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A Comparison of two Predictive Approaches to Control the Longitudinal Dynamics of Electric Vehicles

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Abstract

In this contribution we compare two different approaches to the implementation of a Model Predictive Controller in an electric vehicle with respect to the quality of the solution and real-time applicability. The goal is to develop an intelligent cruise control in order to extend the vehicle range, i.e. to minimize energy consumption, by computing the optimal torque profile for a given track. On the one hand, a path-based linear model with strong simplifications regarding the vehicle dynamics is used. On the other hand, a nonlinear model is employed in which the dynamics of the mechanical and electrical subsystem are modeled.

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Keywords: Model Predictive Control, Automotive, Battery Electric Vehicle, Cruise Control

1. Introduction

Due to climate change and the rising concern about air quality in cities, battery electric vehicles (BEV) are regarded as one possibility to reduce emissions. Provided that the electric energy is harvested by renewable resources, BEVs produce neither CO_2 nor NO_x and significantly less particulate matter compared to conventional and hybrid vehicles. One of the major drawbacks of BEVs is the limited range. This disadvantage gets even more severe when taking into account the large discrepancies between stated range and real driving range [1]. In this paper we propose a model predictive controller (MPC) to optimize the energy consumption of a BEV for which the longitudinal vehicle dynamics are modeled.

There are various attempts to overcome the range limitations. Studies [2,3] have shown that the driving style has a large impact on energy consumption. Therefore, an intelligent controller acting on the drivetrain may enhance the range of BEVs without changing any of the core components, like the battery or the motor. Model predictive control has successfully been applied to conventional and electric cars in the last decade. In [4] the authors use a

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transformation to create a linear model to develop a fast Linear Model Predictive Controller (LMPC) with a quadratic cost function to improve the fuel efficiency of trucks. Dynamic Programming (DP) is another popular approach frequently used in the context of MPC and (automatic) cruise control [5] which is used in [6–8] to reduce the fuel consumption of conventional cars and trucks, respectively.

There are several publications for BEVs (e.g. [9,10]) which make use of the transformation proposed in [4], but they lack a controller capable of covering the entire speed range. This is overcome in [11] by using a DP algorithm to solve a path-discrete nonlinear cost function which is reevaluated in short time intervals.

In this paper we compare two fundamentally different MPC methods: a nonlinear approach (NMPC) based on a highly accurate model and a linear approach (LMPC) based on a simplified linear model and a quadratic cost function. The nonlinear model contains information about the characteristics of the vehicle battery and the resistance forces whereas the linear model only involves the mechanical parts (linearized longitudinal dynamics). On a specified route, we evaluate the quality of the solution and the computational effort of both controllers. As plant we use a validated model of a BEV which is still more accurate than the nonlinear model.

This paper is structured as follows: in Section 2 the general MPC framework is introduced and both problem formulations are given. In Section 3 we compare the approaches and discuss the implications for real-time applicability. The paper concludes with a summary and an outlook in Section 4.

2. Model Predictive Control

Model predictive control is currently a very active area of research. Its main idea is to utilize model based optimization in order to compute an optimal control in real-time. This theory can be used for linear [12] as well as nonlinear processes [13–15] and has its origin in the chemical industry because of its comparatively slow processes. The main concept is that while the system is running, the system input u is computed for a future time interval by solving an optimization problem. To this end, a model is used to predict the system behavior for n_p time steps in the future over the so-called *prediction horizon* H_p, as depicted in Figure 1(a). In order to simplify the optimization problem and reduce the computational complexity, an optimal input is computed only for n_c time steps within the *control horizon* H_c. On the interval $[H_c, H_p]$ the input remains unchanged. Then, the first value of the computed solution is applied to the system on the interval $[0, \Delta t]$ and the next optimization problem is solved on the interval $[\Delta t, \Delta t + H_p]$. Consequently, an optimal solution needs to be provided at every time step. Especially for systems with very fast dynamics, Δt has to be small which implies that the optimization problem has to be solved in a very short time. Depending on the model, the sampling time and the control and prediction horizon, this is still a computational challenge for today's technical systems.

