CAUSAL REASONING IMPROVED BY FUZZY LOGIC FOR DIAGNOSIS OF BOND GRAPH MODELLED UNCERTAIN PARAMETERS SYSTEMS

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Abstract: In this paper, a method for on-line fault detection and isolation (FDI) of bond graph (BG) modelled uncertain parameters systems is proposed. In this case, we don't have to calculate the Analytical Redundancy Relations (RRAs) since residuals are directly generated from the Diagnostic Bond Graph (DBG). Detection is based on fuzzy logic approach. For isolation, two methods exploiting the causal properties of the BG model are used: Fault Signature Matrix (FSM), and exoneration. A real simulation example is provided to show the efficiency of the proposed methods.

1 INTRODUCTION

Presently, Fault Detection and Isolation (FDI) is an increasingly active research domain. FDI consists in identifying when a fault has occurred, the type of fault and its location. A widespread solution for FDI consists in comparing the behaviour of the real system to a theorical model.

FDI methods can be divided into three categories: quantitative methods, qualitative methods and process history based methods (Staroswiecki, 2000); (Venkatasubramanian, 2003.a); (Venkatasubramanian, 2003.b); (Venkatasubramanian, 2003.c).

The most frequently quantitative diagnosis approaches are based on Analytical Redundancy Relations (ARRs), Kalman filters and parameter estimation. The ARRs are relations comparing informations given by the real process to those generated by the theorical model.

The qualitative methods are based on qualitative models such as causal graphs, fault trees or abstraction hierarchies … (Montmain and Gentil, 1999). These models are obtained by analyzing the cause and effect relationships in the process and the association of observations (symptoms) to failures using qualitative operators.

Because of its behavioural, structural and causal properties, the BG tool is used in complex processes modelling and FDI (Samantaray and al., 2008); (Dauphin-Tanguy, 2000); (Dauphin-Tanguy and Tagina, 2000). Its causal properties are used to determine the fault origins; Bond Graph is exploited in both qualitative and quantitative diagnosis methods (Samantaray et al., 2008).

Qualitative methods transform the BG model to a qualitative model expressing the states of variables with qualitative states ([+], [-] or 0) (Montmain and Gentil, 1999). When an inconsistency (fault) is detected, backward and forward propagation procedure can be used for isolation. The BG model can also be transformed to a Temporal Causal Graph (TCG) or tree graph that can be used for FDI (Samantaray et al., 2008).

In quantitative approaches, many methods are proposed. By covering the causal paths in the BG model, Analytical Redundancy Relations (ARRs) can be derived from the energy conservation laws in junctions 0 and 1, the principle of fault signature can then be used to isolate the fault affecting sensors and

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actuators (Tagina, 1995). In (Samantaray et al., 2006), residuals are directly generated in the Diagnostic Bond Graph (DBG), and a fault signature matrix (FSM) is elaborated by covering causal paths from residuals detectors to the components.

Therefore, the efficiency and robustness of these methods depend on the model's accuracy.

In case of uncertain parameters systems, (Djeziri, 2007); (Djeziri et al., 2009) proposed a robust diagnosis algorithm, from a BG model in Linear Fractional Transformations (LFT) form. They derived ARRs in which they separated the quantity of energy given by the uncertain part from the residual to be evaluated, this idea allows the generation of adaptive thresholds for fault detection. A study of sensitivity was elaborated to deduce detectability indexes defining the detectable value of the residual in case of faults and parameters uncertainties. In (Bouallègue et al., 2010), a method for robust fixed and adaptive thresholds is proposed. This method exploits the sensitivity of residuals to different system parameters in order to determine their thresholds; the FSM is used for isolation. In (Bouslama-Bouabdallah et al., 2006), a fuzzy logic approach applied to residuals deduced from the BG model is used in detection stage. For isolation, the FSM is transformed into inference rules allowing the determination of the fault's origin.

The main contribution of this paper is to use the bond graph model directly in the task of robust FDI in case of uncertain parameters systems. The detection module is based on a fuzzy logic system. For isolation, two causal reasoning based methods were proposed.

This paper is organized as follows: Section 2 details the notion of DBG used to generate directly the residuals in the BG model. Section 3 describes the proposed fuzzy detection method. Section 4 presents two isolation methods: signature matrix and exoneration. Section 5 describes the hydraulic benchmark composed of three tanks. Finally, different results and their interpretations are given in section 6.

