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Total cost minimization for next generation hybrid electric vehicles ⋆

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Abstract: The powertrain of a conventional Hybrid Electric Vehicle (HEV) is based on the combination of an internal combustion engine, one or more electric motors and a battery pack, which can be recharged during vehicle operation by regenerative braking or thermal power surplus. Due to the recent advances in plug-in vehicles and battery technologies, upcoming HEVs rely more on their "all-electric range" - for fuel economy and environmental reasons - with the thermal unit playing the role of a range extender. It follows that current energy management systems might not be adequate to exploit the features of the next generation vehicles. In this paper, we propose a different formulation of the energy management problem, which takes into account the total driving cost and the previously neglected (but now important) dynamic variables. By means of simulation studies, we show that the potential of the proposed management policy significantly outperforms the optimal solution of the standard problem.

Keywords: Hybrid Electric Vehicles, Optimal control, Dynamic Programming

1. INTRODUCTION

Hybrid Electric Vehicles (HEVs) are generally regarded to as an effective solution to improve the fuel economy and reduce the pollutant emissions with respect to Internal Combustion Engine (ICE) vehicles.

Since HEVs are usually equipped with (at least) two energy sources, a critical energy management problem arises, that is, a supervisory system is needed to determine how to generate the requested power. In the so-called "mild HEVs", the downsized battery and the electrical motor do not allow to drive the vehicle based just on the electric power, but only to assist the ICE in low efficiency operating points. In this framework, heuristics and rule-based algorithms have shown to provide satisfactory results. On the opposite, highly hybridized powertrains call for more sophisticated control approaches for their higher flexibility, see [Sciarretta and Guzzella, 2007].

In the latter configuration, given a model of the hybrid powertrain, the best performance theoretically achievable over a driving schedule can be computed by means of optimization techniques. A classical approach in HEVs aims at minimizing the overall fuel consumption, concurrently penalizing excessive deviations of the battery state of charge. Such a penalty term is very important for conventional HEVs, in which the minimization of the fuel consumption *tout court* may lead to excessive battery charge depletion. The above optimization approach usually yields a noncausal control policy, which defines a useful upper bound in terms of performance for a given driving cycle.

An effective real-time implementation of the above optimal policy can be found using the so-called Equivalent Consumption Minimization Strategy (ECMS) - based on the Pontryagin Minimum Principle - in which the knowledge of future power requests is replaced by a cycle-dependent parameter, see [Sciarretta and Guzzella, 2007, Sciarretta et al., 2004, Serrao et al., 2009] for further details. Adaptive variants of the ECMS have also been developed and successfully implemented, see [Musardo et al., 2005]. Nonetheless, other real time approaches have been explored, based, *e.g.*, on Model Predictive Control or Robust Control, see [Kessels et al., 2005, Pisu et al., 2003].

Nevertheless, all the above strategies are based on a conventional configuration of the HEV powertrain, that is a combination of an ICE with one or more electric machines and a battery pack, which can be recharged exclusively during vehicle operation by regenerative braking or thermal power surplus. However, the recent technology of plug-in HEVs made it possible to recharge the battery from the grid. Quite simultaneously, progresses in battery technology are making big battery packs more affordable, thus extending the so-called "all-electric range" of such vehicles and leading to a new generation of Series HEVs (SHEVs).

Upcoming HEVs are then more and more conceived as plugin vehicles with a relatively large battery and a significant "all-electric range", with a thermal unit often playing the role of a range extender. In view of this trend, on the one hand, the need for charge sustenance becomes less critical. On the other hand, since the battery has a more significant impact on the overall vehicle cost, the battery operating conditions leading to fast aging should be avoided. It follows that the strategies usually applied on the conventional, parallel HEVs might not be as satisfactory as on conventional vehicles when used on plugin, series HEVs.

