

Cascaded Predictive Control for Energy Efficient Driving of Electric Vehicles

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Abstract

Due to limited battery capacity and therefore limited range, energy efficient driving is especially important in battery electric vehicles (BEVs). In this contribution, one such experimental vehicle and a tailored cascaded structure for energy and driving dynamics control is presented.

The underlying driving dynamics control comprises a model predictive control allocation algorithm (MPCA), which allows for torque vectoring, i.e. an optimal distribution of acceleration or deceleration forces to the wheels to supply the demanded longitudinal force as well as an additional desired yaw momentum in the case of an overactuated vehicle. This method was developed for the topology of the test vehicle EVA-MRM at the Institute of Measurement, Control and Microtechnology for implementation on the on-board control unit. The MPCA is supplemented by an additional model predictive cruise control (PPC), responsible for anticipatory driving with respect to speed limits, traffic lights, and other vehicles.

Keywords: *BEV (battery electric vehicle), control system, efficiency, prediction*

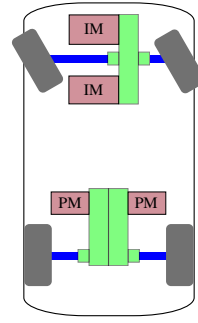
1 Introduction

The use of all-wheel driven power trains offers additional degrees of freedom within driving dynamics control, but also energy efficient driving. For electric vehicles, the distribution of power to all wheels of a vehicle is relatively easy, since one electric motor per wheel can be used making differential gears unnecessary. Also, this enables non-wearing and energy-efficient braking by recuperation and enhanced driving dynamics control by torque vectoring.

In this contribution, a cascaded predictive control structure is presented, which allows for driving dynamics control in the inner control and anticipatory control in the outer control loops. The underlying vehicle topology is based on the test vehicle EVA-MRM shown in Figure 1(a), whose topology as illustrated in Figure 1(b) will be described in detail in Section 2.



(a) Test vehicle EVA-MRM, an all-wheel driven electric passenger car



(b) Power train topology with induction (IM) and permanent magnet motors (PM)

Figure 1: Test vehicle EVA-MRM and its power train topology

The inner control loop described in Section 3 realizes a model predictive control allocation (MPCA) [1], which provides longitudinal force and yaw moment according to the driver's or supervisory control's input. It includes an energy-optimal distribution of forces on the different wheels, taking the actual state of the power train as well as restrictions of battery current or wheel forces into account.

For the outer control loop discussed in Section 4, the paper focuses on anticipatory driving with respect to the upcoming route and traffic. It will be shown that with a model predictive control (MPC) processing some limited knowledge on the upcoming route, substantial decreases of energy consumption of the vehicle can be realized without a significant increase of the trip time.

2 Test Vehicle EVA-MRM

The proposed all-wheel driven electric vehicle with direct drives on each wheel was built by converting a commercially available combustion passenger car. The wheels at the front axis are powered by an asynchronous induction motor each, while each rear wheel is driven by a permanently excited synchronous machine. Figure 2 demonstrates the efficiency maps and maximum torques of both motor types. Single stage reduction gears are employed to transfer the power to each wheel via the drive shafts. The controls are implemented in a rapid prototyping control unit (dSPACE MicroAutoBox II [2]), creating desired torque commands for the different motor controllers. A large traction battery pack composed of 104 LiFePO_4 cells provides energy storage with a nominal voltage of 330 V. It comprises four smaller cases distributed around the vehicle and is supervised by a battery management system (BMS) which controls the high power contactors with a precharge circuit.

Additionally, the vehicle features an electric power heater for the cabin as well as an electric compressor-type air conditioning unit. The latter can also be used to create cold water, which in turn cools ambient air sucked into the battery cases for heat removal. The original vehicle's front radiator has been adopted and augmented by a powerful fan to ensure adequate cooling of the four motors, controllers, and auxiliary systems. These auxiliaries comprise a charging unit as well as a DCDC converter which is utilized to provide the energy necessary in the 12 V circuit to supply several control units, pumps, fans and the remaining vehicle systems. This low voltage system can also be supplied by an additional inverter/charging unit when connected to the grid.

