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ORIGINAL ARTICLE

Decentralized fault detection and isolation using bond graph and PCA methods

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Abstract

This paper proposes a new method for fault detection and isolation of a large-scale system by the bond graph (BG) model and the principal component analysis (PCA) technique in a decentralized architecture. The proposed method is entitled the BG-PCA technique. The main objective is to address the problem of monitoring large-scale system components by fault detection and isolation (FDI) methods. In the modeling framework, the BG model is presented by exploiting its structural and causal properties and the diagnostic bond graph (DBG). In measurement noise and perturbation conditions, the probability density function takes place to generate a clear decision procedure to detect the operating mode. In our approach, we firstly generate the structured residues. Furthermore, with a decentralized architecture, we can locate in what subsystem a fault is first detected. Finally, for isolation, the generation of the structured residues method from PCA is exploited to ensure localization. To validate the suggested BG-PCA algorithm, simulations are computed on a three-tank system to show the efficiency of the proposed FDI method, and satisfactory results are found.

Keywords Bond graph · Principal component analysis · Fault detection and isolation · Diagnostic bond graph · Large-scale system

1 Introduction

With the improvement of the modern technology, large-scale systems are more and more complex. This complexity is mainly due to a high dimensionality and to a strong interconnection between the subsystems. To ensure the reliability, safety, quality, and efficiency of dynamic systems, the monitoring stage is very important. Automatic fault detection and isolation (FDI) of a system increases as the size and complexity of systems rapidly grow.

FDI is a dubfied of control engineering, which concerns process supervision. For real-world applications, the presence of measurement noise or the influence of modeling uncertainty may present problems of performance of fault detection schemes. This theory presents two types of categories: quantitative and qualitative descriptions [1]. The FDI algorithms are usually based on the theory of the comparison between the actual behaviour of the process and the reference behaviour provided by a normal operation model.

Generally, the possibility of detecting and isolating faults mainly depend on the system architecture. In the literature, the majority of FDI methods have been concentrated on centralized systems. Theoretically speaking, several centralized architectures have been used for detection of faults and prediction of failure [2–4]. However, faults are inevitable part of any industrial system and can lead to catastrophic failures if not detected and accommodated in the early stages [5]. Over the past decade, the decentralized control of many industrial systems has been an interesting research topic [6] to facilitate the detection task, especially

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the isolation one, besides the modeling principle. Therefore, the problem of a decentralized architecture of large scale systems has attracted lots of interest, such as Li et al. [6], Boem et al. [7], Reppa et al. [8], Arrichiello et al. [9], Ferdowsi and Jagannathan [5].

In the past few years, different approaches for the design of FDI procedures have been developed, like observers [10], data driven methods [11], parameter estimation [12], and the graphical approaches developed in [13] and [14]. In this context, Zhiwei et al. [20] were interested in approaches based on the exploitation of analytic redundancy relationships (ARRs) from which a graphical or analytical model could be extracted. This approach expressed the difference between information provided by the actual system and that delivered by its normal operation model.

The graphical approaches, as mentioned in [13], were well suited for the analysis of structural properties as the graphical model was separate from the numerical values of the system parameters. In this context, the Bond Graph (BG) tool is more and more used for modeling and fault diagnosis because of its structural, behavioural and causal properties. The BG technique becomes a very suitable tool to deal with large-scale systems, especially those that belong to multi-energetic domains [21]. This technique is presented as a multidisciplinary graphical language, which gives the representation of power transfers for a system, especially within a large scale.

For the purpose of process monitoring, several techniques based on BG are also proposed in the literature. Among the existing work, the processes based on BG have been frequently studied. In the nineties, the graphical aspect of the BG were extended to include health-monitoring applications. In [15], and regarding the detection phase, the behavior model was obtained by using the BG formalism and the degradation models derived from the concept of residues. In [16], the BG aspect was widely utilized for the FDI design with qualitative and causal analysis approaches. Thereafter, from a BG model, a technique to generate ARRs with covering causal paths was presented in [17]. The quantitative approach to generate ARRs was used for FDI design in [18]. For the monitoring process, the Failure Signature Matrix (FSM) was developed in [19].

The step of fault detection with the BG model is determined by the presence of faults indicated by a non-zero value of these indicators. Generally, the localization procedure by BG is based on the classic fault signature matrix generated from the ARRs theory. Nevertheless, this location phase is not the most effective phase because some faults are not isolated. More precisely, the supervision module can provide many problems such as unknown signatures and also residues corresponding to the signature of more than one fault. There are still some problems for the monitoring process based on BG.

In this field, several papers have been published. In [19], the FDI decision module was ameliorated by increasing the number of monitored sensors. The principle of FDI was introduced by [22] and [23], who used reliability data and bayesian networks for the improvement of decision making in ARR-based approaches. In addition, the authors [38] proposed to use BG and timed automata to facilitate the isolation phase. However, for large-scale systems, such methods would have many problems for the representation of the model.

The principal component analysis (PCA) approach was also used for process monitoring in [26, 27]. In the literature, we find the approach that rests on the calculation of contributions to the detection index [28–30]. Then in [31], the authors suggested an approach based on the structuring of residues. When speaking about the fault isolation by the PCA technique, we find methods that may be based either on the distance calculation between the experimental signature and the different theoretical signatures [25] or on the projection of an experimental signature on various theoretical signatures [32].

In our case, we use the fault isolation principle provided by the PCA to validate the location of each structured residue [24, 25] in a decentralized architecture. In this study, a new method for FDI, entitled BG-PCA, in a decentralized architecture is put forward.

The main purposes in this paper concern residue generation and FDI in a new approach using BG model and the PCA method in a decentralized architecture. This approach respectively uses BG and the probability density function with the threshold principle for the generation and detection of residues. Finally, those residues will be localized by a generation-structured method from PCA.

The advantage of the presented method consists in developing a methodology that extends the BG-model-based approach to detect faults and find the cause of a system dysfunction. Moreover, the innovative interest of the presented paper is to isolate faults, which can affect the physical process using the PCA technique and the decentralized architecture. In other words, the fault isolation phase consists in finding how to isolate a fault using both theories. The performance of the proposed method is evaluated using a three-tank system. The simulation results show that the suggested method provides good detection and isolation performances.

This paper is organized as follows: Sections 2 and 3 give a presentation of the BG theory and PCA method, in order to develop a new diagnosis approach. After that, Section 4 details the decomposition problem with the local fault detection and generation of structured residues from PCA. In Section 5, simulation results are given to illustrate the performance of the proposed BG-PCA approach. At the end, some conclusions are presented in Section 6.

2 Bond graph theory

Generally, the graph theory approach is used, independently, at the system parameter values, to study and analyse structured systems. This theory necessitates a low computational burden, which allows dealing with large-scale systems. There are different types of graphical representations, like Digraph, Bipartite graph, Signed graph and finally BG. The difference between BG and the other graphical approaches is that the former is directly generated from the physical system and not from state space equations [33]. In addition, from the BG model, state space equations can be automatically generated and dedicated software is used for it.

2.1 Bond graph model and causal path

The concept of the BG modeling technique was introduced in 1961 by Paynter [34] and formalized by Karnopp et al. [35] and Breedveld et al. [36]. The BG method is a domain-independent graphical description of the dynamic behaviour of different physical systems. Mechanical, hydraulic, electrical, acoustical, material, and thermodynamic systems are described in the same way. This method is supported essentially on energy and on energy exchange. The BG method is a topological modeling language established for the power exchange between the components of a dynamic system, captured in a graphical form. A BG model is an oriented graph G(S,A), where S represents the vertices of physical components and edge A represents the instantaneous power exchanged between nodes. This modeling technique becomes a suitable tool to handle large-scale systems. In general, there are two generic power variables, named effort e and flow f present the energy exchange link associated with every bond, such that $e \times f$ =power. The set elements $\{C, I, R\}$ are passive elements, where C, R and I are respectively the capacitance, inertial and dissipation element.

