# Modeling and Fuzzy logic Control of Electrical Vehicle with an Adaptive Operation Mode

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*Abstract*—**This paper presents the modelling and the traction control of an Electrical Vehicle (EV) speed based on the Energetic Macroscopic Representation (EMR) and the Maximum Control Structure (MCS). The EMR-MCS have been first developed by L2EP (Lille, France). By using a specific Fuzzy Logic Control (FLC) in MCS, an Adaptive operation Mode (AOM) is developed in this paper to reduce the energy consumption of the EV. This AOM can be Economic, Dynamic or Eco-Dynamic (EOM, DOM or EDOM) according to the battery state of charge. The EMR methodology leads to a global model of the studied vehicle and facilitating its control. The results obtained by the new proposed method of MCS-FLC under Matlab/Simulink software tool are given.**

***Keywords-Adaptive Operation Mode; Energetic Macroscopic Representation; Maximum Control Structure; Fuzzy Logic Contro; Electric Vehicl; Battery.***

## I. INTRODUCTION

This Electrical vehicles (EVs) appear to be an interesting alternative to conventional internal combustion engines (ICE) vehicles. However, EVs still have serious limitations. EVs do not have issues with increasing oil prices or pollution problems (at least around the vehicle) but EVs electrical batteries technology is presently very expensive and limited in autonomy. A smooth hybridization of conventional vehicles could be the step to achieve less fuel consumption and fewer emissions [1]. Recent researches have shown the interest of using fuzzy logic control in different engineering applications such as the control strategy of EV. Since fuzzy control is simple, easy to realize, no need for modelling and has strong robustness, it is suitable for nonlinear control where parameters and/or model are unknown or variable.

In this paper, a specific Adaptive Fuzzy Logic Control (AFLC) based on Maximum Control Structure (MCS) is designed to control EV speed. The speed control parameters and the EV operation mode are also adapted on-line according to the battery state of charge (SOC) to reduce the energy used by EV and meet the requested autonomy. EV operation modes can be economic, Dynamic or Eco-Dynamic (EOM, DOM or EDOM) where the EOM (less dynamic) is imposed in order to safe consumption and to obtain an economic (and not dynamic) vehicle, the EDOM corresponds to a medium vehicle speed and the DOM corresponds to a dynamic vehicle (sport vehicle) in which the speed response must be fast. The developed AFLC has the following input parameters: SOC, driver choice (U) and the error and change of error between vehicle speed and its reference. The output is the total reference force ($F_{reftot}$) which corresponds to a torque reference to be applied to the maximum control traction. This paper presents first the EV EMR. The proposed structure and combination between MCS and AFLC are deduced in section III and IV successively. Section V presents the simulation results obtained with the proposed control strategy. Finally, the conclusion is drawn in section VI.

## II. MODELLING OF THE ELECTRIC VEHICLE

### A. *The studied architecture*

First, confirm that you have the correct template for your paper size. This template has been tailored for output on the A4 paper size. If you are using US letter-sized paper, please close this file and download the file for There are several types of motorization for electric traction. At present time, the Direct Current (DC) machines, and more particularly the separated excitation and the permanent magnet synchronous machines are the most widely used. Because of its ease of operation and low cost, the studied EV is driven by a DC machine with a differential mechanical device. It is supplied by a battery through a DC/DC converter. The Fig. 4 illustrates the EV structure which couples the dynamics of vehicle to the electrical motorization. The modelling step is widely inspire from the L2EP researches work [19].

### B. *EMR of the electric vehicle*

The EMR is a graphical modelling tool, which has been introduced in 2000 by L2EP Lab. (Lille, France) to describe complex electromechanical and electrochemical systems [13, 21]. EMR is based on the action-reaction principle to organize the interconnection of sub-systems according to the physical causality (i.e. integral relation) [21, 22]. This description highlights energetic properties of the system (energy accumulation, conversion and distribution) [4, 7]. Moreover, an

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inversion-based control can be systematically deduced from EMR using specific inversion rules [11, 12].

*1) Battery:* The battery can be modelled as an equivalent circuit such as a voltage source in serial with an internal resistor. The following equation allows to find an acceptable approximation of the SOC% [23].

$$SOC\ (t) = SOC\ (0) - \frac{100}{C_N}\int I_{bat}\ (t)\ dt \tag{1}$$

Where SOC(0) is initial battery SOC, $\mathbf{C_N}$ is the Nominal battery Capacitance and $I_{bat}$ is the battery current.

