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A Novel Approach for a Predictive Online ECMS Applied in Electrified Vehicles Using Real Driving Data

Felix Deufel *, Malte Freund and Frank Gauterin

Institute of Vehicle System Technology, Karlsruhe Institute of Technology, 76131 Karlsruhe, Germany; frank.gauterin@kit.edu (F.G.)
* Correspondence: felix.deufel@kit.edu

Abstract: To increase the efficiency of electrified vehicles, many energy management strategies (driving strategies) have been proposed. These include both offline optimization techniques to identify a system's theoretical optimum and online optimization techniques created for onboard use in the vehicle. In the field of online optimization, predictive approaches can achieve additional savings. However, predictions are challenging, and robust usability in all driving situations of the vehicle is not guaranteed. In this study, a new approach for a predictive energy management strategy is presented. It is demonstrated how this so-called predictive Online Equivalent Consumption Minimization Strategy (ECMS) can achieve additional fuel savings compared to a non-predictive Online ECMS by predicting recuperation events using map data. As long as the route is known, map data are available, and the current position of the global navigation satellite system (GNSS) is given, the predictive Online ECMS can be applied. If these requirements are not met, the non-predictive basic implementation can still be used to ensure robust functionality. The methodology is investigated using a backward simulation model of a D-segment vehicle powered by a 48 V hybrid electric system in a P2 topology. A dataset including real driving cycles including map data from Open Street Map (OSM) is used. However, the investigations are limited to the consideration of traffic signal (TS) positions on the upcoming route. Simulation results focus on the interaction between the energy management strategy (EMS) and usable battery energy. More than 1 % average saving potentials compared to a non-predictive implementation are shown. The highest saving potentials are found with a usable battery energy of 100 Wh.

Keywords: electrified powertrains; 48 V system; equivalent consumption minimization strategy (ECMS); model predictive control (MPC); li-ion battery; global navigation satellite system (GNSS); real driving cycles

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1. Introduction

Due to emission regulations and an increase in environmental consciousness in general, a broad variety of alternative drive systems have been developed. These include 48 V hybrid electric vehicles (HEVs), which have the benefit of decreasing CO_2 emissions at moderate system expense, especially for inner-city driving. A 48 V system is described by component dimensioning, topology, and an energy management strategy (EMS) [1]. The EMS has to guarantee a robust operation in various driving situations. An overview of the most common methods provided within [1–8] shows that EMS development has been extensively researched over last years. In this paper, a novel approach for a predictive Online ECMS is presented using real driving cycles. It is demonstrated how, in the case of a known journey and the availability of map data, a predictive Online ECMS is established by using the present Global Navigation Satellite System (GNSS) position. This is the case for instance, when manually entering a route into a navigation system or returning to a previously traveled path which is identified by intelligent algorithms. It is shown how a predictive Online ECMS can achieve additional fuel savings compared to a non-predictive

Online ECMS by predicting recuperation events due to traffic signals (TS). The simulation results focus on the interaction between the EMS and battery.

2. Related Work

The EMS can be subdivided in multiple ways. They can be categorized into rule-based, optimization-based, and learning-based techniques. Mixed forms also exist. Furthermore, offline and online methods can be distinguished. Offline strategies are defined by the need for prior knowledge of the whole driving profile. With this, a specific hybrid design is described, for instance, in terms of possible fuel consumption savings for a certain cycle. The global optimum is determined for benchmark analysis. Online strategies require only limited prior knowledge of the upcoming driving path. The ECMS that is investigated in this work can be assigned to optimization-based EMS concepts. Depending on the particular implementation, an ECMS is associated with either offline or online techniques. Using an Offline ECMS, the global optimum for time-invariant systems is found due to the equivalence to Pontryagin's Minimum Principle (PMP) [9,10], where a so-called equivalence factor λ is found iteratively to solve the optimization problem [11,12]. This Offline ECMS is frequently utilized to find the global optimum in offline applications, especially due to the low computing effort [13]. The 2D-ECMS has been created to investigate topologies with two traction motors [14]. For an Online ECMS, which was first published by Paganelli et al. [15], the idea of a Stae Of Charge (SOC)-dependent control of the equivalence factor λ was effectively implemented [16–26]. In addition, there are predictive Online ECMS techniques where predictions are essential for the ECMS's fundamental operation [18,27]. However, it has also been demonstrated that the introduction of predictive information can enhance non-predictive Online ECMS implementation. The following publications should be mentioned:

- In [28], step functions are used for adjusting λ by taking into account the future energy demand. A 10% improvement compared to a non-predictive Online ECMS solution was reached.
- In [29], optimal recuperation is realized by predictive charging and discharging of the battery. A 6% improvement compared to a non-predictive Online ECMS solution is achieved.
- In [30], velocity prediction using a Convolutional Neural Network (CNN) for optimal λ determination is realized. A 0.2% to 0.5% improvement compared to the non-predictive Online ECMS is presented.
- In [31], velocity prediction is used to determine SOC nodes. A 9.7% improvement compared to the non-predictive Online ECMS solution is given.
- In [32], λ adaptation is realized considering future energy demand with a dynamic prediction horizon. An improvement between 0.3% and 4% compared to the non-predictive Online ECMS is achieved.
- In [33], velocity prediction at intersections considering traffic signal (TS) state and traffic flow leads to an improvement of 0–2% compared to the non-predictive Online ECMS.

