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Fault detection approach based on Bond Graph observers: Hydraulic System Case Study

Ghada Saoudi[1], Rafika ElHrabi[2] and Mohamed Naceur Abdelkrim [2]
[1](MACS Laboratory, National Engineering School of Gabes, Tunisia)
[2](MACS Laboratory, National Engineering School of Gabes, Tunisia)
[3](MACS Laboratory, National Engineering School of Gabes, Tunisia)

ABSTRACT: *The present paper deals with a bond graph procedure to design graphical observers for fault detection purpose. First of all, a bond Graph approach to build a graphical proportional observer is shown. The estimators' performance for fault detection purpose is improved using a residual sensitivity analysis to actuator, structural and parametric faults. For uncertain bond graph models in linear fractional transformation LFT), the method is extended to build a graphical proportional-integralPI observer more robust to the presence of parameter uncertainties. The proposed methods allows the computing of the gain matrix graphically using causal paths and loops on the bond graph model of the system. As application, the method is used over a hydraulic system. The simulation results show the dynamic behavior of system variables and the performance of the developed graphical observers.*

Keywords: *Bond Graph, Fault Detection, Observer, hydraulic system, robustness, BG- LFT*

I. INTRODUCTION

Throughout the past decades, the industrial machines have been developed from manual operation to automation. This led to the increase of the interconnections between their components and to the amplification of their interdependencies. In spite of this soaring complexity, the safety of their operation is highly required and their reliability must be guaranteed.

Admitting the need for high security and availability, they aren't sheltered from failures. They may be susceptible to damage and breakdowns. In the light of this reason, a large community of researchers have been mobilized in recent years to improve the overall performance of the system through the introduction of different diagnosis and supervision techniques. Those procedures focuses on the comparison between the actual system performance and its theoretical reference given by the system's model. Monitoring procedures are composed basically of two methods: model-based and non-model-based.

Model-based approach in its turn is composed of two classes; The first one is the qualitative model based which embodies structural analysis, fault tree graph based approach, temporal causal graphs, signed directed graphs, etc. Indeed, the tree graph based approach can be employed only for processes performing in unchangeable state, the temporal causal graph based approach is suitable only for linear systems. Bearing this in mind, these methods are incongruous for real industrial systems.

The second approach is the Quantitative model based which comprehends parity space, Kalman filters, and observer-based diagnosis. The latter technique has been one of the most used approaches in the industrial automation processesto generate diagnostic signals-residuals. Basically, anobserver is an auxiliary system that estimates the state of thesystem dynamically and monitors the changes. There is an ample multifariousness of standard observer-based methods in the literature for linear and nonlinear systems. Luenberger observer-based approach is one of the most famous and traditional techniques used for residual generation [1].

It is noteworthy that these Model based approaches strongly rely on the availability of an explicit analytical model to accomplish the diagnosis procedure of the process. Nevertheless, this is not always fortuitous in practice, as a meticulous and complete mathematical depiction of the process is never attainable. In fact, obtaining a punctilious model with all known system parameters is an arduous task. Sometimes the mathematical representation of the dynamic system is not fully known. In other applications, the system'sparameters cannot be entirely recognized, or can only be known over a bounded range during the operation of the process.

Furthermore, in the case of process engineering systems, the physical phenomena are strongly coupled and the models are often nonlinear. Because of this integrative and interdisciplinary nature, it is difficult to generate the model of such multi-energetic industrial processes. The more the system complexity rises, the harder the modeling of the system and its disturbances becomes, likewise uncertainsystems where it is hard to figure out the system's structure and its parameters. Accordingly, we point out robustness problems in fault detection and isolation procedure FDI with respect to modelling errors.

Thus, a Powerful Unified Modeling tool is deemed necessary for diagnosis purposes. Bond graph is weighed as an integrated computer aided design for multi energy systems. Bond Graph BG provides the option of designing models for dynamic systems graphically. It provides causal and structural relations between the system's variables, it allows also to deal with tremendous amount of equations describing the system's behavior and to display explicitly the power reciprocity between the process components. That's why, The BG tool is well suited for FDI purpose.

Currently the subject has taken a new dimension since many researchers have turned their attention to FDI based graphical observers techniques;Scholtz and Lesieutre [2] proposed a Graphical observer design applicable for largescale DAE power systems. These developed monitors can estimate the state of the system or detect and identify specific occurrences of faults during its operation, all in the presence of disturbances and uncertainties. Anibal, Belarmino and Carlos [3] developed a method to integrate state observers to estimate initial states for simulation within the consistency-based diagnosis framework using possible conflicts. His work extends the bridge framework for one class of dynamic systems, using the possible conflict concept. The aim of his paper is to improve the robustness of the proposed method through a more precise estimation of the initial state, without modifying its fault isolation capabilities, and its consistency-based approach. The Bond Graph approach also has gained major insight into recent researches. Touati, Merzouki and Bouamama [4] proposed a robust bond graph model-based fault detection and isolation to improve the robustness of the diagnosis system in presence of measurements and parameters uncertainties. Recently, EL Harabi, Ould Bouamama and Abdelkrim[5] developed a bond graph approach to indicate physico-chemical failures and to eliminate unknown variables from coupled thermochemical models.

The outline of the paper is as follows: Section II introduces the background of the bond graph tool. Then, section III describes the graphical proportional observer design while section IV is devoted for residual generation procedure and section V deals with an illustrative example of a hydraulic system. Section VIfurther details the proportional integral observer design& Section VII describes the Robust Residual Generation.The efficiently of the proposed robust fault detection estimator is illustrated on the studied hydraulic system. And finally, section VIII concludes the paper.

