Adaptive Energy Management Scheme for HEVs based on Predicted Optimal Driving Cycle

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***Abstract*—The energy management problem of a specific multi-hybrid plug-in electric bus is addressed in this paper. The bus, on which the study is conducted, is equipped with an internal combustion engine, a hydraulic motor, an electric motor and a battery as the main components of the propulsion drivetrain system of the vehicle. An optimal control scheme based on Pontryagin's minimum principle (PMP) is used in order to ensure a significant improvement in energy efficiency. This control scheme combines speed profile optimization and online parameters adaptation of the energy management strategy to handle uncertainties on the future driving conditions and to accurately control the battery depleting rate. The work proposed in this paper is conducted on a dedicated high-fidelity model of the hybrid bus that was developed on MATLAB/TruckMaker software. The obtained results verify the effectiveness and validity of the developed energy management strategy.**

I. Introduction

This paper details the development of an energy management strategy to optimize the power distribution in a plug-in hybrid bus actuated by three types of power (internal combustion engine, electric motor and hydraulic motor) [1]. In commercially available HEV, the energy management has been traditionally performed using heuristic controllers in which rules are designed to manage the on-board energy of the vehicle [1]. Such control strategies are effective in real-time implementation but they require a careful calibration of the parameters [2]. A significant improvement with respect to such strategies is achieved with model based optimal control methods. These methods can be divided into numerical and analytical approaches. In numerical optimization methods like dynamic programming [3], the global optimum is found numerically under the assumption of full knowledge of the future driving conditions. Unfortunately, the results obtained through dynamic programming cannot be implemented directly due to its high computational demands. To remedy this problem, approximated dynamic programming [3] [4] and stochastic dynamic programming [4] [5] had been suggested as possible solutions. Analytical optimization methods, on the other hand, use a mathematical problem formulation to find an analytical solution that makes the obtained solution faster than the purely numerical methods. Within this category, Pontryagin's minimum principle based energy management strategy is introduced as an optimal control solution [6]. This approach can only generate an optimal solution if implemented offline since in this case the driving cycle is supposed to be known in advance. For online implementation Equivalent Fuel Consumption Minimization (ECMS) methods that lead to suboptimal solutions have been proposed for HEVs [7]. ECMS is based on instantaneous optimization, and is simple enough to be implemented in real-time applications. Model predictive control based methods have been also applied to solve online the energy management problem [8]. One of the main drawbacks of this approach is the high computational power required to calculate the optimal power split at each sampling interval. Among the available energy management theoretical concepts, Pontryagin's minimum principle based optimization turns out to be the most appropriate approach to design an energy management strategy for the considered hybrid bus since it can guarantee, under given conditions, near optimality while keeping the methodology simple [9]. Thus, an adaptation of this optimization approach to a plug-in multi-hybrid bus is proposed in this work and the obtained optimization algorithm is implemented in an overall optimization scheme in order to achieve the most efficient way of bus operation. The key contributions are firstly in formulating the optimization problem so as all the sources of power of the studied hybrid bus are considered by the optimization algorithm. Secondly, the general concepts initially presented in literature are improved by taking into account the motors dynamic limits. And finally, an overall optimization scheme based on the use of predicted optimal velocity trajectory of the bus to adapt the proposed optimization algorithm parameters is proposed. In fact, since the route of the bus, roads levels variations and even traffic lights are well known, prediction of optimal velocity trajectory for the trip can easely be carried out. This available knowledge of the future driving cycle is exploited, in this latter contribution, to make the bus more efficient (even in the presence of exogenous and unpredictable events such as the traffic jam) and to ensure the desired battery depleting level.

The paper is structured as follows: section II describes the dynamic model of the studied system. Section III introduces the proposed energy management strategy. In section IV, several simulations results are presented showing the efficiency of the proposed energy management strategy. Finally, conclusions and some prospects are given in the last section.

