LFT Bond Graph for Online Robust Fault Detection and Isolation of Hybrid Multi-Source System

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Abstract. Green hydrogen is undoubtedly the most promising energy vector of the future because it is captured by renewable and inexhaustible sources, such as wind and/or solar energy, and can be stored over the long in high-pressure cylinders, which can be used to feed the fuel cells to produce the electricity without emitting any pollutants. The system incorporated renewable sources and process used to produce the green hydrogen is the hybrid multi-source system (HMS). The production of hydrogen needs a reliable HMS, which always requires online monitoring for real-time Fault Detection and Isolation (FDI) because the risk of accidents in HMS and safety issues increases due to the possibility of faults. However, online monitoring of FDI is challenging due to the multi-physics dynamics of HMS and the inclusion of uncertain parameters and several disturbances. This paper proposes an online robust fault detection algorithm to detect system faults based on the properties of the graphical linear fractional transformation bond graph (LFT-BG) modeling approach. Here, the analytical redundancy relations (ARRs) and their uncertain parts extracted from the LFT-BG model are used to develop an online robust FDI algorithm for HMS. Numerical evaluations of ARRs and their uncertain parts, respectively, generate the residual signals known as "faults indicators" and their uncertain bounds known as "adaptive thresholds." These thresholds evolve with system variables in the presence of parameter uncertainties for ensuring robust FDI for HMS to minimize false alarms. The validation of this approach is carried out using 20sim software that is familiar with BG modeling.

1.Introduction
Due to the environmental protection requirements, the Hybrid multi-source system (HMS) is involved in the task of storing renewable energy in the form of hydrogen gaze fuel [1]. It might have the same configurations as illustrated in figure 1, which consists of a parallel interconnection of wind turbine (WT) and photovoltaic (PV) generators. The flow of power produced by the WT and PV generators is controlled by AC/DC and DC/DC converters, respectively, to feed the Hydrogen production system (HPS), which usually requires constant power consumption to realize the Hydrogen production task. For that, the storage device (SD) is associated with HMS elements to ensure the constant power consumption of HPS. The SD illustrated in figure 1 consists of a lead-acid battery and DC/DC bidirectional converter. The DC/DC bidirectional converter of the SD controls the battery power flow in the opposite and direct direction, which allows storing the power surplus produced by WT and PV, and compensating for the power deficiency when WT and PV do not ensure the needed power of HPS.
The production of hydrogen fuel needs a reliable HMS, which requires online monitoring for real-time fault detection and Isolation (FDI) because the risk of accidents in HMS and safety issues increase due to the possibility of faults. However, online monitoring for FDI is challenging due to the multi-physics, uncertain dynamics of HMS and the inclusion of uncertainties of the measurements and parameters, and disturbances. These uncertainties complicate the task of FDI in HMS and cause false alarms [2].

The model-based techniques (such as parity space and observers-based techniques) can deal with the FDI issues [3, 4]. The parity space model-based method is intended only for the linear systems model. This method derives the analytical redundancy relations (ARRs), which are given in terms of known signals, variables, and parameters in closed mathematical forms, from the differential equations of the system dynamics presented in the state-space form [3]. On the other hand, the systems model can be used to design the observers for FDI, where the observer's estimation errors represent the fault indicators.

The observer technique can also be applied for the model of the nonlinear system [4]. The residual signals derived from both methods are sensitive to faults, and they are limited to the FDI of sensors and actuators but not of the parametric (component) faults. Thus, the parametric faults corresponding to the HMS component cannot be detected under these methods. Because of many components of the HMS, simplistic models would yield no robust and poor FDI performance.

