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# REAL TIME FUZZY ENERGY MANAGEMENT OF FUEL CELL AND ULTRACAPACITOR POWERTRAINS

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## ABSTRACT

Energy management for systems presenting at least two energy sources is still a challenge. Moreover in Hybrid Electrical Vehicle the power must be managed in real time within system constraints. Energy management is based on efficiency models and data of both sources as function of the delivered power. With efficiency behavior knowledge, an optimization can be made. Logic rules are presented allowing the respect of power demand, power limits of the Fuel Cell System and State of Charge of the supercapacitors used as Storage Element System. The proposed two-step program, based on the fuzzy approach, manages the fuzzy membership functions by means of a simple genetic algorithm. Followed steps are described from the fundamental parameters' identification stage to the optimization program structure able to manage in real time the energy flows in the HEV.

## 1. INTRODUCTION

Hybrid Electrical Vehicle (HEV) proposes various interesting research fields. Several energy sources onboard imply not only an electrical structure design problem but also an efficient energy management strategy [1],[2]. Among the different HEV powertrain topologies, the association of a PEM fuel cell system (considered as the main energy source) with an ultracapacitor pack (considered as a storage element) seems, according to a Ragone plot, as one of the most efficient solutions. The use of a fuel cell system instead of an internal combustion engine assures the zero emission goal.[6]. The use of batteries or a combination of battery and supercapacitor stack as electrical storage element is also considered in many applications depending on the energy management strategy deployed. The pick power demand is more easily supplied by ultracapacitors and the weight of batteries is more impacting in energy consumption than ultracapacitors. In optimal energy management the State Of Charge (SOC) must be tracked and thus estimated. Nowadays, it is easier to roughly model this state in the case of ultracapacitors than batteries. Of course, dimensioning of PEM-FC and ultracapacitors pack must be sufficient to satisfy maximal power demands and to store the necessary energy to be recovered for the requested power demand. In this paper, a given sufficient sizing is considered and thus optimization is only made on power distribution control between both sources.

To optimize the association of two source elements (FC, ultracapacitors) and thus reduce the global fuel ( $H_2$ ) consumption, the most influent parameters must be extracted from the fundamental behavior of the different elements. In this work, the local controls of the Fuel Cell Stack (FCS) and of the ultracapacitor pack are considered effective [3]. Based on the well-known controlled behavior of the two elements, efficiency curves can be obtained and efficiency look-up tables based on actual data are used in optimization algorithms.

Nevertheless, in most cases, the optimization is performed on fixed and previously known mission profiles. Results on power demand repartition depend on the profile used. This approach is not very suitable if real time energy management is considered as the overall objective. Some parameters are added to adapt or to take into account the profile past in order to anticipate in real time the power demand [4][5]. All solutions in real time can only be sub-optimal but optimization in this way means approaching as closed as possible the optimal power corresponding to the minimal consumption. Keeping all instantaneous efficiency maximum is not the solution. To obtain this minimal consumption, a possible solution is to track the maximum instantaneous efficiency over the entire profile.

This paper presents the optimization approach, beginning with the behavioral modeling of all elements (part 2). These models allow to accurately identifying losses and thus efficiency of both energy sources depending on the delivered power. In part 3, the load mission profile used in the optimization process is presented and analyzed (3.1) in order to define some constraints and rules to be satisfied (3.2). Fuzzy logic rules used to link fuel cell power output to load power and state of charge inputs are then presented to select how must be used the two different sources knowing the entire profile (3.3). Optimization of the selected fuzzy logic membership functions is conducted using a genetic algorithm (3.4). This optimization allows to better define the frames and shows good behaviors with disturbances on the profile or present also low consumption with another demand.

## 2. ELEMENTS BEHAVIORS

In an HEV, Proton Exchange Membrane Fuel Cell System PEM-FCS and ultracapacitors (Supercaps) are in most cases linked to the power bus through choppers (Fig 1). Depending on the fuel cell stack design, the optimal working point can be maintained by an accurate control structure to insure cathode and anode pressures, fuel cell's core temperature and other state variables [9][10]. Such controls allow to not only maintain safety on fuel cell but also to establish assumptions and simplifications to easily and accurately describe the global behavior mainly average current and voltage in each element. Knowing the current and voltage values allows identifying component losses (conduction and commutation losses) and thus establishing an efficiency formulation based also on component behavior with component data sheets.