II. Modeling of the hybrid bus

The aim of this section is to illustrate the architecture and the mathematical model of the studied system, i.e., BUSINOVA hybrid bus[1], developed by SAFRA. This bus is composed of an electric motor, a hydraulic motor, an internal combustion engine and battery as the propulsion drivetrain system of the vehicle. The electric motor is a 103 kW permanent magnet electrical machine from Visedo®, developed especially for heavy duty applications. It has six polepairs and its nominal voltage is 500 V [10]. The internal combustion engine is produced by VM Motori®. It delivers a maximum torque of 340 $N.m$ at 1400 rpm and its maximum produced power is 70 kW [11]. The hydraulic motor is a Parker® V14 series with a displacement that varies between 22 and 110 cm^3 [12].

A. Hybrid bus drivetrain architecture

The model of the studied hybrid bus is based on a series-parallel power-split hybrid architecture. A simple block diagram of the power flows on the bus is shown in Figure 1.

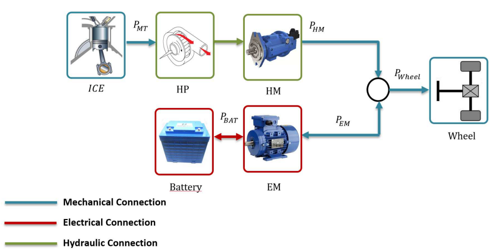


FIG. 1: Block diagram of the drivetrain power flows. (ICE: internal combustion engine, HP: hydraulic pump, HM: Hydraulic motor, EM: electric motor).

The electric and hydraulic motors are both directly connected to the transmission and can ensure simultaneously or independently the traction of the bus. On the other hand, the internal combustion engine is coupled to a hydraulic pump for driving the hydraulic motor and therefore allowing the engine load shifting.

The rotational speeds of the hydraulic motor and the electric motor are imposed by the wheels speed in proportion to the reduction ratios of hydraulic and electric motors respectively. Moreover, the rotational speed ω_{HM} and the torque T_{HM} of the hydraulic motor are expressed as a function of the rotational speed and the torque of the internal combustion engine as follows.

$$\begin{cases} \omega_{HM}(T_{ICE}, D_{HM}) = \dfrac{D_{HP}.\eta_{v_{HM}}.\omega_{ICE}}{D_{HM}.\eta_{v_{HP}}} & \text{(1a)} \\ T_{HM}(T_{ICE}, D_{HM}) = \dfrac{D_{HM}.\eta_{m_{HM}}.T_{ICE}}{D_{HP}.\eta_{m_{HP}}} & \text{(1b)} \end{cases}$$

where ω_{ICE}, T_{ICE} are respectively rotational speed and torque of the engine, and D_{HM}, D_{HP}, $\eta_{m_{HM}}$, $\eta_{m_{HP}}$, $\eta_{v_{HM}}$, $\eta_{v_{HP}}$ are respectively the displacements, mechanical efficiency and volumetric efficiency of the hydraulic motor (HM) and the hydraulic pump (HP).

[1] http://www.businova.com

III. Control oriented model

The amount of residual energy of the battery, commonly represented by the estimation of the battery state of charge SOC or the battery state of energy SOE is the main dynamic state in optimal control of HEVs [13]. In particular, the state equation connects the variation of the battery's remaining energy to the control variable of the system. In the formulation of the energy management problem of the hybrid bus studied in this paper, the SOE instead of the SOC, is considered as the dynamic state $x(t)$. There are several advantages of using the estimated SOE to represent the battery residual energy. Indeed, the energy loss on the internal resistance, the electrochemical reactions and the decrease of the battery voltage are considered in the SOE estimation [14]. Based on the previous assumption of using estimated SOE to represent the battery residual energy, the control oriented model can be represented by:

$$\dot{x}(t) = f(x(t),\ u(t),\ w(t)) \tag{2}$$

where

$$x(t) = SOE(t), \quad u(t) = \begin{bmatrix} T_{HM} \\ \omega_{HM} \end{bmatrix}, \quad w(t) = \begin{bmatrix} T_{wheel} \\ \omega_{wheel} \end{bmatrix} \tag{3}$$

