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ABSTRACT – Hybrid electric vehicles require an adequate energy management strategy in order to actually optimize their consumption. Many real-time controls were recently proposed in literature, but as each study is performed in a specific context, it is difficult to compare their efficiencies. The present paper proposes a comparison between 3 recent promising real-time strategies: adaptive equivalent consumption minimization strategy (A-ECMS), optimal control law (OCL) and stochastic dynamic programming (SDP). Two off-line methods are used as benchmark: Pontryagin's minimum principle (PMP) and dynamic programming (DP). They have the best performance in fuel saving while the other three are near-optimal strategies. Simulation results of a parallel HEV show 5% to 18% fuel economy, compared to a conventional vehicle.

Keywords - hybrid electric vehicle, real-time energy management, optimal control, A-ECMS, OCL, stochastic dynamic programming, Pontryagin minimum principle.

1. INTRODUCTION

Hybrid electric vehicles (HEVs) are widely considered as a promising short-term mean for fuel economy and emission control. HEVs possess one engine (ICE) and at least one electric machine (EM) and battery. The energy provided to the wheels either comes from the ICE, the EM or both. This degree of freedom allows operating the ICE at its best efficiency working points and braking energy recovery. However, the fuel saving and CO_2 emissions reduction strongly depend on the energy management strategy used, and finding robust real-time optimization algorithms remains a challenge.

There is a very rich literature on the subject and many energy management strategies are proposed. They can be divided into four approaches: rule-based strategies [1] [2], instantaneous optimization of an equivalent fuel consumption [3] [4] [5] [6], global optimization [7] [8] and convex optimization [9]. Each strategy is shown to allow a significant reduction of fuel consumption and claimed to have better performances than others. However, the different studies are performed in their own specific context, making it difficult to rate and compare them. The present paper proposes a comparative analysis between three promising real-time strategies, in order to evaluate their pro and cons. For this, the strategies are applied to the same parallel HEV, in the same context. The interest of the paper is that each strategy is implemented using only published material, with a neutral point of view.

The paper is organized as follows: the HEV model and the principle of optimal energy management are described in Section 2. The different strategies to compare are presented in Section 3. The simulation results and the parameter setting influence are discussed for each algorithm in Section 4. Finally, the paper is concluded in Section 5.

2. HEV MODELING AND OPTIMAL ENERGY MANAGEMENT

The present comparison is performed in the case of a full hybrid HEV, with a parallel powertrain architecture and no plug-in capacity (Fig.1). It was studied in a previous work [7] and deemed to have a very good potential for fuel consumption reduction.

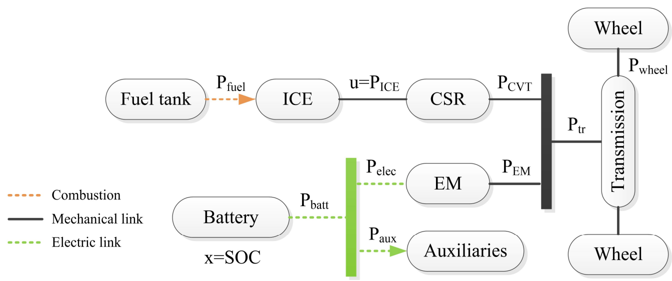

Fig.1 Parallel hybrid electric vehicle powertrain

2.1. Power components modeling

The system corresponds to a B-segment vehicle. The engine (ICE) is a 50-kW 1.0-liter 3-cylinder in-line gasoline engine modeled by a stationary brake specific fuel consumption ($BSFC$ in g/kWh) map. The instantaneous fuel consumption P_{fuel} is then determined by (1), where Q_{LHV} is the lower heating value in kJ/kg.

$$P_{fuel} = 3.6*10^6 Q_{LHV} P_{ICE} BSFC \qquad (1)$$

The electric machine (EM) is a 50-kW synchronous electric machine modeled by its efficiency map $\eta_{EM}(\omega_{EM}, T_{EM})$.

The battery is a Li-ion one modeled by a Thevenin equivalent circuit with internal resistance R_{batt} and open circuit voltage V_{oc_batt}. For a given power P_{batt}, the battery current I_{batt} is obtained by (2), where E_{batt} is the battery energy capacity, related to the battery charge capacity Q_{batt} according to (3).

$$I_{batt} = \frac{E_{batt} - \sqrt{E_{batt}^2 - 4R_{batt}P_{batt}}}{2R_{batt}} \quad (2)$$

$$E_{batt} = Q_{batt}V_{oc\_batt} \quad (3)$$

A continuous speed ratio system (CSR) is used for transmission. A constant power demand P_{aux} is considered for auxiliary systems.

