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TITLE:

AN ADAPTIVE ALGORITHM FOR HYBRID ELECTRIC VEHICLES ENERGY MANAGEMENT

Topic:

- ● FUTURE AUTOMOTIVE TECHNOLOGY
- ○ INTELLIGENT TRANSPORTATION SYSTEMS
- ○ USER FRIENDLY AUTOMOBILE
- ○ ADVANCED PRODUCTION AND LOGISTICS
- ○ VEHICLES & THE ENVIRONMENT

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Abstract:

Hybrid Electric Vehicles (HEVs) improvements in fuel economy and emissions strongly depend on the energy management strategy. The global solution to the HEV control problem can be found with Dynamic Programming if the driving cycle is known *a priori*. It is shown that a local approach gives similar results if a pair of parameters related to the cost of using the electric motor is determined. It is also shown how the optimization on the whole cycle can be reduced to an optimization over shorter missions composed of past and predicted data. Since the value of the parameters is deeply connected to the nature of the driving cycle, the paper presents an adaptive algorithm to determine the best choice of the pair according to the current driving conditions. Initial simulation results show that better fuel economy can be achieved compared to instantaneous minimization techniques. These results are now being implemented on the Ohio State University BuckHybrid 2004, a hybrid-electric version of a production Ford Explorer SUV developed as part of the Ford-U.S. DOE FutureTruck student competition. Experimental results will be presented at the conference.

Place / Date:

Columbus, OH, USA February 2004

I - INTRODUCTION

Hybrid Electric Vehicles (HEVs) have been proposed as a feasible vehicle technology that will help achieving economic and environmental objectives such as reducing oil dependence and polluting emissions. The essence of HEV control is the instantaneous management of the power flow from two different sources, the internal combustion engine (ICE) and the electric motor (EM). The peculiarity of this problem is that while the control actions are local in time, the control objectives, *i.e.* fuel consumption and emissions per mile of travel, are integral. Moreover, the constraint of maintaining the battery state-of-charge (*SOC*) is also an integral constraint. Only if the driving schedule is known *a priori*, can the optimal solution for this global problem be found using Dynamic Programming (DP) (1),(2). However, the Equivalent fuel Consumption Minimization Strategy (ECMS) defines an equivalent fuel flow rate $\dot{m}_{f,equ}(t)$ so that the global fuel consumption minimization can be replaced by a local one (3),(4),(5):

$$\text{Global:}\begin{cases}\min\limits_{\{P_{ice}(t),P_{em}(t)\forall t\}} \int_0^{T_f} \dot{m}_{ice}(t)dt \\ SOC_{min} < SOC(t) < SOC_{max}\end{cases} \Rightarrow \quad \text{Local:}\begin{cases}\int_0^{T_f} \min\limits_{\{P_{ice}(t),P_{em}(t)\forall t\}} \dot{m}_{f,equ}(t)dt \\ SOC_{min} < SOC(t) < SOC_{max}\end{cases} \qquad (1)$$

The global minimization problem and the local one are not strictly equivalent. It is shown that the same control law can be derived applying the local criterion (1), provided that the equivalent fuel consumption is formulated in such a way that it indirectly accounts for the non-local aspects of the problem (3). For that purpose, any instantaneous usage of the EM is converted in terms of future fuel cost by using two average efficiencies $(\overline{\eta}_{chg},\overline{\eta}_{dis})$ that are considered as parameters of the strategy.
The whole driving cycle can be split into missions of appropriate length; it is shown here that a pair $(\overline{\eta}_{chg},\overline{\eta}_{dis})$ can be associated to each mission so that the overall performance provided by the sum of these missions is comparable to the global optimum. The pair $(\overline{\eta}_{chg},\overline{\eta}_{dis})$ strongly depends on the type of mission. Thus, this paper presents an on-the-fly adaptive algorithm to determine the pair that achieves optimal performance while satisfying the charge sustaining constraint. More robustness and better adaptivity can be obtained combining past and predicted vehicle velocity with elevation data from GPS.