In this paper we propose a novel approach - intended for extended range EVs and SHEVs in general - which tries to fully exploit the features of the next generation vehicles. Both the powertrain model and the optimization problem formulation originate from the classical approaches, but some important aspects are suitably reformulated. Specifically, a control-oriented model which also accounts for battery aging is derived, and the corresponding optimization problem is formulated so as to take into consideration all the cost entries related to the electrical part, as well as the

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fuel consumption. By applying Dynamic Programming, see Sniedovich [2010], we show that the potential of this new energy management policy significantly outperforms the optimal solution of the standard problem formulation.

The remainder of the paper is as follows. The energy management problem taking into account the needs of next generation vehicles is formally introduced in Section 2. The optimization problem and its dynamic constraints are then revisited in Section 3 and 4, where, respectively, the control-oriented model and the novel cost function are described in detail. The potential of the new approach is shown in Section 5 on both a urban and a mixed urban-motorway driving cycle using a full-fledged simulator of the vehicle. The paper is ended by some concluding remarks.

2. PROBLEM FORMULATION

Energy management is a control problem to be addressed in Hybrid Electric Vehicles, where the power requested to drive the vehicle can be supplied by two or more energy sources. The problem is commonly investigated by considering a finite time horizon and (possibly) the desired velocity/slope profiles. By means of a powertrain model, such profiles are converted into a profile of the power requested at the link between the power sources. The latter is mechanical power for a parallel HEV and electrical power for a series HEV. The energy management problem can be conveniently faced as an optimization problem oriented to the minimization of a suitable cost function J, given the desired power profile:

$$\begin{aligned} \min_{u} \quad & J = h(x(T)) + \int_0^T g(t, x(t), u(t), w(t))dt \\ \text{s. t.} \quad & \dot{x} = f(t, x(t), u(t), w(t)) \\ & x(0) = x_0 \\ & x(t) \in X \\ & u(t) \in U, \end{aligned} \tag{1}$$

where x is the state variable, u is the control variable, w is an exogenous variable and f, g are nonlinear functions.

A popular approach aims at minimizing the fuel consumption for a desired trip, thus leading to the following choice of the cost function:

$$g(t, u(t)) = \dot{m}_f(t, u(t)). \tag{2}$$

where $\dot{m}_f$ is the fuel mass flow rate. Notice that the dependence on the state has been removed, since fuel consumption can typically be considered as a static function of the power supplied by the unit. Battery state of charge is then commonly selected as the only state variable, according to its well-established definition as the ratio between the actual stored charge and the total capacity [Guzzella and Sciarretta, 2005].

In many cases the solution to the problem stated above may trivially be to drive the vehicle exclusively based on the battery power, which however leads to depleting the battery charge. This is particularly undesirable if the battery capacity is relatively small or if the battery cannot be connected to the grid for recharging, as it is the case for conventional parallel HEVs. To avoid such an issue, the final state cost function $h(x(T))$ can be used. A typical choice for $h(x(T))$ is a function ζ of the deviation between the final state $x(T)$ and the initial state $x(0)$:

$$h(x(T)) = \zeta(x(T) - x(0)). \tag{3}$$

The above formulation has been widely exploited and proved to be successful, see [Sciarretta and Guzzella, 2007].

