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Platoon Merging Distance Prediction using a Neural Network Vehicle Speed Model ⋆

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Abstract: Heavy-duty vehicle platooning has been an important research topic in recent years. By driving closely together, the vehicles save fuel by reducing total air drag and utilize the road more efficiently. Often the heavy-duty vehicles will catch-up in order to platoon while driving on the common stretch of road, and in this case, a good prediction of when the platoon merging will take place is required in order to make predictions on overall fuel savings and to automatically control the velocity prior to the merge. The vehicle speed prior to platoon merging is mostly influenced by the road grade and by the local traffic condition. In this paper, we examine the influence of road grade and propose a method for predicting platoon merge distance using vehicle speed prediction based on road grade. The proposed method is evaluated using experimental data from platoon merging test runs done on a highway with varying level of traffic. It is shown that under reasonable conditions, the error in the merge distance prediction is smaller than 8%.

Keywords: Platooning, Intelligent Transport Systems, Neural Networks, Road Transportation, Platoon Merging Distance, Road Grade

1. INTRODUCTION

Road freight transport is responsible for the majority of today's land based transportation, and its importance is only expected to increase in the future. As it is also a significant contributor to CO_2 emission, developing more intelligent transportation systems, that would increase efficiency, reduce fuel consumption, and also ease the strain on the road infrastructure, is crucial.

Heavy-duty vehicle (HDV) platooning, where the vehicles drive together as a single unit with low intervehicular distances, is well known as a method of reducing fuel consumption. When platooned, each HDV experiences reduced air drag, with small reductions for the leader vehicle and reductions up to 70% for the follower vehicles. Since air drag at high speeds contributes significantly to the resistive force, by reducing it through use of platooning the fuel consumption can be reduced up to 20% (Humphreys et al. [2016]). This reduces operating costs of HDV fleets, while also reducing their ecological impact.

Although platooning is also possible with human drivers, introducing automatic control of vehicle speed allows the HDVs to drive safely with smaller intervehicular distances, which leads to more fuel savings and more efficient utilisation of the road infrastructure. There has been a lot of research on HDV platooning (Bergenhem et al. [2012]), mostly on already formed platoons, regarding platoon stability (Yanakiev and Kanellakopoulos [1995], Ploeg et al. [2014]), safety (Alam et al. [2014]), control (Horowitz and Varaiya [2000], Turri et al. [2014]) etc. However, as vehicles often have different starting points, destinations and time constraints, platoons will need to be formed, merged and split while driving on the road in a realistic large-scale implementation of HDV platooning. This means that HDVs will often have to deviate from their own optimal (with regard to fuel consumption) speeds and routes in order to meet with other HDVs and form a platoon. Once the HDVs successfully catch up and form a platoon, the follower vehicle will experience reduced air drag and consume significantly less fuel. Finally, the vehicles split and go their separate ways in order to arrive at their respective destinations according to their time constraints. The hope is that fuel savings during the time the vehicles drive in a platoon will offset higher fuel consumption during the catch-up phase (Liang et al. [2013]). If platoon formation is delayed due to the influence of traffic (Liang et al. [2015]), or some other effects, the fuel savings are diminished, which can lead to more fuel being spent overall. It is therefore important to have a good prediction of where the two vehicles would meet, in order to be able to calculate predicted fuel savings and make a better informed decision on whether to attempt to form a platoon at all.

The problem considered in this paper is predicting how long it will take two HDVs to form a platoon while driving on a highway at set cruise speeds. This problem was first studied by Liang [2016], Liang et al. [2016], and we will use the data obtained there. The focus of previous work on platoon merging distance prediction was on investigating

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the influence of traffic conditions, not explicitly looking at the influence of the road topography, which we will investigate here. After modelling the influence of road grade, a more in-depth look into the influence of traffic condition will become possible. Our problem is related to the well known problem of travel time prediction. Many prediction models were used for this (Chien and Kuchipudi [2003]), usually for passenger cars, and much of the work is done using traffic models and statistical and machine learning techniques (van Lint [2004]). The behaviour of HDVs differs, however, significantly from the behaviour of cars, due to their large mass and size, speed constraints and the different way they interact with the surrounding traffic. Therefore, different algorithms might be better suited for predicting their behaviour.

