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Diagnosis of automotive fuel cell power generators

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Abstract

Most of car manufacturers around the world have launched important research programs on the integration of fuel cell (FC) power generators into cars. Despite the first achievements, fuel cell systems are still badly known, particularly when talking about fault diagnosis and predictive maintenance. This paper proposes a first step in this way by introducing a simple but also efficient diagnosis-oriented model of a proton exchange membrane fuel cell (PEMFC). The considered diagnosis model is here a fuzzy one and is tuned thanks to genetic algorithms.

Keywords: Fuel cells; Fault diagnosis; Fuzzy logic; Genetic algorithms; Automotive applications

1. Introduction

Electrical energy is now accepted as a clean and universally available source of energy in almost all areas of life. One exception is road traffic. Despite the fact that electrical vehicles dominated the early development of motor cars, the internal combustion engine (ICE) has prevailed because of the high-energy density of petrol. Nevertheless, in the past few years, auto manufacturers around the world have launched important research programs on fuel cells (FCs) as major long term energy-conversion solutions because they offer high fuel economy, through higher efficiency from the stack to the wheel, and substantially lower emissions, particularly of CO_2. Of course, many of these manufacturers have already demonstrated buses or cars powered by fuel cells, most of them by proton exchange membrane fuel cells (PEMFCs). For example, it is possible to name the series of *Necar* (I–V) proposed by Daimler-Chrysler, the *Think FC5* proposed by Ford, the *Hy-wire* proposed by General Motors, the *Demio FCEV* proposed by Mazda, the *H20* proposed by PSA and so on. Most of them are single powered by fuel cells, some hybrid solutions have also been presented, such as the *Honda FCX-V3* [1]. In association with the fuel cell manufacturers, great efforts have already been done in order to improve the stack performances [2].

However, in most cases, the efficiency of the global power system is still reduced due to the lack of specific and optimized auxiliaries. Considering the PEMFC case, a complex and energy-intensive reactant control and conditioning system is required. In fact, compression and humidification of the reactant air are particularly critical, because these processes can require about half the energy produced by the fuel cell. Moreover, the cost of a fuel cell vehicle is still, nowadays, much too high for considering an introduction on the market at a competitive price. The choice of fuel is another crucial problem: shall the hydrogen be directly stored on-board or shall it be produced from fossil fuels? Moreover, if on-board hydrogen storage is chosen, the whole fuel distribution infrastructure should be reconsidered [3]. Finally, fuel cell systems diagnosis tools must be available on the market to perform faults diagnosis and predictive maintenance on the vehicle.

The aim of this paper is to propose a first step in the direction of fuel cell systems diagnosis. To achieve this aim, a diagnosis-oriented model of a fuel cell power generator dedicated to automotive applications is proposed.

Considering only the static behavior of a PEM fuel cell, the fuel cell voltage can be expressed as a function of the current density following (Eq. (1)) [4]:

$$E = E_{\mathrm{t,c}} - \frac{RT}{F}\left[\frac{\ln(i/i_{0,\mathrm{c}})}{1-\alpha} + \frac{i}{i_{0,\mathrm{a}}}\right] + \frac{RT}{zF}\ln\left(\frac{C^{\mathrm{S}}_{\mathrm{O_2}}C_{\mathrm{H_2}}}{C_{\mathrm{O_2}}C^{\mathrm{S}}_{\mathrm{H_2}}}\right) - ir \quad (1)$$

where E is the fuel cell voltage, $E_{\mathrm{t,c}}$ the cathode theoretical potential, R the gas constant, T the temperature, F the Faraday constant, i the current density, $i_{0,\mathrm{c}}$ and $i_{0,\mathrm{a}}$ the cathode

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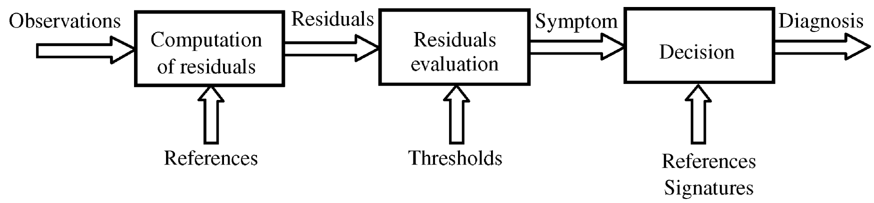

Fig. 1. General diagnosis process.

and anode reaction exchange current density, α the charge transfer coefficient, z the reaction charge number, C_{H_2} and C_{O_2} the hydrogen and oxygen bulk concentrations, $C^S_{H_2}$ and $C^S_{O_2}$ the hydrogen and oxygen electrode surface concentrations, and r is the area specific resistance.

Of course, such an expression is very difficult to use in a diagnosis process for a car manufacturer because the concentrations and the reaction current densities cannot be accessed in real time. Thus, a fuzzy description of the fuel cell behavior has here been preferred.

