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A-ECMS: An Adaptive Algorithm for Hybrid Electric Vehicle Energy Management

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***Abstract*—Hybrid Electric Vehicles (HEV) improvements in fuel economy and emissions strongly depend on the energy management strategy.**

In this paper a new control strategy called Adaptive Equivalent Consumption Minimization Strategy (A-ECMS) is presented. This real-time energy management for HEV is obtained adding to the ECMS framework an on-the-fly algorithm for the estimation of the equivalence factor according to the driving conditions. The main idea is to periodically refresh the control parameter according to the current road load, so that the battery State of Charge (SOC) is maintained within the boundaries and the fuel consumption is minimized. The results obtained with A-ECMS show that the fuel economy that can be achieved is only slightly sub-optimal and the operations are charge-sustaining.

***Keywords*—Automotive, Hybrid Electric Vehicle, Supervisory Control, Optimal Control, Real-time Control.**

I. INTRODUCTION

HYBRID Vehicles are vehicles equipped with at least two different sources of energy. A hybrid powertrain combines two modes of propulsion to achieve results that cannot be obtained with a single drivetrain. In the specific case of Hybrid Electric Vehicles (HEV) that is discussed in this paper, two sources coexist and one of them is electrical.

By virtue of their concept, HEV can offer significant benefits compared to conventional vehicles in reducing pollutant emissions and energy consumption. The presence of an additional degree of freedom for satisfying the driver power demand implies that the performance of an HEV system strongly depends on the control of the power split.

The objective of this paper is to analyze the problem of the HEV control and to propose a new energy management strategy that achieves fuel economy improvement and pollutant emissions reduction.

In particular, the results discussed here refer to the OSU BuckHybrid 2004, a prototype of a pre-transmission parallel hybrid electric vehicle derived from a Ford Explorer 2002 in order to participate to the 2004 FutureTruck Competition. The generic architecture of a pre-transmission parallel hybrid electric powertrain, sketched in Fig. 1. The Internal Combustion Engine (ICE) is a 103-kW, 2.5 liter, direct injection Diesel engine made by *VM motori* and the Electric Motor (EM) is an *Ecostar* 18/32-kW induction motor. The EM is coupled to the drivetrain through a *Goodyear* timing belt that connects sprockets on both the electric motor shaft and the diesel engine crankshaft. The battery box contains a series string of 150 sealed lead-acid two-volt *Hawker Cyclon* E cells (8Ahr), creating a nominal package of 300 V. The maximum allowed current is 90 A in discharge mode (positive current) and 60 A in recharge mode (negative current).

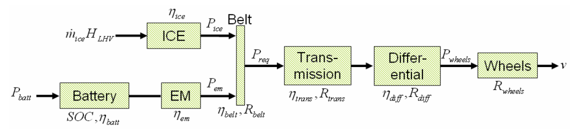

Fig. 1. Schematic of a pre-transmission parallel hybrid electric powertrain

II. VEHICLE MODEL

Two different approaches to the HEV modeling can be adopted: the backward and forward-facing modeling with respect to the physical causality principles. The former makes the assumption that the vehicle meets the target performance, so that the vehicle speed is supposed known and the power request is calculated using the kinematical relationships imposed by the drivetrain. Forward-facing modeling, on the contrary, takes as inputs the driver commands and, simulating the physical behaviors of each component, generates the vehicle performance as output.

The backward-facing approach is beneficial in simplicity and low computational cost, while forward-facing, requiring the resolution of the differential motion equation of the vehicle, needs more computational time. However, when the vehicle modeling serves as a platform for the implementation of the control strategy of an actual vehicle, the forward-facing approach seems more

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appropriate. In this way, the simulator reflects the actual architecture of the vehicle and the control strategy developed in the simulator can directly be implemented in the actual vehicle.

In this paper, a forward quasi-static simulator called Vehicle Performance Simulator (VP-SIM) [1] is used as platform for the implementation of the control strategy of the OSU BuckHybrid 2004. The simulator is developed in the MATLAB/Simulink® environment and it contains three main blocks in its top layer as shown in Fig. 2: the Driver, the Powertrain and the Vehicle Dynamics block.

