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Control of Platooned Vehicles in Presence of Traffic Shock Waves

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***Abstract*—Vehicle platooning has been attracting attention recently because of its ability to improve road capacity, safety and fuel efficiency. Vehicles communicate using Vehicle-to-Vehicle (V2V) wireless communication, making their status (acceleration, position, etc.) available to other vehicles. Shock waves, i.e. zones of reduced traffic speed that propagate upstream, are a well known emergent traffic phenomenon. Since vehicles entering such a zone need to decelerate sharply, shock waves cause a deterioration of fuel economy, driving comfort, and safety. While typically caused by bad driving behavior, recent studies have shown that it is possible to diminish or dissipate shock waves by applying certain good driving behavioral patterns. In this work, we use the information about the traffic situation to adapt the reference speed profile of the platoon we control, in order to mitigate the effect of a shock wave coming from downstream. The platoon leader receives the velocity of the vehicles downstream of the platoon and distance gap between them using V2V communication and it computes the shock wave speed. We show that by doing this we reduce the fuel consumption of the vehicles in the platoon, and improve the traffic situation by helping dissipate the shock wave. We validate our results using microscopic models with the help of a toolchain composed of Matlab, and the SUMO traffic simulator.**

I. Introduction

Although platooning, where vehicles drive as one unit with low inter-vehicular distances, is in principle possible with human drivers, it is only now with the advent of modern vehicle control systems, such as Adaptive Cruise Control (ACC), becoming feasible in realistic road scenarios. While short platoons consisting of a few vehicles can be formed and maintained using only the vehicles' own sensor data, it is shown that this approach does not ensure string stability [1], and thus Vehicle-to-Vehicle (V2V) communication is required in order to robustly regulate spacing of longer platoons. Cooperative Adaptive Cruise Control (CACC), which is an extension to ACC is an enabling technology for the vehicle platoons, enhances the functionality of ACC by integrating V2V wireless communication between vehicles along with other sensors. CACC enables significant reduction in *headway* time (i.e. the time needed by the follower vehicle to reach the position of the preceding vehicle). Wireless communication enables vehicles to share a richer set of information such as acceleration, position, velocity, road intersection and traffic flow status e.g. existence of moving or stationary obstacles. Studies have shown that highway capacity improves by increasing CACC market penetration [2].

In the future, we may expect V2V communication to be commonplace, not only for platooned vehicles, but also for other human-driven vehicles. Platoon of vehicles exchange periodic Cooperative Awareness Messages (CAMs) over V2V communication. As per IEEE 802.11p under the European Telecommunications Standards Institute (ETSI) [3], there are two types of channels – one control channel (CCH) and six service channels (SCHs). The SCHs allow for higher transmission rates e.g., 25Hz, 50Hz, 100Hz. The CCH is dedicated to safety-critical applications like vehicle platooning and it allows for transmission rate ranges from 1-10Hz.

One particularly interesting additional benefit of V2V communication is that it can enable platooned vehicles to know the traffic situation downstream, allowing them to prepare for disturbances originating from the background traffic. For example, using CAMs from downstream vehicles, platooned vehicles might infer that they are approaching a stop-and-go wave, and adjust the speeds and spacings accordingly, improving their safety and fuel economy. A stop-and-go wave, or shock wave can be defined as a wave of slowed or stationary vehicles. They are typically caused by a breakdown of metastable traffic flow that might happen because of some bad driving behavior, e.g. an aggressive lane change that causes the following vehicle to brake, which in turn causes the next vehicle to brake harder and so on [4].

The behavior of shock waves has for long been studied in macroscopic traffic models [5]. Likewise, we may use vehicle trajectory data, to estimate shock wave propagation speed in a microscopic framework [6]. Recently, some works investigate the effects of using new connected and automated vehicle technologies to attenuate the shock waves, e.g. using a real-time lane selection algorithm [7], using the automated vehicles as moving bottlenecks [8], or controlling the car-following behavior of few autonomous vehicles so that stop-and-go waves are dissipated in field experiments [9].

The focus of this work is on improving the control of vehicles in a platoon by including additional information about the downstream traffic conditions. We assume that some vehicles downstream of the platoon communicate their

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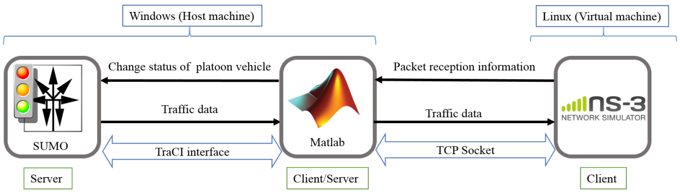


Figure 1: Interaction between ns-3, SUMO and Matlab in CReTS toolchain (ContRol, nEtwork and Traffic Simulator).

