A Stochastic Method for the Energy Management in Hybrid Electric Vehicles

F.Payri[1], C.Guardiola[1], B.Pla[1], D.Blanco-Rodriguez[1]

[a] *CMT Motores Térmicos, Universitat Politècnica de València, Camino de Vera s/n, E-46022 Valencia, Spain*

Abstract

There are many approaches addressing the problem of optimal energy management in hybrid electric vehicles; however, most of them optimise the control strategy for particular driving cycles. This paper takes into account that the driving cycle is not *a priori* known to obtain a near-optimal solution. The proposed method is based on analysing the power demands in a given receding horizon to estimate future driving conditions and minimise the fuel consumption while cancelling the expected battery energy consumption after a defined time horizon. Simulations show that the proposed method allows charge sustainability providing near-optimal results.

Keywords: Energy management, hybrid vehicles, optimal control, stochastic control.
PACS: 5.70.a, 89.40.Bb

Contents

Email addresses: `fpayri@mot.upv.es` (F.Payri), `carguaga@mot.upv.es` (C.Guardiola), `benplamo@mot.upv.es` (B.Pla), `dablarod@mot.upv.es` (D.Blanco-Rodriguez)

[1] This research has been partially supported by Ministerio de Ciencia e Innovación through Project TRA2010-16205 uDiesel and by the Conselleria de Educació Cultura i Esports de la Generalitat Valenciana through Project GV/2103/044 AECOSPH.

1. Introduction

The performance of hybrid electric vehicles (HEV) is determined to a great extent by the control strategy, and then HEV control has been widely studied during last years as can be checked in Sciarreta and Guzzella (2007) and references within. Most of those works address it through the optimal control theory, searching for the control policy that provides the minimum fuel consumption while satisfying other energetic constraints. Dynamic Programming (DP) (Mosbech, 1980; Sundström et al., 2010), Pontryagin Minimum Principle (PMP) (Serrao et al., 2011; Ambühl et al., 2010; Chasse and Sciarretta, 2011) or Model Predictive Control (MPC) (Borhan et al., 2009; Kermani et al., 2012) techniques have been applied to the Energy Management Problem of HEVs, hereinafter EMP. *Ad hoc* methods such as the Equivalent Consumption Minimization Strategy (ECMS) (Paganelli et al., 2001) have been developed to address the EMP, demonstrating similar performance to the methods purely derived from the optimal control theory. In any case, as far as the application of optimal control techniques requires information on the future driving conditions it is necessary to include in the control strategy some kind of driving cycle prediction if those techniques are intended to be applied online.

Vehicles are highly dynamic systems and their power demands depend on many factors (driver style, road, traffic, weather, passengers agenda,...). There are two main sort of methods to estimate future driving demands: those based on external sensors such as Global Position System (GPS) or Intelligent Transportation System (ITS)(Gong et al., 2011) and those based on past information to predict future driving conditions in a stochastic fashion. Amongst this second kind of methods, some authors propose to estimate future power demands with a Markov chain which provides the probability of a set of discrete power demands depending on its current value. Once the future power demands are estimated, the problem can be solved by MPC (Ripaccioli et al., 2010) or by stochastic DP (Liu and Peng, 2008). This paper introduces a control strategy based on the ECMS formulation with a probabilistic estimation of future driving conditions.

According to the previous ideas, the paper is presented as follows: Section 2 contains the description of the case study. For the sake of simplicity, a series HEV is presented as an example to apply the proposed strategy. Nevertheless, the method can be easily adapted to address other powertrain architectures. Section 3 is devoted to the problem formulation. Then, in Section 4 the proposed strategy for the energy management of HEVs is introduced and formal and applied aspects regarding the prediction of the vehicle operating conditions and driving pattern identification are addressed. Section 5 evaluates the presented method by means of an application example in which its performance is compared with the optimal solution of the problem. Finally, the extension of the proposed method for parallel HEVs is presented in the Appendix. The obtained results show that the proposed strategy is able to provide robust solution to the EMP without information about the driving cycle to be optimised.

2. Case Study

The main objective of the paper is to introduce a new method to estimate future driving conditions that allows applying the ECMS strategy to solve the EMP. In particular, the present paper

Table 1: Description of the main vehicle features

Vehicle mass	2000 kg
Engine power	75 kW
Generator power	60 kW
Motor power	150 kW
Battery power	160 kW
Battery energy capacity	6.38 MJ (1.77 kWh)

addresses the EMP in a series HEV as a demonstrative example to show the potential of the proposed optimization method. It should be noted that the method is general and can be also applied to parallel HEVs as shown in the Appendix. The main characteristics of the selected powertrain are summarised in table 1 while figure 1 shows the powertrain architecture and the sign criteria employed.

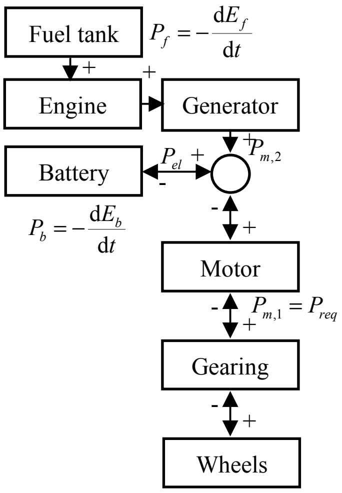

Figure 1: System layout, nomenclature and sign criteria for series hybrid architecture

Due to the lack of a proper experimental facility, the present study has been made by modelling. Paticularlly, the approach proposed by Rizzoni et al. (1999) has been used. With this approach, the power demands in powertrain elements are progressively calculated from the vehicle velocity by means of energy balances done with inverted physical causality. Then, the vehicle is assumed to follow a series of steady states in which the power in the vehicle elements is calculated from the vehicle speed, acceleration and the road grade. In addition, for any powertrain element, its efficiency is mapped with rotational speed and torque, while maximum and minimum torques are defined as functions of the speed.

In the case of series HEVs, since the engine and the generator are rigidly connected, they can be modelled with a single map. Moreover, since the set engine-generator is mechanically decoupled from the vehicle, engine torque and speed can be chosen to maximise its efficiency for any power demand. Hence the set engine-generator is modelled as a simple curve efficiency versus electrical power in the generator, or accordingly fuel consumption versus electrical power in the generator. Regarding batteries, dynamic models are used in order to represent the variations in the battery efficiency with its demanded power and its energy content. The most simple dynamic model of a battery is a zero order equivalent circuit in which:

$$P_{el}(t) = P_b(t, E_b(t)) - I_b^2(t) R(E_b(t)) = I_b(t) V_0(E_b(t)) - I_b^2(t) R(E_b(t)) \tag{1}$$

where P_{el} is the electrical power delivered (or absorbed) by the battery, P_b is the variation in the energy level in the battery (E_b), I_b is the current demand in the battery and its open circuit voltage and equivalent resistance, V_0 and R, are a tabulated function of E_b.

