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An Adaptive Nonlinear Model Predictive Controller for Longitudinal Motion of Automated Vehicles

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Abstract— **This paper presents an Adaptive Nonlinear Model Predictive Controller for longitudinal motion of automated vehicles which incorporates advance information on future speed demand values, as well as on road grade changes. It is used in combination with a state and parameter estimator to adapt to a changing vehicle mass. This allows improved speed tracking capability for horizontal driving and steep hill climbing. Performance is explored through simulation of a driving scenario in a parking garage and shows encouraging improvements in quality of control. It could be shown that even though the controller is optimized for tracking performance, average fuel consumption can be reduced.**

I. INTRODUCTION

In order to achieve precise trajectory following, automated vehicles and cruise controllers need to be able to react to changes in speed demand in presence of disturbances, as for example changing road grade. This task is done by a longitudinal controller, which transforms a motion request from a trajectory planning layer into engine torque and brake demand values. Contrary to manual operation, where future driver inputs can only be unreliably predicted, desired speed profiles of automated vehicles are available with a certain look ahead into the future. Additionally, one can assume that future road grade information can be extracted from detailed environment maps. Incorporating this information into the controller can not only increase the overall performance but, as will be shown later, there are scenarios where state-of-the-art controllers might fail completely. One such scenario is driving onto a steep ramp at slow speed, as it occurs in multi-storey car parks. Here, a sudden change in road grade requires a rapid increase in engine torque to maintain the vehicle at its current speed. Unfortunately, engines have only limited capability to respond to a rapid increase in torque demand. Anticipated driving, which an experienced human driver can perform, should be incorporated into future control systems, helping to overcome these limitations.

Model Predictive Control (MPC) is a control scheme that allows incorporating advance information on desired states and disturbances, whilst considering state and input constraints. It uses a model of the plant dynamics to predict future responses to system inputs over a certain time horizon. By solving an Optimal Control Problem (OCP), minimizing a cost function whilst considering given constraints, optimal input trajectories are calculated. In each time step, the first value the resulting optimal input trajectory is applied, and a new solution to the OCP is found, given the actual system state and new reference values for system output trajectories.

Providing a solution to the OCP at each time step is a computationally expensive task, which makes it challenging to achieve small sample times needed for fast and accurate control. Another limiting factor is the type of hardware available in today's automobiles, where costs are an important driver. Recent developments on automotive architectures ([3], [8], [20]) demonstrate a trend towards a centralized and more powerful computing environment within the automotive domain, making a practical implementation of such algorithms feasible.

Motivated by this development, this paper describes the implementation of an Adaptive Nonlinear Model Predictive Controller (NMPC) for longitudinal control of automated vehicles, which makes use of future road grade and speed information and is able to adapt to a changing vehicle mass. This highly improves tracking performance of the controller in presence of the mentioned disturbances compared to state-of-the-art solutions.

Further information about the motivation for this work and an overview of the system architecture together with a detailed description of the state and parameter estimator used later in this paper has been previously published by the authors in [4] and the interested reader is referred hereto.

The paper is organized as follows: We first give an overview over related work in Section II, explain the NMPC problem formulation in Section III, before presenting simulation results in Section IV. Section V finally gives a conclusion and outlook on future enhancements.

II. RELATED WORK

The task of longitudinal vehicle control needs to be solved for both automated vehicles as well as for cruise control in Advanced Driver Assistance Systems (ADAS). [4] gives a summary of recent developments on longitudinal control strategies of automated vehicles described in [1], [2], [9], [21], [26] and shows that they commonly lack a control layer capable of actively dealing with future road grade changes.

Recent solutions proposed for the cruise control problem (see for example [6], [7], [11], [13], [15], [16], [18], [22], [23]) can be commonly seen as solutions to a special use case for the motion planning layer (see Figure 1) which calculates speed trajectories. All these solutions either only mention to rely on a lower level controller capable of tracking speed trajectories accurately enough, or state to use a Proportional - Integral (PI) type of controller, mostly with an inverse vehicle model to calculate a feed-forward term.

More in detail, [16] presents a solution to generate optimal fuel saving trajectories using future road and traffic information, but states to utilize a PI controller structure with a nonlinear feed-forward term in the longitudinal control layer.