2.2. Optimal energy management

The purpose of optimal power management is to search for the best power split between the internal combustion engine and the electric machine, in order to minimize the fuel consumption over a given driving cycle, while meeting the driver's power demand and maintaining the battery state of charge (SOC).

The problem can be defined by (4), where P_{ICE} and SOC are respectively the control and state variables, also denoted by u and x. J is the total fuel consumption over the considered time interval, while f is the state equation of the system. Since the energy is provided solely by the fuel, the consumption should be calculated with equal initial and final SOC. In between, the SOC variations allow to adjust the ICE working point and to recover braking energy.

$$\begin{cases} Minimize \;\; J = \int_{t_0}^{t_f} P_{fuel}(P_{ICE}(t))dt \\ subject\ to \;\; \dot{SOC} = -\frac{I_{batt}}{Q_{batt}} = f(P_{ICE}, SOC) \\ SOC(t_0) = SOC(t_f) = SOC_{ref} \end{cases} \quad (4)$$

In the case of off-line optimization, the driving cycle is fully known in advance and two mathematical approaches allow solving the problem: Pontryagin's minimum principle (PMP) and dynamic programming (DP) [4]. PMP is very easy to implement and fast, but does not allow to account for constraint on the state variable SOC. It may also fail to reach exactly the constraint on the final state of charge because the instantaneous cost function is discontinuous, and hence not convex, at the origin. On the other hand, DP is a much more cumbersome method, but is more robust and can handle SOC limitations when needed.

In real world, however, the driving cycle cannot be known in advance and so-called "real-time" or "on-line" energy management methods are needed. The optimal consumption and SOC-sustaining constraint can no longer be guaranteed because the information required for that is not available, but one can aim at a near-optimal strategy that increases the fuel economy while taking the final SOC close to its reference value.

3. Real-time control methods

Many real-time energy management strategies have been proposed in literature. In this paper, we focus on three of them, recently published, whose authors report excellent performances compared to previous work. The first one, called adaptive equivalent consumption minimization strategy (A-ECMS) [3] is derived from PMP. The second, called optimal control law (OCL) [6], applies the theory of non linear optimal control theory to the considered system. Last, stochastic dynamic programming (SDP) generalizes DP in the case where the driving cycle to come can be characterized from a statistical point of view [8]. The two off-line methods (PMP and DP) were used to provide reference results.

3.1. Adaptive equivalent consumption minimization strategy (A-ECMS)

This method is based on the PMP [10]. It uses the Hamiltonian function related to (4) and defined by (5), where $p(t)$ is the co-state linked to the state equation of the system.

$$H(p,u,x) = P_{fuel}(u) + p(t)\dot{SOC}(x,u) \quad (5)$$

The optimal control policy P_{ICE}^* is the one that minimizes the function H(p,u,x) at every time step.

In the case of charge-sustaining problems like the one considered here, one can neglect the SOC dependence of the battery parameters and show that the co-state p is constant over time. It represents the equivalent fuel cost of the battery power. A low value favors the use of electric power and leads to a low final SOC, whereas on contrary a high value saves electric energy and leads to a high final SOC. PMP method consists in finding the right value, the one resulting in a final SOC equal to the initial one. In the case of off-line optimization, this value is easily determined by a binary search algorithm using the charge sustaining constraint. This method is also referred to as ECMS for "equivalent consumption minimization strategy" and was intuitively used before establishing its mathematical context through the PMP.

For on-line conditions, many adaptive ECMS were proposed: the idea is to estimate in real-time the equivalent factor p by using some empirical feedback on the current SOC. The main problem of this approach is that the result of the ECMS is extremely sensitive to the value of the equivalent factor, which leads to unstable behaviors. In the present paper, we focus on the algorithm proposed in [3], for which interesting results are reported. The value of the equivalent factor is adjusted at regular intervals of time T, with a correction proportional to the difference between the current and reference SOC values. A new value of p is calculated for each period $[kT, (k+1)T]$ by using (6), where K_p is the gain of the proportional controller.

$$p_{k+1} = \frac{1}{2}(p_{k-1} + p_k) + K_p(SOC_{ref} - SOC(kT)) \quad (6)$$

The parameters of the algorithm are the period T, the gain K_p and the initial guesses p_0 and p_1. Using the value of p at the two previous time steps stabilizes the system behavior. It should be noted that the authors show good results, but do not say anything about the value of those parameters, nor about the procedure to determine them.

