Fault Diagnosis by Bond Graph Functional Observer

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Summary
A diagnosis by functional observers based on bond graph approach is proposed in this paper. Taking into account its structural and causal properties, the bond graph model is used for modeling, residual generation and simulation purposes. The paper also highlights and clarifies the need for the optimization method as LMI (Linear Matrix Inequality), to outline the stability performances. Simulation results on the stringing machine are provided to show the dynamic behavior of system variables and to evaluate the performance of the observer for diagnosis tasks.
Key words:
Diagnosis, Functional observer, bond graph, LMI.

1. Introduction

The observer design problem has received extensive research attention, since the first original work appeared with [1]-[2]. The basic idea behind the observer problem is to estimate the state of the system using the input and output data. During the last decades, important results have been extended to directly estimate a given linear function of the state vector, without having to estimate all the individual states. We talk about the functional observers.
Following the pioneering work of [1]-[2], alternative procedures for solving a general vector state function problem for multiple-output systems are presented in the work of [3].The authors in [4] designed minimum-order functional observers, for time-delay systems with interval time-varying state delays.
An interesting algorithm for the design of functional observer, benefit from the lower Hessenberg form of the observable pair introduced by [5], which considers a particular unresolved aspect functional observer design. The solving of the constrained Sylvester equation helps [6] to design minimal multi-functional observers. In the presence of the unknown inputs, [7] constructed a functional observer by geometric methods. This observer kind played an important role in studying the functional observability or detectability as shown in [8] study. Also, the functional observer contributed in the observer-based feedback controller implementation [9], state estimation [10] and fault detection and isolation purposes [11].

Despite all the contributions related to the linear functional observers yet to date, the diagnosis by functional observer using graphical approach as bond graph tool has not been reported. So our contribution is to extend the graphical functional observer design for modelling, residual generation and diagnosis tasks.
The diagnosis of dynamical systems has been the subject of several research works in the recent years. Using the bond graph approach, for modelling uncertainties parameters, [12] proposed the LFT form (Linear Fractional Transformation). The integration of the LFT form and the bicausality concept helps [13] to generate the equation of the fault estimation. [14] used the multiple observers scheme for fault detection and isolation.
The aim of this paper is to present the methodology of bond graph model to design the functional observer. It also aims to explore the multiple observer schemes for fault detection and isolation. We finished our work with the validation of the simulation results applied on the stringing machine.

2. Methodology of Bond Graph Approach

The modeling using bond graph tool relies on the power transfer between the different subsystems. This transfer based on the generalized variables effort symbolized as e and flux symbolized as f . The product of which constitutes the power. The energy exchange between two elements is presented by a half link indicate the direction of the transfer.
To construct a bond graph model, we add dissipative elements such as the element (R), for thermal transfer or hydraulic resistance, the element (C) for fluid compressibility or storage of masses and volumes, and the element (I) for all phenomena of inertia.
In this paper, the bond graph approach is used for modeling, estimation, diagnosis and simulation of dynamical systems.

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3. Functional Observer Design by Bond Graph Approach

Consider the linear time-invariant system described by

$$\begin{cases} \dot{x} = Ax + Bu \\ y = Cx \\ W = Kx \end{cases} \qquad (1)$$

Where $x \in R^n$ and $y \in R^p$ are the state vector, the output vector of the system, $u \in R^m$ is the input vector of the system and $W \in R^r$ is the vector to be estimated, where $r \le n$. A, B, C and K are known as constant matrices of appropriate dimensions.

We assume that the pair (A, C) is observable, $rankC = p$ and $rankK = r$. So, the matrices A, B, C are partitioned as follows:

$$A = \begin{bmatrix} A_{aa} & A_{ab} \\ A_{ba} & A_{bb} \end{bmatrix},\ B = \begin{bmatrix} B_a \\ B_b \end{bmatrix},\ C = \begin{bmatrix} I & 0 \end{bmatrix} \text{ and } x = \begin{bmatrix} x_a \\ x_b \end{bmatrix} \qquad (2)$$

The aim of the functional observer is to estimate directly the control law $(W = Kx)$ without estimating all its states, Let us propose that $C = (I \quad 0)$ and $K = (K_a \quad K_b)$. So we obtain $x_a = y$ and $x_b = K_b^{-1}(W - K_a y)$.

