Bond graph Model-Based Methods for Fault Diagnosis: A Comparative Study

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***Abstract*—Advanced methods of fault diagnosis become increasingly significant for improving the safety, reliability and efficiently of dynamic systems in various domains of industrial engineering. This paper reviews and compares between three bond graph model-based methods for fault diagnosis. These methods are causality inversion method, augmented Analytical redundancy relation method, and fault/residual sensitivity relation method. These methods are applied on a simulation model of an electrical system. This latter is used to simulate the system variables in both normal and faulty situations and to generate residuals for fault detection and isolation. The results of the case study are compared for highlighting the fault diagnosis performance of a method over another. The result show that the fault/residual sensitivity relation method has batter diagnosis performance when compared to the other methods.**

Keywords—Diagnosis, Bond graph, Causality inversion, augmented Analytical redundancy relation, Sensitivity.

I. INTRODUCTION

Nowadays, the growing demand of safety, reliability, and efficiency of modern industrial systems motivates the development of new fault diagnosis methods for the decision support system. These methods are usually employed for avoiding critical situations that may due to the propagation of the faults, which affect the system dynamics. The fault diagnosis is performed by two steps: alarm generation (Fault detection FD), and the identification the faulty component (Fault isolation I). Via FDI procedures, an alarm can be created if the fault occurs. However, the magnitude of the fault cannot be obtained by these procedures. The magnitude of the fault is obtained using another procedure named fault estimation (FE).

In the last dedicate, several approaches have emerged allowing to design and implement the fault detection and isolation (FDI) procedures using the so-called qualitative and quantitative approaches [1]. The qualitative approach is essentially based on artificial intelligence or recognition forms developed in [2]. This approach consists of distributing the parametric space in different classes corresponding to known modes of operation based on a prior knowledge of the system (model-free). Among the pattern recognition methods used for diagnosis, the principal component analysis (PCA) [3,4] is used which all operation modes (normal and failing) must be known in advance, which often unrealizable in real systems. In order to perform a reliable diagnosis, model-free methods such as AI-based require data of all the possible faulty component which is very expansive and exhausting.

The quantitative approaches are mostly based on state space and input-output models, and are more related to the model-based methods. Some of them use the observer [5,6] to generate (residuals (r)) a difference between the measured output and the reference expected behavior of the system. In this context, the parity space method [7,8] consists in eliminating all the system states in which all system elements are known. Compared to the aforementioned approaches, the BG approach can be an alternative solution for dealing with both sensor, actuator and parameter faults.

The FDI using BG approach is based on the generation of analytical redundancy relations (*ARRs*). Moreover, the residuals represent the numerical evaluation of these *ARRs*, and are used for real time diagnosis. The residuals should converge to zero in normal operation, while in faulty situation the residuals exceed certain values named the thresholds. In addition, the causal and structural properties of the BG model are used to eliminate systematically the unknown variables using a covering causal paths methodology [9]. In BG approach, the fault isolation is performed through the Boolean fault signature matrix (FSM). This matrix is built using the binary sensitivity of the *ARRs*. Thus, the comparison between all fault signatures allows the knowledge of the faulty components that can be detected, and isolated [10].

In the present work, we compare between three methods that intend to improve the fault diagnosis procedure using BG approach. The first is the causality inversion method. The latter is based on the generation of *ARRs* from the BG model in preferred derivative causality, where the number of *ARRs* that can be obtained is equal to the number of junctions having at least an associated detector, plus the number of redundant detectors. These *ARRs* can then be used to build the FSM in order to isolate the faults. The second is the augmented Analytical redundancy relations method. This method allows the generation of different versions of the same *ARR* from each observed junction, so that additional non-redundant *ARRs* can be obtained. The third method is based on the sensitivity relation between the residuals and the faults to generate the fault estimation equations. The comparison between the two estimations of each fault is an additional residual.

The rest of this paper is organized as follows: Section 2 details the causality inversion method for *ARRs* generation and

FSM. The augmented Analytical redundancy relations method, and fault/residuals sensitivity relation method are described in Section 3, and 4 respectively. Application with simulation results and comparative analysis are presented in Section 5. Finally, the conclusions are given in Section 6.

II. CAUSALITY INVERSION METHOD AND FDI

A bond graph is a multidisciplinary graphical modeling language based on energy transfer phenomena. The energy exchange link, called power bond with two generic power variables named flow f and effort e, associated with every bond, where $e \times f = power$ (Fig. 1). The set of possible BG elements is:

$$S = \{R \cup C \cup I \cup TF \cup GY \cup Se \cup Sf \cup De \cup Df \cup J\}$$

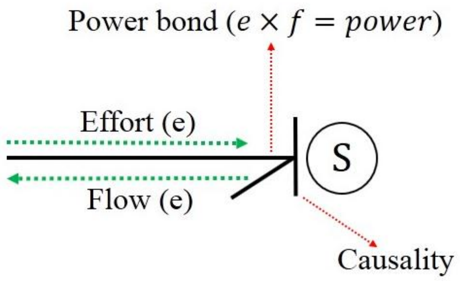

Fig. 1. Bond Graph representation.

