Multiple Faults Isolation for Hybrid Systems with Unknown Fault Pattern

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BSTRACT

This work is concerned with multiple faults isolation for hybrid systems based on Global Analytical Redundancy Relationships (GARRs) approach. GARRs are derived from the Hybrid Bond Graph (HBG) model of a hybrid system with a specified causality assignment procedure. In this article, multiple faults are considered in a complex hybrid system and these faults can develop during a mode when the faults are not detectable. Once a fault is detected, a fault candidates set is generated from mode dependent-fault signature matrix (MD-FSM) tables and a set of fault pattern hypothesis is created from the fault candidates set for further refinement. Fault isolation is carried out using a multiple nonlinear least square optimization (MNLSO) algorithm. The developed technique can deal with multiple faults with unknown pattern. The fault could be of incipient or abrupt nature. The simulation results show the effectiveness of the proposed method.*

1. INTRODUCTION

As the complexity of industrial systems increases, fault detection and isolation (FDI) becomes more and more important since it is a crucial means to maintain system safety and reliability. In general, the nature of faults can be divided into three categories: abrupt fault, incipient fault and intermittent fault. Abrupt faults are step like and persistent, which lead to distinct inconsistency in the monitored system. Incipient faults are slowly developing and usually describe the wear and ageing of system components. Incipient faults are relatively difficult to handle due to the slowly developing nature and the compensation of the feedback control. Intermittent faults usually last for a short time period and are difficult to anticipate. A model based FDI method works by evaluating the system's behavior model using sensor measurement and parameter values. The FDI performance dependents on the quality the model and the modeling is a demanding step. Fortunately, Bond Graph (BG) provides an efficient way to model a complex system with different energy domain, such as mechanical, electrical and hydraulic, etc, in a unified framework. In recent years, BG based FDI has been successfully applied to different engineering fields, such as mobile robot (Arogeti et al., 2009), air conditioning systems, and industrial steam generator (Medjaher et al., 2006), etc.

Many modern complex engineering systems can be modeled as hybrid systems. These systems consist of continuous dynamics and discrete states represented by modes. Within each mode, the system is represented by continuous dynamics and different modes correspond to different continuous behavior. In real life, hybrid systems include examples like Switched mode power converter, high speed printers and so on. Health monitoring of hybrid systems is relatively difficult because system continuous dynamics as well as discrete events must be available for FDI purpose. There are several works concerning hybrid system diagnosis. A discrete model-based approach is proposed for mode estimation and fault detection of hybrid systems (Koutsoukos et al., 2001), where a timed Petri net is used to abstract away the continuous dynamics and to represent only the temporal discrete event evolution of the system. This method, although general, needs domain-specific knowledge for offline generation of a fault-symptom table. The FDI of a hybrid system is based on structured parity residuals, which is also known as analytical redundancy relations (ARRs), and the model is described as a hybrid automaton (Cocquempot et al., 2001). Faults affecting discrete evolution are detected by a mode-tracking technique, based on residuals and discrete dynamical model.

An extended BG-based modeling approach named Hybrid Bond Graph (HBG) is proposed to extend the benefits of BG to hybrid systems. The HBG uses controlled junctions to model discrete mode changes (Mosterman et al., 1998). The concept of HBG has been utilized to develop a qualitative/quantitative diagnosis framework for abrupt parametric faults in hybrid systems (Narasimhan et al., 2007).The fault isolation is based on a qualitative approach, i.e. Temporal Causal Graph (TCG), to narrow the set of fault hypotheses. A similar qualitative fault isolation method is proposed to consider multiple faults for continuous system (Daigle et al., 2007).