In order to facilitate advanced vehicle dynamics control systems, a high precision inertial measurement unit (Genesys ADMA [4]) which fuses information from DGPS to provide measurements and estimations of the vehicle dynamic state is included. All the major communication among the different controlling units is achieved using the CAN bus protocol. The data transmitted on these communication channels and video data from a small camera in addition to auxiliary information is recorded in an on-board computer running Ubuntu 14.04 and the Automotive Data and Time-Triggered Framework (ADTF [3]).

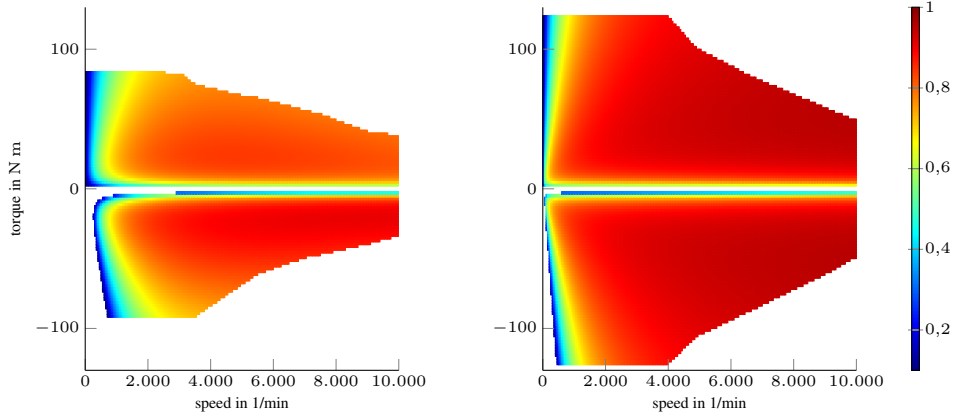


Figure 2: Efficiency maps of the front axle induction motors (left) and rear axle permanent magnet motors (right)

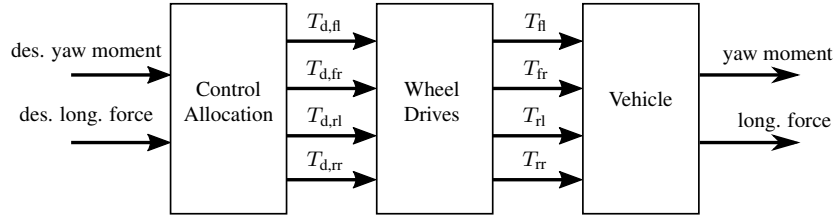


Figure 3: Overview of the powertrain and MPCA structure

3 Model Predictive Control Allocation

In order to optimally control the different motors $i \in \{f, r\}$ (front, rear) and $j \in \{l, r\}$ (left, right) to achieve the desired longitudinal force $F_{x,des}$ and yaw moment $M_{z,des}$ (see Figure 3 for an overview) as demanded from external sources like advanced vehicle control systems or the predictive energy optimal longitudinal controller discussed in Section 4, an advanced algorithm is needed. These values are fulfilled by the redundant drive train in an energy-optimal manner also taking into account limits on the battery current I_{batt} , the longitudinal tire forces $F_{tx,ij}$, and motors torques $T_{des,ij}^{nom}$. The power losses in friction brake $P_{l,brake}$ and traction motors $P_{l,mot}$ are penalized as well in this approach. In total, this poses the problem of control allocation in combination with considerable actuator dynamics which can be solved by model predictive control allocation.

To this end, a nonlinear dynamic optimal control problem (OCP) is set up and solved by means of a highly efficient solving method [5] using the toolbox GRAMPC [7], see [1] for further details. Based on a dynamic model of the motor torque

$$\begin{aligned} \dot{\mathbf{x}}_{ij} &= \mathbf{f}_{ij}(\mathbf{x}_{ij}, u_{ij}) = \begin{bmatrix} -\frac{1}{T_m} T_{act,ij}^{nom} + \frac{1}{T_m} T_{des,ij}^{nom} \\ u_{ij} \end{bmatrix}, \\ \mathbf{x}_{ij} &= [T_{act,ij}^{nom}, T_{des,ij}^{nom}]^T, u_{ij} \in [-\dot{T}_{des,ij}^{nom,+}, \dot{T}_{des,ij}^{nom,+}] \end{aligned} \quad (1)$$

and the nonlinear static torque error maps

$$T_{act,ij} = f_{TT}(T_{act,ij}^{nom}, n_{ij}), \quad (2)$$

the actual longitudinal tire forces

$$F_{tx,ij} = \frac{T_{b,ij} + T_{act,ij}}{r} \quad (3)$$

are obtained as sum of the motor and friction torques, which are modeled as the dynamics

$$\begin{aligned}\dot{x}_b &= f_b(x_b, u_b) = \left[-\frac{1}{T_f} T_b + \frac{1}{T_f} u_b \right], \\ x_b &= T_b, \quad u_b \in [T_b^-, 0].\end{aligned}\quad (4)$$