The additional benefit of our approach is that it facilitates following the progress of the platoon catch-up phase. Since in our algorithm, platoon merge distance prediction is done by integrating the predicted vehicle speed profiles, we can compare the current vehicle position, acquired from the GPS system, with its predicted value. This way, we can know in advance when a platoon merge will be delayed and can adapt our strategy accordingly.

The outline of this paper is as follows. In Section 2 a brief overview of the experiment from which the data were obtained is given. Next, in Section 3, a simplified longitudinal dynamic model of the vehicle is derived. A new platoon merging distance prediction algorithm is proposed in Section 4, and evaluated using the experiment test data in Section 5. Lastly, we conclude our work in Section 6.

2. EXPERIMENT DATA

Here we consider the simplest case of platoon merger. In the experiments (Liang et al. [2016]) two HDVs were driving on an 11 km long stretch of public highway between Stockholm and Södertälje, namely between the Hallunda and Moraberg interchanges. Two standard Scania tractor trucks were used. The lead vehicle had a 480 hp engine and its total weight, including its trailer, was 37.5 tonnes. The follower vehicle had a 450 hp engine, had no trailer and weighed 15 tonnes. The road is fairly hilly, with road grades as high as ±5%. The HDVs, initially apart, attempted to form a two-vehicle platoon by driving with different desired speed adaptive cruise control (ACC) settings. Three different desired speed pairs were considered, $(v_1, v_2) = (75, 85), (75, 89)$ and $(80, 89)$ km/h, where v_1 is the reference speed of the leader vehicle and v_2 of the follower. Downhill speed control was also active, with the offset of 5 km/h, allowing the vehicles to accelerate on downhill slopes and gain speed up to the set limit. The initial distance between the vehicles ranged from 400 m to 1300 m. The part of the experiment data that we used consist of periodical vehicle speed measurements and calculated distance between the vehicles, together with the information about road topography. Since we are primarily interested in the catch-up phase, we will consider the platoon merging completed when the distance between the vehicles is less than 80 m, ignoring phenomena such as persistent drivers (Liang et al. [2016]).

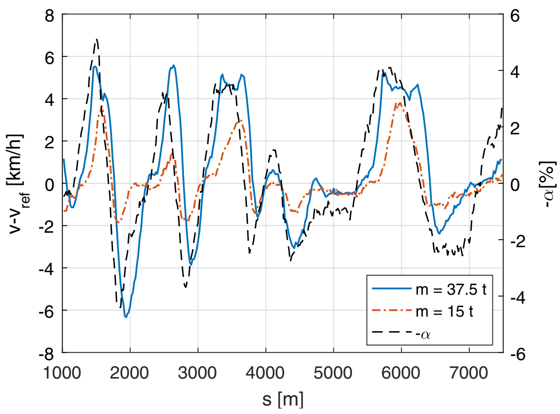


Fig. 1. Speed deviation from the desired speed due to varying road grade for two HDVs with different masses.

3. ROAD AND VEHICLE MODEL

A simplified longitudinal HDV model is considered; a more detailed vehicle model can be found in Gillespie [1992]. By applying Newton's second law of motion, the dynamics of an HDV can be expressed as

$$\begin{aligned} \dot{x} &= v \\ m\dot{v} &= F_t - F_b - F_a - F_r - F_g, \end{aligned}$$

where x is the vehicle's longitudinal position, v the vehicle speed, m the vehicle mass, F_t the traction force, F_b the braking force, F_a and F_r the air drag and roll resistance, respectively and F_g the influence of gravitational force. Due to their large mass, the gravitational force affects HDVs much more than it affects passenger cars. HDVs often need to reduce their speed in order to tackle even small uphill slopes, even when driving at full power, and they need to brake or coast on downhill slopes in order to keep speed within safe bounds. A comparison of speed deviation from the nominal for the two HDVs considered in the experiment is shown on Fig. 1. The data shown are from one of the experiment test-runs. The vehicle speed is shown as a function of position, and negative road grade is shown in the same figure to highlight the dependency.

Since HDVs normally do not drive close to full power, they will be able to tackle smaller uphill slopes without significant loss of speed. In contrast, the ACC with downhill speed control will allow the vehicle speed to increase even on short downhill slopes, in order to save fuel. Therefore, in case there are no long steep uphill slopes, the mean speed of the vehicle will increase, with the heavier vehicle experiencing a larger increase than the lighter ones. This effect cannot be ignored when estimating the platoon merging distance, especially if the weight of the leader and the follower HDV differ significantly as in our experiments.