2 RESIDUALS GENERATION FROM DBG

The generation of Analytical Redundancy Relations (ARRs) from the bond graph model uses the structural relations given by the conservation law in all 0 and 1 junctions and aims to express the unknown variables by those known (inputs and sensors). This method cannot deal with algebraic loops, so, unknown variables cannot be eliminated. So, the structural independence of the different residuals has to be checked with existing residuals.

In (Samantaray et al., 2006), a direct method for ARR generation from BG model is proposed. The causality inversion of detectors (which are considered as sources) has been proposed as a unified approach to generate residuals.

When the bond graph model is assigned preferred differential causality and using inversion of sensor causalities, if necessary, the following five compositions are possible (Samantaray et al., 2006):

1. Inverted causality in effort sensor (De),
2. Inverted causality in flow sensor (Df),
3. non-inverted causality in effort sensor (De),
4. non-inverted causality in flow sensor (Df),
5. Inversion of signal sensor, Ds, to signal source, Ss (for controllers).

Let us consider the case of inverted causality in the effort sensor, De, (see Figure 1). This sensor will be equivalent to an effort source (measurements from real process), so expression of the source loading flow variable is equated to zero (Samantaray et al., 2006). This expression is a residual (it does not involve any states, since all storage elements are in differential causality) which's measured by a virtual flow sensor (Samantaray et al., 2006).

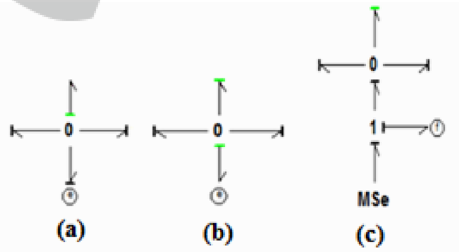

Figure 1: (a) Sensor e in behavioral model, (b) inverted causality in e and (c) substituted representation for inverted causality in e.

The bond graph of the system with these substitutions using preferred derivative causality is called the Diagnostic Bond Graph (DBG) (Samantaray et al., 2008).

3 DETECTION USING FUZZY LOGIC APPROACH

In ideal conditions, residual value is equal to zero in fault free context. In practice, due to the uncertainty and the measurement noise, residuals are different from zero. Thresholds are used to deduce whether systems are in normal functioning mode or faulty mode. Unfortunately, thresholds near to zero can cause false alarms problems because of noise variation; and assigning larger thresholds reduce the fault detection sensitivity (Frank et al., 1997).

Fuzzy logic is the most common solution to overcome the uncertainty problems. Many works used this approach in residuals processing in order to know the system state (Evsukoff et al., 2000) (Bouslama-Bouabdallah et al., 2006).

In this work, we propose fuzzy processing of residuals generated by the DBG in the task of fault detection in case of parameters uncertainty.

From residuals values, two features can be extracted:

- The absolute value of the residuals: r
- Residual variation over a sliding time window: d

$$d = \frac{1}{N}\sum_{i=t}^{t+N-1}\left|r(i)-r(i-1)\right|$$

The choice of the parameter N depends on the residual variation and the noise effects, it is fixed experimentally until we can get clearly the signal trend.

The descriptor sets associated with each feature fuzzy partition are:

r= {“SMALL”, “LARGE”}
d= {“SMALL”, “LARGE”}

These two variables are fuzzified using two trapezoidal membership functions (Figure 2). So, four parameters have to be determined for each function.

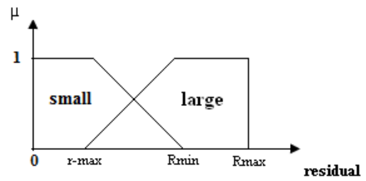

Figure 2: Fuzzy sets of the residuals.

The trapezoidal boundaries of the set SMALL are given by:

r : μ_{small}=[0, 0, r-max, Rmin]
d : μ_{small}=[0, 0, d-max, Dmin]

And for the set LARGE, they are given by:

r : μ_{Large}=[r-max, Rmin, Rmax, Rmax]
d : μ_{Large}=[d-max, Dmin, Dmax, Dmax]

Where:

r-max respectively d-max is the maximum value of the residual respectively residual variation in normal operating mode

Rmin = K_r* r-max.
Dmin= K_d*d-max ,
K_r, K_d is fixed experimentally.

Rmax respectively Dmax: is the maximum value respectively variation of residual in faulty case.

