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Soft Computing Approach for Data Validation

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Terminology

In this section, some useful definitions are given.
Fault: An unpermitted deviation of at least one characteristic property or parameter of the system from the acceptable, usual or standard condition.
Failure: A permanent interruption of a system's ability to perform a required function under specified conditions.
Error: A deviation between a measured or computed value of an output variable and its true one.
Residual: A fault indicator based on a deviation between measurements and model-equation-based computations.
Fault Detection: Determination of faults present in a system and the time of detection.
Fault isolation: Determination of the kind, location and time of detection of a fault. Follows fault detection.
Failure identification: Determination of the size and time-variant behavior of a fault. Follows fault isolation.
Fault diagnosis: Determination of the kind, size, location and time of detection of a fault. Follows fault detection. Includes fault isolation and identification.
Analytical redundancy: Use of more (not necessarily identical) ways to determine a variable, where one way uses a mathematical process model in analytical form.

I. Introduction

IN safety critical processes, like nuclear reactors, chemical plants or aerospace,[1,2,6,9] it has become more and more important to detect a fault and to isolate a faulty component. Indeed, the total failure of a component can increase the number of emergency shut–downs of a process and cause catastrophes involving human fatalities and material damage. A system, which includes the capacity of detecting, isolating, identifying or classifying faults, is called a

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fault diagnosis system. The good functioning of the *FDI* (Fault Detection and Isolation) unit is very important for the decision making phase.

Model-based fault diagnosis methods have been extensively developed during the last three decades.[4] First common step of these methods is generally the generation of residual signals, which act as fault indicators. Residuals are ideally close to zero under no-fault conditions, minimally sensitive to noises and disturbances, and maximally sensitive to faults. The second step is generally the residual evaluation, namely design of decision rules based on these residuals. To generate residuals, various approaches have been discussed in the literature. Generally, these techniques use the three main concepts: observers,[3–5] parameter estimation[7] and parity space relations.[8,10]

In this paper, we explore parity space approach in static case to propose a soft computing algorithm for measurement validation in the aerospace field. Indeed, the Vulcan 2 rocket engine is used to propel the main cryotechnic stage of the European heavy launcher. At the end of 2002, a mechanical failure of the divergent having in charge to accelerate gases has been known. Many improvements on the divergent itself, the room of propulsion and the turbopumps were made in order to solve the problem. In parallel, it is very important to supervise all data coming from the sensor system, for inputs and outputs. Section II describes the problem and defines the objective of this work. In Section III, we propose a data validation scheme based on parity space approach. Three steps are necessary. Residuals must be generated, structured and finally evaluated for decision. Section IV describes the complete structure of proposed algorithm. For illustration, some new simulation results are given in Section V.

II. Problem Statement

Let (S) be a nonlinear system characterized by 5 inputs $u = [u_1 \quad u_2 \quad u_3 \quad u_4 \quad u_5]$ and 4 states $x = [x_1 \quad x_2 \quad x_3 \quad x_4]$. Each input or state is measurable at least once (Table 1). Let $\Im$ be the whole instrumentation system containing 16 sensors.

Some elements are to be considered: the system (S) is a black box; in a defined operating domain D, 18 static linear models around operating points are given with influence matrices $M_{q \in \{1,\ldots,18\}}$.

Table 1 Variables and measures[1].

Input vector u		Output vector x	
Variables	Measures	Variables	Measures
u_1	$\tilde{u}_1$	x_1	$\tilde{x}_{1,1},\ \tilde{x}_{1,2},\ \tilde{x}_{1,3}$
u_2	$\tilde{u}_2$	x_2	$\tilde{x}_{2,1},\ \tilde{x}_{2,2}$
u_3	$\tilde{u}_3$	x_3	$\tilde{x}_{3,1},\ \tilde{x}_{3,2}$
u_4	$\tilde{u}_{4,1}, \tilde{u}_{4,2}$	x_4	$\tilde{x}_{4,1},\ \tilde{x}_{4,2}$
u_5	$\tilde{u}_{5,1}, \tilde{u}_{5,2}$		

Symbol $\sim$ is used to represent the measure of a variable. For example, $\tilde{x}_{1,j}$ is the ith measure of variable x_1.

