Signed Bond Graph for health monitoring of PEM fuel cell

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ABSTRACT
To guarantee the safe operation of the Fuel Cell (FC) systems, it is necessary to use systematic techniques to detect and isolate faults for diagnosis purposes. The problematic for Fault Detection and Isolation (FDI) model-based of fuel cell consists in that such system is bad instrumented, its model is complex (because of coupling of multi-physical phenomena such as electrochemical, electrical, thermo fluidic…) and the numerical values related to it are not always known. This is why qualitative model (based on existence or not of the links between variables and the relations) is well suited for fuel cell diagnosis. In this paper, we propose a new graphical model (named Signed Bond Graph) allowing to combine both qualitative and quantitative features for health monitoring (in terms of diagnosis and prognosis) of the fuel cell. The innovative interest of the presented paper is the use of only one representation for not only structural model but also diagnosis of faults which may affect the fuel cell. The developed theory is illustrated by an application to a Proton Exchange Membrane Fuel Cell (PEMFC).

1. INTRODUCTION
During the last decade, FC systems have received significant attention and they are expected to play a significant role in future environmentally friendly power generation facilities [8]. Among many varieties of fuel cells, the PEMFC has shown to be the most promise for various industries including the transportation, residential and also portable applications. As a consequence, its modeling has become an important research issue [6] [7]. Roughly speaking, A PEMFC is a device that produces electricity from a chemical reaction. This reaction generates electrical current (which can be directed outside the cell to power an electrical motor for example), requires a fuel (namely hydrogen) and oxygen, and releases water and heat. FC systems are vulnerable to faults that can cause the disruption or the permanent damage. It was shown from Failure Modes and Effects Analysis (FMEA) that the state of hydration of the membrane electrode assembly (water flooding and drying) is one of the major challenges in PEMFCs FDI and control reconfiguration. To guarantee the safe operation of the FC systems, it is necessary to use systematic techniques to detect and isolate faults for the purpose of diagnosis.
Different diagnosis approaches dealing with water management exist. Among these approaches, one can cite the soft computing techniques. Hissel et al. [2] for instance proposed a solution to perform such diagnosis using fuzzy logic tuned thanks to genetic algorithms. On an other work, Yousfi Steiner et al. [1] proposed an improved diagnosis procedure based on the comparison between measured parameters and parameters calculated by an Artificial Neural Network (ANN) in case of normal operation. One drawback to using ANNs, is that they require a large diversity of training in normal and faulty situations for real operation in order to become viable.

From one hand, a great part of the fuel cell diagnosis is based on experimental methods using signal processing. Among these methods, one can cite the polarization curve approach and the Electrochemical Impedance Spectroscopy (EIS) [5]. Chen et al. [4], for example used frequency of pressure drop signal as a diagnostic tool for PEM fuel cell stack dynamic behaviors. Because of complexity of the model, few of consulted papers deals with model based diagnosis. They aim to generate fault indicators called residuals [9]. Among the residuals generation methods, Bond Graph (BG) as a multidisciplinary and unified graphical modeling language has proved its efficiency to generate fault indicators in a systematic and generic way using specific algorithms. These algorithms are based on covering causal paths [10] implemented in dedicated softwares [11]. But as every residual generation method, BG models are limited to a single fault diagnosis which assumes the observation of only one effect for one component's fault. However, within a real system such as PEMFC, one element's fault can manifest several effects (increase the temperature and the pressure, for example) and implies the propagation of the fault to other elements.

In addition, two different communities have developed Model Based Diagnosis namely Fault Detection and Isolation (FDI) community (based on residuals generation methods) and DX community emanating from Artificial Intelligence field and dealing with qualitative models [12]. During the last decade, different research groups proposed a common frame-work for sharing and comparing techniques from both communities. This effort turned into what it is known as BRIDGE community. This latter tries to propose new approaches integrating the best from both communities and to deal with quantitative and qualitative models [13] [14]. The approach we propose in this paper fits into the BRIDGE community.

