Predictive Online Control for Hybrids

Resolving the conflict between global optimality, robustness and real-time capability

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Abstract— **In this paper an approach for the real time optimal control of vehicles with more than one source for providing traction power (e.g. HEVs) is presented. After a short classification of existing approaches and their respective characteristics the new modular concept as a combination of two algorithms is introduced. For the basic online management an equivalent consumption minimization strategy (ECMS) is implemented. The adaption towards changing driving conditions is realized by an independent calculation and adjustment of the main decision criterion of the ECMS towards the predicted operational profile using a calculation time optimized dynamic programming approach.**

Keywords - Hybrid electric vehicle; energy management; online control; supervisory control; equivalent consumption minimization strategy; dynamic programming

I. Introduction

The complexity of hybrid power trains demands supervisory controllers which are able to profitably use the new degree of freedom compared to conventional cars like the flexible distribution of the traction power to the prime mover. Besides fulfilling the drivers request the most common control objective is to achieve minimum fuel consumption and low emissions. These main targets are superposed by additional requirements like high driving performance and safe operation. To justify the additional technical effort of HEVs it is essential to tap the full fuel reduction potential given by the hardware in all driving conditions through an optimal control.

II. Existing approaches

At present there are three main classes of competing approaches for the supervisory control of hybrid electric vehicles (HEVs) which can be classified by the three main properties optimality, the use of prediction data and the kind of achieving the control objective as shown in fig. 1. The majority of already implemented control strategies belong to the class of heuristic rule based controllers. This approach has a manageable complexity and needs only low computational resources but it also has a limited adaptivity and achieves suboptimal results due to the indirect optimization via changing the rules of the controller e.g. by varying thresholds. From the aspect of optimality model based predictive control using dynamic programming (DP) techniques is the most favorable class of algorithms obtaining the global solution under direct use of prediction data. It represents the best possible solution of the control problem with respect to the used discretization of time, state space and inputs. The biggest disadvantage is the high computational effort which is opposed to a real time implementation for the online control of a vehicle.

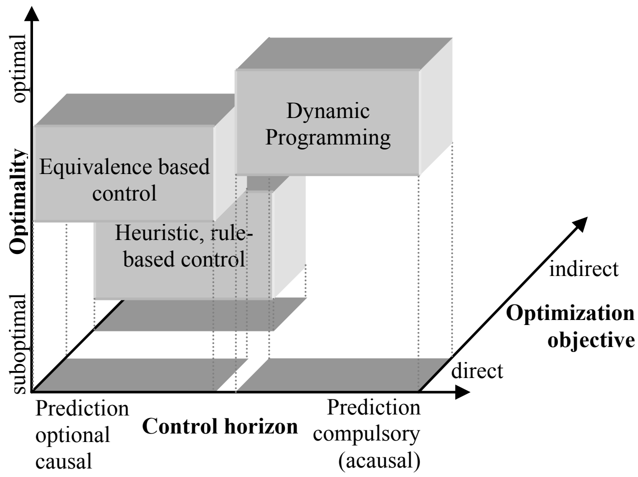

Figure 1. Classification of control approaches, global evaluation of optimality assuming a priori known driving cycles

A compromise between the two mentioned control approaches are the equivalence based control algorithms, which aim for a direct local optimal solution of the problem using an equivalent between the available energy paths to evaluate which combination of the traction sources is most appropriate for the current power demand. The use of prediction data is not essential but for reaching a balanced state of charge of the energy storage system, a high adaptivity and global optimality the equivalence factor has to be chosen carefully under consideration of past and future driving conditions. This results in the need for a possibility to transform a predicted velocity and elevation profile into an appropriate value pattern for the equivalence factor.

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III. Equivalence based control as a combined approach

The combination of a real time capable equivalent based strategy for the online control of the vehicle with a model based predictive optimal control using dynamic programming for the calculation of the equivalence factor appears to be a suitable approach resolving the conflict between global optimality, robustness and real time capability.