II. BACKGROUND

In the last decades of the 19th century, L. Kelvin and JC. Maxwell perceived that a variety of phenomena breed identical forms of equations by drawing physical analogies between fluid dynamics (hydrodynamics) andelectromagnetic phenomena. Between the 1940s and 1950s, Paynter dealt with interdisciplinary projects encompassing hydroelectric plants, analog and digital computing, nonlinear dynamics, and control. He discovered that similar formsof equations are generated by dynamic systems in a widerange of domains (electrical, fluid, and mechanical); i.e, such systems are analogous. Hence, Paynter merged the notion of an energy port into his approach, and thus bond graphs was hyped up.

Created in 1961 by Paynter [6] and subsequently developed by Karnopp and Rosenberg [7] and Karnopp [8], the bond graph is a graphical depiction of systems based on power transfer. This approach, based on analogies between the diverse fields of physics (mechanics, chemical, electrical, hydraulics, thermal) allows a unique representation of their engineering components. The bond graph pattern is derived from the laws of physics, where the inputs and outputs are power or energy. A bond graph model includes storage and dissipative elements (R; L;C) and its topology is represented by the junction structure. The notion of causality determines the input-output relations of the junction structure. Causality is affected in a way that maximizes the number of storage elements (I and C) in integral causality and defines a resolvable input-output pattern (no unity gain causal loop).

III. DESIGN OF A BOND GRAPH OBSERVER

The present section introduces the procedure to design a proportional observer using the bond graph tool (see Pichardo Almarza, Rahmani and Dauphin-Tanguy [9]and Pichardo-Almarza, Rahmani, Dauphin-Tanguy and Delgado [10]. The algorithm is formulated as follows:
algorithm is formulated as follows:

- Step 1: Investigation of the existence of redundant outputs

Verifying the presence of redundant outputs is the firstcondition to scrutinize when synthesizing a bond graph observer. The advantage of this step is avoiding pointless calculations. In fact, the identification of the nonredundant outputs permits the calculation of the BG observer gain K with minimal size. This condition can be checked by computing the row of the observation matrix C (difference between the number of detectors De and Df , and the detectors that cannot be dualized in the BG model in integral causality).

- Step 2: Verification of the observability of the BG model of the system

With reference to Sueur and Dauphin-Tanguy (1989)'s theorem [11], a bond graph model is structurally observable if and only if the below conditions are satisfied:

1. On the BG model in integral causality, there is a causal path between the system's dynamic components I and C and the detector De or Df . Or,
2. On the derivative BG model, all dynamic elements accept a derivative causality. If there are dynamic elements persisting in integral causality, the dualization of the detectors De and Df is essential.

-Step 3: Design of the observer bond graph model

This step allows building the BG model that corresponds to the observer equation. The generated model, named BGO, comprehends the integral bond graph model of the system towhich the expression $K(y-\hat{y})$ is aggregated. Figures 1 and 2 show the linear output injection in the dynamic elements I and C, by appending modulated flow source for an I element and modulated effort source for a C element.

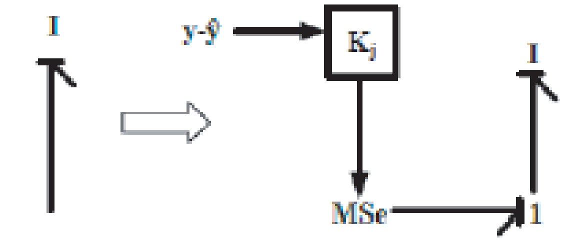


Fig 1. Linear output injection to an *I* element.

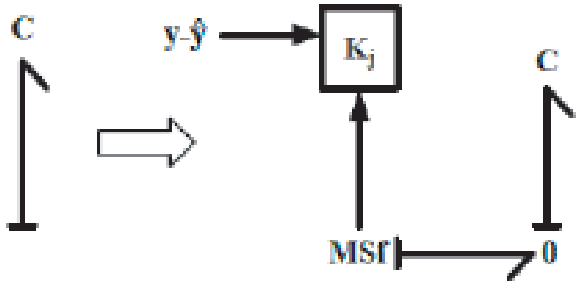


Fig 2. Linear output injection to a *C* element.

Step 4: Calculation of the BG observer gain

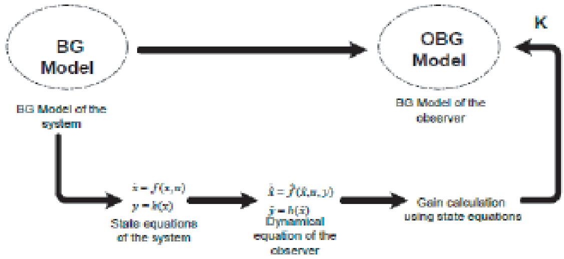
The observer gain computation can be performed using two different methods as showed in figure 3. The first is based on the calculation of the state equations from the bond graph model of the system and the determination of the gain K using the traditional methods. The second consists on the formal calculation of the characteristic polynomial P(A−KC) directly from the BG model of the observer by applying causal paths and loops. It uses exclusively causal manipulations and structural properties on the bond graph model without any calculations using Rahmani (1993) 's theorem cited below:

Theorem [12]: The value of each coefficient of the characteristic polynomial

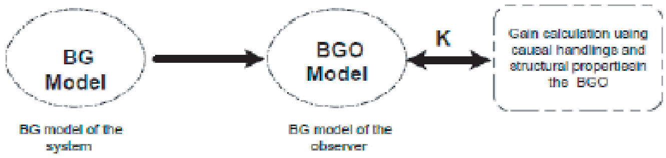
$$P_A(s) = s^n + \alpha s^{n-1} + \cdots + \alpha_{n-1} s + \alpha_n \quad (1)$$

Equal to the constant term (without the operator of Laplace s) 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.

