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Data-Driven Prediction and Predictive Control Methods for Eco-Driving in Production Vehicles

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Abstract: This paper presents a study of perception and robust model-predictive control (MPC) strategies in realistic traffic environments, which are simulated using data from real-world driving experiments. In this paper, we consider a heterogeneous traffic environment, which includes human-driven vehicles, and study the performance of currently available automation in production vehicles. We then present a data-driven preceding vehicle's velocity and position prediction algorithm, and a robust MPC strategy that optimizes fuel consumption and takes into account the prediction errors. Data used in this paper are taken from experiments using a 2018 Cadillac CT6 vehicle. Simulation results show up to 6.39% energy efficiency improvement.

Keywords: Autonomous Vehicles, Motion control, Optimal control theory, Modeling for control optimization, Learning and adaptation in autonomous vehicles.

1. INTRODUCTION

According to the Intelligent Transportation System Joint Program Office (ITS-JPO) of USA, safety, fuel efficiency, mobility and emissions are some of the major issues of the current transportation system. Vehicle automation and connectivity is expected to address these issues, since they are considered to be more efficient in catering these factors than human-driven vehicles (HDVs). However, full (hundred percent) market penetration of automated vehicles (AVs) or connected and automated vehicles (CAVs) in the transportation system cannot be expected in the near future. Hence, these AVs and CAVs will share the road with HDVs, whose intent and actions are harder to predict and suboptimal with respect to some global objective. Thus, it is important to focus on developing perception and control strategies for AVs and CAVs that take into account the presence of HDVs in the system. Moreover, it is important to study the impact of these strategies in real-world driving scenarios, and capabilities of the current production vehicles.

According to a report in Metz et al. (2007) by the United States Environmental Protection Agency, 29% of the greenhouse gas emissions in the United States is contributed by the transportation sector. According to the ITS-JPO website, traffic congestion costs $87.2 billion to the U.S. economy. The report in fue (2020) suggests 142 and 123 billion gallons of gasoline was consumed in 2019 and 2020 in the US, respectively. Although introduction of more electric and hybrid electric vehicles can alleviate these issues, majority of the on-road vehicles are conventional vehicles. Thus, it is important to focus on different ways in which the fuel efficiency of a conventional vehicle can be improved. The fuel efficiency of a vehicle depends on several factors, such as engine characteristics, powertrain architecture, vehicle aerodynamics, and road and weather conditions. Apart from these, the fuel efficiency of a vehicle has been shown to depend on the way a vehicle is driven Van Mierlo et al. (2004); Zhou et al. (2016). Generally, improved fuel economy is achieved when the acceleration and braking of a vehicle are minimized. This has prompted most control strategies to focus on driving the vehicle at a constant cruising velocity Chang and Morlok (2005); Hellström et al. (2010); Hooker (1988).

Numerous research Asadi and Vahidi (2011); Hellström et al. (2010); Mahler and Vahidi (2014); Rakha and Kamalanathsharma (2011) have aimed at improving the fuel efficiency while considering a full market penetration of AVs, which includes our previous works Canosa and HomChaudhuri (2018); HomChaudhuri et al. (2016, 2015, 2017). The majority of these works focus on making the vehicle move at a constant cruising velocity Chang and Morlok (2005); Hellström et al. (2010), avoiding red light idling and minimizing braking and acceleration for urban traffic scenarios Asadi and Vahidi (2011); Mahler and Vahidi (2014); Rakha and Kamalanathsharma (2011), and explicitly utilizing an approximate fuel consumption model in their cost function HomChaudhuri et al. (2016, 2015, 2017); Kamal et al. (2013); Rakha and Kamalanathsharma (2011). Du and Pisu (2016); Du et al. (2018) focused on developing velocity regulation methods at the traffic infrastructure level to improve the fuel economy of CAVs, while HomChaudhuri and Bhattacharyya (2022); Häusler et al. (2016) investigated motion planning methods to improve fuel economy and ensure collision avoidance. Since these works consider all the vehicles to be AVs or CAVs, they can assume that the positions and velocities of the vehicles surrounding the ego AV or CAV is fully available

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to it, which is not a valid assumption in the presence of HDVs.

