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Multi-thresholds for fault isolation in the presence of uncertainties

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ABSTRACT

Monitoring of the faults is an important task in mechatronics. It involves the detection and isolation of faults which are performed by using the residuals. These residuals represent numerical values that define certain intervals called thresholds. In fact, the fault is detected if the residuals exceed the thresholds. In addition, each considered fault must activate a unique set of residuals to be isolated. However, in the presence of uncertainties, false decisions can occur due to the low sensitivity of certain residuals towards faults. In this paper, an efficient approach to make decision on fault isolation in the presence of uncertainties is proposed. Based on the bond graph tool, the approach is developed in order to generate systematically the relations between residuals and faults. The generated relations allow the estimation of the minimum detectable and isolable fault values. The latter is used to calculate the thresholds of isolation for each residual.

1. Introduction

Fault detection and isolation (FDI) algorithms are crucial to ensure a good and safe system functioning. This motivates the researchers to develop new approaches in order to achieve the optimal objectives. In the last decades, several approaches have been developed for the so-called quantitative and qualitative methods of fault diagnosis. The qualitative approaches are essentially based on the abstraction hierarchies or the causal models [1]. These approaches are mainly based on the artificial intelligence. In [2], the problem of fault diagnosis is solved by forming logical statements derived from a signed Directed Graph. Another approach based on pattern recognition is developed in [3]. The quantitative approaches are mostly based on input–output and state space models [4].

Several techniques dealing with fault isolation in the presence of uncertainties have been developed, among them, the parity space approach [5,6], the observers [7–9], and bond graph (BG) approach. In [6], the residuals have been generated using the parity space approach in the presence of statistical uncertainties. The approach is based on the projection of the residual onto directions only sensitive to individual faults. The observer approach is based on the generation of a bank of observers. Each observer must be only sensitive to one considered fault [9]. Most of the developed approaches deal only with sensor and actuator faults, without considering parameter faults. Compared to these works, the BG approach can be an alternative solution for dealing with both sensor/actuator and parameter faults. The basic idea of this approach is to use the binary sensitivity of the ARRs which is generated from the bond graph model, to build the so-called fault signature matrix. This matrix allows the comparison between the binary signatures of the considered faults to make decision on fault isolation [10]. However, in the presence of uncertainties, the binary decision cannot be performed without considering the residual thresholds.

The problem of fault detection and isolation in the presence of uncertainties has been considered in [11–13]. Two main approaches are available: intervals and statistical tests. Most of the proposed methods deal with the intervals approach in order to generate adaptive thresholds. In fact, the intervals approach is preferred especially when the distribution of the uncertain error is unknown. In addition, the distribution of uncertainties is not easy to be obtained in real applications.

In this work we use the intervals approach to generate detectability and isolation thresholds. Where the residual is compared to the threshold to detect the fault. When the residual is greater than the threshold value, the fault is detected. In addition, the fault signature is obtained from a set of residuals, but in case of uncertainties, some of the sensitive residuals may not exceed the thresholds because of their low sensitivities to the fault. In this paper, we propose a new technique of fault isolation in the presence of uncertainties in order to avoid a false decision on fault isolation. The idea is based on the generation of multi-thresholds by taking into consideration the sensitivity relations between the residuals and the considered faults. For each considered fault, a set

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of thresholds (called thresholds of isolation) is associated. The fault is isolated only if all the sensitive residuals exceed these thresholds.

The remainder of the paper is organized as follows: in Section 2, the main fundamentals of the bond graph tool are presented. In Section 3, the generation steps of the analytical redundancy relations (ARRs) and their thresholds are presented. In Section 4, the proposed approach dealing with multi-thresholds is presented. Section 5 presents the applicability of the proposed approach by resorting to an intelligent autonomous vehicle. Finally, we conclude this work with some remarks and suggestions for further works.

2. Bond graph analysis

A bond graph (BG) is a multidisciplinary graphical modeling tool based on energy transfer phenomena. It has been introduced by Paynter [14] in 1969. The modeling methodology is based on the representation of each physical phenomenon, such as the energy storage (capacity C and inertia I), energy dissipation (resistance R), energy sources (source of effort Se and source of flow Sf) and energy transformation (transformer TF and gyrator GY), by a graphical element. The energy exchange is represented by a directed bond that includes two variables: effort (e) and flow (f), where $Power = e \times f$. Other graphical elements (0: same effort and 1: same flow) named junctions are used to relate the above elements. As an example, Fig. 1(b) represents the bond graph model of the electrical RL circuit with a DC tension source Se shown in Fig. 1(a). In this model, the inductance Le is represented by an I-element, the electrical resistance is represented by an energy dissipation element R and the DC tension source U is modeled by a source of effort Se.