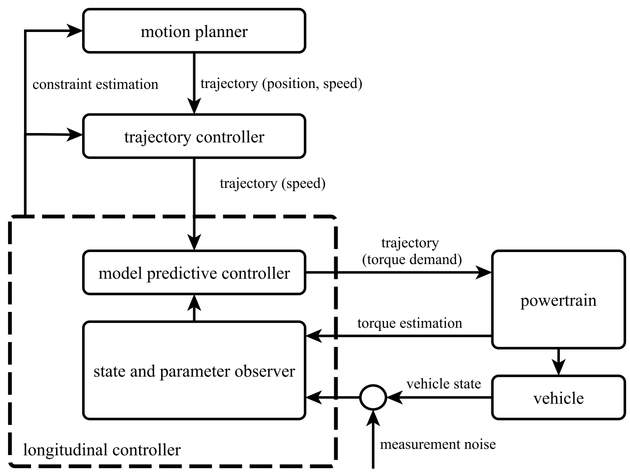

Fig. 1. Proposed controller structure for longitudinal vehicle control.

[7] proposes an approach combining a motion planning and longitudinal control layer in a hybrid MPC, which is able to solve the Adaptive Cruise Controller problem. It is based on a nonlinear vehicle equation in which air and friction resistance is considered, but no road grade or vehicle mass variation is taken into account. Since it is designed for the sole task of following a leading vehicle on a highway, this architecture cannot be used for automated driving in all possible scenarios. [11] applies Explicit MPC techniques to design a predictive cruise controller for a Hybrid Electric Vehicle. For the longitudinal control layer, the application of a PID controller is also stated. [15] proposes a two layer approach and uses a simple PID controller to calculate throttle and brake input signals in the lower layer, which cannot anticipate future information. [23] uses the hybrid fuzzy PID controller from [24] in the longitudinal control layer, which does not incorporate road grade information at all and by nature is not capable to perform anticipated control.

Various solutions exist treating with the problem of vehicle speed tracking control. With the introduction of torque based Engine Management Systems (EMS) in the last decade, approaches like [10], have become obsolete. There, highly nonlinear empirical models, which approximate the vehicle response to changes in accelerator pedal value, have to be calibrated in time-consuming vehicle tests. In modern EMS, the engine characteristic is already incorporated in a torque model which offers a torque demand interface. This torque model is calibrated during the engine calibration process using a huge amount of measurement data collected on an engine test bed, and therefore provides a very high accuracy.

Fuzzy logic type solutions [5], [24] or gain scheduling approaches [19], [23] do not require a detailed model but suffer from a very high tuning effort. [12] designed a time-varying parameter adaptive vehicle speed controller without the need to rely on an accurate vehicle model; nevertheless, it is very sensitive to correct tuning of adaptation gains to avoid oscillations. Changes in road grade are only treated as a disturbance.

[25] suggests a two layer approach where the upper layer is defined as a linear MPC problem which creates a demand acceleration for the lower level, and nonlinearities of the vehicle model are incorporated in a lower level feed-forward control. Aerodynamic drag, rolling resistance and road grade influences are neglected and treated as a disturbance.

[14], [17] propose specialized solutions using nonlinear model predictive control for speed tracking and include strategies to control engine parameters like variable valve lift, and hence, are only applicable to vehicles with combustion engines with such parameters. We clearly do not consider engine parameters in our approach and suggest leaving this task to the EMS, which results in a more modular architecture.

To summarize, to the best of the authors' knowledge, none of the existing solutions incorporate advance knowledge of both vehicle speed and road grade information into the longitudinal controller (also called low level controller or actuator controller in many publications) and consider constraints at the same time. This combination is regarded as the main contribution of this paper. In contrary to gain scheduling and fuzzy solutions, the proposed approach aims to avoid high tuning effort, whilst improving tracking performance.

III. Nonlinear Model Predictive Controller

A. Problem formulation

Before stating the problem formulation we introduce the nonlinear longitudinal vehicle model as a combination of vehicle dynamics and powertrain equations.