From these forces, the primary goals follow from geometrical considerations based on the distances l_f, l_r between center of gravity and the front and rear axle, respectively, as well as the track width l_s and the steering angle δ :

$$\begin{aligned}M_z &= (F_{ty,fl} + F_{ty,fr}) l_f \cos \delta + (F_{tx,fl} + F_{tx,fr}) l_f \sin \delta \\ &\quad - (F_{tx,fl} - F_{tx,fr}) l_s \cos \delta + (F_{ty,fl} + F_{ty,fr}) l_s \sin \delta \\ &\quad - (F_{ty,rl} + F_{ty,rr}) l_r - (F_{tx,rl} - F_{tx,rr}) l_s, \\ F_x &= (F_{tx,fl} + F_{tx,fr}) \cos \delta + (F_{ty,fl} + F_{ty,fr}) \sin \delta \\ &\quad + F_{tx,rl} + F_{tx,rr}.\end{aligned}\quad (5)$$

$$(6)$$

Utilizing the power loss and torque error maps, a representation for the battery current

$$I_{\text{batt}} = \frac{1}{U_{\text{batt}}} \sum_{i,j} P_{\text{mech},ij} + P_{\text{l,mot},ij}. \quad (7)$$

can be obtained from the sum of mechanical and loss power using a measurement of the actual battery voltage U_{batt} .

Finally, the combined model of the overall drive train dynamics

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{u}) = \begin{bmatrix} \mathbf{f}_{fl}(\mathbf{x}_{fl}, u_{fl}) \\ \mathbf{f}_{fr}(\mathbf{x}_{fr}, u_{fr}) \\ \mathbf{f}_{rl}(\mathbf{x}_{rl}, u_{rl}) \\ \mathbf{f}_{rr}(\mathbf{x}_{rr}, u_{rr}) \\ f_b(x_b, u_b) \end{bmatrix}, \quad \mathbf{x} = \begin{bmatrix} \mathbf{x}_{fl} \\ \mathbf{x}_{fr} \\ \mathbf{x}_{rl} \\ \mathbf{x}_{rr} \\ x_b \end{bmatrix}, \quad \mathbf{u} = \begin{bmatrix} u_{fl} \\ u_{fr} \\ u_{rl} \\ u_{rr} \\ u_b \end{bmatrix}, \quad (8)$$

is obtained. Based on this model, the nonlinear OCP

$$\min \quad J(\mathbf{x}_k, \bar{\mathbf{u}}) = \int_{t_k}^{t_k+T} l(\bar{\mathbf{x}}(t), \bar{\mathbf{u}}(t)) dt \quad (9)$$

$$\text{s.t.} \quad \dot{\bar{\mathbf{x}}}(t) = \mathbf{f}(\bar{\mathbf{x}}(t), \bar{\mathbf{u}}(t)), \quad \bar{\mathbf{x}}(t_k) = \mathbf{x}_k, \quad (10)$$

$$u_{ij}(t) \in [-\dot{T}_{\text{des},ij}^{\text{nom},+}, \dot{T}_{\text{des},ij}^{\text{nom},+}], \quad u_b(t) \in [T_b^-, 0], \quad (11)$$

over the prediction horizon T chosen as 200 ms using the running cost

$$\begin{aligned}l(\mathbf{x}, \mathbf{u}) &= (\mathbf{x} - \hat{\mathbf{x}})^T \mathbf{Q}(\mathbf{x} - \hat{\mathbf{x}}) + (\mathbf{u} - \hat{\mathbf{u}})^T \mathbf{R}(\mathbf{u} - \hat{\mathbf{u}}) \\ &\quad + \gamma_1 (M_z - M_{\text{des},z})^2 + \gamma_2 (F_x - F_{x,\text{des}})^2 \\ &\quad + \gamma_3 P_{\text{l,mot}} + \gamma_4 P_{\text{l,brake}} \\ &\quad + \gamma_5 \sum_{ij} \text{pen} \left(F_{tx,ij}, F_{tx,ij}^-, F_{tx,ij}^+ \right) \\ &\quad + \gamma_6 \sum_{ij} \text{pen} \left(T_{\text{des},ij}^{\text{nom}}, T_{\text{act},ij}^{\text{nom},-}, T_{\text{act},ij}^{\text{nom},+} \right) \\ &\quad + \gamma_7 \text{pen}(I_{\text{batt}}, I_{\text{batt}}^-, I_{\text{batt}}^+)\end{aligned}\quad (12)$$