Indeed, we introduce a new graphical model called Signed Bond Graph (SBG). This model uses a qualitative reasoning allowing to generate multiple behavior predictions (i.e. possible conflicts). Since the SBG is constructed from the Bond Graph (BG) model, the use of this latter as a quantitative method for residuals generation allows to eliminate the possible conflicts which are inconsistent or not physically possible even though they sound logical from a qualitative point of view. Finally, a global supervision module based SBG is proposed. This module uses both qualitative and quantitative reasoning for faults detection and isolation of PEM fuel cell.

The rest of the paper is organized as follows. Section 2 presents an overview of the global developed diagnosis procedure based on integration of behavioral and causal properties of BG and qualitative aspect of the SBG. Section 3 presents the BG model of the PEM fuel cell and the procedure for fault indicators generation. Section 4 presents the deduced SBG and its features for qualitative reasoning. Section 5 concludes the paper by highlighting the strengths of the proposed approach.

2. SBG FOR GLOBAL SUPERVISION

Two steps can be distinguished in the global diagnosis procedure we propose. The first one is its diagnosability analysis and monitoring algorithms generation carried out offline before industrial design. The second one is its on-line implementation of qualitative and quantitative algorithms for real time fault detection and isolation for singleand multiple faults.

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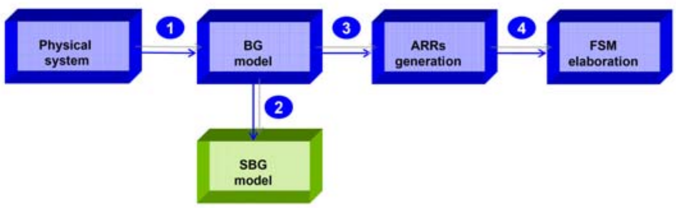

Figure1. Design step

2.1 The design of the diagnosis module

The design of the diagnosis module rests on four steps which are illustrated in Fig.1 and summarized as follow. In a first time, the BG model is built based on the physical system architecture and the power exchanges between the different components. Judicious causality marks are assigned to indicate the order according to which the unknown variables are processed from the known ones. This step will be detailed in the next section. In a second time, the SBG is directly derived from the BG model by using a developed methodology allowing the model checking and dealing with qualitative features with regards to power sign, direction of power variables and so on. In the same time, a numerical processing of the BG is performed and leads to the automatic generation of Analytical Redundancy Relations (ARR). Then, the structure of the ARRs is exploited to generate the Fault Signature Matrix (FSM) which associates to each detectable fault a signature.
Within the BG methodology, the ARRs generation procedure rests on the BG causal features and uses the theory of unknown variables elimination using covering causal paths (from unknown to known variables (measured)) algorithms. Indeed, the relations between system variables can be easily displayed graphically using BGs and they can be defined under a symbolic form using symbolic computation software [11]. According to the deduced ARRs, a fault signature matrix which crosses ARRs in columns and faults F in rows is built in order to evaluate the possibilities the system has to detect and isolate faults. The algorithm of ARRs generation can be found in [15].

2.2 The on-line exploitation

Once the diagnosis module is correctly designed, it can be online exploited to detect and isolate fault when possible. This diagnosis procedure is illustrated in Fig.2 and can be summarized as follows.

In a first time, ARRs are calculated using the measured outputs and the control inputs which represent the known variables of the system. From the values of these ARRs, a coherence vector is obtained. If its value is different from (0, 0 ...0), it is then compared to the fault signatures regrouped in the FSM. This leads to a list of potential faults and allows the extraction of a subset of fault candidates. Using the measured values, the consistency of the possible conflicts generated off-line from the SBG, is checked as well and abnormal situations are identified. In a last step, the consistency between the results obtained according to the ARRs evaluation and the possible conflicts generation is tested. If consistency there is, some faults may be isolated. In the opposite case, a partial result is given.