The bases of a fuzzy diagnosis model are recalled in the first part of this paper. Then, the description of the most commonly seen faults on a fuel cell system is done, underlining from what kind of measures on a real fuel cell vehicle these faults must be deducted. In the second part of the paper, the fuzzy logic diagnosis model of the PEMFC power generator is described. This fuzzy diagnosis model is here tuned thanks to genetic algorithms. Finally, simulation and experimental results will be discussed.

2. Fuzzy diagnosis on a fuel cell power generator implemented in a vehicle

2.1. Bases of fuzzy diagnosis

As in all other diagnosis methods, the first step in the diagnosis process is here to obtain *residuals* (Fig. 1) by comparing what is currently obtained on a considered system (called *observations*) to what is normally obtained on this system under the same operating conditions (called *references*). These residuals have to reflect the faults on the process but also to avoid disturbances (caused by noise or modeling errors).

The residuals have then to be quantified to produce *symptoms*. The main problem is here to fix thresholds for each residual from whose a default will be considered. The objective of this quantification stage is thus to determine if a fault is occurring on the system. The last stage in the diagnosis process is then to find the cause of the fault. This is done by comparing the symptoms to *references signatures* coming, in most cases, from expert knowledge on the considered system.

The computation of residuals is most commonly done by using analytical models of the considered system. This can be easily done and is the most powerful when the physical relations and the physical parameters of the system are well-known. When the system is more complex and/or when the physical parameters of this system are not easily measurable, a fuzzy modeling of the system can be considered [5,6]. Two different kinds of fuzzy model for residuals generation can be considered: the Open Loop Model (OLM) (Fig. 2) and the Closed Loop Model (CLM) (Fig. 3) [7].

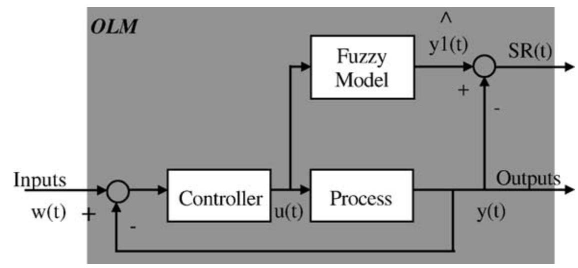

Fig. 2. OLM fuzzy model for residuals evaluation.

Considering the OLM, the fuzzy model is placed parallel to the process and is submitted to the same solicitation $u(t)$ where t is the time. The deviation $\mathrm{SR}(t)$ of output predictions $\hat{y}_1(t)$ from output measurements $y(t)$ is then evaluated to produce residuals:

$$\mathrm{SR}(t) = \hat{y}_1(t) - y(t) \tag{2}$$

Considering the CLM case, the fuzzy model is also placed parallel to the process but in another closed loop with its own controller. In this case, the performance of the real system

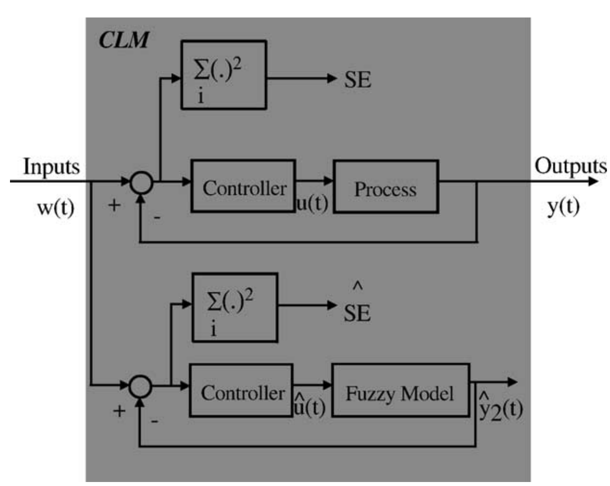

Fig. 3. CLM fuzzy model for residuals evaluation.

is controlled thanks to the squared error between desired and actual process output (Eq. (3)) within a time window of predefined length ($t_0 - t_1$).

$$\Delta\mathrm{SE} = \widehat{\mathrm{SE}} - \mathrm{SE} \tag{3}$$

with

$$\widehat{\mathrm{SE}} = \int_{t_0}^{t_1} (w(t) - \hat{y}_2(t))^2 \, \mathrm{d}t \tag{4}$$

$$\mathrm{SE} = \int_{t_0}^{t_1} (w(t) - y(t))^2 \, \mathrm{d}t \tag{5}$$

The quantification of the evaluated residuals (through the different thresholds) to produce symptoms can, of course, also be done thanks to fuzzy logic. In such a case, the thresholds are fuzzy ones, varying around their nominal values. In any case, a fault is detected on the process if at least one symptom is not nominal.