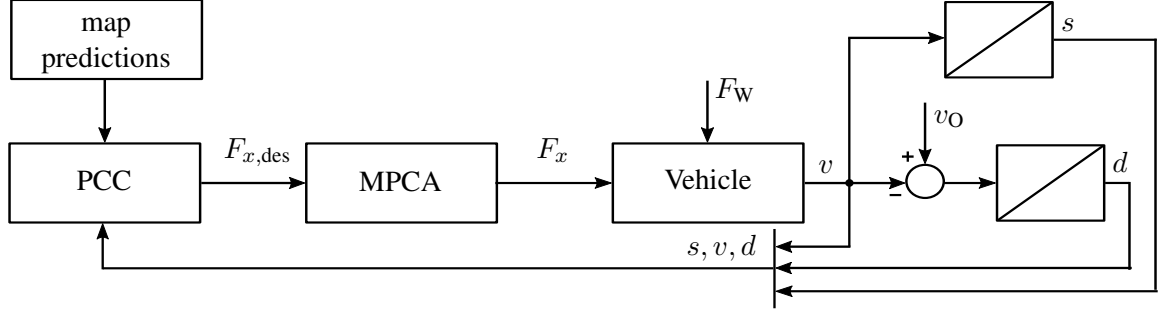


Figure 4: Overview of the proposed cascaded control algorithm

and the external barrier terms

$$\text{pen}(x, x^-, x^+) = \begin{cases} (x - x^+)^2 & \text{if } x > x^+ \\ (x - x^-)^2 & \text{if } x < x^- \\ 0 & \text{else} \end{cases} \quad (13)$$

for state-dependent constraints is formulated to ensure optimal operation in consideration of all the different optimization targets. The importance of these targets correspond to the relative values between $\gamma_{1,...,7}$, and the diagonal entries in $\mathbf{R}$ and $\mathbf{Q}$. These two penalize the deviation of the input $\mathbf{u}$ from the desired values $\hat{\mathbf{u}} = \mathbf{0}$ and the deviation of the state $\mathbf{x}$ from preallocated values $\hat{\mathbf{x}}$, respectively. Both parameters mainly improve the condition of the OCP in light of the significant redundancy, while the preallocated values

$$\hat{\mathbf{T}}_w = \left(\mathbf{b}_M^\dagger M_{\text{des},z} + \mathbf{b}_F^\dagger F_{\text{des},x} \right) r \quad (14)$$

are calculated using the pseudo-inverse of a simplified representation of (6), where only the influence of the longitudinal tire forces is considered in the geometry parameters $\mathbf{b}_F$ and $\mathbf{b}_M$.

Despite the considerable complexity and highly nonlinear terms in the OCP, computation times of about 4 ms can be achieved on the MicroAutoBox II owing to the highly efficient solving method, well below the motor controller update rate of 20 ms.

4 Predictive Cruise Control

Based on the MPCA algorithm presented in the last section, an energy-optimal predictive cruise controller (PCC) can be employed to provide desired values for the longitudinal force $F_{x,des}$ in accordance to radar information concerning preceding vehicles, predictive knowledge regarding traffic lights, road's curvature and longitudinal slope as well as speed limits. Figure 4 gives an overview of the proposed cascaded control structure with the low-level control allocation (MPCA scheme) and the high-level vehicle longitudinal controller (PCC scheme). In the high-level controller, the vehicle position, velocity, and distance to preceding vehicles is considered as the state $\mathbf{x} = [s, v, d]^T$. Additionally, the road slope and the velocity of a preceding vehicle are considered as the disturbance $\mathbf{d} = [\alpha(s), v_O(t)]^T$ acting on the system dynamics. Based on this predictive information, the driving resistances

