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► **To cite this version:**

Stéphane Caux, Walid Hankache, Maurice Fadel, Daniel Hissel. On-line fuzzy energy management for hybrid fuel cell systems. *International Journal of Hydrogen Energy*, 2010, 35 (5), pp.2134-2143. 10.1016/j.ijhydene.2009.11.108 . hal-03574364

**HAL Id: hal-03574364**

**<https://ut3-toulouseinp.hal.science/hal-03574364>**

Submitted on 15 Feb 2022

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# On-line fuzzy energy management for hybrid fuel cell systems

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## ABSTRACT

Fuel Cell Hybrid Vehicles (FCHV) can reach near zero emission by removing the conventional internal combustion from the vehicle powertrain. Nevertheless, before seeing competitive and efficient FCHV on the market, at market prices, different technical, economic, and social challenges should be overcome. A typical hybrid fuel cell powertrain combines a fuel cell stack and a dedicated energy storage system along with their necessary power converters. Energy storage systems are used in order to enhance the well-to-wheel efficiency and thus reducing the hydrogen consumption. An efficient management of power flows on the vehicle, allows optimizing the recovery of energy braking. Moreover, working in the fuel cell maximum efficiency leads to reduced thermal losses and thus to the downsizing of the heat exchangers. This paper presents an enhanced control of the power flows on a FCHV in order to reduce the hydrogen consumption, by generating and storing the electrical energy only at the most suitable moments on a given driving cycle. While the off-line optimization-based on dynamic programming algorithm offers the necessary optimal comparison reference on a known demand, the proposed strategy which can be implemented on-line, is based on a fuzzy logic decision system. The fine tuning of the fuzzy system parameters (mainly the membership functions and the gains), is made using a genetic algorithm and the fuzzy supervisor shows performing results for different load profiles.

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### Keywords:

Energy management  
Fuel cell hybrid vehicle  
Fuzzy logic  
Genetic algorithm

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## 1. Introduction

Energy management strategies remain a main subject of interest, where many industrials and academic researchers are actively involved in recent studies as well as for residential application [1], decentralized generation [2], and for hybrid electric vehicles which are of paramount importance for autonomy and real time management. Until this day, no specific approach or strategy has been able to impose itself as the best solution in each actual situation and a considerable work has thus to be done in order to compare and evaluate different strategies [3]. Nevertheless, the different approaches used can be classified in two categories:

1. Optimization-based strategies, such as optimal control or dynamic programming, which often require an *a priori* knowledge of the whole power profile and they are often used off-line [4,5].
2. Rules-based management strategies used on-line, which mainly used deterministic or fuzzy logic and artificial intelligence [6–8].

The high-level fuel cell vehicle supervision strategies and more precisely, the power split management between the fuel cell and the associated electrical energy storage element, remain less considered in literature. Nevertheless, different strategies applied in a conventional hybrid vehicle can be

easily adapted to a fuel cell vehicle [9]. In this context, the application of a real time control strategy for fuel cell vehicles based on optimal control theory [10] or based on the minimization of a specifically defined equivalent consumption [11] can be mentioned.

When the entire power demand profile is well known, the optimal-path can be found from the end to the beginning using for example the dynamic programming algorithm. Such solution is of course off-line, due to the necessity to compute the optimal solution from ending conditions to initial ones. The cost function is minimized off-line and the dynamic programming delivers the best solution for this given profile. Initial and ending energy levels of the storage element are classically given and lot of non-linear constraints have to be introduced to take into account the power limitations of each source and the minimal and maximal states of charge of the storage elements. The computation time is thus obviously increased.

In [13], the instantaneous power delivered by the battery is chosen as an index, it is based on the power demand and the state of charge of that battery. This study uses a statistical method based on the results first obtained by the dynamic programming algorithm. As exposed before, the dynamic programming should only be used off-line to compute the optimum solution as a reference, and the quality of on-line algorithms can be evaluated if the result obtained is closed or not to this optimum. Instead of computing off-line the global optimum, a real problem exists in dealing with optimization in real time. Studying a multiple power sources system and trying to respect dimensioning constraints leads commonly to establish logic-rules to follow. Expanding these rules to fuzzy rules can help the controller to select the power repartition depending on the power demand, the Fuel Cell best possible efficiency if the battery is full (SOC<sub>max</sub>) or empty (SOC<sub>min</sub>) etc. This approach leads to a fuzzy system which is more likely a decision system (supervisor) based on fuzzy rules than a fuzzy controller [12]. Of course, rules and membership functions' shapes reveal numerous degrees of freedom impacting on the global powertrain energy consumption. The on-line management strategy presented in this paper is based on a fuzzy inference system optimized by means of a genetic algorithm and is compared to off-line dynamic programming.

In a first step (part 2), the powertrain is detailed showing all efficiencies and losses taken into account in this study (fuel cell behaviour, air compressor, inverter and supercapacitor losses...). In part 3.1, the fuzzy inference system is built by choosing the appropriate system input and output membership functions and a set of fuzzy rules. To obtain an optimal set of parameters, a genetic algorithm is then used and presented in 3.2. In part 4, comparisons using two different actual profiles are done to evaluate the on-line performances of the proposed algorithm. The proposed solution underlines a high robustness due to the accurate fuzzy management of the stored energy.

## 2. Powertrain characterization

The considered FCHV is a series architecture hybrid vehicle [14,15]. The core of the FCHV is a hybrid powertrain based on

a fuel cell (FC) stack and an electrical energy storage element (SE). The basic structure of the FCHV is shown in Fig. 1.