This paper addresses the FDI model-based issues by exploiting the graphical linear fractional transformation bond graph (LFT-BG) to design online monitoring of HMS components for FDI. As the LFT-BG modeling approach models all HMS physics and includes disturbances, process, parameter, and measurement uncertainties, FDI's proposed method earns the robustness against all uncertainties to prevent false alarms. The LFT-BG modeling approach is known by the causal properties (derivative and integral causal properties) representing the cause and effect between system variables. These causal properties help to generate directly from the uncertain bond graph model the fault indicators by decoupling the uncertainties from the faults and perform the isolability and monitorability analysis based on fault signature matrix (FSM), which is exploited to verify the ability of the proposed approach to localize the fault or set of faults in the HMS [6]. The derivative causal property is preferred for FDI to avoid unknown initial conditions. While the integral causal property is preferred for behavioral and simulation studies [5]. The HMS LFT-BG model developed under the derivative causal property is used to derive ARRs and their uncertain parts in terms of known signals, variables, and parameters in closed mathematical forms. Numerical evaluations of ARRs and their uncertain parts generate the residual signals that are "fault indicators" and their uncertain bounds that are "adaptive thresholds," respectively. These thresholds evolve with system variables in the presence of uncertainties [5,9]. The proposed approach monitors the WT, PV, and SD components without including the power converters in the study and validated by using 20sim software.

![Figure 1. HMS configuration.](image-url)
The paper contains four other sections. Section 2 presents a brief theory of LFT-BG to derive the online robust monitoring for FDI. Section 3 presents the process to develop online robust monitoring for FDI and monitorability and isolability analysis for fault localization using the HMS's LFT BG model. Section 4 shows the simulation study, and this paper is ended with a conclusion.

2. Bond graph theory for fault detection and isolation

2.1 Conventional bond graph theory
BG is a graphical language used to model multi-physical systems. It is a union of two sets of elements denoted by \( S = \theta \cup A \), where \( A \) is a set of power bonds denoted by the half arrows, which show the exchange of power that is a product of effort \( e \) and flow \( f \) between the system components. In contrast, \( \theta \) is a set of elements used to model the system components. The elements of \( \theta \) are the resistance \( R \), capacitance \( C \), inductance \( I \), transformer \( TF \), gyrator \( GY \), effort source \( Se \), flow source \( Sf \), effort sensor \( De \) and flow sensor \( Df \). The element \( R \) models the system components having the linear dynamic. The elements \( C \) and \( I \) model the system components having the same dynamics as the capacitance and inductance, respectively, which correspond to the system components storing the energy. The elements \( Se \) and \( Sf \) model the system components generating the power in the form of effort and flow, respectively. The elements \( TF \) and \( GY \) model the system components transforming the power without causing any loss. The elements \( De \) and \( Df \) represent the sensors that obtain the effort and flow measurements, respectively. The whole BG elements are connected through the power bonds and junctions "1" and "0" by respecting their properties (flow equality and effort equality, respectively) [6].

Moreover, BG formalism is known by the causal properties, which are the integral and derivative causal properties. These properties are the way to know how the system components are acting between them, as illustrated in figure 2. The causal properties are presented in BG by the cross-stroke in one of the power bond sides. \( S_1 \) acts on \( S_2 \) by an effort, and \( S_2 \) replies to \( S_1 \) by a flow (effort causality) if the cross-stroke is placed on the right side. On the other hand, the cross-stroke placement on the left side shows \( S_1 \) acts on \( S_2 \) by a flow, and \( S_2 \) replies to \( S_1 \) by an effort (flow causality). The use of integral and derivative causal properties is to simulate the dynamic of modeled multi-physical systems and develop online monitoring for FDI, respectively, before the online implementation [9].

![Figure 2. Causality presentation.](image)

2.2 Linear fractional transformation for modeling the uncertainties in bond graph
The HMS parameter identification bears difficulties, which prevents obtaining the nominal values of HMS parameters in the real process. In this case, each HMS parameter can be expressed by an interval of values, where its minimum and maximum values are related to the parameter's uncertainty. Also, the HMS parameters may vary in the range of values, which can also be related to the parameter uncertainties, due to unknown disturbance in the absence of faults. This issue complicates FDI's task for HMS and is considered as the main cause of false alarms. For more robustness of the FDI algorithm, LFT presentation is used to incorporate the uncertain part of the HMS parameter in the BG model [5,9].