II - GLOBAL VS. LOCAL OPTIMIZATION

Dynamic Programming

When the driving schedule is known *a priori*, *i.e.* the velocity profile of the vehicle is known from $t=0$ to $t=T_f$, a solution to the global optimization problem is provided by Dynamic Programming. A simplified quasi-stationary model of an HEV that considers the battery *SOC* as the only dynamic state is used to calculate the fuel consumption.
The control problem is formulated as follows: given the speed and thus the power required at each discrete time instant $t \in \left[0, T_f\right]$, determine the optimal control input P_{em} that minimizes the fuel consumption over this interval:

$$J = \sum_{t=0}^{T_f} \dot{m}_{ice}(t, P_{em})\Delta t \quad \text{with the constraints:}\begin{cases}SOC_{min} < SOC(t) < SOC_{max} \\ P_{req}(t) = P_{ice}(t) + P_{em}(t)\end{cases} \qquad (2)$$

The solving algorithm, the Dynamic Programming proposed by Bellmann (6), proceeds backwards from time $t = T_f$ to time $t = 0$, evaluating the cost of going from one state to another. Starting from $SOC(T_f)$, a cost matrix $J(t, SOC)$ is calculated using the recursive rule:

$$J(t+i, SOC(t+i)) = \min_{P_{em}} \left\{ J(t+i+1, SOC(t+i) - P_{em}\Delta t) + \dot{m}_{ice}(t+i, P_{em})\Delta t \right\} \tag{3}$$

At the end of the algorithm, $J(t, SOC(0))$ contains the total cost of going from the state corresponding to $SOC(0)$ to the state corresponding to $SOC(T_f)$. Then, proceeding forward, the arguments of J (*i.e.* the values of P_{em} that minimize the fuel consumption) give the sequence of control inputs that should be sent to achieve that result.

<u>Equivalent Fuel consumption Minimization Strategy</u>

As mentioned in the Introduction, the ECMS is based on the definition of the equivalent fuel consumption $\dot{m}_{f,equ}(t)$ as the sum of the actual fuel consumption of the ICE $\dot{m}_{ice}(t)$ and the equivalent fuel consumption of the EM $\dot{m}_{em,equ}(t)$:

$$\dot{m}_{f,equ}(t) = \dot{m}_{ice}(t) + \dot{m}_{em,equ}(t) \tag{4}$$

The equivalent fuel consumption of the EM $\dot{m}_{em,equ}(t)$ can be calculated converting an instantaneous usage of the EM in terms of future/past fuel cost or saving. The energy provided by or to the EM is converted in equivalent fuel via the component efficiencies. Since the electrical energy in-flows and out-flows of the battery are non-local in time, the conversion efficiencies can be defined only in statistical sense.
The operating conditions of a parallel hybrid vehicle can be classified in three modes:

- Charging mode, i.e. when the ICE is providing power to the battery and the wheels: $P_{ice} > 0, P_{em} < 0$ and $P_{req} > 0$
- Discharging mode, i.e. when both the and the EM are providing power to the wheels: $P_{ice} > 0, P_{em} > 0$ and $P_{req} > 0$
- Recovering mode, *i.e.* regenerative braking $P_{ice} = 0, P_{em} < 0$ and $P_{req} < 0$

Considering the architecture of the parallel hybrid vehicle sketched in Appendix, the analysis of the power flows trough the components all operating modes leads to the following expression of the equivalent fuel consumption of the EM $\dot{m}_{em,equ}(t)$:

$$\dot{m}_{equ,em}(t) = \begin{cases} \dfrac{1}{\overline{\eta}_{chg}} \cdot \dfrac{1}{\eta_{em}(P_{em}(t)) \cdot \eta_{batt}(P_{em}(t))} \cdot \dfrac{P_{em}(t)}{H_{LHV}} & P_{em} > 0 \\ \overline{\eta}_{dis} \cdot \eta_{em}(P_{em}(t)) \cdot \eta_{batt}(P_{em}(t)) \cdot \dfrac{P_{em}(t)}{H_{LHV}} & P_{em} < 0 \end{cases} \tag{5}$$

where:

$\overline{\eta}_{chg}$: average efficiency in all charging conditions

$\overline{\eta}_{dis}$: average efficiency in all discharging conditions

The statistical expressions of the average efficiencies for a parallel hybrid vehicle are reported in the Appendix.

Thus, the ECMS algorithm depends on two parameters $(\overline{\eta}_{chg}, \overline{\eta}_{dis})$ that can be tuned in order to minimize the fuel consumption while respecting the charge-sustaining constraint.

