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Influence of the Prediction Horizon Length of a PHEV Energy Management on Fuel Consumption

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Abstract

The use of information about the future vehicle trajectory is especially advantageous for the energy management strategies of Plug-in Hybrid Electric Vehicles. This is based on the fact that for minimal fuel consumption the stored electric energy should be consumed until the end of the trip, if the trip length exceeds the electric range of the vehicle. Therefore, best results are achieved by an optimization of the torque distribution between both electric motor and combustion engine knowing the whole trajectory until the next use of a recharging station. Due to the long recharging times this means usually an optimization until the end of the trip.

A drawback of such long predictive horizons is the high computation cost. Another is the increasing model uncertainty due to the use of simplified powertrain models for the prediction algorithm and also the reliability of the predicted trip information. Therefore, one aim is to reduce the prediction horizon as much as possible without increasing significantly the fuel consumption. To save computation cost of the optimization and decrease the influence of model uncertainties, in this paper an energy management for Plug-in HEV calculating the global optimum for the whole trip is compared to optimization with different prediction horizon lengths. To define the desired SOC at the end of the prediction horizon a linear reference SOC function is used. Depending on the chosen prediction length the trajectory is divided into several sections, each one standing for one prediction horizon. At the entrance to every section the energy management calculates the optimal torque set point for the whole next section (prediction horizon). In order to exclude the influence of the optimization algorithm, Dynamic Programming is used to calculate the global optimum.

Keywords: optimization, parallel HEV, PHEV (plug in hybrid electric vehicle), power management

1 Introduction

With the upcoming of Plug-in Hybrid Electric Vehicles (PHEV) and the expected increase of sales numbers in the next years, the use of predictive energy management strategies (EM) gain importance. In comparison to autonomous HEV, PHEV dispose of a recharging possibility along with a battery which has a significantly higher capacity than in autonomous HEV.

The difference to strategies for autonomous HEV is the possible use of two independent energy sources, the fuel and the electric energy. While for autonomous HEV the stored electric energy at the end of the trip is of minor importance, for PHEV it should minimized as much as reasonable as it can be refilled after the trip without the use of the combustion engine. In that way, fuel consumption can be minimized [1].
The easiest energy management implementation without the necessity of prediction is the all-electric-range strategy (AER) [2]. With the AER strategy the vehicle which behaves in the beginning of the driving cycle like an electric vehicle. After having consumed the stored electric energy in the battery the battery switches to a normal HEV driving mode. This strategy is easy to implement, but it is suffering of the drawback to use the stored electric energy already in the beginning of the trip and so having less potential to avoid afterwards bad efficiency regions of the combustion on trips longer than the electric autonomy of the vehicle. Therefore, to minimize fuel consumption, a predictive strategy is needed which distributes the stored electric energy over the whole driving cycle. It has been shown that compared to the AER strategy the fuel consumption can be reduced when distributing the electric energy on the whole driving cycle [3], [4].
This prediction is only necessary for cycles which are longer the electric range of the vehicle, as for shorter cycles it is sufficient to stay during the whole cycle in electric mode. That is why a predictive strategy is only needed for longer trip and, therefore, the prediction part of the strategy can reach high computation cost. As the computation costs increase with the prediction horizon, a compromise between fuel saving and prediction horizon length has to be found.
In the following, simulation results for a parallel plug-in HEV using an AER strategy are compared to Dynamic Programming (DP) optimized strategies using different prediction horizon lengths.

For the presented predictive EM strategy, it is supposed that information about the whole trip length and additionally velocity and road slope information about the current prediction section are available to the strategy. This information will be in future available due to satellite navigation systems as GPS and the central collection and processing of tracking data of mobiles and vehicles.

