Preprints of the 19th World Congress
The International Federation of Automatic Control
Cape Town, South Africa. August 24-29, 2014

An Adaptive Driver Model for Driving Cycle Prediction in the Intelligent Truck

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Abstract: Intelligent vehicles have significant potential to improve the worldwide traffic situation with regard to both safety and efficiency. Commercial vehicles are an ideal application of intelligent driver assistance systems because of their precisely defined operational limits and professional drivers. For many driver assistance systems, a prediction of the future driving cycle is necessary. This research presents an approach towards predicting the future velocity profile using a gain scheduled driver model together with a longitudinal vehicle model. The parameters of the driver model are estimated during vehicle operation using recursive least squares identification. Assuming repeated operation of the vehicle on the same route, the driver model is supplied with the desired velocity at a particular position and outputs the predicted velocity trajectory. In a case study, the benefit of prediction is shown in a hybrid hydraulic truck with predictive optimized energy management.

Keywords: Driving cycle prediction, intelligent truck, driver model, gain scheduling, recursive least squares, predictive energy management.

1. INTRODUCTION

During the last decades, research in both academia and industry has shown an ongoing interest in intelligent systems related to automotive applications, see Bishop [2000] for an overview. An increase in vehicle safety was possible through driver assistance systems such as electronic braking systems, adaptive cruise control systems or collision avoidance systems. The current improvements regarding vehicle efficiency are not only achieved through alternative propulsion systems, but also through intelligent energy management systems, e.g., in hybrid or electric vehicles (Back et al. [2002], Hellstroem et al. [2007], Deppen et al. [2011]). Many driver assistance systems require a prediction of driver or vehicle behavior. Typical predictive systems can be found in the field of powertrain management systems, e.g., predictive shifting strategies (Mueller et al. [2004]) or predictive energy distribution in hybrid vehicles (Kessels and van den Bosch [2007], Kaszynski and Sawodny [2011]). Predictive energy management has many advantages over rule-based approaches that do not incorporate any forecasting techniques. Including information about the future driving cycle enables the intelligent vehicle to operate in the most efficient setting while guaranteeing good drivability at the same time. A large number of research projects therefore concentrates on predictive controllers in passenger vehicles or trucks, e.g. Back et al. [2002], Kaszynski and Sawodny [2011], but only few approaches towards the problem of driving cycle prediction have been reported (Hermes et al. [2009], Bender et al. [2013]). One promising field for predictive systems are commercial vehicles. These vehicles usually operate within precisely defined operating conditions, i.e. they perform one typical task over and over again. Typical examples are distribution vehicles, garbage trucks or city buses. Additionally, these vehicles are characterized by heavy weight and frequent stop-and-go behavior, which makes them very promising candidates for hybridization (see Wu et al. [2004], Baseley et al. [2007]). Since these vehicles always operate in the same urban region, it is possible to associate typical velocities with a particular vehicle position as shown by Bender et al. [2013]. However, learning complete velocity trajectories results in the need for a large database and a high computational effort, which is typically not applicable in standard electronic control units (ECUs). In this work, velocity trajectory prediction is achieved through a longitudinal vehicle model in combination with an adaptive driver model. As an input for the driver model, a target velocity associated with the current vehicle position is supplied by a database that has been built up during previous vehicle operations on the same route. The driver model is based on the intelligent driver model (Kesting et al. [2010]) with gear dependent acceleration exponents. The prediction approach presented within this work has the advantage of low complexity and interpretable parameters. The driver model parameters can be identified from measurement data, but also during vehicle operation using the recursive least squares algorithm. The remainder of this paper is organized as follows: Section 2 outlines the longitudinal dynamics of the considered 7.5 t truck and the model of the vehicle with its main components. Section 3 focuses on the development of a prediction system consisting of a combined driver and vehicle control loop, identification of its parameters during vehicle operation and validating its capability of predicting driver behavior. Section 4 provides simulation results from a case study, namely a hybrid hydraulic truck

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with predictive energy management optimization. Final conclusions and an outlook on future work are given in Section 5.