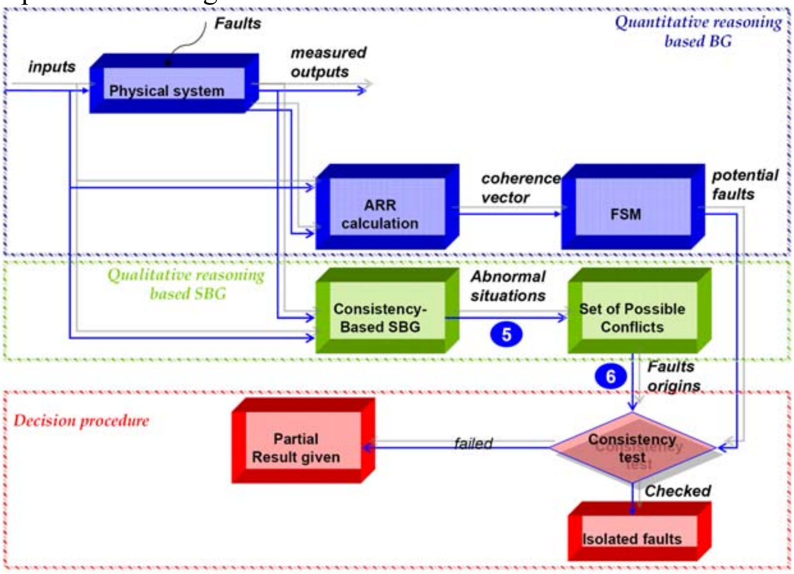

Figure 2. On line exploitation

3. PEM FUEL CELL BOND GRAPH MODELLING

In this section, we present the fuel cell system's Word Bond Graph which represents the technological level of the model where global system is decomposed into different subsystems (see Fig.3). Comparing with classical block diagram, the input and output of each subsystem define power variables represented by a conjugated pair of effort-flow labeled by a half arrow. Indeed, the Word Bond Graph provides a top-level overview of the fuel cell system and is useful for initial conception of the behavioral system model. The pair of power variables used for the studied fuel cell system are: (Pressure, Mass Flow) = ($\boldsymbol{P},\dot{\boldsymbol{m}}$), (Temperature, Enthalpy Flow) = ($\boldsymbol{T},\dot{\boldsymbol{H}}$), (chemical potential, molar flow)=($\boldsymbol{\mu},\dot{\boldsymbol{n}}$) and (Voltage, Current) = ($\boldsymbol{U},\boldsymbol{i}$). We note that for chemical process two kinds of power variables are used: the pair chemical potential-molar flow ($\boldsymbol{\mu},\dot{\boldsymbol{n}}$) for transformation phenomena and the pair chemical affinity-A (J/mol) and speed of reaction J (mol/s). These variables are associated respectively with mechanical, thermal, chemical and electrical domains. Because of the complexity of the overall system and for the sake of clarity, we will focus within this paper only on the heart of the fuel cell system model. While the temperature of hydrogen and oxygen are constants, we consider only the transformation respectively of hydrogen and oxygen mass flow. This transformation is modeled by the Transformer TF bond graph element with a modulus M molar rate (mol/m^3) as represented in bond graph model (Fig. 4).

3.1 BG model and fault indicators generation of the PEM fuel cell

The Bond Graphs have been successfully used for analysis and synthesis of different kinds of systems involving different domains. Fig. 4 presents the proposed BG model of a 6 kW, 45 volts PEM fuel cell feeding a 100Vdc DC/DC converter (The polarization curve obtained by simulation is given in Fig.5). The transformers TF_{an} and TF_{ca} modulated by molar rate represent chemical transformations related respectively to the hydrogen flow through the anode and the oxygen flow through the cathode. On the other hand, TF_e represents the transformation of the variations of the Gibbs free energy, into electrical energy assuming that the Gibbs free energy can be converted into electrical energy, the theoretical potential E of the fuel cell corresponds to Gibbs free energy, ΔG of main oxydo reduction reactions such that $E = \frac{-\Delta G}{nF}$.

