

FAULT DIAGNOSIS IN FUEL CELLS BASED ON BAYESIAN NETWORKS

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Abstract. *In this paper, a supervisor system, able to diagnose different types of faults during the operation of a proton exchange membrane fuel cell (PEMFC), is introduced. The diagnosis is developed by applying Bayesian networks, which qualify and quantify the cause-effect relationship among the variables of the process. The fault diagnosis is based on the on-line monitoring of variables easy to measure in the device such as voltage, electric current, and temperature. The fault effects are studied based on experiments on a fault tolerant fuel cell, which are reproduced in a fuel cell model. A database of fault records is constructed from the fuel cell model, reducing the time necessary to obtain the fault records and avoiding permanent damage to the equipment.*

Keywords: *Bayesian Networks, Fault Diagnosis, Fuel Cells*

1. INTRODUCTION

In the last few years humans are concerning more about environmental issues like global heating. In this context, major efforts to reduce greenhouse gas emissions have increased the demand for pollution-free energy sources, and governmental agencies and private-sector are investing in R&D to support programs for clean energy generation including hydrogen-based energy generation.

Similar to batteries, fuel cells are electrochemical devices that generate electricity. However fuel cells can be continuously fueled. Most recent developments in proton exchange membrane fuel cell (PEMFC) technology have made it the most promising for stationary and mobile applications in the range up to 200 kW. They are characterized by high efficiency, high power density, no aggression to the environment, no moving parts, and superior reliability and durability.

Generally, PEMFC uses hydrogen as a raw material which, under certain pressure, is supplied into a porous conductive electrode (the anode). The H_2 spreads through the electrode until it reaches the catalytic layer of the anode, where it reacts, separating protons and electrons. The H^+ protons flow through the electrolyte (a solid membrane), and the electrons pass through an external electrical circuit, producing electrical energy. On the other side of the cell, the oxygen (O_2) spreads through the cathode and reaches its catalytic layer. On this layer, the O_2 , H^+ protons, and electrons produce liquid water and residual heat as sub-products (Larmine and Dicks, 2000).

Several papers have been published considering the fuel cell (FC) operation in normal conditions (Corrêa et al., 2003) (Corrêa et al., 2004) (Larmine and Dicks, 2000); but few of them addressed the FC operation under fault conditions. Faults are events that cannot be ignored in any real equipment, and their consideration is essential for improving the operability, flexibility, and autonomy of any automatic device.

In this paper, a fault diagnostic supervisor is designed to execute online diagnosis, which indicates the cause of an incipient fault. The supervisor uses a Bayesian network arrangement to establish the cause-effect relationship, and to calculate the probability of the most likely fault cause. An early alert of an incipient fault allows decisions to avoid degradation of other components and catastrophic faults in the equipment. A FC model able to reproduce the effects of faults on a fault tolerant fuel cell (FTFC) is introduced. The supervisor and the FC model were integrated using the MatLab/SimuLink® environment to conduce the tests and evolution of the equipment.

This paper is organized as follows. In section 2, the considering FTFC is presented. In section 3, the FC model is introduced. In section 4, four types of faults in PEMFC are considered: faults in the air fan, faults in the refrigeration system, growth of the fuel crossover, and faults in hydrogen pressure. Section 5 presents a short background of Bayesian networks, and introduces the fault diagnostic supervisor for PEMFC. Finally section 6 presents the conclusions of this work.

2. THE FAULT TOLERANT FUEL CELL (FTFC)

The design of a fault diagnostic supervisor can be made, in principle, in two ways: by the human-expert knowledge elicitation or by the analysis of the operation of a FC in faulty conditions; since the former requires an exhaustive analysis of various experts' knowledge, we adopt the second approach and a FTFC has been constructed at the PSERC laboratory of the CSM (Colorado School of Mines) in order to perform the analysis of a FC. This FTFC is constituted by a control system, a sensor system, and a power system. The control system allows the adjust (either manual or

automatic) of the speed of the air-reaction fan and the refrigeration fan. These tasks can be executed either by microcontrollers (inside the FTFC) or by PC (using LabView® software). The sensor system allows monitoring the voltage (V_S), electric current (I_{FC}), temperature (T), and relative humidity (HR_{OUT}). These tasks also can be made by the LabView® software which can be applied for monitoring the speed of the fans too. The air for reaction and the air for refrigeration are separated on different routes which simplifies the monitoring process of some variables. The power system is formed by one AvistaLabs® cartridge containing four proton exchange membranes (PEM).

The FTFC allows the operation and the monitoring of the system even when faults occur. Fig. 1 illustrates the monitoring of the FTFC; this figure shows the FTFC, the load, and a PC with the LabView® software executing the monitoring process.