Using the LFT methodology, uncertainties on parameters are considered as an additive or multiplicative, as written in (1) and (2) where \( \beta \) is an example of any system parameter to illustrate the
LFT methodology, $\beta_n$ is the $\beta$ nominal value, $\delta_\beta$ is the relative uncertainty, and $\Delta_\beta$ is the absolute uncertainty.

$$\beta = \beta_n \pm \Delta_\beta$$

$$\beta = \beta_n (1 \pm \delta_\beta)$$

To illustrate how uncertainty is integrated into the BG using the LFT presentation methodology, consider the BG $R$ element's case. Let consider $R = R_n (1 \pm \delta_R)$ the real value of the $R$ element.

Assume that the causality of this element $R$ is assigned in flow causality. Then, the effort of $R$ is written as follows:

$$e_R = R \cdot f_R = R_n (1 \pm \delta_R) \cdot f_R = R_n f_R \pm \delta_R R_n f_R$$

$$= e_{Rn} + e_{\delta R}$$

(3)

According to (3), the uncertainty of $R$ integrated into BG under flow causality is given as shown in figure 3a, where $De^*$ is used to measure $e_{Rn}$, and $e_{\delta R}$ is introduced by $MSe^*$.

Assume now the causality of $R$ is assigned in effort causality. Then, the flow is given as follows:

$$f_R = \frac{1}{R} e_R = \frac{e_R}{R_n (1 \pm \delta_R)} = \frac{1}{R_n} (1 \pm \delta_{1/R}) e_R$$

$$= e_{Rn} + e_{\delta_{1/R}}$$

(4)

$$= \frac{e_R + \delta_{1/R} e_R}{R_n} = f_{Rn} + f_{\delta_{1/R}}$$

according to (4), the uncertainty of $R$ integrated into BG under effort causality is given as shown in figure 3b, where $Df^*$ is used to measure $f_{Rn}$, and $MSf^*$ introduces $f_{\delta_{1/R}}$.

The LFT presentation of elements $C$, $I$, $GY$, and $TF$ in BG can be performed in the same way as the element $R$ [9].

![Figure 3. Causality presentation.](image)

2.3 Online robust fault detection based on the linear fractional transformation bond graph

The design process of the online robust FDI consists of the ARRs, and their adaptive thresholds, which are developed by the use of the properties of the junctions ("0" and "1") where there is a SSe or SSf that correspond to the sensors used for monitoring [7,9]. The ARR is the sum of incoming power bonds efforts minus the sum of outgoing power bonds efforts if junction "1" is used. Also, the ARR can be the sum of incoming power bonds flows minus the sum of outgoing power bonds flows if the junction "0" is used. All ARR parameters must be known, and the uncertain parts are neglected [7].

The mathematical expression of ARR can be written as follows:

$$ARR = \sum_{\text{in}} e_{\text{in}} + e_{\text{in}} - \sum_{\text{out}} e_{\text{out}} + e_{\text{out}}$$

$$= \Psi (SSe, SSf, SE, SF, \Theta_n)$$

or

$$ARR = \sum_{\text{in}} f_{\text{in}} + f_{\text{in}} - \sum_{\text{out}} f_{\text{out}} + f_{\text{out}}$$

$$= \Psi (SSe, SSf, SE, SF, \Theta_n)$$

(5)

(6)

where $e_{\text{in}}$, $e_{\text{out}}$, $f_{\text{in}}$, $f_{\text{out}}$, $\Theta_n$ are the nominal incoming effort, outgoing effort, incoming flow, outgoing flow, and BG elements parameters, and $e_{\text{in}}$, $e_{\text{out}}$, $f_{\text{in}}$, $f_{\text{out}}$ are the neglected incoming effort, outgoing effort, incoming flow, and outgoing flow, respectively, generated by the uncertain parts. The adaptive
threshold \( a \) is the sum of the absolute value of uncertain parts neglected in (5) or (6). It can be written as follows:

\[
a = \sum |f_{\text{in}}| + \sum |f_{\text{out}}| \]

\[
= \Psi (\Sigma S\alpha, \Sigma S\beta', \Sigma S\gamma, \alpha_n, \theta_n) \tag{7}
\]

or

\[
a = \sum |f_{\text{in}}| + \sum |f_{\text{out}}| \]

\[
= \Psi (\Sigma S\alpha, \Sigma S\beta', \Sigma S\gamma, \alpha_n, \theta_n) \tag{8}
\]

where \( \delta_\theta = \{\delta_R, \delta_C, \delta_I, \delta_TF, \delta_TF\} \) and \( \Theta_n = \{R_n, C_n, I_n, GY_n, TF_n\} \). The fault indicators are the numerical evaluation of \( ARRs \) called "residual signals." \( r = \text{eval}(ARR) \). Theoretically, \( r \) should be zero, but \( r \) is not zero due to noises and parameter uncertainties. If \(-|a| \leq r \leq |a|\), then the system operates in the nominal conditions (no faults). Else, faults occur in the system [9].

