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Genetic Algorithm Fuzzy Logic Energy Management Strategy for Fuel Cell Hybrid Vehicle

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Abstract: The use of fuel cell hybrid vehicles is a potential transport solution achieving zero emission once technical, economic, and social challenges are overcome. Energy management strategies on board remain an important research subject in a quest to find an efficient power splitting between the fuel cell system and the energy storage element of the hybrid powertrain. This paper proposes an online strategy based on a fuzzy decision system. Fine tuning of the fuzzy system parameters, mainly the membership functions, is made possible using a powerful optimisation tool which is a genetic algorithm. This optimisation procedure takes into consideration the minimisation of the hydrogen consumption while satisfying the requested power over a given driving cycle.

Keywords: Fuel Cell Vehicle, Fuzzy Logic, Genetic Algorithm, Energy Management, Consumption Minimisation

1. INTRODUCTION

Energy management strategies for hybrid electric vehicles remain a main subject in recent studies where many industrials and researchers are actively implicated. To this day, no specific approach or strategy was able to impose itself as a best solution in each and every situation and a considerable work has to be done, therefore, in order to group and compare different adopted strategies. Nevertheless, the different approaches used for this purpose can be classified in two categories which include rule based strategies and optimisation based strategies Salmasi (2007). Optimisation based strategies such as optimal control or dynamic programming based methods often require an a priori knowledge of the power profile and, thus, they are often used offline Delprat et al. (2004), Lin et al. (2003). On the other hand, rule based strategies include basic deterministic rules or fuzzy rules Lee et al. (2000), Langari and Won (2005). Fuel cell vehicles control strategies and precisely the power split between the fuel cell and the storage element, which is the subject of this study, remain less exploited in literature. Nevertheless, different strategies applied in a conventional hybrid vehicle can be easily adapted to a fuel cell vehicle Rodatz et al. (2003). In this context, we could mention, among others, the application of a real time control strategy for fuel cell vehicles based on optimal control theory Bernard et al. (2007) or based on the minimisation of the equivalent consumption ECMS Rodatz et al. (2005). The online management strategy

presented in this paper is based on a fuzzy inference system optimized by means of a genetic algorithm. This approach is classified among on-line rule based strategies while further offering an optimisation possibility provided by the use of the genetic algorithm. In a first step, the fuzzy inference system is built by choosing the appropriate system inputs and output membership functions and fuzzy rules set. Fine tuning of the fuzzy system requires a good expertise on one hand but also a time consuming trial and error phase on the other hand. To overcome this procedure while obtaining an optimal set of parameters, a genetic algorithm is used in a second step. It is necessary to mention that the applied fuzzy system is more likely a decision making system based on fuzzy rules than a fuzzy controller. More or less similar to this system, we find power management applications applied to series or parallel conventional hybrid architectures. For example, Zeng and Huang (2007) propose a fuzzy system to control the throttle angle degree of the internal combustion engine according to the battery state of charge and to the requested traction torque. In the work of Zhu et al. (2006), the instant power of the battery is chosen based on the power demand and the state of charge of that battery using a statistical method based on the results of a dynamic programming algorithm.

2. POWERTRAIN CHARACTERIZATION

A fuel cell vehicle is classified among series architecture hybrid vehicles in which the entire set of an internal

combustion engine coupled to an electric generator is replaced by a fuel cell system. This latter is responsible of generating the necessary electric energy requested by the electric motor. The basic structure of the fuel cell vehicle is shown in Fig. 1.

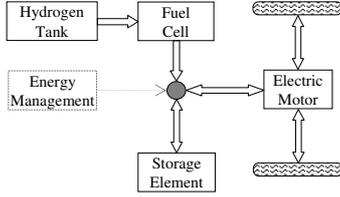


Fig. 1. A fuel cell vehicle basic structure

The core of the fuel cell vehicle is a hybrid powertrain formed of a fuel cell (FC) and a storage element (SE). A standard model of the powertrain is considered in this study as shown in Fig. 2 Caux et al. (2005). This powertrain is composed of the fuel cell system connected to the DC bus by means of a boost DC converter from one hand and of a supercapacitors pack type storage element connected also on the same bus by means of a current reversible boost converter. The electric motor, generally a synchronous one, is connected to the DC bus through a voltage inverter.

