Exploiting Driving History for Optimising the Energy Management in plug-in Hybrid Electric Vehicles

Héctor Climent[a], Benjamín Pla[a], Pau Bares[a], Varun Pandey[a,*]

[a] *CMT-Motores Térmicos, Universitat Politècnica de València, Camino de Vera 6D, 46022, Valencia, Spain*

Abstract

This paper proposes an Energy Management Strategy (EMS) for a plug-in parallel Hybrid Electric Vehicle (pHEV) with the goal of minimising the fuel consumption while fulfilling the constraint on the terminal battery State-of-Charge (SoC). The proposed strategy assumes that the route was previously covered several times by the vehicle, in order to extract information about the feasible operating conditions in the driving cycle. Note that this situation is usual in commuting and daily trips. In this sense, the history of vehicle speeds and positions are used to build space-dependent transition probability matrices that are latter used for driving cycle estimation by means of Markov-Chain approach. Once the driving cycle is estimated, the torque-split problem in parallel hybrid powertrain is addressed using the Equivalent Consumption Minimisation Strategy (ECMS), where the associated boundary value problem of finding the weighting factor between battery and fuel cost that drives the SoC to the desired level at the end of the estimated cycle is solved and applied to the system. Finally, in order to make up for cycle estimation error, the ECMS is solved recurrently. For the sake of clarity, the proposed strategy is initially developed and analysed in a modelling environment. Then tests in an engine-in-the-loop basis are done for validation. In order to show the potential of proposed strategy, results are presented using a trade-off between the fuel consumption and the

*Corresponding author
Email address: vapan2@mot.upv.es (Varun Pandey)

terminal-SoC for four different methods: the optimal power-split that requires a priori knowledge of the driving cycle for benchmarking, online ECMS with a fixed cycle estimation (average speed profile obtained from previous trips on the route), the proposed method, i.e. online ECMS with a dynamic cycle estimation and finally a rule-based charge depleting and charge sustaining strategy. The results demonstrate that the online ECMS outperforms the rest of online applicable methods.

Keywords: Plug-in Hybrid Electric Vehicles, Energy Management Strategy, Online Optimal Control, Stochastic Driving Prediction, Adaptive-ECMS, Markov Chain Principle

2020 MSC: 00-01, 99-00

---

1. Introduction

With two energy sources Hybrid Electric Vehicles (HEVs) present a system with higher degree-of-freedom and improved possibilities for reducing fuel consumption and emission than traditional Internal Combustion Engine (ICE) based vehicles . The achievable improvement in fuel economy depends strongly on the vehicle and the driving cycle; realistic figures range from below 10% for mild hybrids to more than 30% for highly hybridized vehicles as shown by the authors in [1]. This potential is even larger in the case of plug-in Hybrid Electric Vehicles (pHEV) since the energy to move the vehicle does not necessarily come from the ICE. Authors in [2], use real-world driving data of a mid-sized sedan pHEVs with 40 miles of Electric Vehicle (EV) range and report 71% reduction in gasoline consumption as compared to conventional vehicle. This potential can be realised through optimisation in any of the three HEV system levels: the powertrain topology(series HEV, parallel HEV, series-parallel HEV), the technology and sizing of the components and the EMS [3, 4, 5]. Extensive literature is explored by the authors in [6, 7] regarding the topology of HEVs. However, the present work is focused on developing an EMS for but not limited to a pHEV architecture. This topology is chosen for demonstrating the EMS, but the proposed strategy is general and can be extended to other architectures (e.g. Series HEV).

The full potential of the pHEV can be realized with a smart EMS that optimizes energy flow within the vehicle. The objective of EMS is essentially to minimise fuel consumption of the vehicle while fulfilling driver power demands and restraining the battery SoC (SoC) within a certain range. In general, the pHEVs operating modes are classified by the author in [2] as

The EMS is broadly classified by authors in [6] as : rule-based and optimisation-based. Heuristic methods, based in exhaustive calibration to consider the large set of operating conditions that the vehicle may face, is widely explored in the literature [8, 9, 10, 11]. These methods require exhaustive experiments and experience to set-up a rule based control scheme such as Charge-Depleting (CD) and Charge-Sustaining (CS). In CD, the battery is the main energy source, so despite SoC may fluctuate, on-average it decreases while driving. In CS, the ICE is used frequently to avoid the battery depletion. Optimal Control (OC) methods are based on applying a control policy that minimises a predefined cost function by exploring their impact with the aid of a model. The classical OC approach is done offline since it requires a priori knowledge of the driving cycle. Amongst OC techniques applied to the EMS are Dynamic Programming [12] and Pontryagin's Minimimum Principle [13]. In general, the main drawback of optimisation-based method is that they require a detailed description of the problem to be optimised, so a-priori knowledge of the driving cycle, which rules them out from on-board application due to their lack of causality. On the contrary, they are often used to obtain a standard optimal solution for comparing the results obtained with the online methods.

In order to cope with limitations of both heuristic and optimal Control approaches, several model based approaches have been proposed, most of them based to some extent on OC, but sacrificing optimality for the sake of applicability. Amongst them, one can find Equivalent Consumption Minimization Strategy (ECMS) proposed by [14] and Deterministic or Stochastic Model Predictive Control [15]. The ECMS is probably the most widely explored approach with several versions, all of them showing near-optimal results with a challenge of properly determining the equivalent factor between fuel and battery power(hereinafter EF) [16]. The values of EF are cycle-dependent and hence pose the issue of requiring a priori knowledge of future driving conditions. In order to achieve near-optimal results, the EF should be adapted as the driving scenario varies. Method falling in this category are referred in the literature as Adaptive-ECMS(A-ECMS) strategy [17, 18]. The EF adaptation is addressed by taking advantage of the driving information [19, 20] to estimate the suitable values that weighs the fuel and battery energy sources to keep the SoC in a given range with minimum fuel consumption (or other defined cost, such as CO2 emissions, economical cost, etc.)

