*Chapter 6: Fault Diagnostics*

# A Bond Graph Model-Based Fault Detection and Isolation

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## 1. Introduction

Industrial systems are more and more complex due, in part, to their growing size and to the integration of new technologies. With ageing, these systems become more vulnerable to failures and their maintenance difficult and expensive. According to statistical data, 70% of industrial accidents are due to human errors [39]. In spite of the advances achieved in the control domain and in the computational capabilities in the field of process engineering, severe accidents have occurred in the last years: AZF of Toulouse, Union Carbide's Bhopal plant in India, the explosion at the Kuwait Petrochemical's Mina Al-Ahmedi refinery which resulted in hundreds of millions of dollars in damages, but especially the injury and death of many people. To avoid these situations and in order to satisfy additional requirements of productivity, operational availability and safety; industrials and researchers are looking for innovative tools and methods. To do this, one of the possible levers consists in detecting as soon as possible the probable failures on the system. Indeed, once the fault is detected and diagnosed, one can proceed to maintain the system in order to reduce its global life cycle costs, to increase its availability, to improve the safety of operators and to reduce the environmental incidents. Maintenance tasks can be curative or preventive. In curative maintenance framework, the components are replaced only when they are not able to fulfil the task for which they are designed. To support the curative maintenance, Fault Detection and Isolation (FDI) procedures can be implemented.

FDI procedures are based on the comparison between the actual process behaviour and the theoretical reference process behaviour given by a model. Reviews of process fault detection and isolation methods can be found in [36, 37, 38, 40, 12]. According to the knowledge and the quality of data available for the process, the FDI methods developed and reported in the literature can be classified into two main approaches, namely: qualitative FDI and quantitative FDI.

Quantitative FDI approach [11, 27] (also called model-based approach) includes parity space methods, parameter estimation techniques, state observers, etc. It can be used in the case where the process for which one aims to perform a fault diagnostic is sufficiently known so that a model that reflects as faithfully as possible its dynamic behaviour can be derived. Thus, quantitative methods are strongly dependent on the availability of an explicit analytical model to perform FDI on the process. The obtained model is used to generate what is called fault indicators (analytical redundancy relations, residuals, etc.). The online evaluation and analysis of these indicators allow to detect and to isolate faults affecting the process.

Qualitative FDI approach [37, 38], does not use specifically analytical models and its methods are generally derived from artificial intelligence techniques (neural networks, expert systems, case based reasoning, etc.). Instead of quantitative methods, the qualitative approach can be used in cases where the analytical model is difficult to obtain or simply does not exist.

The detection and the isolation of the faults on a given process consist in two main steps. The first step provides the possible inconsistencies between the process model and its actual behaviour. These discrepancies are called residuals and are in fact signals resulting from the comparison between the model's outputs and the actual outputs of the process measured by the sensors [36]. This comparison can be obtained from analytical or knowledge based constraints, called redundancies. A good account of such redundancy based methods is given in [8, 22, 18]. The second step in a FDI method is the decision procedure, which allows locating or isolating the fault and possibly identifying its origin.

In quantitative model based approache, getting a refined model with all known parameters, and which can reflect faithfully the behaviour of the system, is not a trivial task. Moreover, in real engineering systems, the physical phenomena (hydraulic, thermal, chemical, etc.) are strongly coupled and the models are often nonlinear. Modelling such processes needs a multidisciplinary and a unified tool. This is why, the bond graph methodology [32, 13, 19] as a graphical and a unified multi-energy domain modelling tool is proving to be a convenient representation.

Various bond graph based qualitative and quantitative FDI approaches have been developed to detect and to isolate faults in single or piecewise single energy domains [31, 15, 16, 7]. These methods rely on the generation of what is called Analytical Redundancy Relations (ARRs).

An ARR is a static or a dynamic constraint which links the time evolution of the known variables when the system operates according to its normal operation model. It can be derived from a set of equations or constraints by eliminating the unknown variables. For this, various structural analysis or polynomial approaches can be used [8]. In linear cases, the elimination of unknown variables can be performed by using projection techniques leading to parity space residuals (note that a residual is a result of a numerical evaluation of its corresponding ARR) [5]. However, eliminating the unknown variables is not always an easy task, especially for nonlinear systems.

