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Energy-optimal adaptive cruise control combining model predictive control and dynamic programming

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ABSTRACT

In this paper a novel approach for energy-optimal adaptive cruise control (ACC) combining model predictive control (MPC) and dynamic programming (DP) is presented. The approach uses knowledge about a given route to precalculate a position-dependent energy-optimal speed trajectory using DP while taking information like speed limits, road slope, and travel time into account during the optimization. A simple MPC framework is used to control the traction force of the host vehicle such that the vehicle speed follows the energy-optimal speed trajectory as good as possible while ensuring safety-related constraints like distance to a preceding vehicle or speed limits. To show the benefits of the approach, a comparison of the energy consumption between the host vehicle and the preceding vehicle on the same route is performed. For the speed profile of the preceding vehicle, data from real test drives is used. Simulations show that the approach leads to a significant reduction of the energy consumption compared to the preceding vehicle on the same route. Furthermore, the simulations indicate that the approach achieves high energy savings even with a poor prediction model for the preceding car. Moreover, the approach has shown to run very fast, indicating its real-time capability.

1. Introduction

In recent years the reduction of the energy consumption in vehicles has become a major research topic due to a variety of reasons. From an economical point of view the reduction in energy consumption leads e.g. to a more cost efficient transportation of goods or passengers as less fuel is needed for the same route. Furthermore, by reducing the energy consumption also the CO_2 emissions are reduced. The transportation sector contributes with 23% to the world's CO_2 emissions related to fuel combustion (IEA, 2016) and has therefore a great potential for reductions. As a result, reducing the energy consumption is very appealing for meeting emission requirements for manufacturers as well as governments. From a functional point of view the reduced energy consumption is also very beneficial as this directly tackles one of the major drawbacks of current electric vehicles, namely the limited range. Reduced energy consumption directly converts to an increase in the possible maximum range or, indirectly, in a reduced charging time.

Considerable research has been devoted to constructive approaches like more efficient engine designs (downsizing) or lightweight materials. Another more recent research direction is focused on the benefits that can be obtained by the control of the complete vehicle. One widely used approach to reduce the energy consumption is the adjustment of the driving behavior in an efficient way (eco-driving), which has been shown to be very promising for reducing the fuel consumption and emissions in various traffic scenarios (Barth & Boriboonsomsin, 2009; McDonough et al., 2012, 2013; Mierlo, Maggetto, de Burgwal, & Gense, 2004; Rolim, Baptista, Duarte, & Farias, 2014).

This led to the development of eco-driving assistance systems. The main goal of such a system is to provide information via a human machine interface (HMI) to the driver on how to adjust his or her driving behavior to reduce the energy consumption and emissions. The literature is rich in papers that formulate the determination of an optimal driving strategy as an optimization problem (Sciarretta, De Nunzio, & Ojeda, 2015). For the realization of such a framework many different strategies have been proposed.

In Wu, Zhao, and Ou (2011) the eco-driving assistance framework is formulated as an online optimization problem which outputs an optimal acceleration or deceleration to a driver or an autonomous vehicle. The optimization is based on a representation of the fuel consumption depending on the vehicle speed. Furthermore, constraints regarding the traffic, e.g. headway spacing, speed limits, and traffic lights, are considered during the optimization. Simulations for this approach have shown good reductions in fuel consumption. However, the approach focuses mainly on pure reduction of fuel consumption and uses no

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prediction model to describe the environment which may be beneficial to determine the optimal acceleration/deceleration. In addition no information about the topology of the road ahead is used which have been shown to have a major impact on the optimal driving strategy (Hooker, 1988). Other approaches use knowledge about a given route and its parameters such as road slope, maximum speeds, and curvature to derive an optimal speed trajectory. A very common approach is to formulate an optimization problem based on a model of the vehicle and its energy/fuel consumption which is then solved via dynamic programming (DP) (Bellman & Dreyfus, 1962), leading to a globally optimal driving strategy for a given route. In Dib, Serrao, and Sciarretta (2011), Dib, Chasse, Di Domenico, Moulin, and Sciarretta (2012), Lin, Görges, and Liu (2014) and Nouveliere, Mammar, and Luu (2012) dynamic programming is used to obtain an optimal driving strategy for a conventional or electric vehicle. In all cases a reduction in the fuel or energy consumption could be achieved in simulations or test drives. However, one major problem of DP is that it is very computation-intensive. Due to this it is not well suited for an online optimization requiring real-time capability. Therefore, most approaches calculate a speed profile for a given route beforehand and display it during driving on the HMI. These approaches do not consider information about the surrounding traffic in the optimization problem itself. Therefore, the speed proposal may not reflect the appropriate action with regard to the traffic state. This is often addressed by adding equipment for headway measurement (e.g. lidar, radar) and adding distance warnings to the HMI to be followed by the driver. A different approach is proposed in Ozatay et al. (2014) where a cloud-based concept is presented for addressing the computational complexity of DP.

In more recent research the reduction of the energy consumption is considered along the problem of interfering traffic based on advanced driver assistance systems (ADAS). ADAS have shown to increase the safety in many accident scenarios (Hummel, Kühn, Bende, & Lang, 2011). With ADAS like the adaptive cruise control (ACC) many vehicles are by now endowed with the technical equipment for implementing energy efficient driving strategies without direct interaction with the driver. Moreover, ACC provides additional safety benefits due to the distance control functionality and therefore addresses interfering traffic easily. The availability of an interface for control of the vehicle speed and acceleration has inspired researchers to combine ACC functionality with different control strategies to improve energy efficiency and safety alike.