The presented prediction approaches show a wide range of possibilities for the development of predictive driving strategies. When comparing the results, it should be noted that different boundary conditions, vehicle models, and types of ECMS were used in each publication. The approach of [28], for example, has only been tested on previously known very hilly routes and is therefore only useful in very specific scenarios. Therefore, a comparison and evaluation of the results is of limited value. However, for the authors of the paper, these investigations form the basis for developing their own predictive approach. In [34], an approach utilizing the recuperation potential has already been published. It was shown that noticeable CO_2 reduction potentials occur, in particular, with limited battery capacity. Detailed investigations regarding predicting torque for predictive EMS are presented in [35,36]. However, it was shown that the prediction of the future torque is very difficult and often only possible with a certain degree of uncertainty. Therefore, this paper presents a novel approach for a predictive Online ECMS considering recuperation potentials using map data without the need for torque predictions. Additionally, a comparison to a non-predictive Online ECMS is provided.

3. Modeling

In vehicle simulation, forward and backward simulation can be distinguished. Forward simulation models are based on the physical causality of the system by comparing the target velocity with the actual vehicle velocity using a driver model. A velocity can then be calculated for each time step based on the acceleration brought on by the control input of the driver model. In contrast, a backward simulation model presupposes that the vehicle adheres to a predetermined profile of acceleration and velocity. Therefore, no driver model is necessary [4]. The verified backward calculation model of a 48 V HEV (P2 topology, see Figure 1) with an Offline ECMS and an iteratively calculated λ from the work of [13] is applied.

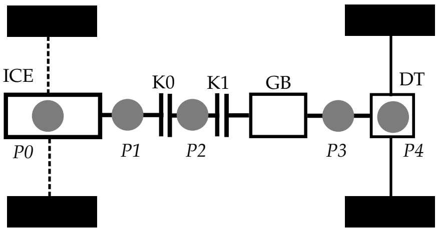

Figure 1. Topologies of HEVs in parallel configuration from [34].

In this model, torque is calculated from the longitudinal dynamics of the vehicle. Hereby, the wheel radius as well as the transmission ratios of the vehicle are taken into account. The correlations from longitudinal dynamics are shown below. The different parameters and their corresponding units are listed in Table 1.

$$F_{Wheel} = F_{air} + F_{roll} + F_{acc} + F_{slp} \quad (1)$$

$$F_{air} = c_w \cdot A \cdot \frac{\rho}{2} \cdot v^2 \quad (2)$$

$$F_{roll} = m \cdot g \cdot cos\alpha \cdot f_R \quad (3)$$

$$F_{acc} = m \cdot a \quad (4)$$

$$F_{slp} = m \cdot g \cdot sin\alpha \quad (5)$$

Table 1. Parameters and units of the driving resistances.

Drag Coefficient	c_w	0.3
Projected Frontal Area	A	2.5 m^2
Air Density	ρ	1.2 kg/m^3
Vehicle Mass	m	1600 kg
Gravitational Acceleration	g	9.81 m/s^2
Rolling Resistance Coefficient	f_R	0.012

An internal combustion engine (ICE), electric motor (EM), and gearbox (GB) are modeled using stationary maps. The 48 V battery is represented by a simple inner resistance model. Equations (6) and (7) are used to compute the battery voltage under load U_{bat} and the corresponding battery current I_{bat}. Therefore, the battery power P_{em}, the battery losses $P_{em,loss}$, and the power from auxiliary consumers P_{aux} are considered. Moreover, the open-circuit voltage U_{OCV} and the inner resistance R_i are required. In addition, as a measure of energy deviation from the starting conditions, an energy deviation dE from reference SOC is calculated (Equation (8)). It is used as a criterion for a neutral energy balance [34]

$$I_{bat} = \frac{P_{em} + P_{em,loss} + P_{aux}}{U_{bat}} \tag{6}$$

$$U_{bat} = U_{OCV}(SOC) - R_i(SOC) \cdot I_{bat} \tag{7}$$

$$dE = \int U_{bat} I_{bat} dt \tag{8}$$

The battery is of a nickel–mangan–cobalt/graphite cell type. R_i and U_{OCV} are calculated using SOC-specific component data. However, for simplification a large 48 V battery (>10 kWh) with constant SOC characteristics (SOC = 70%) is used within the investigations. Other effects, such as degradation of the battery and its impact on CO_2 emissions, are neglected [13]. The recuperated energy is determined using a simplified logic considering the limits of the electrical components and the application of the mechanical brake.