2 Vehicle Structure

In the following section the structure and parameters of the simulated vehicle are described.
As vehicle base a SEAT Ibiza ST is used. The drivetrain has a parallel structure, that is the electric motor and combustion engine are mounted on the same drive shaft so that their torques are added. The 51 kW combustion engine can be separated by a clutch to allow electric driving (figure 1)

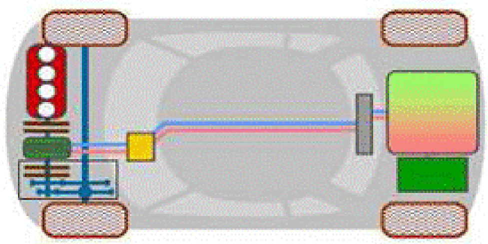

Figure 1: Drivetrain of a parallel PHEV

The gearbox disposes of 7 gears to allow the engine working in a high efficiency region. The battery has a capacity of 4 kWh. To avoid damage to the battery and allow at the end of the trip the use of the vehicle without recharging, the strategy leaves 1.2 kWh at the trip end in order to make it possible to use a HEV charge sustaining operation mode.

Table 1: Vehicle Parameter used in simulation

Vehicle Mass	1450 kg
A_f	2.2
Gear Number	7
$P_{ICE,max}$	51 kW
$T_{ICE,max}$	110 Nm
$P_{EM,max}$	40 kW
$T_{EM,max}$	250 Nm
$E_{battery}$	4 kWh
$E_{battery,min}$	0.8 kWh
$V_{battery}$	300 V

3 Driving Cycle

The simulation takes place on a real life driving cycle from SEAT Technical Centre in Martorell to Barcelona City. The distance is 33.3 km and last 2306 s (figure 2). It consists of a short urban part at the beginning and a longer one at the end. The highway part has velocities up to 115 km/h.

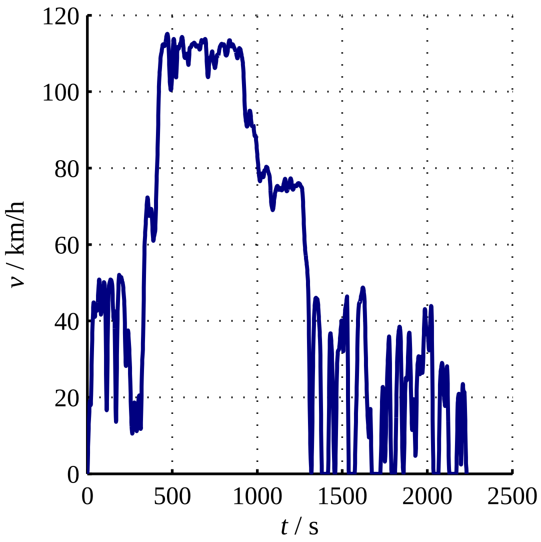

Figure 2: Vehicle velocity profile of the driving cycle used in simulations

The cycle is hilly with a maximal slope up to 4%. The characteristics of the cycle and the vehicle cause that it is not possible to drive the whole trip in pure electric driving mode, but that the combustion engine has to be used.

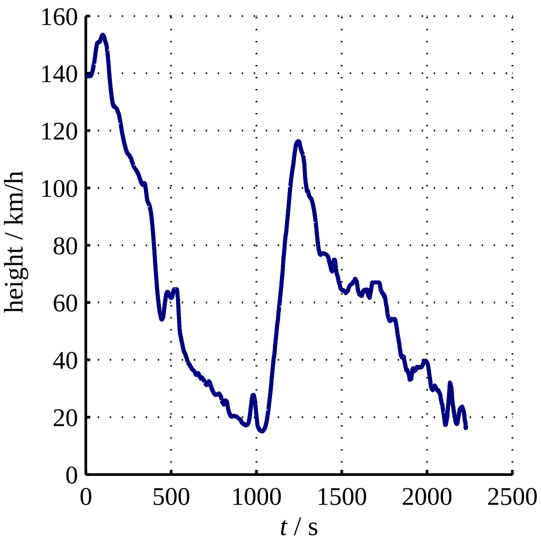

Figure 3: Height profile of the driving cycle used in simulations

4 Vehicle Models

The used models are built in the simulation environment Modelica/Dymola. Two different kinds of models are used. The optimization with DP takes place on a backward model, which is stationary and therefore allows higher simulation speed. This model is used for the optimization algorithm. Afterwards, the obtained results are applied to a forward model. This forward model contains dynamic elements and is used to verify the results from the optimization algorithm.
The forward model is validated with measurement data from a roller test bench. In the following the different model components are shortly described.