In order to model the influence of varying road grade on the vehicle speed, we can either use a cruise control model, if available, or identify the dependence from data. If we group all resistive forces, excluding gravitational force, with the traction force and braking force into $F_p = F_t - F_b - F_a - F_r$, this propulsive force can be treated as the control output of the cruise controller, applied to overcome the resistive forces and keep the vehicle speed close to its reference value. The cruise controller can adjust the propulsive force, within the constraints imposed by maximum engine torque. Then, the speed dynamics of a vehicle can be expressed as

$$m\dot{v} = F_p - mg\sin\alpha. \tag{1}$$

We assume that F_p will be a non-linear function of vehicle speed deviation from its reference speed, and of road grade, i.e. $F_p = F_p(v - v_{\text{ref}}, \alpha)$. The road grade, of course, does not depend on time, and only changes with position. We obtain the speed measurements for both vehicles, as well as the distance between them, translate them to spatial domain and consider vehicle speed as a function of vehicle position. We consider equally spaced points along the road, $s_k = k \cdot \Delta s$, where the road segment length Δs is small enough to capture the dynamics of the system, but large enough so that $\Delta s > T_s v_{max}$, i.e., vehicles do not pass through segments of length Δs in less than T_s. Then, to each s_k along the vehicle trajectory, for all vehicles i, we assign

$$t_{i,k} = \min\left\{\tau : x_i(\tau) > s_k\right\},$$
$$v_{i,k} = \frac{\int_{t_{i,k}}^{t_{i,k+1}} v_i(\tau)\mathrm{d}\tau}{t_{i,k+1} - t_{i,k}},$$

where $t_{i,k}$ is the time vehicle i enters segment $[s_k, s_{k+1}]$, and $v_{i,k}$ its average speed while in the segment.

Lastly, the road grade α_k is taken as average road grade over the road segment $[s_k, s_{k+1})$.

Using

$$\frac{\mathrm{d}v}{\mathrm{d}t} = \frac{\mathrm{d}s}{\mathrm{d}t}\frac{\mathrm{d}v}{\mathrm{d}s} = v\frac{\mathrm{d}v}{\mathrm{d}s}$$

we rewrite (1) into

$$v\frac{\mathrm{d}v}{\mathrm{d}s} = \frac{F_p}{m} - g\sin\alpha$$

which we can integrate and approximate by taking $\sin(\alpha) \approx \alpha$ for small α, since road slopes will typically be less than 5%, giving us

$$\frac{m}{2\Delta s}\left(v_{i,k}^2 - v_{i,k-1}^2\right) = F_{p,i}(v_{i,k-1} - v_{i,\text{ref}}, \alpha_{k-1}) - mg\alpha_k.$$

Now, function

$$\frac{F_{p,i}}{m} = \frac{F_{p,i}(v_{i,k-1} - v_{\text{ref}}, \alpha_{k-1})}{m} = \frac{v_{i,k}^2 - v_{i,k-1}^2}{2\Delta s} + g\alpha_k \tag{2}$$

can be learned from data, and using this model, we can predict vehicle speed for the whole length of the road of interest, as

$$v_{i,k} = 2\Delta s\sqrt{v_{i,k-1}^2 + \frac{F_{p,i}(v_{i,k-1} - v_{\text{ref}}, \alpha_{k-1})}{m} - g\alpha_k}, \tag{3}$$

initializing $v_{i,0}$ to the last available speed measurement, or to $v_{i,\text{ref}}$. It turns out that (2) can be approximated using a simple feedforward neural network. A comparison between the measured speeds and the speed prediction acquired this way, for a part of a test run, is shown on Fig. 2.

4. PLATOON MERGE DISTANCE PREDICTION

In this section, we introduce our new prediction algorithm for the platoon merge distance. As the algorithm requires vehicle speed prediction, we first discuss some simpler speed models, and then give the neural network speed

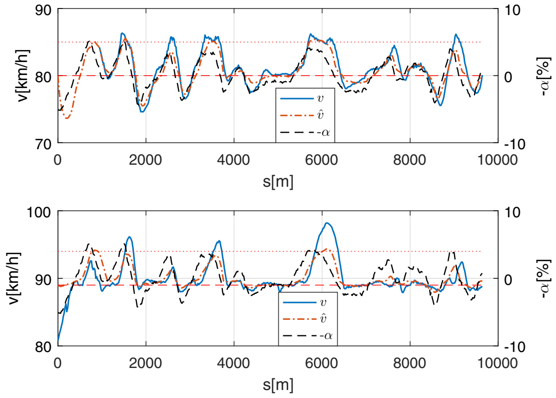


Fig. 2. Predicted ($\hat{v}$) and measured (v) speed for the leader and the follower vehicle and negative road grade.

model in more detail. Finally, we comment on how the the proposed models were trained from data.

