PHIL Implementation of Energy Management Optimization for a Parallel HEV on a Predefined Route

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Abstract—Real-time energy management of HEVs is a key point for performing effective fuel economy optimization. Offline methods have been developed for energy management optimization when the drive cycle is known. Online real-time methods can provide good results but can only ensure suboptimal management. In this study it is assumed that information about the route is available in advance. Using this knowledge, global optimization methods can be used in real-time control to approach optimal fuel consumption while keeping the SOC of the batteries at a desired level. Such a method is presented in this paper. The developed strategy is implemented in a real time experiment using the Power Hardware-In-the-Loop principle. Measured fuel consumption and the obtained battery SOC trajectory demonstrate good performance of the proposed control.

Index terms - Hybrid Electric Vehicle, energy management, Fuel consumption, optimization, PHIL.

I. INTRODUCTION

Hybrid Electric Vehicles (HEVs) represent an effective solution to reduce consumption of fossil fuels and CO2 emissions. Several hybrid configurations with different hybridization ratios are possible and can operate in battery charge sustaining mode or in charge depleting mode for Plug-in Hybrid (PHEV). Consequently, a large number of solutions should be investigated and optimized. Energy management of these vehicles is an important issue and should provide the most efficient instantaneous power split between the Internal Combustion Engine (ICE) and electric motor(s). Using offline computations, the optimality of the energy management according to a criterion (minimum of fuel consumption for example) can be reached when the drive cycle is known.

The best known methods used for this purpose are dynamic programming [1]-[6] and optimal control theory [7, 8]. For real-time control several energy management strategies have been classified into categories in [9], [10] and [11]. Common methods include rule-based methods [12], fuzzy logic controllers [13, 14], intelligent energy management agents [15, 16] and instantaneous optimization such as the Losses Minimization Strategy [17] or the Equivalent Consumption Minimization Strategy [18, 19]. In this work, a real time energy management strategy is developed based on a method that has been proven to give optimal results in offline simulation.

The optimal control theory using Lagrange formulation is a commonly used global optimization method. The advantage of this method is that it only needs one parameter (λ), called the Lagrange multiplier, to be identified. This parameter is computed such that the battery state of charge reaches a specified value at the end of a given drive cycle. The resulting algorithm is an open loop control that achieves optimal energy management for offline applications. However, utilizing this algorithm in real-time control can lead to an uncontrolled battery SOC as the (λ) value is strongly dependent on the driving conditions. Most likely the vehicle will not follow the predefined speed profile for which (λ) was calculated. This would result in a deviation of the battery state of charge from the optimal trajectory and might reach unacceptable values. It is therefore necessary to modify this algorithm to obtain a closed loop control of the battery state of charge.

In this work, it is assumed that the route is known in advance. For this particular case of an HEV following a predefined trip a closed loop optimal control is obtained by using a fast online estimation of (λ). This estimation relies on the knowledge of route information and the actual battery state of charge. The resulting algorithm has a low computation cost since a part of the energy management controls can be computed offline. Dynamic programming is an alternative method that can be adapted online in a stochastic approach as reported in [20, 21]. However, we believe it requires higher computational effort.

In order to experimentally validate the proposed control method, a PHIL (Power Hardware In the Loop) technique is used. This approach uses real-time simulation of parts of the vehicle (chassis and gear box), while other key components such as batteries and the ICE are physically tested. This can be considered as a further step after the offline simulation in order to demonstrate the effectiveness of the energy management algorithm.

In this paper, an online energy management strategy based on optimal control theory is developed and adapted.
The goal is to find the control action \( \alpha(i) \) at the engine state to obtain the torque at the wheel \( T_w(i) \) and the state of the engine \( \phi(i) \). As a consequence, \( \omega_v(i) \) and \( T_w(i) \) being known, it is sufficient to set a value for \( T_e(i) \) and \( k(i) \) to define the operation of the entire powertrain: \( T_e(i) \) is deduced from (2), \( \omega_v(i) \) and \( \omega_e(i) \) are obtained using (1). Therefore, all the global optimization algorithms and real time control strategies will be formulated using only \( T_e(i), k(i) \) and \( \phi(i) \) (the engine state) as the control variables.

