Preprints of the 19th World Congress
The International Federation of Automatic Control
Cape Town, South Africa. August 24-29, 2014

Stochastic Dynamic Programming based Energy Management of HEV's: an Experimental Validation

T. Leroy * **F. Vidal-Naquet** * **P. Tona** *

* *IFP Energies nouvelles, 1 et 4 avenue de Bois-Préau, 92852 Rueil-Malmaison, France*

Abstract: This paper addresses an experimental validation of an energy management strategy on a parallel Hybrid Electric Vehicle (HEV). The strategy under consideration is based on Stochastic Dynamic Programming. The control law (determining the torque split between the engine and the motor) is computed off-line by solving an infinite horizon optimization problem. It results in a time-invariant state feedback controller function of vehicle acceleration and velocity, battery state of charge and engine state. This controller is first validated in simulation and then implemented in the vehicle electronic control unit. Experimental results highlight the good behavior of the control strategy. During a 35 km urban route, the strategy succeeds in regulating the battery state of charge and judiciously uses the powertrain.

Keywords: Hybrid vehicles; Automotive control; Energy management systems; Optimal control; Stochastic dynamic programming; On-line control.

1. INTRODUCTION

The past few years have seen an unprecedented effort towards the definition of energy management strategies able to manage the energy flow in hybrid electric vehicles (HEV, see Serrao [2009] for a complete survey). Focusing the analysis on the charge sustaining hybrids, it is possible to identify two directions that have been followed by the industry and by academia.

On the one hand, vehicle manufacturers have predominantly been developing heuristic controllers, also called rule-based controllers. If such controllers have proven being effective and reliable for practical applications, they also present a structural disadvantage in terms of fuel consumption with respect to the local optimal control strategies (see Opila et al. [2009]) and require a long and expensive development process.

On the other hand, academic institutions have been proposing a variety of control strategies, some requiring information about the future driving conditions (off-line strategies), others not needing any future information (on-line strategies). Among the former, it is possible to mention the Pontryagin's Minimum Principle (Chasse and Sciarretta [2011], Serrao et al. [2009]) and the Dynamic Programming (Perez et al. [2006]). These strategies, also referred to as global optimal strategies, are very useful for reference purposes thanks to the guarantee of optimality they provide. Nevertheless, they cannot be implemented in real vehicles without future driving conditions identification. Conversely, several local optimal strategies belonging to the group of on-line strategies have been developed with the thought in mind that in a real vehicle information about the future vehicle state is usually unavailable. It is evident how such strategies are more suitable for practical implementation on a vehicle. Among these strategies, a particular interest has been given to the Equivalent Consumption Minimization Strategy, in its various declinations (Paganelli et al. [2001], Musardo et al. [2005], Chasse and Sciarretta [2011]). More recently, the potentialities of the Stochastic Dynamic Programming have been illustrated (Tate et al. [2008], Leroy et al. [2012], Bardini and Leroy [2013]).

More and more studies of the literature focus on online energy management strategies. Nevertheless, very few include experimental results (Kermani et al. [2009], Paganelli et al. [2001] Opila et al. [2012]). Experimental tests are however necessary to validate the potential of optimal control strategies, in terms of consumption but also in terms of driveability, implementation and calibration. All this in a context including numerous additional constraints in comparison with ideal world of simulation.

The contribution of the paper is to present experimental results of an optimal energy management strategy, namely Stochastic Dynamic Programming (SDP). The SDP based control strategy is designed for a parallel charge sustaining hybrid vehicle. The control law is computed off-line by solving an infinite horizon optimization problem and takes the shape of a time-invariant state feedback controller. This control law is implemented in the existing control software of the vehicle electronic control unit. Compared to ideal hypothesis that are used for designing the control strategy (straightforward system modeling, neglected dynamics), lots of constraints due to real-life context may modify the expected behavior.

The paper is organized as follows. The hybrid electric vehicle is presented in the next section. Then, the steps of the control design are detailed: system modeling, definition of the control problem and problem resolution. The obtained control law is validated in simulation before real-life testing. The fourth section deals with energy management implementation in the existing vehicle control software. Finally, some experimental vehicle results consisting of a 35 km route under urban conditions are presented.

