On Adaptive-ECMS strategies for hybrid electric vehicles

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Abstract — *The problem of adapting the equivalence factor of the Equivalent Consumption Minimization Strategy (ECMS) to achieve a real time implementable sub-optimal solution of the problem of energy management in hybrid electric vehicle (HEV) has been the object of extensive research over the last decade. Contributions in the open literature range from methods based on prediction of driving cycle to driving pattern recognition to feedback from state of charge. In this paper, we first propose a classification of the methods that have been proposed to design an Adaptive-ECMS (A-ECMS) controller and then we carry out a comparative analysis in simulation of three adaptation laws falling into the class of algorithms of adaptation through feedback of SOC. Simulation results are performed on a parallel hybrid vehicle and show the performances of the three adaptation laws as compared to the optimal ECMS (a suitable proxi for the global optimal solution given by the dynamic programming algorithm). Keywords: ECMS, PMP, adaptive, HEV, Hybrid Electric Vehicles, Energy Management*

INTRODUCTION

The goal of this paper is to provide an overview of the available approaches to online energy management strategies for HEVs, implemented according to the structure of Adaptive-ECMS controllers. The paper begins with a reminder of the derivation of ECMS from Pontryagin's Minimum Principle, then provides a review of the available approaches to online implementation of this strategy, followed by a section comparing simulation results of three strategies.

1 HEV OPTIMAL CONTROL PROBLEM

It is well-known that Pontryagin's minimum principle can be applied to the HEV energy management problem to derive its optimal solution [1,?], in the form of the ECMS. Consider a hybrid vehicle following a prescribed driving cycle. If all fast dynamics in the powertrain are neglected, as well as the thermal phenomena, the vehicle can be described as a system in which the battery state of charge (SOC) x is the only state variable. The system state equation is then

$$\dot{x}(t) = f(x, u, t) = -\frac{1}{Q_{batt}} I_{batt}(x, u, t) \qquad (1)$$

where I_{batt} is the battery current and Q_{batt} the battery charge capacity.

The control variable $u(t)$ represents a measure of the power split between the two forms of energy storage systems on board (fuel and battery); for instance, the ratio of the engine power to the total power demand.

The optimal control problem solved by the energy management module consists in the minimization of the performance index

$$J(u) = \int_0^{t_f} L(u, t)dt. \qquad (2)$$

In the case fuel consumption minimization is the only optimization objective, the instantaneous cost is the fuel flow

rate, or the power equivalent to it:

$$L(u,t) = P_{fuel}(u,t) = Q_{lhv}\dot{m}_f(u,t) \qquad (3)$$

(Q_{lhv} being the constant fuel energy density).

The optimization problem is extended to the time interval $[0, \ t_f]$ and is subject to several constraints. These include:

Initial conditions and system dynamics:

$$x(0) = x_0 \qquad (4)$$

$$\dot{x}(t) = f(x,u,t) \qquad (5)$$

Instantaneous constraints:

$$u_{min}(t) \le u(t) \le u_{max}(t) \quad \forall t \in [0, \ t_f] \qquad (6)$$

$$x_{min} \le x(t) \le x_{max} \quad \forall t \in [0, \ t_f] \qquad (7)$$

Global constraints:

$$x(t_f) = x_f \qquad (8)$$

1.1 Optimal control solution

The global optimal energy management control problem which consists in minimizing (2) subject to (1), (4), (6), (7) and (8) is reduced to an instantaneous minimization problem on the Hamiltonian function H.

The Hamiltonian is written as [2]

$$H(x,u,t) = P_{fuel}(u,t) - \lambda(t) \cdot \frac{1}{Q_{batt}} I_{batt}(x,u,t). \qquad (9)$$

From [2] the co-state is decoupled into two factors, one constant (the battery total energy [1] E_{batt}) and the other dimensionless (the term $s(t)$), as:

$$\lambda(t) = -E_{batt}s(t) = -V_{oc,max}Q_{batt}s(t). \qquad (10)$$

When λ is replaced with this expression, the Hamiltonian function can be interpreted as an equivalent power

$$H(x,u,t) = P_{fuel}(u,t) + s(t) \cdot P_{ech}(x,u,t) \qquad (11)$$

where $s(t)$ represent the *equivalence factor*, i.e. a weighting factor that transforms the battery power into fuel power. $P_{ech}(\xi,u,t) = V_{oc,max}I_{batt}(\xi,u,t)$ is the electrochemical power, i.e. the power that corresponds to the effective battery discharge. The term equivalence factor comes from the fact that in charge-sustaining HEVs, where all energy comes ultimately from the fuel, the battery charge or discharge are translated respectively into equivalent fuel consumption or equivalent fuel savings (by replacing use of fuel energy with use of electrochemical energy). In fact, Eq. (11) was

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1. The battery energy is the product of its charge capacity and open circuit voltage at full charge: $E_{batt} = Q_{batt}V_{oc,max}$.

originally derived from intuitive considerations on energy balance, which resulted in the *equivalent consumption minimization strategy* or ECMS [3].