### III. GLOBAL OPTIMIZATION FOR ENERGY MANAGEMENT

#### A. Principle

To formulate the global optimization problem, the driving conditions \( \{T_e(i), \omega_e(i)\} \) have to be known over a finite time horizon \( N: i \in [0, N-1] \). The goal is to find the control actions (engine torque \( T_e \) and gear number \( k \)) of the hybrid power train, for each sampling time \( i \), in order to minimize a criterion, here the fuel consumption over the drive cycle:

\[
\min_{T_e, k} J = \sum_{i=0}^{N-1} C_f(T_e(i), k(i))
\]

Where:

- \( C_f \) is the fuel consumption function.
- \( T_e \) is the engine torque.
- \( k \) is the gear number.

#### B. Optimization Algorithm

The optimization problem is solved using a genetic algorithm. The algorithm is implemented in a real-time in a PHIL setting. The paper is organized as follows: In Section II the vehicle under consideration is presented. The third section describes the global optimization of the energy management method. Section IV shows the theoretical aspect of the proposed online control method and Section V presents the PHIL configuration and the test bench used for experiments. Experimental results are presented and discussed in Section VI.
The cost function then becomes
\[
\min J = \sum_{i=0}^{N-1} D(k(i), T_r(i)) \cdot \theta(i) \cdot \Delta
\]

where \( D(k(i), T_r(i)) \) is the fuel flow (in g/s) required to propel the vehicle at the speed \( \omega_e(i) \) with torque \( T_e(i) \) applying the control inputs \( k(i) \) and \( T_r(i) \). \( D(k(i), T_r(i)) \) is easily derived from the fuel consumption map with \( T_r \) and \( \omega_e \), using relations (1)-(2).

The battery is considered as a dynamic system with \( x(i) \) representing the remaining energy stored in the battery (in the following also referred to state of energy \( \text{Soe} \)), given by
\[
x(i+1) = x(i) - P_{\text{bat}}(k(i), T_r(i), \theta(i)) \cdot \Delta
\]

with \( P_{\text{bat}}(k(i), T_r(i), \theta(i)) \) being the power delivered by the battery (including battery losses) to ensure driving conditions \( (\omega_e(i), T_r(i)) \) with the control values \( (k(i), T_r(i)) \). \( P_{\text{bat}}(k(i), T_r(i), \theta(i)) \) is calculated using the electric motor efficiency map and a simple battery model.

The total power provided by the battery is therefore computed by
\[
P_{\text{bat}} = E_{\text{bat}} \cdot I_{\text{bat}} = T_e \cdot \omega_e + LM(T_e, \omega_e) + R_{\text{bat}} \cdot I_{\text{bat}}^2
\]

where \( LM(T_e, \omega_e) \) represents the loss in the electric motor and its inverter, \( R_{\text{bat}} \) is the battery internal resistance, \( E_{\text{bat}} \) is the battery open circuit voltage and \( I_{\text{bat}} \) represents the battery current.

The equation above is then solved as a second order equation to find the battery current for a given motor operating point. \( P_{\text{bat}} \) can be written as follows:
\[
P_{\text{bat}} = \frac{E_{\text{bat}}}{2R_{\text{bat}}} (E_{\text{bat}} - \sqrt{E_{\text{bat}}^2 - 4R_{\text{bat}}^2 (T_e \cdot \omega_e + LM(T_e, \omega_e))})
\]

Using (1) and (2), the battery power map can be expressed for a given vehicle operating point \( (\omega_e(i), T_r(i)) \).

To minimize criterion (3), one may choose the obvious solution \( T_r(i) = T_{\text{min}}(i) \quad \forall i = 0..N-1 \) that results in the minimum fuel consumption but leads to a full battery discharge as well. To avoid this solution, a state of energy constraint has to be considered:
\[
x(N-1) = x(0) + \Delta \text{Soe}
\]

With \( \Delta \text{Soe} \) a desired state of energy variation over the whole drive cycle.

