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# ISOLATION DECISION FOR A MULTI-AGENT-BASED DIAGNOSTIC SYSTEM

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Abstract: The variety of diagnostic methods proves that none can pretend to be much better than the others. A significant improvement of industrial applications can only be achieved when FDI problems are dealt with and solved in a framework of integrated use of different FDI methods. This paper presents a study about the possible cooperation between detection methods. Two different isolation methods, which analyze symptoms provided by observer-based and signal-based detection algorithms, are compared using a two water tank system: one method is based on signature tables and the other one is based on a logical approach. Strategic aspects are also stressed. 

Keywords: Complex systems, Fault diagnosis, Fault Detection and Isolation, State Observer, Signal-based diagnostic.

## 1. INTRODUCTION

Fault Detection and Isolation (FDI) is becoming now a major area of control science. This is firstly explained by the increasing complexity of industrial processes. Safety is a major subject of interest, for the process itself, for its environment and for men living around. Plant automation must thus include other objectives than process control to be a significant and complete solution for large plant dependability: plant safety and availability management, on-line diagnosis and resulting supervisory or maintenance policy are now common topics of interest. A second reason for the interest in FDI is purely financial. As a shut-down, induced by the necessity of respecting security constraints, is very costly, the interest of the supervision system is easily understandable : avoiding an emergency shut-down is often more relevant from an economical viewpoint than slightly improving the quality of finished product or saving energy, thanks to sophisticated control laws.

Diagnosis is usually decomposed into two steps. The detection step provides symptoms from known physical variables, such as control variables or measurements, and from tests relying, for instance, on analytical, signal, knowledge or data based models. The isolation step collects symptoms from the detection one. It provides the possible diagnoses. A diagnosis may be literally defined as a plausible state of a physical system.

Many different diagnostic approaches have been developed among control scientists (Frank, *et al.*, 2000; Gertler, 1998; Isermann, 1997; Patton, 1997). The probably most common approach relies on an analytical model of the process to be diagnosed. This model is used to generate symptoms, called residuals, either using a parity space approach or a bank of observers. The various symptom behaviors are analyzed under some fault hypotheses, such as sensor or actuator faults. A signature table (whose columns correspond to faults and whose rows correspond to one symptom) is probably the simplest tool to use for isolating a fault with various symptoms.

Signal processing is another rather widespread diagnostic tool (Basseville, 1988; Basseville and Nikiforov, 1993). In this case, the analysis of a signal typical characteristic (such as its mean, its correlation, its spectrum, its probability density) is used for generating symptoms and making a decision. Decision depends on a template parameterized model, which may be based on the normal process behavior knowledge (for instance the signal is zero-mean) or on some faulty behavior knowledge (for instance, a fault gives rise to some extra frequency contents in the spectrum).

Less known by the control community is a logical framework for diagnosis that raised from studies in the artificial intelligence area (Reiter, 1987; De Kleer, 1987; Greiner, 1989; Poole, 1988). Nevertheless, there are some links between the logical approach and the control ones, which have been studied recently (Cordier, *et al*., 2000). This framework leads to logically sound results.
The possible collaboration between several diagnostic methods will be studied in this paper. Section 2 will present the general architecture of a multi-agent-based diagnostic system supported by ECC/IST, called MAGIC. Within this system, several agents (Jennings, *et al.*, 1998) supporting different detection algorithms and focusing on specific parts of the system to be diagnosed, communicate their results to another type of agent dedicated to fault isolation. It performs the diagnostic analysis at the overall system level. A two tanks system example will be introduced in section 3. This simple example will be used to compare several isolation approaches. Symptom generation is presented in section 4 and isolation using a classical signature table in section 5. Section 6 introduces some possible signal-based method extensions. Section 7 shows the diagnostic reasoning using a logical framework and a conclusion follows.