The FDI method proposed in section 3 is based on the use of a bond graph tool. This method is particularly suitable for multi-physical systems, where several types of energy are involved. The use of bond graph allows easily deriving analytical models, eliminating the unknown variables and generating ARRs. The elimination process is based on the exploitation of the causal and the structural properties of bond graph [6, 31, 25, 23, 22].

## 2.    Definitions and Terminology

For the sake of clarity, and before presenting the proposed model-based FDI method, it is useful to recall some necessary definitions and terminology used hereafter.

*Chapter 6: Fault Diagnostics*

- **Bond graph generalised variables:** in the following FDI method, the effort (*e*) and the flow (*f*) are used as the generalised bond graph variables. The flow can represent the velocity, the current, the hydraulic flow and other analogue variables depending on the physical domain. Similarly, the effort can represent a force, a torque, a voltage, a pressure and other analogue variables.

- **Analytical Redundancy Relation (ARR):** a constraint derived from an over-constrained sub-system and expressed in terms of known variables of the process [29]. The general form of an ARR is given by the following expression:

$$f(K) = 0 \qquad (1)$$

where *K* is the set of known variables and/or parameters. In a bond graph sense, the set of known variables represents the outer vertices (the flow *Df* and the effort *De* detectors, the flow *Sf* and the effort *Se* sources, the modulated flow *MSf* and effort *MSe* sources, the process inputs *u* and the process parameters θ) [23]. Thus, equation (1) becomes:

$$f(De, Df, Se, Sf, MSe, MSf, u, \theta) = 0 \qquad (2)$$

- **Residual:** numerical evaluation of an ARR.

$$r = f(K) \qquad (3)$$

A residual $r_i$ is sensitive to faults of the $j^{th}$ component if and only if one (or more) parameter belonging to the $j^{th}$ component appears in $r_i$.

- **Fault signature:** binary matrix $S_{ij}$ built from the structure of the residuals. It is obtained by using the following test:

$$S_{ij} = \begin{cases} 1, & \text{if the } i^{th} \text{ residual is sensitive to faults in the } j^{th} \text{ component} \\ 0, & \text{otherwise} \end{cases} \qquad (4)$$

The matrix $S_{ij}$ provides the logic for the process fault isolation once the monitoring system has detected a fault. Each component has a corresponding signature and its fault is isolable if and only if its signature is unique, i.e. different from the signatures of all other components.

- **Coherence vector:** $C = [c_1, c_2, ...., c_n]$ indicates whether or not a fault (only one fault at each time is assumed in the following method) is present in the process. Each element $c_i$ of C is obtained from a defined decision procedure: $\Phi_i(r_i)$; i.e. $c_i = \Phi_i(r_i)$.

Note that when $c_i = 1$, i.e. $C \neq [0, 0, ...., 0]$, an alarm is generated. Theoretically, if the system is fault-free, then the value of each residual $r_i (i = 1, ..., n)$ is equal to zero. But in practice and in the simplest case, $|\Psi_{\Delta T}(r_i)|$ is bounded by a small value $\varepsilon_i$; where $\Psi_{\Delta T}$ is a residual pre-processor, e.g. a moving average for a

duration of $\Delta T$. The term $\varepsilon_i$ is due to modelling errors and measurement noises. In the simplest case, each element $c_i$ of C is obtained by using the following decision procedure:

$$c_i = \begin{cases} 1, & \text{if} \quad |r_i| > \varepsilon_i \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

The chosen value of $\varepsilon_i$ must neither be too big to avoid the missed alarms (non-detection), nor be too small to avoid the false alarms.

### 3. Bond Graph Model-Based FDI

In the following FDI method, the set of ARRs and the corresponding residuals are obtained from a bond graph model by eliminating the unknown variables. This elimination is possible only when the corresponding system of equations derived from the bond graph model is over-determined (or over-constrained). According to [30], in a set of constraints or equations, a causal assignment associating one or more variables with the set of constraints is called a matching. Those variables which cannot be matched cannot be calculated. Variables which can be matched in more than one way can be calculated by different (redundant) means, thus providing a mean for fault detection and a possibility for reconfiguration. Indeed, any finite-dimensional bipartite graph [30] can be canonically decomposed into three unique sub-graphs with specific properties: an over-constrained subsystem which means that the variables have to satisfy more constraints than the number of unknown variables, a just-constrained subsystem, and an under-constrained subsystem which has less number of constraints than the number of unknown variables.