The proportional observer gain is obtained by identifying the characteristic polynomial of the observer P(A−KC) to the desired polynomial $P_d(s)$ in order to fix the poles of the observer.



(a) Classical method based on the calculation of the state equations.



(b) Graphical Method based on the direct use of the BGO.

Fig3. Comparison between the graphical and bond graph techniques

IV. RESIDUAL GENERATION

The obtained observers are applied to filter the known signals and generate residuals. The procedure is described in figure 4.

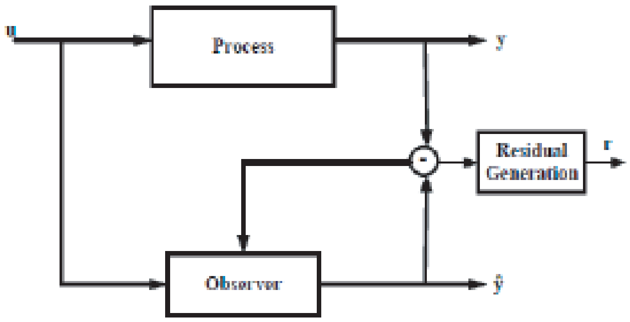


Fig4. Residual Generation

Residual equations are defined as mentioned below:

- Residual state estimation: $r = x - \hat{x}$

- Residual output estimation: $r = y - \hat{y}$

The fault detection hinge on the analysis of the residual output estimations (r) and their sensitivity to faults. In the next section, the developed technique is applied on an hydraulic system.

V. CASE STUDY: HYDRAULIC SYSTEM

Bond Graph model of the hydraulic system: Let's consider the symbolic diagram of the system and its BG model shown in figures 5 and 6.

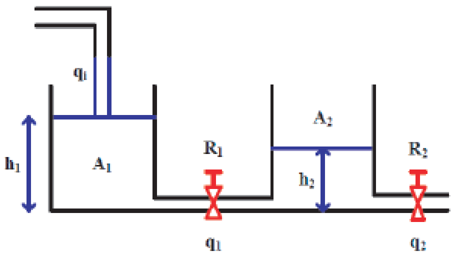


Fig5. Hydraulic system with two tanks

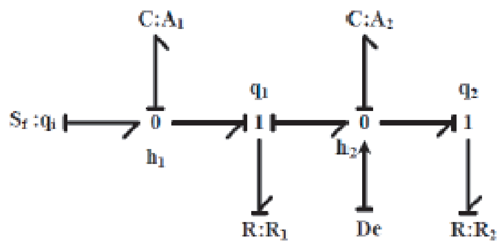


Fig6. Bond Graph Model of the System

The system parameters are defined in Table 1.

Parameter	Symbol	Value
Tank Section 1	A_1	$1m^2$
Tank Section 2	A_2	$2m^2$
Hydraulic Resistance	R_1	$10m(m^2s^{-1})^{-1}$
Hydraulic Resistance	R_2	$20m(m^2s^{-1})^{-1}$

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

_ **Step 1:** Investigating the presence of redundant outputs: This condition isn't useful in our case, since the BG model of the hydraulic system has a unique detector.

_ **Step 2:** Checking the model's structural observability: The derivative bond graph model DBG is presented in figure 7.

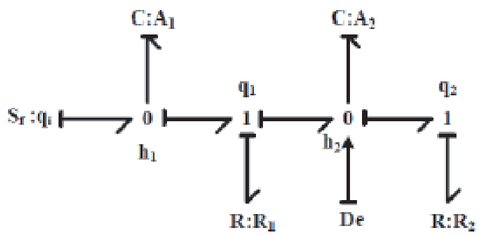


Fig7. Bond Graph model in derivative causality

As it is revealed previously, the structural observability can be easily made out by a structural analysis of the bond graph model. It is crystal clear that, on the DBG there is no causality conflict and all the dynamic components admit a derivative causality. Thus, the model of the hydraulic system is structurally observable.

_Step3: Design of the bond graph observer BGO: The Bond Graph model of the observer BGO can be depicted as shown in figure 8.

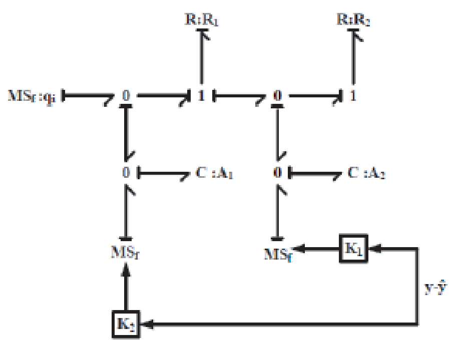
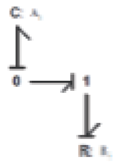
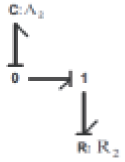
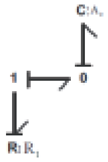
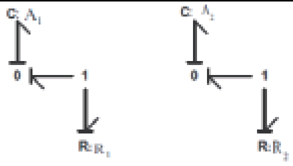


Fig7. Bond Graph model of the observer

_ **Step 4:** Gain Calculation: The state variables of the system, Figure 6, are associated to two storage elements C in integral causality. The order of model is, therefore, equal to 2: $x = [x_1 \; x_2]^T$.