Note concerning the state of charge (SOC) and the state of energy (SoE) in a battery:

The state of charge (SOC) is generally used as the indicator of the battery state. The state of charge SOC (in %), used in this paper, is defined as:
\[
\text{SOC} = \frac{-100}{3600 \cdot C_{\text{bat}}} \int \eta_e I_{\text{bat}} dt
\]

Where \( I_{\text{bat}} \) is the battery current, positive in discharge mode, \( \eta_e \) is the Faraday efficiency, and \( C_{\text{bat}} \) the nominal battery capacity in Amps-hours.

The Faraday efficiency is considered only in charge mode in order to take into account the fact that not all the charges entering the battery will be available. It can either be considered as constant (0.95 in our paper) or depending on SOC.

It is also noted that regarding equation (7) and equation (4), a SOC constraint can be related to a SoE constraint and expressed according to the state variable (x):
\[
\Delta \text{Soe} = g(\Delta x) \quad \Delta \text{Soe} = g^{-1}(\Delta \text{Soe})
\]

Throughout this paper we chose to use the SOC to represent the different results while solving the optimization problem using SoE as the state variable.

An interesting and particular case is \( \Delta \text{Soe} = 0 \) for which the vehicle propelling is only due to the energy drawn from the fuel. In this case, the battery is only used as a temporary energy buffer.

The resulting optimization problem can be written as:

Criterion: \( \min J = \sum_{i=0}^{N-1} D(k(i), T_r(i)) \cdot \theta(i) \cdot \Delta \)

Constraints: \( (k(i), T_r(i), \theta(i)) \in \Omega \)
\[
x(N-1) = x(0) + \Delta \text{Soe}
\]

With \( \Omega \) the set of admissible values for the controls \( (k(i), T_r(i)) \) given by
\[
\Omega(i) = \left\{ (T_r, k \cdot \theta) \in \mathbb{R} \times \left\{1, \ldots, N_{\theta}\right\} \times \left\{0; 1\right\} / T_{\text{min}}(i) < T_r(i) < T_{\text{max}}(i) \wedge k \in K(i) \right\}
\]

with \( N_{\theta} \) being the number of gears and \( K(i) = \left\{ k(i) \in \left\{1, \ldots, N_{\theta}\right\} / \omega_{\text{min}}(i) \cdot R(k(i)) < \omega_{\text{max}}(i) \wedge \alpha_{\text{min}}(i) < \omega_e(i) \cdot R(k(i)) \cdot \rho < \alpha_{\text{max}}(i) \right\} \)

representing the set of admissible gears at each sample time \( i \).

B. Lagrangian approach

To solve the global optimization problem, two types of methods are commonly used: Dynamic Programming method [2] and the Lagrange approach [7]. As the proposed online control is derived from the Lagrangian approach, the outline of this method is given here. For more information, the reader may refer to [7].

First the dynamics of the system (4) are introduced in the criterion (3) using the Lagrange parameters \( \lambda(i) \). The cost function then becomes
\[
\min J = \sum_{i=0}^{N-1} D(k(i), T_r(i)) \cdot \theta(i) \cdot \Delta - \sum_{i=0}^{N-1} \lambda(i) \left( x(i+1) - x(i) + P_{\text{bat}}(k(i), T_r(i), \theta(i)) \right) \Delta
\]

This represents a modified criterion that takes into account the constraint (5) by introducing an instantaneous weight (Lagrange multiplier) on the state of energy variation.

The modified criterion is minimum when the first partial derivatives of the criterion \( J \) along each axis (state, control, multiplier) are equal to zero for all sample times.