– C: The physical modeling phenomenon relates effort to displacement, given in (1), like capacitors, springs, etc.

$$\phi_C \frac{d}{dt}(f(t)) = e(t) \tag{1}$$

– I: The modeling phenomenon is related to the momentum, given in (2), like mass, inductors, etc.

$$\phi_I \frac{d}{dt}(f(t)) = e(t) \tag{2}$$

– R: The modeling phenomenon relates effort and flow, given in (3), like electric resistors, diodes, etc.

$$\phi_R(f(t)) = e(t) \tag{3}$$

The set elements $\{S_e, S_f : Sources\}$ are active ports like gravity and pumps. The sensors $\{D_e, D_f\}$ are essentially the sources of information.

The latter set of elements $\{TF, GY, 0, 1\}$ are the junction elements where TF is the transformer element and GY is the gyrator element. The 0 (or 1) junction is used to connect many submodels with the same effort (flow), and the sum of the flows (efforts) are equal to zero.

On the other hand, to obtain an efficient result of the physical behaviour of the system, the computation of the cause and the effect must be decided systematically [21]. In this context, the causality in BG models is defined by a perpendicular stroke on each bond. In the BG domain, aforementioned in Fig. 1, system A imposes an effort $e(t)$ to system B, which in turn responds with a flow $f(t)$.

2.2 Residue generation from BG model

Automatically, a great number of methods have been dedicated for FDI. In the litterature, the FDI methods can be divided into two significiant categories: qualitative and quantitative methods [37]. All these methods use the approach of residual functions. In most of the cases, the residue which ought to be zero during normal operation is defined by the difference between an estimated value and a measured one. In the BG framework, FDI is mainly based upon ARRs and using algebraic observers [33]. Then this residue is produced by the ARR.

The ARR relation, Classically, is a constraint relation derived from an over-constrained system or subsystem [21]. It is defined in terms of only known variables of the process. From the BG model, the generation of ARR is a hard computational task and a recursive procedure especially for non-linear systems [38]. In the mathematical context of BG modelling, any f function of a set of known variables is as follows (4):

$$f(D_e, D_f, S_e, S_f, MSe, MSf, \theta, u) = 0 \tag{4}$$

where (D_e) is the effort sensors, (D_f) is the flow sensors, (S_e) is the effort sources, (S_f) is the flow sources, (MSe) is the modulated effort sources, (MSf) is the modulated flow sources and (θ) is the process parameters.

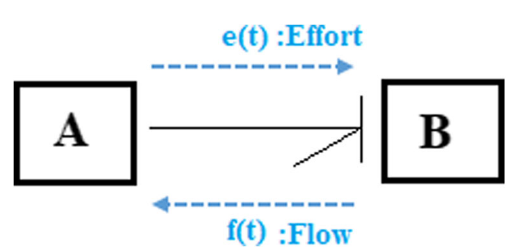

Fig. 1 Causality assignment rule

Generally, in the BG model, the preferred derivative causality with dualized sensors is utilized to avoid unknown initial condition problems. In [39], and from the BG models, by using the causality inversion algorithm, the ARR method for simple systems was presented. Furthermore, in [19], a direct method, called DBG, for residue generation from BG is proposed.

3 PCA-based process diagnosis

Even though the PCA principle appeared in 1889. PCA research and applications are still very interesting domains in study [42]. However, PCA has been used in the statistical process control area for fault detection such as process monitoring like in Raich and Cinar [40] and MacGregor et al. [41]. Compared to several methods of dimensional reduction, this method is more used to a set of variables that vary linearly [49]. Despite its performance, it cannot perform suitably for the variations in nonlinear data. To overcome this problem and reach our objective, the Kernel PCA (KPCA) is given. The KPCA method can efficiently compute principal components in high dimensional feature spaces utilizing integral operators and nonlinear kernel functions [43]. The main advantage of KPCA is that it solves an eigenvalue problem without involving a nonlinear optimization.

The principle of this technique is to project an observed data matrix to a new high dimensional space, called feature space and denoted F, with a nonlinear mapping function ϕ. Let us consider x(k)=$[x_1, x_2, ..., x_n]^T$ the centered and reduced data matrix in the input space. The data matrix X can be decomposed as follows:

$$X = \hat{X} + \tilde{X} \tag{5}$$

where $\tilde{X}$ presents the remaining components and $\hat{X}$ is the projection to the principal components. In this part and after the fault detection, it is necessary to talk about the fault location. To meet this target, several methods have been developed in the literature. Concerning the PCA analysis [44], we find three approaches:

- Location by reconstruction
- Location by calculation of contributions
- Generation of structured residues

In this paper, we use the third approach. The structured residues are so constructed that each residue is sensitive to a particular subset of faults. The purpose of this approach is to obtain a strong isolation for each faut, which permits locating defective variables. However, we have to express a theoretical fault signature matrix for the structuring of residues, where each residue is sensitive to a particular subset of faults [24].

4 Decomposition problem

In this section, the FDI method we suggest is composed of four steps. In the first place, we divide the system in two subsystems. After that, we generate residues r_i for each subsystem. Next with the probability density, the residues are evaluated to detect whether a fault exists or not. Finally, the PCA approach is used to isolate the faulty components.

4.1 Local fault detection

In this section, we will be interested in detecting the defect as soon as a fault happens, to ensure the demands of the reliability and safety of systems. Generally, the fault detection technique plays an important role in many areas, such as chemical process [45] and mechanical equipment [46]. Many fault detection methods, in the past decades, have been developed, and most of them have focused on nonlinear systems [47]. For a large-scale interconnected system, it is still a challenging research direction. In the fault detection step, residues are equal to zero when the process is in a normal operating mode. Yet on account of measurement noises, uncertainties, and system interconnections, their values make variations in a normal and faulty operation mode. The proposed fault detection method is based on a decentralized architecture. The local fault detection scheme suggested in this paper is formed in Fig. 2.

For each subsystem, residues are generated by the BG model. Using the Bayesian filter, we can avoid the system noises. Then, the residues are evaluated by the probability density function and finally detected by the inverted Chi-square distribution in Fig. 3.