Where n is 2, the number of electrons involved in the above reaction, and F is the Faraday's constant (96,485 Coulombs / electronmol). This relation is modeled by TF bond graph element $TFe : nF$. Junction structures are used in order to connect several elements of the BG model (R, C and I) by a 0-junction when the effort variable is the same and the flows are different and by a 1-junction when the flow is the common variable. Hence, the 0-junction expresses the effort conservation and indicates that the flows sum is equal to zero. Whereas the 1-junction expresses the flow conservation and indicates that the efforts sum is equal to zero. De and Df (sensors) represent respectively the effort detector and flow detector.

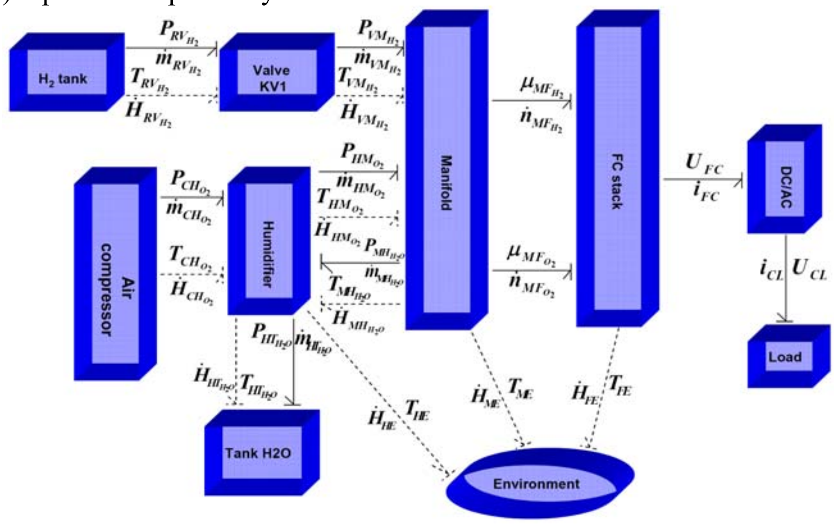

Figure 3. Word BG of the PEM fuel cell

Se and Sf represent respectively the effort source and flow source. R_v represents the inlet H_2 valve which is modeled hence by hydraulic resistance modulated by an information bond x (control signal). Re represents the friction of the diffusion through the surface of the backing layer for the O_2. The thermal losses are modeled by an active resistance element-RS such as activation losses, diffusion losses, concentration losses …