4.1 Prediction Model

Platoon merge distance prediction is based on predicting future vehicle speeds based on varying road grade. A significant advantage of speed prediction based merge distance prediction is that it gives us a prediction of the inter-vehicle distance profile during the whole catch-up phase. This means that a disturbance that will change the platoon merging time can be detected immediately, and when it happens, the prediction can be recalculated taking into account the updated information. Additionally, the new information can be used to re-plan desired vehicle speed profiles in order to compensate for the disturbance.

We define the platoon merge distance prediction $\hat{x}_m$ at some time t_0, with initial intervehicular distance $d(t_0)$, as the distance the follower vehicle will have travelled from that time until the the time when the predicted intervehicular distance $\hat{d}$ first becomes smaller than the predefined value d_{PL} (in this paper we set $d_{PL} = 80\,\text{m}$),

$$\hat{x}_m(t_0) = \hat{x}_2(\hat{t}_m) - x_2(t_0),$$
$$\hat{t}_m(t_0) = \min\left\{t \geq t_0 : \hat{d}(t|t_0) \leq d_{PL}\right\}.$$

We predict the follower vehicle position $\hat{x}_2(t|t_0)$ and intervehicular distance $\hat{d}(t|t_0)$ by integrating the obtained vehicle speed predictions

$$\hat{x}_2(t|t_0) = x_2(t_0) + \int_{t_0}^{t} \hat{v}_2(\tau|t_0)d\tau,$$
$$\hat{d}(t|t_0) = d(t_0) + \int_{t_0}^{t} \left[\hat{v}_1(\tau|t_0) - \hat{v}_2(\tau|t_0)\right]d\tau.$$

The simplest vehicle speed prediction model assumes that both vehicles perfectly follow their desired speed set by the ACC. In that case, vehicle speed predictions are taken to be constant and platoon merging time and distance predictions are simply

$$\hat{t}_m(t_0) = \frac{d(t_0) - d_{PL}}{v_2 - v_1},$$
$$\hat{x}_m(t_0) = (d(t_0) - d_{PL})\frac{v_2}{v_2 - v_1}, \tag{4}$$

where $\hat{v}_1 = v_1 = v_{1,\mathrm{ref}}$, $\hat{v}_2 = v_2 = v_{2,\mathrm{ref}}$.

However, due to the changing road grade, traffic conditions and other exogenous effects, vehicle speeds will change. It has already been shown that even if there is no influence of traffic, even the mean speed deviation will be different for different vehicles (Fig. 1). Therefore, the prediction can be improved by incorporating v_1 and v_2 in (4) as mean speeds during the catch-up phase for the training set of the given experiment scenario.

Somewhat better results can be obtained by modelling the vehicle speed deviation from its nominal value as a piecewise linear function of the moving average of road grade $\bar{\alpha}_k$,

$$v_{i,k} = v_{i,\mathrm{ref}} + v_{i,\mathrm{ref}} \cdot \begin{cases} k_{i,\alpha_+}\bar{\alpha}_k & \bar{\alpha}_k \geq 0 \\ k_{i,\alpha_-}\bar{\alpha}_k & \bar{\alpha}_k < 0, \end{cases} \tag{5}$$

where k_{i,α_+} and k_{i,α_-} are parameters that multiply positive and negative $\bar{\alpha}_k$ respectively. We use different coefficients for positive and negative grades because the vehicles are affected differently by uphill and downhill slopes, and the distance over which we average road grade is determined empirically. It should be noted that this model only works when vehicle speed stays close to the reference speed, i.e. when there are no long uphill slopes.

Finally, we obtain vehicle speed predictions $v_k = v(s_k)$ as a function of vehicle positions by using a neural network model of the propulsive force (2) in (3). The current position of the follower vehicle, $x_2(t_0)$ is taken as the starting point and $v_{i,0} = v_i(t_0)$.