4.1 Combustion Engine

The fuel consumption of the combustion engine and modeled by a measured consumption map of the used engine. The revolution number and the torque demand calculated by the model are used to interpolate the corresponding fuel consumption.

4.2 Electric Motor

For the Electric Motor the electric losses are modelled by an electric losses map. As for the combustion engine the revolution number and the torque are used to interpolate the corresponding electric losses and so the electric power input or output.

4.3 Battery and Inverter

The battery is modelled with discrete elements of the internal resistance and capacitance in the forward model while in the backward model is used a fixed efficiency. Also for the inverter in both model types a constant efficiency is assumed.

5 Energy Management

The energy management has to control the energy content of the battery during the trip. This is done by the change of the torque distribution of the demanded torque by the driver to the electric motor and the combustion engine. By this way the change between the different operating modes recuperation, electric, boost and charge is controlled. For plug-in HEV and trips longer than the electric range it is wished to substitute as much fuel energy by electric energy so that the fuel consumption is minimized. That is, when starting the trip with SOC_{max}, at the end of the cycle there should remain SOC_{min} with a before defined cushion to allow to use the vehicle in charge sustaining mode.

The initial SOC of the battery is defined as 0.9. This, with a minimal SOC of 0.25, leads to an electric energy of $E_{battery}$= 2.6 kWh which can be consumed over the trip length.

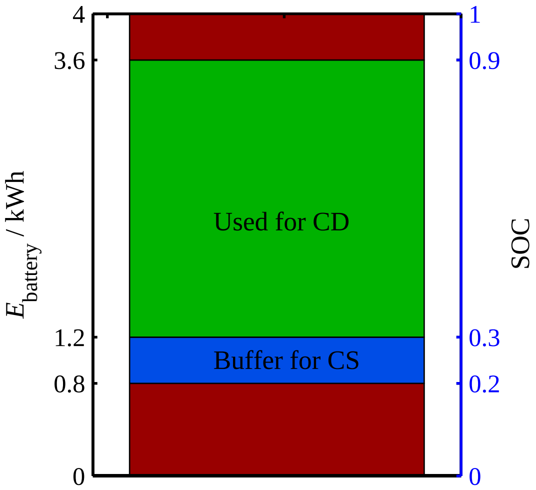

Figure 4: Electric energy used during the charge depleting mode (CD) and the buffer reserved for charge sustaining mode (CS) at the end of the cycle

5.1 AER

In AER the vehicle starts in pure electric mode until the minimal SOC is reached. Then the strategy switches to a charge sustaining strategy as used in autonomous HEV. Due to the highway section of the cycle, in second 693 of the cycle the minimal SOC is already reached and the vehicle leaves the pure electric mode. For the rest of the cycle it stays in a charge sustaining mode as it is also used for autonomous HEV.

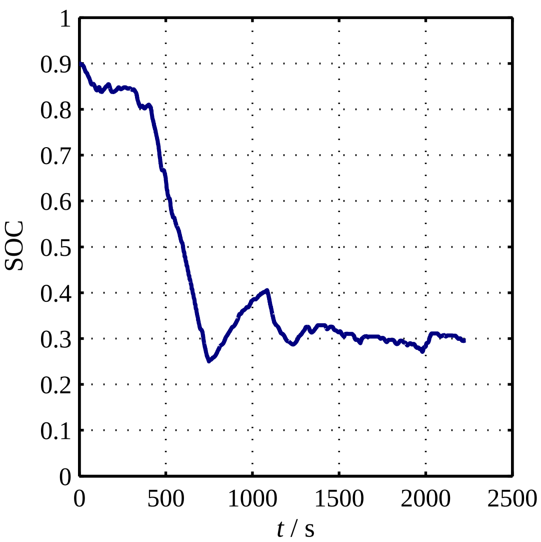

Figure 5: SOC evaluation with AER management

5.2 Dynamic Programming

Dynamic Programming is a common algorithm to calculate the global optimal solution of a stochastic optimization task. However, as here the optimization task is assumed to be not stochastic, the resulting problem is a shortest way problem [5].

