A Novel Adaptive Operation Mode based on Fuzzy Logic Control of Electrical Vehicle

O. Kraa\textsuperscript{a}, M. Becheri\textsuperscript{b}, M.Y. Ayad\textsuperscript{c}, R. Saadi\textsuperscript{a}, M. Bahi\textsuperscript{a}, A. Aboubou\textsuperscript{a} and I. Tegani\textsuperscript{a}

\textsuperscript{a} Laboratory of Energy Systems Modeling, o.kraa@mselab.org, Mohamed Kheider University, Biskra, Algeria
\textsuperscript{b} FCLab FR CNRS 3539 FEMTO-ST UMR CNRS 6174, mohamed.becherif@utbm.fr, UTBM Belfort, France
\textsuperscript{c} Industrial Hybrid Vehicle Applications, ayadmy@gmail.com, France

Abstract

This research study presents an Adaptive Operation Mode (AOM) of an Electric Vehicle (EV) in order to reduce its energy consumption. This AOM can be Economic, Dynamic or Eco-Dynamic (EOM, DOM or EDOM) according to the battery State Of Charge (SOC). The control principle is based on specific Adaptive Fuzzy Logic (AFL) combined with the Maximum Control Structure (MCS) of EMR simulator of the studied vehicle. The AFL-MCS contributes to the robustness of motor drives of the vehicle and is used to meet the required autonomy regarding to the SOC. Also, to ensure the reaching and sustaining of speed and stability of the EV control with the on-line adaptive EV performances. Finally, the computer simulation results verify the validity of the proposed controller and developed AOM and demonstrate that the proposed control scheme provides robust dynamic characteristics with saving 10% of SOC.

1. Introduction

The growth in consumption of fossil fuels accompanied by an increasing concentration of greenhouse gases in the atmosphere and the inevitable exhaustion of fossil resources expected by the end of this century are the basis of orientation towards the use of Electric Vehicles (EVs). In order to answer to the new constraints of study of more complex electromechanical systems, such as the EVs and wind turbines, an Energetic Macroscopic Representation (EMR) is proposed. The EMR has been first developed by L2EP laboratory (Lille, France) and has been applied to energetic and multi-physic systems by Femto-ST CNRS Lab (Belfort, France) [1]. It does not have the role to replace the traditional representations, but rather to supplement them by a more overall view. Maximum Control Structure

\* Corresponding author. Tel: +33 (0) 3 84 58 33 46; fax: +33 (0) 3 84 57 00 32.
\textit{E-mail address:} ayadmy@gmail.com

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(MCS) results directly from an inversion of the considered EMR modelling. On the other hand, the 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 system (AFL) 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 SOC to reduce the energy used by EV and meet the requested autonomy.

2. Modelling of the electric vehicle

2.1. Architecture of studied EV

The general scheme of the studied EV is represented by Fig. 1. (a) which couples the dynamics of the vehicle to the electrical motorization. It’s an EV driven by a DC machine with a differential mechanical device. It is supplied by a battery through a DC/DC converter.

2.2. 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. The EMR formalism has already been used in many real-world applications such as for fuel cell modelling systems [1], control and modelling of hybrid vehicle [2] and control of wind energy generation systems [3]. The EMR consists of three kinds of elements which are named source elements, conversion elements and accumulation elements.

2.2.1. The EV supply source

Different electric sources and energy management methods are developed by authors for the EVs applications [5,6], but in this works a simple lithium battery has been used. The battery can be modelled as an equivalent circuit such as a voltage source in serial with an internal resistor. The following equation allows finding an acceptable approximation of the SOC [7].

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

Where \( SOC(0) \) is the initial battery SOC, \( C_N \) is the nominal battery capacitance and \( I_{bat} \) is the battery current.

2.2.2. Chopper

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

\[
\begin{aligned}
U_{chop} &= \alpha_{chop} V_{bat} \\
I_{chop} &= \frac{1}{\alpha_{chop}} I_{bat}
\end{aligned}
\] (2)

Where \( \alpha_{chop} \) is the chopper amplification gain where \( (\alpha_{chop} = \frac{1}{1-\alpha}) \) and \( \alpha \) is the duty ratio. \( I_{chop}, U_{chop} \) are the chopper current and voltage, and \( V_{bat} \) is the battery voltage.