A standard model of the powertrain is considered in this study [15]. The electrical structure of this powertrain (Fig. 2), is composed of the fuel cell system connected to the DC bus by means of a boost DC converter and a supercapacitor bank is also connected to the same DC bus by means of a current buck/boost converter. The electric motor driving the wheels is connected to the DC bus through a voltage inverter and is considered demanding the instantaneous power  $P_{dem}$ . Of course, more complex powertrains could be considered, but here the study is focusing on the on-line power flows management. The proposed strategies can be easily extrapolated on more complex powertrain topologies.

Each electric energy source defines an energy path representing a given power flow. Primary path is formed by the Fuel Cell (including ancillaries) with its associated converter. A second energy flow path is defined by the Storage Element and its reversible converter to allow energy delivery and braking energy recovery. The connexion of these two energy paths forms a virtual electric node supplying the requested power to the wheels.

Therefore, the power demand  $P_{dem}$  is obtained using the sum of the net power delivered by the fuel cell system  $P_{FC_{Cbus}}$  and by the storage element  $P_{SE_{Cbus}}$  to the DC bus. It is obvious that a part of the power delivered by both sources is lost along the path. It is therefore necessary to identify the system energy balance highlighting the main power losses across these paths.

In this study, to be as closed as possible to reality, upon a real lightweight transport application case, the different powertrain elements sizing was defined. Sizing considerations impose limitations on the maximal and minimal power delivered by the fuel cell, respectively  $P_{FC_{max}}$  and  $P_{FC_{min}}$ , on the supercapacitors delivered and absorbed power, respectively  $P_{SE_{max}}$  and  $P_{SE_{min}}$  and finally on the maximal and minimal energy charged of the storage element  $SOE_{max}$  and  $SOE_{min}$  (State Of Charge – SOC is generally used for battery and in percent, nevertheless to be more general a state of energy – SOE is used and if SOE is max classical SOC = 100%,  $SOE_{min}$  means SOC = 25%). All of these practical values are given in Table 1. In order to avoid to deal with hybridization rate, mass influence on power demand and other 'systemic-level' considerations [16,17], the power demand is here analysed and a FC power is chosen to be able to furnish solely the max power demand. Quite the same power levels are chosen for SE and FC elements leading to a full hybrid vehicle. This *a priori*

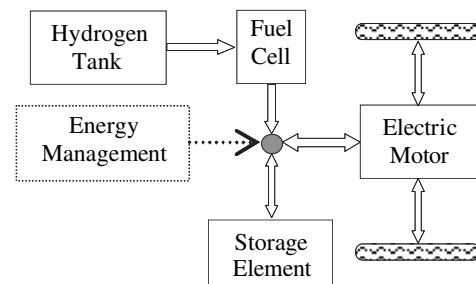
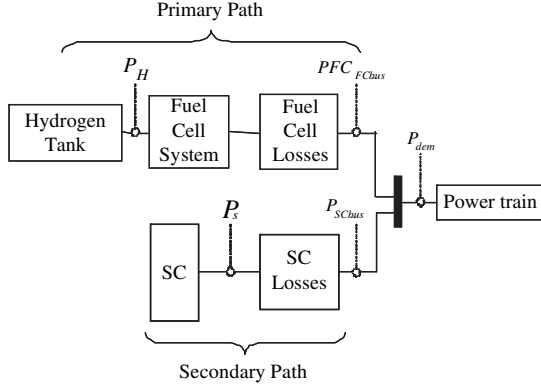


Fig. 1 – FCHV basic topology.



**Fig. 2 – Power and losses distribution along the hybrid powertrain.**

sizing of the FCHV also allows to find all possible solutions in power splitting (from no use of the FC stack to no use of SE) to satisfy  $P_{dem}$ .

### 2.1. Fuel cell system losses

The fuel cell system energy balance is given in Fig. 3. The considered total losses of this fuel cell system,  $L_{FCS}$  given in eq. (1) and is the sum of the fuel cell internal losses  $L_{FC}$  (activation losses, ohmic losses and gas transport losses), the power converter losses due to the conduction and commutation losses of the converter semiconductors  $L_{conv}$ , and finally the electric energy losses across the fuel cell ancillaries (here considered mainly located in the air compressor)  $L_{comp}$ .

$$L_{FCS}(P_{FC\_bus}) = L_{FC}(P_{FC\_bus}) + L_{conv}(P_{FC\_bus}) + L_{comp}(P_{FC\_bus}) \quad (1)$$

Ancillaries (mainly the air compressor) are power consuming, hence reducing the delivered net energy. The total fuel cell system efficiency  $\eta_{FCS}$ , given in eq. (2), is therefore the product of the efficiencies of the fuel cell  $\eta_{FC}$ , the converter  $\eta_{conv}$ , and the compressor  $\eta_{comp}$ .

$$\eta_{FCS} = \eta_{FC} \cdot \eta_{conv} \cdot \eta_{comp} \quad (2)$$

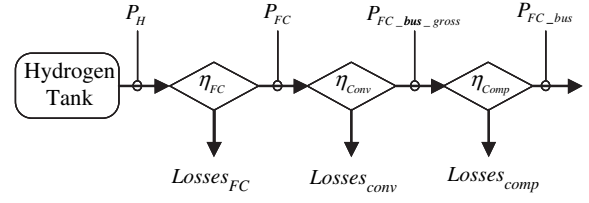
In the following paragraphs, different models are briefly exposed and used to identify the efficiencies of each element and thus the total fuel cell system efficiency as a function of delivered power.