In order to assess the potential of the proposed strategy at real driving conditions, experimental data was collected during a test campaign of three weeks in which every car trip of a non professional driver was recorded. It should be underlined that the routes recorded were those usually driven by the considered driver. Measurements were done in Valencia during October 2011 with a light duty vehicle. No precipitations were observed during the test campaign, the average ambient temperature was 17.4°C. The driver covered a total distance of 557 km in both urban and extra-urban conditions with an average velocity of 33.6 km/h.

During tests, a GPS was used and the Engine Control Unit (ECU) readings were accessed by means of a On-Board Diagnosis (OBD) communication system to measure vehicle velocity and engine parameters, mainly speed and estimated torque. The operating points in the engine map for urban and extra-urban cycles are represented in the upper part of figure 2 with a colorscale of probability ($\mathbf{Pr}(P_e)$) that range from light grey (low probability) to black (high probability). Engine speed and torque values allow to estimate power requirements during the driving cycle. Then, the lower part of figure 2 shows the fit of engine power demands during different driving tests to normal distributions. The selection of normal distribution has been done arbitrarily in order to be easily observable in figures. Nevertheless, the presented method is completely general and can be applied independently of the probability distribution of the driving conditions. In any case, in figure 2 urban cycles are clearly distinguished from extra-urban cycles due to their lower mean driving power. Therefore, in the present paper only two kinds of driving modes have been considered, namely urban and extra-urban driving cycles. It should be noted that those two distributions describe the driving patterns of the driver in the present study, and that depending on the particular conditions of each driver, the obtained distributions may be grouped in more than two clusters, depending on vehicle location or other variables (time, weather,...).

Since the vehicle employed to obtain the driving cycles has a conventional engine-based powertrain, its OBD communication system provides the estimated torque of the engine but does not supply the braking power. The proposed strategy requires an estimation of the power requirements including braking power, then a backwards vehicle model has been used to calculate the power demands (P_{req}) from vehicle speed, inertial, rolling and aerodynamic parameters. The power distributions ($\mathbf{Pr}(P_{req})$) obtained with the model are shown in figure 3. It can be observed that according to the engine power values obtained, extra-urban driving cycles show a higher mean requested power. The control strategy presented in Section 4 will be based on the supposition that the vehicle will be driven according to those distributions.

The performance of the proposed method has been evaluated in real driving conditions by means of its application to the cycle shown in figure 4, which comprises both urban and extra-urban driving conditions. As shown in figure 4 there are four segments easily identified in the trip. Urban driving from the cycle start to 1500 seconds approximately, then highway driving

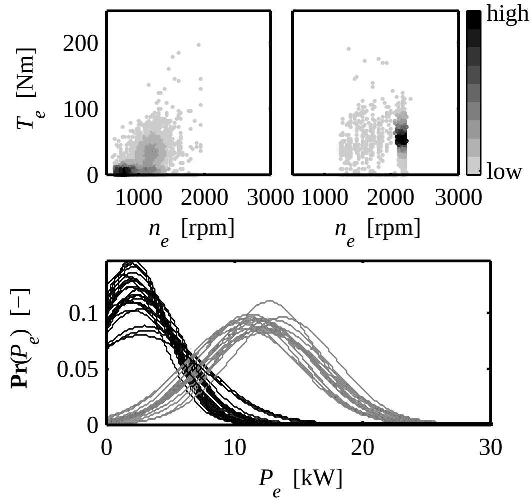

Figure 2: Upper plots: Operating points in the engine speed -torque ($n_e - T_e$) map for urban (left) and extra-urban driving tests (right) and qualitative representation of its frequency $\mathbf{Pr}(P_e)$. Lower plot: Fit of the engine power (P_e) during urban (black line) and extra-urban (grey line) tests to normal distributions

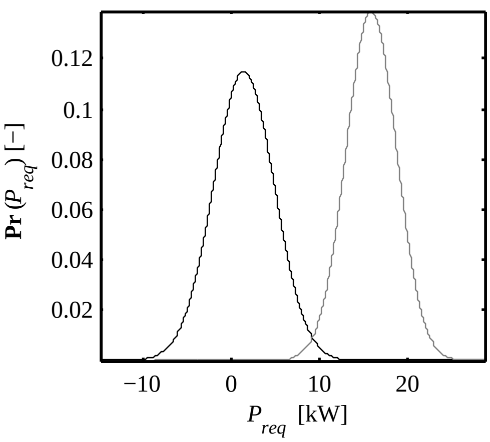

Figure 3: Fits of the power required by the vehicle (P_{req}) during urban (black line) and extra-urban (grey line) tests to normal distributions

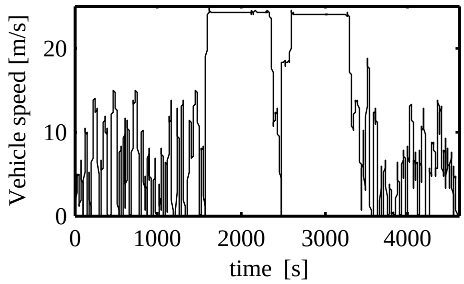

Figure 4: Driving cycle to evaluate the performance of the proposed strategy

until 2500 seconds, then the vehicle turns and runs another stretch with highway driving and finally urban driving until the starting point.