$$F_W = F_L + F_R + F_S. \quad (15)$$

can be computed. One major contribution is constituted by the air resistance

$$F_L \approx \frac{1}{2} \rho_L c_w A v^2 \quad (16)$$

defined by the vehicle cross section A , air friction coefficient c_w , and air density ρ , neglecting head winds. Furthermore, the rolling resistance

$$F_R = c_r mg \cos(\alpha(s)) \text{sign}(v) \approx c_r mg \cos(\alpha(s))v \quad (17)$$

is considered, defined by the vehicle mass m , acceleration due to gravity g , the road slope angle α and the rolling resistance coefficient c_r , which is valid for $v > 0$. Finally, driving resistance due to road slope is represented by

$$F_S = mg \sin(\alpha(s)). \quad (18)$$

Utilizing map and radar information, $\mathbf{d}$ is assumed to be available as a prediction. Combined with the dynamics of the distance to the preceding vehicle, this leads to the overall state-space model

$$\mathbf{f}(\mathbf{x}, u, t) = \begin{bmatrix} x_2 \\ \frac{K_P}{m}u - \frac{\rho L c_w A}{2m}x_2^2 - c_r g \cos(d_1(x_1))x_2 - g \sin(d_1(x_1)) \\ d_2(t) - x_2 \end{bmatrix} \quad (19)$$

with the input $F_{x,\text{des}}$, which exhibits time-dependency due to the disturbance prediction. The underlying MPC algorithm is modeled by the constant K_P which represents the steady-state relation between F_x and $F_{x,\text{des}}$. Based on this model, a corresponding OCP

$$\min_{u(\cdot)} \mathbf{J}(\mathbf{x}_k, \bar{u}) = V(\bar{\mathbf{x}}(t_k + T_{\text{hor, PPC}})) + \int_{t_k}^{t_k + T_{\text{hor, PPC}}} l(\bar{\mathbf{x}}(t), \bar{u}(t), t) dt \quad (20a)$$

$$\text{s.t. } \dot{\bar{\mathbf{x}}}(t) = \mathbf{f}(\bar{\mathbf{x}}(t), \bar{u}(t), t_k + t), \quad \mathbf{x}(t_k) = \mathbf{x}_k, \quad u(t) \in [u_{\min}, u_{\max}] \quad (20b)$$

can be formulated over the moving horizon $T_{\text{hor, PPC}}$ with a chosen length of 40 s. It comprises an integral cost term

$$l(\mathbf{x}, u, t) = l_{\text{sl}}(\mathbf{x}) + l_{\text{tl}}(t, \mathbf{x}) + l_{\text{pv}}(\mathbf{x}) + l_{\text{pl}}(x_2, u) + l_{\text{ef}}(\mathbf{x}, u) + l_{\text{dv}}(\mathbf{x}) \quad (21)$$

which in turn consists of several parts to ensure legal driving within the speed limits ($l_{\text{sl}}(\mathbf{x})$), adherence to traffic lights ($l_{\text{tl}}(t, \mathbf{x})$), an appropriate distance to the preceding vehicle ($l_{\text{pv}}(\mathbf{x})$), the physical limits of the vehicle ($l_{\text{pl}}(x_2, u)$), energy-efficient behavior $l_{\text{ef}}(\mathbf{x}, u)$, and a velocity tracked closely to the desired value ($l_{\text{dv}}(\mathbf{x})$). For the latter, 90 % of the legal limit is chosen. The end cost in (20)

$$V(\mathbf{x}) = v_1(\mathbf{x}) + v_2(\mathbf{x}). \quad (22)$$

is composed of two parts. While the first

$$v_1(\mathbf{x}) = \xi_1 \text{pen}(x_2, -\infty, v_{\text{des}}) + \xi_2 \text{pen}(x_2, v_{\text{des}}, \infty) \quad (23)$$

ensures adherence to an appropriate velocity interval by means of two independently weighted penalty functions, the second

$$v_2(\mathbf{x}) = \xi_3 \text{pen}(x_3, d_{\text{O,def}}, d_{\text{O,def}}) \quad (24)$$

enforces a default value for the distance $d_{\text{O,def}}$ to the preceding vehicle, in each case at the end of the prediction horizon. In addition to the information regarding the future disturbance $\mathbf{d}$, predictive information regarding the legal speed limits, speed limits due to road curvature, traffic light cycles, and preceding vehicle is considered as well by this approach.