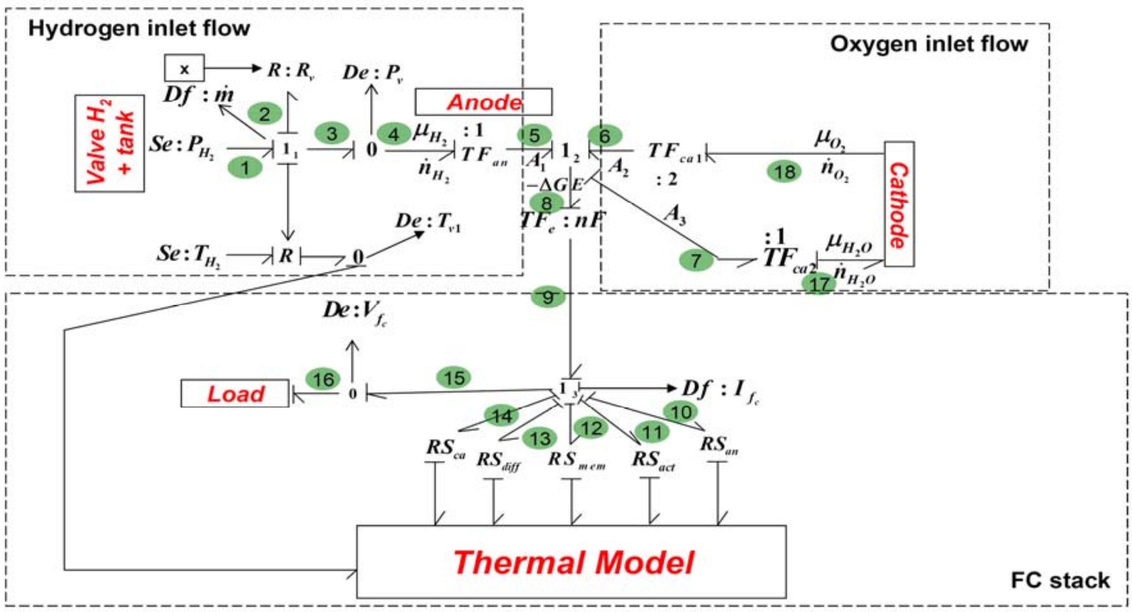

Figure 4. BG model of the PEM fuel cell

Much more details about the BG approach can be found in [16].

Let now focus on Fig.4 in order to deduce the ARRs:

From the Junction (1_1), the following equations can be written:

(1.1) $e_1 - e_2 - e_3 = 0$

(1.2) $\quad \boldsymbol{e_1 = P_{H_2}}$

(1.3) $\quad \boldsymbol{e_2 = f(f_2, x)}$

(1.4) $\quad \boldsymbol{f_2 = f_3 = \dot{m}}$

(1.5) $\quad \boldsymbol{e_3 = e_4 = P_v}$

From equations (1.1), (1.2), (1.3), (1.4) and (1.5), we can deduce the first ARR as follows:

(1.6) $\quad \boldsymbol{P_{H_2} - f(f_2, x) - P_v = 0}$

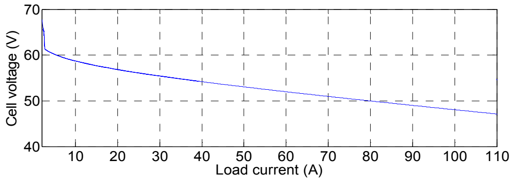

Figure 5. Polarization curve of the PEM fuel cell (6 Kw, 45 Volts)

Similarly, from the junction (1_3), we can write:

(1.7) $\quad \boldsymbol{e_9 - e_{10} - e_{11} - e_{12} - e_{13} - e_{14} - e_{15} = 0}$

(1.8) $\quad e_{10} = f_{10} \times RS_{an}$; $e_{11} = f_{11} \times RS_{act}$; $e_{12} = f_{12} \times RS_{mem}$; $e_{13} = f_{13} \times RS_{diff}$; $e_{14} = f_{14} \times RS_{ca}$; $e_{15} = V_{fc}$

(1.9) $\quad \boldsymbol{f_9 = f_{10} = f_{11} = f_{12} = f_{13} = f_{14} = f_{15} = I_{fc}}$

(1.10) $\quad \boldsymbol{e_8 = nF \times e_9}$

(1.11) $\quad e_6 = f(P_{O_2}; T_{O_2})$; $P_{O_2} = f(\dot{m}_{O_2}; P_{H_2O})$; $e_5 = f(T_{v1}; e_4)$

(1.12) $\quad e_7 = f(P_{H_2O}; T_{H_2O})$

From equations (1.7) to (1.12), the second ARR is then deduced:

(1.13) $f(T_{v_1}, P_v) + f\left[f(\dot{m}_{O_2}, P_{H_2O}), T_{O_2}\right] - nF \times$

$\left[I_{fc} \times (RS_{act} + RS_{diff} + RS_{ca} + RS_{an} + RS_{mem}) + V_{fc}\right] - f(P_{H_2O}, T_{H_2O}) = 0$

From junction (1_2) and by following the same procedure, the third ARR can be obtained as follows:

