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Research article

Local energy management in hybrid electrical vehicle via Fuzzy rules system

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Abstract: The energy management of Hybrid Electric Vehicles (HEV) has been the subject of a great scientific effort in recent years. Moreover, in HEV the power must be managed in real time within system constraints. The proposed approach based on a fuzzy controller, uses different set of rules depending on different phases present in a mission profile. The challenge is to compute offline these rules and to manage online a decision method to switch optimally from one rule to the other depending on the power demand. From the proposed segmentation/prediction of the requested power profile to follow, derives a switch condition between three different rules in order to decrease the fuel consumption instead of applying a unique rule computed globally on a given profile. This strategy drives the fuel cell (FC) to operate at the points of best performance. It has been verified that if this method is applied online on an unknown profile, the consumption obtained is almost optimal.

Keywords: energy management; hybrid vehicle; Multi-source systems; mission analyze; fuzzy controller; segmentation

1. Introduction

The number of registered vehicles is increasing, and although the new internal combustion engines are less polluting, pollution problems are becoming increasingly critical, particularly for greenhouse gas emissions that are responsible for global warming of the planet [1]. One way to fight against these emissions is to implement other kind of energy sources (renewable energy: wind, solar, and new environmental friendly sources: fuel cell...) [2]. All-electric vehicles have been presented as a promising solution, thanks to their independence from oil. But their lack of autonomy does not allow them today to permanently replace conventional vehicles; hence the development of another concept: hybrid vehicles [3–5].

A hybrid vehicle uses at least two different energy sources to take advantage of the benefits of each organ and thereby improve the overall efficiency of the transmission. The storage element can be recharged on board the vehicle, which avoids costly installation of new infrastructure: the autonomy of the vehicle depends then only on the capacity of its tank conventional vehicle [6]. Hybridization is one of the promising alternatives in the short and medium term. Having two types of source makes it possible to recover the energy and to choose the operating point with the best efficiency for the primary source [7,8].

In order to evaluate the contribution of hybridization and its potential in terms of fuel economy, an overall assessment must be considered by analyzing the cost of the energy flow to achieve the traction function. This cost depends on the operating modes and power distribution policies between different sources. The primary source is intended to provide power on long trips requiring high autonomy and to charge the storage element when needed [9,10]. The braking energy is recovered by the secondary source which also responds to power peaks during acceleration. This combination is supposed to meet the requirements of reducing fuel consumption and pollutant emissions.

The fuel cell produces electricity from hydrogen and oxygen without release of pollutants. This is why it is used in the automotive sector [11]. The Fuel Cell Stack is usually associated with almost one element of storage of electrical energy to power an electric motor in a full hybrid electrical structure. This secondary source of energy is composed of either batteries or super capacitors. Among the advantages of hybrid vehicle is that kinetic energy can be recovered and stored in order to be used later.

Energy management has been a hot topic since the 2000 and has been the subject of much publicity. Several approaches have been developed to minimize fuel consumption and reduce emissions of greenhouse gas by satisfying the power demand at every moment with full respect for the constraints of energy and power elements [12]. In this context, in [13], authors deal with the problems of energy management and control of energy sources. Also, Garcia-Arregui et al. and Zhou et al. propose a simple mission filtering approach [14,15]. Besides, Neffati et al. and Sabri et al. have developed management algorithms based on fuzzy rules [16,17].

There are two main strategies in order to define the distribution of power [18,19]:

1. Offline strategy: If the road section is known, it is possible to use offline strategies for global optimization; this approach is only possible in offline simulation [20,21].
2. Online strategy: In real time the road section is not known. The control strategies used are generally suboptimal but based on offline learned optimized references [22–27].

The proposed real time controller is based on fuzzy rules optimized offline on a given profile. Membership function positions are impacting the consumption [28]. It is clear that the phase of generating optimized fuzzy rule by genetic algorithm requires prior knowledge of the path traveled offline [15]. It would be wise to generate different rules in order to find a set of parameters that can be easily adjusted according to the nature of the mission profile in which the vehicle will be submitted. This paper focuses on the management of electric power of such hybrid electrical vehicle. It demonstrates if an optimization is made globally on a profile including two different phases it is quite the same to switch from two rules than applying the global one and can be made online.

Firstly, the different elements used in HEV are presented in part 2 with regards to their efficiency characteristics. Besides, three optimized fuzzy controllers are presented: Analyzing Urban, Road mixed and Highway power profiles. In part 3, segmentation and switching decision method is presented conducing to the discussion and comparison of results in part 4.

2. Problem description

2.1. Elements behaviors

For this study, we will consider a generator set formed by a fuel cell and supercapacitors. The different elements of this system have been dimensioned a priori in order to satisfy the power demands, using either a source or two sources simultaneously (Figure 1). Energy management consists in splitting optimally the power demand between the available sources. Depending on the efficiency provided by each source, the minimum hydrogen consumption is reached when, on given profiles, each source delivers its power with a maximum global efficiency.

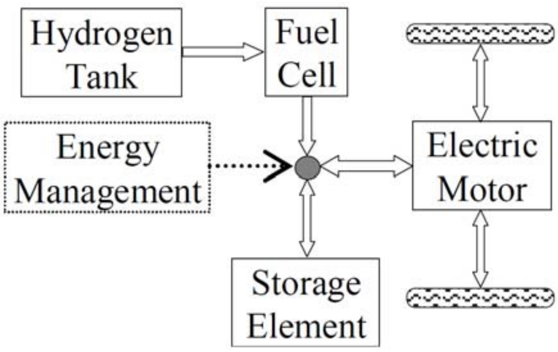


Figure 1. HEV elements (FC Stack—Storage Element Stack).

