Robust Fault Diagnosis Observer of Dynamical Systems Modelled by Bond Graph Approach

Abderrahmène Sallami, Nadia Zanzouri, Mekki Ksouri ***University Tunis El Manar***

National Engineering School of Tunis Laboratory ACS Department of Electrical Engineering Box 37, 1002 Tunis Belvedere

Summary
This paper proposes a robust diagnosis observer of dynamical systems modeled by Bond Graph approach. The observer design is achieved by using graphical methods taking advantage of structural properties of the bond graph model. The fault indicators are generated in the presence of parameter uncertainties. Simulation results are used to show the dynamic behavior of system variables and to evaluate the performance of the observer for fault diagnosis.
Key words:
Bond graph, Dynamical Systems, Robust Diagnosis Observer

1. Introduction

The increasing complexity of the dynamical systems and the high reliability required of them have created the need of fault detection and isolation (FDI) techniques. This development has been demonstrated by a large number of publications [1]. Indeed, the complete knowledge of the state system is often necessary to develop a control law or the establishment of a monitoring strategy or diagnosis.
Many standard observer-based techniques exist in the literature for linear and nonlinear systems [2]. Luenberger observer-based approach [3], in which an observer plays the role of the residual generation module, is one of the most famous techniques used for residual generation.
Dynamical systems are composed of elements belonging to multiple energy domains (thermal, hydraulic, mechanical, electrical, etc.). The causal properties of the bond graph methodology can help to derive state space form of the system and to design fault detection and isolation (FDI) algorithms, i.e. the generation of fault indicators [4]. In this way, by bond graph (BG) models, it becomes possible to obtain the behavioral knowledge of the system and to improve its monitoring.
The first bond graph approach for the design of Luenberger observers has been developed by Karnopp [5] for a control purpose. Pichardo-Almarza et al. [6] are proposed a bond
graph approach for building reduced order Luenberger observers and proportional integral observer. These techniques are not used for FDI. Our contribution is to extend theses observers for fault diagnosis.
The diagnosis of uncertain systems has been the subject of several research works in recent years [7]. Dauphin-Tangy and al [8] are proposed two methods for modelling uncertainties by using bond graph approach. The first method is based on describing parameter uncertainties as bond graph elements, and the second method introduces the LFT form (Linear Fractional Transformation) for uncertainties modelling.
The innovative interest of the present paper is the use of the Luenberger observer by bond graph tool for modelling and robust diagnosis, taking into account the parameter uncertainties. In this way, by applying the bond graph methodology using LFT model, it becomes possible to obtain physical knowledge of the systems and to improve their monitoring by deducing residuals fault indicators and consequently, to insure the best safety able to detect and to isolate imperfections.
This paper is organized as follows: Section II deals with observer design based on bond graph approach. Section III proposes a robust diagnosis observer using the BG. An illustrative example of a DC motor is developed in section IV and shows the efficiently of the proposed method.

2. Diagnosis by Observer Using Bond Graph Approach

2.1 Bond graph modeling

The bond graph approach was defined in 1961 by Henry Paynter [9] and then developed by Karnopp [10].
This energetic approach serves to emphasize analogies between different fields of physics (mechanics, electricity, hydraulics, thermodynamics, acoustics, etc.) and to represent in uniform multidisciplinary physical systems. Because of its structure and causal properties, the bond graph tool is more and more used for modeling and fault diagnosis. The causal properties of the bond graph tool were initially used for the determination of the origin of the faults.

Manuscript received January 5, 2012
Manuscript revised January 20, 2012

In this paper, the BG is used for modeling, state estimation, diagnosis and simulation of dynamical systems.

2. 2 Principle of Diagnosis by observer approach

The diagnosis using the observer state estimation is a method that has become the most widely used industry [2]. The principle of such method is given in figure 1.

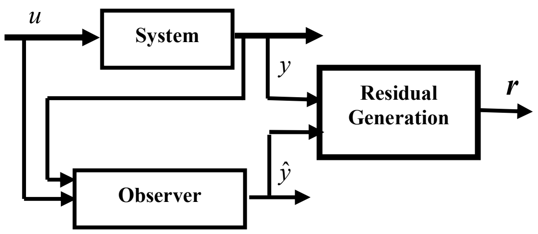

Fig. 1 Diagnosis by observer design

Residuals equations have the following forms:

- Residual state estimation: $r_x = \widetilde{X} = x - \hat{x}$
- Residual output estimation: $r_y = \widetilde{Y} = y - \hat{y}$

The diagnosis consists on analyzing the residual outputs estimations (*r*) and their sensitivity to faults.