The set of elements $\{R, C, I\}$ models the system parameters where R, C, and I *are* the dissipation element, capacitance element, and inertial element respectively. The latter along with the elements $\{GY, TF, 0, 1\}$ define the global structure of the system where GY and TF are the gyrator element and transformer element respectively. Sensors are represented by effort (Se), and flow (Sf) detectors. Junction 1 (or 0) implies that all the connected bonds have same flow (or effort) and the sum of efforts (or flows) equals zero. Sf and (Se) are the sources of flow and effort, respectively. For more information about BG modeling, see [11].

A. ARRs generation using the causality inversion method

The FDI using bond graph approach is based on the generation of *ARRs*. The latter represent the physical constrain lows calculated from an observable and over-constrained subsystem and they have the form: $h(K) = 0$ for any function h and set of known variables K. Evaluation of an *ARR* yields a residual $(r) : r[h(K)]$. In order to obtain the *ARRs* in a systematical manner, Ould Bouamama et al. [12] introduced the causality inversion method.

Definition 2. Inversion of detectors, this means that the flow (Df) (or effort (De)) detector used for modeling (Fig. 2a) becomes (SSf) (or SSe) and imposes the flow (or effort) to the1 (or 0) junction connected to this detector used for diagnosis (Fig. 2b) respectively [14].

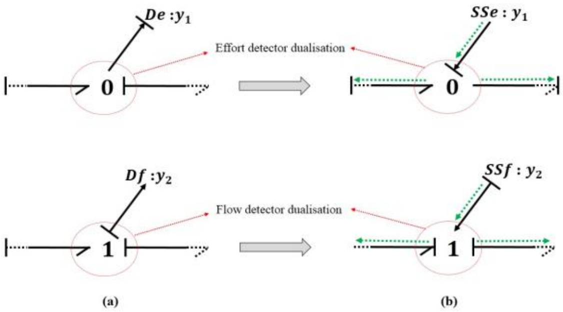

Fig. 2. Inversion of detectors.

The following steps are taken to generate *ARRs* in a systematic way using the causality inversion method:

Step 1: Obtain the BG model of the system in preferred derivative causality, by inverting detectors when possible. Thus, the BG model of diagnosis is obtained.

Step 2: From the BG model of over-constrained system, an *ARR* is obtained from each observed junction by writing its junction equation and eliminating the unknown variables by using the causal path propagation.

Step 3: For any non-dualized detector, a materiel redundancy is presented in the system. The latter exists if there are causal paths from one or more detectors in inverted causality to the non-inverted one, without passing through any two-port or passive element. In this case, *ARR* is equal to the difference between the measures of the redundant detectors [13].

B. Fault isolation using fault signature matrix

The fault isolation can be done using the FSM that can be directly deduced either from the *ARRs* or from the BG model directly. In the FSM, the Boolean relations ($S_{i,j} \in \{0,1\}$) between the residuals and the parameters are represented, as illustrated in Table 1. Where the rows are the parameters that represent the components ($C_{i,j} = 1, 2, \ldots..m$) and the columns are the residuals ($r_{i,j} = 1, 2, \ldots..n$).

Let us define $S^{m \times n}$ as a matrix of Boolean values $S_{i,j}$, where:

$S_{i,j} = \{1$ When j^{th} $ARR(r_j)$ contains the parameter of the i^{th} component.

$S_{i,j} = \{0$ Otherwise.

Let us define G (column I_b) as an isolability vector, where:

$g_i = \{1$ When the signature is unique.

$g_i = \{0$ Otherwise.

TABLE I. FAULT FIGNATURE MATRIX

	r_1	r_2	$\cdots$	r_n	Db_m	Ib_m
C_1	$S_{1,1}$	$S_{1,2}$	$\cdots$	$S_{1,n}$	Db_1	Ib_1
C_2	$S_{2,1}$	$S_{2,2}$	$\cdots$	$S_{2,n}$	Db_2	Ib_2
C_m	$S_{m,1}$	$S_{m,2}$	$\cdots$	$S_{m,n}$	Db_m	Ib_m

III. AUGMENTED ANALYTICAL REDUNDANCY RELATION METHOD

In [12,13], it was shown that the number of *ARRs* which can be obtained by the causality inversion method is equal to the number of junctions having at least an associated detector. However, this last statement is not always valid. The causality inversion method only finds part of the possible solution set, because this method does not exploit all possible sensor combinations. Moreover, if sensor combinations are performed, augmented *ARRs* can be obtained [14]. These combinations can improve the diagnosis procedure, and consequently increase the number of the isolable faults.