The Fuel cell Stack FC and the Storage Element Stack FS are characterized by their efficiency and energy sizing [18]. At each time the sum of power sources must provide the power profile demand. The optimization problem is resumed in Figure 1 where it is also noticed the size of each element. Each element size is defined and energy management will be made with decision controller dealing with these min and max power and energy limits (Figure 2).

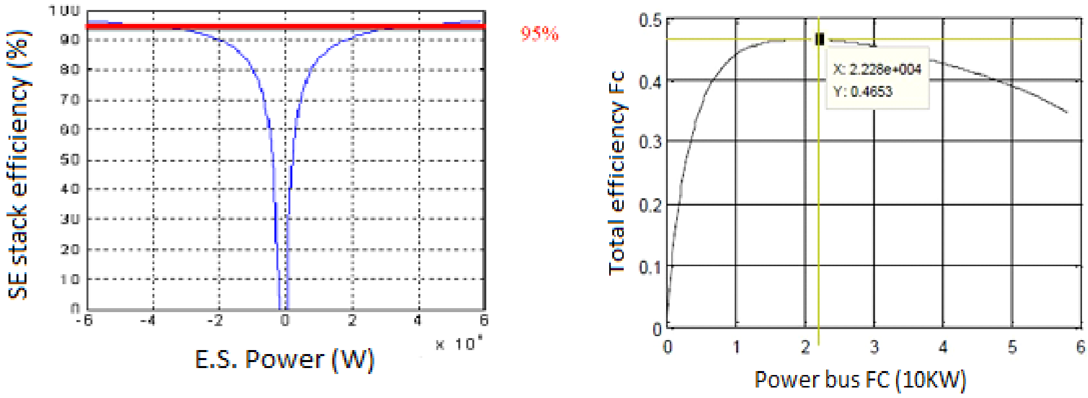


Figure 2. FC Stack—Storage Element Stack: Efficiency and sizing.

The energetic model of the generator is characterized by different energetic flows. The storage of chemical energy is represented by the hydrogen reservoir while the storage of electrical energy is represented by the super-capacitors as shown in Figure 3.

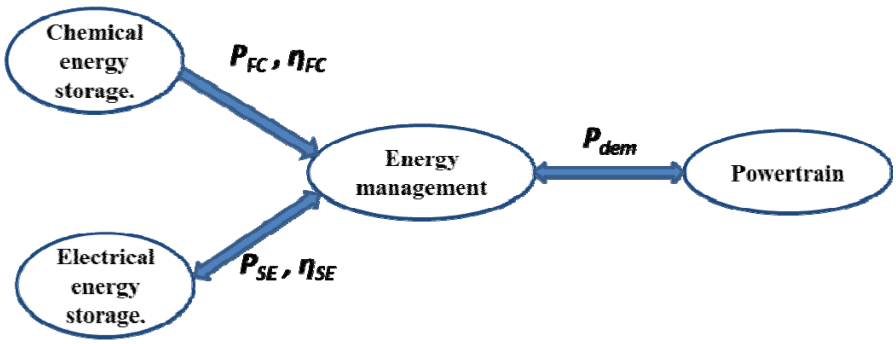


Figure 3. Energy Model generator of hybrid fuel cell.

2.2. Power demand mission

The various modes of operation of the vehicle can be classified into three broad categories; depending on the environment of use. We have a set of typical circulation missions, established by the French Institute of Science and Technology for Transport, Development and Networks IFSTTAR (Institut Français des Sciences et Technologies des Transports, de l'Aménagement et des Réseaux) from a statistical study on a set of real missions [29,30]. We adopt the same classification used in the work done by Chapoulie in [31], these missions can be classified by type of path:

- An Urban mission: characterized by low power requirements and a succession of repeated accelerations and decelerations. Operating speeds are between 0 and 20 km/h, for power lines between −5 and 42 kW (Figure 4).

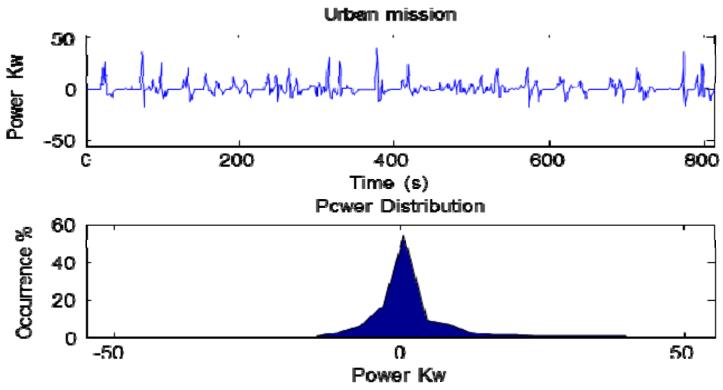


Figure 4. Power distribution of the urban profile.

- A Road mission (between urban and highway cycle): it concatenates a series of transient and quasi-permanent patterns with speeds ranging between 40 and 80 km/h for power limit of −39 to 51 kW (Figure 5).

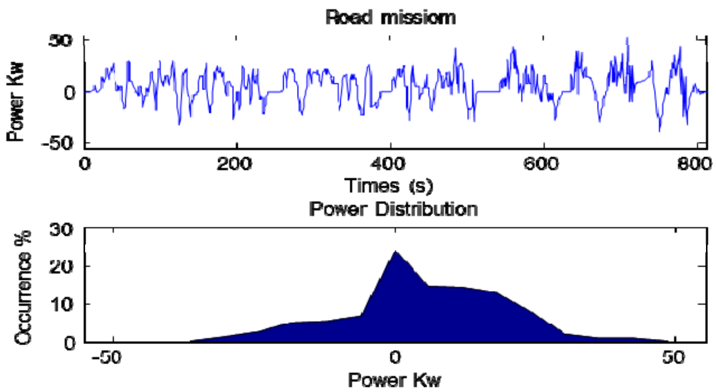


Figure 5. Power distribution of the road profile.