$u(t)$ is the control input and $w(t)$ is an exogenous input. The above model can be rewritten as follows.

$$\dot{x}(t) = \frac{d\ SOE(t)}{dt} = -\frac{P_{BAT}}{E_{max}} = -\frac{P_{EM}}{\eta E_{max}} \tag{4}$$

Depending on whether the battery is in discharging phase ($\dot{SOE} \leq 0$) or in charging phase ($\dot{SOE} \geq 0$), η is defined as follows [15]:

$$\eta = \begin{cases} \eta_{BAT} & \text{in discharging phase} \\ 1/\eta_{BAT} & \text{in charging phase} \end{cases} \tag{5}$$

Equation (4) is obtained from the battery internal resistance model [15]. In this equation, E_{max} is the maximum energy that can be stored in the battery, η_{BAT} is the efficiency of the battery, P_{BAT} is the power delivred by the battery and P_{EM} is the power consumed by the electric motor to produce torque T_{EM} at speed ω_{EM}.

IV. Energy management strategy

A. Optimal control problem formulation

Since our primary goal is to minimize the energy consumption of the bus, the energy management problem is formulated as an optimal control problem. The objective is to find, at each sample time, the optimal value of the control input that minimizes a cost function representing the power consumption of the drivetrain. This minimization of the cost function must be done under a certain number of constraints. In fact, the drivetrain components dimensioning imposes minimum and maximum limits on the exchanged powers. These limits form the following constraints:

- The internal combustion engine and electric motor have limited operating ranges. Therefore, provided or absorbed torques must be comprised between minimum and maximum limits.

$$T_{EM}^{min} \leq T_{EM}\ \ (t) \leq T_{EM}^{max} \tag{6}$$

$$T_{HM}^{min}\left(T_{ICE}^{min}, D_{HM}\right) \leq T_{HM} \leq T_{HM}^{max}\left(T_{ICE}^{max}, D_{HM}\right) \tag{7}$$

  The maximum and minimum torque limits of the internal combustion engine and electric motor vary according to the variation of the system's operating point (torque-speed). Look-up tables are therefore used to determine their values at each time.

- The instantaneous power demand of the drivetrain should always be satisfied, which results in,

$$\rho_1 T_{HM}(T_{ICE}, D_{HM}) + \rho_2 T_{EM}(t) - T_{wheel}(t) = 0 \tag{8}$$

  where ρ_1 and ρ_2 are the gearbox' reduction ratios of hydraulic and electric motors respectively. The total torque at the wheels is equal to the sum of the torques delivered by each of the motors proportionally to the reduction ratios.

Compared with energy management problem formulation for charge sustaining HEV [13], there is no sustainability constraint on the final *SOE* for plug-in HEV allowing the charge depleting operation. Thus, the energy consumed on the entire cycle does not come exclusively from the fuel since most of the available electrical energy is supplied from the grid. This implies that the cost function must take into account all the energy sources used to ensure the traction of the bus. This is why the cost function J to be minimized over the time interval $[t_i,\ t_f]$ is defined based on the total electric and fuel energy consumed by the vehicle as follows.

$$J = \int_{ti}^{tf} P_F\left(u(t)\right) + P_{BAT}\left(u(t)\right) dt \tag{9}$$

where P_F is the instantaneous power of the fuel (engine power input). As in several other papers dealing with this topic [13], it is expressed in terms of the fuel flow rate $\dot{m}_f$ and the lower heating value of the fuel ($Q_{LHV} = 43MJ/kg$) using the formulation given in equation (10).

$$P_F\left(u(t)\right) = \dot{m}_f\left(u(t)\right)\ Q_{LHV} \tag{10}$$

The control variables (T_{HM} and ω_{HM}) are linked together trough the hydraulic motor dynamics, therefore, there can only be one target control value at a time. In this paper, we have chosen to leave the rotation speed free so that it will be imposed by the wheels speed. The hydraulic motor torque is thus the only remaining control variable that can be used to decide how to split the driver's demanded power.