For each residual, we have established a set of inference rules which are presented in the following table:

Table 1: Rules base of the fuzzy system.

d \ r	Small	Large
Small	Normal	Fault
Large	Fault	Fault

Rules are obtained using MIN-MAX inference method, the MIN operator represents the logic function AND, and the MAX operator for the logic function OR.

The output of this fuzzy system is a fault index indicating whether the concerned residual is in normal operating mode or faulty mode (Figure 3).

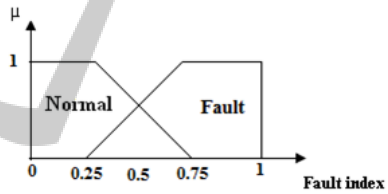

Figure 3: Residual defuzzification.

4 THE PROPOSED FAULT ISOLATION METHODS

Many procedures issued from FDI and Artificial Intelligence communities were proposed in the task of Fault Isolation. Causal properties of the BG tool could be used in many methods such as Fault Signature Matrix (FSM) and the exoneration algorithm. In this work, these two methods are combined with fuzzy reasoning in order to improve FDI efficiency.

4.1 Signature Matrix

In FDI terminology, the Fault Signature Matrix (FSM) crosses ARRs in rows and faults in column (Cordier et al., 2004) (Biswas et al., 2009). Fault isolation uses structural properties of the ARR expressed in terms of a binary fault signature matrix S, which describes the participation of various components (physical devices, sensors, actuators and controllers) in each residual and forms a structure that links the discrepancies in components to changes in the residuals (Cordier et al., 2004).

Let us consider that fj is a fault affecting component Cj, then in the binary fault signature matrix F is,

$$F_{ij} = \begin{cases} 0, & \text{if the occurence of fault } fj \text{ does not affect } ARRi \\ 1, & \text{if the fault } fj \text{ will violate } ARRi \end{cases}$$

From the DBG model, the analysis of the causal paths to each residual is used to generate these signatures (Samantaray et al., 2006). In fact, every component causally linked to the residual detector can affect its value. Let us consider the DBG of Figure 4:

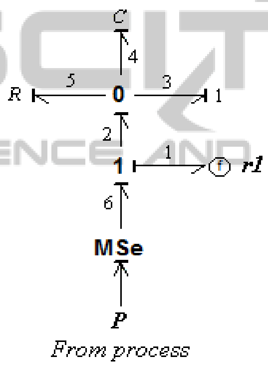

Figure 4: Example of DBG.

If we consider residual detector *r1*, the next causal paths can be found:

C→f4→f2→f1→r1

R→f5→f2→f1→r1

P→e6→e2→e4→C→f4→f2→f1→r1

Then, any variation in components C, R and sensor P can affect the value of residual r1. In the same way, and using all residuals, we can deduce the FSM.

In this work, fuzzy detection module output is exploited in isolation task. So, a fuzzy fault signature matrix F is defined as follows:

$$F_{ij} = \begin{cases} Small, & \text{if the occurence of fault } fj \text{ does not affect } ARRi \\ Large, & \text{if the fault } fj \text{ will violate } ARRi \end{cases}$$

4.2 Exoneration

4.2.1 Principle of Exoneration

Exoneration principle is a fundamental concept that is often used implicitly in diagnosis (Cordier et al., 2004); (Fagarasan et al., 2004). It uses consistency of tests (residuals) to check if its support can be faulty or not. The supports of a residual are variables that can affect it and change its value. The exoneration algorithm manages two lists, a list of components whose state is normal, LN and a list of suspect components LS. LS is made by the union of the inconsistent test supports that are not exonerated by the consistent tests (Fagarasan et al., 2004).

The steps of the algorithm are the followings (Fagarasan et al., 2004):

1. Initialize L_N and L_S to the empty list $L_N = L_S = \{\emptyset\}$.
2. At each sampling time and for each test Ti:

2.1. IF *Ti* result is *consistent*, THEN *Ti* support *Ci* is considered normal thus added to L_N, $L_N=\{C_i \cup L_N\}$ and deleted from L_S, $L_S=L_S \backslash C_i$

2.2. IF *Ti* result is *inconsistent*, *Ti* support *Ci* is suspected of being faulty and its components that are not in L_N are added to L_S, $L_S=\{C_i \cup L_S\} \backslash L_N$.

Finally, after the analysis of the tests, the components in L_S represent the final diagnosis.

4.2.2 Exoneration Improved by Fuzzy Logic

This algorithm is based on fuzzy logic to check the consistency of the residuals. To use the fuzzy detection module results, some improvements have to be done.

