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The Fuel Saving Potential of Long-Term SOC-Prediction Demonstrated on Two Different Operational Strategies for Parallel Hybrid Drivetrains

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Abstract

This paper describes a long term SOC-prediction method using topographic informations to enhance the fuel saving capability of parallel hybrid cars. There are a lot of approaches to determine the torque or power split in a parallel hybrid drive train. This prediction method can be adapted to all of these approaches if they use the SOC as a guideline for the use of electric driving energy. The impact of these long-term prediction method on two different torque split strategies is represented in this paper.

Keywords: parallel HEV , battery, energy, power management

1 Introduction

There are a lot of different approaches to calculate good operation points for parallel hybrid drive trains. Most strategies take only in-car-data into there calculations. Therefore it is just possible to minimise the fuel consumption for one calculation step. These local minima do not lead to a global minimum of fuel consumption. The global minimum can only be calculated with the full knowledge of the driving conditions of a given route after the drive is finished.

But if there is information about the route ahead the car, like the altitude profile and speed zones, one can improve the strategies to push the fuel consumption closer to the global minimum.

This paper describes how this information can be used to improve the fuel saving capacity. The impact of this method on two different analytical operational strategies is demonstrated.

2 Long term prediction method

With a global optimisation tool for a given route the absolute minimum of fuel consumption can be calculated afterwards. As a side result the optimal state of charge (SOC) profile for this route is also determined.

In Figure 2.1 the SOC calculated with a Bellmann algorithm is compared to the SOC as generated by an on-line operational strategy for a specific driving cycle containing up- and downhill stretches with altitudedifferences of up to ??? m. Two different effects can be seen. In area 1 of Fig. 2.1 the on-line strategy avoids to discharge the battery to a level as deep as the off-line algorithm does. That happens because the on-line algorithm does not know the altitude conditions of the drive. The off-line algorithm knows that at a distance of 8000 m a long decline starts and that a lot of energy can be regenerated. So the necessary energy balancing of the on-line algorithm avoids a deeper discharge. In area 2 a fast discharge can be seen with the on-line strategy. After the regeneration of downhill energy the SOC has a high level and the energy balancing of the on-line strategy leads to this discharge with the aim to avoid an overcharge of the battery at the one hand and to keep charging capacities for further recuperations on the other hand.

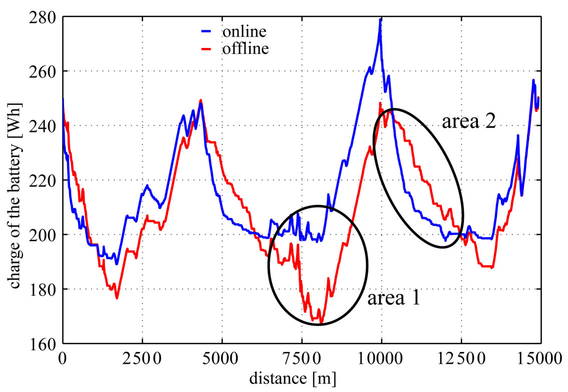

Figure 2.1: Difference between on-line and off-line calculated SOC

Here, too, the limited knowledge of the future driving conditions leads to a suboptimal behavior of the on-line strategy. The optimal behavior of the off-line algorithm gives a deeper discharge in area 1 and a slower discharge in area 2. The reason for this is the total knowledge of the driving conditions on the route.
But the complete knowledge of the driving conditions ahead of the car is not necessary to determine an SOC curve close to the optimal SOC curve in Figure 2.1. The altitude characteristic in Figure 2.2 belonging to the SOC curve in Figure 2.1 demonstrates an inverse correlation between the SOC and the momentary altitude.

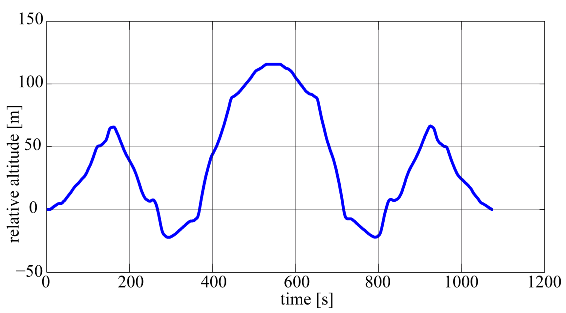

Figure 2.2: Altitude level belonging to the SOC characteristic of Figure 2.1

So obviously the average SOC depends strongly on the altitude characteristic of the route.
It has been found that by feeding the Bellman algorithm with just the altitude curve and the average speed of a route the SOC curve created comes near to the off-line SOC curve in Figure 2.1 [3]. By adding more information to the speed input on the Bellmann algorithm the SOC curve comes even closer to the optimal SOC curve. For example, the speed limits on a route are an additional information for the possible speed of the car on this route. An SOC curve calculated with this additional information approximates close to an optimal SOC curve calculated with he full information from a drive in the past. Because of the dependence between SOC curve and altitude characteristic other optimal SOC curves on the same route but for different drives (i.e. at different velocities) can also be approximated by a general SOC curve created only with speed limits and altitude information. This approximated SOC curve can be used to guide the on-line operational strategy and so the differences between the off-line optimisation and the on-line algorithm from figure 2.1 can be minimised.