2.2.3. Traction Motor

The used motorization consists of a Direct Current Motor supplied by a DC/DC voltage inverter. DCM is modelled with classical relationships. The armature current (Iarm) is the state variable of armature windings and is obtained from the supply voltage and the electromotive force \( e_{em} \):

\[
L_{arm} \frac{dI_{arm}}{dt} = U_{chop} - e_{em} - R_{arm} I_{arm}
\] (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 link current to the produced motor torque ($T_{mot}$). As shown in (4) the $e_{em}$ is also deduced from the nominal motor rotation $\Omega_{nom}$ [8,9]:

\[
\begin{cases}
T_{mot} = k\phi I_{arm} \\
e_{em} = k\phi \Omega_{nom} \\
k\phi = \frac{U_{nominal} - R_{arm}I_{nominal}}{\Omega_{nominal}}
\end{cases}
\] (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)[9].

\[
\begin{cases}
T_{gear} = k_{gear} T_{mot} \\
\Omega_{mot} = k_{gear} \Omega_{gear}
\end{cases}
\] (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 the motor rotation speed.

2.3. Modelling of the mechanical coupling

2.3.1. Differential mechanical

The torque reduction is shared fairly on the left and the right wheels, as well the rotation speed as shown in (6)[10].

\[
\begin{cases}
T_{diff left} = \frac{1}{2} T_{gear} \\
T_{diff right} = \frac{1}{2} T_{gear} \\
\Omega_{diff} = \frac{1}{2} (\Omega_{left} + \Omega_{right})
\end{cases}
\] (6)

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

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\end{cases}
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Where $\Omega_{diff}$, $T_{diff left}$ and $T_{diff right}$ are the differential speed rotation, left and right torques after differential.

2.3.3. Left and right wheels

The wheels have to produce a linear motion from a rotational motion. The traction forces can be calculated from the torque of the differential, and the wheel rotation from the vehicle velocity [10-13].
2.3.4. 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):

$$M \frac{dV_{veh}}{dt} = F_{tot} - F_{res}$$

where $M$ is the vehicle mass. The chassis is an accumulation element, hence the velocity is chosen as a state variable. The modelling of the traction system using EMR simulator allows the implementation of some controls such as the MCS and the speed control in order to ensure the system stability.

3. Inversion of EMR simulator

The MCS is composed of several inversion blocks and different EMR 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 [11].

In this work, a novel AFLC strategy is developed by authors to invert the accumulation element in MCS and to adapt the vehicle performance and makes the EV works with an adaptive operation mode which reduces its energy.

3.1. Inversion of standard elements

The electric or mechanical conversion elements are directly inverted to obtain the reference output. The inversion of the mechanical coupling allows the repartition of the estimated force on the two wheels, where the inversion of the wheels is directly obtained and leads to the reference torque of mechanical differential.

3.2. Inversion of accumulation elements

The classical inversion of accumulation bloc using the PID 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 batteries SOC. 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.

3.2.1. Inversion of chassis

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

$$F_{ref} = Con \left( V_{vehref} - V_{vehmes} \right)$$

where $Con \left( x_{ref} - x_{mes} \right)$ is the controller of the variable $x$ toward its reference.

In this paper, a specific AFLC is proposed and developed by authors (see section 4) to invert this accumulation element contrary to the controller which is proposed by [8,11,12] where an IP (Integral + Proportional) controller is used.

3.3. 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.

$$U_{chop-ref} = Con \left( I_{armref} - I_{armmes} \right) + e_{em}$$

4. Development of fuzzy logic-based control

The basic idea in this work is the use of an AFLC to invert the accumulation element in MCS and to adapt the Performance of EV. Then, the EV can work in an adaptive operation mode.
4.1. 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 values of output MFs range of FLC (FLC-MFs) to vary them during the control of the system to obtain the desired OMP as presented in Fig. 1. (a). The FLS inputs are the battery SOC and the signal $U$ which represents the driver choice (acceleration). The FLS outputs are the desired values FLC output MFs. This FLC is nonlinear system [14], which allows to estimate the $F_{ref_{tot}}$ corresponding to the torque reference to be applied to the EV motor.

Table 1. The rule base system OF FLC.