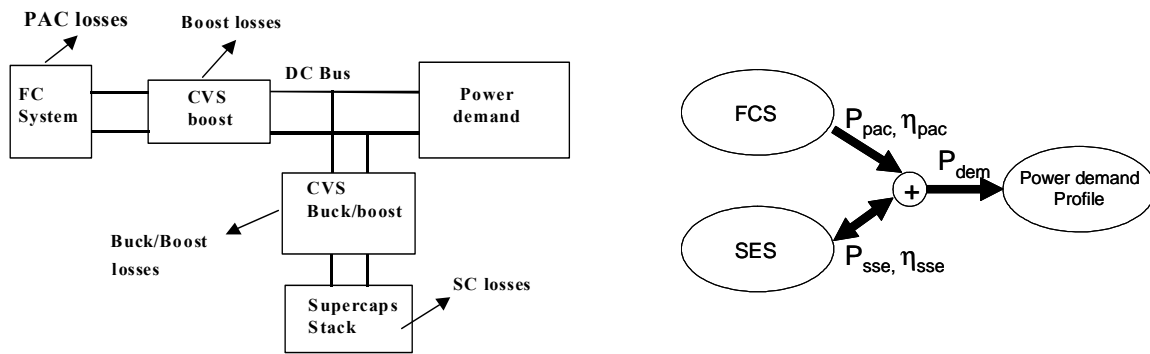


Fig 1. : Global powertrain scheme for efficiency analyze

So, a current node is considered summing: positive current coming from FCS and positive (discharge) or negative (charge) current from the Storage Element System- SES, to obtain the power demand every time.

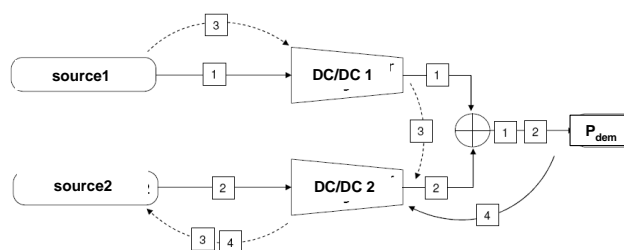


Fig 2. : Global possible power flow

For energy management the power flow must provide the power demand  $P_{dem}$ , for traction but for internal management, the power flow can have different ways and functions. In fact, following way 1 on Fig2 let the FCS providing all the desired power, following way2 let the Storage Element System providing the power and of course way 1 and 2 are cumulative. A degree of freedom can be introduced for energy management considering the reversibility of the storage element. The SES-source2 can be charged by a negative power demand (braking recovery) and/or be charged by the fuel cell itself (way 3 and/or 4). Considering all these

possibilities allows the control program to define power references for both sources allowing optimal operation.

A global behavior focusing on efficiency formulation must be established before running optimization algorithm. Using sufficient accurate formulations, fuel cell efficiency curve can then be extracted. For the ultracapacitor pack, losses are represented by a simple resistance and knowing experimentally these losses (or using data sheets) allows extracting efficiency of such element  $\eta_{ses}$ .

Fuel Cell System is formed by the fuel cell itself whose efficiency is linked to its polarization curve, its ancillaries (mainly the compressor for air pressure and flow control) and DC/DC chopper. The global efficiency  $\eta_{fcs}$  is the product of the efficiency of the three elements.

Efficiency curves for the fuel cell system  $\eta_{fcs}$  and for the charge/discharge of storage elements  $\eta_{ses}$  are given in Fig3. Power references must now be shared between the two power sources and optimized in order to minimize the H<sub>2</sub> consumed for a particular power profile demand [7],[8].