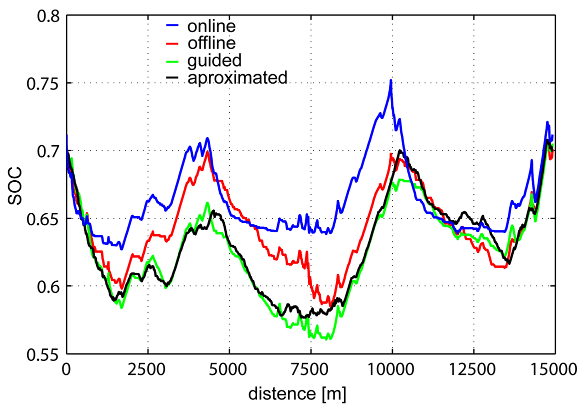

Figure 2.3: Comparison between different SOC characteristics

Figure 2.3 shows the already known blue and red SOC characteristics of Figure 2.1: in blue the SOC from the unmodified on-line strategy and in red the SOC calculated by the Bellman algorithm representing the global optimum for this drive. The black line marks the SOC characteristic that was generated by feeding the Bellman algorithm with the speed limits and the altitude characteristic of the route. If this characteristic is used to guide the on-line strategy the result is the green SOC line.
From distance 7500 m to 15000 m the average speed of the car was near the speed limit of the route and therefore the green, black and red SOC characteristic are close to each other. From distance 2500 m to 7500 m the speed limit and the average speed of the car was different. That leads to a bigger difference between the optimal SOC (red) and the approximated SOC (black).
The green SOC following the approximated SOC avoids the two discrepancies marked in Figure 2.1: the discharge does not stop like in area 1 and the fast discharge in area 2 is also avoided.

For the approximation of any SOC curve to an SOC curve that is optimal for a given route different methods can be used. The method used for the approximation in Figure 2.3 uses speed limits and altitude levels. But it is also possible to generate a reference SOC curve just with he average speed of the route ahead. Then the difference between the optimal and the reference curve is of course bigger than with the method used for Figure 2.3. The best results can be achieved when the route has been driven at least three or four times in the past. For each drive the optimisation algorithm can calculate an optimal SOC curve; after e.g. four drives an average SOC curve can created from these four optimal SOC curves. Because this average SOC curve contains the typical speed characteristics of the route it gets better with every additional drive (similar driving conditions assumed). So the guidance comes closest to the optimum.