2.3 Design observer by bond graph approach

To design the observers, we have to check the observability of the system. From a Bond Graph point of view proposed by Sueur and Dauphin-Tanguy [11], a bond graph model is structurally observable if the following two conditions are satisfied:

(i) There are at least causal paths linking a sensor for each dynamic element I or C in the integral causality when we put the bond graph in integral preferred causality.

(ii) Second condition: All the elements I or C admitting derivative causality when we put the bond graph in derivative causality, and we dualized sensors.

The observer equation using bond graph variables is shown in eq.(1) :

$$\begin{cases} \dot{\hat{x}}(t) = \begin{pmatrix} \dot{\hat{p}}_I \\ \dot{\hat{q}}_C \end{pmatrix} = A\begin{pmatrix} \hat{p}_I \\ \hat{q}_C \end{pmatrix} + Bu(t) + K(y(t) - \hat{y}(t)) \\ \hat{y}(t) = C\begin{pmatrix} \hat{p}_I \\ \hat{q}_C \end{pmatrix} \end{cases}$$

With $\hat{x}(t)$ is the estimate state vector, $\hat{y}(t)$ is the estimate output, u(t) is the input vector, y(t) is the output vector, p and q are the energetic variables of BG modeling (p: momentum, q: displacement), A, B and C are constant matrices with appropriate dimension. K is the observer gain.

The structure of Luenberger observer based on BG modeling is presented in figure 2.

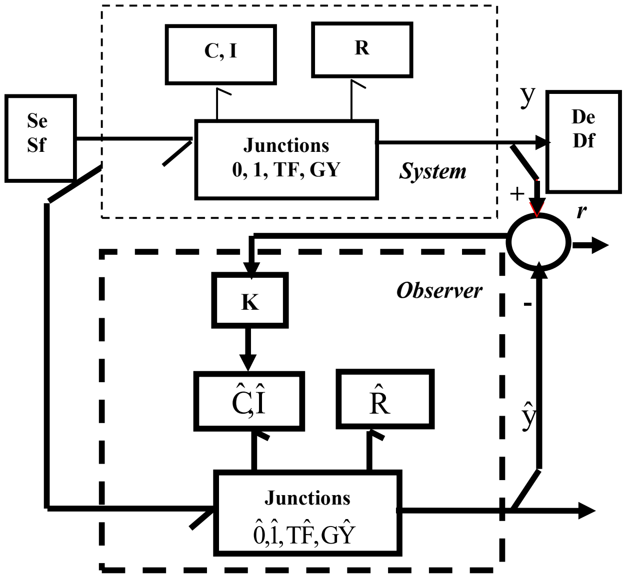

Fig. 2 Structure of a Luenberger observer based on BG

For the diagnosis, we have to determine the residual output estimate (r).