Recently, a new concept of Global Analytical Redundancy Relations (GARRs) has been proposed to extend the Analytical Redundancy Relations (ARRs)-based fault diagnosis to hybrid systems (Low et al., 2010). GARRs describe the behavior of the hybrid system at all operating modes and they are derived systematically from the hybrid bond graph model of the hybrid system. GARRs lay the base for some issues related to health monitoring of hybrid systems, such as monitoring ability analysis (Low et al., 2010), mode tracking (Arogeti et al., 2010), single fault parameter estimation (Yu et al., 2010), and fault prognosis (Yu et al., 2010).

This paper proposes an innovative quantitative Fault isolation technique for hybrid systems with multiple faults of unknown nature under the condition that faults start at a non-detectable mode. The fault could be abrupt fault or incipient fault and unknown in advance. Once a fault is detected, a set of fault candidates is generated from the mode dependent-fault signature matrix (MD-FSM) tables, and a set of fault pattern hypothesis is established from the fault candidates set. A multiple nonlinear least square optimization (MNLSO) algorithm is presented, in which a bank of NLSO estimators runs in parallel, each based on one element in the fault pattern hypothesis set chosen from the fault isolation module, to estimate the parameter values for abrupt faults or the parameters of the dynamics of incipient faults. The objective function values of all NLSO estimators are compared to choose the true faults with correct nature.

This paper is organized as follows: Section II presents a method for hybrid system modeling and GARRs. Section III provides the details on how to create the set of fault pattern hypothesis from the fault candidates set. The MNLSO algorithm is also addressed. Section IV discusses an example with multiple faults of unknown pattern, and simulation is carried out to verify the proposed methodology. Finally, concluding remarks are given in Section V.

2. BOND GRAPH MODELLING AND GARRs

Bond Graph is a pictorial representation of systems with complex energy interactions and it is based on the energy conservation law (Karnopp et al., 2006). The generalized representation of the system's components in BG allows us to build and combine the behavioral model of a complex system in multiple domains. Fundamentally, a physical system can be described by BG components which include source elements Se and Sf, dissipative element R, storage elements C and I, four junctions 0, 1, TF and GY. These elements are linked by lines representing power bonds. For each bond, there are two energy variables: effort and flow to describe the states of the components. A casual stroke of a bond indicates the direction of effort, while the flow points in the opposite direction. Generally, BG method is considered as not only a modeling tool, but also as a methodology for analysis of dynamical systems and also as an auxiliary technique for controller design. Moreover, a BG model allows a structure analysis of the system and offers different techniques for model simplification, order reduction and sensor placement.

Unlike other modeling method such as state space modeling, the system structure and all components under consideration are clearly presented on the graph. Therefore, it is convenient for fault isolation. BG modeling has been used for both qualitative and quantitative FDI. In quantitative BG based FDI, there are two kinds of methods, namely, analytical or symbolic based method and numerical based method. Symbolic based method usually needs the derivation of ARRs, and through elimination of unknown variables from the corresponding BG model using causal path, ARR equations can be obtained and FSM can be established. In order to derive ARRs, all the storage elements in the BG model are assigned derivative causality by allowing inversion of sensor causality when necessary. The number of residuals theoretically is equal to the number of sensor mounted on the system. As for numerical based method, also termed Diagnostic Bond Graph (DBG), the numerical values for the residuals can be obtained, and the FSM is not generated from the closed form ARRs like classic symbolic based method, but from the causal path. Nevertheless, if the residuals in DBG are represented by equations from the DBG model, they are exactly the same as those ARRs of symbolic based method, and FSM also will be same. When ARRs cannot be symbolically solved, DBG is preferred (Samantaray and Ould Bouamama, 2008).