<u>Comparison</u>

The global minimization problem and the local one are not strictly equivalent. However, the solution provided by ECMS follows very closely the global optimum obtained with DP, as shown in Fig. 1 for a FUDS cycle. Besides the SOC sustainability, the results are similar in terms of fuel economy as well: 29.13 mpg of bio-diesel for DP and 29.09 mpg for ECMS.

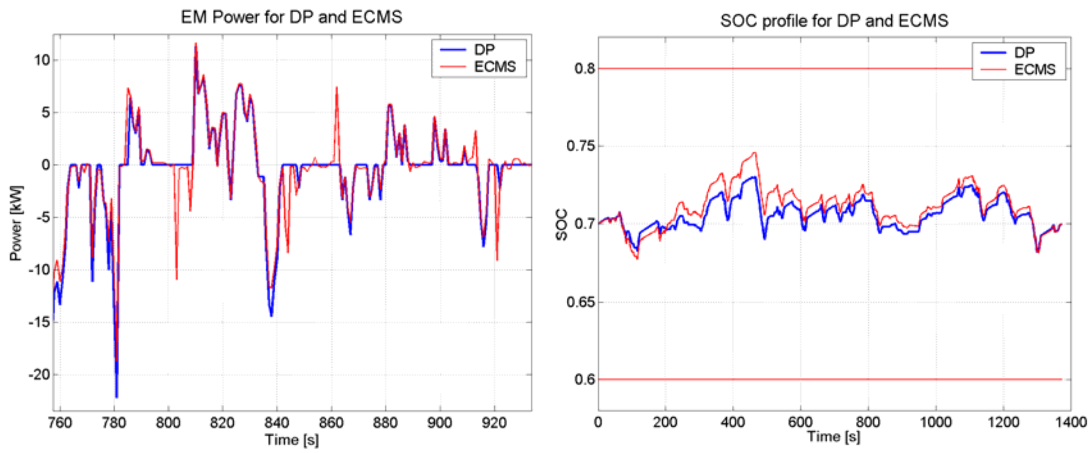


Fig. 1 Comparison of the electric power (left) and the SOC (right) for a FUDS cycle with DP and ECMS

ECMS proves to be an excellent candidate for the implementation of a real-time control strategy on an actual HEV (7),(8). The major drawback of DP is in fact that a full knowledge of the future driving cycle is needed in order to find the optimal control policy. Moreover, DP is computationally too heavy and not suited to real-time applications.
Nonetheless, the global-local equivalence can be achieved only if the pair $(\overline{\eta}_{chg}, \overline{\eta}_{dis})$ is well chosen *for a given driving schedule*; otherwise the ECMS is no longer able to sustain the battery SOC at reasonable levels. In fact, different characteristics of the cycles, such as the number of recovering/charging/discharging opportunities, change significantly the average efficiencies and consequently the cost of operating the EM. The optimal values of $(\overline{\eta}_{chg}, \overline{\eta}_{dis})$ for common cycles are presented in Table 1.

Table 1 Optimal values of the average efficiencies that minimize the fuel consumption

	FUDS	**FHDS**	**FT03**	**ECE**	**EUDC**	**NEDC**	**JP10-15**
$\overline{\eta}_{chg}$	0.40	0.45	0.32	0.40	0.42	0.40	0.46
$\overline{\eta}_{dis}$	2.55	2.28	1.54	2.69	2.62	2.66	2.11

The charge-sustaining region and the iso-fuel consumption contours for the FUDS cycle are shown in Fig. 2. The comparison between the SOC obtained with the optimal pair $(\overline{\eta}_{chg}, \overline{\eta}_{dis})$ and the SOC obtained with a non-optimal pair is shown in Fig.3.
To achieve the best results from the ECMS, it is then necessary to properly choose the average efficiencies $(\overline{\eta}_{chg}, \overline{\eta}_{dis})$ according to the current driving conditions.