Hence, at each sample time, the optimal control is given by:
\[
\frac{\partial J'}{\partial \hat{\lambda}(i)} = 0 \Leftrightarrow x(i+1) = x(i) - P_{\text{batt}}(k(i), T_i(i), \Theta(i)) \Delta
\]  
(10)

\[
\frac{\partial J'}{\partial x(i)} = 0 \Leftrightarrow \lambda(i-1) - \lambda(i) = 0
\]  
(11)

\[
\frac{\partial J'}{\partial T(i)} = 0
\]  
(12)

\[
\frac{\partial D(k(i), T_i(i), \Theta(i))}{\partial T_i(i)} - \lambda(i) \frac{\partial P_{\text{batt}}(k(i), T_i(i), \Theta(i))}{\partial T_i(i)} = 0
\]  
(13)

The second part of equation (11) (ie. \( \lambda(i-1) - \lambda(i) = 0 \)) is obtained when deriving the \( i \)th and the \((i-1)\)th terms of \( J' \) along \( x(i) \) and under the assumption that \( D \) and \( P_{\text{batt}} \) are independent from \( x(i) \). This equation leads to \( \lambda(i-1) = \lambda(i) \) at each time \( i \) and thus to a constant value \( \hat{\lambda}(0) \) during the whole cycle.

Note: Another formulation of the optimization problem uses an instantaneous function \( H \) (the Hamiltonian) to be minimized and leads to the same solution specified by (11) and (13).

Using an appropriate piecewise second order approximation of the maps \( D(k(i), T_i(i), \Theta(i)) \) and \( P_{\text{batt}}(k(i), T_i(i), \Theta(i)) \), analytic solutions of (13) may be obtained for a given \( \hat{\lambda}(0) \). Figures 2 and 3 show typical values of the fuel flow and battery power maps for a given operating point \((\omega_w = 50 \text{rad/s}, T_e = 500 \text{Nm})\) and for different gear numbers. For each segment \( j \) of the curves, the corresponding approximation can be written as follows:

\[
D_j(k, T_e) = \alpha_j(k) T_e^2 + \beta_j(k) T_e + \gamma_j(k)
\]  
(14)

\[
P_{\text{batt},j}(k, T_e) = \alpha_{j'}(k) T_e^2 + \beta_{j'}(k) T_e + \gamma_{j'}(k)
\]  
(15)

For a given \( \lambda(0) \) the control sequence \( (k(i), T_i(i)) \) that minimizes the criterion \( J' \) may be computed using Equations (13)-(15). A certain drive cycle then results in a specific final state of charge (Recall: fixing the wheel torque and speed together with a known engine operating point specifies battery power). Therefore, given the drive cycle, the overall state of energy variation is only a function of \( \lambda(0) \).

\[
\Delta \text{Soe} = \Delta x = x(N-1) - x(0) = f(\hat{\lambda}(0))
\]  
(16)

However, it is not possible to obtain for all drive cycles an exact analytic expression of \( \hat{\lambda}(0) \) that ensures the state of energy constraint (6). From simulation of several drive cycles (see Figure 6) it was observed that the function \( f(\hat{\lambda}(0)) \) is smooth and monotonic. Therefore the value of \( \hat{\lambda}(0) \) that leads to a desired final state of energy - \( \text{Soe'} \) can be computed numerically using a bisection search method. An algorithm to implement this optimization method in real-time with low computational cost will be presented in the following section.

C. \( \hat{\lambda}(0) \) estimation method

As mentioned above, for a desired final state of energy \( \text{Soe'} \), the \( \hat{\lambda}(0) \) value resulting in optimal control can be found using the bisection method. However, at each search point, optimal control and resulting battery power \( P_{\text{batt}} \) has to be computed, which could be time consuming. In order to overcome this issue the fact that \( P_{\text{batt}} \) is a function of only \( \omega_w, T_e, k \) and \( \hat{\lambda}(0) \) will be used here.