2. VEHICLE MODEL

A mathematical model of the vehicle is needed both for the prediction system and for simulation purposes. Within the developed prediction algorithm, the vehicle model represents the plant of the feedback loop. Modeling of the vehicle components was performed similar to previous work (Guzzella and Sciarretta [2007], Kaszynski and Sawodny [2011]). Note that for the developed prediction system, a forward model is used, i.e., the simulation input is given by a desired velocity and the simulation outputs are the actual velocity trajectory together with the corresponding signals for the current gear, the fuel consumption etc. As a direct consequence, a driver model is needed as a controller in order to generate the inputs necessary for the vehicle model.

2.1 Longitudinal Dynamics

For our purposes, a restriction to the vehicle's longitudinal dynamics is sufficient. Prediction of the lateral behavior is not part of this work and therefore not included in either the vehicle or the driver model. The longitudinal dynamics are given by

$$J\dot{\omega} = T_{\mathrm{prop}} - T_{\mathrm{ext}}, \tag{1}$$

where J is the combined moment of inertia, ω is the circular frequency determined by the effective wheel radius r and the vehicle velocity v,

$$\omega = \frac{v}{r}. \tag{2}$$

T_{prop} is the resulting propulsion torque caused by the vehicle propulsion system. For the case of a conventional diesel engine, the propulsion torque is given by

$$T_{\mathrm{prop}} = T_{\mathrm{d}}\mu_{\mathrm{g}}\mu_{\mathrm{diff}} + T_{\mathrm{brake}}, \tag{3}$$

where T_{d} is the torque provided by the diesel engine, μ_{g} and μ_{diff} are the torque conversion ratios of the gearbox and the differential, respectively, and T_{brake} is the torque delivered by the brake. T_{ext} consists of external resistance forces such as air drag and rolling resistance, see e.g. Kaszynski and Sawodny [2011].

2.2 Vehicle Components

The diesel engine is modeled via a lookup-table and serves as a source of torque T_{d} depending on the rotational speed n_{d}. The maximum diesel torque $T_{\mathrm{d,max}}$ at time instant t_k is given by

$$T_{\mathrm{d,max}}(t_k) = f_{\mathrm{d}}(n_{\mathrm{d}}(t_k)). \tag{4}$$

We assume the vehicle to have either an automated or a manual gearbox. Shifting is performed according to a strategy that uses the current gear G_k, the current vehicle velocity v_k and the current diesel engine load to determine the appropriate subsequent gear G_{k+1},

$$G_{k+1} = f_{\mathrm{G}}\left(G_k, v_k, \frac{T_{\mathrm{d},k}}{T_{\mathrm{d,max},k}}\right). \tag{5}$$

The intelligent truck is equipped with the standard CAN bus interface for in-vehicle communication. Precise vehicle localization can be achieved using differential satellite positioning in combination with inertial sensors and sensor fusion techniques.

3. PREDICTION SYSTEM

The prediction system provides the intelligent vehicle with a prediction of the anticipated velocity trajectory, see Fig. 1. In a first step, the final velocity desired by the driver, $\hat{v}_{\mathrm{target}}$, needs to be predicted. This is achieved using the assumption that the vehicle is operated on the same route repeatedly. Hence, typical target velocities can be associated with a particular vehicle position. These target values are stored in a database and used later for prediction, when the vehicle arrives at the same position again. The desired velocity is then used as an input for a simulated control loop consisting of an adaptive driver model and the above outlined vehicle model. The control loop outputs a complete anticipated velocity trajectory $\hat{v}(t)$ for the following acceleration process. Prediction can be performed whenever the vehicle comes to a halt. In the following, variables referring to prediction values are indicated by a hat-superscript.