3.2. Optimal control law (OCL)

A-ECMS are basically empirical methods. A more rigorous approach, based on non-linear regulation and disturbance rejection, was proposed in [6]. The authors use analytical close-form of the power components (Willans line for the ICE, average efficiency for the EM and the battery) in order to establish a state feedback control law which guarantees optimality and asymptotic stability. As a result, the control variable P_{ICE} directly depends on the difference between the current and reference SOC values. Since no minimization is needed at each step of time, the method is faster for implementation on real vehicles. Furthermore, the theoretical context is clear and there is only one tuning parameter, with respect to which the method is not over-sensitive.

Let us denote ξ, the difference between the reference and current SOC: $\xi(t) = SOC_{ref} - SOC(t)$. The optimal control law is expressed as:

$$P_{ICE}^{*} = \frac{\mu^2\xi^2}{36(K\mu\xi + p_3)} \quad (7)$$

where μ is a constant to calibrate, p_3 is a coefficient calculated using the Willans line model of the ICE (see section 4.1.2), and K is a constant depending on the average efficiencies of the battery and the EM and the battery maximum energy capacity $E_{\text{batt\_max}}$, according to (8).

$$K = \frac{\overline{\eta_{batt}}}{E_{batt\_\max}\overline{\eta_{EM}}} \quad (8)$$

3.3. *Stochastic dynamic programming (SDP)*

Dynamic programming is a multi-stage decision-making process which allows solving optimization problems that can be broken down into several sub-problems of the same nature [11]. It applies well to the optimization of cumulative costs in dynamic systems, such as (4).

Dynamic programming requires the problem to be discretized in time. Let us denote respectively 0 and N the indexes of the initial and final time steps, $x_k = SOC(t_k)$ and $u_k = P_{ICE}(t_k)$. The discretized problem is given by (9).

$$\begin{cases} Minimize \;\; J = \sum_{k=0}^{N-1} P_{fuel}(u_k).\Delta t \\ subject\ to \;\; x_{k+1} = x_k - \dfrac{I_{batt}(u_k)}{Q_{batt}}.\Delta t \\ x_0 = x_N = SOC_{ref} \end{cases} \quad (9)$$

A so-called cost-to-go function, denoted $J_k(x_k)$, is defined at each time step t_k. It corresponds to the minimum cost that can be obtained by optimal control from the state x_k at time t_k to the final state x_N. This cost is calculated backwards, starting from the final time, according to (10). $u_k{}^*(x_k)$ denotes the optimal control for at time t_k, it depends on x_k.

$$\begin{cases} J_N(x_N) = penalty\ cost\ of\ the\ final\ state \\ J_k(x_k) = \min_{u_k}\left\{P_{fuel}(u_k) + J_{k+1}(x_{k+1})\right\} \\ u_k{}^*(x_k) = \underset{u_k}{\operatorname{argmin}}\left\{P_{fuel}(u_k) + J_{k+1}(x_{k+1})\right\} \\ \text{where } x_{k+1} = x_k - \dfrac{I_{batt}(u_k)}{Q_{batt}}.\Delta t \end{cases} \quad (10)$$

$J_N(x_N)$ is a penalty function on the final state, which favors $x_N = SOC_{ref}$. At the end of the process, $J_0(x_O)$ represents the optimal fuel consumption from the initial to the final state. The optimal control policy $u^* = \{u_k{}^*, 0 \le k \le N-1\}$ is rebuilt by a forward process. The reader is referred to [11] for more details about the method.