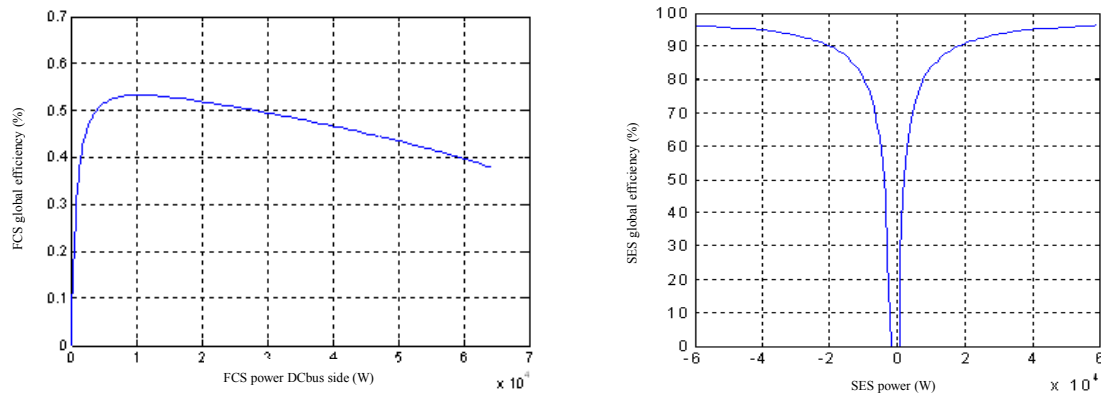


Figure 3. FCS and Storage Element efficiency depending on delivered power.

When the power demand profile is known a priori, offline optimization solutions exist. Yet, obtaining an online controller able to react with uncertainties on the profile, keeping as closed as possible the optimal reference, is still a challenge.

### 3. POWER DEMAND AND STRATEGIES

The fuel cell system can provide electrical power to the powertrain or/and to the ultracapacitor. Moreover, as previously explained, the ultracapacitor pack will store a part of the regenerative braking energy (depending on the efficiency of the buck/boost chopper and on the state-of-charge of the ultracapacitor pack). The optimal strategy is to recover all energy which can be recovered during braking phases and use it for traction during other phases. Charge and discharge phases are not only driven by the profile but also by rules allowing modifying the FCS operating point. The size of both sources and hybridization rate are important issues in this case [11]. In this paper there is no system dimensioning optimization, all sources are considered to be properly sized (sufficient Min Max Power and Sufficient energy storage space). Based on the power demand and both sources efficiency the main goal is to compute the power flow distribution in real time.

#### 3.1 Power demand profiles and rules

Dynamic programming is one of the most popular and effective method in optimization field when the entire profile is known a priori [5], [11]. Using a sampled representation of the storage element state of energy and using fixed time step to discretize the time, a cost matrix can be defined. Starting from the end point of the power requirement profile and going backward to its beginning, the dynamic program method allows finding the optimal path (optimal set of power references in order to minimize the H<sub>2</sub> consumption respecting numerous constraints).

The main problem of this solution is that the entire power profile must be known a priori. So the time consuming optimization can only be made off-line. If perturbations arise, losses are not controlled without a

new computation of the optimal path. Depending on the length of the power profile, the algorithm can be very time consuming and cannot be used in real time.

Thus, a second approach consists of managing the two power sources by means of logic rules defined to use the Fuel Cell System at the optimal efficiency point (this power management method can be called Maximum Efficiency Point Tracking: MEPT accordingly to the Maximum Power Point Tracking control strategy that is used in wind turbine and solar photovoltaic systems control) and to constraint the storage element between its low and high State Of Charge limits.

Fig 4 presents the two different mission power's profiles used for optimization and validation. Analyzing these profiles allows comparing average and maximal positive and negative power demands. The two profiles are a little bit different but both considered a sub-urban power demand less than 90kW measured on a personal HEV, with 50% hybridization (70kW for FCS size and +/-60kW for SES size). Of course, Urban or MotorWay profiles exist, but it is well known that in such different class of profiles a common optimal solution is not possible. Using the chosen profiles and HEV sizing the optimization can now starts.