#### 2.1.1. Fuel cell efficiency

The energy efficiency of the fuel cell is proportional to its voltage as given in the following equation, where  $N_{cell}$

**Table 1 – System power and energy constraints.**

Symbol	Quantity Value
$PSE_{min}$	-60 kW
$PSE_{max}$	60 kW
$SOE_{min}$	400 kW s
$SOE_{max}$	1600 kW s
$PFC_{min}$	0 kW
$PFC_{max}$	70 kW



**Fig. 3 – Fuel cell system energy balance.**

represents the number of elementary cells forming the fuel cell stack and is expressed referred to the Higher heating Value (HHV) of hydrogen:

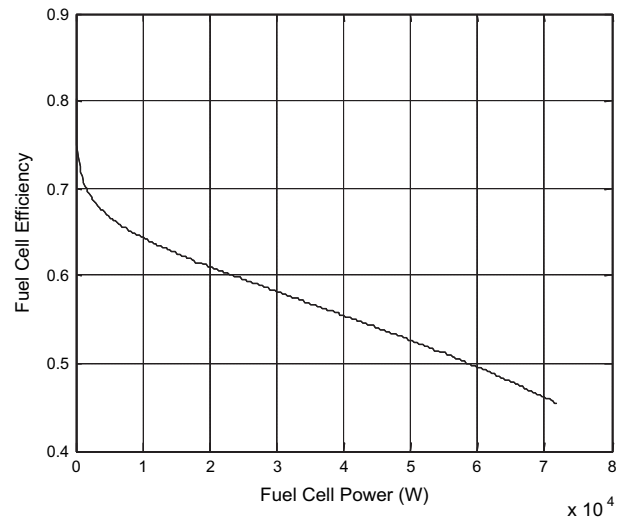
$$\eta_{FC}(P_{FC}) = \frac{V_{FC}(P_{FC})}{1.48 \cdot N_{cell}} (\%HHV) \quad (3)$$

It is therefore necessary to develop a model in order to predict the fuel cell voltage response  $V_{FC}$  to a given power request. The model used in this study is based on the quasi-static model of Amphlett [18] initially designed for an elementary cell which expresses the fuel cell voltage  $V_{FC}$  in eq. (4) as a function of the current in the stack  $I_{FC}$ , the partial pressures of oxygen  $P_{O_2}$  and hydrogen  $P_{H_2}$  on the catalyst, the temperature of the stack,  $T_{FC}$ , and the hydration level of the polymer membrane  $\lambda_{H_2O}$ :

$$V_{FC} = f(I_{FC}, P_{O_2}, P_{H_2}, T_{FC}, \lambda_{H_2O}) \quad (4)$$

The voltage of a single-cell is equal to the electro-dynamics' potential  $E$  (which is constant for such kind of electro-chemical reaction), added by the activation voltage losses and the ohmic losses. The gas transport losses are not considered here; as they are predominant only at very high current densities and the FC control will avoid all operation in this area. The adaptation of this model to a  $N_{cell}$  cell stack is made possible with a simple scaling factor, based on simplifying assumptions [19,20].

The fuel cell model is implemented under Matlab/Simulink™ environment. The model experimental validation is



**Fig. 4 – Energetic efficiency of the fuel cell.**

done on a 20-cell stack (700 W max) test bench. The calibration of the model requires the identification of the parameters used in the voltage law. The principle of the identification method is a multiple linear regression by the method of least squares [19]. The obtained fuel cell energy efficiency versus fuel cell power is given in Fig. 4.

### 2.1.2. Air compressor power consumption

The power absorbed by the air compressor  $P_{comp}$  is given as a function of the air flow entering the stack  $F_{air\_in}$  (representing the air massic flow passing through the compressor).

$$P_{comp} = \frac{Cp \cdot T_e}{\eta_m \cdot \eta_c} \left( \left( \frac{P_{cath}}{P_{atm}} \right)^{\frac{\gamma-1}{\gamma}} - 1 \right) \times F_{air\_in} \quad (5)$$

Where  $T_e$  is the controlled air temperature,  $\eta_m$  the motor drive efficiency,  $\eta_c$  the compressor efficiency,  $P_{cath}$  the pressure inside the cathodic compartment of the FC stack,  $P_{atm}$  the atmospheric pressure,  $Cp$  the thermal capacitance of air and  $\gamma$  a specific coefficient equal to 1.4 for air compression.

The air flow derived in eq. (6) is expressed as a function of delivered current  $I_{FC}$ , using the well known Faraday's law for perfect gas conditions:

$$F_{air\_in} = St_{O_2} \cdot M_{air} \cdot \frac{N_{cell} \cdot I_{FC}}{4X_{O_2} \cdot F} \quad (6)$$

where  $St_{O_2}$  is the stoichiometric ratio,  $M_{air}$  the number of air moles,  $X_{O_2}$  the molar fraction of oxygen (21% in ambient air),  $F$  the Faraday's constant.

Finally, the power losses due to the compressor power consumption as a function of the fuel cell delivered power are thus given in Fig. 5.

### 2.1.3. Boost converter efficiency

These losses are identified using IGBT and diode datasheets and the resulting efficiency is shown in Fig. 6 for two given switching frequencies.