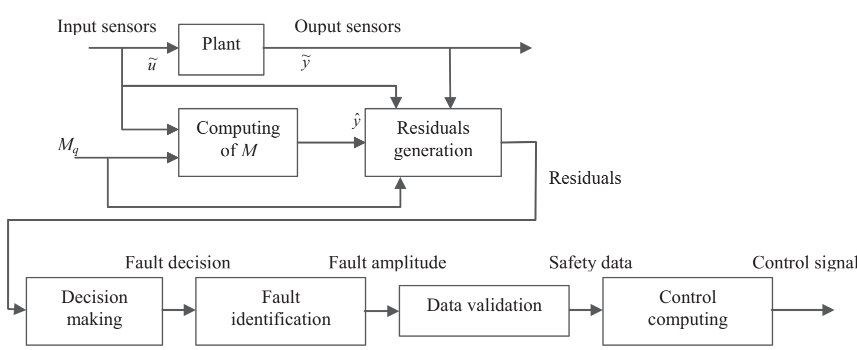

Fig. 1 Structure of data validation scheme.

Then, the model can be described by:

$$x(t) = x(t-1) + M(t-1)\,(u(t) - u(t-1)) \tag{1}$$

where $M = \{m\_\{i, j\}\}$, $i = 4$ and $j = 5$, represents the new influence matrix at $t-1$, computed by interpolation from the system state at $t-1$ and the known influence matrices M_q.

The problem consists in the detection and isolation of the sensor faults using all measurements and static models.

The proposed algorithm includes four phases (figure 1): Structured residual generation, decision-making, fault identification and data validation.

III. Data Validation Scheme

In this section, we develop the various phases of our approach, from residual generation to data validation.

A. Structured residual generation

The principle consists in using analytical redundancy relations due to the model. The model links the control vector to the state vector through (1). A distinction is made between direct and systematic residual generation. The first one directly compares the outputs of sensors with those of models to build residuals. The second one uses the principle of elimination of unknown variables, based on parity space approach.

1. Direct Residuals Generation

We suppose that the initial state introduced by $x(0)$, which represents the first point belonging to the operating domain, is given by valid measurements. This assumption of nominal operation is necessary to initialize our algorithm. Since inputs are measured, the state is given by:

$$x(t) = x(t-1) + M(t-1)\,(\tilde{u}(t) - \tilde{u}(t-1)) \tag{2}$$

At each time t, a comparison between $x(t)$ and $\tilde{x}$ permits us to generate the following residual vector:

$$r(t) = \tilde{x}(t) - x(t) \tag{3}$$

The components of this residual vector depend on inputs and outputs measurements. Table 2, called signature table, indicates then the relationships between the residuals and the variables. All coefficients are either 1 or 0 respectively according to whether or not a residual depends on a variable. Each column represents the fault signature of the corresponding sensor.

This table shows that a fault on any input affects all the residuals. But a fault on an output affects only one single residual. We conclude that: all sensor faults (inputs and outputs) are detectable, but only faults of output sensors are isolable contrary to those of input sensors.

The principle of residuals generation has to take into account the fact that some inputs or outputs can be measured with several sensors. Taking into account the significant number of sensors, it was necessary to find a procedure allowing us to explore in a systematic and rigorous way all data, to generate all redundancy relations.

Table 2 Occurrence of variables in residuals.