The adaptation techniques in the literature are classified in two categories- The first category is adaptation based on the driving cycle prediction. The equivalence factor is estimated online based on a look-ahead horizon defined in terms of energy at the wheels, to determine at each instant the most likely behaviour [21, 22]. In the literature, the task of driving cycle prediction is usually performed using Neural-Network (NN) and Markov-Chain (MC) based methods. In the article by authors in [23], a comparison of the two approaches is shown in terms of prediction accuracy and computation speed. The MC based method is shown to outperform the NN based method. In the article [24], authors proposed a RBF-NN speed prediction method integrated to the A-ECMS. This method used open-loop speed prediction derived from the current vehicle state. The second category of the adaptation methods rely on the unproven but rational hypothesis that driving cycles with similar statistical properties in certain energy related variables are expected to have similar EFs. To recognise the driving cycle characteristics, the authors in [25, 26, 27, 28] use statistic and clustering techniques to classify the driving type. Most of the pattern recognition algorithms in the literature first identify the kind of driving conditions the vehicle is undergoing, and then select the most appropriate equivalence factors from a predefined set.

This article addresses the adaptation using a method within the first category mentioned above. In the original A-ECMS, introduced by the authors in [29], the algorithm predicts the mission that the vehicle is following and determines the optimal EF for the current mission by the direct optimization method. The cycle prediction does not account for the deviation in the predicted and the actual vehicle velocity. To this end, a close-loop driving cycle prediction method based on the MC approach is introduced in the A-ECMS. The driving prediction uses the historical information to obtain space dependent transition probability matrices and then uses Markov principle to recursively predict the driving cycle and update the EF based on the online ECMS results. In this way, the paper introduces two main novelties: On the one hand, the MC is space-dependent to take into account that the characteristic driving depends(amongst other things) on the vehicle location (e.g. urban versus highway) so the EF will depend on that. On the other hand, the predicted speed and the EF adapt themselves periodically during the control horizon window (CHW) such that, at any instance the power-split is optimal and the expected terminal SoC is close to the desired level.

Presenting the described idea, the paper is structured as follows: First, in section 2, the Proposed Study is described. Then, in 3, the HEV model used during the study is presented. Section 4 describes the problem formulation. Next, is the experimental set-up in section 5 followed by obtained results and discussion in section 6. Finally, the conclusions of the work are highlighted in section 7.

2. Proposed Study

The main objective of the study is to develop an online applicable EMS for a pHEV that exploits the information obtained when the vehicle recurrently covers a given route. For application purposes, a commuting driving route of 21 km including rural, highway and urban areas was chosen. The route was covered 50 times during consecutive working days.

Regarding the vehicle, a pHEV is chosen to show the potential of developed

Table 1: Description of the main vehicle features

Vehicle mass	2120 kg
Engine power	98 kW
Motor power	24.5 kW
Battery energy capacity	0.0432 MJ
Number of gears	6

strategy while the method can be adapted to deal with other powertrain types (series, series-parallel, charge sustaining, etc.). In this architecture, i.e parallel arrangement ,the vehicle can be driven by the internal combustion engine (ICE), the electric motor (EM), or both simultaneously. Thus, there are different solutions to provide the power required by the driver with different costs and impacts in future operation, which poses an interesting optimisation problem. The battery is charged either by an external power source, by the ICE or by regenerative braking through the electric motor. The main characteristics of the vehicle considered in the present paper are shown in table 1, while the layout and main energy flows in the powertrain are shown in figure 1.

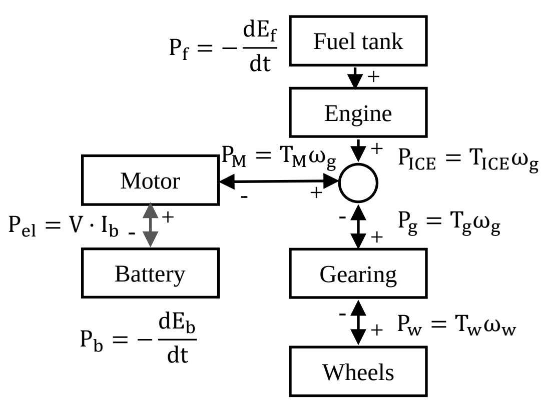

Figure 1: System layout, nomenclature and sign criteria for the parallel pHEV architecture considered in this paper.

The addressed problem will be to optimize the power-split of the pHEV in order to minimise the fuel consumption of the vehicle on the considered route avoiding SoC excursions over the battery limits.

3. HEV model

The model used to compute the optimal power-split in the present paper follows the approach based on longitudinal vehicle dynamics, backward propagation and quasi-steady behaviour of ICE and motor presented by [30] and used in most of the EMS optimization works [31, 32, 33]. While the model may be over-simplified to consider aspects such as pollutant emissions or control of particular elements, this approach provides a suitable balance between simplicity for real-time applications and plant representativeness in terms of fuel consumption, since the characteristic times of power-split decisions are, in general, larger than those of motors and ICEs [6]. Note that with this approach, a suitable estimation of vehicle speed (and therefore) acceleration trajectories can be used to progressively compute the required power in powertrain elements by means of energy balances done with inverted physical causality. In a first step the torque at the wheels (T_w) can be obtained from vehicle speed and acceleration trajectories ($v(t)$ and $\dot{v}(t)$)as:

$$\begin{aligned} T_w = r_w[m.\dot{v}(t) + \frac{1}{2}\rho_a.A_f.c_d.v^2(t) + \\ c_r.m.g.cos(\gamma) + m.g.sin(\gamma)] \end{aligned} \tag{1}$$

where r_w is the wheel radius, m is an equivalent vehicle mass, ρ_a is the air density, A_f the frontal area of the vehicle, c_d its aerodynamic drag coefficient, c_r the rolling friction coefficient, γ is the road angle and g the gravitational acceleration. Note that wheel speed (ω_w) can be also obtained from the corresponding values for vehicle and the wheel radius.