Applying Newtons equilibrium of forces, including forces from a time invariant road grade influence, aerodynamic forces and rolling resistance, vehicle speed dynamics yields, with the notation described in Table I, to:

$$\begin{aligned}(m + I_{res})\; a = \frac{\eta_{pwt}\, R\, M_e - M_{br}}{r_{eff}} - \\ m\, g\; (\sin\varphi + C_{rr}\, \cos\varphi) - C_{aero}\, v^2 \quad (1)\end{aligned}$$

A detailed derivation of this equation is not presented here but can be found in [4]. Reordering and discretizing (1) with a sampling time T yields with $k \in \mathbb{N}$ to the function g:

$$\begin{aligned}a_k = \mathrm{g}(M_{w,k}, v_k, \varphi_k, m) = \frac{M_{w,k}}{(m + I_{res})\; r_{eff}} \quad (2)\\ - \frac{1}{m + I_{res}}\Big(mg\,(\sin\varphi_k + C_{rr}\cos\varphi_k) - C_{aero} v_k^2\Big)\end{aligned}$$

with $M_{w,k} = \eta_{pwt}\, R\, M_{e,k} - M_{br,k}$, and for the vehicle speed v the function f can be written:

$$\begin{aligned}v_{k+1} = \mathrm{f}(v_k, a_k, k) = \\ = T\, a_k + v_k = T\, \mathrm{g}(M_{w,k}, v_k, \varphi_k, m) + v_k \quad (3)\end{aligned}$$

Additionally, for a more realistic behavior, we consider first order dynamics to represent the delay of the torque response

$M_{w,k}$ to a torque demand M_{dem}. This is modeled with the time constant τ in a function h as:

$$M_{w,k} = \mathrm{h}(M_{dem,k}) = \frac{1}{\frac{\tau}{T}+1}\left(M_{dem,k} - M_{w,k-1}\right) + M_{w,k-1} \tag{4}$$

To take into account the difference between a more direct response of brake torque demand as well as engine torque reduction compared to engine torque build up, a different time constant τ is derived as follows:

$$\tau = \begin{cases} \tau_e, & \text{if} \quad (M_{dem} > M_{w,k-1}), \\ & \text{and } (M_{w,k-1} > M_{drag}), \\ \tau_{br}, & \text{otherwise.} \end{cases} \tag{5}$$

with M_{drag} being the (constant) maximum negative drag torque the engine can produce.

The full state equation f resolves with the input $u_k = M_{dem,k}$ to

$$v_{k+1} = T\,\mathrm{g}\big(\mathrm{h}(u_k), v_k, \varphi_k, \widehat{m}\big) + v_k \tag{6}$$

Remark 1: We highlight that in (III-A) the vehicle mass m is assumed constant during the whole prediction horizon, but changes in vehicle mass are considered by feeding the equation with the current estimate $\widehat{m}$ from the state and parameter observer from Section III-B.

We assume that at each time instant k a desired speed value $v_{des,k}$ is provided over a finite advance knowledge horizon of N_a steps. The objective is to find a control sequence $\{u_k | k \in \mathcal{N}_p\}$, with $\mathcal{N}_p = \{0, \ldots, N_p\}$, which is variable over a control horizon of N_c steps for all $k \in \{0, \ldots, N_c\}$ with $N_c < N_p$ and remains constant for all $k \in \{N_c+1, \ldots, N_p\}$, minimizing a performance index J over a prediction horizon of N_p steps, with $N_a, N_c, N_p \in \mathbb{N}$:

$$\begin{aligned} J(\mathbf{v}, \mathbf{v}_{des}, \mathbf{u}) = &\sum_{k=0}^{N_p} q\,(v_k - v_{des,k})^2 \\ &+ \sum_{k=0}^{N_c-1} \left(r\,u_k^2 + s\,(u_k - u_{k+1})^2\right) \end{aligned} \tag{7}$$

with $v_{des,k} = v_{des,N_a} \forall (k > N_a)$ and tunable parameters q to penalize deviations from the desired speed trajectory, r and s to penalize values and changes between subsequent values in the input sequence $\mathbf{u}$, respectively.

Now at each time step we have to solve the OCP defined as follows:

$$\begin{aligned} \underset{\mathbf{u}}{\text{minimize}} \quad & J(\mathbf{v}, \mathbf{v}_{des}, \mathbf{u}) && \text{(8a)} \\ \text{subject to} \quad & v_{k+1} = \mathrm{f}(v_k, u_k, k)\;\forall k \in \mathcal{N}_p, && \text{(8b)} \\ & v_k = \widehat{v}_0, && \text{(8c)} \\ & M_{w,\min} \le u_k \le M_{w,\max}, \forall k \in \mathcal{N}_p && \text{(8d)} \end{aligned}$$