After some algebraic manipulations, the linear functional observer has the following form

$$\begin{cases} \dot{\hat{z}} = E\hat{z} + Dy + Hu \\ \hat{W} = \begin{pmatrix} \dot{\hat{p}}_I \\ \dot{\hat{q}}_C \end{pmatrix} = P\hat{z} + Fy \end{cases} \qquad (3)$$

With $y \in R^p$, $u \in R^m$, $W \in R^r$ is the vector to be estimated, where $r \le n$. $E = A_{bb} - L A_{ab}$, $D = A_{ba} - L A_{ab} L - L A_{aa} + A_{bb} L$, $H = B_b - L B_a$, $P = K_b$, $F = K_a + K_b L$. A_{aa}, A_{ab}, A_{ba} and A_{bb} are the sub-matrices of the state matrix. L is the observer gain, p and q are the energetic variables of bond graph modeling.

The dynamic of the estimation error is defined as

$$e = W - Kx = z - Tx \qquad (4)$$

Assumptions:

$\hat{W}$ in (3) is an asymptotic estimate of W for any x_0, $\hat{W}_0$ and any u, if and only if the following assumptions are satisfied:

1. E is a Hurwitz matrix, i. e., has all its eigenvalues in the left-hand side of the complex plane.
2. $TA - ET = DC$
3. $PT + FC = K$ (5)
4. $H = TB$

Where T is a constant matrix, as $\lim_{t \to \infty}(z - Tx) = 0$.
Then the estimation error dynamics are written as:

$$\dot{e} = Ee \qquad (6)$$

Using the bond graph tool, the steps of designing a functional observer are formulated as follows [15]:

Step 1: Checking of the existence of the redundant outputs
The property of existence of redundant outputs, summarized in the bond-graph rank ($bg - rank[C]$) which can confirm the rank of the model's matrices. Indeed, the $bg - rank[C]$ is equal to the number of detectors in a model that can be dualized without creating causality conflicts. So, the $bg - rank[C]$ will be equal to the number of non-redundant outputs; $bg - rank[C] = p$.

Step 2: Investigating the structural observability of the system bond graph model
To design the observers, we have to check the observability of the system. According to [16]'s theorem, a bond graph model is structurally observable if and only if the below conditions are satisfied:
When we put the bond graph model of the system with preferred integral causality, there is a causal path linking the sensors for each dynamic element I or C.

When the bond graph model of the system is affected with derivative causality, all the elements I and C have derivative causalities and the sensors are dualized.

Step 3: Selection of X_a

From the bond graph point of view, the non-estimable variables in bond graph model are the state variables associated to the dynamical elements which are connected directly to the detectors by a causal path or through the R element.

Step 4: Change of X_a *causality*

We change the causality of the dynamical elements associate with X_a which is made from the initial bond graph model into a derivative causality, as shown in Fig. 1.

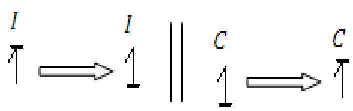


Fig.1 Derivative causality of the elements associated with X_a

Step 5: Injection of the term Fy

As in the case of the full order observer design, we consider the term Fy as an error signal which comes from an extra junction on the effort or flow source bond via an active bond, and injected it on the dynamical elements associated to the state variable, which has a linear function with the control variable by the modulated source, as shown in Fig. 2.

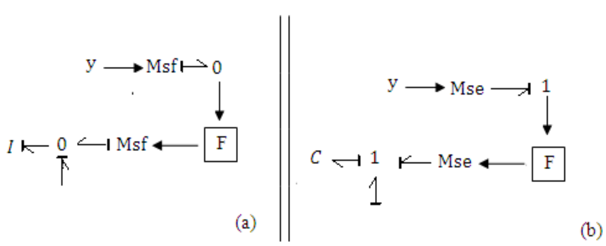


Fig. 2 Fy injection to: (a) I element, (b) C element

Step 6: Sum of the term P

In the observer bond graph model, the term P is added with a modulated source. Indeed, it's the flow when the control variable is associated to the C element (and it's the effort when the control variable is associated to the I element), as shown in Fig. 3.