Many previous works have studied heterogeneous traffic environments, which included both HDVs and AVs or CAVs. However, many of them, such as Cui et al. (2018); Monteil and Russo (2019); Rios-Torres and Malikopoulos (2018), have only studied the impact of the HDVs on the fuel economy of the traffic network. The effect of partial market penetration of CAVs for a merging scenario was analyzed in Rios-Torres and Malikopoulos (2018). Rios-Torres and Malikopoulos (2018) studied low, medium, and heavy traffic conditions, and concluded that fuel consumption in heterogeneous environments can be reduced only for low traffic situations, despite the fuel optimal driving pattern of the CAVs. Cui et al. (2018) showed that upto 6% improvement in fuel efficiency can be achieved when a HDV follows a CAV that is implementing eco control algorithms. A manual to automated mode switching algorithm for level 3 and level 4 autonomy was proposed in Monteil and Russo (2019). Input to state stability analysis of a platoon consisting of HDVs and CAVs was also studied in Monteil and Russo (2019). A data driven adaptive dynamic programming based approach was studied in Gao et al. (2017), which focused on optimizing fuel usage of an autonomous vehicle when it followed a human-driven vehicle. Most of the literature that focus on partial penetration of CAVs model the human drivers in the context of car following. For example, Monteil and Russo (2019) used a car following model, where the acceleration profile was modeled with a nonlinear function of distance from preceding vehicle and their relative velocity. Gipps (1981); Rios-Torres and Malikopoulos (2018) used Gipp's car following model to model human behaviour while Khodayari et al. (2012) exploited neural networks to model car following behaviour of human drivers.

Despite many previous works on energy efficient mobility in the presence of V2V and V2I connectivity, a major portion of those works assume all vehicles to be autonomous, and ignore the presence of human-driven vehicles. Developing energy efficient strategies for the AVs or CAVs in the presence of HDVs is challenging, because the HDVs add significant uncertainty in the system. Moreover, the actions of the HDVs can be highly suboptimal with respect to the AV's objective, such as energy efficiency improvement, and that can significantly impact the AV strategies. Hence, in this research, we aim to address these research gaps by developing control methods and a HDV's velocity prediction method.

In this paper, we study automated driving behavior in production vehicles (2018 Cadillac CT6), and make an effort to develop perception and robust energy-efficient control strategies for AVs operating in real-world environments. We have developed a data-driven Neural Network (NN)-based HDV velocity (and position) prediction method with real-world driving data, and a robust model-predictive control (MPC) strategy to optimize energy consumption, while ensuring robust collision avoidance. We compare our strategy in a real-world environment involving 2018 Cadillac CT6 vehicle.

Predicting human driver's velocity profile is a complex task that depends on various internal and external driving factors. Neural Networks (NN) have shown a promising performance in learning highly nonlinear relations between their input and output data. Hence, a NN-based approach is employed in this paper to predict the preceding human driver's velocity profile. Among the existing neural network structures, Recurrent Neural Network (RNN) is capable of capturing sequential information present in the input data Yu et al. (2019) because of having recurrent connections in its hidden layer that enable storing the temporal state of the network. Long Short-Term Memory (LSTM) network, which is a variant of RNNs, performs better than the traditional RNN networks in learning temporal dependency of longer range sequences Yu et al. (2019). LSTM uses a set of gates to control the memorizing process. A common LSTM unit is composed of a cell, an input gate, an output gate and a forget gate as schematically shown in Fig. 1. These gates allow the LSTM to keep or forget information during training process, thus making it possible to learn long sequences by keeping relevant information to make predictions and forgetting non-relevant data. Therefore, an LSTM neural network is developed here to predict velocity profile of the preceding human-driven vehicle over a future horizon. The LSTM-based velocity and hence position predictions are used by the robust MPC solver that tightens the collision avoidance constraints using the learning error.

The paper contributions can be listed as (i) development of a LSTM-based velocity prediction algorithm using real-world driving data, (ii) development of robust MPC-based energy efficiency improvement strategy that takes into account the prediction errors, and (ii) generation of real-world simulation environments using experimental data and comparing energy efficiency results with a current production vehicle (2018 Cadillac CT6).

The paper is organized as follows, Section 2 details the problem to be solved, while Section 3 discusses the proposed approaches. The simulation results and the paper conclusions are provided in Section 4 and 5, respectively.