The equivalence factor $s(t)$ in (11) is proportional to the co-state $\lambda(t)$ and evolves, in principle, according to

$$\dot{s}(t) = -s(t)\frac{\partial P_{ech}(x,u,t)}{\partial x}. \qquad (12)$$

Eq. (12) is often neglected because the actual variation of s is very small, thus $\dot{s}(t) \approx 0$ and $s(t) = s_0$.

The solution obtained is really optimal only in off-line implementation, since it depends on the value of the co-state s, which is obtained using iterative search in order to find the only value that generates a charge-sustaining solution, in which $SOC(t_f) = SOC(t_0)$. The iterative search is possible thanks to the fact that there is a direct and bi-univocal relation between the value of the co-state and the value of SOC reached at the time t_f (as shown in Figure 1).
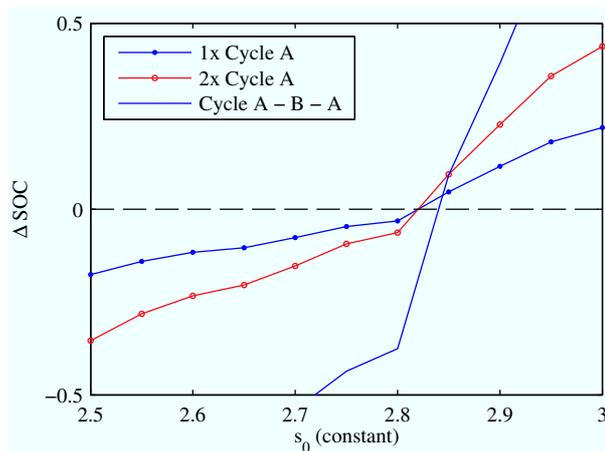

Figure 1

Effect of s on final SOC value. Note the correlation between the type and length of driving cycle and the effect of s_0 on the final ΔSOC

2 ADAPTIVE ECMS METHODS

ECMS can generate the optimal energy management solution for a given cycle, provided that the strategy is properly tuned by choosing the appropriate value of equivalence factor. The equivalence factor plays a crucial role in the charge sustaining ECMS; it trades off chemical against electric power.

As shown in Figure 1, if the equivalence factor is very large, then the ECMS tends to recharge the battery in almost all operating points. If the equivalence factor is very small, then the ECMS favors pure electric driving.

Since perfect tuning is possible only with a-priori knowledge of the cycle, research efforts have been directed towards online adaptation of ECMS, in order to achieve quasi-optimal results even without a-priori tuning of the strategy. Although all these methods were named A-ECMS, they inherently differ from each other for the method used to update the equivalence factor.

We recognize three categories of methods we can group the different approaches to design A-ECMS. They are:

A. adaptation based on driving cycle prediction;

B. adaptation based on driving pattern recognition;

C. adaptation based exclusively on feedback from SOC.

Combinations of the methods have also been proposed. In particular, SOC feedback is always necessary for online implementation, and therefore it is used methods A and B as well, even if it is not the main adaptation variable. Method A uses information about the future (predicted), while methods B and C only use current/past information. In the following a description of the methods falling into each of three groups is given, highlighting their main characteristics.

In general, the three categories above do not represent stand alone methods for A-ECMS implementation, but rather a framework to design the update and adaptation of the equivalence factor; their accuracy can be improved if used together with other techniques.

2.1 Adaptation based on driving cycle prediction

The driving principle behind this class of methods is: when no information on future driving conditions is available, optimal fuel economy cannot be guaranteed. Thus, this family of algorithms aim at using any sort of future information to feed the ECMS control module with the more suitable value of equivalence factor.