The characteristic polynomial of the state matrix PA(s) is calculated using Rahmani (1993)'s theorem by generating he gain of causal cycles families as showed in table 2.

a_i	Family of Causal Cycles	Gain
a_1		$G_a = (-1)\cdot\frac{-1}{R_1A_1s}$
a_1		$G_b = (-1)\cdot\frac{-1}{R_2A_2s}$
a_1		$G_c = (-1)\cdot\frac{-1}{R_1A_2s}$
a_2		$G_d = \frac{1}{R_1R_2A_1A_2}$

So, the characteristic polynomial of the system is defined as:

$$P_A(s) = s^2 + \left(\frac{1}{R_1A_1} + \frac{1}{R_2A_2} + \frac{1}{R_1A_2}\right)s + \frac{1}{R_1R_2A_1A_2} \quad (2)$$

The poles of the observer, roots of the desired characteristic polynomial, are chosen to be slightly faster than those of the model. The values of the desired poles are respectively z1 = 0.318 and z2 = 0.032.
Hence, the characteristic polynomial of the system becomes:

$$P_d(s) = s + 0.35s + 0.01 \quad (3)$$

The characteristic polynomial $P_{(A-KC)}(s)$in closed loop is determined from the BGO using same procedure cited above:

$$P_A(s) = s^2 + \left(\frac{1}{R_1A_1} + \frac{1}{R_2A_2} + \frac{1}{R_1A_2} + \frac{k_2}{A_2} + \frac{k_1}{R_1A_2}\right)s + \left(\frac{1}{R_1R_2A_1A_2} + \frac{k_2}{A_2A_1R_1}\right) \quad (4)$$

The identification between $P_d(s)$ and $P_{(A-KC)}(s)$ leads to the gain values $k_1 = 2$ and $k_2 = 0.15$.

Simulation results:

The initial conditions of the BG model's states in integral causality are considered null. Before carrying out simulation of different faulty scenarios on the 20-sim software, it isessential to validate the BG model (see Figure 9).

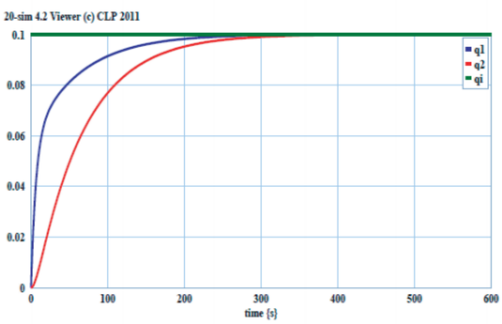


Fig9. Evolution of input/output flows

The structure of the graphical observer and the *BG* model of the system are given in the below diagram (see figure 10).

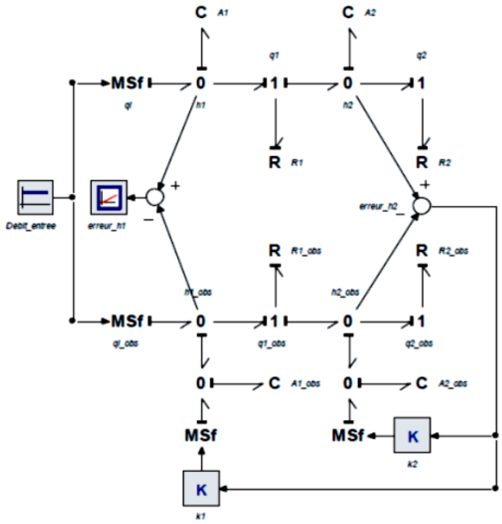
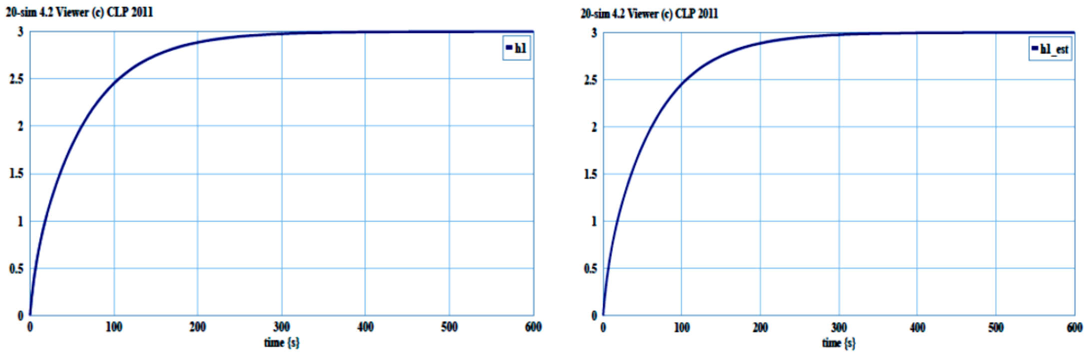


Fig 10. Hydraulic system and its observer

The figure 11 shows a clear precision of estimation of the system's state variables. We perceive that the paths of the estimated variable $h1est$ and the state variable $h1$ are indistinguishable and the estimation error is null(see figure 12).



(a) State variable evolution $h1$. (b) Estimated state variable evolution $h1est$.

Fig 11. Evolution of $h1$ and $h1est$.