The studies are based on real driving cycles including four different drivers. These real driving cycles were already used and presented in [35,36]. Hereby, relevant map data from Open Street Map (OSM) was matched with the original GNSS tracks according to Figures 2 and 3. For detailed information on the preprocessing of the driving data, please refer to [36].

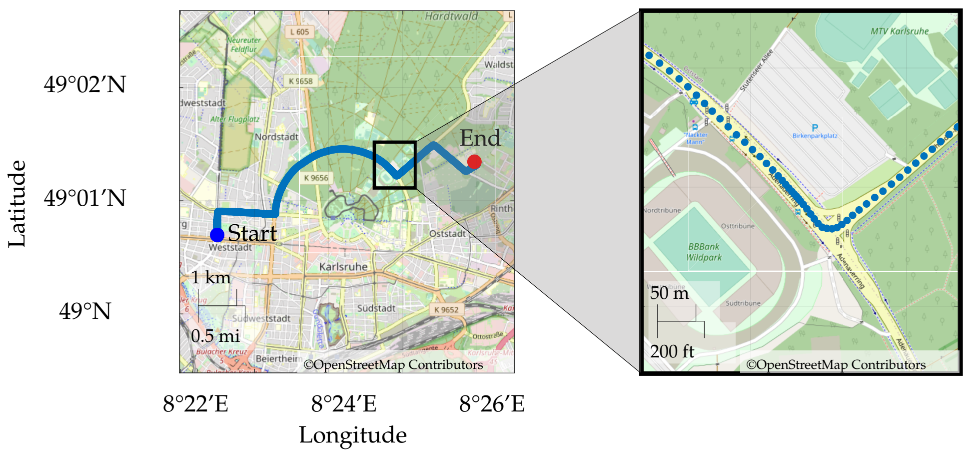

Figure 2. Visualization of available driving data. From [36].

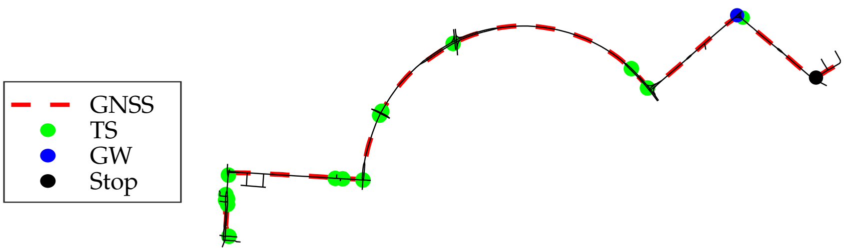

Figure 3. Visualisation of identified Open Street Map (OSM) data including GNSS track, traffic signal (TS), give way (GW), and stop. From [36].

This publication is limited to the cycles of Driver 1, which covers 63 cycles of city driving, country road driving, and highway driving of a total duration of 30 h and almost 3000 km (for more information, see [35]). For the design of a non-predictive Online ECMS, three representative cycles are selected for each road type. These nine cycles should represent real operation as good as possible. The most important characteristics are shown below (Table 2).

In Figure 4, the traffic signal (TS) density is shown for the 63 cycles. Cycles marked in dark gray are selected for the exemplary application of the newly developed predictive Online ECMS approach. The chosen cycles are characterized by at least one TS per km.

Table 2. Real driving cycles to parametrize non-predictive Online ECMS.

Road Type	Avg. vel. in km/h	Max. vel. in km/h	Dist. in km	Dur. in h	Stand-still in %
City	28	69	6	0.2	26
	19	60	4	0.2	39
	25	62	11	0.4	21
Country Road	73	110	39	0.5	1
	57	90	17	0.3	6
	67	118	41	0.6	5
Highway	108	168	164	1.5	2
	116	189	162	1.4	1
	101	176	74	0.7	6

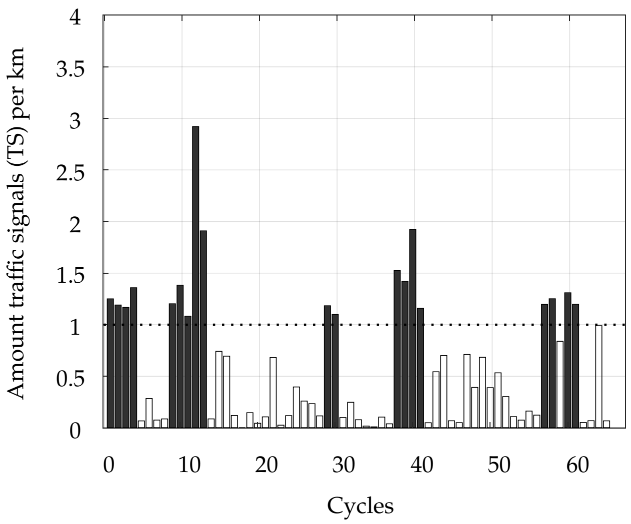

Figure 4. Overview of the 63 driving cycles. As the investigations are limited to the consideration of TS positions, TS per km are shown for each cycle. Cycles marked in dark gray are selected for the exemplary application of the newly developed predictive Online ECMS approach. These cycles are characterized by at least one TS per km.