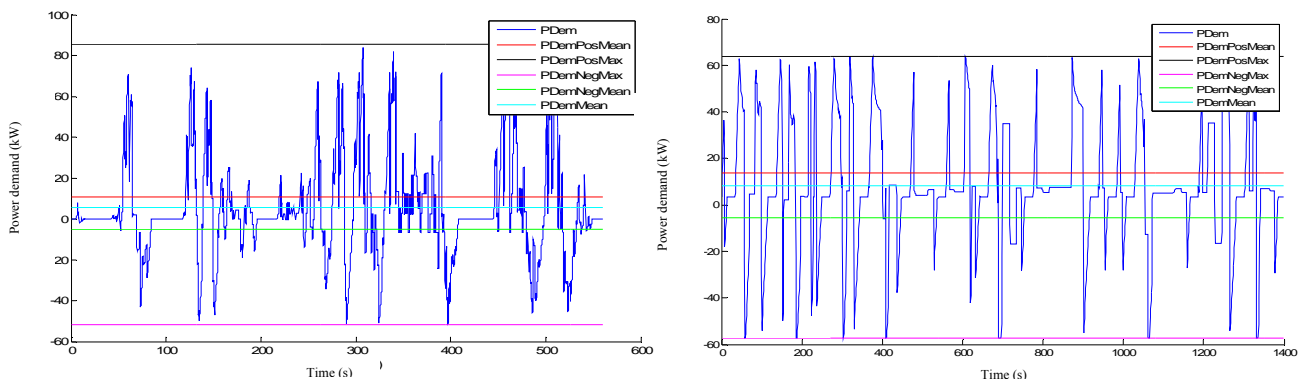


Figure 4. Profil INRETS. / Profil ESKISEHIR.

For the real time optimization point of view the proposed approach lies in two steps. The first one is to logically analyze what must be done during the profile evolution in order to define useful rules. These rules are thus used to design a fuzzy logic inference system. Finally a genetic algorithm is used to optimize the size and shape of the fuzzy system inputs and output membership functions.

### 3.2 First strategy

At this stage three important constraints are identified: power demand must be satisfied (sum of the two instantaneous powers), Min and Max values on FCS and SES power must be respected, State Of Charge (SOC) of SES must be tracked and controlled. So, during profile evolution the control algorithm chooses power references restraining both the state of charge of the storage element and the fuel cell delivered power in two fixed windows:

The first is defined by [SOCmin SOCmax] and the second by [PFCSmin PFCSmax].

The window allowing to choose the FCS references is directly linked to its efficiency thus allows maintaining as much as possible, the fuel cell operating point in low power values to remain in the optimal efficiency zone.

In Fig 5, SOC=[ 600kWs 1000kWs], Pfc=[ 8kW 20kW], even if a low consumption is obtained there is two main problems: power demand is not always delivered, the Pfc reference is strongly discontinuous. To avoid this problem, larger windows must be used (that mean higher consumption), or several windows must be defined.

Following logic and fuzzy logic help the designer to define several zone maintaining low consumption Nevertheless, the first algorithm presents serious limitations. Indeed, based on deterministic rules and fixed value's limits, it allows very abrupt power variations. Moreover, the use of only two windows, limits its performances. In order to deal with both matters, fuzzy logic based algorithm is designed with fuzzy rules on one hand and an overlapping windows (membership functions) on the other hand.