- A Highway mission: characterized by high power applications with a high concentration of operating point on a speed range of 70 to 120 km/h, with power limits −53 kW and 54 kW (Figure 6).

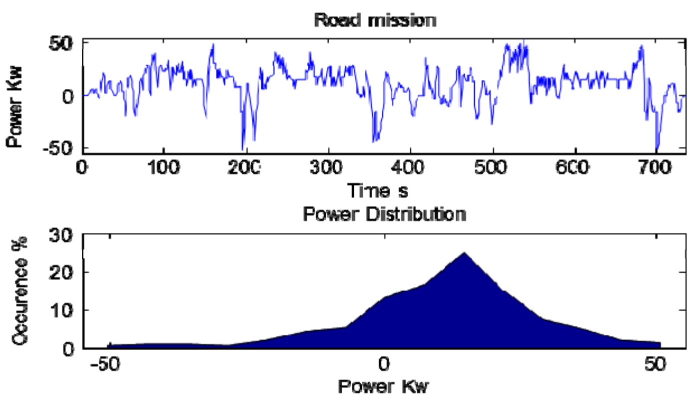


Figure 6. Power distribution of the highway profile.

A Lot of studies can be found to recognize some typical information in such different profiles. Statistic approach can select the average power and the power variance to classify them. More complex pattern recognition (clustering, spectral analysis, power density computation…) can be found [32,33]. However in all cases there is a lot need of information to have the correct identification and such computation must be made offline and can't be used in real time to help the controller to switch from one profile to another. Moreover, a priori, splitting the power demand with regard to the dynamic of sources (low power variation manage by fuel cell, high transient manage by supercaps), in order to find a rational method for the characterization of power profiles, it is interesting to analyze the characteristic powers of each mission. The Table 1 illustrates the ratios between the maximum positive and negative powers, the average powers demanded on the entirety of each profile and the average of the positive powers.

Table 1. Characteristics of profiles to be studied.

Mission type	Urban	Road	Highway
Max Power (kW)	42	51	54
Min Power (kW)	−17	−39	−53
Average P (kW)	1.3	5.1	11.3
Normalized average P/Pmax (%)	3.1	10	21
Positive Power average (kW)	5.6	13.8	17.7

2.3. Optimization problem formulation

The problem of energy optimization for the hybrid vehicle is to find the best way to distribute, store and consume energy, while optimizing the consumption of hydrogen over the entire mission [21].

2.3.1. Dynamic equation

In general, a dynamic optimization problem is governed by the set of following equations [29]:

$$\dot{x}(t) = f(x(t), u(t), t) \tag{1}$$

$$\int_{t_i}^{t_f} \gamma(x(t), u(t), t)dt \tag{2}$$

$$\psi(x(t), u(t)) = 0 \tag{3}$$

$$\varphi(x(t), u(t)) \leq 0 \tag{4}$$

where $x(t)$ represents the state variables, $u(t)$ the control variables and $\gamma(t)$ the cost function. The constraints imposed on the system are represented by the functions $\psi(t)$ and $\varphi(t)$. The beginning of the bounded course is marked by t_i and its end by t_f.

2.3.2. State equations

In this work, we consider a power supply consisting of a fuel cell and a super-capacitor. We note $P_{ES}(t)$ the power supplied/absorbed by the Storage Element. This variable is limited and its role is to make energy exchanges, resulting from the links between P_{dem} and P_{FC}. The state variable x, represents the state of the energy of the storage element $E(t)$. The equation governing the dynamics of the system is written in this case:

$$\dot{E}(t) = -P_S(t) \tag{5}$$

P_S represents the power supplied/absorbed by the super-capacitor pack. Its expression as a function of the useful power P_{ES} and the efficiency of the storage element η_{ES}, is given by the following formula:

$$P_S(t) = \begin{cases} \dfrac{P_{SE}(t)}{\eta_{SE(P_{SE}(t))}} & \text{Discharging} \\ P_{ES}(t)\eta_{ES(P_{ES}(t))} & \text{Charging} \end{cases} \tag{6}$$

2.3.3. Cost and Performance Criterion FC

The instantaneous hydrogen consumption $\gamma(t)$ depends on the power provided by the P_{FC} fuel cell system and the total output of the η_{FC} generator set. The cost criterion is therefore expressed as follow:

$$J_{H_2} = \int_{t_i}^{t_f} \gamma(x(t), u(t), t)dt \tag{7}$$

$$\gamma(x(t), u(t), t) = \frac{P_{FC}(t)}{\eta_{FC(P_{FC}(t))}} \tag{8}$$

2.3.4. Constraints

The sizing of the system imposes constraints on the powers and the energy levels.