The speed (ω_g) at the gearbox input to satisfy the demanded wheel speed can be calculated using the transmission ratio (ν_g) depending on the selected gear (g_n):

$$\omega_g = \nu_g(g_n).\omega_w \tag{2}$$

and assuming a transmission efficiency (ν_g) depending on the selected gear, the torque at gearbox input yields:

$$T_g = \begin{cases} \frac{T_w}{\eta_g(g_n)\nu_g(g_n)}, & \text{if } T_w \geq 0 \\ \frac{T_w \cdot \eta_g(g_n)}{\nu_g(g_n)}, & \text{if } T_w < 0 \end{cases} \tag{3}$$

where the case with $T_w \geq 0$ represents the powertrain propelling the vehicle while $T_w < 0$ represents braking according to the sign criteria defined in figure 1. The torque coupler divides the required torque using the following balance:

$$T_g = T_{ICE} + T_M \tag{4}$$

Then, the fuel quantity ($\dot{m}_f$) can be computed from the engine torque and speed with a map based on experimental data:

$$\dot{m}_f = \begin{cases} f_{ICE}(T_{ICE}, \omega_g), & \text{if } T_{ICE} > 0 \\ 0, & \text{if } T_{ICE} \leq 0 \end{cases} \tag{5}$$

The engine is shut-off, if no torque is required, i.e., the clutch is then disengaged and the injection is stopped. The electric motor is also modelled using quasi-static approach where the power of electric motor is modelled as an experimentally identified function of torque and speed.

$$P_{el} = f_M(T_M, \omega_g) \tag{6}$$

The battery is modelled with an electrically equivalent circuit consisting on a voltage source and a resistance, so:

$$V_b = V_0 + R.I_b \tag{7}$$

where V_b is the battery voltage, V_0 is the battery open circuit voltage. R is the internal resistance of the battery depending on the SoC and I_b is the battery current that can be computed from the electrical power demand (P_{el}) as:

$$I_b = \frac{V_0 - \sqrt{V_0^2 - 4.R.P_{el}}}{2.R} \tag{8}$$

Provided the battery voltage and current, the discharging power of the battery becomes:

$$P_b = V_b I_b \tag{9}$$

and the SoC in the battery will evolve as:

$$S\dot{o}C = -\frac{I_b}{C_b} \tag{10}$$

with C_b the battery capacity.

Note that in the current approach, provided that the torque demand (T_g) can be obtained from the vehicle speed prediction, the engine torque will be the only control variable (u):

$$u = T_{ICE} \tag{11}$$

while the only model state (x) is SoC :

$$x = SoC \tag{12}$$

and making use of equations 4 6-10 its dynamics can be expressed as:

$$\dot{x} = -\frac{V_0(x) - \sqrt{V_0(x)^2 - 4R(x) f_M(T_g(v, \dot{v}, \gamma) - u, \omega_g)}}{2R(x)C_b} \tag{13}$$

that only depends on the control action (u), disturbances such as vehicle speed, acceleration and road profile ($v, \dot{v}, \gamma$) and the state itself (x).

4. Problem formulation and proposed solution

The problem previously described fits perfectly in the field of Optimal Control, as the extensive literature on EMS shows [34, 35, 36]. The associated OC Problem can be written as:

$$\begin{cases} \arg\min_u \int_0^\tau \dot{m}_f(u,v)dt \\ \dot{x} = g(x,u,v,\dot{v},\gamma) \\ h(x,u,v,\dot{v},\gamma) \leq 0 \end{cases} \tag{14}$$

where, for the sake of readability, the explicit dependence of the variables on time has been omitted, τ is the driving cycle duration, g is a function describing the state dynamics (equation 13) and h represents the local constraints imposed on the state and control variables in order to guarantee the physical operation limits (maximum and minimum limits on battery SoC and power, speed and torque of powertrain elements).

Regarding the solution of system 14, one can observe that provided the dependence on $\tau, v, \dot{v}$ and γ a proper estimation of such parameters is needed. In fact, the optimal solution of the problem can only be obtained if perfect knowledge of the driving cycle is available. Assuming a suitable approximation of those variables, there is a wide set of solutions in literature consolidated by the authors in [37]. Amongst them, those derived from the ECMS are widespread since provide a feasible on-board application. The ECMS is aimed to replace the integral problem presented in equation 14 with a set of equivalent problems to be solved at every time step:

$$J = P_f + \mu P_b \tag{15}$$

where the parameter μ, is a weighting factor between fuel and battery energy sources. An analytical derivation of the ECMS can be obtained from the Pontryagin's Minimum Principle [38], in any case, intuition shows that a penalty on the battery use should be included in the cost function to avoid its depletion. The selection of the proper value of μ depending on the driving conditions is the key aspect of the ECMS. Provided a driving cycle ($\tau, v, \dot{v}$ and γ) the value of μ that fulfils with constraints in problem 14, and particularly the limitations in SoC.

According to suitability of the ECMS method and the requirement of a driving cycle estimation, the proposed controller is presented in figure 2.

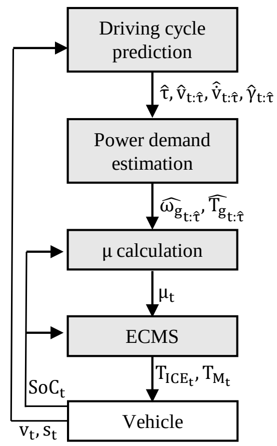

Figure 2: Proposed control architecture where s_t is the current vehicle position, $\hat{}$ represents an estimated variable and subindex $t : \hat{\tau}$ represent the evolution from current time (t) to the estimated end of the cycle ($\hat{\tau}$)

The prediction block uses the current vehicle position (s_t) and speed (v_t) to estimate the driving cycle main parameters, consisting on the duration $\hat{\tau} - t$, vehicle speed and acceleration sequences ($\hat{v}_{t:\hat{\tau}}$ and $\hat{\dot{v}}_{t:\hat{\tau}}$) and estimated road slope evolution during the cycle ($\hat{\gamma}_{t:\hat{\tau}}$). The prediction block is based on the previous work by the authors in [39, 40]. The process starts recording instantaneous vehicle velocity on a real vehicle during several trips on a particular route. Then, in order to take into account the particularities of driving conditions depending on the vehicle position, e.g. differences between urban and highway driving, the obtained velocity profiles are divided into several segments, in the case at hand with 1km length. Short driving cycles obtained for each segment are used to model the vehicle speed as a Markov process, where the vehicle speed is considered a random process (V) satisfying:

$$
\begin{aligned}
P(V_{n+1} = v_{n+1} | V_1 = v_1, V_2 = v_2, \ldots, V_n = v_n) \\
= P(V_{n+1} = v_{n+1} | V_n = v_n)
\end{aligned}
\tag{16}
$$

where v_j represent possible values of V, subindex n is the present time, $n+1$ represents some point in the future and subindex $1, 2, ..., n-1$ points in the past. Equation 16 states that given the present state ($V_n = v_n$) the probability for this random process for the next future ($V_{n+1} = v_{n+1}$) is independent of the past. In this sense, estimating the transmission matrix can be done by observing the sequences of states and the frequency in the transitions between them. For practical reasons, the data has been discretised in steps of 1 km/h in velocity. Let $N_{i,j}$ the number of times the vehicle speed is i in a given time ($V_{n+1} = i$) provided that was j in the previous instant ($V_n = j$). The probability of being in state i given that it was in state j in the previous time can be estimated as:

$$P(V_{n+1} = i | V_n = j) = p_{ij} = \frac{N_{ij}}{\sum_j N_{ij}} \tag{17}$$

where p_{ij} is introduced for the sake of brevity. In this sense, expression 17 allows to estimate a transition matrix by counting the transitions that have occurred in the previously recorded driving cycles, on the same interval of the route. Once the TPMs have been built, the vehicle position within the route is used to choose the corresponding TPM. After identification, the Cumulative Probability Function (CPF) is constructed by integrating TPM rows. Then at every time-step, the next vehicle speed is selected generating a random number between 0 and 1 ($r \in [0, 1]$) choosing the vehicle speed whose CPF is equal to this random number r. The integration of the vehicle speed allows to compute the next vehicle position in the route, which is used to estimate the road slope and identify the next TPM to be used. The process will be repeated in time until the vehicle destiny is reached. The detailed description of the synthesis process is presented in Figure 3.

Note that the availability of the current vehicle position requires a tracking device, e.g. GPS. On the other hand, the estimation of the road profile needs cartographic information and the specification of the route in order to compute the road slope by interpolating the estimated position obtained from integration of $\hat{v}_{t:\hat{\tau}}$.

Once the driving cycle is estimated, the power demand block calculates the

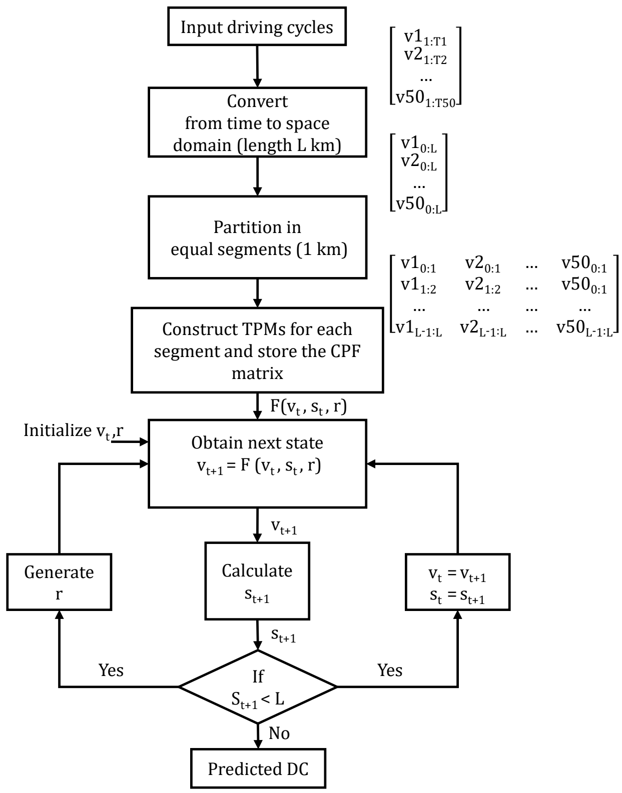

Figure 3: Driving cycle prediction method

desired torque and speed based on the model described in section 3 using $\hat{\tau}$, $\hat{v}_{t:\hat{\tau}}$, $\hat{\dot{v}}_{t:\hat{\tau}}$ and $\hat{\gamma}_{t:\hat{\tau}}$.

The inputs to the μ calculation block are the estimated torque and speed vectors ($\hat{T}_{g_{t:\hat{\tau}}}$ and $\hat{\omega}_{g_{t:\hat{\tau}}}$) and the current SoC ($SoC_t$). The optimal μ in the sense of that leading to minimum SoC at the end of the estimated driving cycle is iteratively calculated, in the case at hand by bisection method. Note that the condition of minimum SoC at the end of the cycle is chosen since due to the plug-in nature of the vehicle the fuel consumption is minimised at this condition. In any case, the target SoC can be modified adding a new calibration parameter to the control strategy or considering the initial SoC to assure the change sustainability in the case of a non-plug-in HEV. The calculated μ is applied during a predefined control horizon (CHW), where the ECMS block calculates the optimal torque split between the ICE and the Electric motor at every time-step. The CHW is a sliding distance window whose size decides the frequency at which the μ is updated during the trip in order to compensate the deviations in the SoC due to driving cycle estimation errors. In the present work a 1 km CHW is used to avoid excessive computation cost.

5. Experimental set-up

The experimental validation of the proposed EMS has been carried out in an engine test bench by means of an engine-in-the-loop approach. In particular, a Diesel engine with specifications as in table 2 has been tested while rest of the powertrain characteristics are presented in table 1 has been simulated. To this aim, the engine is coupled to an asynchronous Horiba DYNAS 3 dyno which is controlled with a Horiba SPARC through the PC interface Horiba STARS. The dyno is able to perform steady-state and transient tests to simulate the engine behaviour in real driving missions. The test bench is equipped with a dSpace Microauto164 box II that simulates the HEV powertrain and interacts with the dyno by means of modifying the engine throttle to follow the torque demand from the EMS. The dSpace system interfaces with Matlab/Simulink where the complete powertrain can be simulated by implementing forward versions of the models described in section 3, and the EMS described in section 4 is programmed.