*2) Chopper:* It is an electric converter (without energy accumulation and supposed without losses). It is represented as a conversion element (square pictogram), the relationships of the chopper are:

$$\begin{cases} U_{chop} = \alpha_{chop} V_{bat} \\ I_{chop} = \dfrac{1}{\alpha_{chop}} I_{bat} \end{cases} \tag{2}$$

Where $\alpha_{chop}$ is chopper amplification gain and $\alpha$ is the duty ratio. $I_{chop}$ and $U_{chop}$ are the chopper current and voltage and $V_{bat}$ is the battery voltage.

*3) Direct Current Machine:* DCM is modelled with classical relationships. The armature current ($I_{arm}$) is the state variable of armature windings and is obtained from the supply voltage and the electromotive force ($e_{em}$):

$$L_{arm} \frac{dI_{arm}}{dt} = U_{chop} - e_{em} - R_{arm} I_{arm} \tag{3}$$

Where $R_{arm}$ and $L_{arm}$ are the resistance and inductance of the armature windings. This device is thus an accumulation element due to the presence of the inductance (integration). An electromechanical conversion links both currents to the produce motor torque $T_{mot}$. As shown in (4) the $e_{em}$ is also deduced from the nominal rotation speed $\Omega_{nom}$[5-7]:

$$\begin{cases} T_{mot} = k\Phi I_{aarm} \\ e_{em} = k\Phi\Omega_{nom} \\ k\Phi = \dfrac{U_{arm}^{nom} - R_{arm} I_{arm}^{nom}}{\Omega_{nom}} \end{cases} \tag{4}$$

Where k is the machine constant parameter related to the torque and to the e.m.f. $\Phi$ is the magnetic flux. The following equation allows to find the numerical value for the mechanical conversion (shaft + gearbox).

$$\begin{cases} T_{gear} = k_{gear} T_{mot} \\ \Omega_{mot} = k_{gear} \Omega_{gear} \end{cases} \tag{5}$$

Where $T_{gear}$ and $\Omega_{gear}$ are the torque and speed rotation after reduction, $k_{gear}$ is the gearbox reduction coefficient and $\Omega_{mot}$ is motor rotation speed.

*4) Mechanical:* The torque reduction is shared fairly on the left and the right wheel, just as the speed of rotation as shown in (6).

$$\begin{cases} T_{diff_{left}} = \dfrac{1}{2} T_{gear} \\ T_{diff_{right}} = \dfrac{1}{2} T_{gear} \\ \Omega_{diff} = \dfrac{1}{2}\left(\Omega_{left} + \Omega_{right}\right) \end{cases} \tag{6}$$

Where $\Omega_{diff}$, $T_{difflef}$ and $T_{diffright}$ are the differential speed rotation, left and right torque after differential.

*5) Left and right wheel:* The wheels have to produce a linear motion from a rotational motion. The traction forces can be calculated from the torque of differential, and the wheel rotation from the vehicle velocity [6, 7, 14].

$$\begin{cases} F_{left} = \dfrac{1}{R_{weel}} T_{diff_{left}} \\ w_{left} = \dfrac{1}{R_{weel}} v_{veh_{left}} \\ F_{right} = \dfrac{1}{R_{weel}} T_{diff_{right}} \\ w_{right} = \dfrac{1}{R_{weel}} v_{veh_{right}} \end{cases} \tag{7}$$

where $R_{wheel}$ is the radius of wheel, $F_{lef}$, $w_{left}$, $F_{right}$ and $w_{right}$ are the forces and speed rotations for the left and right wheels, respectively.

*6) Mechanical coupling:* Both traction forces $F_{lef}$ and $F_{right}$ are coupled to produce the total traction force $F_{tot}$ as shown in (8). By differentiating linear velocities of both the left and right wheels, one can take into account the radius of curvature ($R_{courb}$) and the width of the vehicle ($l_{\_veh}$) (distance between the rear wheels) [6].

$$\begin{cases} F_{tot} = k_{left} + F_{right} \\ v_{veh_{left}} = \dfrac{R_{courb} + \frac{l_{veh}}{2}}{R_{courb}} v_{veh} \\ v_{veh_{right}} = \dfrac{R_{courb} - \frac{l_{veh}}{2}}{R_{courb}} v_{veh} \end{cases} \tag{8}$$

*7) Chassis:* The vehicle velocity $V_{veh}$ is obtained with the classical dynamics relationship from the traction force $F_{tot}$ and $F_{res}$ as shown in (9):

$$M \frac{dv_{veh}}{dt} = F_{tot} - F_{res} \tag{9}$$

where M is the mass of vehicle. The chassis is an accumulation element, hence the velocity is chosen as a state variable.