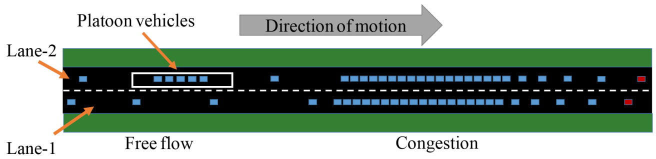


Figure 2: SUMO GUI – a five-vehicle platoon driving on a two lane road segment approaching a stop-and-go wave.

speeds and the distance gap between them, allowing us to detect and identify a shock wave, and adapt the speed of platooned vehicles accordingly. By reducing their speed in a timely and smooth manner, platooned vehicles avoid having to brake harshly when they reach the shock wave, avoiding a potentially dangerous situation. The control of platooned vehicles is composed of two-layers, the upper-layer which is responsible for receiving information from the preceding vehicle and computing vehicle's desired acceleration. Model Predictive Control (MPC) [16] is the control framework chosen for this layer because of its ability to handle constraints on inputs and states. The upper-layer of the platoon leader has more advanced functionality, it receives information from vehicles downstream of the platoon and detects the formed shock wave, computes the shock wave speed and changes the reference speed to adapt the platoon to the approaching shock wave. The upper-layer controller for the leader follows a predefined trajectory in case there is no vehicles ahead of the platoon and no detected shock wave. If there exists some vehicles in front of the leader, the leader follows the speed of the preceding vehicle and keeps safe distance which is longer than the distance between platooned vehicles. The lower-layer which is designed using state feedback control method, is responsible for reaching the desired acceleration set by the upper-layer.

Our approach is tested using CReTS toolchain [10] (ContRol, nEtwork and Traffic Simulator), which is a co-simulation framework that connects Matlab (for control design), the traffic simulator SUMO (for generating real driver behavior) [11], the network simulator ns-3 (for simulating V2V communication) (see Figure 1). Using microscopic simulations in SUMO, we compare the fuel consumption of platooned vehicles and show that preemptively lowering their speed leads to better fuel economy.

The outline of this paper is as follows. First, in Section II, we present the motivating scenario that is studied. Next, in Section III, we give models of platooned vehicles and the background traffic, which are then used in Section IV to derive a control law for the platoon. Finally, in Section V, we describe the simulation setup and results, and in Section VI we conclude our paper.

II. Motivating Scenario

The scenario we are looking at in this work consists of a platoon of five vehicles driving in congested traffic and encountering a shock wave originating from some point downstream (see Figure 2). Although in the SUMO traffic simulator, such a shock wave will not arise on its own, we can simulate it by forcing adjacent vehicles on all lanes to temporarily reduce their speed. This causes the incoming traffic (free flow region) to cluster behind them, and due to vehicles accelerating slower than braking, a shock wave is formed and starts propagating upstream.

Having detected a shock wave in its path, platooned vehicles can adjust their speeds accordingly. By reducing their speed, the vehicles can act as a moving bottleneck, thus restricting the traffic flow at their position, and if this inflow into the shock wave is lower than the discharging flow, the wave length will decrease and the shock wave will eventually dissipate. We consider three scenarios including a shock wave. (i) uncontrolled scenario, in this scenario there is no information received via V2V communication and therefore there is no early adaptation to this situation. Therefore the platoon will suddenly enter the shock wave with huge drop in velocity to avoid crash with other vehicles. With the availability of the V2V communication we define two scenarios, (ii) preemptive deceleration scenario, where the speed of platooned vehicles is slowly decreased to the low speed of the vehicles driving inside the shock wave. Platooned vehicles in this scenario will avoid hard braking but no improvement in dissipating the shock wave. (iii) Predictive deceleration scenario, in this scenario platooned vehicles can react prior to reaching the shock wave. Therefore they do not reach such low speed as in previous scenario. Acting as a moving bottleneck, fewer vehicles will enter the shock wave so this will help in damping the shock wave faster.

Figure 2 shows a realistic highway scenario simulated in SUMO with a road section of 3km length and two lanes (Lane-1 and Lane-2) in each direction. Platooned vehicles drive on the left-hand lane (Lane-2), without lane changing. The distance between the platoon leader and the congested area is 1300m at the beginning of the simulation time. The speed and acceleration of all vehicles range from 0 to 30m/s (108km/h), and from -5 to 3m/s^2, respectively. We assume that vehicles communicate via IEEE 802.11p; network congestion is ignored for simplicity where packet loss and network delay are not considered in this work. The driving behavior of human-driven vehicles in SUMO is governed by the Intelligent Driver Model (IDM) [15].

Note that it is assumed that vehicles ahead of the platoon are equipped with V2V devices with high transmission power. This assures that network coverage is sufficient such that information of vehicles at least 1km ahead of the platoon can be received by the platoon leader [12].

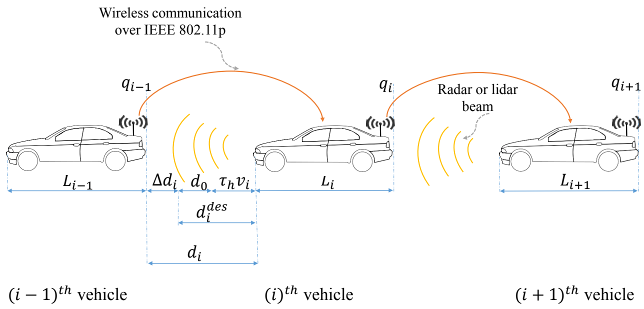


Figure 3: Consecutive vehicles in a platoon.