2. PROBLEM DESCRIPTION

We first describe the system dynamics, followed by the energy-efficient optimal control problem that the autonomous vehicle needs to solve. The instantaneous power generated at the engine helps the vehicle to move forward after compensating for the losses due to friction and aerodynamic drag. The losses can be modeled as a second order polynomial function of velocity with ABC coefficients as

$$F_{loss} = A + Bv + Cv^2 \tag{1}$$

where A accounts for the tire rolling resistance, B factors other speed dependent frictional losses, and C accounts for the aerodynamic drag. These parameters for the 2018 Cadillac CT6 (the test vehicle) with mass $M = 2041.2\ kg$ are $A = 208.31\ N$, $B = 4.67\ Ns/m$ and $C = 0.38\ Ns^2/m^2$ EPA (2022). Hence, the actual acceleration 'a' of the vehicle can be modeled using the force of propulsion (Mu) and the losses F_{loss} as

$$\begin{aligned} Mu &= Ma + F_{loss} \\ Mu &= Ma + (A + Bv + Cv^2) \\ a(\tau) = \dot{v}(\tau) &= u(\tau) - \frac{C}{M}v^2(\tau) - \frac{B}{M}v(\tau) - \frac{A}{M} \end{aligned} \tag{2}$$

and the vehicle dynamics can be represented as in (3), where s is the position and u is the control action.

$$\begin{bmatrix}\dot{s}(\tau)\\ \dot{v}(\tau)\end{bmatrix} = \begin{bmatrix} v(\tau) \\ u(\tau) - \frac{C}{M}v^2(\tau) - \frac{B}{M}v(\tau) - \frac{A}{M}\end{bmatrix} \tag{3}$$

Given the above system dynamics, the energy-efficient optimal control problem is given by

$$\min_u \sum_{\tau=k}^{k+T-1} \frac{\dot{m}_f(\tau)}{v(\tau)} + w_1(v_T(\tau) - v(\tau))^2 \tag{4a}$$

$$\text{subject to } s(\tau+1) = s(\tau) + T_s v(\tau) \tag{4b}$$

$$v(\tau+1) = v(\tau) + T_s a(\tau) \tag{4c}$$

$$a(\tau) = u(\tau) - \frac{C}{M}v^2(\tau) - \frac{B}{M}v(\tau) - \frac{A}{M} \tag{4d}$$

$$s^l(\tau) - s(\tau) \geq d_{min} + \alpha v(\tau) \tag{4e}$$

$$v_{min} \leq v(\tau) \leq v_{max}, \quad u_{min} \leq u(\tau) \leq u_{max} \tag{4f}$$

where $s^l(\tau)$ is the position of the preceding vehicle (which is unknown), $\dot{m}_f$ is the rate of fuel consumption, d_{min} is a predefined safety distance, α is the headway time, and T_s is the sampling time. The first term in the cost function in (4a) tries to minimize the fuel consumption per unit distance, i.e., maximize miles per gallon, and the second term penalizes deviation from a desired target velocity v_T, which is generally the road speed limit.

A major challenge in solving the above problem in (4) is predicting the future positions $s^l(\tau)$ of the preceding vehicle over the time horizon T, so that collision avoidance constraint in (4e) can be accurately enforced. Additionally, an accurate estimate of the rate of fuel consumption $\dot{m}_f$, as a function of velocity and acceleration, is needed to solve the above problem.

3. APPROACH

3.1 Data-driven Prediction Method

Predicting the future velocity profile of a human-driven vehicle is a complex problem, and depends on many factors. It depends on factors such as the road's speed limits, traffic and environmental situations, and also the driver's driving pattern. Since the autonomous vehicle only has the information of the previous position and velocity measurements of the preceding vehicle, we predict the future velocities (and hence positions) of the preceding vehicle based on its previous velocities. For this, recurrent neural networks, and more specifically LSTM networks, seem to be an effective approach to learn the nonlinear mapping between the past and future velocities. Hence, an LSTM network is incorporated into our proposed control structure to predict velocity (and position s^l) of the preceding vehicle over each horizon. The input of the developed LSTM network is the historical vehicle's velocity sequence, and its output is the vehicle's future velocities over the prediction horizon, as shown in Fig. 1. The length of the past and future horizons (H_P and H_F, respectively) are considered to be 10 discrete time units.