1. Initialize L_N and L_S to the empty list $L_N = L_S = \{\emptyset\}$
2. At each sampling time and for each test *Ti*:

2.1. IF *Ti* result is *NORMAL*, then *Ti* support *Ci* is considered normal thus added to L_N, $L_N=\{C_i \cup L_N\}$ and deleted from L_S, $L_S=L_S \backslash C_i$

2.2. IF *Ti* result is *FAULT*, then *Ti* support *Ci* is suspected of being faulty and its components that are not in L_N are added to L_S, $L_S=\{C_i \cup L_S\} \backslash L_N$

5 APPLICATION EXAMPLE

5.1 Test Bench Presentation

Let us consider the following hydraulic system (Figure 5):

Figure 5: Real system.

This system is composed of three tanks T1, T2 and T3 respectively of diameters D1, D2 and D3; water level in tanks, H1, H2 and H3 (proportional respectively to the pressures P1, P2 and P3) is measured by level sensors. This system is fed by two pumps which deliver flows Sf1 (flow of entrance at T1) and Sf2 (flow of entrance at T3).

Tanks T1 and T2 communicate through valve V12 and tanks T2 and T3 through valve V23 of diameter Sv. Each tank has a draining valve noted Vi (i=1 to 3). Flow going out from valves V1 and V2 is measured by flow sensors f1 and f2.

5.2 System BG Modelling

A procedure described in (Tagina, 1995) allows elaborating the BG model of the system in integral causality (Figure 6) as well as the corresponding model in derivative causality (Figure 7).

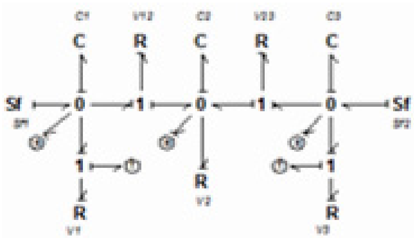

Figure 6: BG model in preferred integral causality.

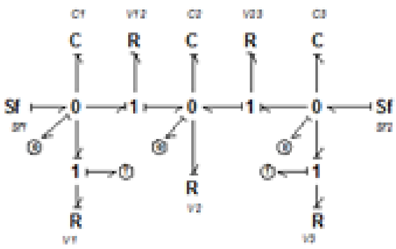

Figure 7: BG model in preferred differential causality.

The coupling between the two precedent models produces the DBG of Figure 8:

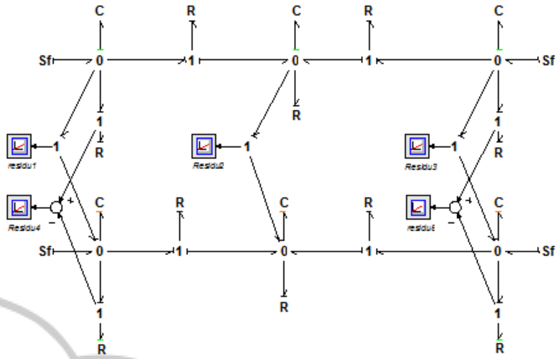

Figure 8: DBG of the three tanks system.

From Figure 8, the following FSM can be determined:

Table 2: Fault signature matrix of the three tanks system.

	r1	r2	r3	r4	r5
Sf1	1	0	0	0	0
Sf2	0	0	1	0	0
V1	1	0	0	1	0
V12	1	1	0	0	0
V2	0	1	0	0	0
V23	0	1	1	0	0
V3	0	0	1	0	1

The supports of each residual deduced from the DBG are given below:

C_1:{Sf1, V1, V12}
C_2:{V12, V2, V23}
C_3:{Sf2, V23, V3}
C_4:{V1}
C_5:{V3}

6 EXPERIMENTAL RESULTS

6.1 Case of Normal Operating Mode

In Figure 9, different residuals in normal operating mode are presented.

We notice that residuals have low values around zero; this variation is due to parameters uncertainties.

From Figure 9, we can deduce different boundaries numeric values of the trapezoidal memberships functions in the fuzzy detection module. Different isolation methods were applied with those boundaries. The results are given in Figure 10. All the fault indexes of different methods are equal to zero indicating that there are no faulty components.