The proposed method consists of two stages which can be seen in Figure 4. The first stage is computed offline. Here, a look-up table of optimal control values of \( P_{\text{batt}} \) as a function of \( \lambda(0), \omega_w, T_e \) and \( k \) is computed. For this purpose the continuous input variables \( \lambda(0), \omega_w \) and \( T_e \) are discretized. In the following this look up table is denoted by \( M(\lambda(0), \omega_w, T_e, k) \). If the optimal control problem is solved for a vehicle with automatic gear box the fourth dimension for different gear values can be omitted. The gear shifting is then included in the process of finding the optimal vehicle operation for a given wheel speed and torque. Figures 5 a) - f) show the shape of \( M \) in a graph where battery power is plotted as a function of wheel speed and wheel torque for different \( \lambda(0) \) values. Graphs a)- c) represent the case of a vehicle with automatic gear box where \( k \) is integrated in the optimization. \( M \) for a vehicle with a manual transmission, where the gear is imposed by the driver, can be seen in graphs d)-f).

In the second stage, which is computed online, the goal is to estimate a value of \( \hat{\lambda}(0) \) that, given the drive cycle, results in the desired \( \Delta \text{Soe'} \) target. This value will be denoted by \( \hat{\lambda}(0) \) and is calculated as follows:

Assuming the drive cycle is known, for a chosen \( \hat{\lambda}(0) \) value, the final state of energy can be computed.
Utilizing the stored matrix $M$, linear interpolation techniques are applied to compute $P_{\text{mat}}$ corresponding to each time step in the cycle.

$$P_{\text{mat}}(\hat{\lambda}(0), \omega_u(i), T_u(j)) = \text{interp}_\text{lin}(M, \hat{\lambda}(0), \omega_u(i), T_u(j))$$ (17)

The final state of energy in the end of the cycle can be calculated by

$$\Delta \text{Soe} = \Delta \lambda(\hat{\lambda}(0)) = \sum_{j=1}^{N_f} P_{\text{mat}}(\hat{\lambda}(0), \omega_u(j), T_u(j)) \Delta$$ (18)

Most likely $\Delta \text{Soe} \neq \Delta \text{Soe}^*$ but a bisection search method can be used to find a $\hat{\lambda}(0)$ such that $\Delta \text{Soe} = \Delta \text{Soe}^*$. Figure 6 shows typical $\Delta \text{Soe}(\hat{\lambda}(0))$ curves for different drive cycles.

Instantaneous expected Soe$^*$ (or Soc) can be calculated as a trajectory over the drive cycle by

$$\text{Soe}^*(i) = \text{Soe}^*(0) - \sum_{j=0}^{i} P_{\text{mat}}(\hat{\lambda}(0), \omega_u(j), T_u(j)) \Delta$$ (19)

This information is used later in real time implementation to trigger the $\hat{\lambda}(0)$ estimation process.

In order to evaluate the developed estimation method a comparison of the described algorithm (Method 2) with the basic Lagrange optimal control strategy (Method 1) is performed. In Figure 7 simulation results of the two methods are shown. In both cases optimal control is applied to the vehicle in off line simulation assuming the drive cycle is known and given the constraint $\Delta \text{Soe}^* = 0$.

The state of charge deviation between Method 1 and Method 2 can be observed in the third plot.

The $\hat{\lambda}(0)$ values and the corresponding $\Delta \text{Soc}$ for the two methods are the following:

Method 1: $\hat{\lambda}(0) = -5.32e-5$, $\Delta \text{Soc} = 0.0\%$

Method 2: $\hat{\lambda}(0) = -5.34e-5$, $\Delta \text{Soc} = 0.5\%$

The instantaneous Soc deviation between the two methods of calculation does not exceed ±0.5 % in this case.
Using the experimental data of several runs over route one and two, the predefined speed profile (PSP) will be defined as a set of wheel speeds and wheel torques \( \left( \omega_w(j), T_w(j) \right) \), \( \forall j = 0, \ldots, N-1 \) where \( N \) is the number of samples. The choice of one among different profiles (such as in Figure 8 and 9) can be made randomly or according to a criterion (the mean profile for example). In the following, the PSP is chosen randomly.