3.2 Rate of fuel consumption model

To solve the optimal control problem in (4), we also need to model the rate of fuel consumption of the ego vehicle. In our experiments (data available at Liv (2022)),

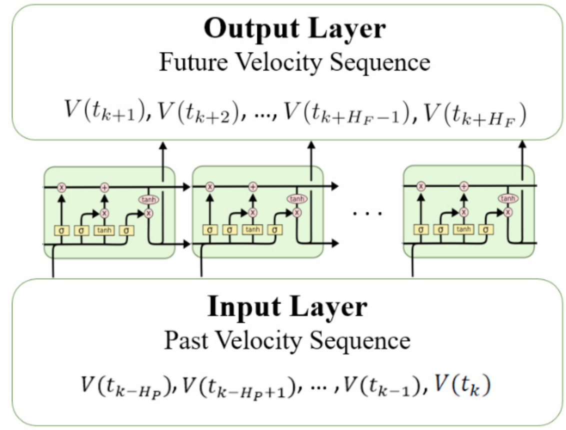

Fig. 1. Proposed LSTM-based velocity prediction model.

we collected data on the instantaneous rate of fuel consumption(obtained from CAN signals) of the 2018 Cadillac CT6 (test vehicle) at a 10 Hz frequency, and a model for the rate of fuel consumption, $\dot{m}_f$ (cc/s), as a function of velocity v and acceleration a, is obtained by fitting a 3[rd] degree polynomial on the on-road test data. The 3[rd] degree polynomial equation for the rate of fuel consumption of 2018 Cadillac CT6 is given in (5) and the plot of fitted data and the actual data points is given in Fig. 2. The mean and standard deviation of the error (between the experimental and the fitted rate of fuel consumption) are -1.33×10^{-14} cc/s and 0.43 cc/s, respectively.

$$\begin{aligned}\dot{m}_f(v,a) = &\ 0.5826 + 0.05113v - 0.08799a - 0.00211v^2 \\ &+ 0.1565va + 0.02387a^2 + 7.975 \times 10^{-5}v^3 \\ &- 0.001037v^2a + 0.0465va^2 + 0.02267a^3\end{aligned} \tag{5}$$

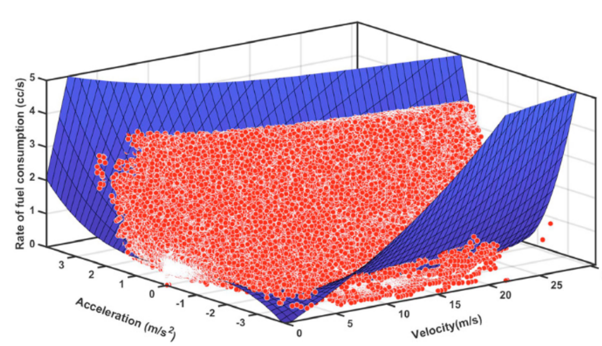

Fig. 2. Plot of fitted fuel consumption. The red dots represent experimental data points.

3.3 Robust Model Predictive Control

Since the data-driven prediction approach is subject to prediction error, we reformulate the problem in (4) by tightening the constraint (in (6e)) to make it robust to the prediction errors. The reformulated problem is given by Problem 1.

Problem 1.

$$\min_{u} \sum_{\tau=k}^{k+T-1} \frac{\dot{m}_f(\tau)}{v(\tau)} + w_1(v_T(\tau) - v(\tau))^2 \tag{6a}$$

$$\text{subject to } s(\tau+1) = s(\tau) + T_s v(\tau) \tag{6b}$$

$$v(\tau+1) = v(\tau) + T_s a(\tau) \tag{6c}$$

$$a(\tau) = u(\tau) - \frac{C}{M}v^2(\tau) - \frac{B}{M}v(\tau) - \frac{A}{M} \tag{6d}$$

$$s^l(\tau) - s(\tau) \geq (d_{min} + \beta(\tau+1-k)e_{rms}T_s) + \alpha v(\tau) \tag{6e}$$

$$v_{min} \leq v(\tau) \leq v_{max}, \quad u_{min} \leq u(\tau) \leq u_{max} \tag{6f}$$

where the target velocity V_T is considered to be the road speed limit ($\approx$ 65 mph) and the rate of fuel consumption in (5) is converted to fuel consumed per unit distance by dividing it with the velocity of the vehicle. (6b), (6c) and (6d) represent the vehicle dynamics as described in (2) and (3) and T_s is the sampling time which is taken to be 1 second. (6e) is the tightened constraint, which helps to ensure the collision avoidance in the presence of prediction errors. The position s^l of the preceding vehicle is obtained from its predicted velocity as described in section 3.1. We formulate the collision avoidance in a robust fashion in which the safety distance grows linearly over the MPC horizon, thus tightening the constraint. e_{rms} here is the root-mean-square error of velocity prediction and β is a safety factor with $\beta \in [0, 1]$. In this work, β is formulated as a constant or linearly decreasing function over prediction horizon. With a decreasing β, we enforce robust collision avoidance in the near-future of the horizon and relax it in the far-future. Solving the problem at every time instant (as done in any MPC approach) alleviates any safety issue due to such relaxation. The bounds on the vehicle velocity and control action are shown in (6f).