3. Online robust fault detection and isolation for hybrid multi-source system

In this section, the process to obtain the LFT-BG model of the HMS, which has the same configuration presented in section 1 (see figure 1), under the derivative causal property is briefly explained. It is obtained by joining the nominal BG models of HMS components in the single model and including the parameter uncertainties using LFT presentation. The obtained HMS LFT BG model will be used to drive the \( ARRs \) and their adaptive thresholds to monitor the WT, PV, and SD in the presence of uncertainties without considering the power converters.

WT component consists of a mechanical part deriving the synchronous electrical generator. The mechanical part is illustrated in figure 4a, and its BG nominal model is illustrated in figure 4b. It consists of the propeller driving a gearbox. This mechanical part is connected to the electrical synchronous machine through a shaft characterized by two parameters: \( J \) is the inertia moment, and \( \sigma \) is the viscous friction coefficient. The propeller, which is the generator of torque \( Tear \) deduced from the wind speed \( W_S \) and direction \( W_D \), converts the wind's kinetic power to mechanical power. The Gearbox provides the suitable torque \( \Omega \) to derive the synchronous electrical generator for generating the electrical power, where the torque provided by Gearbox is equal to \( Tear/G = Jd\Omega/dt + f\Omega \) [10]. In the BG approach, the power variables are as follows: \( e \) is the torque, and \( f \) is the rotational speed. The source of effort \( MSE \) models the propeller: \( Tear \) and the Gearbox by \( TF:1/G \) element. As the same \( \Omega \) drives all shaft particles, the shaft part is modeled by \( I:J \) and \( R:\sigma \) connected to the junction "1".

![Figure 4](image)

**Figure 4.** a) diagram of WT mechanical part, b) nominal BG model of WT mechanical part.

The synchronous electrical generator of the WT component illustrated in figure 5a consists of two parts: the moving and the fixed parts. It converts the mechanical power provided by the mechanical part to the electrical power when the moving part rotates due to shaft rotation. The permanent magnet
used to make the moving part generates a magnetic field circulation, which excites the fixed part's winding to produce the electrical current. The nominal BG model illustrated in figure 5b of the synchronous electrical generator (power variables: e is the voltage; f is current) is obtained based on the park transformation technique [11]. The elements $ MGY : 3/2pl_{d},\frac{1}{2}Ω, MGY : -3/2pl_{q},\frac{1}{2}Ω $ and $ GY : 3/2pλΩ $ model the interaction of magnetic field circulation with the winding of the fixed part when the moving part is rotating, $ p $ is the generator pole pairs, and $ λ $ is the flux density of the permanent magnet, and the elements $ R : R_{dn}, R : R_{qn}, I : L_{dn}, I : L_{qn}, v_d, v_q, i_d $ and $ i_q $ refer to the electrical characteristic of the fixed part winding, where $ R_{dn} $ and $ R_{qn} $ are the resistances in the direct and quadratic axis, respectively, $ L_{dn} $ and $ L_{qn} $ are the inductances in direct and quadratic axis, respectively, $ v_d $ and $ v_q $ are the winding voltages in the direct and quadratic axis, respectively, and $ i_d $ and $ i_q $ are the winding currents in the direct and quadratic axis, respectively. The synchronous electrical generator's real outputs are $ i_a, i_b, i_c, v_a, v_b, $ and $ v_c $. They are obtained using the inverse Park transformation of $ v_d, v_q, i_d $ and $ i_q $.