The main idea of the proposed control is to use the PSP as a reference profile in order to estimate an initial value \( \hat{\lambda}(0) \). During real-time use of the vehicle, \( \hat{\lambda}(0) \) is estimated and updated when an event occurs (see Section 4.3).

B. Real time optimization

Let us recall that if the vehicle followed the PSP, it would be possible to predict the necessary value of \( \hat{\lambda}(0) \) to bring the battery state of energy from its initial value \( x(0) \) to a final value \( x_i = x(\tilde{N}-1) \). From Equations (11)-(13)-(18) it can be seen that if the drive cycle is known, at each sample time \( i \), the control is only a function of \( \lambda(0) \). Therefore, the real-time control can be reduced to the identification of the value \( \lambda(0) \) that compensates for the difference between the actual speed profile followed by the vehicle and the PSP.

At some sampling time \( i \), the proposed control strategy consists of updating the value of \( \lambda(0) \) according to:

\[
\Delta Soe = x_i - x(i)
\]

\[
d(i) = \sum_{j=0}^{\lambda(i)} \omega_w(j) \cdot r_w \cdot \Delta
\]

where \( r_w \) is the wheel radius.

The actual speed may differ from the predefined speed \( \omega_w(i) \neq \tilde{\omega}_w(i) \) due to disturbances such that the actual covered distance \( d(i) \) differs from the predefined distance \( d(i) \neq \tilde{d}(i) \)

\[
d(i) = \sum_{j=0}^{\lambda(i)} \omega_w(j) \cdot r_w \cdot \Delta
\]

with the predefined distance \( \tilde{d}(i)=\sum_{j=0}^{\lambda(j)} \omega_w(j) \cdot r_w \cdot \Delta \) at sample time \( i \).

The remaining part of PSP is defined by \( \left( \omega_w(j), T_w(j) \right) \) \( j = j_i, \ldots, \tilde{N} \) where \( j_i \) is given by

\[
d(i) = \tilde{d}(j_i)
\]

The same optimization strategy is applied to the remaining part of PSP:

System: \( \tilde{x}(j+1) = \tilde{x}(j) - P_{\text{real}} \left( j, \tilde{T}, \tilde{k}, \tilde{\theta} \right) \cdot \Delta \)

Criterion:

\[
\min J = \sum_{j=0}^{\lambda(j)} \left[ D(j, \tilde{T}, \tilde{k}, \tilde{\theta}) \cdot \Delta - \hat{\lambda}(j) \cdot \tilde{x}(j+1) - \tilde{x}(j) + P_{\text{real}} \left( j, \tilde{T}, \tilde{k}, \tilde{\theta} \right) \cdot \Delta \right]
\]
Under constraints:
\[ T_{\text{max}}(k(j)) \leq T_s(j) \leq T_{\text{max}}(k(j)) \]
\[ \dot{x}(j) = \kappa(j) \]
\[ x(\hat{N}-1) = x_j \]

When applying the developed algorithm (part 2 of Figure 4) to the remaining part of PSP, one can estimate a new value \( \hat{x}(j) \) that theoretically leads to the desired \( x_j \).

A new predefined state trajectory \( \hat{x} \) is calculated using Equation (19).

C. Real time update of \( \hat{x}(0) \)

In real time implementation \( \hat{x}(0) \) has to be updated in order to control the battery charge. This can be done according to a criterion or after a fixed period of time. To achieve efficient control of the battery \( \text{Soe} \), we choose to update \( \hat{x}(0) \) when the actual value of the state of energy \( \text{Soe}(i) \) differs significantly from the value of the predefined state of energy \( \text{Soe}^*(i) \) i.e.: \[ |x(i) - \hat{x}(i)| > \epsilon, \]
(corresponding to \( |\text{Soe}(i) - \text{Soe}^*(i)| > \epsilon \).

An example of this process is shown in Figure 10. In this case \( \hat{x}(0) \) is updated twice throughout the predefined itinerary.