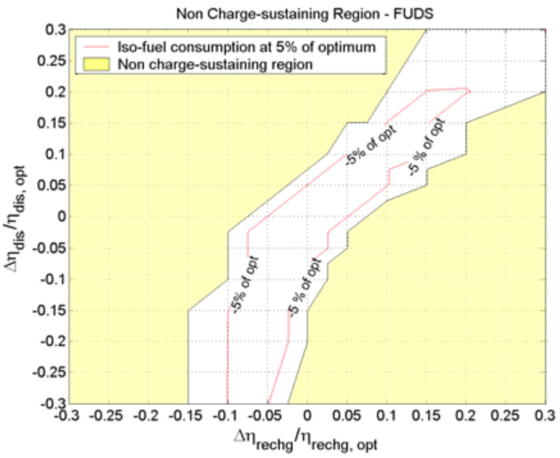


Fig. 2 Iso-fuel consumption contour and non charge-sustaining region

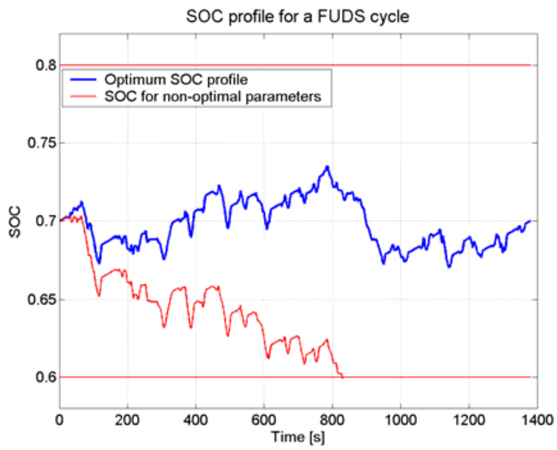


Fig. 3 SOC for optimal and non-optimal parameters: in the latter case a wrong evaluation of the equivalent cost leads to a non charge-sustaining behaviour

III - ADAPTIVE ECMS

As illustrated in section II, the match of $(\overline{\eta}_{chg}, \overline{\eta}_{dis})$ with the current driving schedule is critical. This section presents an on-the-fly adaptive algorithm that determines the pair achieving optimal performance while satisfying the charge sustaining constraint.

The concept of driving cycle can be generalized as mission. A mission is defined here as a trait T of the vehicle route where the net electrical energy flow is zero. In fact, the electrical energy stored in the battery (≈ 1 MJ, with 0.6<SOC<0.8) can be neglected in comparison with the chemical energy stored in the tank (≈ 10 GJ). Thus, in HEVs the battery is used as an energy buffer, so that, for a long run, the net electrical energy flow can be considered zero:

$$\int_0^T P_{batt}(t)dt \approx 0 \tag{6}$$

The whole driving cycle is split into missions of length T. The optimal solution for each mission j is calculated using DP and gives a fuel consumption m_j. The duration T of the mission is determined so that $\sum_j m_j$ is close to the optimal fuel consumption over the whole cycle. The table below shows that with T longer than 50 s the cycle can be treated as sum of shorter missions without significantly affecting the performance.

Table 2 Total fuel consumption obtained splitting FUDS and FHDS cycles in missions of duration T

FUDS	**T**	10	20	50	100	150	200	Full cycle
	mpg	27.14	27.9	28.72	29.02	29.02	29.1	29.13
FHDS	**T**	10	20	50	100	150	200	Full cycle
	mpg	29.38	29.5	29.75	29.88	29.79	29.89	29.9

From section II and the previous discussion, a solution close to the global optimum can be obtained by matching $(\overline{\eta}_{chg}, \overline{\eta}_{dis})$ to each mission and not to the whole cycle. This pair can be chosen by imposing the condition (6), which can also be translated in requiring a flat SOC trend over the mission.

The core of the Adaptive ECMS (A-ECMS) is an algorithm for the on-line estimation of $(\overline{\eta}_{chg}, \overline{\eta}_{dis})$ according to the current mission. The main idea of the algorithm is to find the pair of average efficiencies that assures a flat SOC trend over the mission. Since the fuel consumption is close to the optimal one within the charge-sustaining region, as it is shown in Fig. 2, this criterion leads to results close to the optimal one.

The slope θ_{SOC} of the SOC trend over the mission can be related to the variation $(\delta\overline{\eta}_{chg}, \delta\overline{\eta}_{dis})$ of the average efficiencies with respect to their optimal values trough a sensitivity plane:

$$\theta_{SOC} = a_1 \frac{\delta\overline{\eta}_{chg}}{\overline{\eta}_{chg}^{opt}} + a_2 \frac{\delta\overline{\eta}_{dis}}{\overline{\eta}_{dis}^{opt}} \tag{7}$$

where the coefficients (a_1, a_2) are determined by fitting simulation results for different cycles.

