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Bond Graph model-based fault estimation in presence of uncertainties: Application to mechatronic system.

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Abstract. This paper deals with the fault estimation problem of uncertain systems using Bond graph model-based technique. The main objective is to enhance the fault estimation procedure based on the generation of the fault estimation threshold, in order to overcome the problem related to errors in the estimated fault. The novelty of the proposed method is the generation of the fault estimation error using the fault estimation equation, which can be generated from the Bond graph model. The proposed methodology is validated via simulations of a mechatronic system.

Keywords: Bond graph model-based, Fault detection and isolation, Fault estimation, Uncertainties, Mechatronic system.

1 Introduction

Nowadays, due to the growing demand on the mechatronic system's efficiency, in order to achieve the maximal performance, the complex dynamic system was developed. However, as a consequence, the rate of component malfunctions augments with the complexity of systems. These malfunctions are called faults, which may appear in different parts of the system, namely: actuators, sensors, and system plants.

In general, fault detection and isolation (FDI) algorithms, can be divided into model-based and signal-based approaches, as presented in [1]. Model-based FDI algorithms depend mainly on the accuracy and the quality of the system model, which can be performed by graphical or analytical techniques. The basic idea of

FDI using model-based approaches is to compare the real system behavior with a reference behavior describing the normal operation. Via FDI procedures, an alarm can be created if the fault occurs. However, the magnitude of the fault cannot be obtained by these procedures. However, the magnitude of the fault is obtained using another procedure named fault estimation (FE). In addition, an accurate fault estimation can determine the type, magnitude and dynamic behavior of the fault. Fault estimation is the initial step for the design of fault-tolerant control (FTC) procedure. However, once the fault is estimated, the FTC must react to the estimated fault by using an appropriate controller [2].

Recently, several techniques dealing with fault estimation in the presence of uncertainties have been developed, such as parity space approach [3, 4], advanced observers [5, 6], and stable factorization approach [7]. Among the problems encountered in the use of these approaches, the convergence of the estimation error and the accuracy of the results. In [8-10], a fault estimation method has been developed using the bond graph approach and its causal and structural properties. The method has been applied to a real dynamic system in order to estimate the fault on the dynamics of a mechatronic system. Compared to the aforementioned works, our contribution is to deal with the presence of uncertainties using the same tool.

In the present work, we propose an algorithm of fault estimation by considering the presence of uncertainties using bond graph approach. This work is applicable to more complex and general systems. In addition, our approach can deal with parameter faults, which is not the case for the existing approach such as advanced observers, parity space, and stable factorization approaches.

The paper is organized into 5 Sections. After the introduction, Section 2 introduces the bond graph modeling methodology and the robust FDI procedure. In Section 3, the developed method for fault estimation in the presence of uncertainties is presented. Section 4 presents the applicability of the proposed methodology through simulations on a mechatronic system. Finally, conclusions are given in Section 5.

2 Bond graph modeling and robust FDI

2.1 Basic elements of BG

In BG, there are ten possible components named bond graph elements $S=\{R \cup C \cup I \cup TF \cup GY \cup Se \cup Sf \cup De \cup Df \cup J\}$. The dissipative R-elements are described by algebraic relationship $\Phi_R(e, f)=0$; potential storage energy C-

elements are quantified by the following integral equation $\Phi_C(e, \int f(t)dt) = 0$; and kinetic storage energy *I*-elements are modeled by an integral equation linking flow and integral of effort $\Phi_I(f, \int e(t)dt) = 0$. $\Phi_{GY}(\{e_1; f\}, \{f_2; e_2\}) = 0$, and $\Phi_{TF}(\{e_1; f_2\}, \{f_2; e_1\}) = 0$ are used to represent gyrators and transformers, respectively. (Sf) , and (Se) are the sources of flow and effort. Sensors are represented by effort (De) , flow (Df) detectors. Finally, J (which can be one or zero junction), is used to connect the element having the same flow (0-junction) or effort (1-junction). For more information about BG modeling, see [11].