The optimization problem is then to find the hydraulic torque that should be provided at every sample time in order to minimize the total energy consumed while checking the constraints thus mentioned above (cf. equations (6) to (8)). To these constraints it is added a new constraint (11) which aims to limit the admissible control region in order to take into account the limits of the hydraulic motor dynamics and consequently taking into account the limits of the internal combustion engine dynamics.

$$\frac{dT_{HM}}{dt} - \xi \geq 0 \tag{11}$$

with ξ is the maximum hydraulic torque variation measured over a short period of time.

To introduce constraints in the optimization problem, these are transformed into equality constraints. The constraint (11) can be rewritten as follows.

$$\frac{dT_{HM}}{dt} - \xi - \dot{\varepsilon}^2 = 0 \tag{12}$$

where ε is a slack variable.

By using equation (8), it is possible to rewrite the constraints (6) and (7) as a single constraint on the control variable as follows.

$$\tilde{T}_{HM}^{min}\left(T_{HM}^{min}, T_{EM}^{max}\right) \leq T_{HM} \leq \tilde{T}_{HM}^{max}\left(T_{HM}^{max}, T_{EM}^{min}\right) \tag{13}$$

with

$$\tilde{T}_{HM}^{min} = \max(\rho_1.T_{HM}^{min}, T_{wheel} - \rho_2.T_{EM}^{max}) \tag{14}$$

$$\tilde{T}_{HM}^{max} = \max(\rho_1.T_{HM}^{max}, T_{wheel} - \rho_2.T_{EM}^{min}) \tag{15}$$

It means that when the torque applied to the wheel is too significant to be only produced by the electric motor, the $\tilde{T}_{HM}^{min}$ limit imposes a minimum torque on the hydraulic motor. Additionally, $\tilde{T}_{HM}^{max}$ limit prevents the electric motor torque set-point to become less than T_{EM}^{min}.

Finally, using a 2^{nd} order approximation , the constraint (13) is written as the equivalent form given by (16),

$$-T_{HM}^2 + \alpha T_{HM} + \beta = 0 \tag{16}$$

with $\alpha = \tilde{T}_{HM}^{max} - \tilde{T}_{HM}^{min}$ and $\beta = \tilde{T}_{HM}^{max}\ .\ \tilde{T}_{HM}^{min}$.

B. Energy management algorithm

With the optimization problem fully defined, Pontryagin's minimum principle can be used to give numerical solution. According to Pontryagin's minimum principle, minimizing the cost function given in (9) is equivalent to minimizing the Hamiltonian function H of the system at each instant of time.

$$\begin{aligned} H\left(x(t),\ u(t),\ \lambda(t)\right) = P_F\left(\ \rho_1 T_{HM}(t), \frac{1}{\rho_1}\omega_{HM}(t)\right) \\ -\left(\frac{\lambda(t)}{\eta E_{max}} - 1\right)\ P_{ME}\left(\rho_2 T_{EM}(t),\ \frac{1}{\rho_2}\omega_{EM}(t)\right) \end{aligned} \tag{17}$$

where $\lambda(t)$ is the costate (or the Langrange multiplier). For the considered energy management problem, an extended Hamiltonian function is defined to account for the constraint (12) and (16). The additional terms are introduced using a new Lagrange multiplyers (i.e., $\gamma(t)$ et $\sigma(t)$ respectively).

$$H(x(t),\ u(t),\ \lambda(t),\ \gamma(t),\ \sigma(t)) = P_F\left(\rho_1 T_{HM}(t), \frac{1}{\rho_1}\omega_{HM}(t)\right) - \left(\frac{\lambda(t)}{\eta E_{max}} - 1\right) P_{ME}\left(\rho_2 T_{EM}(t),\ \frac{1}{\rho_2}\omega_{EM}(t)\right) + \gamma(t)\left(-T_{HM}^2 + \alpha T_{HM} + \beta\right) + \sigma(t)\left(\frac{dT_{HM}}{dt} - \xi\right)^2 \tag{18}$$