The experimental scheme followed to simulate the HEV behaviour is depicted in figure 4. The actual vehicle speed, acceleration and road grade from the driving cycle is used by the powertrain model to compute the torque and speed demand (T_{g_t} and ω_{g_t}), which is used as input for the ECMS with the SoC from the battery model and the weighting factor μ coming from the corresponding block described by figure 2. The ECMS will choose the engine demanded torque ($T^0_{ICE_t}$) and the corresponding motor torque ($T^0_{M_t}$) that minimises equation 15 while satisfying the torque demand. A map-based engine model is able to apply

Stroke x Bore[mm]	84.8 x 75
Displacement[cc]	1498
Compression ratio	16:1
Number of Cyl.	Inline 4
Valves per Cyl.	4
Rated Torque	300Nm @ 1750rpm
Emission std.	Euro 6

Table 2: Engine specification.

the throttle according to the engine desired operating conditions ($T^0_{ICE_t}, \omega_{g_t}$). The calculated throttle is applied to the engine, which is turning at ω_{g_t} as imposed to the dyno. Of course, the engine will produce a torque (T_{ICE_t}) that will not exactly correspond to the desired value ($T^0_{ICE_t}$). It has been assumed that the electric motor will be able to absorb the deviations from the desired engine torque (ΔT_{ICE_t}) instantaneously, which is a feasible hypothesis since the characteristic time of the motor and battery is substantially lower than that of the engine. This approach allows comparing different EMS approaches with exactly the same driving cycle, note that without this hypothesis, i.e. if the motor is not able to absorb engine torque deviations, those deviations will lead to variations in the speed that finally will affect the driving cycle. In this sense, the torque measured in the test bench is used as feedback for the simulation environment and small deviations from the demanded engine torque are assumed to be absorbed by the motor, leading to modifications in the battery SoC.

Regarding the engine instrumentation, specific sensors for temperatures, pressures, flows and pollutant emissions have been used along the air and fuel path. Specially important are the open Electronic Control Unit (ECU) allowing registering engine variables and eventually modify its control, and the fuel balance FQ2100 .

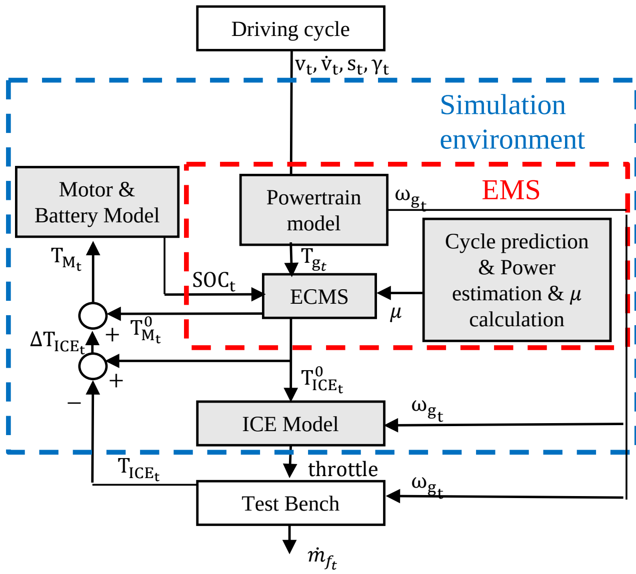

Figure 4: Hardware-in-the-loop architecture to test the EMS in an engine test bench.

6. Results

In order to compare the performance of the proposed EMS with other alternatives, a benchmark considering the following candidates has been done:

- CD-CS: The standard, Charge Depleting - Charge Sustaining strategy. For convenience, in CD-CS a low weighting factor μ is employed, from the beginning of the driving cycle until the battery SoC reaches the minimum value and then μ is increased or decreased online to keep the SoC as constant as possible.

- ACP + ECMS (Average Cycle Prediction + ECMS): The driving cycle is not known in advance however, as the considered route has been previously covered 50 times, the average vehicle speed at every point of the route (represented by black line in 5) is used as an estimation of the driving cycle to feed the power demand estimation block in 2, then calculate μ and apply the ECMS. The value of μ is updated after a given space window (1 km) to make up for deviations in the SoC.

- MCP + ECMS (Markov based Cycle Prediction + ECMS): The driving cycle is not known in advance and the method proposed in 4 is used following all the steps in figure 3. Several predicted vehicle speed profiles are presented by the gray lines in figure 5.

- Optimal (Equivalent Consumption Minimisation Strategy): The driving cycle is known in advance and an optimal weighting factor (μ) is applied during the complete driving cycle to minimise fuel consumption with a constraint in the minimum SoC.

The predicted vehicle speeds using the MC based method and the average of the registered speeds is shown in figure 5.

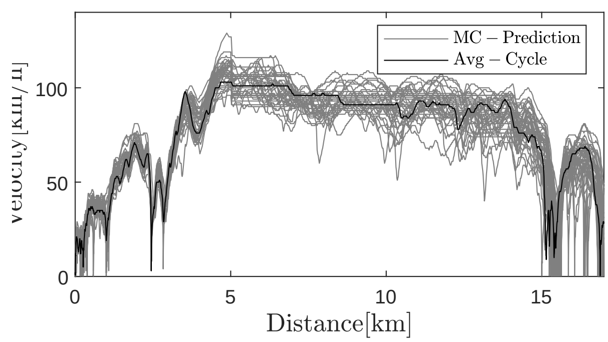

Figure 5: Real driving missions

In order to assess the performance of the proposed control strategy in a wide set of scenarios, a simulation campaign using forward versions of the powertrain model presented in section 3 is performed. The trade-off between fuel consumption and terminal SoC for 50 driving cycles using each strategy is presented in figure 6. The target terminal SoC is 0.15 $\pm$ 0.05 for each strategy. The dispersion of the fuel consumption for the similar value of the terminal SoC for each strategy is presented in 7. It can be noticed that the MCP+ECMS strategy is nearest and CD-CS is farthest from the optimal; hence proving the potential of the current intervention. The performance of CD-CS which does not take into account any prediction is inferior to the other two prediction based methods (MCP and ACP).

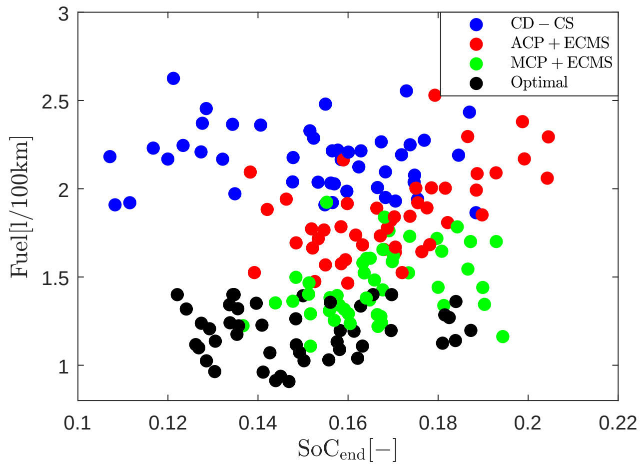

Figure 6: Simulation based validation, the black dots represents the optimal results of all the driving cycle, blue dots represents the charge depleting charge sustaining strategy, red dots represents the results with average cycle prediction strategy and gray dots are with the proposed Markov chain based driving cycle prediction method.