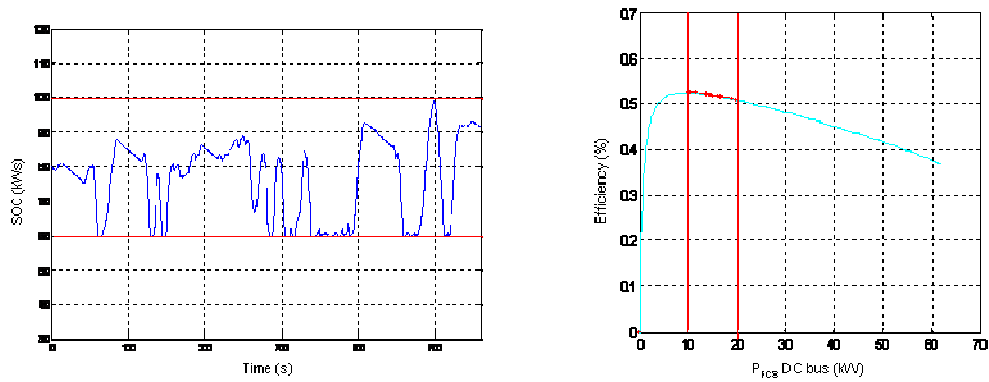


Figure 5 : First optimization results: Maximum Efficiency Tracking

The lack of future power demand knowledge provides poor consumption optimization and cannot ensure neither the recovery of all braking energy (Part of the negative power is lost in the brakes), nor providing all power demand picks. Optimization program must react in such situation and keep global losses as little as possible.

### 3.3 Fuzzy logic – step 1

The chosen membership functions are presented in Fig 6. The logic rules are here based on previous understanding of the systems. Results obtained, depend directly on the number of fuzzy rules and the shape and size of the fuzzy membership functions. Classical trapezoid membership functions are chosen to represent the two inputs and one output of the system. The two system inputs are the power demand  $P_{Dem}$  and the State of Charge  $SOC$  (computed depending on the power demand) while the output is the optimal power  $P_{fcs}$  to be delivered by the FCS.

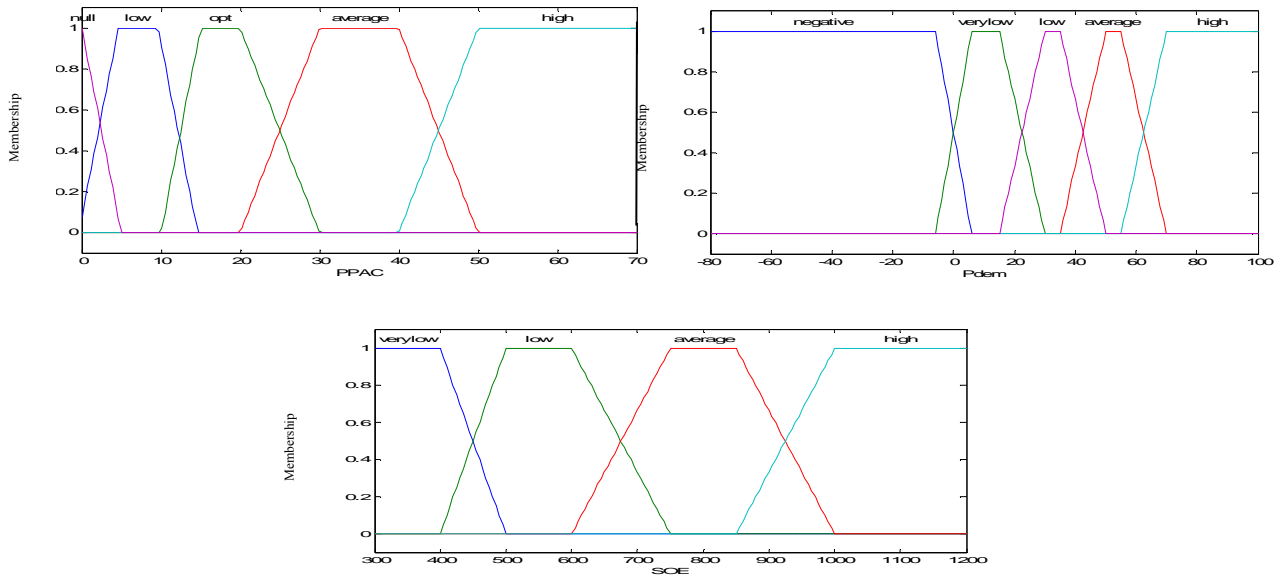


Figure 6: Fuzzy system inputs and output Membership functions.