4. Methodology

In the concept of an ECMS, an equivalent fuel consumption is calculated taking into account the fuel's lower heating value, Q_{lhv} and an equivalence factor λ to convert battery power into fuel power. Using the equivalent fuel consumption a cost function J is stated, where the optimization problem P is written as follows [13]:

$$P : \min_{u} \int J(u, x)dt \tag{9}$$

$$J(u, x) = \dot{m}_{fuel} + \lambda \frac{P_{bat}}{Q_{lhv}} \tag{10}$$

The local constrains are given as follows:

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \tag{11}$$

$$P_{bat,min} \leq P_{bat}(t) \leq P_{bat,max} \tag{12}$$

$$T_{ICE,min} \leq T_{ICE}(t) \leq T_{ICE,max} \tag{13}$$

$$T_{EM,min} \leq T_{EM}(t) \leq T_{EM,max} \tag{14}$$

$$n_{ICE,min} \leq n_{ICE}(t) \leq n_{ICE,max} \tag{15}$$

$$n_{EM,min} \leq n_{EM}(t) \leq n_{EM,max} \tag{16}$$

The presented inequalities represent the SOC-limits and maximum battery power. Also, the limitations of both torque and speed from ICE and EM are considered. At each time step, the ideal torque split (control variable in the optimization problem) is determined by minimizing P. As a state variable the SOC is used. In an Offline ECMS, a constant λ is found iteratively for time-invariant systems. For an online-capable implementation of the ECMS, the idea of a SOC-dependent control of the equivalence factor λ was implemented in several studies [16–26]. In this work, an average equivalence factor $\lambda_{Offline,avg}$ is used for the Online ECMS. However, this does not guarantee charge-sustaining (CS) behavior in online operations: depending on the cycle, the SOC trajectories result in an excessive charging or discharging of the battery. Therefore, a penalty term is added. According to $dSOC$, (difference between the real SOC and the reference SOC), the value of the energy (λ) is either raised or lowered. As concluded in [25,37], the trigonometric penalty function is better than a proportional penalty function: it allows tiny deviations from the reference SOC but strongly penalizes significant deviations. Therefore, the penalty term consists of the penalty factor kp_{SOC} multiplied by the cubic derivation of SOC $dSOC^3$ (see Equation (17)). In terms of CS operation, the deviation of the battery's energy content at the end of the cycle is limited to a specific value. These presumptions are used to establish the proper kp_{SOC} for the non-predictive Online ECMS.

$$\lambda(t) = \lambda_{Offline,avg} - kp_{SOC} \cdot dSOC(t)^3 \tag{17}$$

In this paper, a novel approach for a predictive Online ECMS that considers map data to achieve saving potentials compared to the non-predictive Online ECMS implementation is presented. The investigations are limited to the consideration of TS positions on the upcoming route. The appearance of a TS within the upcoming horizon (represented by $flag_{TS}$) has a direct impact on λ using an additional parameter kp_{TS}:

$$\lambda(t) = \lambda_{Offline,avg} - kp_{SOC} \cdot dSOC(t)^3 - kp_{TS} \cdot flag_{TS} \tag{18}$$

A summary of the applied methodology is given by Figure 5.

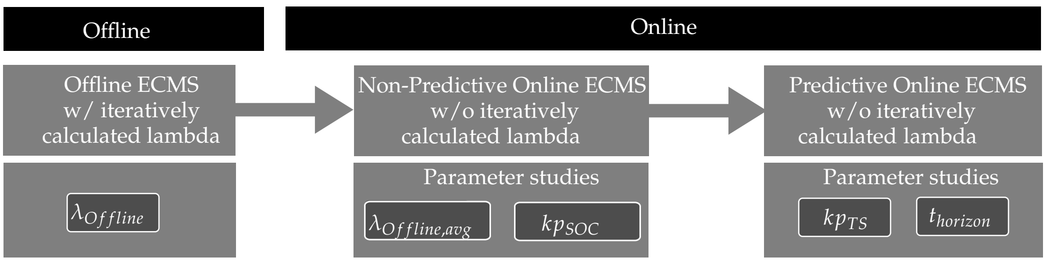

Figure 5. Applied methodology for predictive Online ECMS.