2.2 Robust FDI to parameter uncertainties

The FDI in the presence of parameter uncertainties using the BG approach is based on the decoupling of the nominal and the uncertain parts of the analytical redundancy relations ARRs directly from the graphical model. This approach has been developed in [12] using the linear factional transformation named BG-LFT representation. In this approach, the BG elements are replaced by BG-LFT elements in order to obtain the uncertain BG. The nominal part of ARRs is used to generate the residuals, while the uncertain part is used to generate the adaptive thresholds in real-time [13]. In general, an ARR is represented as a constraint derived from an over-constrained subsystem and depends on the known inputs (Se, Sf) , the modulated known inputs (MSe, MSf) , the system parameters (θ) , and the measurement after the dualization (inversion) of the detectors (SSe, SSf) [14].

The following steps are taken to generate systematically the uncertain and nominal parts [15]:

- **Step 1:** obtain the BG model of the system in preferred derivative causality, by dualizing the causality of the detectors when possible.
- **Step 2:** model the parametric uncertainties on the nominal BG, to obtain the corresponding uncertain BG.
- **Step 3:** write the ARRs of the model from “0”or “1” junction having at least an associated detector, where energy conservation equation dictates that sum of flows or efforts, respectively, is equal to zero.

Where the known flow or effort variables are eliminated using covering causal paths from unknown variables to known [16].

- **Step 4:** For all ARRs derived from observed junctions, the adaptive threshold is obtained by adding the maximal absolute value of the different part of the ARRs $(-a \le r \le a)$.

3 The generation of fault estimation equations in the presence of uncertainties

The fault estimation procedure is based on the generation of the fault estimation equation directly from the BG model using the causal paths in order to eliminate the unknown variables and to generate an accurate fault estimation. The latter case is not always obvious, and this is due to the presence of uncertainties on the system. Therefore, in this section, we propose a method for the generation of the fault estimation equation in the presence of uncertainties and the generation of the fault estimation error. This method is based on the residuals information. This means that the faults are estimated when the residuals exceed the adaptive threshold after fault detection. The fault estimation equation is generated in a systematic way directly from the BG model. Then, the fault estimation error is generated using this equation. This can be done using the following procedure:

- Apply the LFT transformation to the BG model in order to model the actuator, sensor, and parameter faults, and apply the bi-causality to the sources and the detectors that represent the faults [17].
- Generate the fault estimation equation using the sensitivity relation between the residuals and the faults [18].
- From the estimation equations of the fault, the expression of the fault estimation error can be obtained in interval form:

$$\left[F_A - \left|\Delta F_A\right|, F_A + \left|\Delta F_A\right|\right]$$

Where ΔF_A is the uncertainty (deviation), over the estimated fault value (F_A).

For more illustration, let us consider a pedagogical R-L-C electrical circuit as shown in Fig. 1a, and modeled by BG (Fig 1b). The representation of the fault in the sensor $(SSf : I_m)$ can be performed as shown in Fig 2a, using the FBG-LFT. From the model of Fig .2b, the following estimation equation of the sensor fault can be obtained:

$$F_{SSf} = -\left((SSf : I_m) - C_1 \frac{d(SSe : v_m)}{dt} \right)$$

The estimation equation of the sensor fault in the presence of uncertainties is equal to:

$$F_{SSf} + \Delta F_{SSf} = -\left((SSf : I_m) - (C_1 + \delta_{C_1} C_1) \frac{d(SSe : v_m)}{dt} \right)$$

$$F_{SSf} + \Delta F_{SSf} = \underbrace{-\left((SSf : I_m) - C_1 \frac{d(SSe : v_m)}{dt} \right)}_{F_{SSf}} + \underbrace{\left(\delta_{C_1} C_1 \frac{d(SSe : v_m)}{dt} \right)}_{\Delta F_{SSf}}$$