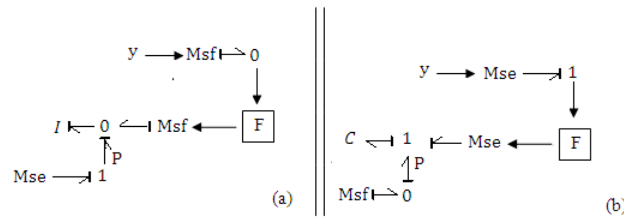


Fig. 3 Addition of the term P in the observer bond graph model: (a) I element, (b) C element

3.1 Functional Observer Gain Computing

Thereafter, we compute the observer gain via bond graph method. Indeed, the observer gain L can be computed using two different methods. The first consists in the traditional methods using the state equations calculation from the system bond graph model. The second is based on the formal calculation of the characteristic polynomial $P_{(A_{bb}-LA_{ab})}(s)$ respectively. It uses the causal manipulations and structural properties on the bond graph model without any calculations using [17]'s theorem cited below :

The value of each coefficient of the characteristic polynomial

$$P_A(s) = s^n + \alpha s^{n-1} + \ldots + \alpha_{n-1} s + \alpha_n \tag{7}$$

equal to the constant term (without the Laplace operator) of the total gain of the families of causal cycles of order i in the bond graph model. The gain of each family of causal cycles must be multiplied by $(-1)^d$ if the family consists of d disjoined causal cycles.

Thus, the causal analysis to calculate the observer gains is made only with the family of causal cycles in the observer's bond graph.

We compute now the state feedback gain with LMI (Linear Matrix Inequality) method [18].

The closed-loop system of (1) is quadratically stable, if and only if the following LMI are feasible:

$$\begin{cases} P \succ 0 \\ (A-BK)^T P + P(A-BK) + 2\alpha P \leq 0 \end{cases} \tag{8}$$

Where P is a symmetric, positive and defined matrix, and α is the decay rate.
The controller design is the result of the following LMI problem, where Q is a symmetric, positive and defined matrix

$$\begin{cases} Q \succ 0 \\ (A+\alpha I)Q + Q(A+\alpha I)^T + BY + Y^T B^T \prec 0 \end{cases} \tag{9}$$

The resulting controller feedback gain is given by:

$$K = -YP \tag{10}$$

Where Y and P are the solutions, such that LMI problem given by (8) is feasible.

4. Diagnosis by Functional Observer Using Bond Graph Approach

4.1 Principle of Diagnosis by Functional Observer

The structure of functional observer by bond graph model is presented in Fig.4.

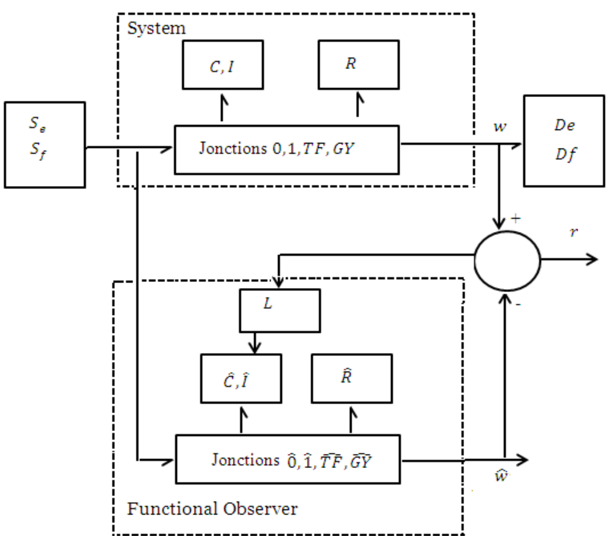


Fig. 4 Structure of functional observer bond graph model

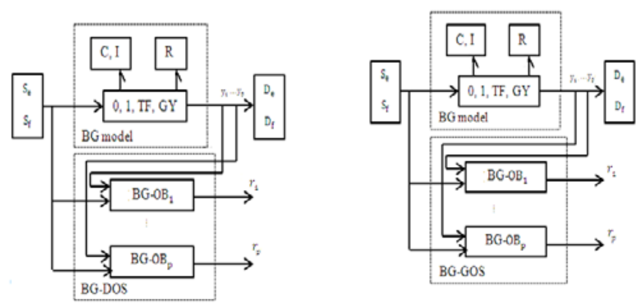
The diagnosis consists on analysing the residual output estimation r and their sensitivity to the faults. The residual equation has the following form:

$$r = W - \hat{W} \tag{11}$$

4.2 Strategies of Fault Isolation by Functional Observer Design

The multiple observer set based on analytical models proposed in the literature for FDI are: Dedicated observer scheme (DOS): the i^{th} observer is driven by the i^{th} output and all inputs. Other outputs are considered unknown [19].