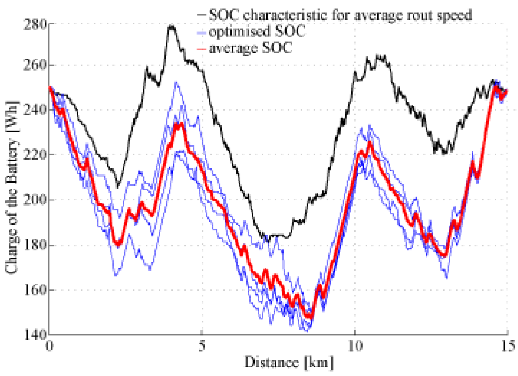

Figure 2.4: Comparison between different methods of SOC approximation

Figure 2.4 shows the difference between the SOC approximation with average speed ***and*** altitude information (black) and the approximation using the average SOC of former optimised drives. The use of optimised SOC (blue) to generate an average SOC (red) leads to the best fuel economy because the average SOC curve contains the most information about the route.
Independent of the method that was used to generate the approximate SOC curve this curve is just a guidance for the on-line strategy. The on-line strategy should never follow them exactly.
Figure 2.3 shows the difference between the guided (green) and the approximated (black) SCO characteristic. The reason for this differences that the approximated (black) SOC characteristic is no a fixed reference variable, it rather marks the centre of a tolerance band. If the real SOC is within the tolerance band it is not necessary to intervene. If it leaves the tolerance band then the on-line strategy must be influenced in such a way as to bring back the actual SOC value to the designated band. The way to influence the strategy depends on the algorithm that is used to calculate the operation points. The only requirement every strategy must fulfil is that the SOC is the central and direct parameter for the decision how the battery energy is used. Two different strategies with different ways to connect energy usage and SOC are presented in the next section.
The strategy which calculates the operation points of the drive train components can and must have the possibility to react on actual driving situations. The approximated SOC curve can not include information about driving situations ahead of a car on an new route. It can only be an average SOC reference because it includes no prediction of the speed details of a route . The handling of the speed details must be done by the on-line strategy.
One of the effects of a guidance of the SOC value is the difference between maximum SOC and minimum SOC, see Figure2.3. With guidance the difference increases by 2 %. The increase of the SOC difference is disadvantageous for the lifetime of the battery [4]. With different test cycles it has been shown that the difference between minimal and maximal SOC correlates with the amount of energy that is regenerated during uninterrupted downhill driving. Because of this correlation the increase of the maximum SOC difference on these test cycles has not risen above 3 %. So it can be said that guidance of the on-line strategy has just little effect on the ageing of the battery.
The potential of the long-term prediction method to improve fuel economy depends strongly on the implementation of the on-line algorithm that is used to calculate the operation points. In the next section the impact of prediction on analytical strategies is demonstrated.

3 Cost function based operational strategies

Every hybrid drive train needs an operational strategy. This strategy has to determine the operation points of the drive train components. This can be done by experience-based strategies or by analytical methods. In this paper we go into detail only with analytical methods. These strategies are called analytical because they

calculate the operation points of the internal combustion engine (ICE) and the electric motor based on actual information. The power demand of the driver and the rotational speed of the engine and the electric motor are the input information. The calculation provides the gear, the torque of the combustion engine and the torque of the eclectic motor.
The analytic equation (1) here is called a cost function. Every possible power combination of electric motor power and combustion engine power that sum up to the power demand of the driver is tested for its cost.
Every operation point belongs to a specific power and has its own efficiency. The efficiencies are included in cost factors (2) and (3) where the cost factor k_{ICE} handles the efficiency of the combustion engine the cost factor k_B includes the electrical efficiencies of the battery and the electric motor.

$$\dot{K}_{tot} = k_{ICE} \cdot P_{ICE} + k_B \cdot P_E \tag{1}$$

$$k_{ICE} = \frac{k_{ICE0}}{\eta_{ICE}(n, M)} \tag{2}$$

$$k_B = \frac{k_{B0}}{\eta_E \cdot \eta_B} \tag{3}$$

By using all possible values for the electric motor torque at a given rotational speed every possible combination of engine powers and efficiencies is tested for cost efficiency. The power combination with the lowest cost will be set up for the drive train.
The influence of the SOC on the cost calculation is represented by the battery base cost value $k_{B,0}$. The function of this value is to take care of the energy balance in the battery. If the SOC in the battery is low it is not advisable to take out further energy. If the SOC is high it is a good idea to increase the energy output. The value k_B can be calculated with different methods. It even can be set equal to 1 if the power values in equation (1) are normalised to the power demand of the driver. In the next paragraphs two different ways to determine the battery base cost value are introduced.

3.1 Cost function with real cost calculation

This method works like a marketplace for electrical energy. The battery has stored an amount of energy and the energy has a specific price like €/kWh. k_{B0} represents this price for the algorithm. Energy is bought to store it in the battery when the generation price is lower then k_{B0}. That could happen if the energy comes from regenerative braking where a cost of zero is assumed because no fuel has to be spent for this energy. It can also happen because of a high value of k_{B0}. According to equation (3) a high k_{B0} means a high k_B. This leads to a high value for electric power costs in equation (1). But if k_{ICE} is lower than k_B equation (1) generates a lower cost by multiplying k_B with a negative power. Negative power means charging of the battery and an enhanced load on the ICE.
The price k_{B0} is calculated continually. For charging equation (6) is used. If electric energy is generated by using the combustion engine k_{ICE} has an according value depending on the operation point of the engine. It is used to calculate the value of the new amount of energy stored in the battery. Dividing it by the new amount $E_{B,n+1}$ gives the new specific price of the electric energy.
Regenerated energy would come for free and therefore k_{ICE} in equation (6) should become zero. But then the new amount of energy only affects the price over the increase of $E_{B,n+1}$. This could lead to balance problems between the amount of energy and its price. If regenerated energy comes for no cost its value is also zero. In equation (5) this is realised by a k_{ICE} of 0. By this equation (5) turns to equation (4) The recuperated energy ΔE_E now affects the base cost factor only by its presence in equation (6)

$$k_{B0,n+1} = \frac{k_{B0,n} \cdot E_{B,n} \cdot \eta_{B,n}}{E_{B,n+1}} \tag{4}$$