2.2. Faults on a vehicle fuel cell power generator

The faults that have to be detected and diagnosed on a fuel cell power generator implemented in a vehicle are very numerous: from the major damage on the stack itself, which implies the replacement of it, to the temporary variations of the system output values that can be easily corrected through the fuel cell control system.

Among these various faults, two have been considered so far. The first one is the accumulation of nitrogen and/or water in the anode compartment. In fact, in the PEMFC, oxygen from the air reacts at the cathode with electrons taken from the electrode and H^+ protons from the electrolyte, to form water according to Eq. (6).

$$O_2 + 4e^- + 4H^+ \rightarrow 2H_2O \tag{6}$$

If no water is present at the anode, a back diffusion of water from cathode to anode will take place, depending on the thickness of the electrolyte membrane and the relative humidity of each side. The same phenomenon will also take place considering nitrogen which is present in the reactant air. Therefore, accumulation of nitrogen and/or water in the anode compartment may occur, especially when the PEMFC is operating in dead-end mode with only a few flushes in the anode compartment.

The second considered fault is an important drying of the proton exchange membrane. This drying can occur because the drying effect of air is non-linear in its relationship to temperature [8]. When the temperature increases, the membrane dries out (if no extra humidification of the reactant gases is present) resulting in a drastic fall of the fuel cell system electrical efficiency.

These two faults have been studied in preference and priority to the others. Firstly, they will often take place on a fuel cell vehicle. Secondly, they can be corrected thanks to the fuel cell system control. Thirdly, they do not imply a major and non-reversible damage on the stack.

For the generation of residuals and thus the fault diagnosis process, only as few measurements on the system as possible have been considered. Indeed, the on-line faults diagnosis on fuel cell power generators should not imply a lot of expensive additive sensors. Therefore, among the various available measurements on a laboratory fuel cell power generator (current, voltage, air and hydrogen flows, inlet and outlet pressures, temperatures, single cell voltages, ...), only the current and the voltage have here been chosen to perform the diagnosis process [9,10]. Maybe these two measurements are not enough to fulfill the faults localization process, but as many information as possible will be extracted from these two measurements.

3. Fuzzy diagnosis model of a proton exchange membrane fuel cell power generator

3.1. Description

The considered fuel cell system is constituted by a PEMFC that can be operated with pure or reformed hydrogen on the anode side and with air or oxygen on the cathode side. The experimental stack is here only a low power stack, but the results (and the fuzzy diagnosis model) can be easy extrapolated to a more powerful fuel cell system. The stack is made up of 20 cells (area $100\,\mathrm{cm}^2$) and is able to supply an electrical power up to 500 W under 12 V. The range of the operating temperatures begins at 15 °C to go as far as 70 °C. Additional to the anode and cathode gas circuits, a coolant desionized water circuit is used to extract the calories from the stack.

The chosen method, for obtaining a fuzzy diagnosis model of this fuel cell system, consists in determining a so-called satisfaction rate (noted SR), by comparing the obtained voltage-current operating point to the expected nominal operating point. This satisfaction rate is then normalized between 0 and 1 (1 is the better rate that can be obtained). The expected nominal operating point is fixed by the static voltage-current characteristic of the stack. An OLM has been considered for the computation of residuals. This method is less time consuming considering on-line diagnosis case of the fuel cell system. Indeed, only one controller output value has to be computed during the sampling period.

3.2. Diagnosis-oriented fuzzy modeling of a PEMFC

According to what has been explained in the previous paragraph, the first step is to identify the expected nominal operating points. Therefore, the experimental static characteristic of the PEMFC stack under nominal operating conditions has been plotted (Fig. 4). Notice that, as the behavior of a fuel cell system presents a hysteresis regarding current evolution, this experimental static characteristic is the best one that can be obtained on the considered fuel cell system.

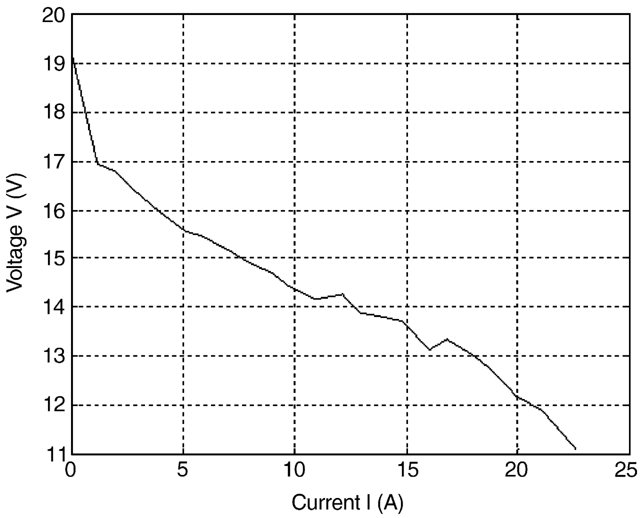

Fig. 4. PEM fuel cell stack voltage/current characteristic.