3. Problem Formulation

According to previous section, this paper examines the EMP in a series HEV, *i.e.* find the control law $u(t)$ over a defined driving run with duration $t_f - t_0$ that minimises the cost:

$$J = \int_{t_0}^{t_f} P_f\left(u(t), t\right) \mathrm{dt} \tag{2}$$

where P_f is the fuel power consumed and u is the power supplied by the engine. According to the model described in section 2 the only state of the system is the energy stored in the battery (E_b), whose dynamic equation is:

$$\dot{E}_b = -P_b \tag{3}$$

where P_b is the battery power (which is considered positive when the battery is being discharged and negative when the battery is being charged according to the sign criteria provided in figure 1). The problem is constrained since the total power provided by the powertrain must be equal to the mechanical power required by the vehicle. The formulation of this constraint depends on the powertrain layout. As shown in figure 1, in the series architecture the vehicle wheels are exclusively driven by an electric motor (or a set of electric motors), hence:

$$P_{req}(t) = P_{m,1}(t) \tag{4}$$

Limits related to speed and power ranges in powertrain elements should be also included in the minimisation problem as additional constraints:

$$P_{m,i,min}\left(w_{m,i}\right) \leq P_{m,i}\left(u(t)\right) \leq P_{m,i,max}\left(w_{m,i}\right) \tag{5}$$

$$0 \leq P_{ice}\left(u(t)\right) \leq P_{ice,max}\left(u(t), w_e\right) \tag{6}$$

$$P_{b,min}\left(E_b(t)\right) \leq P_b\left(u(t), E_b(t)\right) \leq P_{b,max}\left(E_b(t)\right) \tag{7}$$

where w represents rotational speed, subscript m, i represents the i^{th} electrical motor, subscript *ice* refers to the internal combustion engine and subscript b refers to battery, whose efficiency depends on its energy level.

To conclude with the mathematical formulation of the EMP, an additional constraint on the energy level in the battery at the end of the trip may be applied. If no constraints were applied to the final state of charge of the battery the fuel consumption would be minimised by depleting the battery, and then limiting potential fuel savings in the future. Therefore, as opposed to Plug-in Hybrid Electric Vehicles (PHEV), which are able to recharge their batteries from the grid, the net battery energy consumption at the end of a trip should be roughly zero in a standard HEV, which means that ultimately all the energy consumed by the vehicle should come from the fuel. In this sense, the condition of charge-sustainability is usually addressed by a hard constraint, imposing the integral of the battery power to be zero over the driving cycle (Serrao et al., 2011), following:

$$\int_{t_0}^{t_f} P_b\left(u\left(t\right), E_b\left(t\right), t\right) \mathrm{dt} = 0 \tag{8}$$

Nevertheless, posing a hard constraint on the battery energy level at the end of the trip is a simplification that may be too restrictive to some studies, since the integral of battery power ought to be roughly zero over the life of the vehicle, but not necessarily during a particular driving cycle. To avoid this constraint, some authors propose to introduce in the cost function the deviation in the battery energy level (or most commonly battery state of charge) from its initial conditions (Liu and Peng, 2008), which results in a feedback control law.

In this paper, the charge sustainability condition will be assured by applying the control policy which makes the net battery energy consumption to be zero as times tends to infinity. The method is detailed in Section 4.

The EMP in HEVs represented in equations (2) to (7) has been successfully addressed in a number of papers by means of the application of optimal control theory (Sciarreta and Guzzella, 2007). One of the most widely employed approaches is the ECMS, originally proposed by Paganelli et al. (2001) which is aimed to replace the integral problem presented in equation (2) with a set of problems to be solved at each instant. In fact, neglecting system constraints and dynamics, the EMP described by equations (2) and (8) is converted into a static optimisation problem that can be addressed by the method of Lagrange multiplier:

$$f = P_f + sP_b \tag{9}$$

where the parameter s, traditionally defined as an equivalent factor between fuel and battery energy sources, is in reality a Lagrange multilplier that should be chosen to fulfill the constraint on the integral of the battery power at the end of the cycle (8).

It should be noted that just as the rest of optimal control approaches, the ECMS requires *a priori* knowledge of the entire driving cycle, at the case at hand to choose a suitable value for parameter s that sustains the battery charge. In this sense, s is usually obtained by means of shooting methods to reach the desired final energy level in the battery (Serrao et al., 2011) or by the analysis of the DP solution (Guardiola et al., 2012). The impact of driving style, road profile or traffic conditions on vehicle fuel consumption and optimal control has been addressed in literature, for example in Wang and Lukic (2011) and references within. Therefore, despite optimising the s parameter for a specific driving cycle, its application to other conditions usually leads to suboptimal solutions even compromising the charge sustainability. Note that high values of the parameter s will shift the minimum to the thermal solution, while low s parameters will promote the electrical solution, as can be deduced from equation (9). Since perfect knowledge of future driving conditions can be rarely assumed, with exception of emission test cycles, Musardo et al. (2005) introduced the Adaptive ECMS (A-ECMS) proposing an on-the-fly algorithm for the estimation of parameter s.

In order to obtain information about future driving conditions two kind of methods are usually employed. The first kind of methods is based on the use of GPS and ITS techniques to obtain information about the road conditions, trip distance or traffic (Bin et al., 2009). Methods of the second kind rely on the statistical analysis of previous driving patterns to predict future driving conditions. Regarding this second type of methods some authors, Gong et al. (2011) propose to characterise driving patterns with mean values and standard deviations of performance indexes such as velocity, acceleration or power amongst others. The Markov chain modelling approach is another statistic method to generate future velocity or power demand profiles based on historical driving conditions (Gong et al., 2010) in order to use DP (Liu and Peng, 2008) or MPC techniques (Johannesson et al., 2007; Ripaccioli et al., 2010) to solve the optimisation problem with a deterministic vehicle model but a stochastic driving cycle .

In the same line than previous works, this paper proposes to employ past driving information to estimate the proper value for the s parameter that minimises the fuel consumption keeping the battery level within a certain interval when applying the ECMS formulation to a HEV operating in an unknown driving cycle.

4. Proposed strategy

The basic idea underlying the proposed method is to estimate future driving power requirements (P_{req}) in a stochastic fashion and then apply the $\overline{s}$ parameter which balances the expected battery energy consumption over an infinite time horizon. Then, the value of $\overline{s}$ to be applied at each instant is found by solving the following equation recurrently:

$$\overline{s} = \arg\min_{s} \left\{ \left(\overline{\Delta E_b} - \mathbf{E}\left\{ \Delta E_b \left(P_{req}, E_b, s \right) \right\} \right)^2 \right\} \tag{10}$$

where $\overline{\Delta E_b}$ refers to battery energy consumption that leads to the battery to the desired final state. In this sense, if battery sustainability is pursued, the term $\overline{\Delta E_b}$ will be equal to the difference between the initial and the current energy level in the battery. Meanwhile, $\mathbf{E}\{\Delta E_b\}$ denotes the expected battery energy consumption over an infinite horizon.