Table 1 describes the fuzzy logic rules mapping the input membership functions to the output ones. Only five levels are chosen on inputs to consider enough accuracy on sources levels on positive/negative power demand (negative null [1], very low power[2], low power[3], average power[4], max high Power[5]). It is quite difficult to find the optimal combination of these membership functions. In fact based on trial and errors and expert analyses of the responses obtained, a non global optimization can be found. In fact, it is easy to see if a membership is too large or not when a result shows no solicitation on Storage Element or violate constraints on Power or something like that. But, it is difficult to observe interaction and to found an optimal set of parameters. The best possible solution provides better power repartition but needs a lot of human expertise and tests to be found.

Table 1. Fuzzy rules.

$P_{Dem}$ \ SOC	Very Low	Low	Average	High	Negative
Very Low	Average	High	High	High	Null
Low	Optimal	Average	Average	Average	Null
Average	Low	Low	Optimal	Optimal	Null
High	Low	Low	Low	Optimal	Null

### 3.4 Optimized Fuzzy strategy – step2

As previously exposed, a difficult point is often the tuning of the numerous parameters in such systems. The optimization of the positions of the membership functions is made possible by the use of a genetic algorithm which is briefly described in this section.

For this sake, a fixed number of 5 trapezoid membership functions is chosen for each input and output as shown in Fig 7. With the assumptions made, 8 parameters are necessary to characterize each variable. Therefore, the chromosome of the genetic algorithm is composed with the 3x8 membership terminations and a classical GA is used to minimize the chosen criterion. The criterion to be minimized is the entire  $H_2$  consumption (computed by integration from beginning to the end of the profile) to which penalties are added. Penalties are introduced to reject solutions when the sum of  $P_{fcs}$  and  $P_{ses}$  do not reach the power demand  $P_{dem}$ . The goal is to satisfy the main constraints in this HEV application which is the power requested by the electrical traction motors. This penalty is simply computed with the absolute square error  $K \cdot |P_{dem} - (P_{fcs} + P_{ses})|^2$ . To be noted that a weight coefficient  $K$ , allows to strictly or roughly respect the power demand that provides a certain sensitivity on the solution. In our case  $K$  is adjusted to neglect the error on power demand.

Moreover, parameter' values of the membership functions, have to respect the given order i.e.  $1 < 2 < 3 < 4 < 5 < 6 < 7 < 8$ . Therefore, a penalty is also added when a solution do not respect this order. In this case an infinite value on the criterion is forced.

