

Robust diagnosability of PEMFC based on Bond Graph LFT.

B.OULD BOUAMAMA¹, M. BRESSEL^{2,1}, D. HISSEL² and M. HILLAIRET²

Abstract— Fuel cell (FC) is one of the best alternatives of fossil energy. Recently, the research community of fuel cell has shown a considerable interest for diagnosis in view to ensure safety, security, and availability when faults occur in the process. The problematic for model based FC diagnosis consists in that the model is complex because of coupling of several kind of energies and the numerical values of parameters are not always known or are uncertain. The present paper deals with use of one tool: the Linear Fractional Transformation bond graph tool not only for uncertain modelling but also for monitorability (ability to detect and isolate faults) analysis and formal generation of robust fault indicators with respect to parameter uncertainties. Application concerns FC system.

Keywords—Bond graph, Fuel Cell, Fault Detection and Isolation (FDI), Robust Diagnosis, Structural Analysis.

I. INTRODUCTION

Fuel cell (FC), the devices that convert chemical energy, such as hydrogen, are an ideal electrical power source: lower/zero emission, silent, high efficiency. A FC produces only electricity, water, and heat, thereby eliminating pollution at the energy conversion. This is one of the reasons why fuel cell is attractive. Recently, the research community of FC has shown a considerable interest for Fault Detection and Isolation (FDI) in order to ensure safety, security, when faults occur. These faults must be detected early and sometime estimated and accommodated

The problematic for FDI of FC consists in that the model is complex where occur several kind of energies (Electrical, mechanical, electro-chemical) and the numerical values are not always known or uncertain. This is why structural model (based on existence or not of the links between variables and the relations) is well suited for analysis and FDI design. Few works deal with structural analysis applied to fuel cell systems.

There has been a significant research in the area of model based fault detection [1]-[4]. The analytical redundancy approach consists in finding the over constrained subsystem (representing the monitorable part of the overall system) since it is the only one to exhibit some redundancies. The first step consists in generating a set of residuals (relations between the known variables of the system) used for alarm generation in presence of faults. The second step consists in fault isolation using the generated fault indicators (called Analytical Redundancy

Relations (ARRs)) from which is deduced the fault signature matrix using specific logic.

A key factor determining the performance of FDI techniques is the model accuracy. Once this is established, the FDI performance in terms of monitorability or diagnosability (the ability to detect and isolate faults) can be established by formal analysis of the analytical fault models derived from the system models. FDI methods based on quantitative analysis suffer from a number of problems. Their behaviors are typically defined by high order differential equations with complex nonlinearities that are hard to model and analyze using analytical or numerical schemes. However, graphical methods present a big interest because their models capture system structure by representing the system variables and set of behavior equations just as nodes and arc. Furthermore, the graph structure is independent of the numerical values of the system parameters. This is why graphical methods are well suited for defining qualitative diagnosis methods.

A graph theory was enormously developed and widely used to study the structural analysis problem [5]-[8]. Determination of diagnosability properties (which components can be monitored and how to make them monitorable based on optimal sensor placement) could be very useful before industrial implementation.

Most of developed graphical models are based on directed and bipartite graphs which are powerful and efficient to study many system properties, such as observability, controllability and diagnosability. However, bipartite graphs and digraphs use analytical mathematical models for generating the structural model. The digraph [5] is usually generated and formed from linear state equations and the bipartite graph is deduced from the set of constraints (derived from state equations or first principle methods) [9], [6], [4].

For the digraph [5], the diagnosability analysis concerns only actuators and sensors while the graph is deduced from state equation (nodes are inputs, state variables and measurement). Lack of the cited methods consist in that the architecture of the system is not explicitly displayed, the considered faults are generally input and output vertices of the graph and are not associated with a physical component while dynamic model is given under analytical equations or state space format (often linear).

¹Belkacem OULD BOUAMAMA, Full Professor with Lille University, Ecole Polytechnique de Lille, Avenue Paul Langevin, 59655 Villeneuve d'Ascq. belkacem.ouldbouamama@polytech-lille.fr

^{1,2}Mathieu BRESSEL is a Ph.D student with Lille University and France University of Franche-Comte. Bressel.mathieu@gmail.com

² Daniel HISSEL and Mickael HILLAIRET are Full Professor FC-LAB Research, FR CNRS 3539, Rue Thierry Mieg, 90010 Belfort, France. daniel.hissel@univ-fcomte.fr

Hybrid diagnosis approaches combine between advantages of model and qualitative (expert, pattern recognition, fuzzy ...) based methods. In [10] a fuzzy neuronal model for residuals generation and analytical redundancy to fault isolation are integrated to improve fault isolation (because of fuzzy reasoning) and fault detection (because of analytical model).

In cited publications, used models for robust FDI are given under appropriate form and the uncertainties are not explicitly associated with physical parameters but with evolution matrix of the state equation. Furthermore, the parity space and observer methods are well suited for sensors and actuators FDI. The generated ARR parameters do not have a physical perception and cannot be associated with physical component faults. Methods based on filtering concern more noise measurements than parameter uncertainties.

Bond graph methodology as multidisciplinary tool based on power exchange has proved its powerful for dynamic modelling of complex and multiphysic systems. Exploitation of its structural and causal properties for systematic generation of ARR, monitorability analysis and use of its functional aspect to introduce directly the physical parameter uncertainties through the bond graph (R, I and C) elements can help for robust fault detection generating residual thresholds.

The paper deals with robust Fault Detection and isolation with respect to parameter uncertainties based on Linear Fractional Transformation form (LFT) Bond graph. The innovative interest of the proposed methodology is the use only one representation for two tasks (i) the structural monitorability and the fault signatures with no need for any numerical calculation and (ii) systematic generation of robust Analytical Redundancy Relations (ARR) and adaptative residual thresholds for sensitivity analysis. Furthermore, the parameter uncertainties are introduced graphically in the bond graph model then explicitly displayed. The methodology is applied to the nonlinear Fuel Cell.