Total losses in the boost converter are equal to conduction losses due to the presence of a non-zero saturation voltage in

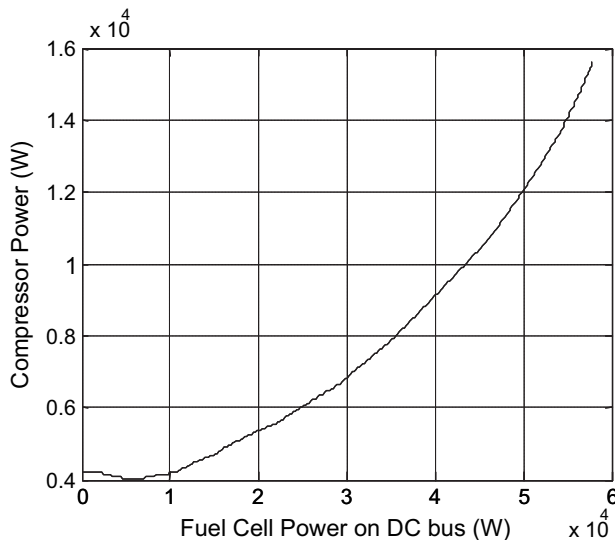


Fig. 5 – Air compressor power consumption.

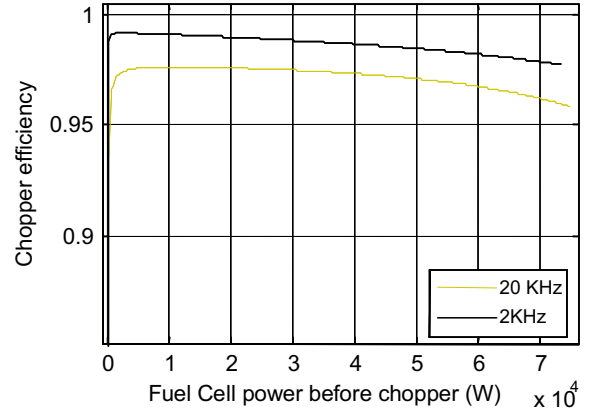


Fig. 6 – Converter efficiency.

the diode and IGBT when they are conducting and switching losses in IGBT as current and voltage do not change instantaneously.

### 2.1.4. Total fuel cell system efficiency

The total fuel cell system efficiency resulting from the product of each of the elementary efficiencies previously identified is given in Fig. 7 revealing a maximum efficiency point (about 46%) at a given fuel cell power of about 22 kW.

This curve is the first data to use in the optimization energy management problem to minimize hydrogen consumption and thus to increase FCHV autonomy.

## 2.2. Electrical storage element losses

The energy balance of the storage element  $L_{SE}$  considers the losses due to the internal resistance  $L_{SC}$  and due to the current reversible converter losses  $L_{conv}$  (cf. eq. (7)).

$$L_{SE}(P_{SE\_bus}) = L_{SC}(P_{SE\_bus}) + L_{conv}(P_{SE\_bus}) \quad (7)$$

$$L_{SC} = R_{SC} \cdot I_{SC\_eff}^2 \quad (8)$$

$R_{SC}$  is chosen to be constant here not only to simplify the supercapacitor modelling but also to be able to maximise the

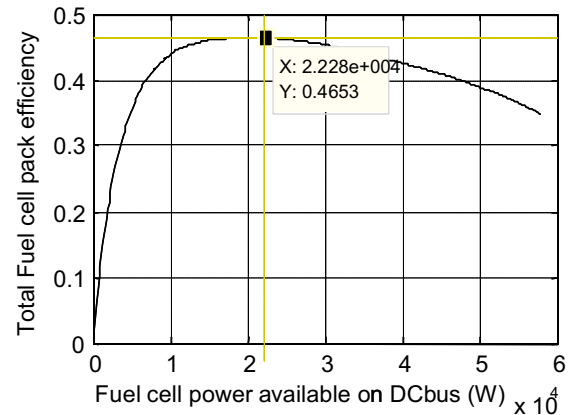


Fig. 7 – Total fuel cell system efficiency.

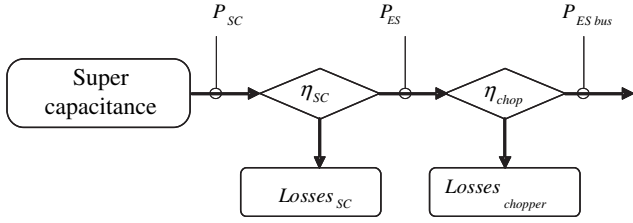


Fig. 8 – Total electrical storage system efficiency.

losses in this part as a first approximation. Moreover, in case of this electrostatic storage, this model is more convenient than in batteries (due to their different electro-chemical storage behaviour) [20,21]. Finally, the global losses from the growth power to the net power delivered to the DC bus are shown in Fig. 8.

### 2.3. Powertrain representation

Having characterized the global efficiency of each energy path, the problem can therefore be represented as in Fig. 9.

The primary power source is therefore represented by its useful power at the electric node,  $P_{FC}$ , and an efficiency value  $\eta_{FC}$ , allowing us to estimate the real hydrogen consumed energy. Furthermore, the storage system is also represented by its delivered power  $P_{SE}$  and a global efficiency  $\eta_{SE}$ , allowing computing the effective quantity of energy actually stored in the supercapacitors and thus their actual state of charge variation.(Fig. 10).