Therefore the regenerated energy pushes the price to slow so that the price after a recuperation is to high for the now to big supply. Too little energy will be sold at this price. To solve this problem an average k_{ICE} over the last 100 seconds could be calculated and used instead of zero in equation (6).
As the price is regulated by supply and demand it will rise while the battery is discharged. Again equation (6) is used to determine the rising price. k_{ICE} in equation (6) represents the price that would have to be paid if the electric energy uld have to be provided from the combustion engine. That works fine as long as the power demand of the driver can be satisfied just by the combustion engine. But if the combination of both engine and electriv motor is needed then k_{ICE} can not be determined exactly

and has to be approximated as a plausible value.

$$\begin{aligned} \Delta E_{E,n} &= M_{E,n} \cdot 2\pi n_E \cdot \eta_{E,n} \cdot \eta_{B,n} \cdot \Delta t \\ E_{B,n+1} &= E_{B,n} - \Delta E_{E,n} \end{aligned} \quad (5)$$

$$k_{B0,n+1} = \frac{k_{B0,n} \cdot E_{B,n} + \dfrac{\Delta E_{B,n} \cdot k_{ICE}}{\eta_{E,n} \cdot \eta_{B,n}}}{E_{B,n+1}} \quad (6)$$

If the long-term prediction as described in section 2 is used to generate an SOC characteristic for the route ahead this characteristic could be used to guide the cost function algorithm. In Figure 3.1 the green line shows the fuel consumption of the guided algorithm. The blue line shows the fuel consumption of the unguided algorithm and the red line marks the global minimum. The decrease in fuel consumption is significant: the unguided strategy needs about 6 % more fuel then the guided strategy.

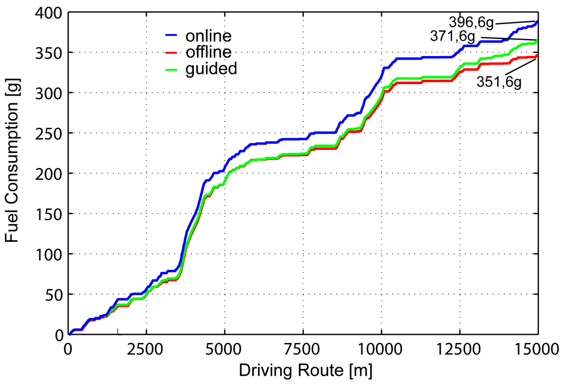

Figure 3.1: Comparison of fuel consumption guided, unguided and optimal operation strategy

For different test cycles a decrease in fuel consumption of between 3 % and 6 % can be achieved. Merely motorway cycles can hardly be improved by guidance of the SOC because the benefit from hybrid drivetrains is very small for this kind of cycles.
The guiding of the algorithm is realised just by an addition of an SOC-dependend value to equation (6).

3.2 Cost function with linear equation

Like the method described in section 3.1 the balancing of the engine and electric motor is done by equation (1). But the calculation of the base cost factor k_{B0} is done with equation (7) [2].

$$k_{B0} = a \cdot SOC + b \quad (7)$$

The parameter “a” is always negative and a

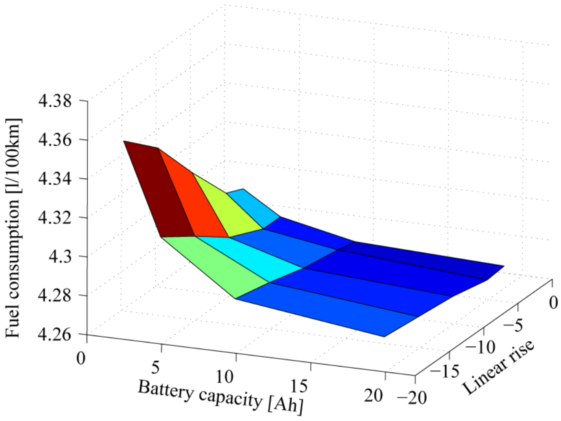

Figure 3.2: Dependence of fuel consumption on linear rise factor a and battery capacity