The measured slope θ_{SOC} over a mission identifies via the sensitivity plane an infinite set of pairs of corrections $(\delta\overline{\eta}_{chg}, \delta\overline{\eta}_{dis})$ (see Fig. 4). An *a priori* probability density function, built simulating different cycles with different pairs of $(\overline{\eta}_{chg}, \overline{\eta}_{dis})$, can be used to discern the best candidates of $(\overline{\eta}_{chg}, \overline{\eta}_{dis})$ (see Fig. 5). Combining the sensitivity plane and the probability density function, the algorithm finds the most probable correction $(\delta\overline{\eta}_{chg}, \delta\overline{\eta}_{dis})$ to be applied to the current average efficiencies to keep the SOC trend flat over the mission. Thus, the new pair can be considered the optimal choice of parameters for the current mission.

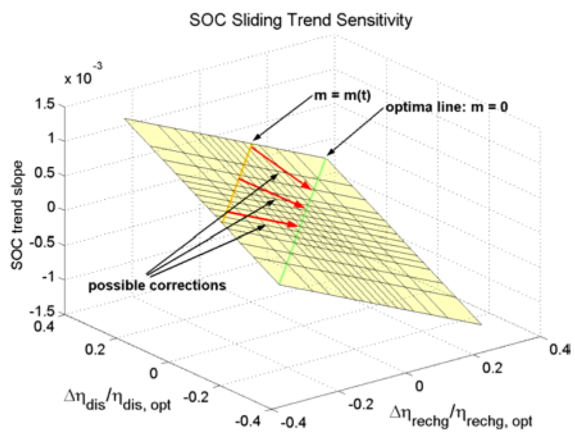


Fig. 4 From a measured slope, the possible corrections towards the optima line are determined through the sensitivity plane

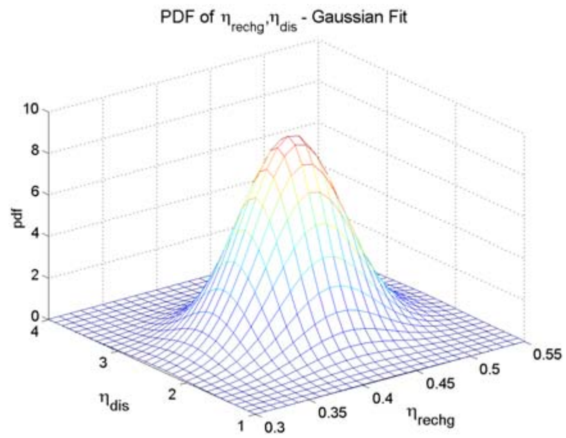


Fig. 5 Probability density function of the charge-sustaining average efficiencies

In order to achieve the best performance, the mission starting at time *t* should be known. The algorithm would then choose $(\overline{\eta}_{chg}, \overline{\eta}_{dis})$ and the control of the vehicle would be optimized for the next *T* seconds. In real driving conditions this information is obviously not available, while it is possible to keep record of the past driving conditions. With the assumption that the driving schedule will not change dramatically, the A-ECMS can be applied to a mission of *T* seconds in the past. The selected values of $(\overline{\eta}_{chg}, \overline{\eta}_{dis})$ are then adopted in the minimization of the fuel consumption until a new pair is calculated.

Simulations show that this assumption is reasonable and it is verified in most of the cases. Nonetheless, it may happen that a sudden variation of the driving cycle characteristics, such as a grade, takes place. In this case, the selected pair would not lead to optimal control. A possible trade-off that increases the adaptability and the robustness of the A-ECMS is to consider a mission composed by past data and future data, where information in the future comes from a prediction of the driving cycle. The velocity profile can be considered a time-series and a linear autoregressive model that describes it can be identified exploiting past data (9),(10). The K-steps predictor of this model will provide the velocity in the next K time instants and the GPS will provide accurate data about elevation. The velocity prediction is affected by an error that increases with K; for K = 20 s or more the fit with actual data becomes poor (see Fig. 6), but the prediction is still useful to understand what the driving cycle is likely to be.