Then, from this equation of fault estimation, the equation of fault estimation error can be generated as an interval:

$$\left[F_{SSf}-\left|\Delta F_{SSf}\right|, F_{SSf}+\left|\Delta F_{SSf}\right|\right]=\left[\begin{array}{c}\underbrace{-\left((SSf:I_m)-C_1\frac{d(SSe:v_m)}{dt}\right)-\left|\left(\delta_{C_1}C_1\frac{d(SSe:v_m)}{dt}\right)\right|}_{F_{SSf}-\left|\Delta F_{SSf}\right|},\\ \underbrace{-\left((SSf:I_m)-C_1\frac{d(SSe:v_m)}{dt}\right)+\left|\left(\delta_{C_1}C_1\frac{d(SSe:v_m)}{dt}\right)\right|}_{F_{SSf}+\left|\Delta F_{SSf}\right|}\end{array}\right]$$

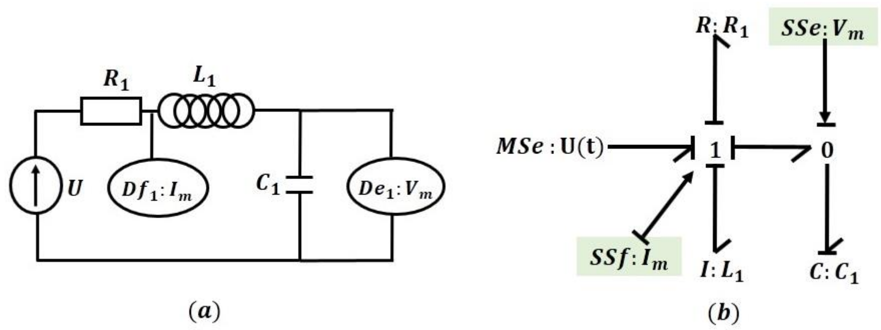

Fig. 1. (a) RLC circuit, (b) BG model of the circuit.

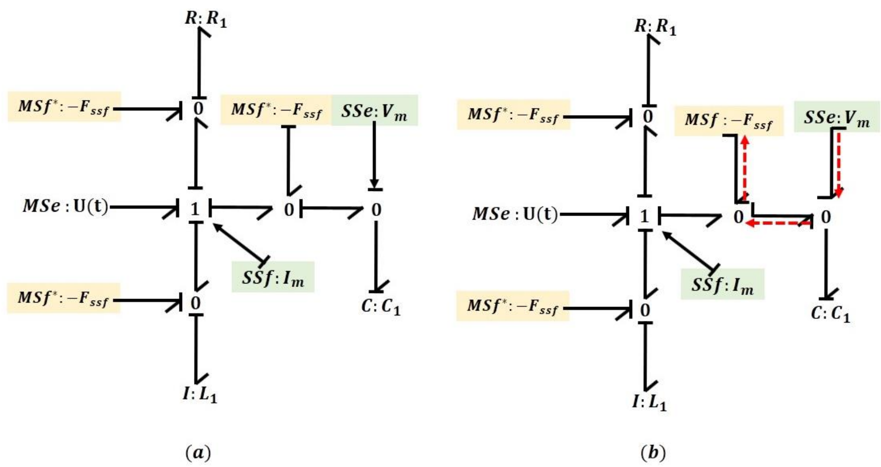

Fig. 2. (a) Sensor fault modeling, and (b) Sensor fault estimation.

4 Case study on mechatronic system

In this section, we validate the presented method of fault estimation in presence of uncertainties on mechatronic torsion bar 1.0 system (Fig .3), which is the subject of experimental-simulation study in [19]. Where only the parameter uncertainties are taken into consideration. This paper does not detail bond graph models and the system functioning. Instead, readers are referred to [20, 21] for description of the latter. Matlab $2014a^{®}$ and Simulink $2014a^{®}$ have been used for simulations purposes.