A. *Equivalent consumption minimization strategy (ECMS)*

Instead of solving the whole control problem globally ECMS finds the local optimal solution for the power proportion of electrical and internal combustion engine at each time step under consideration of an energetic equivalence factor λ. This value is needed to evaluate the power of the combustion engine P_{IC} and the electric machine P_{EM} in one combined equivalent power P_{Eq} through projecting them to an equivalent chemical energy flow of the tank as

$$P_{Eq} = P_{IC}(M_{IC}, n_{IC}) + \lambda \cdot P_{EM}(M_{EM}, n_{EM}) + P_{pen}. \tag{1}$$

An increasing equivalence factor λ makes electrical energy more expensive and intensifies the use of the combustion engine and effects the recharge of the electric energy storage. In contrast a decreasing equivalence factor λ leads to a preference of the electric motor to fulfill the traction demand of the driver.

To prevent low driving comfort caused by frequently changing the power train states like gear shifting, high gradients of torque or engine speed, engine shut down and restart an additional penalizing cost term P_{pen} is added for the evaluation of the optimal operation points in (1). Hence short-lasting and low differences in the cost function will not effect the systems control process.

The penalty power P_{pen} is assessed dynamically, depending on the duration since the previous state change. The integral penalty for each shift is adjusted by estimating the equivalent energetic losses:

$$\int P_{pen}(t - t_{shift}) = E_{loss}. \tag{2}$$

To achieve the global optimal solution for the control trajectory and to sustain the battery charge using ECMS the equivalence factor λ needs to be adapted over time. The easiest way is to implement lookup tables where precalculated values for λ are stored depending on different input values like current battery charge, average power flow and others. The ECMS then passes into a heuristic strategy. Another approach is to use a controller (PI) which changes λ aiming for a given target battery charge. A remarkable algorithm of adapting λ is known as A-ECMS [1], where past and predicted wheel power demands of the vehicle are used to evaluate the drive train efficiencies and to estimate the optimal charge sustaining value of λ.

The disadvantage of these adaption methods is their immanent suboptimality compared to the global optimal solution even for accurate prediction data. Therefore in the next section an algorithm determining the global optimal solution is presented. In section III.C this real time incapable algorithm will be used to asynchronously calculate the optimal λ for the ECMS real time controller.

B. *Predictive dynamic programming*

Model based predictive dynamic programming is a convenient way to calculate the global optimal control trajectories for a priori known driving cycles or predicted velocity and elevation profiles for a requested battery charge at the end of the cycle (integral constraint) [3], [4], [5].

In a first phase (Initialization) the required torque and the resulting rotational speed of the wheels are calculated. These values are used to deduce the required speed and torque at the transmission input for all possible gears. The torque is then split to the machines in a discrete grid and the resulting input power ratings of ICE and EM are calculated.

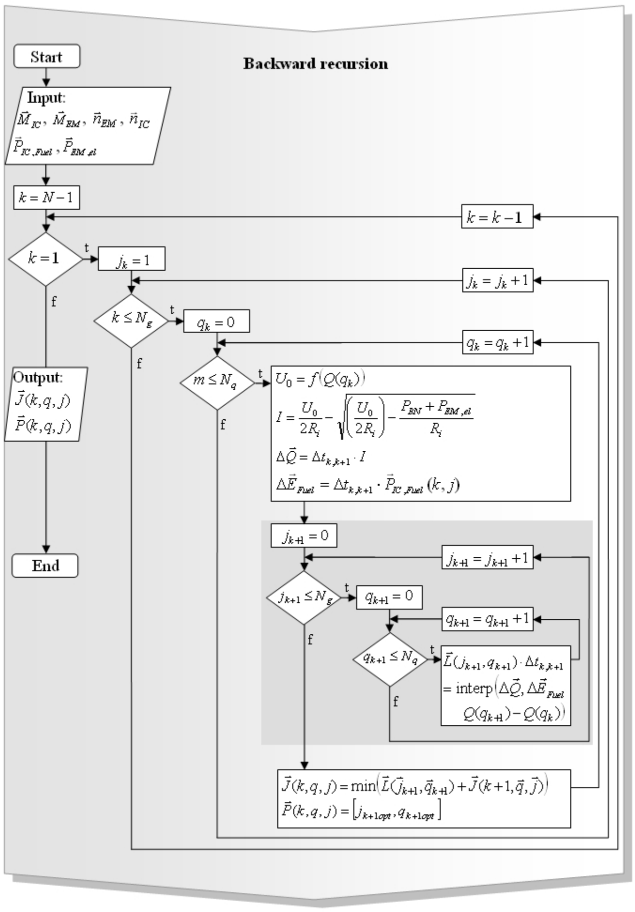

Figure 2. Original progam flow chart of the backward recursion process of DP consisting of the three main loops over time (index k), gear (index g) and battery charge (index q)