Assuming vehicle speed is constant on a road segment $[s_k, s_{k+1})$, vehicle speed predictions in time domain are

$$\hat{v}_i(t|t_0) = v_{i,k}, \quad t_{i,k} \leq t < t_{i,k+1},$$

where $t_{i,k}$ are times at which the vehicle i reaches $x = k \cdot \Delta s$,

$$t_{i,k} = \sum_{j=1}^{k} \frac{\Delta s}{v_{i,j}}.$$

Another prediction algorithm was proposed in Liang [2016]. There, platoon merge distance estimates are obtained from a linear regression model

$$\hat{x}_m(t_0) = p_1 + p_2\rho + p_3\left(d(t_0) - d_{PL}\right)\frac{v_2}{v_2 - v_1}, \tag{6}$$

where ρ is the average traffic density, p_1, p_2 and p_3 are regression parameters, p_3 is multiplied by the nominal platoon merging distance. In this model, only the influence of traffic density is considered.

4.2 Speed Prediction Model Training

We used the vehicle speed data from the experiments to train the two proposed vehicle speed prediction models, the neural network approximation model (2)–(3) and the simple road grade moving average piecewise linear model (5). Roughly half of the experiment data was used for training and the rest was used for testing, and only the test runs which resulted in successful platoon formation were considered. Models for the leader and the follower vehicle speed prediction were trained independently.

Several neural network structures were tested, and best results were acquired using a neural network with two hidden layers with five and three nodes and hyperbolic tangent sigmoid activation functions. The output of the l-th hidden layer of neurons is given by an $n^{(l)}$-dimensional column vector

$$x^{(l)} = \sigma^{(l)}\left(W^{(l)}\begin{bmatrix} 1 \\ x^{(l-1)} \end{bmatrix}\right),$$

where $\sigma(s)$ is the activation function that is applied elementwise and $W^{(l)}$ is the $n^{(l)} \times (n^{(l-1)} + 1)$ weights matrix. The output of the neural network is

$$y = W^{(L)}\begin{bmatrix} 1 \\ x^{(L-1)} \end{bmatrix}.$$

The output of the neural network is thus a nonlinear function of its inputs, $y = f_w(x^{(0)})$, parametrized by its weight matrices $W^{(l)}$, $l = 1, 2, 3$, which are trained using a back-propagation algorithm.

Input and target data for both neural networks are

$$x_k^{(0)} = \left[v_k - v_{\mathrm{ref}} \;\; \alpha_k\right]^\top,$$
$$y_k = \frac{v_k^2 - v_{k-1}^2}{2ds} + g\alpha_k.$$

By adopting this simple model, we assume that the behaviour of the vehicles only depends on local road topography. This allows us to use this model on any road segment whose topography is represented in the training data. Since highways in general follow similar topographic guidelines, most highways should be covered, except for road segments with long uphill or downhill slopes, which were not present in the training data. To enable generalization to these road segments, more data would need to be collected by running more experiments on different roads. Most often, however, the deviations in behaviour are due to the influence of traffic conditions, which are not covered by this model and must be addressed separately.

The training data from all three scenarios was considered together, excluding data points if the distance between the vehicles is smaller than 200 m, vehicle speed differs from the goal speed by more than 10 km/h or the distance from the start is less than 200 m. These data points are excluded in order to avoid speed changes that occur during the final platoon merging maneuver or if the vehicle is forced to brake, and to give the follower vehicle enough time to reach its goal speed. Finally, to reduce computational effort, the trained neural networks are implemented as look-up tables. Values of F_p/m are shown in Fig. 3. We can see that in general, applied propulsive force will increase with road grade and vehicle speed deviation. This increase is faster around the origin ($v \approx v_{\mathrm{ref}}, \alpha \approx 0$) and it gets slower for larger speed discrepancies and road grades because the engine power is limited.