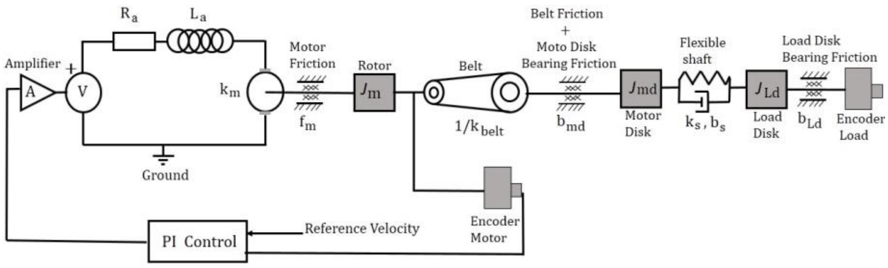

Fig. 3 Schematic model of the mechatronic system.

The nominal BG model in preferred integral causality used for simulation of this system is illustrated in Fig .4, where four dynamic parts are distinguished: DC motor system, belt and motor disk, flexible shaft, and load disk.

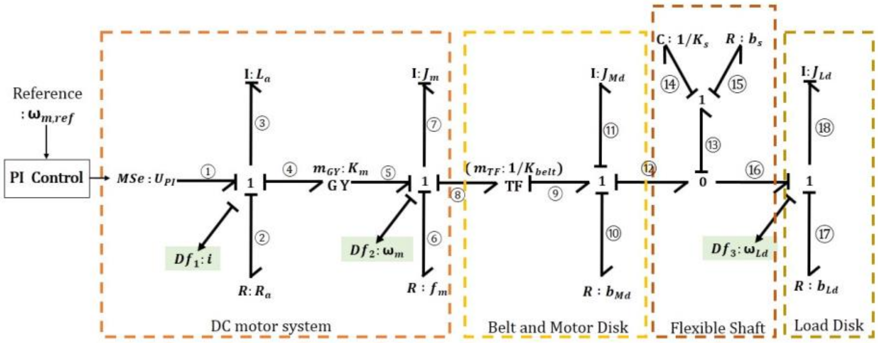

Fig. 4 Bond graph model in preferred integral causality of the nominal system.

From the BG model of the system in preferred derivative causality with parametric uncertainties of Fig. 5, three ARRs can be generated according to the procedure of causality inversion method (see Section 2.2):

$$ARR_1 : U_{PI} - R_a i - L_a \frac{di}{dt} - K_m \omega_m + a_1 = 0$$

$$ARR_2 : K_m i - J_m \frac{d\omega_m}{dt} - f_m \omega_m - \frac{1}{K_{belt}} \begin{pmatrix} \frac{J_{Md}}{K_{belt}} \frac{d\omega_m}{dt} + \frac{b_{Md}}{K_{belt}} \omega_m + \\ K_S \int \left(\frac{\omega_m}{K_{belt}} - \omega_{Ld} \right) dt + b_S \left(\frac{\omega_m}{K_{belt}} - \omega_{Ld} \right) \end{pmatrix} + a_2 = 0$$

$$ARR_3 = K_S \int \left(\frac{\omega_m}{K_{belt}} - \omega_{Ld} \right) dt + b_S \left(\frac{\omega_m}{K_{belt}} - \omega_{Ld} \right) - J_{Ld} \frac{d\omega_{Ld}}{dt} - b_{Ld} \omega_{Ld} + a_3 = 0$$

Where a_1, a_2 and a_3 are the uncertain part of ARR_1, ARR_2, and ARR_3, respectively.