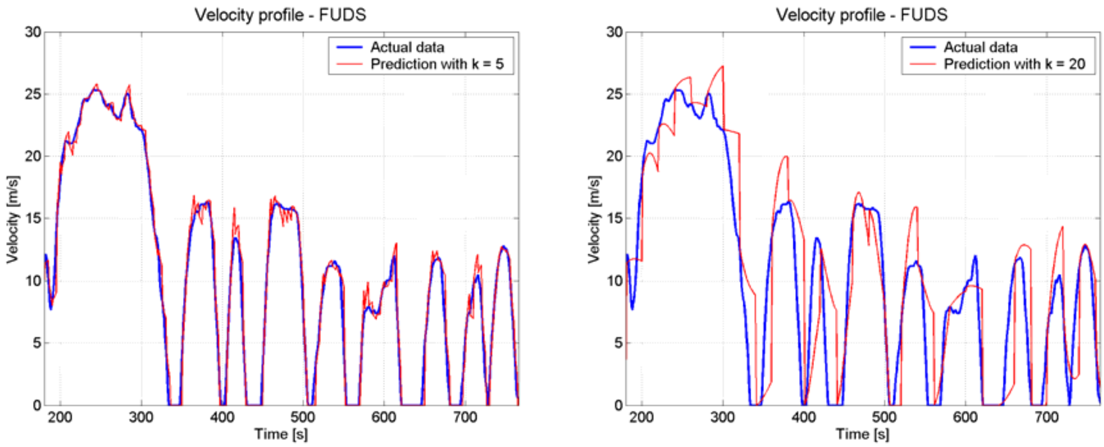


Fig. 6 For short horizons (left) the prediction is accurate; otherwise (right) only the trend is reproduced

Since the actual power split is determined by the A-ECMS at each time-instant and based on measured data, even a rough prediction is useful to choose $(\overline{\eta}_{chg}, \overline{\eta}_{dis})$ without making significant mistakes in the instantaneous fuel consumption minimization. Thus, the mission consists of M seconds in the past and K seconds in the future, where $M + K = T$.

IV - RESULTS

Performances of the algorithm have been evaluated using a Matlab/Simulink simulator. The authors developed the model enhancing VP-SIM, a forward quasi-static vehicle simulator (11), (12). The original scalable and composable model was adapted to the Ohio State University BuckHybrid 2004, a hybrid-electric version of a production Ford Explorer SUV, using maps for the ICE and the EM. The essential data of the vehicle are summarized in the Appendix.

In accordance with section III, the duration T of the mission was chosen 120 s. In order to achieve better adaptivity to the mission, the size K of the prediction horizon is set to 20 s, so that the mission consists of 100 s in the past and 20 s in the future. For proving the robustness and the adaptivity of the algorithm, the A-ECMS was tested for different cycles and the results were compared with the performance obtained using the ECMS with optimal values of $(\overline{\eta}_{chg}, \overline{\eta}_{dis})$.

Fig. 7 shows the SOC profiles obtained with A-ECMS and ECMS for two FUDS cycles.

Even though the SOC profiles are quite different on the cycle scale, it is possible to recognize some patterns associated with shorter missions. In fact, the overall fuel consumptions measured in both cases are very close: 29.09 mpg bio-diesel with ECMS and 28.67 mpg with A-ECMS. It is worth noticing that A-ECMS achieves this result without any prior knowledge of the average efficiencies, because it inherently evaluates the proper cost of hybrid operation.

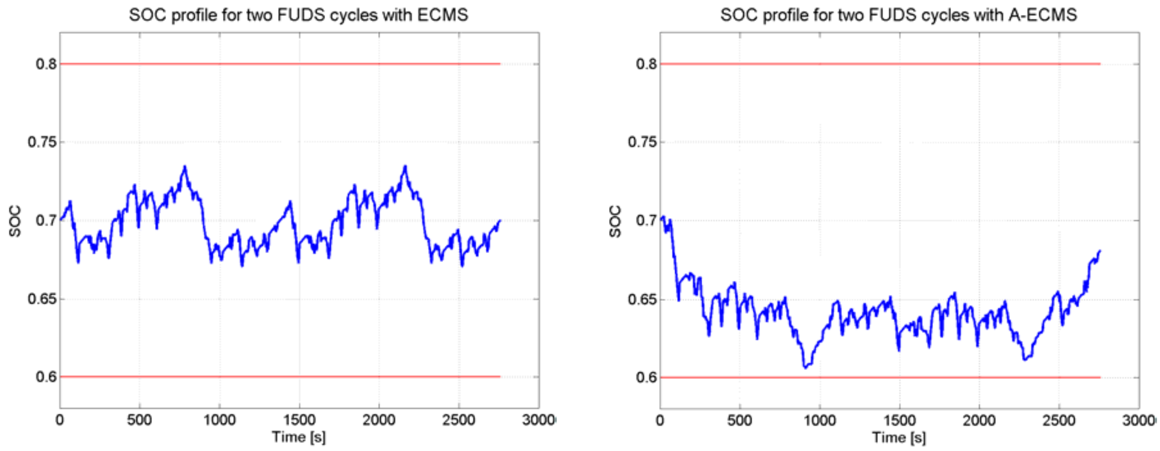
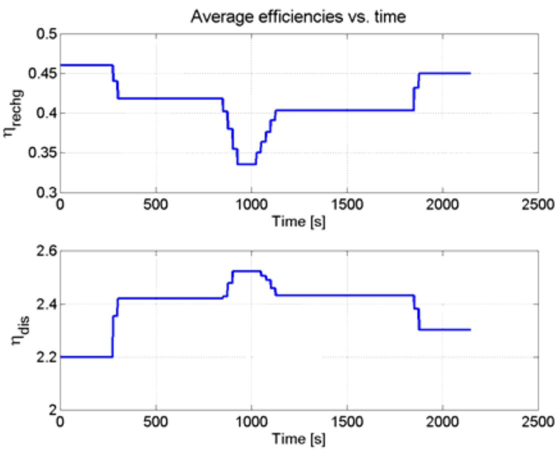