$$P_{SE}(t) + P_{FC}(t) - P_{dem}(t) = 0 \tag{9}$$

$$P_{SE\_min} \leq P_{SE}(t) \leq P_{SE\_max} \tag{10}$$

$$P_{FC\_min} \leq P_{FC}(t) \leq P_{FC\_max} \tag{11}$$

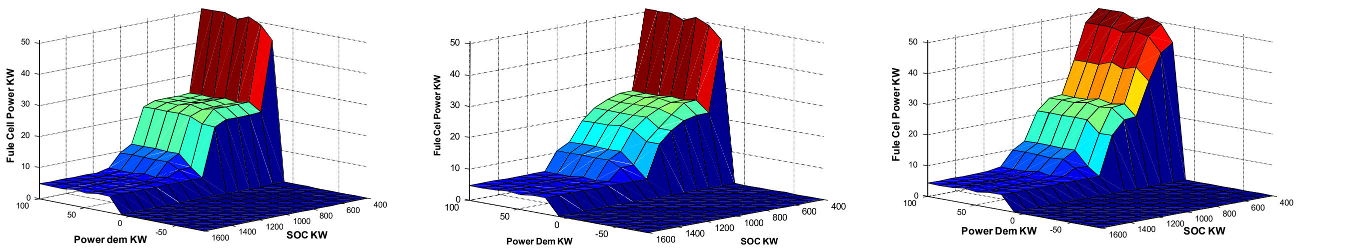
$$\Delta_{SOC} = SOC_f - SOC_i = 0 \tag{12}$$

SOC: state of charge.

The hybrid generator group formed by the secondary source of energy and the fuel cell must ensure the instantaneous power demand of the powertrain (P_{dem}). Energy management strategy on line is based on a fuzzy system. The controller serves to identify the instantaneous power to be supplied by the fuel cell P_{FC} for a given state of charge E and a power demand P_{dem}.

3. Energy management techniques

The fuzzy inference system is characterized by rules that are already optimized offline by a genetic algorithm GA [18] and generate the specific rules for each profile as shown in Figure 7. The GA makes it possible to optimize the choice of the parameters of the fuzzy controller and to generate its specific rules for each profile that link the input variables to the output variable in order to obtain the lowest hydrogen consumption [23]. Once the optimal parameters identified, the optimized fuzzy controller will be used in energy management online without prior knowledge of the power mission.



a- Rule 1- Urban profile b- Rule 2 – Road profile c- Rule 3 – Highway Profile

Figure 7. Three optimized fuzzy rules (linking P_{dem}/SOC to optimal P_{FC}).

The main objective is to permanently ensure the requested power along a mission profile, minimizing the hydrogen consumption (H_2) as much as possible and respecting the imposed constraints, especially those on the state of charge of the storage element. On the first, we propose a criterion based on two parameters of the specifications, in particular the consumption of hydrogen from the FC and the average energy error MSE, it is proposed to multiply the MSE by 100 so that it has influence on the criterion 1:

$$\text{Criterion \_1} = \text{tot\_Consumption} + \text{MSE}*100$$

The constraint of maintaining the state of charge is not taken into account in this first form of the criterion. One way to improve the results obtained, in terms of accuracy of total cost calculation is to introduce the constraint on the state of charge and use a penalty function. The latter introduces an additional "artificial" hydrogen consumption when the state of charge is below the initial one, which results in a negative SOC variation 'when'.

$$\text{Criterion \_2} = \text{tot\_Consumption} + \text{MSE}*100 + \text{recharge artificielle (if } \Delta \text{ soc} < 0)$$

3.1. Reference consumption

To be able to identify the effectiveness of the energy management method applied to each power profile, we will refer to two consumption references:

a. Only use the fuel cell to provide traction (a required positive power): Negative powers will not be recovered (braking energy will be dissipated as heat in the brakes), and we may have energy errors if there are power demands that exceed the maximum power that can be provided by the FC (Table 2).

Table 2. Consumption without storage element.

Profiles	Profile 1	Profile 2	Profile 3
Reference consumption without storage kJ	5815	15451	23084

b. Dynamic Programming DP: This strategy considers the FC and the supercapacitors as two sources of energy for the application of the dynamic algorithm. The goal of this method is to find the optimal consumption while respecting all the constraints imposed in particular the constraint on ΔSOC for maintaining the initial and final state of charge equal (Table 3).

Table 3. Dynamic Programming consumption.

Profiles	Profile 1	Profile 2	Profile 3
Total consumption with DP KJ	5986	12667	20099
Δ soc (kJ)	0	0	0

3.2. Segmentation method

The segmentation method consists of decomposing the profile into several segments with three consecutive instant. It is necessary to note that interested is made on positive power, since the optimization consists in satisfying a requested power and not distributing a recovered power. The following Figure 8 illustrates the principle of segmentation; the red line denotes the average power of each segment (duration 3s).

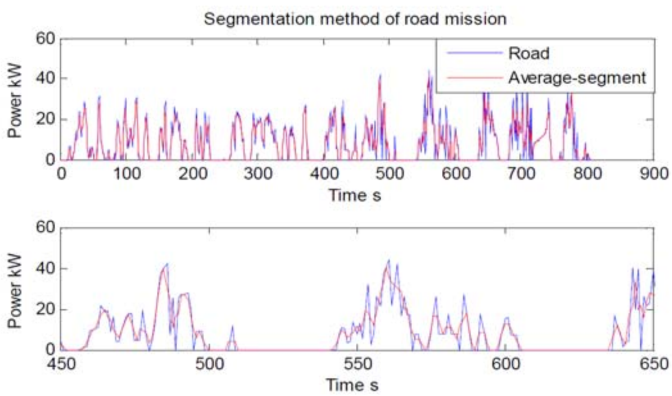


Figure 8. Segmentation method of road mission and zoom on time [450–650s].

The segmentation method allows adding an average power demand during three consecutive instant (window size of three instant). This sliding windows allows to avoid a lot of excessive switching at consecutive instant (chattering) and also can be seen as a predictive window that force the future to be the same as the present. If the two previous power demands indicate variation of profile let the controller switching and changing the rule to use.