![Figure 5. a) diagram of the WT synchronous electrical generator, b) nominal BG model of the WT synchronous electrical generator.](image)

PV Component consists of a series of solar cells that capture solar irradiation (S) and convert it to electrical power. This PV component can be considered as the current source producing $ i_{ph} $ as depicted in figure 6a, and its nominal BG model is illustrated in figure 6b, where $ MSf : i_{ph} $ is used to model the $ i_{ph} $ current source and $ R : R_{shn}, R : R_{Dn}, $ and $ R : R_{sn} $ are used to model the particles causing the power loss, where $ R_{shn}, R_{Dn}, $ and $ R_{sn} $ are the equivalent shunt resistance, the equivalent resistance of diode deduced from the semi-conductor characteristic of the panel, and equivalent series resistance, respectively. This component's output power is the product of $ i_p $ and $ v_p $, which are photovoltaic current and voltage, respectively [12].

![Figure 6. a) Diagram of the PV panel equivalent circuit, b) nominal BG model of PV.](image)
The SD component consists of the lead-acid battery, which can be considered as a voltage source \( V_{oc} \) (the \( V_{oc} \) value depends on the state of charge SOC of battery) and represented by the equivalent circuit as shown in figure 7a. The nominal BG model of this component is illustrated in figure 7b, where \( \text{MSe}: V_{oc} \) is used to model the voltage sources, \( C: C_{dl} \) is used to model the double-layer capacitance of lead-acid battery, and \( R: R_{dl} \) and \( R: R_i \) are used to model the particles causing the loss of power, which are the charge transfer and internal resistances, respectively. This component's output power is the product of \( i_b \) and \( v_b \), which are the lead-acid battery current and voltage, respectively.

\[
\begin{align*}
\text{SOC}\% & \rightarrow V_{oc} & C_{dl} & \rightarrow i_b & R_{dl} & v_b \\
\text{(a)} & & & & \text{MSe}: V_{oc} & i_b & v_b \\
\text{(b)} & \end{align*}
\]

Figure 7. a) Equivalent circuit of lead-acid battery, b) Nominal BG model of SD component.

Regrouping the nominal BG models of the HMS components with including the uncertainties of the parameters using the LFT presentation, make the HMS LFT-BG model, as illustrated in figure 8. The sensors used to monitor the HMS components are SSf1, SSf2, SSf3, SSf4, SSf5, and SSe1, which measure \( \Omega_m, i_{dm}, i_{qm}, i_{bm}, i_{vm}, \) and \( v_{cdlm} \), respectively. In fact, there are no real sensors devices to measure \( i_{dm}, i_{qm} \), and \( v_{cdlm} \). These measurements are performed by inverse Park transformation (measuring first \( i_a, i_b, \) and \( i_c \), and then using park transformation to deduce \( i_{dm} \) and \( i_{qm} \)) and observer technique, respectively [11,4].

Figure 8. HMS LFT-BG model under derivative causality property.

Figure 9 presents a part (corresponds to the SD component) of the HMS LFT-BG model to illustrate the process used to derive the ARRs and adaptive thresholds using the definition presented in section 2.3. The junction used to drive the ARR is the junction where the monitoring sensor SSe1: \( v_{cdlm} \) is placed.
Figure 9. Part of the HMS LFT-BG model for illustrating the design process of ARRs and their adaptive thresholds.

It is obtained that:

\[
i_b - f_{C_{dl}} - f_{R_{dl}} = b_b \left( f_{C_{dl}} + f\delta_{C_{dl}} \right) - \left( f_{R_{dl}} + f\delta_{R_{dl}} \right)
\]

(9)

Neglecting \( f\delta_{C_{dl}} \) and \( f\delta_{1/R_{dl}} \), the mathematical expression of the resulted ARR is written as follow:

\[
ARR_i = i_b - f_{C_{dl}} - f_{R_{dl}} = b_m - C_{dl} \frac{dv_{C_{dl}}}{dt} - \frac{v_{C_{dl}}}{R_{dl}}
\]