III. Modelling

In this section we establish the models required for control and simulation. Platooned vehicles are described in more detail, while the background traffic adheres to a car-following model. Finally, traffic shock waves are described and their behavior outlined.

A. Platoon model

Distributed platoon model is considered in this work; each vehicle has a model of itself (vehicle model) and its relation with its preceding vehicle (inter-vehicle dynamics).

The model of vehicle i combines a simplified model of the longitudinal dynamics of the vehicle with the dynamics of the engine system. The throttle actuator which adjusts throttle angle is modeled as a DC motor [13], [14]. The combined model is given by:

$$\dot{x}_i^v = A_i^v x_i^v + B_i^v u_i^v, \tag{1}$$

where A_i^v and B_i^v are the state and input matrices respectively, u_i^v is the duty cycle of the input to the motor and $x_i^v = [a_i \quad \dot{a}_i]^T$ is the state vector, where a_i and $\dot{a}_i$ are the acceleration and the rate of change of acceleration of vehicle i, respectively. Moreover, state matrix A_i^v and input vector B_i^v of vehicle i are defined as:

$$A_i^v = \begin{pmatrix} 0 & 1 \\ \frac{-1}{\tau_i \tau_i^a} & \frac{-(\tau_i+\tau_i^a)}{\tau_i \tau_i^a} \end{pmatrix} \in \mathbb{R}^{2\times 2}, B_i^v = \begin{pmatrix} 0 \\ \frac{K_i K_i^a}{\tau_i \tau_i^a} \end{pmatrix} \in \mathbb{R}^{2\times 1},$$

where τ_i, τ_i^a, K_i, K_i^a are model parameters of vehicle i.

To obtain the platoon model under the Predecessor-Follower (PF) topology[1], the inter-vehicle longitudinal dynamics are defined to relate vehicle i to vehicle $i-1$. This is done by adding two new states, Δv_i and Δd_i. They represent the speed difference and the gap error between the vehicles, respectively and they are defined as follows, (see Figure 3),

$$\Delta d_i = d_i - d_i^{des},$$
$$\Delta v_i = v_{i-1} - v_i,$$

where Δd_i is the error between the actual gap (d_i) and the desired inter-vehicle gap (d_i^{des}) between vehicle i and vehicle $i-1$. Δv_i is the velocity error between vehicle i and vehicle $i-1$, where v_i denotes the velocity of vehicle i. d_i and d_i^{des} are defined as,

$$d_i^{des} = d_0 + \tau_h v_i,$$
$$d_i = q_{i-1} - q_i - L_i,$$

where d_0 is the gap between vehicles at standstill, τ_h is the constant headway time (the time vehicle i needs to reach the position of vehicle $i-1$ when $d_0 = 0$). L_i, q_i are the length and position of vehicle i, respectively.

Combining the vehicle model with the inter-vehicle dynamics we obtain the following platoon model,

$$\dot{x}_i^p = A_i^p x_i^p + B_i^p u_i^p + G_i^p a_{i-1}, \tag{2}$$

where the state $x_i^p = [a_i \quad \dot{a}_i \quad \Delta d_i \quad \Delta v_i]^T$. a_{i-1} is the acceleration of the preceding vehicle and $G_i^p = [0 \quad 1]^T$. A_i^p and B_i^p are the state and input matrices.

B. Background traffic model

We use the well-known Intelligent Driver Model (IDM) to model the remainder of the traffic. The time-continuous IDM is an accident-free model producing realistic acceleration trajectories. The acceleration of each vehicle is defined as,

$$\dot{v} = a\left[1 - \left(\frac{v}{v_f}\right)^{\delta} - \left(\frac{\Delta d_{des}(v, \Delta v)}{d}\right)^2\right], \tag{3}$$

where d is the actual gap between vehicles, the desired gap is defined as,

$$\Delta d_{des}(v, \Delta v) = d_0 + \tau v + \frac{v \Delta v}{2\sqrt{ab}}, \tag{4}$$

τ is the headway time, v and v_f are the actual speed and the desired speed, respectively. The term $(v\Delta v) / \left(2\sqrt{ab}\right)$ in Eq. 4 achieves an accident-free "intelligent" braking strategy where b defines the comfortable deceleration value.

According to Eq. 3, vehicles have a tendency to accelerate with acceleration,

$$a_{accel} := a\left(1 - \left(\frac{v}{v_f}\right)^{\delta}\right)$$

on a free road and a tendency to brake with deceleration,

$$a_{decel} := -a\left(\frac{\Delta d_{des}(v, \Delta v)}{d}\right)^2.$$

Starting from a standstill, and assuming there are no vehicles in front of it, a vehicle will accelerate with maximum acceleration $a_{accel} = a$. As its velocity increases, the acceleration will decrease until becoming zero for $v = v_f$, with the exponent δ governing how smooth the transition is. Conversely, if a vehicle is reaching an obstacle, such as a red light or a slow vehicle, it will brake with deceleration a_{decel}.

[1]In PF topology, a vehicle receives information via wireless communication from its direct predecessor only.