Fig. 7 Comparison of the SOC profiles obtained with ECMS (left) and A-ECMS (right)

Moreover, there are cases where it is not possible to find an optimal pair of $(\overline{\eta}_{chg}, \overline{\eta}_{dis})$ for the ECMS in order to minimize the fuel consumption and guarantee the charge-sustaining condition. In fact, in driving schedules with very different characteristics, such as a succession of an urban and a highway cycle, the average efficiencies cannot be considered constant. In these situations, a simple ECMS approach would not work properly, unless features like a penalty function are introduced to keep the SOC within the boundaries. On the contrary, Fig. 8 and 9 illustrate how the possibility of adapting the average efficiencies to the current mission allows achieving good performance and controlling the SOC profile.



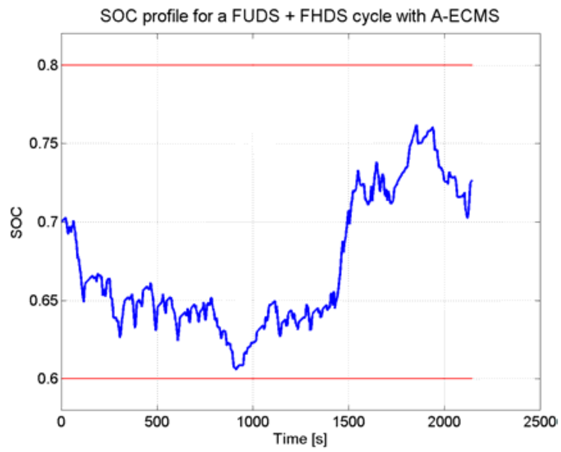


Fig. 8 Average efficiencies profiles for FUDS+FHDS **Fig. 9** SOC profile for FUDS+FHDS

V – CONCLUSION

A sub-optimal control strategy for HEV energy management has been developed. Computer simulations show that the overall performance is only slightly lower than the global optimum. In exchange, robustness to different driving conditions is achieved.
The strategy is now being implemented on the Ohio State University BuckHybrid 2004, a hybrid-electric version of a production Ford Explorer SUV, for real-driving on-the-road testing and for taking part to the Ford-U.S. DOE FutureTruck student competition.