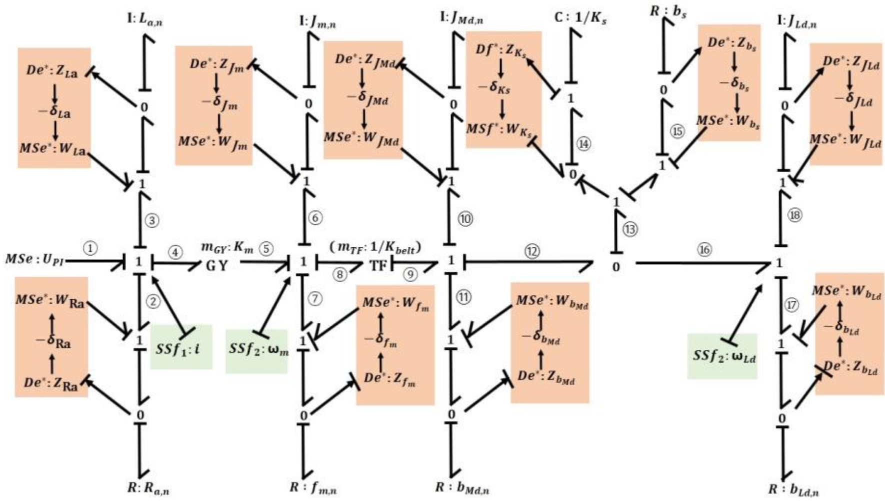

Fig. 5 BG model of the mechatronic system with parameter uncertainties.

$$a_1 = -\delta_{R_a} R_a i - \delta_{L_a} L_a \frac{di}{dt}$$

$$a_2 = -\delta_{J_m} J_m \frac{d\omega_m}{dt} - \delta_{f_m} f_m \omega_m - \frac{1}{K_{belt}} \begin{pmatrix} \frac{\delta_{J_{Md}} J_{Md}}{K_{belt}} \frac{d\omega_m}{dt} + \frac{\delta_{b_{Md}} b_{Md}}{K_{belt}} \omega_m + \\ \delta_{K_S} K_S \int \left(\frac{\omega_m}{K_{belt}} - \omega_{Ld} \right) dt + \delta_{b_S} b_S \left(\frac{\omega_m}{K_{belt}} - \omega_{Ld} \right) \end{pmatrix}$$

$$a_3 = \delta_{K_S} K_S \int \left(\frac{\omega_m}{K_{belt}} - \omega_{Ld} \right) dt + \delta_{b_S} b_S \left(\frac{\omega_m}{K_{belt}} - \omega_{Ld} \right) - \delta_{J_{Ld}} J_{Ld} \frac{d\omega_{Ld}}{dt} - \delta_{b_{Ld}} b_{Ld} \omega_{Ld}$$

Let us consider a fault affecting the current sensor of the DC motor as illustrated in Fig. 6, the following estimation equation can be generated using the sensitivity relation between r_2 and the fault in $Df_1 : i$ (see Section 3):

$$F_{SSf_1} = \frac{K_m i - J_m \frac{d\omega_m}{dt} - f_m \omega_m - \frac{1}{K_{belt}} \left(\begin{array}{l} \frac{J_{Md}}{K_{belt}} \frac{d\omega_m}{dt} + \frac{b_{Md}}{K_{belt}} \omega_m + \\ K_S \int \left(\frac{\omega_m}{K_{belt}} - \omega_{Ld} \right) dt + b_S \left(\frac{\omega_m}{K_{belt}} - \omega_{Ld} \right) \end{array} \right)}{K_m}$$

Moreover, the fault estimation in presence of uncertainties can be expressed as:

$$F_{SSf_1} + \Delta F_{SSf_1} = \frac{K_m i - (J_m + \delta_{J_m} J_m) \frac{d\omega_m}{dt} - (f_m + \delta_{f_m} f_m) \omega_m}{K_m} - \frac{\left(\begin{array}{l} \frac{(J_{Md} + \delta_{J_{Md}} J_{Md})}{K_{belt}} \frac{d\omega_m}{dt} + \\ \frac{(b_{Md} + \delta_{b_{Md}} b_{Md})}{K_{belt}} \omega_m + \\ (K_S + \delta_{K_S} K_S) \int \left(\frac{\omega_m}{K_{belt}} - \omega_{Ld} \right) dt + \\ (b_S + \delta_{b_S} b_S) \left(\frac{\omega_m}{K_{belt}} - \omega_{Ld} \right) \end{array} \right)}{K_{belt} K_m}$$