Note that the battery energy consumption depends not only on the power required by the vehicle and the system state E_b, but also on the s parameter, which will determine the battery power consumption at each instant in order to minimise cost. Discretizing the set of possible power demands in n values equally spaced, the probability of any power demand ($P_{req,j}$) can be obtained from figure 3 if the driving conditions (urban or extra-urban) are known. Then, for a given value of s, the expectation of the battery energy consumption is calculated in a discrete approach as:

$$\mathbf{E}\{\Delta E_b\} = \sum_{j=1}^{n} \mathbf{Pr}\left(P_{req,j}\right) \lim_{N\to\infty} \left\{ \sum_{k=1}^{N} \gamma^k P_b\left(P_{req,j}, E_b, s\right) \Delta t\,(k) \right\} \tag{11}$$

where $\Delta t\,(k)$ refers to the time increment at the kth step, $\mathbf{P}r\left(P_{req,j}\right)$ is the probability of a given power requirement $P_{req,j}$ according to the corresponding histogram in figure 3 and $\gamma < 1$ is a discounting factor to assure the convergence of the infinite sum.

If the battery works in a narrow enough range, the effect of the battery energy level on the battery power may be neglected, then $P_b = P_b\left(P_{req}, s\right)$. In addition, if constant time steps are considered, equation (11) is simplified to:

$$\mathbf{E}\left\{\Delta E_b\right\} = \sum_{j=1}^{n} \left\{ \mathbf{P}r\left(P_{req,j}\right) P_b\left(P_{req,j}, s\right) \Delta t \lim_{N\to\infty} \left\{ \sum_{k=1}^{N} \gamma^k \right\} \right\} \tag{12}$$

or similarly:

$$\mathbf{E}\left\{\Delta E_b\right\} = \beta \sum_{j=1}^{n} \mathbf{P}r\left(P_{req,j}\right) P_b\left(P_{req,j}, s\right) \tag{13}$$

where $1 \leq \beta < \infty$ is defined as a time horizon:

$$\beta = \lim_{N\to\infty} \left\{ \sum_{k=1}^{N} \gamma^k \right\} \Delta t \tag{14}$$

In the previous expressions, the battery power for a any of the discretized values of $P_{req,j}$ and s is calculated at each time step by minimising equation (9). Then the difference between the current and the objective energy level ($\overline{\Delta E_b}$) is used to choose the value of s which cancels the argument in equation (10) over the time horizon defined by β.

In order to reduce the computation cost, the optimal s parameter ($\overline{s}$) can be calculated for different battery energy levels and then mapped as function of the energy stored in the battery, or more conveniently as a function of the battery state of energy, hereinafter SoE, which is defined as:

$$SoE = \frac{E_b}{E_{b,max}} \tag{15}$$

where E_b and $E_{b,max}$ are the current and the maximum energy stored in the battery respectively. Note that the hypothesis of negligible effect of the battery energy level on the battery power (*i.e.* E_b does not affect to the relation between P_{el} and P_b) is fundamental to allow the simplification of equation (14), and then the mapping of $\overline{s}$.

An example of those kind of maps is shown in figure 5, where the $\overline{s}$-SoE map is calculated in order to keep the state of the battery around 0.6 with the power distributions shown in figure 3. As expected, $s(SoE)$ is a monotonic curve with lower values of s when increasing SoE. It can be observed how a time horizon β of 1 second implies an abrupt step in $\overline{s}$ when the energy state of the battery passes through the reference level 0.6 since the control system should reach the desired energy level within a short time frame. As the horizon (β) increases the slope of the curve becomes smoother.

It should be noted that the $s(SoE)$ curves shown in Figure 5 are similar to those proposed by Serrao et al. (2011) to correct excessive excursions in the SoE. The linear evolution in the optimal s parameter for a given time horizon in a wide range of SoE is also in line with the proposal of some authors (*e.g.* Tulpule et al. (2009)) of correcting the value of the s parameter with a proportional feedback based on the difference between the desired and current SoE. The contribution of the present paper with regards to both cited approaches is that, the curves presented in

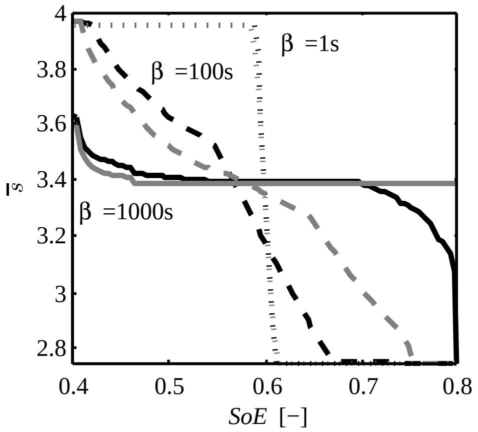

Figure 5: $\bar{s}$ as a function of SoE to balance the battery energy consumption after β = 1 s (dotted line), β = 100 s (dashed line) and β = 1000 s (continuous line) during urban (black line) or extra-urban (grey line) conditions supposing an initial SoE of 0.6

figure 5 are derived from the statistical analysis of the driving conditions, rather than applying an heuristic rule. Hence the present paper introduces a physically based and intuitive framework for calibrating the EMS, providing an optimal $s(SoE)$ curve for a given driving power distribution and control horizon β.

Figure 5 also shows the differences between the s parameters to be applied in urban and extra-urban driving conditions, pointing out the impact of the driving conditions on the optimal solution of the EMP. In this sense, two different approaches are proposed to deal with the changes in the driving patterns, namely, a clustering approach which considers different power histograms modeling different driving styles and an adaptive approach aimed to modify a single histogram to model the current driving style.

4.1. Clustering approach

For the sake of simplicity, only the two histograms shown in figure 2 are to be considered in this section, while the proposed method can be easily extended to take into account a larger number of driving styles. For the case at hand, since parameter s is mapped in figure 5 for both urban and extra-urban conditions, it is necessary to identify the driving conditions in order to apply the proper map. Vehicle location, if GPS is available, can be a suitable method to identify if urban or extra-urban $\bar{s}$ tables should be applied. However, simple change detection algorithms as those proposed in Basseville and Nikiforov (1993) can be used to detect changes in the driving pattern. The method adopted in the present paper is based on assuming that the probability function before and after the change is known. In this sense, the probability functions shown in figure 2 are supposed to be the only two possible driving patterns. Then, considering the sequence of vehicle power requirements as a sequence of independent random variables with a probability density $\mathbf{P}r_{urb}\left(P_{req}\right)$ or $\mathbf{P}r_{e-urb}\left(P_{req}\right)$, the problem lies in detecting the time in which the vehicle power demands pass from one distribution to another. To reach this goal the log-likelihood ratio is defined by:

$$l\left(P_{req}\right) = \log \frac{\mathbf{P}r_{e-urb}\left(P_{req}\right)}{\mathbf{P}r_{urb}\left(P_{req}\right)} \tag{16}$$

where for a given power demand P_{req}, the terms $\mathbf{P}r_{urb}\left(P_{req}\right)$ and $\mathbf{P}r_{e-urb}\left(P_{req}\right)$ represent the probability of that power demand in the urban and extra-urban distributions.