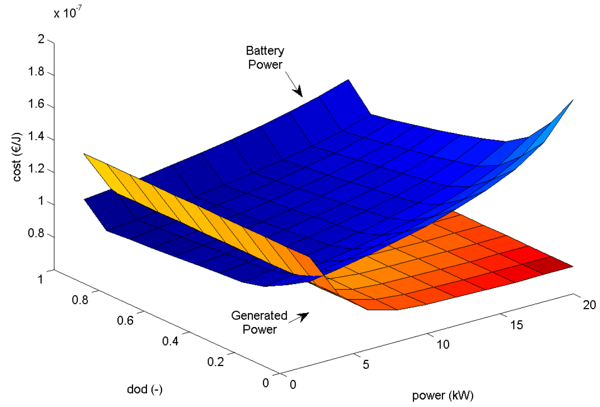

Fig. 1. A comparison of battery and generated power costs

Nonetheless, current trend in HEVs market is oriented towards grid-rechargeable vehicles with a large battery pack, thus allowing large “all-electric range”, typically suited for every-day urban use. The increasing commercial success of plug-in HEVs and Extended Range EVs may be regarded to as a symptom of such a trend. As a consequence, on the one hand, battery charge sustenance may become a minor problem for next generation vehicles. On the other hand, while the battery accounts for an increasing share of the overall vehicle cost, intensive usage can lead to accelerated aging and should be considered in the power dispatch management.

As an example, consider a series HEV equipped with a $100Ah$ battery pack and a $25kW$ CNG thermal power unit (the complete model of the vehicle will be described in Section 5). A nice feature of SHEVs is the absence of direct mechanical coupling between the wheels and the internal combustion engine, which allows to run it at an arbitrary operating point. Hence, assume that the thermal unit is always operating at its maximum efficiency, given the desired power profile. The cost per watt of the power supplied by the two on-board sources can be evaluated, as a function of the battery state of charge and the generated power, in Figure 1. It can be noticed that, if both the grid-recharge energy cost and the share of battery value depleted are accounted for in the total cost of the battery power, *the optimal trade-off between the two sources is not trivial and depends on the operating point.* Its variability obvious reflects the underlying aging model, since the grid energy cost is practically constant.

The aim of this work is then to focus on SHEVs, whose powertrain architecture is also the reference for Extended Range EVs, and reformulate Problem (1) such that the real total cost of a driving cycle is minimized. This requirement calls for a more detailed control-oriented model of the powertrain, that will be therefore suitably extended in the next section.

3. CONTROL ORIENTED MODELING

To start with, consider that, in a series HEV, the sum of the battery power P_b and the thermally generated power P_r has to match the electrical power supplied to the traction motor P_m needed to drive the vehicle:

$$P_m(t) = P_r(t) + Pb(t). \tag{4}$$

From now on, let $u(t) = P_r(t)$ be the control variable and $w(t) = P_m(t)$ be an exogenous disturbance. A circuit model of the battery is then well suited to infer the flowing current given the battery power (see, *e.g.* [Guzzella and Sciarretta, 2005]). Specifically, in this work, we consider the battery voltage as the result of the sum of an open circuit term and an ohmic term accounting for Joule dissipation:

$$v_b = v_{oc} + R_b i_b. \tag{5}$$

The battery current can then be directly computed from the power as

$$i_b = \frac{v_{oc} - \sqrt{v_{oc}^2 + 4R_b P_b}}{2R}. \tag{6}$$

Both v_{oc} and R_b can in principle be dependent on several variables, such as the state of charge, the temperature and the current. In this work, we only consider the dependency on the state of charge. For simplicity, we assume that the resistance is constant and the open circuit voltage is an affine function of state of charge as

$$v_b^{oc}(t) = aq(t) + b, \tag{7}$$

where a and b are real parameters.

To account for battery energy flows, a model of the dynamics of the state of charge is needed. Generally, such a variable is defined as the ratio between the actual charge stored in the battery and the total battery capacity, therefore its derivative can be written as

$$\dot{q}_b(t) = \frac{\dot{Q}(t)}{Q_b} = -\eta_b(t)\frac{i_b(t)}{Q_b}. \tag{8}$$