For diagnosis and control, two elements have been added: effort detector De and flow detector Df. These elements model the sensors (detectors) such as velocity, current, and voltage sensors. In diagnosis, the sensors are replaced by SSe (replacing De) and SSf (replacing Df) which represent signal sources. These two elements impose information to the model in order to calculate and estimate the system states. Fig. 2(a) shows the bond graph model of the electrical circuit, represented in Fig. 1(a), with a current sensor $Df:i$. This model shows that the system imposes the information to the detector. However, in diagnosis, the detectors are replaced by $SSf:i$ which impose the information of the detector to the model in order to verify the junction equation (Fig. 2(b)).

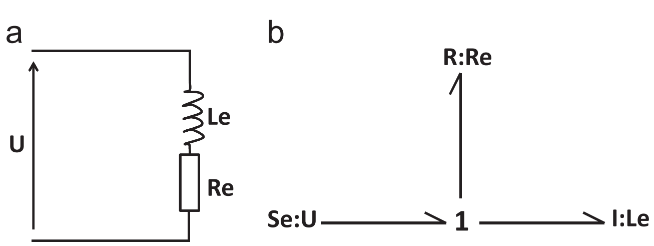

Fig. 1. Electrical circuit and its bond graph model.

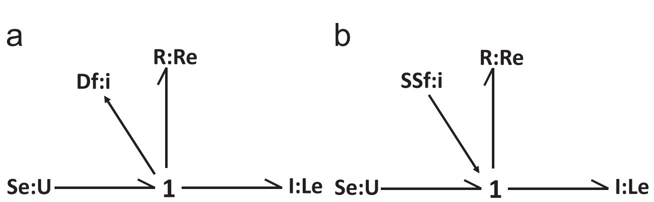

Fig. 2. (a) Bond graph model with a flow detector and (b) bond graph model with a dualized flow detector.

In fact, the bond graph model can be used to perform the monitoring and diagnosis through energy conservation equations, called analytical redundancy relations (ARRs) [15]. The latter can be systemically generated from the graphical model using junction equations. As an example, the equation of the 1-junction shown in Fig. 2b is given as follows:

$$U - Le\frac{di}{dt} - Re\, i = 0 \tag{1}$$

Eq. (1) represents an ARR. Its evaluation must be close to zero in normal operation. However, if the evaluation is different from zero, then, a fault is detected.

The ARRs are calculated and evaluated in real time to detect and isolate the faults. In fact, the ARRs are closed to zero in a normal situation. Otherwise, in faulty situations, they exceed certain thresholds that define the admitted changing in system behavior (parameter uncertainties) and noise (measurement uncertainties).

3. ARRs and thresholds generation

The FDI in the presence of parameter and measurement uncertainties using the bond graph approach is essentially based on the decoupling of the uncertain and nominal parts of the ARRs, directly from the graphical model. This approach has been developed in [16,17] using the linear fractional transformation (BG-LFT). It consists in replacing the bond graph elements by their BG-LFT representation in order to obtain decoupled ARRs. The nominal part of the ARR is used to calculate the fault indicator (residual), while the uncertain part is used to calculate the threshold in real time.

In general, an ARR is represented as a constraint that depends on the parameters of the system (θ), the measurement (SSe, SSf), and the known inputs $(Se, Sf, MSe, MSf) : ARR = f(SSe, SSf, Se,\ Sf,\ Mse,\ MSf, u, \theta)$. In BG-LFT model, the $ARRs$ can be decoupled into two parts, the nominal part:

$$ARR_n = f(SSe, SSf, Se, Sf, Mse, MSf, u, \theta_n) \tag{2}$$

and the uncertain part a:

$$a = f(\delta_{SSe,SSf}, \delta_\theta \theta_n) \tag{3}$$

where θ_n is the nominal parameter, and δ_θ is the parameter uncertainties. Noting that the nominal and the uncertain parts can be systematically generated from the BG model using the following procedure [17]:

- *Step* 1: Put the model in preferred derivative causality if possible.
- *Step* 2: Model the measurement and the parameter uncertainties.
- *Step* 3: Write the ARRs of the model using the equations of energy conservation, and use the causal paths to eliminate the unknown variables.
- *Step* 4: Write the ARRs of redundant detectors.
- *Step* 5: For all ARRs derived from the equations of energy conservation, the threshold is obtained by adding the maximal absolute values of the different parts of the ARRs containing the measurement errors.

For example, the characteristic equation of the R element in resistance causality, with parameter uncertainty can be written as follows:

$$\begin{aligned} e_R &= f_R(1+\delta_R)R_n, \\ e_R &= f_R R_n + f_R \delta_R R_n, \\ e_R &= f_R R_n - W_R, \end{aligned} \tag{4}$$

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