If $\mathbf{P}r_{urb}\left(P_{req}\right) < \mathbf{P}r_{e-urb}\left(P_{req}\right)$ then the vehicle is more likely to be at extra-urban conditions and the ratio of probabilities is larger than one, so the log-likelihood ratio (l) is positive, and *vice versa*. Accordingly, the proposed detection algorithm consists in given a sampling window with fixed size κ, decide at each time step (k) if P_{req} follows the urban or the extra-urban probability function by means of the evaluation of the parameter:

$$L(k) = \sum_{i=k-\kappa}^{k} \log \frac{\mathbf{P}r_{e-urb}\left(P_{req}(i)\right)}{\mathbf{P}r_{urb}\left(P_{req}(i)\right)} \tag{17}$$

Then the decision rule is given by:

$$\begin{array}{l} \mathbf{P}r\left(P_{req}\right) = \mathbf{P}r_{e-urb}\left(P_{req}\right) \quad if \quad L > 0 \\ \mathbf{P}r\left(P_{req}\right) = \mathbf{P}r_{urb}\left(P_{req}\right) \quad if \quad L \leq 0 \end{array} \tag{18}$$

4.2. Adaptive approach

Another possibility to deal with changes in the driving style is to use an adaptive approach. The main idea underlying this method is to update online the probability functions shown in figure 3 by using the power demand provided by the vehicle model. The proposed method starts with the definition of a window size (τ) and initial probability distributions for power demands. Then, the power required in the current instant (i) can be obtained by applying the quasi-static vehicle model. Each time step (one second in the present paper), the actual power demanded is introduced in the database while the power demands in instant $i - \tau$ are removed. Finally, the new probability distribution is calculated and $\bar{s}$ can be obtained.

5. Results and Discussion

The performance of the proposed method has been evaluated in real driving conditions by means of its application to the cycle shown in figure 4 with both clustering and adaptive approaches.

5.1. Clustering approach

Regarding the clustering approach, figure 6 shows the performance of the detection algorithm with two different window sizes (κ). It can be observed that in both cases the algorithm is able to predict the driving conditions with good accuracy. Nevertheless, low κ values give rise to higher sensibilities, then allowing a faster detection of sudden changes in driving patterns, but also increasing the probability of false alarms. For the next simulations, the κ parameter was set to 250 seconds in order to provide a reasonable tradeoff between detection capabilities and probability of false alarms.

Another tuning parameter of the method is the time horizon β. Figure 7 shows the fuel economy (km/kg of fuel) versus the final SoE, it can be observed that for this cycle, setting a time

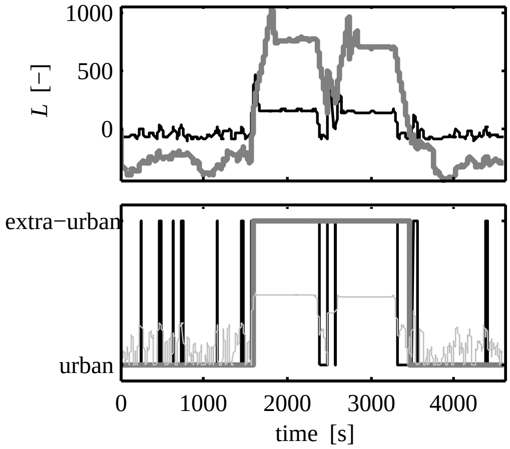

Figure 6: Evolution of the L parameter (upper plot) and detection of urban or extra-urban driving conditions (lower plot) with a sampling window (κ) of 50 seconds (black line) and 250 seconds (grey line). The light grey line represents qualitatively the vehicle speed

horizon β=100 s provides the nearest results to DP. The SoE variations within the cycle show that a wide range of values for β ranging from 50 to 200 seconds provide a suitable solution in the SoE interval of $[0.5, 0.7]$. In any case, the optimal value of the time horizon should depend on the prediction accuracy and also on the operating range of the battery: when only poor predictions of the power demands are available low values of parameter β should be used in order to avoid excessive excursions of the SoE. This reasoning provides insights on the idea of mapping the time horizon β with the SoE, *i.e.* associating low predicting horizons to SoEs far from the reference in order to avoid charge depletion or overcharging. Admittedly, it would improve the robustness of the solution at the cost of some optimality loss.

The particular solutions for the cases of $\beta = 100s$ and $\beta = 500s$ are presented in figure 8 where the bottom plot shows the evolution of the SoE during the cycle. According to the values of $\overline{s}$ shown in figure 5, simulations with low β values show strong variations in the s parameter from one time step to another that allow the SoE to variate in a narrow range around the desired final value.

The upper plot of figure 8 shows the evolution of the fuel consumption. Differences between the signals are difficult to be appreciated due to two main reasons. On the one hand, similar results are obtained within the range of β parameters tested. On the other hand, the fuel consumption obtained shows a noisy behaviour due to the quasi-steady approach employed which allows the cost function to reach similar values in separated points of the control space. This involves that small variations in the required power lead to a switch between different control inputs. Note that the real system will have some inertia, and sharp variations in the power split are not possible. In order to avoid such behaviour the modification of the current control inputs should be penalised.

Figure 8 also shows the optimal evolution in SoE calculated by means of DP considering an effective SoE range of 0.2, *i.e.* SoE ranging from 0.5 to 0.7 during the trip. Of course, the proposed method provides suboptimal solutions to the problem, however, it should be noted that in the case of DP, the driving profile is *a priori* known and the final SoE is imposed.