This paper is organized as follows: section II recalls LFT bond graph for Robust FDI model based. The third section concerns robust ARR generation from diagnostic LFT bond graph. The methodology is applied to a complex multiphysic Fuel Cell in a fourth part. Finally conclusions and perspectives are exposed in the fifth section.

II. LFT BOND GRAPH FOR UNCERTAIN MODELLING

A. Bond graph definition

The key to bond graph modeling is the representation (by a bond) of power as the product of two generic variable named power variables (efforts and flows) with elements acting between these variables and junction structures to put the system together. As shown in Figure 1(a), the power exchanged between two systems A and B indicated by a bond is the product of two variables: an intensive variable (e.g. pressure, electrical potential, temperature, chemical potential, force, etc.) called effort (e) and a derivative of extensive variable (e.g. volume flow, current, entropy flow, velocity, molar flow, etc.) referred to as flow (f). One important structural property of the bond graph is its causality concept. Indeed, the determination of causes and effects in the system is directly deduced from the graphical representation. In the bond graph, it is denoted by the causal stroke indicating that the effort acts to the right. The side

of the causal stroke for the flow is in the reverse direction. As example in Figure 1(a₁), assigned causality means that system A imposes efforts on B as indicated by corresponding block diagram given by the Figure 1(b₁). In the figure 1 (a₂) and (b₂) the flow is imposed to system B. Independently of the causality, the direction of the positive power is indicated by the half-arrow on the bond. The bond graph uses the notion of integral causality but, do not consider it obligatory. If the model does not allow the interconnection of two elements with respect to the integral causality, the BG formalism offers the possibility to use derived causality and so remain close to the structural representation of the system.

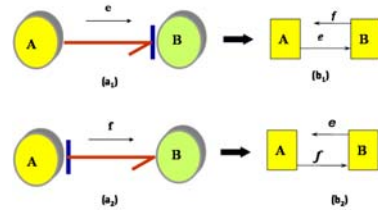


Fig. 1 : Bond Graph representation (a) and causality (b)

A bond graph which is a graph, $G(S;A)$ is a unified graphical language for multi-physic domains. Comparing with other graphical model (where nodes are variables), the nodes S represent physical components, subsystems, and other basic elements called junctions. While the edges A , called power bonds represent the power exchanged between nodes.

The set of components named bond graph element is: $S = \{R \cup C \cup I \cup TF \cup GY \cup Se \cup Sf \cup De \cup Df \cup J\}$. Only a limited number of elements are necessary to describe the majority of systems. The R -element represents a passive energy dissipation phenomenon, while C , and I model the passive energy storage (under potential and kinetic format) elements. (Se), and (Sf) are the sources of effort (intensive variable) and flow (derivative of extensive variable), respectively. Sensors are represented by flow (Df), and effort (De) detectors. Finally, J (which can be a zero or a one junction), is used to connect the elements having the same effort (1-junction), or flow (0-junction). The conservative energy laws are obtained from the latter. TF , and GY are used to represent transformers and gyrators, respectively to modelize transformation of energy from one domain into another. In the literature, many research works have been published on bond graph theory (initially invented by Paynter in 1961 [11]) for modelling [12] and further for supervision, control analysis and automated modelling [13].

The difference between BG and the other graphical approaches is that the former is directly generated from the physical system, and not from state space equations. In addition, from the BG model state space equations can be automatically generated [13], using dedicated software. Additionally, system components are clearly represented in the BG model.

One of the powerful of the BG is its causal and structural properties. Indeed, from FDI and supervision point of view, the causal properties of the bond graph model were initially used for determination of the faults origin and later for FDI system design in determinist case.

B. LFT Bond graph uncertain modelling

Generally in industry the mechatronic system parameters are considered uncertain. For the robustness of the diagnostic algorithm, the parameter uncertainties are taken into account in the modeling step using Linear Fractional Transformations (LFT) Bond Graph.

LFT are very generic objects used in the modeling of uncertain systems. The methodology consists of separating the nominal part of the uncertain part of a model, as illustrated in Fig. 2.

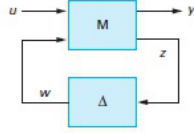


Fig. 2: LFT representation

The nominal values are grouped into an augmented matrix noted M, and uncertainties, whatever their type (structured and unstructured parametric uncertainties, modeling uncertainties), are gathered in diagonal structure matrix Δ .

$$\begin{cases} \dot{x} = Ax + B_1 w + B_2 u \\ z = C_1 x + D_{11} w + D_{12} u \\ y = C_2 x + D_{21} w + D_{22} u \end{cases} \quad (1)$$

Where $x \in \mathfrak{R}^n$ state variables, $y \in \mathfrak{R}^p$ measurement variables, $u \in \mathfrak{R}^m$ input variables, $w \in \mathfrak{R}^l$ and $z \in \mathfrak{R}^l$ regroup respectively the inputs and auxiliary outputs. n, p, l and m positive integers, A, B, C, and D appropriate dimensions matrix.

The bond graph methodology allows easy, by causal manipulations, check these properties directly on the bond graph model.

To represent uncertainty in a parameter θ , different forms can be used:

- Additive uncertainty

$$\theta = \theta_n \pm \Delta\theta \text{ with } \Delta\theta \geq 0$$

- Multiplicative uncertainty

$$\theta = \theta_n (1 + \delta_\theta) \text{ with } \delta_\theta = \frac{\pm \Delta\theta}{\theta_n}$$

Where $\Delta\theta$, $\delta\theta$ and θ_n are absolute and relative uncertainty and nominal value respectively.