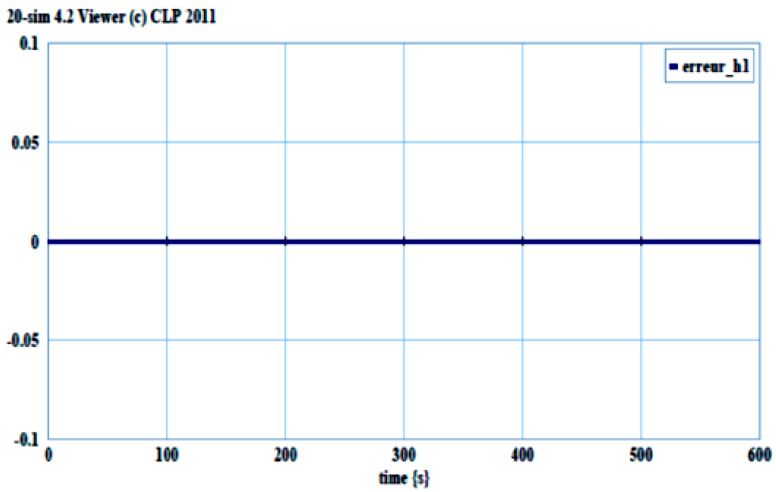
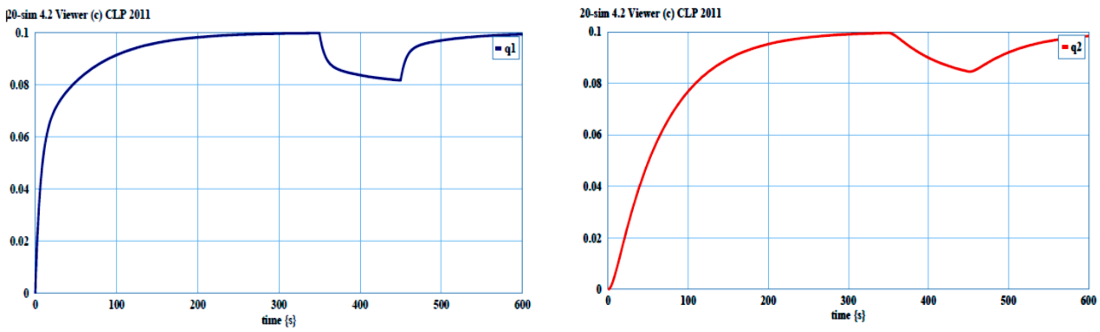


Fig12. Estimation error

In order to ensure the effectiveness of the fault detection method using graphical observer, three fault Scenarios are considered:
Actuator Failure: A pump failure by turning off the powersupply
Structural Failure: A water leak in the tank $T1$
Parametric Failure: A plug at the pipe that moves water to the outside(Corking or partial blockage of the valve).

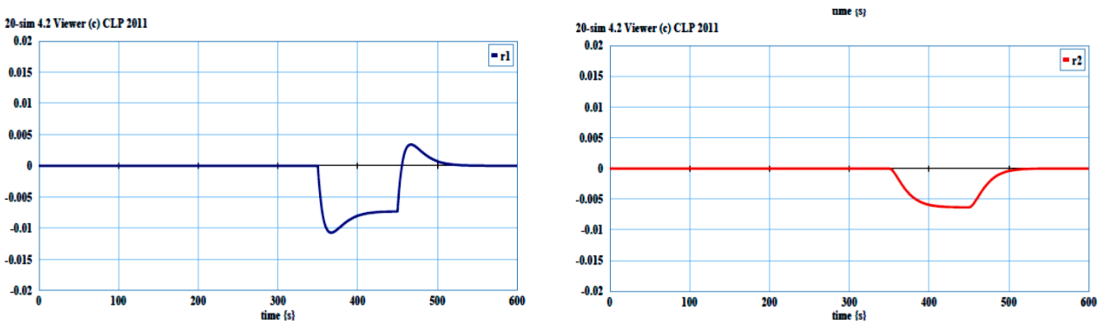
- **Fault scenario** 1**: Actuator fault**

We consider now an actuator fault occurring between 350s and 450s. The outputs are affected by this fault and drawn aside from their nominal values, as it is shown in figure 13.



(a) Evolution of the output $q1$. (b) Evolution of the output $q2$.
Fig13. Evolution of the output $q1$ and $q2$.

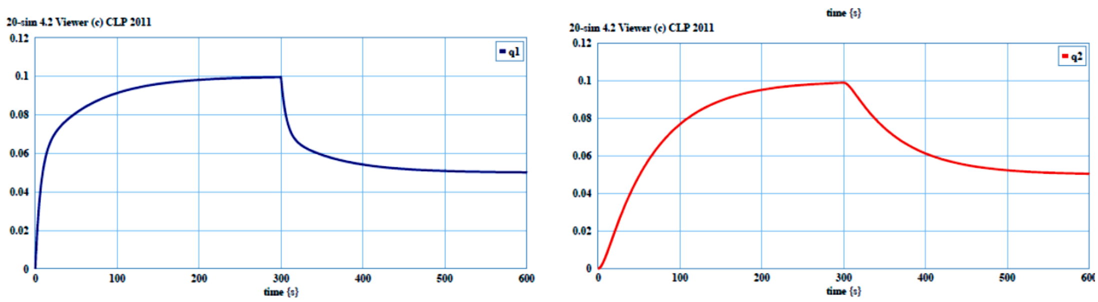
It is clear that in faulty-free case, residual signal are equal to zero but, during the interval of time[350s450s], they are different from zero (see figure14).