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4.2. Basic concepts of fuzzy logic

4.2.1. Fuzzification Interface

It transforms the input parameters, SOC, the signal $U$, the error $\xi$ and the change of error $\frac{d\xi}{dt}$ between $v_{veh_{ref}}$ and $v_{veh_{mes}}$, of the AFLC from distinct quantities to fuzzy quantities [15]. The nine-term sets are negative big (NB), negative average (NA), negative small (NS), zero negative (ZEN), zero (ZE), zero positive (ZEP), positive small (PS), positive average (PA) and positive big (PB) are used to define FLC output and inputs linguistic variables. The seven-term sets: low, average (avg), high, Economic Choice (EC), Eco-Dynamic Choice (EDC), Dynamic Choice (DC) and Adaptive Choice (AC) are applied to define input 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 values of FLC-MFs which allows improving and the adjustment of the EV performance (fast, medium or slowly EV response).

4.2.2. 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 ($j = 1, 2, \ldots, M$) is shown in (12) [14-17].

$$R^j : IF \ x_1 \ is \ A^j_1 \ and \ x_2 \ is \ A^j_2 \ and \ \ldots \ \ and \ x_n \ is \ A^j_n \ THEN \ z \ is \ B^j$$ (12)

$x_i (i = 1, 2, \ldots, n)$ are the fuzzy system input parameters. The fuzzy output variables are denoted $z$. The membership functions $\mu_{\xi}(x_i)$ and $\mu_{\frac{d\xi}{dt}}(x_i)$ are represented as the input linguistic terms $A^j_i$. $B^j$ is the linguistic terms for the fuzzy output [15-17]. All rule base system of FLC and FLS and FLC memberships function are shown in Table. 1 and Fig. 2 respectively.

5. Simulation results

The EMR and MCS using the AFLC of EV are directly converted into a Matlab/Simulink model as illustrated in Fig. 3. In the following simulations, battery, chopper and gears are considered ideal and without losses. The parameters of the DCM, main geometrical data and inertial properties of the vehicle and wheels are given in [9].
Simulation was carried out with standard European driving cycles. Fig. 4 (a) and (b) 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 (fast dynamic vehicle) in which the response must be fast (Fig. 4. (a), in this case \( U = DC \)). The second is an EOM (Fig. 4. (b), in this case \( U = EC \)), less dynamic is imposed in order to safe consumption and to obtain an economic vehicle. It is clearly seen that the vehicle velocity follows its reference without steady error and overtaking. By using the EMR and AFLC-SMC of EV simulator, a difference between the velocities of wheels illustrated in Fig. 5. (a), where at 65 s the vehicle makes a turn during 3.46 s which is considered as a disturbance for testing the control robustness.
Fig. 4. Reference and vehicle velocities with (a) EOM (b) DOM.

Fig. 5. (a) Left and right vehicle velocities (b) Reference and measured EV speeds with the AOM SOC%=78%.

Fig. 6. (Reference and measured EV speeds with the AOM (a)SOC%=100% (b)SOC%=60%.

Fig. 7. SOCs (SOC(0)=100%), EV speeds and Distances comparisons of EV with AOM and classic DOM.
Indeed, when the vehicle makes a turn, the wheels left and right are not running with the same speed. Where the left wheel slow down and the right wheel speed up for the turn. The results in Fig. 5. (b) and 6 are obtained for different values of SOC(0) where the EV last is simulated with the AOM \((U = AC)\), it is clear that the AFLC works better and acts on the EV dynamic performance to adapt it during the control of system according to the SOC. Under the same driving cycles and simulation conditions, Fig. 7. (a) and 7. (b) show a comparison between the EV autonomy of two different operation modes. One is a DOM (sport vehicle). The second is the AOM, as it is indicated in Fig. 7. The AOM saves 10% of SOC %. However, with the classical DOM, SOC% is null when using the same driving cycle.

6. Conclusions

A new ADOM for EV has been proposed in this paper in order to reduce the energy consumption or to meet the required autonomy regarding to the battery SOC. It 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 [8] 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. This drawback of the MCS can be overcome using the presented FLC to invert these kinds of EMR elements. This simulation results show 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 with adaptive parameters. Than, the combination of fuzzy control strategy with SMC becomes a good alternative.

References