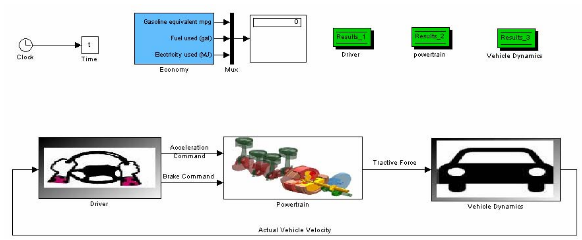


Fig. 2. Simulink implementation of VP-SIM

The software implementation of the Powertrain block is structured to directly resemble the layout of the physical system and its top layer is shown in Fig. 3. The ICE and EM are modeled using steady-state maps of the engine and the motor provided by the constructors. The battery is modeled with a Thevenin equivalent circuit. The open-circuit voltage V_{oc} is considered a function of the SOC, while the internal resistance R_{in} is function of the SOC but also of the operating mode (charging/discharging). These functions are available from experimental data published by the constructor. The SOC is obtained integrating the following differential equation:

$$Q_{max}\frac{dSOC(t)}{dt} = -I(t)$$

where Q_{max} is the total charge that the battery can hold. The Driver module compares the desired vehicle speed with the actual vehicle velocity and, through a PI controller, calculates the accelerator or brake commands. These signals are sent to the Powertrain to calculate the tractive force at the wheels. The actual vehicle velocity is then calculated by considering the tractive force and the total force needed to overcome the aerodynamic, grade and rolling resistance.

After the simulation is completed, vehicle performance, such as fuel economy, vehicle speed trace, battery state of charge (SOC), engine and electric machine operating points, can be displayed.

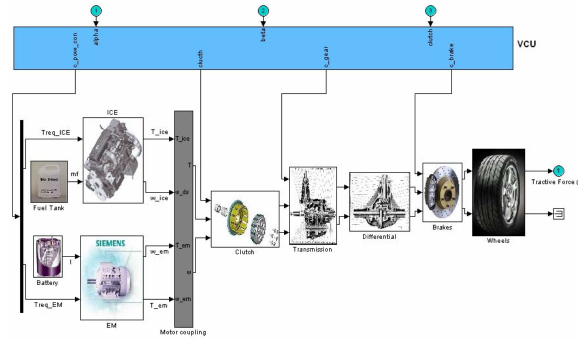


Fig. 3. Simulink implementation of the pre-transmission parallel hybrid powertrain of the OSU BuckHybrid 2004

A detailed and complex model as VP-SIM is desirable for evaluating the performance achievable by the actual configuration of the vehicle. However, such a model requires excessive computation time for the calculation of the optimal control policy with advanced control techniques, such as Dynamic Programming (DP, see Section IV). For this purpose, a simplified quasi-static backward model is more appropriate. Obviously, the results obtained with the two approaches are not directly comparable. In fact, the presence of the driver implies that the road loads are different and, even if the vehicle speed traces are similar, the torque requests calculated backwards and forwards are rather different. Hence, even the same control strategy would lead to different torque splits and the performances measured with the two models would differ. Thus, the simplified model is retained as base for the comparison of the control strategies presented along this paper. However, the new control strategy proposed here (A-ECMS) is also implemented in VP-SIM, in order to be directly implemented in the actual vehicle.

III. Problem Statement

The essence of HEV control is the instantaneous management of the power flow from the ICE and the EM. The HEV control strategy aims at minimizing the vehicle fuel consumption, while also attempting to minimize engine emissions.

These objectives are global, in the sense that the quantity to be minimized is integral over the whole trip, while the control actions are local in time. Furthermore, the control is subject to integral constrains, such as nominally maintaining the SOC, and local constraints, such as meeting the driver demand and respecting the components limitations.

Mathematically, the problem can be formulated as follows (here, pollutant emissions are not taken into account):

$$J_{T_t} = \int_0^{T_f} \dot{m}_{ice}(P_{ice}(t)) H_{LHV}\, dt$$

$$\{P_{ice}^{opt}(t), P_{em}^{opt}(t)\} = \arg \min_{\{P_{ice}(t), P_{em}(t)\}} J_{T_t} \quad t = 0 \ldots T_f$$

$$\text{subject to: } \begin{cases} P_{req}(t) = P_{ice}(t) + P_{em}(t) \\ SOC_{min} < SOC(t) < SOC_{max} \quad \forall t \\ 0 \le P_{ice}(t) \le P_{ice,max}(t) \\ P_{em,min}(t) \le P_{em}(t) \le P_{em,max}(t) \end{cases}$$

where: P_{req} is the driver power demand.

P_{em} is the power of the electric motor.

P_{ice} is the power of the engine.

$\dot{m}_{ice}(\bullet)$ is the fuel mass flow rate.

SOC is the battery state of charge.