5. Results

In the investigations fuel consumption is minimized, whereby there is a proportional relationship between fuel consumption and CO_2 emissions. The CO_2 values presented in this work are calculated with the relation 1 l/100 km = 23.2 gCO_2/km. First, the Offline ECMS is used to iteratively determine the optimum $\lambda_{Offline}$ value for each of the nine cycles selected (Table 2). An overview is given in Table 3. $\lambda_{Offline}$ ranges from 2.55 to 2.88. The lowest λ values occur during city driving. The highest lambda values, on the other hand, occur on highways.

Table 3. Results from Offline ECMS for real driving cycles from Table 2.

Road Type	$\lambda_{Offline}$	CO_2 (g/km)
City	2.61 2.55 2.61	134.16 139.87 144.42
Country Road	2.74 2.70 2.64	124.69 122.31 172.21
Highway	2.81 2.75 2.88	148.40 168.92 169.08

The non-predictive Online ECMS is parametrized according to [34]. Cycles with high TS density are typically city driving cycles. Therfore, a $\lambda_{Offline,avg,city}$ of 2.60 is chosen (Table 4). Parameter studies, which will not be discussed in detail, result in a kp_{SOC} of 3.57 to achieve charge-sustaining (CS) operation. For further information the reader is referred to [34]. A battery-specific parametrization of the non-predictive Online ECMS is waived in this publication.

Table 4. Final parametrization for non-predictive Online ECMS.

$\lambda_{Offline,avg,city}$	2.60
kp_{SOC}	3.57

In the next step, a predictive Online ECMS is to be parametrized to show additional saving potentials for routes with a high density of TS (Figure 4). In contrast to [34], the route itself and the Global Navigation Satellite System (GNSS) position are assumed to be known for this predictive Online ECMS. It is also expected that the appropriate map data are available. Both parameters kp_{TS} and horizon length $t_{horizon}$ have to be specified. The investigations will be carried out for different battery sizes. Parameter ranges to identify the best parametrization of kp_{TS} and $t_{horizon}$ are given in Table 5.

Table 5. Ranges to identify optimal parameters kp_{TS} and horizon length $t_{horizon}$ of the predictive Online ECMS for a usable battery energy of 25 Wh, 50 Wh, 75 Wh, 100 Wh, 200 Wh, 300 Wh, 400 Wh, 500 Wh and 1000 Wh.

	Min	Max
kp_{TS}	0	5
$t_{horizon}$ in s	5 s	100 s

In Figure 6, CO_2 reduction potentials in % over kp_{TS} for different $t_{horizon}$ in the case of a usable battery energy of 25 Wh are given for the selected cycles with high TS density from Figure 4. For formatting reasons, the plots are restricted to 16 out of 19 cycles. For each cycle, there exists an individual kp_{TS} with a corresponding $t_{horizon}$ which leads to the best results. It can also be seen that above a certain value of kp_{TS}, there is no further influence on CO_2. To ensure robust applicability, a parametrization for the overall largest CO_2 savings potential for each battery size can be determined based on these investigations.

A behavior similar to that shown in Figure 6 is seen for a usable battery energy of 100 Wh in Figure 7.

In Figure 8, the velocity, the presence of a TS, and the SOC trajectories are presented over time for an exemplary cycle with 100 Wh usable battery energy. This includes both the non-predictive Online ECMS and the predictive Online ECMS for the chosen $\lambda_{Offline,avg,city}$ = 2.60 using the ideal kp_{TS} and $t_{horizon}$ setting. Additionally, the SOC trajectory is given for a non-predictive Online ECMS with a λ of 2.70.

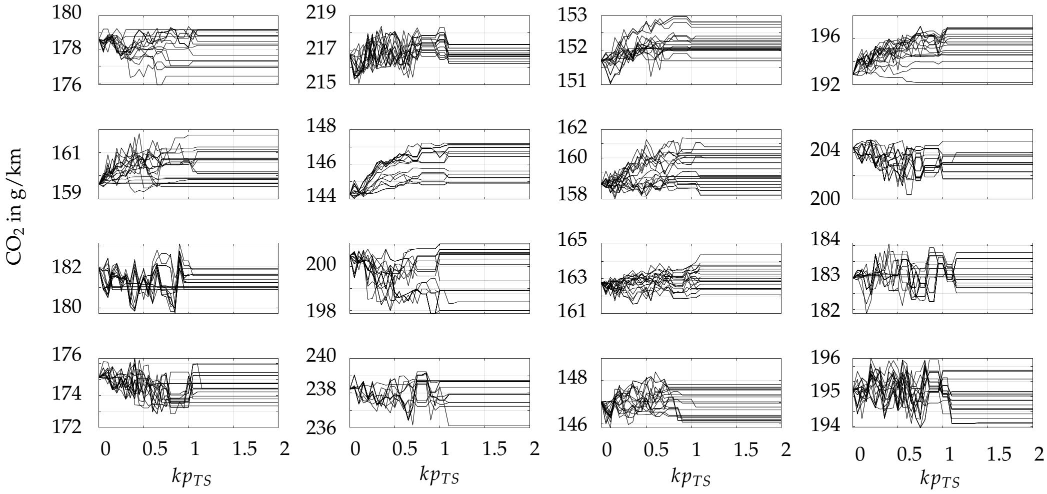

Figure 6. Usable battery energy 25 Wh: CO_2 over kp_{TS} of several $t_{horizon}$ for predictive Online ECMS (16/19 cycles). Each graph represents a specific $t_{horizon}$.