Real life driving cycles are not known exactly in advance, but the itinerary is, and the driving cycle can be described as a random process. For example, at a given point of the itinerary, the speed of the vehicle can be modeled as a random variable and a probability distribution. The optimization problem is reformulated according to (11), where w_k is a random variable modeling the uncertainty of the driving cycle at time t_k and $E_{w_k}(.)$ represents the expectation calculated according to w_k probability distribution.

$$\begin{cases} Minimize \;\; J = E_{w_k}\left(\sum_{k=0}^{N-1} P_{fuel}(u_k, w_k).\Delta t\right) \\ subject\ to\ x_{k+1} = x_k - \dfrac{I_{batt}(u_k, w_k)}{Q_{batt}}.\Delta t \\ x_0 = x_N = SOC_{ref} \end{cases} \quad (11)$$

The cost-to-go function $J_k(x_k)$ now corresponds to the minimum average cost that can be obtained by optimal control from the state x_k at time t_k to the final state x_N. This cost is still calculated backwards, according to (12).

$$\begin{cases} J_N(x_N) = penalty\ cost\ of\ the\ final\ state \\ J_k(x_k) = \min_{u_k} E_{w_k}\left\{P_{fuel}(u_k) + J_{k+1}(x_{k+1})\right\} \\ u_k{}^*(x_k) = \underset{u_k}{\operatorname{argmin}}\, E_{w_k}\left\{P_{fuel}(u_k) + J_{k+1}(x_{k+1})\right\} \\ \text{where } x_{k+1} = x_k - \dfrac{I_{batt}(u_k, w_k)}{Q_{batt}}.\Delta t \end{cases} \quad (12)$$

At the end of the process, $J_0(x_O)$ represents the average optimal fuel consumption from the initial to the final state and $u_k{}^*(x_k)$ is the control policy enabling to reach it. The forward process is applied to the in-line driving cycle. It builds the optimal control policy $u^* = \{u_k{}^*, 0 \le k \le N-1\}$ for the corresponding realization of the random driving cycle. The actual cost may not be the lowest one for the considered cycle, but it is in an average sense. Once again, the reader is referred to [11] to fully understand the method.

From a practical point of view, it should be underlined that the heavy computation, corresponding to the backward part of the algorithm, is done only once and off-line, when all possible realizations of the random process are evaluated. During the in-line process, only the forward part of the algorithm is applied to the actual driving cycle, and this part is fast.

SDP is a well established method, but the quality of the results relies on the quality of the random process model. In the considered problem, a good statistical representation of the driving cycles is needed, and this is a challenging problem. In the present paper, an approach derived from the one proposed in [8] is tested, because it is rather simple and the authors report good results. The driving cycle is modeled as a random speed characterized by a normal distribution $N(\mu, \sigma)$, obtained using traffic data of a regular home-office route.

4. SIMULATION RESULTS AND DISCUSSION

4.1. *Implementation of the different methods*

The different strategies were implemented and tested. As the current official European driving cycle NEDC is known to poorly represent real world driving behavior, the forthcoming WLTC cycle is used (Fig.2). The setting parameters of the different strategies were determined off-line using these data.

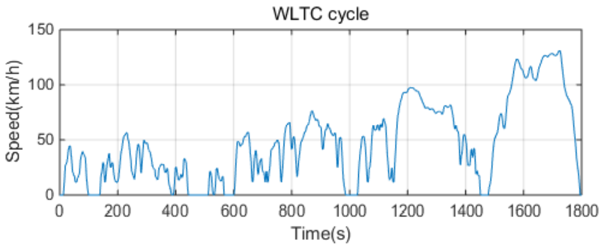

Fig.2 WLTC driving cycle profile

The power demand corresponding to this speed profile is determined by the dynamic equation of the vehicle:

$$P_{wheel} = (\frac{1}{2}\rho_{air} AC_d v_{wheel}^2 + \mu_r Mg + Ma)v_{wheel} \qquad (13)$$

where ρ_{air} is density of air; A is the reference area; C_d is the drag coefficient; μ_r is the rolling resistance coefficient; M is the vehicle mass; g is the gravitational acceleration; a is the vehicle acceleration

The setting parameters were determined off-line using the WLTC cycle. It should be noted that authors usually do not give much information about this procedure, although it is an important point for a good implementation.

4.1.1. *A-ECMS method*

The setting parameters of the algorithm are the period T, the gain K_p and the initial guesses p_0 and p_1. They are determined by a trial-and-error procedure, which objective is to reach the lowest consumption for the WLTC cycle while respecting the final SOC constraint. When doing so, one notices that the results are very sensitive to the parameters, and that there is no obvious trend or rule of the thumb to help.