HBG extends the ability of BG to model hybrid systems using controlled junctions. However, changes in configuration through the various operating modes of the system can result in reassignment of causality. The derivation of GARRs from HBG needs consistent causality description at all modes. Such description can be achieved by the Diagnostic Hybrid Bond Graph (DHBG) (Low et al., 2008). A DHBG is a HBG that is assigned with proper set of causalities, such that the causality of every active BG component is valid and consistent at all modes. In a DHBG, a controlled junction output variable is only allowed to be the input variable of the following: a 1-port component (R , C and I); a source element if the source if null when the junction is OFF; another controlled junction of different type which shares the identical state; or a 2-port component (TF , GY) with two controlled junctions at its both side having identical state. In all of the cases mentioned above, the causality change due to the mode changes of the controlled junction is limited to the bonds connected to the inactive components, therefore a DHBG is achieved. For all other cases, for example, if the controlled junction output variable is an input variable of a standard BG junction (i.e. 1-type junction and 0-type junction), causality conflicts will result in reassignment of causality and a DHBG is not achieved. If a component output variable is fed to a component that is inactive when the junction is OFF, then the controlled junction is said to be in its preferred causality. If all the controlled junctions in HBG are assigned with preferred causality, then the causality conflicts can be avoided. A systematic causality assignment procedure, named Sequential Causality Assignment Procedure for Hybrid systems (SCAPH) is developed to provide preferred causality for controlled junctions.

Similar to ARRs for FDI of continuous systems, a set of unified constraint, named Global Analytical Redundancy Relations (GARRs), is developed to describe the behavior of a hybrid system at all modes (Low et al., 2010). Without loss of generality, GARR equations take the following form

$$g_l(\theta,\alpha,De,Df,u)=0 \text{ for } l=1,2,\ldots,m \quad (1)$$

where m represents the number of GARRs derived from the HBG; $\theta=[\theta_1,\theta_2,\ldots,\theta_m]^T$ denotes the nominal parameters of the HBG components which are assumed to be known during fault-free operation; $\alpha=[a_1,a_2,\ldots a_q]^T$ indicates the mode switching states of the q controlled junctions; u represents system input; De and Df denote the effort and flow sensors.

Once the GARR equations are obtained, the mode dependent-fault signature matrix (MD-FSM) tables can be established, from which the monitoring ability analysis of the monitored hybrid system can be carried out. Since the hybrid systems are multiple modes in nature, different components may exhibit different monitoring ability under different modes.

3. MULTIPLE FAULTS ISOLATION

Table 1 MD-FSM at $a=0$.

	r_1	r_2	r_3	D_b
θ_1	1	0	0	1
θ_2	0	0	0	0
θ_3	0	0	1	1
θ_4	0	1	1	1
θ_5	0	0	0	0
θ_6	0	1	0	1

Table 2 MD-FSM at $a=1$.

	r_1	r_2	r_3	D_b
θ_1	1	0	0	1
θ_2	0	0	1	1
θ_3	0	0	1	1
θ_4	0	1	1	1
θ_5	0	0	1	1
θ_6	0	1	0	1

Fault detection process evaluates the GARRs $g_l(\theta,n)$ of a hybrid system with n being the discrete sampling index. If a fault-detectable component, i.e. $\theta_i\in\theta$, is faulty, the GARRs $g_l(\theta,n)$ that contains θ_i will be nonzero, and hence a fault is detected. After a fault is detected, N finite sample data are captured, so $n=1,2,\ldots,N$. The fault isolation module is activated and its objective is to find a set of suspected fault candidates leading to the fault signature observed from the fault detection process. If a fault is detected at the time of mode change, then the fault candidates only include the parameters of such fault signature which is non-detectable in the previous mode. This indicates that if a fault occurs at the detectable mode, it will be detected before mode changes; on the contrary, if a fault occurs at the non-detectable mode, this fault will be detected only when the system enters a new mode in which the fault is detectable. Let us consider Mode Dependent-FSM (MD-FSM) tables shown in Table 1 and Table 2. In the tables, $\alpha\in\{0,1\}$ represents the operating mode of the hybrid system; θ_i , $i=1,\ldots,6$, denote the parameters; r_i , $i=1,\ldots,3$, denote the three residuals. The initial mode is $a=0$, and the modes change at 5 second. When residual r_3 becomes abnormal at 5 second, it leads to a coherence vector $C=\begin{bmatrix}0 & 0 & 1\end{bmatrix}$ at mode $a=1$, from Table 2 the fault could be due to changes of either θ_2, θ_3 or θ_5, or their combination, however, the fault is detected at the time of mode change, and only θ_2 and θ_5 are non-detectable at previous mode $a=0$, therefore, the suspected fault candidates set could be $\delta=\{\theta_2,\theta_5,\theta_2\,\&\,\theta_5\}$. Note that in the MD-FSM, the fault isolability (I_b) is not involved because unlike fault analysis under single fault assumption, even the fault signature of a component is unique, it is still possible that the signature results from one or more faults occurring simultaneously. Since the pattern of fault, i.e. abrupt fault or incipient fault, is unknown in advance, a fault pattern hypothesis set is generated from the fault candidates set. Since both θ_2 and θ_5 could be abrupt fault or incipient fault, the fault pattern hypothesis set is:

$$\varsigma=\{\theta_2^A,\theta_2^I,\theta_5^A,\theta_5^I,\theta_2^A\,\&\,\theta_5^A,\theta_2^I\,\&\,\theta_5^I,\theta_2^A\,\&\,\theta_5^I,\theta_2^I\,\&\,\theta_5^A\}$$

where θ_i^A denotes abrupt fault and θ_i^I denotes incipient fault, and any of these elements occurring supports the inconsistency.

From parameter identification viewpoint, $g_l(\theta,n)=0$ if the parameters θ are the physical parameters of the system. If the fault is incipient fault, the original parameter identification problem is transformed into the incipient fault dynamical model coefficient identification problem. Assume that the incipient fault follows the dynamic behavior of $\dot{\theta}=a\cdot\theta$, so if θ_i is the true incipient fault, then the GARR $g_l(\theta,n)$ that contains θ_i can be reformulated as

$$g_l(sol,\theta_j,n),\ \text{with}\ sol=\theta_i(0)\exp(a\cdot t) \qquad (2)$$
$$t=n\cdot t_s,\ j=1,\ldots,m\ \text{and}\ j\neq i$$

where t_s is the sampling period. Note that in the solution the initial condition $\theta_i(0)$ is not equal to the nominal value of θ_i since the fault initiates at the non-detectable mode, therefore, $\theta_i(0)$ is also an unknown coefficient which needs to be estimated.

Generally, $g_l(\theta,n)$ is a nonlinear function of θ, so without loss of generality, the estimation process is formulated as a nonlinear least-square problem. Let θ' is a set containing true abrupt fault parameters and incipient fault dynamical model coefficients and initial condition values, and the objective function for the nonlinear least square problem based on N samples of data as follows

$$J(\theta')=\frac{1}{2}r^T r \qquad (3)$$

where $r=\begin{bmatrix}r_1 & r_2 & \cdots & r_N\end{bmatrix}^T$,

and $r_n=\begin{bmatrix}g_1(\theta',n) & g_2(\theta',n) & \cdots & g_m(\theta',n)\end{bmatrix}^T$ for $n=1,2,\ldots,N$.

According to Gauss-Newton method, the iterative solution which minimize the objective function (3) is

$$\theta'_{k+1}=\theta'_k-H_J(\theta'_k)^{-1}\nabla J(\theta'_k) \qquad (4)$$

where k denotes the iteration index , and

$$\nabla J(\theta'_k)=\frac{\partial r(\theta'_k)^T}{\partial\theta}\cdot r(\theta'_k),\ H_J(\theta'_k)=\frac{\partial r(\theta'_k)^T}{\partial\theta}\cdot\frac{\partial r(\theta'_k)}{\partial\theta}.$$

The NLSO estimator is applicable to the condition where there is one element in the fault pattern hypothesis set, if there are more than one element in the set, a multiple nonlinear least square optimization (MNLSO) algorithm is proposed, in which each NLSO estimator is based on one element in the fault pattern hypothesis set, to estimate the parameter values for abrupt faults or the parameters of the dynamics of incipient faults. The bank of NLSO estimators run in parallel, and the objective function of all estimators are compared to choose the true faults with correct pattern. The Block diagram of the MNLSO based fault isolation method is shown in figure 1, in which p denotes the number of elements in the fault pattern hypothesis set.