4. SIMULATION RESULTS

We used a segment of 5 minutes duration of the data on real world operational scenario available on Liv (2022). In this drive time, we observed multiple instances where a vehicle from an adjacent lane cuts-in (such incidents will be described as ‘cut-ins’), and it is observed that the test vehicle decelerates a lot to accommodate the cutting-in vehicles. This deteriorates the fuel efficiency of the test vehicle. The test vehicle travelled a distance of 7409.72 m and the fuel efficiency calculated using (5) is 30.19 mpg. Fig. 3 shows the speed of test vehicle and the gap with its preceding vehicle (when a vehicle cuts-in, that becomes the preceding vehicle). Sudden drop in the gap in Fig. 3 represents vehicles cutting in.

First, we evaluate the data-driven velocity prediction algorithm in Section 3.1. A collection of 11 trips chosen from the Argonne’s driving cycles dataset (Liv (2022)) are used for training the LSTM network. 20649 input/output samples are derived from the driving cycles data with 70% of them used for training the network, and the rest used for the network’s validation. The developed neural network’s structure includes a hidden layer with 100 LSTM blocks or neurons, and a dense output layer that makes a 10 time units prediction. The Rectified Linear Unit (ReLU) activation function is used for the LSTM blocks. The network is trained for 300 epochs and a batch size of 128 is used.

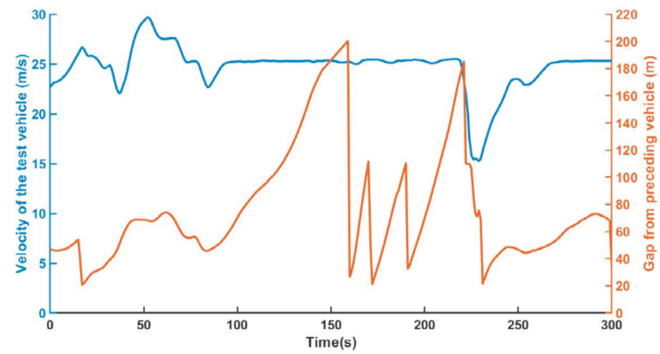

Fig. 3. Plot showing the actual velocity of the test vehicle and distance from the preceding vehicle.

LSTM network’s velocity prediction for the preceding vehicle is illustrated in the upper plot of Fig. 4. The average of Root Mean Square Error (RMSE) of predictions over all the horizons is 1.5 m/s. The cumulative distribution function (CDF) plot of RMSE of predictions is also shown (the lower plot of Fig. 4). The CDF plot shows that 90% of velocity predictions over horizons of 10 seconds, have an RMSE less than 2.86 m/s.

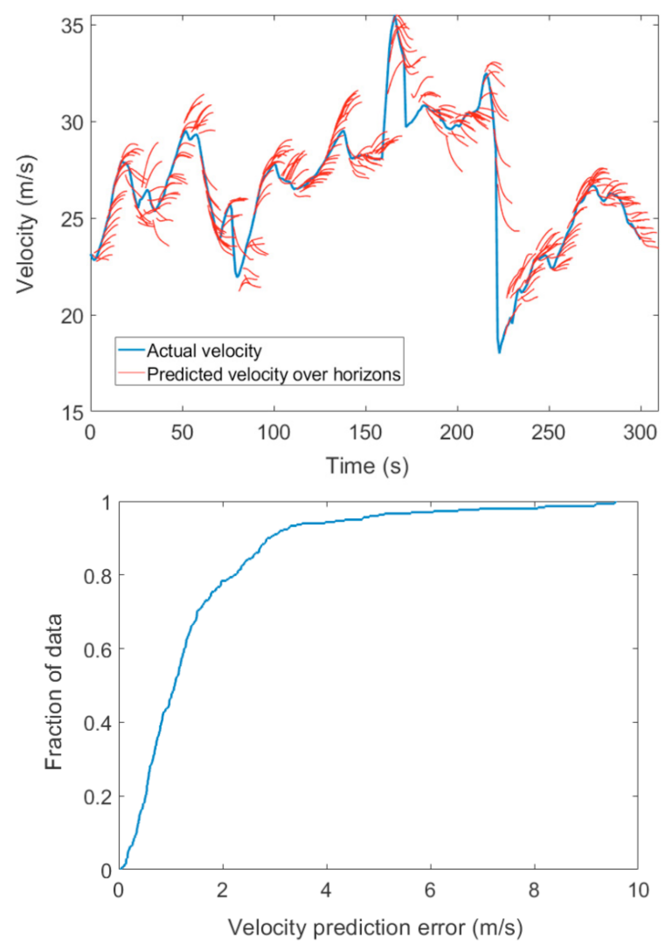

Fig. 4. Velocity prediction for the preceding vehicle and CDF of the prediction error (RMSE).