Let us use an illustrative example to explain the above method. Fig. 3a shows a BG model in preferred derivative causality used for diagnosis, where the two detectors have been dualized to corresponding sources of information ($De : y_1 \rightarrow SSe : y_1$) and ($Df : y_2 \rightarrow SSf : y_2$). By applying the causality inversion method, two *ARRs* can be obtained:

$$ARR_1 = f_1(y_1, y_2, I_0, \ldots) = 0 \tag{1}$$

$$ARR_2 = f_1(y_1, y_2, \ldots) = 0 \tag{2}$$

However, consider that the source of signal $SSe : y_1$ is disregarded, and only $SSf : y_2$ is used for diagnosis as depicted in Fig.3b. In this case, an augmented *ARR* of the following form can be obtained:

$$ARR_3 = f_3(y_2, I_0, \ldots) = 0 \tag{3}$$

Following the same procedure while using the information from the signal source $SSe : y_1$, and ignoring the one of $SSf : y_2$, another augmented *ARR* can be generated:

$$ARR_4 = f_4(y_1, I_0, \ldots) = 0 \tag{4}$$

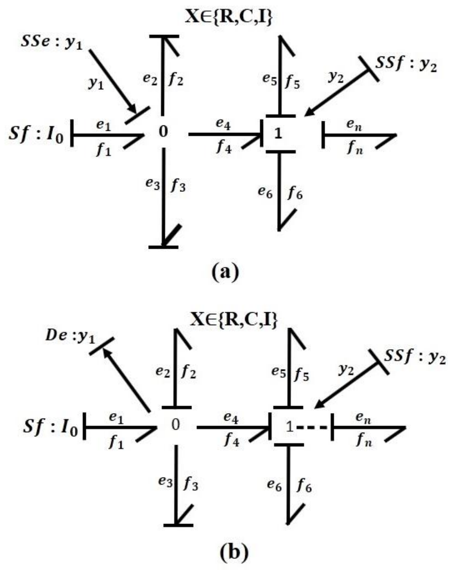

Fig. 3. BG model in preferred derivative causality, (a) Both $SSe : y_1$ and $SSf : y_2$ are dualized, and (b) Without dualizing $De : y_1$.

Nevertheless, these combinations do not allow generating the extra *ARRs* from the covering path procedure. Therefore, the bicausality notion is proposed, which is introduced in [15].

IV. FAULT/RESIDUALS SENSITIVITY METHOD

If faults have a same Boolean signature and two sensitive residuals, they can be isolated if the sensitivity relations between the faults and the residuals are different [16]. As an example, let us consider two faults (F_1, F_2) and two residuals (r_1, r_2) where:

- Γ_{F_1,r_1} is the sensitivity relation between F_1 and r_1 .
- Γ_{F_1,r_2} is the sensitivity relation between F_1 and r_2 .
- Γ_{F_2,r_1} is the sensitivity relation between F_2 and r_1 .
- Γ_{F_2,r_2} is the sensitivity relation between F_2 and r_2 .

As reported by [17], the faults can be estimated from a sensitive residual by using the sensitivity relation. So, each fault (F_1 or F_2) can be estimated from r_1 and r_2 . The comparison between the two estimations of each fault is a residual. The latter is not sensitive to the estimated fault. Using the procedure illustrated in Fig. 4, the following equations can be generated:

$$\begin{cases} (a) : F_1 = \Gamma_{F_1,r_1}(r_1) \\ (b) : F_1 = \Gamma_{F_1,r_2}(r_2) \\ (c) : F_2 = \Gamma_{F_2,r_1}(r_1) \\ (d) : F_2 = \Gamma_{F_2,r_2}(r_2) \end{cases} \tag{5}$$

We remark that the fault F_1 is calculated with two ways, and using two estimation equations (Eq. 5a and Eq. 5b). This fault is isolated if the two results of these two estimation equations are equal, and in the same time the two estimation equations of the second fault F_2 (Eq. 5c and Eq. 5d) are not equal.

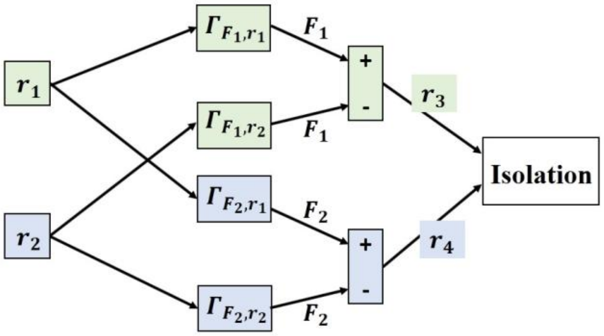

Fig. 4. Fault isolation using fault/residuals sensitivity relations.

The fault/residual sensitivity relation is obtained from the BG model using the following rules:

- Model the fault by replacing the BG element by its BG linear fractional transformation (BG-LFT) element [18], Where the modulated source MSe (or MSf) represents the effort (or flow) generated by the fault.
- Apply the bi-causality on the modulated source and the sensor associated with a residual in order to eliminate the unknown variables appearing in the expression of the sensitivity relation.
- Use the causal and the structural proprieties of the BG to generate the sensitivity relation between the fault and the residual.