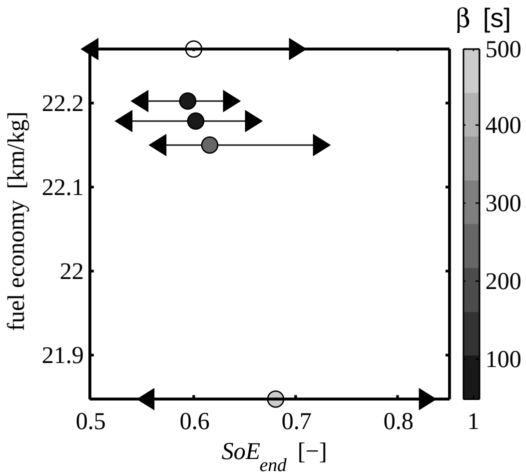

Figure 7: Fuel economy (km/kg of fuel) versus final SoE for different time horizons (β) from black (β=50 s) to light grey (β=500 s). White dot shows the optimal results obtained with DP and arrows represent the range of variation of the SoE during the test.

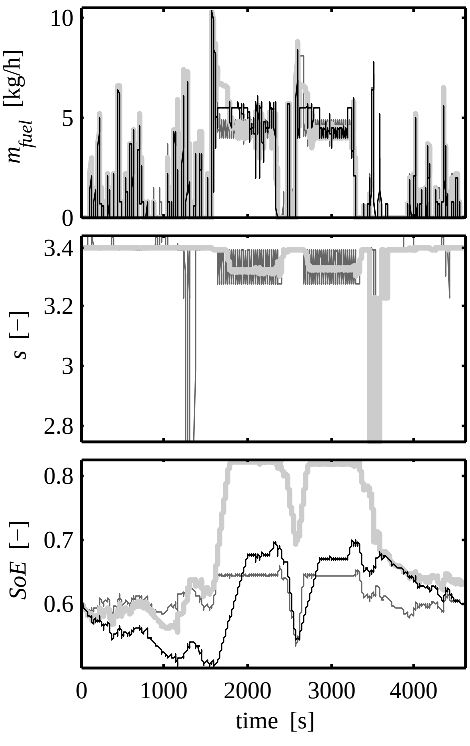

Figure 8: Evolution of the fuel consumption (upper plot), s parameter (middle plot) and SoE (bottom plot) with β=100 s (dark grey) and β=500 s (light grey). The black line represents the optimal solution obtained with DP.

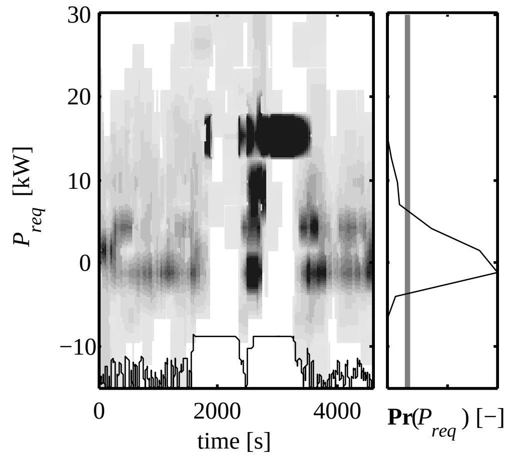

Figure 9: Evolution of the probability matrix during the tested cycle and qualitative representation of the vehicle speed. The colorscale represents the probability of a given required power at a given instant according to the probability matrix adaption, ranging from low probability in white to high probability in dark grey. Right plots show the probability distributions at the beginning (grey line) and the end of the trip (black line).

5.2. Adaptive approach

Regarding the results with the adaptive approach, Figure 9 shows the evolution of the probability functions according to the exposed method. At the begining of the test a homogeneous probability distribution has been considered, and the method is able to rapidly adapt the probability distribution acording to the power requirements. It can be noticed that in extra-urban driving, figure 9 shows how the distribution gets progressively sharper with a most probable power requirement around 18kW, which is consistent with the histogram shown in figure 3. This is due to the fact that the cycle only considers highway driving (with almost constant speed) in extra-urban conditions. Then, as the vehicle returns to the urban environment, approximately at second 3800, the most likely demanded power is progresively reduced to a similar level to that shown in figure 3 and the probability distribution curve becomes flatter due to the hetereogeneity in the operating conditions that can be found in urban driving.

The impact of the time horizon (β) and the receding horizon (τ) on the strategy performance can be observed in figure 10. As in the case of the clustering approach, reducing the time horizon β involves a final SoE nearer to the desired value (0.6 in the present case study). Regarding the effect of the windowsize (τ) used to calculate the probability distrubution of the required power, it can be observed that for a narrow window (namely 100 seconds) the s parameter applied involves a depletion in the SoE. This reduction in the final SoE increases with β. Also, for final SoEs near the desired value increasing the τ up to 200 seconds involves an increase in the fuel economy, nevertheless, larger receding horizons do not involve any advantage for this particular cycle. It can be also noted that for higher values of τ the s parameters applied involve an increase of the SoE at the end of the cycle. Despite the general conclusions on the time horizon β effect on the strategy performance, it is not worth to draw conclusions about which is the best value of τ to apply, since this result depends entirely on the duty cycle. In any case, as a rule of thumb, the receding horizon should be large enough to capture the driving pattern in a general fashion.

In figure 11 the evolution in the fuel consumption, s parameter and SoE obtained in the best

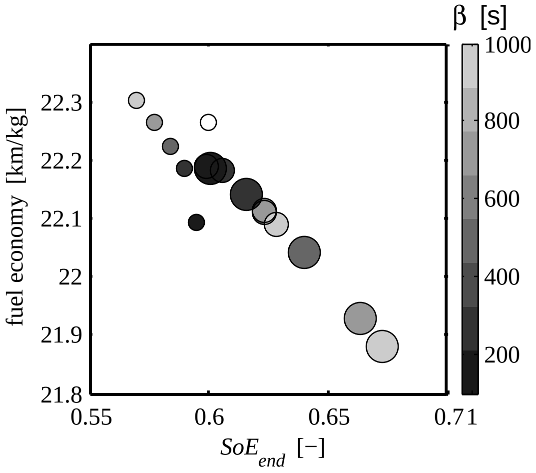

Figure 10: Fuel economy (km/kg of fuel) versus final SoE for different time horizons (β) from black (β=100 s) to light grey (β=500 s). The marker size represents the receding horizon (τ) used to calculate the power probability distribution: 100 s for small markers, 200 s for medium markers and 300 s for big markers. White dot represents the optimal results obtained with DP.

adaptive simulation (τ=300s and β=100s) is compared with that obtained with DP.