In addition, a power profile can be found several characteristics and various power classes. From the previous analysis, and in order to establish a method for real-time optimization, a subsequent switching method of manipulating the rules according to the required power through the segmentation method is proposed. This approach is not really a filtering and not really pattern recognition but is the based-knowledge to conduce intelligent switching at the controller level.

The segmentation method is to decompose the space of power and each segment is characterized by its average power to indicate the membership of each segment to a specified mission.

For example: The beginning of any mission always belongs to the urban mission «Rule 1», since at startup power demand is generally low [0, X_1]. Mission Road contains areas that are characterized by urban mission, and other areas that are characterized by the mission highway [X_2, P_{max}], because the mission Road is located between the two [X_1, X_2] (Figure 9).

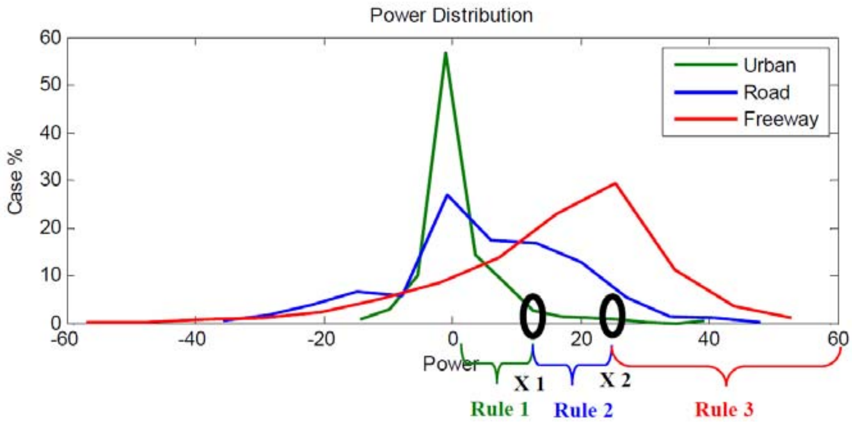


Figure 9. Profiles analyses and decision values X_1, X_2 evaluation.

After the optimal rules were identified (Rule 1, Rule 2, Rule 3), the optimized fuzzy logic controller will be used in the energy management, switching optimally from this three possibilities. In order to establish a method for real-time optimization, a method of switching consisting in an accurate segmentation method is proposed. The segmentation method splits the space power into segments and to characterize each segment by its average power to indicate the membership of each segment to a specified mission (Urban, Road and Highway). The switching of rules is done from a program that uses the power indicator. Then it treats the average power of segments to give everyone a clue, 'knowing that the values of the segments are the average power of a sliding window'. This will allow the segmentation algorithm to choose the optimal rule to be used among the existing rules (Figure 10).

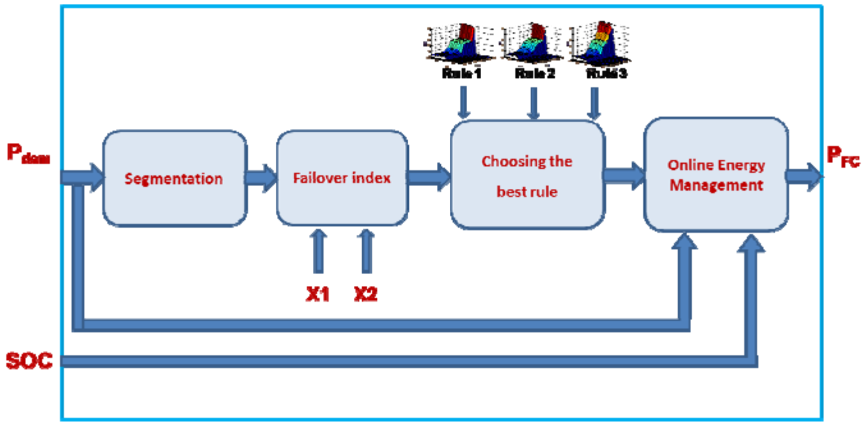


Figure 10. Complete real time Fuzzy Switching Algorithm FSA.

The fuzzy switching algorithm FSA operates as follows:

If power segment is low, «Index» = 1 then use the «Rule 1».

If power segment is medium, «Index» = 2 then use the «Rule 2».

If power segment is strong, «Index » = 3 then use the «Rule 3».

The calibration algorithm which is reflected in the choice of position points ‘index 1, 2 and 3’ to the switching algorithm to switch between different rules is a tricky work. In order to validate the choice of these points, the genetic algorithm can be a good solution for this problem.

3.3. *Second optimization*

After generating optimization rules with genetic algorithm in [28], the application of these three different rules for each profile can also be optimized through the optimal computing of levels X_1 and X_2 using also Genetic Algorithm (GA) [21]. The genetic algorithm is a search heuristic that mimics the process of natural evolution. This heuristic is routinely used to generate useful solutions to optimization and search problems. A classical genetic algorithm (implemented in Matlab®) was used in order to generate a suitable set of parameters by choosing the best hydrogen consumption (fitness/cost function) for the different profiles to converge towards the two optimal X_1, X_2 shown in Table 4.

Table 4. optimized values for decision control.

	X_1	X_2	Consumption kW.s
Profile 1	13.9	15.1	3390
Profile 2	6.1	32.3	11031
Profile 3	14.8	15.2	19710

Comments: optimizing X_1 and X_2 with genetic algorithm can decrease the hand-made choice difficulty. In some profile analysis, it is evident for human being but for some profile it is tricky and the Genetic Algorithm is the way used here to be sure to have an optimal choice on a given profile. eg: X_1 = 13.89, X_2 = 15.1 applied on Profile 1, provide 3390 kW consumption, which is the lowest consumption obtained with the optimized set X_1, X_2 other combination provide higher consumption.

