A FUZZY PARAMETRIC APPROACH FOR THE MODEL-BASED DIAGNOSIS

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Abstract: This paper presents a new approach for the model-based diagnosis. The model is based on an adaptation with a variable forgetting factor. The variation of this factor is managed thanks to fuzzy logic. Thus, we propose a design method of a diagnosis system for the sensors defaults. In this study, the adaptive model is developed theoretically for the Multiple-Input Multiple-Output (MIMO) systems. We present the design stages of the fuzzy adaptive model and we give details of the Fault Detection and Isolation (FDI) principle. This approach is validated with a benchmark: a hydraulic process with three tanks. Different defaults (sensors) are simulated with the fuzzy adaptive model and the fuzzy approach for the diagnosis is compared with the residues method. The first results obtained are promising and seem applicable to a set of MIMO systems.

1 INTRODUCTION

The automatic control of technical systems requires a fault detection to improve reliability, safety and economy. The diagnosis is the detection, the isolation and the identification of the type as well as the probable cause of a failure using a logical reasoning based on a set of information coming from an inspection, a control or a test (AFNOR, CEI) (Noura, 2002 - Szederkényi, 1998). The model-based diagnosis is largely studied in the literature (Ripoll, 1999 – Maquin, 1997 – Isermann, 1997). These methods are based on parameter estimation, parity equations or state observers. (Ripoll, 1999 - Maquin, 1997 – Isermann, 2005). The goal is to generate the indicators of defaults through the generation of residues (Isermann, 1984).

This paper deals with the problem of the model-based diagnosis by using a parametric estimation method. We particularly focus our study on an approach with an adaptive model. Many methods exist which enable the design of these adaptive models (Ripoll, 1999).

Many works tackle the model-based diagnosis from a fuzzy model of the processes (Querelle et al., 1996 – Kroll, 1996 – Liu et al., 2005 – Evsukoff et al., 2000 – Carrasco et al., 2004).

Sala et al. (Sala et al., 2005) notices that "Higher decision levels in process control also use rule bases for decision support. Supervision, diagnosis and condition monitoring are examples of successful application domains for fuzzy reasoning strategies".

In our work, unlike these approaches, fuzzy logic is used to design the parametric model.

In all cases, for the model-based approaches, the quality of the fault detection and isolation depends on the quality of the model.

It is possible to improve the model identification by implementing an original method based on a parameters adjustment by using a Fuzzy Forgetting Factor (FFF) (Lafont et al., 2005).

The idea, in this study, is to use the variations of the fuzzy forgetting factors for the fault detection and isolation.

Thus, we propose an original method based on a fuzzy adaptation of the parameter adjustments by introducing a fuzzy forgetting factor.

From these factors (one by output), we can generate residues for the fault detection and isolation. A numerical example, with several types of sensors defaults (the bias and the calibration default), is presented to show the performances of this method.

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2 A NEW APPROACH: THE "FUZZY FORGETTING FACTOR" METHOD

In this section, after having presented the classical approach for the on-line identification, we present a new method of adaptation based on the fuzzy forgetting factor variation.

We consider a non-linear and non-stationary systems modeling. Consequently, an on-line adaptation is necessary to obtain a valid model capable of describing the process and allowing to realize an adaptive command (Fink et al., 2000). A common technique for estimating the unknown parameters is the Recursive Least Squares algorithm with forgetting factor (Campi, 1994 – Uhl, 2005 – Trabelsi et al., 2004).