	$\tilde{u}_1$	$\tilde{u}_2$	$\tilde{u}_3$	$\tilde{u}_4$	$\tilde{u}_5$	$\tilde{x}_1$	$\tilde{x}_2$	$\tilde{x}_3$	$\tilde{x}_4$
$r(\tilde{x}_1)$	1	1	1	1	1	1	0	0	0
$r(\tilde{x}_2)$	1	1	1	1	1	0	1	0	0
$r(\tilde{x}_3)$	1	1	1	1	1	0	0	1	0
$r(\tilde{x}_4)$	1	1	1	1	1	0	0	0	1

2. Systematic Residual Generation

In the case of sensors under no-fault conditions, we can write the relationships between variables and their measurements; we neglect here the presence of measurement errors. In our case, these relationships are given by:

$$\begin{aligned}\tilde{x} &= f(x)\\ \tilde{u} &= g(u)\end{aligned} \tag{4}$$

where input and output measurements vectors are: $\tilde{u} = [\tilde{u}_1 \quad \tilde{u}_2 \quad \tilde{u}_3 \quad \tilde{u}_{4,1} \quad \tilde{u}_{4,2} \quad \tilde{u}_{5,1} \quad \tilde{u}_{5,2}]$ and $\tilde{x} = [\tilde{x}_{1,1} \quad \tilde{x}_{1,2} \quad \tilde{x}_{1,3} \quad \tilde{x}_{2,1} \quad \tilde{x}_{2,2} \quad \tilde{x}_{3,1}\tilde{x}_{3,2} \quad \tilde{x}_{4,1} \quad \tilde{x}_{4,2}]$ respectively and, f and g two linear functions.

Then, the system is completely described by (1) and (4). In the following, to simplify, the equation (1) will be replaced by the equation (5) such that the variables (x and u) represent the variations:

$$x(t) = M(t-1)u(t) \tag{5}$$

The equation (4) stays unchanged while considering x and u as variations of the corresponding variables. To relieve writings, we can link together measurement (4) and model (5) equations by:

$$F\left(\begin{pmatrix} x \\ u \end{pmatrix}\right) = G\left(\begin{pmatrix} \tilde{x} \\ \tilde{u} \end{pmatrix}\right) \tag{6}$$

where F and G are linear functions calculated to separate known $(\tilde{x}, \tilde{u})^T$ and unknown $(x, u)^T$ variables.

The expression (6) is particularly attractive to establish analytical redundancy relations. These relations have to contain only known variables, i.e. the measurements and the coefficients of the influence matrix M, representing the system model. To obtain this, it is necessary to eliminate from (6) the unknown variables $\{x, u\}$ in order to keep only the known vectors $\{x_m, u_m\}$. For that, the parity space approach can be explored as following.

Parity space principle: Let F and G of (6) be two linear functions given by:

$$F(X) = \Phi \cdot X \tag{7a}$$

$$G(\tilde{X}) = \Theta \cdot \tilde{X} \tag{7b}$$

for any vector $X = (x, u)^T \in \Re^{16}$, where Φ and Θ are matrices of suitable dimensions.

Step 1: Find a matrix Ω, such that:

$$\Omega\Phi = 0 \tag{8}$$

The objective is to project the known vector $\tilde{X}$ in a space $^{\#}\text{Span}(\Omega) = \text{Span}(\Phi)^{\perp}$, orthogonal on $\text{Span}(\Phi)$, where the unknown vector X does not appear. For a measurement vector at k, we can write:

$$G(k) = r(k) + G_{\Phi}(k) \tag{9a}$$

$$r(k) \in \text{Im}(\Phi)^{\perp} \tag{9b}$$

$$G_{\Phi}(k) \in \text{Im}(\Phi) \tag{9c}$$

$$r(k) = \Omega G(k) = \Omega\Theta\tilde{X}(k) \tag{9d}$$

Step 2: Knowing Ω, solution of (8), we can then generate the residuals vector r by multiplying (6) on the left by Ω:

$$r = \Omega G\left(\begin{pmatrix} \tilde{x} \\ \tilde{u} \end{pmatrix}\right) \tag{10}$$

$^{\#}$Span(Ω) represents the space generated by the columns of the matrix Ω.