with the estimated speed $\widehat{v}_0$ from the state observer in III-B, and the wheel torque limits $M_{w,\min} = \eta_{pwt}\,R\,M_{drag} - M_{br,\max}$ and $M_{w,\max} = \eta_{pwt}\,R\,M_{e,\max}$. To calculate the control inputs, at each time step the first element M_{dem} of the optimal input sequence $\mathbf{u}$ is split into demand values for brake and engine as follows:

$$M_{e,dem} = \begin{cases} \big(1/(\eta_{pwt}\,R)\big)\,M_{dem}, & (M_{dem} > M_{drag}) \\ M_{drag}, & (M_{dem} \le M_{drag}) \end{cases} \tag{9}$$

$$M_{br,dem} = \begin{cases} 0, & (M_{dem} > M_{drag}) \\ \eta_{pwt} R\,M_{drag} - M_{dem}, & (M_{dem} \le M_{drag}) \end{cases} \tag{10}$$

B. State observer

Because the speed signal measurement is noisy and the true value of the vehicle mass is not accessible, the combined state and parameter observer presented in [4] is used. This state observer is based on an Extended Kalman Filter and combines noisy measurements of vehicle speed and acceleration with the engine torque estimation calculated in the EMS and provides filtered estimations of vehicle speed and acceleration. Additionally, it is able to estimate the unknown vehicle mass. Due to the relation in (1), an accurate knowledge of the vehicle mass has a big influence on the correct prediction of vehicle speed as a reaction to engine and break torque input and improves tracking performance.

TABLE I

VEHICLE EQUATION SYMBOLS AND PARAMETER

Symbol	Description	[Unit]
v	Vehicle speed	[m/s]
M_w	Wheel torque	[Nm]
M_{dem}	Wheel torque demand	[Nm]
M_e	Engine net torque	[Nm]
M_{br}	Brake torque	[Nm]
φ	Road grade	[deg]
τ	Time constant of torque response	[s]
m	Vehicle mass	2000 [kg]
I_{res}	Mass resulting from powertrain inertia	50 [kg]
η_{pwt}	Powertrain efficiency	0.89 [-]
R	Powertrain ratio	8.446 [-]
r_{eff}	Effective wheel radius	0.3 [m]
M_{drag}	Maximum negative engine drag torque	-20 [Nm]
g	Gravitational constant	9.81 [N]
C_{rr}	Rolling resistance coefficient	0.015 [-]
C_{aero}	Aerodynamic drag coefficient	0.4262 [kg/m]

IV. PRESENTATION AND DISCUSSION OF RESULTS

To validate the proposed controller, a scenario similar to one occurring in a parking garage is performed in a simulation. The vehicle should follow a speed profile (see Figure 2) starting from 1 m/s with a step to 5 m/s at time t = 5 s. At time t = 10 s, speed is reduced in another step back to 1 m/s (to drive around a corner). Although step changes in speed are unreasonable, step response behavior brings useful insights to overall controller performance. At t = 15 s, the vehicle enters a ramp, which results in a step of road grade from 0 to 0.15 rad until at t = 20 s, the vehicle leaves the ramp and continues driving on a horizontal plane. Another speed step to 5 m/s is carried out at between t = 25 s and t = 30 s before between t = 40 s and t = 45 s, the vehicle is on a second ramp, only this time the ramp is steeper with a gradient of φ = 0.35 rad.

A. Simulation details

The simulation was implemented in Matlab and two simulations were carried out for comparison. The first was carried out using a conventional PI - controller and the second using the proposed adaptive NMPC controller (Figure 2).

The PI - controller has a nonlinear feed-forward term to calculate the steady state engine torque demand value and an anti-windup on the integral part. For simplicity and to keep tuning effort reasonable, no gain scheduling approach as proposed in some papers was used. The feed-forward term is a reverse model of (1), calculating the actual demand acceleration value by differentiation of the reference speed signal. The adaptive NMPC controller uses the state and parameter observer we developed in [4], and the controller parameters used are shown in Table II.

As a plant model, (1) was used with the parameter values given in Table I. The simulation was carried out with a sampling time of 0.01 s for both plant and PI - controller, whereas the NMPC controller was running at a reduced sampling time of 0.1 s. On the measurements for vehicle speed and acceleration, colored noise was added, before feeding the EKF to calculate filtered estimates of $\widehat{v}_k$ and the vehicle mass adaptation value $\widehat{m}_k$, of which the latter was only used for NMPC, since such a feature is not regarded state of the art.