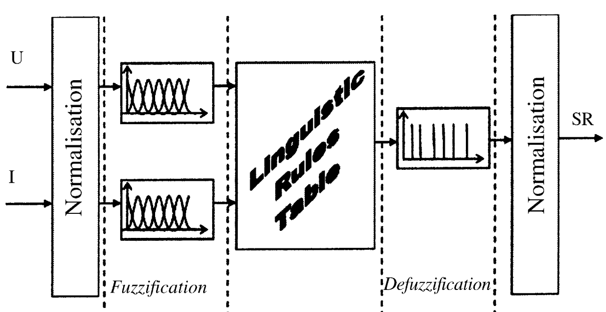

Fig. 5. Sugeno-type fuzzy model.

Then, a fuzzy model of the fuel cell system has to be built. As previously said, this model should use only two inputs: the voltage V and the current I. The single output of this fuzzy model is here directly the satisfaction rate SR (which should be equal to 1 on the PEMFC static characteristic). So, considering the whole diagnosis process, this fuzzy model will directly provide a residual at its output, which can be evaluated in a next step to produce a symptom. The closer to 1 this residual will be, the better the performances of the fuel cell system will be.

The calculation of the satisfaction rate is done thanks to a two-inputs one-output Sugeno-type fuzzy system [11] (Fig. 5).

The first stage is the normalization of the two inputs U (voltage) and I (current) between their min and max values. This results in two normalized inputs, noted U_n and I_n that vary between 0 and 1. Then, seven membership functions are used for the fuzzification process. The seven membership functions on both inputs are Gaussian ones; the membership degree of input $U_n(t)$ at the fuzzy subset k ($k \in [1, \dots, 7]$) described by membership function $\mu_{U,k}$ is thus given by Eq. (7)

$$\mu_{U,k}(t) = \exp\left(-\frac{(U_n(t) - m_{U,k})^2}{2\sigma_{U,k}^2}\right) \tag{7}$$

where $m_{U,k}$ and $\sigma_{U,k}$ are respectively the middle position and the standard deviation of membership function $\mu_{U,k}$.

In the same way, the membership degree of input $I_n(t)$ at the fuzzy subset m ($m \in [1, \dots, 7]$) described by membership function $\mu_{I,m}$ is given by Eq. (8)

$$\mu_{I,m}(t) = \exp\left(-\frac{(I_n(t) - m_{I,m})^2}{2\sigma_{I,m}^2}\right) \tag{8}$$

where $m_{I,m}$ and $\sigma_{I,m}$ are respectively the middle position and the standard deviation of membership function $\mu_{I,m}$.

As a Sugeno-type fuzzy system is used, the output membership functions are only singletons, in our case seven singletons ("Z": Zero; "VS": Very Small; "S": Small; "M": Medium; "B": Big; "VB": Very Big; "XB": eXtra Big). The considered linguistic rules table is a classical sloping diagonal table (Table 1) [12]. For example, this rules table is read as follows (Eq. (9)):

$$\begin{array}{l}\text{IF } (U_n(t) \text{ is Very Small “VS”) AND } (I_n(t) \text{ is Big “B”)} \\ \text{THEN (SR}(t) \text{ is Very Big “VB”)}\end{array} \tag{9}$$

Thus, as a matter of fact, the defuzzified satisfaction rate is the following (Eq. (10)):

$$\mathrm{SR}(t) = \frac{\sum_{k=1}^{7}\sum_{m=1}^{7}(\mu_{U,k}(t)\mu_{I,m}(t))\mu_{\mathrm{SR},mk}}{\sum_{k=1}^{7}\sum_{m=1}^{7}(\mu_{U,k}(t)\mu_{I,m}(t))} \tag{10}$$

The positions and the shapes of the different membership functions have been determined through an optimization procedure which is described in the next part of this paper. The seven singletons at the output have been fixed during this optimization procedure (so as to reduce the number of freedom degrees). Moreover, as the satisfaction rate should