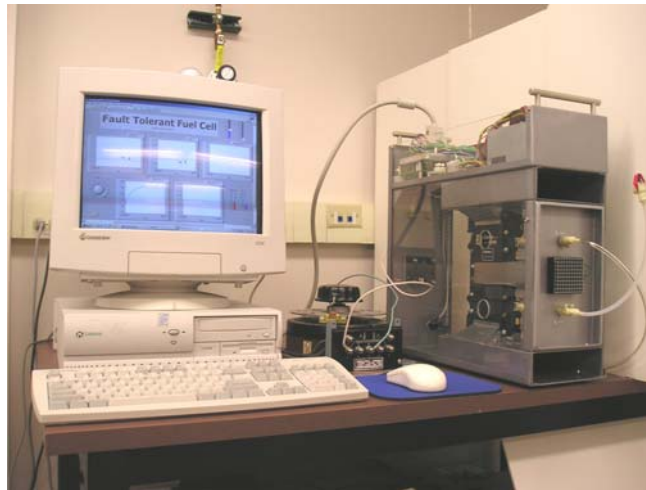


Figure 1. Monitoring of the FTFC

Figure 2 illustrates the evolution of several variables such as FTFC output voltage (V_S), electric current (I_{FC}), temperature (T) and airflow volume using the software LabView® when the FTFC operates in normal conditions.

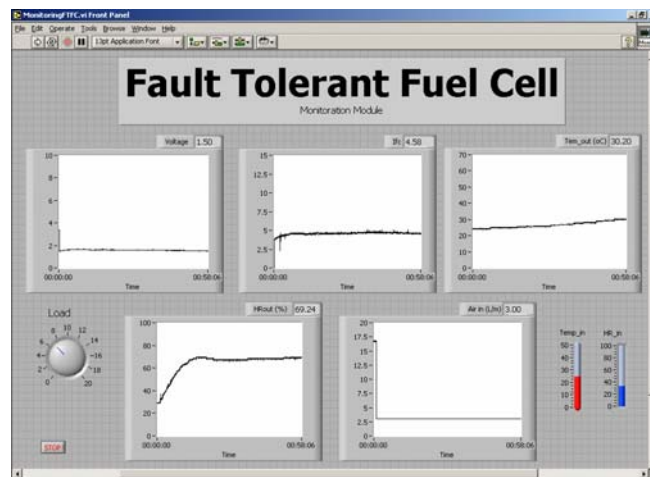


Figure 2. Evolution of the FTFC's variables in normal conditions.

The FTFC was tested in different fault conditions. Figure 3 illustrates the evolution of the output voltage (V_S), electric current (I_{FC}), and relative humidity (HR_{out}) when the H_2 pressure is reduced at $t = 10$ minutes.

Figure 4 illustrates the evolution of the output voltage (V_S), electric current (I_{FC}), and relative humidity (HR_{out}) when the air-reaction volume is reduced at $t = 30$ minutes.

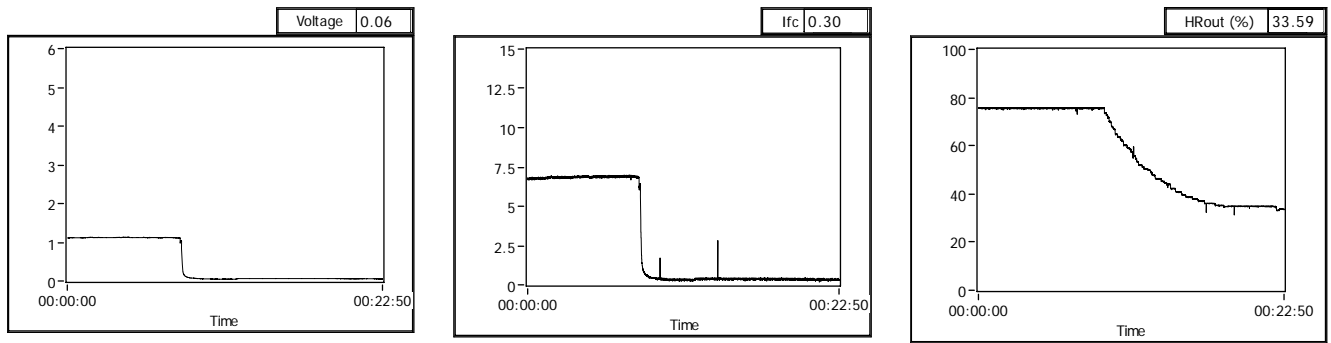


Figure 3. Evolution of the FTFC's variables by reduction of H₂ pressure.