(10)

where \( i_{bm} \) is the measurement value of \( i_b \) obtained by \( SSf_5 \). The adaptive threshold associated with \( ARR \) is the absolute sum of \( f\delta_{C_{dl}} \) and \( f\delta_{1/R_{dl}} \), which can be written as follows:

\[
0 a_i = \left| f\delta_{C_{dl}} \right| + \left| f\delta_{1/R_{dl}} \right| = \left| \pm \delta_{C_{dl}} \frac{dv_{C_{dl}}}{dt} \right| + \left| \pm \delta_{1/R_{dl}} \frac{v_{C_{dl}}}{R_{dl}} \right|
\]

(11)

Then, other ARRs and their adaptive thresholds, which are used to monitor the HMS components, will be developed as explained in the previous example. They can be written as follows:

\[
ARR_1 = \frac{3}{2} p L_{q_m} i_{q_m} \Omega_m - L_{d_m} \frac{di_{m}}{dt} - R_{d_m} i_{m} \Omega_m
\]

(12)

\[
ARR_2 = \frac{3}{2} p \Omega_m \left( \dot{\epsilon} - L_{d_m} i_{m} \right) - L_{q_m} \frac{di_{m}}{dt} - R_{q_m} i_{m} \Omega_m
\]

(13)

\[
ARR_3 = r_{cur} - f_n \frac{d\Omega_m}{dt} - \sigma_n \Omega_m - \frac{3}{2} p \delta i_{q_m}
\]

(14)

\[
ARR_4 = \frac{R_{sh}}{R_{d_m} + R_{d_m}} (v_{ph} - i_{pm}) - R_{sn} i_{pm} \Omega_m
\]

(15)

\[
ARR_6 = \left( v_{oc} - v_{C_{dl}} \right) - v_{m} - R_{n} i_{bm}
\]

(16)

\[
a_1 = \frac{3}{2} \delta_{q_m} p L_{q_m} i_{q_m} \Omega_m + \delta_{d_m} L_{d_m} \frac{di_{m}}{dt} + \frac{\delta R_{d_m}}{R_{d_m}} i_{d_m}
\]

(17)

\[
a_2 = \frac{3}{2} \delta_{q_m} p L_{q_m} i_{q_m} \Omega_m + \delta_{d_m} L_{d_m} \frac{di_{m}}{dt} + \frac{\delta R_{d_m}}{R_{d_m}} i_{d_m}
\]

(18)

\[
a_3 = \delta_{f_{n}} \frac{d\Omega_m}{dt} + \delta_{n} \sigma_n \Omega_m
\]

(19)

\[
a_4 = \delta_{R_{q_m}} \left( v_{ph} - i_{pm} \right) + \frac{\delta R_{s_m}}{R_{s_m}} i_{pm}
\]

(20)

\[
a_5 = \delta_{R_{q_m}} \left( v_{ph} - i_{pm} \right)
\]

(21)
After deriving the $ARRs$ from the LFT-BG model of HMS, the Fault signature matrix (FSM) illustrated in table 1 and table 2 are performed on the obtained $ARRs$. They consist of the fault signatures used to carry out the monitorability $M_b$ and isolability $I_b$ analysis as follows: $M_b=1$ if the fault is sensitive at least to one $ARR$. $M_b=0$ in the opposite case. $I_b=1$, if the fault has a unique signature. Else, $I_b=0$ [6].

Table 1 and table 2 show that any fault cannot be isolated separately. However, the presented analysis shows that the faults can be isolated by sets depicted by specific colors. Each set represents the same signature. This way can, at least, localize the fault at the specific HMS part where they occur.

### Table 1. Fault signature matrix, $M_b$: monitorability index, $I_b$: isolability index.

| Faults→ | $ARR_1$ | $ARR_2$ | $ARR_3$ | $ARR_4$ | $ARR_5$ | $ARR_6$ |
|---------|---------|---------|---------|---------|---------|---------|
| $R_d$   | 1       | 1       | 1       | 1       | 1       | 1       |
| $v_{an}$| 0       | 0       | 0       | 0       | 0       | 0       |
| $L_d$   | 1       | 1       | 1       | 1       | 1       | 1       |
| $v_{ap}$| 0       | 0       | 0       | 0       | 0       | 0       |
| $t_{an}$| 1       | 1       | 1       | 1       | 1       | 1       |
| $J$     | 0       | 0       | 0       | 0       | 0       | 0       |
| $\sigma$| 1       | 1       | 1       | 1       | 1       | 1       |
| $R_s$   | 0       | 0       | 0       | 0       | 0       | 0       |
| $v_{ap}$| 0       | 0       | 0       | 0       | 0       | 0       |
| $t_{an}$| 1       | 1       | 1       | 1       | 1       | 1       |
| $C_{d}$ | 0       | 0       | 0       | 0       | 0       | 0       |
| $R_{d}$ | 1       | 1       | 1       | 1       | 1       | 1       |
| $t_{an}$| 1       | 1       | 1       | 1       | 1       | 1       |