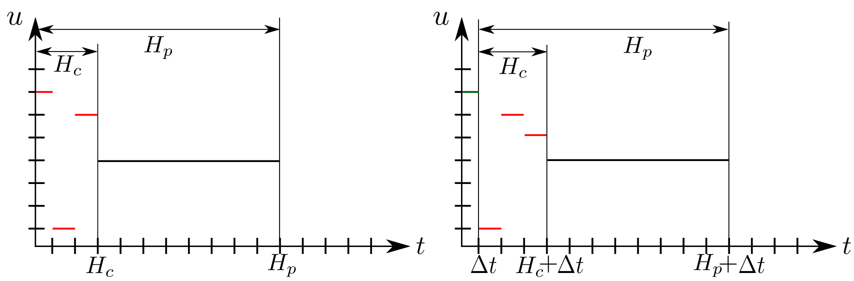


Fig. 1. The general model predictive control concept. (a) Solve an optimal control problem on the interval $[0, H_p]$. (b) Solve the next optimal control problem on the interval $[\Delta t, H_p + \Delta t]$.

Using model predictive control, a system can often be controlled much better than with conventional control strategies since in every time step an optimal input for the process with respect to a specified objective is calculated. The objectives may include, for example, following reference trajectories or minimizing the energy consumption of the system. Furthermore, constraints on the input as well as the state variables can be considered directly within the optimization algorithm.

In order to compare the two MPC approaches, we develop a test scenario with realistic speed limitations and stop signs (cf. Figure 3(b)). The objective is to compute the torque profile which minimizes the energy consumption while remaining close to the speed limit, i.e. we prescribe a reference speed $v_{ref}(t)$ which is always 90% of the speed limit $v_{max}(t)$. Moreover, we set a lower bound $v_{min}(t)$ which is 80% of the speed limit, respectively. During transient phases, e.g., a change in the speed limit from 50 km/h to 70 km/h, the constraints are relaxed. We denote this constraint generation process as *preprocessing*. In the following, we will adapt the general MPC framework presented above to develop an intelligent cruise control for a BEV using two approaches of different complexity.

2.1. Nonlinear MPC

First, we formulate the nonlinear MPC problem. In order to maintain differentiability, we implement the very accurate model described in [16] with slight simplifications, namely by setting the temperature to a constant value and by disregarding the so-called *protection circuit* of the battery. After some algebraic manipulations, this results in a system of four coupled, nonlinear ordinary differential equations for the state variables *vehicle speed* v, *battery state of charge* S and the long term and short term voltage drops $u_{d,L}$ and $u_{d,S}$:

$$\dot{v} = \frac{1}{m_v e + m_L}\left(\frac{u}{r_w} - \frac{1}{2}\rho_{air} A_v c_w(v) v^2 - m_v g \sin(\alpha) - m_v g c_r \cos(\alpha)\right), \tag{1}$$

$$\dot{S} = \frac{1}{2C_{cell} N_p N_s R_o}\left(\sqrt{(N_p N_s)^2 \left(V_{oc}(S) - u_{d,L} - u_{d,S}\right)^2 - 4 N_p N_s P_{el} R_o} - N_p N_s \left(V_{oc}(S) - u_{d,L} - u_{d,S}\right)\right), \tag{2}$$

$$\dot{u}_{d,L} = -\frac{1}{2C_{TL} N_p N_s R_o}\left(\frac{u_{d,L}}{R_{TL}} + \sqrt{(N_p N_s)^2 \left(V_{oc}(S) - u_{d,L} - u_{d,S}\right)^2 - 4 N_p N_s P_{el} R_o} - N_p N_s \left(V_{oc}(S) - u_{d,L} - u_{d,S}\right)\right), \tag{3}$$

$$\dot{u}_{d,S} = -\frac{1}{2C_{TS} N_p N_s R_o}\left(\frac{u_{d,S}}{R_{TS}} + \sqrt{(N_p N_s)^2 \left(V_{oc}(S) - u_{d,L} - u_{d,S}\right)^2 - 4 N_p N_s P_{el} R_o} - N_p N_s \left(V_{oc}(S) - u_{d,L} - u_{d,S}\right)\right). \tag{4}$$