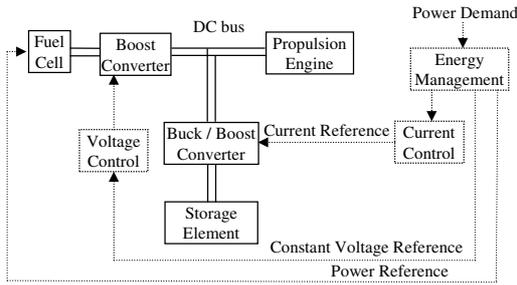


Fig. 2. Powertrain bloc diagram

Each of the electric energy sources defines an energy path representing a certain power flow (Fig. 3). Primary path is formed by the fuel cell (and ancillaries) with its associated converter. On the other hand, a second energy flow path is defined by the storage element and its buck/boost converter. The connexion of these two energy paths forms a virtual electric node supplying the desired power request. Therefore, the power demand, P_{dem} is the sum of the useful power delivered by the fuel cell system, P_{FC_bus} and by the storage element P_{SE_bus} . It is evident that a part of the power delivered by both sources is lost as heat along the path. It is therefore necessary to identify the system energy balance highlighting the main power losses across these paths. The total losses of the fuel cell system, which are considered in this study, are the sum of the fuel cell losses due mainly to the thermodynamic efficiency of the electrochemical reaction and to voltage drops across this fuel cell, the power converter losses due to the conduction and commutation losses of the converter semiconductors, and finally the electric energy losses across the fuel cell auxiliaries. These auxiliaries and mainly the air compressor are electricity consuming hence reducing the useful

delivered energy. On the other hand, the energy balance of the storage element considers the losses of the supercapacitor pack due to its internal resistance and of the current reversible converter.

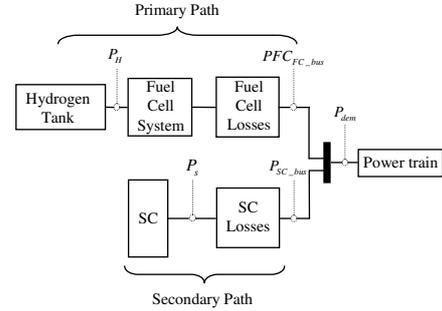


Fig. 3. Power and losses distribution along the hybrid powertrain

The identification of these losses and therefore the characterization of the global efficiency of each path, is made possible using a simulation model under Matlab/Simulink. The resulting fuel cell system efficiency is given in Fig. 4. On the other hand a fixed efficiency of 93% is chosen for the storage element for simplification.

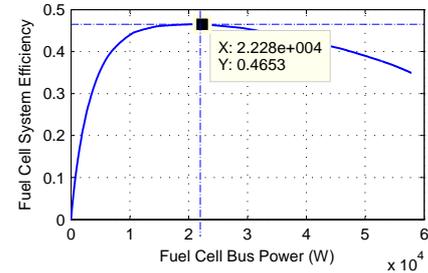


Fig. 4. Fuel Cell System Global Efficiency

Having characterized the global efficiency of each energy path, the powertrain could therefore be represented in the abstract model of Fig. 5. The primary power source is therefore represented by its useful power at the electric node, P_{FC} and an efficiency value, η_{FC} allowing us to estimate the real hydrogen consumed energy. On the other hand, the storage system is also represented by its delivered power, P_{SE} and a global efficiency, η_{SE} allowing to compute the effective amount of energy actually stored in the supercapacitor and thus its actual state of charge variation.

For us to base the study upon a real lightweight transport application case, the different powertrain elements sizing was taken into consideration in simulation. 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 pack delivered and absorbed power, respectively P_{SE_max} and P_{SE_min} and finally on the maximal and minimal state of charge or state of energy of the storage element, SOE_{max} and SOE_{min} .