decrease of “a” will restrict the use of electric power for ICE support because a small change of the SOC will lead to a large change of the base cost factor, and according to equation (1) a large base cost factor makes the use of positive electric power expensive. The parameter b is positive and can be used to shift the average SOC to different areas.
Figure 3.2 shows the dependence of the fuel consumption on the linear rise factor a and the battery capacity. It can be seen that a big negative factor always results in the highest fuel consumption. With a big factor a the effect of just a small change in battery charge on the cost function (1) is increased and therefore the use of electric energy is limited because of the fast rising of k_{B0} by just a small decrease in SOC. Contrary to this a flat linear equation always leads to an increase of electric energy turnover.
But it can also be seen that a small battery always increases the fuel consumption. By adapting the linear equation to the battery size this effect can be minimised.
This really simple mapping of the SOC to the cost factor solves some balancing problems of the method described in section 3.1.
The influence of the SOC guiding at the on-line algorithm here easily can be realised just by shifting the line, i.e. adjusting the parameter “b” in equation (7). In Figure 3.3 an example for the base cost factor line (blue) is shown.

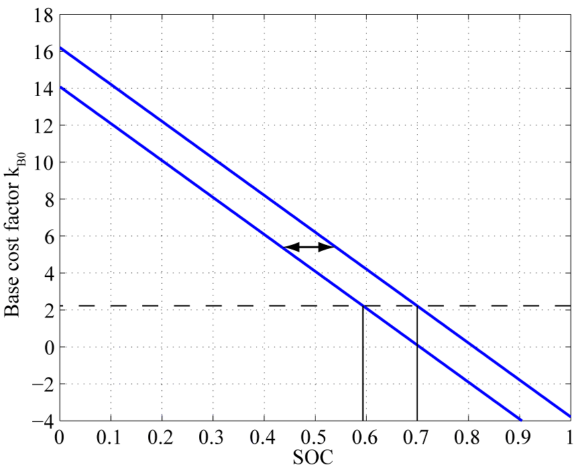

Figure 3.3: Shift of the base cost factor line

The dashed line marks an empirical value for the base cost factor averaged over all time. The crosspoint of the base cost factor line and the dashed line marks the averaged SOC that should be reached by the strategy. If now another averaged SOC shall be reached by the on-line strategy the blue line must be shifted in a way that the new crosspoint meets the new average SOC.
The guiding SOC curve now represents the new averaged SOC values of the approximated new optimal SOC line.
If the prediction method described in section 2 is used to decrease fuel consumption the improvement is not so impressive because the unguided algorithm using the linear equation produces a very low fuel consumption already. Figure 3.4 shows the result. The green line again marks the guided operational strategy. The blue line shows the fuel consumption of the unmodified strategy. The red line again represents the global minimum. The fuel consumption advantage of the guided strategy as compared to the unmodified strategy without SOC guidance here is just about 1%.

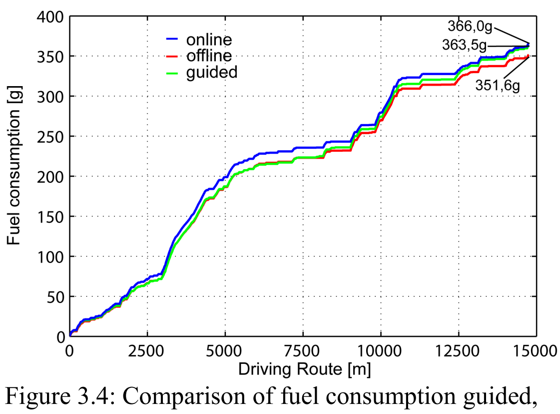

Figure 3.4: Comparison of fuel consumption guided, unguided and optimal operation strategy

With an sample of test cycles the decrease in fuel consumption is between 0.5 and 2 %.

4 Conclusion

We have shown that it is possible to generate an SOC reference curve from altitude profiles and generic speed informations like the average speed or the speed limits of a given route. If it is possible to determine an SCO curve optimised from a number of rides on the same route the guiding algorithm performs best. This is of particular interestand easy to handle for e.g. city bus transport which always follows the same route.
The benefit of guiding the real SOC along the reference curve depends strongly on the operational strategy.
The long-term prediction method can be used with any operational strategy that uses the SOC as a decision value for the way electric energy is used in the drivetrain.

5 Symbols

P_{ICE} = power of the ICE
P_E = power of the electric motor
ΔE_B = Energy change for one calculation step
E_B = Energy stored in battery
η_{ICE} = efficiency of the ICE
η_E = efficiency of the electric motor
η_B = efficiency of the battery
K_{tot} = total Cost
k_{ICE0} = base cost factor of the ICE
k_{B0} = base cost factor of electric energy
k_{ICE} = cost factor of the ICE
k_B = cost factor for the electric power
M_E = torque of electric motor
n_E = speed of electric motor
Δt = time of one calculation step

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