Notice that the battery capacity Q_b decreases with the battery aging. From now on, let us assume that the battery is no longer useful when the capacity decreases below 80% of the nominal capacity. This capacity fade effect can be accounted for by making the actual value of Q_b dependent on the aging measure ξ_b:

$$Q_b(t) = Q_b^{nom}(1 - 0.2\xi_b(t)). \tag{9}$$

The battery depth of discharge is conventionally defined as the ones' complement of the state of charge:

$$d_b(t) = 1 - q_b(t). \tag{10}$$

For what concerns the modeling of the battery aging, we should first say that this is a widely discussed topic in the literature. Aging happens with normal battery usage, but several operating conditions have proved to be particularly detrimental for battery life. Then, modeling of battery aging is still an open research subject, mainly for the high complexity of the involved phenomena, see, *e.g.*, [Onori et al., 2012, Todeschini et al., 2012, Millner, 2010]. Moreover, aging may appear as the reduction of battery capacity or the increase of battery resistance (which leads to a reduction of the delivered power) and the two phenomena always evolve in parallel. Depending on the particular application, one may be interested in monitoring just one out of the two.

Since we focus on relatively large battery packs, it is reasonable to assume that the power fade will be negligible with respect to the capacity fade. For the sake of simplicity, we adopt a rather simple aging model, assuming the aging rate to be proportional to the absolute value of the current flowing in the battery:

$$\dot{\xi}_b(t) = \sigma_b(q_b(t), i_b(t))\frac{|i_b(t)|}{Q_l}. \tag{11}$$

The coefficient σ_b is often referred to as "severity factor" in the literature. This factor is equal to one in normal operating conditions and bigger than one in harsh operating conditions which lead to accelerated aging. The normalization coefficient Q_l is the throughput of the electrical charge over the entire battery life. It follows that $\xi = 0$ at the beginning and $\xi = 1$ at the end of its life.

Concerning the thermal generation unit, notice that it basically consists of an internal combustion engine, mechanically coupled to an electrical generator, and the efficiency of both the power generators depends on the speed and the torque at a given operating point. In SHEVs, the most efficient operating point can always be selected (the engine is only electrically linked to the electrical motor) and the efficiency η_r can be considered to be a static function of the requested power. We should remark here that such an assumption requires a lower level control system that continuously adjusts the mechanical operating point depending on the current power request. Given this setting, under the assumption of quasi-static operation [Guzzella and Sciarretta, 2005], the fuel mass flow rate can be computed as:

$$\dot{m}_f(t) = \frac{P_r(t)}{\eta_r(P_r(t))\lambda_r}, \tag{12}$$

where λ_r represents the fuel lower heating value.

4. TOTAL COST MINIMIZATION APPROACH

To account for the different requirements of next generation SHEVs and plug-in HEVs, we modify the optimization problem in (1) by selecting the cost function as

$$g(t, x(t), u(t)) = \alpha\dot{d}_b(t) + \beta\dot{\xi}_b(t) + \gamma\dot{m}_f. \tag{13}$$

In (13), three cost items are now considered: the grid energy needed to recharge the battery, the share of total battery value depleted and the fuel consumption. Denoting the monetary cost of $1Wh$ of grid electric energy as C_g, the grid energy cost coefficient is obtained as:

$$\alpha = C_g v_b^{nom} Q_b^{nom}. \tag{14}$$

In a similar way, denoting the battery monetary cost per $1Wh$ of energy storage capability as C_b, the battery value cost coefficient is computed as:

$$\beta = C_b v_b^{nom} Q_b^{nom}. \tag{15}$$

The fuel cost coefficient is instead easily obtained as:

$$\gamma = C_f/\rho_f, \tag{16}$$

where C_f is the cost of a liter of fuel and ρ_f if the fuel density.

Notice that such a cost functions shows some important differences from the standard one, among which the fact that both the fuel cost and the battery cost items are included in the cost function. The different terms are then heterogeneous and they would be characterized by different measurement units. However, the main advantage of such a setting is that the use of a "monetary cost" instead of the "energy consumption" allows us to sum up all the terms without problems. Moreover, no Lagrangian multipliers need to be computed (like in the ECMS) and no final state cost function has to be taken into account.