Let us explain the above rules through an illustrative example (Fig. 5a and 5b). (Fig. 5a) represents a faulty R-element in conductive causality modeled by BG-LFT, where the modulated source $MSf : w_R$ represent the flow generated by the multiplicative fault $F_{1/R}$, $Df^* : Z_R$ is a fictive sensor, and R is the nominal parameter.

Fig. 6b shows a subsystem containing a faulty R-element in conductive causality and a detector SSe modeled by BG-LFT. From the 0-junction connected to the detector SSe, the following *ARR* can be generated:

$$ARR = f_{SSe} + f_1 - f' = 0; \qquad f_{SSe} = 0;$$
$$ARR = f_1 - \left(\frac{1}{R}\right) e_{SSe} - \left(\frac{1}{R} F_{1/R}\right) e_{SSe} = 0; \tag{6}$$

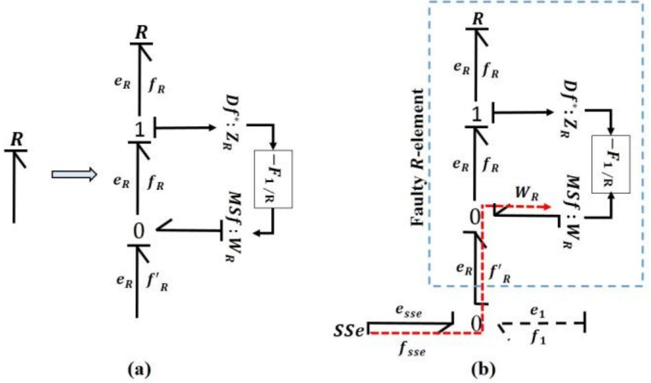

Fig. 5. (a) Faulty R-element in conductive causality, and (b) Bi-causal faulty R-element.

Where the inactive variable f_{SSe} is equal to zero. This means that the inactive variable of an effort and flow detector are the flow and the effort, respectively. Without the presence of the fault $F_{1/R}$, the residual is given by

$$r = f_1 - \left(\frac{1}{R}\right) e_{SSe} \tag{7}$$

In the presence of the fault, the residual is equal to:

$$\left(\frac{1}{R} F_{1/R}\right) e_{SSe} \tag{8}$$

Thus, if the fault is null the residual is zero. In addition, the residual is equal to the inactive variable of the detector f_{SSe}. This means that the residual is represented in BG model by the inactive variable of the associated detector. Therefore, it is possible to generate the sensitivity relation between the residual and the fault from the BG model. This can be done by using Mason's rule [19].

V. APPLICATION

In this section, the fault diagnosis performance of each method previously described is compared by applying them to an electrical system (Fig. 6a). The obtained FSM by each method is analyzed in order to conclude about fault isolability capability. The system is composed of two capacitance elements ($C : C_1$ and $C : C_2$), a resistance element ($R : R_1$), a transformer element ($TF : 1/N$), and the source of flow that represented by the current input $Sf : I_0$. The system is equipped with two voltage sensors represented in the model by $De : e_{m1}$ and $De : e_{m2}$. The BG model in preferred derivative causality of this electrical system is illustrated in Fig. 6b, where the derivative causality is assigned to it, and the detectors are replaced by signal sources of effort ($SSe : e_{m1}$ and $SSe : e_{m2}$).

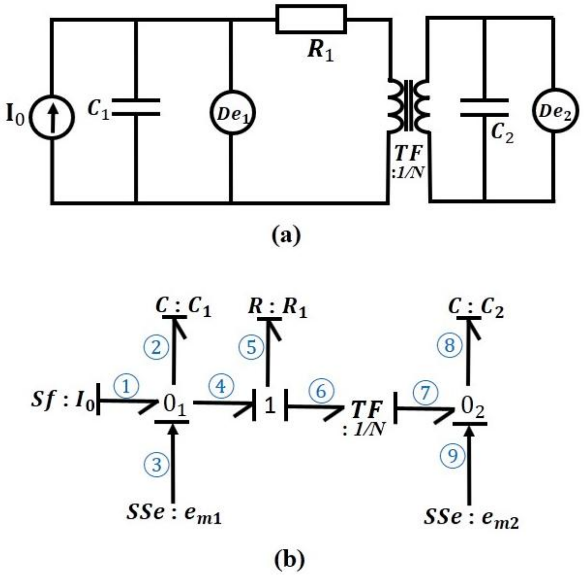

Fig. 6. (a) Schematic model of the electrical system, and (b) Bond Graph model of the electrical system in derivative causality.