As it can be applied only on a discrete optimization task, a discretization grid for the time and the states of the model has to be defined. A finer grid means higher exactness but lower computation speed. As the algorithm is considering all possible solutions of the problem, the computation cost is quite high. Furthermore, a simple problem has to be defined as the computation cost increases exponentially with the states of the optimization problem. Especially time dependent states are problematic, as the computation cost increase exponentially with the number of states.

5.2.1 Algorithm

The system to which the optimization is applied can be generally be described by

$$x_{k+1} = f_k(x_k, u_k) \quad (1)$$

where x_k and u_k are the state and the control variable at time step k. Here the control variable is the torque of the electric machine T_{EM} while the state variable is the SOC of the battery.

The control problem can be described as finding the optimal control sequence

$$\pi^o = \{u(1), u(2), \ldots. u(N)\} \quad (2)$$

which minimizes

$$J^o(x_o) = \min_{\pi \in \Pi} J_\pi(x_o) \quad (3)$$

where Π is the set of all possible control sequences, J the sum of the fuel consumption at every time step and x_0 the system state at time step $k = 0$.

5.2.2 Application

To examine the influence of the prediction horizon on the fuel consumption, three different prediction section lengths are defined. Firstly, the section length is the whole driving cycle, which means that the DP seeks the global optimum of fuel consumption for this driving cycle. Afterwards, the trip length is first divided in two and later in four parts, which leads to prediction section lengths of

16666 m and 8333 m, respectively. The SOC to be achieved at the end of one prediction section is defined by a linear function over the distance.

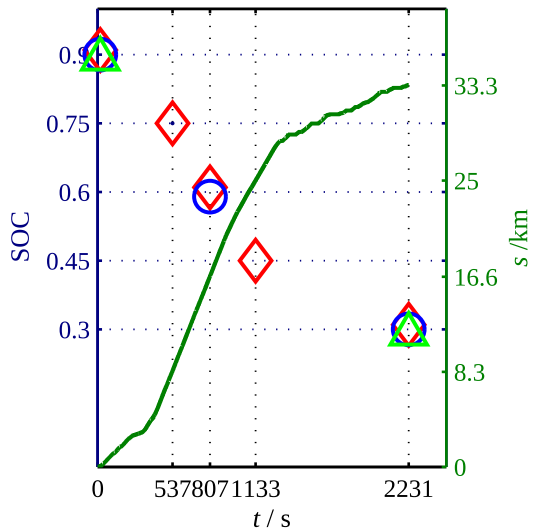

Figure 6: A linear function is used to define the SOC points at the end of every prediction section. The red rhombus shows the four defined points for the prediction horizon length of 8.3 km, the blue circle for 16.7 km and the triangle for 33.3 km.

6 Simulation Results

The global optimum calculated by DP gives an optimum of 1.95 l/100 km (table 2). This is an improvement of 26 % in respect to the used AER strategy which consumes 2.67 l/100. The change of the prediction horizon length from 33.3 km to the half of the cycle (16.7 km) shows in contrast no significant change of the fuel consumption, the difference is less than 1 %.

Table 2: Fuel and electric consumption in charge depleting mode

Energy Manage-ment	Prediction Section Length /m	Fuel consumption / l/100 km	$\Delta E_{battery}$ /kWh
DP	33333	1.95	2.6
DP	16666	1.96	2.6
DP	8333	2.37	2.6
AER	0	2.65	2.6

The evaluation of the SOC during the cycle using prediction section lengths of 33.3 km and 16.7 km are almost identical (figure 7), which explains the small deviation of the fuel consumption. This very slight difference occurs because of the fact that the beforehand fixed SOC point (by the linear SOC curve, figure 6) at 0.6 at the half the trip distance corresponds very well to the curve of the global optimum. However, a further reduction of the prediction section to one quart of the cycle (8.3 km) raises the fuel consumption to 2.37 l/100 km. Here the SOC curve shows obvious differences to the global optimum during the highway part of the cycle.