## 3. Energy management formulation

The energy management problem is formulated here as a global dynamic optimization problem under constraints. The hydrogen consumption is quantified as a cost function to be minimized. The system's dynamic equation is:

$$\dot{E}(t) = -P_s(t) \quad (9)$$

where the energy level stored  $E$ , is the state variable and the power  $P_s$  the control variable.

The cost function to minimize eq. (10) is the "total consumed energy" of hydrogen  $E_{H_2}$  over a given period of time  $[t_f - t_i]$ .

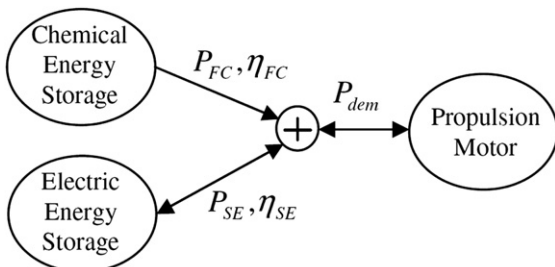


Fig. 9 – Fuel cell vehicle schematic model.

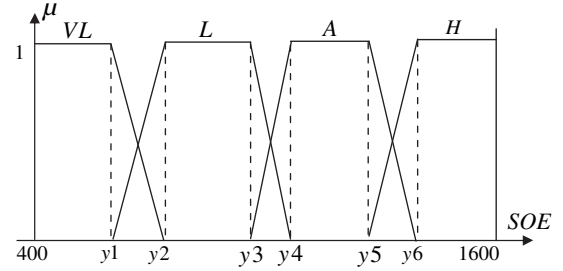


Fig. 10 – Input variable membership functions for Storage Element.

$$E_{H_2} = \int_i^t \frac{P_{FC}(t)}{\eta_{FC}(P_{FC}(t))} dt \quad (10)$$

Using the previously defined efficiency, the cost criterion is thus:

$$\gamma = \frac{P_{FC}(t)}{\eta_{FC}(P_{FC}(t))} \quad (11)$$

The system is subject to non-linear constraints of inequality related to the constraints linked to the design of the stack eq. (12) and the storage element power eq. (13) and state of energy eq. (14):

$$P_{SE\_min} \leq P_{SE}(t) \leq P_{SE\_max} \quad (12)$$

$$P_{FC\_min} \leq P_{FC}(t) \leq P_{FC\_max} \quad (13)$$

$$E_{min} \leq E(t) \leq E_{max} \quad (14)$$

Moreover, satisfying the power demand imposes an equality constraint:

$$P_{SE} + P_{FC} - P_{dem} = 0 \quad (15)$$

An additional condition eq. (16) is imposed artificially in order to ensure that the state of energy is maintained at the end of the cycle to facilitate the optimization procedure and cycling the power demand without any more consideration from an energy management point of view.

$$E(t_f) = E(t_i) \quad (16)$$

Solving such problem in real time uses discrete algorithms, allowing to compute and refresh the power splitting with respect to the sampling period; meaning:

- Sampling the time and the state of charge space.
- Finding the optimal trajectory that starts from the initial energy at instant  $k = 0$  to the same final energy at instant  $k = N$ .
- Finding the value of the storage element optimal power at each time step by applying the following equation:

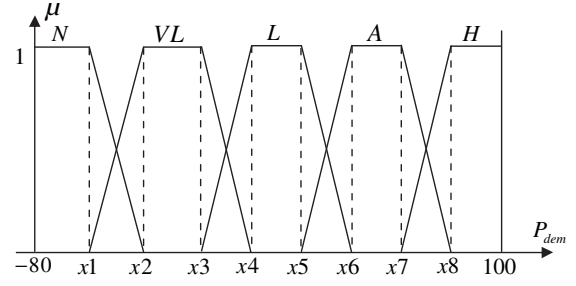
$$P_s^{j1,j2} = \frac{E_{j2} - E_{j1}}{\Delta t} \quad (17)$$

### 3.1. Fuzzy logic (FL) based decision system

Knowing the whole driving cycle and thus the power demand, and running off-line, Dynamic Programming software allows for example a global optimization [24]. Results correspond to a sequence at each sampling time fixing  $P_{FCk}$  and  $P_{SEk}$  which can only be replayed in real time if the actual driving cycle is the same. Results obtained off-line are used as a reference but the program cannot be used in real time. To avoid this important assumption and to derive a real time energy management for this kind of system, fuzzy rules can be established to manage both fuel cell power and state of energy of the storage element.

The fuzzy approach [22] is here preferred to neural networks [23] in order to avoid to deal with ‘how to learn’ problems and to have a continuity from local behaviour to global one. Fuzzy rules also keep a minimum human analyse possible in the optimization phase. The implemented fuzzy decision system uses here two input variables (that are the state of energy of the storage component SOE and the required propulsion power  $P_{dem}$ ), the output variable being the fuel cell delivered power  $P_{FC}$ . The universe of discourse of each of these variables is defined by the power and energy size constraints. Each of these spaces is divided into a defined number of subsets describing a general state of the designated variable. The state of energy of the storage element can therefore be considered as “very low” (VL), “low” (L), “average” (A), or “high” (H). Similarly, the required power can be considered as “negative” (N), “very low”, “low”, “average”, or “high”. Finally, the fuel cell delivered power can be “Null” (N), “very low”, “low”, “average”, or “high”. All this linguistic values are resumed in Table 2 (a linguistic “OR” is supposed to be existing between the different rules).