*8) Environment:* The external environment of the vehicle is considered as a mechanical load and is modelled in EMR with a mechanical source element which is used for both source and load. It yields a resistive force $F_{res}$ to the motion from the vehicle velocity.

$$F_{res} = \frac{1}{2}\rho\varsigma_x S_{front} v_{veh}^2 \qquad (10)$$

Where $\rho$, $\varsigma_x$ and $S_{front}$ are the density of air, the vehicle penetration coefficient and the vehicle front surface.

## III. MAXIMUM CONTROL STRUCTURE OF THE STUDIED VEHICLE

The MCS is composed of several inversion blocks and different REM parts. Then, the EMR blocks are inverted regardless of practical issues: the conversion blocks are directly inverted and the accumulation blocks are inverted using controllers in order to respect physical causality [6-9].
In this work, an AFLC strategy will be adopted to invert the accumulation element in MCS and to adapt the vehicle performance.

### *A. Inversion of standard elements*

Mechanical differential and reduction elements are directly inverted to obtain the reference of the duty ratio.

### *B. Inversion of chassis*

The inversion of the accumulation element associated with the chassis (9) leads to a velocity controller [6,10,11]:

$$F_{tot_{Ref}} = Con(V_{veh_{REf}} - V_{veh_{mes}}) \qquad (11)$$

where *Con* $(x_{ref} - x_{mes})$ is the controller of the variable $x$.
In this paper, a specific AFLC is proposed and developed by authors (see section IV) to invert this accumulation element contrary to the controller which is proposed by [10,11,13] where an IP (Integral + Proportional) controller is used.

### *C. Inversion of Armature*

The inversion of the armature winding (3) leads to the armature current controller IP and the e.m.f. $e_{em}$ compensation [9].

$$U_{chop_{Ref}} = Con(I_{arm_{REf}} - I_{arm_{mes}}) + e_{em} \qquad (12)$$

### *D. Inversion of chopper*

The chopper has a time-invariant relationship. Consequently, its mathematical relationship is directly inverted to obtain the reference of the duty ratio $\alpha_{chpRef}$ :

$$\alpha_{chop} = \frac{U_{chop_{Ref}}}{V_{bat_{mes}}} \qquad (13)$$

The classical inversion of accumulation bloc using the PI or IP controller needs the calculation of the controller parameters (integral and proportional gains). This task is not obvious and parameters are constant whatever the vehicle mode is (economic or dynamic). In order to overcome this problem, authors propose to use the FL technique instead of the PI or IP controller which provides an easy and parametric way to control the system and to adjust the vehicle mode.

## IV. DEVELOPMENT OF THE ADAPTIVE CONTROL STRATEGIES BASED ON FUZZY LOGIC

The challenging tasks associated with FLC design has always been, to choose appropriate membership functions, minimum rule base and the most suitable fuzzifer and defuzzifers [15]. Having made these choices, the fuzzy controller has to be tuned to deliver the desired response. Multiple simultaneous adjustments of rules, membership functions (MFs) and gains make the optimum tuning even more difficult. Many techniques have been used to overcome this difficulty (rules and membership functions design) [15,16,21] such as a neural network techniques [17] and Genetic Algorithm [18]. The basic idea in this work is the use an AFLC to invert the accumulation element in MCS and to adapt the Operating Mode Performance (OMP) of EV. Then, the EV will be work in an adaptive operation mode.

### *A. Adaptive Fuzzy Logic Control design*

The developed AFLC includes two fuzzy logic structure (FLS). The first one is FLC which was adopted to invert the accumulation element associated with the chassis, the second one is a simple FLS, which acts on the physical values of output MFs range of FLC (FLC-MFs) to vary them during the control of the system to obtain the desired OMP as it indicated in Fig. 1. The FLS inputs are the battery SOC and the signal $U$ which represents the driver choice (acceleration). The FLS outputs are the desired physical values of FLC output MFs. This FLC is non linear controller [18], which estimates the $F_{totRef}$ corresponding to the torque reference to be applied to the EV motor.