The OCP was implemented without any performance optimization using Matlab's function fmincon with an interior point method. On a Windows Laptop with an Intel(R) Core(TM)i7-3520M CPU with 2.9GHz and 8GB RAM, execution time for the NMPC calculations was in average 0.07 s and a maximum value of 0.17 s.

TABLE II
SIMULATION PARAMETERS

Symbol	Description	Value
N_p	Prediction horizon	15
N_c	Control horizon	15
N_a	Advance knowledge horizon	10
q	Speed deviation weight	3e5
r	Input weight	0
s	Input difference weight	1
T_{nmpc}	Controller sampling time	0.1 [s]
T_s	Simulation / PI controller sampling time	0.01 [s]
τ_e	Time constant of engine torque response	0.15 [s]
τ_{br}	Time constant of brake torque response	0.05 [s]
$\widehat{m}_0$	Initial vehicle mass estimation	1200 [kg]

B. Result discussion

Comparing the two results, one can observe that the proposed adaptive NMPC outperforms the PI controller especially in showing no tendency to over- and undershoots, as they occur as a reaction to the step response and sudden change in road grade.

The overshoots with the PI controller are mainly caused by the need for a relatively high integral part in order to compensate for steady errors on ramps. A wrong torque demand calculation due to a wrong vehicle mass estimation $\widehat{m}_0$ in the feed-forward term of the PI controller increases the need for integral compensation.

Looking at the vehicle speed signal of the PI controller result in Figure 2 at t = 40 s, when entering the steep ramp, we can observe a big deviation from the reference speed. The PI controller cannot recover to the demand value until leaving the ramp, since engine torque is saturated by the engines' torque limit. This effect is well known to motorists driving an unknown car with a weaker engine they are used to, as it might happen when driving out of a garage with a rental car. The only way to avoid switching back gears to recover (which would increase fuel consumption) or stalling the engine if already in first gear, is to perform anticipated driving: accelerating shortly before entering the ramp to compensate for a delayed engine torque build up.

This is exactly the behavior of the NMPC. Looking at the resulting speed for the NMPC controller, we can see that at the reference speed steps and the road grade changes, the vehicle starts to accelerate (or decelerate) in an anticipated fashion before the step happens. Slightly before entering the ramps, the vehicle has built up enough speed reserve to overcome the impact on vehicle acceleration and stays on the reference value, even at the second steeper ramp, where the PI controller fails completely because of the engine torque being saturated by the torque limitation.

Another result (Table III) was obtained by comparing the average of engine torque values. Engine torque is correlated to fuel consumption of the vehicle, and hence gives an indication on fuel savings. This means that even though no estimation of fuel consumption was included in the cost function, and the controller was optimized for precise trajectory following, a reduction in fuel consumption of about 3% could be achieved. By setting the input weight r, which was kept zero during this simulation and penalizes torque demand, the controller could easily be tuned to further reduce fuel consumption, but, only at the expense of tracking performance. Additionally, the improvement in RMSE of speed deviation shows a reduction from 0.681 to 0.622.

TABLE III
RESULTS: AVERAGE ENGINE TORQUE AS AN INDICATION OF FUEL CONSUMPTION AND ROOT MEAN SQUARE ERROR (RMSE)

Controller	Average engine torque	relative	RMSE
PI	56.15	100%	0.681
NMPC	54.67	97.4%	0.622