3. Robust Diagnosis by Observer Using the Bond Graph Model

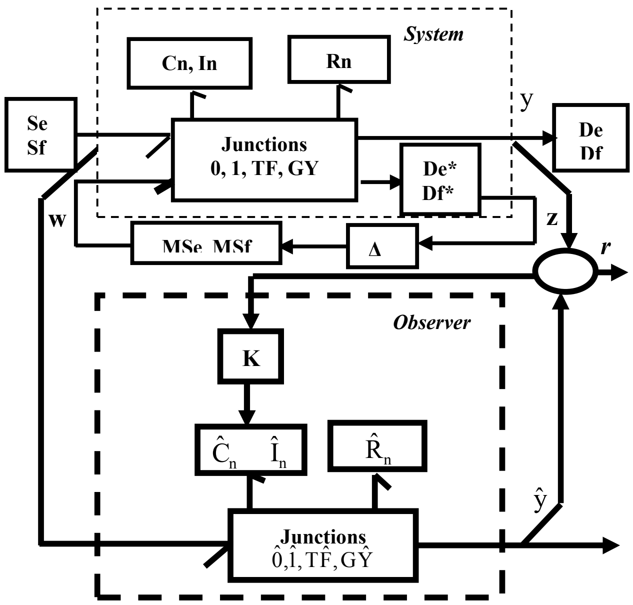

Fig. 3 Luenberger observer based on BG-LFT modeling

The modeling of linear systems with uncertain parameters by BG approach has been developed by [8]. The uncertainty of a bond graph element is another element of the same type, causally linked to the element or the rest of the nominal model. The diagnosis by analytical redundancy relations (ARRs) of the system subject to uncertainly parameters is developed in [12]. In this paper, we propose a robust diagnosis of uncertainty system by observer design based on BG approach. The obtained system is shown in figure 3.

The uncertainty regardless of type (parametric uncertainties, uncertainty modeling, measurement noise ...) are combined in a Δ block. w and z respectively include the inputs and auxiliary outputs.

4. Robust residual generation

The residual generation from a Luenberger observer using bond graph approach is summarized as the following steps:

(i) Verify that the bond graph model of the system is structurally observable;
(ii) Construction of the observer using the bond graph;
(iii) The symbolic expression of residual is deduced from the following equation: $r = y - \hat{y}$ (2)
(iv) The residual is in the form (3):

$$r : \Phi\left(\sum w_i, R_n, I_n, C_n, TF_n, GY_n\right) \qquad (3)$$

5. Application

5. 1 Bond graph model of DC motor

Consider the circuit diagram of a direct current (DC) motor and its bond graph model given in figure 4. For this system, we detect faults at the sensors (Df_1, Df_2).

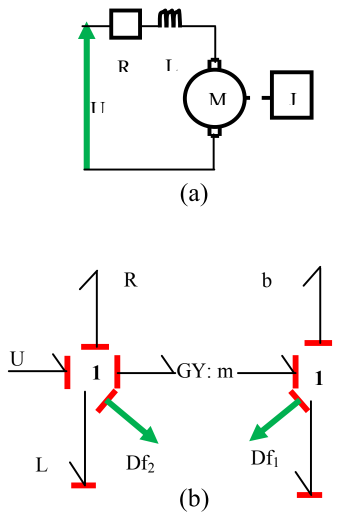

Fig. 4 a) A DC motor b) bond graph model of DC motor

The states equations are:

$$\begin{cases} \begin{pmatrix} \dot{x}_1 \\ \dot{x}_2 \end{pmatrix} = \begin{pmatrix} \dot{\Omega} \\ \dot{i} \end{pmatrix} = \begin{bmatrix} -\frac{b}{j} & \frac{k}{j} \\ -\frac{k}{L} & -\frac{R}{L} \end{bmatrix} \begin{pmatrix} \Omega \\ I \end{pmatrix} + \begin{bmatrix} 0 \\ \frac{1}{L} \end{bmatrix} U \\ y = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{pmatrix} \Omega \\ I \end{pmatrix} \end{cases} \qquad (4)$$

Table 1: The parameters values of the DC motor

Symbol	***Designations***	***Nominal Values***	***Uncertainties***
U	Voltage motor	220V	
E	Electromotive force	218.9V	
R	Rotor resistance	1Ω	aR=0
L	Rotor inductance	5mH	aL=0.000052
b	Coefficient of viscous	10−4 Nm/rd. s−1	ab=0
J	Moment of inertia	10−3 Kg.m2	aJ=0.000012
m	Coefficient of the torque	0.2Nm/A	
i	Current	0.54A	
Ω	Speed	1097 rpm	

5.2 Diagnosis by observer using bond graph approach

We have verified the existence conditions of observer design of the DC motor system modeled by BG:

When we put the bond graph model of DC motor with preferred integral causality, there is a causal path linking the sensors Df_1 and Df_2 for each dynamic element L and J (figure 5.b). Also, when the bond graph model of DC motor is affected with derivative causality, all the elements L and J have derivative causalities and the sensors Df_1 and Df_2 are dualized.

The Luenberger observer using bond graph approach is represented by figure 5.