## 2. MAGIC ARCHITECTURE

The extreme variety of diagnostic methods proves that, unfortunately, none of them can pretend to be much better than the others. They are rather dedicated to different types of problems, and based on different knowledge about the system to be diagnosed. It is thus quite evident that for diagnosing a whole process, different methods have to be used. A significant improvement of industrial applications can only be achieved when FDI problems are dealt with and solved in a framework of integrated use of different FDI technologies from the integrated viewpoint of sub-systems and system components. It is the objective of an EC-research project in the field of FDI, "Multi-Agents-based Diagnostic Data Acquisition and Management in Complex Systems (MAGIC)", to provide a general purpose architecture and a set of tools to be used for the detection and diagnosis of incipient or slowly developing faults in complex systems (Köppen-Seliger et al., 2002). Each diagnostic method, with this architecture, is embedded in an Agent-type, able to communicate results with the other MAGIC system Agents.

It is evident that it is not sufficient to use separate diagnostic methods to obtain the correct diagnosis at the overall system level. Studying the possible collaboration between several methods is one of the scientific challenges of Magic. The different **Diagnostic Agents** (D-agents) will provide results either on the same subsystem or on different subsystems physically linked together. These results can be formalized in terms of:

- symptoms, and their confidence level,
- information on the symptom validity, related to the hypotheses underlying the diagnostic methods,
- hypotheses related to physical process components states (normal/abnormal for instance).

Let us take an example to clarify this categorization: a linear state observer-based D-agent computes residuals and checks if residuals are between predefined thresholds. The symptom to thresholds distance gives an idea of its confidence level. Its validity is based on the confidence on the model. For example, if the actual operation point is far from the linear area, the validity level of the model and symptom decreases. Hypotheses about components could be the valve $V_i$, the sensors $S_i$ and the DC motor $M_i$ are in their normal state to obtain the model used by the observer.

The **Diagnostic Decision Agent** (DD-Agent) must take a final and global decision about the overall process state. The main difficulty is that the symptoms concern different subsystems, which are not independent. Sensors may be common to 2 different subsystems. A subsystem may include another one. Symptoms may be obtained thanks to different detection algorithms such as observer-based or signal-based approaches, applied to the same subsystem. However, all the symptoms have to be analyzed all together for obtaining reliable diagnoses.

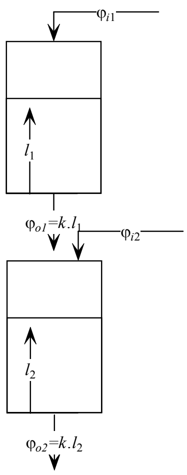
## 3. EXAMPLE DESCRIPTION

An example will be used all along this paper to stress the properties of different isolation methods.
The example consists in two identical 50 cm height water tanks, the first one (index 1) filling the second one (index 2). The tanks input flows are $\varphi_{i1}$ and $\varphi_{i2}$. The output flows are $\varphi_{o1}$ and $\varphi_{o2}$. The levels are $l_1$ and $l_2$. The tank $T_i$ section is equal to $S$. The valve openings are controlled by a DC voltage. Each tank output flow $\varphi_{oi}$ is proportional (parameter $k$) to the water level $l_i$.

With respect to the FDI approach, a state space model for the overall system has been designed:

$$\begin{cases} \begin{bmatrix} \dot{l}_1 \\ \dot{l}_2 \end{bmatrix} = \begin{bmatrix} -k/S & 0 \\ k/S & -k/S \end{bmatrix} \begin{bmatrix} l_1 \\ l_2 \end{bmatrix} + \begin{bmatrix} 1/S & 0 \\ 0 & 1/S \end{bmatrix} \begin{bmatrix} \tilde{\varphi}_{i1} \\ \tilde{\varphi}_{i2} \end{bmatrix} \\ \begin{bmatrix} \tilde{l}_1 \\ \tilde{l}_2 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} l_1 \\ l_2 \end{bmatrix} \end{cases} \qquad (1)$$

The logical approach requires a more detailed model including validity conditions and related component state hypotheses. Further information is thus added to each equation, to represent the model validity conditions (for instance linearity). The physical component concerned by the model and its state (normal: ¬AB, Abnormal: AB) is also a useful diagnostic information. In the example, each component is supposed unfaulty (¬AB(component)). The system description ( 2 ) composed by 8 component models is thus obtained.