Then, a verification of the method suitability is done experimentally on the test cell described in section 5. A single driving cycle has been chosen to confirm the modelling results previously discussed. Figure 8 shows the driving cycle (vehicle speed and gear) in the top plot, the evolution of μ and SoC with the tested strategies in the central plots, and the accumulated fuel consumption in the bottom plot. One can observe how knowing the driving cycle in advance (Optimal) allows to choose a constant weighting factor μ between fuel and battery energy that allows the ECMS to obtain the minimum fuel consumption fulfilling with the constraint in minimum SoC of 0.15. Of course, the solution that minimises fuel consumption leads to the minimum SoC when the vehicle reaches the destiny and can be potentially recharged. On the opposite side, CD|CS leads to a substantial fuel increase despite fulfilling with the SoC constraint. It is clear that CD|CS depletes the battery too early providing noticeable fuel savings in

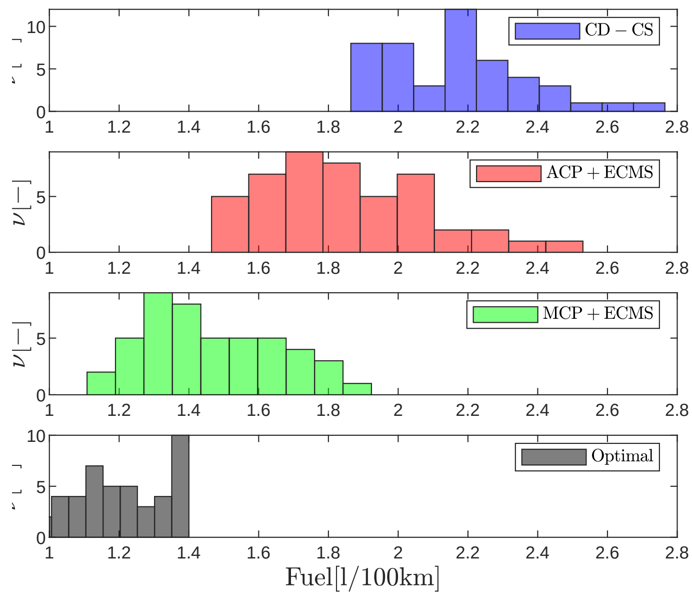

Figure 7: Frequency of fuel consumption for simulations of 50 driving cycle using different EMS

the first part of the cycle (until second 600) approximately but an excessive penalty in the last phase of the cycle. Regarding MCP + ECMS, it can be observed how the filtering due to driving cycle averaging leads to a smooth estimated driving cycle with too low dynamics, and this fact leads to a noticeable deviation from the optimal results despite it still improves the results compared to the CD|CS strategy, which at some point shows that despite being vague, the average driving cycle provides some description of the actual driving cycle. Finally, the proposed strategy leads to the nearest results to the optimal solution due to the better description of the driving cycle offered by the Markov based driving cycle estimator.

As a summary, figure 9 shows the Pareto front obtained by several driving cycles applying constant μ with a priori knowledge of the cycle, and the rest of EMS considered. Provided the same SoC at the end of driving cycle, the fuel consumption in CD — CS , ACP+ECMS and MCP+ECMS is 52%, 35% and

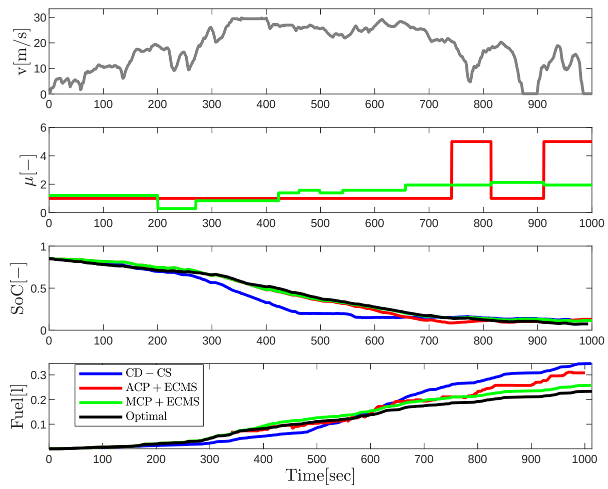

Figure 8: Evolution of experimental results in the considered driving cycle with four EMSs

11% higher than the optimal.

In 10, the engine operating points are presented overlapping the efficiency map for the entire trip using four strategies. The black dots in figure represent the engine operating points in each scenario. The patches mark the boundary of operating points for each scenario. Clearly, in the case of optimal strategy the engine operates largely in the high efficiency zone. In MCP + ECMS the patch area is smaller in comparison with CD − CS and ACP + ECMS

7. Conclusion and outlook

In a real driving mission the uncertainty in speed profiles lead to suboptimal energy management strategy in the pHEV. A new method based on the online speed prediction and adaptive ECMS is proposed to optimise the EMS while keeping the battery SoC close the target. The objective is to minimise the fuel consumption while staying close to the desired terminal SoC for a real driving mission. The developed method uses Markov based driving cycle prediction method to adapt the equivalent factor based on the current SoC and the vehicle

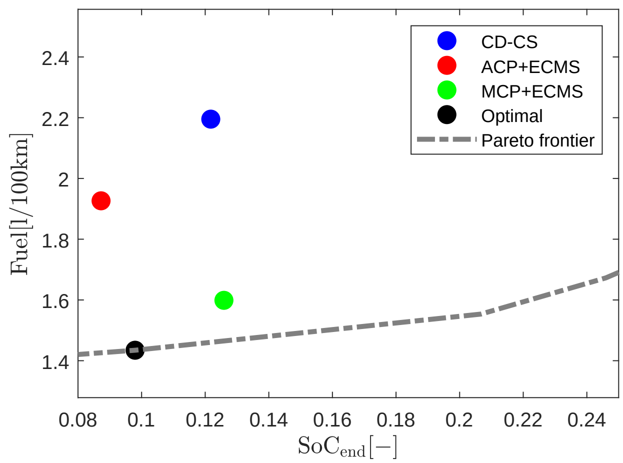

Figure 9: Experimental Validation, the gray line is the Pareto frontier, while blue, green, red and black dots represents results obtained with four EMSs

position. The method is validated using a simulation and an experiment based case study on two real driving missions. The experiments were conducted on an engine test bench with the help of vehicle model (Matlab/Simulink) in dSPACE environment. The developed method is compared with the three state-of-the-art methods: The ECMS (offline approach), Adaptive ECMS (online approach) and the Charge depleting strategy (online approach). The results from the developed online method show significant improvement in the fuel consumption as compared to the Adaptive ECMS and the Charge depleting strategy. As compared to the offline method, where the driving mission is known in advance the fuel consumption is 11% higher in the developed method which is an improvement if compared with the other two real-time applicable strategies.