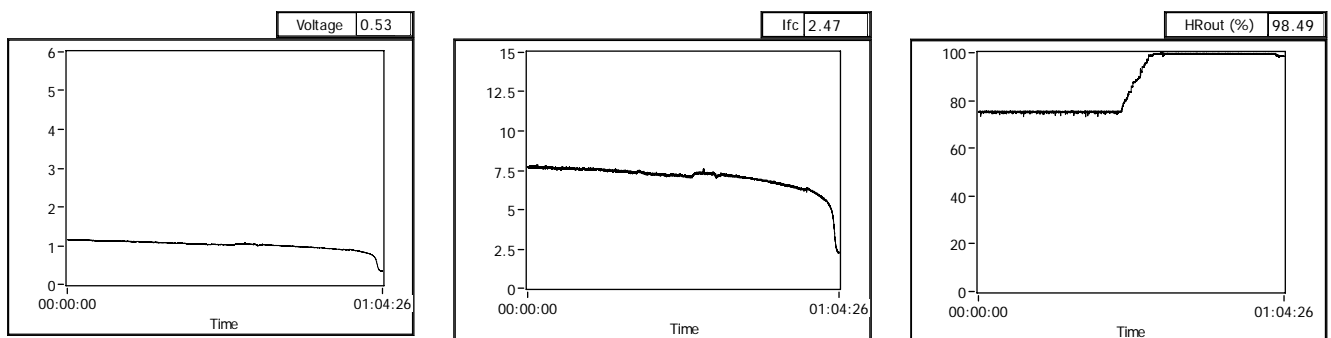


Figure 4. Evolution of FTFC's variables by reduction of the air-reaction volume.

The analysis of the FTFC behavior under faulty conditions requires a considerable number of cases in order to obtain a reliable model of the system. Unfortunately, the generation of each case requires about two hours of supervised experiments; therefore, the construction of a database with a considerable number of cases became highly time-consuming. Also, fault effects such as membrane breaking or drying of membrane imply permanent damage to the FTFC. The effects of different types of faults can be simulated adapting a FC model, avoiding damage to the equipment and reducing the time necessary to obtain the fault records.

3. THE FUEL CELL (FC) MODEL

A FC model to simulate operation in normal conditions was developed by Corrêa et al. (2003). In this paper, the polarization curve obtained with the model is compared to the polarization curve of the manufacturing data sheet to validate the model. The FC model is based on the calculation of voltage, temperature, and humidity, Eqs. (1) to (3), respectively.

The voltage is obtained by the equation:

$$V_{FC} = E_{Nernst} - V_{act} - V_{ohmic} - V_{con} \quad (1)$$

where: E_{Nernst} is the thermodynamic potential of the cell and is a function of the hydrogen pressure (P_{H_2}), oxygen pressure (P_{O_2}), and the operating temperature. V_{act} is the voltage drop due to the activation of the anode and the cathode, and is a function of the electric current (I_{FC}), the oxygen concentration (CO_2), and the coefficients ξ_i ($i = 1...4$), which are specific for each type of FC. V_{ohmic} is the ohmic voltage drop associated with the conduction of protons through the membrane, and electrons through the internal electronic resistance; is a function of the contact resistance to electron flow (R_C), and the resistance to proton transfer through the membrane (R_M). R_M is a function of the specific resistivity of membrane (ρ_M), the thickness of membrane (ℓ), the active area of the membrane (A), the electric current (I_{FC}), and the coefficient ψ which depends on the type of membrane. V_{con} represents the voltage drop resulting from the mass transportation effects, which affects the concentration of the reacting gases, and is a function of a constant B which depends on the type of FC, the maximum electric current density permitted (J_{max}), and the electric current density produced by the cell (J). In general, $J = J_{out} + J_n$ where J_{out} is the real electrical output current density, and J_n is the fuel crossover and internal loss current.

Considering a stack composed of several FCs, the output voltage is: $V_S = nr \cdot V_{FC}$, where nr is the number of cells composing the stack.

The variation of temperature in the FC is obtained with the following differential equation:

$$\frac{dT}{dt} = \frac{\Delta\dot{Q}}{M \cdot C_s} \quad (2)$$

where: M [kg] is the whole stack mass; C_s [J/K·kg] is the average specific heat coefficient of the stack; and $\Delta\dot{Q}$ is the rate of heat variation (i.e. the difference between the rate of heat generated by the cell operation and the rate of heat removed). Four types of heat can be removed: heat by the reaction air flowing in the stack (Q_{rem1}), by the refrigeration system (Q_{rem2}), by water evaporation (Q_{rem3}), and by heat exchanged with the surroundings (Q_{rem4}).

The relative humidity HR_{out} of the output air is calculated from the equation

$$HR_{out} = \frac{P_{w_{in}} + P_{w_{gen}}}{P_{sat_out}} \quad (3)$$

where: $P_{w_{in}}$ is the partial pressure of the water in the inlet air-reaction; $P_{w_{gen}}$ is the partial pressure of the water generated by the chemical reaction; and P_{sat_out} is the saturated vapor pressure in the output air.