The execution of this algorithm leads for the whole set of sensors to the following set of residuals:

$$
\begin{aligned}
r_1 &= \tilde{x}_{1,1} - \tilde{x}_{1,2} \\
r_2 &= \tilde{x}_{1,2} - \tilde{x}_{1,3} \\
r_3 &= \tilde{x}_{2,1} - \tilde{x}_{2,2} \\
r_4 &= \tilde{x}_{3,1} - \tilde{x}_{3,2} \\
r_5 &= \tilde{x}_{4,1} - \tilde{x}_{4,2} \\
r_6 &= \tilde{u}_{4,1} - \tilde{u}_{4,2} \\
r_7 &= \tilde{u}_{5,1} - \tilde{u}_{5,2} \\
r_8 &= \tilde{x}_{1,1} - m_{11}\tilde{u}_1 - m_{12}\tilde{u}_2 - m_{13}\tilde{u}_3 - m_{14}\tilde{u}_{4,1} - m_{15}\tilde{u}_{5,1} \\
r_9 &= \tilde{x}_{2,1} - m_{21}\tilde{u}_1 - m_{22}\tilde{u}_2 - m_{23}\tilde{u}_3 - m_{24}\tilde{u}_{4,1} - m_{25}\tilde{u}_{5,1} \\
r_{10} &= \tilde{x}_{3,1} - m_{31}\tilde{u}_1 - m_{32}\tilde{u}_2 - m_{33}\tilde{u}_3 - m_{34}\tilde{u}_{4,1} - m_{35}\tilde{u}_{5,1} \\
r_{11} &= \tilde{x}_{4,1} - m_{41}\tilde{u}_1 - m_{42}\tilde{u}_2 - m_{43}\tilde{u}_3 - m_{44}\tilde{u}_{4,1} - m_{45}\tilde{u}_{5,1}
\end{aligned}
\tag{11}
$$

As shown in Table 3, each residual (from r_1 to r_{11}), zero under no-fault conditions, is sensitive to a specified set of sensors. For example, r_1 is sensitive only to sensor faults caused by $\tilde{x}_{4,1}$ and $\tilde{x}_{4,2}$. The residuals r_{12} to r_{20} are to be determined later. Through residuals r_1 to r_{11}, all faults are detectable (each input or output sensor appears at least once in a residual) but only the output sensor faults are isolable (all corresponding columns are strongly different). For that, other set of residuals is necessary to detect at least any unique sensor fault. The following paragraph is concerned with computing a set of structured residuals according to an elimination procedure.

Table 3 All generated residuals.

	Inputs							Outputs								
Residuals	$\tilde{u}_1$	$\tilde{u}_2$	$\tilde{u}_3$	$\tilde{u}_{4,1}$	$\tilde{u}_{4,2}$	$\tilde{u}_{5,1}$	$\tilde{u}_{5,2}$	$\tilde{x}_{1,1}$	$\tilde{x}_{1,2}$	$\tilde{x}_{1,3}$	$\tilde{x}_{2,1}$	$\tilde{x}_{2,2}$	$\tilde{x}_{3,1}$	$\tilde{x}_{3,2}$	$\tilde{x}_{4,1}$	$\tilde{x}_{4,2}$
r_1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
r_2	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
r_3	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
r_4	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0
r_5	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0
r_6	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0
r_7	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0
r_8	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0
r_9	1	1	1	1	0	1	0	0	0	0	1	0	0	0	0	0
r_{10}	1	1	1	1	0	1	0	0	0	0	0	0	1	0	0	0
r_{11}	1	1	1	1	0	1	0	0	0	0	0	0	0	0	1	0
r_{12}	1	1	1	0	0	1	0	1	0	0	1	0	0	0	0	0
r_{13}	1	1	1	0	0	1	0	1	0	0	0	0	0	1	0	0
r_{14}	1	1	1	0	0	1	0	1	0	0	0	0	0	0	0	1
r_{15}	0	1	1	1	0	1	0	1	0	0	1	0	0	0	0	0
r_{16}	0	1	1	1	0	1	0	0	0	0	0	0	1	0	0	0
r_{17}	0	1	1	1	0	1	0	0	0	0	0	0	0	0	1	0
r_{18}	1	0	1	1	0	1	0	0	0	0	1	0	1	0	1	0
r_{19}	1	0	1	1	0	1	0	1	0	0	0	0	1	0	1	0
r_{20}	1	1	0	1	0	1	0	1	0	0	1	0	1	0	1	0

3. Generation of Structured Residuals

This is a complementary concept to isolate the detected faults. For that, it is interesting to study now the same problem for any partial sensor set. The objective is to:

- make separable the fault signatures, i.e. the columns of the table of occurrence must be strongly different.
- examine the set of sensors that can be lost, while continuing to solve the *FDI* procedure.