### *B. Fuzzification Interface:*

It will transform the input parameters, *SOC*, the signal $U$, the error $\zeta$ and the change of error $d\zeta/dt$ between $v_{veh\ ref}$ and $v_{veh\ mes}$ of the AFLC from distinct quantity to fuzzy quantity. A five-term set negative big (NB), negative (N), zero (ZE), positive (P), positive big (PB) is applied to define output and inputs linguistic variable of FLC. A seven-term set low , average (avg), high, Economic Choice (EC), Eco-Dynamic Choice (EDC), Dynamic Choice (DC) and Adaptive Choice (AC) is applied to define inputs linguistic variable of FLS (*SOC* and $U$). For the FLS output, (E), (ED) and (D) Choice (EDC), Dynamic Choice (DC) and Adaptive Choice (AC) is applied to define inputs linguistic variable of FLS (*SOC* and $U$). For the FLS output, (E), (ED) and (D) terms are defined. Where E, ED and D are corresponding to a predefined vector of physical values of FLC-MFs which allow to improve and adjustment of the EV performance (fast, medium or slowly EV response).
Choice (EDC), Dynamic Choice (DC) and Adaptive Choice (AC) are applied to define inputs linguistic variable of FLS (*SOC* and $U$). For the FLS output, (E), (ED) and (D) terms are defined. Where E, ED and D are corresponding to a predefined vector of physical values of FLC-MFs which allow to improve and adjustment of the EV performance (fast,

medium or slowly EV response).

### *C. Rule Base System*

The fuzzy rule base is a set of linguistic rules defined with IF-THEN conditions. The rule base which has the *M* number of rules ($j=1, 2,..., M$) is shown in (14)[15-17].

$$R^j = \text{If } x_1 \text{ is } A_1^j \text{ and } x_2 \text{ is } A_2^j \text{ and...and } x_n \text{ is } A_n^j \qquad (14)$$
$$\text{Then } z \text{ is } B^j$$

$x_i$ (i=1, 2,..., n) are the fuzzy system input parameters. The fuzzy output variables are denoted z. The membership functions $\mu_\zeta(xi)$ and $\mu_{d\zeta/dti}{}^j(xi)$ are represented as the input linguistic term $A_i^j$. $B^j$ is the linguistic term for the fuzzy output [17,21]. All rule base system of FLS and FLC shown in TABLE I and TABLE II respectively. The equation (15) shows the first rule assigned for the rule base system of FLC shown in TABLE I.

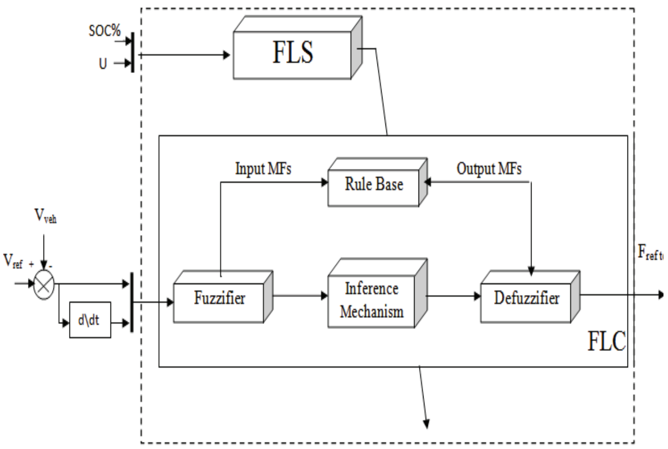


Figure 1. Membership functions for (a) FLC input (b) FLC output

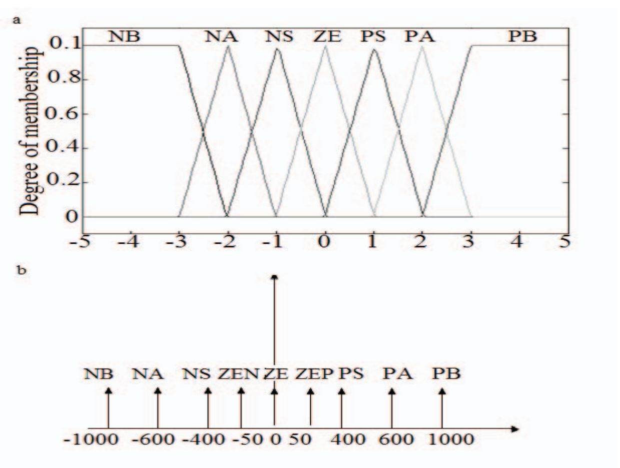


Figure 2. Membership functions for (a) ζ (b) *dζ/dt* FLC inputs

$$R^1 = \text{If } x_1 \text{is } \mu_\zeta \text{ (N) and } x_2 \text{ is } \mu_{\frac{d\zeta}{dt}} \text{ (N)} \qquad (15)$$
$$\text{Then } F_{tot_{Ref}} \text{ is NB}$$

### *D. Inference Machine*

According to the fuzzy quantity of input parameters, inference machine will find corresponding rules in rule base predefined, and use centrobaric method and minimum inference machine to get the output parameter which is the fuzzy quantity of $F_{tot\ ref}$. The simplest membership functions are adopted using straight lines.They are a Triangular and Trapezoidal membership for both input and output fuzzy sets (Fig. 2 and 3). These straight line membership functions have the advantage of simplicity.