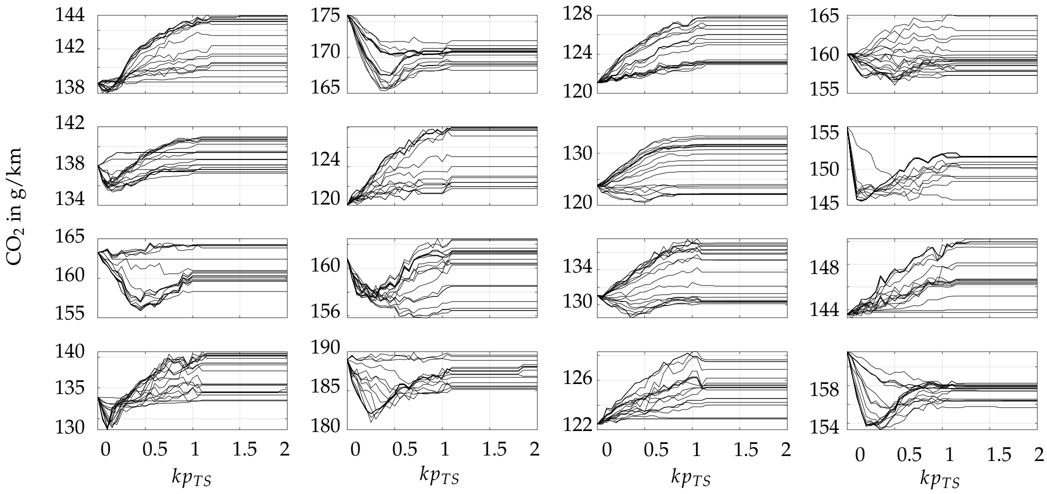

Figure 7. Usable battery energy 100 Wh: CO_2 over kp_{TS} of several $t_{horizon}$ for predictive Online ECMS (16/19 cycles). Each graph represents a specific $t_{horizon}$.

In a first step, the analysis focuses on both the non-predictive and the predictive Online ECMS for $\lambda_{Offline,avg,city}$ = 2.60. At t = 340 s as well as at t = 370 s and t = 500 s there is a correlation between the traffic light position and the speed. Speed is reduced in all three cases and leads to corresponding recuperation phases. At time points t = 370 s and t = 500 s, significantly higher recuperable energies are observed in the SOC trajectory for the predictive Online ECMS. At t = 340 s, on the other hand, there is no increase in recuperable energy. In contrast to those three points mentioned above, however, it is also possible that no significant reduction in speed and therefore no recuperation phase occurs despite the presence of a traffic light. This is shown, for example, at t = 200 s and t = 280 s. This can happen, for example, when the traffic light is green. While the recuperable energy remains unchanged at t = 280 s, CO_2 emissions can increase locally at t = 200 s compared to the non-predictive ECMS: the battery state of charge is kept longer with the predictive Online ECMS, which is associated with additional ICE operation. It is concluded that the predicitve Online ECMS can have both positive and negative effects on the optimality of the EMS. At some timesteps a local improvement is achieved when applying the predictive Online ECMS by better taking into account recuperation potentials. At other timesteps, a local increase in CO_2 emissions is achieved due to additional operation of the ICE. There are also situations where there is no impact on the optimality of the EMS. Ultimately, the decisive factor is which effects predominate. Overall, a well-parametrized predictive

Online ECMS leads to a reduction in fuel consumption compared to the non-predictive Online ECMS.

In a second step, the SOC trajectory for λ of 2.70 should also be considered. A closer look at the non-predictive SOC trajectorys of $\lambda_{Offline,avg,city}$ = 2.60 and λ = 2.70 reveals that CO_2 reduction potentials by applying a predictive Online ECMS are highly dependent on the chosen non-predictive basic implementation: At t = 380 s, the additional energy hub for the use of recuperated energy is much higher for λ = 2.70 than for $\lambda_{Offline,avg,city}$ = 2.60. Anyway, both non-predictive Online ECMS implementations reach the upper SOC limit multiple times and therefore both λ seem to be too high for the shown driving cycle. It is concluded that significant saving potentials can already be achieved by an adequate choice of non-predictive Online ECMS. At the same time, however, the additional savings from the proposed predictive Online ECMS using recuperation potentials compared to a non-predictive implementation are reduced.