For illustration, consider a pedagogical example of the LFT modeling of R element. Consider R-element in resistance (imposed flow) causality. The characteristic law corresponding to R-element in the linear case (Fig. 3) is given as follows:

$$e_R = R \cdot f_R \quad (2)$$

The parameter value of R element (which can represent hydraulic restriction, mechanical friction, electrical resistance ...) is never known with accuracy in the real process. In case of uncertainty on a parameter R, equation (2) becomes:

$$e_R = R_n \cdot (1 + \delta_R) \cdot f_R = R_n \cdot f_R + \delta_R \cdot (R_n \cdot f_R) = e_{Rn} + e_{Runc} \quad (3)$$

This uncertainty can be represented in the bond graph model as explained by the LFT bond graph model of Figure 3.

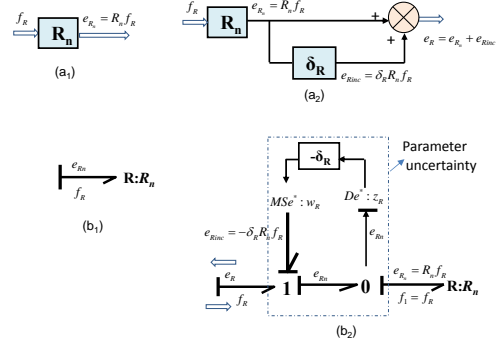


Fig.3: Nominal (a) and uncertain (b) model of R-element represented by bloc diagram (a1) and (a2) and by LFT Bond graph (b1) and (b2).

Constitutive equations (2) and (3) can be represented by a bloc diagram (Fig.3 (a1) and Fig. 3 (a2)) or by their corresponding BG models (Fig.3 (b1) and 2 (b2)). The BG model of uncertain R-element (Fig.3 (b2)) is built by introducing an effort source $Mse^* : w_R$ modulated by a virtual effort sensor signal $De^* : z_R$ and the relative uncertainty $\delta_R \cdot e_R$. Based on assigned causality (shown by the causal stroke position) in the BG model, the following equation is deduced from 1 junction:

$$e_R = e_{Rn} + e_{Runc}$$

Where $Mse^* : w_R = \delta_R \cdot R_n \cdot f_R = e_{Runc}$ represents the supplementary effort (flow in conductance causality) variable added by the uncertainty of the resistance. If the uncertainty is null, the initial nominal model (Fig.3 b1) is obtained.

III. ROBUST ARR GENERATION FROM LFT BOND GRAPH

Classically, an ARR is a constraint derived from an over-constrained subsystem and expressed in terms of known variables of the process.

In a BG sense, an $ARR = f(SSe; SSf; Se; Sf; MSe; MSf; \theta)$, where θ is the parameters vector, SSe and SSf are signal sources of effort and flow, there are obtained from the sensors of effort De and flow Df .

Numerical evaluation of the ARR gives a residue r

$$r = Eval(ARR)$$

The generation of robust analytical redundancy relations from a bond graph is summarized by the following steps:

- Try to assign a preferred derivative causality on the nominal BG; if it is possible (then the system is over-constrained thus monitorable). The bond graph model is put in preferred derivative causality (while initial conditions in real systems are unknown).
- Build the LFT BG model

- From all 0 and 1 junctions which contain at least one detector, a candidate ARR is deduced by expressing the energetic assessment on the junction:

$$\sum b_i f_{in} + \sum Sf + \sum w_i = 0 \text{ for 0 junction and,}$$

$$\sum b_i e_{in} + \sum Se + \sum w_i = 0 \text{ for 1 junction.}$$

$\sum Sf$ and $\sum Se$ are input known sources of flow and effort (input control in general case). $b_i = \pm 1$ is a Boolean variables depending on the power direction toward the junction. The unknown variables are e_{in} and f_{in} : They are eliminated using covering causal paths from unknowns to known ones.

- Transform candidate ARR to an ARR after substituting unknown variables by known ones:

$$ARR = \Phi(\{\theta_n\}, \sum SSf, \sum SSe, \sum w_i) = 0 \quad (4)$$

$\{\theta_n\}$ is the set of nominal parameters *i.e.* values of bond graph elements R, C, I.... $\sum SSf$ and $\sum SSe$ are measurement (known) variables provided by sensors and control inputs. $\sum w_i$ is the sum of modulated inputs corresponding to uncertainties on the elements related to the considered junction.

A. Generation of adaptive thresholds

The generated ARR consists of two parts well separated, a nominal part noted r_n :

$$r_n = \Phi(\{\theta_n\}, \sum SSf, \sum SSe) = 0 \quad (5)$$

and an uncertain part noted $a = \sum w_i$, where

$$w_i = \Phi(\{\theta_n\}, \sum SSf, \sum SSe, \{\delta_\theta\}) = 0 \quad (6)$$

$\{\delta_\theta\} = \{\delta_R\} \cup \{\delta_I\} \cup \{\delta_C\} \cup \{\delta_{TF}\} \cup \{\delta_{GY}\}$ are respectively the values of multiplicative uncertainties on the elements R; I; C; RS; TF and GY.

From equations (4), (5) and (6), it gives

$$r_n + \sum w_i = 0 \Rightarrow r_n = -\sum w_i \quad (7)$$

Let us define a threshold of the residual noted a as:

$$a = \sum |w_i|$$

Thus an adaptive threshold of the residual is generated in the form of an envelope:

$$-a \leq r_n \leq a \quad (8)$$

Finally the obtained ARRs consists of two perfectly separate parts, a nominal residu noted r_n which describe system

operation, and the uncertain part noted a , which represents the threshold of the system normal operating.