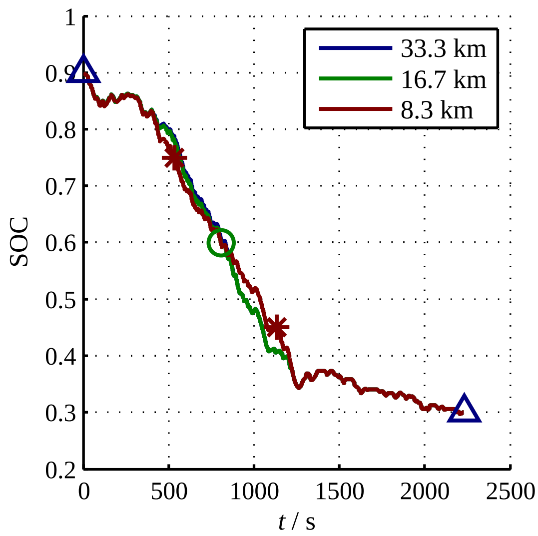

Figure 7: SOC profile of DP with different prediction horizon lengths

The higher consumption using the 8.3 km prediction section length is caused by the fact, that the beforehand defined SOC points at the end of the prediction sections do not coincide with the global optimum (table 3). So is the SOC after the first quarter of the trip distance fixed to 0.75, while the optimal value is 0.783.

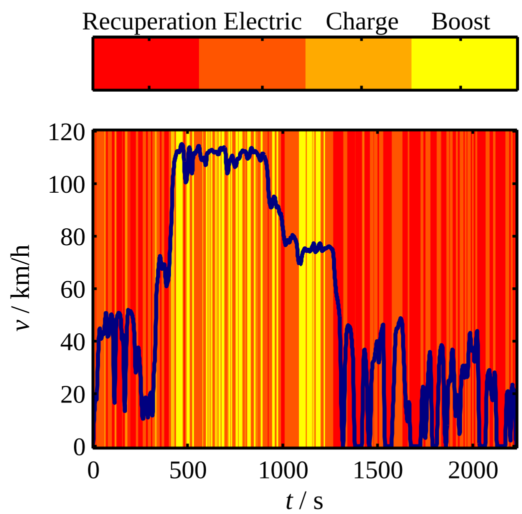

Figure 8: Driving modes during trip with prediction horizon of 33.3 km

Also at the end of the third quarter, the linear SOC function does not coincide with the global optimum, causing the strategy to behave sub-optimal. So is the optimal SOC value at the end of the third quarter 0.406, while the linear function defines here 0.45 (table 3). Due to this, the vehicle spends more time in charge mode on the highway than optimal.
The reason for the deviation between the global optimum and the linear function in this point is that during the second half of the used cycle the slope is negative (figure 3). This and the lower average speed during this part in the urban area lead to a lower electric cosumption. Therefore, in the global optimal strategy only the electric an drecuperation mode is used (figure 8). As this information is not included in the linear SOC curve, the consumption cannot be optimal.

The described effect shows clearly the negative effect of a reduced prediction horizon. Due to the negative slope and the lower average vehicle speed of the last urban part of ther trip there is less electric energy necessary. The strategies using the longer prediction section can anticipate that. This is possbile because there is always one part of the highway cycle included in which it is possible to consume electric energy which is not needed for the last trip part. However, the strategy using the shorter prediction horizon makes less use of the boost mode on the highway part at the end of the third quart. As a result, the engine operating points concentrate in less efficient regions than the global optimum (figures 9, 10).

Table 3: SOC at end of every quarter of the trip distance according to the used prediction section length

t / s	0	536	807	1133	2231
s / m	0	8333	16666	25000	33333
DP 33333 m	0.9	0.783	0.608	0.406	0.3
DP 16666 m	0.9	0.777	0.6	0.406	0.3
DP 8333 m	0.9	0.75	0.6	0.45	0.3

It can be stated that even for the global optimum the engine operating points do not concentrate in the highest efficiency regions. Comparing the efficiency engine map to the one of the used electric motor (figure 11), it can be seen that when both engine and motor are used at the same time, the strategy chooses a compromise between the highest efficiency regions of both machines.