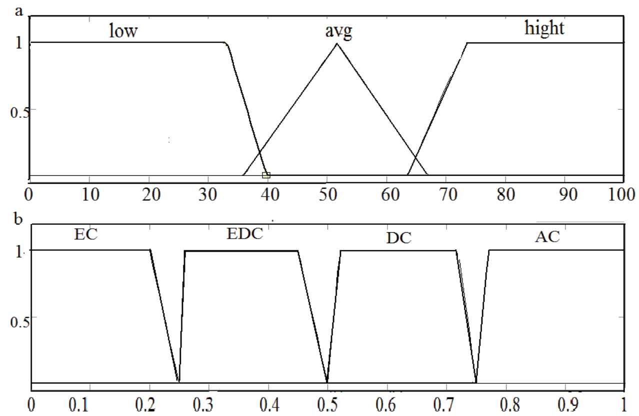


Figure 3. Membership functions for (a) SOC (b) U of FLS inputs

TABLE I. THE RULE BASE SYSTEM FLS

| ζ<br>dζ/dt | N | ZE | p |
|---|---|---|---|
| N | NB | ZE | PB |
| ZE | N | ZE | P |
| P | P | ZE | PB |

TABLE II. THE RULE BASE SYSTEM OF FLC

| SOC%<br>U | Low | Avg | High |
|---|---|---|---|
| EC | E | E | E |
| ECD | ED | ED | ED |
| DC | D | D | D |
| AC | E | ED | D |
| EC | E | E | E |
| EC | E | E | E |