IV. Optimal Solution to the Control Problem

The energy management of HEV is essentially a global optimization problem whose objective is to determine the power split between the ICE and the EM that minimizes fuel consumption and pollutant emissions. The solution can be seen as a sequence of commands at each time instant that achieves this goal. Since a driving cycle usually lasts hundreds or even thousands of seconds and at each instant tens of possible values of ICE and EM power must be evaluated, it is evident that a "brute force" enumeration of the solutions is not conceivable. A more efficient optimization procedure is provided by Dynamic Programming (DP), instead. This technique is in fact well suited to multistage processes requiring a sequence of interrelated decisions [2], [3].

The control of an HEV with minimum fuel consumption and emissions is a global problem and the control action taken at each time instant affects the following. Thus, Dynamic Programming (DP) is a well-suited technique to find the optimal solution to the control problem. The vehicle is considered a discrete dynamic system. A simplified model is necessary to reduce the computational burden of DP. The energy stored in the battery (or equivalently its SOC) is the dynamic state and the power output of the EM is the control variable. The power requested by the driver is determined from the vehicle velocity through kinematical relations and the cost of each allowed torque split at a given time instant is evaluated by the backward DP algorithm. At the end of it, the trajectory from the initial to the final SOC which minimizes fuel consumption gives the optimal solution, *i.e.* the sequence of values of power that the EM must provide. The SOC constraint is automatically satisfied by the discretization of the state variable, that is set between SOC_{min}=0.6 and SOC_{max}=0.8.

The fuel consumption obtained with DP for the Federal Urban Driving Schedule (FUDS) is 25.7 mpg (miles per gallon gasoline) and for the Federal Highway Driving Schedule (FHDS) is 26.0 mpg. The operating points of the ICE for those cycles are reported in Fig. 4; Fig. 5 shows the SOC profiles for those cycles.

It is worth noting how the ICE operating points are concentrated in the high efficiency region of the ICE, which explains why hybrid electric vehicles can achieve better fuel economy than conventional vehicles. Moreover, the vehicle is charge-sustaining by construction: the final value of SOC is imposed as initial condition of the DP backward algorithm.

The DP approach proposed in this section has the great advantage of dealing in a reasonable time with an optimization problem that would be otherwise impossible to handle. It seems then that DP is the perfect tool for optimal control of HEV, in the sense that it solves the problem and it also finds the optimal solution, but there are some obstacles to its effective use in the embedded control systems of a vehicle.

The DP algorithm is based on a fundamental hypothesis. Since it is a global approach to a problem that has a certain extent in time, the problem must be known and well formulated for all its duration. In other words, the driving schedule over which the fuel consumption is minimized must be entirely known at the beginning of the trip. In fact, the final state is the initial condition of the recursive rule. In addition to the critical assumption of a problem formulated in a global way, DP also encounters some practical difficulties: its computational requirement. Even if it is very efficient compared to other approaches, the number of operations that must be carried out and the amount of data that must be kept in memory lead to a simulation time of several hours on a Pentium 4 PC.

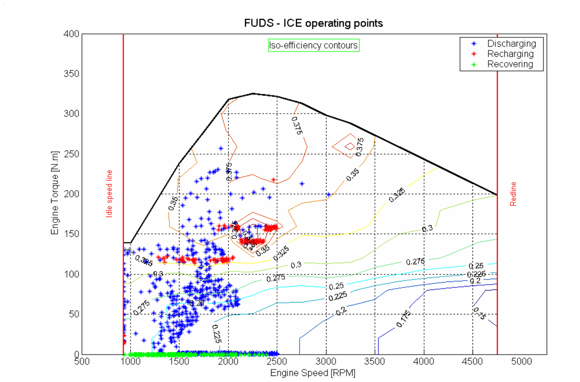
In conclusion, it is imperative to find a more flexible and cheaper approach to determine the best instantaneous torque split achieving good overall performance. The solution will necessarily be suboptimal, and DP will be a powerful validation tool to compare the new solution to the global optimum.