Each linguistic value is designated by a membership function, which assigns to each value of that variable a membership degree. Here, trapezoidal-type membership functions have been chosen over the universe of discourse. Fig. 11 represents the trapezoidal membership functions of the Storage Element state of energy, between  $SOE_{max}$  and  $SOE_{min}$ . The trapezoidal-type membership functions are chosen for their simplicity and their real time implementation facility. The number of these membership functions remains an arbitrary choice based on a human expertise; nevertheless, it can be said that there’s no interest in using too much membership functions. Figs. 12 and 13 represent respectively the chosen membership functions for the DC bus requested power and the fuel cell delivered power.



**Fig. 11 – Power demand  $P_{dem}$ , input variable membership function.**

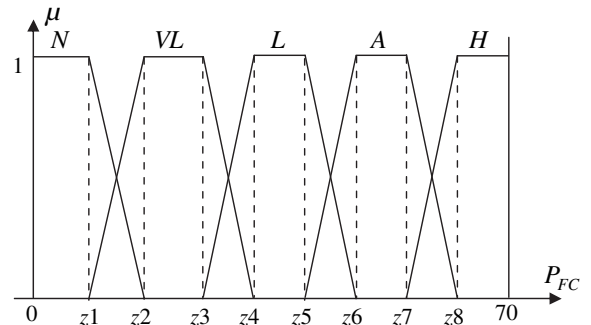
The inference system is composed by a number of 20 rules linked by an OR operator. Each rule presents a condition introduced by the IF symbol and a conclusion, or action introduced by THEN symbol. An example of the system rules is:

IF  $P_{dem}$  is “very low” AND SOE is “low” THEN  $P_{FC}$  is “low”.

The general idea behind these rules is that the fuel cell stack delivers as much power as the requested power is high and/or the state of charge of the storage element is low. In addition, the fuel cell delivers as low power as the requested power is low or the state of charge of the storage element is high enough to provide this power.

### 3.2. Membership functions optimization using a genetic algorithm (GAFL)

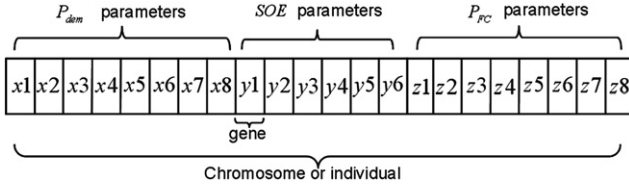
The choice of the membership function parameters ( $x_i$ ,  $y_i$ ,  $z_i$  on Figs. 11–13) is usually made by trial and error and a time consuming experimental procedure is necessary to obtain the proper set of parameters directly linked to the possible minimization of the global hydrogen consumption on the FCHV [22]. To overcome this problem, a genetic algorithm [25] is here used to find the optimal set which minimizes a certain criterion [26]. The classical genetic algorithm optimization method follows different steps, consisting of selecting specific individuals regarding their fitness function to which are applied the mutation and crossover operators. The new created individuals are again evaluated to maintain the best individuals or the individuals that better adapt to the imposed criterion [25].



**Fig. 12 – Fuel Cell Power output variable membership function.**

**Table 2 – Fuzzy logic based decision system inference matrix:  $P_{FC}$  level depending on SOE and  $P_{dem}$ .**

PFC		$P_{dem}$				
		VL	L	A	H	N
SOE	VL	A	H	H	H	N
	L	L	A	A	A	N
	A	VL	VL	L	L	N
	H	VL	VL	VL	L	N



**Fig. 13 – Identified parameters considered as a chromosome gene.**

The algorithm stops when the stop criterion is met. The stop criterion chosen in this study is the reach of a fixed number of generations  $N_{gen}$ .

The individual contains all the needed data which is, in this case, the requested parameters allowing the membership functions identification. Taking into consideration previous hypotheses made on the shape and type of the membership functions, a chromosome of 22 parameters is sufficient to represent the membership functions and thus the fuzzy system. These parameters are the different  $x_i$ ,  $y_i$  and  $z_i$ , the chromosome thus formed by the concatenation of these parameters is shown in Fig. 14.

Another important issue is the definition of the fitness function which evaluates the performance of each individual. In our case, the target is the minimization of the hydrogen consumption while ensuring the power required along the entire vehicle driving cycle. Maximizing the evaluation function  $F_{eval}$  eq. (18) consists in minimizing an optimization criterion  $C_{opt}$  as given in eq. (19). This criterion takes into consideration the total consumed hydrogen energy (in kW s) on a fixed time interval of the driving cycle  $E_{H_2}$ , as given in eq. (20), and a value quantifying the mean quadratic error  $e_{quadr}$  measured between the required power and the power actually provided.

$$F_{eval} = \frac{1}{C_{opt}} \quad (18)$$

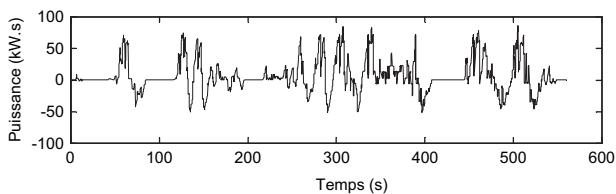
$$C_{opt} = \frac{E_{H_2}}{k} + e_{quadr} \quad (19)$$

$$E_{H_2} = \sum_i \frac{P_{FC}(i) \cdot \Delta t}{\eta_{FC}(P_{FC}(i))} \quad (20)$$

where  $e_{p_{dem}}$  is the instantaneous power error between the required power,  $P_{dem}$ , and the actually provided power  $P_{prov}$ :

$$e_{p_{dem}}(i) = P_{dem}(i) - P_{prov}(i) \quad (21)$$

To be noticed, the dynamic programming solution respects the profile  $P_{dem}(t)$  but this real time solution should sometimes



**Fig. 14 – ESKISEHIR: Power profile of a tram on the line of ESKISEHIR.**

not respect it, but eq. (21) ensures that not furnishing  $P_{dem}$  is prohibitive (but not excluded).