B. Isolation decision step

1) Fault signature matrix

The structure of the residues $r = [r_1 \dots r_n]$ forms a fault signature matrix (FSM) binary) which crosses residuals r in rows and set of faults which may affect set of components $E = [E_1 \dots E_m]$ (which may affect component E) in columns: The values of Boolean element matrix s_{ij} are assigned as follows:

$$s_{ij} = [s_{j1}, s_{j2}, \dots, s_{jn}] = \begin{cases} 1 & \text{if the element } E_j \in ARR_i \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

E_j is the j^{th} component (*i.e.* BG element). The signature vector of each component fault E_j is given by the row vector

$$V_{E_j, j=1, \dots, m} = [s_{j1}, s_{j2}, \dots, s_{jn}]$$

A fault which may affect the component E_j is detectable if $\exists i_{(i=1, \dots, n)} : s_{ij} \in V_{E_j} \neq 0$ and isolable if its signature V_{E_j} vector is unique:

$$\forall \ell_{(\ell=1, \dots, m)}, V_{E_j} \neq V_{E_\ell} (j \neq \ell)$$

The purpose of the location procedure is to provide (before implementation), the list of failures which can be detected and localized.

IV. APPLICATION

A. Fuel Cell description and faults

Figure 4 shows the scheme of fuel cell system and the possible faults occurring in this system. The system consists in four circuits of matter and energy: air, hydrogen, humidification and electrical circuit. Hydrogen valve is used to control the flow of fuel gas H_2 . The purpose of the air filter is to remove solid particles such as dust, pollen, molds and bacteria. The motor-compressor's role is to increase the air pressure by reducing its volume. Humidifier is a device that increases the moisture in the air compressed and filtered through the circuit of humidification. Fluid manifold distributes the gas under uniform guaranteeing the supply of fuel gas of each cell of stack. Fuel Cell is the heart of the system which consists of several cells depending on the power that was almost required. The fan ensures the low temperature of the stack in normal operation; batteries and converter DC / AC batteries allow storage of electrical energy generated by the battery and inverter allows conversion DC / AC.

To measure the physical variables of fuel cell system (FCS), several sensors were installed: flow and pressure of hydrogen, air flow, current and velocity of compressor, water pressure coming out of stack current, voltage and temperature of stack. Sometimes, electrical storage devices are used to prevent any

stiff electrical transient on the FC stack and to enable braking energy recovery in case of use in transportation.

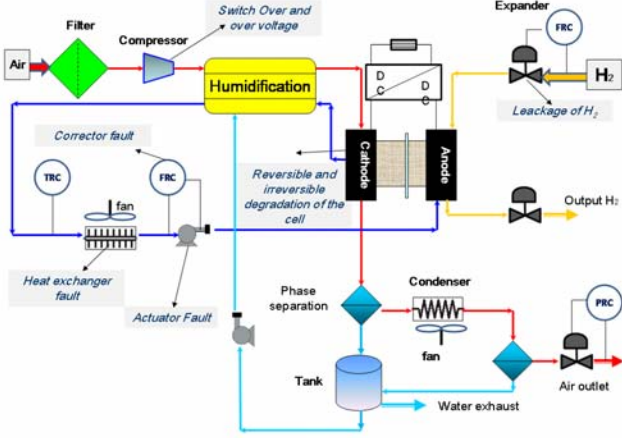


Fig. 4: Overview of the Fuel Cell system

B. Word bond graph

In the bond graph theory, the graphical graph model represents the physical level of the model, causality the algorithmic level, deduction of equations the mathematical. The technological level is represented by the word bond graph (Fig.5) which consists of decomposing the global system into subsystems. Comparing with classical bloc diagram, input and output of each subsystem are the exchanged power (not an information signal) represented by a half arrow labeled by the two conjugated power variables effort-flow. The used power variable (for pseudo and true bond graph) are the pair voltage-current (U, i) for electrical system, pressure-mass flow (P, \dot{m}) for hydraulic phenomena, temperature-enthalpy flow (T, \dot{H}) for thermal convection, chemical potential-molar flow (μ, \dot{n}) for chemical reaction and temperature-thermal flow (T, \dot{Q}) for thermal conduction and the pair chemical affinity-speed reaction (J, A) for chemical and electrochemical reaction. In the bond graph model (Fig.6), n_F and ΔG are respectively number of Faraday, and Gibbs energy.

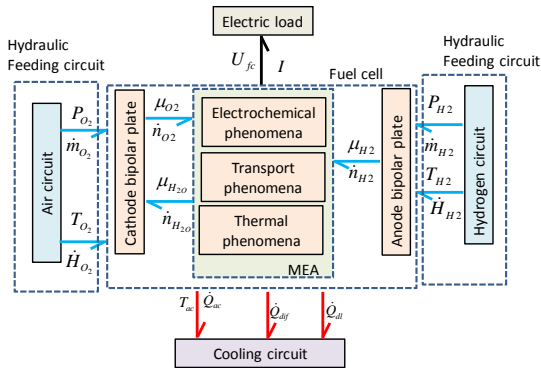


Fig. 5: Word bond graph of the fuel cell system

C. Determinist ARR generation

The bond graph model in derivative causality (suited for diagnosis) is presented in Fig. 6. The ARR will be generated

in derivative causality (instead of integral causality) because the initial condition are not known in real process. In the diagnostic bond graph all detectors (De and Df) are dualised to a Source of Signal SSe and SSf (for more details refer to [14])