V. Equivalent Consumption Minimization Strategy

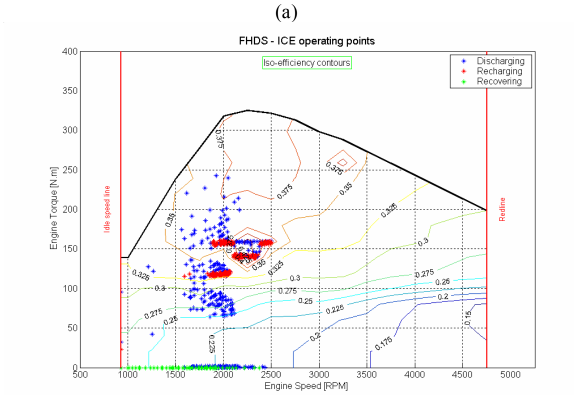
As illustrated in the previous section, although Dynamic Programming represents a powerful tool for solving the global optimization problem of energy management of HEV, it is not suitable for real-time applications.

In this section, a promising approach to the real-time control is presented. The main idea is to reduce the global criterion to an instantaneous optimization problem, introducing a cost function dependent only on the system variables at the current time.

In general terms, the local criterion can be formulated as follows:

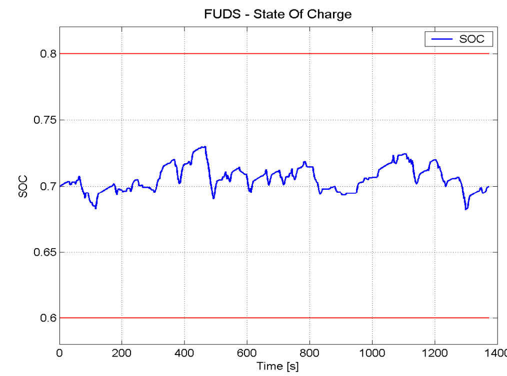


(a)

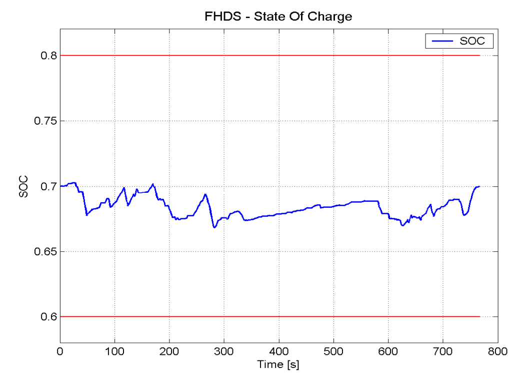


(b)

Fig. 4. Distribution of the ICE operating points for the optimized hybrid mode: (a) FUDS and (b) FHDS



(a)



(b)

Fig. 5. Optimal SOC trajectory for (a) FUDS and (b) FHDS cycles

At time t:

$$J_t = J_t(P_{ice}(t), P_{em}(t))$$

$$\{P_{ice}^{opt}(t), P_{em}^{opt}(t)\} = \arg \min_{\{P_{ice}(t), P_{em}(t)\}} J_t$$

$$\text{subject to:} \begin{cases} P_{req}(t) = P_{ice}(t) + P_{em}(t) \\ SOC_{min} < SOC(t) < SOC_{max} \quad \forall t \\ 0 \le P_{ice}(t) \le P_{ice,max}(t) \\ P_{em,min}(t) \le P_{em}(t) \le P_{em,max}(t) \end{cases}$$

Because of the *SOC* self-sustainability requirement, the cost function has to take into account not only the fuel consumption, but also the variations in the stored electrical energy. To deal with such aspects, various approaches have been proposed. In some cases, a tuning parameter, which is adjusted according to the current *SOC* deviation by means of a PID controller, is introduced into the cost function minimization [4]. In other cases, the cost function is the sum of all losses in the electrical and thermal paths [5].

Another, more promising approach was used in [6], [7]. It consists of evaluating the instantaneous cost function as a sum of the fuel consumption and an equivalent fuel consumption related to the SOC variation (Equivalent Consumption Minimization Strategy, ECMS). According with this approach, the instantaneous cost function is the sum of the fuel consumption $\dot{m}_{ice}(\bullet)$ and of an equivalent fuel consumption related to the use of the EM:

$$J_t = \dot{m}_{ice}(P_{ice}(t)) + \varsigma(P_{em}(t))$$

where the function $\varsigma(P_{em}(t))$ represents the fuel equivalent of the electrical energy. It is clearly recognized that the electrical energy and the fuel energy are not directly comparable, but an equivalence factor is needed. The equivalence between electrical energy and fuel energy is basically evaluated by considering average energy paths leading from the fuel to the storage of electrical energy. The assumption behind this approach is that every variation in the state of charge will be compensated in the future by the engine running at the current operating point. With this assumption the equivalent fuel flow rate due to the use of the EM is:

$$\text{With: } \gamma = \frac{1+\mathrm{sign}(P_{em}(t))}{2}$$

$$\varsigma(P_{em}(t)) = \gamma \cdot s_{dis} \frac{1}{\eta_{batt}(P_{em})\eta_{em}(P_{em})} \frac{P_{em}(t)}{H_{LHV}} + (1-\gamma) \cdot s_{chg} \cdot \eta_{batt}(P_{em})\eta_{em}(P_{em}) \frac{P_{em}(t)}{H_{LHV}}$$

where s_{dis} and s_{chg} represent the equivalence factors when the electrical energy is discharged, respectively recharged, and can be considered as control parameters of the ECMS approach. Thus, the local criterion at each time *t* is:

$$J_t = \dot{m}_{ice}(P_{ice}(t)) + \dot{m}_{em,equ}(P_{em}(t))$$

$$\dot{m}_{em,equ} = \gamma \cdot s_{dis} \frac{1}{\eta_{em}(P_{em})\eta_{em}(P_{em})} \frac{P_{em}}{H_{LHV}}$$

$$(1-\gamma) \cdot s_{chg} \eta_{em}(P_{em})\eta_{em}(P_{em}) \frac{P_{em}}{H_{LHV}}$$

$$\gamma = \frac{1+\mathrm{sign}(P_{em})}{2}$$

$$\{P_{ice}^{opt}(t), P_{em}^{opt}(t)\} = \arg \min_{\{P_{ice}(t), P_{em}(t)\}} J_t \quad \text{if } P_{req}(t) \geq 0$$

$$\{P_{ice}^{opt}(t) = 0, P_{em}^{opt}(t) = P_{req}\} \quad \text{if } P_{req}(t) < 0$$

$$\text{subject to: } \begin{cases} P_{req}(t) = P_{ice}(t) + P_{em}(t) \\ SOC_{min} < SOC(t) < SOC_{max} \quad \forall t \\ 0 \leq P_{ice}(t) \leq P_{ice,max}(t) \\ P_{em,min}(t) \leq P_{em}(t) \leq P_{em,max}(t) \end{cases}$$

ECMS strongly depends on the definition of the equivalent cost of the use of the equivalence factors. Unfortunately, those equivalence factors vary with the driving conditions so that a pair of equivalence factors (s_{dis}, s_{chg}) that is suitable for a driving cycle will lead to poor performance or even no charge sustaining conditions for others.

An interesting exercise in order to assess the potential of the ECMS approach is to find the pair of equivalence factors (s_{dis}, s_{chg}) that minimizes the fuel consumption for a given driving cycle. The overall fuel consumption can be considered as function of the equivalence factors and a systematic optimization can be used in order to find the equivalence factors that minimize the overall fuel consumption constrained to the SOC sustainability, *i.e.* final SOC equal to initial SOC. It should be noticed that such a control cannot be implemented in real-time, since the equivalence factors cannot be calculated *a priori*, *i.e.* the systematic optimization can be applied only if the driving cycle is known.

Using the optimal pair of equivalence factors, ECMS gives 25.7 mpg on FUDS and 25.9 mpg on FHDS, comparable with the results given by DP. Although this strategy cannot be implemented in real-time (since the optimum equivalence factors are not known), the results show the ECMS potential for achieving performance very close the global optimum. Thus, the ECMS principle represents a promising approach for formulating a control strategy for HEV. This aspect will be discussed in more details in the next section.

VI. DP VS. ECMS

A. Optimal Solution and Local Minimization

The most significant indicator of the performance of a control strategy for HEV energy management is the fuel economy, expressed in miles per gallon of gasoline. Table I summarizes the results obtained with DP and optimal ECMS for some standard driving schedules.

TABLE I
FUEL ECONOMY FOR DIFFERENT DRIVING CYCLES: DP VS. ECMS

Driving Cycle	ECMS opt	DP
FUDS	25.7	25.7
FHDS	25.9	26.0
ECE	24.5	24.5
EUDC	24.7	24.8
NEDC	24.5	24.5
JP1015	25.1	25.2

The performances in terms of fuel economy are practically the same for the local ECMS solution and the optimal DP solution. Thus, it can be asserted that a very slightly sub-optimal solution can be achieved with a technique much simpler that the one leading to the optimal policy. The assumptions and the limits of this statement will be extensively discussed in the next sub-section.

B. The Optimality of ECMS

The results shown above are very promising, in the sense that a slightly sub-optimal solution can be achieved with a straightforward instantaneous minimization. Nevertheless, it must be pointed out that it is still a theoretical approach that cannot be implemented in a real-time vehicle controller. In particular, it lacks the flexibility necessary to attain optimal performance in every situation.