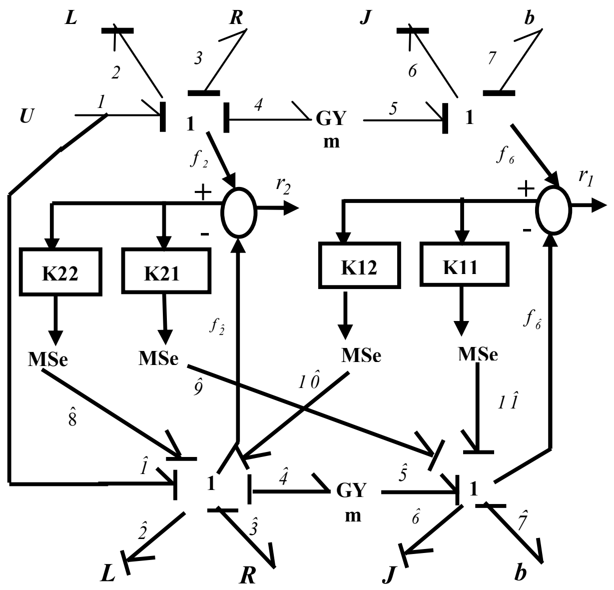

Fig. 5 Luenberger observer of DC motor by BG

We have simulated the system with 20sim. Figure 6 shows the real and estimates state evolution.

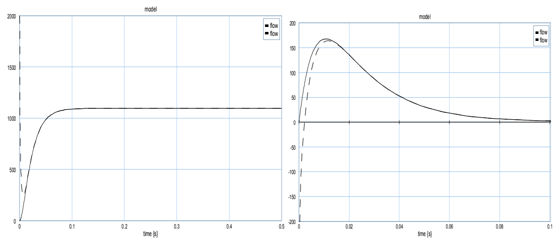

Fig. 6 State variables evolutions

5. 3 Residual generation in normal operating

From BG model of figure 6, we can deduce the residual r_1 and r_2.

- The residual r_1: $r_1 = \tilde{f} = f_6 - f_{\hat{6}} = Df_1 - f_{\hat{6}} = 0$

Therefore

$$(1 + m^2 Rb + m^2 RK_{11} + mK_{12}) + s(m^2 RJ + m^2 Lb + m^2 LK_{11}) + s^2(m^2 LJ) = 0 \quad (5)$$

- The residual r_2: $r_2 = \tilde{f}_2 = f_2 - f_{\hat{2}} = Df_2 - f_{\hat{2}} = 0$

Therefore

$$(1 + mK_{21} + m^2 bK_{22} + m^2 bR) + s(m^2 JR + m^2 JK_{21} + m^2 Lb) + s^2(m^2 LJ) = 0 \quad (6)$$

Figure 7 shows that the residuals converge to zero.

a)

b)

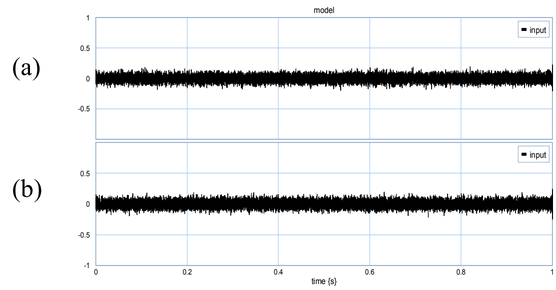

Fig. 7 a). Residual r1 in the normal operating
b). Residual r2 in the normal operating

5. 5 Diagnosis observer based on BG-LFT model

Figure 9 shows the Luenberger observer of the DC motor using the BG- LFT model.