We define the wheel torque u as input to the plant (Equation (1)). An overview of further constants and variables is shown in Table 1. For more details, we refer to [16]. The mechanical system (1) and the electrical system (2) – (4) are connected by the electrical efficiency $\eta = 0.9$:

$$P_{el} = \frac{P_{mech}}{\eta} = \frac{vu}{r_w \eta},$$

where r_w is the wheel radius. Finally, we can compute the battery current which needs to be constrained in order to prevent prohibitively large currents:

$$I = \frac{\sqrt{(N_p N_s)^2 \left(V_{oc}(S) - u_{d,L} - u_{d,S}\right)^2 - 4 N_p N_s P_{el} R_o} - N_p N_s \left(V_{oc}(S) - u_{d,L} - u_{d,S}\right)}{-2 N_s R_o}.$$

The *open circuit voltage* $V_{oc}(S)$ is approximated by a third order polynomial and all values have been set according to a real electric vehicle. Figure 2(a) shows an excellent agreement of the sophisticated BEV model described in [16] and the above stated differential equations.

Table 1. Specification of the problem parameters

Physical constants & environment				
Air density	gravity constant	street inclination		
ρ_{air}	g	α		
Mechanical parameters				
Vehicle and load mass	mass factor	wheel radius	reference surface	force coefficients
m_v, m_l	e	r_w	A_v	c_r, c_w
Electrical parameters				
Number of battery cells	Resistances	Capacities	Electrical power	Efficiency
N_s, N_p	R_o, R_{TL}, R_{TS}	C_{TL},C_{TS}	P_{el}	η

Having established the model, we can now formulate the optimal control problem that is solved on the prediction horizon H_p, where we set $H_c = H_p$ within each iteration of the MPC algorithm:

$$\begin{aligned} &\min_u J = -S(t+H_p) + \beta \int_t^{t+H_p} \left(v(t) - v_{ref}(t)\right)^2 dt, \qquad (5)\\ \text{s.t.} \quad & S,\ v,\ u_{d,L},\ u_{d,S} \text{ satisfy (1)–(4)},\\ & v_{min}(t) \leq v(t) \leq v_{max}(t),\\ & I_{min}(t) \leq I(t) \leq I_{max}(t), \end{aligned}$$

where β is a regularization parameter, typically of small value. The resulting optimal control problem (5) is transformed into a high-dimensional nonlinear optimization problem and solved by using an SQP [17] algorithm (cf. [18]).

2.2. Linear Model Predictive Control

As the name suggests, LMPC is based on a linear plant model within the controller. The plant model is commonly defined as a discrete state space model of the following form [19]:

$$\begin{aligned} \mathbf{x}(k+1) &= \mathbf{A}\mathbf{x}(k) + \mathbf{B}\mathbf{u}(k),\\ \mathbf{y}(k) &= \mathbf{C}\mathbf{x}(k) + \mathbf{D}\mathbf{u}(k). \end{aligned} \qquad (6)$$

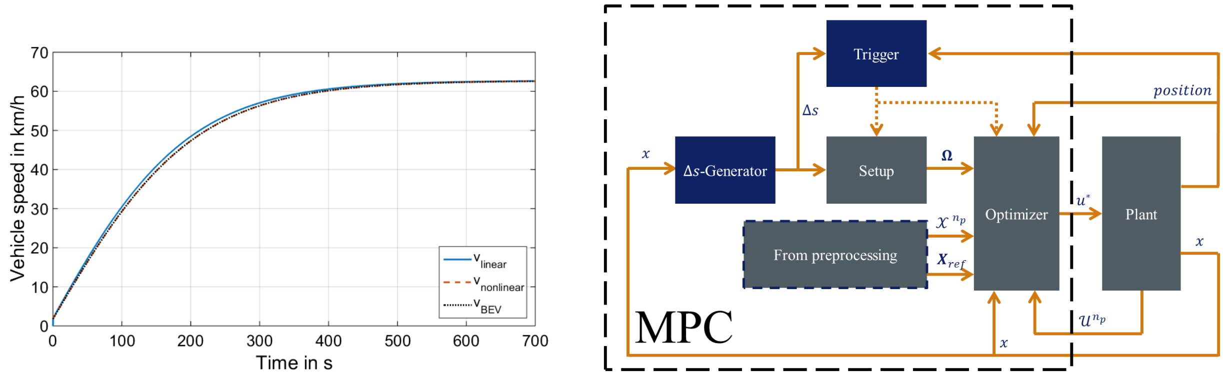
Here, $\mathbf{x}$ represents the vector of system states and $\mathbf{u}$ the vector of controlled inputs, where $\mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D}$ are the system matrix, the controlled input matrix, the output matrix and the direct-feedthrough matrix, repectively. In order to formulate the dynamics described in Section 2.1 as a linear model, we use a path-discrete kinetic energy formulation as described in [4,9,10]. The resulting model is linear with respect to the scalar state variable $x = v^2$. By the addition of a friction term b_{fr} to Equation (6) and by setting the states as output, we obtain:

$$\begin{aligned} x(k+1) &= ax(k) + bu(k) + b_{fr}\\ y(k) &= x(k). \end{aligned} \qquad (7)$$

In contrast to existing methods, we use a dynamic step size Δs. This enables the controller to cover low speeds more accurately. When comparing the dynamical behavior of the simplified model to the accurate simulation model [18], we observe a good agreement (cf. Figure 2(a)).

Equation (7) can be used iteratively to develop the prediction model:

$$\mathbf{X}(k) = \mathbf{\Phi}\mathbf{x}(k) + \mathbf{\Gamma}\mathbf{U}(k) + \mathbf{\Gamma}_{fr}. \qquad (8)$$



(a) (b)

Fig. 2. (a) Model validation for an input of u = 100 Nm = *const*. Blue: linear model, Dashed Red: nonlinear model, Dotted Black: Sophisticated BEV model. (b) Simulation and controller design.

Here, $\mathbf{X}(k) \in \mathscr{X}^{n_p}$ consists of the predicted states $\mathbf{x}(k+i), i = 1, \ldots, n_p$ and $\mathbf{U} \in \mathscr{U}^{n_p}$ consists of the corresponding inputs $u(k+i), i = 0, \ldots, n_p - 1$, where n_p denotes the number of steps in the prediction horizon and $\mathscr{X}^{n_p}$ and $\mathscr{U}^{n_p}$ are the feasible sets for the states and the inputs, respectively. Further information can be found in [19–21]. The resulting optimization problem is as follows:

$$\mathbf{U}^* = \arg\min_{\mathbf{U}} J = (x - x_{ref})^T q (x - x_{ref}) + (\mathbf{X} - \mathbf{X}_{ref})^T \mathbf{Q} (\mathbf{X} - \mathbf{X}_{ref}) + \mathbf{U}^T \mathbf{R} \mathbf{U}, \tag{9}$$

where $\mathbf{Q}$ and $\mathbf{R}$ define diagonal positive definite weight matrices for the inputs $\mathbf{U}$ and state deviations from the reference state $\mathbf{X}_{ref}$ along the prediction horizon H_p. The actual state deviation $x - x_{ref}$ is weighted by q. For simplicity, we omit the step indication (k) in problem (9). The problem is solved by an *interior-point-convex* algorithm implemented in the solver *quadprog* provided by the optimization toolbox of MATLAB.

The controller has been implemented in a Simulink model. Since Simulink is time based, a dynamic step size generator was created which triggers the MPC routine every Δs meters. A schematic view of the simulation and controller components is shown in Figure 2(b). As a consequence of the adaptive step length, the coefficients $a = a(\Delta s), b = b(\Delta s)$ and $b_{fr} = b_{fr}(\Delta s)$ are updated every time (cf. Equation (7)). Furthermore, the MPC block contains the optimization setup and and the optimizer. After a successful optimization the optimal input $u^* = \mathbf{U}^*(1)$ is given to the accurate plant model. The new state, i.e. the vehicle speed, and the constraints on the torque (governed by the battery management system) are fed back into the controller and the described process is repeated until the end of the prescribed scenario is reached.