2. VEHICLE

2.1 Vehicle architecture

The hybrid electric vehicle considered for this study is a parallel full hybrid leisure activity vehicle. This prototype is used as a laboratory car for experimental validation of models and hybrid control strategies. Its architecture is presented in Figure 1, and its basic specifications are reported in Table 1.

Architecture	Pre-transmission parallel
Engine	4 cylinders, 1.4 L, 63 kW
Motor	38 kW
Transmission	Automated manual gearbox
Battery	Li-ion, 39 Ah
Vehicle Mass	1720 kg

Table 1. Basic vehicle information

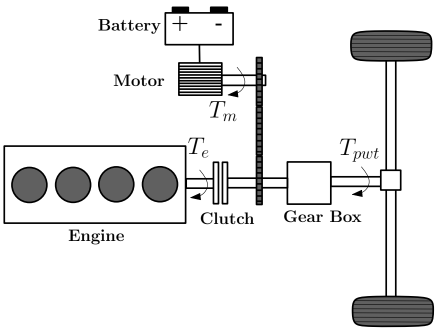


Fig. 1. Vehicle architecture scheme.

The electric motor is located upstream the transmission, and is permanently coupled to the 5-speed automated manual gearbox primary shaft through a series of gear wheels, reducing the electric motor rotation speed by a total ratio of r_{tr}. By design, this ratio ensures that both engine and electric motor can simultaneously reach their maximum speed. The electric motor is used for full electric mode, take-off assistance, and battery recharge. Notice that although the vehicle is a plug-in hybrid electric vehicle, it is used as a non plug-in one for this study since the paper focuses on charge sustaining control strategy.

2.2 Notes on the pre-transmission architecture

On the one hand, its pre-transmission positioning permits a wider range of use of the electric motor. On the other hand, torque interruption cannot be avoided during gearshifts, and the permanently increased primary shaft inertia is an issue : it implies a specific electric motor speed control during gearshifts to avoid damaging the gearbox. For a extended description of the gearshift control algorithms, please refer to Zito [2012].

3. CONTROLLER DESIGN AND SIMULATION VALIDATION

3.1 Notes on the system model

The model here employed consists of a low-dimensional dynamical model neglecting transient engine operation. The states of the system are: the velocity of the vehicle, its acceleration, the battery State of Charge (SOC), and the engine state, designated by v, a, x, and e_{on}, respectively. The engine state e_{on} is identified by a Boolean variable, with $e_{on} = 0$ when the engine is off and $e_{on} = 1$ when it is on. For a more compact notation, let $\boldsymbol{X}_k = (v_k, a_k, x_k, e_{on,k})^T$ be the state of the system at the k^{th} time sample.

Let $T_{e,k}$, $T_{m,k}$, and $T_{pwt,k}$ be, respectively, the torque of the engine, the torque of the motor, and the torque delivered by the powertrain to the wheel, all at the time instant k (see Figure 1 for the representation of the different torques in the powertrain). $T_{pwt,k}$ is an input to the energy management strategy, its value mainly depends on the position of the accelerator pedal. Let $u_k \in \mathcal{U}_k$ be the control variable, defined as

$$u_k = T_{e,k}$$

with $\mathcal{U}_k$ encompassing all the feasible values of the control variable at time k. The choice of the engine torque (over the motor torque) as the control variable is arbitrary since once the torque identified by the control variable is defined, the other torque is univocally defined by

$$(T_{e,k} + T_{m,k} \cdot r_{tr} \cdot \eta_{tr}) \cdot r_{gb,k} \cdot \eta_{gb,k} = T_{pwt,k} \qquad (1)$$

where $r_{gb,k}$ is the reduction ratio between the engine and the wheel for the selected gear at time k, r_{tr} and η_{tr} are the reduction ratio and efficiency between the motor and the primary shaft respectively, $\eta_{gb,k}$ is the efficiency of the path to the wheels.