The optimal control law which minimize the Hamiltonian H must satisfy the following necessary conditions for optimality:

$$\frac{\partial H(t)}{\partial u(t)} = \frac{\partial H(t)}{\partial T_{HM}(t)} = 0 \tag{19}$$

$$-\frac{\partial H(t)}{\partial x(t)} = -\frac{\partial H(t)}{\partial SOE(t)} = \dot{\lambda}^*(t) \tag{20}$$

$$\frac{\partial H(t)}{\partial \lambda(t)} = \dot{x}^*(t) \tag{21}$$

$$\frac{\partial H(t)}{\partial \gamma(t)} = -T_{HM}^2 + \alpha T_{HM} + \beta = 0 \tag{22}$$

$$\frac{\partial H(t)}{\partial \sigma(t)} = \left(\frac{dT_{HM}}{dt} - \xi\right)^2 = \dot{\varepsilon} \tag{23}$$

The costate λ is determined by the condition (21).
The condition (19) determines the optimal control trajectory $T_{HM}^*(t)$. If this necessary condition is satisfied, then the optimal hydraulic torque $T_{HM}^*(t)$ must be given by equation (24).

$$T_{HM}^*(t) = \arg\min_{T_{HM}\in U} H(SOE(t), T_{HM}(t), \lambda(t)) \tag{24}$$

where U is defined as the admissible control set.
After the hydraulic motor torque is obtained, the internal combustion engine torque and speed are calculated according to the desired speed and torque of the hydraulic motor.
For a perfectly known driving cycle, there exists only one value of the costate for which the solution that minimizes the Hamiltonian H at each sample time is also the one that satisfies the terminal condition on the final value of SOE. This corresponds to the global optimal solution of the problem. However, the assumption of perfect knowledge of the driving cycle is not true in practice because of the variation of traffic conditions. An optimal speed profile can, however, be predicted for each trip of the bus based on the actual driving conditions. Indeed, buses run on the same route every day, stop invariably at similar locations and they could even have some dedicated lanes of the road in some cities which facilitates driving conditions prediction compared to other type of vehicles. Therefore, several studies have been conducted to optimize bus speed profiles [16]. With this approach in mind and to further improve the energy management strategy proposed in this paper, the optimal speed profile is first determined by using a dedicated speed profile optimization algorithm based on a predictive intelligent control [17]. The speed profile optimization is always carried out at the beginning of each new trip of the bus. However, the optimal speed profile could be recalculated during the trip if the actual value of the buss speed is a lot far away from the optimum due, for example, to an unplanned stop. Once the optimal speed profile is obtained, it is used to calculate an optimal state trajectory, which will be used online, as a reference value SOE_{ref}, to guide the choice of the costate value. In fact, the speed profile optimization alone does not allow to fully handle the uncertainties on the driving conditions. In this paper, the speed profile optimization is therefore combined with an online adaptation algorithm of the costate to totally take into account driving conditions variation. The resulting overall online optimization algorithm, which is proposed in this paper, adapts the costate in real-time based on the speed profile adaptation algorithm results. The aim is to achieve the desired final SOE value at the end of the considered driving interval despite the lack of knowledge of the driving conditions. To reach this goal, the actual SOE value is approximated to its reference value SOE_{ref} obtained from speed profile optimization algorithm. The objective here is not to track the reference SOE trajectory but to use the information about the optimized driving cycle that it contains (acceleration, braking, road slope, etc.) to adapt the costate value depending on the characteristics of the route and the new driving conditions. The overall energy management scheme is illustrated in Figure 2.

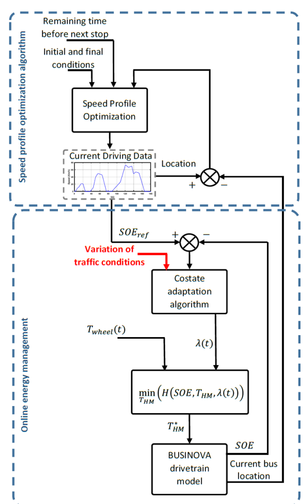


FIG. 2: Block diagram of the proposed strategy.