In the following, we will show how to generate residuals improving the *FDI* procedure for input sensor faults. Any sensor subset can be considered to improve this isolation task. Here, we show only one case for illustration.

Case of $\tilde{u}_{4,1}$ and $\tilde{u}_{4,2}$ input measurements

To improve the *FDI* procedure of these inputs, the problem is reduced to increase the number of residuals not depending on them. For that, we solve the residual generation problem without taking into account these input measurements. Indeed, for the set of sensors $\Im\backslash\{\tilde{u}_{4,1}, \tilde{u}_{4,2}\}$, the problem can be posed as following. Let $\tilde{u}$ and $\tilde{x}$ be given by: $\tilde{u} = [\tilde{u}_1 \quad \tilde{u}_2 \quad \tilde{u}_3 \quad \tilde{u}_{5,1} \quad \tilde{u}_{5,2}]$ and $\tilde{x} = [\tilde{x}_{1,1} \quad \tilde{x}_{1,2} \quad \tilde{x}_{1,3} \quad \tilde{x}_{2,1} \quad \tilde{x}_{2,2} \quad \tilde{x}_{3,1} \quad \tilde{x}_{3,2} \quad \tilde{x}_{4,1} \quad \tilde{x}_{4,2}]$.

The execution of the proposed procedure, to generate new residuals (10), gives the following new residuals.

$$\begin{aligned}
r_{12} &= -m_{24}\tilde{x}_{1,1} + m_{14}\tilde{x}_{2,1} + (m_{11}m_{24} - m_{14}m_{21})\tilde{u}_1 + (m_{12}m_{24} - m_{14}m_{22})\tilde{u}_2 \\
&\quad + (m_{13}m_{24} - m_{14}m_{23})\tilde{u}_3 + (m_{15}m_{24} - m_{14}m_{25})\tilde{u}_{5,1} \\
r_{13} &= -m_{34}\tilde{x}_{1,1} + m_{14}\tilde{x}_{3,2} + (m_{11}m_{34} - m_{14}m_{33})\tilde{u}_1 + (m_{12}m_{34} - m_{14}m_{32})\tilde{u}_2 \\
&\quad + (m_{13}m_{34} - m_{14}m_{33})\tilde{u}_3 + (m_{15}m_{34} - m_{14}m_{35})\tilde{u}_{5,1} \\
r_{14} &= -m_{44}\tilde{x}_{1,1} + m_{14}\tilde{x}_{4,2} + (m_{11}m_{44} - m_{14}m_{41})\tilde{u}_1 + (m_{12}m_{44} - m_{14}m_{42})\tilde{u}_2 \\
&\quad + (m_{13}m_{44} - m_{14}m_{43})\tilde{u}_3 + (m_{15}m_{44} - m_{14}m_{45})\tilde{u}_{5,1}
\end{aligned} \tag{12}$$

The occurrence of measurements in r_{12}, r_{13} and r_{14} is given in Table 3. Some remarks can be done: the solution of residuals generation problem exists even without the sensors $\tilde{u}_{4,1}$ and $\tilde{u}_{4,2}$; the faults of $\tilde{u}_{4,1}$ and $\tilde{u}_{4,2}$ are now detectable and isolable; the same result can be obtained to isolate the faults of $\tilde{u}_{5,1}$ and $\tilde{u}_{5,2}$. Other residuals are required to complete the *FDI* procedure. Indeed, using our approach, we can obtain the residuals r_{15} to r_{20} (Table 3).