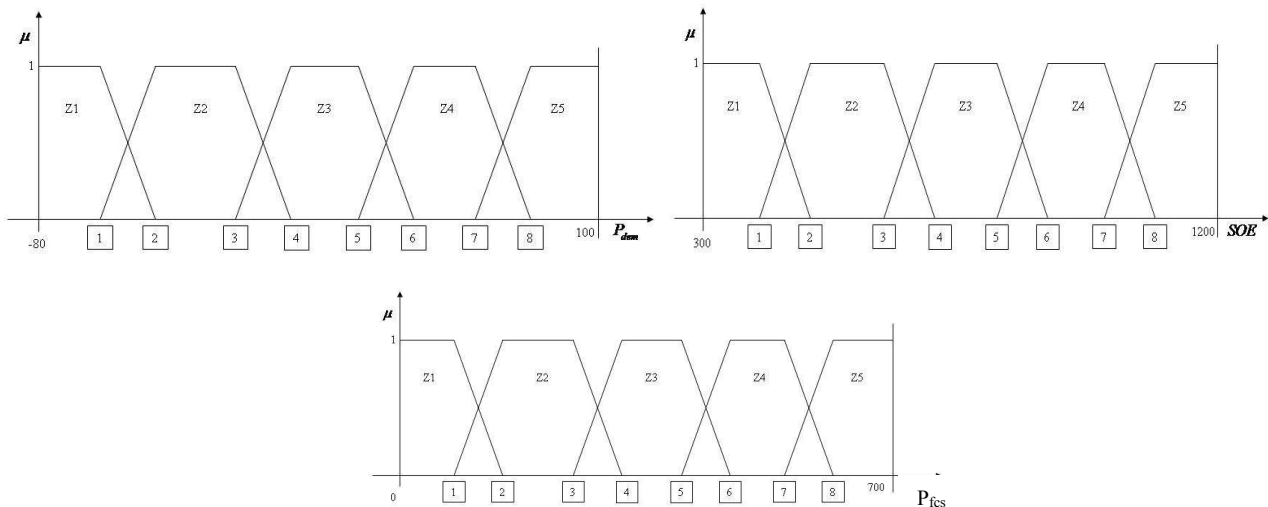


Figure 7 : 3 membership' functions for the genetic algorithm optimized fuzzy logic system GAFL

All parameters of GA are chosen as in classical problem found in literature [13]. With chromosome of 24 elements, a randomly created population of 200 individuals is chosen for the initial population. The number of generation is fixed to 200. Classical crossover, mutation and selection formulation and probability are used. Some adjustments may be introduced but have been judged not significant in this study.

Fig 8 shows all membership functions defined with the GAFL. Using these rules, a full solicitation of the storage element is made, respecting both  $P_{fcs}$  and  $P_{ses}$  min and max values.

Table 2 shows consumption obtained with these rules (GAFL) on the INRETS profile and the same method is used on an other profile named ESKISEHIR to test the solution. On both profiles the optimized rules provide low consumption.

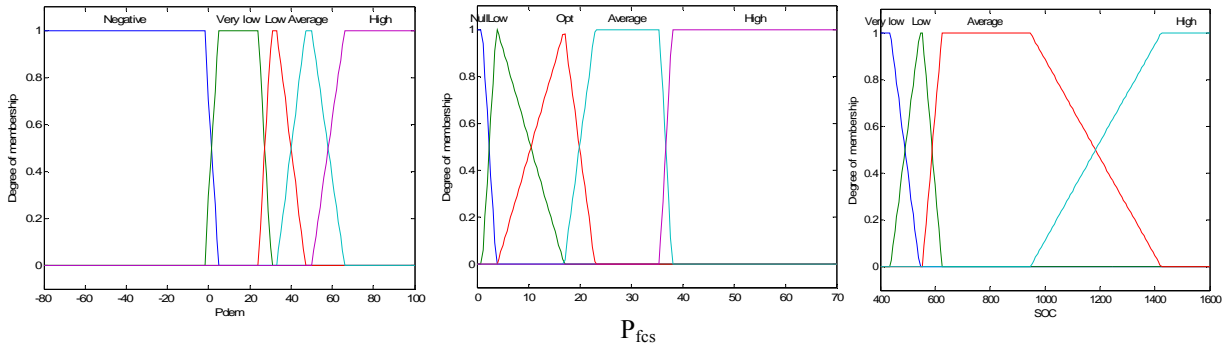


Figure 8: Optimized membership' functions using INRETS profile.

Comparisons are also made with the 3 other methods. The first step fuzzy logic is called Hand-Made Fuzzy solution (H-M Fuzzy) and results are shown to indicate the benefit of GA. Also added for comparison purposes, the consumption results obtained with previous studies made off-line on the entire profile with Dynamic Programming (DP) and the results obtained with two fixed windows (2windows). To show the interest having the Storage Element System, the consumption using only a Fuel Cell System for traction is shown (FCS only)

Table 2. Results obtained with fuzzy rules optimized by : Genetic Algorithm GAFL, Hand-made Fuzzy rules H-M Fuzzy, Dynamic Programming DP, and consumption with no storage capability, FCS only.

Méthod	INRETS Profile		ESKISEHIR Profile	
	Total Cons.	ErrEnergy	Total Cons.	ErrEnergy
GAFL	8.3613e3	9.92e-14	2.5652e4	2.09e-012
H-M Fuzzy	9.1226e3	37.0916	2.6446e4	63.3587
2Windows	9.912 e3	87.2	2.70e4	22.727
DP	8.4053e3		2.47 e 4	
FCS only	1.4087e4		3.6261e4	

The GAFL solution is very near to DP solution and demonstrates an effective optimization easily made. GA allows to reach a better solution than the trial and error method made accurately with a lot of computation time and analyses (8361kW instead of 9122kW or 9912kW). But, some power demand are not satisfied (no null energy error in ErrEnergy column). To be noticed even if the GAFL consumption is 8361kW a power error exists and the best DP consumption is minimal and equal to 8405kW.