For normal operation of the FC, proper temperature and humidity should be maintained. If the HR_{out} is much less than 100%, then the membrane dries out and the conductivity decreases. On the other hand, a HR_{out} greater than 100% produces accumulation of liquid water on the electrodes, which become flooded and block the pores, making gas diffusion difficult. The result of these two conditions is a fairly narrow range of normal operating conditions. In abnormal conditions such as flooding or drying, parameters (such as R_C and Ψ) that are normally constant start to vary.

Figure 5 (adapted from Larminie and Dicks, 2000) illustrates the effects of variation in temperature and HR_{out} for different stoichiometrical air relationships ($\lambda = 2$, $\lambda = 4$). The stoichiometry λ is the relationship between inlet air divided by the air necessary for the chemical relation.

In general, these parameters are based on manufacturing data and laboratory experiments, and their accuracy can affect the simulation results. In Corrêa et al. (2004), a multi-parametric sensitivity analysis is performed to define the importance of the accuracy of each parameter. The accuracy was analyzed in normal conditions, considering variations around $\pm 10\%$ of their normal values. However, in fault conditions, those variations can be stronger, as presented in sections 4.1 through 4.4.

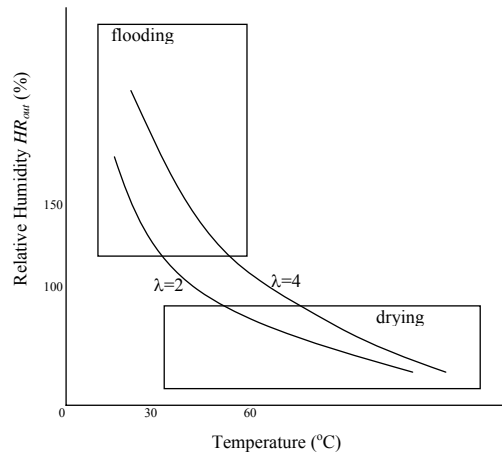


Figure 5. Temperature and Relative Humidity HR_{out} for $\lambda=2$ e $\lambda=4$.

4. FAULTS IN FUEL CELLS (FC)

In general, two categories of fault detection can be considered (Frank, 1992):

- Faults that can be detected by monitoring a specific variable. For example, fuel leaks can be detected by installing a specific gas sensor. In this case, a diagnosis is not necessary.
- Faults that cannot be detected directly by monitoring or faults that need some type of diagnosis.

In practice, fault detection on commercial FC equipment is limited to detection of faults of the first type. This work focuses on fault detection of the second type.

Four types of faults in PEMFCs are considered in this study: *a)* fault in the air fan, *b)* fault in the refrigeration system, *c)* growth of fuel crossover and internal loss current, and *d)* fault in hydrogen pressure. The effects of these faults and the behavior of the FTFC in fault operating conditions are included in the FC model.

4.1 Fault in the air reaction fan

A reduction of the reaction air by a fault in the air fan can produce two major effects: *(i)* accumulation of liquid water that cannot be evaporated, thus affecting the resistivity of electrodes, and *(ii)* reduction of O_2 concentration below that necessary for a complete reaction with the H_2 .

The variation of resistivity produces an increase in the ohmic voltage drop (V_{ohmic}), and consequently reduces the output voltage of the FC (V_{FC}).

The second effect of a fault in the air-reaction fan occurs when λ is below the practical and recommended value. In this case, the O_2 concentration is reduced and the exit air completely depleted of O_2 . This reduction of O_2 concentration produces a negative effect on the E_{Nernst} and the increment on the V_{act} . Figure 6 illustrates the evolution of output voltage (V_S), electric current (I_{FC}), water volume accumulated, relative humidity (HR_{out}), and stoichiometry, when a partial fault in the air fan occurs at $t=30$ minutes.