At each moment *k*, we obtain a model, such as:

$$y(k+1) = A(k).y(k) + B(k).u(k) \tag{1}$$

with y the outputs vector and u the command vector,

$$\varphi(k) = (y(k)\, u(k))^T \tag{2}$$

$$\hat{y}(k+1) = \hat{\theta}^T(k).\varphi(k) \tag{3}$$

$$\hat{\theta}(k+1) = \hat{\theta}(k) + m(k+1).P(k).\varphi^T(k).\varepsilon(k+1) \tag{4}$$

$$\varepsilon(k+1) = y(k+1) - \hat{y}(k+1) \tag{5}$$

$$P(k+1) = \frac{1}{\lambda(k)}\left[P(k) - \frac{P(k)\varphi(k)\varphi^T(k)P(k)}{\lambda(k) + \varphi^T(k)P(k)\varphi(k)}\right] \tag{6}$$

with $\hat{\theta}(k)$ the estimated parameters vector (initialized with the least-squares algorithm), $.\varphi(k)$ the regression vector, $\varepsilon(k+1)$ the a-posterior error, $P(k)$ the gain matrix of regular adaptation and $\lambda(k)$ the forgetting factor.

If the process is slightly excited, the gain matrix $P(k)$ increases like an exponential (Slama-Belkhodja and de Fornel, 1985). To avoid this problem, and the drift of parameters, a measure $m(k)$ is introduced as:

$$m(k+1) = 1 \; if \; \left|\frac{u(k+1) - u(k)}{u_{\max}}\right| > S_u \tag{7}$$

$$\text{or } if \; \left|\frac{y(k+1) - \hat{\theta}^T(k).\varphi(k)}{y_n}\right| > S_y \tag{8}$$

$$m(k+1) = 0 \; if \; \left|\frac{u(k+1) - u(k)}{u_{\max}}\right| < S_u \tag{9}$$

$$\text{and } if \; \left|\frac{y(k+1) - \hat{\theta}^T(k).\varphi(k)}{y_n}\right| < S_y \tag{10}$$

with y_n the nominal value of y.

The adaptation is suspended as soon as the input becomes practically constant and/or as soon as the output y reaches a predefined tolerance area from the thresholds S_y and/or S_u. In the opposite case, and/or when a disturbance is detected on the input, the adaptation resumes with $m(k) = 1$.

The adaptation gain can be interpreted like a measurement of the parametric error. When an initial estimation of the parameters is available, the initial gain matrix is:

$$P(0) = G.I \tag{11}$$

With $G << 1$ or $Trace < 1$ and I : identity matrix.

We choose as initial values:

$$P(0) = \begin{bmatrix} 0.1 & 0 & 0 & 0 \\ 0 & 0.1 & 0 & 0 \\ 0 & 0 & 0.1 & 0 \\ 0 & 0 & 0 & 0.1 \end{bmatrix} \tag{12}$$

and

$$\lambda(0) = 0.96 \tag{13}$$

2.1 Methods of the Forgetting Factor Variation

The considered class of the system imposes to use a method with a variable forgetting factor in order to take into account the non-stationarity of the process.

Generally, the adaptation of a model is obtained by using a Recursive Least Squares algorithm with forgetting factor. The forgetting factor can be constant or variable.

There are different classical methods of the forgetting factor variation as, for example, the exponential forgetting factor. The variation of λ is defined as:

$$\lambda(k+1) = \lambda_0 . \lambda(k) + (1 - \lambda_0) \quad (14)$$

$$\text{where } 0 < \lambda_0 < 1 \quad (15)$$

with the typical values:

$$\lambda_0 = 0{,}95...0{,}99; \lambda(0) = 0{,}95...0{,}99 \quad (16)$$

This method consists in increasing λ to 1 rapidly.

Andersson proposes to modify the gain matrix $P(k+1)$ of the Recursive Least Squares algorithm to improve the model (Andersson, 1985). This method introduces an Adaptive forgetting Factor through Multiple Models (AFMM) in considering the RLS algorithm as a special case of the Kalman filter. $\hat{\theta}(k+1)$ is approximated with a sum of many Gaussian density functions. Moreover, when the process is subjected to jumps, this method enables us to reduce the importance of the gain matrix $P(k+1)$ in adjusting a parameter.

A new identification algorithm, inspired by these two methods (exponential and Andersson), is proposed. This approach presents a Fuzzy Forgetting Factor (Lafont et al., 2005).