The local minimization would return exactly the optimal solution only if the pair of equivalence factors are perfectly tuned. Their values are strictly cycle-dependent and can be calculated only for a perfectly known driving schedule. Hence, the ECMS leading to the exact optimal solution would have the same weakness of DP. The drawback is that the optimal choice of (s_{chg}, s_{dis}) is different for each driving schedule, as reported in Table II.

One may observe that all the values look rather close. Nonetheless, the control strategy is so sensitive to them that the pair that is suitable for the FUDS, for instance, will not be optimal for the FHDS. From a practical standpoint, it means that the strategy should be properly tuned every time that the nature of the driving cycle changes.

TABLE II
OPTIMAL CHOICE OF THE EQUIVALENCE FACTORS FOR DIFFERENT DRIVING CYCLES

Driving Cycle	sdis	schg
FUDS	2.59	2.63
FHDS	2.45	2.61
ECE	2.55	2.65
EUDC	2.37	2.71
NEDC	2.50	2.63
JP1015	2.50	2.73

There is no choice of the parameters that can be performed only once as initialization of the control strategy and applied in every situation. The control performance is very sensitive to the variation of the equivalence factors. In fact, small perturbations of the control parameters lead to non-charge sustaining operation (see Fig. 6).

In conclusion, a local minimization can lead to good performance only when the pair (s_{chg}, s_{dis}) is optimized for a precise driving cycle. Unfortunately, the system is very rigid and slight deviations from these values can jeopardize the vehicle operations. For a real-time energy management a more flexible solution must be investigated, keeping the performance as close as possible to the global optimum.

VII. A-ECMS: A REAL-TIME CONTROL STRATEGY

A real-time energy management for HEV is obtained adding to the ECMS framework a device able to relate the control parameters to the current velocity profile. In this paragraph, an on-the-fly algorithm for the estimation of the equivalence factors according to the driving conditions is presented. The main idea is to periodically refresh the control parameters according to the current road load, so that the *SOC* is maintained within the boundaries and the fuel consumption is minimized. In particular, the algorithm identifies the mission that the vehicle is following and determines the optimal equivalence factors for the current mission. The mission is built combining past and predicted data, so that a trade off between adaptivity and accuracy on the estimation of the equivalence factors is achieved. In presence of altitude variations, the prediction of the vehicle velocity is not sufficient to identify the road load. In this case, the use of external information, such as GPS, is necessary to provide accurate data about elevation.

If the mission is treated as a short cycle and if its length is such that the overall performance is close to the optimum, a systematic optimization can be used for the determination of the equivalence factors to be applied to the current mission.

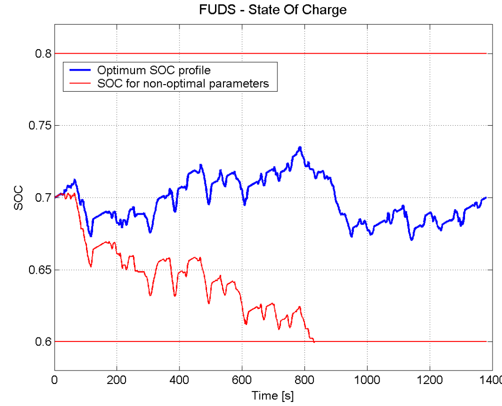


Fig. 6. SOC for optimal and non-optimal parameters: in the latter case a wrong evaluation of the equivalent cost leads to a non charge-sustaining behavior

Thus, at each instant when the equivalence factors must be updated, the algorithm first builds the current mission combining past and predicted vehicle speed and GPS data, then determines the control parameters that minimize the fuel consumption, while respecting the charge sustainability constraint. The resulting strategy is called Adaptive Equivalent Consumption Minimization Strategy (A-ECMS), with emphasis on the role of the online adaptive algorithm for the estimation of the equivalence factors according to the current driving conditions.

The high-level block diagram of the algorithm is sketched in Fig. 7.

The core of the A-ECMS is the on-the-fly algorithm for the estimation of the equivalence factors according to the driving conditions. The control parameters for the current mission can be determined using a systematic optimization. This approach leads to an exact estimation of the equivalent cost, but requires solving a bi-dimensional minimization problem. For mission of length of about 100 seconds, the computation burden is still heavy for a real-time implementation.