(1.14) $\dfrac{1}{nF} \times \left[f(T_{v_1}, P_v) + f(P_{O_2}, T_{O_2}) - f(P_{H_2O}, T_{H_2O})\right] -$

$I_{fc} \times (RS_{act} + RS_{diff} + RS_{ca} + RS_{an} + RS_{mem}) - V_{fc} = 0$

The fault signature matrix (FSM) is derived directly from these three ARRs namely (1.6), (1.13) and (1.14). It is given in Table 1. According to these ARRs, the FSM which crosses ARRs in rows and faults F in columns is built in order to evaluate the possibilities the system has to detect and isolate faults. Boolean matrix element a_{ij} equals 1 if the i^{th} residual is affected by the j^{th} fault. The on-line residuals evaluation leads to the formulation of a binary coherence vector $C = (c_1 c_2 \ldots c_n)$, whose elements, c_i $(i = 1,\ldots,n)$, are determined from a decision procedure φ which generates the alarm conditions. A simple decision procedure can be used for instance, $C = \varphi$ $(r_1, r_2 \ldots r_n)$, whereby each residual, r_i is tested against a threshold ε, fixed according to parameter uncertainties, sensor noises and so on.

In Table 1, the vector (R1, R2, R3) is the signature of the fault. The only isolated faults are those having the same signature, i.e. different from the signatures of all other element (such as the signature V = (1, 1, 1) corresponding to the H_2 pressure sensor). However, due to the non presence of enough unique signatures, faults affecting the other elements can not be isolated. According to the FSM, we notice that a fault related to the drying out of the membrane or the flooding of the cathode can be detected. However, it can not be isolated because these two faults have the same signature. Hence, the quantitative evaluation of the fault indicators (residuals) is not sufficient for distinguishing between the two faults related to the water management. This is why, we proposed to introduce a qualitative reasoning based BG model allowing to get a much more accurate diagnosis according to the strategy explained in section 2. Hence, we develop in the next section a new model called Signed Bond Graph (SBG) allowing possible conflict generation.

4. QUALITATIVE REASONING BASED SBG

A SBG is a new dynamic graphical model built from BG approach. This model allows to gather and exploit qualitative and quantitative features in order to carry out diagnosis and supervision of dynamic systems. We developed an algorithm for automatically building the SBG from the BG. At present we present an overview of the proposed model and same definitions related to the qualitative reasoning based SBG.

4.1 SBG MATHEMATICAL FORMALISM

Definition 1. A Signed Bond Graph **G(X,A,L,S)** is a labeled graph where: **X** is a set of nodes representing

Table 1. PEM Fuel cell Fault signature matrix

Fault	R1	R2	R3	D (Detectability)	I (Isolability)
Drying of the membrane	0	0	1	**1**	**0**
Flooding of the cathode	0	0	1	**1**	**0**
H2 valve regulator	1	0	0	**1**	**0**
H2 mass flow sensor	1	0	0	**1**	**0**
H2 pressure sensor	1	1	1	**1**	**1**
H2 temperature sensor	0	1	1	**1**	**0**
Fuel cell current sensor	0	1	1	**1**	**0**
Fuel cell voltage sensor	0	1	1	**1**	**0**
Cathode water temperature sensor	0	1	1	**1**	**0**
Cathode water pressure sensor	0	1	1	**1**	**0**