2.2 The Proposed Approach

We use fuzzy logic to modify the forgetting factor in an automatic and optimal way (Jager, 1995). Thus, we have defined a «fuzzy box» of Mamdani type by using the following variables: $\lambda(k)$ and $\Delta\varepsilon(k)$ in input and $\lambda(k+1)$ in output (Figure 1).

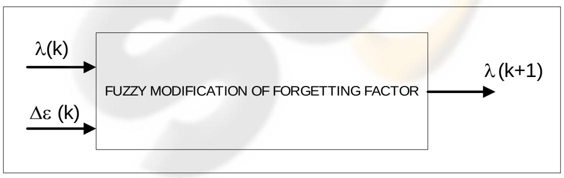

Figure 1: Fuzzy box.

$\Delta\varepsilon(k)$ represents the variation of the mean error on the N last samples:

$$\Delta\varepsilon(k) = \frac{1}{N} \sum_{j=k-N+1}^{k} (\varepsilon(j) - \varepsilon(j-1)) \quad (17)$$

$\Delta\varepsilon(k)$ had been defined with three membership functions: one for the negative error, one for the null error and one for the positive error (Figure 2). A study of observed process allows to determine the values: $\{-\eta_{max}; -\eta_{min}; \eta_{min}; \eta_{max}\}$.

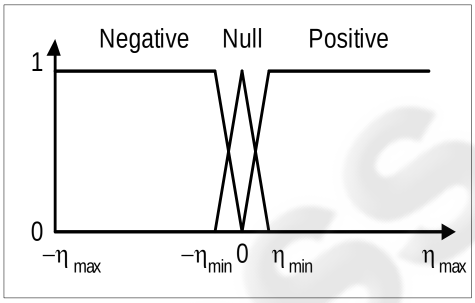

Figure 2: Fuzzyfication of the error variation.

The membership functions of the input $\lambda(k)$ and the output $\lambda(k+1)$ are identical (Figure 3).

According to the application, the bounds [0.8 ; 1] can be reduced.

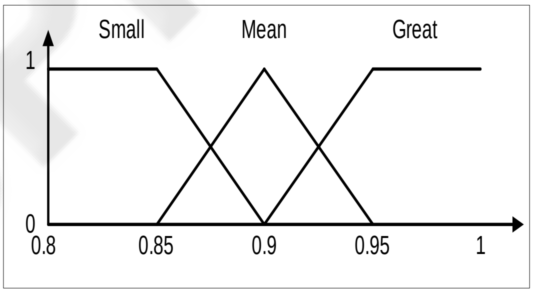

Figure 3: Fuzzyfication of the lambda.

The inference rules are based on the variation method of the exponential forgetting factor. In this case, the forgetting factor must be maximum when the modeling of the system is correct (small error variation). Also, we have been inspired by Andersson's work. When there is an important non-stationarity, the forgetting factor must decrease.

If $\lambda(k)$ is $F^1_{n_\lambda}$ and $\Delta\varepsilon(k)$ is $F^2_{n_\varepsilon}$ then $\lambda(k+1)$ is $F^3_{n'_\lambda}$, where $F^1_{n_\lambda} \in \{F^1_1, F^1_2, F^1_3\}$ is the set of membership functions of the input variable $\lambda(k)$, $F^2_{n_\varepsilon} \in \{F^2_1, F^2_2, F^2_3\}$ is the set of membership functions of the input variable $\Delta\varepsilon(k)$ and $F^3_{n'_\lambda} \in \{F^3_1, F^3_2, F^3_3\}$ is the set of membership functions of $\lambda(k+1)$.

The rules for the output $\lambda(k+1)$ are defined in table 1.

Table 1: Rules for the variation of the forgetting factor.