$$\begin{cases} [CM_1] & \left\{ S\frac{dl_1}{dt} = \varphi_{i1} - \varphi_{o1}, 0<l_1<50cm, \neg AB(T_1) \right\} \\ [CM_2] & \left\{ \varphi_{o1} = kl_1, -, \neg AB(R_1) \right\} \\ [CM_3] & \left\{ S\frac{dl_2}{dt} = \varphi_{i2} + \varphi_{o1} - \varphi_{o2}, 0<h_2<50cm, \neg AB(T_2) \right\} \\ [CM_4] & \left\{ \varphi_{o2} = kl_2, -, \neg AB(R_2) \right\} \\ [CM_5] & \left\{ \tilde{l}_1 = l_1, LF, \neg AB(S_1) \right\} \\ [CM_6] & \left\{ \tilde{l}_2 = l_2, LF, \neg AB(S_2) \right\} \\ [CM_7] & \left\{ \tilde{\varphi}_{i1} = \varphi_{i1}, -, \neg AB(V_1) \right\} \\ [CM_8] & \left\{ \tilde{\varphi}_{i2} = \varphi_{i2}, -, \neg AB(V_2) \right\} \end{cases} \qquad (2)$$

In ( 2 ), $T_i$ represents the tank (i=1 for upper tank, respectively i=2 for lower one), $R_i$ the restriction, $S_i$ the level sensor, $V_i$ the valve.

Each component model $CM_i$ contains 3 parts. The first one is an analytical model. The second one is the model validity condition and the last one is the related component state.

Let's consider model $CM_1$. The analytical model expresses the material balance. This model may be used only if the water level is smaller than 50 cm because it doesn't describe what happens in case of overflow. The related component $T_1$ is in normal state. Model $CM_5$ represents the water level $l_1$ sensor $S_1$. The analytical model is simple; the sensor $S_1$ state is normal. The model validity "LF" means that the model is only valid at Low Frequencies.

A simulator has been designed for a given set of parameters. It involves measurement noise and a structural noise on component $R_1$. The physical variable normal behaviors are shown in Fig. 1.

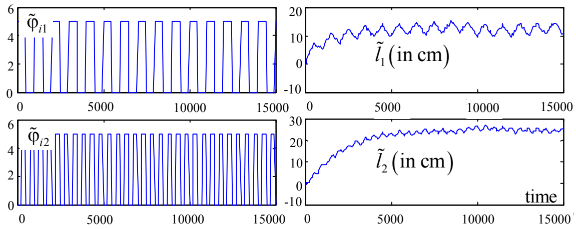



Fig. 1: Physical variable normal behaviours.

## 4. SYMPTOM GENERATION

With respect to usual FDI observer-based approaches, different kinds of state observers insensitive to specific sensor and actuator faults have been designed.

The first residual generator, *Test 1* ( 3 ), has been computed from ( 1 ) in order to be insensitive to $l_1$ measurement:

$$\begin{cases} \begin{bmatrix} \dot{\hat{l}}_1 \\ \dot{\hat{l}}_2 \end{bmatrix} = \begin{bmatrix} -k/S & -k_1 \\ k/S & -k/S - k_2 \end{bmatrix} \begin{bmatrix} \hat{l}_1 \\ \hat{l}_2 \end{bmatrix} + \begin{bmatrix} 1/S & 0 & k_1 \\ 0 & 1/S & k_2 \end{bmatrix} \begin{bmatrix} \tilde{\varphi}_{i1} \\ \tilde{\varphi}_{i2} \\ \tilde{l}_2 \end{bmatrix} \\ r_1 = \left| \tilde{l}_2 - \hat{l}_2 \right| \end{cases} \qquad (3)$$