3.1 Prediction of the Desired Velocity

Many vehicles operate on the same route repeatedly, e.g., distribution vehicles or garbage trucks. These vehicles always reach similar velocities at particular locations. This is due to environmental influences (road curvature, traffic lights, speed limits, position of garbage containers) and driver characteristics. Therefore, a database can be built up that associates specific vehicle speeds with a particular vehicle position given through GPS coordinates. Previous work used this fact to iteratively learn and save complete velocity trajectories (Bender et al. [2013]). However, this approach resulted in high efforts regarding storage space and computation, and is therefore not applicable in standard ECUs. Hence, in the presented approach we only store a single value (the desired velocity) for every stopping position. When the vehicle comes to a halt at the same position repeatedly, the stored value is iteratively adapted using weighted averaging (Bender et al. [2013]). Vehicle stopping positions are defined by

$$\mathbf{\Theta}^{(i)} = \left\{[x(t_k), y(t_k)]^T \mid v(t_{k-1}) > 0,\, v(t_k) = 0\right\} \tag{6}$$

Each stopping position $\mathbf{\Theta}^{(i)}$ is associated with a particular velocity reached during the acceleration process following the halt at $\mathbf{\Theta}^{(i)}$,

$$v_{\mathrm{target}}^{(i)} = \left\{\max v(t),\ t \in \mathcal{T}^{(i)}\right\}. \tag{7}$$

$\mathcal{T}^{(i)}$ denotes the time interval corresponding to the velocity profile occurring between vehicle stops $\mathbf{\Theta}^{(i)}$ and $\mathbf{\Theta}^{(i+1)}$. A database update is performed after the vehicle has finished its operation. After the first operation on a new route, the database is initialized by

$$\hat{v}_{\mathrm{target},0}^{(i)} = v_{\mathrm{target}}^{(i)},\ \forall\, i = 1, ..., N, \tag{8}$$

$$\hat{\mathbf{\Theta}}_0^{(i)} = \mathbf{\Theta}^{(i)},\ \forall\, i = 1, ..., N. \tag{9}$$

N denotes the number of appeared acceleration intervals $\mathcal{T}$. After consecutive operations, the saved values are

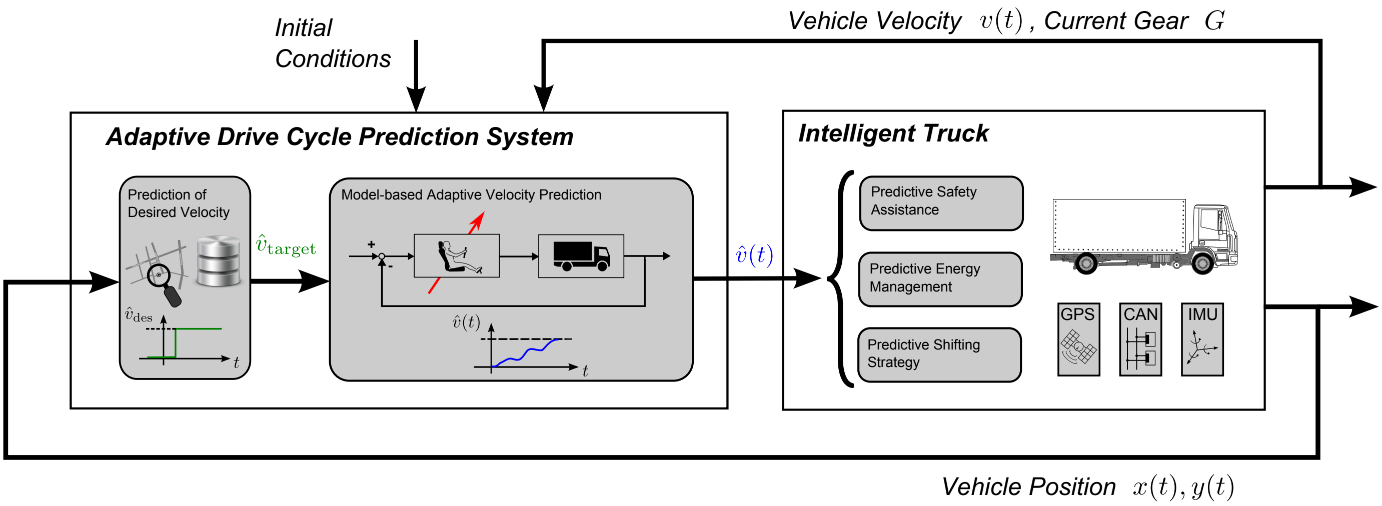

Fig. 1. Overall setup consisting of the adaptive drive cycle prediction system and the intelligent truck including predictive assistance systems. Inputs to the prediction system are the vehicle velocity $v(t)$, the current vehicle position $[x(t), y(t)]$ and initial conditions (gear, state of charge). The prediction system outputs the anticipated velocity trajectory $\hat{v}(t)$. Note that prediction is performed once for each vehicle stop.