3. Results

Both methods are applied to a realistic test scenario with varying speed limits from 0 km/h up to 100 km/h. Stop signs are modeled by an upper speed limit of 1.8 km/h. The artificial test track has a length of 6 km and, for simplicity, there is no street inclination profile. The objective is to compute optimal wheel torque profiles regarding energy efficiency and following a desired speed trajectory, which equals 90% of the speed limit. We use the following initial values:

$$v(t_0) = 45\,\text{km/h}, \qquad S(t_0) = 75\%, \qquad u_{d,L}(t_0) = 0\,\text{V}, \qquad u_{d,S}(t_0) = 0\,\text{V}.$$

3.1. Parameter Studies

The nonlinear problem formulation (5) exhibits numerous local optima which makes it crucial to determine initial guesses close to the optimal solution. However, we can make use of the MPC concept of a receding horizon, taking the optimal solution obtained in the previous loop as the initial guess. In this way, convergence behavior is achieved.

Before comparing the results to the linear approach, we perform a parameter study for the prediction horizon H_p and the regularization parameter β (cf. Equation (5)). As expected, a larger prediction horizon yields better results since the vehicle can react earlier to future events. This is most evident in situations where the speed limit changes or stop signs occur. With increasing value of the regularization parameter β, we observe a reduced *arrival time* t_a (cf. Table 2, where the reduction of battery charge $\Delta S := S(t_0) - S(t_a)$ is shown). This is also not surprising since the minimization of the battery charge reduction results in speed profiles close to the lower bound. Increasing β can be interpreted as changing the weighting between two competing objectives as in multiobjective optimization [22]. The same parameter study is performed for the linear model with the result that solutions with arrival times and reductions of battery charge similar to those obtained by the NMPC approach were obtained.

Table 2. Results of the parameter analysis (regarding the regularization parameter β).

β	ΔS	t_a
10^{-4}	3.69%	354 s
10^{-5}	3.52%	362 s
10^{-6}	3.28%	382 s

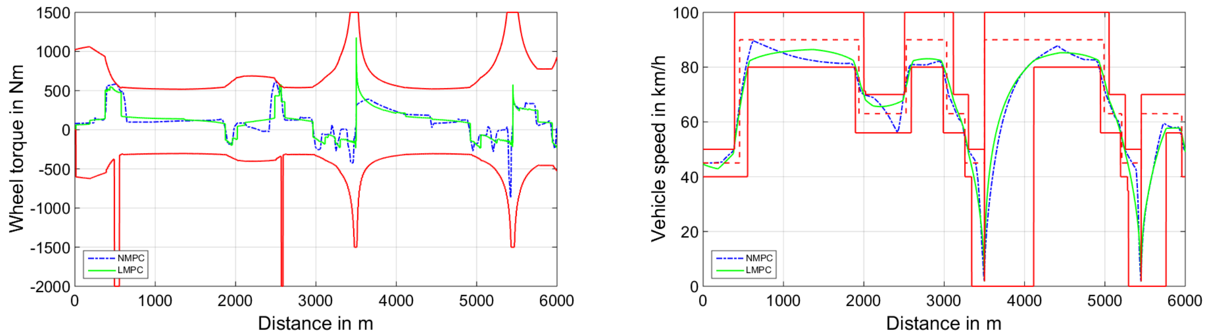
3.2. Comparison

In this section, we compare both approaches with respect to the quality of the solutions, i.e. the loss of battery charge, and the computational effort, respectively. Since the approaches are very different and therefore require different configurations, we compare the best results obtained with both approaches. We set $H_p = 24$ s and the step size to one second, i.e. $n_p = 24$.