Generalized observer scheme (GOS): the i^{th} observer is driven by all outputs and all inputs except the i^{th} output [20].
We have extended this scheme to the FDI purpose of dynamic systems modeled by bond graph approach. A bank of BG_DOS and BG_GOS structures for FDI sensor are depicted in Fig.5.



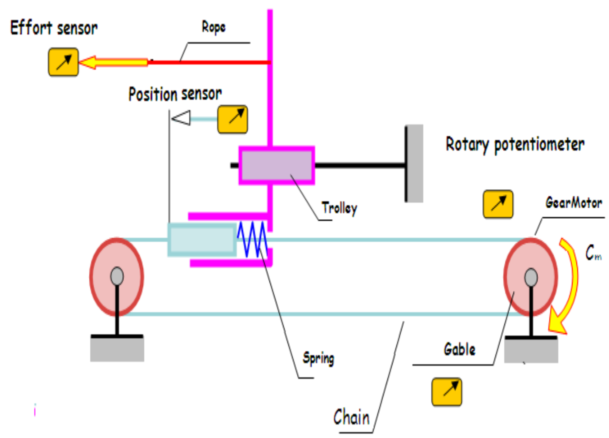
(a) (b)
Fig. 5 Bond graph bank observer structure: (a) BG-DOS Structure, (b) BG-GOS Structure

The residuals deduced from the observer bank are grouped in the FDI table. Its rows and columns correspond to faults and residuals. The table is filled with binary values (fault signature). When we found zero (0), we deduce that the residual is robust to the fault, while when we found one (1), we prove that the residual is sensitive.

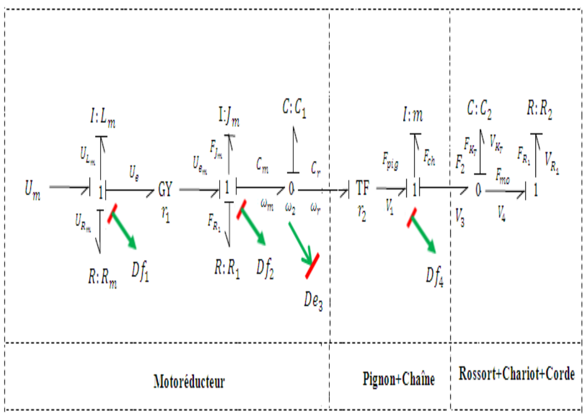
5. Application

5.1 Bond Graph Model of Stringing Machine

We consider the circuit diagram of the stringing machine and its bond graph model given in Fig. 6. We detect faults at the sensors De_3 and Df_4.



(a)



(b)

Fig. 6 (a) A stringing machine, (b) bond graph model of stringing machine

From the Fig. 6b, we can detail the bond graph model of the system. In fact, the DC motor is used to associate the physical phenomenon or components considered by the induced current I_m, and by the mechanic part which depends on the rotation speed of its axe. Whether, U_m is the induced tension, R_m is the resistance, L_m is the inductance, R_1 is the resistive viscous friction, and J_m is the moment of the rotor inertia and the shaft of inertial type. The gyrator element has as r_1 constant, and transforms the electromotive force into rotation speed of the reducer tree. The compressibility of the tree is presented by C_1 element. The third block transforms the rotation movement into translation movement via winding up the rope which is presented as the transformer element witch has as r_2 constant. The mass of the chain is given by m and the frictions at the gable are negligible. We consider that the tree is of elastic type (whether $C_2 = \frac{K_r}{1+K_r/K_c}$ (K_r is the spring stiffness and K_c is the rope stiffness), the loss resistance is given by R_2). The mass of the trolley is negligible.

From Fig. 6b, we can deduce the gear motor equations:

$$U_{L_m} = U_m - U_{R_m} - U_e \quad (12)$$

$$U_{R_m} = R_m I_m$$

$$p_{L_m} = \int U_{L_m} dt$$

$$U_e = r_1 \omega_m$$

$$U_{e_m} = r_1 I_m$$

$$F_{J_m} = U_{e_m} - F_{R_1} - C_m \quad (13)$$

$$F_{R_1} = R_1 \omega_m$$

$$p_{J_m} = \int F_{J_m} dt$$

$$\omega_r = \omega_m - \omega_2$$

The gable + chain equations:

$$F_{pig} = 1/r_2 C_r \quad (14)$$

$$\omega_r = 1/r_2 V_1$$

$$F_{ch} = F_{pig} - F_{mo}$$

$$p_m = \int F_{ch} dt$$

And the spring + trolley + rope equations:

$$V_{K_T} = V_3 - V_4 \quad (15)$$

$$F_{K_T} = \psi_{C_2}\left(\int V_{K_T}\,dt\right)$$

$$q_{C_2} = \int V_{K_T}\,dt$$

The state equation is:

$$\begin{cases} \begin{pmatrix} \dot{P}_{L_m} \\ \dot{P}_{J_m} \\ \dot{q}_{C_1} \\ \dot{P}_m \\ \dot{q}_{C_2} \end{pmatrix} = \begin{bmatrix} -R_m/L_m & -r_1/J_m & 0 & 0 & 0 \\ r_1/L_m & -R_1/J_m & -1/C_1 & 0 & 0 \\ 0 & 1/J_m & 0 & -1/m r_2 & 0 \\ 0 & 0 & 1/C_1 r_1 & 0 & -1/C_2 \\ 0 & 0 & 0 & 1/m & 0 \end{bmatrix} \begin{pmatrix} P_{L_m} \\ P_{J_m} \\ q_{C_1} \\ P_m \\ P_{C_2} \end{pmatrix} + \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} u \\ \begin{pmatrix} Df_1 \\ Df_2 \\ De_3 \\ Df_4 \end{pmatrix} = \begin{bmatrix} 1/L_m & 0 & 0 & 0 & 0 \\ 0 & 1/J_m & 0 & 0 & 0 \\ 0 & 0 & 1/C_1 & 0 & 0 \\ 0 & 0 & 0 & 1/m & 0 \end{bmatrix} x \end{cases} \quad (16)$$

The Table 1 shows the parameters values of the stringing machine .

Table 1: Parameters values

Symbol	***Designation***	***Nominal values***
R_m	Rotor resistance	1.1Ω
L_m	Rotor inductance	$1mH$
J_m	Moment of geared motor	$0.05Kg.m^2$
R_1	Coefficient of viscous	$0.28N.m/rad/S$
r_1	Coefficient of torque	$0.0386N.m/A$
r_2	Reduction ratio	$0.01N.m/A$
m	Chain mass	$0.3Kg$
K_r	Spring stiffness	$4N/mm$
K_c	Rope stiffness	$32.7N/mm$
C_1	Coefficient of compressibility	10^{-4}
C_2	Coefficient of compressibility	0.00028
R_2	Loss resistance	$1000N.m/rad/S$

5.2 Diagnosis by Functional Observer using Bond Graph Approach

Before starting the design of the graphical functional observer as mentioned above the following steps must be validated:

Step 1: Investigating the presence of redundant outputs:
In the bond graph model of Fig 6b, the detectors can be dualized without creating any causality conflict ; $bg\_rank(C) = 4$ .Thus, the measurements in the Df_1, Df_2 De_3 and Df_4 sensors are non-redundant outputs.

Step 2: Checking the model's structural observability:
The derivative bond graph model is presented in Fig 7

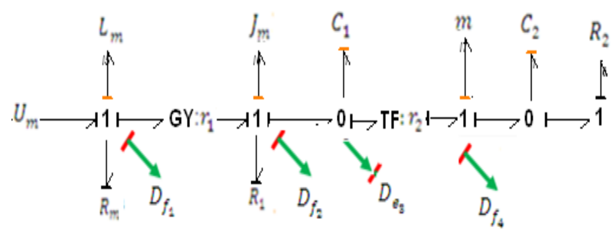


Fig. 7 Bond graph model in derivative causality

It's clear that, on the bond graph model in derivative causality, all the dynamic components admit a derivative causality and there is no causality conflict. Thus, the model of the stringing machine is structurally observable.
Let us now design a functional observer to estimate, the string tension racket response.

Step 3: Selection of x_a

x_a is made directly from the bond graph model of the system; there is a causal path (or through the R element) between the detectors and all the dynamical elements. Thus,

$$x_a = \begin{pmatrix} p_{Lm} & p_{Jm} & q_{C1} & p_m \end{pmatrix}^T.$$

Step 4: Change of x_a causality

The change of x_a causality is made directly from the bond graph model, as shown in Fig. 8.

