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Battery state of charge management strategies for a real-time controller of a Plug-in Hybrid Electric Vehicle

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Abstract

This paper deals with the development of energy management strategies for a hybrid electric vehicle (HEV), aiming to reduce the global energy consumption. The vehicle is a Plug-in HEV, and its model had been validated on New European Driving Cycle (NEDC). A real-time model-based supervisory controller is implemented, called Equivalent Consumption Minimization Strategy (ECMS), and it is compared with the original heuristic control.

Three ways to manage the energy stored in the battery along the driving mission are presented. Predictive information is then introduced to increase vehicle driveability. Conclusions summarize the benefits of such approach, showing satisfactory results also considering the driver comfort.

Keywords: Plug-in HEV; ECMS; Energy management; Supevisory controller; Predictive driving.

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1. Introduction

In the last few years hybrid vehicles have become a promising solution for lowering on-road vehicle emissions, while increasing their global efficiency. The most widespread hybridization is the electrified one, the hybrid electric vehicle (HEV). If the battery can be externally recharged, the vehicle is referred to as Plug-in HEV(PHEV). On board a HEV, there are different control units (usually one for each machine) and they are all managed by a supervisory unit, that coordinates the powertrain control. Here it is defined the energy management strategy (EMS), which is the algorithm that defines how to split the power request between the electrical and thermal paths. Different authors have discussed the topic of energy management for hybrid vehicles [1-3] and, in general, the controllers can be classified in three distinct categories: heuristic [4-5], sub-optimal [6-8] and optimal [9-11].

In the vehicle considered for this activity there are two EMS available, one rule-based and the other is sub-optimal, referred to as Equivalent Consumption Minimization Strategy (ECMS). Using this latter, it is possible to define a state of charge management strategy (SoCMS), which governs the battery usage along the entire driving mission. In this activity, three SoCMSs have been implemented and compared: Charge-Sustaining (CS) [1-3,6-7]; Charge-Blended (CB) [12-13] and Charge-Depleting/Charge-Sustaining (CD-CS).

Using external information, such as vehicle speed profile and road slope, supposed to be exactly known for a certain fixed horizon, it has been possible to improve the vehicle driveability.

Nomenclature

CB	Charge Blended
CD-CS	Charge-Depleting/Charge Sustaining
CS	Charge Sustaining
ECMS	Equivalent Consumption Minimization Strategy
EM	Electric motor
ISG	Integrated Starter-Generator
MiL	Model in the Loop
SoCMS	State of Charge Management Strategy

2. Vehicle

This activity has been conducted using a PHEV with a complex architecture. The powertrain includes:

- Pure electric path, two electrical machines on the front axle, each with a maximum power of 140 kW;
- Hybrid path, an internal combustion engine (5.2 liters, maximum power 449 kW) directly coupled to an electrical machine (serving as starter generator), plus a six gears automatic transmission.

As additional data, the vehicle mass is 1950 kg and the battery capacity is 30 Ah.

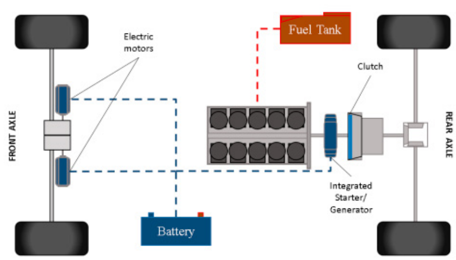

Fig. 1. Powertrain layout

All the vehicle parts, components and controllers, have been modelled in MATLAB/Simulink & SimScape.
In the model-in-the-loop environment there is a driver model that generates pedals positions and the calculation chain reaches the wheels, where the acceleration is calculated. Only vehicle longitudinal dynamics is considered, and the forces acting on the vehicle are modelled as follows:

$$F_i(t) = m\ddot{x}(t) \quad (1)$$

$$F_a(t) = \frac{1}{2}\rho_{air}A_f c_x \dot{x}^2(t) \quad (2)$$

$$F_r(t) = c_r(t)mgcos(\alpha(t)) \quad (3)$$

$$F_g(t) = mgsin(\alpha(t)) \quad (4)$$

The vehicle model has been validated using experimental results recorded during NEDC test, where it has been used a rule-based energy management strategy.

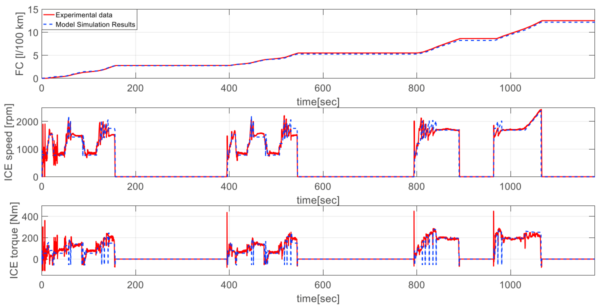

Fig. 2. Vehicle model validation

A 2.6% error in the overall fuel consumption is committed, therefore the model reliability is proven.