Gathering the states own dynamics, the system dynamics write as

$$\boldsymbol{X}_{k+1} = F(\boldsymbol{X}_k, u_k) \qquad (2)$$

Among the states, particular interest is dictated by the SOC dynamics, following

$$x_{k+1} = g(x_k, u_k)$$

For a thorough treatise on the formulations presented above, the reader is invited to refer to Guzzella and Sciarretta [2007].

3.2 Definition of the control problem

Considering a single objective optimization directed to minimize the fuel consumption alone, the instantaneous cost function C is defined as

$$C(\boldsymbol{X}_k, u_k) = Q_{fuel}(\boldsymbol{X}_k, u_k) \qquad (3)$$

where $Q_{fuel}(\cdot)$ is the fuel mass flow in the engine at the instant k.

The control problem consists in finding the control law $u^\star$ that minimizes the integral fuel consumption over the driving cycle while meeting the system constraints

$$u^\star = \arg\min_{u\in\mathcal{U}} \left[\sum_{k=1}^{N} C(\boldsymbol{X}_k, u_k)\right]$$

$$\text{subject to} \begin{cases} \boldsymbol{X}_{k+1} = F(\boldsymbol{X}_k, u_k) \\ x_N = \bar{x} \\ G(\boldsymbol{X}_k, u_k) \leq 0 \end{cases} \tag{4}$$

N being the final sample time. The first constraint consists in the system following its dynamics (2). The second constraint imposes the final SOC value being equal to a target value $\bar{x}$ - a necessary condition for insuring the self sustainability of the battery SOC. The third constraint groups into function G all the instantaneous system constraints, such as the imposition of the SOC level within given boundaries or the powertrain torque limits.

3.3 Stochastic Dynamic Programming

Shortest path problem An on-line solution for the constrained optimization problem defined in (4) is provided by the Stochastic Dynamic Programming (for an extended treatise on the subject, refer to Bertsekas [2005]). The first prerequisite for employing the SDP for energy management of the powertrain is seeing the driving cycle as a Markov chain. This means assuming that the next time step acceleration solely depends on the current vehicle state and not on previous ones. Such a statement implies game-shifting consequences as it entails the elimination of the time dimension from the optimization problem (4). In this way the problem is reported from a global optimization to a local optimization, whose solution is a control law that can be easily implemented on-line.
The cost function C_{sdp} is given by

$$C_{sdp}\left(\boldsymbol{X}_k, u_k\right) = Q_{fuel}\left(\boldsymbol{X}_k, u_k\right) + \beta\left(e_{on,k+1} - e_{on,k}\right)^2$$

where β is a proportionality coefficient determining the cost associated with an engine event. The control variable $u^\star$ is found by solving the stochastic shortest path problem

$$\begin{aligned} u^\star\left(\boldsymbol{X}_k\right) &= \arg\min_{u\in\mathcal{U}} \mathbb{E}\left[\sum_{n=1}^{\infty} C_{sdp}\left(\boldsymbol{X}_n, u^\star\right)\right. \\ &\quad \left. + \alpha\left(x_k - \bar{x}\right)^2 \cdot P\left(V_{on,k+1} = 0\right)\right] \end{aligned} \tag{5}$$

where V_{on} defines the vehicle state (equals to 0 if the vehicle is off and equals to 1 if the vehicle is on). The selected control strategy $u^\star$ is the one that minimizes the expected cost (i.e. the cost of each system state times the probability of it taking place) over an infinite horizon, starting from the present system condition $\boldsymbol{X}_k$. Considering that, with the removal of the time dependence, the terminal condition in (4) is lost, the control on the SOC oscillations is realized by means of a penalty in the cost function proportional to the distance from the target SOC, $\bar{x}$. The importance of this penalty is determined by the value of parameter α, another proportionality coefficient. It is also noteworthy to point out that this cost is, again, a probabilistic cost, having as a multiplier the probability of shutting off the vehicle (key off) in the following time step [1] (Tate et al. [2008]).