Historically, this was the first adaptation approach. In fact, A-ECMS was first proposed in [4] (and [5,?] by the same group of authors). In this series of papers, the term A-ECMS was coined and conceived as a real-time energy management strategy 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 being a periodical refresh of the control parameter according to the current road load, based on prediction of driving conditions. The identification of the driving mission combined with past and predicted data are used to determine the optimal equivalence factor over the optimization segment. The ECMS module is effectively augmented with a device able to relate the control parameters to the current velocity profile. The reference SOC is kept constant in this A-ECMS prediction scheme.

In [6], the online estimation of the equivalence factor is based on a look-ahead horizon defined in terms of energy

at the wheels, thus measurements are used to determine at each instant the most likely behavior (charging or discharging) in the near future.

In [7] instead, an adaptation scheme similar to [4] is presented which uses a predictive reference signal generator (pRSG) in combination with a SOC tracking-based controller (implemented in the form of feedback from SOC) for the battery SOC. The pRSG computes the desired battery SOC trajectory as a function of vehicle position such that the recuperated energy is maximized despite the constraints on the battery SOC. To compute the SOC reference trajectory, only the topographic profile of the future road segments and the corresponding average traveling speeds must be known.

In [8], the authors use a Model Predictive Control (MPC) based strategy and utilize the information attainable from Intelligent Transportation Systems (ITS) to establish a prediction based real-time controller structure. A constant reference SOC is considered and A-ECMS implemented as in [4] is compared with a MPC type controller based on the prediction of future torque demand. The performances of the two controllers are very similar, indicating that A-ECMS with driving mission prediction is somehow equivalent to MPC. What emerges from the paper is also the importance of information provided by ITS and the impact of the accuracy of ITS information on HEV energy consumption.

2.2 Adaptation based on driving pattern recognition

In [9] an approach for A-ECMS based on driving pattern recognition is presented. In this research, a driving pattern recognition method is used to obtain better estimation of the equivalence factor in different driving conditions. While the vehicle is running, a time window of past driving conditions is analyzed periodically and recognized as one of the representative driving patterns, according to the scheme of Figure 2.

A finite number of possible driving patterns is recognized, each corresponding to a pre-defined value of the equivalence factor (pre-computed from offline optimization). The battery SOC management is also maintained using a PI controller to keep the SOC around a nominal value (thus using feedback from SOC). Differently from the methods seen before, such control algorithm does not require the knowledge of future driving cycles and has a low computational burden but higher memory requirement. Results obtained in this research show that the driving conditions can be successfully recognized and good performance can be achieved in various driving conditions while sustaining battery SOC within desired limits.

2.3 Adaptation based on feedback from SOC

The most recent and interesting approaches developed to design A-ECMS are based on the feedback of the current
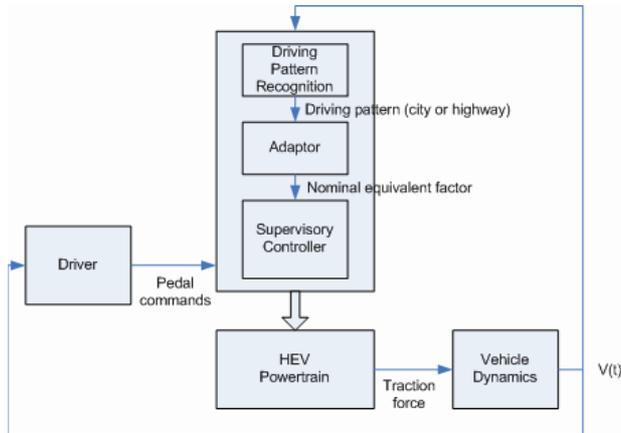
Figure 2

A-ECMS scheme based on pattern recognition ([9]).

Figure 3

adaptation law block diagram based on SOC feedback.

SOC [10,11,12]. All these methods try to change dynamically the value of the equivalence factor in order to contrast the SOC variation (and thus maintain its value around the reference level). In all these methods the SOC reference is considered constant.

Conceptually, these approaches differ in that, while [10,11] update the equivalence factor at each time instant, [12] relies on the concept of charge-sustaining horizon, imposing charge-sustainability over a finite time horizon. If, on one hand these methods are easy to implement, robust and computationally cheap, on the other hand their performance relies on a suitable tuning of the parameters. This operation, most of the time very tedious, represents the only weakness of these methods. The prediction of driving mission can definitely help to find better guesses of those parameters thus improving optimality, as well as speed of convergence and robustness.

3 COMPARISON OF ADAPTATION METHODS BASED ON SOC FEEDBACK

As mentioned, in this class of methods the equivalence factor $s(t)$ is corrected with a feedback on the system state, in order to reach the reference value at steady state, according to the scheme of Figure 3.