The defined criterion is therefore given according to the eq. (19) where  $k$  is a scaling factor between consumption and error values. The choice of this factor also allows adjusting the required accuracy since the more  $k$  is low, the more the minimization of consumption versus error is made easier and vice versa.

The actually provided power is the sum of the fuel cell delivered power,  $P_{FC\_cor}$ , and of the power supplied or absorbed by the storage element  $P_{SE\_cor}$  (after correction of their values by taking into consideration the saturations over these power and state of charge values).

$$P_{prov}(i) = P_{FC\_cor}(i) + P_{SE\_cor}(i) \quad (22)$$

Furthermore, the fitness function will allow handling further constraints imposed on the individual parameters by using a penalty function that penalizes the non-feasible solutions reducing their fitness function [26]. These further constraints are given in eq. (23).

$$\begin{aligned} x_i &< x_{i+1} & i = 1, \dots, 7 \\ y_i &< y_{i+1} & i = 1, \dots, 5 \\ z_i &< z_{i+1} & i = 1, \dots, 7 \end{aligned} \quad (23)$$

Individual with parameters which do not verify these conditions are penalized with a quite high criterion  $C_{opt}$ . This allows the genetic algorithm to progressively move away from these non-feasible values.

To summarize, the genetic algorithm is used to optimize the fuzzy logic decision system. This optimization is made off-line using a specific mission power profile. The optimized rules obtained can manage in real time the power demand and split it accurately between the two available sources.

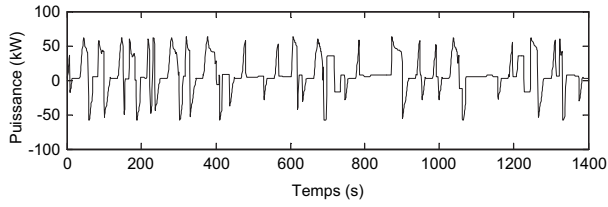
## 4. Results, robustness and comparison

This section presents all tests made to evaluate algorithms and optimized fuzzy supervisor performances using two different power demands. Each one corresponds to actual measurements made on vehicles following a given path. The use of both profiles is possible after having applied the necessary scaling factor in order to adapt the power level to our application size considerations. Fuzzy controller results using GA optimization made (GAFL) are compared to results obtained with Dynamics Programming (DP) or non-optimized rules (FL). Finally, the fuzzy logic system is implemented under Matlab™ environment using the Fuzzy Logic Toolbox®. OR and AND operators are represented by the “Min–Max” method while the defuzzification is made possible by computing the centre of gravity of the resulting membership function.

### 4.1. Mission profiles

Two actual mission profiles are used for validation: Fig. 16 named INRETS corresponds to a personal car in suburban area [14], Fig. 15 named ESKISEHIR corresponds to a tramway line in Turkey [15].





**Fig. 15 – INRETS: Power profile of a hybrid vehicle in urban area.**

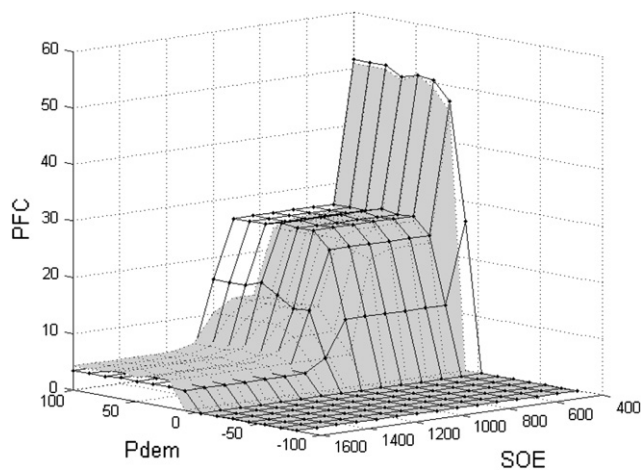
#### 4.2. Simulation – results

To prove the necessity of an energy storage management, Table 3, shows the gain (% of consumption reduction) when the fuel cell is used as the only source (F.C. alone with no hybridization) and when a storage element is used and managed by dynamic programming path (D.P.).

These results are given only to show the necessity to charge and discharge a storage element during the profile and show D.P. is able to found a path minimizing the criterion and satisfying all constraints. But this optimal-path is computed off-line and this path is optimal if and only if the power demand did not change, which does not correspond to reality and the goals of real time energy management.

Fuzzy supervisor is optimized off-line with INRETS profile and manages on-line the power demand. Results are given only in terms of consumption and compared in Table 4. GAFL is the optimized rules and FL corresponds to the results of the hand tuned fuzzy logic system (no ‘optimal’ optimization), showing the clear improvement made with applying the genetic algorithm. As explained before, the same sampling time and energy are chosen ( $\Delta E = 1 \text{ kW s}$   $\Delta t = 1 \text{ s}$ ).