$\Delta\varepsilon(k) \setminus \lambda(k)$	Small	Mean	Great
Negative	Small	Mean	Great
Null	Mean	Great	Great
Positive	Small	Small	Mean

The inference method is based on the max-min and the defuzzification is the centre of gravity.

$$\mu(z) = \max\left(\min\left(\min\left(\mu_{F^1_{n_\lambda}}(\upsilon), \mu_{F^2_{n_\varepsilon}}(\nu)\right)\right), \mu_{F^3_{n'_\lambda}}(z)\right) \quad (18)$$

With $n_\lambda = 1$ to 3, $n_\varepsilon = 1$ to 3 and $n'_\lambda = 1$ to 3.

$$\lambda(k+1) = \frac{\int \mu(z).z.dz}{\int \mu(z).dz} \quad (19)$$

The number of forgetting factors is equal to the number of model outputs.

3 GENERATION OF RESIDUES AND DECISION-MAKING

3.1 Classical Method

The residuals are analytical redundancy generated measurements representing the difference between the observed and the expected system behaviour. When a fault occurs, the residual signal allows to evaluate the difference with the normal operating conditions.

The residuals are processed and examined under certain decision rules to determine the change of the system status. Thus, the fault is detected, isolated (to distinguish the abnormal behaviours and determine the faulty component) and identified (to characterize the duration of the default and the amplitude in order to deduce its severity).

A threshold between the outputs of the system and the estimated outputs is chosen in order to proceed to the decision-making.

The residues $r_j = \left|(y_j - \hat{y}_j)\right|$ are calculated to estimate the case where there is no failure and the case of sensor default. A threshold t is taken: if $r_j \le t$ *then* $r_j = 0$.

At each instant k, the different r_j are checked in order to establish a diagnosis.

3.2 Approach with Fuzzy Lambda

Our method uses the fuzzy lambda to detect and isolate a default on a sensor. For the MIMO system, the algorithm generates one lambda for each output.

Let λ_j, with $j = 1$ to n, n: number of outputs.

The residues $r'_j = 1 - \lambda_j$ are calculated to estimate the case where there is no failure and the case of sensor default. A threshold t' is taken: if $r'_j \le t'$ *then* $r'_j = 0$.

At each instant k, the different r'_j are checked in order to establish a diagnosis as shown in table 2.

Table 2: Analysis of residues.

Analysis of residues	Diagnosis
$\forall\ j, r'_j = 0$	No failure
If $\exists$ *one and only one* $r'_j \neq 0$, $t' = index\{r', r'_j \neq 0\}$	Sensor default

4 APPLICATION

4.1 Benchmark Example: A Hydraulic Process (Jamouli, 2003)

The approach proposed previously has been validated on a benchmark: a hydraulic process. This system is a hydraulic process composed of three tanks (Figure 4). The objective of the regulation is to be able to have a constant volume of the fluid. The three tanks have the same section: S.

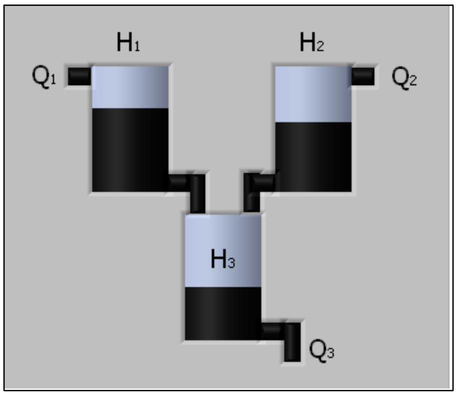

Figure 4: A hydraulic process.

The physical model of this system is obtained with the difference between the entering and outgoing flows which make evolve the level of each tank.

The state model is described by:

$$\begin{aligned} \dot{X} &= A.X + B.U \\ Y &= C.X + D.U \end{aligned} \tag{20}$$

$$\begin{aligned} &X = \left[h_1\ h_2\ h_3\right]^T, U = \left[q_1\ q_2\right]^T \\ &and\ Y = X \end{aligned} \tag{21}$$

The vector of outputs is the same as the state vector and, thus, the observation matrix C is an identity matrix with a size 3x3.