All of these values are given in table 1.

Table 1. System power and energy constraints

P_{SE_min}	P_{SE_max}	P_{FC_min}	P_{FC_max}	SOE_{min}	SOE_{max}
-60 kW	60 kW	0 kW	70 kW	400 kW.s	1600 kW.s

3. FUZZY LOGIC BASED DECISION SYSTEM

The implemented fuzzy decision system uses two input variables which are the state of charge 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 universes of discourse is divided into a defined number of subsets describing a general state of the designated variable. The state of charge of the storage element can therefore be considered “very low” (VL), “low” (L), “average” (A), or “high” (H). Similarly, the required power could be considered as “negative” (N), “very low”, “low”, “average”, or “high”. Finally, the fuel cell power could be “Null” (N), “very low”, “low”, “average”, or “high”.

Each subset is designated by a membership function which assigns to each value of that variable a membership degree to that subset. In this regard, trapezoidal type membership functions are chosen to designate each of the fuzzy sets spread over the universe of discourse. Fig. 6 represents the trapezoidal membership functions of the SE state of charge, between SOE_{max} and SOE_{min} . Fig. 7 and Fig. 8 represent respectively the chosen membership functions of the required power and fuel cell delivered power.

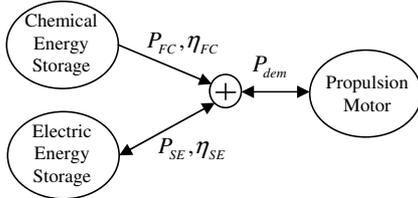


Fig. 5. Fuel Cell Vehicle Abstract Model

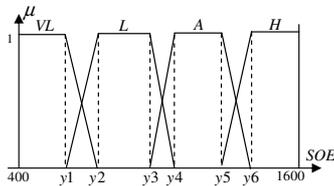


Fig. 6. SOE input variable membership functions

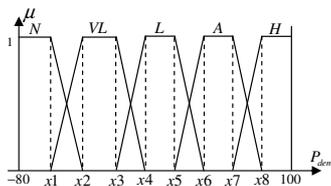


Fig. 7. P_{dem} input variable membership functions

The trapezoidal type membership functions are chosen for their simplicity, and the number of these membership functions remains an arbitrary choice based on the expertise acquired towards the system operation principles. This expertise is consolidated with the bibliographic research from one hand and with trial and error on the other hand. It is necessary to precise that the choice of these functions is directly related to the set of fuzzy rules characterizing the fuzzy decision system by linking the system inputs to the unique output.

The inference system is composed by a number of 17 rules linked by an OR operator. Each rule presents a condition preceded by the IF symbol and a conclusion, or action preceded 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 entire rules set can be represented graphically in an inference matrix as shown in table 2. At the intersection of a matrix line and column linked to the input variable, lays the corresponding set of the output variable. The general idea behind these rules is that the fuel cell delivers as much power as the required power is high and / or the state of charge of the storage element is low. On the other hand, the fuel cell delivers as low power as the required power is low or the storage element is high enough to provide this power. From this general idea, the choice of these rules remains an arbitrary choice that tends to ensure a continuous passage of power from its highest level to its lowest one using the intermediate levels.

Table 2. Fuzzy logic based decision system inference matrix

		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

Finally, we have to precise that 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. The choice of the membership function parameters is usually made by trial and error and a time consuming experimental procedure is necessary to obtain the proper set of parameters. To overcome this problem, a genetic algorithm is used to find the optimal set which minimizes a certain criterion.