4. Results and discussion

The results obtained by applying the method of segmentation and switching rules on the different profiles are shown in the following Figures 11,12 and 13.

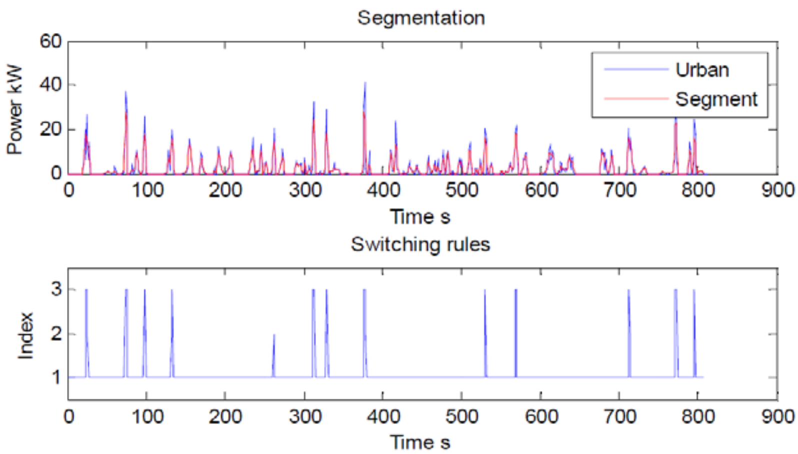


Figure 11. Urban: Application of rule 1: 96%—Application of rule 2: 1%—Application of rule 3: 3%.

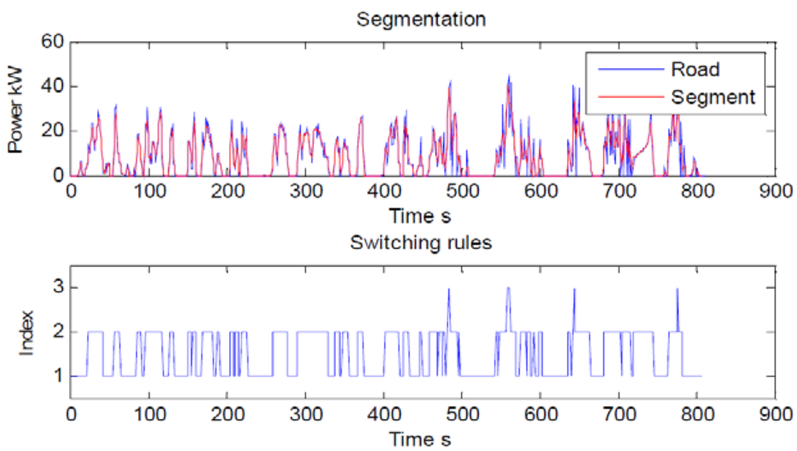


Figure 12. Road: Application of rule 1: 51%—Application of rule 2: 48%—Application of rule 3: 1%.

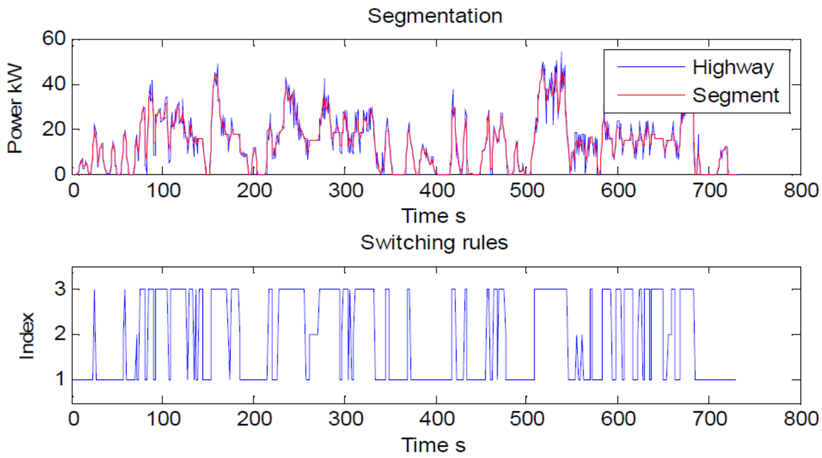


Figure 13. Highway: Application of rule 1: 53%—Application of rule 2: 4%—Application of rule 3: 43%.

The following Table 5 lists the consumption values obtained by applying:

- A single rule for each profile.
- A fuzzy switching Algorithm FSA.
- A dynamic programming DP.
- The consumption without storage.

Table 5. Comparison of global consumption using: one optimized rules or three switched rules.

(The last two lines is the optimal result obtained with Dynamic Programming (DP) approach and Reference consumption without storage kW.s)

	Profile 1—Urban		Profile 2—Road		Profile 3—Highway	
Fuzzy	1 rule	FSA	1 rule	FSA	1 rule	FSA
FC Conso (kW.s)	3390	3390	11020	11031	19660	19710
Soc (kW.s)	−420	−419	−188	−188	−53	−46
Artificial Cost (kW.s)	1132	1130	494	494	131	111
Total Cost (kW.s)	4522	4520	11514	11526	19791	19821
D.P. (kW.s)	5986		12667		20099	
Consumption without storage (kW.s)	5815		15451		23084	

The results presented in Table 5, highlight that applying a rule optimized on a given profile provides the lowest consumption. If a different rule is applied, the consumption increases. But these results demonstrate also that switching accurately between three rules did not really change the consumption. That mean the controller is able to dynamically switch the rules and reach the optimal consumption. The goal to decide online what controller should be used is now open.