The ideal optimal solution of problem (1) using (13) can be found using Dynamic Programming, see Sniedovich [2010] for more details. Specifically, in order to apply the dynamic optimization algorithm, the discrete time equivalent of the model has to be considered:

$$x_{k+1} = f_k(x_k, uk, w(k)),\ k = 0, 1, ..., N - 1. \tag{17}$$

By Backward Euler method, the discrete time state equation is found to be:

$$d_{b,k+1} = d_{b,k} + \\ - T_s \eta_{b,k} \frac{b + a d_{b,k} - \sqrt{(b + a d_{b,k})^2 + 4R(u_{b,k} - w_{b,k})}}{2RQ_b}. \qquad (18)$$

The cost function minimized by the algorithm will be defined in a discrete time domain as well:

$$g_N(x_N) + \sum_{k=0}^{N-1} g_k(x_k, u_k, w_k), \qquad (19)$$

where the discrete time cost function is defined as

$$g_k(x_k, u_k, w_k) = \\ \alpha \frac{d_{b,k+1} - d_{b,k}}{T_s} + \beta \frac{\xi_{b,k+1} - \xi_{b,k}}{T_s} + \gamma \frac{m_{f,k+1} - m_{f,k}}{T_s}. \qquad (20)$$

In a similar way, the aging model is replaced by a discrete time counterpart:

$$\xi_{b,k+1} = \xi_{b,k} + \\ - T_s \sigma_{b,k} \frac{|b + a d_{b,k} - \sqrt{(b + a d_{b,k})^2 + 4R(u_{b,k} - w_{b,k})}|}{2RQ_l} \qquad (21)$$

as well as the fuel consumption model:

$$m_{f,k+1} = m_{f,k} - T_s \frac{P_{r,k}}{\eta_r(P_{r,k})\lambda_r}. \qquad (22)$$

According to the Dynamic Programming principle, given the initial state x_0 the optimal cost, $J^*(x_0)$ equals the cost $J_0(x_0)$, where the latter results as the final step of the following algorithm, which proceeds backwards in time from $N-1$ to 0:

$$J_N(x_N) = g_N(x_N) \qquad (23)$$

$$J_k(x_k) = min_u\{g_k(x_k, u_k, w_k) + J_{k+1}(f_k(x_k, u_k, w_k)\}, \\ k = 0, 1, ..., N-1 \qquad (24)$$

If we define μ_k^* as the control law minimizing the right hand term in the equation above:

$$u_k^* = \mu_k^*(x_k) = \arg\min_u\{g_k(x_k, u_k, w_k) + J_{k+1}(f_k(x_k, u_k, w_k)\}, \\ \forall k, \forall x_k, \qquad (25)$$

then the policy $\pi^* = \{\mu_0^*, ...\mu_{N-1}^*\}$ can be proven to be optimal, see Sniedovich [2010].

5. SIMULATION RESULTS

To test the proposed approach, we designed and implemented a full-fledged simulator of a SHEV using a backward-facing approach, which is very well suited to simulate the overall energetic behavior over time scales of the same order as standard driving cycles. As a general rule, backwards-facing simulators are developed using quasi-static approximate models of the components of interest, the focus of the simulator being on the overall energy consumption rather than on the detailed dynamic behavior. The simulator is structured in three main blocks modeling the vehicle dynamics, the battery and the thermal generator, and is briefly described next.

Concerning the vehicle dynamics part, the vehicle longitudinal dynamics describe how the required velocity and slope profiles affect the torque and rotational speed of the wheels according to the force/torque balance equations

Table 1. Control oriented model parameters

Control Oriented Model parameters					
a	$15[V]$	Q_l	$5 \cdot 10^5[\frac{Ah}{life}]$	ρ_f	$1[\frac{kg}{l}]$
b	$115[V]$	v_b^{nom}	$125[V]$	C_g	$0.2[\frac{€}{kWh}]$
R_b	$150[m\Omega]$	η_b	$1[-]$	C_b	$500[\frac{€}{kWh}]$
Q_b^{nom}	$100[Ah]$	λ_r	$47[\frac{kJ}{g}]$	C_f	$1[\frac{€}{l}]$

