boldsymbol{G}(z)\boldsymbol{u}(k) = \\ &\boldsymbol{H}(z)\left[\boldsymbol{S}_F(z)\boldsymbol{p}(k) + \boldsymbol{N}_F(k)\Delta\boldsymbol{\theta}_F\right. \\ &\left. + \boldsymbol{S}_D\boldsymbol{q}(k) + \boldsymbol{N}_D(k)\Delta\boldsymbol{\theta}_D + \boldsymbol{S}_N(z)\boldsymbol{v}(k)\right]\end{aligned} \quad (15)$$

where it has been used (1). These equations are moving average (MA), so they are called ***MA parity equations*** or ***residuals***. This approach is also known as the ***prediction approach***, and it is a closed-loop approach. It is based on building a simulator in which the previous state estimation are replaced by the measured state.

Considering now MA parity equations given by (19), without noise, faults and disturbances, only with modelling errors

$$\boldsymbol{r}(k) = \boldsymbol{H}(z)\boldsymbol{y}(k) - \boldsymbol{G}(z)\boldsymbol{u}(k) = \Delta\boldsymbol{G}(z)\boldsymbol{u}(k) - \Delta\boldsymbol{H}(z)\boldsymbol{y}(k) \quad (16)$$

Then, while

$$|\boldsymbol{r}(k)| < |\Delta\boldsymbol{G}(z)\boldsymbol{u}(k) - \Delta\boldsymbol{H}(z)\boldsymbol{y}(k)| \quad (17)$$

no fault can be signalled. The evaluation of (17) can be done by performing a ***worst-case prediction*** using the system nominal model, ***G(z)*** and ***H(z)***, and the modelling errors, ***ΔG(z)*** and ***ΔH(z)***. Here, the approach proposed by Puig (2000) will be presented for a SISO system. Then, using (13), (17) can be rewritten as

$$\begin{aligned} &\boldsymbol{r}(k) = \boldsymbol{H}(z)\boldsymbol{y}(k) - \boldsymbol{G}(z)\boldsymbol{u}(k) = \\ &(1 + h_1 z^{-1} + \cdots + h_m z^{-m})y(k) - \\ &(g_1 z^{-1} + \cdots + g_n z^{-n})u(k) \end{aligned} \quad (18)$$

and at every time instant *k*, the interval for the predicted measure, $[\hat{y}_k^-, \hat{y}_k^+]$, can be computed solving the following optimisation problems:

$$\hat{y}_k^+ = max\left(\sum_{i=1}^{n} g_i u(k-i) - \sum_{j=1}^{m} h_j y(k-j)\right) \quad (19)$$

subject to:

$g_i \in \left[g_i^-, g_i^+\right]$ and $h_j \in \left[h_j^-, h_j^+\right]$ with *i=1,...,n* and with *j=1,...,m*. And analogously for $\hat{y}_k^-$ substituting *max* for *min* in (19).

4. PASSIVE ROBUSTNESS BASED ON INTERVAL OBSERVERS

The ARMA parity equations are based on the simulation of the system behaviour. Then, the residual is generated by comparing the simulated behaviour with the real behaviour, expecting to be zero in the absence of noise and faults. However, in general this is not true, due to the actual system and its simulated behaviour are not initialised identically and due to the unmodeled dynamics. It is generally possible to force the convergence of the simulator adding a proportional feedback to the simulator equations, building an observer. This approach is known as the ***observer (or estimation) approach***, and it is a closed-loop approach.

Considering now the observer equation, without noise, faults and disturbances, only with modelling errors:

$$\begin{aligned} &\hat{\boldsymbol{x}}_{k+1} = \boldsymbol{A}(\boldsymbol{\theta})\hat{\boldsymbol{x}}_k + \boldsymbol{B}(\boldsymbol{\theta})\boldsymbol{u}_k + \boldsymbol{K}(\boldsymbol{y}_k - \hat{\boldsymbol{y}}_k) \\ &\hat{\boldsymbol{y}}_k = \boldsymbol{C}(\boldsymbol{\theta})\hat{\boldsymbol{x}}_k \\ &\boldsymbol{\theta} \in \boldsymbol{\Theta} \end{aligned} \quad (20)$$

where: $\boldsymbol{K}$ is the observer gain and it has been designed for the nominal case guaranteeing acceptable performance for all $\boldsymbol{\theta} \in \boldsymbol{\Theta}$. Then, the evaluation of the interval for estimated measurements: $[\hat{\boldsymbol{y}}_k^-, \hat{\boldsymbol{y}}_k^+]$ in order to evaluate the interval for residuals: $[\boldsymbol{r}_k^-, \boldsymbol{r}_k^+]$ can be done by means fo a ***worst-case estimation***. Worst-case estimation can be formulated as a worst-case simulation. Using (20), as the expression of the estimator model, it can be reorganised as:

$$\hat{\boldsymbol{x}}_{k+1} = \boldsymbol{A}_o\hat{\boldsymbol{x}}_k + \boldsymbol{B}_o\boldsymbol{u}_k^o \quad (21)$$

where: $\boldsymbol{A}_o = \boldsymbol{A} - \boldsymbol{KC}$, $\boldsymbol{B}_o = [\boldsymbol{B} \quad \boldsymbol{K}]$ and $\boldsymbol{u}_k^o = [\boldsymbol{u}_k \quad \boldsymbol{y}_k]^t$. Then using (21), the problem of worst-case estimation, i.e., the problem of determining $\left[\hat{\boldsymbol{x}}_k^-, \hat{\boldsymbol{x}}_k^+\right]$ can be solved with the same algorithm used for worst-case simulation presented in (14).

5. COMPARING THE DIFFERENT INTERVAL BASED APPROACHES

Once the different interval based approaches have been presented they will be compared qualitatively.

5.1 Computational complexity

When extending simulation and estimation approaches to the interval case, two new problems appear: the problem of propagation of uncertainty (***wrapping effect***) (Moore,1966) and the problem of range evaluation of a interval function (***global optimisation***) (Hansen,1992). The first problem is related to the use of a crude approximation (a box) for the real state space region. It can be avoided completely referring all computations to the initial state or in an approximate way using a sliding window (Puig,1999). The second problem can be viewed as a global optimisation problem that could be solved with rigorous global search algorithms (Puig,1999). On the other hand, the extension of prediction approach to the interval case is not affected by the wrapping effect due to it do not use previous state estimations. Moreover, in this case the associate optimisation problem is linear being possible to be solved using linear programming (i.e., the simplex algorithm). As a conclusion, prediction approach is the less computationally complex, while the two other approaches have a similar computational complexity.

5.2 Sensitivity to model errors and initial conditions

The simulation approach is very sensitive to the unmodeled dynamics and the usually unknown initial conditions because no correction with measures is added, tending to diverge very easily. The two other approaches avoid this problem because of the use of measures to correct the prediction or estimation.

5.3 Sensitivity to faults

On the other hand, the simulation approach is the most persistently sensitive to faults in the sense that when a fault appears it signals its existence constantly, although it is very conservative (thick envelopes due to no correction with measures is introduced). On the other hand, the two other approaches are less conservative (tighter envelopes thanks to the correction with measures) and very sensitive to faults when they appear, but also tend to follow the faulty system, especially if the fault is in the sensor used to correct the prediction/estimation. When prediction or estimation approach is used a bank of observers (Frank,1988) or a set of structured residuals (Gertler,1998) must be used to decouple the faults in the sensor used to correct the estimation/prediction from the plant faults.

5.4 Sensitivity to noise

The prediction approach because substitutes the estimation of the state by its measure is very sensitive to noise. The observation approach is less sensitive because the correction of the estimated state is partial and controlled by the observer gain. Finally, the simulation approach is the most insensitive of the three approaches to the noise effect because no correction of the estimated state is introduced. To deal with the noise, they should be complemented with approaches based on statistical tests, as in the case of the classical fault detection methodologies based on numbers instead of intervals (Basseville, 1993).

6. APPLICATION EXAMPLE

The application example, proposed in this paper, to test in simulation the different proposed approaches to robust fault detection, deals with an industrial smart actuator consisting of a flow servovalve driven by a smart positioner, intended to be used as a FDI benchmark in the context on the European DAMADICS project. The smart actuator consists of a control valve, a pneumatic servomotor and a smart positioner (Fig. 1). Using identification techniques based on least-squares, a discrete-time model for booster, E/P transducer, servomotor and displacement transducer has been obtained. Using physical modelling, the following structure for the model has been derived:

$$G(z)=\frac{X(z)}{U(z)}=\frac{b_1 z^2+b_2 z+b_3}{z^3+a_1 z^2+a_2 z+a_3} \qquad (22)$$

where: X(z) is the position of the valve measured by the displacement transducer (in volts), U(z) is the output of the PID controller (in volts).