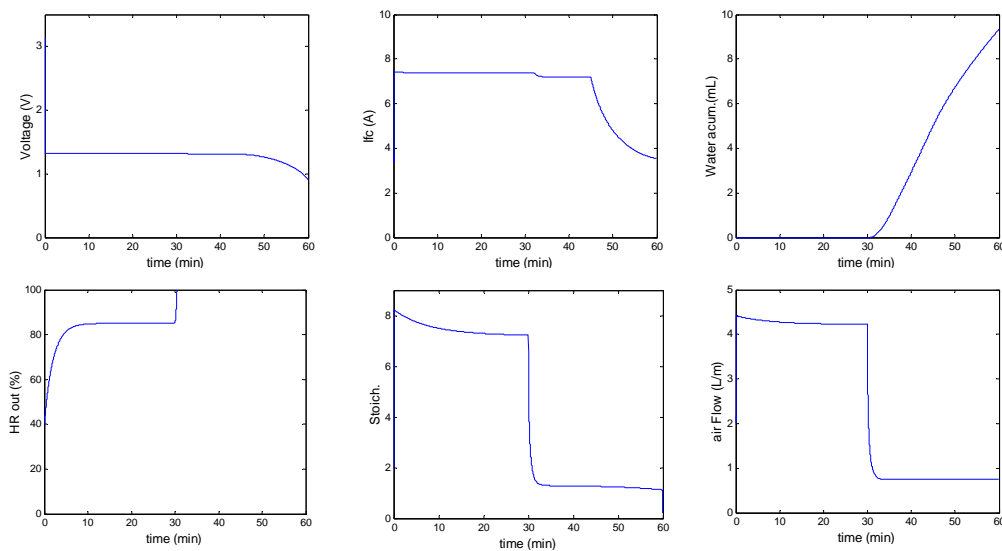
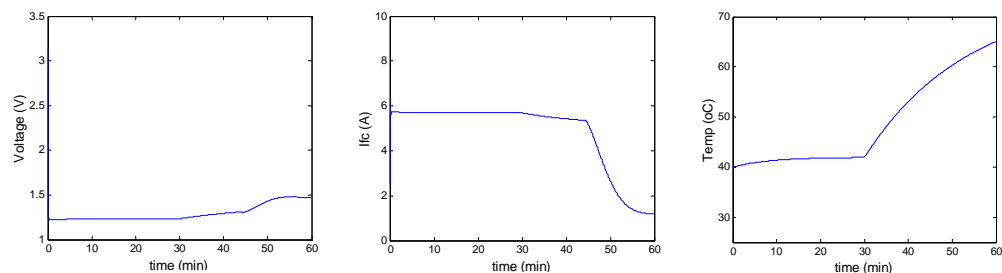


Figure 6. Evolution of the FC model by air-reaction fault.

4.2 Fault in the refrigeration system

The refrigeration system maintains temperature within operating conditions. When the temperature increases, the reaction air has a drying effect and reduces the relative humidity (HR_{out}). A low HR_{out} can produce a catastrophic effect on the polymer electrolyte membrane, which not only totally relies upon high water content, but is also very thin (and thus prone to rapid drying out). The drying of the membrane changes the membrane's resistance to proton flow. Figure 7 illustrates the evolution of output voltage (V_S), electric current (I_{FC}), temperature, relative humidity (HR_{out}), and stoichiometry produced by a fault in the refrigeration system (i.e. a reduction of Q_{rem2}) at $t=30$ minutes.



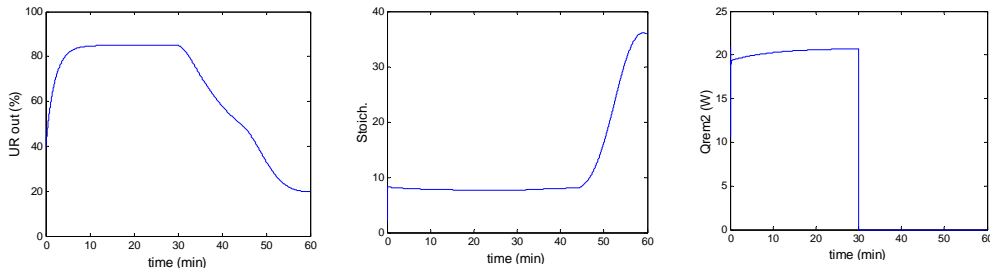


Figure 7. Evolution of the FC model by refrigeration system fault.

4.3 Increase of Fuel Crossover (J_n)

There is a small amount of wasted fuel that migrates through the membrane. It is defined as fuel crossover and is produced by some hydrogen that diffuse from the anode (through the electrolyte) to the cathode, reacting directly with the oxygen and producing no current for the FC.

In normal conditions, the flow of fuel and electrons through the membrane (J_n) is very small, typically representing only a few mA/cm². A sudden increase in this parameter can be associated with either abnormal ion membrane conduction or rupture of the membrane. This variation of J_n produces an increase in the concentration voltage drop (V_{con}), and therefore a reduction of V_{FC} . Fig. 8 illustrates the evolution of output voltage (V_S), electric current (I_{FC}), generated heat (Q_{gen}), output power (P_{ow}), and stoichiometry produced by an increase in the fuel crossover from 0.022 to 0.2 A/cm² at $t=30$ minutes.