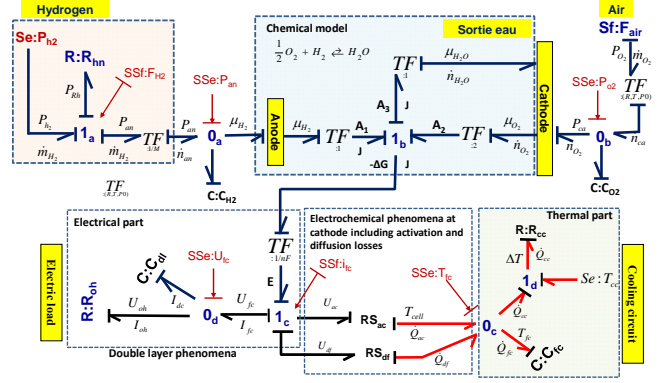


Fig. 6: Bond graph model of the Fuel cell

The hydrogen flow (with a pressure of P_{H_2}) measured by the flow detector $SSf:F_{H_2}$ is regulated via the valve R_{hn} modelled by R bond graph element. The inlet pressure at the anode (after hydraulic losses due of the valve) is measured by pressure sensor $SSe:P_{an}$. The transformer $TF_{1/M}$ is used to modelize the transformation from mass flow variable [kg/s] to molar flow [mole/s]. M is the modulus representing the molar mass [kg/mole]: ($\dot{n} = \frac{\dot{m}}{M} \left[\frac{kg \cdot mole}{s \cdot kg} \right] = \left[\frac{mole}{s} \right]$). The elements $C:C_{H_2}$ and $C:C_{O_2}$ are the capacitors representing the storage of hydrogen and oxygen. In the chemical section, is modelled the oxidation reduction reaction. The driving force is the chemical affinity (analog to voltage in electricity). The transformers show the transformation from reactants (O_2 and H_2) to product H_2O and the corresponding modulus $1/\nu_i, (i = 1, 0.5, 1)$ represent the stoichiometric coefficients. The resulting driving force of the chemical block is the free Gibbs energy ΔG calculated from 1_b junction: $\Delta G = A_1 + A_2 - A_3$. The transformation of chemical phenomena to electrochemical field is realized in a bond graph model by the transformer $TF_{3/nF}$ to obtain thermodynamic potential E according the equations:

$$E = \frac{\Delta G}{nF}$$

n is the exchanged electron mole number and F is the Faraday constant.

In the electrical part appears the double layer phenomenon modelled by $C:C_{dl}$ bond graph element. This double layer capacitor fixes the dynamics of the activation phenomena. The ohmic losses which includes all the losses in conductors (electrolyte and electrodes) and connections is modelled by $R:R_{oh}$ element. The main losses being in the membrane. Thus this parameter is sensitive to drying of the membrane and water flooding in channels failure. Those damages are considered as irreversible if the Fuel Cell health monitoring.

The thermal phenomena are important in a Fuel Cell. Ambient temperature is represented by an effort source $Se:T_{cc}$. Activation and the diffusion losses are modelled by RS_{ac} and

RS_{df} bond graph element. RS element is an active resistance which generates thermal energy. The thermal resistance in the cooling circuit is modelled by resistive R:R_{cc} element, the storage of thermal energy (measured by the temperature sensor SSe:T_{fc}) in the Fuel Cell is represented by the storage C element C:C_{fc}.

D. Monitorability analysis

The goal of this subsection is to determine the structural monitorability: based on fixed specification and existing instrumentation architecture which faults affecting the Fuel Cell system can be detected and isolated?

1) Analytical Redundancy Relations generation

Based on algorithm exposed above, ARR can be generated from the bond graph model of Figure 6.

- From 1_a junction (associated with flow sensor SSf:F_{H2}, the ARR candidate is deduced from the conservative law equation : sum of efforts (pressure) is equal to zero :

$$RRA_1 : P_{H_2} - P_{an} - P_{Rh} = 0 \quad (10)$$

Unknown variables are P_{H_2} , P_{an} , P_{Rh} . They will be eliminated using covering causal path from unknown to known variables as follows:

- $P_{H_2} = Se : P_{H_2}$. $Se : P_{H_2}$ is a source of hydrogen pressure measured by a pressure sensor (known)
- P_{an} is measured by a pressure sensor in the anode $P_{an} = SSe : P_{an}$
- P_{Rh} is calculated from the Bernouli nonlinear equation linking the pressure across the valve P_{Rh} and the flow \dot{m}_{H_2} through the valve according the equation $\Phi(\dot{m}_{H_2}, R_h, P_{Rh}) = 0$ ($P_{Rh} = R_{hm} (\dot{m}_{H_2})^2$). While the flow variable \dot{m}_{H_2} is measured by the sensor flow $SSf : F_{H_2}$, ($\dot{m}_{H_2} = SSf : F_{H_2}$) the variable P_{Rh} can be numerically evaluated : $P_{Rh} = R_{hm} (F_{H_2})^2$ (R_{hm} is the nominal value of hydraulic resistance parameter). The causal path is $SSf : F_{H_2} \rightarrow \Phi(R_h, P_{Rh})^{-1} \rightarrow P_{Rh}$

Thus the first ARR is then generated replacing known variable in equation (10):

$$ARR_1 = P_{H_2} - P_{FC} + R_{hm} (F_{H_2})^2 \quad (11)$$

This covering causal paths leads to an oriented graph (Fig.7) showing the way unknown variable are calculated.

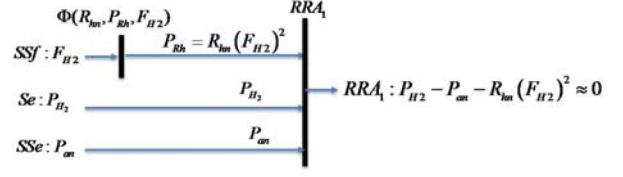


Fig. 7: Oriented graph associated with ARR1

Using the same methodology, other ARRs are generated. Let consider three of them. Two additional ARRs from 0_a and 0_b junctions can be provided.