3. Driving cycle

The reference route for this activity has been a recorded real driving emission test cycle that, as suggested by regulation, presents three different driving conditions: urban, rural and highway.

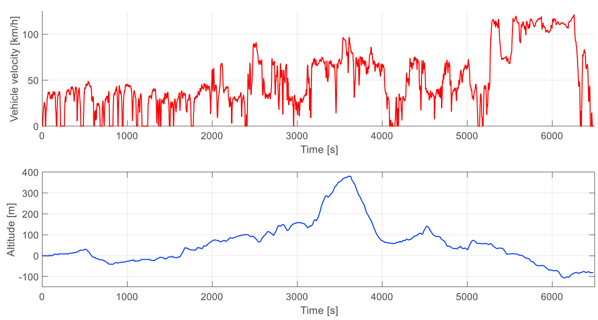

Fig. 3. Speed and altitude traces over time

This cycle is more representative of real driving conditions if compared with shorter and less dynamic cycles, like NEDC.

4. Supervisory controllers

4.1 Rule-Based EMS

The controller model has the possibility of switching between two different supervisory EMS.
The first one can be categorized as rule-based, or heuristic, in the following indicated as “Rule-Based” or “RB”, and it is also implemented in the real vehicle.

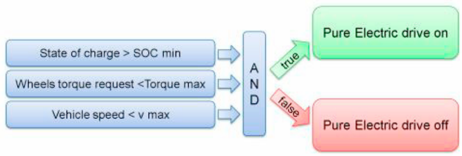

Fig. 4. Heuristic driving mode selection

Three state variables are used for the driving mode definition and precisely the SOC, torque request at the wheels and vehicle velocity.
If it is in pure electric mode, the vehicle is propelled only using the electric path. If at least one of the logical conditions shown in Fig. 4 is false, the vehicle is in hybrid mode. When this happens, the integrated starter generator is used to recharge the battery, while the electric machines on the front axle are used to support the ICE.

4.2 Equivalent Consumption Minimization Strategy

The second controller is called ECMS and is widely known among who deals with hybrid electric vehicle control. It has the aim of finding the best torque split factor between the electrical and thermal path, defined as:

$$u(t) = \frac{T_{ELE}(t)}{T_{TOT}(t)} \tag{5}$$

in which u is the torque split factor, T_{ele} is the torque request to the electrical machines and T_{tot} is the total torque request at the wheels.
The idea, since its first concept [8], is to convert the electrical power consumption into an equivalent fuel consumption, sum it with the actual fuel consumption of the engine and then minimize such sum. The equivalent fuel rate formulation is reported in (6).

$$\dot{m}_{eq}(t) = \dot{m}_f(t) + \dot{m}_{bat}(t) = \dot{m}_f(t) + \frac{s}{Q_{lhv}} * P_{bat}(t) \tag{6}$$

Where terms mean: $\dot{m}_f$ is the engine instantaneous fuel consumption; $\dot{m}_{bat}$ is the fuel consumption equivalent to the used electrical power; P_{bat} is the electrical power demand; Q_{lhv} is the fuel lower heating value; s is the equivalence factor. The control problem to which this EMS is related, aims to minimize the Hamiltonian of the problem, that is the equivalent fuel consumption. Let the state of charge be defined as:

$$\dot{\xi}(t) = f(\xi, u, t) = -\frac{I_{bat}(\xi, u, t)}{Q_{bat}} \tag{7}$$

where ξ is the battery state of charge, u is the control action, I_{bat} is the battery current and Q_{bat} is the battery charge capacity. Once these parameters are known, it is possible to define H, which is the Hamiltonian [14]:

$$H(\xi, u, s, t) = \dot{m}_{eq}(\xi, u, s, t) = s(t) * \frac{P_{bat}(t)}{Q_{LHV}} * f(\xi, u, t) + \dot{m}_f(u, t) \tag{8}$$

The following relation is used to find the optimal control action $u*$, which is also the optimal split factor:

$$u^*(t) = \arg\min_u H(\xi, u, \lambda, t) \tag{9}$$

4.2.1 Equivalence Factor

Three formulations for s parameter have been evaluated during this activity, each one defines a different SoCMS for the cycle. The state of charge management strategy is the battery usage plan the controller chooses for the driving mission.