[1] This implies the SOC in mainly regulated when the vehicle is close to the zero velocity-zero acceleration state. This constraint is relaxed when the vehicle is far from a potential key off.

Problem resolution Figure 2 presents a scheme of the resolution of problem (5).

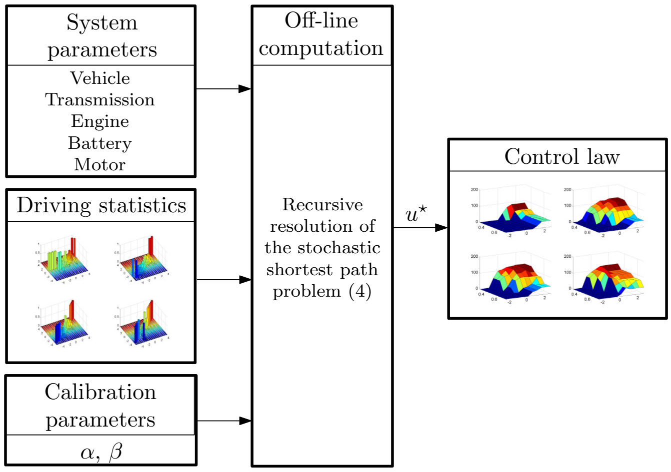


Fig. 2. Resolution of the shortest path problem.

The resolution of problem (5) requires three types of inputs.
First, some *system parameters* are necessary to model the system: vehicle (mass, road law), transmission (gear ratios and efficiencies), engine (fuel map, torque extrema), battery (capacity, SOC limits, nominal voltage, internal resistance), motor (torque extrema, efficiency).
The second input is the *driving statistics*. Indeed, the probability associated to the future system states are derived from a statistical analysis of a sample of official driving cycles and real-driving routes (Leroy et al. [2012]).
The last inputs are the *calibration parameters*. The values of these parameters are chosen with the goal of minimizing the fuel consumption while insuring the system compliance with the constraints in (4). Parameter α is tuned to allow a sufficient SOC maintainability and parameter β is calibrated to avoid having too many engine events (Bardini and Leroy [2013]).

In practice, the definition of the strategy consists in solving recursively (5) off-line for all the possible combinations of the four states v, a, x, and e_{on}, which are properly discretized.

The output of the off-line computation is a four dimensional map, with the states on the axes and containing the optimal values of the control variable $u^\star$. During the vehicle utilization, the map dictates the optimal value of the engine torque for the current vehicle state, managing the energy split in the powertrain on-line. Figure 3 shows the required engine torque for different speed, acceleration and SOC, in case the engine is on. On the one hand, the engine torque is high at low SOC while the electric motor torque is negative to recharge the battery. On the other hand, at high SOC, the engine torque is lower than the powertrain torque requested, the rest being carried out by the electric motor. In addition, notice that the SOC regulation is relaxed at high speed as mentioned above.

3.4 Simulation results

Before being implemented in the Electronic Control Unit (ECU) of the vehicle, the strategy is validated in simula-

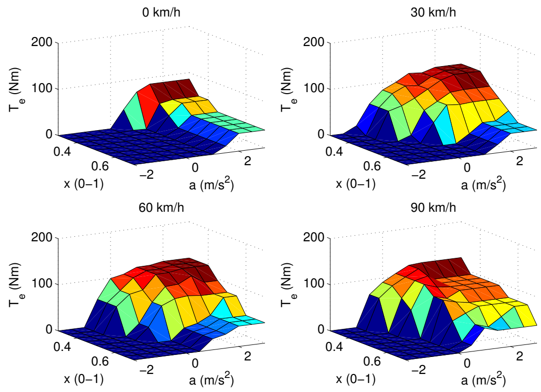


Fig. 3. Control law obtained via SDP.

tion. This validation consists in testing the strategy over a sample of 100 random cycles (see Leroy et al. [2012]) representing different driving conditions (urban, suburban, and mixed), in order to assess the robustness to real-life utilization conditions.