- From junction 1_c is deduced the second ARR

$$ARR_2 : E - U_{fc} - U_{ac} - U_{df} = 0 \quad (12)$$

The unknown variables are eliminated using known complex electrochemical formula as follows:

$$E = \frac{\Delta G}{nF} = \frac{A_1 + A_2 - A_3}{nF}$$

$$U_{ac} = \frac{2RT_{fc}}{nF} \sinh^{-1} \left(\frac{I_{fc}}{2I_{fc0}} \right)$$

$$U_{df} = \frac{RT_{fc}}{nF} \ln \left(1 - \frac{I_{fc}}{I_{fc1}} \right)$$

Where:

$$U_{fc} = Se : U_{fc}$$

$$A_1 = \mu_{H_2}, \quad A_2 = \frac{1}{2} \mu_{O_2}, \quad A_3 = \mu_{H_2O}, \quad \text{where:}$$

$$\mu_{H_2} = \mu_0^{H_2} + RT_{H_2} \ln(P_{H_2}), \quad \mu_{O_2} = \mu_0^{O_2} + RT_{O_2} \ln(P_{O_2})$$

$$\mu_{H_2O} = \mu_0^{H_2O} + RT_{H_2O} \ln(P_{H_2O})$$

Finally the second ARR is obtained:

$$ARR_2 = \mu_0^{O_2} + RT_{MP_{H_2}} \ln(P_{H_2}) + \frac{1}{2} [\mu_0^{O_2} + RT_{MP_{O_2}} \ln(P_{O_2})] - \mu_0^{H_2O} + RT_{H_2O} \ln(P_{H_2O}) - Se : U_{fc} - \frac{2RT_{fc}}{nF} \ln \left(\frac{I_{fc}}{2i_0} \right) - \frac{RT_{fc}}{nF} \ln \left(1 - \frac{I_{fc}}{i_l} \right) \quad (13)$$

Where :

R is the perfect gas constant, i_0 exchanged current density, $i_l = \frac{nFDC}{\delta}$ with: D the gas diffusion coefficient through water, C the concentration of the species which diffuse to the electrode / gas interface, and δ is the diffusion layer width.

This ARR expresses the electrochemical phenomena at cathode including activation and diffusion losses. Thus ARR₂ is sensitive to Dry and flooding failure and to other sensors and parameters including in this expression.

- From junction 0_c is generated the third ARR:

$$ARR_3 = \dot{Q}_{ac} + \dot{Q}_{df} - \dot{Q}_{cc} - \dot{Q}_{fc} = 0$$

The unknown variables are eliminated according equations:

$$\dot{Q}_{ac} = (R_{ac})^2 I_{fc}, \quad \dot{Q}_{df} = (R_{dc})^2 I_{fc}, \quad \dot{Q}_{cc} = R_{cc} (T_{fc} - T_{cc})$$

$$\text{and } \dot{Q}_{fc} = C_{fc} \frac{dT_{cc}}{dt}$$

Finally ARR_3 can be given as:

$$ARR_3 = (R_{ac})^2 I_{fc} + (R_{dc})^2 I_{fc} - R_{cc} (T_{fc} - T_{cc}) - C_{fc} \frac{dT_{fc}}{dt} \quad (14)$$

- From junction 0_d is deduced the fourth ARR

$$ARR_4 : I_{fc} - I_{dc} - I_{oh} = 0$$

The unknown variables are eliminated from:

$$I_{fc} = SSf : I_{fc}, \quad I_{oh} = \frac{U_{fc}}{R_{oh}}, \quad I_{dc} = C_{dl} \cdot \frac{dU_{fc}}{dt}$$

Thus:

$$ARR_4 = I_{fc} - \frac{U_{fc}}{R_{oh}} - C_{dl} \cdot \frac{dU_{fc}}{dt} \quad (15)$$

E. Monitorability analysis

The technical specifications can be fixed based on Fault trees built from Failure Mode and Effects Analysis (FMEA) to determine pertinent components to be monitored. This part developed offline is not considered here. For our case let consider the following equipment and phenomena to be supervised: Hydrogen valve R_h , drying (Dry) of the membrane and water flooding (Wf) in channels failure, thermal resistance of cooling circuit R_{cc} , set of hydrogen flow F_{h2} and temperature of FC T_{fc} sensors. In Table 1 is given fault signature matrix. M_b and I_b are detectability and isolability indexes respectively. They are equal to one if the considered fault is detectable (the signature vector is different from zero) and isolable (signature vector unique) respectively. Regarding the fixed technical specification all faults which may affect the FC system are detectable but only faults which may affect R_h , R_{cc} and T_{fc} component are isolable (their signature vector are unique).

TABLE 1
MONITOTABILITY ANALYSIS

I_b	1	0	0	1	0	1
M_b	1	1	1	1	1	1
ARR/Fi	R_h	Dry	Wf	R_{cc}	F_{h2}	T_{fc}
ARR ₁	1	0	0	0	1	0
ARR ₂	0	1	1	0	0	1
ARR ₃	0	0	0	1	0	1
ARR ₄	0	1	1	0	0	0

Flooding and drying cannot be isolated because both cause a voltage drop (including ohmic, diffusion and activation losses). To overcome this problem, the decision stage of the algorithm (based on experimental data analysis) developed in [15] makes use of the first derivative of a voltage related fault indicator, assuming that the dynamic behavior of this indicator over the

time period during which the failure occurred is always sufficiently different between flooding and drying out.

Somme redundant sensors can be added to improve the isolability performances but in the FC heart it's not convenient to add sensors inside the device. This operation can been also automated using the software developed by the author [13].

We note that most of these approaches are based on physico-chemical phenomena inside the FC. [16], and [17] provide a review of diagnostic methods using experimental measurements according to two items: electrochemical techniques, and physical/chemical methods.

F. Robust ARR generation

The monitorability analysis is based on determinist ARRs. In fact, once the fault indicators generated and monitorability analysis carried out offline, the second step consist in real time online implementation (Fig.8). While residuals are never equal to zero because of measurement and parameter uncertainties, the goal of the next step is to determine the adaptative thresholds noted $|a|$ in order to avoid false alarms from the same model used for monitorability analysis.