Table 1
Linguistic rules table

(U_n, I_n)	$\mu_{U,1}$ "Z"	$\mu_{U,2}$ "VS"	$\mu_{U,3}$ "S"	$\mu_{U,4}$ "M"	$\mu_{U,5}$ "B"	$\mu_{U,6}$ "VB"	$\mu_{U,7}$ "XB"
$\mu_{I,1}$ "Z"	$\mu_{\mathrm{SR},11}$ "Z"	$\mu_{\mathrm{SR},12}$ "VS"	$\mu_{\mathrm{SR},13}$ "S"	$\mu_{\mathrm{SR},14}$ "M"	$\mu_{\mathrm{SR},15}$ "B"	$\mu_{\mathrm{SR},16}$ "VB"	$\mu_{\mathrm{SR},17}$ "XB"
$\mu_{I,2}$ "VS"	$\mu_{\mathrm{SR},21}$ "VS"	$\mu_{\mathrm{SR},22}$ "S"	$\mu_{\mathrm{SR},23}$ "M"	$\mu_{\mathrm{SR},24}$ "B"	$\mu_{\mathrm{SR},25}$ "VB"	$\mu_{\mathrm{SR},26}$ "XB"	$\mu_{\mathrm{SR},27}$ "VB"
$\mu_{I,3}$ "S"	$\mu_{\mathrm{SR},31}$ "S"	$\mu_{\mathrm{SR},32}$ "M"	$\mu_{\mathrm{SR},33}$ "B"	$\mu_{\mathrm{SR},34}$ "VB"	$\mu_{\mathrm{SR},35}$ "XB"	$\mu_{\mathrm{SR},36}$ "VB"	$\mu_{\mathrm{SR},37}$ "B"
$\mu_{I,4}$ "M"	$\mu_{\mathrm{SR},41}$ "M"	$\mu_{\mathrm{SR},42}$ "B"	$\mu_{\mathrm{SR},43}$ "VB"	$\mu_{\mathrm{SR},44}$ "XB"	$\mu_{\mathrm{SR},45}$ "VB"	$\mu_{\mathrm{SR},46}$ "B"	$\mu_{\mathrm{SR},47}$ "M"
$\mu_{I,5}$ "B"	$\mu_{\mathrm{SR},51}$ "B"	$\mu_{\mathrm{SR},52}$ "VB"	$\mu_{\mathrm{SR},53}$ "XB"	$\mu_{\mathrm{SR},54}$ "VB"	$\mu_{\mathrm{SR},55}$ "B"	$\mu_{\mathrm{SR},56}$ "M"	$\mu_{\mathrm{SR},57}$ "S"
$\mu_{I,6}$ "VB"	$\mu_{\mathrm{SR},61}$ "VB"	$\mu_{\mathrm{SR},62}$ "XB"	$\mu_{\mathrm{SR},63}$ "VB"	$\mu_{\mathrm{SR},64}$ "B"	$\mu_{\mathrm{SR},65}$ "M"	$\mu_{\mathrm{SR},66}$ "S"	$\mu_{\mathrm{SR},67}$ "VS"
$\mu_{I,7}$ "XB"	$\mu_{\mathrm{SR},71}$ "XB"	$\mu_{\mathrm{SR},72}$ "VB"	$\mu_{\mathrm{SR},73}$ "B"	$\mu_{\mathrm{SR},74}$ "M"	$\mu_{\mathrm{SR},75}$ "S"	$\mu_{\mathrm{SR},76}$ "VS"	$\mu_{\mathrm{SR},77}$ "Z"

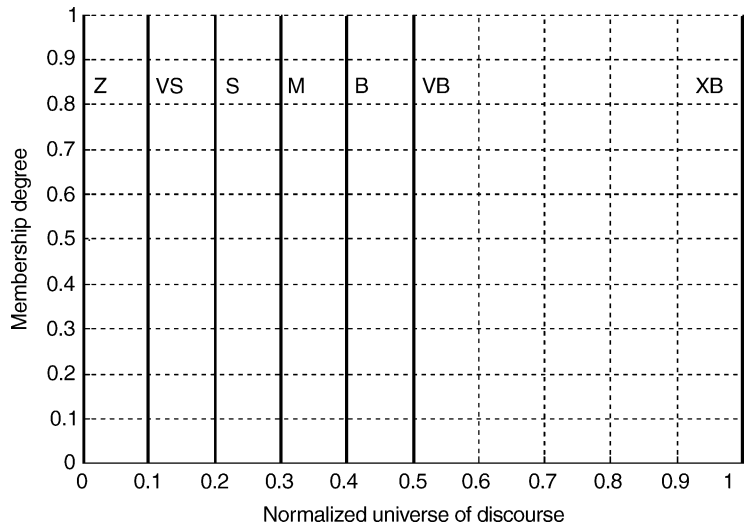

Fig. 6. Satisfaction rate output singletons positions.

equal 1 on the static characteristic of the fuel cell and should decrease rapidly around this characteristic (to ensure a good stiffness of the diagnosis process), these seven singletons have been placed as described by Fig. 6.

4. Tuning of the fuzzy diagnosis model using genetic algorithm

4.1. Genetic algorithm for fuzzy system optimization

The positions and the shapes of the seven membership functions at each input were tuned using a specific genetic algorithm (GA) [13,14]. Twenty-four parameters have here to be tuned: the membership functions positions $m_{U,2}$ to $m_{U,6}$ and $m_{I,2}$ to $m_{I,6}$ (varying on the normalized universe of discourse between 0 and 1) and the different standard deviation values $\sigma_{U,k}$ and $\sigma_{I,m}$ (limited to vary between 0.02 and 0.15 for avoiding too narrow or too wide membership function shapes).