To overcome this drawback, the bi-dimensional problem can be reduced to a one-dimensional non-linear optimization, assuming a unique equivalence factor for the recharging and discharging mode:

$$s_{dis}(t) = s_{chg}(t) = s(t)$$

In order to assess the validity of this assumption, Table III reports the fuel economy obtained applying the systematic optimization procedure to different regulatory driving cycles with a pair and with a unique equivalence factor, respectively.

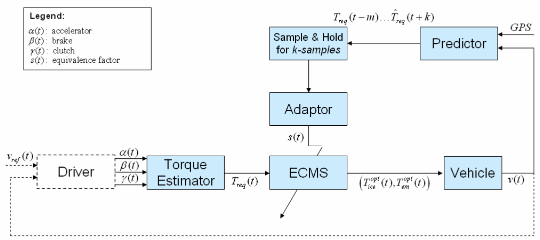


Fig. 7. Control Block Diagram of the A-ECMS

TABLE III

FUEL ECONOMY FOR DIFFERENT DRIVING CYCLES: OPTIMAL ECMS WITH TWO CONTROL PARAMETERS, OPTIMAL ECMS WITH ONE CONTROL PARAMETER VS. DP

	ECMS opt 2 par			ECMS opt 1 par		
Driving Cycle	s_{dis}	s_{chg}	**mpg**	s	**mpg**	**DP**
FUDS	2.59	2.63	25.7	2.61	25.7	25.7
FHDS	2.45	2.61	25.9	2.54	25.8	26.0
ECE	2.55	2.65	24.5	2.60	24.5	24.5
EUDC	2.37	2.71	24.7	2.48	24.7	24.8
NEDC	2.50	2.63	24.5	2.51	24.5	24.5
JP1015	2.50	2.73	25.1	2.69	25.1	25.2

The performances are practically the same for both optimal ECMS and very close to the DP optimal solution. Thus, the assumption of unique equivalence factor for the recharging and discharging mode can be considered valid and maintains the effectiveness of all the conclusions carried out in the previous chapters. It is worth noting that the equivalence factor s is always between s_{dis} and s_{chg}, so that the unique equivalence factor can be interpreted as the result of an averaging of the equivalence factors in recharging and discharging mode.

A. Results

The Adaptive-ECMS must address the issues related to the implementation of a real-time controller for HEV energy management. Recalling the discussions of the previous chapters, they can be summarized in the following points:

1) Minimization of fuel consumption and pollutant emissions
2) Maintain of the battery SOC (charge-sustaining vehicle)
3) Validity in every driving condition
4) Causality, *i.e.* no *a priori* knowledge required
5) Real-time implementation

A-ECMS meets the last two requirements by construction. In fact, the use of the prediction in the portion of mission that describes the driving cycle ahead replaces any form of *a priori* knowledge; the power split actually sent to the powertrain is determined at every time instant, so that even unexpected changes in the road load or driver behavior are immediately taken into account. This sub-section presents the main results proving the effectiveness of A-ECMS in fulfilling all the other requirements as well, and the interest of its introduction in HEV energy management strategies.

The first indicator of the performance of the control strategy is the gas mileage achieved over a set of regulatory cycles that reproduce common driving situations and are used for official estimates. Table IV compares the performance of the optimal solution obtained with DP over the full cycle, the solution obtained with a perfectly tuned one-parameter ECMS and the solution from A-ECMS. All the results are obtained on the simplified backward model already used in the previous sections.

Table V reports the A-ECMS results obtained with the full vehicle simulator VP-SIM. Also indicated is the final SOC of the battery; when different from the initial value of 0.7, its equivalent cost is taken into account in a correction of the fuel consumption of the ICE. It can be noticed that the final SOC is always included in the boundaries and the strategy is charge-sustaining for every cycle.

TABLE IV

FUEL ECONOMY IN MPG FOR REGULATORY CYCLES WITH DIFFERENT CONTROL STRATEGIES. THE PERCENTAGE OF IMPROVEMENT OVER THE PURE THERMAL MODE IS ALSO REPORTED

	Pure thermal	DP		ECMS opt		A-ECMS	
Driving Cycle	**mpg**	**mpg**	**Improv.**	**mpg**	**Improv.**	**mpg**	**Improv.**
FUDS	22.1	25.7	16.4%	25.7	16.3%	25.5	15.5%
FHDS	24.8	26.0	4.9%	25.8	4.1%	25.8	3.9%
ECE	20.8	24.5	18.2%	24.5	18.0%	24.5	17.9%
EUDC	23.3	24.8	6.3%	24.7	6.2%	24.7	6.1%
NEDC	22.2	24.5	10.7%	24.5	10.7%	24.4	10.1%
JP1015	21.0	25.2	20.1%	25.1	19.8%	24.8	18.2%