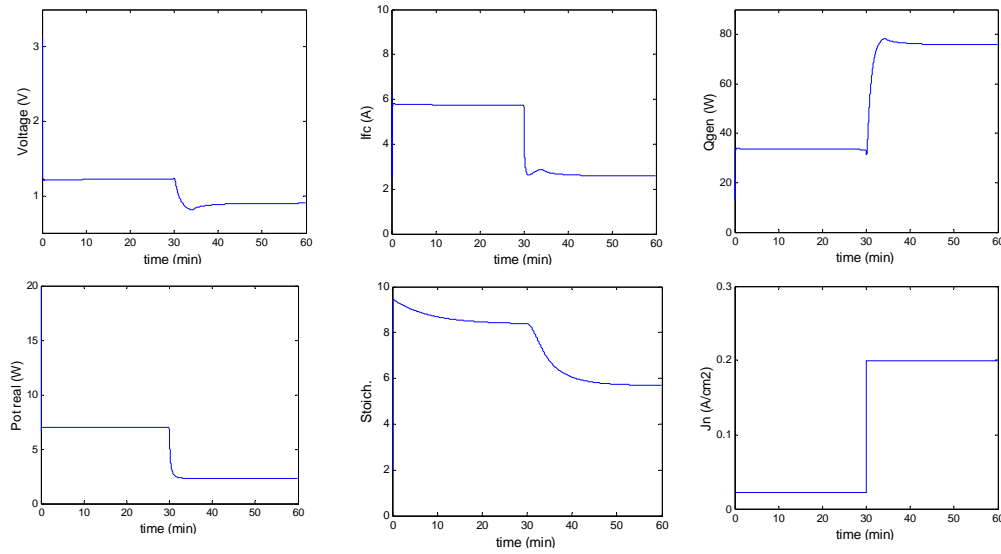


Figure 8. Evolution of the FC model by membrane breaking

4.4 Fault in Hydrogen Pressure

In general, for mobile and stationary applications, hydrogen is supplied by a high-pressure bottle, which is then reduced by a pressure regulator. In normal conditions, the hydrogen pressure is assumed to be constant (generally between 1 and 3 atm). A lower pressure negatively affects the performance of the FC. The reduction of H₂ pressure decreases the E_{Nernst} , increases the V_{act} , and has a corresponding effect on V_{FC} (see Eq. (1)). Fig. 9 illustrates the evolution of output voltage (V_S), electric current (I_{FC}), generated heat (Q_{gen}), stoichiometry, and relative humidity (HR_{out}) produced by a reduction of the H₂ pressure.

When a fault occurs, an interconnected dependence among the variables is established; in general, all the variables perform some kind of changes that hinders the diagnosis of the fault cause. To qualify and quantify the dependence among the variables, a Bayesian network is constructed to conduct the fault diagnosis.

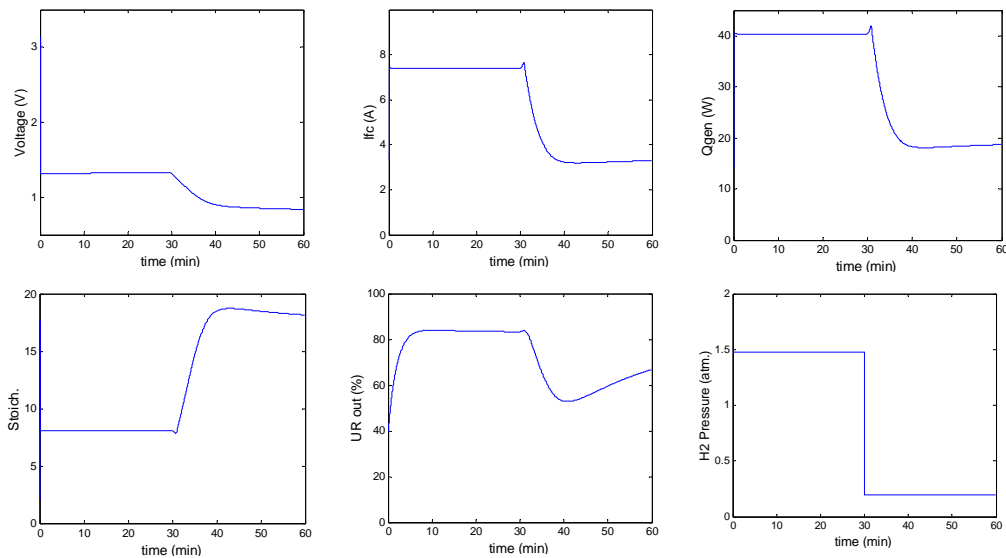


Figure 9. Evolution of the FC model by H_2 pressure fault.

5. BAYESIAN NETWORKS FOR FAULT DIAGNOSIS

A Bayesian belief network is a tool that graphically represents causal influences among a set of nodes in which each node represents a random variable or an uncertainty. These nodes can assume two or more values and for each node X_i , every other node that has a direct influence on it, is called a *parent of X_i* ($pa(X_i)$). A Bayesian network consists in a structure and a set of parameters, where the structure is represented by a directed acyclic graph (DAG) and the parameters are represented by a conditional probability table (CPT) that represents the conditional probabilities of a node given the set of its parents.

The construction of the graph topology to describe a diagnostic process can be conducted in two ways:

- based on knowledge elicitation about the system, where relationships among variables are established;
- based on system manuals, handbooks and human knowledge about the process; or
- based on learning methods using databases of records of past operations.