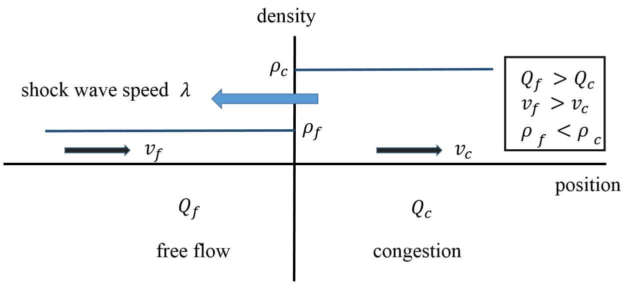


Figure 4: Shock wave between two different traffic flow states.

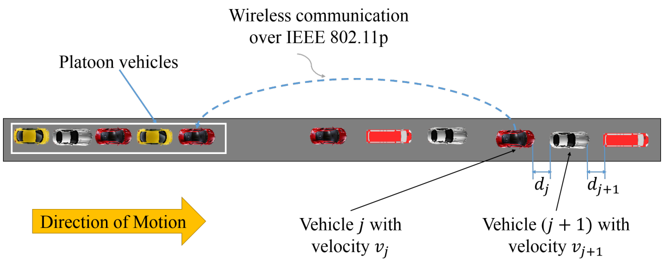


Figure 5: How the platoon leader computes shock wave speed.

C. Shock waves

Shock waves in traffic flow, i.e. discontinuous jumps between two different traffic states (see Figure 4) that propagate upstream or downstream, typically arise due to some inhomogeneity of road characteristics (bottleneck, red traffic light, on-ramp, etc.), but may also appear due to traffic breakdown in a form of a stop-and-go wave. Depending on traffic density and flow on both sides of the discontinuity, the shock wave may propagate either upstream or downstream, and the speed of its propagation is given according to the Rankine-Hugoniot condition,

$$\lambda = \frac{Q_c - Q_f}{\rho_c - \rho_f}, \tag{5}$$

where Q_c and Q_f are traffic flows, and ρ_c and ρ_f are traffic densities downstream and upstream of the shock, respectively. Since the average traffic speed v is tied to traffic flow and density, $Q = v\rho$, another characteristic of the shock wave is that there will be a sharp decrease in vehicle's speed before and after crossing the boundary, $v_f > v_c$. For a platoon of vehicles driving with short inter-vehicular gaps, this abrupt deceleration serves as a major disturbance, potentially endangering the safety of the vehicles. Therefore, it is desirable for platooned vehicles to preemptively adjust their speeds prior to reaching the shock wave.

Although the behavior of shock waves is typically described in macroscopic models, traffic data obtained from stationary sensors might be insufficient, insufficiently detailed, or too delayed to be used for immediate platoon speed adaptation. Instead, we use the communicated data from individual vehicles, which is also readily available in microscopic traffic models. In order to compute the shock wave speed, a formula similar to Eq. 5 is obtained where average values are replaced with individual vehicle values, as in [6],

$$\lambda_\mu = \frac{(\frac{v_j}{d_j}) - (\frac{v_{j+1}}{d_{j+1}})}{(\frac{1}{d_j}) - (\frac{1}{d_{j+1}})}, \tag{6}$$

where v_j is the speed of vehicle j and d_j the gap between vehicles j and $j+1$, as shown in Figure 5.

IV. Control Structure of Platooned Vehicles

Multi-layer control structure is adopted for platooned vehicles. The lower layer controller is a state-feedback controller runs with a sampling rate of 2ms. The output of this controller is the motor duty cycle which controls the vehicle acceleration [10]. The upper-layer controller uses Model Predictive Controller (MPC) with a longer sampling period (100ms) complying with the IEEE 802.11p communication standard.

A. MPC: Upper-layer controller

In MPC, an optimization problem is solved every time step subject to constraints on inputs and states. A quadratic cost function is chosen so that the problem is convex and a global minimum can be found. The MPC problem is defined as follows,

$$\begin{aligned} J = {} & x_i(N+k|k)^T P x_i(N+k|k) + \\ & \sum_{j=0}^{N-1} \Big[(x_i(j+k|k)^T Q x_i(j+k|k) + \\ & \qquad u_i(j+k|k)^T R u_i(j+k|k)) \Big] \end{aligned} \tag{7}$$

subject to

$$\begin{aligned} x_i(j+k+1|k) = {} & \Phi_i x_i(j+k|k) + \Gamma_i u_i(j+k|k) + \\ & \Psi_i a_{i-1}(j+k|k),\ j = 0, \ldots, N-1 \end{aligned} \tag{8}$$

$$x_{min} \leq x_i(j+k+1|k) \leq x_{max},\ j = 1, \ldots, N-1 \tag{9}$$

$$u_{min} \leq u_i(j+k|k) \leq u_{max},\ j = 0, \ldots, N-1 \tag{10}$$

where J is the cost function, N is the horizon length, $x_i(j+k|k)$ is the predicted state at step $j+k$ of vehicle i when the prediction is done at step k. $x_i(k|k)$ is the measured state of vehicle i. $u_i(j+k|k)$, $j = 0, \ldots, N-1$ is the sequence of optimal control inputs that will be computed where only the first value will be applied. Q, R and P are the weighting parameters. Eq. 9 and Eq. 10 define the upper and lower bounds of the state and input constraints, respectively.