Although the linear model possesses significantly simplified dynamics, the calculated solutions provide very good results. In particular, the results regarding the arrival time and the energy efficiency are of comparable quality to the solutions obtained with the NMPC approach. The results are visualized in Figures 3(a) and 3(b), where the speed and the torque profiles are compared. The numerical values are shown in Table 3. The NMPC approach has a slightly higher energy efficiency. However, the arrival time is larger so that the average velocity is lower. The difference in the arrival time is mainly caused by the way how the stop signs are approached, it could be observed that the nonlinear approach provides longer braking maneuvers than the linear approach (cf. Figure 3(a) at 3500 m and 5450 m). Moreover, the velocity profile obtained by LMPC appears to be more comfortable due to a smoother velocity profile, which seems to be a convenient side effect of the simplified dynamics. The depicted drops of the lower input boundary indicate the activation of the so-called *constraint management* due to infeasible solutions. Once activated the input constraints are modified and the LMPC algorithm is called again. This process repeats until a feasible solution is found. It has been observed that the slight deviation between plant and model, i.e. the plant-model-mismatch, causes the activation of the constraint management.

When considering the computational effort, we observe a crucial difference between the linear and the nonlinear approach. This is emphasized in Figure 4, where the average computational time for a single optimization is plotted as a function of the prediction horizon H_p. The LMPC using a quadratic programming method exhibits an approximately linear dependency whereas the NMPC approach (using an SQP-method and derivative approximations by finite differences) shows a quadratic dependency. For this reason, the NMPC approach can quickly lose its real-time applicability for step sizes Δt of order 1 s and below.

To conclude, we can state that both methods have proven to be real-time applicable, i.e. they can be solved in far less than $\Delta t = 1$ s, and yield satisfactory results. However, if done properly, deriving a linear model is beneficial with respect to the computational effort as well as the driving comfort with only a minimal loss in energy efficiency compared to the nonlinear approach.



(a) (b)

Fig. 3. Best results regarding energy efficiency. Solid red: Upper and lower limits. Dash-dotted blue: Nonlinear MPC. Solid green: Linear MPC. (a) Wheel torque trajectories. (b) Vehicle speed trajectories. Dashed red: Reference speed.

Table 3. Comparison of the best results obtained with the LMPC and NMPC approach.

Method	Prediction horizon H_p (= H_c)	Step size Δt	ΔS	t_a
LMPC	24 s	1 s	3.12%	366 s
NMPC	24 s	1 s	3.09%	394 s

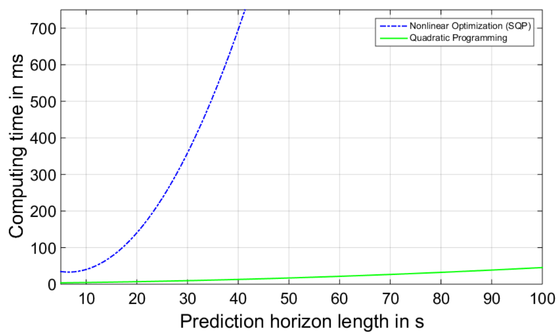


Fig. 4. Average computational time solving an optimization problem. Dash-dotted blue: Nonlinear Optimization routine *fmincon* using an SQP-method (used in NMPC). Green: Quadratic Programming routine *quadprog* (used in LMPC).

4. Conclusion and Outlook

In this contribution a comparison of a linear and a nonlinear model predictive control approach for a battery electric vehicle has been carried out. While the nonlinear approach utilizes a very accurate model of the EV, the linear model is highly simplified. However, due to appropriate modeling, the linear approach has proven to be competitive with respect to the solution quality. Moreover, the computational effort is significantly lower, especially for large prediction horizons, and the resulting speed profiles appear to be more comfortable for a potential driver. On the one hand, one can decrease the computing time of the nonlinear approach using analytically or automatically computed derivatives. On the other hand, the linear approach already provides very accurate results with significantly lower computational effort. Thus, it can be concluded that for range enhancement of BEVs a linear formulation seems to be favorable.

Consequently, we plan to further improve the linear model predictive controller in the future. The constraints on the state will be replaced by a penalty term in the cost functional, thereby further improving robustness and computational speed, since infeasible solutions and therefore recalculations will be avoided. Another point which we are going to address and which is a key feature to autonomous driving is the implementation of a distance control. Furthermore, the correlation with the heating ventilation and air-conditioning is currently analyzed [23] and will be integrated in the MPC framework. Additionally, we will investigate the influence of route topology. We are considering to compare our approaches with test drives.

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