Finally, simulation results of the proposed predictive control scheme using SIMULINK in combination with IPG CARMAKER [6], a comprehensive vehicle dynamics simulation software, are discussed. In the first considered scenario, knowledge regarding traffic lights is utilized to choose an energy-optimal vehicle velocity trajectory by avoiding stop-and-go scenarios due to traffic lights. Resulting trajectories

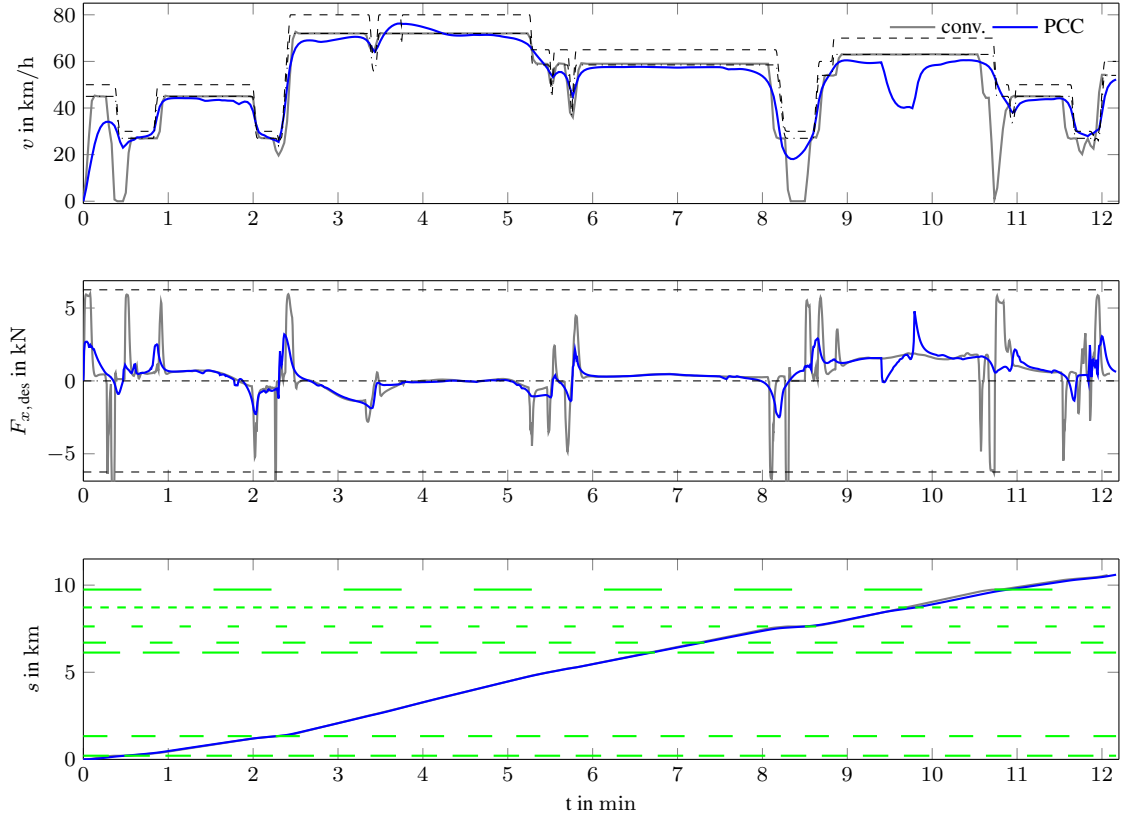


Figure 5: Comparison between conventional strategy (gray) and predictive control scheme (blue) using knowledge regarding traffic light signals (green)

of the vehicle velocity, acting longitudinal force, the traveled distance as well as the traffic lights' positions and green phases (indicated as green lines in the bottom plot) are demonstrated in Figure 5. While the conventional strategy included in the simulation environment performs three stops due to red traffic signals, the predictive control scheme avoids stopping altogether by appropriately varying the vehicle's velocity. Accordingly, the trajectory of the longitudinal force demonstrates significant improvements in the power demand which, owing to the predictive control scheme, is reduced by about 10 % compared to the built-in, conventional strategy. Furthermore, the maximum battery current is substantially lowered and the usage of the friction brake can be avoided almost entirely compared to the conventional strategy. A preceding vehicle is considered additionally in the second scenario illustrated in Figure 6. The preceding vehicle (red lines) is operated by the conventional strategy as well and therefore exhibits similar behavior. The results show that despite the more complex scenario, stops can still be avoided facilitating efficient operation of the vehicle. The predictive scheme demonstrates a higher variability in the velocity trajectory to ensure an appropriate distance between the vehicles as well as minimizing unnecessary accelerations due to traffic lights. Even higher energy savings of about 14 % for this scenario demonstrate the impressive performance of this approach.