In this optimization strategy, the value of the costate is found at each sample time according to (25).

$$\lambda(t) = \tau(t)\lambda_{max} + (1-\tau(t))\lambda_{min} \tag{25}$$

with

$$\lambda(t)|_{\tau=0.5} = \lambda_0 = \frac{\lambda_{min}+\lambda_{\max}}{2} \tag{26}$$

λ_0, λ_{min} and λ_{max} are respectively the initial, the minimum and the maximum values of the costate λ. The costate variation range (i.e., $[\lambda_{min}, \lambda_{max}]$) is chosen sufficiently large to handle all types of uncertainties on the knowledge of the driving cycle including unplanned stops. $\tau(t)$ is a tuning parameter such as $\tau \in [0,1]$ and τ_0 is its initial value fixed at 0.5. The problem of the evaluation of $\lambda(t)$ is therefore transferred to the evaluation of $\tau(t)$.

The parameter $\tau(t)$ is estimated in real-time using the *SOE* feedback as stated in equation (27).

$$\tau(t) = tau_0 - \frac{\mu(SOE(t) - SOE_{ref}(t))}{\Delta SOE_{max}} \tag{27}$$

where SOE_{ref} is the optimal *SOE* trajectory calculated offline, ΔSOE_{max} is the maximum amount of energy that can be consumed from the battery during the whole drive cycle, and μ is a constant calibration parameter.

The objective of the suggested formula in equation (27) is to find at each time the value of τ needed to bring back the actual *SOE* to its desired value SOE_{ref}. In other words, when the battery *SOE* has a different value from the desired SOE_{ref}, the parameter τ is modified to give priority to the use of the electric motor or to the hydraulic motor and thus it tries to discharge the battery or, on the contrary, to capture as much braking energy as possible to charge the battery.

V. Simulation results

The implementation of the proposed energy management strategy is carried out using a dedicated high-fidelity model of the hybrid bus, that was developed on Matlab/TruckMaker software, in order to investigate their performance in a test platform which reproduces accurately the real operating behavior of the bus.

In Figure 3(a), an example of a driving cycle obtained under the assumption of unknown traffic conditions is illustrated by a red continuous line. It is supposed to represent the effects of fluctuating traffic conditions when the driver tries to follow the regular cycle represented by the blue dashed line. The total traveled distance is the same as in the regular driving cycle, but the driver behavior is different (i.e., quicker or slower accelerations/decelerations). In addition, an unplanned stop is introduced in this driving cycle to represent situations that induce a high level of uncertainty (i.e., traffic jam, traffic lights, etc.). As can be seen in Figure 3(b), If the parameters adaptation is not carried out, lack of knowledge of traffic conditions affects the ability of the energy management strategy to respect the constraints on the final *SOE* and consequently, the bus uses more battery energy than the one allowed. To cope with this important issue, the proposed adaptive PMP based energy management strategy adapts online the value of the costate λ. The overall performances of the proposed adaptive energy management strategy are stated in Figure 4. The contribution of the fuel energy and the electric energy to the total power and torque at the wheels is illustrated in Figure 4(a) and 4(b) respectively. The *SOE* profile is also illustrated in Figure 4(c). According to Figure 4 (a), it is shown that the distribution of the power demand between the electric motor and the hydraulic motor is correctly assured and the required power at the wheels is totally satisfied over the entire driving cycle. The dynamic limits of the motors defined during the synthesis of the energy management strategy are also respected as can be seen in these figures. Ones the parameters are adjusted by the dedicated parameters adaptation algorithm, the proposed energy management strategy finds the optimal power split which operates the engine around its maximum efficiency curve to minimize the power consumption of the drivetrain. The fluctuation range of the power delivered by the engine is directly related to the amount of electric energy available for electric assist and it allows to always satisfy the constraints of the final *SOE* of the battery despite the lack of knowledge of the driving conditions. It is to be noted that the desired final value of *SOE* after nine hours of driving is 17%. The working hypothesis behind this assumption is to use the maximum amount of energy that can be consumed from the battery in one day driving. As can be seen in Figure 4(c), a battery discharge of 0.4% is observed at the end of the driving cycle simulated in this test, which corresponds, by extrapolation, to the desired battery depleting rate after nine hours driving period. Otherwise, the energy management strategy doesn't use the engine to charge the battery, because its efficiency is too low and thus recharging the battery using fuel energy is not cost-effective.