4.1.2. *Optimal Control Law*

The parameters of the OCL are denoted K, p_3 and μ. K and p_3 are determined using physical parameters of the system, whereas μ is a constant to calibrate. K is given by (8) and requires to calculate the battery and EM average efficiencies.

p_3 is calculated using the Willans line model of the ICE, which states that at given speed ω_{ICE}, the input (chemical) power is as an affine function of the output (mechanical) power (14).

$$P_{fuel}(t) = e_0(\omega_{ICE}(t)) + e_1(\omega_{ICE}(t)).P_{ICE}((t)) \qquad (14)$$

Fig.3 shows the Willians lines corresponding to the ICE used in the present study.

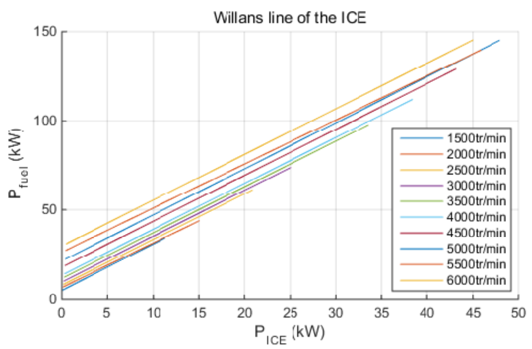

Fig.3 Willans lines of the ICE for different rotational speeds ω_{ICE}

The OCL is based on a close form of the Willans lines, in which the speed dependence of the slope e_1 and intercept e_0 is neglected. The coefficient p_3 is then defined by :

$$p_3 = \frac{e_1}{Q_{LHV}} \qquad (15)$$

Lastly, after the numerical values of the parameters K=3.18.10^{-7}, p_3=5.86.10^{-5} kg/J have been calculated, the parameter μ is tuned in order to obtain the expected final SOC for the WLTC driving cycle.

4.1.3. *Stochastic dynamic programing*

In the case of SDP, the problem is to model the driving cycle as a random process. As in [8], the vehicle velocity is assumed to be a random variable with a normal distribution $N(\mu,\sigma)$ (Fig.4). The parameters μ and σ are inferred from the WLTC data by the maximum-likelihood estimation.

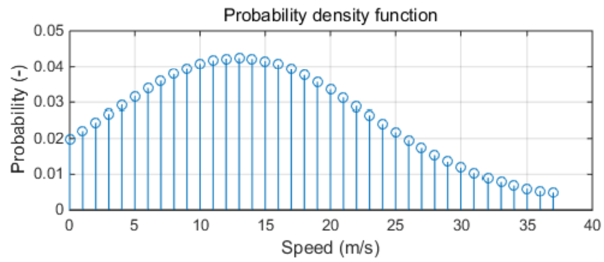

Fig.4 Probability density function of speed based on the WLTC cycle

4.2. *Results for the WLTC cycle*

The different strategies, including PMP and DP which give the lowest possible consumption, were applied to the WLTC driving cycle. Table 1 reports the results in terms of fuel consumption and fuel saving with respect to the consumption of a conventional vehicle (CV) driving the same cycle:

$$\text{Fuel saving (\%)} = \frac{J_{HEV} - J_{VC}}{J_{VC}} \times 100\% \qquad (16)$$

The control policies found by every strategy as well as the associate SOC evolution are plotted in Fig.5 and Fig.6.

Table 1. Simulation results on the WLTC cycle

Strategy	**Parameter setting**	**Fuel consumption (liter per 100km)**	**Fuel saving (%)**	**Computation time**
PMP	du=1kW	3.48	-18.7	0.1s
DP	du=1kW; dx=0.1%	3.53	-17.5	2s
A-ECMS	du=1kW; p_0=p_1=50; T=20s; K_p=10	3.74	-12.2	0.1s
OCL	μ=65kg	4.07	-4.9	0.1s
SDP	du=1kW; dx=0.1%; dv_{wheel}=1m/s	3.88	-9.3	Forward: 3min Backward: 0.1s
CV	-	4.28	-	-

The results show that DP and PMP have similar performances. However, DP requires much more computation time, which is the main reason why it is often abandoned [12]. Yet, this method remains interesting if one needs to account for SOC limitation [7].

The SOC trajectory is quite different from one real-time optimization strategy to another (Fig.6). Since the future driving pattern is not known a priori, the final SOC differs from the initial one.