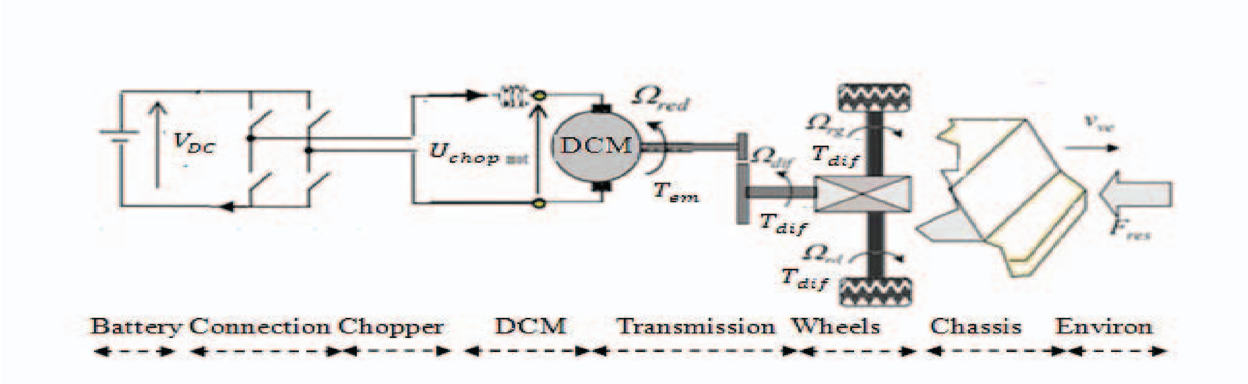


Figure 4. Components of studied architecture

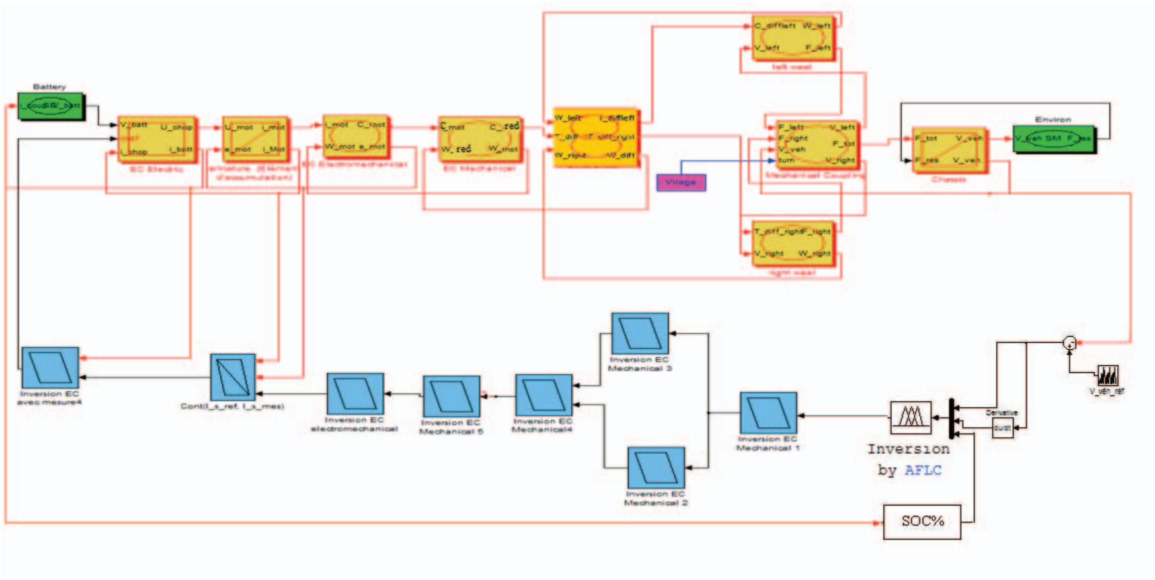


Figure 5. EMR and SMC using FLC for the studied system under Matlab/Simulink [Adapted version of the given in 19]

## V. SIMULATION RESULTS

The EV EMR is based on the one given by the L2EP lectures [10,19]. The MCS using the AFLC is directly converted into a Matlab/Simulink model as illustrated in Fig. 5. Indeed, by choosing appropriated inputs and outputs for subsystems, the actions-reaction organization yields the block description of this software. In the following simulations, the battery, shopper and gears are considered ideal and without losses. The parameters of the DCM are given in Table III. The main geometrical data and inertial properties of the vehicle and wheels are shown in Table IV . Simulation was carried out with standard European driving cycles (suitable for both urban and highway, medium and high speed). From the concept of EMR approach and its SMC, a reference velocity profile that the vehicle must follow is imposed. At 65 s the vehicle makes a turn during 3.46 s.

Fig. 6 and 7 show a comparison between the reference and the vehicle velocity controlled using AFLC based MCS. The EV works with two different operation modes. One corresponds to a dynamic vehicle (sports vehicle) in which the response must be fast (Fig. 6, in this case $U$ = $DC$). The second is an

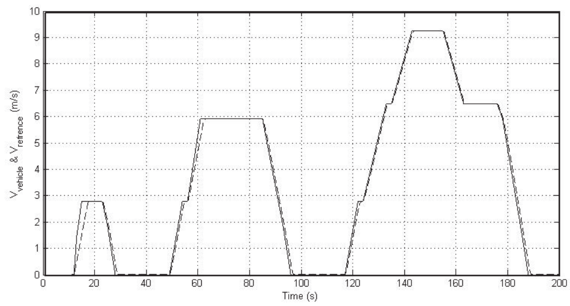


Figure 6. Reference and vehicle velocities MCS with DOM

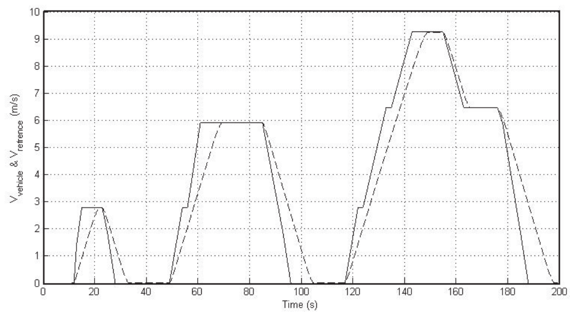


Figure 7. Reference and vehicle velocities MCS with EOM

economic operation s mode (Fig. 7 in this case U = EC), less dynamic is imposed in order to safe consumption and to obtain an economic (and not dynamic) vehicle. It is clearly seen that the vehicle velocity follows its reference without steady error. By using the EMR and SMC EV simulator, a difference between the velocities of wheels illustrated in Fig 8 is shown. Indeed, when the vehicle makes a turn, the wheel left and right is not running at the same speed. Where the left wheels slow down and the right wheels speed up to traverse the turn. Fig 8 shows the velocities of left and right wheels obtained by using FLC based MCS. After obtained Economic and Dynamic response of the EV. This last is simulated with the Adaptive Operation Mode ($U = AC$). Following results are obtained for different values of *SOC(0)* (Fig. 9-11). From these results, it is clear that the AFLC works better and acts on the EV dynamic performance to vary it during the control of system according to SOC:

- if the *SOC%* is between [100 65], the EV response is fast.
- if the *SOC%* is between [65 35], the EV response is medium.
- if the *SOC%* is between [35 0[, the EV response is slowly .