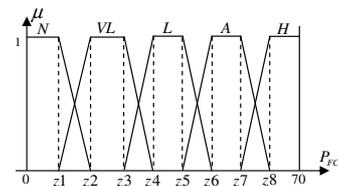


Fig. 8. P_{FC} output variable membership functions

4. MEMBERSHIP FUNCTIONS OPTIMISATION USING A GENETIC ALGORITHM

The genetic algorithm optimisation method follows the flowchart presented in Fig. 9. First, an initial population of N_{pop} individuals is created, each individual forming a specific combination of the parameters to be optimised. At each step of the genetic algorithm, the fuzzy inference system is built using the corresponding individual parameters. An evaluation or fitness function is then calculated for each individual with respect to a certain criterion. The following step consists of selecting specific individuals regarding their fitness function to which are applied the operators of mutation and crossover. The new created individuals in this step are again evaluated to maintain the best individuals or the individuals that better adapt to the imposed criterion. These individuals form the population of the next generation which undergoes the same process as its previous generation. The algorithm stops whenever the stop criterion is met. The stop criterion chosen in this study is the reach of a fixed number of generations N_{gen} .

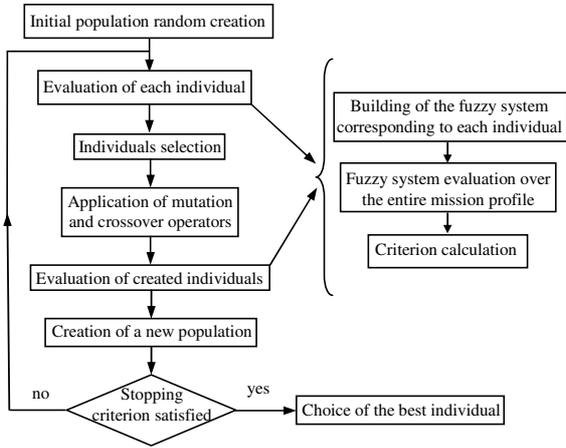


Fig. 9. Genetic algorithm fuzzy logic flowchart

Coding of the individual also called chromosome is a delicate issue. The individual contains all the information needed which is, in this case, the necessary parameters allowing the membership functions identification. Taking into consideration previous hypotheses made on the shape and type of the membership functions, a number 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 as shown in figures 6, 7 and 8. The chromosome thus formed of the concatenation of these parameters is shown in Fig. 10.

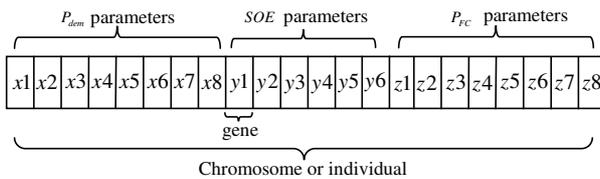


Fig. 10. Identified parameters considered as a chromosome genes

Another important issue is the definition of the fitness function which will evaluate the performance of each individual. In our case, the aimed target is the minimisation of the hydrogen consumption while ensuring the power required along the entire vehicle driving cycle. Maximizing the evaluation function F_{eval} consists of minimizing an optimisation criterion C_{opt} as given in equation (1). 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 equation (3), and a value quantifying the mean quadratic error e_{quadr} measured between the required power and the power actually provided. The defined criterion is therefore given according to the equation (2) where k is a scaling factor between consumption and error values. The choice of this factor also allows to adjust the required precision since the more k is low, the more we favour the minimization of consumption versus error and vice versa.

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

$$C_{opt} = \frac{E_{H_2}}{k} + e_{quadr} \quad (2)$$

$$E_{H_2} = \sum_i \frac{P_{FC}(i) \cdot \Delta t}{\eta_{FC}(P_{FC}(i))} \quad (3)$$

The expression of the mean quadratic error e_{quadr} (in kW) is given in the following equation:

$$e_{quadr} = \sqrt{\frac{\sum_{i=1}^N (e_{P_{dem}}(i))^2}{N}} \quad (4)$$

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

$$e_{P_{dem}}(i) = P_{dem}(i) - P_{prov}(i) \quad (5)$$

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 with taking into consideration the saturations over these power and state of charge values.

$$P_{prov}(i) = P_{FC_cor}(i) + P_{SE_cor}(i) \quad (6)$$

Furthermore, the fitness function will allow us to handle further constraints imposed on the individual parameters by using a penalty function that penalizes the non feasible solutions reducing their fitness function Carlos and Coello (2002). These further constraints are given in equation (7). Individuals which parameters do not verify this condition are penalized with a quite high criterion C_{opt} . This allows the genetic algorithm to progressively depart away from these non feasible values.