The results are presented in Table 2. The designed strategy is compared to some reference [2]. The initial SOC is common to all cycles and equal to 50%. The consumption obtained by SDP is close to the optimal. The mean of the final SOC is above 45%, meaning that the charge sustainability is well ensured [3]. The number of engine events is limited to 2 events/minute by adjusting parameter β.

	Consump-tion [l/100 km]	**Final SOC** [%]	**Engine events** [nb/min]	**Gain / engine only** [%]
Engine only	6.93	-	-	-
Ref opti	4.13	50	6.3	40.4
SDP	4.66	46.8	2	32.8

Table 2. Simulation results for 100 random cycles.

4. IMPLEMENTATION

The SDP-based energy management strategy is integrated into the main control algorithm of the hybrid electric vehicle. Figure 4 gives a scheme of the location of the strategy in the vehicle control software.

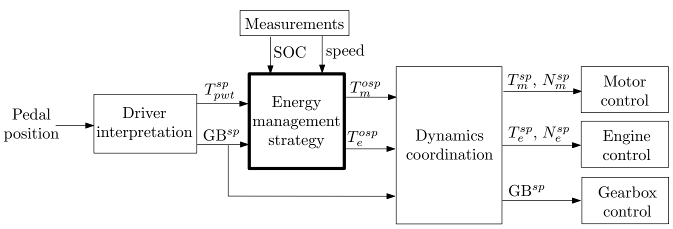


Fig. 4. Implementation of the SDP-based energy management strategy.

[2] Reference results are obtained using a Pontryagin's Minimum Principle based control strategy assuming the 100 cycles perfectly know in advance. These results constitute the optimum that can be reach by the vehicle.

[3] Note that parameter α is calibrated to ensure that the final SOC in all the 100 random driving cycles is equal or greater than 40%. The SOC excursion is also kept between the SOC limits.

Focus on the software integration is mainly to ensure a safe operation of the vehicle and an acceptable driveability performance. Now, the corresponding blocs of Figure 4 are detailed.

Driver interpretation Using driver input and operating conditions, torque to the wheel T_{pwt}^{sp} and transmission ratio GB^{sp} setpoints are computed. The gearshift laws are designed off-line using the Pontryagin's Minimum Principle, taking into account a balance between sportiness and fuel economy (Vidal-Naquet and Zito [2012]).

Energy management strategy Optimal engine torque setpoint, T_e^{osp}, is calculated by linear interpolation of the previously computed map presented in Section 3.3. The inputs are: the vehicle acceleration setpoint (derived from the powertrain torque setpoint, T_{pwt}^{sp}, using the vehicle parameters), the measured vehicle velocity, the estimated battery SOC (given by the Battery Management System) and the current engine state.
Optimal motor torque setpoint, T_m^{osp}, is then computed thanks to equation (1). Notice that, based on driveability constraints, full electric mode is forced under a given vehicle speed.

Dynamics coordination Transients phenomena and coordination of the powertrain components are dealt with here. For example, gearshifts imply the following events: engine torque cut-off, clutch opening, motor torque cut-off, gearbox disengaging, primary shaft speed synchronization using the motor, gearbox engaging, clutch closing, and torque application. The engine is also synchronized with the primary shaft. As a consequence, *dynamics coordination* output setpoints can be either torque or speed setpoints (T_m^{sp}, T_e^{sp}, N_m^{sp}, N_e^{sp}).
Furthermore, torque interruptions, as well as steep changes of optimal torque setpoints, need to be carefully filtered, to avoid producing a very degraded driving comfort.
Dynamics compensation is also made: when the observed engine torque is different from its setpoint, because of its slow response time or during clutch operation, the torque difference is compensated using the electric motor.

Low-level controllers Additional strategies are developed to protect powertrain components and take into account their dynamic limitations. Using the electric motor, an anti-jerk filter is added to prevent strong oscillations of the vehicle driveline during transients. Thermal derating of the motor, as well as battery protection, diminishes the available electric torque dynamically, and cannot be directly integrated in the SDP based energy management. Furthermore, the thermal torque available during warm-up is limited, to prevent engine damage.