It can be observed that despite significant differences, the adaptive method is able to stay close to DP without any information on the future driving cycle, nor on the vehicle location. In addition, it should be noted that those results have been obtained starting from an homogeneous distribution which is far from the real one. On the other hand, a significant drawback of the adaptive approach is that despite $\overline{s}$-SoE curves can be calculated offline in the clustering approach, as far as the probability functions are continuously modified due to the adaption, this method requires online calculation of those curves. Note that while in equation 12, the term $P_b\left(P_{req,j}, s\right)$ can be mapped, the term $\mathbf{P}r\left(P_{req,j}\right)$ varies with time. Therefore, the clustering approach is less computationally intensive, but has harder memory requirements. Regarding fuel consumption, DP optimal solution showed a fuel economy of 22.3 km/kg of fuel, while the fuel economy obtained with the best clustering and adaptive configurations was 22.2 km/kg of fuel in both cases. Then both methods show a similar performance and provide solutions near the optimal without *a priori* knowledge of the driving cycle. In this sense, the trade-off between computation cost an memory will define the best solution to be implemented in a vehicle.

6. Conclusions

This paper has presented a new strategy for near-optimum power management in HEVs. The well-known ECMS method is upgraded by means of a stochastic estimation of future driving conditions based on past information of the vehicle power demands.

The proposed method is based on estimating future probability distribution of power demands from past power requirements and obtain the s parameter which holds the expected the battery energy level in a defined value after a given horizon. In fact, one of the contributions of the paper is the introduction of a control strategy for HEVs able to keep the battery sustainability avoiding

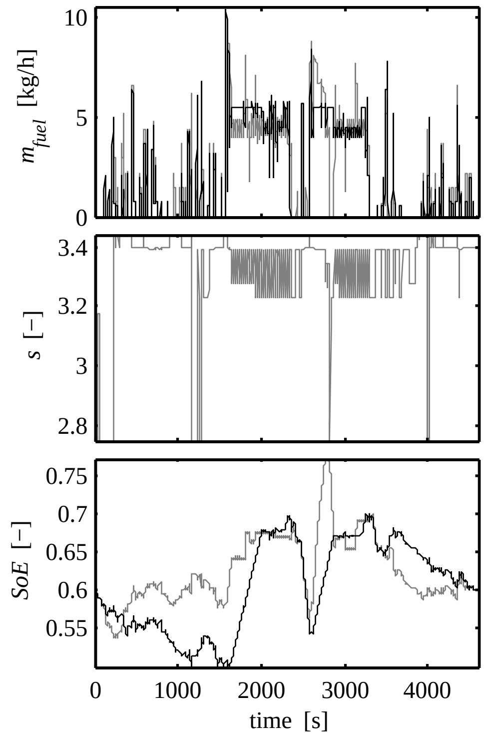

Figure 11: Evolution of the fuel consumption (upper plot), s parameter (middle plot) and SoE (bottom plot) with the adaptive method with β=100 s and τ=300 s (grey line). Black line represents the optimal state of energy and fuel consumption evolution according to the DP solution.

excesive excursions in the SoE without the application of correction coefficients heuristically derived. Accordingly, for any driving power distribution and control horizon (β), the proposed strategy allows to derive the optimal $s(SoE)$ curve. In this sense, a contribution of the present paper is to provide a physically based framework to calibrate other EMS as those consisting of compensations of the s parameter depending on the SoE deviation from its desired value.

In order to deal with abrupt changes in the driving conditions or driving style, two approaches have been presented:

- The clustering approach which is based on identifying the current driving pattern by using the log-likelihood ratio (or information on the vehicle location) and then apply the corresponding probability distribution of power demands amongst a set of possible distributions. In this paper two driving patterns, namely urban and extra-urban, have been considered, however, the method can be extended to consider a larger set of driving patterns.

- The adaptive method in which a single probability function is continuously modified in order to represent the driving conditions obtained during a given receding horizon.

The application of the method with both clustering or adaptive approaches to real world driving conditions show that it is able to provide near-optimal results without any information of future driving conditions.

7. References

D. Ambühl, O. Sundström, A. Sciarretta, and L. Guzzella. Explicit optimal control policy and its practical application for hybrid electric powertrains. *Control Engineering Practice*, 18:1429–1439, 2010.

M. Basseville and I. V. Nikiforov. *Detection of Abrupt Changes: Theory and Application*. Prentice-Hall Inc, ISBN 0-13-126780-9, 1993.

Y. Bin, Y. Li, Q. Gong, and Z. R. Peng. Multi-information integrated trip specific optimal power management for plug-in hybrid electric vehicles. In *2009 American Control Conference*, pages 4607–4612, St. Louis, MO, USA, June 2009.

A. A. Borhan, A. Vahidi, A. M. Phillips, M. L. Kuang, and I. V. Kolmanovsky. Predictive energy management of a power-split hybrid electric vehicle. In *2009 American Control Conference*, pages 3970–3976, St. Louis, MO, USA, June 2009.

A. Chasse and A. Sciarretta. Supervisory control of hybrid powertrains: An experimental benchmark of offline optimization and online energy management. *Control Engineering Practice*, 19:1253–1265, 2011.

Q. Gong, S. Midlam-Mohler, v marano, G. Rizzoni, and Y. Guezennec. Statistical analysis of phev fleet data. In *2010 Vehicle Power and Propulsion Conference*, pages 1–6, Lille, France, September 2010.

Q. Gong, P. Tulpule, V. Marano, S. Midlam-Mohler, and G. Rizzoni. The role of its in phev performance improvement. In *2011 American Control Conference*, pages 2119–2124, San Francisco, CA, USA, June-July 2011.

C. Guardiola, B. Pla, S. Onori, and G. Rizzoni. A new approach to optimally tune the control strategy for hybrid vehicles applications. In *IFAC Workshop on Engine and Powertrain Control, Simulation and Modeling ECOSM'12*, Rueil-Malmaison, France, October 2012.

L. Johannesson, M. Åsbogård, and B. Egardt. Assessing the potential of predictive control for hybrid vehicle powertrain using stochastic bynamic programming. *IEEE Transactions on Intelligent Transportation Systems*, 8(1):71–83, 2007.

S. Kermani, S. Delprat, T. M. Guerra, R. Trigui, and B. Jeanneret. Predictive energy management for hybrid vehicle. *Control Engineering Practice*, 20:408–420, 2012.