![Figure 10. Example of \( \hat{x}(0) \) updates during a predefined route](image)

Initially, the \( \hat{x}(0) \) value is estimated using the whole PSP. When the difference between the actual \( \text{Soe} \) (continuous line) and the predefined \( \text{Soe}^* \) (dashed line) reaches the threshold \( \epsilon \), a new value of \( \hat{x} \), \( \hat{x}(j) \), is estimated using the remaining part of PSP. A new \( \text{Soe}^* \) trajectory is calculated with \( x(i) \) as initial value and \( x_j \) as final target. Applying \( \hat{x}(j) \) the real time optimal control leads to a \( \text{Soe} \) profile on the distance between \( d(i) \) and \( d(j) \), which is different from the predefined state of energy profile computed for distance \( d(i) \) to \( d_j \). This is due to a difference between the actual vehicle speed and the PSP. At the distance \( d(i) = \hat{d}(i) \) the error threshold is reached again and a new value \( \hat{x}(j) \) is estimated using the remaining part of the PSP from \( d(i) \) to \( d_j \).

V. PHIL SIMULATION AND CONTROL

In this section, real-time control on a predefined route is implemented using PHIL simulation where some parts of the vehicle are simulated and the others are physically tested.

The experimental test bench is based on a high dynamic load with a maximum power of 120 kW. This load consists of an induction motor/generator (dyno) fed by bidirectional AC/DC DC/AC inverters which develops a torque of \( \pm 250 \) Nm with a high dynamic response (Figure 11). For the considered configuration, the simulated parts are developed under VEHLIB [22, 23] (Figure 12). The reader is referred to [24] for the description of the corresponding models. The tested components under test are:

- the diesel ICE
- the electric storage system
- the electric machine and its inverter
- the clutch.

**Figure 11. Test bench synoptic in the parallel hybrid configuration.**

**Figure 12. All simulation VEHLIB-based model of the parallel Hybrid vehicle.**

Simulink® models of the simulated components are implemented in a real time version of VEHLIB which assures the interface with the measured signals as inputs and control signals as outputs (Figure 11). The PHIL model is
then compiled and executed using the Mathworks® Real Time Workshop (RTW) and DS1005&DS2201 Dspace® configuration.

At each sample time, the driver model gives the reference torque to be provided by the transmission (required wheel torque), using a speed PI controller. Using the energy management strategy (Figure 4), the ICE torque reference \( T_e^* \) and the EM torque reference \( T_m^* \) are calculated. The ICE torque reference is then converted into a throttle demand \( U_{th}^* \) using a map and communicated to the Engine ECU through the real time interface. The EM torque reference is limited in the ECU by the BMS (Battery Management System) using battery current, voltage and temperature measurements. Then the limited torque reference is transmitted to the EM inverter. The \textit{dyno} receives a reference speed corresponding to the calculated primary gear box speed. The observed \textit{dyno} torque (measured torque corrected with \textit{dyno} inertia) is transmitted to the model as the actual primary gear box torque. The clutch control is binary with an imposed dynamic in order to reduce torque variations. The clutch control logic is directly related to the ICE state. In electric mode, where the clutch is disengaged, the clutch position reference \( U_{clutch}^* \) is equal to 1 for a clutch opening. In hybrid mode (engine on) \( U_{clutch}^*=0 \), the clutch has to be engaged.

In this paper, gear shifts optimization is not activated and only imposed gear numbers are considered.

For more details on the PHIL control used here, the reader can refer to [24].

VI. EXPERIMENTAL RESULTS

For each type of itinerary (urban and road presented in section 4.1), two speeds profiles have been randomly selected among all the registered cycles. The first one is considered as the PSP for the experimentation while the second is replayed as the actual drive cycle to be performed by the vehicle. The implemented real time control allows close-to-optimal torque splitting between the ICE and the motor as well as an update for the Soc control.

A. Control variable results

The control variables identified in Section 2 are plotted in Figure 13 for the urban cycle and in Figure 14 for the road cycle.