TABLE V

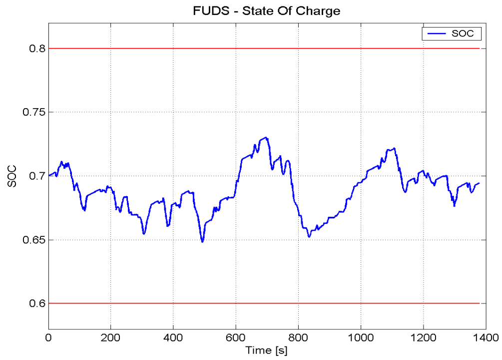
A-ECMS: FT-SIM RESULTS

Driving cycle	**mpg**	***SOC* fin**
FUDS	26.3	0.695
FHDS	26.1	0.655
ECE	22.3	0.732
EUDC	23.7	0.701
NEDC	23.8	0.733
JP10-15	25.3	0.705

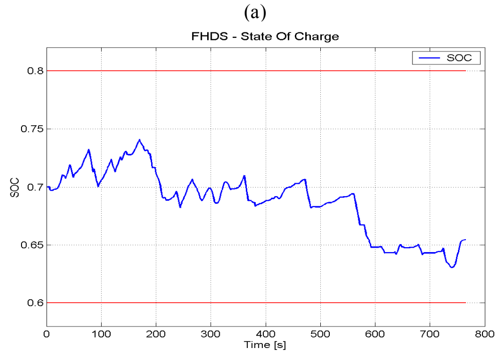
In order to confirm and analyze the results above, the case of FUDS and FHDS cycles is investigated in more detail.

Fig. 8 shows the SOC profiles. In both cases the SOC trajectory over time stays within the boundaries. The SOC constraints are fulfilled and the vehicle is overall charge-sustaining. This important achievement is a consequence of the definition of equivalent cost for the use of the EM: when correctly estimated, *i.e.* when the correct value of s is determined, it implicitly compensates the natural tendency to deplete the battery of the consumption minimization.

Comparing these plots to the corresponding SOC profiles obtained with DP (Fig. 5), several differences become evident. Solving the problem by mission introduces oscillations. In fact, when significant changes in the cycle patterns occur, the equivalent cost does not reflect the cycle characteristics and for short periods the SOC deviates from the reference value of 0.7.



(a)

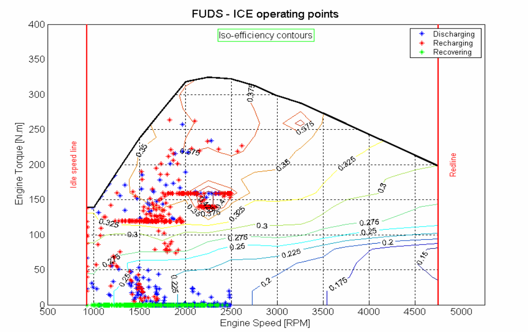


(b)

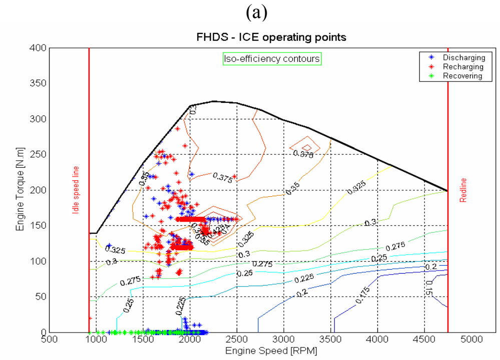
Fig. 8. A-ECMS SOC trajectory for (a) FUDS and (b) FHDS cycles

However, the algorithm reacts to the changed situation and adapts the equivalence factor, thus keeping the SOC within the prescribed limits.

The distribution of the ICE operating points confirms the validity of A-ECMS. As shown by the clustering of dots in Fig. 9, the EM motor in recharging mode is often used as a variable load for the ICE, so that the latter can work in the highest efficiency regions. Moreover, the bottom area with lower efficiency is almost completely avoided: in these situations, the ICE efficiency would be very poor and the small power request is satisfied by the EM instead.



(a)



(b)

Fig. 9. Distribution of the ICE operating points with A-ECMS: (a) FUDS and (b) FHDS

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