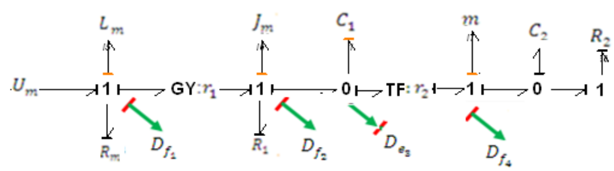


Fig. 8 Change of the dynamical elements associated with x_a causality

The injection of Fy is made as it is shown in Fig 9

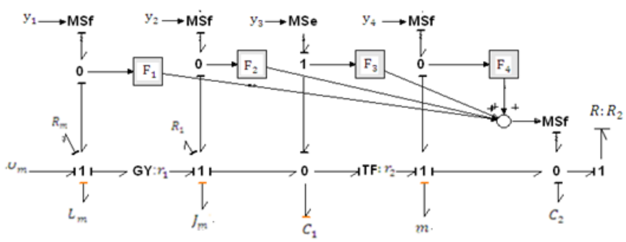


Fig. 9 Injection of the term Fy in the model of the observer

Step 6: Sum of the term P

We add the term P, the observer bond graph model is designed as it's shown in Fig 10.

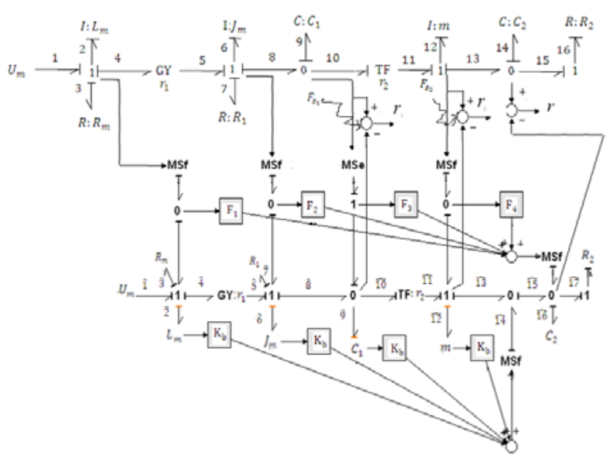


Fig. 10 Bond graph model of the functional observer

5.3 Functional Observer Gain Computing

Applying [17]'s theorem in the observer model (Fig. 10), we found one first order causal cycle. Then, selecting α_1 as the desired coefficient of the characteristic polynomial:

$$P_{(A_{bb-L}A_{ab})}(s) = s + \alpha_1 \tag{17}$$

The calculus of L is directly derived from α_1 because

$$\alpha_1 = G_1 = -\frac{F_4}{C_2} = -\frac{(K_a + K_b L_4)}{C_2} \tag{18}$$

Then, L_4 is calculated from (18)

$$L_4 = -\frac{(\alpha_1 C_2 + K_a)}{k_b} \tag{19}$$

The functional observer gain is

$$L = 10^4 (0 \quad 0 \quad 0 \quad -1.048)$$

Applying [18]'s theorem, in the system (1) and observer structure (2), leads to the following gains matrix

$$K = 10^{-5} (-3.915 \quad 0 \quad 0 \quad 0 \quad 0) \text{ with } \alpha = 10^4 \tag{20}$$

We have simulated the system with 20Sim. The Fig.11 shows the real and estimated state evolution.

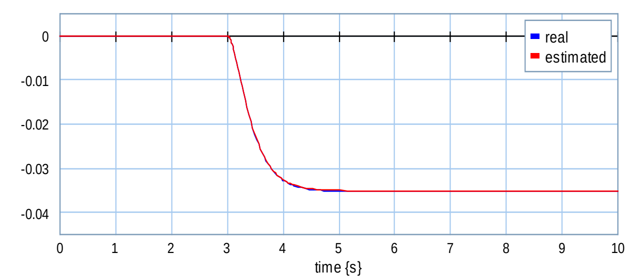


Fig. 11 State variables evolutions

5.4 Residual Generation in normal operation

From the bond graph model of Fig.10, we can deduce the residual r.

$$r = e_{14} - \hat{e}_{16} \tag{21}$$

With
$$e_{14} = \frac{1}{C_2} \int \left[C_2 \frac{d}{dt} \left(\frac{1}{r_2} y_3(t) \right) - m \frac{d}{dt} y_4(t) \right] dt \tag{22}$$

And

$$\hat{e}_{16} = 4K_{a_1} + 3K_{a_2} + 2K_{a_3} + K_{a_2} L_1 + K_{a_3} L_2 + K_{a_4}(L_3 + 1) + K_b L_4 \tag{23}$$

The Fig.12 shows that the residual converges to zero.