adapted whenever a similarity criterion based on the stopping positions is satisfied,

$$\left.\begin{aligned} \hat{v}^{(j)}_{\text{target},c+1} &= \frac{c \cdot \hat{v}^{(j)}_{\text{target},c} + v^{(i)}_{\text{target}}}{c+1} \\ \hat{\boldsymbol{\Theta}}^{(j)}_{c+1} &= \frac{c \cdot \hat{\boldsymbol{\Theta}}^{(j)}_{c} + \boldsymbol{\Theta}^{(i)}}{c+1} \end{aligned}\right\} \begin{array}{l} \text{if} \left\|\hat{\boldsymbol{\Theta}}^{(j)} - \boldsymbol{\Theta}^{(i)}\right\| \leq \delta \\ \forall\, i = 1, ..., N, \\ \forall\, j = 1, ..., M. \end{array} \tag{10}$$

Therein, N denotes the number of acceleration intervals appearing in the last cycle and M denotes the number of entries already included in the database. The subscript c equals the number of previously identified acceleration intervals that have been included for determining $\hat{v}^{(j)}_{\text{target},c}$. If a new stopping position has appeared in the last cycle, the database is extended similarly to the initialization given by Eqs. (8)-(9).

3.2 Driver Model

Driver models are a well investigated topic in automotive research, see e.g. Hess and Modjtahedzadeh [1990] or Ungoren and Peng [2005]. They can serve a variety of purposes, e.g. the simulation of reference driving cycles (Bender et al. [2013]) or the assessment of traffic flow (Kesting et al. [2010]). Generally speaking, the driver represents the controller in a feedback loop consisting of the driver and the vehicle. Depending on the application field of the driver model, different levels of complexity are appropriate. In this work, the driver model needs to satisfy the following requirements:

- small number of parameters for fast tuning
- good representation of longitudinal acceleration behavior in the 0-70 km/h interval
- capability for online adaptation of the model parameters

One of the first driver models was presented by Hess and Modjtahedzadeh [1990]. This work follows a control theoretic approach by modeling the driver as a controller but primarily focuses on human steering behavior. A variety of modeling approaches include preview elements, e.g. MacAdam [1980]. Note that most driver models focus on the lateral dynamics in order to simulate lane changing or collision avoidance behavior, e.g. Moon and Choi [2011]. In contrast, the driver model presented here focuses on the longitudinal vehicle behavior.

For our purpose, we modify the intelligent driver model introduced by Kesting et al. [2010] to build a controller

$$\hat{u}(t;\delta) = \left[1 - \left(\frac{\hat{v}(t)}{\hat{v}_{\text{des}}}\right)^{\delta}\right]. \tag{11}$$

This driver model shows good free-road acceleration behavior for both freeway and city traffic and has the advantage of only a single model parameter. However, the nonlinearity of the vehicle model calls for different free acceleration exponents δ depending on the currently chosen gear. This problem is addressed through the concept of gain scheduling, see e.g. Åström and Wittenmark [2008]. For each gear, a different δ is applied, which results in a total number of N_{G} parameters, where N_{G} is the number of available gears. Note that gain scheduling results in a switching controller

$$\hat{u}_{\text{G}}(t;\delta) = \begin{cases} \hat{u}(t;\delta_1) & \text{if } \hat{G} = 1 \\ \hat{u}(t;\delta_2) & \text{if } \hat{G} = 2 \\ \vdots & \\ \hat{u}(t;\delta_{\text{G}}) & \text{if } \hat{G} = N_{\text{G}}. \end{cases} \tag{12}$$