4.1.1. Encoding of a chromosome, population size

A binary string is here used for the encoding of chromosomes. Each of the 24 parameters that have to be tuned is encoded using 6 bits resulting in a 144 bits chromosome for one individual in the population. The population size is chosen equal to 200 and is randomly initialized.

4.1.2. Objective function

The considered optimization criterion is the sum of the obtained satisfaction rates on 35 points placed along the fuel cell static characteristic. The max level of this objective function is also the normalized value 35. Notice that a penalty factor of 0.7 is applied on the objective function result when the resulting different membership functions positions $m_{U,k}$ and $m_{I,m}$ are not ranked in ascending order.

4.1.3. Offspring generation, crossover and mutation

Half of the offspring generation is constituted using a tournament selection. Two individuals are randomly selected and the best one survives to new generation (with a probability of 80%). The rest of offspring generation is constituted using a two point crossover method. The two parents are randomly selected and two crossover points are also randomly selected on the chromosomes. Next, two mutation bits are selected on each offspring individual. Finally, the best individual of last generation always survives to new generation.

4.1.4. GA optimization

Fig. 7 presents the compared evolutions of best individual objective function, worst individual objective function, median individual objective function and mean objective function during GA optimization process. As it can be seen, 200 generations have been used to perform this optimization

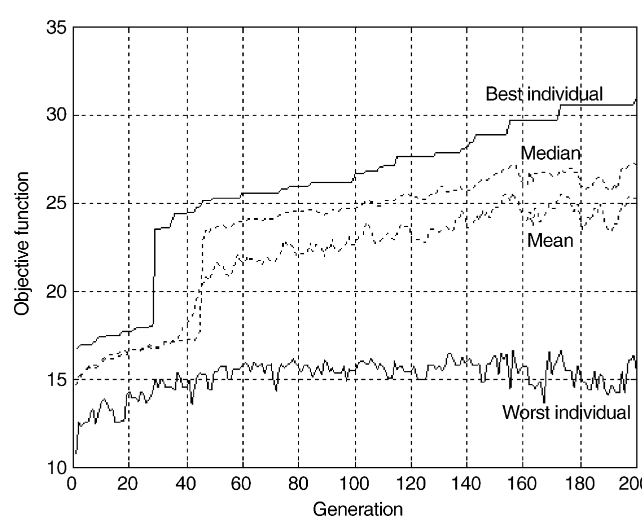

Fig. 7. GA optimization process of membership functions.

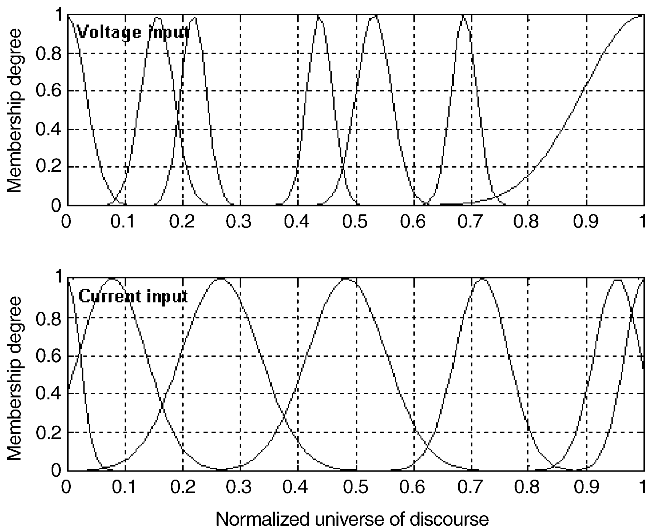

Fig. 8. Inputs membership functions after optimization.

process and the best individual presents an objective function value of 30.9.

4.2. Optimization results

Fig. 8 presents the inputs membership functions positions and shapes corresponding to the best individual in population after 200 generations.

The satisfaction rate SR obtained at the output, using the tuned Sugeno-type fuzzy system is given by Fig. 9. On the same figure (Fig. 9) are presented the satisfaction rate (on the whole range of current and voltage) and the static characteristic of the fuel cell power generator. As it can be seen on this figure, SR is very closed to 1 near the static characteristic and decreases rapidly to reach 0 around this characteristic. This ensures a very good stiffness for the residual generation process and thus for the whole fuzzy diagnosis process.