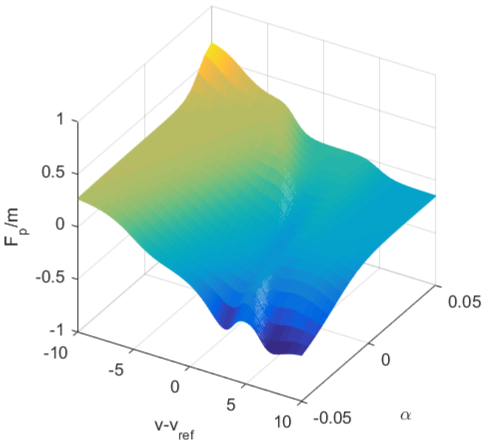
For the road grade moving average piecewise linear model we have four linear regression equations of the form

$$\frac{v_k - v_{\mathrm{ref}}}{v_{\mathrm{ref}}} = k_{m,\alpha_\pm}\bar{\alpha}_k,$$

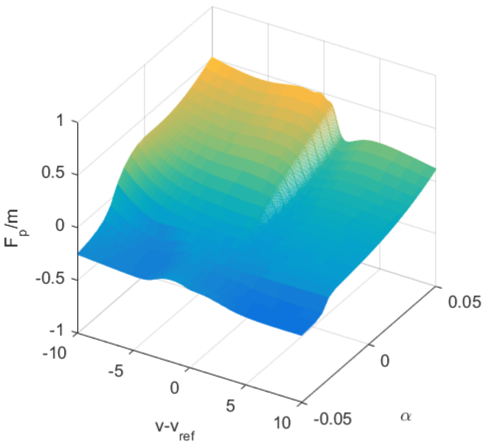
one for uphill (α_+) and one for downhill (α_-) slopes for each vehicle. Here, road grade is averaged over 400 meters and the values of the regression parameters are $k_{1,\alpha_+} = -1.28$, $k_{1,\alpha_-} = -1.81$ for the leader and $k_{2,\alpha_+} = -0.32$, $k_{2,\alpha_-} = -0.73$ for the follower vehicle. We can see that the speed of both vehicles is more affected by downhill slopes than uphill slopes. The effect is more

Table 1. Comparison between the predicted merge distance errors for different models.

Test-scenario	Constant v_{ref} RMSE	Constant v_{ref} STD	Constant mean v RMSE	Constant mean v STD	Linear regression RMSE	Linear regression STD	Grade moving average RMSE	Grade moving average STD	Neural network RMSE	Neural network STD
(75,85)km/h	1492.65	704.58	1275.65	700.42	1062.09	663.22	814.51	700.49	678.65	579.22
(75,89)km/h	1386.28	948.91	1289.35	952.21	1077.51	937.26	1060.23	956.22	865.83	829.03
(80,89)km/h	1658.93	837.86	1287.53	870.10	1231.15	832.36	975.07	861.52	835.46	786.28
Total	1516.22	855.45	1284.41	851.30	1127.10	835.14	959.11	846.51	800.49	741.33



(a) Leader



(b) Follower

Fig. 3. F_p/m as a function of $v - v_{\mathrm{ref}}$ and α for the leader and the follower vehicle.

pronounced on the leader vehicle, since it is significantly heavier than the follower vehicle.

5. EXPERIMENTAL RESULTS

Platoon merging distance prediction based on the two proposed vehicle speed prediction methods is evaluated using the test data set, and compared with the results obtained using the linear regression model (6) from Liang [2016]. The comparison is summed up in Table 1 and box plots of relative errors are shown in Fig. 4. The relative error is defined as the ratio between the distance prediction error and the actual platoon merging distance. Also shown are naive estimates according to (4), assuming vehicle speed is constant. We can see that the neural network based approach shows consistently better results, with the smallest root mean square error and standard deviation. The grade moving average method achieves results comparable to those given by linear regression (6).

Once the future speed profile is predicted, it is easy to adopt some empirical criterion for recalculating the platoon merge distance predictions. This enables us to only recalculate speed profile predictions when the measured speed deviates from its predicted value due to some disturbances or model mismatch, instead of recalculating them periodically. The results of applying one such recalculation criterion for one test run are shown on Fig. 5. Here, recalculations were done at most once per 400 m, when speed deviations are more than 3 km/h. The speed of the follower vehicle will be recalculated twice, once at $x_2 = 600$ m and another time at $x_2 = 1020$ m. We can see that recalculating the speeds improves the platoon merging distance prediction, from approximately 393 m (4.12% of the current remaining distance) at the start of the test run to 170 m (1.9%) after 600 m, and down to 70 m (0.8%) after another 420 m.