In Table 5 results using Fuzzy Logic (FL) approach are closed to the optimal consumption obtained with DP but always higher. To be noticed in this rules-based solution, the final constraint (initial energy equal to final energy for storage element) is not imposed, but GAFL and FL reach quite the same values and are comparable. If cycling capability is



**Fig. 16 – Fuzzy system characteristic surfaces generated with the genetic algorithm using both mission profile.**

**Table 3 – Energy storage improvement.**

	D.P.	F.C. alone	Gain
INRETS	9189.7 kW s	14891 kW s	38.28%
ESKISEHIR	31826 kW s	48043 kW s	33.75%

requested, the criterion to be minimized should include it in order to tune optimally the fuzzy rules. Moreover in these cases few  $P_{dem}(t_k)$  are not satisfied, but may be included in other consideration, the non-delivered power contributes to the low consumption and can be used for an ‘eco-driving’ signal, and if the braking energy is not fully used for traction that can be used for heating or comfort ancillaries in the vehicle.

#### 4.3. Robustness and optimization

After applying the genetic algorithm to the fuzzy logic system, the optimized characteristic surface of this fuzzy system is given in Fig. 16 for both mission profiles. The grey surface represents the INRETS profile while the wired surface represents the ESKISEHIR profile. It is clear that these two surfaces present slight differences related to the differences between the two power demand profiles. Indeed, the ESKISEHIR profile presents a higher mean power compared to the INRETS profile which is translated by a higher demand on the fuel cell power as shown on this figure.

The evolution of the state of energy of the storage element along the driving cycle is shown in Fig. 17 for the INRETS profile and in Fig. 18 for the ESKISEHIR profile.

As the optimization of the fuzzy logic system is made on a specific mission profile, the obtained fuzzy system tends to adapt on that specific profile while not presenting the same performances when applied to other profiles.

Therefore, a further attention should be given to the study of the robustness of this method. For this sake, tests are conducted on the performance of the system optimized on the INRETS profile and applied on the ESKISEHIR one and vice versa.

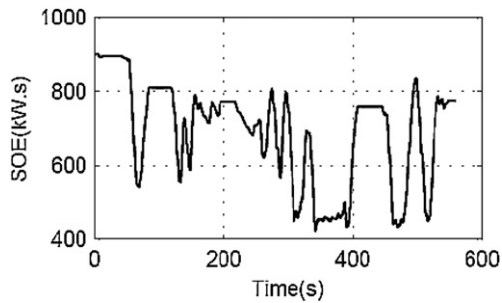
Results of this crossing application are given in Table 5 where:

**Table 4 – Comparison of the obtained results applying different control strategies.**

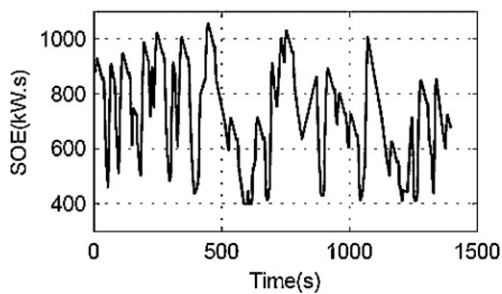
Profile	Algorithm	Consumption	Improvement
INRETS	F.L.	10 866 kW s	27%
	G.A.F.L.	8359.9 kW s	43.8%
ESKISEHIR	F.L.	33 358 kW s	30.5%
	G.A.F.L.	29 802 kW s	37.9%

**Table 5 – Robust results of GAFL supervisor.**

	Inr–Inr	Esk–Inr	Esk–esk	Inr–Esk
Gain	43.8%	41.5%	37.5%	35.6%



**Fig. 17 – Supercapacitors state of energy along the INRETS driving cycle.**



**Fig. 18 – Supercapacitors state of energy along the ESKISEHIR driving cycle.**

- Inr-Inr: System optimized on the INRETS profile and applied on the INRETS profile.
- Esk-Inr: System optimized on the ESKISEHIR profile and applied on the INRETS profile.
- Esk-Esk: System optimized on the ESKISEHIR profile and applied on the ESKISEHIR profile.
- Inr-Esk: System optimized on the INRETS profile and applied on the ESKISEHIR profile.

These results show that the algorithm performance remains quite acceptable when differentiating the testing profile from the optimization profile. We should, nevertheless, notice that this performance is made possible since the two considered power profiles do not present major differences in terms of harmonic content.

## 5. Conclusion

A fuzzy logic based decision system is applied in order to properly manage the power split between the power source (fuel cell stack) and the electrical storage element (supercaps) of the hybrid electric generator in a fuel cell vehicle. The fuzzy system parameters are optimized using a genetic algorithm aiming to reduce the hydrogen consumption over a given actual driving cycle. The performance and robustness of the optimized fuzzy system are tested on two different driving cycles showing good results as compared to a dynamic

programming based algorithm (which needs to know the driving cycle before tuning and cannot be considered for real time applications). As future perspectives, a thorough study will be made to define a quantitative relation between a given driving cycle (class of profile) and the optimized parameters obtained with the genetic algorithm in order to allow an easy tuning and an adaptation of the fuzzy system without having to repeat the optimization procedure.

## Acknowledgments

INRETS : to provide actual measurements obtained on actual vehicle and trip and interests given in energy management in transport application.

FEMTO/FCLAB : to provide actual data obtain on fuel cell test bench developed in Belfort (France) and collaboration to this study.

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