In order to use MPC, the platoon model in Eq. 2 has to be discretized using Zero-Order Hold (ZOH) (refer to [10] for more details). After discretization, the predictive model for vehicle i can be obtained as shown in Eq. 8. The predicted state $x_i(j+k|k)$ is defined as,

$$x_i(j+k|k) = \begin{bmatrix} a_i(j+k|k) \\ \delta a_i(j+k|k) \\ \Delta d_i(j+k|k) \\ \Delta v_i(j+k|k) \end{bmatrix}.$$

$a_{i-1}(j+k|k)$ is the predicted acceleration of the preceding vehicle. We consider that the future evolution of the acceleration of the preceding vehicle is constant. Therefore, it does not affect the optimization process.

B. Leader vehicle in the platoon

The platoon leader is assumed to be driven by a human driver who follows a predefined acceleration trajectory. Due to road congestion, other traffic members may decide to change their lane and overtake platooned vehicles. In case that the distance between the platoon leader and its predecessor is less than 30m, the upper-layer controller for the leader (MPC controller) is switched on and its targets are:

1) To keep the headway time τ_h =2s between the leader and its predecessor.
2) To avoid rear-end collision.
3) To maintain a constant speed equal to the speed of its preceding vehicle.

The gap between the platoon leader and its predecessor and the velocity of the predecessor are assumed to be obtained using on-board sensors such as Lidar. Therefore, the acceleration of the preceding vehicle (used as feedback in MPC) can be determined by dividing the difference in velocity by the time step.

C. Follower vehicles in the platoon

The platoon is assumed to drive with maximum speed of 100km/h. The headway time τ_h between the platoon leader and its followers is considered to be 0.2s. The upper layer for each platooned vehicle uses MPC to achieve certain objectives such as:

1) Minimizing the gap between the vehicles to achieve a desired and safe inter-vehicle distance.
2) Tracking the speed and acceleration profiles of the preceding vehicle.
3) Minimizing sudden changes in acceleration to maintain passenger comfort.

The upper-layer controller of each platoon member receives its current state via in-vehicle network and the state of its preceding vehicle via IEEE 802.11p wireless communication. MPC controller computes the desired acceleration and delivers it to the lower layer as a new acceleration reference.

D. Adapting to shock waves

For platooned vehicles to react to a shock wave, shock wave has to be detected first, which can be done using the information received from the vehicles downstream of the platoon. The platoon leader computes shock wave speed λ_μ using Eq. 6. Since λ_μ changes over time due to the instantaneously changing velocity and gap between vehicles, our algorithm does not require the exact value of λ_μ. Instead, $\lambda_\mu < 7$ is used to detect the presence of a shock wave. For example, using the following information received from the 20^{th} vehicle and the 26^{th} vehicle ahead from the platoon leader: d_i=7m, d_{i+1}=26m, v_i=10m/s and v_{i+1}=28m/s, then shock wave speed can be calculated as λ_μ =3.3m/s. λ_μ is computed based on the information received from vehicles that are 1km ahead from the platoon leader which is assumed to be enough distance for the platoon to react and adjust its reference speed.

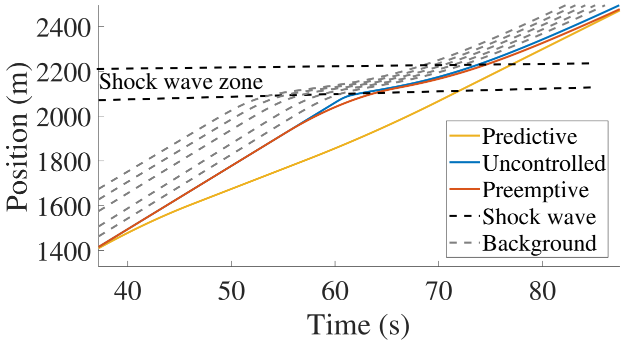


Figure 6: Adapting to the shock wave. Uncontrolled: the platoon reaches the shock wave at $t = 60$s. Preemptive: the platoon decelerates just before entering the shock wave ($t = 55$s). Predictive: the platoon decelerates well ahead of the shock wave ($t = 35$s).

We define three different ways to show how the platoon can react to a shock wave: (i) uncontrolled scenario (ii) preemptive deceleration scenario (iii) predictive deceleration scenario. In the following we explain in detail each of these scenarios. Figure 6 shows an overview of the three scenarios. The horizontal region bounded by black dashed lines is the shock wave zone which is formed by holding some vehicles at low speed. Vehicles who enter this zone (gray dashed lines in Figure 6) have to slow down their speed and after releasing the slow moving vehicles they speed up again. The blue, red and yellow curves in Figure 6 refer to the trajectories of the platoon leader in the three scenarios. Traces of other vehicles are omitted for simplicity.

1) Uncontrolled scenario: In this scenario it is assumed that no information is available regarding the formed shock wave and platooned vehicles enter the shock wave (see the blue line in Figure 6). In this case platooned vehicles will have to apply hard braking in order to avoid collision with each other and with the vehicles in front, which may cause accidents or discomfort driving.