Table 2. Series HEV simulator parameters

Series HEV simulator parameters					
M	$950[kg]$	C_x	$0.22[-]$	ρ	$1.18[\frac{kg}{m^3}]$
R_w	$0.25[m]$	C_v	$0[\frac{kg}{s}]$	r	$3.5[-]$
A	$2[m^2]$	C_r	$0.008[-]$	η_t	$0.98[-]$

$$M\ddot{x} = \frac{T_w}{R_w} - F_b - F_f \qquad (26)$$

$$\omega_w = \frac{x}{R_w} \qquad (27)$$

where x is the vehicle longitudinal position, T_w and ω_w are the wheel torque and angular speed, F_b and F_f are the mechanical braking and friction forces, R_w is the wheel radius and M is the vehicle mass. The friction term can be detailed as:

$$F_f = -Mg\sin\theta - C_r Mg\cos\theta - C_v\dot{x} - \frac{1}{2}\rho A C_x \dot{x}^2 \qquad (28)$$

in which the four elements in the right hand term represent, respectively, the slope, the roll drag force, the viscous drag force and the aerodynamic drag force. A, C_x, C_v, C_r, are respectively the vehicle reference area and the drag, viscous and roll coefficients, while ρ is the air density and g is the gravitational constant.

The transmission - with ratio r - connecting the wheels axle with the traction motor can be modeled as

$$T_m = \begin{cases} \frac{1}{r\eta_t} T_w, & T_m > 0 \\ \frac{\eta_t}{r} T_w, & T_m < 0 \end{cases} \qquad (29)$$

$$\omega_m = r\omega_w \qquad (30)$$

where T_m, ω_m are the motor torque and angular speed and η_r is the efficiency of the transmission.

The power absorbed by the traction electric motor can then be calculated as:

$$P_m = \begin{cases} \frac{T_m \omega_m}{\eta_m(T_m, \omega_m)}, & P_m > 0 \\ T_m \omega_m \eta_m(T_m, \omega_m), & P_m < 0 \end{cases} \qquad (31)$$

The part devoted to battery modeling is based on Equations (5), (8), (11). To simulate the strategy on a more realistic model of the system, both the resistance and the open circuit voltage are modeled as nonlinear, static functions of the state of charge and of the current. The part devoted to thermal generator modeling is based on Equations (12).

Tables 1 and 2 report the parameters used in the simulator concerning the control-oriented model of the powertrain and the vehicle, respectively.

In the remainder of the section, two different examples are illustrated: a FTP urban driving cycle and a mixed urban/highway driving cycle. The aim of the two scenarios is to show how the optimal solution looks like when the cycle is achievable and unachievable using only the electric

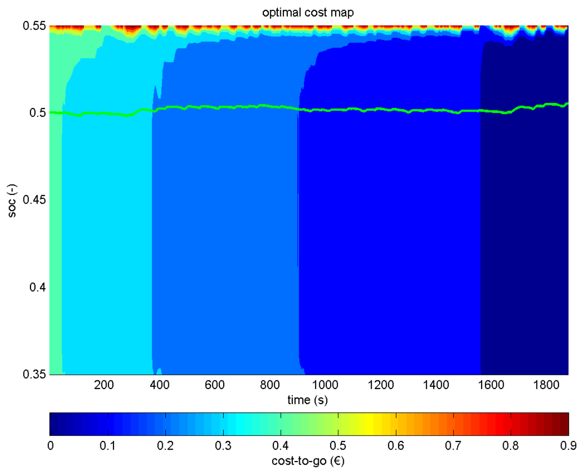

Fig. 2. The optimal cost-to-go map for the proposed cost function in the case of the FTP urban driving cycle