The considered system contains two sensors connecting to two junctions (0_1 and 0_2). Thus, according to the causality inversion method (see section 2), two *ARRs* can be generated:

$$ARR_1 = I_0 - C_1 \frac{e_{m1}}{dt} - \frac{e_{m1} - \frac{1}{N} e_{m2}}{R_1} \tag{9}$$

$$ARR_2 = \frac{e_{m1} - \frac{1}{N} e_{m2}}{N R_1} - C_2 \frac{e_{m2}}{dt} \tag{10}$$

Hence, the evaluation of these *ARRs* gives two residuals r_1, and r_2 . By considering that faults may affect all system compenenets, the following fault signature matrix represented in Table 2, can be obtained from (9, 10). We remark that all system components are detectable (Db), however the capacitance element $C:C_2$ is the only fault that can be isolated.

TABLE II. THE FSM OBTAINED BY THE CAUSALITY INVERSION METHOD

Faults/residuals	r_1	r_2	Db	Ib
$De:e_{m1}$	1	1	1	0
$De:e_{m2}$	1	1	1	0
$Sf:I_0$	1	0	1	0
$C:C_1$	1	0	1	0
$R:R_1$	1	1	1	0
$TF:1/N$	1	1	1	0
$C:C_2$	0	1	1	1

Consider that, at a time, only one of the existing detectors is used for diagnosis, where only $De:e_{m2}$ is used for diagnosis. Then the bi-causality is propagated from the double source ($SeSf:e_{m2}$) to $DeDf^*:\hat{e}_{m1}$, as depicted in Fig. 7a, in order to estimate the voltage ($\hat{e}_{m1}$). The system remains observable and over constrained, and since the sensor $De:e_{m1}$ is not isolable (Table 2), it is possible to compute an additional non-redundant ARR_3 without using $De:e_{m1}$ for diagnosis. In addition, the following constraint can be generated:

$$\hat{e}_{m1} = \frac{1}{N} e_{m2} + R_1 N C_2 \frac{de_{m2}}{dt} \tag{11}$$

Finally, in order to obtain ARR_3 (12), e_{m1} is replaced by $\hat{e}_{m1}$ in ARR_3.

$$ARR_3 : \mathrm{I}_0 - C_1 \frac{\hat{e}_{m1}}{dt} - \frac{\hat{e}_{m1} - \frac{1}{N} e_{m2}}{R_1} = 0. \tag{12}$$

Following the same procedure while using only the information from the signal source $SSe:e_{m1}$ and ignoring the one of $SSe:e_{m2}$ (Fig. 7b). In addition, the following constraint can be obtained:

$$\hat{e}_{m2} = N\left(e_{m1} - \mathrm{R}_1\left(\mathrm{I}_0 - C_1 \frac{de_{m1}}{dt}\right)\right). \tag{13}$$

Finally, in order to obtain ARR_4 (14), e_{m2} is replaced by $\hat{e}_{m2}$ in ARR_4 .

$$\mathrm{ARR}_4 : \frac{e_{m1} - \frac{1}{N}\hat{e}_{m2}}{N\ \mathrm{R}_1} - C_2 \frac{d\hat{e}_{m2}}{dt} = 0. \tag{14}$$

These four ARRs are used to compute a new FSM, illustrated in Table 3. We Remarque that all the system components are detectable and the set of isolable faults is the following: $[C:C_2, De:e_{m1}, De:e_{m2}]$ Therefore, with this method, two new faults are isolable.

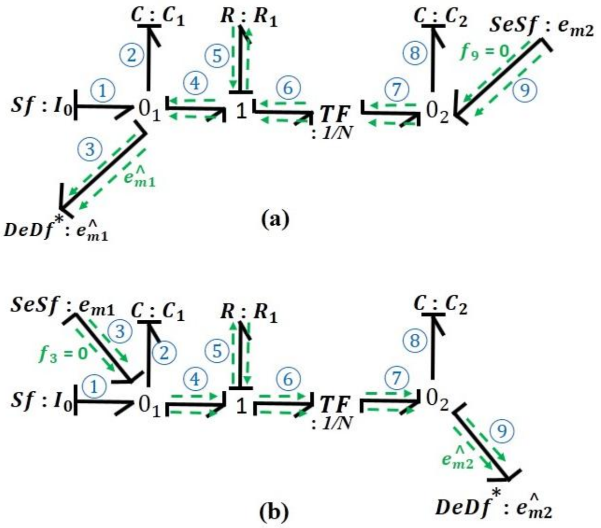

Fig. 7. (a) BG model of the system in bi-causality for $\hat{e}_{m1}$ estimation, and (b) BG model of the system in bi-causality for $\hat{e}_{m2}$ estimation.