The input to the control loop consisting of driver and vehicle model is given through

$$\hat{v}_{\text{des}}(t;\hat{G}) = \begin{cases} \min(\hat{v}_{target}, v_{ST_{1,2}}) & \text{if } \hat{G} = 1 \\ \min(\hat{v}_{target}, v_{ST_{2,3}}) & \text{if } \hat{G} = 2 \\ \vdots & \\ \min(\hat{v}_{target}, v_{ST_{N_{\text{G}}-1,N_{\text{G}}}}), & \text{if } \hat{G} = N_{\text{G}}. \end{cases} \tag{13}$$

with $v_{ST_{r,s}}$ being shifting thresholds that indicate typical velocities at which a change of gears usually takes place.

Hence, the desired velocity is constructed of steps with values depending on the predicted current gear $\hat{G}$ and the predicted target velocity $\hat{v}_{\text{target}}$. According to Eq. (11), the controller variable always satisfies $u \in [0,1]$. Additionally, we limit its rate of growth for more realistic behavior. The control variable is then used to determine how much of the maximum propulsion torque is applied to the vehicle model during acceleration ($\hat{T}_{\text{brake}} = 0$),

$$\hat{T}_{\text{prop}} = \hat{u}_{\text{G}}(t) \cdot \hat{T}_{\text{prop,max}}. \quad (14)$$

Figure 2 illustrates the control loop consisting of the vehicle and the adaptive driver model.

3.3 Recursive Driver Identification

The various gains for the driver model need to be adapted according to individual driver behavior. In order to allow for online adaptation of the parameters, a recursive least squares (RLS) approach was chosen due to its low computational requirements and continuous operation mode (see e.g. Nelles [2001]). Combining the vehicle dynamics with the driver model leads to

$$J\frac{\dot{v}}{r} = \left[1 - \left(\frac{v(t)}{\hat{v}_{\text{des}}}\right)^{\delta}\right] T_{\text{prop,max}} - T_{\text{ext}}. \quad (15)$$

where the prediction variables $\hat{v}$ and $\hat{T}_{\text{prop,max}}$ have been replaced with the variables corresponding to the actual vehicle behavior. For the RLS framework to be applicable, the parameter to be identified θ needs to be in a linear relationship with the measurement output y and the regression vector ϕ,

$$y = \theta \cdot \phi. \quad (16)$$

Hence, we modify Eq. (15) to obtain

$$\underbrace{\lg\left(1 - \frac{J\frac{\dot{v}}{r} + T_{\text{ext}}}{T_{\text{prop,max}}}\right)}_{=y} = \underbrace{\delta}_{=\theta} \cdot \underbrace{\lg\left(\frac{v(t)}{\hat{v}_{\text{des}}}\right)}_{=\phi}. \quad (17)$$

Both y and ϕ can be computed from available CAN bus data and known vehicle parameters. In order to identify the various parameters δ_{G}, the RLS equations

$$L_k = \frac{P_{k-1}\phi_k}{\lambda + \phi_k^2 p_{k-1}} \quad (18)$$

$$\theta_k = \theta_{k-1} + L_k\left[y_k - \phi_k\theta_{k-1}\right] \quad (19)$$

$$P_k = \frac{1}{\lambda}\left[1 - L_k\phi_k\right] p_{k-1} \quad (20)$$

need to be applied for each gear separately. Therefore, identification of the parameter δ_{G} can be performed as long as the vehicle is operated in gear G. The latest identification result will be used for initialization once the same gear is chosen again. It is important to note that

(1) The desired vehicle speed $\hat{v}_{\text{des}}$ is computed according to Eq. (13) with $\hat{v}_{\text{target}}$ assumed to be known from previous operations at the same position.
(2) The identified driver parameters δ will be real-valued as long as the computed maximum available propulsion torque is larger then the required propulsion torque,

$$T_{\text{prop,max}} \geq J\frac{\dot{v}}{r} + T_{\text{ext}}. \quad (21)$$

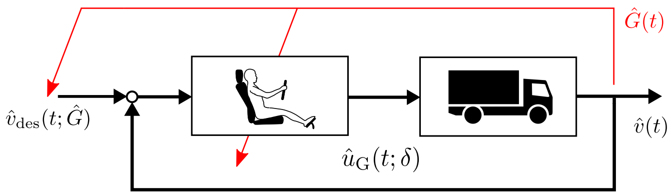

Fig. 2. Control loop consisting of the adaptive driver model and the vehicle model.