(a) Residual response $r1$. (b) Residual response $r2$.
Fig14. Residual Response in abnormal operation

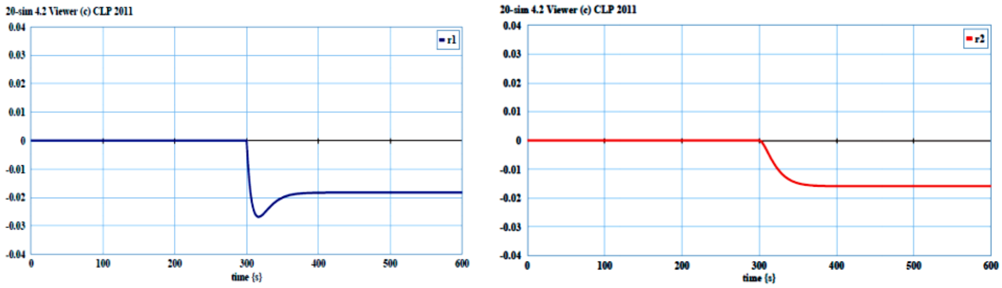
- **Study case** 2**: Structural fault**

The structural fault is represented physically by the appearance of a leakage in the first tank. Indeed, the reduction of the water's height generates a fall of the pressure as well as the flow (see figure 15). This reduction is modeled by the addition of a modulated flow source MSf at 300s. On the bond graph model, this source is represented by a bond denoted Ys leads to a junction $0h1$. The fault magnitude is equal to $0.05m3.s-1$.



(a) Response of $q1$ in case ofstructural failure. (b) Response of $q2$ in case ofstructural failure.
Fig15. Case of Structural Fault.

The dynamics of the system has changed and theresidues are different from zero from the moment 300*s*as showed in figure 16.

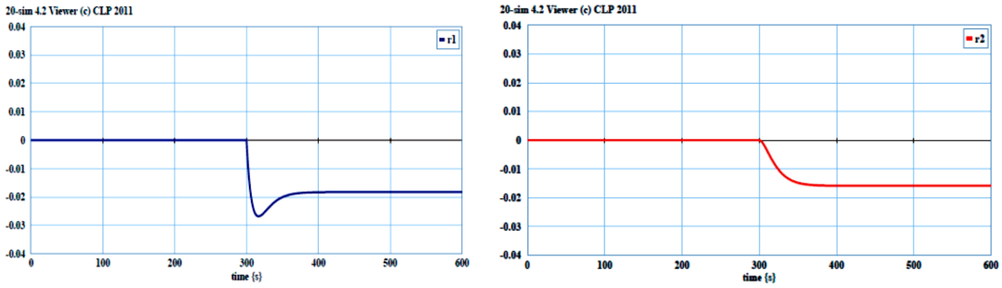


(a) Residual response in abnormal operation *r*1. (b) Residual response in abnormaloperation *r*2.

Fig16. Residual response in abnormal operation.

- **Scenario** 3**: Parametric fault**

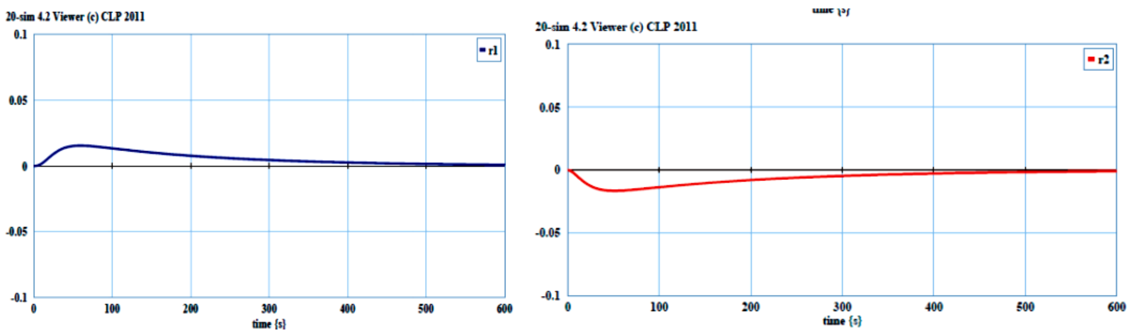
The parametric fault is an abnormal deviation of theparameter *i* from its nominal value.We see, in figure17, that the parametric fault slowsdown the system as it couldn't reach its permenantregime before 600*s*.



(a) Response of *q*1 in case ofparametric failure. (b) Response of *q*2 in case ofparametric failure.

Fig 17. Case of parametric failure

The figure 18 shows the sensitivity of the residuals in presence of the parametric fault.



(a) Residual response in abnormal operation *r*1. (b)Residualresponse in abnormaloperation *r*2.

Fig 18. Residual response in abnormal operation

VI. Design of a Bond Graph *PI* observer

Conventional PI observer

The proportional observer is itself a linear dynamic system. Its input values are the values of measured outputs from the original system, and its state vector generates missing information about the state of the original system. The observer can be regarded as a dynamic device that, when connected to the available system outputs, generates the entire state. However, the idea of a proportional integral observer, figure 19, is to use additionally the integral of the error as follows:

$$\hat{w} = \int_0^t (y(\tau) - C\hat{x}(\tau))d\tau \quad (5)$$

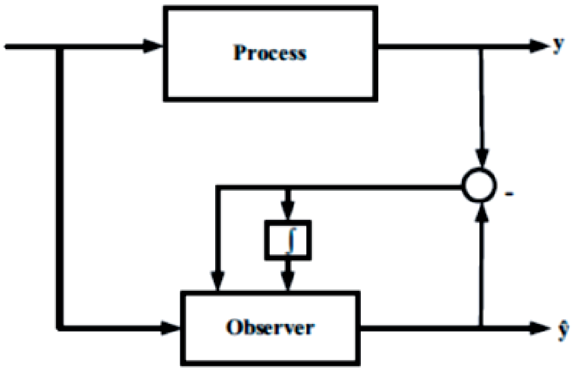


Fig19. Proportional Integral Observers diagram.