In the second phase (Backward Recursion) these time discrete values are used to build a global cost-to-go-matrix

$\vec{J}(k,j,q)$ as shown in fig 2. For the given discrete charge $Q(q_k)$ of the battery the open circuit voltage U_0 is defined before calculating the accordant current I, the change of battery state of charge ΔQ and the required fuel energy ΔE_{Fuel}. For all possible subsequent charge $Q(q_{k+1})$ and gear points $g(j_{k+1})$ the resulting fuel energy has to be calculated by interpolating $\Delta E_{Fuel}(\Delta Q)$ for the discrete points of $Q(q_{k+1})-Q(q_k)$.

Before the optimal cost value is assigned Bellman's recursive equation

$$\vec{J}(k,q,j) = \min\left(\vec{L}(\vec{j}_{k+1},\vec{q}_{k+1}) \cdot \Delta t_{k,k+1} + \vec{J}(k+1,\vec{q},\vec{j})\right) \quad (3)$$

has to be evaluated considering all possible paths from the current to the next time step as shown in fig. 3.

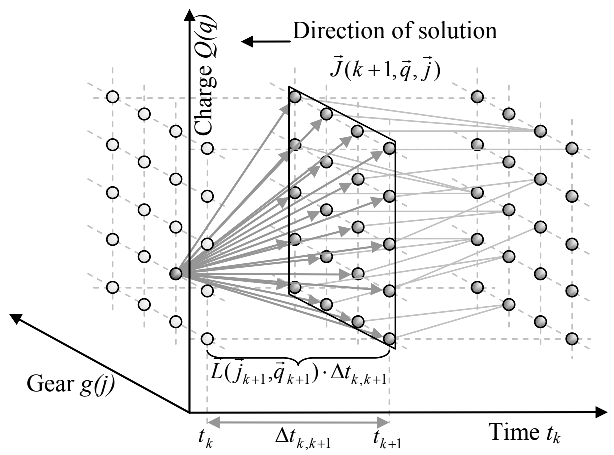

Figure 3. Graphical representation of solving equation (4) through backward recursion

In the last phase (Forward Calculation) the optimal gear and charge path from the starting point is reconstructed using the saved indices in matrix $\vec{P}(k,j,q)$ of the best successive point. The operating points of the engines are recalculated based on these paths.

The tree main program loops of the backward recursion including two sub-loops for possible succeeding points cause large calculation effort. Even for an implementation under non real time conditions a significant speed-up is necessary especially for fine discretization of high capacity energy storages and long prediction horizons. Therefore an optimization of the algorithm under using the specific properties of the considered problem including the following improvements is implemented:

- Variable time discretization depending on predicted change of velocity and acceleration and resulting wheel power
- Dynamic calculation of the limits of the state of charge depending on predicted power demand at wheels to reduce the state space
- Use of nearly charge independent behavior of open circuit voltage of the considered $LiFePO_4$ batteries for order reduction of the optimization problem
- Pre-calculation of optimal gear
- Vectorization and parallelization of the algorithm for increased performance on modern multi-core processors [6].

The biggest improvements are achieved through the order reduction of the control space and the precalculation of the optimal gear for every change of charge and its corresponding power split. The input torque and speed of the gearbox depend for a given required wheel torque on the transmission ratio in the available gears. For each gear the resulting change of charge and fuel energy can be calculated depending on the discretized power ratio between EM and ICE. The optimal gear can be found by evaluating fuel cunsumption for each power split and its corresponding change of charge as shown in fig. 4.