The aforementioned analysis can be applied on bond graph to perform structural analysis. In fact, the structure of any physical system can be represented by a bond graph model. A bond graph model with a correct causality means that the corresponding system of equations is solvable and then the set of unknown variables can be calculated. This is exactly what is meant by a just determined system. Similarly, if the causality cannot be assigned completely and correctly, the resulting system of equations is termed under-determined. The over-determined sub-systems correspond to the observable sub-graphs in the bond graph model of the system and are used to generate the list of ARRs.

In following FDI method, the model is assumed to satisfy the following conditions:

- All the storage elements in the behavioural bond graph model are in integral causality.

- All the states of the system are observable in the given operating range.

- When preferred derivative causality is assigned to storage elements in the bond graph model, there are no causal loops involving storage elements.

- A single fault hypothesis is considered.

The main steps of the FDI bond graph based method to generate the ARRs, the residuals and the corresponding fault signature matrix are summarized hereafter. Interested readers can find more details about the method in [25, 22].

- Build the bond graph model in preferred integral causality.

- Put the bond graph model in preferred derivative causality (with sensor causality inversion if necessary).

- Write for each junction its corresponding equations.

- Write the constitutive equation for each bond graph element.

- Eliminate the unknown variables from each junction equation involving a detector (or a sensor) by covering the causal paths on the bond graph model in derivative causality.

- Generate the ARRs, the residuals and the corresponding fault signature matrix.

Note that the number of generated ARR is equal to the number of detectors (or sensors) on the bond graph model for an observable system and with none unresolved algebraic loops [22].

## 4. Application Example

The FDI method presented in the previous section is applied on a mechatronic system shown in Fig. 1 and taken from [13].
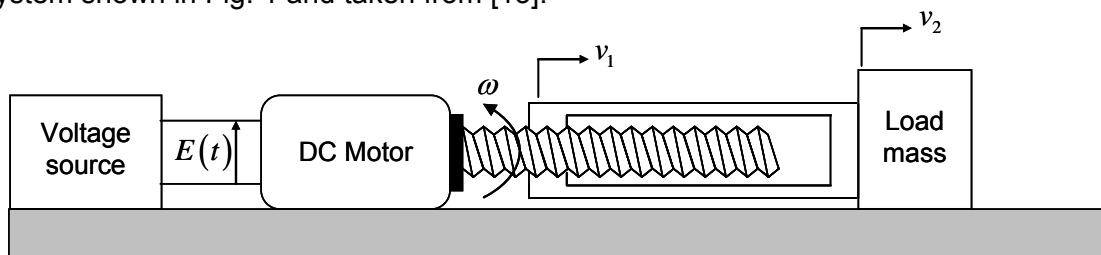


Figure 1. A mechatronic system.

Figure 1 shows the physical part of a load positioning system without the sensors and the controller. The corresponding bond graph model in preferred integral causality of the system is given in Fig. 2, where the $C:1/k$ element represents the elasticity of the tube connecting the nut to the load mass. The model in Fig. 2 contains 2 additional sensors represented by two flow detectors: $Df:\omega$ and $Df:v_2$.
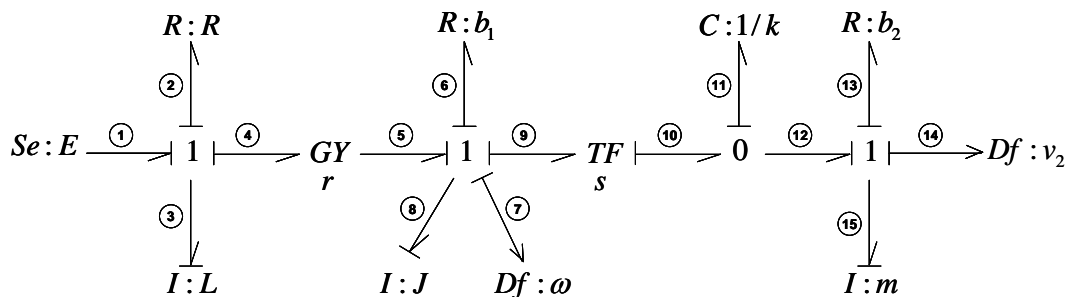


Figure 2. Bond graph model in preferred integral causality.