This system, considered as linear around a running point, has been identified in using an ARX structure. The discrete model is obtained by using a sample period equal to 0.68 seconds.

The model describes the dynamical behaviour of the system in terms of inputs/outputs variations around the running point $\left(U_0\ Y_0\right)$.

$$U_0 = \left(0.8\ \ 1\right)^T\ Y_0 = \left(400\ \ 300\ \ 200\right)^T$$

$$\begin{aligned} x(k+1) &= A_d.x(k) + B_d.u(k) \\ y(k) &= C_d.x(k) + D_d.u(k) + no(k) \end{aligned} \tag{22}$$

The sensors noise $no(k)$ considered is a normal distribution with mean zero and variance one.

This system is completely observable and controllable.

A quadratic linear control, associated to an integrator, enables to calculate the feedback gain matrix K from the minimization of the following cost function:

$$J = \frac{1}{2}.\sum_{k=0}^{N}\left(x^T(k).Q.x(k) + u^T(k).R.u(k)\right) \tag{23}$$

$$u(k) = -K.x(k) \tag{24}$$

As shown in section 2, for each output, a forgetting factor is assigned. λ_1, λ_2 and λ_3 vary independently in function of the error between the process outputs and the model outputs.

For this application, the values $\eta_{\min}$ and $\eta_{\max}$, described in section 2.2, are respectively 1.25 and 10. The model is adapted to follow the process behaviour.

4.2 Sensors Defaults

For the sensors, two types of defaults have been tested: the bias and the calibration default. The simulation of the bias default has been carried out by substracting a constant value β from the real value: for example $h_{1\,real} = h_{1\,sensor} - \beta$.

The simulation of the calibration default is obtained by multiplying the real value by a coefficient γ: for example $h_{1\,real} = h_{1\,sensor} * \gamma$.

The environment of the supervision enables to see the good detection of defaults. As soon as a failure is detected, the algorithm stops and indicates which sensor has a default (Figure 5). The physical model is represented by the dotted line curve and the parametric model by the solid line curve. For this example, the default is simulated, at sample 10, on the sensor h_1. The diagnosis is depicted by a circle on figure 5. The algorithm has detected the default at sample 12.

We have simulated the classical method and our approach with the bias default and the calibration default for the three sensors (h_1, h_2, h_3). To compare these two methods, we vary the values β and γ.

4.3 Results

In table 3 and table 4, we show the performances of the two methods. For this, we define a rate which is the percentage of detection on 100 tests.