The developed method is a step towards an optimal online control of the complex HEV energy management strategy. It allows taking into account driving cycle characteristics depending on vehicle position and update the EF accordingly. The proposed method can be extended to other HEV architectures and in future can be tested on the real vehicle which is commuting regularly between two destinations.

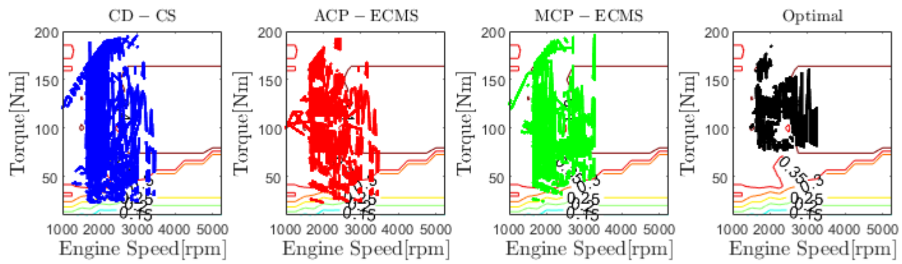

Figure 10: Engine operating points overlapping the engine efficiency maps for four methods during experimental campaign

References

[1] A. Sciarretta, L. Guzzella, Control of hybrid electric vehicles, IEEE Control Systems 27 (2) (2007) 60–70. doi:10.1109/mcs.2007.338280.

[2] T. Markel, Plug-in hybrid electric vehiclescurrent status, long-term prospects and key challenges, Tech. rep., National Renewable Energy Laboratory (8 May 2006).

[3] X. Lü, Y. Wu, J. Lian, Y. Zhang, C. Chen, P. Wang, L. Meng, Energy management of hybrid electric vehicles: A review of energy optimization of fuel cell hybrid power system based on genetic algorithm, Energy Conversion and Management 205 (2020) 112474. doi:10.1016/j.enconman.2020.112474.

[4] K. Ç. Bayindir, M. A. Gözüküçük, A. Teke, A comprehensive overview of hybrid electric vehicle: Powertrain configurations, powertrain control techniques and electronic control units, Energy Conversion and Management 52 (2) (2011) 1305–1313. doi:10.1016/j.enconman.2010.09.028.

[5] H. Dong, J. Fu, Z. Zhao, Q. Liu, Y. Li, J. Liu, A comparative study on the energy flow of a conventional gasoline-powered vehicle and a new dual clutch parallel-series plug-in hybrid electric vehicle under NEDC, En-

ergy Conversion and Management 218 (2020) 113019. doi:10.1016/j.enconman.2020.113019.

[6] D.-D. Tran, M. Vafaeipour, M. E. Baghdadi, R. Barrero, J. V. Mierlo, O. Hegazy, Thorough state-of-the-art analysis of electric and hybrid vehicle powertrains: Topologies and integrated energy management strategies, Renewable and Sustainable Energy Reviews 119 (2020) 109596. doi:10.1016/j.rser.2019.109596.

[7] T. H. Bradley, A. A. Frank, Design, demonstrations and sustainability impact assessments for plug-in hybrid electric vehicles, Renewable and Sustainable Energy Reviews 13 (1) (2009) 115–128. doi:10.1016/j.rser.2007.05.003.

[8] L. Guzzella, A. Sciarretta, Vehicle Propulsion Systems. Introduction to Modeling and Optimization,, Berlin:Springer-Verlag, pp. 190, 2005.

[9] S. J. Moura, H. K. Fathy, D. S. Callaway, J. L. Stein, A stochastic optimal control approach for power management in plug-in hybrid electric vehicles, IEEE Transactions on Control Systems Technology 19 (3) (2011) 545–555. doi:10.1109/tcst.2010.2043736.

[10] Q. Gong, Y. Li, Z.-R. Peng, Trip-based optimal power management of plug-in hybrid electric vehicles, IEEE Transactions on Vehicular Technology 57 (6) (2008) 3393–3401. doi:10.1109/tvt.2008.921622.

[11] B. Duan, Q. Wang, X. Zeng, Y. Gong, D. Song, J. Wang, Calibration methodology for energy management system of a plug-in hybrid electric vehicle, Energy Conversion and Management 136 (2017) 240–248. doi:10.1016/j.enconman.2016.12.068.

[12] Q. Gong, Y. Li, Z.-R. Peng, Trip based power management of plug-in hybrid electric vehicle with two-scale dynamic programming, in: 2007 IEEE Vehicle Power and Propulsion Conference, IEEE, 2007. doi:10.1109/vppc.2007.4544089.

[13] N. W. Kim, D. H. Lee, C. Zheng, C. Shin, H. Seo, S. W. Cha, Realization of pmp-based control for hybrid electric vehicles in a backward-looking simulation, International Journal of Automotive Technology 15 (4) (2014) 625–635. doi:10.1007/s12239-014-0065-z.

[14] G. Paganelli, T. M. Guerra, S. Delprat, J.-J. Santin, M. Delhom, E. Combes, Simulation and assessment of power control strategies for a parallel hybrid car, Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering 214 (7) (2000) 705–717. doi:10.1243/0954407001527583.

[15] L. Johannesson, M. Asbogard, B. Egardt, Assessing the potential of predictive control for hybrid vehicle powertrains using stochastic dynamic programming, IEEE Transactions on Intelligent Transportation Systems 8 (1) (2007) 71–83. doi:10.1109/tits.2006.884887.

[16] P. Tulpule, V. Marano, G. Rizzoni, Effect of traffic, road and weather information on PHEV energy management, in: SAE Technical Paper Series, SAE International, 2011. doi:10.4271/2011-24-0162.

[17] S. Onori, L. Serrao, G. Rizzoni, Adaptive optimal supervisory control methods, in: SpringerBriefs in Electrical and Computer Engineering, Springer London, 2015, pp. 79–87. doi:10.1007/978-1-4471-6781-5_7.