In order to derive appropriate equations and generate the ARRs and the corresponding residuals, the bond graph model of Fig. 2 is put in derivative causality as shown in Fig. 3.
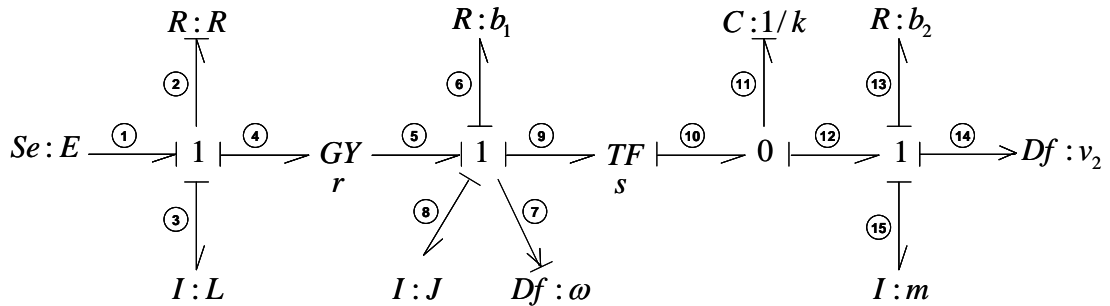


Figure 3. Bond graph model in derivative causality.

The junction ("1", "GY", "1", "TF", "0" and "1") equations obtained from the bond graph model of Fig. 3 are given by the following expressions:

$$\begin{cases} f_1 = f_3 = f_4 = f_2 \\ e_2 = e_1 - e_3 - e_4 \end{cases} ; \begin{cases} e_4 = r.f_5 \\ e_5 = r.f_4 \end{cases} ; \begin{cases} f_5 = f_6 = f_8 = f_9 = f_7 \\ e_7 = e_5 - e_6 - e_8 - e_9 \end{cases} ; \begin{cases} e_9 = s.e_{10} \\ f_{10} = s.f_9 \end{cases} ; \begin{cases} e_{10} = e_{11} = e_{12} \\ f_{12} = f_{10} - f_{11} \end{cases} ; \quad (6)$$

$$\begin{cases} e_{12} = e_{13} + e_{14} + e_{15} \\ f_{13} = f_{14} = f_{15} = f_{12} \end{cases} \quad (7)$$

Note that in the above equations only generalized bond graph variables are used. They will be replaced by the physical variables once the ARRs are obtained.

Similarly, the constitutive equations corresponding to the bond graph elements of Fig. 3 are expressed as follow:

$$f_2 = \frac{1}{R} e_2 \; ; \; e_3 = L \frac{df_3}{dt} \; ; \; e_6 = b_1 f_6 \; ; \; e_7 = J_1 \frac{df_7}{dt} \; ; \; f_{11} = \frac{1}{k} \frac{de_{11}}{dt} \; ; \; e_{13} = b_2 f_{13} \; ; \; e_{15} = m \frac{df_{15}}{dt} \quad (8)$$

The ARRs can then be generated by using the above equations. For this application, two ARR can be obtained. Indeed, because the system is fully observable, the number of ARRs is equal to the number of detectors (or sensors) in the model. Each ARR is derived by writing the junction equation to which the detector is connected.

Thus, the first ARR comes from junction equation to which the flow detector $Df : \omega$ belongs:

$$e_7 = e_5 - e_6 - e_8 - e_9 \quad (9)$$

The replacement of each unknown variable of the above equation by known leads to an ARR. Thus $e_7 = 0$, which a strict application of the definition of a flow detector. The remaining variables of equation (9) can be eliminated by using the following equations:

$$e_5 = r.f_4 = r.f_2 = \frac{r}{R}.e_2 = \frac{r}{R}.\left( E - L\frac{df_3}{dt} - r.f_7 \right) \tag{10}$$

where

$$f_3 = f_4 = \frac{e_5}{r} = \frac{1}{r}.\left( e_6 + e_8 + e_9 \right) \tag{11}$$

and

$$e_6 = b_1.f_7 = b_1.\omega \;\; ; \;\;\; e_8 = J_1.\frac{d\omega}{dt} \;\; ; \;\;\; e_9 = s.e_{10} = s.\left( e_{13} + e_{14} + e_{15} \right) = s.\left( b_2.v_2 + 0 + m.\frac{dv_2}{dt} \right) \tag{12}$$