$$\Delta F_{SSf_1} = \frac{-\delta_{J_m} J_m \frac{d\omega_m}{dt} - \delta_{f_m} f_m \omega_m - \frac{1}{K_{belt}} \left(\begin{array}{l} \frac{\delta_{J_{Md}} J_{Md}}{K_{belt}} \frac{d\omega_m}{dt} + \frac{\delta_{b_{Md}} b_{Md}}{K_{belt}} \omega_m + \\ \delta_{K_S} K_S \int \left(\frac{\omega_m}{K_{belt}} - \omega_{Ld} \right) dt + \delta_{b_S} b_S \left(\frac{\omega_m}{K_{belt}} - \omega_{Ld} \right) \end{array} \right)}{K_m}$$

From the expression of the sensor fault estimation in the presence of uncertainties, the fault estimation error can be generated as follows (see Section 3):

$$\left[F_{SSf_1}-\left|\Delta F_{SSf_1}\right|,F_{SSf_1}+\left|\Delta F_{SSf_1}\right|\right]=\left[\begin{array}{l}\dfrac{K_m i-J_m\dfrac{d\omega_m}{dt}-f_m\omega_m-\dfrac{1}{K_{belt}}\left(\begin{array}{l}\dfrac{J_{Md}}{K_{belt}}\dfrac{d\omega_m}{dt}+\dfrac{b_{Md}}{K_{belt}}\omega_m+\\ K_S\displaystyle\int\left(\dfrac{\omega_m}{K_{belt}}-\omega_{Ld}\right)dt+b_S\left(\dfrac{\omega_m}{K_{belt}}-\omega_{Ld}\right)\end{array}\right)}{K_m}-\\ \left|\dfrac{-\delta_{J_m}J_m\dfrac{d\omega_m}{dt}-\delta_{f_m}f_m\omega_m-\dfrac{1}{K_{belt}}\left(\begin{array}{l}\dfrac{\delta_{J_{Md}}J_{Md}}{K_{belt}}\dfrac{d\omega_m}{dt}+\dfrac{\delta_{b_{Md}}b_{Md}}{K_{belt}}\omega_m+\\ \delta_{K_S}K_S\displaystyle\int\left(\dfrac{\omega_m}{K_{belt}}-\omega_{Ld}\right)dt+\delta_{b_S}b_S\left(\dfrac{\omega_m}{K_{belt}}-\omega_{Ld}\right)\end{array}\right)}{K_m}\right|,\\ \dfrac{K_m i-J_m\dfrac{d\omega_m}{dt}-f_m\omega_m-\dfrac{1}{K_{belt}}\left(\begin{array}{l}\dfrac{J_{Md}}{K_{belt}}\dfrac{d\omega_m}{dt}+\dfrac{b_{Md}}{K_{belt}}\omega_m+\\ K_S\displaystyle\int\left(\dfrac{\omega_m}{K_{belt}}-\omega_{Ld}\right)dt+b_S\left(\dfrac{\omega_m}{K_{belt}}-\omega_{Ld}\right)\end{array}\right)}{K_m}+\\ \left|\dfrac{-\delta_{J_m}J_m\dfrac{d\omega_m}{dt}-\delta_{f_m}f_m\omega_m-\dfrac{1}{K_{belt}}\left(\begin{array}{l}\dfrac{\delta_{J_{Md}}J_{Md}}{K_{belt}}\dfrac{d\omega_m}{dt}+\dfrac{\delta_{b_{Md}}b_{Md}}{K_{belt}}\omega_m+\\ \delta_{K_S}K_S\displaystyle\int\left(\dfrac{\omega_m}{K_{belt}}-\omega_{Ld}\right)dt+\delta_{b_S}b_S\left(\dfrac{\omega_m}{K_{belt}}-\omega_{Ld}\right)\end{array}\right)}{K_m}\right|\end{array}\right]$$