B. Decision Making

The nature of the information contained in a residual plays a very important role to define the type of tests. In our case, several phenomena are interesting to be clarified. All generated residuals contain: measurement noises and modeling errors.

Taking account several tests in nominal case with no fault, modeling errors are always limited by ε%. Increasing the number of influence matrices M_q in D decreases this percentage. An appropriate number of matrices permits us to obtain ε very small. This result strongly participates to reduce the rate of false alarm.

Let $\boldsymbol{r}_i$ be any residual from $\boldsymbol{r}_1$ to $\boldsymbol{r}_{20}$. With the assumption that the modeling errors are very small (or can be neglected), we have $\boldsymbol{r}_i \approx N[0, R]$ (Gaussian noise) when there is no failure. A failure will make $\boldsymbol{r}_i$ to become non-zero and/or its covariance larger than R. Then, failure detection can be performed by usual statistical testing techniques between the hypotheses:

$$\begin{gathered}
H_0\colon \boldsymbol{r}_i \approx N[0, R] \\
H_1\colon H_0 \text{ not true}
\end{gathered} \tag{13a}$$

Subject to the false alarm probability

$$\Pr\,[\text{accept } \mathrm{H}_1|\mathrm{H}_0 \text{ true}] = \eta \tag{13b}$$

A simple testing based on the variant threshold γ_i can be applied, such that:

$$|\boldsymbol{r}_i^j| \geqslant 3\,\gamma_i \quad \text{Failure} \tag{14a}$$

$$|\boldsymbol{r}_i^j| < 3\,\gamma_i \quad \text{No Failure} \tag{14b}$$

where $\boldsymbol{r}_i^j$ is the last computed value of the residual and γ_i^2 the noise-free variances of the residuals, computed on a sliding window Π of size L, given by the interval $[r_i^{j-L-1}, r_i^{j-1}]$. Following each computation of the residuals, a test (14) is applied. Based on the outcomes of the individual tests, a Boolean instantaneous signature vector Σ is formed so that coefficients $(\Sigma_i) = 1$ if failure, $\Sigma_i = 0$ otherwise, where $1 \leq i \leq 20$. Each coefficient (Σ_i) is associated to a residual r_i. To isolate sensor failures, it is necessary to compare instantaneous signature vector Σ with the columns of Table 3. Then, a fault is isolated on a sensor i, if the corresponding failure signature is realized.

C. Fault Identification and Data Validation

Once the fault is detected and isolated, it is very important to identify its amplitude for compensation. Finally, the data validation consists in keeping only operational sensors for control system process.

IV. Algorithm

The algorithm of the proposed approach can be described in two main phases.

Design phase: In this phase, the problem consists in generating residuals for solving *FDI* procedure in the case of unique sensor faults. Some points are necessary. We start with the whole set of sensors $\Im$.

1. Find the set of residuals given by (10),
2. Test: Are unique sensor faults detectable and isolable?
   a. If yes, design phase is over,
   b. Else, choose a sensor subset $\Im_s$ included in $\Im$, representing one or several sensors not isolable. To the complete residual set, let $\Im_s \backslash \Im_s$ be the sensor system and go to 1.

Computing phase: Once all residuals are defined, this phase consists in the following steps:

1. Compute the residual vector r^j at j,
2. Compute the variance vector γ on the windows $[r_i^{j-L-1}, r_i^{j-1}]_{j>L}$,
3. Test the residuals, using (14), and compute Boolean signature vector Σ,
4. Compare Σ with the columns of signatures table (Table 3) to isolate the fault.

V. Simulation Results

In this section, we present now some simulation results based on our algorithm applied to the studied system. All signals have been normalized between 0 and 1.