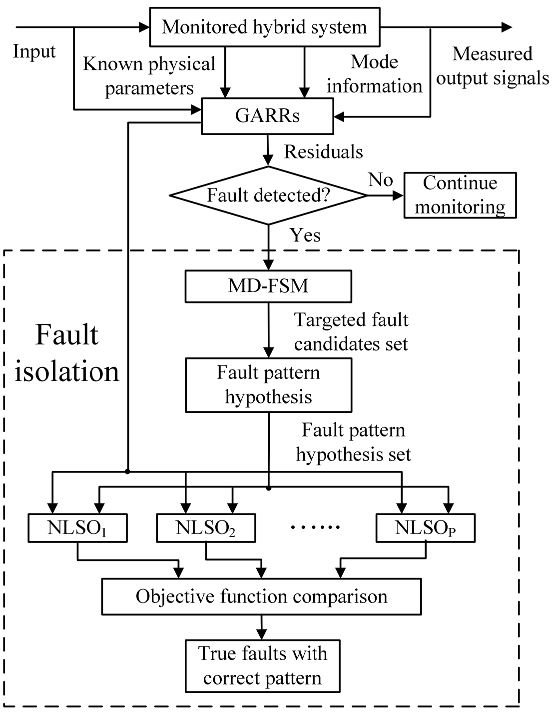

Figure 1 Block diagram of the MNLSO based fault isolation method.

4. ILLUSTRATIVE EXAMPLE

4.1 *System Description*

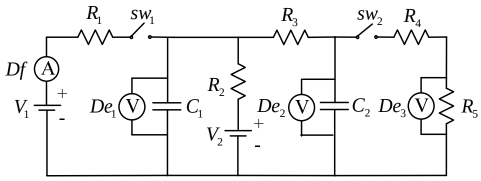

Figure 2 A hybrid system: an electric circuit.

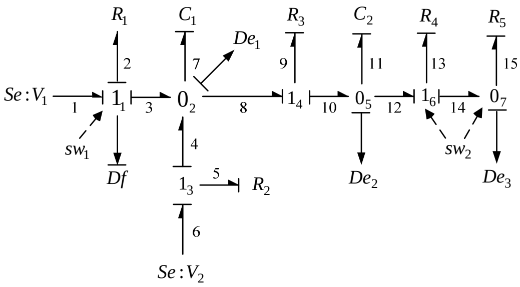

Figure 3 DHBG of the electric circuit.

Figure 2 presents an example of hybrid system in electrical domain whose DHBG is depicted in figure 3. The system consists of five R elements $\{R_1, R_2, R_3, R_4, R_5\}$, two C elements $\{C_1, C_2\}$, two switches sw_1 and sw_2, one current (flow) sensor Df, and three voltage (effort) sensors $\{De_1, De_2, De_3\}$.

First, consider the constitutive relation of junction 1

$$e_1 - e_2 - e_3 = 0 \tag{5}$$

Since f_2 is measurable, $f_2 = Df$ [16], and the causal paths lead e_2 to

$$e_2 = R_1 \cdot Df \tag{6}$$

Substituting (6) into (5), GARR_1 is achieved

$$GARR_1 = a_1(V_1 - R_1 \cdot Df - De_1) = 0 \tag{7}$$

Next, consider 0_2 junction attached to De_1, the constitutive relation of this junction can be expressed as

$$a_1 f_3 + f_4 - f_7 - f_8 = 0 \tag{8}$$

Then tracking back the causal paths yields

$$\begin{gathered} f_3 = Df \\ f_4 = f_5 = \frac{1}{R_2} e_5 = \frac{1}{R_2}(e_6 - e_4) = \frac{1}{R_2}(V_2 - De_1) \\ f_7 = C_1 \frac{d}{dt} e_7 = C_1 \frac{d}{dt} De_1 \\ f_8 = f_9 = \frac{1}{R_3} e_9 = \frac{1}{R_3}(e_8 - e_{10}) = \frac{1}{R_3}(De_1 - De_2) \end{gathered} \tag{9}$$