In the end, one can easily understand that all these strategies create discrepancies between the optimal command from the energy management strategy and the final torques actually applied to the engine and the electric motor. Still, the energy management controller was designed using a very simple model, which proved to be sufficient, as it is demonstrated in the next section.

5. EXPERIMENTAL RESULTS

The following results come from a 35 km route under urban conditions. The initial SOC is about 70 %. A first macroscopic analysis is done on the whole route. Then a focus is put on a particular part of the journey to highlight the system behavior during transient conditions.

5.1 Whole route

Figure 5 presents experimental results over the whole urban route. Figure 5(a) gives the vehicle speed, the engine state and the battery state of charge. During the first part of the route, motor only mode is favored. Indeed, during the first 1500 seconds, the battery SOC is largely above the target (50 %). Then, the energy management strategy succeeds in keeping the SOC around to the target value. Notice that the duration of the journey is not know in advance. If the vehicle had been shut down before the end of the route, final battery SOC whould have been identically well maintained. This is a very important aspect that highlights the robustness of the proposed strategy. Figure 5(b) presents the engine and motor torques (reported to the primary shaft). One can notice that the engine torque is used more in the second part of the route to ensure the battery SOC sustainability. Negative motor torque permits to recharge the battery during the vehicle decelerations.

Figure 5 emphasizes that, despite the energy management strategy is derived from a simple model that neglects many transient and constraint aspects, the controller succeeds in sustaining the battery SOC. Unfortunately, rolling test bench was not available to valid the strategy in terms of fuel consumption. Nevertheless, Figure 6 highlights that the engine is mainly used in its best efficiency area, i.e. at high torque.

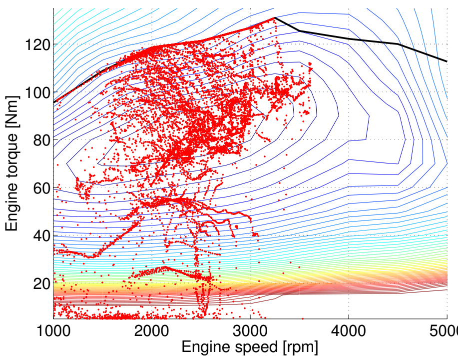


Fig. 6. Engine utilization points during driving.

5.2 Zoom on a part of the route

Figure 7 details a part of the experiment presented in Figure 5. The upper figure gives the vehicle speed profile and the engine state. This speed profile is made up of a take off followed by a deceleration (due to traffic), then another acceleration followed by a roughly constant speed and finally a braking until vehicle stop. The second figure reports the evolutions of the accelerator pedal position and the gear ratio. The third one presents the engine and motor torque setpoints coming from both energy management strategy and dynamics coordination -T_e^{osp}, T_m^{osp}, T_e^{sp} and T_m^{sp}- and the global torque powertrain, T_{pwt}^{sp}, required by the driver. Finally, the bottom figure gives the engine speed and primary shaft speed.

At the beginning, the vehicle is propelled thanks to the motor during take off. When the driver requires a high torque through the accelerator pedal, the engine is started. The electric motor ensures the torque transition until the clutch is closed, which happens when the engine speed setpoint is reached. Notice that the engine and motor torque setpoints are modified by the *dynamics coordination* block. When the vehicle decelerates, the engine is turned off and motor torque becomes negative to ensure battery recharging.

The next acceleration requires the engine which is then turned on again. During the gear shift at 3870 s, the dynamics coordination specifies a zero engine torque while the clutch is open and requires a certain motor torque to ensure a good gearshift (needed to limit the inertia, see Section 2.2).

Then, the vehicle speed is oscillating around 40 km/h during about 40 s. The driver controls the speed by adjusting the accelerator pedal. The resulting powertrain torque oscillates between positive and negative values. During this part, the engine torque is higher than the powertrain torque, meaning the battery is being recharged (negative motor torque). It is really important to notice that, despite a negative powertrain torque, engine is not turned off and follows the variation of the required powertrain torque. This highlights the ability of the SDP-based strategy to be relevant in terms of driveability (providing the driver with the expected engine response to the pedal).