In this section we review three ways to achieve adaptation of the equivalence factor through SOC feedback. The first approach was suggested by Chasse et al. [11], who proposed a method based on a simple proportional controller of the form:

$$s(x,t) = s_0 + k_P \left(x_{ref} - x(t) \right) \qquad (13)$$

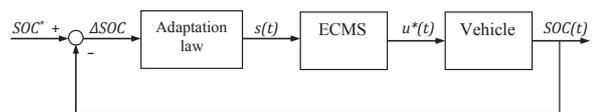The second method was proposed in [10] and [13] and consists in the following adaptation law, based on a PI

controller:

$$s(x,t) = s_0 + k_P \left(x_{ref} - x(t) \right) + k_I \int_0^t \left(x_{ref} - x(\tau) \right) d\tau \qquad (14)$$

In the following, Eqs. (13) and (14) are referred to as *continuous A-ECMS (P)* and *continuous A-ECMS (PI)*, respectively. In practice, in (14) the integral action is added to the proportional one used in (13), in order to guarantee better performance when tracking a constant reference value, at the price of having three tuning parameters $(s_0, \ k_P, \ k_I)$ instead of two $(s_0, \ k_P)$. The adaptation is performed at each time instant.

The third adaptation law considered in this paper is a discrete time function proposed in [12]:

$$s_k(x,T) = \frac{s_{k-1} + s_{k-2}}{2} + k_P^d \left(x_{ref} - x(T) \right) \qquad (15)$$

hereafter called *discrete A-ECMS*. Eq. (15) is in the form of autoregressive moving average (ARMA) model, with two autoregressive terms and one moving average term. The key feature of (15) is that the adaptation takes place at regular intervals of duration T, rather than at each time instant. This allows for large excursion of SOC as opposed to a quasi-constant SOC trend obtained when using (13) and (14), as also shown in the simulation results.

The adaptation methods based on driving cycle prediction or pattern recognition can also be cast into the formalization provided by (14), because they can be interpreted as methods for tuning s_0 and/or x_{ref} during the vehicle operation, using external information to provide a better estimate of the baseline equivalence factor or the reference SOC profile.

4 SIMULATION RESULTS

In this section, the three A-ECMS strategies based on SOC feedback are compared in simulation, being applied to the same vehicle model. The test case is a simple parallel hybrid vehicle with the characteristics shown in Table 1. The driving cycles are part of the Artemis family: Urban, Extra-urban and a composition of the two.

The vehicle model is purely longitudinal and quasi-static, including vehicle inertia and the standard representation
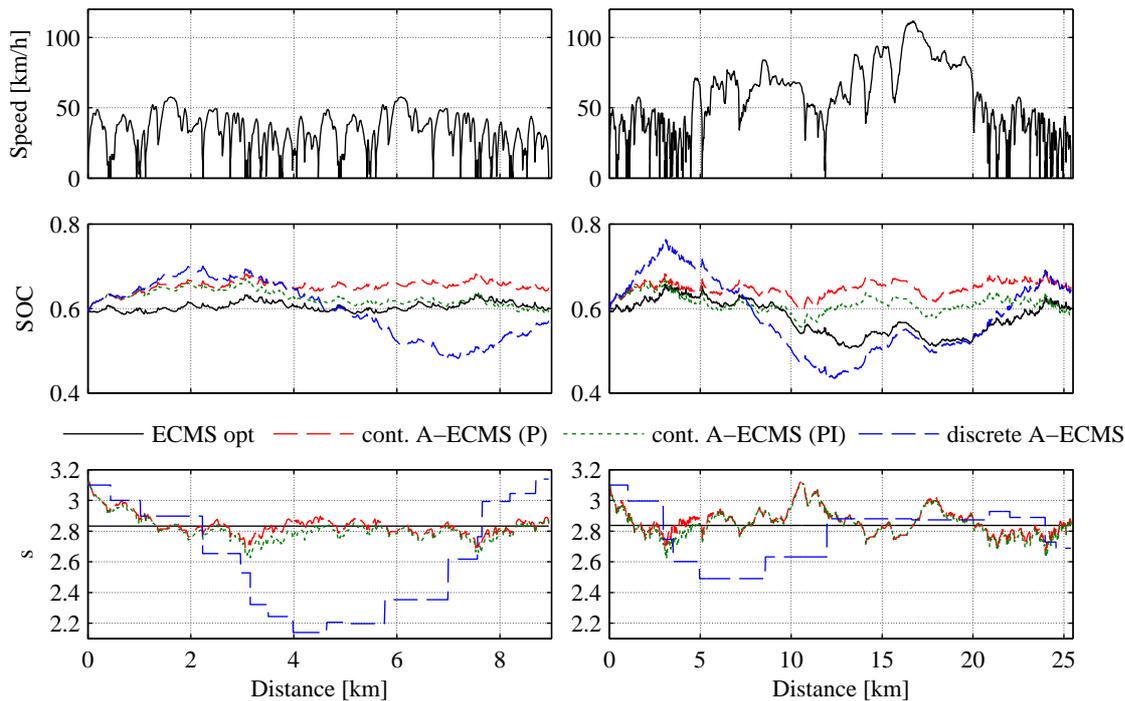
Figure 4