Moreover, as it can be seen on Fig. 9, the satisfaction rate will remain in the neighborhood of 1 if the current suddenly

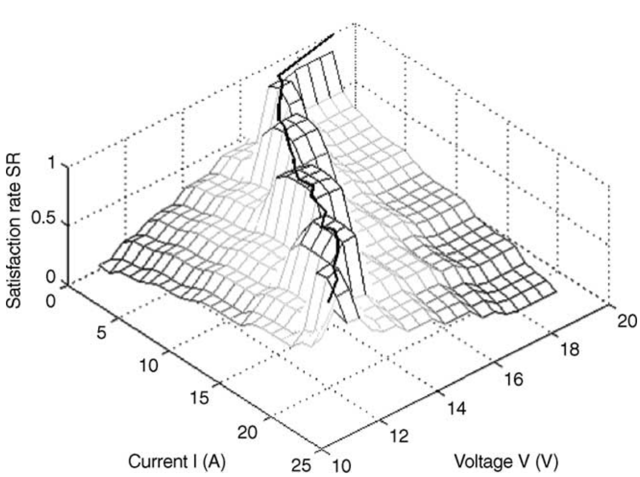

Fig. 9. Fuzzy satisfaction rate vs. current and voltage.

vary without a voltage modification. This case takes place during fuel cell transient states. In fact, due to the hydrogen and oxygen that are present in excess in the cathode and anode compartment, the fuel cell is able to provide instantaneously a relatively important overcurrent without an important voltage variation [15].

5. Experimental results

5.1. Accumulation of nitrogen and water in the anode compartment

The first fault that has been experimentally diagnosed using the proposed fuzzy diagnosis model is the accumulation of water and nitrogen in the anode compartment in case of a dead-end mode use of the fuel cell. A fixed and non-fuzzy threshold has here been used for the residual evaluation. Fig. 10 presents the experimental results obtained on the 500 W PEMFC. Fixing the threshold at a 0.9 level, a symptom is produced thanks to the fuzzy diagnosis model in less than 150 s. This threshold value has been chosen considering a trade-off between three important things:

- The first one is the required accuracy of the diagnosis system versus accumulation of N_2 and H_2O in the anode compartment; the aim is here to ensure in any case a minimum voltage value for each single cell. Such a minimum voltage strategy leads also to an increase of the fuel cell stack durability.
- The second one is the obtained stiffness of our diagnosis system. As it is presented in Fig. 10, the satisfaction rate is decreasing rapidly between 0.95 and 0.65 satisfaction rate levels and that, for a relatively small fuel cell stack voltage modification.

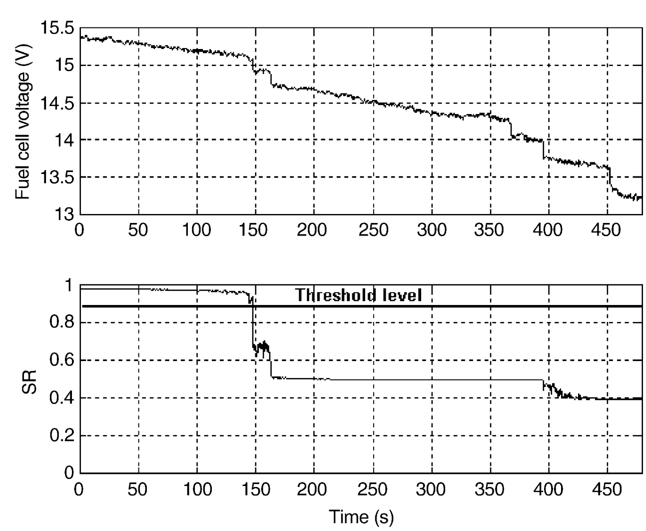

Fig. 10. Evolution of voltage and SR when accumulation of nitrogen and water occurs in anode compartment of the fuel cell.

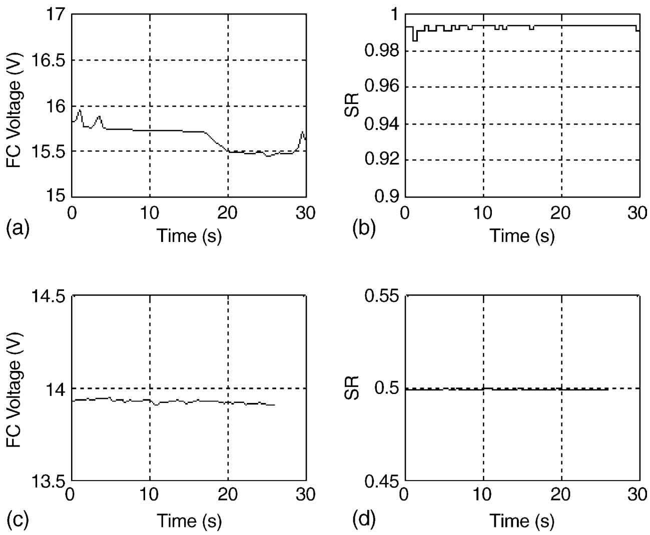

Fig. 11. Evolution of voltage and SR when temperature increases. (a) FC voltage; current = 6 A; operating temperature = 18 °C. (b) Satisfaction rate; current = 6 A; operating temperature = 18 °C. (c) FC voltage; current = 6 A; operating temperature = 50 °C. (d) Satisfaction rate; current = 6 A; operating temperature = 50 °C.