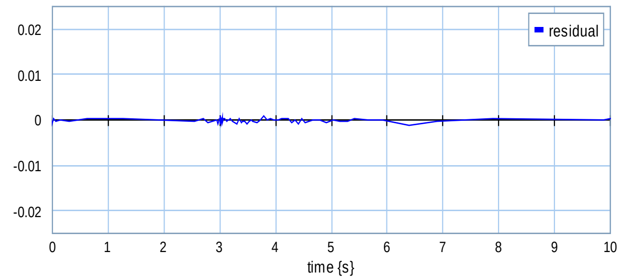


Fig. 12 Residual evolution in normal operation

5.5 Residual Generation with Sensors Faults

The sensors De_3 and Df_4 are affected by faults F_{S1} (from $1s$ to $2s$) with amplitude equal to 0.02 .and F_{S2} (from $7s$ to $8s$) with amplitude equal to 0.01.
So, the residuals are

- $r_1 = (e_9 + F_{S1}) - \hat{e}_9$ (24)

With

$$e_9 = \frac{1}{C_1}\int \left[C_1 \frac{d}{dt} y_3(t) + F_{S1} \right] dt \quad (25)$$

And

$$\hat{e}_9 = \frac{1}{C_1}\int [K_b] dt \quad (26)$$

- $r_2 = (f_{12} + F_{S2}) - \hat{f}_{12}$ (27)

With

$$f_{12} = \frac{1}{m}\int \left[m \frac{d}{dt} y_4(t) + F_{S2} \right] dt \quad (28)$$

And

$$\hat{f}_{12} = \frac{1}{m}\int [K_b] dt \quad (29)$$

The equations show that the residual are sensitive to sensor fault. The Fig. 13 confirms that the residual is sensitive to the sensor fault F_S.

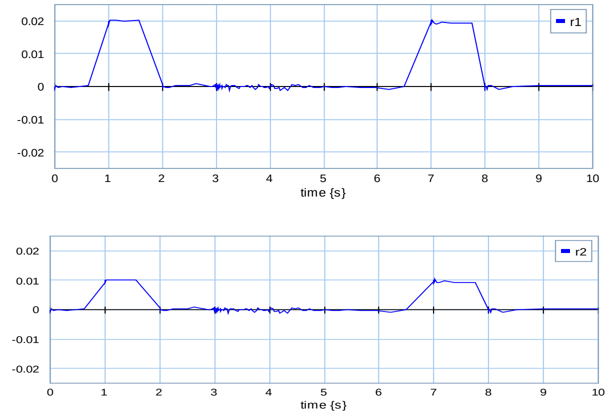
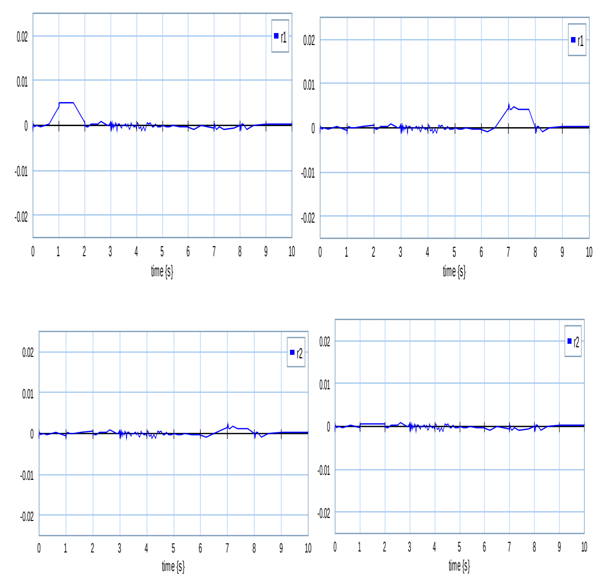


Fig. 13 Residual evolution with sensors faults

5.6 Robust Sensor Fault Isolation

We apply the BG-DOS and BG-GOS struture on the bond graph model. The residual is sensitive to the sensor fault. The residual evolution is given by Fig.14. So, the deduced binary signatures can perfectly isolate the fault (see the table below)



(a) DOS (b) GOS

Fig. 14 Residuals r_1 and r_2

Table 2: Binary Signature

	De_3	Df_4
r_1	1	*0*
r_2	0	*1*

BG-DOS

	De_3	Df_4
r_1	0	*1*
r_2	1	*0*

BG-GOS

6. Conclusion

This paper has proposed a diagnosis by functional observer based on bond graph approach. The interest of this paper is the manipulation of only one representation, the bond graph for modelling and observer designs to generate the residuals. The simulation results on the stringing machine show a good accuracy of the proposed observer, in spite of some limitations such as the necessary time for estimation and stabilization. At the last particular attention will be paid to the study of the fault tolerant control based on bond graph functional observer in future research works.