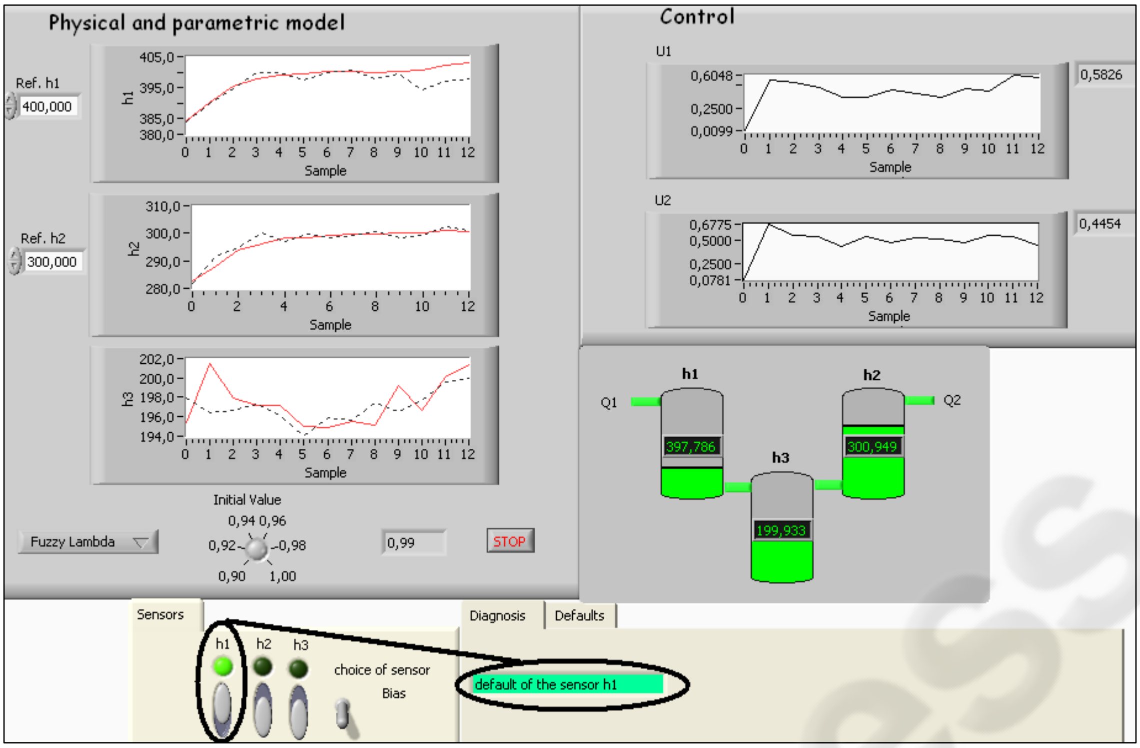

Figure 5: Supervision.

We can note that the fuzzy method gives better results. Indeed, when the default is weak (β <7 or γ >0.97), the rate of detection is more important.

On the other hand, the results are similar. To improve the detection with the classical method, the threshold t could be decreased but that implies an important rate of false alarm. Indeed, if the threshold is weaker than the importance of the noise, the algorithm stops in an inopportune way.

Table 3: Rate of detection for the bias default.

Bias default Rate of detection in percentage		β				
		4	5	6	7	8
Classical method Threshold: $t = 5.5$	h_1	6	42	88	98	100
	h_2	6	42	80	100	100
	h_3	22	42	80	90	100
Fuzzy method Threshold: $t' = 0.1$	h_1	64	84	100	100	100
	h_2	76	92	98	100	100
	h_3	86	92	98	100	100

Table 4: Rate of detection for the calibration default.

Calibration default Rate of detection in percentage		γ			
		0.99	0.98	0.97	0.96
Classical method Threshold: $t = 5.5$	h_1	24	100	100	100
	h_2	2	84	100	100
	h_3	0	8	80	98
Fuzzy method Threshold: $t' = 0.1$	h_1	70	100	100	100
	h_2	48	100	100	100
	h_3	36	68	92	100

4.4 Sensitivity to the Measure Noise

The measure noise has a great significance on the fault detection. The presented values are the minimal values which the method can detect.

In the case where the measure noise is more important, these results can be upgraded by modifying the values η_{min} and η_{max} defined in section 2.2. If the measure noise is very large, it is necessary to increase these initial values. By doing that, a tolerance compared with the noise is admitted. A compromise should be found between the noise level and the variation of $\eta_{\min}$ and $\eta_{\max}$. Indeed, the algorithm can detect a false alarm.

5 CONCLUSIONS

This paper presents an original method of model-based diagnosis with a fuzzy parametric approach. This method is applicable to all non-linear MIMO systems for which the knowledge of the physical model is not required. We define a Fuzzy Forgetting Factor which allows to improve the estimation of model parameters, and to detect and isolate several types of faults. Thus, the fuzzy adaptation of the forgetting factors is used to detect and isolate the sensor fault. The results are illustrated by a benchmark system (a hydraulic process) and comparisons between the classical method and this method is depicted in table 3 and table 4.

The method is efficient to detect and isolate only one sensor default at the same moment. The proposed approach is able to detect faults which correspond to a bias and a calibration default for a sensor.

A possible extension would be to determine the values $\eta_{\min}$ and $\eta_{\max}$, described in section 2.2, in an automatic way according to the sensor noise.

Moreover, it would be interesting to develop the FFF method for the actuator defaults.

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