There are tools for the construction of Bayesian networks based on knowledge elicitation that makes it very attractive (Beinlich and Herskovits, 1990), however, its efficacy completely depends on the expert human knowledge about that domain.

In this work, the construction of a Bayesian network for fault diagnosis begins with the generation of a graph applying probabilistic methods, and it is then refined using domain knowledge. The complete sequence consists of the following steps:

1. Construction of the database -- the records are provided from a mathematical model of a PEMFC implemented on MatLab®. Field experiments could also provide those records, however, two major problems should be considered: i) large amounts of data are necessary, and ii) variables such as Q_{gen} , flooding, λ , etc, impose additional challenges to the monitoring stage.
2. Implementation of search-and-score algorithms (e.g. the Bayesian-Score (K2) (Cooper and Herskovits, 1992) and MCMC (Murphy, 2000)) to find the initial structure. The probabilistic approaches were implemented using the Bayesian Network Toolbox developed for MatLab® (Murphy, 2000).
3. Arrange of groups of variables in layers. Fault causes, sensors, and pattern recognition are considered in such layers.
4. Constraint-based conditions and knowledge application for the improvement of the structure.
5. Calculation of conditional probabilities on the final structure. In this research, the maximum posteriori likelihood algorithm (Pearl, 1988) was applied.

5.1 Generation of database

Binary states of the variables are considered (0=normal, 1=abnormal). The general procedure is to monitor a specific variable; if after a fault takes place and the value of such variable is off a certain tolerance band, then a flag should be turned to "1".

The next step is the construction of a vector containing the value of all variables. This vector corresponds to a single case in the database with values of all variables considered in a certain period. A database of fault records with 1,000 cases was constructed.

From the mathematical model, the evolution of variables that can be difficult to monitor on a real equipment (such as Q_{gen} or λ) can be observed. Records of all variables are essential for the construction of the network structure avoiding hidden variables. The probabilistic calculation of the diagnosis is simpler if there are no hidden variables (Pearl, 2000).

5.2 Search and Score Algorithms

The Bayesian-Score (K2) and the Markov Chain Monte Carlo (MCMC) algorithms were implemented in separated ways. The K2 algorithm adds parents to a single node the addition of which most increases the score of the resulting structure. When the addition of no single parent increases the score, we stop to add parents to a node and we go to the next node. Before the algorithm begins, the possible parents of every variable must be defined. Therefore, the human-expert experience is important to define that order.

The MCMC algorithm starts at a specific point in the space of all possible DAGs. The search is performed through all the nearest neighbors, and it moves to the neighbor that has the highest score. If no neighbor has a higher score than the current point, a local maximum was reached and the algorithm stops. A neighbor is the graph that can be generated from the current graph by adding, deleting or reversing a single arc.

In practice, the search-and-score algorithms are not exact and are used only as initial approximations. Also since the K2 and MCMC algorithms apply different tradeoffs for searching the structure, those algorithms can produce different results; therefore, knowledge about the conditional independence among the variables should be applied.

5.3 Layers of the Bayesian network

For a better understanding of the relationship among variables, those are separated in several layers. In the final structure, three layers are considered: fault causes, sensors, and pattern recognition. Fault causes are the possible causes of the fault such as fault in the air fan (a_F), fault in the refrigeration system (r_F), growth of J_n , and low H_2 pressure. Sensors are the variables that can be easily monitored (such as output voltage (V_S), electric current (I_{FC}), power, temperature, and H_2 pressure (p_{H_2})). Pattern recognition is associated with variables difficult to monitor in a real equipment, but that play an important role in a cause-effect structure and define a fault pattern. Those variables are: generated heat (Q_{gen}), stoichiometrical air relationship (λ), volume of air flow (FI), drying of membrane (Dr), flooding of electrodes (F), overload (Ov), and relative humidity (HR_{out}).

5.4 Constraint-based conditions and knowledge

First, the fusion of the results applying several probabilistic algorithms confirms the edges present in different structures, second, the remaining edges are submitted to erasing based on constrains and domain knowledge.

Some of the considered constraints are: i) independence among the fault causes (J_n , a_F , r_F , H_2), where only one fault takes place each time and one fault cause does not influence other fault causes; in other words, there are not edges between two causes; ii) independence among sensors (Pow , I_{FC} , V , T , p_{H_2}) where the monitored variable is not influenced by other variables, only by the effects monitored by itself, and iii) general knowledge about patterns influences.

Fig. 10 illustrates the resulting Bayesian network structure for fault diagnosis in PEMFC.