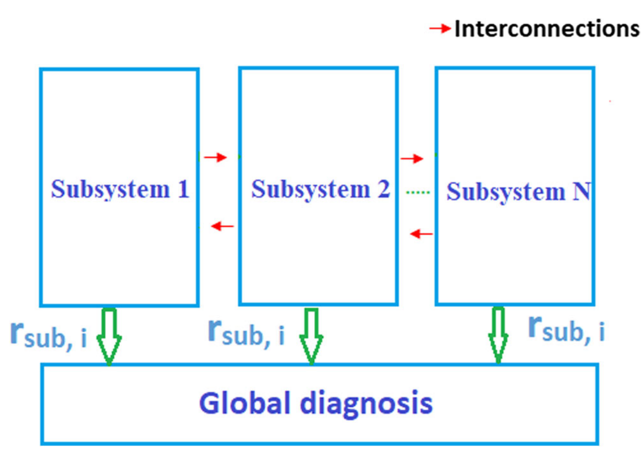

Fig. 2 Decentralized process architecture

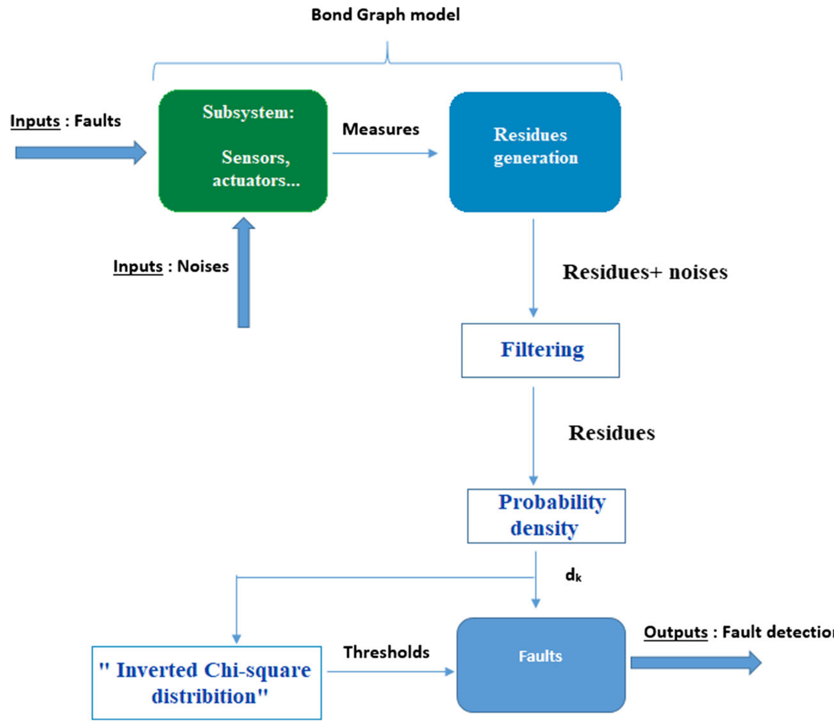

Fig. 3 Description of proposed approach of local detection

Subsequently, the proposed procedure for residue evaluation for each subsystem is based on the probability density and filtering. According to these conditions, the detectability is based on the simple fault structure and requires neither the generation of the causal schema nor the fault signature matrix. For fault evaluation and detection, firstly, the residues are generated through the BG model. Afterwards, the residue values are evaluated by the probability density function. The principle of latter is defined by the Algorithm 1.

Algorithm 1 Probability density

Input: Residues r_k, noise V_k, Number of observations N
Output: d_k
For $(0 <= i <= N)$ **THEN**
Likelihood $l_k(i)$
$$l_k(i) = \frac{1}{\sqrt{(2\pi)^m det[V_k]}} \exp\left(-\frac{1}{2} r_k^{iT} V_k^{-1} r_k^i\right)$$
probability density d_k
$$d_k = -\log(l_k(i))/N$$
END For

With the measurement noise V_k, the likelihood $l_k(i)$ can be expressed as follows [48]. The parameter d_k determines the fault detection logic. As shown in Algorithm 1, the parameter d_k, which is the decision rule for fault detection, is defined by the state probability density information $l_k(i)$. To ensure better fault detection, we use the threshold to evaluate the results. In this part, we will use the probability density, as well as the thresholds [45] to ensure whether the residues belong to the defective mode of operation. Algorithm 2 describes the detection and evaluation theory. In this step, we can detect the faults within the studied system. By this principle, the residue measures will be used in the isolation phase. To indicate the state of normal or abnormal situation, fault detection is considered a significant step. In this section, the abnormal situations are detected and evaluated fistly the probability density and then by the threshold.

Algorithm 2 Detection

Input: Probability density D
Output: Threshold 1,threshold 2, detection
a=mean(D)
b=var(D)
$g = \frac{b}{2*a}$
$h = \frac{2*a^2}{b}$
Threshold 1 $= g * chi2inv(0.70, h)$
Threshold 2 $= g * chi2inv(0.30, h)$
If (threshold 2 $\leq d_i$) **and** ($d_i \leq$ threshold 1)
Detection $\longleftarrow$ False
Else
Detection $\longleftarrow$ True
End if

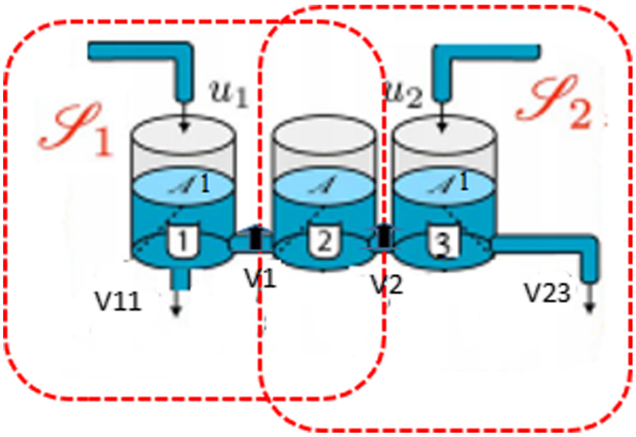

Fig. 4 Structure of three-tank system under consideration

Table 1 Various physical parameter values

Parameters	Value	Unit
Diameter of tank T_1	0.25	m
Diameter of tank T_2	0.30	m
Diameter of tank T_3	0.25	m
Coefficient of valve V_1, V_{11}, V_2, V_{23}	0.01	$\sqrt{Kg.m}$
Density of water	0.01	m^3/s
Gravitational constant	9.81	$kg.m^{-1}$
Density of fluid	1000	Kg/m^3
Flow rates of pump 1	0.00025	m^3/s
Flow rates of pump 2	0.00025	m^3/s

4.2 Fault isolation: Generation of structured residues

The fault isolation step can be done by several methods. The most used method by the BG model is the Fault Signature Matrix (FSM) which can be deduced from the BG model directly. It is important to underline that this fault signature matrix presents a problem at the level of fault isolation. For large-scale systems, many components present the same signature. In that case, it is difficult to identify the defect.

Our contribution to this paper is the use of the advantages of the decentralized architecture with the principle of the theoretical fault signature matrix defined by the PCA method. Simply, when each residue is sensitive to a single fault, we can use the principle of theoretical fault signature matrix [31]. Then, strong isolation is best adapted by column structures. In that case, each fault code has the same number of 0 in a different pattern.

5 Experimental results

5.1 System decription

In this section, to improve the effectiveness and feasibility of the proposed decentralized adaptive residue generator, we use the three-tank system in Fig. 4.