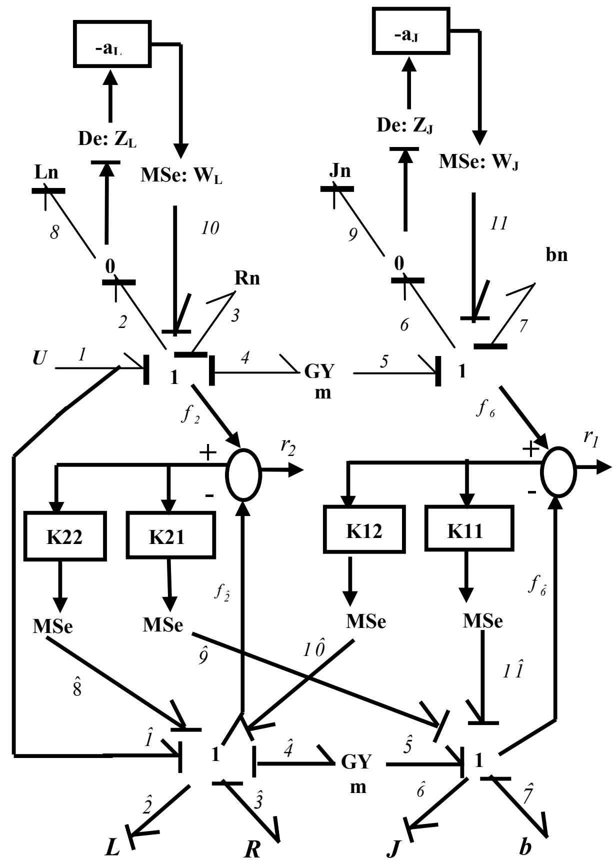

Fig. 9 Luenberger observer of the DC motor using the bond graph model LFT

From BG model (figure 9), we can deduce the residual R_1 and R_2.

- The residual R_1: $R_1 = \tilde{f} = f_6 - f_{\hat{6}}$

Therefore

$$(1+m^2R_nb_n+m^2R_nK_{11}+mK_{12})+s(m^2R_nJ_n+m^2L_nb_n)+s^2(m^2L_nJ_n)$$
$$-(w_J(s))(m^2R_n+sm^2L_n)-m(w_L(s))=0 \quad (9)$$

The eq. (9) is composed of two parts: the first part corresponds to the normal residual evolution (r_1) and the second part represents the residual evolution related to uncertainty parameters (d_1).

$$\begin{cases} R_1=r_1+d_1 \\ r_1=(1+m^2R_nb_n+m^2R_nK_{11}+mK_{12})+s(m^2R_nJ_n+m^2L_nb_n)+s^2(m^2L_nJ_n) \\ |d_1|=(w_J(s))(m^2R_n+sm^2L_n)+m(w_L(s)) \end{cases}$$

- The residual R_2: $R_2=\tilde{f}_2=f_2-\hat{f}_2$

Therefore

$$(1+mK_{22}+m^2b_nK_{21}+m^2b_nR)+s(m^2J_nR_n+m^2J_nK_{21}+$$
$$m^2L_nb_n)+s^2(m^2L_nJ_n)-(w_L(s))(m^2b_n+sm^2J_n)-m(w_j(s))=0 \quad (10)$$

The residual R_2 (10) includes a nominal part (r_2) and a second part related to uncertainty parameters (d_2).

$$\begin{cases} R_2=r_2+d_2 \\ r_2=(1+mK_{22}+m^2b_nK_{21}+m^2b_nR)+s(m^2J_nR_n+m^2J_nK_{21}+ \\ m^2L_nb_n)+s^2(m^2L_nJ_n) \\ |d_2|=(w_L(s))(m^2b_n+sm^2J_n)+m(w_j(s)) \end{cases}$$

ARRs based on BG-LFT model

For the purpose to compare the proposed diagnosis observer design with ARRs technique of uncertain systems developed by [12]. We have apply the ARRs to the DC motor. Figure 10 shows the BG-LFT model of the system.

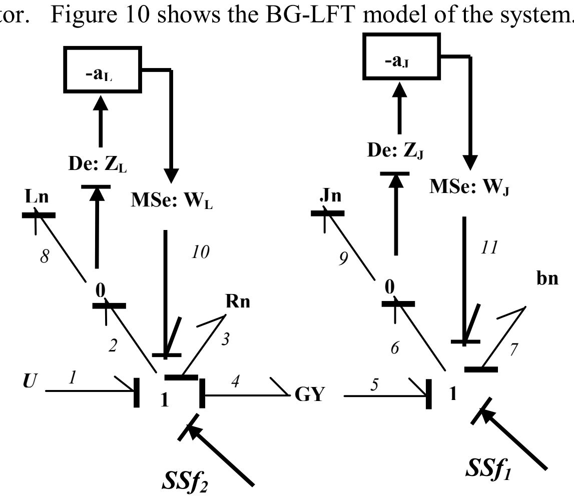

Fig. 10 LFT-BG model of the DC motor

From BG model (figure 10), we can deduce the ARRs:

- ARR_1 : $e_5-e_6-e_7=0$

$$mSSf_2-b_nSSf_1-J_n\frac{dSSf_1}{dt}-+w_{Jn}=0 \quad (11)$$

(11) is composed of two parts, the first part related to normal residual and the second part to the uncertainty parameter.

$$\begin{cases} RRA_1=r_1+d_1 \\ r_1=mSSf_2-b_nSSf_1-J_n\dfrac{dSSf_1}{dt} \\ d_1=|w_{Jn}| \end{cases}$$

- ARR_2 : $e_1-e_2-e_3-e_4=0$

$$U-R_nSSf_2-L_n\frac{dSSf_2}{dt}-mSSf_1+w_{Ln}=0 \quad (12)$$

$$.\begin{cases} RRA_2=r_2+d_2 \\ r_2=U-R_nSSf_2-L_n\dfrac{dSSf_2}{dt}-mSSf_1 \\ d_2=|w_{Ln}| \end{cases}$$

Comparison of observer design and RRAs based on BG modeling

Table 2: The advantages and disadvantages of the two diagnosis methods.

	ARRs	***Observer***
Advantages	For simple system, it is easy to generate ARRs Robust to uncertain parameters Fault Detection and Isolation	Simple to implement. Requires no additional sensors. Very interesting for the synthesis of control law. Robust to uncertain parameters Fault Detection and Isolation
Disadvantages	Adding sensors to generate residuals Generation is very difficult for complex systems. ARRs are not enable to integrate the Fault Tolerant Control and fault estimates	Isolation by bank observer

6. Conclusion

In this paper, a fault detection and isolation (FDI) by observer technique based on BG modeling is proposed. The observer is designed by using graphical tools taking advantage of structural properties of the bond graph model. The fault indicators are generated in the presence of parameter uncertainties. Our future works concern the bank observer by bond graph for location sensor fault or actuator fault (DOS and GOS). New techniques will be developed for the fault isolation and location.

References

[1] R. Isermann. "*Fault diagnosis of machines via parameter estimation and knowledge processign* - tutorial paper, " Automatica, 29(4): 815–836, 1993.

[2] J.P. Gauthier, H. Hammouri, S. Othman. "*A Simple Observer for Nonlinear Systems Applications to Bioreactors*, "IEEE Transactions on Automatic Control, Vol.37, pp.875–880, 1992.

[3] D.G. Luenberger, "*An introduction to observers*" IEEE Transactions on Automatic Control, Vol.16, pp.596–602, 1971.

[4] O. Bouamama, B.; Samantaray, A. K., Medjaher, K., Staroswieck, & Dauphin-Tanguy, G. "*Model builder using functional and bond graph tools for FDI design*," Control Engineering Practice, Vol. 13, pp. 875–891, 2005.

[5] D. Karnopp, "*Bond graphs in control: Physical state variables and observers*". Journal of the Franklin. Institute 308 221–234, 1979.

[6] C. Pichardo-Almarza, A. Rahmani, G. Dauphin-Tanguy, M. Delgado, "*Bond graph approach to build reduced order observers in linear time invariant systems*," in: Proceedings of 4th MATHMOD, Fourth International Symposium on Mathematical Modelling , 2003.

[7] O. Adrot, D. Maquin et J. Ragot. "*Diagnosis of an uncertain static system*,". In 39th IEEE Conference on Decision and Control, pages 4150–4154, Darling Harbour, Australia, 2000.

[8] G. Dauphin-Tanguy. C. Sié Kam, "*How to Model Parameter Uncertainies in a Bond Graph Framework*". ESS'99, Erlangen. Germany. pp. 121-125, 1999.

[9] H.M. Paynter. "*Analysis and design of engineering systems*,". M.I.T.Press, 1961.

[10] D.C. Karnopp, R.C. Rosenberg. "*Systems Dynamics: a Unified Approach*,". MacGraw Hill, 1983.

[11] C. Sueur, G. Dauphin-Tanguy. "*Structural Controllability and Observability of linear Systems Represented by Bond Graphs*,". Journal of Franklin Institute. Vol. 326. pp. 869-883, 1989.

[12] M. Djeziri, R. Merzouki, B. Ould Bouamama, and G. Dauphin-Tanguy, "*Robust Fault Diagnosis by Using Bond Graph Approach*". IEEE Transactions on Mechatronics, Vol. 12, N°6, December 2007.