The gear number is not calculated by the optimization algorithm but is imposed using a simple law on the ICE speed thresholds. The resulting control is plotted in the lower graph of the two figures. The engine state plots, given in the middle of the figures, show acceptable switching frequency from electric to hybrid mode (about 25 times for each cycle).

B. Soc control results

The Soc calculated using the measured battery current is controlled by the \( \hat{\lambda}(0) \) update algorithm using a Soc error \( \epsilon \) of 3 % between the predefined and the effective Soc. The Soc target for the end of the cycle is chosen to be equal to the initial Soc (60%).

![Fig. 13. Diagram of the HEV HIL control, Urban cycle.](image)

![Fig. 14. Diagram of the HEV HIL control, road cycle.](image)

![Fig. 15. Speed, Soc and \( \hat{\lambda}(0) \) for the urban cycle](image)

![Fig. 16. Speed, Soc and \( \hat{\lambda}(0) \) for the road cycle](image)
Figure 15 and Figure 16, respectively for the urban and the road cycle, show the predefined and the effective speed of the vehicle, the predefined and the effective soc of the battery and the values of $\lambda(0)$ with several updates during the cycle. One can note that in the two cases presented in this paper the soc is well maintained close to the predefined instantaneous soc. The final soc deviation from the soc target is 2% for the urban cycle and 2.5% for the road cycle, which is a satisfying results.

C. Fuel consumption results

As the aim of the proposed control is to approach the optimal fuel consumption in real time, one should analyze the experimental results in term of fuel economy. The test bench presented in Section 5 is equipped with an exhaust gas measurement device allowing fuel consumption calculation. It also includes a fuel scale for fuel mass measurement. Usually, the uncertainty between the calculated fuel value and the measured mass is lower than 2%. When the error is larger, the test is not validated.

The assessment of the optimality of the proposed method is performed as follows:

- the drive cycle is performed several times in an open loop (without estimation and updating $\lambda(0)$), with different values of $\lambda(0)$ using only the optimal control of Figure 4 (called GO in the following figures).
- the drive cycle is performed several times under full real-time control and using a randomly chosen reference cycle as PSP. Each time, a different final soc target is demanded in order to cover a significant soc variation window. The corresponding results are called PRES in Figures 17 a) and b).

As expected, Figure 17 (a) for the urban cycle and b) for the road cycle) shows a slight decrease of the system efficiency for the predefined real-time control (PRES) compared to the open loop global optimization (GO). The open loop global optimization (GO) with an imposed $\lambda(0)$ value is supposed to be the best strategy for fuel saving leading to a non-controlled final soc (this assumption depends on the accuracy of the models). We can however observe very close consumption results for the two methods on a wide window of soc variation with approximately the same slope. A decrease of less than 3% of the system efficiency is registered for the proposed control compared to the open loop global optimization (GO) for both urban and road cycles.

VII. Conclusion

A real time control strategy, derived from optimal control theory, and applied to the case of a parallel HEV used on a predefined route is presented and implemented in a PHIL simulation process.

The predefined route could be a well-identified trajectory for a bus route for example, but could also be the daily home-to-job route for a private use. In this case, the instantaneous speed can be registered during the first uses of the vehicle, and then applied as the predefined route when the driver selects the corresponding trip through a GPS for example.

The developed method, based on Lagrange optimization approach, gives the instantaneous strategy for the optimal engine and electric motor torques to be applied. A key parameter, Lagrange multiplier, allows the battery charge to be controlled. Using a registered drive cycle on the predefined route, the Lagrange multiplier is estimated and updated. The update of this parameter occurs when the actual battery state of charge becomes significantly different from the predefined trajectory.

Experimental results showed a good performance of the proposed method for the fuel consumption measured on the test bench in a PHIL configuration, as well as a good battery soc control. The robustness of the method has been tested in pure simulation by choosing different reference routes among the registered cycles. The results showed the same behaviour as that presented in this paper.

Good performance of the soc target following allows the proposed method to be used in the case of charge depleting strategies for Plug-in HEVs. In this case, the soc target can be continuously variable according to a strategy taking into account different parameters.

References

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