Fig. 5 DBG of subsystem 1

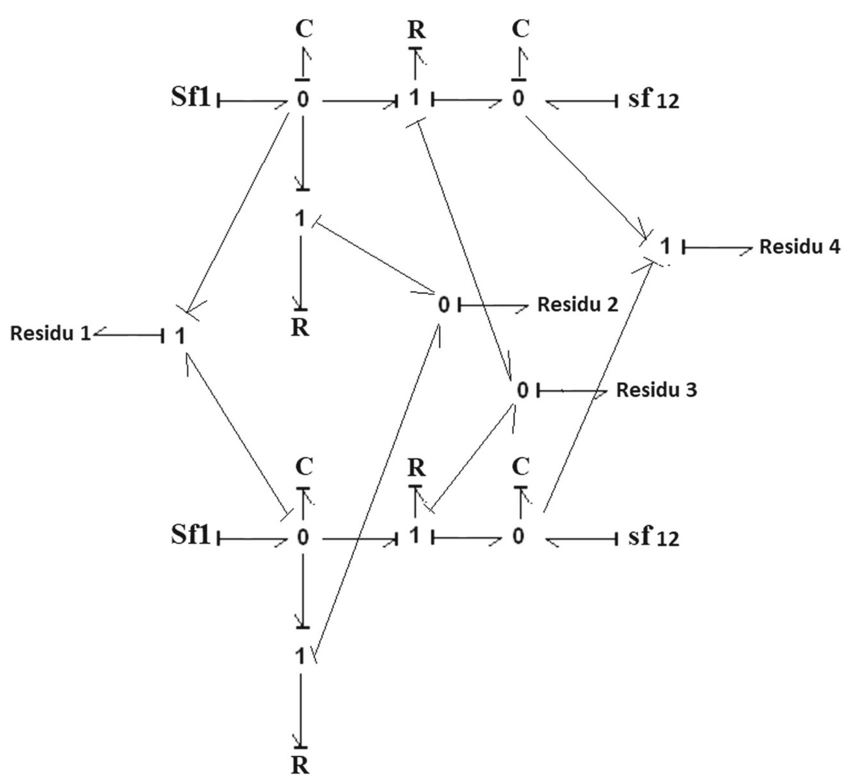

Table 2 Strongly isolating incidence matrix of subsystem 1

	T_1	T_2	V_{11}	V_1
r_{11}	0	1	1	1
r_{21}	1	0	1	1
r_{31}	1	1	0	1
r_{41}	1	1	1	0

This test bench is composed of three tanks, T1, T2 and T3, of diameters A1, A2 and A3, respectively. Then, the water level in tanks h1, h2, and h3 is measured by level sensors. The three tanks are fed by two pumps. Each tank has a draining valve V_i. The communication between tanks T1 and T2 are through valve V_1, and between tanks T3 and T2 are through valve V_2. In the case study, the system is treated as two subsystems, S_1 and S_2, as demonstrated in Fig. 4. Each subsystem has two tanks, three valves and a water pump. Tank T2 and valve V_2 are common points between the two subsystems.

The various physical parameters, indicated in Table 1, are used to determine the BG model process.

5.1.1 BG model of subsystem 1

Taking into account the characteristics of all components in the process, we elaborate the BG model of subsystem 1 and subsystem 2 in the integral and derivative causality. The different elements of the process are molded as follows:

- The tanks are constituted by the storage elements C,
- The pump are constituted by the flow source SF,
- The valves are constituted by the restriction elements R,
- All the elements are linked via 0 and 1 junctions.

Furthermore, the coupling between the model in preferred integral causality and differential causality of susbsytem 1 is given by Fig. 5.

5.1.2 Theoretical structure matrix of subsystem 1

The theoretical fault signature matrix from subsystem 1 is given by Table 2. Each line of this matrix represents the structure of the residues, and the columns represent the signatures of faults. A “0” at an intersection indicates that the residue does not respond to a fault, while a ”1” indicates that it does.

Thus, every component, which presents a matrix line, corresponds to an elimination procedure. In each of the four partial components, one variable is missing. With the experimental data available, these submodels can be obtained directly by the state probability density information. For subsytem 1, strong fault isolation responses are plotted in Fig. 6. The results are arranged in accordance with the