APPENDIX

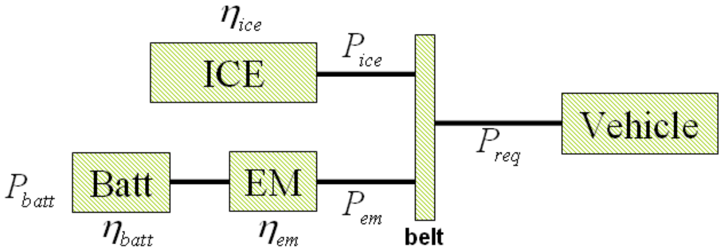


Fig. A1 Architecture of a parallel HEV

Table A1 Definition of the average efficiencies

Average ratio of energy recovered/charged	$\overline{R} = \left\langle \dfrac{\int_0^t \lfloor P_{batt}(\tau) \rfloor_{recov} \, d\tau}{\int_0^t \lfloor P_{batt}(\tau) \rfloor_{chg} \, d\tau} \right\rangle_{\text{all conditions}}$
Average efficiency in charging mode	$\overline{\eta}_{chg} = \overline{\eta}^*_{chg}(1+\overline{R})$ $\overline{\eta}^*_{chg} = \left\langle \int_0^t \eta_{batt}(\tau)\eta_{em}(\tau)\eta_{ice}(\tau) d\tau \right\rangle_{\text{all charging conditions}}$
Average efficiency in discharging mode	$\overline{\eta}_{dis} = \left\langle \int_0^t \dfrac{\eta_{batt}(\tau)\eta_{em}(\tau)}{\eta_{ice}(\tau)} d\tau \right\rangle_{\text{all discharging conditions}}$

Table A2 FutureTruck characteristics

VM motori engine CIDI 2.5L 4 cylinder, 4 strokes

Siemens 1PV5105-4WS15-Z AC induction

Vehicle mass: 2311 [Kg]
Frontal area: 2.92 [m^2]
Drag coefficient: 0.45
Rolling Resistance coefficient: 0.015

Battery type: Hawker Lead Acid E-Cell
Cell Nominal Voltage: 2 [V]
Cell capacity: 8 [Ah]
Maximum current Discharge: 90 [A]
Maximum current Recharging: 60 [A]
Number of cells in series: 150
Upper limit of SOC: 0.8
Lower limit of SOC: 0.6

Belt efficiency: 0.9
Belt ratio: 1.8
Gear ratio (1^{st} to 5^{th}): [3.38 2.04 1.3 1 0.78]
Gear efficiency: 0.95
Differential ratio: 3.73
Differential efficiency: 0.95
Wheel radius: 0.36 [m]

REFERENCES

(1) Sciarretta A., Guzzella L., Onder C. H., ,"On the Power Split Control of Parallel Hybrid Vehicles: from Global Optimization towards Real-time Control", Automatisierungstechnik 51, 5/2003.

(2) Lin C. C., J. M. Kang, J. W. Grizzle, and H. Peng, "Power Management Strategy for Parallel Hybrid Electric Truck", IEEE Transactions of Control Systems Technology, Vol. 11, No. 6, November 2003.

(3) Paganelli, G., Ercole G., Brahma A., Guezennec Y. and Rizzoni G., "General Supervisory Control Policy for the Energy Optimization of Charge-Sustaining Hybrid Electric Vehicles" , JSAE Review 22, pp 511-518, 2001.

(4) Paganelli, G., Tateno M., Brahma A., Rizzoni G. and Guezennec Y., "Control Development for a Hybrid-Electric Sport-Utility Vehicle: Strategy, Implementation and Field Test Results", Proc. American Control Conference, VA, pp. 5064–5069, June 2001.

(5) Paganelli, G., Delprat S., Guerra T.M., Rimaux J. and Santin J.J., "Equivalent Consumption Minimization Strategy for Parallel Hybrid Powertrains", IEEE, 2002.

(6) Bellman R. E. and S. E. Dreyfus, "Applied Dynamic Programming", Princeton University Press, 1962.

(7) Sciarretta A., Guzzella L. and Back M., "Optimal Control of Parallel Hybrid Electric Vehicles", IEEE Transactions on Control Systems Technology, accepted for publication, Ref. 2002-122

(8) Sciarretta A., Guzzella L. and Back M., "A Real-time Optimal Control of Parallel Hybrid Electric Vehicles with On-board Estimation of the Control Parameters", 1st IFAC Symposium on Advances in Automotive Control (AAC04), Salerno, Italy, April 19-23, 2004 (accepted for publication)

(9) Bittanti S., "Teoria della Predizione e del Filtraggio", Pitagora Editrice, 1997.

(10) Bittanti S., "Identificazione dei modelli e Controllo adattativo", Pitagora Editrice, 1997.

(11) Rizzoni G., Guzzella L., and Baumann B. M.,, "Unified Modeling of Hybrid Electric Vehicle Drivetrains", IEEE/ASME Trans. on Mechatronics, Vol. 4, No. 3, pp. 246–257, 1999.

(12) Rizzoni G., Guezennec Y., Brahma A., Wei X. and Miller T., "VP-SIM: A Unified Approach to Energy and Power Flow Modeling Simulation and Analysis of Hybrid Vehicles", SAE, Paper No. 00FCC-64, 2000.