5 Conclusions

In this contribution, the experimental vehicle operated by the Institute of Measurement, Control and Microtechnology at Ulm University has been introduced. Towards a comprehensive control strategy, a cascaded control structure for energy-optimal vehicle operation was proposed. While a short-horizon MPCA scheme reliably operates the power train while adhering to constraints, the hereby achieved reduction of complexity can be exploited by the PPC scheme which operates on a much longer horizon. The

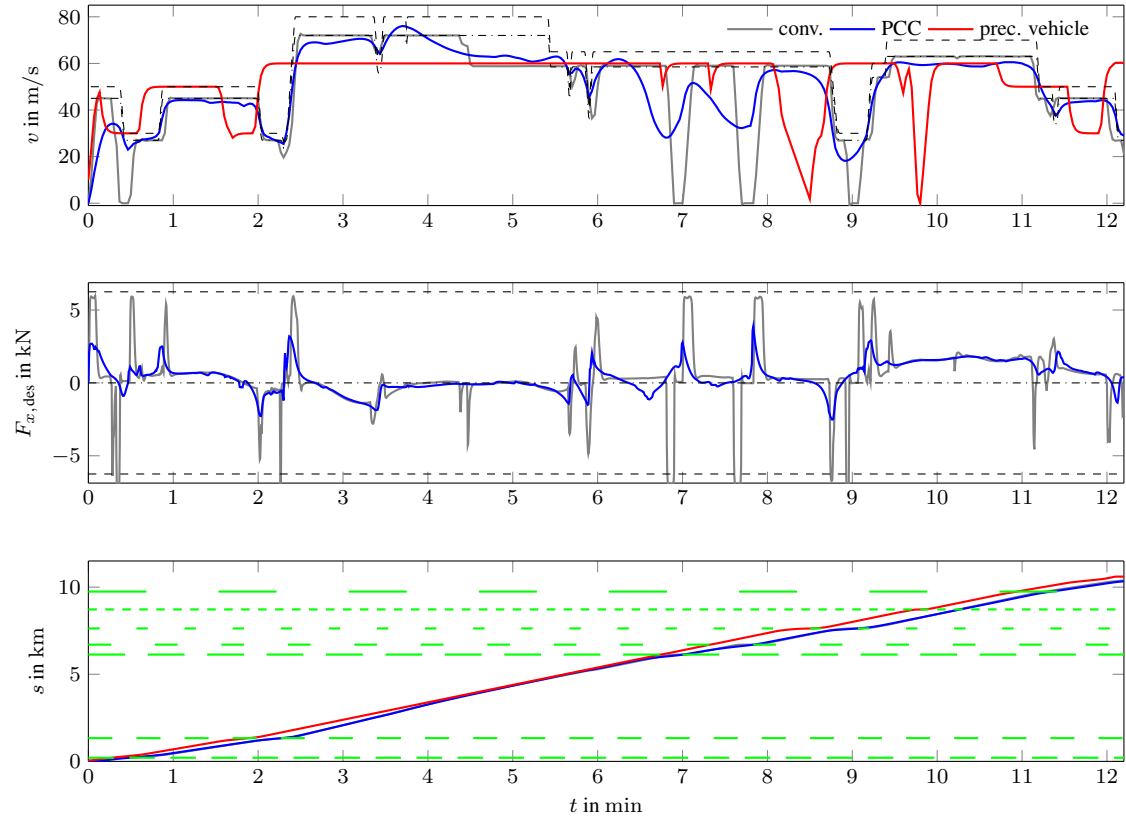


Figure 6: Comparison between conventional strategy (gray) and predictive control scheme (blue) using knowledge regarding traffic light signals (green), for the case of driving with a preceding vehicle (red)

results show that by exploiting predictive information, a significant improvement in energy consumption and brake wear can be achieved.

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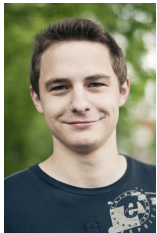
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