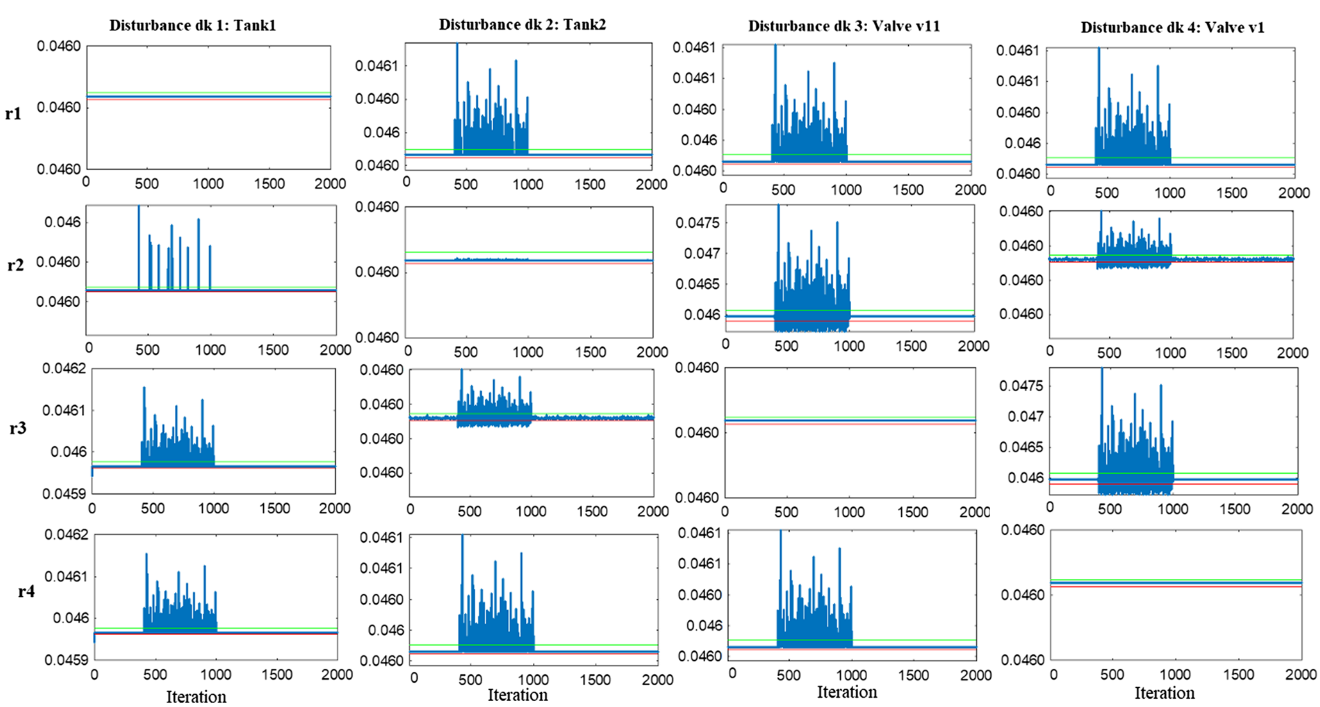

Fig. 6 Example of fault isolation results

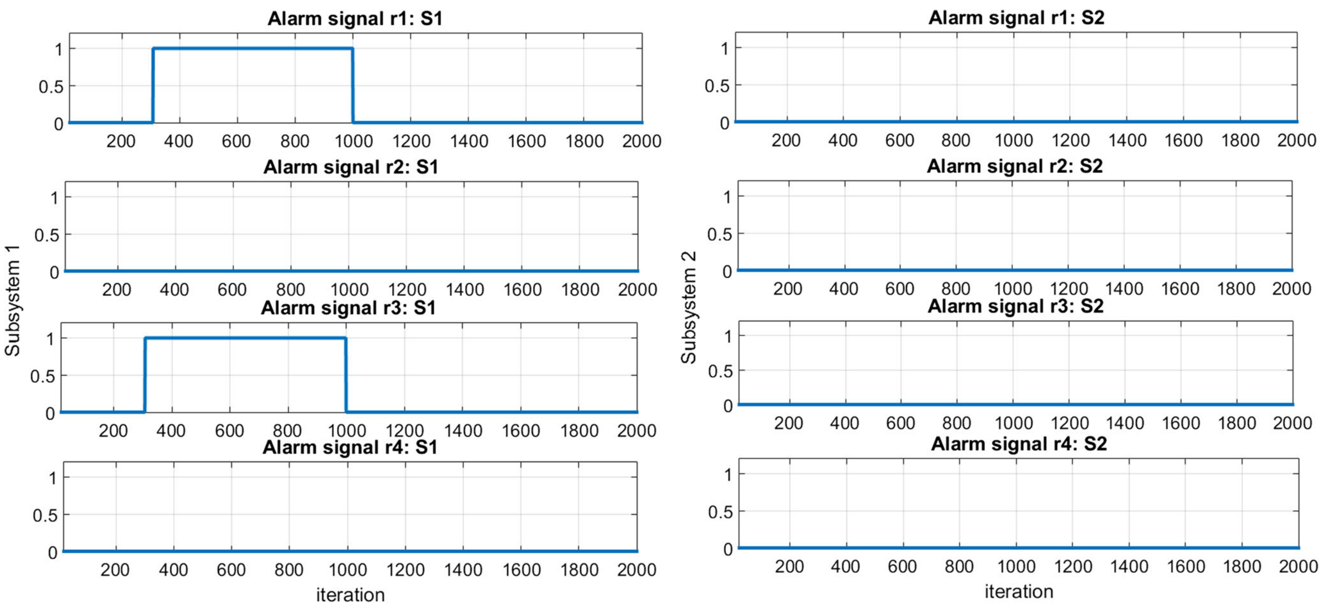

Fig. 7 Results of detection for valve V_{11} fault

theoretical structure matrix. We find that each row shows the response of the same residue to the various faults, while each column is the response of the residual set to a particular fault [31]. According to the experimental values, we see that some of the residues, in each fault situation, respond whereas the others do not.

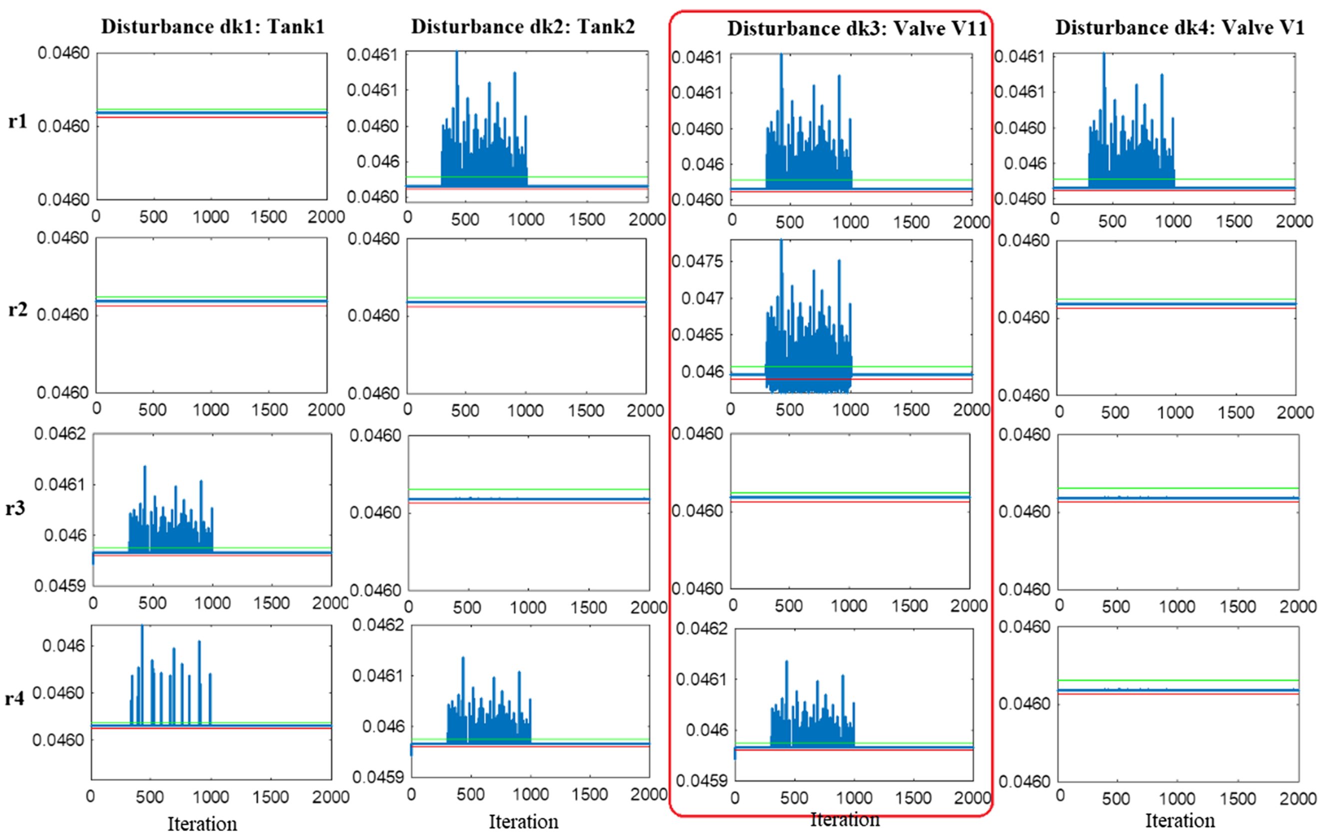

Fig. 8 Fault responses in Scenario 1

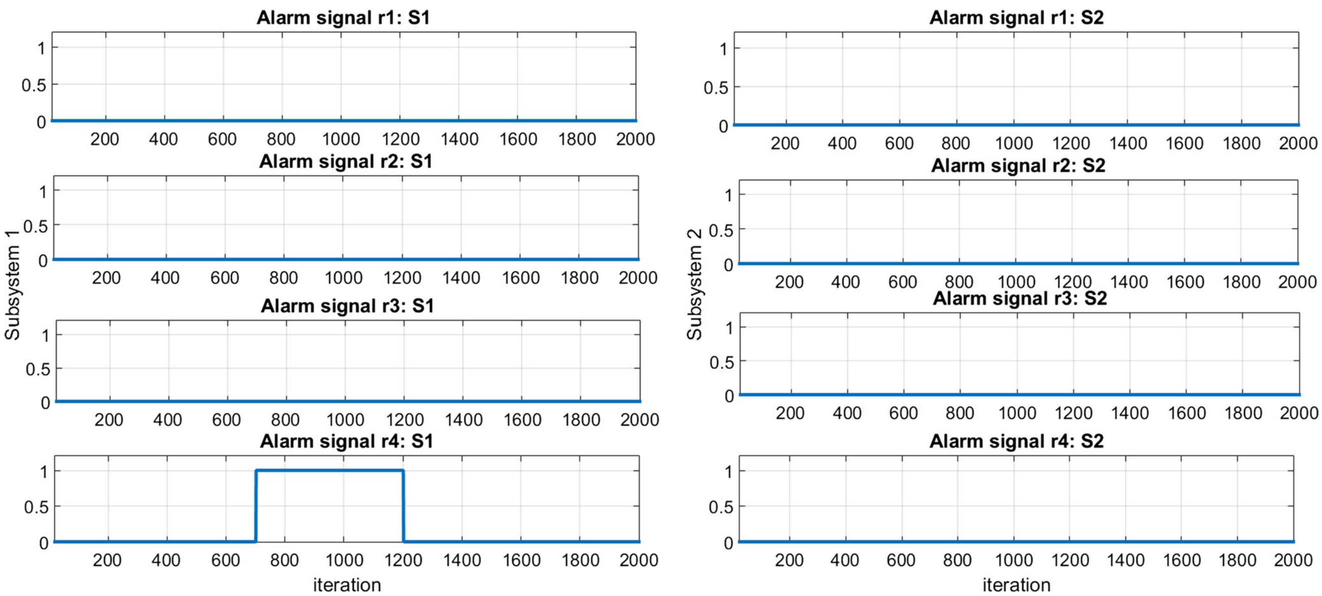

Fig. 9 Results of detection for valve V_1 fault

5.2 Simulation results

In this section, we present the simulation results of the three-tank system. The BG model and the theoretical fault signature matrix from PCA are construted using MATLAB SIMULINK and MATLAB. Three failure scenarios are simulated.