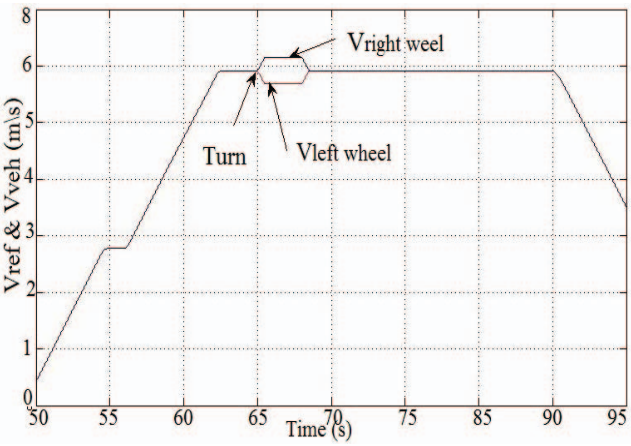


Figure 8. Membership functions for (a) SOC (b) U of FLS inputs

TABLE III. PARAMETERS OF DCM

| Parameter | Value |
|---|---|
| $P_{utilnom}$ | 32 $kW$ |
| $L_{arm}$ | 0.0065$H$ |
| $R_{arm}$ | 0.35$W$ |
| $J_m$(Rotor inertia) | 0.12$kg.m^2$ |

TABLE IV. PARAMETERS OF DCM

| Parameter | Value |
|---|---|
| $M_{veh}$ (vehicle mass) | 1000$kg$ |
| $l_{veh}$ (rear wheel track) | 1.6$m$ |
| $d_{axe}$ (wheelbase ) | 2.4$m$ |
| $R_{wheel}$ (Wheel radius) | 0.52$m$ |
| $J_{weel}$ (Inertia of wheel) | 4.3$Kg.m^2$ |
| $A_f$(frontal surface of vehicle) | 21.6$m^2$ |
| $\rho$ (Density of the air) | 1.2$Kg$ |

Under the same driving cycles and simulation conditions, figures 12 and 13 present the obtained results. Fig. 12 and 13 show a comparison between the EV autonomy of two different