Two other unknown input state observers have been designed. *Test 2* ( 4 ) is independent of $\varphi_{i1}$ and thus of valve $V_1$ state:

$$\begin{cases} \dot{\hat{l}}_2 = \left(-k/S - k_3\right)\hat{l}_2 + \begin{bmatrix} 1/S & k/S & k_3 \end{bmatrix} \begin{bmatrix} \tilde{\varphi}_{i2} \\ \tilde{l}_1 \\ \tilde{l}_2 \end{bmatrix} \\ r_2 = \left| \tilde{l}_2 - \hat{l}_2 \right| \end{cases} \qquad (4)$$

and Test 3 ( 5 ) is independent of both $l_2$ and $\varphi_{i2}$ (they cannot be handled separately):

$$\begin{cases} \dot{\hat{l}}_1 = \left(-k/S - k_4\right)\hat{l}_1 + \begin{bmatrix} 1/S & k_4 \end{bmatrix} \begin{bmatrix} \tilde{\varphi}_{i1} \\ \tilde{l}_1 \end{bmatrix} \\ r_3 = \left| \tilde{l}_1 - \hat{l}_1 \right| \end{cases} \qquad (5)$$

It is possible for each test to obtain the corresponding testable subsystem (TSS) (Ploix, *et al.*, 2002). The TSS related to a given test is the set of component models used to design this test. The 3 tests ( 3 ), ( 4 ), ( 5 ) have the following TSS:

$$\begin{cases} \text{test 1: } CM_1 \cup CM_2 \cup CM_3 \cup CM_4 \cup CM_6 \cup CM_7 \cup CM_8 \\ \text{test 2: } CM_2 \cup CM_3 \cup CM_4 \cup CM_5 \cup CM_6 \cup CM_8 \\ \text{test 3: } CM_1 \cup CM_2 \cup CM_5 \cup CM_7 \end{cases} \qquad (6)$$

Residuals have been generated and low-pass filtered. Thresholds have been empirically set to 125% of each residual maximum absolute value during an unfaulty simulation (Fig. 2, scenario 1).

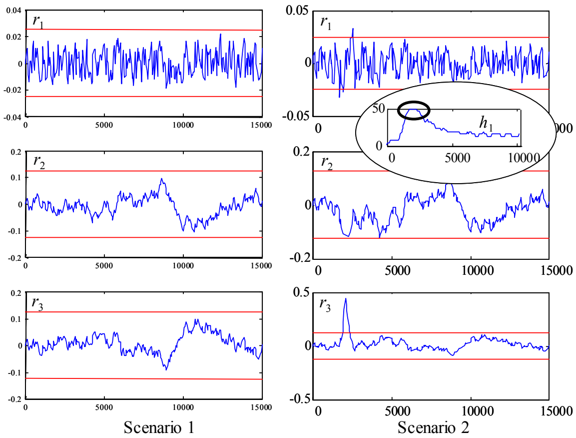



Fig. 2: Symptoms during normal behaviours, from top to bottom $r_1$, $r_2$, $r_3$.

Although the state is normal in scenario 2, tests 1 and 3 detect symptoms. Actually, the water level in upper tank $T_1$ is equal to 50 cm at the time the symptoms appear. Therefore these tests are invalid and the symptoms have not to be taken into consideration during this time interval.

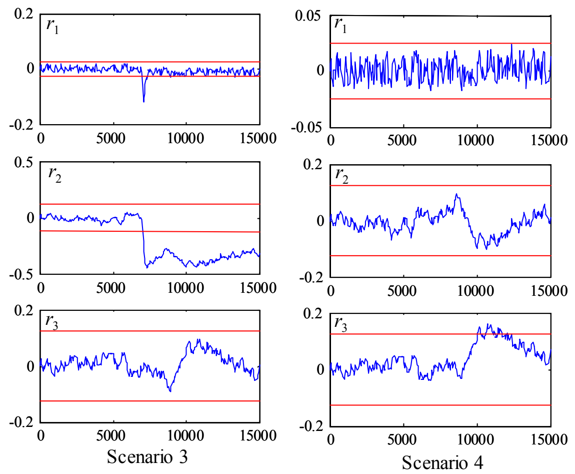



Fig. 3: Scenarios 3 and 4.