5.2.1 Fault affecting valve V_{11}

When a bias fault is produced on valve V_{11}, between iterations 300 and 1000, only residues 1 and 3 deviate from their normal values of subsytem 1. The detection module signals this derivation, as depicted in Fig. 7.

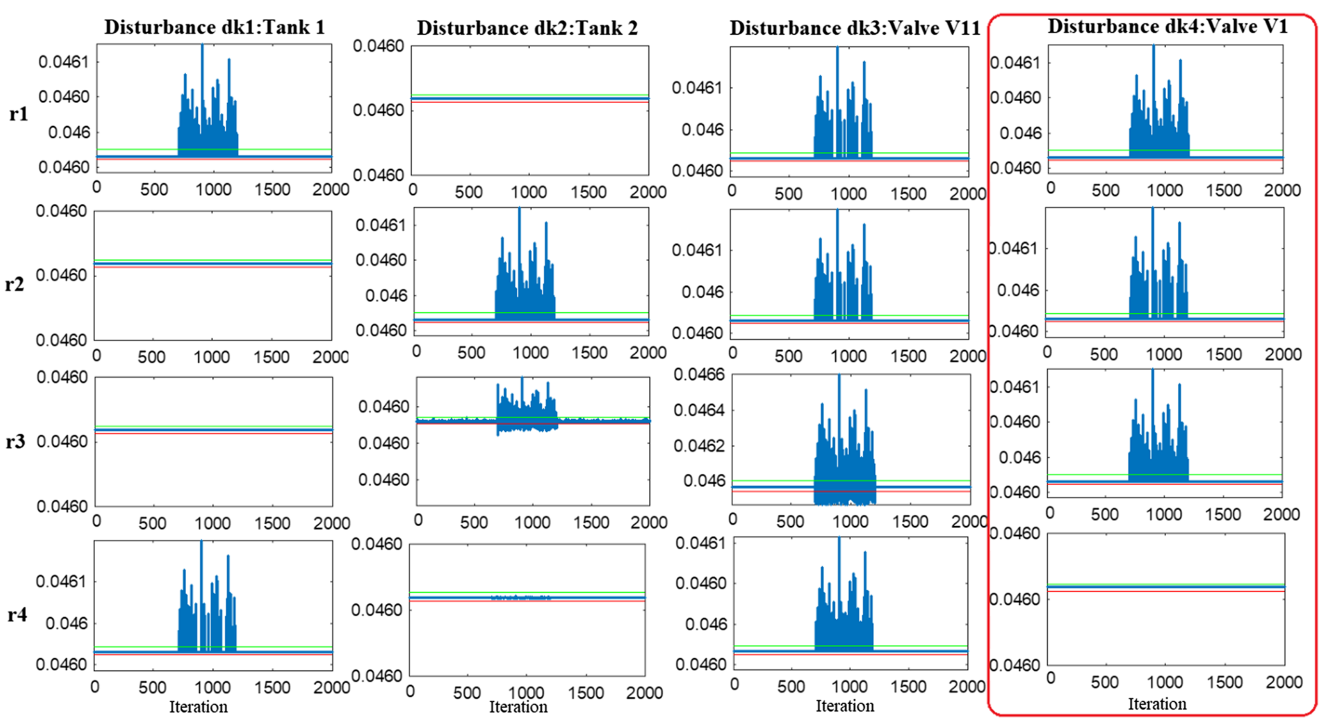

Fig. 10 Fault responses in scenario 2

With the decentralized architecture, the fault is produced from subsystem 1. To better locate the fault, we use the theoretical fault signature matrix, given in Table 2, utilizing the PCA method. From Fig. 8, each row shows the response of the same residue to the various faults. On the other hand, each column is the response of the residue is set to a particular fault. When we just focus in procedure 3, only the third column is identical to theoretical fault signature matrix presented by Table 2. Fig. 8 demonstrates that the fault is from valve V_{11} and is indicated by the red circle.

5.2.2 Fault affecting valve V_1

A fault is produced on valve V_1 between iterations 700 and 1200 with a value of 20%. Only residue 4 of subsytem 1 deviates from its normal values. The detection module signals this derivation, as represented in Fig. 9.

The fault is produced from subsystem 1 thanks to decentralized architecture. Thanks to the theoretical fault signature matrix from PCA, we can localise the fault. Clearly in Fig. 10, some of the residues respond, while the others do not in each presented default situation. From fault codes designed for component 4, their presence is possible to detect. The obtained fault codes are exactly what is expected, i.e., the simulated behavior at one of the columns of the theoretical fault signature matrix in Table 2. Then, the fault from valve V_1 is indicated by the red circle in Fig. 10.

Table 3 Strongly isolating incidence matrix of subsystem 2

	T_3	T_2	V_2	V_{23}
r_{12}	0	1	1	1
r_{22}	1	0	1	1
r_{32}	1	1	0	1
r_{42}	1	1	1	0

5.2.3 Fault affecting valve V_{23}

When a simple fault, which 30%, is produced on valve V_{23} between iterations 1000 and 1700, only residues 4 and 1 from subsystem 2 deviates from its normal values. The detection module signals this derivation, as illustrated in Fig. 11.

To validate the fault location, a strong faut isolation matrix from subsystem 2 is given by Table 3.

For subsytem 2, the fault isolation responses are depicted in Fig. 12. The fault responses are plotted in Fig. 12, where each column corresponds to a fault code given in Table 3, and each row to the same residue 4. The results are arranged in accordance with the theoretical structure matrix when we use just residue 4 and we do not have an identical result for residue 1. The results of the last column of conpoment 4 are arranged as regards the theoretical strong isolation matrix. Then, the fault is from valve V_{23}. In summary, the simulation results are found to be in complete agreement with the theory.