Substituting (9) into (8) gives

$$\begin{aligned} GARR_2 &= a_1 Df + \frac{1}{R_2}(V_2 - De_1) \\ &- C_1 \frac{d}{dt}(De_1) - \frac{1}{R_3}(De_1 - De_2) = 0 \end{aligned} \tag{10}$$

Using the junction 0_5 with De_2, yields

$$f_{10} - f_{11} - a_2 f_{12} = 0 \tag{11}$$

By following the causal paths, the flow variables f_{10}, f_{11} and f_{12} can be represented as

$$\begin{gathered} f_{10} = f_9 = \frac{1}{R_3} e_9 = \frac{1}{R_3}(e_8 - e_{10}) = \frac{1}{R_3}(De_1 - De_2) \\ f_{11} = C_2 \frac{d}{dt} e_{11} = C_2 \frac{d}{dt} De_2 \\ f_{12} = f_{13} = \frac{1}{R_4} e_{13} = \frac{1}{R_4}(e_{12} - e_{14}) = \frac{1}{R_4}(De_2 - De_3) \end{gathered} \tag{12}$$

The third GARR_3 can be obtained by combining (11) and (12)

$$\begin{aligned} GARR_3 &= \frac{1}{R_3}(De_1 - De_2) - C_2 \frac{d}{dt}(De_2) \\ &- a_2 \frac{1}{R_4}(De_2 - De_3) = 0 \end{aligned} \tag{13}$$

Finally consider junction 0_7, with the constitutive relation

$$f_{14} - f_{15} = 0 \tag{14}$$

Tracking the casual paths, gives

$$f_{14} = f_{13} = \frac{1}{R_4} e_{13} = \frac{1}{R_4}(e_{12} - e_{14}) = \frac{1}{R_4}(De_2 - De_3) \tag{15}$$

$$f_{15} = \frac{1}{R_5} e_{15} = \frac{1}{R_5} De_3 \tag{16}$$

Then GARR_4 is given by

$$GARR_4 = a_2 \left[\frac{1}{R_4}(De_2 - De_3) - \frac{1}{R_5} De_3 \right] = 0 \tag{17}$$

From the four GARRs derived, the MD-FSM can be obtained in Table 3~ Table 6.

Table 3 MD-FSM at $a_1 = 0$, $a_2 = 1$.

	r_1	r_2	r_3	r_4	D_b
C_1	0	1	0	0	1
C_2	0	0	1	0	1
R_1	0	0	0	0	0
R_2	0	1	0	0	1
R_3	0	1	1	0	1
R_4	0	0	1	1	1
R_5	0	0	0	1	1

Table 4 MD-FSM at $a_1 = 1$， $a_2 = 0$.

	r_1	r_2	r_3	r_4	D_b
C_1	0	1	0	0	1
C_2	0	0	1	0	1
R_1	1	0	0	0	1
R_2	0	1	0	0	1
R_3	0	1	1	0	1
R_4	0	0	0	0	0
R_5	0	0	0	0	0

Table 5 MD-FSM at $a_1 = 0$， $a_2 = 0$.

	r_1	r_2	r_3	r_4	D_b
C_1	0	1	0	0	1
C_2	0	0	1	0	1
R_1	0	0	0	0	0
R_2	0	1	0	0	1
R_3	0	1	1	0	1
R_4	0	0	0	0	0
R_5	0	0	0	0	0

.