For example in Khayyam, Nahavandi, and Davis (2012) an adaptive neuro-fuzzy inference system based ACC is proposed considering driving resistances and a look-ahead strategy to predict future road slopes in order to achieve a fuel efficient driving strategy for the ACC.

Another popular approach is model predictive control (MPC) that is used to derive an optimal control sequence with the main objective of reducing the fuel consumption while ensuring safety- or ride comfort-related constraints. A great number of realizations for such a framework are reported in the literature. An approach on combining ACC and MPC was given in Luo, Liu, Li, and Wang (2010) with the goal of providing ride comfort, fuel economy, safety, and car-following. In this approach fuel economy is addressed by smoothing the acceleration which has been shown to be very beneficial in Mierlo et al. (2004). Ride comfort and safety criteria are easily addressed in MPC by introducing constraints on e.g. maximum speed and acceleration as well as inter-vehicle distance. In Li, Li, Rajamani, and Wang (2011) the objectives of fuel economy, ride comfort, and safety criteria are introduced as three different cost functions and then formulated as a single MPC optimization problem. This paper also uses constraints to further limit acceleration and jerk. An additional approach that addresses fuel efficiency by minimizing the acceleration is suggested in Zhang and Vahidi (2011) where a stochastic model (Markov chain) is used to predict the velocity of a preceding vehicle. In Kamal, Imura, Hayakawa, Ohata, and Aihara (2014) an approach is presented which uses MPC to control a host vehicle in dense traffic and improve the traffic flow by keeping a safe inter vehicle distance while reducing acceleration and braking and therefore the fuel consumption. It is shown that by including information about several preceding as well as a single following vehicle in the prediction model of the MPC a single host vehicle is capable of reducing the impact of jamming waves. Another very recent approach for an MPC-based eco ACC is presented in Turri, Kim, Guanetti, Johansson, and Borrelli (2017) which shows good reductions in fuel consumption and fast computation times by avoiding unnecessary braking while still maintaining a safe distance and reducing the jerk in a car following scenario.

More recent approaches use models of the energy consumption as cost function to handle energy efficiency in MPC similar as in DP-based eco-driving systems. Compared to DP-based eco-driving systems most MPC frameworks need to use simplified or approximate models of the energy consumption. The reason for this is that MPC is based on online optimization and therefore needs to be solved very fast making a simple problem formulation crucial for real-time capability. The online optimization, however, allows to additionally consider information about topology and current traffic conditions by including data from digital maps and prediction models of preceding traffic in the optimization problem, resulting in a more realistic optimal driving strategy. With the flexibility that the online optimization offers the MPC scheme is very beneficial for a wide variety of applications, e.g. fuel-optimal control of rendezvous maneuvers for vehicles as suggested in Sciarretta and Guzzella (2005). The biggest challenge with using MPC is to find a good tradeoff between complexity of the optimization problem (prediction model of preceding vehicle, model of energy consumption and constraints) and performance of the control scheme without losing real-time capability.

A piecewise-linear approximation of the fuel consumption map for a fixed gear of a conventional vehicle is used as cost function to achieve fuel efficiency in Moser, Waschl, Kirchsteiger, Schmied, and del Re (2015) and Schmied, Waschl, and del Re (2015). In the first paper a second-order polynomial nonlinear autoregressive model is identified to predict the behavior of a preceding vehicle based on measurements of the traffic in an urban environment. A high reduction in fuel consumption could be achieved as well as real-time capability, however, with a prediction model limited to urban traffic. The second paper considers different stochastic approaches for the velocity prediction of the preceding vehicle using additional data from vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. The paper indicates high reductions in fuel consumption but does not mention its real-time capability. In all of the papers mentioned above the influence of the driving resistance, e.g. factors like road slopes, which can have significant influence on the fuel efficiency are not considered in the model.

The influence of the driving resistance and road geometry is often addressed when improving the fuel efficiency of heavy-duty vehicles as can be seen e.g. in Hellström, Ivarsson, Åslund, and Nielsen (2009) and Huang, Bevly, Schnick, and Li (2008). In both papers a reduction in fuel consumption could be reached without increasing trip time. A very recent approach for fuel-efficient platooning of heavy duty vehicles (HDVs) on highways based on MPC is presented in Turri, Besselink, and Johansson (2017). In this approach a fuel-efficient speed trajectory is calculated for the whole platoon of HDVs. An underlying MPC control scheme is then adopted to follow the speed trajectory while ensuring a safe operation of the platoon. For both, MPC and dynamic programming, information about speed limits and road slope are regarded during optimization. The results show that this approach leads to good fuel savings. However, (Turri, Besselink, & Johansson, 2017) do not consider the handling of interfering traffic and the application of the approach to other vehicle classes.

In this paper a novel approach for energy-efficient ACC combining MPC and DP is proposed. The MPC is used for following an energy-optimal speed trajectory while additionally regarding preceding traffic and ensuring various constraints. The energy-optimal speed trajectory is calculated offline for the given route before the trip using DP and