- Finally, the third one is the required robustness of the symptom generation process, especially its ability of avoiding disturbing wrong alarms on the system.

5.2. *Drying of the proton exchange membrane*

Fig. 11 presents the FC voltage and satisfaction rate evolutions for a 6A current and for an ambient operating temperature (Fig. 11a and b) or a 50 °C operating temperature (Fig. 11c and d). As it can be seen on these figures, the satisfaction rate is much closed to 1 when operating under ambient temperature and decreases to 0.5 when operating at 50 °C. Notice that no extra gas humidification was used for these experiments. As in the last part of this paper, a fixed threshold (0.8 in our case) has been used for the symptom evaluation process. The choice of this second threshold value has been made according the same physical reasons as described for the accumulation fault. Nevertheless, as the drying of the membrane is less dynamical than the accumulation of nitrogen and water in the anode compartment, it's possible to wait for a longer time before generating a symptom, therefore a lower threshold value (0.8 in our case) has been chosen.

5.3. *Decision*

The last stage in the diagnosis process is the decision stage. In our case, a decision must be taken to detect which fault (H_2O/N_2 accumulation in the anode compartment or PEM drying) is currently occurring on the system. Due to the fact that only one symptom SR(t) has been produced thanks to the fuzzy model, the computation of the filtered first time derivative of this satisfaction rate is very useful (Fig. 12). The cutoff pulsation is here placed at a $1/\tau_f = 0.1$ rad/s level.

In fact, considering the two considered faults on the fuel cell system, the decrease of SR(t) in case of accumulation of water or nitrogen in the anode compartment is much swifter (experimentally about 10 times swifter) than in the case of PEM drying. Therefore, using the filtered first derivative of SR(t) and using a fixed threshold (value dth = 0.002 here, this numerical value has been obtained thanks to different tests on the real system and taking into account the noise level that is present in the output of the fuzzy model SR(t)) on this time derivative signal, it is easy to detect which kind of fault is currently occurring on the system. In our case, a set/reset flip-flop has also been added on the derivative signal to retain the input of the AND gate (Fig. 12). Using this proposed fault localization process, when a PEM drying occurs on the fuel cell, SR(t) is going under the 0.8 satisfaction rate level, but the first derivative does not go over the so-called dth threshold. Thus, only a drying fault is detected thanks to the diagnosis process. The system is then shut down to avoid any major damage on the fuel cell stack. Electrical load should be removed and wet air provided to humidify the proton exchange membrane. If a two high level of water or nitrogen is present in the anode compartment, both the satisfaction rate and the first derivative are going over the proposed thresholds, resulting only in a H_2O/N_2 fault.

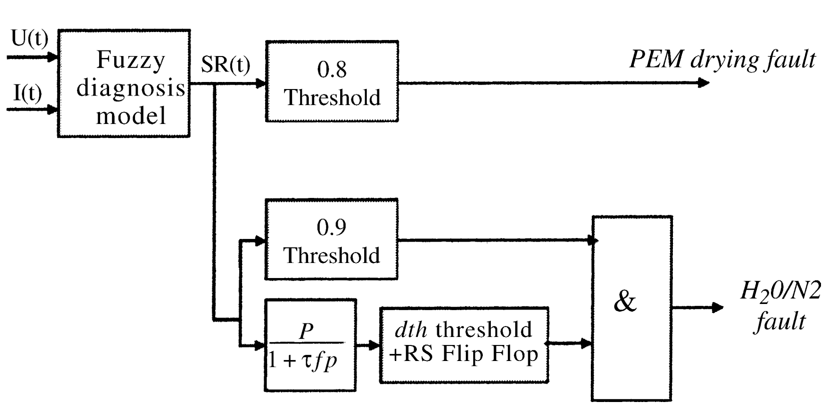

Fig. 12. Fault localization process.

In this case also, the system is shut down and the diagnosed fault is provided to the user, who can then flush the anode compartment. Thus, in the two considered fault cases on the fuel cell system, the fuzzy diagnosis process has proved its ability to fulfill the fault localization process.

6. Conclusion

To achieve the aim of the commercialization of no emission vehicles, an interesting solution could be the use of a fuel cell power generation device instead of the internal combustion engine (ICE). However, several milestones have to be overcome before FC vehicles appear on the market at a commercial price. One of them is the necessary development of powerful FC diagnosis tools to increase the reliability of such systems. This paper proposes a solution to perform such diagnosis tools using fuzzy logic. Of course, the proposed methodology takes only into account at the present time two types of faults (accumulation of water/nitrogen in the anode compartment and drying of the membrane). Nevertheless, the same kind of methodology could be applied for a greater number of considered faults. In this case, the best solution would probably be to define and to tune accurately (according to human expert knowledge) one different fuzzy surface per considered fault and to propose a logic to obtain, from the different generated residuals, the right fault diagnosis.

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