- *Charge-Sustaining*

In this case, the formulation of s is:

$$s(t) = \left\{1 - k_p \left[\frac{\xi(t) - \left(\frac{\xi_{max} + \xi_{min}}{2}\right)}{\left(\frac{\xi_{max} - \xi_{min}}{2}\right)}\right]^n\right\} * \left[k_a\left(\xi_{ref} - \xi(t)\right) + \left(\frac{s_{k-1} + s_{k-2}}{2}\right)\right] \tag{10}$$

Where:

- $\xi_{(t)}$, ξ_{max}, ξ_{min}, ξ_{ref} are respectively the actual, upper, lower, and reference value of the state of charge;
- s_{k-1}, s_{k-2} are the values of the equivalence factor at the previous two adaptation steps;
- k_p, k_a, n are parameters used to tune the strategy.

This strategy follows a target SOC value that is constant and equal to the initial state of charge, as clarified by Fig. 5.

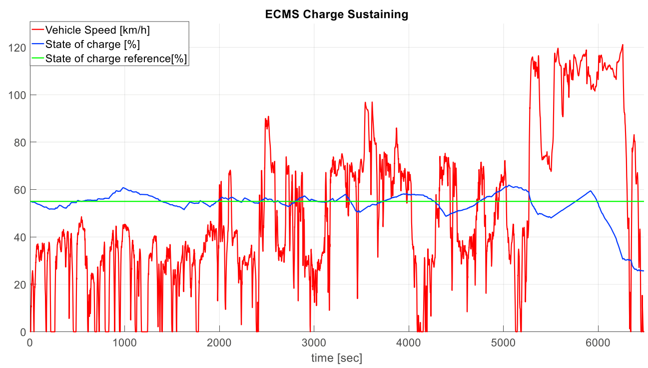

Fig. 5. ECMS Charge Sustaining

- *Charge-Blended*

CB is a battery charge management strategy that works similarly to the charge-sustaining mode, but follows a target that linearly decreases with the driven distance, starting from the initial value of the SOC.

This solution is preferable for PHEVs, since it allows to reach the end of the driving mission with a low SOC level. In following figure, the SOC trend and the reference value for the same variable are shown.

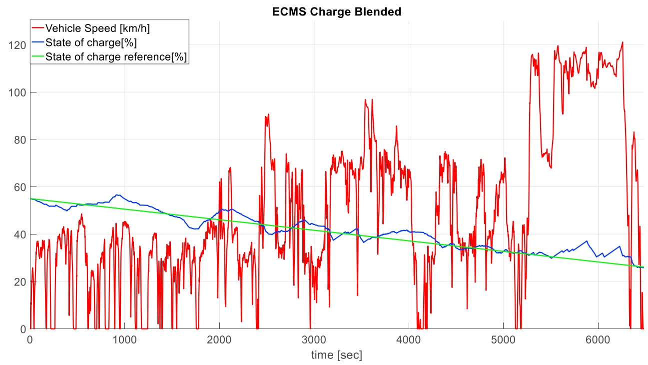

Fig. 6. ECMS Charge Blended

- *Charge-Depleting/ Charge-Sustaining*

In general, a CD-CS policy is intended as an electrical energy usage plan that firstly discharges the battery until a certain SOC level and then sustains the charge around that value. The idea behind this approach is that, if the vehicle can be externally recharged at the end of the driving mission, it is worthless to add other constraints on the state of charge value, to keep it around a reference value. Accordingly, the expression of s (11) is formulated such that the only requirements is to keep the SOC within the physical limitations.

$$s(t) = \left\{ 1 - k_p \left[\frac{\xi(t) - \left(\frac{\xi_{max} + \xi_{min}}{2} \right)}{\left(\frac{\xi_{max} - \xi_{min}}{2} \right)} \right]^3 \right\} * s_0 \tag{11}$$

The formulation (11) is basically the same as (10) but without the charge-sustaining capability. The parameter s_0 is a gain used to tune the strategy and represents the initial cost of using electrical energy.

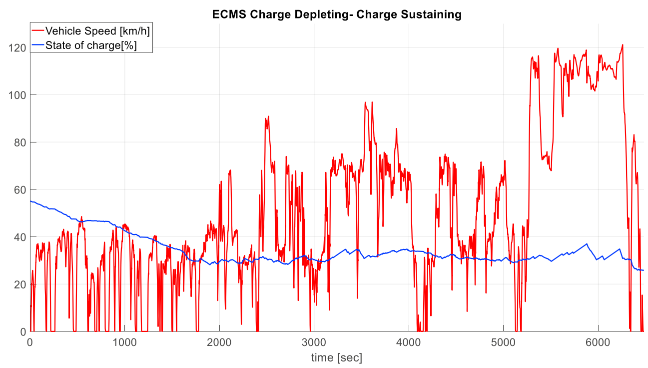

Fig. 7. ECMS Charge Depleting- Charge Sustaining

4.3 Controllers comparisons

The baseline for evaluating the benefits of a real-time physics-based controller is the performance in terms of fuel consumption of the RB controller, that shows a charge-depleting/charge-sustaining behaviour, as clarified in Fig. 8.