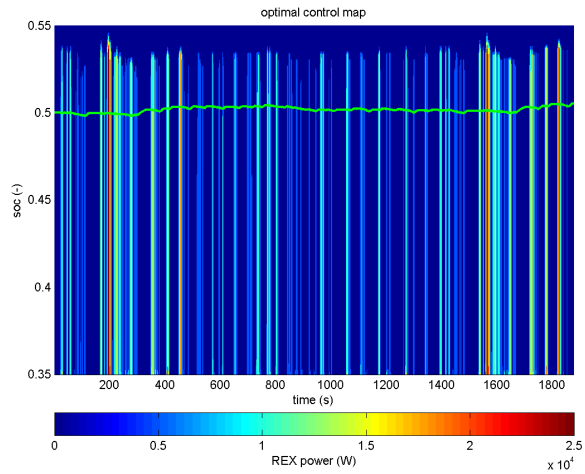

Fig. 3. The optimal control map for the proposed cost function in the case of the FTP urban driving cycle

power supply. The proposed strategy will be also compared with the standard approaches.

5.1 *FTP urban driving cycle*

The first case study is the simulation of the series hybrid vehicle on a FTP Urban driving cycle, with the battery initially at 50% of charge and under 4 different control policies:

- minimization of the total driving cost (the approach proposed in this paper);
- pure minimization of the fuel consumption, *i.e.*, full electric mode as long the battery charge is above 0% and then full thermal power mode;
- ECMS-like strategy, *i. e.* minimization of the fuel consumption with a linear penalty term on the final state of charge;
- fuel minimization with constraint $q_b(T) = q_b(0)$.

To start with, it should be remarked that the minimization of the right hand term of (25) must be performed at each calculation step. This can be easily achieved if both the state x and the input variable u are discretized over grids of finite dimensions. In this work, we consider 60 values for the state grid and 20 values for the input grid for all the considered scenarios.

Figure 2 shows the values of the optimal cost-to-go function, computed for values of the state of charge between 35% and 55%, considering the proposed cost function for a series hybrid vehicle on the FTP urban driving cycle. The green line highlights the optimal state trajectory. The corresponding optimal control map is shown in Figure 3.

The comparative results for this case study are reported in Figure 4 and Table 3. As Figure 4 shows, the full electric driving depletes more than 10% of the battery charge, while the total driving cost minimization leads to a slight battery recharging. Notice that the penalization term for the final state of charge is herein tuned such that an almost perfect charge sustenance is achieved.

The proposed strategy attains the minimum driving cost, as shown in Table 3, while the full electric mode leads to a nearly 50% higher cost and the other two strategies still have sensibly higher driving cost. It is interesting to notice that the two fuel minimization strategies with charge sustenance achieve different driving costs. More specifically, the strategy with linear penalty term on the final state of charge attains a lower cost, as there is no mandatory recharge of the battery at the end of the cycle.

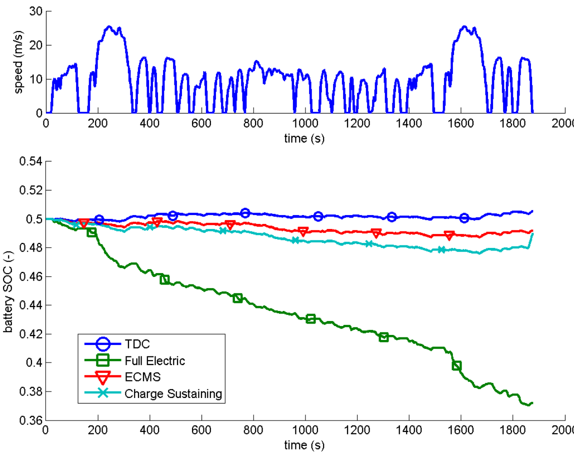

Fig. 4. A comparison of battery SOC trends during the FTP urban driving cycle with different control strategies

Table 3. A comparison of total driving cost and fuel consumption for the FTP urban driving cycle with different control strategies

	TDC	Full Electric	ECMS	Charge Sustaining
Cost [€]	0.47	0.59	0.49	0.52
Fuel [g]	314	0	274	278

On the other hand, the lowest fuel consumption is trivially attained with the full electric driving, as shown in Table 3, since the mission is within the “all electric range” of the vehicle. The other fuel minimization strategies attain similar results, while the proposed strategy leads to the highest fuel consumption.