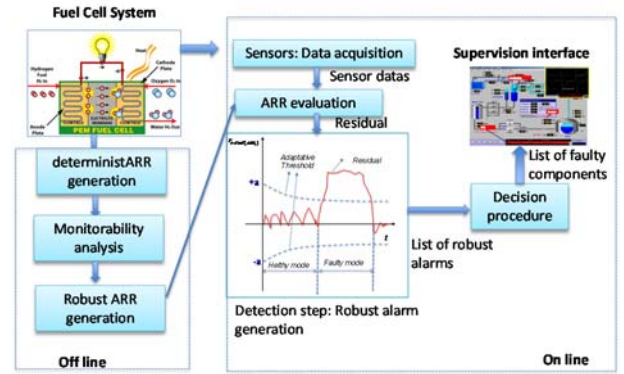


Fig. 8: Implementation steps of robust FDI

For simplicity, consider the first robust ARR generation from the bond graph model of the hydrogen valve. The nominal (a) and uncertain bond graph model (b) are given Fig. 9

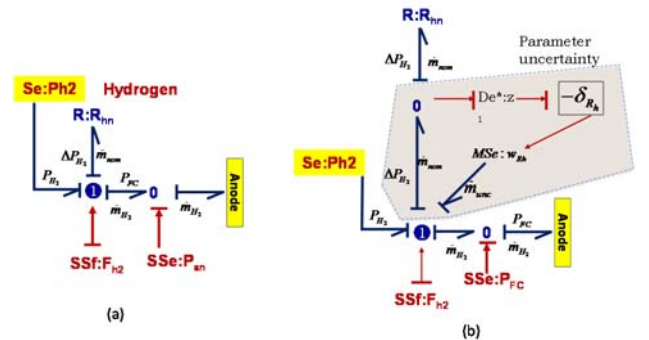


Fig.9: Nominal (a) and uncertain BG model of hydrogen valve

The relative uncertainty of the hydrogen valve parameter is δ_{Rh} . The resistance R_h parameter of the valve is :

$$R_h = R_{hm} + \delta_{Rh} \cdot R_{hm}$$

From 1 junction (Fig. 9 (b), the ARR candidate is :

$$ARR_1 : P_{H_2} - P_{an} + MSe : w_{Rh} = 0$$

The unknown variables are then eliminated as follows:

$$\begin{aligned} De^* : z &= (SSf : F_{h2})^2 \cdot R_{hm} \\ Mse : W_{Rh} &= (SSf : F_{h2})^2 \cdot R_{hm} \delta_{Rh} \\ P_{Rh} &= R_{hm} (F_{h2})^2 \end{aligned}$$

Finally the uncertain residual is

$$ARR_1 = P_{h2} - P_{an} - R_{hm} (F_{h2})^2 + w_{Rh} = ARR_{1n} + \Delta ARR_1 = r_{1n} + w_{Rh}$$

Which can be decomposed into nominal part and uncertain part:

$$\begin{cases} r_{1n} = P_{h2} - P_{an} - R_{hm} (F_{h2})^2 \\ a_1 = |w_{Rh}| = |\delta_{Rh} \cdot R_{hm} (F_{h2})^2| \end{cases} \quad (16)$$

The threshold can be easily fixed (it is adaptative because it depends on flow sensor value $a_1 = \pm \delta_{Rh} \cdot R_{hm} (F_{h2})^2$ (see Fig. 8 detection step).

Other robust ARR can be generated if the same way:

$$\begin{aligned} ARR_3 &= (R_{acn} + \sigma_{Rac} R_{acn})^2 I_{fc} + (R_{dcn} + \sigma_{Rdc} R_{dcn})^2 I_{fc} \\ &\quad - (R_{ccn} + \sigma_{Rcc} R_{ccn}) (T_{fc} - T_{cc}) - (C_{fcn} + \sigma_{Cfc} C_{fcn}) \frac{dT_{cc}}{dt} \\ &= r_{3n} + w_{r3} \end{aligned}$$

The threshold is :

$$\begin{aligned} a_3 = |w_{r3}| &= \left| 2 \cdot \sigma_{Rac} R_{acn} + (\sigma_{Rac} R_{acn})^2 + 2 \cdot \sigma_{Rdc} R_{dcn} + (\sigma_{Rdc} R_{dcn})^2 \right. \\ &\quad \left. - (T_{fc} - T_{cc}) \sigma_{Rcc} R_{ccn} - \sigma_{Cfc} C_{fcn} \frac{dT_{cc}}{dt} \right| \cong 2 \cdot \sigma_{Rac} R_{acn} \\ &\quad + 2 \cdot \sigma_{Rdc} R_{dcn} - (T_{fc} - T_{cc}) \sigma_{Rcc} R_{ccn} - \sigma_{Cfc} C_{fcn} \frac{dT_{cc}}{dt} \end{aligned}$$

$$\begin{aligned} ARR_4 &= I_{fc} - \frac{1}{R_{ohn}} (1 + \delta_{V/Roh}) U_{fc} - (C_{dln} + \delta_{cdl}) \cdot \frac{dU_{fc}}{dt} = \\ &= I_{fc} - \frac{U_{fc}}{R_{ohn}} + C_{dln} \frac{dU_{fc}}{dt} - \delta_{V/Roh} U_{fc} - \delta_{cdl} \frac{dU_{fc}}{dt} \\ &= r_{4n} + w_{R4} \end{aligned} \quad (17)$$

$$a_4 = |w_{R4}| = \left| -\delta_{V/Roh} U_{fc} - \delta_{cdl} \frac{dU_{fc}}{dt} \right|$$

Where $\delta_{V/Roh} = -\frac{\Delta R_{oh}}{R_{ohn} + \Delta R_{oh}}$ because the bond graph element is in conductance causality (the effort is imposed).