Thus :

$$f_3 = \frac{1}{r}.\left( b_1.\omega + J_1.\frac{d\omega}{dt} + s\left( m.\frac{dv_2}{dt} + b_2.v_2 \right) \right) \tag{13}$$

The first ARR is then given by the following equation:

$$ARR_1 : \frac{r}{R}.\left( E - \frac{L}{r}\frac{d}{dt}.\left( b_1.\omega + J_1.\frac{d\omega}{dt} + s\left( m.\frac{dv_2}{dt} + b_2.v_2 \right) \right) - r.\omega \right) - b_1.\omega - J_1.\frac{d\omega}{dt} - s\left( m.\frac{dv_2}{dt} + b_2.v_2 \right) = 0 \tag{14}$$

The corresponding residual is given by the following relation:

$$r_1 : \frac{r}{R}.\left( E - \frac{L}{r}\frac{d}{dt}.\left( b_1.\omega + J_1.\frac{d\omega}{dt} + s\left( m.\frac{dv_2}{dt} + b_2.v_2 \right) \right) - r.\omega \right) - b_1.\omega - J_1.\frac{d\omega}{dt} - s\left( m.\frac{dv_2}{dt} + b_2.v_2 \right) \tag{15}$$

The second ARR can be generated by writing the junction equation to which the detector $Df : v_2$ is connected. It can be obtained by applying the same approach as for ARR$_1$.

$$e_{12} = e_{13} + e_{14} + e_{15} \tag{16}$$

The elimination of the unknown variables in equation (13) is performed as follows:

$$e_{14} = 0 \;\; ; \;\;\; e_{15} = m.\frac{df_{15}}{dt} = m.\frac{dv_2}{dt} \;\; ; \;\;\; e_{12} = e_{11} = k\int f_{11}dt = k\int \left( f_{10} - f_{12} \right)dt = k\int \left( s.\omega - v_2 \right)dt \tag{17}$$

The second ARR is then:

$$ARR_2 : k\int \left( s.\omega - v_2 \right)dt - m.\frac{dv_2}{dt} - b_2.v_2 = 0 \tag{18}$$

However, in order to avoid initial conditions, a derivative operation is done on the above equation. Thus the final second ARR is:

$$ARR_2 : k\left(s.\omega - v_2\right) - m.\frac{d^2 v_2}{dt^2} - b_2.\frac{dv_2}{dt} = 0 \tag{19}$$

The corresponding residual is:

$$r_2 = k\left(s.\omega - v_2\right) - m.\frac{d^2 v_2}{dt^2} - b_2.\frac{dv_2}{dt} \tag{20}$$

The fault signature matrix corresponding to this mechatronic example is deduced from $ARR_1$ and $ARR_2$. The rows of this binary matrix correspond to the residuals and the columns correspond to the possible faults on the physical components of the system.

|  | DC motor | Screw-nut | Elasticity | Load | Sensor $\omega$ | Sensor $v_2$ |
|---|---|---|---|---|---|---|
| $r_1$ | 1 | 1 | 1 | 1 | 1 | 1 |
| $r_2$ | 0 | 1 | 0 | 1 | 1 | 1 |
| $D_b$ | 1 | 1 | 1 | 1 | 1 | 1 |
| $I_b$ | 0 | 0 | 0 | 0 | 0 | 0 |

Table 1. Fault signature matrix

In addition to rows representing the residuals, two additional rows are added: the fault detectability $D_b$ and the fault isolability $I_b$. A "1" value on respectively $D_b$ and $I_b$ columns means that faults on the corresponding components are detectable and isolable. Similarly, the presence of a "1" value on $r_1$ and $r_2$ columns shows the influence of the corresponding components on the residual variations. From table 1, one can conclude that all the faults are detectable but none is isolable.

## 5. Conclusion

A model based FDI method is presented, where the model is built by using the bond graph tool. The method is suitable and applicable for multi-physical systems where several energy domains are involved. The most part of the work of this method consists in constructing a correct and faithful bond graph model that represents the physical phenomena of the system. Once this task performed the ARRs and residuals generation is straightforward.

However, the real implementation of the proposed FDI method needs other tasks which are not presented here. They concern the processing of the data provided by the sensors, the definition of the fault thresholds and the implementation of the decision logic to detect and to isolate the faults.

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