TABLE III. FSM OF THE SYSTEM OBTAINED BY AUGMENTED ARRS

Faults/residuals	r_1	r_2	r_3	r_4	Db	Ib
$De:e_{m1}$	1	1	0	1	1	1
$De:e_{m2}$	1	1	1	0	1	1
$Sf:I_0$	1	0	1	1	1	0
$C:C_1$	1	0	1	1	1	0
$R:R_1$	1	1	1	1	1	0
$TF:1/N$	1	1	1	1	1	0
$C:C_2$	0	1	1	1	1	1

According to the fault signature matrix (Table 2), four faults ($R:R_1, De:e_{m1}, De:e_{m2}$ and $TF:1/N$) have the same signature {11}, and two residuals (r_1 and r_2) are sensitive to them. So, these four faults can be isolated using the fault estimation equations (see section 4).

Let us now consider a fault affecting the parameter element $R:R_1$. It is estimated from two ways by using the residuals r_1 and r_2 . The two estimation equations of $R:R_1$ parameter fault from r_1 (Fig. 8a) and from r_2 (Fig. 8b) can be obtained:

$$\left\{\begin{array}{l} F^1_{1/R_1} = \dfrac{1}{\dfrac{1}{R_1}\left(e_{m1} - \dfrac{1}{N}e_{m2}\right)} r_1 \\[2ex] F^2_{1/R_1} = \dfrac{-N}{\dfrac{1}{R_1}\left(e_{m1} - \dfrac{1}{N}e_{m2}\right)} r_2 \end{array}\right. \rightarrow r_3 = F^1_{1/R_1} - F^2_{1/R_1} \tag{15}$$

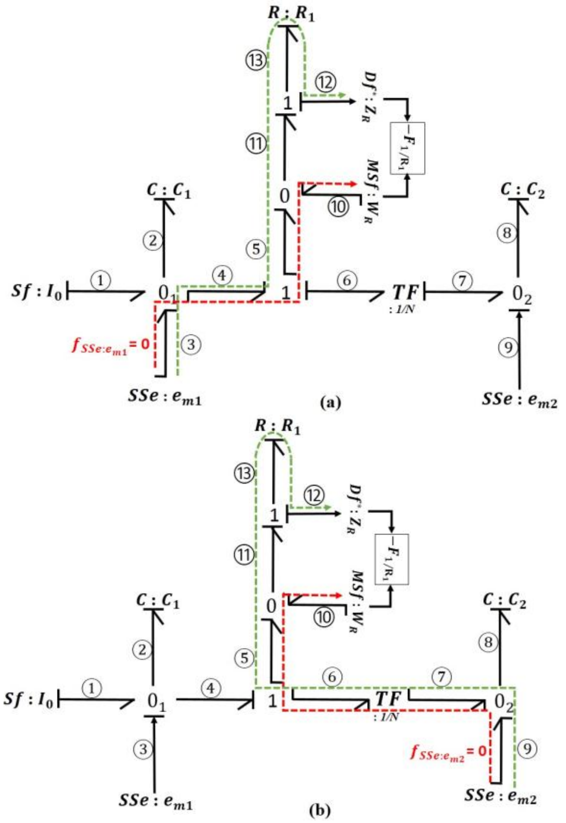

Fig. 8. (a,b) Fault estimation of $R:R_1$ parameter fault using (r_1 and r_2).

We notice that the residual r_3 is not sensible to the faults that affect the $R:R_1$ parameter component because F^1_{1/R_1} and F^2_{1/R_1} are the estimations of this fault. Following the same procedure, we can obtain the estimation equations of $De:e_{m1}$, $De:e_{m2}$, and $TF:1/N$. Where r_4, r_5 and r_6 are the residuals generated from the comparison of the two estimation equations of each fault respectively. Finally, by considering these new residuals, the fault signature matrix illustrated in Table 4 is obtained. It can be noticed that this method clearly increase the number of isolable faults of the system. In this case, five system components can be isolated. Therefore, with this method, two new faults can be isolated compared with the two methods that described previously.

TABLE IV. FSM WHEN THE FAULT/RESIDUAL SENSITIVITY PERFORMED

Faults/residuals	r_1	r_2	r_3	r_4	r_5	r_6	Db	Ib
$De:e_{m1}$	1	1	1	0	1	1	1	1
$De:e_{m2}$	1	1	1	1	0	1	1	1
$Sf:I_0$	1	0	-	-	-	-	1	0
$C:C_1$	1	0	-	-	-	-	1	0
$R:R_1$	1	1	0	0	1	1	1	0
$TF:1/N$	1	1	1	1	1	0	1	0
$C:C_2$	0	1	-	-	-	-	1	1

A. *Simulation Results*

To verify the efficiency of each method, an application using simulation data has been done. The input and output signals of the electrical system are depicted in Fig. 9. The four *ARRs* 9, 10, 12, 14 obtained using the augmented ARRs method were tasted in normal situation, and the residuals is evaluated in real time, as depicted in Fig. 10. As expected, the residuals (r_1, r_2, r_3 and r_4) are close to zero and do not exceed the thresholds (the red dashed lines). This means that the electrical system is healthy (fault free case).