Using the predicted velocity of the preceding vehicle, we solve Problem 1 in a robust MPC framework. The rate of fuel consumption as given in (5) is used in estimating the cost. The positions of the preceding vehicle is adjusted so that the gap remains the same as that for the on-road test. In this way, we ensured that the test vehicle had a similar experience during simulation as that with the on-road scenario. The parameter w_1 prioritizes the time to reach the destination over fuel efficiency. Higher the value of w_1, quicker the destination is reached, but at the cost of fuel efficiency. The parameter β weighs between robustness and optimality. Greater the value of β, the system will be more robust, but it too decreases the fuel efficiency. The effects of w_1 and β on the fuel efficiency is depicted in Table 1.

	parameters w_1, β	Fuel efficiency (mpg)	Distance travelled (m)	percent change in mpg
Actual	-	30.19	7409.72	-
MPC with perfect prediction	$1e-3, 0$	32.06	7414.18	6.19
MPC	$0.9e-3, 1$	32.43	7250.15	7.42
	$0.95e-3, 1$	32.12	7347.57	6.39
	$1e-3, 1$	31.75	7434.55	5.17
	$1e-3, 0.85$	31.87	7438.01	5.56
	$1e-3, 0.7$	31.97	7441.08	5.90
	$1e-3, [0.7, 0.3]$	31.98	7443.79	5.96

Table 1.

For perfect prediction, the gap from the preceding vehicle over the MPC horizon is taken to be the actual gap during the on-road test and the fuel efficiency in this case with $w_1 = 1e-3$ is 32.06 mpg which is a 6.19% improvement from that of the production vehicle. When the positions of the preceding vehicle over the MPC horizon are derived from the velocity profile predicted as discussed in section 3.1, the fuel efficiency of the test vehicle improves by 5.17% for parameter values $w_1 = 1e-3$ and $\beta = 1$. The improvement in fuel efficiency is further increased to 5.9% when robustness is sacrificed by reducing β to 0.7 as shown in Table 1. The last row of Table 1 represents the scenario where the parameter β is modeled as a linearly decreasing function where $\beta = 0.7$ when $\tau = k$ and $\beta = 0.3$ when $\tau = k + T - 1$. The fuel efficiency in this scenario is improved by 5.96%.

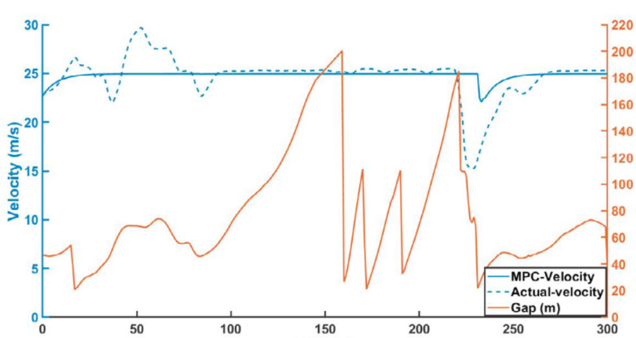

Fig. 5. Plot showing the velocity of the test vehicle and distance from the preceding vehicle obtained from solving Problem 1 with $w_1 = 1e-3$, $\beta = 0.7$.

The simulated velocity profile of test vehicle when $w_1 = 1e-3$ and $\beta = 0.7$ is shown in Fig. 5. The vehicle using a model predictive controller mostly cruises without acceleration compared to the actual test scenario where its velocity oscillates more. Also the variation in velocity is smaller for simulated case compared to the actual case in the events of cut-ins. These factors help the model predictive controller to result in a better fuel efficiency compared to that of the production vehicles.

5. CONCLUSION

In this paper, we use data collected from real-world driving experiments to evaluate the performance of a production vehicle in relation to energy efficiency. The data shows that the production vehicle is suboptimal in its driving profile, especially in the events of cut-ins. We developed a LSTM-based velocity prediction algorithm to predict the velocity of preceding vehicle and incorporated it in a robust MPC controller to improve the energy efficiency. Simulation studies show that the proposed method is capable of improving the energy efficiency of the production vehicle.

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