J. Liu and H. Peng. Modeling and control of a power-split hybrid vehicle. *IEEE Transactions on Control Systems Technology*, 16(6):1242–1251, 2008.

H. Mosbech. Optimal control of hybrid vehicle. In *Proceedings of the International Symposium on Automotive Technology & Automation*, pages 303–310, 1980.

C. Musardo, G. Rizzoni, Y. Guezennec, and B. Staccia. A-ECMS: An adaptive algorithm for hybrid electric vehicle energy management. *European Journal of Control, Fundamental Issues in Control, Special Issue*, 11(4-5), 2005.

G. Paganelli, G. Ercole, A. Brahma, Y. Guezennec, and G. Rizzoni. General supervisory control policy for the energy optimization of charge-sustaining hybrid electric vehicles. *JSAE Review*, 22(4):511–518, 2001.

G. Ripaccioli, D. Bernardini, S. di Cairano, A. Bemporad, and I. V. Kolmanovsky. A stochastic model predictive control approach for series hybrid electric vehicle power management. In *2010 American Control Conference*, pages 5844–5849, Baltimore, MD, USA, June-July 2010.
G. Rizzoni, L. Guzzella, and B. Baumann. Unified modeling of hybrid electric vehicle drivetrains. *IEEE/ASME Transactions on Mechatronics*, 4(3):246–257, 1999.
A. Sciarreta and L. Guzzella. Control of hybrid electric vehicles. *IEEE Control System Magazine*, 27(2):60–70, 2007.
L. Serrao, S. Onori, and G. Rizzoni. A comparative analysis of energy management strategies for hybrid electric vehicles. *Journal of Dynamic Systems, Measurement, and Control*, 133:1–9, 2011.
O. Sundström, D. Ambühl, and L. Guzzella. On implementation of dynamic programming for optimal control problems with final state constraints. *Oil & Gas Science and Technology*, 65(1):91–102, 2010.
P. Tulpule, V. Marano, and G. Rizzoni. Effects of different phev control strategies on vehicle performance. In *2009 American Control Conference*, pages 3950–3955, Saint Louis, USA, June 2009.
R. Wang and S. M. Lukic. Review of driving conditions prediction and driving style recognition based control algorithms for hybrid electric vehicles. pages 1–7, September 2011.

Appendix A. Extension of the proposed method for parallel HEV architectures

Consider a parallel HEV in which a conventional engine transmission powertrain is assisted by an electrical motor/generator supplied by a battery, so the engine and the motor can drive the vehicle individually or simultaneously. Since the engine is mechanically coupled to the wheels, the vehicle speed and the gear ratio force the engine to operate at a defined speed at each instant. Then, while for a given power demand series HEVs allow to choose the engine speed which leads to the lower fuel consumption, in parallel HEVs the engine speed is imposed by the vehicle operating conditions.

The main implication of this difference in powertrain topology on the generalisation of the proposed method to parallel HEVs is that the probability densities of the combinations between engine speed and torque demands ($\mathbf{Pr}(n_e, T_e)$) shown in the upper plot of figure 2 should be considered instead of the simpler histograms of figure 3. In this sense, for the particular case of a parallel HEV, equation (10) becomes dependent on engine speed (n_e) and demanded torque (T_e), and reads:

$$\overline{s} = \arg\min_{s} \left\{ \left(\overline{\Delta E_b} - \mathbf{E}\left\{ \Delta E_b \left(n_e, T_e, E_b, s \right) \right\} \right)^2 \right\} \tag{A.1}$$

where discretizing the set of possible engine speeds and torque demands in n_n and n_T values respectively, the expected battery energy consumption (ΔE_b) after a given time horizon (β) can be obtained as:

$$\mathbf{E}\left\{ \Delta E_b \right\} = \beta \sum_{i=1}^{n_n} \sum_{j=1}^{n_T} \mathbf{P}r\left(n_{e,i}, T_{e,j} \right) P_b\left(n_{e,i}, T_{e,j}, s \right) \tag{A.2}$$

Note that the effect of E_b on P_b has been neglected, which is a suitable approach if the SoE varies in a narrow range. As an example, figure A.12 shows the evolution of the fuel consumption, s parameter and SoE for both the s-ECMS strategy and the DP solution. It is shown that with time horizons of the same order than those used in the series HEV, the proposed control method is able to sustain the battery state of energy in the case of the parallel architecture, in this case with a penalty in fuel consumption of 3.5%.

It should be noted that the fuel penalty obtained for the HEV configuration (0.5%) has been increased to 3.5% when applying the method to a parallel HEV. The reason for this behaviour is related to the HEV architecture itself, since the engine is completely decoupled from the wheels

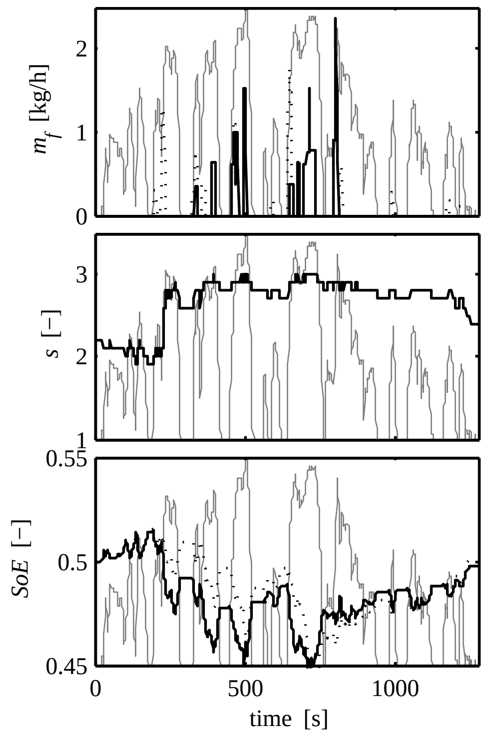

Figure A.12: Evolution of the fuel consumption (upper plot), s parameter (middle plot) and SoE (bottom plot) for a parallel HEV during an arbitrary driving cycle with the proposed adaptive method and β=100 s (black line). The dotted line represents the optimal state of energy and fuel consumption evolution according to the DP solution.

in the series HEV, it can work in a narrow area near its sweet-spot, and then differences in fuel consumption between strategies with the same final SoE are small, and the EMP is reduced to find a charge sustaining strategy. In the case of the parallel HEV the operating range of the engine is extended, then differences in fuel consumption between strategies are amplified.