BG elements, $A \subset X \times L \times S \times X$ is a set of labeled and signed arcs such that each arc indicates both a power variable which can be either flow or effort and a sign related to energy exchange, $L = \{l_i \,/\, l_i \in \{e_i, f_i, e_{m_i}, f_{m_i}\}\}$ is a set of labels corresponding to two conjugated power variables measured f_{m_i}, e_{m_i} or unmeasured e_i, f_i written above or to the left of the arc, $S = \{s_i \,/\, s_i \in \{+, -, 0, \varnothing\}\}$ is a set of signs written below or to the right of the arc such that $+$, $-$, 0 and $\varnothing$ correspond respectively to a power supply, power consumption, power conservation and no power (such as detectors which bring only signal and are not involved in power exchange) and $i \in \mathbb{N}^*$. The set of nodes $X = \{x_i \,/\, 1 \le i \le nb_E\}$ can be partitioned as: $X = X_{Ce} \cup X_S \cup X_D \cup X_{Co} \cup X_{Tr}$ where $X_{Ce} = \{x_{Ce_i} \,/\, x_{Ce_i} \in \{J_{0i}, J_{1j}\}\}$ is a subset of nodes corresponding to central elements that distribute power and have linear structural relations. $X_S = \{x_{S_i} \,/\, x_{S_i} \in \{S_{e_i}, S_{f_i}, MS_{e_i}, MS_{f_i}\}\}$ is a subset of nodes corresponding to sources elements which supply energy into the system. Sources may impose either an effort or a flow onto a system.
$X_D = \{x_{D_i} \,/\, x_{D_i} \in \{D_{e_i}, D_{f_i}\}\}$ is a subset of nodes corresponding to effort and flow detectors. $X_{Co} = \{x_{Co_i} \,/\, x_{Co_i} \in \{R_i, C_i, L_i\}\}$ is a subset of passive physical elements consuming energy. $X_{Tr} = \{x_{Tr_i} \,/\, x_{Tr_i} \in \{TF_i, GY_i\}\}$ is a subset of nodes corresponding to energy conservative elements, the energy is neither stored nor produced and the instantaneous input power equals the instantaneous output power. nb_E is the number of Bond Graph elements in the BGM and $i \in \mathbb{N}^*$.

4.1 SBG for qualitative diagnosis

For any observation $obs \subset OBS$ of the system (square nodes) in a given time, a SBG model can determine qualitatively whether each measured node has deviated from its normal state, as well as the direction of deviation, according to a set of threshold values. By the use of reasoning in the SBG model, the observation obs propagates through arcs. The resulting paths are called fault propagation paths or consistent paths. The elements which belong to this path form a set of possible conflicts. Indeed, the idea behind the labeled and signed arcs of the SBG it that the propagation starts from a measured node and propagates through arcs. Hence, it affects different nodes corresponding to the set of elements ***COMPS*** by checking the sign of each arc. The propagation is stopped either when a consistency is noted or when a measured node is reached.

Definition 2. A pattern of a SBG model is a function $\Gamma : \{l_i\} \rightarrow \{+, 0, -\}$ that links each label l_i to a specified sign according to the observation node x_{D_i}. Hence, $\Gamma(l_i)$ $(l_i \in X)$ is the sign of the arc l_i, $i \in \mathbb{N}^*$:

$$\Gamma(l_i) = 0 \ \text{ if } \left| l_i - l_{in} \right| \prec \varepsilon l_i$$

$$\Gamma(l_i) = + \ \text{ if } \ l_i - l_{in} \geq \varepsilon l_i$$

$$\Gamma(l_i) = - \ \text{ if } \ l_{in} - l_i \geq \varepsilon l_i$$

Where εl_i is the threshold.

The corresponding SBG (see Fig.5) of the PEM fuel cell is constructed directly from the BG model which is given by Fig. 4. Then, the fault propagation is carried out from the observed nodes (corresponding to the sensors) in order to determine qualitatively the set of fault candidates according to the inconsistencies within the SBG model.