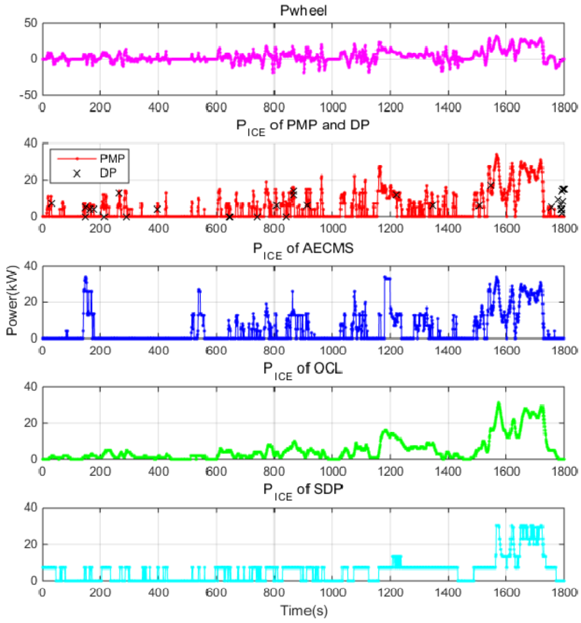

Fig.5 Optimal control policy for the WLTC cycle

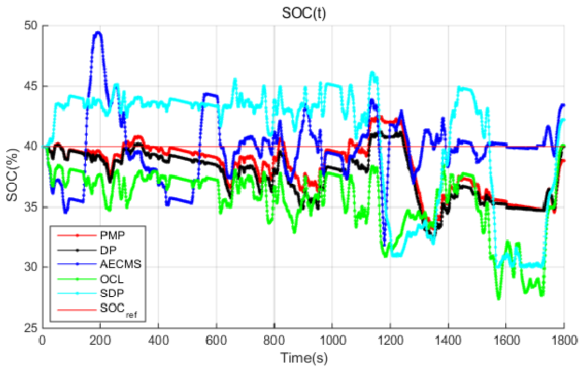

Fig.6 Battery SOC trajectories

The A-ECMS tries to adjust the equivalent fuel-cost of electrical power to its optimal value. This optimal equivalent cost depends on the driving cycle and can be obtained off-line using the PMP. Fig.7 shows its optimal value and how it is adjusted on line by the A-ECMS method.

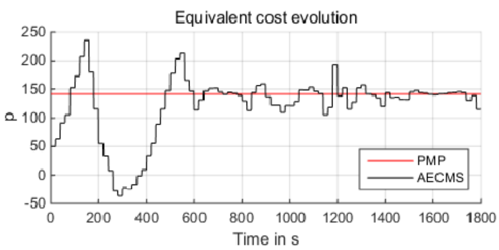

Fig.7 A-ECMS' equivalent cost evolution with time

According to Fig.6, the OCL favors battery discharge along the driving cycle and tries to refill it during the final deceleration, while the A-ECMS tends to keep the battery SOC close to its reference value all along the cycle. The SDP requires a fair amount of ICE power from time to time during lower propulsion power phases to maintain the SOC level. When a bigger power demand comes, unlike the A-ECMS which acts immediately to recharge the battery, the SDP allows remaining at a low SOC and waiting for braking energy recovery.

Furthermore, most of the SDP's computation time indicated in the Table 1 is taken to determine the matrix J(x,t), which can be calculated off-line. Its application on line takes just as much as the A-ECMS.

4.3. Results in the case of INRETS cycles

From Table 1, A-ECMS seems to be the best real-time strategy among the three. To confirm it, a series of ten INRETS cycles [13], with different average speeds (Table 2), was used for robustness analysis. The parameters settings are equal to those optimal found for the WLTC cycle, whose average speed is 47 km/h.

Table 2. INRETS cycles

Type	**Urban**					**Road**			**Highway**	
Cycle	**UL1**	**UL2**	**UF1**	**UF2**	**UF3**	**R1**	**R2**	**R3**	**A1**	**A2**
Average speed (km/h)	4	7	10	19	24	32	41	57	74	95

Fig.8 illustrates the HEV consumption economy compared to a CV and the difference in energy between the final and initial battery states. Each of them is plotted as a function of the cycle average speed.