To be noticed: the fuzzy controller results are also compared to DP optimal solution. The D.P consumption is higher because it takes into account one more constraint made on the final State Of Charge (SOC) which must be the same as the initial (charge sustaining from start to end facilitating cycling missions).

In order to have a basis of comparison between the different management methods proposed, it is mandatory to have the same constraints and to bring the final state of charge to its initial state. One way to improve the calculation of the total cost is to introduce the constraint on the state of charge and to use a function of overconsumption. The latter introduces an artificial additional hydrogen consumption when the state of charge is below the initial one, this translates into a variation of negative SOC ($\Delta soc < 0$), for the case $\Delta_{SOC} > 0$, the discharge does not cause extra cost of H_2 consumption by discharging the elements in the garage for example either in resistors or in the distribution network.

The constraint of maintaining the state of charge is not taken into account in this first form of the criterion. One way to improve the results obtained, in terms of accuracy of total cost calculation is to introduce the constraint on the state of charge and use a penalty function. The latter introduces an additional 'artificial' hydrogen consumption when the state of charge is below the initial one, which results in a negative SOC variation 'when'.

The FSA end the profile with a difference (shown as ΔSOC), so an extra consumption is added to artificially recharge the storage element. To do this, the power is chosen artificially to be given by the Fuel Cell Stack at its maximum power (that provides a not so bad FCS efficiency). This condition adds an extra cost which is less than the cost used during the profile during D.P. computing. That explains the total consumption with fuzzy is a little bit less consuming than D.P. results.

To be also noticed in Figure 14, the difference is impacting the energy stored and delivered by the storage element. The switch at time (80 seconds) changes the rest of the profile due to switching that increases the consumption. But if the switching is not frequent, with a short duration, or if the switch did not affect high power (case in highway power demand) the consumption is sub-optimal but very closed to the optimal.

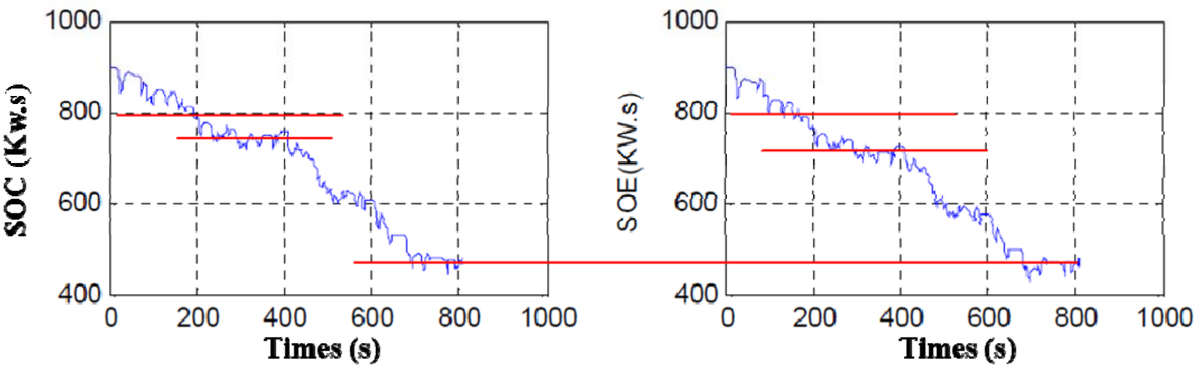


Figure 14. SOC management with the two Fuzzy approaches (1 Rule vs FSA) using urban profile.

5. Conclusions

This work has been devoted to online management based on fuzzy rules. This method has been improved by the segmentation and switching method FSA. The switching between the rules is associated with an optimal distribution of the requested power online learned and optimized offline.

This work results from a succession of local optimizations, thus a decrease of the global consumption has been obtained. The results obtained show that the energy management based on fuzzy rules can be likened to a management of the state of charge of the storage element under stress of minimizing the energy delivered by the non-reversible source (FC). This energy management strategy makes it possible to take into account the evolution of the state of charge of the storage element at each instant and in addition forces the fuel cell to operate at its best points of efficiency.

A 'predictive' management strategy has been proposed; this method is inspired by the fuzzy rules method and has given satisfactory results in terms of consumption. A fuzzy decision layer makes it possible to switch the rules according to a prediction of the mission profile and to apply the right set of rules, especially on an unknown path or on path zones identified as closest to the known profiles.

This work shows that the fuzzy rules-based power management strategy has improved consumption compared to applying a single optimized rule to another profile.

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Conflict of interest

The authors declare that there is no conflict of interest in publishing this paper.

References

1. Chu S, Majumdar A (2012) Opportunities and challenges for a sustainable energy future. *Nature* 488: 294–303.
2. Ferrero E, Alessandrini S, Balanzino A (2016) Impact of the electric vehicles on the air pollution from a highway. *Appl Energy* 169: 450–459.
3. Chan CC, Wong YS, Bouscayrol A, et al. (2009) Powering sustainable mobility: roadmaps of electric, hybrid, and fuel cell vehicles [point of view]. *Proc IEEE* 97: 603–607.
4. Ehsani M, Gao Y, Emadi A (2009) Modern electric, hybrid electric, and fuel cell vehicles: fundamentals, theory, and design. 2nd ed. CRC Press.
5. Fu Z, Li Z, Si P, et al. (2019) A hierarchical energy management strategy for fuel cell/battery/supercapacitor hybrid electric vehicles. *Int J Hydrogen Energy* 44: 22146–22159.
6. Zhou H, Bhattacharya T, Tran D, et al. (2011) Composite energy storage system involving battery and ultracapacitor with dynamic energy management in microgrid applications. *IEEE Trans Power Electron* 26: 923–930.