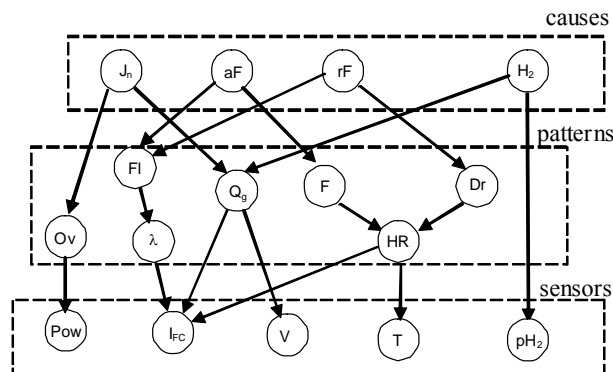


Figure 10. Bayesian network structure for fault diagnosis in a PEMFC.

Network structures representing a diagnostic process play a fundamental role for fault tolerant machines since they can be associated with fault treatment processes, (i.e. performing the fault diagnosis to identify the fault cause and executing the automatic recovery process). In (Riascos and Miyagi, 2001), (Miyagi and Riascos, 2006) and (Riascos et al., 2003) fault detection and fault treatment were analyzed, the case studied were automatic recovery processes in electric autonomous guided vehicles and machining processes.

5.3 The Online fault diagnosis

Inference in Bayesian networks is the computation of a conditional probability $p(X_q|X_E)$, where X_q is the variable of interest (e.g. the most probable fault cause) and X_E is the variable or set of variables that have been observed (i.e. the effects observed by sensors and transformed into logic outputs).

There are many different algorithms for calculating the inference in Bayesian networks, which apply different tradeoffs among speed, complexity, generality, and accuracy. The on-line fault supervisor executes the fault diagnostic inference by applying the probability propagation in trees of clusters (PPTC) algorithm, which is an exact method of inference and that, generally, can be applied to any type of Bayesian network structure (Cozman, 2001).

Figure 11 illustrates the conduction of an on-line fault diagnosis. This test was performed by externally forcing the output of the refrigeration system to zero, (this simulates a fault condition). In this case, the supervisor detects abnormal variations in some variables during the operation of the FC; these variations constitute the evidence. Then, the conditional probabilities were calculated for all fault causes (J_n , aF , rF , and H_2) and shown on the supervisor's display. According to the supervisor, the most probable fault cause is rF (fault in the refrigeration system) with 94% probability. The second probable cause is an increase of J_n with 44% probability, and causes aF and H_2 have 0% probability.

In all tests performed, the supervisor always indicated the true cause as the most probable cause.

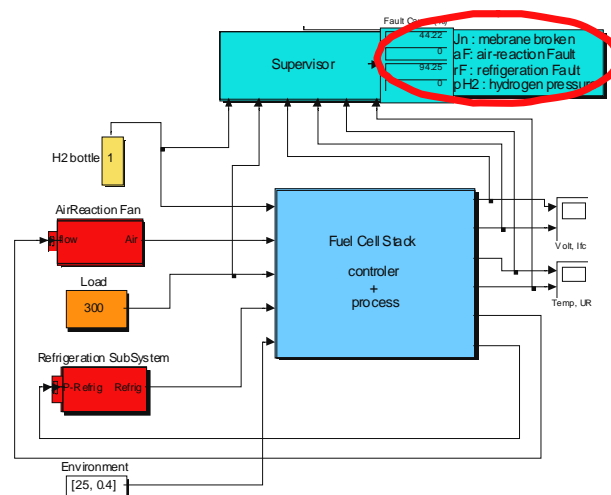


Figure 11. Online fault diagnosis execution

In general, the variation of electrical variables (such as output voltage (V_S), and electric current (I_{FC})) is faster than the variation of thermo-dynamical variables (e.g. temperature). Therefore, the diagnosis of faults such as rF takes more time (in this case, around 20 seconds); actually, this speed depends entirely on the accuracy of the sensors.

According to our experience, a worse case scenario still allows fault detection in less than one minute. But, even one minute is a good speed for detecting incipient faults before a catastrophic effect takes place in the fuel cell system.

6. CONCLUSIONS

The design of a supervisor system to perform on-line fault diagnosis in fuel cells was implemented. The execution of the diagnosis was based on a Bayesian network, which qualifies and quantifies the cause-effect relationship within the variables.

Fault records of some variables were constructed including variables difficult to monitor in a real machine. The record of all relevant variables is essential for the construction of the network structure avoiding hidden variables, especially in intermediary layers.

After the construction of the Bayesian network, the inference calculation is based on observations of variables relatively easy to monitor with sensors such as voltage, electric current, temperature, etc. This allows the implementation of fault diagnostic processes in real equipment.

The fault diagnostic tests have shown agreement between the inference results and the original fault causes.

In general, the fault diagnostic tests were fast enough to detect incipient faults before a catastrophic effect took place in the fuel cell system.

Topics such as the study of fault effects in fuel cells, the construction of network structures for fault diagnosis in fuel cells, and their association to fault treatment processes are still under study, and are open to research contributions.

8. ACKNOWLEDGEMENTS

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