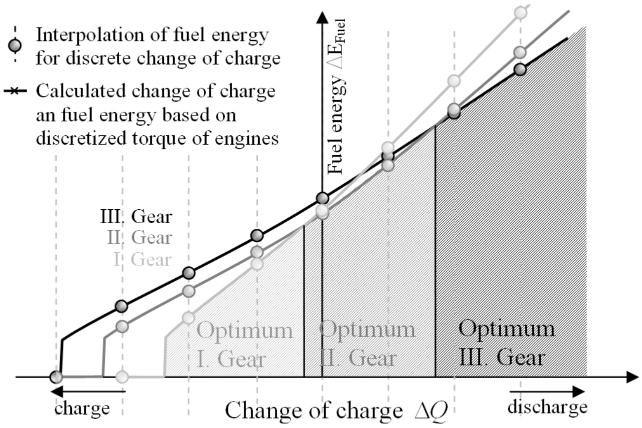

Figure 4. Interpolating the fuel energy for discrete changes of charge and precalculation of the change of charge depended optimal gear

The number of required calls of the target function in the backward recursion could be reduced from

$$N_{call} = N_t \cdot \left(N_g \cdot N_q\right)^2 \quad (4)$$

from the conventional implementation to only

$$N_{call} = N_t \cdot N_q \cdot N_{\Delta Q} \cdot \quad (5)$$

The increased effort in the initialization phase caused by the precalculation of the optimal gears has only small influence on the calculation speed.

Under consideration of all improvements the overall calculation time is speeded up from several hours [1], [7] to seconds up to a few minutes (grid depending) for an example calculation of the whole NEDC on an Intel Pentium Q6600. The maximum relative charge error caused by neglecting the charge dependency of the battery open circuit voltage was calculated by the total differential method to be lower than 2%.

With the achieved computing speed improvement the DP is appropriate to meet the basic requirements like accuracy and limited update time as an adaption mechanism for the equivalence factor for the real car implementation as shown in the next section.

C. *Implementation of the DP adapted ECMS (DP-ECMS)*

To calculate the optimal time and charge depending values of the ECMS equivalence factor the cost-to-go matrix $\vec{J}(k,j,q)$ of DP is derived locally with respect to the changing battery charge as follows

$$\lambda(t_k,Q)=\frac{d}{dQ\cdot U_0}\vec{J}(t_k,Q). \tag{6}$$

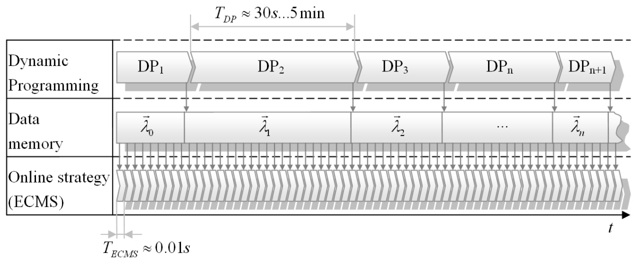

Figure 5. Asynchronouse operation of DP and ECMS

DP and ECMS work asynchronously as shown in fig. 5 coupled by a data buffer since the time for the evaluation of the DP depends on the length of the prediction horizon and the used discretization and is therefore non deterministic.

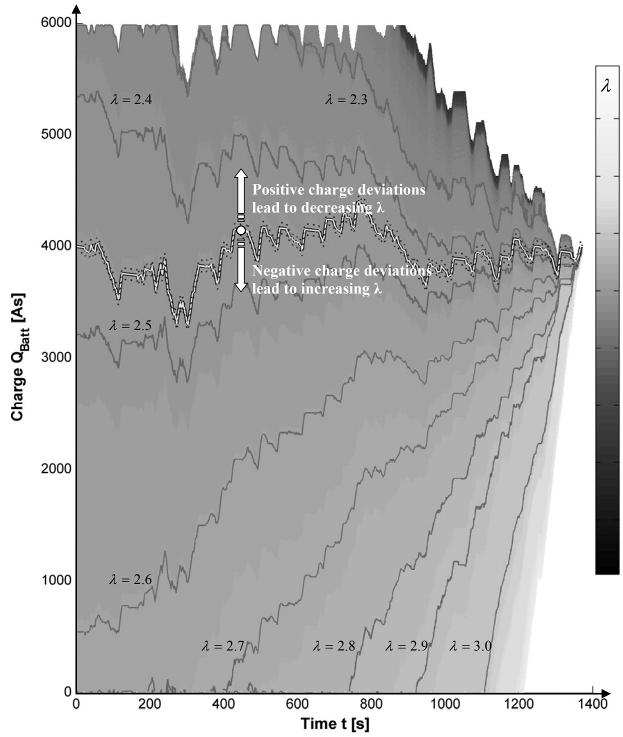

Figure 6. Equivalent cost matrix over time and battery charge with curves of constant λ, representing correspoding optimal charge trajectories