The neural network model predicts nominal vehicle speeds reasonably well in nominal conditions (Fig. 2). However,

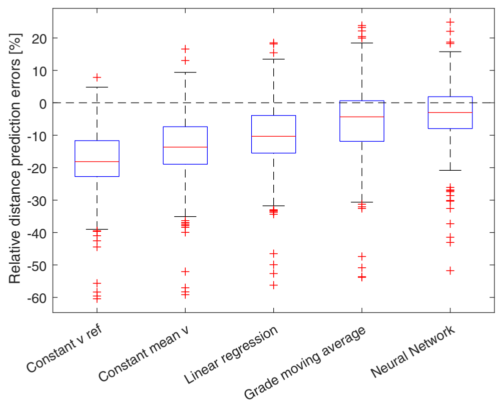


Fig. 4. Box plots of relative platoon merge distance prediction errors.

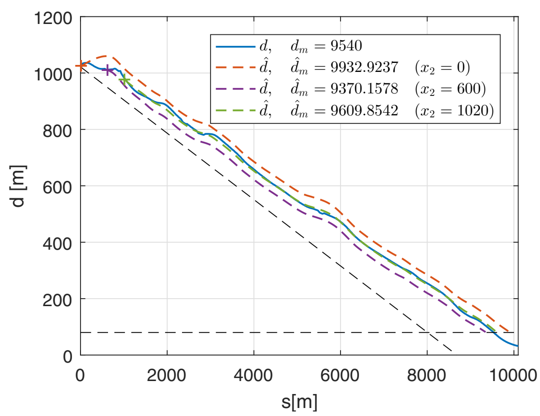


Fig. 5. Recalculated merge distance predictions.

the vehicles will often deviate from their nominal behaviour, resulting in larger discrepancies between the predicted and actual speed and causing outliers in merging distance prediction. Most often, we cannot be sure what caused the deviation. In a number of test runs, the cruise control goal speeds were set wrong, and a vehicle drove slower or faster than intended. The nominal downhill speed control offset, set to 5 km/h, was exceeded in some test runs (clearly visible on Fig. 2), and in some other test runs, the offset was reduced to 3 km/h. Apart from these situations, the traffic conditions are the most likely cause of larger deviations from nominal vehicle behaviour, especially when the nominal speed of the vehicles was close to the speed limit. Additionally, there is an on and off-ramp approximately in the middle of the road stretch, which will often cause a drop in the follower vehicle speed even for medium traffic densities. This effect is especially noticeable if the lead vehicle has just passed the ramp at the time the follower vehicle approaches it.

The box plots (Fig. 4) show that the mean error for all methods is negative, i.e., all methods on average predict that the platoon will merge sooner than it actually does. The neural network speed model gives the smallest median and mean relative errors, -3% and -4%, respectively. This bias effect can be explained by the influence of traffic conditions. In general, the influence of the surrounding traffic conditions on HDVs is hard to see when the speed of the vehicles is much lower than the average speed on the road. In the first test-scenario, the follower vehicle was driving with nominal speed of 85 km/h, while the speed limit on the road was 100 km/h, and the road grade was the main cause of its speed deviation. In two other scenarios, the influence of traffic conditions was much more apparent, resulting in larger root mean square errors (835.46 and 865.83 versus 678.65).

6. CONCLUSION

In this paper, we have examined how the changing road grade affects the catch-up phase of two HDVs attempting to form a platoon while driving on a highway. The vehicles were driving with cruise control and downhill coasting control, and with different desired speeds. A method for predicting the platoon merging distance based on vehicle speed predictions taking into account road topography was proposed. The speed prediction was done using a neural network model of net propulsive force, which was trained on experiment training data set. The proposed method was tested on experimental data, showing a reduction in prediction errors when compared to other methods. We did not consider the influence of traffic conditions, and we see better results when the traffic on the road is less dense. The prediction works better when the desired vehicle speed is lower, since then the vehicle is less susceptible to the influence of traffic around it.

It is clear that traffic conditions play a major role in the platoon merging phase, and that they cannot be ignored if we want to make a good merging distance prediction. The algorithm given in this paper can be used to isolate the influence of road grade, in order to make it easier to investigate the influence of traffic conditions. The driver behaviour also influence the HDVs, and phenomena such as persistent drivers need to be considered when attempting to form a platoon in traffic. We did not consider look-ahead cruise control, which would lead to a different, net propulsive force model. Investigating these, and other effects is left for future work.

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