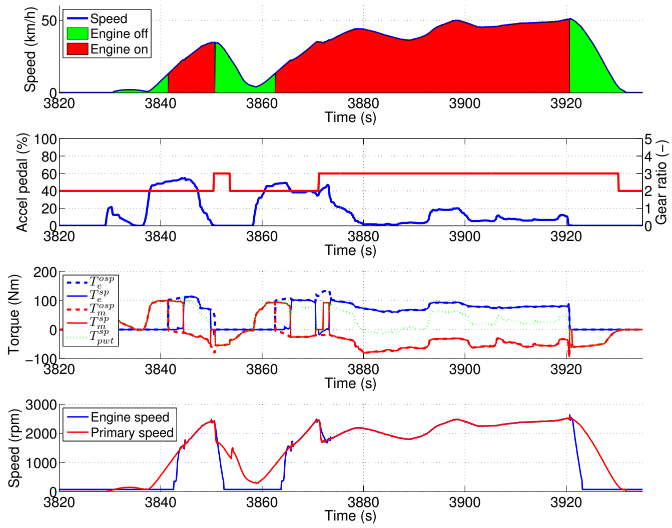
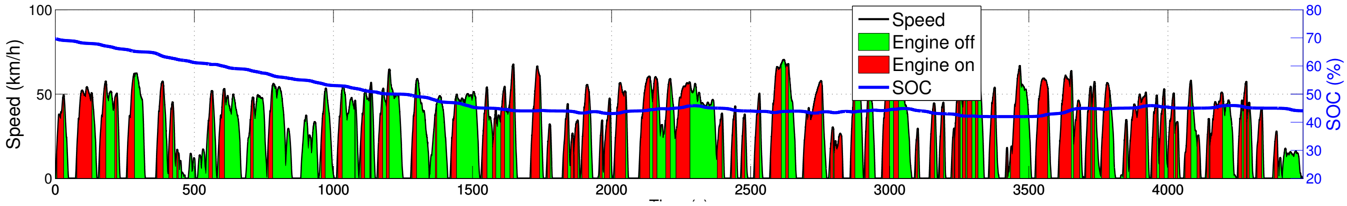


Fig. 7. Zoom on a particular part of the driving cycle.

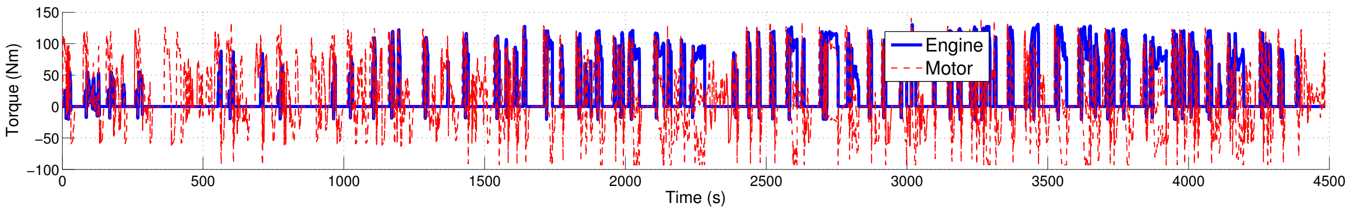
6. CONCLUSION

This paper presents an experimental validation of an energy management strategy based on Stochastic Dynamic Programming.

First, the methodology for designing the torque split controller is presented. It consists in an off-line resolution of an infinite horizon optimization problem. The resulting time-invariant control law (engine torque) takes the shape of a straightforward four dimensional map with the states on the axes (vehicle acceleration and velocity, battery SOC, engine state). The strategy is calibrated off-line to match the performance objectives (low consumption, SOC



(a) Battery state of charge and engine events during driving.



(b) Engine and motor torque evolution during driving.