2) Preemptive deceleration: In this scenario the platoon leader avoids hard braking by decelerating preemptively to reach the speed of the vehicles driving inside the shock wave (see the red line in Figure 6). This yields a smoother speed trajectory. However platooned vehicles still need to decrease their speed to low values. Here the reaction is based on the information received from the vehicles that are < 100m ahead from the platoon.

3) Predictive deceleration: In this scenario, with the availability of the information of other vehicles over V2V wireless communication and the presence of the automated vehicles, a shock wave can be detected and damped by controlling the speed of platooned vehicles. The platoon leader detects the formation of the shock wave via calculating λ_μ based on the information received, for example, from the 20^{th} vehicle

Acceleration (m/s^2)	3
Deceleration (m/s^2)	5
Length (m)	4
Maximum speed (m/s)	30
Tau (s)	0.7
Delta	4
minGap	0
lcStrategic	150
lcSpeedGain	350

Table I: IDM Parameters used in SUMO.

and the 26^{th} vehicle ahead from the platoon leader. Having detected the shock wave at time $t = 33$s, platooned vehicles reduce their speed to some value (here taken to be 65km/h). At time $t = 55$s, when platooned vehicles detect that the shock wave is starting to dissipate, their reference speed is increased to 83km/h (see Figure 7c). By doing so, platooned vehicles help to dissipate the shock wave by restricting the inflow of vehicles into it, acting as a moving bottleneck. Applying this kind of control further improves fuel efficiency and drive comfort.

V. Simulation

In this section we present the set-up and results of simulations in which we test our control law.

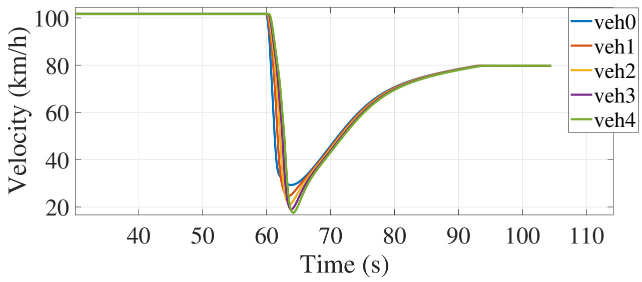
A. Simulation setup

IDM is the car-following model implemented in SUMO with the parameters shown in Table I. The **minGap** attribute corresponds to d_0 i.e. the gap between vehicles at standstill. **Tau** and **Delta** correspond to τ and δ in Eq. 4 and Eq. 3, respectively. The attributes **Acceleration**, **Deceleration** and **Maximum speed** define the maximum acceleration, deceleration, speed for regular vehicles in SUMO.

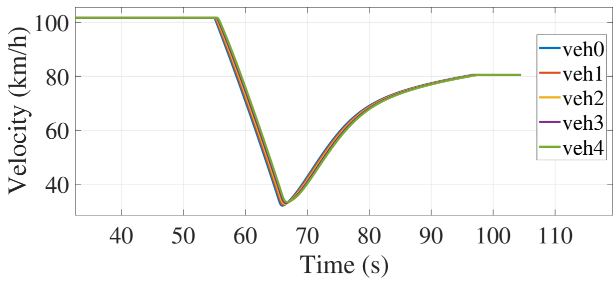
The default lane-changing model implemented in SUMO and used in our case study is the model developed by Jakob Erdmann [17]. The attribute **lcStrategic** $\in [0, \infty[$ defines the eagerness for performing strategic lane changing. Higher values result in earlier lane changing. **lcSpeedGain** $\in [0, \infty[$ defines the eagerness to perform lane changing to gain speed. Higher values results in more lane changing.

In order to create a shock wave on a two-lane road in SUMO, two vehicles are selected to drop their speed from 28m/s (100km/h) to 5.556m/s (20km/h) (the red-colored vehicles in Figure 2). They keep their speed fixed at 5.556m/s for 40s. Other vehicles are forced to slow down their speed to 5.556m/s to avoid collision with those slow-moving vehicles. By keeping the speed of the red-colored vehicles fixed at 5.556m/s for 40s, the shock wave will propagate backward. In other words, more vehicles will enter the congested region and the length of the slow-moving vehicles will increase (see Figure 8).

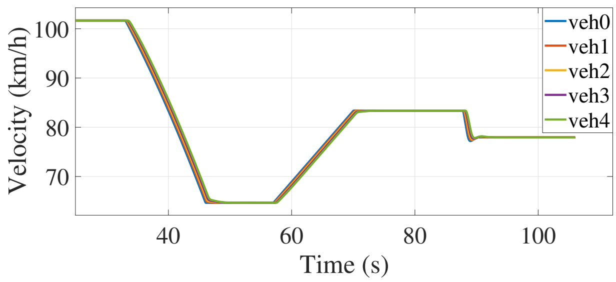
To keep the shock wave formed for 40s, the red-colored vehicles should drive on a different lane. This can be done in SUMO by manually placing those vehicles on separate lanes with same horizontal position and disabling lane changing property for those vehicles. Otherwise the shock wave will be dissipated early or may not be formed at all because vehicles



(a) Uncontrolled scenario – platooned vehicles have entered the shock wave with huge drop in velocity.