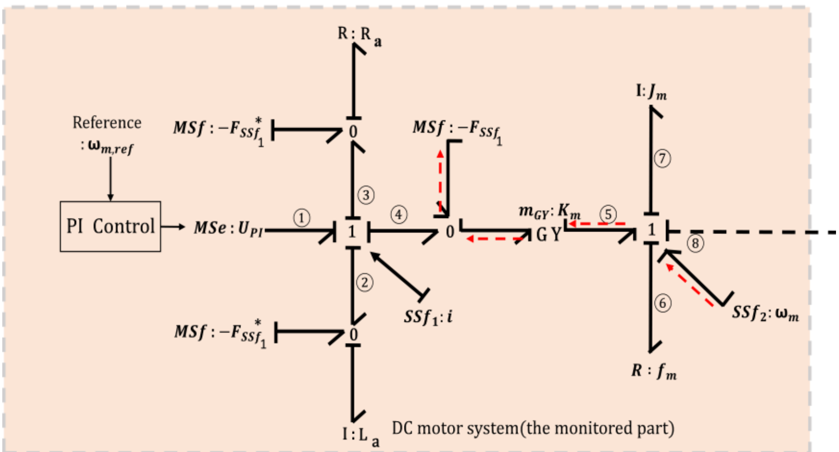

Fig. 6 Fault estimation using BG-LFT and the bi-causality.

The simulation results of the mechatronic system in the normal situation are shown in Fig. 7 and Fig. 8. As expected, the three residuals are close to zero and do not exceed the adaptive thresholds. This means that the system is healthy.

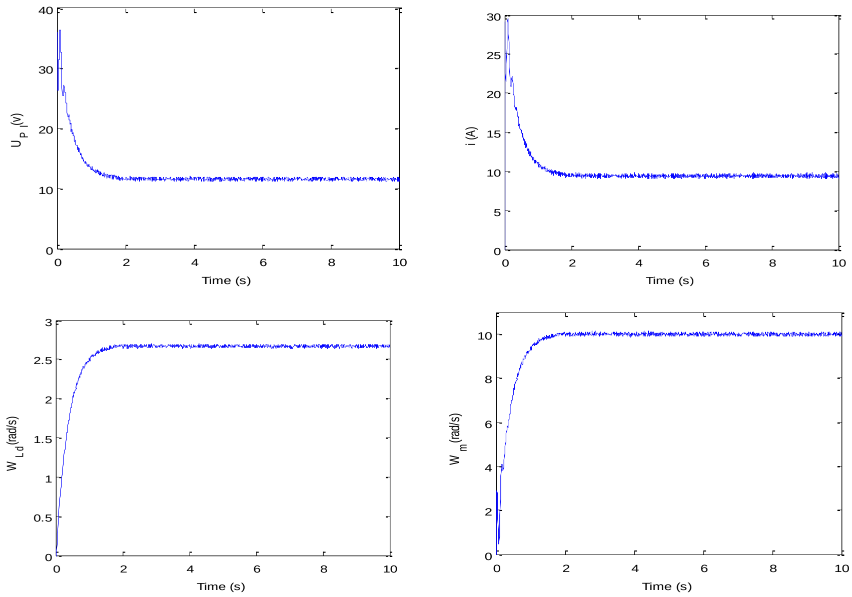

Fig. 7 Inputs and outputs of the mechatronic system.

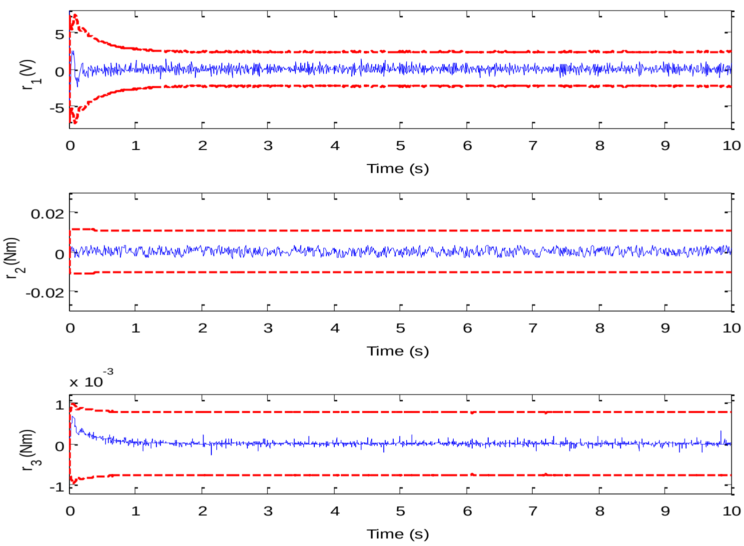

Fig. 8 r_1 , r_2 and r_3 with uncertainties in the normal situation.