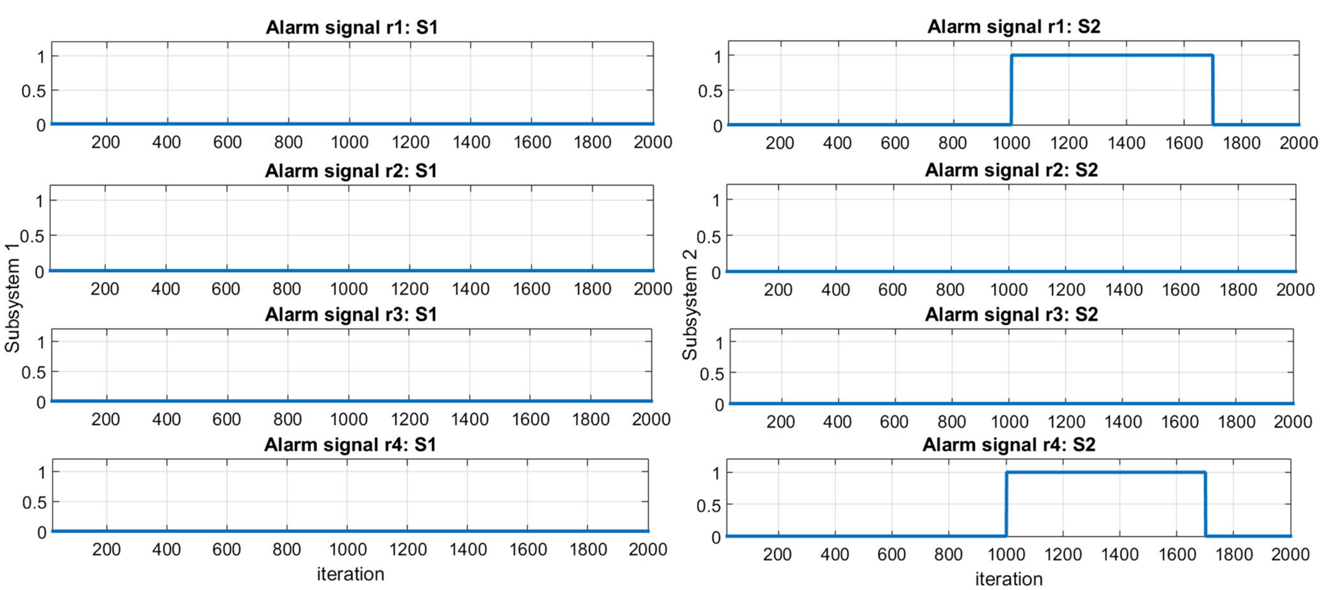

Fig. 11 Results of detection for valve V_{23} fault

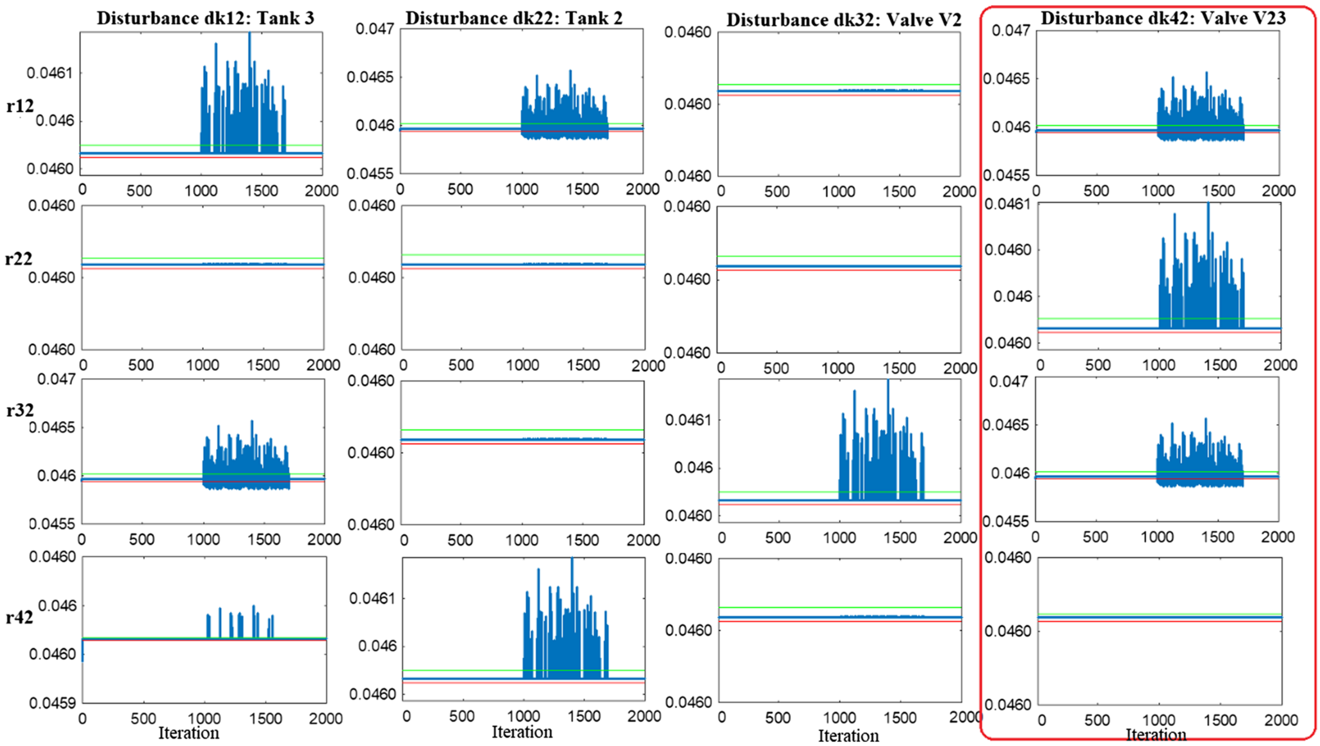

Fig. 12 Fault responses in scenario 3

6 Conclusions

In this paper, the main interest is to present the FDI process with the BG and PCA methods in the decentralized architecture.

At the first time, a BG model in a decentralized process is put forward. Then the suggested BG is used for local fault detection. Indeed, we have proposed to use the probability density function with the threshold principle to ensure the fault structure. This approach is based in the decentralized architecture, which helps to frame the place of failure. Its purpose is to obtain a strong isolation for each fault allowing the location of defective variables.

The implementation of the localization method is relatively easy, but it has a drawback, which lies in the number of necessary tests for the frequent degradation of the experimental signatures. As a result, the partial triggering of the tests is linked only to the location property (highly localizing matrix) but not according to the residue sensitivity to the faults. However, the improvement of the decision fault isolation making aims to take a decision for non-isolable failure or unknown signatures using the decentralized architecture.

Nevertheless, the procedure of the fault isolation by the theoretical fault signature matrix from the PCA method is suggested to identify exactly the faulty component. We first create a strongly isolating incidence matrix by a theoretical principle. Second, we compare the practical submodel with the theoretical fault signature matrix. The proposed BG-PCA approach shows its efficiency since it is detected in a decentralized mode to speed up the detection principle and it is isolated from components' singles faults in the presence of noises.

References

1. Leonhardt S, Ayoubi M (1997) Methods of fault diagnosis. Control Eng Pract 5(5):683–692
2. Staroswiecki M (2000) Quantitative and qualitative models for fault detection and isolation. Control Eng Pract 14(3):301–325
3. Biswas G, Cordier MO, Lunze J, Trave-Massuyes L, Staroswiecki M (2004) Diagnosis of complex systems: Bridging the methodologies of the FDI and DX communities. IEEE Trans Syst Man Cybern B Cybern 34(5):2159–2162
4. Zhong M, Zhang L, Ding S, Zhou D (2017) A probabilistic approach to robust fault detection for a class of nonlinear systems. IEEE Trans Ind Electron 64(5):3930–3939