(3) In order to incorporate time variant driver behavior, we choose a forgetting factor $\lambda = 0.99$.

Figure 3 illustrates the performance of the developed prediction system. The upper plot shows the actual vehicle velocity (solid) together with the predicted vehicle velocity (dotted) and the input to the driver model (dashed). The simulated velocity was taken from vehicle measurements on a testing track. It can be seen that the predicted and actual trajectories are in good agreement. Gear shifting points were particularly well predicted, as can be seen in the middle plot. The lower plot shows the results of the RLS identification. Since the vehicle is only operated in the first four gears, only acceleration exponents for these gears are shown. Note that the parameters are only adapted once the associated gear is chosen. The parameter values used for prediction are the values at the beginnings of the gray areas. Note that the initial gear used for accelerating (first or second gear within the shown example) is an initial condition that needs to be supplied to the prediction system.

4. CASE STUDY: HYBRID HYDRAULIC TRUCK

In order to further test the developed prediction system and to assess its prediction performance, a case study based on the model of a hybrid hydraulic vehicle was performed. Such vehicles use an additional hydraulic propulsion system mainly consisting of an axial piston pump and a hydraulic accumulator to save fuel. Whenever the vehicle brakes, kinetic energy is converted into hydraulic energy and then stored in the accumulator. During acceleration, the pump is used as a motor to convert the hydraulic energy back into kinetic energy. This results in fuel savings and less exhaust emissions, see Baseley et al. [2007] or Bender et al. [2013] for details of the considered vehicle. Within the vehicle model, the propulsion torque given by Eq. (3) is extended through an additional term which results in

$$T_{\text{prop}} = (T_{\text{d}} + T_{\text{h}})\mu_{\text{g}}\mu_{\text{diff}} + T_{\text{brake}} \quad (22)$$

with T_{h} being the hydraulic torque contributed by the axial piston unit. During hybrid vehicle operation, the required propulsion torque needs to be distributed among the two propulsion systems. The torque assigned to the hyraulic system is given by

$$T_{\text{h}} = \begin{cases} \min\left(\max\left(\frac{T_{\text{prop}}}{\mu_{\text{diff}}}, T_{\text{h,min}}\right), T_{\text{h,max}}\right), & \text{if } u_{\text{h}} = 1, \\ 0 \text{ otherwise.} \end{cases} \quad (23)$$

where $T_{\text{h,min}}$ and $T_{\text{h,max}}$ are the minimum and maximum available hydraulic torque. The remaining torque is assigned to the diesel engine and the brake, respectively. Whether the hydraulic propulsion system is activated