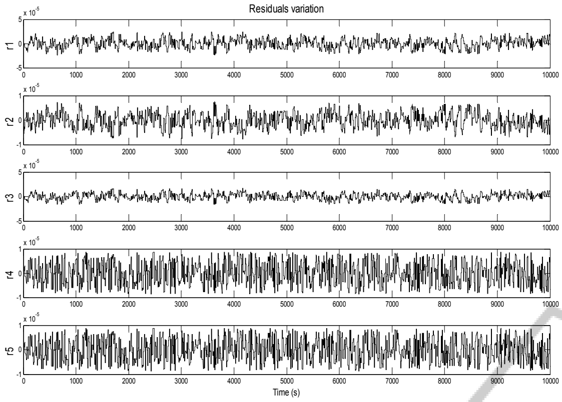

Figure 9: Residuals evolution in normal operating mode.

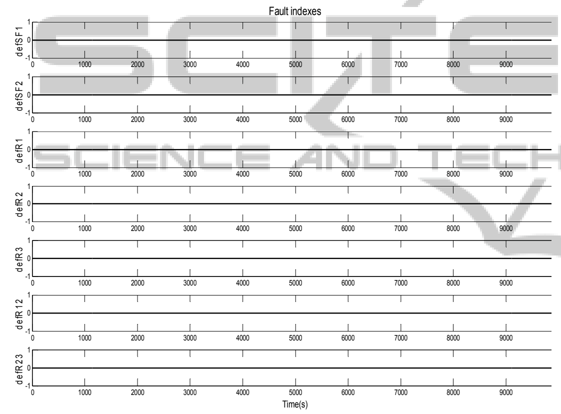

Figure 10: Fault indexes with fault signature and exoneration.

6.2 Case of Faulty Operating Mode

In case of faulty operating mode, some residuals deviate from their normal values and isolation methods are then used to identify the faulty component.

6.2.1 First Case: Fault affecting Valve V12

We totally fill in valve V12 at time 5000s; Figure 11 illustrates the evolution of the different residuals.

We notice, at the occurrence of the fault, residuals sensors r1 and r2 deviation; all the other residuals do not exceed normal functioning thresholds, the signature (1, 1, 0, 0, 0) is equivalent to fault in component V12 (Table 2).

Figure 12 represents the fault indexes generated by the fuzzy FSM method. We notice that fault's origin is perfectly identified. In fact, fault index DefR12 passes to 1 at instant 5000s.

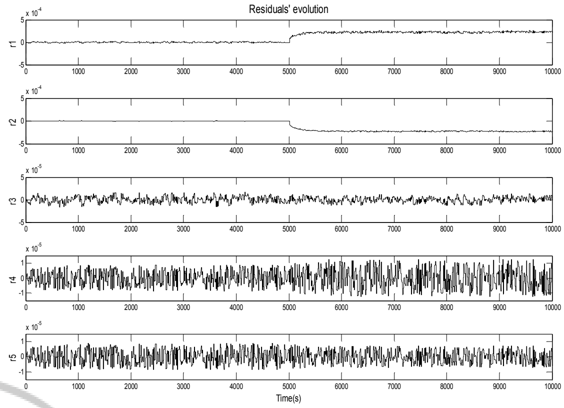

Figure 11: Residuals evolution in case of V12 fault.

Figure 12 represents the fault indexes generated by the fuzzy FSM method. We notice that fault's origin is perfectly identified. In fact, fault index DefR12 passes to 1 at instant 5000s.

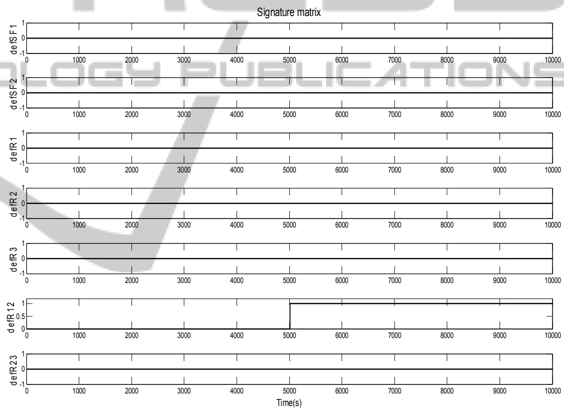

Figure 12: Fault indexes with fault signature matrix.

The results of localization by exoneration algorithm are shown in Figure 13. In this case, the fault indexes of components SF1, V2 and V12 passed to 1 at time 5000s. Then, we obtain 3 candidates components: {SF1, V2, V12}.