Comparison of the strategies: evolution of SOC and equivalence factor, with initial condition $s_0 > s_{opt}$. Left: Artemis Urban cycle (2 repetitions); right: sequence of Artemis Urban / Extra Urban / Urban).

TABLE 1

Main characteristics of the vehicle

Vehicle mass	1800 kg
Engine max. power	100 kW
Motor max. power	25 kW
Battery energy capacity	1.5 kWh (5400 kJ)

of road load based on rolling and aerodynamic resistances. The backward simulation approach is used, i.e. the torque demand is computed from the prescribed vehicle speed and acceleration. This allows for completely fair comparison of the strategies, since in all cases the total power delivered at the vehicle is exactly the same. The battery model is represented by a purely resistive circuit, with both open-circuit voltage and resistance dependent on the state of charge.

The simulation time step is set at 1 second, which is coherent with the modeling hypotheses.

In the continuous A-ECMS (P and PI) the equivalence factor is updated at each time step. The value of the proportional feedback gain is set to $k_P = 5$ following the suggestion in [11], while the integral gain was set to $k_I = 0.005$ after some manual tuning.

As for the discrete A-ECMS, the adaptation period is set to $T = 120$ s, which is deemed to be a time long enough for the imposition of charge-sustainability, but short enough

to allow the correction of the equivalence factor before the SOC limits are reached. The value of the feedback gain is tuned manually to $k_P^d = 3$.