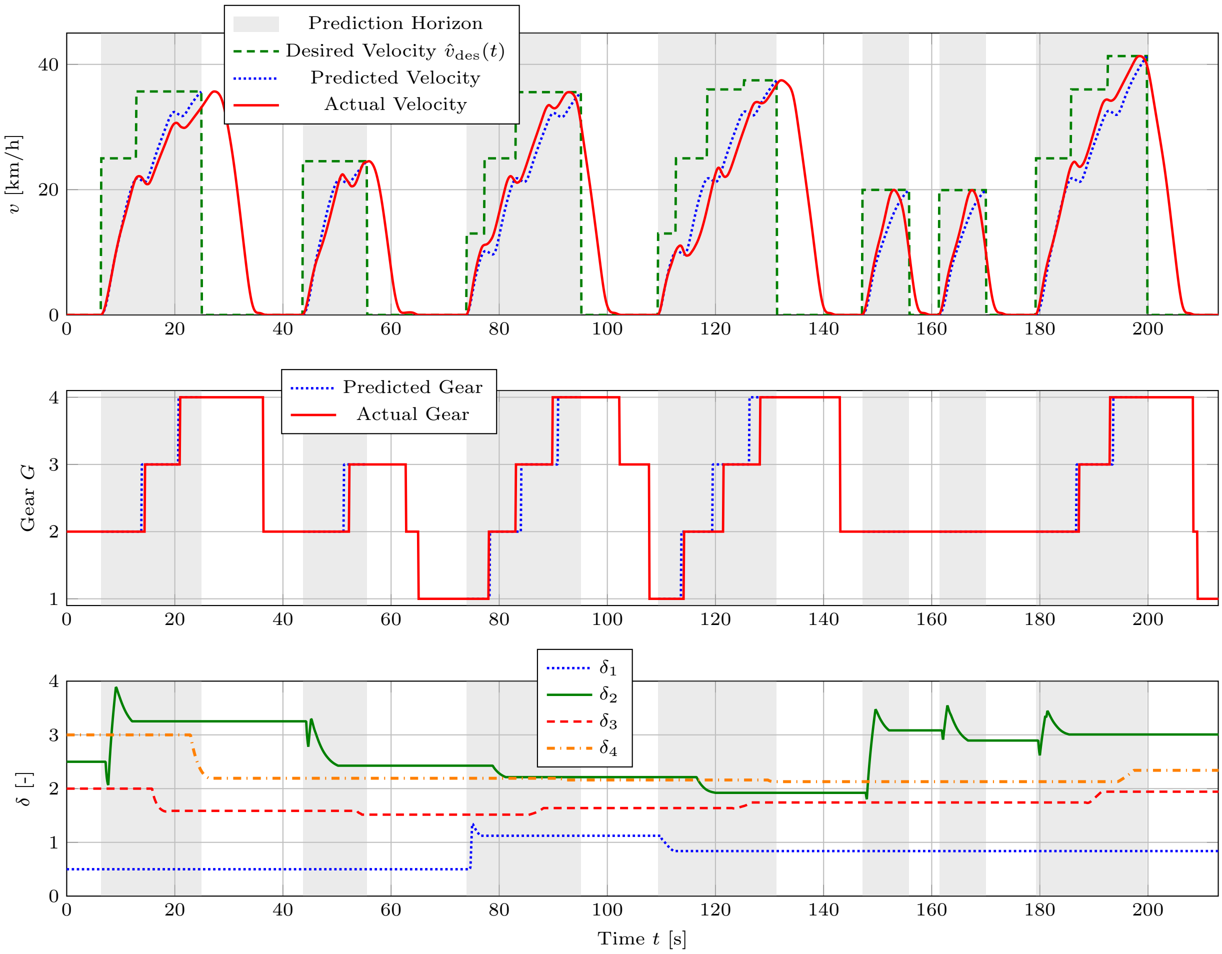

Fig. 3. Simulation results from the developed prediction system. In the upper two plots, the predicted and actual trajectories for the velocity and the current gear are shown together with the desired velocities used as an input for the driver model. The lower plot illustrates the RLS identification results for the free acceleration exponents.

($u_h = 1$) or deactivated ($u_h = 0$) is determined by the energy management strategy. For the nonpredictive baseline strategy, the axial piston unit is used whenever possible,

$$u_h(t) = 1 \ \forall t. \tag{24}$$

Additional fuel savings can be achieved through numerical optimization of the activation phases,

$$\min_{u_h \in \{0,1\}} \int_0^{T_P} q_{dies}(\tau) d\tau \tag{25}$$

s.t.