$I_b$ = 0

### Table 2. Fault signature matrix carried out on the faults may occur in $R_{d}$, $v_{lim}$, $v_{cllim}$.

| Faults→ | $ARR_{S_1}$ | $ARR_{S_2}$ | $ARR_{S_3}$ | $ARR_{S_4}$ | $ARR_{S_5}$ | $ARR_{S_6}$ |
|---------|-------------|-------------|-------------|-------------|-------------|-------------|
| $R_d$   | 0           | 0           | 1           | 0           | 0           | 0           |
| $v_{an}$| 0           | 0           | 0           | 0           | 0           | 0           |
| $v_{ap}$| 0           | 0           | 0           | 0           | 0           | 0           |

$I_b$ = 1

### 4. Simulation study

The simulation study is carried out to validate the robust monitoring for FDI of HMS in the presence of system uncertainties. The simulation consists of implementing the $ARRs$ with their adaptive thresholds and the $HMS$ model under the operation state in the 20sim software, where the parameter random variations (HMS parameters variate in the interval of values related to the relative uncertainties) are included in the HMS model to simulate the parameter uncertainties. One scenario is performed to validate the proposed approach, which consists of injecting the faults in certain parameters: $R_d$, $\Omega_m$ (sensor fault), $\sigma$, $R_s$, and $R_i$ at different times: 10s, 30s, 38s, 45s, and 50s, respectively. There is in the simulation a process used to cancel the injected faults to let the faults affecting the system during a period of time. The simulation results are presented in figure 10 and figure 11.

According to the obtained results, the residuals signals generated from the developed $ARRs$ are not in the zero value and vary randomly due to the parameter uncertainties. Their thresholds are adaptively evolving with the evolution of system variables. The adaptive evolution of the thresholds helps to prevent the residual signals from going out of their thresholds bounds when there is no fault. When faults occur in the HMS, the residuals generated by $ARR_1$, $ARR_2$, $ARR_3$, $ARR_4$, and $ARR_6$ go out of their thresholds bounds at different times due to the presence of faults. When the faults are canceled, the
residual signals generated by the $ARRs$, which are previously mentioned, return to the threshold bounds. It is noticed that only the residual signal generated by $ARR_5$ is not affected and kept inside its thresholds bound during the whole simulation time. According to the monitorability and isolability carried out in section 3, $ARR_5$ is not sensitive to any fault simulated in this scenario. For this reason, the residual signal of $ARR_5$ is not affected by these faults. This part of the validation scenario and the presence of faults at different times have been performed to verify the monitorability and isolability analysis discussed in section 3 based on the FMS technique.

![Figure 10](image1.png)

**Figure 10.** Numerical evaluation of the residuals: $r1$, $r2$, $r3$ with their adaptive thresholds.

![Figure 11](image2.png)

**Figure 11.** Numerical evaluation of the residuals: $r4$, $r5$, $r6$ with their adaptive thresholds.

5. Conclusion
The obtained results prove the LTF-BG modeling approach's effectiveness in designing the online robust monitoring to detect and isolate faults in the HMS. The online FDI process earns the robustness from the adaptive thresholds, which evolve with the evolution of the system variables in the presence of parameter uncertainties. Furthermore, the indicators of faults under this approach are only sensitive to faults. This study shows the LFT-BG approach’s ability to model with accuracy way the HMS. As LFT-BG allows all phenomena acting negatively on the system to take part in the model, dealing with these issues, as mentioned earlier,
becomes easy when LFT-BG is used, and improving the fault isolation capability under single and multiple faults requires more sensors of monitoring that will be the future work.

6. References

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