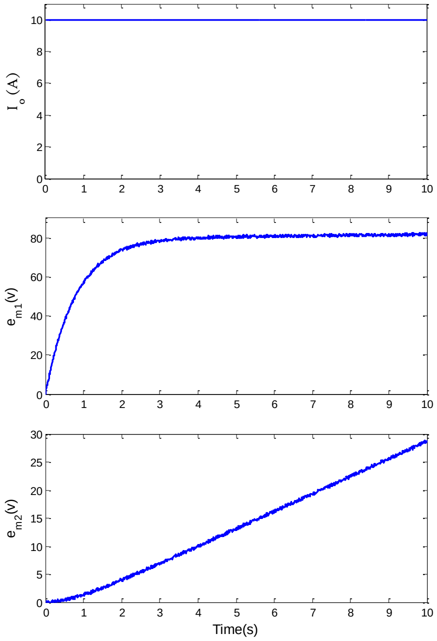

Fig. 9. The input and output signals of the system in normal functioning.

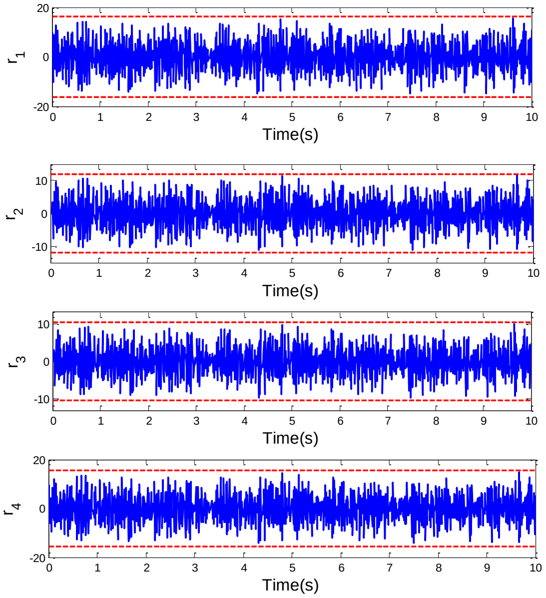

Fig. 10. r_1, r_2, r_3 and r_4 in normal functioning.

An additive fault is then introduced in the voltage sensor ($De:e_{m2}$) at time t=5s, which is not isolable by the causality inversion method. The signal of the faulty/healthy voltage sensor ($De : e_{m2}$) is illustrated in Fig. 11.

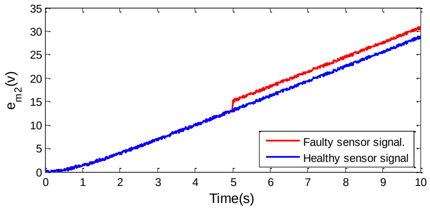

Fig. 11. The output of the faulty/healthy ($De : e_{m2}$) voltage sensor fault.

From the fault signature matrix (Table 3), the residuals sensitive to the introduced fault are r_1, r_2, and r_3. The residuals in case of ($De : e_{m2}$) voltage sensor fault are illustrated in Fig. 12. As the structural results concluded, the residuals r_1, r_2, and r_3 detect this fault and exceed the thresholds, while r_4 does not detect this fault because it is not sensitive to it. The signature {1110} in this case is the same as the signature of the $De : e_{m2}$ voltage sensor fault. It is then possible to conclude that a fault in the voltage sensor $De : e_{m2}$ can be isolated when the sensor data combinations method is performed.

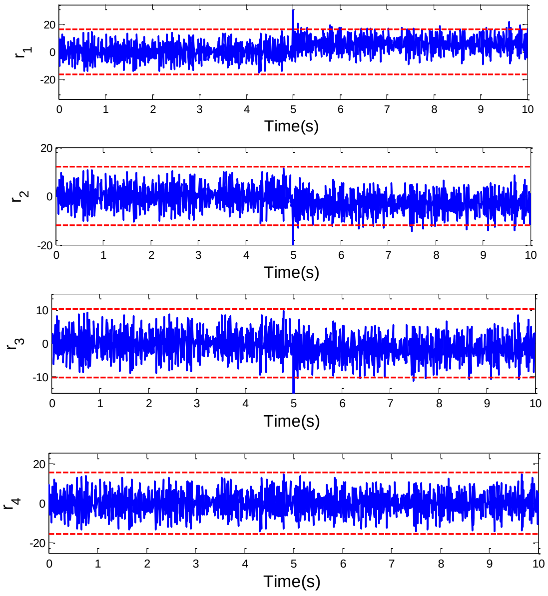

Fig. 12. r_1, r_2, r_3 and r_4 in case of ($De : e_{m2}$) voltage sensor fault.