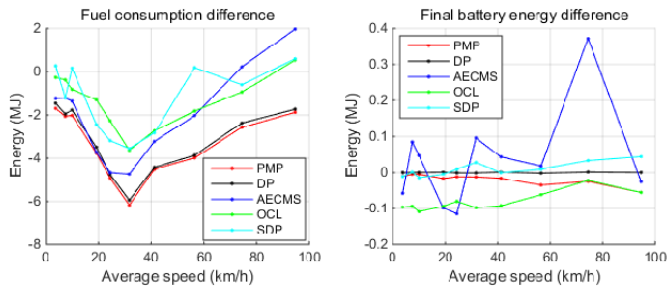

Fig.8 Real-time strategies' results for INRETS cycles, compared to off-line strategies'

The A-ECMS result shows a good fuel economy for urban or road trips using the parameters calculated for the WLTC cycle which is a combination of all three driving types (Fig.8). However, the same parameter setting is not adapted to highway cycles. A parameter specific to each type of driving conditions (urban, road and highway) may help to improve the results. It should be noticed that with three parameters (p_0=p_1, T and K_p) to adjust at the same time, any wrong guess of parameter setting may make HEV burning more fuel even than a CV.

The OCL method was developed to obtain an easier calibration than A-ECMS. According to the author of [6], it gives a solution close to the optimal one and is stable enough to work for any driving cycle with one single parameter (μ). The reduction of the number of strategy parameters indeed eliminates the setting difficulty. However, by testing different INRETS cycles, the robustness analysis of the OCL method shows that OCL fails to decrease significantly the fuel consumption and insure charge sustaining at the same time (Fig.9).

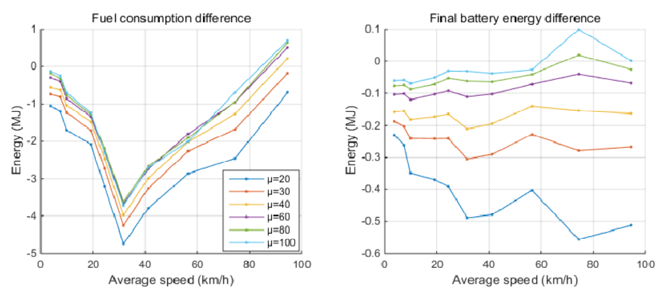

Fig.9 OCL results for INRETS cycles, for six different values of the setting parameter of the method

The SDP, a proven method in other area, uses statistics to model the driver's future power demand and calculates an average optimal solution. The implementation proposed in [8] was tested and shows poor results (Fig.8). In fact, the SDP performance relies on an adequate probability distribution of the vehicle's driving speed. In previous subsection 4.2, the SDP method shows an average performance between A-ECMS and OCL because it used the same real-time simulation cycle as statistical data to calculate the control policy $u_k^*(x_k)$ in (12). This statistical model based on the WLTC cycle is certainly not adequate for INRETS cycles.

It should be noted that an adequate probability distribution of the vehicle's driving speed requires a large amount of data. This can be seen as a drawback or on the contrary as a way to include more information about the current trip of the vehicle.

5. Conclusions

Three promising real-time strategies from the literature have been selected and implemented. Once well calibrated off-line, none of them guarantees an excellent fuel economy in any real-world driving conditions while taking the final SOC close to its reference value.

A-ECMS performances are largely affected by the setting parameters. With parameters correctly chosen, it is able to approach the maximal fuel saving under certain circumstances. However, three parameters to adjust at the same time make it difficult to achieve manually. A genetic algorithm may help but will surely increase the computational load.

With only one parameter to set, OCL's calibration phase is much easier than A-ECMS. The simulation results show that it is also more robust, but is not as powerful as A-ECMS on the fuel economy. Besides, this method may not be as sensitive to parameter setting as A-ECMS, but an inaccurate value could lead to higher consumption.

SDP always meets the SOC-sustaining requirement but its fuel saving performance is not better than OCL. In fact, SDP is a optimization method based on mathematical models. The quality of its results relies directly on the accuracy of the probability distribution of the vehicle's driving conditions. In this article as in [8], only the vehicle speed is considered. However, the power demand in (13) depends not only on the instantaneous speed, but also on its variation.

The further work will be:

- Improving A-ECMS' robustness by applying a set of parameters specific to each type of driving conditions (urban, road and highway)
- Searching for the adequate range of OCL's parameter values for real-world application
- Implementation of SDP based on both vehicle velocity and associate power demand using Markov chains [14]

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