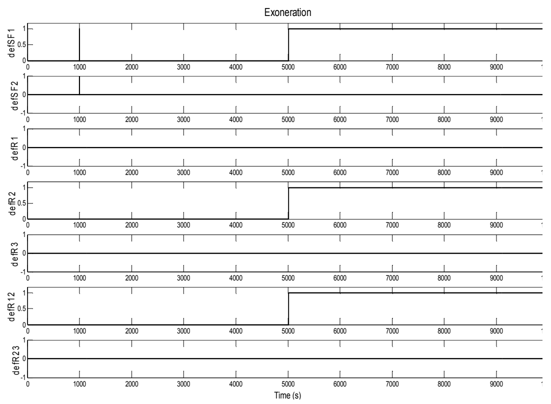

Figure 13: Fault indexes with exoneration algorithm.

6.2.2 Second Case: Fault Affecting Valve V3

We suppose that valve V3 is closed at instant 5000s, Figure 14 presents the evolution of the different residuals in this case.

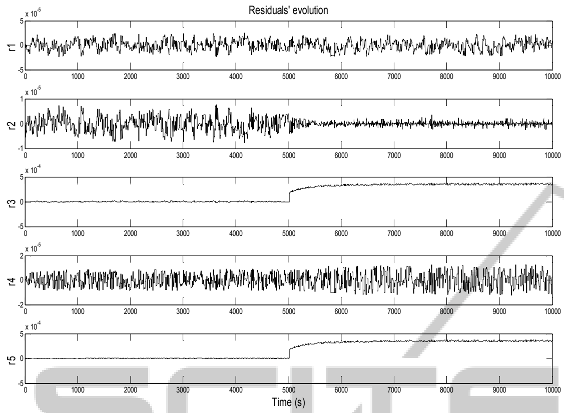

Figure 14: Residuals evolution in case of V3 fault.

We notice that residuals r3 and r5 are affected by this fault and make a distinctive variation from their normal values. The signature (0, 0, 1, 0, 1) represents fault in component V3 (Table 2)

In Figure 15, fault indexes obtained by signature matrix method are shown. This method localizes perfectly the faulty component (V3).

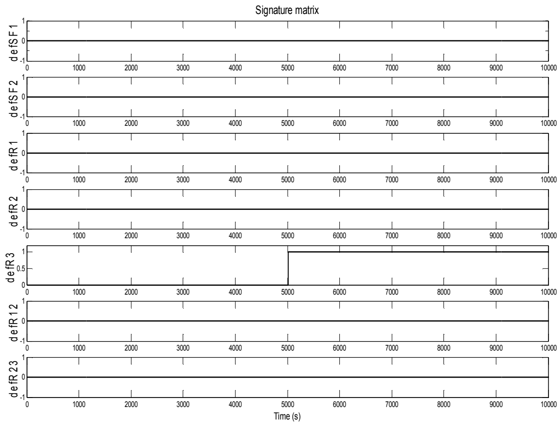

Figure 15: Fault indexes with fault signature matrix.

Localization indexes determined by exoneration procedure are given in Figure 16. They identify two candidates to the fault: SF2 and V3.

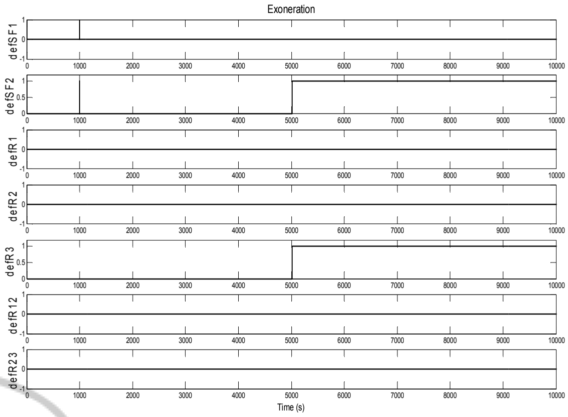

Figure 16: Fault indexes with exoneration algorithm.

7 CONCLUSIONS

In this paper, fuzzy logic approach and causal properties of the BG model are combined for FDI. The residuals generated from the DBG are processed in the fuzzy detection module. Output is a fault index indicating whether the residual is faulty or it is in fault free case.

Causal properties of the BG model allow using 2 localization methods: FSM and exoneration algorithm. Our principle criterion to judge proposed methods performances is the false alarm rate. The FSM has proved its superiority in case of single fault hypothesis. Exoneration methods give a conflict set composed of more than one element in most cases.

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