(b) Preemptive deceleration – lowering the platoon speed slightly before entering the shock wave.



(c) Predictive deceleration – platoon speed has been lowered down using the information received via IEEE 802.11p.

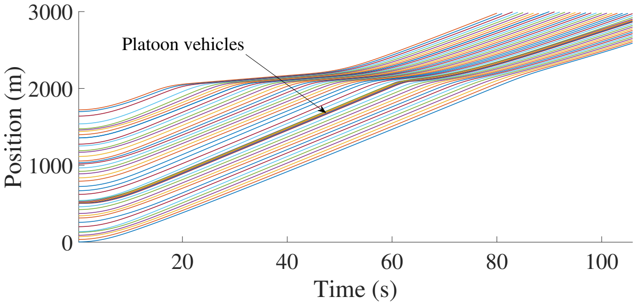
Figure 7: Velocity of platooned vehicles.

will change their lanes to avoid the slow moving vehicles. The attribute **lcSpeedGain** (see Table I) is set to zero in SUMO files for those vehicles to disable lane changing.

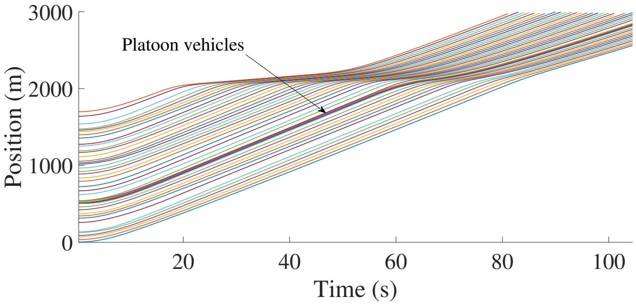
B. Simulation results

The behavior of platooned vehicles are shown in Figure 7a, 7b, 7c. *veh0*, *veh1*, *veh2*, *veh3*, and *veh4* in these figures refer to platoon leader, 1^{st}, 2^{nd}, 3^{rd}, and 4^{th} following vehicle, respectively.

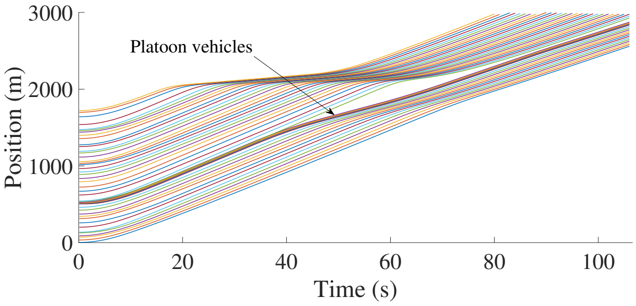
1) Uncontrolled scenario: As shown in Figure 7a, at time $t = 60$s the platoon leader's speed sharply decreases from free flow speed (100km/h) to the speed of vehicles in congestion (32km/h) when suddenly entering the shock wave. This sudden drop in velocity necessitates applying hard braking which in real-life applications might cause an accident due to possible delays in its application. String stability is not preserved, and the follower vehicles need to reduce their speed even further than the platoon leader (at time $t = 62$s). Figure 8a shows the trajectories of all vehicles on Lane-2 where the platoon drives. Other vehicles enter the



(a) Uncontrolled scenario – no adaptation to shock wave is considered.



(b) Preemptive deceleration – platooned vehicles slow down right before entering the shock wave to avoid hard braking.



(c) Predictive deceleration – platooned vehicles slow down earlier to avoid driving with low speed.

Figure 8: Position trajectories for vehicles on Lane-2.

shock wave zone after platooned vehicles which means that the queue length of the slow vehicles will keep increasing until the shock wave dissipates.

2) Preemptive deceleration scenario: As shown in Figure 7b, the velocity profile of platooned vehicles is significantly improved compared to the uncontrolled scenario. By lowering the velocity five seconds in advance (at time $t = 55$s) before entering the shock wave, string stability is preserved and hard braking is avoided. As shown in Figure 8a, the trajectories of vehicles on Lane-2 are very similar to those in the uncontrolled scenario.

3) Predictive deceleration scenario: With the availability of shock wave formation to the platoon leader, severe changes in acceleration yet velocity of platooned vehicles and other vehicles can be avoided. As shown in Figure 7c, the velocity of the platoon leader decreases from 100km/h to 65km/h when a shock wave is detected. Acting as a moving bottleneck, fewer vehicles enter the shock wave and therefore the wave length decreases (see Figure 8c) and eventually is dissipated. This leads to a smoother acceleration profile, better fuel efficiency, and also improves the overall traffic situation.

Fuel economy

Different factors affect fuel consumption such as travel distance and time and weather conditions. However, the most significant factors for fuel economy that also considered in this paper, are vehicle-related and driver-related factors such as engine, vehicle's velocity and acceleration and smooth driving behavior [18].