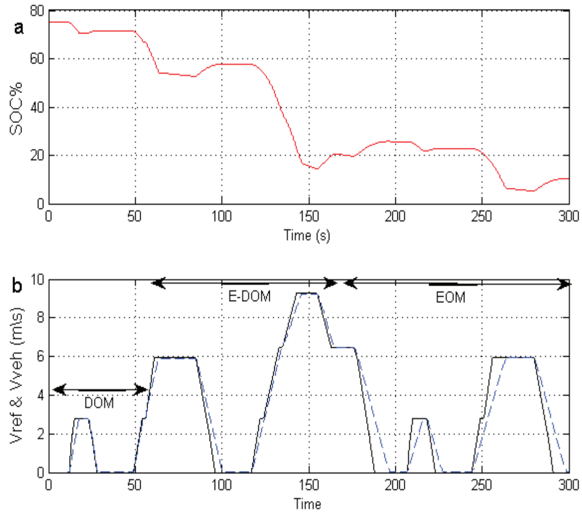


Figure 9. (a)SOC (SOC(0)=75%) (b)Reference and measured EV speeds with the AOM

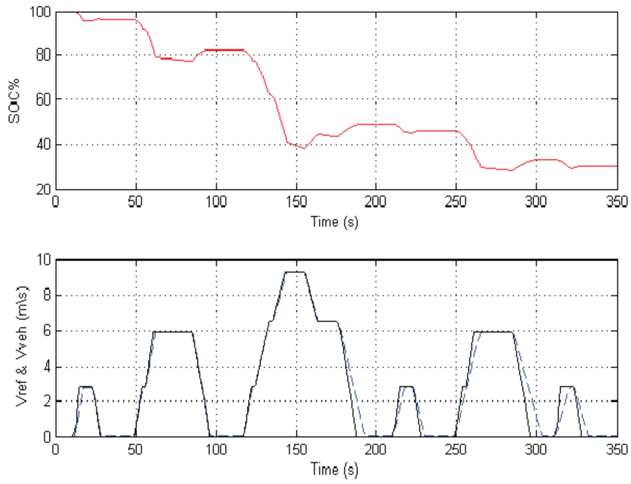


Figure 10. (a)SOC (SOC(0)=100%) (b)Reference and measured EV speeds with the AOM

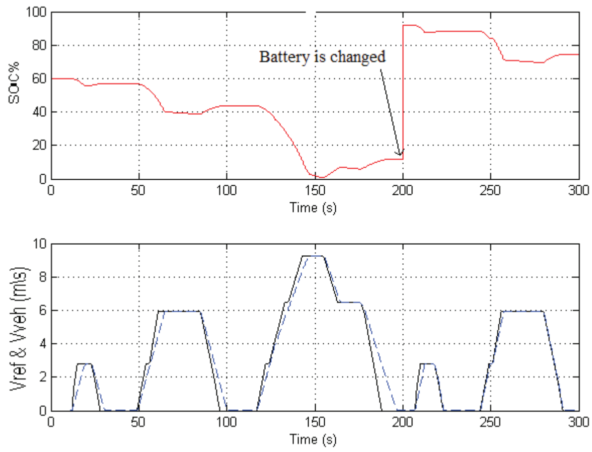


Figure 11. (a)SOC (SOC(0)=60%) (b)Reference and measured EV speeds with the AOM

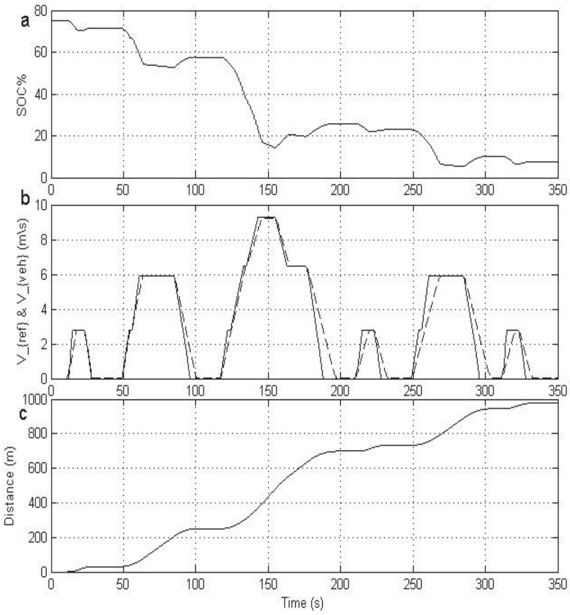


Figure 12. (a)SOC (SOC(0)=78%) (b)Reference and measured EV speeds with the AOM (c)Distance

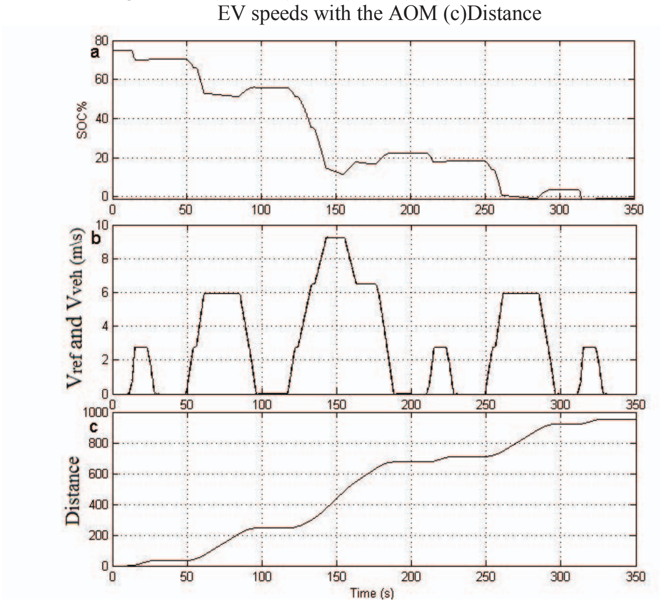


Figure 13. (a)SOC% (SOC%(0)=78%) (b)Reference and measured EV speeds with the

operation modes. One is a DOM where the vehicle response is fast (sport vehicle). The second is the AOM, as it is indicated in Fig. 12.a and Fig. 13.a, the AOM saves 10% of SOC %. However, with the classical DOM, SOC% is null when using the same driving cycle.

## VI. Conclusions

Different operation modes for EV have been proposed in this paper in order to reduce the energy consumption or to meet the required autonomy regarding to the battery SOC. The so called Adaptive Operation Mode (AOM) makes the EV works with an adaptive performance. It can be fast, medium or less dynamic according to the battery SOC. The SMC technique developed by [19] is enhanced using a specific AFLC instead of a simple PI or IP control. The classical PI, IP or PID controller needs the adjustment of controller gains. Moreover, the gains determination is not easy and need to be adjusted if the operating conditions change. This drawback of the MCS can be overcome using the presented FLC to invert these kinds of EMR elements. The AFLC can be viewed as a non linear IP (or PID) controller with adaptive parameters which are automatically tuned according to the operating point and the battery state of charge. This problem is solved by using an intelligent controller based on fuzzy logic system with minimum number of rules. This study shows a good agreement between different types of EV operation mode. The AFLC can be dedicated entirely to MCS of dynamic system and it offers a robust and a realizable controller acting as a nonlinear (and optimized) PID. Than, the combination of fuzzy control strategy with SMC becomes a good alternative.

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