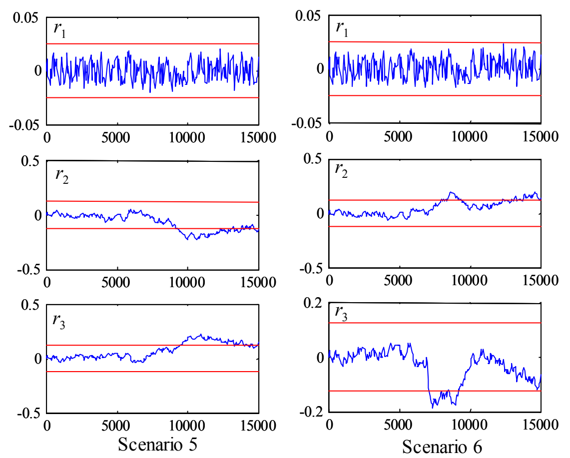



Fig. 4: Scenarios 5 and 6 ($r_1$, $r_2$, $r_3$).

Different fault scenarios are shown in Fig. 3 and Fig. 4 and used in sections 5, 6 and 7. They correspond to faults appearing abruptly at $t$=7000 s:

- Scenario 3: sensor $S_1$ offset (5cm);
- Scenario 4: valve $V_1$ offset (0.2 l.s$^{-1}$);
- Scenario 5: Fault in the upper tank restriction $R_1$;
- Scenario 6: sensor $S_2$ offset (5cm) and valve $V_2$ offset (0.2 l.s$^{-1}$).

Isolation methods will be now compared on these several scenarios.

## 5. ISOLATION WITH A SIGNATURE TABLE

Usually, signature tables only focus on actuator and sensor faults, discarding other kinds of faults. Applying this approach to the residuals ( 3 )( 4 )( 5 ) leads to Table 1.

Table 1: Signature table

| | $\tilde{\varphi}_{i1}$ | $\tilde{\varphi}_{i2}$ | $\tilde{l}_1$ | $\tilde{l}_2$ |
|---|---|---|---|---|
| $r_1$ | 1 | 1 | 0 | 1 |
| $r_2$ | 0 | 1 | 1 | 1 |
| $r_3$ | 1 | 0 | 1 | 0 |

Let's consider the 3rd scenario. The actual signature is $[1\ 1\ 0]^T$. The first symptom is temporary but it still has to be taken into consideration from its detection time because it appears only on transient behaviors and because faults are not supposed to disappear by themselves. From Table 1, faults on $V_1$ and on $S_2$ are both possible. The signature Table 1 is not isolable thus this result is unsurprising. Note that the true diagnosis belongs to this fault set.

Scenario 4 leads to the signature $[0\ 0\ 1]^T$, which is not in Table 1. The fault amplitude is not important enough for detecting a symptom with $r_1$. The use of a signature table implicitly assumes that the lack of a symptom is given as much importance as its presence.

Scenario 5 corresponds to a fault, which has not been considered in the signature table. A fault on $S_1$ is misdiagnosed. To avoid this kind of mistake, all the possible faults should be considered in the signature table. However, this is unrealistic.

Scenario 6 shows the resulting symptoms induced by two simultaneous faults, which is not considered in Table 1. Signature table-based approach generally does not consider multiple faults. Therefore, the resulting diagnosis is wrong. To avoid this problem, all fault combinations should be considered in signature tables. Nevertheless, this is also unrealistic.

Actually, the use of a signature table implicitly assumes that the set of possible faults is limited to those appearing in the signature table and that all the expected symptoms are detected.