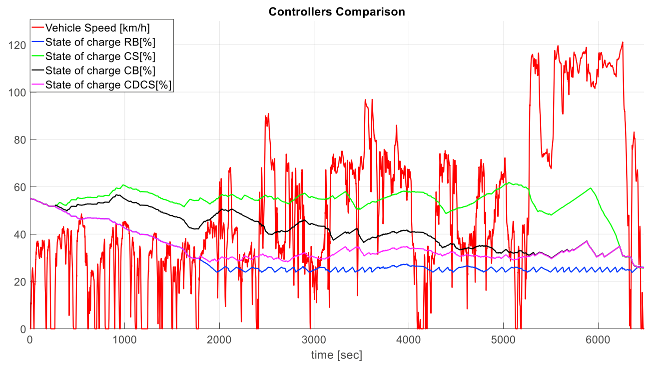

Fig. 8. Controllers comparison

All the controllers have been forced to reach the end of the driving mission with the same battery state of charge, hence the electrical energy consumption is identical for all of them, since they have the same amount of energy left in the battery. Consequently, it is possible to compare their performance only evaluating the actual fuel consumption.
Fig. 8 shows that the minimum value allowed for the state of charge is 24%, which is the limit imposed by the manufacturer to ensure the battery integrity with time. This limitation is also included in all the considered control algorithms, to avoid permanent and significant aging effects on the battery behaviour. In fact, this phenomenon could influence the overall vehicle performance, since it could significantly reduce the battery life (in terms of capacity and number of cycles allowed).
Moreover, from Fig.8 it can be identified the behaviour of each SoCMS: CS keeps the SOC around a reference constant value of 55%. The CB policy follows a target that is 55% at the beginning and then linearly decreases with the distance. CD-CS strategy firstly discharges the battery and then sustains the charge around a low value.

Table 1. Fuel consumption using different SOC strategies

Strategy	Fuel Consumption [l/100 km]	Difference [%]
Heuristic	9.27	0.00
ECMS Charge Sustaining	8.77	-5.39
ECMS Charge Blended	8.66	-6.58
ECMS Charge Depleting/Charge Sustaining	8.53	-7.98

As the numerical results underline, the CD-CS approach is more suitable in the case of a PHEV, while CS approach is more suitable if no external recharge is available (HEVs) and CB approach could be interesting in case of a low speed zone placed in the middle of the driving mission.

5. Driveability

This section deals with the possibility of using external information to increase the vehicle driveability. It is supposed to exactly know the vehicle speed trajectory and road slope profile for a certain distance ahead of the actual position, 50, 250 and 500 meters. The approach is basically the same as the ECMS with CD-CS behaviour, but here the minimization of the equivalent fuel consumption is done for a horizon ahead of the vehicle. Mathematically, the cost function to be minimized is:

$$H\,(\xi, u, \lambda, k) = \sum_{k=1}^{h} \dot{m}_{eq}\,(\xi, u, s, k) = \sum_{k=1}^{h} s_k * \frac{P_{bat_k}}{Q_{LHV}} * f(\xi, u, k) + \dot{m}_f(u, k) \qquad (12)$$

Where h is the horizon length and the other terms are as in (8). A solution like this helps reducing the number of ICE off/on transitions, even if it leads to worse fuel economy, because in this case the optimal control action is chosen only once for the entire horizon. The baselines for this comparison are the original rule-based controller, for the number of ICE transitions, and ECMS with CD-CS state of charge management strategy, for the fuel consumption.

Tab.3 shows that both with 250 and 500m it is possible to reduce the ICE off/on transitions with respect to the original controller, while maintaining a 1.5 % of fuel saving. With a 50m horizon, instead, it is possible to save around 2.0% of the fuel while adding just six more ICE transitions over a driving mission that lasts 6483 seconds.

Table 2. Driveability analysis results

Strategy	Fuel Consumption	ICE Off-On
	[l/100 km]	[-]
Heuristic	9.27	39
ECMS CD/CS – Instantaneous	8.53	75
ECMS CD/CS – 50 m prediction	9.08	45
ECMS CD/CS – 250 m prediction	9.13	33
ECMS CD/CS – 500 m prediction	9.13	24

6. Conclusions and future works

This work presents the implementation of two different EMS in a vehicle-controller model in the loop environment. It has been evaluated the potential fuel saving of a more physical approach like ECMS, which is better performing than the original one, regardless of the state of charge management strategy chosen.
It is also shown that a battery usage plan like CD-CS leads to better fuel economy, if the vehicle is a PHEV.
In the last section it is reported a preliminary study on the usage of external information to increase the driveability. It is evaluated the cost, in terms of fuel consumption, of reducing the ICE transitions between Off and On state.
Future work will deal with finding the best trade-off between fuel consumption and vehicle driveability, and the evaluation of the minimum overall fuel consumption obtainable, using real-time dynamic programming algorithms.

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