Table 6 MD- FSM at $a_1 = 1$， $a_2 = 1$.

	r_1	r_2	r_3	r_4	D_b
C_1	0	1	0	0	1
C_2	0	0	1	0	1
R_1	1	0	0	0	1
R_2	0	1	0	0	1
R_3	0	1	1	0	1
R_4	0	0	1	1	1
R_5	0	0	0	1	1

4.2 *Simulation Result*

MATLAB 7.0 is used to test the proposed fault isolation method for the hybrid system. The physical parameters of the circuit are: $V_1 = 7\text{Volt}$, $V_2 = 1\text{Volt}$, $R_1 = 670\Omega$, $R_2 = 215.6\Omega$, $R_3 = 67.5\Omega$, $R_4 = 215.4\Omega$, $R_5 = 509\Omega$, $C_1 = 10000\mu\text{F}$, $C_2 = 4700\mu\text{F}$, sampling time t_s is 0.05 s. Two faults are introduced, the first one is a gradual buildup of resistance introduced in R_4 at $t = 5\text{s}$, the coefficient of the incipient fault is set as $a = 0.05$, and the other one is an abrupt fault introduced in R_5 at $t = 6\text{s}$, in which R_5 changes from 509Ω to 350Ω. The fault profile is shown in figure 4. The switches programming is shown in Figure 5. Figure 6 illustrates the responses of residuals due to the faults in R_4 and R_5, in the figure, dash line denotes the thresholds $\varepsilon_1 = 2e-3$, $\varepsilon_2 = 2e-2$, $\varepsilon_3 = 0.6e-3$ and $\varepsilon_4 = 5e-4$. If the residual exceeds the predetermined threshold, and system is considered as faulty. According to the MD-FSM tables, it is obvious that the faults in R_4 and R_5 initiate at a non-detectable mode, i.e. $a_1 = 0$ and $a_2 = 0$, hence the faults cannot be detected until the system enters a mode in which the

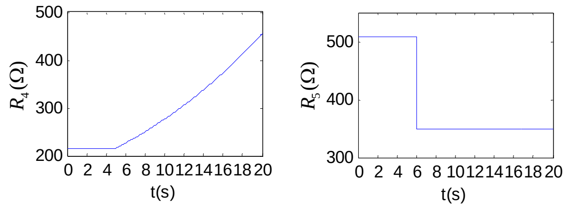

Figure 4 Fault profile in electrical circuit.

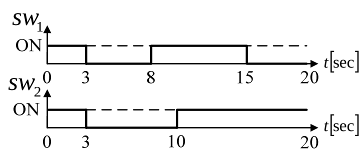

Figure 5 Switches programming for simulation.

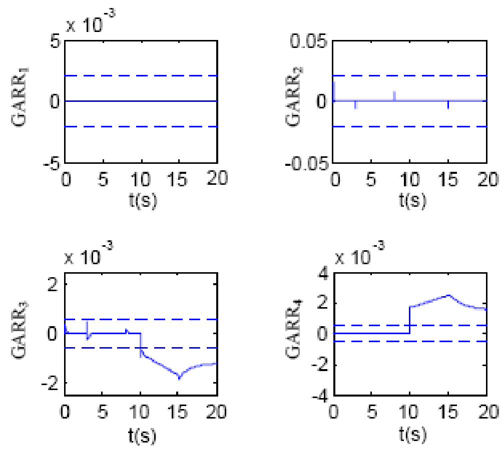

Figure 6 Residual responses for multiple faults.