## 6. ISOLATION WITH SIGNAL-BASED METHODS

Using a normal behavior model in parallel with the plant, a residual can be computed, namely

$$r_{l,i} = \tilde{l}_i - l_i, \quad i = 1:2 \qquad (7)$$

where $\tilde{l}_i$ is the level measure. $l_1$ is computed using model ( 1 ) and $\varphi_{i1}$, while $l_2$ is obtained using ( 1 ),

$\varphi_{i2}$ and $\tilde{l}_1$. Then, the TSS as defined in ( 6 ) associated with $r_{l,1}$ and $r_{l,2}$ are:

$$\begin{cases} \text{test 4 : } CM_1 \cup CM_2 \cup CM_5 \cup CM_7 \\ \text{test 5 : } CM_2 \cup CM_3 \cup CM_4 \cup CM_5 \cup CM_6 \cup CM_8 \end{cases} \qquad (8)$$

Notice that those TSS are identical to tests 3 and 2 in ( 6 ) respectively. As it can be seen (and expected!) in Fig. 5, those residuals are sensitive to actuator, sensor and process faults.

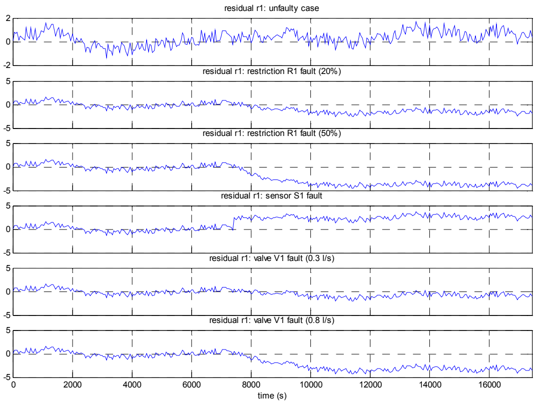



Fig. 5: residual $r_{l,1}$ corresponding to scenarios 3, 4, 5.

Signal-based methods provide extra tools for diagnostic purpose. They allow a new reading of information about the process behavior. For instance, spectral analysis may produce symptoms on the spectral contents modification for a given signal. Extra process knowledge allows isolation and identification of the related fault so that the whole fault diagnosis can be achieved (Salles, *et al.*, 1998; Simani, *et al.*, 2000).

Therein, different signal processing methods have been applied to the level measure $\tilde{l}_i$ and to the residuals ( 7 ) in order to extract information indicative of a particular fault. For instance, the residual $r_{l,1}$ autocorrelations have been compared for different fault scenarios (see Fig. 6 for scenario 5 as defined in section 4). While patterns seem very different, they are quite close from those induced by actuator or sensors faults (scenarios 3 and 4), which can be seen in Fig. 7. Using a change in mean detection algorithm, a faulty situation is detected for all scenarios. Then, residuals $r_{l,i}$ and level measure $\tilde{l}_i$ spectra have been computed for abnormal behavior data. Using spectral analysis, fault isolation cannot be achieved for this particular application. Actually, it is not surprising because the spectral contents are really poor. Furthermore, fault effects neither distort enough spectrum nor introduce extra spectral peak. Notices that spectrograms computed using a Short Time Fourier Transform achieve here a good detection, but they do not give isolation information.

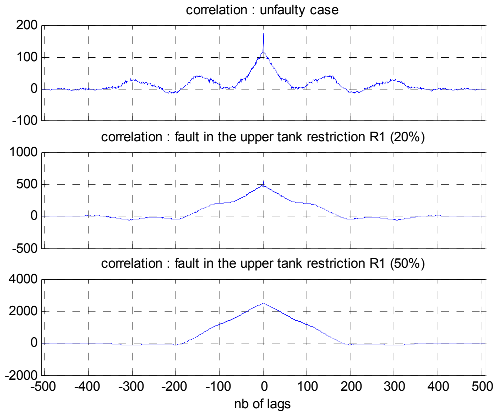



Fig. 6: $r_{l,1}$ autocorrelations (restriction R1 fault).

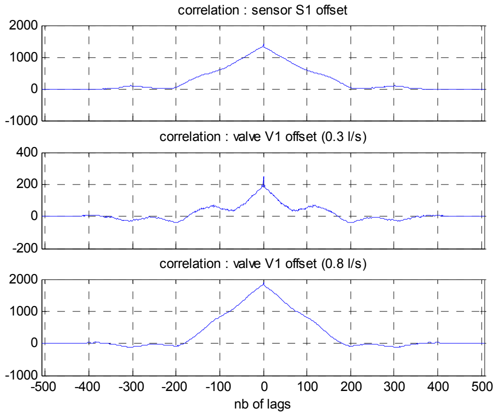



Fig. 7: $r_{l,1}$ autocorrelations (sensor $S_1$, actuator $V_1$ faults).