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

To summarize, the genetic algorithm is used to optimize the fuzzy logic decision system. This optimisation is made offline using a specific mission power profile. Once the optimized parameters found and the corresponding optimal fuzzy logic system built, this latter is therefore ready to

be used in an online energy management strategy (with no a priori knowledge of the future power request). This optimisation is made possible by using two different power mission profiles. The first one, the INRETS profile represents an electric vehicle circulating in an urban environment Jeanneret et al. (1999) Trigui et al. (2004) while the second, the ESKISEHIR profile, represents a tramway running on the ESKISEHIR line and this after having applied the necessary scaling factor in order to adapt the power level to our application size considerations. These two profiles are represented in figures 11 and 12.

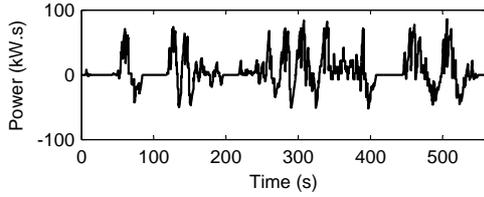


Fig. 11. INRETS mission power profile

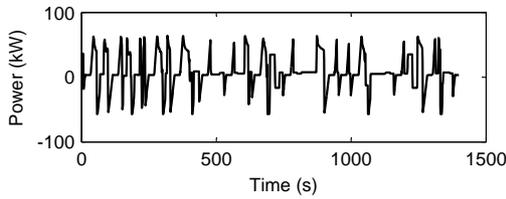


Fig. 12. ESKSEHIR mission power profile

After applying the genetic algorithm to the fuzzy logic system, the optimized characteristic surface of this fuzzy system is given in Fig. 13 for both mission profiles. The grey surface represents the INRETS profile while the dotted surface the ESKISEHIR profile. It is clear that these two surfaces present slight differences related 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.

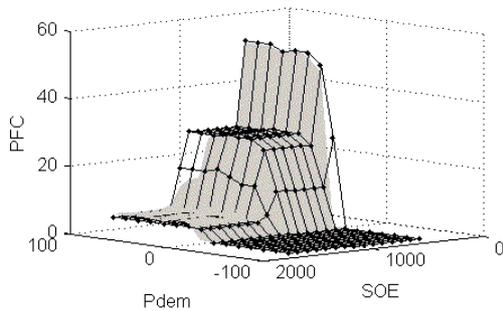


Fig. 13. Fuzzy system characteristic surfaces generated with the genetic algorithm using both mission profiles

In order to evaluate the performance of the proposed strategy, table 3 shows the hydrogen energy consumption as calculated in equation (3) and the improvement (in %) made on the consumption reduction as compared to the

case where the fuel cell is used alone with no hybridization. This table compares the results obtained with the optimized fuzzy system GAFL with the results of the hand tuned fuzzy logic system FL showing the clear improvement made with applying the genetic algorithm. It also compares these results with those obtained by applying a global optimisation method which is the dynamic programming algorithm (D.P.). This latter comparison shows the powerful performance of this algorithm as it provides close results to the D.P. algorithm.

Table 3. Comparison of the obtained results applying different control strategies

Profile	Algo.	Cons.	Improv.
INRETS	D.P.	9 189.7 kW.s	38 %
	F.L.	10 866 kW.s	27 %
	GAFL	8 359.9 kW.s	43.8 %
ESKISEHIR	D.P.	31 826 kW.s	33.7 %
	F.L.	33 358 kW.s	30.5 %
	GAFL	29 802 kW.s	37.9 %

The evolution of the state of charge of the storage element along the driving cycle is shown in Fig. 14 for the INRETS profile and in Fig. 15 for the ESKISEHIR profile. Fig. 16 presents the resulting power split between the fuel cell and the storage element after applying the optimized fuzzy system along the INRETS profile while Fig. 17 represents the power split on the ESKISEHIR profile.