Fig. 5. Experimental results obtained on vehicle during driving.

maintainability, number of engine events) using a hundred of randomly generated cycles, assessing the robustness of the strategy regarding very different driving conditions.
Second, the controller is implemented in the electronic control unit of the vehicle. Additional constraints not taken into account in the controller design are added downstream the control strategy (namely dynamics coordination and hardware constraints).
Finally, an experimental validation on a pre-transmission parallel hybrid vehicle is realized. Results show that, despite the simple model used for the controller, the energy management strategy succeeds in maintaining the battery state of charge while ensuring a good engine utilization and good driveability. This proves the capacity of a control optimal based strategy to be relevant in an HEV industrial context.

ACKNOWLEDGEMENTS

The authors would like to gratefully thank Damiano Bardini, Gianluca Zito and Florian Perretti for their support.

REFERENCES

D. Bardini and T. Leroy. Impact of driveability constraints on local optimal energy management strategies for hybrid powertrains. In *Proc. of IFAC Symposium on Advances in Automotive Control*, 2013.

D.P. Bertsekas. *Dynamic Programming and Optimal Control*, volume 1-2. Athena Scientific, 3rd edition, 2005.

A. Chasse and A. Sciarretta. Supervisory control of hybrid powertrains: An experimental benchmark of offline optimization and online energy management. *Control Engineering Practice*, 19(11):1253 – 1265, 2011. ISSN 0967-0661.

L. Guzzella and A. Sciarretta. *Vehicle propulsion systems: introduction to modeling and optimization.* Springer Verlag 2nd ed., 2007.

S. Kermani, S. Delprat, T.M. Guerra, and R. Trigui. Predictive control for hev energy management: experimental results. In *Vehicle Power and Propulsion Conference, 2009. VPPC'09. IEEE*, pages 364–369. IEEE, 2009.

T. Leroy, J. Malaizé, and G. Corde. Towards real-time optimal energy management of hev powertrains using stochastic dynamic programming. In *Vehicle Power and Propulsion Conference, VPPC'12*, 2012.

C. Musardo, G. Rizzoni, Y. Guezennec, and B. Staccia. A-ecms: An adaptive algorithm for hybrid electric vehicle energy management. *European Journal of Control*, 11 (4-5):509, 2005.

D.F. Opila, X. Wang, R. McGee, J.A. Cook, and JW Grizzle. Fundamental structural limitations of an industrial energy management controller architecture for hybrid vehicles. *ASME Conference Proceedings*, 2009(48920): 213–221, 2009.

D.F. Opila, X. Wang, R. McGee, and JW Grizzle. Real-time implementation and hardware testing of a hybrid vehicle energy management controller based on stochastic dynamic programming. *Journal of Dynamic Systems, Measurement, and Control*, 135(2), 2012.

G. Paganelli, G. Ercole, A. Brahma, Y. Guezennec, and G. Rizzoni. General supervisory control policy for the energy optimization of charge-sustaining hybrid electric vehicles. *JSAE review*, 22(4):511–518, 2001.

L.V. Perez, G.R. Bossio, D. Moitre, and G.O. Garcia. Optimization of power management in an hybrid electric vehicle using dynamic programming. *Mathematics and Computers in Simulation*, 73:244 – 254, 2006. ISSN 0378-4754.

L. Serrao. *A comparative analysis of energy management strategies for hybrid electric vehicles.* PhD thesis, Ohio State University, 2009.

L. Serrao, S. Onori, and G. Rizzoni. ECMS as a realization of pontryagin's minimum principle for HEV control. In *Proc. of the American Control Conference*, pages 3964–3969, 2009.

E. Tate, J.W. Grizzle, and H. Peng. Shortest path stochastic control for hybrid electric vehicles. *International Journal of Robust and Nonlinear Control*, 18(14):1409–1429, 2008.

F. Vidal-Naquet and G. Zito. Applied optimal energy management strategy for driveability. In *Vehicle Power and Propulsion Conference, VPPC'12*, pages 358–363, 2012.

G. Zito. AMT control for parallel electric vehicles. In *FISITA, C04-022*, 2012.