The solution obtained from ECMS when optimally tuned with constant equivalent factor, denoted as *ECMS opt*, is used as benchmark in our study (it is equivalent to the optimal solution obtained with dynamic programming, as shown in [14]). This optimal solution is obtained by performing an iterative search of the constant value of s that generates $\Delta SOC = 0$. Figure 4 shows a comparison of the three adaptation strategies to the *ECMS opt*. The results are presented for two driving cycles. In both cases, the initial value of equivalence factor is higher than the optimum. It is possible to observe that – as expected – the introduction of the integral feedback in the continuous A-ECMS allows for the equivalence factor to converge towards the optimal value, and the SOC variation to converge towards zero. On the other hand, the P-only case shows some residual error and is less effective. The discrete A-ECMS allows by design more ample SOC variation than the continuous counterparts, thanks to the less frequent correction; its ability to reduce the SOC difference at the end of each cycle is comparable to the continuous PI version. All strategies are very close to each other and to the optimal ECMS solution in terms of corrected fuel consumption (i.e fuel consumption accounting for differences between initial and
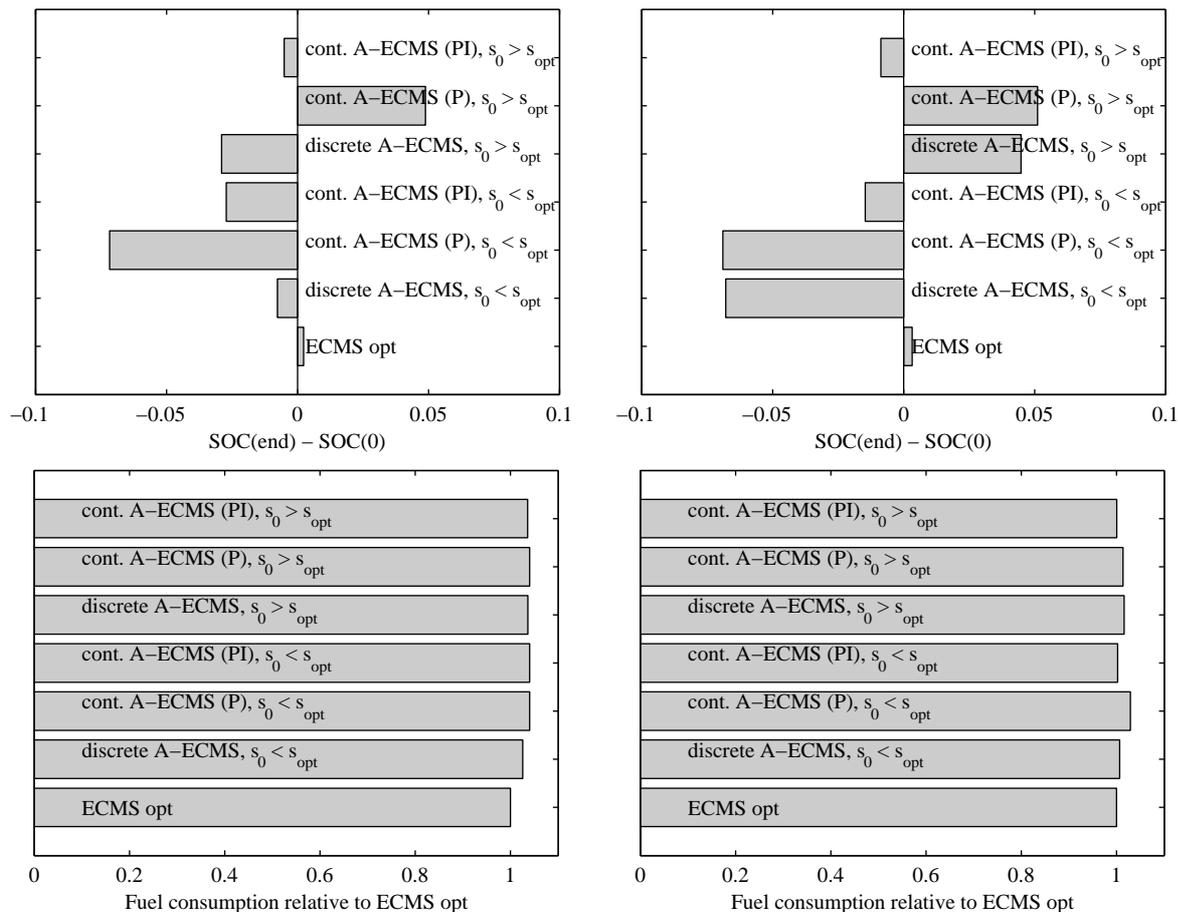
Figure 5

Comparison of the strategies with synthetic metrics: SOC variation over the cycle and fuel consumption (corrected with SOC variation). Left: Artemis Urban cycle (2 repetitions); right: sequence of Artemis Urban / Extra Urban / Urban.

final SOC). Overall, it appears that this kind of feedback-corrected strategies are capable of generating a solution which is both robust (SOC does not deviate excessively) and quasi-optimal (fuel consumption is very close to the optimal result). The continuous PI appears visually to be more stable (smaller SOC deviation), while the discrete A-ECMS allows for more ample use of the battery. Synthetic metrics comparing all strategies are shown in Figure 5, in which two cases are considered for the initial equivalence factor: either higher or lower than the optimal value. From these results, the continuous PI method appears to provide the solution with the lowest SOC variation at the end of the cycle, while all the methods are fairly close to the optimum in terms of the corrected fuel consumption (the difference is in the order of 1-2 %).

5 CONCLUSION

This paper proposed an overview and comparison of Adaptive-ECMS strategies for HEVs. We presented a com-

parative analysis of three A-ECMS algorithms belonging to the family of methods which use feedback from SOC to perform the adaptation of the equivalence factor for online energy management. The results show that methods exclusively based on SOC feedback and accounting for cumulated error (continuous PI or discrete A-ECMS) provide solutions that are robust and very close to the optimum, which means that more advanced adaptation methods, based for example on driving cycle prediction, would not significantly improve the overall results. This conclusion is valid for the cases shown here, in which the SOC does not reach the boundary values, but it may not be true for vehicles with very small batteries, of for more extreme driving cycles, e.g. including important altitude variation: in that case, the ability to predict a substantial change in power demand may make the difference between reaching or not the SOC boundaries, and therefore may allow to improve the overall results. Therefore, future work will also include comparison of A-ECMS methods based on driving cycle prediction, for driving cycles including altitude and/or a smaller battery.

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