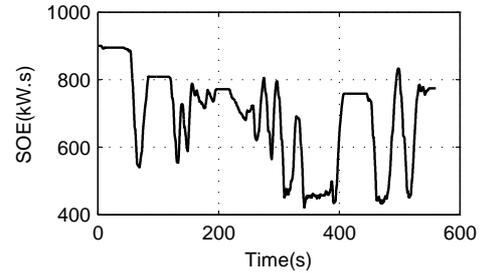


Fig. 14. Supercapacitors state of energy along the INRETS driving cycle

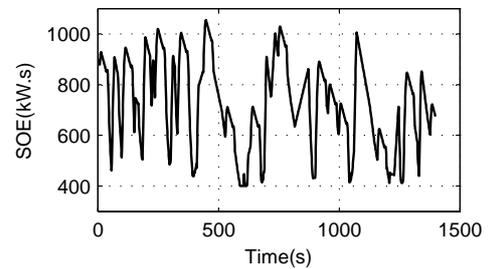


Fig. 15. Supercapacitors state of energy along the ESKISEHIR driving cycle

As the optimisation 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 performance when applied to different other profiles. Therefore, a further attention should be given to the study of robustness of this method. For this sake, we have tested the performance of the system optimised on the INRETS

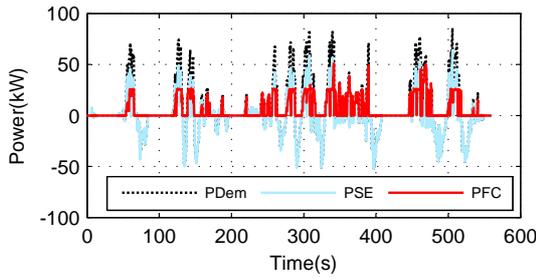


Fig. 16. Optimal power split generated by the genetic algorithm using the INRETS mission profile

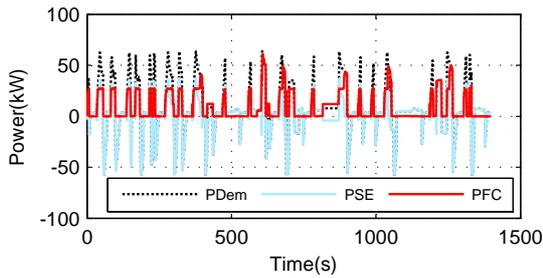


Fig. 17. Optimal power split generated by the genetic algorithm using the ESKISEHIR mission profile

profile and applied on the ESKISEHIR one and vice versa. Results of this crossing application are given in table 4 where :

- **Inr-Inr**: System optimised on the INRETS profile and applied on the INRETS profile.
- **Esk-Inr**: System optimised on the ESKISEHIR profile and applied on the INRETS profile.
- **Esk-Esk**: System optimised on the ESKISEHIR profile and applied on the ESKISEHIR profile.
- **Inr-Esk**: System optimised 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 optimisation profile with a relatively neglected error as the required power is well satisfied all along the driving cycle.

Table 4. Consumption and mean quadratic error resulting of the application of the optimised fuzzy system

	Inr-Inr	Esk-Inr	Esk-Esk	Inr-Esk
Improvement	43,8 %	41,5 %	37,9 %	35,6 %
M.Q.E.	$1,5 \cdot 10^{-13}$	$1,6 \cdot 10^{-13}$	$2,4 \cdot 10^{-14}$	$2,3 \cdot 10^{-14}$

5. CONCLUSION

A fuzzy logic based decision system is applied in order to properly manage the power split between the power source and storage element of the hybrid electric generator in an fuel cell vehicle. The fuzzy system parameters were optimised using a genetic algorithm aiming to reduce hydrogen consumption over a given driving cycle. The performance and robustness of the optimised fuzzy system was tested on two different mission power profiles showing quite acceptable results as compared to a dynamic programming based algorithm. As future perspectives, a thorough study

will be made to define a quantitative relation between a certain profile and the optimised parameters obtained with the genetic algorithm in order to allow easy tuning and adaptation of the fuzzy system without having to repeat the optimisation procedure.

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