$$v(\tau) = \hat{v}(\tau), \tau \in [0, T_P], \tag{26}$$

$$\text{Eqs. (1)-(14)}$$

$$\text{Eqs. (22)-(24),}$$

with $q_{dies}(\tau)$ representing the instantaneous fuel consumption given as a function of the current engine speed and the engine torque, see Bender et al. [2013]. This optimization problem requires the prediction of the velocity trajectory $v(\tau)$, which will be delivered by the above described prediction system. For more details on the optimization problem and additional constraints, see Kaszynski and Sawodny [2011]. In the following, the hybrid hydraulic vehicle with predictive energy management will be used to assess the performance of the developed prediction system. Based on nine variations of the OC bus cycle (see Bender et al. [2013]), iterative learning of the target velocities corresponding to a particular vehicle position was performed. Then, a tenth variation of the reference cycle was used for vehicle simulation. Table 1 summarizes the simulation results: using the developed prediction system together with the optimized energy management strategy resulted in fuel savings of additional 4.3% compared to the hybrid vehicle with baseline energy management. If the exact future velocity trajectories were known, savings of additional 5.1% would have been possible. This means about 84% of the overall savings potential were achieved using the presented prediction approach. Figure 4 shows two example acceleration intervals from the performed simulation. The predicted trajectory (dotted line) was used to determine the optimal activation phases, which led to a variation in shifting behavior (solid line) compared to the baseline strategy (dashed line). For the shown acceleration interval, two activation phases were determined. As a consequence, shifting from third to fourth gear was performed about 3 seconds earlier as compared to the baseline strategy. Note that the simulated vehicle is equipped with an automated transmission, therefore instantaneous gear shifts without any interruption of traction force could be assumed in contrast to the testing vehicle mentioned in Section 3.

Table 1. Fuel consumption savings for the hybrid hydraulic vehicle (HHV).

Vehicle configuration	Normalized consumption
Conventional vehicle	100%
HHV, baseline strategy	83.5%
HHV, predictive strategy	79.2%
HHV, cycle known	78.4%

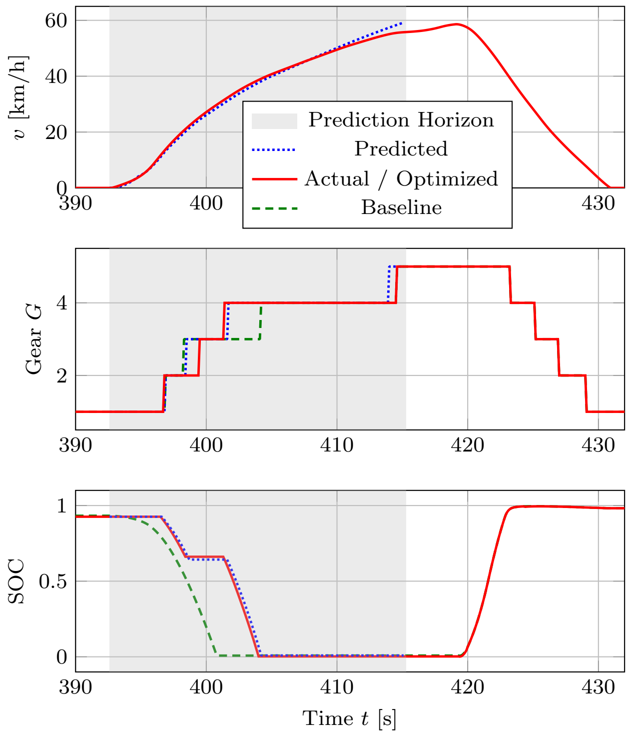

Fig. 4. Simulation results for the hybrid hydraulic vehicle case study. During the shown acceleration interval, the predictive strategy leads to the state of charge (SOC) decreasing in two phases which results in earlier shifting from third to fourth gear.

5. CONCLUSIONS

Driving cycle prediction is of interest in various transportation applications with regard to safety and efficiency. For many applications, the assumption of repeated vehicle operation on the same route is valid, therefore typical target velocities can be associated with a particular vehicle position. Using the predicted target velocity as an input for a control loop consisting of a driver model as controller and a model of the considered vehicle as plant, the future velocity trajectory can be predicted. The used driver model with gear dependent acceleration exponents can be identified during vehicle operation using RLS identification and showed satisfactory prediction results. The developed prediction system was used in a case study on predictive energy management optimization in hybrid hydraulic vehicles. The predictive strategy yielded additional fuel savings compared to the non-predictive baseline energy management. Further research in the context of this project will focus on the implementation of the developed algorithms in a hybrid testing vehicle. Additionally, traffic influence will be taken into account.

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