[18] Z. Lei, D. Qin, L. Hou, J. Peng, Y. Liu, Z. Chen, An adaptive equivalent consumption minimization strategy for plug-in hybrid electric vehicles based on traffic information, Energy 190 (2020) 116409. doi:10.1016/j.energy.2019.116409.

[19] F. Payri, C. Guardiola, B. Pla, D. Blanco-Rodriguez, A stochastic method for the energy management in hybrid electric vehicles, Control Engineering Practice 29 (2014) 257–265. doi:10.1016/j.conengprac.2014.01.004.

[20] Y. Yu, , J. Jiang, P. Wang, J. Li, A-EMCS for PHEV based on real-time driving cycle prediction and personalized travel characteristics, Math-

ematical Biosciences and Engineering 17 (6) (2020) 6310–6341. doi:10.3934/mbe.2020333.

[21] A. Sciarretta, M. Back, L. Guzzella, Optimal control of parallel hybrid electric vehicles, IEEE Transactions on Control Systems Technology 12 (3) (2004) 352–363. doi:10.1109/tcst.2004.824312.

[22] D. Ambuhl, L. Guzzella, Predictive reference signal generator for hybrid electric vehicles, IEEE Transactions on Vehicular Technology 58 (9) (2009) 4730–4740. doi:10.1109/tvt.2009.2027709.

[23] S. Xie, X. Hu, Z. Xin, L. Li, Time-efficient stochastic model predictive energy management for a plug-in hybrid electric bus with an adaptive reference state-of-charge advisory, IEEE Transactions on Vehicular Technology 67 (7) (2018) 5671–5682. doi:10.1109/tvt.2018.2798662.

[24] C. Sun, F. Sun, H. He, Investigating adaptive-ECMS with velocity forecast ability for hybrid electric vehicles, Applied Energy 185 (2017) 1644–1653. doi:10.1016/j.apenergy.2016.02.026.

[25] C. Guardiola, B. Pla, D. Blanco-Rodríguez, A. Reig, Modelling driving behaviour and its impact on the energy management problem in hybrid electric vehicles, International Journal of Computer Mathematics 91 (1) (2013) 147–156. doi:10.1080/00207160.2013.829567.

[26] F. Payri, C. Guardiola, B. Pla, D. Blanco-Rodriguez, On a stochastic approach of the (ecms) method for energy management in hybrid electric vehicles, IFAC Proceedings Volumes 45 (30) (2012) 341–348. doi:10.3182/20121023-3-fr-4025.00041.

[27] B. Gu, G. Rizzoni, An adaptive algorithm for hybrid electric vehicle energy management based on driving pattern recognition, in: Dynamic Systems and Control, Parts A and B, ASMEDC, 2006. doi:10.1115/imece2006-13951.

[28] S. il Jeon, S. tae Jo, Y. il Park, J. moo Lee, Multi-mode driving control of a parallel hybrid electric vehicle using driving pattern recognition, Journal of Dynamic Systems, Measurement, and Control 124 (1) (2000) 141–149. doi:10.1115/1.1434264.

[29] C. Musardo, G. Rizzoni, Y. Guezennec, B. Staccia, A-ECMS: An adaptive algorithm for hybrid electric vehicle energy management, European Journal of Control 11 (4-5) (2005) 509–524. doi:10.3166/ejc.11.509-524.

[30] G. Rizzoni, L. Guzzella, B. Baumann, Unified modeling of hybrid electric vehicle drivetrains, IEEE/ASME Transactions on Mechatronics 4 (3) (1999) 246–257. doi:10.1109/3516.789683.

[31] X. Li, L. Han, H. Liu, W. Wang, C. Xiang, Real-time optimal energy management strategy for a dual-mode power-split hybrid electric vehicle based on an explicit model predictive control algorithm, Energy 172 (2019) 1161–1178. doi:10.1016/j.energy.2019.01.052.

[32] X. Hu, T. Liu, X. Qi, M. Barth, Reinforcement learning for hybrid and plug-in hybrid electric vehicle energy management: Recent advances and prospects, IEEE Industrial Electronics Magazine 13 (3) (2019) 16–25. doi:10.1109/mie.2019.2913015.

[33] J. Ritzmann, A. Christon, M. Salazar, C. Onder, Fuel-optimal power split and gear selection strategies for a hybrid electric vehicle, in: SAE Technical Paper Series, SAE International, 2019. doi:10.4271/2019-24-0205.

[34] L. Tang, G. Rizzoni, Energy management strategy including battery life optimization for a HEV with a CVT, in: 2016 IEEE Transportation Electrification Conference and Expo, Asia-Pacific (ITEC Asia-Pacific), IEEE, 2016. doi:10.1109/itec-ap.2016.7513014.

[35] Q. Jiang, F. Ossart, C. Marchand, Comparative study of real-time HEV energy management strategies, IEEE Transactions on Vehicular Technology 66 (12) (2017) 10875–10888. doi:10.1109/tvt.2017.2727069.

[36] Y. Du, Y. Zhao, Q. Wang, Y. Zhang, H. Xia, Trip-oriented stochastic optimal energy management strategy for plug-in hybrid electric bus, Energy 115 (2016) 1259–1271. doi:10.1016/j.energy.2016.09.056.

[37] F. Zhang, L. Wang, S. Coskun, H. Pang, Y. Cui, J. Xi, Energy management strategies for hybrid electric vehicles: Review, classification, comparison, and outlook, Energies 13 (13) (2020) 3352. doi:10.3390/en13133352.

[38] L. Serrao, S. Onori, G. Rizzoni, ECMS as a realization of pontryagins minimum principle for HEV control, in: 2009 American Control Conference, IEEE, 2009. doi:10.1109/acc.2009.5160628.

[39] J. M. Luján, C. Guardiola, B. Pla, V. Pandey, Impact of driving dynamics in RDE test on NOx emissions dispersion, Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering 234 (6) (2019) 1770–1778. doi:10.1177/0954407019881581.

[40] J. M. Luján, B. Pla, P. Bares, V. Pandey, Adaptive calibration of diesel engine injection for minimising fuel consumption with constrained NOx emissions in actual driving missions, International Journal of Engine Research (2020) 146808742091880doi:10.1177/1468087420918800.