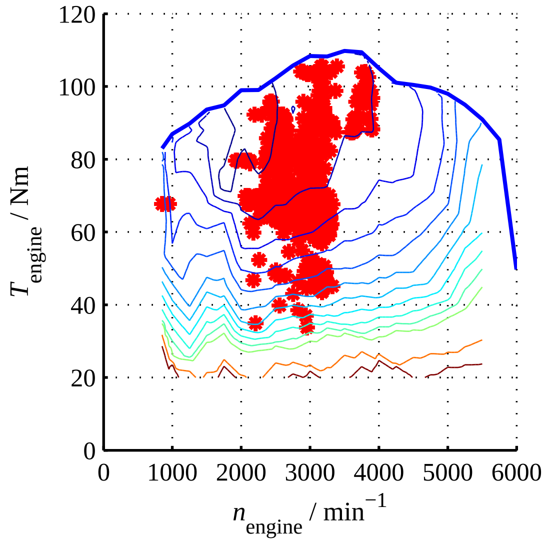

Figure 9: Engine Operating Points during trip using a prediction horizon of 33.3 km

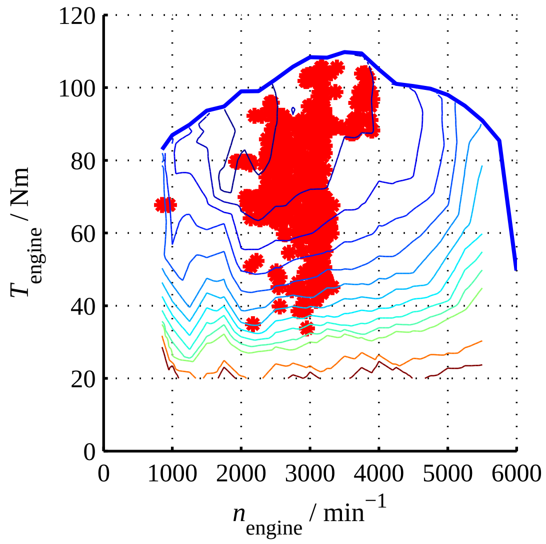

Figure 10: Engine Operating Points during trip using a prediction horizon of 16.7 km

7 Conclusions

As the controlled variable of the energy management of a PHEV is the SOC, using a predictive strategy the desired SOC value at the end of the perdiction horizon has to be known. Therefore, beside the question of the prediction horizon length the question arises of the function which defines the desired SOC at the end of the prediction horizon. If the prediction horizon comprises the whole trip, the final SOC depends only on the necessary buffer to allow driving in charges sustaining mode. If the prediction horizon is chosen to be only one part of trip, a function is needed to calculate the respective final SOC value.

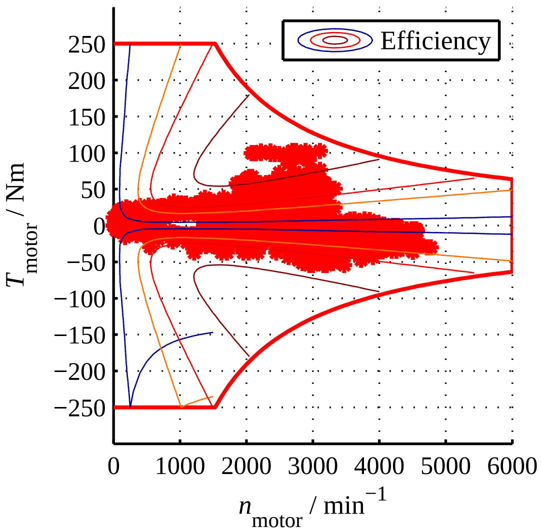

Figure 11: Motor Operating Points during trip using a prediction horizon of 33.3 km

Here, a linear function in respect to the trip distance is used. It can be shown, that the use of a linear SOC function in respect to the trip distance allows appropriate results, if the prediction horizon is sufficiently long. This is especially important if the trip changes its characteristics. In the used cycle there is in the last part negative slope combined with low vehicle speed, leading to a small energy demand of the drivetrain. This leads to non-optimal results for short prediction horizons. Nevertheless, the achieved results are still better than the not optimal AER strategy.

To avoid not optimal fuel consumption when using a linear SOC function, the prediction horizon has to be chosen appropriately long in respect to trip parts with energy demand which is over or below the average.

Another approach would be to choose another function to calculate the final SOC of the prediction horizon which also considers certain cycle characteristics, as urban or highway sections and the slope of the road.

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