5.2 *Mixed urban-highway driving cycle*

The second case study considers the same policies and the same vehicle of the previous one, when driving on a mixed

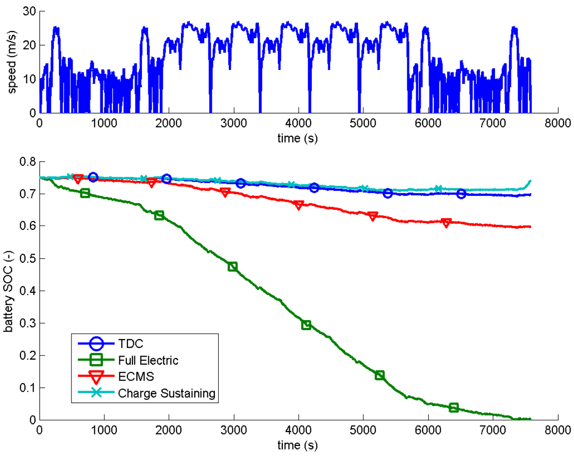

Fig. 5. A comparison of battery SOC trends during the FTP highway driving cycle with different control strategies

Table 4. A comparison of total driving cost and fuel consumption for the FTP highway driving cycle with different control strategies

	TDC	Full Electric	ECMS	Charge Sustaining
Cost [€]	2.88	3.57	2.99	3.09
Fuel $[g]$	1860	200	1570	1960

urban-highway driving schedule. This cycle is given by an FTP urban cycle followed by 5 FTP highway driving cycles and another FTP urban cycle. In this case, the initial state of charge of the battery is 75%.

Figure 5 shows that the proposed strategy results to be slightly charge depleting, leading to an overall decrease of the battery state of charge of less than 5%. The fuel minimization strategy with final SOC penalization in this case does not achieve a perfect charge sustenance, as the same tuning parameters of the previous case are employed. This strategy actually requires to adapt the penalization coefficient to the driving cycle. As for the full electric mode, in this case, the mission is beyond the "all electric range" of the vehicle, and therefore, the thermal unit is used even if it depletes the battery charge.

Similarly to the previous case, the full electric strategy leads to the worst results in terms of total cost, as shown in Table 4. The other strategies lead to quite similar results, but the minimum is attained with the proposed strategy as expected.

Opposite considerations hold for the fuel consumption results, see Table 4. Also in this case the full electric scenario requires the least fuel, while the proposed strategy leads to the highest consumption. In this case, the two fuel minimization strategies show quite a remarkable difference, due to the fact that more thermal power is needed to achieve perfect charge sustenance.

6. CONCLUSIONS

In this paper, we propose a novel approach for optimal energy management in SHEVs. Specifically, we reformulate the standard optimization goal as the overall cost given by the cost of the grid energy, the battery life and the fuel consumption over a given trip. The use of a "monetary cost" instead of the standard "energy consumption" allows us to sum up heterogeneous terms without need of tuning Lagrangian multipliers like in the ECMS and incorporating final state constraints. In this paper, the model of the powertrains has also been modified accordingly, to take into account the dynamic effect of battery aging.

Although battery charge sustenance is not an explicit goal of the method, simulations on a full-fledged model of the vehicle show that the proposed approach generally leads to charge sustaining control policies. This feature cannot be generalized but it will be object of future works, as well as the implementation of real-time control strategies achieving the total cost minimization. In those future works, the result of this paper will be used as a benchmark to evaluate different control approaches.

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