However unsuccessful signal processing methods are for diagnosis purpose in this particular context, they provide powerful tools for industrial processes diagnosis. They must be combined with other more traditional methods (Combastel, *et al.*, 2002) such as for instance observer-based or parity equations ones. Thus, they provide further information (spectrum, correlation, etc.) which fill in the process state knowledge.

## 7. ISOLATION WITH LOGICAL REASONING

In this section, the diagnosis is performed thanks to a logical reasoning isolation method presented in (Ploix et al, 2002). This method relies on the model (2), which details the implicit assumptions related to each test. Table 2 summarizes these assumptions. It may be easily deduced from (6).

Table 2: Matrix of component state assumptions

| | $\neg AB(T_1)$ | $\neg AB(R_1)$ | $\neg AB(T_2)$ | $\neg AB(R_2)$ | $\neg AB(S_1)$ | $\neg AB(S_2)$ | $\neg AB(V_1)$ | $\neg AB(V_2)$ |
|---|---|---|---|---|---|---|---|---|
| Test 1 | 1 | 1 | 1 | 1 | | 1 | 1 | 1 |
| Test 2 | | 1 | 1 | 1 | 1 | 1 | | 1 |
| Test 3 | 1 | 1 | | | 1 | | 1 | |

For a sound logical approach, all the related symptoms are not supposed to be necessarily detected.

Scenario 3 leads for instance to the 7 following possible faulty states: $AB(T_2)$, $AB(S_2)$, $AB(V_2)$, $AB(R_2)$, $AB(R_1)$, $AB(T_1)$^$AB(S_1)$ or $AB(V_1)$^$AB(S_1)$. The four first ones are the most plausible (see definition in (Ploix *et al.*, 2002)). For this scenario, the signature table-based approach finds only two diagnoses among the 7 ones. Conversely, the logical approach is complete.

Scenario 4 leads to the following diagnoses: $AB(T_1)$, $AB(S_1)$, $AB(V_1)$ or $AB(R_1)$ where the 3 first ones are the most plausible. For this scenario, the signature table-based approach does not lead to any diagnosis whereas the logical approach founds the true system state: $AB(V_1)$.

Scenario 5 leads to the following results: $AB(S_1)$, $AB(R_1)$ or 8 possible double fault diagnoses, where the first one is the most plausible. The restriction fault, $AB(R_1)$, is found by the logical approach although it has not been modeled. The assumptions related to each tests contain enough information to retrieve to true system state.

Scenario 6 leads to the same diagnoses than those of scenario 5. The true system state belongs to the double fault diagnoses: $AB(S_2)$^$AB(V_1)$. Because of its completeness, the logical reasoning supports multiple faults diagnosis without requiring very large signature tables.

## 8. CONCLUSIONS

In this paper, two fault isolation approaches have been compared. They make use of results obtained from observer-based or signal-based diagnostic methods and rely on one hand on a signature table and on the other hand on a logical reasoning.

A simple example is used to illustrate the difficulty of making a diagnosis at the global level of a complex process, using symptoms obtained from various methods applied to different subsystems. It shows the necessity of having a global isolation reasoning. It is evidenced that the diagnostic strategy needs to separate clearly the symptom detection (and eventually a local isolation) from the global fault isolation. This enlightens the difficulty and the scientific interest of the MAGIC project.

The logical approach needs to formalize clearly all hypotheses underlying the diagnosis. It is thus more difficult and time consuming that the classical signature table technique. But, as a consequence, it is complete. It provides the various possible diagnoses, including multiple faults possibility, all of them logically sound.

The MAGIC project integrates various diagnostic agents based on different hypotheses, implementing different methods and specialized to different sub-processes. Thus achieving a relevant isolation with few possible diagnoses can be expected.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