An additive fault is introduced in the current sensor $(Df_1 : i)$ equivalent to 2A at time t=5s. In this case, the responses of the residuals r_1, r_2 and r_3 are given in Fig .9, where r_1, r_2 are affected by it, while r_3 does not detect this fault because it is not sensible to it. We remark from Fig .10 that the fault in the current sensor is estimated with its thresholds successfully.

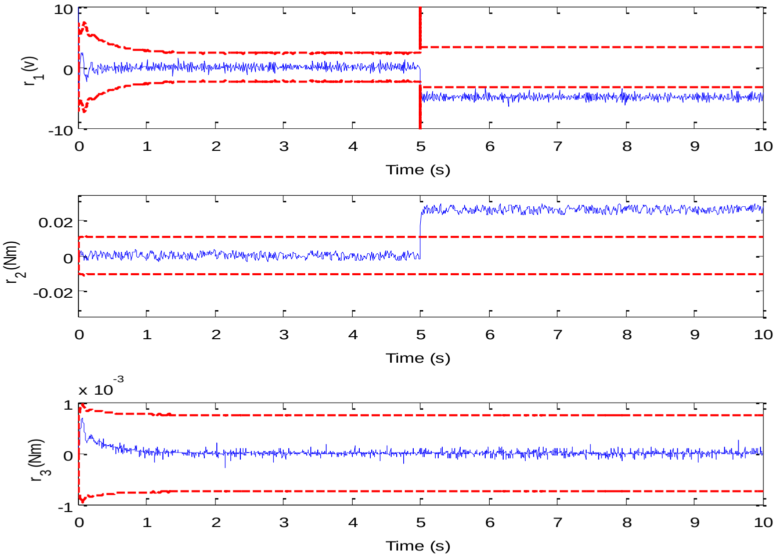

Fig. 9 r_1, r_2 and r_3 with uncertainties in faulty situation.

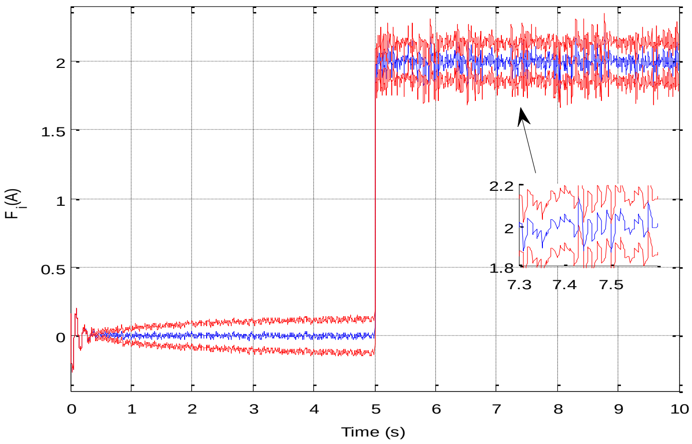

Fig. 10 Fault estimation using the residuals with considering the thresholds.

5 Conclusion

In this paper, a procedure of fault estimation in the presence of uncertainties using the bond graph model-based technique has been presented. The robust *ARRs* are generated from a bond graph model. The procedure of fault modeling and estimation is performed using the BG-LFT representation and the bi-causality notion, which allows the automation of the procedure of the generation of the estimation equation of the fault. The fault estimation error is generated using these fault estimation equations. The developed procedure is validated on a mechatronic system.

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