An update of the equivalence factor matrix is performed as soon as changed input values are available from the prediction data source for the DP algorithm. Through the use of the cost-to-go matrix *λ(Q,t)* (fig. 6) as a kind of adaptive look up table for the optimal, time and charge dependent equivalence factor a feedback is introduced. Possible drifts of the state of charge caused by model deviations and unconsidered disturbances are compensated through changes of *λ*. The resulting control scheme is shown in fig. 7.

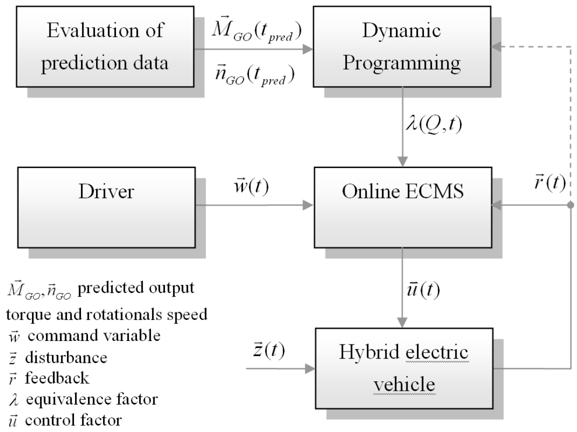

Figure 7. Control scheme of the combination of dynamic programing (evaluation of prediction data) and ECMS realtime controller

IV. SIMULATION MODEL

For the verification of the predictive supervisory controller the customized Modelica library "eVehicleLib" [8] including a dynamic car model of the PHEV and its energetic subsystems is used. This plant model differs from the quasi static model implemented in the DP and ECMS controller through detailed modeling of synchronization processes of the clutch and the gearbox, the response times and maximum torque gradients. The acausal modeling approach for the plant allows the direct use of the systems differential equations without considering the direction of solving the system. Additionally the use of physical interfaces allows building models whose structure is very close to their real counterparts. The consequent use of model classes and inheritance enables an easy exchange, adaption and extension of parts and subsystems of the model [9]. A validated model of a conventional powered vehicle (Audi A2) is taken as a basis for the HEV model.

In contrast to the plant model the ECMS controller is implemented in Matlab Simulink, where the predictive dynamic programming is imported from Matlab m-code using a s-function. The communication between the Modelica simulation environment Dymola and the controller model is realized utilizing the special Dymola Simulink interface block. The results of different performed simulations are shown in the next chapter.

V. RESULTS

To evaluate the potential of the developed approach it was benchmarked towards existing control algorithms as shown in the next subchapters.

A. *Evaluation of optimality of DP-ECMS*

Though DP calculates the global optimal control trajectories for a priori known velocity and altitude profiles these results are used as a theoretical benchmark for evaluating the optimality of the DP-ECMS. Therefore the whole driving profile was used for prediction and the resulting control trajectories were applied to the dynamic car model.