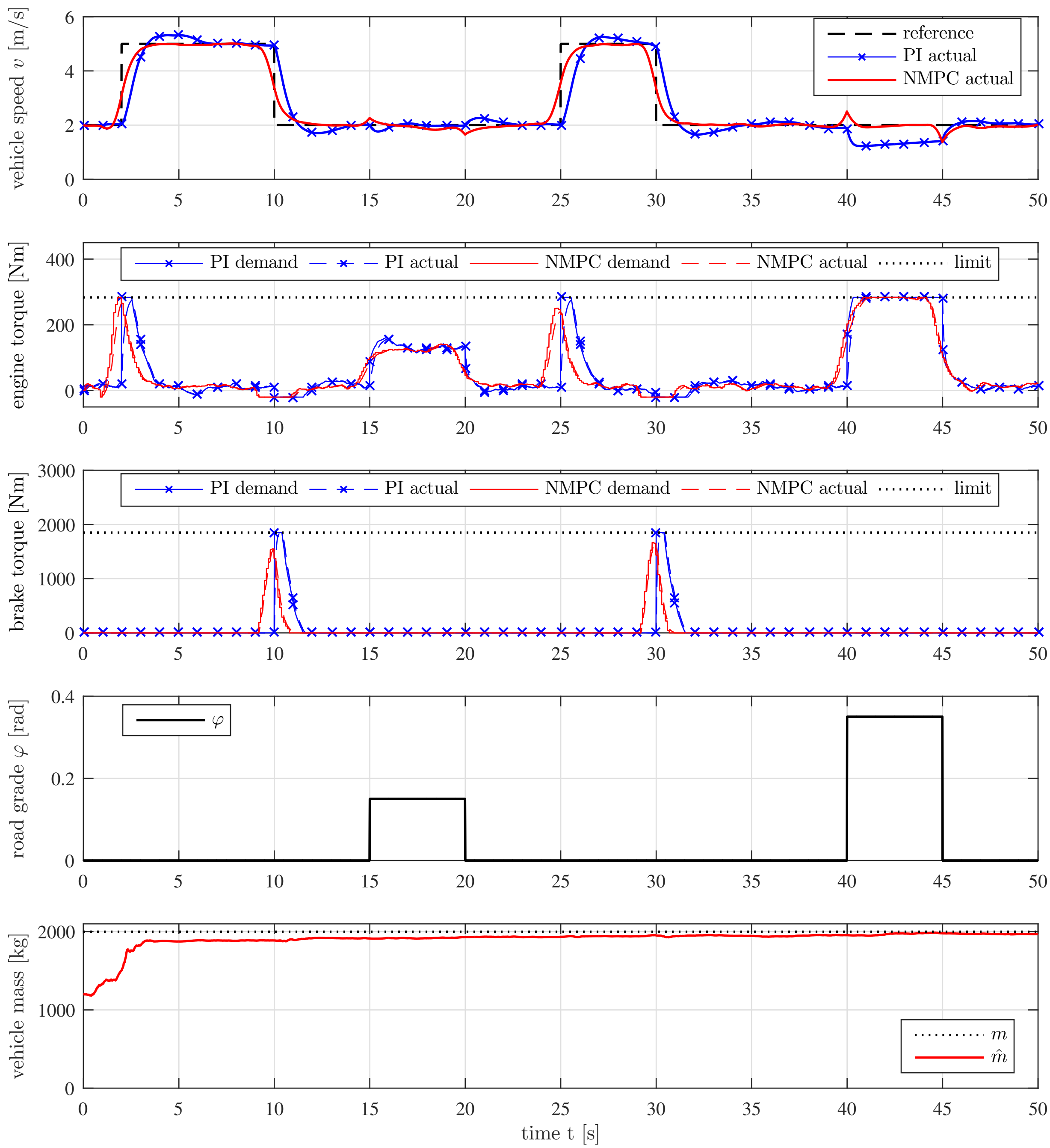

Fig. 2. Simulation results comparing conventional feed-forward PI controller and adaptive NMPC controller.

V. Conclusion and Outlook

An Adaptive Nonlinear Model Predictive Controller was presented for the task of longitudinal speed tracking control of an automated vehicle. The controller structure allows incorporating advance knowledge of the desired speed profile as well as road grade information, which is treated as external disturbance in other publications. Simulation results showed that this improves tracking results not only during regular driving, but also when entering steep ramps, as it occurs for example in parking garages. Using an Extended Kalman Filter to estimate the unknown vehicle mass, which has a big impact on forces acting on the vehicle on ramps and during acceleration, makes the approach robust to changes in the number of passengers or vehicle load. The resulting controller is easy to tune and designed to be integrated into an architecture for both fully automated vehicles as well as for ADAS systems. It could be shown, that even though the controller was tuned for optimal tracking performance, fuel consumption can be reduced.

Some aspects are planned to be examined in future: For the practical implementation on real time hardware, the computational time needed for solving the OCP needs to be reduced compared to the current non-optimized implementation in Matlab, for example by using a fast solver in the programming language C. Also, investigations on controller stability and robustness are planned. A validation of the concept in a more realistic car simulation tool will be done before vehicle tests should be carried out.

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