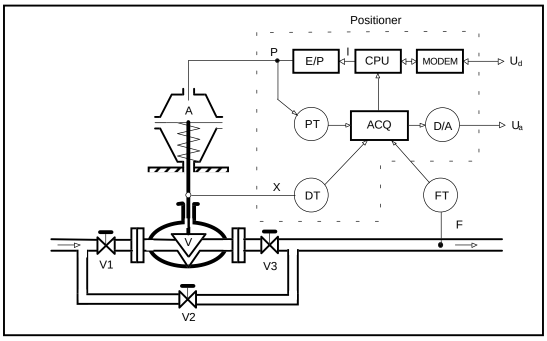

Fig. 1 DAMADICS smart actuator

Using the model (22) with parameters in their corresponding 99% confidence intervals, the corresponding worst-case simulation, prediction and estimation (observer gain K=[0.5,0.05]) of the smart positioner when operating in closed loop (Fig. 1) when applying a step set-point of 0.0095m under normal operation conditions (without fault) until k=150 are presented in Fig. 2, Fig. 3 and Fig. 4, respectively. At k=150, an abrupt additive fault of size 0.0025 (sensor bias) appears in the displacement sensor. It can be observed some of the properties of the approaches proposed in this paper: the prediction (Fig. 3) and the observation approach (Fig. 4) detect the fault when it appears, but after some samples due to these approaches use the faulty sensor to correct the prediction/observation, they tend to follow it and after some samples disappears the fault indication. On the other hand, the approach based on simulation (Fig.2) because it does not use the sensor measurement, once the fault appears, it is indicated permanently. It also can be observed that the tighter confidence intervals for the predicted normal behaviour are the ones produced by prediction/observation while the ones produced by simulation are very wide due to in the first two approaches sensor measurements are used to correct the predicted behaviour.

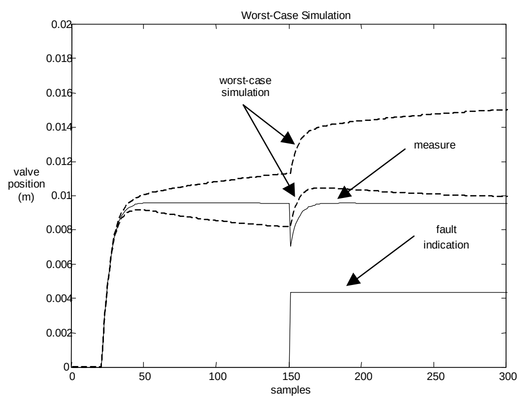

Fig. 2 Fault detection using ARMA interval parity equations (worst-case simulation)

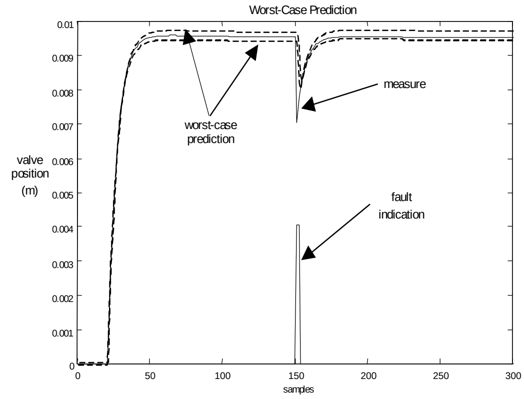

Fig. 3 Fault detection using MA interval parity equations (worst-case prediction)

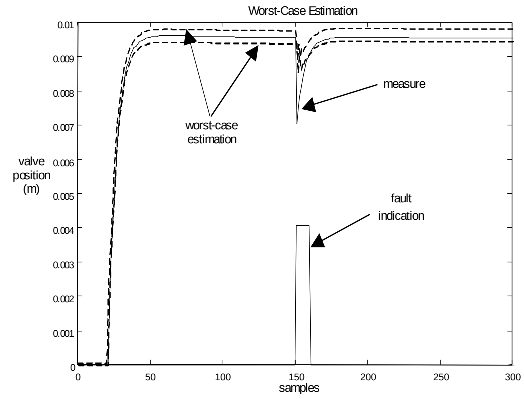

Fig. 4 Fault detection using interval observers (worst-case estimation)

7. CONCLUSIONS

In this paper, two approaches to passive robust fault detection have been presented: interval parity equations and interval observers. After presenting how faults, disturbances and modelling error affect the residuals, classical approaches to fault detection based on parity equations and observers have been adapted in the case of parameter structured uncertainties in the model, and more specifically, in the case of using interval models. Once presented the different approaches, they are compared presenting their benefits and drawbacks. Finally, the proposed methods for passive robust fault detection have been tested and compared using an industrial actuator used as FDI benchmark in the European project DAMADICS.

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