In SUMO, the default open source emission model is represented as a continuous function of the instantaneously changing velocity and acceleration (see Eq. 11) [19]. The emission model is based on the data from the Handbook of Emission Factors for Road Transport (HBEFA[2]) database. HBEFA provides emission factors (e.g. CO_2 emissions and fuel consumption) for current vehicle categories such as passenger cars, light duty vehicles, heavy duty vehicles, and motorcycles; each divided in different categories that covers a wide variety of traffic situations. Data are extracted from HBEFA for different traffic situation and using curve fitting, the coefficients $\mathcal{C}_0,\ \mathcal{C}_1,\ \mathcal{C}_2,\ \mathcal{C}_3,\ \mathcal{C}_4,\ \mathcal{C}_5$ for the emission model Eq. 11 can be obtained. The coefficients of this model change with the vehicle and emission type.

$$\mathcal{F} = \mathcal{C}_0 + \mathcal{C}_1 v + \mathcal{C}_2 va + \mathcal{C}_3 v^2 + \mathcal{C}_4 va^2 + \mathcal{C}_5 v^3. \qquad (11)$$

In this work, emission models of all vehicle are modeled in SUMO using emission class HBEFA3/PC-G-EU4 (Euro-4 passenger car with a gasoline engine). Platooned vehicles in all scenarios reach almost the same positions by the end of the simulation time. Therefore the consumed fuel is computed over the same travelled distance to have fair comparison.

Figure 9 shows the instantaneously changing fuel consumption as a function of vehicle's velocity and acceleration. It compares between the consumed fuel for $veh0$ and $veh4$ for the three scenarios. Figure 9 shows that, a smooth driving behavior as in predictive deceleration scenario reduces the consumed fuel for the platoon. Whereas more fuel is consumed due to an aggressive driving behavior as in the uncontrolled scenario.

Total fuel consumption of platooned vehicles are computed and shown in Figure 10. It is shown that the total consumed fuel in the predictive deceleration scenario is the lowest compared to the preemptive and the uncontrolled scenarios. In comparison to the uncontrolled scenario, Table II summarizes fuel reduction rates for the five platooned vehicles in preemptive and predictive scenarios. Table II shows that the platoon leader saves 16.6% of the fuel if the predictive scenario is followed, while lower fuel consumption rates are obtained for the following vehicles. Similarly, the leader saves 5.56% of the fuel if preemptive deceleration scenario is applied. Similar fuel reduction rates are expected to be obtained for other traffic members, in particular for vehicles

[2]http://www.hbefa.net/

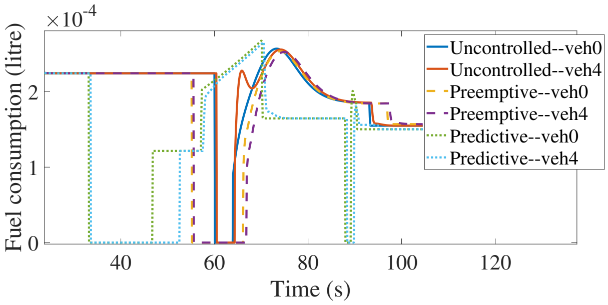


Figure 9: Fuel consumption as a function of the instantaneously changing vehicle's velocity and acceleration.

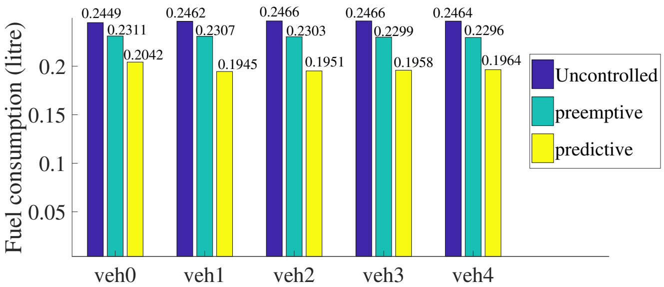


Figure 10: Total consumed fuel for platooned vehicles in litre.

which drive behind the moving bottleneck. The reason is that they are forced to follow similar reference speed as platooned vehicles.

VI. Conclusion

In this paper we have shown that it is possible to use the information received over V2V communication in order to improve the driving behavior of platooned vehicles. The additional information allows the vehicles to adapt their speed reference in response to disturbances originating from the surrounding traffic. While this approach can also be used for single vehicles, it is particularly effective when applied to platoons, since follower vehicles greatly benefit from knowing the exact behavior the leader vehicle will have in the future. By using this information, we are able to maintain string stability and improve the fuel economy and driver comfort. Moreover, since this behavior smooths the traffic flow, we can expect the overall traffic situation to be improved, possibly even resolving the shock wave before the platoon enters it.

	Fuel reduction	
	preemptive deceleration	predictive deceleration
veh0	5.56%	16.60%
veh1	6.31%	21.01%
veh2	6.62%	20.88%
veh3	6.75%	20.57%
veh4	6.85%	20.29%

Table II: Fuel reduction for preemptive and predictive deceleration scenarios compared to the uncontrolled scenario.

In the future, the interaction between platooned vehicles and the background traffic should be modelled in more detail, and used to devise more advanced control laws. Taking into account that the platoon acts as a moving bottleneck when slowed down will lead to more precise prediction of shock wave behavior, and consequently, better control performance.

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