7. Khaligh A, Li Z (2010) Battery, ultracapacitor, fuel cell, and hybrid energy storage systems for electric, hybrid electric, fuel cell, and plug-in hybrid electric vehicles: state of the art. *IEEE Trans Veh Technol* 59: 2806–2814.
8. Song Z, Hofmann H, Li J, et al. (2015) A comparison study of different semi-active hybrid energy storage system topologies for electric vehicles. *J Power Sources* 274: 400–411.
9. Cao J, Emadi A (2012) A new battery/ultracapacitor hybrid energy storage system for electric, hybrid, and plug-in hybrid electric vehicles. *IEEE Trans Power Electron* 27: 122–132.
10. Vulturescu B, Trigui R, Lallemand R, et al. (2013) Implementation and test of a hybrid storage system on an electric urban bus. *Trans Res Part C* 30: 55–66.
11. Salmasi FR (2007) Control strategies for hybrid electric vehicles: Evolution, classification, comparison, and future trends. *IEEE Trans Veh Technol* 56: 2393–2404.
12. Zandi M, Payman A, Martin JP, et al. (2011) Energy management of a fuel cell/supercapacitor/battery power source for electric vehicular applications. *IEEE Trans Veh Technol* 60: 433–443.
13. Hankache W, Caux S, Hissel D, et al. (2008) Real time fuzzy energy management of fuel cell and ultracapacitor powertrains. *Fundamentals and Developments of Fuel Cell Conference–FDFC Nancy*, France.
14. Garcia-Arregui M, Turpin C, Astier S (2007) Direct connection between a fuel cell and ultracapacitors. *Proceeding International Conference on Clean Electrical Power* 474–479.
15. Yu H (2019) Fuzzy logic energy management strategy based on genetic algorithm for plug-in hybrid electric vehicles. *In 2019 3rd Conference on Vehicle Control and Intelligence*, 1–5.
16. Neffati A, Guemri M, Caux S, et al. (2013) Energy management strategies for multi-source systems. *Electr Power Syst Res* 102: 42–49.
17. Sabri MFM, Danapalasingam KA, Rahmat MFA (2018) Improved fuel economy of through-the-road hybrid electric vehicle with fuzzy logic-based energy management strategy. *Int J Fuzzy Syst* 20: 2677–2692.
18. Caux S, Hankache W, Hissel D, et al. (2010) On-line fuzzy energy management for hybrid fuel cell systems. *Int J Hydrogen Energy* 35: 2134–2143.
19. Zhou D, Ravey A, Al-Durra A, et al. (2017) A comparative study of extremum seeking methods applied to online energy management strategy of fuel cell hybrid electric vehicles. *Energy Convers Manage* 151: 778–790.
20. Shen J, Khaligh A (2015) A supervisory energy management control strategy in a battery/ultracapacitor hybrid energy storage system. *IEEE Trans Transp Electrif* 1: 223–231.
21. Guemri M, Neffati A, Caux S, et al. (2014) Management of distributed power in hybrid vehicles based on DP or Fuzzy Logic. *Optim Eng* 15: 993–1012.
22. Zhou D, Al-Durra A, Gao F, et al. (2017) Online energy management strategy of fuel cell hybrid electric vehicles based on data fusion approach. *J Power Sources* 366: 278–291.
23. Neffati A, Caux S, Fadel M (2012). Fuzzy switching of fuzzy rules for energy management in HEV. *IFAC Proc* 45: 663–668.
24. Neffati A, Caux S, Fadel M (2013) Double fuzzy logic decision in HEV energy management. *World Electric Vehicle Symposium and Exhibition*: 1–5.
25. Xiong R, Cao J, Yu Q (2018) Reinforcement learning-based real-time power management for hybrid energy storage system in the plug-in hybrid electric vehicle. *Appl Energy* 211: 538–548.

26. Zhou D, Al-Durra A, Matraji I, et al. (2018) Online energy management strategy of fuel cell hybrid electric vehicles: a fractional-order extremum seeking method. *IEEE Trans Ind Electron* 65: 6787–6799.
27. Chen Z, Xiong R, Wang C, et al. (2017) An on-line predictive energy management strategy for plug-in hybrid electric vehicles to counter the uncertain prediction of the driving cycle. *Appl Energy* 185: 1663–1672.
28. Caux S, Hankache W, Fadel M, et al. (2010) PEM fuel cell model suitable for energy optimization purposes. *Energy Convers Manage* 51: 320–328.
29. Mensing F, Trigui R, Bideaux E (2011) Vehicle trajectory optimization for application in ECO-driving. *IEEE Vehicle Power and Propulsion Conference*: 1–6.
30. Mensing F, Bideaux E, Trigui R, et al. (2013) Trajectory optimization for eco-driving taking into account traffic constraints. *Trans Res Part D: Transp Environ* 18: 55–61.
31. Chapoulie P (1999) Modélisation systémique pour la conception de véhicules électriques multi-sources: application aux véhicules équipés de générateurs photovoltaïques ou de supercondensateurs. Doctoral dissertation, Toulouse, INPT.
32. Garcia-Arregui M, Turpin C, Astier S (2007) Direct connection between a fuel cell and ultracapacitors. *Proceeding International Conference on Clean Electrical Power* 474–479.
33. Langari R, Won JS (2005) Intelligent energy management agent for a parallel hybrid vehicle—part I: System architecture and design of the driving situation identification process. *IEEE Trans Veh Technol* 54: 925–934.