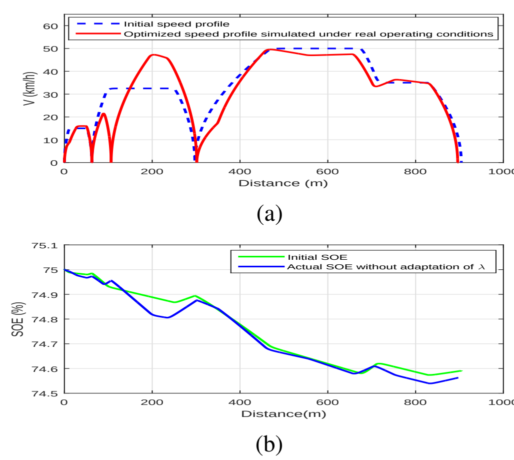
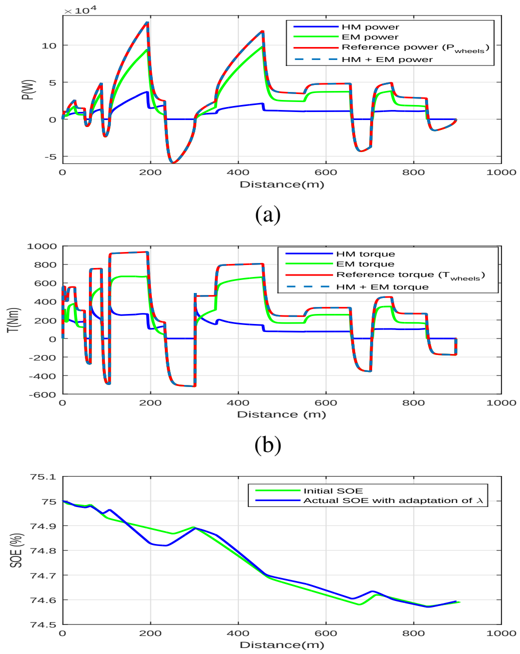


FIG. 3: Optimized driving cycle used to simulate unknown (or fluctuating) traffic condition: (a) driving cycle, (b) SOE trajectory from the proposed strategy without parameters adaptation

VI. Conclusion

An optimal energy management strategy, based on Pontryagin's minimum principle, is designed in this paper for a plug-in multi-hybrid bus. The proposed approach combines



(a)

(b)

(c)

FIG. 4: Simulation results of the proposed energy management strategy: (a) power distribution profile, (b) torque distribution profile, (c) SOE profile.

the system's dynamical equations with the control objectives formulated in the form of a cost function and constraints to determine at each instant the optimal value of the control variable which minimizes the power consumption of the hybrid bus. Furthermore, based on the characteristics of the studied urban bus, which runs generally on the same routes, the energy management strategy is further improved by searching the optimal driving cycle for each bus trip and adapting the energy management strategy parameters accordingly. Therefore, the final battery SOE level is controlled by selecting an appropriate value of the costate. The validation tests results show that the proposed optimization approach can ensure optimal operation for the hybrid bus while having the advantage of being very simple to implement in practice thanks to its high computational efficiency. Nonetheless, to achieve this performance level, good accuracy for estimating road traffic conditions is required. In future works, additional optimization criteria such as: reduction of battery aging and pollutant emissions will be added to the already existing optimal control algorithm. The tradeoff between the different optimization criteria will be investigated in order to achieve the most efficient drivetrain operation.

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