5. Ferdowsi H, Jagannathan S (2017) Decentralized fault tolerant control of a class of nonlinear interconnected systems. IFAC Proceedings 15(2):527–536
6. Li W, Gui W, Xie Y, Ding S (2009) Decentralized Fault Detection System Design For Large-scale Interconnected System. IFAC Proceedings 42(8):816–821
7. Boem F, Ferrari RMG, Parisini T (2011) Distributed fault detection and isolation of continuous-time non-linear systems. Eur J Control 17(5-6):603–620
8. Reppa V, Polycarpou MM, Panayiotou CG (2015) Decentralized isolation of multiple sensor faults in large-scale interconnected nonlinear systems. IEEE Trans Autom Control 60(6):1582–1596
9. Arrichiello F, Marino A, Pierri F (2015) Observer-based decentralized fault detection and isolation strategy for networked multirobot systems. IEEE Trans Control Syst Technol 23(4):1465–1476
10. Odendaal HM, Jones T (2014) Actuator fault detection and isolation: an optimised parity space approach. Control Eng Pract 26:222–232
11. Taouali O, Elaissi I, Messaoud H (2012) Online identification of nonlinear system using reduced kernel principal component analysis. Neural Comput & Applic 21(1):161–169
12. Mulumba T, Afshari A, Yan K, Shen W, Norford LK (2015) Robust model-based fault diagnosis for air handling units. Energy Build 86(1):698–707
13. Ould Bouamama B, Biswas G, Loureiro R, Merzouki R (2014) Graphical methods for diagnosis of dynamic systems. Annu Rev Control 38(2):199–219
14. Mojallal A, Lotfifard S (2017) Multi-physics graphical model based fault detection and isolation in wind turbines. IEEE transactions on smart grid
15. Samantaray AK, Ould Bouamama B (2008) Model-based process supervision: a bond graph approach. Springer Science & Business Media
16. Biswas G, Simon G, Mahadevan N, Narasimhan S, Ramirez J, Karsai G (2003) A robust method for hybrid diagnosis of complex systems. IFAC Proceedings 36(5):1023–1028
17. Ould Bouamama B, Medjaher K, Samantaray AK, Staroswiecki M (2006) Supervision of an industrial steam generator. Part I: Bond graph modelling. Control Eng Pract 14(1):71–83
18. Medjaher K, Zerhouni N (2013) Hybrid prognostic method applied to mechatronic systems. Int J Adv Manuf Technol 69(1-4):823–834
19. Samantaray AK, Medjaher K, Ould Bouamama B, Staroswiecki M, Dauphin-Tanguy G (2006) Diagnostic bond graphs for online fault detection and isolation. Simul Model Pract Theory 14(3):237–262
20. Gao Z, Cecati C, Ding SX (2015) A survey of fault diagnosis and fault-tolerant techniques—Part I: Fault diagnosis with model-based and signal-based approaches. IEEE Trans Ind Electron 62(6):3757–3767
21. Jha MS, Dauphin-Tanguy G, Ould Bouamama B (2016) Particle filter based hybrid prognostics for health monitoring of uncertain systems in bond graph framework. Mech Syst Signal Process 75(6):301–329
22. Yang S, Bian C, Li X, Tan L, Tang D (2018) Optimized fault diagnosis based on FMEA-style CBR and BN for embedded software system. Int J Adv Manuf Technol 94(9-12):3441–3453
23. Zaidi A, Ould Bouamama B, Tagina M (2012) Bayesian reliability models of Weibull systems: State of the art. Int J Appl Math Comput Sci 22(3):585–600
24. Gertlert J, Li W, Huang Y, McAvor T (1998) Isolation enhanced principal component analysis. IFAC Proceedings 31(10):185–190
25. Halligan GR, Jagannathan S (2011) PCA-Based fault isolation and prognosis with application to pump. Int J Adv Manuf Technol 55(5-8):699–707
26. Chaouch H, Najeh T, Nabli L (2017) Multi-variable process data compression and defect isolation using wavelet PCA and genetic algorithm. Int J Adv Manuf Technol 91(1-4):869–878
27. Marcondes Filho D, SantAnna AMO (2016) Principal component regression-based control charts for monitoring count data. Int J Adv Manuf Technol 85(5-8):1565–1574
28. Alcala CF, Qin SJ (2010) Reconstruction-based contribution for process monitoring with kernel principal component analysis. Ind Eng Chem Res 49(17):7849–7857
29. Guo W, Zhao H, Gao X, Kong L, Li Y (2018) An efficient representative for object recognition in structural health monitoring. Int J Adv Manuf Technol 94(9-12):3239–3250
30. Jaffel I, Taouali O, Harkat MF, Kong L, Messaoud H (2015) Online process monitoring using a new PCMD index. Int J Adv Manuf Technol 80(5-8):947–957
31. Gertler J, Li W, Huang Y, McAvoy T (1999) Isolation enhanced principal component analysis. AIChE Journal 45(2):323–334
32. Zhang Z, Wang Y, Wang K (2013) Intelligent fault diagnosis and prognosis approach for rotating machinery integrating wavelet transform, principal component analysis, and artificial neural networks. Int J Adv Manuf Technol 68(1-4):763–773
33. Touati Y, Merzouki R, Ould Bouamama B (2012) Robust diagnosis to measurement uncertainties using bond graph approach: Application to intelligent autonomous vehicle. Mechatronics 22(8):1148–1160
34. Playtner H (1961) Analysis and design of engineering systems. MIT, Cambridge
35. Karnopp DC, Margolis DL, Rosenberg RC (1990) System dynamics: a unified approach
36. Breedveld PC (1984) Essential gyrators and equivalence rules for 3-port function structures. J Frankl Inst 318(2):77–89
37. Bouallegue W, Bouslama S, Tagina M (2017) Robust fault detection and isolation in bond graph modelled processes with Bayesian networks. Int J Comput Appl Technol 55(1):46–54
38. Dhouibi H, Bochra M, Messaoud H, Simeu-Abazi Z (2014) Diagnosis approach using bond graph and timed automata. MOSIM 2014, 10ème Conférence Francophone de Modélisation, Optimisation et Simulation
39. Ould Bouamama B (2003) Bond graph approach as analysis tool in thermofluid model library conception. J Frankl Inst 340(1):1–23
40. Raich A, Çinar A (1996) Process disturbance diagnosis by statistical distance and angle measures. IFAC Proceedings 29(1):6602–6607
41. MacGregor JF, Kourti T, Nomikos P (1996) Analysis, monitoring and fault diagnosis of industrial processes using multivariate statistical projection methods. IFAC Proceedings 29(1):5941–5946
42. Jaffel I, Taouali O, Elaissi I, Messaoud H (2013) A new online fault detection method based on PCA technique. IMA J Math Control Inf 31(4):487–499
43. Fazai R, Taouali O, Harkat MF, Bouguila N (2016) A new fault detection method for nonlinear process monitoring. Int J Adv Manuf Technol 87(9-12):3425–3436
44. Harkat MF, Mourot G, Ragot J (2006) An improved PCA scheme for sensor FDI: Application to an air quality monitoring networkg. J Process Control 16(6):625–634
45. Lahdhiri H, Taouali O, Elaissi I, Jaffel I, Harakat MF, Messaoud H (2017) A new fault detection index based on Mahalanobis distance and kernel method. Int J Adv Manuf Technol 91(5-8):2799–2809

46. Chatti N, Guyonneau R, Hardouin L, Verron S, Lagrange S (2016) Model-based approach for fault diagnosis using set-membership formulation. Eng Appl Artif Intel 55:307–319s
47. Fazai R, Mansouri M, Taouali O, Harkat MF, Bouguila N (2018) Online reduced kernel principal component analysis for process monitoring. J Process Control 61:1–11
48. Yin S, Zhu X (2015) Intelligent particle filter and its application to fault detection of nonlinear syste. IEEE Trans Ind Electron 62(6):3852–3861
49. Harkat MF (2003) Détection et localisation de défauts par analyse en composantes principales. PhD thesis, Institut National Polytechnique de Lorraine-INPL