References

[1] D. G. Luenberger, “Observer for multivariable systems,” IEEE Transactions on Automatic Control, vol.11, no.2, pp.190-197,1966.

[2] D. G. Luenberger, “An introduction to observers,” IEEE Transactions on Automatic Control, vol.16, no.6, pp.596-602, 1971.

[3] J. B. Moore and G. F. Ledwich, “Minimal- order observers for estimating linear functions of a state vector,” IEEE Transactions on Automatic Control, vol.20, pp.623-632, 1975

[4] J. B. Moore and G. F. Ledwich, “Functional observer design for related system with interval time-varing delays,” International Journal of System Science, vol.48.no. 5, pp.1060-1070, 2017.

[5] C.C. Tsui, “A new algorithm for the design of multifunctional observers,” IEEE Transaction on Automatic Control, vol.30, no.1, pp.89-93, 1985.

[6] R. Mohajerpoor, H. Abdi and S. Nahavandi, “A new algorithm to design minimal multi-functional observers for linear systems,” Asian Journal of Control, vol.18, no.3, pp.842-857, 2016.

[7] G.. Gonte ,A. M. Perdon and E. Zattoni, “Unknown input observers for hybrid linear systems with state jumps,” IFAC, vol.50, no.1, pp.6458-6464, 2017.

[8] M. Darouach, “Existence and design of functional observers for linear systems,” IEEE Transactions on Automatic Control, vol.45, no.5, pp.940-943, 2000.

[9] M. Aldeen and H. Trinh, “Reduced-order linear functional observer for linear systems,” IEEE Pro. Control Theory, vol.146, no.5, pp.399-405, 1999.

[10] W. Y. Leong, “Functional state observers design for interconnected time-delay systems,” Thesis Dekin University, 2016.

[11] H. M. Tran and H. M. Trinh, “Minimal-order functional observer-based residual generators for fault detection and isolation of dynamical systems,”Mathematical Problems in Engineering, vol.ID.2740645, 2016.

[12] G. Dauphin-Tanguy and C. Sié Kam, “How to model parameter uncertainties in a bond graph framework,” ESS’99 Erlangen: Germany, pp.121-125, 1999.

[13] Y. Touati, B. Ould-Bouamama and R. Merzouki, “Fault estimation using bicausal bond graph and linear fractional transformation,” 7th IEEE Conference on Industrial Electronics and Applications (ICIEA), Singapore, Singapore July 18-20, 2012

[14] A. Sallami, N. Zanzouri and M. Ksouri, “Robust fault diagnosis observer of dynamical systems modeled by bond graph approach,” 8th IFAC Symposium on Fault Detection Supervision and safety of Technical Processes (SAFEPROCESS), Mexico City-Mexico, August 29-31 2012.

[15] R. Attafi and N. Zanzouri, “State feedback controller based on bond graph observers,” Journal of Computer Science and Network Security (IJCSNS), vol.18, no.4, pp.116-125, April 2018.

[16] C. Sueur and G. Dauphin-Tanguy “Structural controllability and observability of linear systems represented by bond graph,” Journal of the Franklin Institute, vol.326, no.6, pp.869-883, 1989.

[17] A. Rahmani, C. Sueur and G. Dauphin-Tanguy, “Pole assignement for systems modeled by bond graph,” Journal of the Franklin Institute, vol.331, no.3, pp.299-312, 1994.

[18] G. Scorletti and G. Duc, “An LMI approach to decentralized H8 control,” International Journal of Control, vol.74, pp.211-224, 2001.

[19] R. N. Clarke, D. C. Fosth and V. M. Walton, “Detecting instrument malfunctions in control systems,” IEEE Transactions on Aerospace and Electronic Systems, vol.11, no.4pp.465-473, 1975.

[20] J. Wünnenberg and P. M. Frank, Sensor fault detection via robust obsrvers. In System Fault Diagnnosis Reliability & Related Knowledge-based Approach, Dordrecht: Reidel Press, 1987.

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