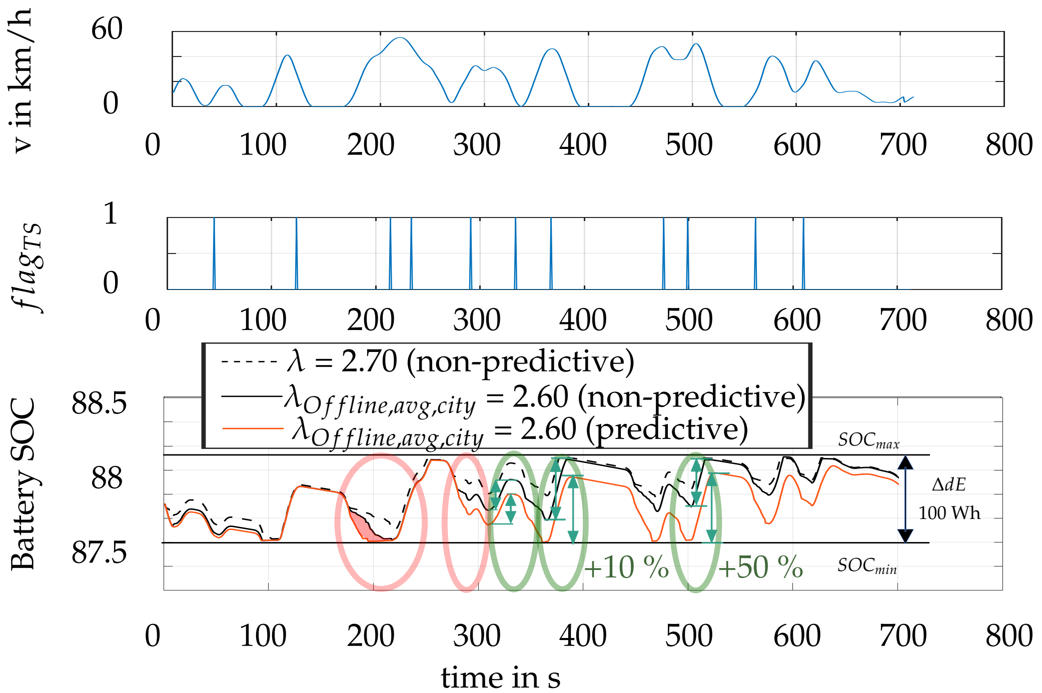

Figure 8. Usable battery energy 100 Wh: velocity (upper graph), $flag_{TS}$ (middle graph), and battery SOC over time (lower graph). Both for non-predictive Online ECMS (black) and predictive Online ECMS (orange) with $t_{horizon}$: 65 s, kp_{TS} = 0.2. In addition, the course for the non-predictive Online ECMS with λ = 2.70 is plotted (black dashed).

As already stated, Figure 8 reveals that λ reductions also occur when the battery is already discharged before a recuperation phase is initiated (t = 200 s). Therefore, a dependence of kp_{TS} on SOC is introduced in a follow-up work. Thus, when SOC is around the lower limit, no reduction in the value of the electric energy (λ) is allowed. Apart from this measure, a dependence of kp_{TS} on the occurrence of the recuperation potential in the prediction horizon could also be added. If the TS is quite close, the influence should be large. If the TS is in the later part of the studied horizon, the influence is reduced.

In contrast to Figures 6 and 7, there are no additional saving potentials for a predictive implementation when a large battery (usable battery energy 1000 Wh) is used, see Figure 9. Here, a significant deterioration is observed for all kp_{TS}. This is in line with the findings already made in the context of [34] that considering recuperation potentials in a predictive Online ECMS does not lead to any noticeable saving potential for large batteries compared to a well-parametrized non-predictive Online ECMS.