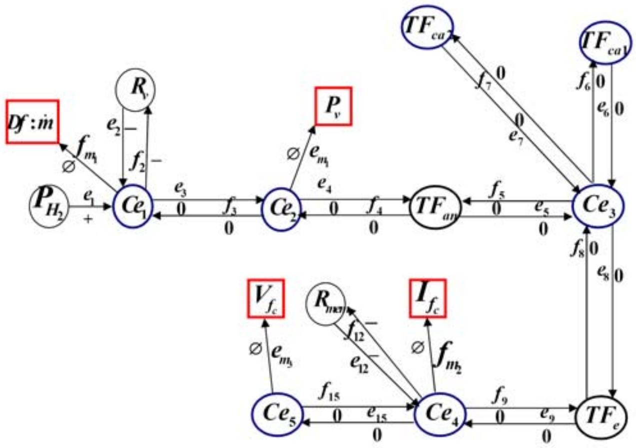

Figure 5. SBG model of the PEM fuel cell

Let now focus, for instance, on the faults corresponding to water management (flooding and drying). We simulate a fault affecting the membrane. The evaluation of the residuals gives the signature V = (0,0,1). Hence, a fault is detected but we can not distinguish between a flooding and a drying out according to this quantitative evaluation. The analysis based on the SBG model allows having an accurate diagnosis according to the sensor values acquired in both normal and faulty situations (see simulations in Fig. 6). It is worth noting that all the possible propagation paths and Possible Conflicts (PC) are generated off-line from the SBG model. Then, according to the quantitative evaluation based residuals, we use only the suitable PCs that can explain the set of observations and which are consistent with the residuals evaluation outcomes. For the considered fault scenario, the following paths deduced from the set of observations (Fig. 6) are exploited in order to determine the fault upon occurrence:

(1.16) $\boxed{f_{m_1}^+} \rightarrow f_3^+ \rightarrow f_4^- \rightarrow f_5^- \rightarrow f_8^+ \rightarrow f_9^+ \rightarrow \boxed{f_{m_2}^+}$

(1.17) $\boxed{e_{m_3}^+} \rightarrow e_{15}^+ \rightarrow e_2^- \rightarrow f_{12}^- \rightarrow \boxed{f_{m_2}^-}$

(1.18) $\boxed{e_{m_3}^+} \rightarrow e_{15}^+ \rightarrow e_9^- \rightarrow e_8^- \rightarrow e_5^+ \rightarrow e_4^+ \rightarrow \boxed{e_{m_1}^+}$

We notice an inconsistency in the PC (1.17), because the value of the load current f_{m_2} increases according to the simulations. However, PCs (1.16) and (1.18) match the observations. Hence, the element involving in the PC (1.18) is the origin of this possible conflict namely the resistance of the membrane. As it is known, the resistance of the membrane is sensitive to the drying out of the membrane. This is why, we can deduce from this qualitative propagation, that the fault is drying of the membrane and hence we isolate the fault (which is not possible when we rely only on the FSM) despite the fact that we do not have any sensor inside the membrane to measure the resistance of the membrane.

4. CONCLUSION

A new approach has been presented for fault diagnosis of the PEM fuel cell especially with regard to water management problems. This approach is based on residuals generation approach (quantitative features) and on a new qualitative model called SBG both emanating from the BG formalism. Hence, the proposed global supervision module allows a better and more accurate diagnosis.

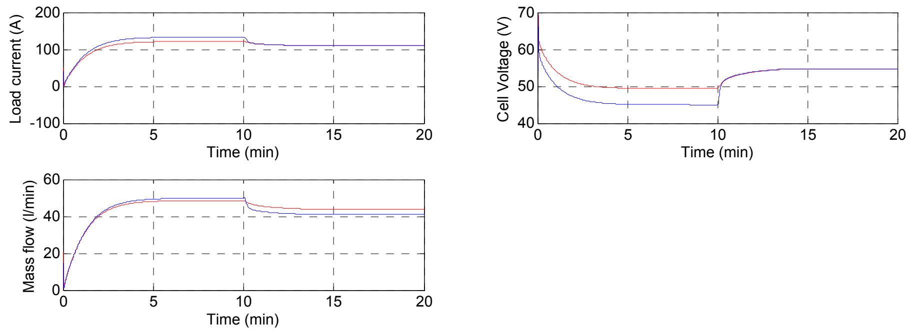

Figure 6. Simulation results of the PEM fuel cell (6 Kw, 45 Volts)

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