Let us now consider another fault affecting the parameter element $R : R_1$. This fault is not isolable either by causality inversion method or by augmented ARRs method. According to the fault signature matrix (Table 4), this fault can be isolated using the fault estimation equations. This is verified by the simulations results shown in Fig. 13. The estimations of the faults is don after the detection of the fault (Fig. 14). This means that the estimation is off when the residual (r_1 and r_2) values is less than the threshold. The two estimations of F_{1/R_1} from r_1, and r_2 are equal while the others are not (Fig. 13). This means that the residual r_3 is equal to 0, which is the comparison between the two estimations of the fault F_{1/R_1} from r_1, and r_2 while r_4, r_5 and r_6 are equal to 1 because their estimations from r_1, and r_2 are not equal. In this case, the fault on $R : R_1$ parameter element is isolated.

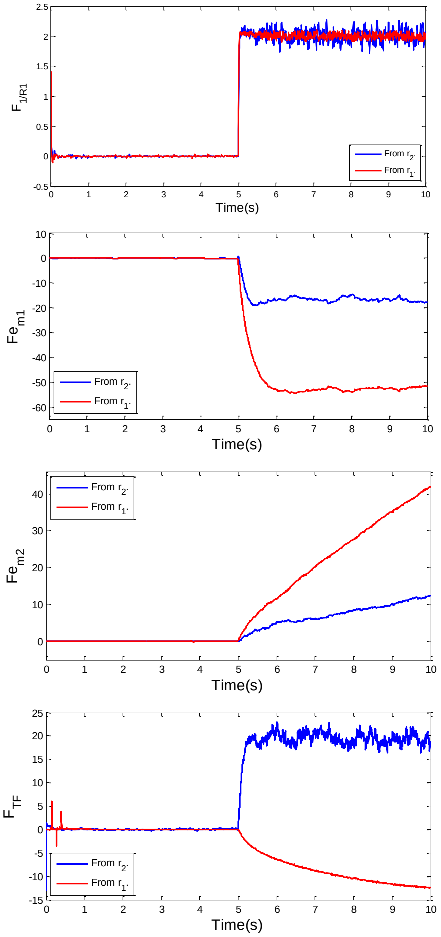

Fig. 13. $F_{1/R_1}, F_{e_{m1}}, F_{e_{m2}}$ and F_{TF} from r_1 and r_2 in case of ($R : R_1$) fault.

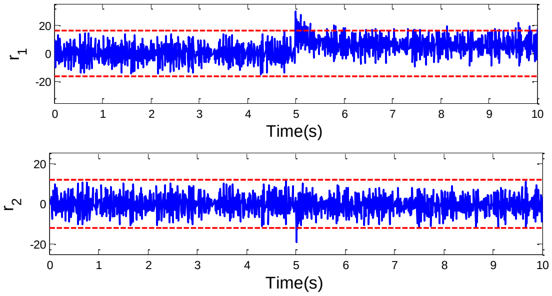

Fig. 14. r_1 and r_2 in case of ($R : R_1$) fault.

B. Ccomparative Analysis

The advantages, drawbacks, and limitations of each method are summarized as follows:

1. Advantages:

1.1. Causality inversion method:

The *ARRs* is obtained in a systematic way using covering causal path methodology to eliminate the unknown variables. The diagnosis information is considered with less calculation.

1.2. Augmented ARRs method:

Can generate different versions of the same *ARR* without adding new sensors. Excellent capability for sensors fault isolation even if these faults has only one sensitive residual.

1.3. Fault/residual sensitivity method:

The estimated fault information can be used to decide an appropriate control action that compensate the faults. Represent a simple and systematic way to obtain the sensitivity relation directly from the graphical model.

2. Drawbacks and limitations:

2.1. Causality inversion method:

Cannot isolate the faults that have the same signature (see Table 2). Does not exploit all possible sensor combinations.

2.2. Augmented ARRs method:

The system must remain over-constrained and observable when ignoring one of the sensors used for diagnosis, and this is not always available in all systems. The additional *ARRs* generated by this method contain 1 or 2 order derivative of the input signal (see Eqs. (12) and (14)), which amplify the measurement error. This can be cause an error on the fault isolation. A parameter fault can be isolated using this method if and only if its signature is different from all parameter and actuator faults (see Table 3 and Table 3 of [14]).

2.3. Fault/residual sensitivity method:

The generation of the sensitivity relations between the fault and the residual by using Mason's rule is only limited in the linear case and inverted non-linear systems.

VI. CONCLUSIONS

In this paper, a comparative study between three methods using bond graph approach and its causal and structural proprieties for fault diagnosis has been presented. The study indicates that both sensor data combinations and fault estimation methods are the extension of the causality inversion method. The first method combines the sensor data in order to generate additional non-redundant *ARRs*. These additional *ARRs* enable to obtain the different set of fault signatures. The second use the sensitivity relations between the fault and the residual, in order to generate the fault estimation equations. These equations are used to improve the isolation of the faults have the same fault signature. Each of these methods has its own advantages and limitations. The result show that the fault/residuals sensitivity method can isolate more faults when compared to other methods.

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