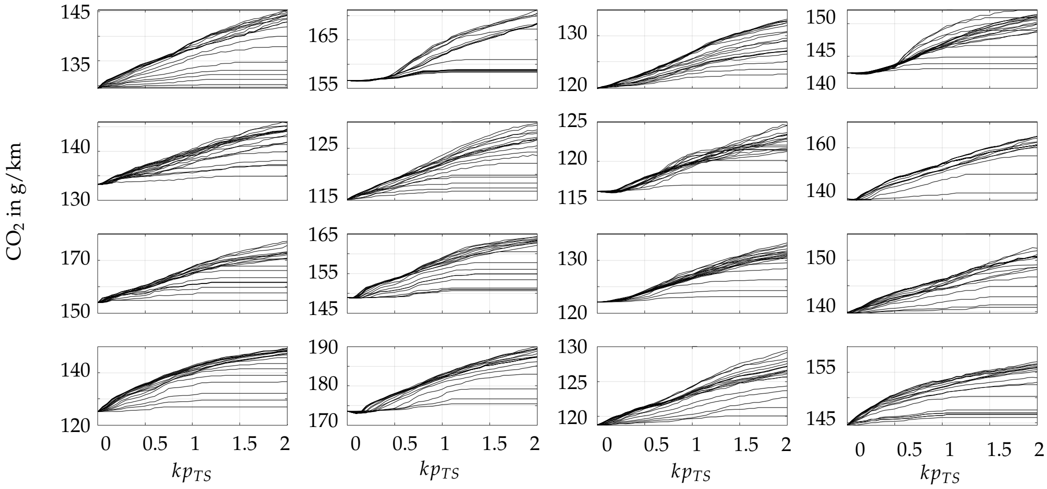

Figure 9. Usable battery energy 1000 Wh: CO_2 over kp_{TS} of several $t_{horizon}$ for predictive Online ECMS (16/19 cycles). Each graph represents a specific $t_{horizon}$.

As shown in Figure 10, an overall improvement is observed when applying a predictive Online ECMS. However, the saving potentials depend strongly on the usable energy content of the battery. The highest saving potentials exist with a usable battery energy of 100 Wh. With lower battery capacities, the saving potentials using a predictive implementation become less. For a usable battery energy larger than 100 Wh, no more significant saving potentials are found. The corresponding parameters for each battery size are listed in Table 6.

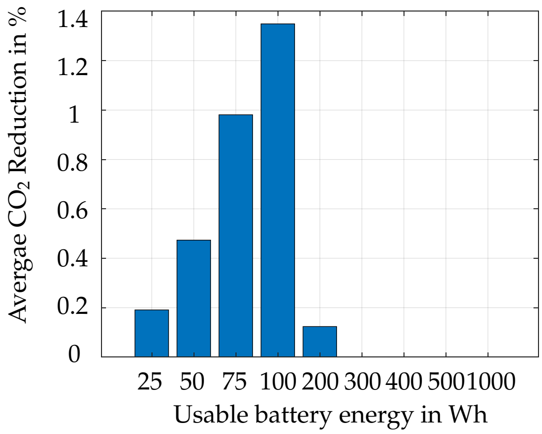

Figure 10. Potentials of the proposed predictive EMS for different usable battery energies: Average CO_2 reduction in % when applying the predictive Online ECMS compared to the non-predictive Online ECMS.

Table 6. Optimal overall parameters of the predictive Online ECMS for different battery sizes including average CO_2 reduction potentials compared to the non-predictive Online ECMS (Figure 10).

Usable Energy in Wh	$\mathbf{kp_{TS}}$	Horizon in s	Reduction $\mathbf{CO_2}$ %
25	0.35	30	0.19
50	0.15	40	0.47
75	0.35	45	0.98
100	0.20	50	1.35
200	0.05	25	0.12
300	No additional CO_2 reduction potentials by applying the proposed predictive Online ECMS considering TS		
400			
500			
1000			

6. Conclusions

In this study, a new approach for a predictive energy management strategy (EMS) was presented, which complements the existing field and provides starting points for future studies. It was demonstrated how a predictive Online Equivalent Consumption Minimization Strategy (ECMS) can achieve additional fuel savings compared to a non-predictive Online ECMS by predicting recuperation events using map data. Within the investigations, TS from the upcoming road profile are considered in the predictive Online ECMS, whereby more than 1 % average saving potentials compared to a non-predictive implementation were shown. The highest saving potentials are found with a usable battery energy of 100 Wh. With lower usable battery energy, the saving potentials decrease using the proposed predictive implementation. For batteries larger than 100 Wh, no more significant saving potentials are found. Furthermore, a big dependence of the added value by implementing a predictive Online ECMS from the basic non-predictive Online ECMS is revealed. In a follow-up work, a dependency of kp_{TS} on SOC could be introduced. Thus, if the battery state of charge is already at SOC_{min}, no additional reduction in the value of the electrical energy (λ) is allowed. Furthermore, a dependence of kp_{TS} on the occurrence of the recuperation potential in the predicted horizon can be implemented. If the recuperation occurs early in the time horizon, a large influence is aimed at; if it occurs late in the horizon, a small influence should be realized. Apart from that, the predictive Online ECMS could be enhanced by using additional map data, telemetry data or information from Radar, Lidar, and camera. Also, Car-to-Car (C2C) and Car-to-X (C2X) communication could be used to consider the status of the traffic signal.

To apply the predictive Online ECMS the route must be given and the current position of the global navigation satellite system (GNSS) must be known. Subsequent studies could investigate, how intelligent methods can be used to better estimate the current position of the vehicle or to predict the route. In order to validate the proposed predictive Online ECMS, an implementation in the real vehicle is required. For such an implementation in a real vehicle, the upcoming velocity has to be approximated to transfer map information from the distance domain to the time domain. Alternatively, a specific future distance could be used instead of the specified time horizon in the proposed predicitve Online ECMS.

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