V. CONCLUSIONS AND PERSPECTIVES

The electrochemical components, especially a fuel cell, are naturally multi-disciplinary components rather well-adapted to this approach: chemistry, electrochemistry, thermal and electrical engineering are concerned. Furthermore because of its cost and necessary availability, Fault Detection and Isolation design in order to ensure safety, security, when faults occur is needed. The problematics of FC diagnostics are: insufficient instrumentation architecture, complex and non-stationary dynamic models, numerical values of parameters are not well known and uncertain.

Use of bond graph tool as multidisciplinary tool not only for modelling but also for monitorability analysis (to determine before implementation which components can be supervised), and generation of robust fault indicators to improve the performance of alarm detection step directly from the graph is the innovative interest developed in the paper.

The next research work will devoted to online implementation of generated algorithms applied to a real Proton Exchange Membrane Fuel Cell (PEMFC) system in the framework of industrial project named "Propice" that aims to develop Prognostics & Health Management (PHM) methods applied to PEM FC.

ACKNOWLEDGMENT

This work is performed in part of ANR Project "Propice" ANR-12-PRGE-0001

<http://www.propice.ens2m.fr/> that aims to develop Prognostics & Health Management (PHM) methods applied to PEM Fuel cell.

REFERENCES

- [1] C. Spiegel. "PEM Fuel Cell Modeling and Simulation Using Matlab", *Elsevier Academic Press*, 2008.
- [2] J.T Pukrushpan, A.G. Stefanopoulou and H. Peng. "Control of Fuel Cell Power Systems: Principles, Modeling, Analysis and Feedback Design (Advances in Industrial Control)", *Berlin: Springer Verlag*, 2004.
- [3] V. Venkatasubramanian, R. Rengaswamy and S.N. Kavuri. "A review of process fault detection and diagnosis. Part II: Qualitative

- models and search strategies". *Computers and Chemical Engineering* 27 (3), pp.313-326, 2003.
- [4] V. Venkatasubramanian, R. Rengaswamy, K. Yin and S.N. Kavuri. "A review of process fault detection and diagnosis. Part I: Quantitative model-based methods". *Computers and Chemical Engineering* 27 (3), pp.293-311, 2003.
- [5] Commault, C., Dion, J. M., & Agha, S. Y. Structural analysis for the sensor location problem in fault detection and isolation. *Automatica*, 44, 2074–2080, 2008.
- [6] M. Krysander, J. Aslund, and M. Nyberg. "An efficient algorithm for finding minimal overconstrained subsystems for model based diagnosis. *IEEE Transactions on System's, Man, and Cybernetics - Part A: Systems and Humans*, 38(1), pp. 197-206, 2008.
- [7] C. Svärd, and M. Nyberg. "Residual Generators for Fault Diagnosis using Computation Sequences with Mixed Causality Applied to Automotive Systems". *IEEE Transactions on Systems, Man, and Cybernetics, Part A: Systems and Humans*, 40(6):pp.1310-1328, 2010.
- [8] L.Travé-Massuyès, T.Escobet, and X. Olive. "Diagnosability analysis based on component supported analytical redundancy relations". *IEEE Transactions on Systems, Man, and Cybernetics-Part A*, 36(6), pp. 1146-1160, 2006.
- [9] M. Blanke, M. Kinnaert, J. Lunze, and M. Staroswiecki. *Diagnosis and Fault-Tolerant Control*. Springer Verlag, 2006
- [10] F.J. Garcia, V. Izquierdo, L.J.de Miguel, J.R.Peran, (2000). "Fault diagnostic system using analytical fuzzy redundancy" *Engineering Applications of Artificial Intelligence*, Vol.13.pp.441-450
- [11] Paynter (H.). "Analysis and design of engineering systems". *MIT Press*, 1961.
- [12] J.U. Thoma and B. Ould Bouamama "Modeling and Simulation in Thermal and Chemical Engineering: Bond Graph Approach". *Springer Verlag*, ISBN: 3540663886, 219 pages, 2000.
- [13] Ould Bouamama, M. Staroswiecki and A.K. Samantaray. "Software for Supervision System Design In Process Engineering Industry". *6th IFAC, SAFEPROCESS*, pp. 691-695.Beijing, China, 29-1 sept. 2006.
- [14] K. Samantaray and B. Ould Bouamama. "Model-based Process Supervision. A Bond Graph Approach". *Springer Verlag, Series: Advances in Industrial Control*, 490 p. ISBN: 978-1-84800-158-9, Berlin, 2008.
- [15] D. Hissel, M.C. Pra, and J.M. Kauffmann. "Diagnosis of automotive fuel cell power generators". *Journal of Power Sources*, 128:239–246, 2004.
- [16] J. Wu, X.Z. Yuan, H. Wang, M. Blanco, J.J. Martin, and J. Zhang. "Diagnostic tools in pem fuel cell research" : *part ii physical /chemical methods. International Journal of Hydrogen Energy*, 33:1747–1757, 2008.
- [17] J. Wu, X.Z. Yuan, H. Wang, M. Blanco, J.J. Martin, and J. Zhang. "Diagnostic tools in pem fuel cell research: Part i electrochemical techniques". *International Journal of Hydrogen Energy*, 33(6):1735–1746, 2008.

Belkacem Ould Bouamama is full Professor is full Professor, and head of the research at Lille University, France» He is the leader of Bond Graph group at CRIStAL Laboratory (associated with the CNRS, French National Center For Scientific Research) where his activities concern Integrated Design for Supervision of System Engineering.

Daniel Hissel is Full Professor at the University of Franche-Comte in France and Director of the Fuel Cell Lab Research Federation (CNRS). He also leads a research team devoted to hybrid electrical systems in the FEMTO-ST Institute (CNRS).

Mathieu Bressel is Ph.D. student at the University of Franche-Comte and Lille University France.

Mickaël Hilairet a Full Professor at the University of Franche-Comté, Belfort, France. His main research interests are drives control, estimation, diagnosis, and control of fuel cell system.