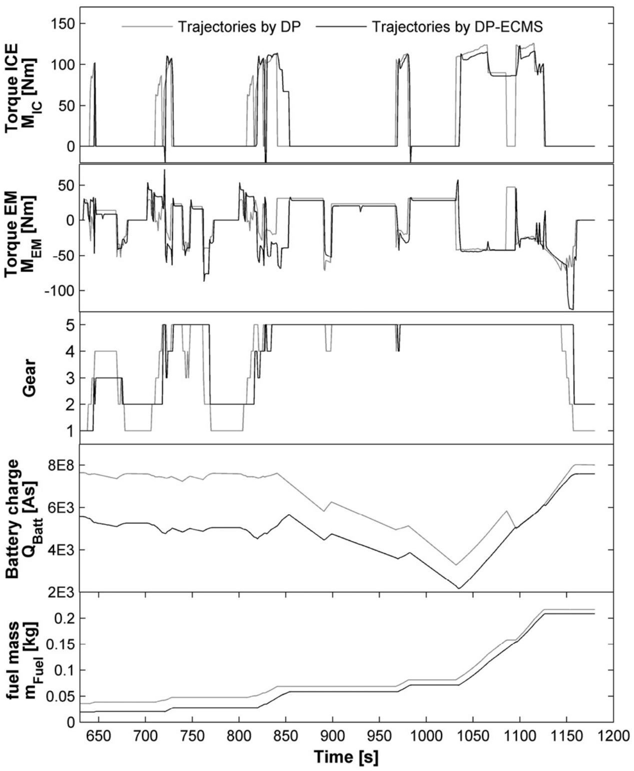

Figure 8. Comparison of system control and system response for ideal prediction using DP-ECMS and DP (excerpt of the NEDC)

Fig. 8 shows an example section of the system response to both strategies for the NEDC. The engine torques and the chosen gears show the same tendentious behavior though they are not identical for both approaches because the integrated cost terms of the ECMS penalize changes of gear and torque gradients. On the one hand DP-ECMS yields much less changes of gear achieving a higher driving comfort. On the other hand the restricted use of the degrees of freedom lead to a significant negative deviation in battery charge compared to the global optimal charge trajectory of DP which is almost completely compensated at the end of the cycle. For determining the fuel consumption the charge deviation is taken into account by assuming the combustion engine to drive the electric machine as a generator at the global optimal operation point. The resulting energy effort using DP-ECMS exceeds the calculated optimum only by 0.2% in this case.

Tab. 1 shows the numerical results for the charge deviation, the fuel consumption and number of changes of gear for NEDC and FTP 72 for different control approaches. Besides DP different methods of adapting λ for charge sustaining ECMS are compared. The simplest approach is to iteratively optimize the constant equivalence factor [10]. The difficulty results from the discontinuous behavior of the charge difference over the cycle caused by the integrated penalizing costs. Changing the static value of λ from 2.6782 to 2.6783 in FTP 72 causes the charge deviation to switch from -168 As to +150 As. Hence it is impossible to find a charge neutral solution for constant λ in this example. The iterative solution to find the optimal value for λ is only applicable for offline solutions.

TABLE I. COMPARISON OF FUEL CONSUMPTION, CHARGE DEVIATION AND NUMBER OF CHANGES OF GEAR FOR DIFFERENT CONTROL APPROACHES

Control approaches			Results for FTP 72 and NEDC			
			Charge deviation ΔQ [As]	***Fuel consumption***		***Change of gear N_G***
				original V/s [l/100km]	***corrected[a] V/s [l/100km]***	
Offline DP (Reference)			293	1.932	1.932	284
			451	2.301	2.301	114
ECMS	***Offline optimized λ=const.***		-241	2.116	2.173	161
			-11	2.324	2.327	49
	Optimized PI-charge control on average QBatt		-80	2.189	2.208	172
			936	2.655	2.655	43
	Asynchronouse update using DP	***Optimized PI-charge control on DP-Q_{Batt} trajectory***	-135	2.128	2.160	143
			-243	2.323	2.386	55
		Control using matrix $\lambda(Q_{Batt}, t)$	-57	2.180	2.194	168
			-210	2.252	2.306	50

a. The corrected fuel consumption is calculated assuming only a compensation of negative charge deviations in motor-generator-mode, positive deviations stay uncorrected

Dynamic adaption of λ overcomes this disadvantage. The simplest approach is the non predictive PI-control on an average state of charge set point. A good control performance close to the optimum could be achieved for use cases with an equally distributed power demand like in the FTP 72 cycle. The high recuperative braking potential at the end of the NEDC shows the disadvantage of the non predictive charge control leading to a significant positive charge deviation. The predictive PI-control uses the optimal charge trajectory calculated by DP as a time variant set point. The results are comparable to the DP-ECMS using the equivalence factor matrix.