faults are detectable, i.e. $t = 10s$. Figure 5 reveals that residual r_3 and r_4 are sensitive to the faults at mode $a_1 = 1$ and $a_2 = 1$. All observations have been captured from the moment that a fault is detected. With an observation window of 10 seconds, two hundred of sample data ($N = 200$) are collected after the fault occurrence. From the MD-FSM table at that mode, R_4 and R_5 have fault signature $[0 \quad 0 \quad 1 \quad 1]$ and $[0 \quad 0 \quad 0 \quad 1]$, respectively. According to the MD-FSM table at mode $a_1 = 1$ and $a_2 = 1$, R_4 and R_5 are non-detectable at previous mode $a_1 = 1$ and $a_2 = 0$, and the fault signature $[0 \quad 0 \quad 1 \quad 1]$ may result from one or more faults occurring simultaneously, and also the faults are detected exactly at the time of mode change, hence the targeted fault candidates set is $\delta = \{R_4, R_4 \,\&\, R_5\}$. Since no fault pattern information is available in advance, in order to achieve fault isolation, the fault pattern hypothesis set is obtained as $\varsigma = \{R_4^A, R_4^I, R_4^I \,\&\, R_5^I, R_4^A \,\&\, R_5^I, R_4^I \,\&\, R_5^A, R_4^A \,\&\, R_5^A\}$. To further refine the isolation results, six NLSO estimators in MNLSO run in parallel, each based on one element from the fault pattern hypothesis set.

Table 7 Objective function values comparison.

Fault pattern	R_4^A	R_4^I	$R_4^I \,\&\, R_5^I$
Objective function values	0.38e-4	0.27e-4	0.53e-4
Fault pattern	$R_4^A \,\&\, R_5^I$	$R_4^I \,\&\, R_5^A$	$R_4^A \,\&\, R_5^A$
Objective function values	0.10e-4	0.03e-4	0.17e-4

Table 7 lists the objective function values of different element in the fault pattern hypothesis set. It is obvious that the faults are in $R_4 \,\&\, R_5$ with fault pattern $R_4^I \,\&\, R_5^A$, not in the other elements in the fault pattern hypothesis set. Figure 7 shows the estimated values for $R_4^I \,\&\, R_5^A$ versus iterations, the estimated results are $\theta^{'} = [\hat{a} \quad \hat{R}_4(0) \quad \hat{R}_5] = [0.049 \quad 275.89 \quad 349.24]$, which are very close to the designed values $[a \quad R_4(0) \quad R_5] = [0.05 \quad 276.57 \quad 350]$. The simulation results confirm that the proposed method can accurately isolate multiple faults with unknown fault pattern for hybrid systems.

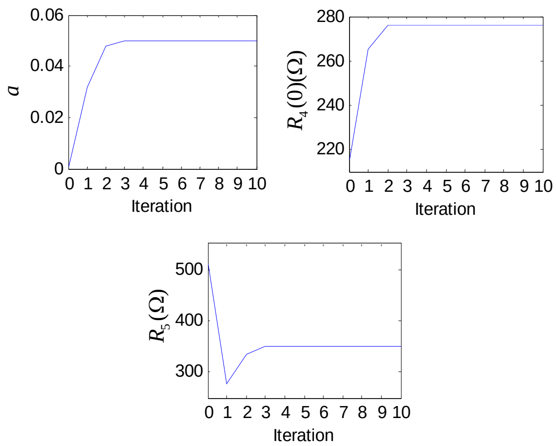

Figure 7 Estimated parameters $\theta^{'} = [\hat{a} \quad \hat{R}_4(0) \quad \hat{R}_5]$.

5. CONCLUSION

In this paper, a method dealing with multiple faults isolation is proposed for hybrid systems with unknown fault pattern. The unified property of GARRs is utilized to formulate the fault estimation problem as a nonlinear least square optimization, and solve it using Gauss-Newton technique. Since the fault pattern is unknown in advance, once the fault candidates set is obtained, a fault pattern hypothesis set is created for further refinement. A MNLSO algorithm is presented to find the true faults with correct pattern. The simulation results suggest the effectiveness of the proposed method. Future works will be devoted to multiple faults isolation for hybrid systems with unknown mode changes.

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