GA-FL optimization using the second profile provides a minimum of 25652kW. Using the rules obtained in Fig 8 (made with INRETS) and running the ESKISEHIR profile, provides consumption equal to 27031kW. All constraints are respected and better efficiency is obtained as shown in Fig 9.

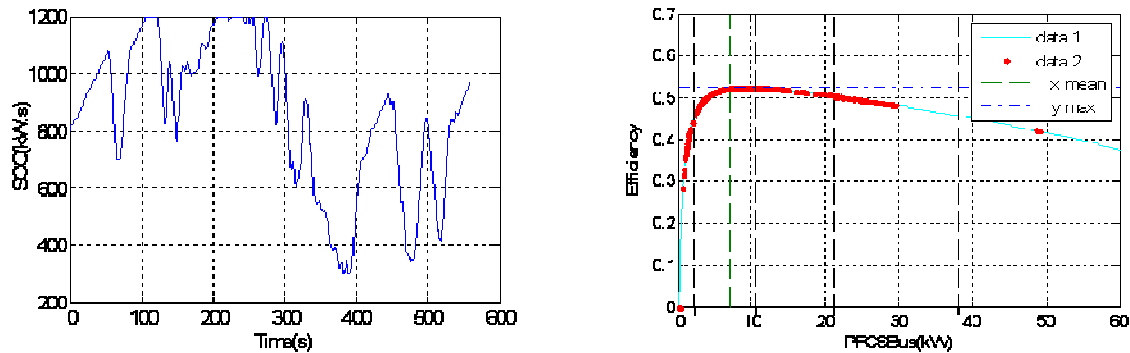


Figure 9: SOC window and FCS Efficiency window.

The storage element is fully used and numerous instantaneous efficiency points for the fuel cell are located in the maximal zone. Also identified 5kW, 12kW, 22kW, 35kW vertical lines corresponding to the fuzzy



zone limit around which the power can be chosen. Straighter zone has been defined by GA to be able to change power references remaining in optimal zone. That means low losses, better FCS efficiency working and thus H<sub>2</sub> minimization. Zero power indicated in Fig 9, do not mean to stop the Fuel Cell, in fact, the power demand for traction is zero, but the fuel cell still deliver power for ancillaries and comfort elements and is never stopped (so, can not start cooling). Powers chosen around 50kW are linked to max power demand to be delivered and even if the efficiency is poorer they must be chosen during the trip.

#### 4. DISCUSSION

The objective of the proposed paper is to present a hybrid electrical energy management strategy for transportation applications (based on fuel cell systems and ultracapacitors). Classical optimization algorithms are used and compared for a specific power requirement profile. Dynamic programming used off-line which provides a solution knowing the entire profile is presented. Logic rules managing fuel cell efficiency and state of charge of ultracapacitors are also presented.

The rules allow fixing some optimal performances and allow reacting in real time in case of different power demand or perturbation on a well known profile. An optimization of fuzzy rules by genetic algorithm made off-line is finally presented and results with real time profile adaptation are shown. A real time optimized set of rules allows reacting and adapting the references, even if perturbations arise in the profile, minimizing effects on the fuel consumption. So, the best solution is obtained when the rules is used with the profile used to build it. But, with one set of fuzzy rules, results are very near to the ideal one and fuzzy logic provides a good response. So, if rules are defined, in real time even if there are disturbances or a power demand quite different to follow, the consumption will be as little as possible

A profile analysis and a classification of profiles must be made to define the set of rules to choose (Urban/Sub-urban/Motorway) to obtain the corresponding optimal set of parameters. A local adaptation with penalty link to real time events may be a solution to locally minimize disturbances effect. Adaptation, prediction or memory evolution can make the link with other works made on optimal control adapted for real time too.

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