B. *Evaluation of the robustness of DP-ECMS*

Robustness includes both criteria stability and adaptability. The cybernetic stability of the DP-ECMS is guarantied by the fundamental characteristic of the equivalence factor matrix to be monotonically decreased at increasing battery charge. Negative deviations from the optimal SOC trajectory therefore lead to an increasing λ encouraging the use of the generative operation modes leading to increasing battery charge and vice versa. In the extreme case of violating the charge limits the extreme values of λ will be applied ensuring an immediate charging or discharging.

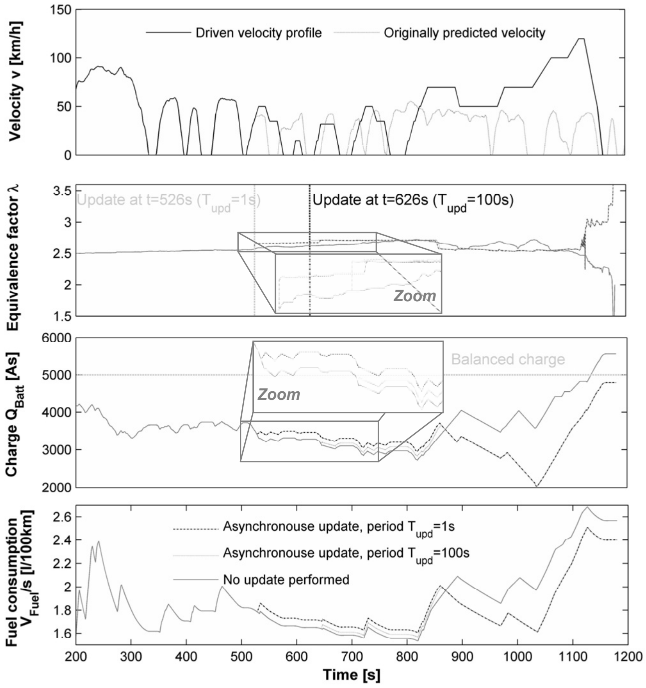

Figure 9. Comparison of system response for different (1s, 100s, no update) update times of DP to the changed prediction and driven velocity profile

The ambition of DP-ECMS to adapt to changing driving situations was tested by leaving the originally predicted velocity profile of the FTP 72 at t=625s and following the NEDC. This is comparable to a driver leaving the originally planned route to aim for a new destination. Fig. 9 shows the results of the calculated value patterns for λ, battery charge and fuel consumption for an adaption of the λ matrix through DP after one and after 100 seconds after the route change compared to the results with no recalculation. It is obvious that an advantageous control trajectory leading to an almost balanced battery charge is only achievable in the case of recalculating the equivalence factor. Worthwhile the update interval of λ seems to be of low influence on the results.

C. Real time capability of DP-ECMS

Through the asynchronous operation of DP and ECMS the update time of the predictive calculation is only restricted by the appearance of changes in the predicted track profile. The ratio of predicted time to calculation time was 20 for an exemplary calculation of the NEDC. So the updated λ matrix would be available after 60 s in worst case (15000 charge grid points, 1000 time grid points). Basing on the results of the previous chapter this delay appears to be acceptable.

The ECMS core algorithm itself is deterministic and therefore has a definite calculation time. The calculation effort is depending on the used discretization of the control variables. The real time implementation with a cycle time of 10 ms was realized on the PC.

VI. Conclusion and Outlook

An approach for the online control of a parallel HEV was introduced combining global optimality from predictive DP and real-time capability of ECMS. Simulation results show the applicability of the developed approach meeting the requirements for optimality, real time capability and robustness. The presented results for the parallel hybrid were obtained assuming an ideal prediction over the full range with full prediction accuracy and probability.

To estimate a more realistic potential of DP-ECMS real prediction sources like map based approaches, track recognition, traffic information and car surrounding information sensor systems with their individual prediction properties will be integrated. The most promising approaches will be implemented in a research vehicle for real world testing.

To prevent the battery from extensive cycling additional penalty functions will be added to the basic evaluation of the ECMS depending on the loss of capacity through the energy throughput.

The controller and system model will be extended to serial an combined drive train architectures like plugin hybrids (PHEV) and range extended battery electric vehicles REBEV, offering the possibility to switch the control objective between cost-efficient (fuel prices vs. electricity prices), fuel-efficient and CO_2-efficient control (under consideration of emissions of electric power generation at the power plant).

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