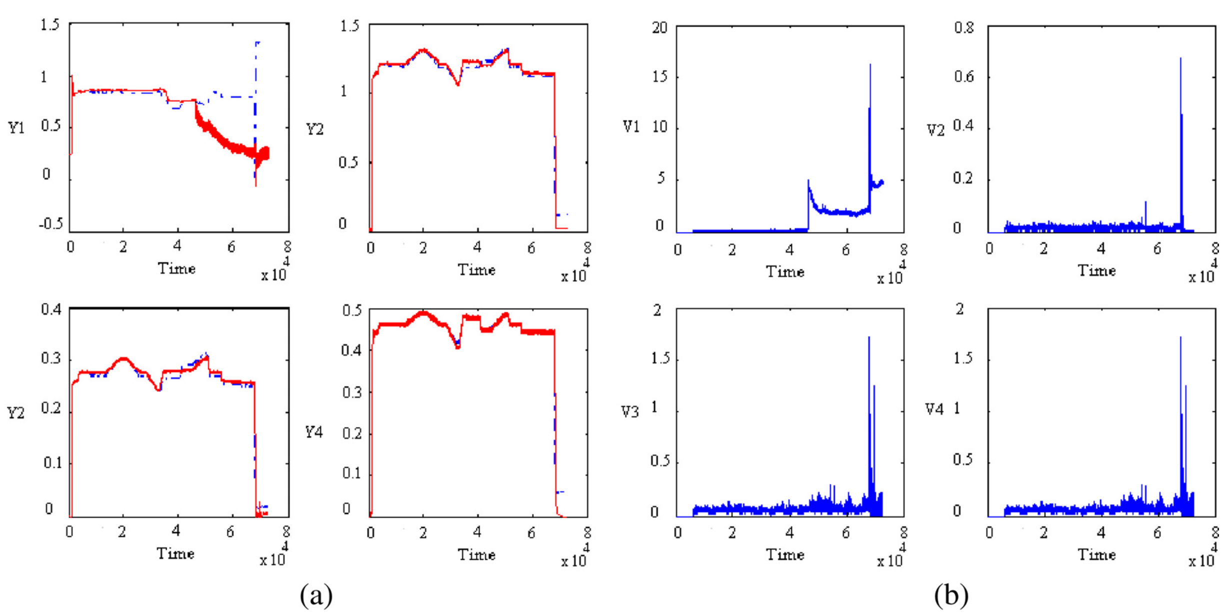

Fig. 2 Simulation results.

Figure 2a gives an illustrative comparison between model outputs (- - -) and measurements (—), s. t.: $Y1 = \tilde{x}_{1,1}$, $Y2 = \tilde{x}_{2,1}$, $Y3 = \tilde{x}_{3,1}$ and $Y4 = \tilde{x}_{4,1}$ (acquisition frequency = 125 samples/s, duration = 576 s). For $Y1$, at 369.5 s (46200 samples), we can observe a deviation between model output and measurement. It is an event to be detected and isolated by our proposed approach. The last part of the line graphs corresponds to the end of the test. On a sliding window of size 10, $V1$, $V2$, $V3$ and $V4$ are respectively computation results of variances of residuals between $Y1$, $Y2$, $Y3$ and $Y4$, and corresponding outputs of the model (Figure 2b). At 369.5 s, using an appropriate threshold, we can detect a deviation between the model and the real system, i.e. the appearance of a fault.

The considered fault is detected after a delay of 2 sample periods, which corresponds to 16 ms. Here, we show only 4 out of the 20 computed residuals for isolation. In fact, after a fault is detected, we can generate an instantaneous signature vector Σ. The isolation consists in comparing columns of Table 3 with the instantaneous signatures generated at the end of the detection phase. If vector Σ corresponds to a column in Table 3, then one deduces that the corresponding sensor is faulty. In our case, it is the 8th column of Table 3, corresponding to sensor $\tilde{x}_{1,1}$. The final objective of our work is to replace faulty measured data by valid computed data.

VI. Conclusion

A data validation algorithm based on the parity space approach has been developed. This algorithm permits us to detect and isolate easily any single sensor fault from the control feedback. Indeed, detectability and isolability of all sensor faults are guaranteed thanks to analytical and physical redundancy. Performances in terms of false alarms, delays in detection, . . . have been improved by data filtering, residual computing (strongly independent) and testing based on the sliding window principle.

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