Then, the *PI* observer for the model is written using thisset of equations:

$$\begin{cases} \frac{d\hat{x}}{dt} = A\hat{x} + Bu + Kp(y - C\hat{x}) + KI\hat{w} \\ \frac{d\hat{w}}{dt} = y - C\hat{x} \\ \hat{y} = Cx \end{cases} \quad (6)$$

where x in R^n, y in R^q, and u in R^m are respectively the state, the measurement output and the control input vectors. *A*, *B* and *C* are constant matrices of proper dimensions. K_I and K_p are respectively the integral and proportional gains. Hence, the error equation ($e_x = x - \hat{x}$ and $e_w = \hat{w}$) is defined as:

$$\begin{pmatrix} \frac{de_x}{dt} \\ \frac{de_w}{dt} \end{pmatrix} = \begin{pmatrix} A - K_pC & -K_I \\ C & 0 \end{pmatrix} \begin{pmatrix} e_x \\ e_w \end{pmatrix} \quad (7)$$

Bond Graph PI observer

The algorithm allowing the design of the graphical *PI* observer is presented below.

- Step 1: Checking the existence of any redundant outputs.
- Step 2: Checking the structural observability of the model.
- Step 3: Construction of the proportional bond graph observer.
- Step 4: Construction of the bond graph *PI* observer

The Bond Graph model is defined with the changes described in figures 20 and 21. In the same way, modulated effort sources (respectively flow sources) are used when the state variable is associated with an *I*-element (respectively a *C*-element) to apply the integral action in the observer [13].

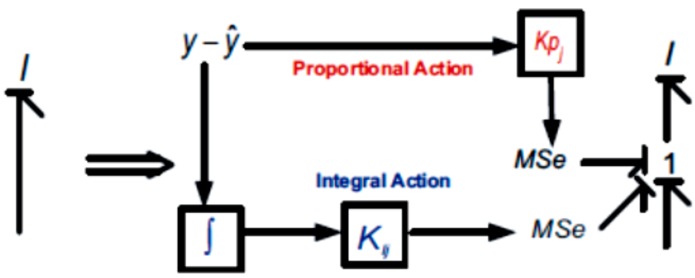


Fig 20. Linear output injection: case of an *C* element.

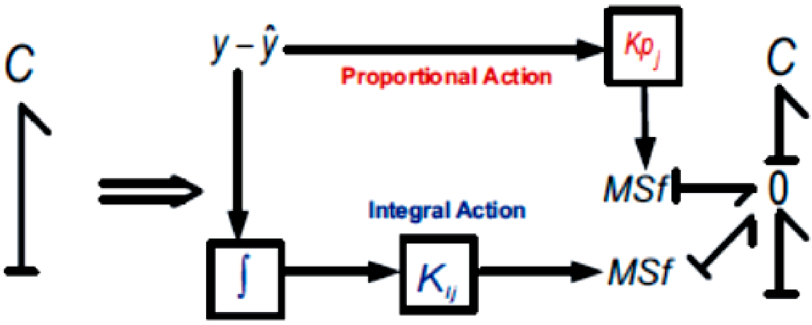


Fig 21. Linear output injection: case of an *C* element.

VII. Robust Residual Generation

Inspired from *BG − LFT* representation introduced byDjeziri, Bouamama and Merzouki [14], graphical *PI* observers are used to generate robust residual signals byfollowing these steps:

i. Verify that the uncertain bond graph model in *LFT* form of the system is reachable and structurally observable;
ii. Construction of the *BG PI* observer;
iii. The residual signal (residual output estimation) is deduced from this equation: $r = y - \hat{y}$.

In the next section, we will illustrate the effectiveness andthe performance of the developed graphical *PI* estimatorcomparing to proportional one via the hydraulic systemwith two tanks. The robustness of the *PI* observer will betested by adding a parameter uncertainty to the system undermultiplicative form.

Simulation Results

Consider the sketch of the same studied system. The associated graphical *PI* observer is deduced by verifying the following steps: Steps 1, 2 and 3 are already checked in the previous section, so let's start by building the *PI* observer.

- Step 4: Construction of the *PI* observer based bond graph (*BGO*). The proposed *BG PI* observer is described in figure 22 after modifying the bond graph model.

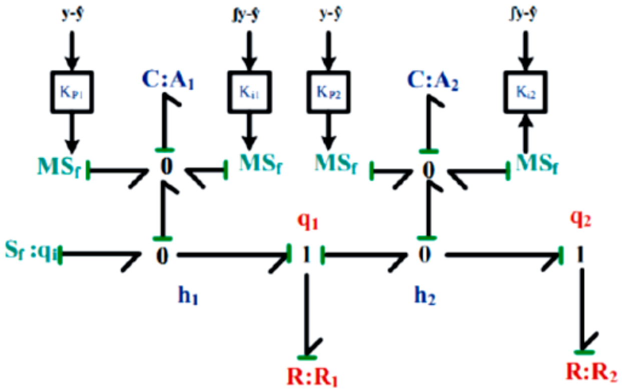


Fig22. Bond Graph model of the PI observer

- Step 5: Gain calculation of the BG PI observer. K_p, the gain of the proportional observer is already calculated previously using causal manipulations. K_p is defined as:

$$K_p = \begin{bmatrix} 2 \\ 0.15 \end{bmatrix}$$

Then, we can apply the same method (i.e generating the gain of all the existing causal cycles families in the BG model of the system and its observer) to compute K_I using the calculated values of K_p for the proportional graphical observer, with the following poles selection:

$$s = \begin{bmatrix} -0.318 \\ -0.032 \\ -0.0033 \end{bmatrix}$$

Hence, the desired polynomial for the PI observer is:

$$P_d(s) = s^3 + 0.3533s^2 + 0.1115s + 0.00003$$

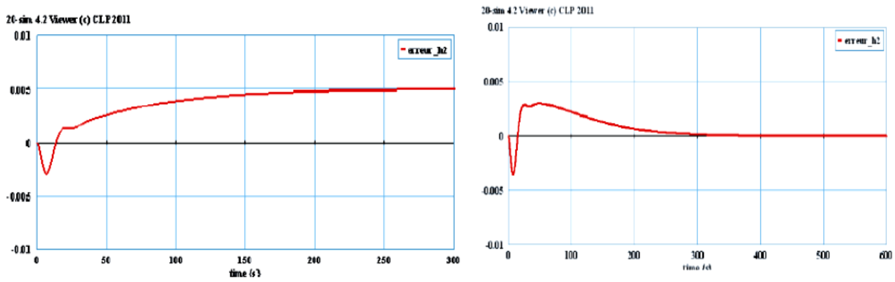
with these coefficients, we obtain now three equations depending on the components of K_I and K_p . We use the values of K_{p2} calculated for the graphical proportional observer and after the calculation of the family of causal cycles of order $1-3$, we can calculate the new K_{p1} and K_I vector that generate the coefficients of the desired polynomial.

Finally, we obtain the following gains:

$$K_p = \begin{bmatrix} K_{p1} \\ K_{p2} \end{bmatrix} = \begin{bmatrix} -0.2467 \\ 0.15 \end{bmatrix}$$

$$K_I = Kp = \begin{bmatrix} K_{I1} \\ K_{I2} \end{bmatrix} = \begin{bmatrix} 0.00373 \\ -0.00718 \end{bmatrix}$$

The initial conditions of the *BG* model states in integral causality are considered null. Simulation tests were implemented in $20-sim$ software. In this part, the performance of the proportional and the PI observers are evaluated in presence of modeling errors. Thus, let's consider that the hydraulic resistance parameter *R*2 for the *OBG* have a variation of -10 percent in comparison with the parameters of the *BG model.*



Estimation error via the Proportional *BG*Observer. (b) Estimation error via the*BG P I*observer.

Fig23. Comparison.

We conclude that the estimation error converges to zero despite the presence of modeling errors in the observers parameters unlike to the graphical proportional observer (see figure 23).

Now, Let's use the *BG PI* observer for a robust fault detection purpose.

In LFT Bond Graph, parameter uncertainties are represented under a multiplicative form at the level of bond graph component, which is the section 2 in our hydraulic system, see figure 24.

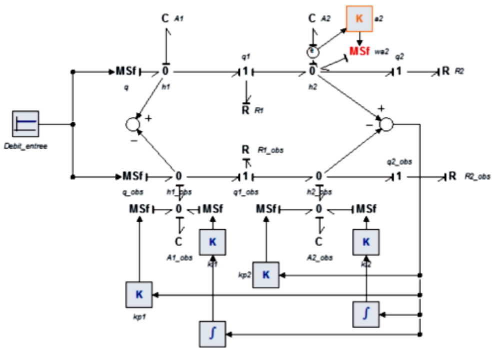


Fig 24. LFT model of the system and its observer with multiplicative uncertainty.

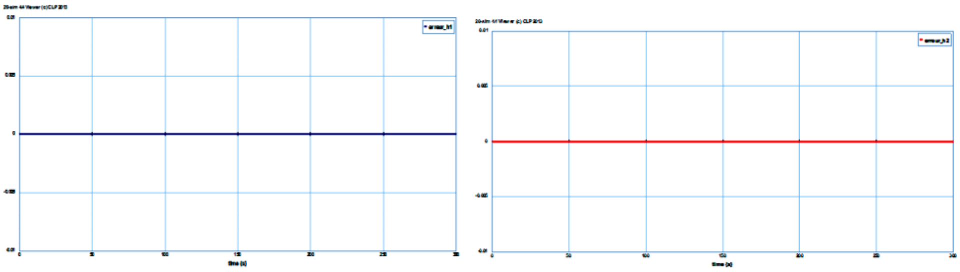


Fig25. Estimation errors in presence ofparameter uncertainty

As it is shown in figure 25, the estimations errors are null in presence of the parameter uncertainty; Hence, the graphical linear observer provides a robust estimation against the presence of parameter uncertainties. The method improves the performance and the efficiency of the bond graph *PI* observer and it can be used to generate fault indicators as it guarantees the robustness of the fault detection procedure.

VIII. CONCLUSION

This paper delves into the Bond Graph approach from conceptual ideas to simulation results. Adopting the Bond Graph methodology that empowers the modeling of multi-energetic systems, it explores the fault detection based on Bond Graph observers. The innovative interest of this paper is the use of only one representation, the bond graph model, for both modeling and observers design to generate residuals. In presence of parameter uncertainties, a robust fault detection procedure is also performed on a $BG - LFT$ model using structural properties and causal manipulations. Finally, the developed approach is validated by an application on a hydraulic system.

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