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Cooperative Multi-Lane Shock Wave Detection and Dissipation via Local Communication

Nilesh Suriyarachchi[1], Christos Mavridis[1] and John S. Baras[1]

***Abstract*— Traffic shock waves are well-known naturally occurring phenomena that lead to unnecessary congestion in highway networks. Introducing connected autonomous vehicles (CAVs) to highways of human-driven vehicles (HDVs) allows for the development of traffic control schemes that can mitigate the effects of the shock waves. In this work, we propose a shock wave detection algorithm based on communication between CAVs with local traffic information. The proposed methodology is suitable for multi-lane mixed traffic highways of arbitrary structure, i.e., it is not limited to closed-circuit ring roads. We show that the detection information can be used to design a class of proactive shock wave mitigating CAV controllers. The choice of the controller can depend on design parameters such as the aggressiveness of the driving behavior allowed. We also demonstrate the importance of the positioning of autonomous agents in multi-lane scenarios. The shock wave dissipation efficiency is evaluated on a three lane highway loop using realistic traffic simulations and low CAV penetration levels.**

I. INTRODUCTION

Transportation systems are shifting from human-driven vehicles to autonomous vehicles capable of real-time perception, communication, decision making, and control, without the need for human intervention. These modern connected autonomous vehicles (CAVs), equipped with on-board sensing and communication technology, are capable of solving many persistent traffic-related problems, such as highway merge bottlenecks and the presence of traffic shock waves that lead to unnecessary congestion in highway networks [1], [2].

In this work, we focus on the problem of dissipating stop and go waves in highway networks, by exploiting the communication and sensing capabilities of modern CAVs to use them as Lagrangian sensors and actuators, collecting local information about and controlling the state of the highway traffic via vehicle to vehicle (V2V) communication. One of the main driving factors that enables this is the advent of 5G networking, which allows V2V communication with higher bandwidth and lower latency [3]. Shock waves, also known as stop and go waves, are traffic phenomena during which vehicles are forced to accelerate and decelerate in a periodic manner. As a result, traffic throughput decreases while the overall fuel consumption increases. During high traffic density conditions, shock waves are often easily triggered by otherwise normal driving behaviors, e.g., condensed highway merge junctions, obstacles on the side of the road or road construction activities. The main contributing factor to shock wave generation is identified as the latency involved in human decision making [1]. Finally, once a shock wave is formed, natural resolution of these conditions only occurs when the demand (vehicles using the highway) reduces. As such, during high density periods, shock waves can last for hours [4].

Literature review

Prior to research using autonomous vehicles, the dissipation of shock waves has been attempted using variable speed limits [5] which can only be applied at specific highway locations having the needed infrastructure. Field experiments were conducted by Sugiyama *et al.* [4] and Stern *et al.* [6] to study the effects of shock waves and the possibilities in using CAVs for shock wave dissipation. There, vehicles were placed in a single file loop, and in [6], a single ego CAV was used to apply a control strategy. The application of control to vehicle platoons to help reduce shock waves in single lane roads was studied in [7]. An optimal control approach was explored in [8], and could incorporate multiple ego (CAV) vehicles on a single lane ring-road. Research into the use of deep reinforcement learning techniques for shock wave dissipation control is also shown in [9]. However, such approaches make the unrealistic assumption that ego vehicles have access to the global traffic state. The use of V2V communication can potentially bypass the need for global traffic knowledge and has been used for shock wave suppression in [10] where the idea of changing driving parameters when shock waves are detected in the downstream is explored. Finally, while most of these approaches yield effective results in single lane ring roads, when considering multi-lane highways with no closed-loop assumptions, the shock-wave detection and control strategies need to be revised. Our previous work [11], used V2V communication for shock wave dissipation, but used a simple step control causing CAVs to perform hard breaking and did not handle lane changing decision making.

Contribution

In this paper, we develop a shock-wave detection and dissipation approach that (i) bypasses the assumption that global traffic information is available to CAVs at any time, and (ii) is appropriate for general multi-lane road structures, i.e., it is not limited to single-lane ring roads. We utilize the local sensing and communication capabilities of CAVs to develop a shock-wave detection algorithm that can be used to design a proactive controller that is shown to alleviate the traffic congestion caused by the shock wave. A

[1]Electrical and Computer Engineering Department and the Institute for Systems Research, University of Maryland, College Park, Maryland, USA. Email: {nileshs,mavridis,baras}@umd.edu.
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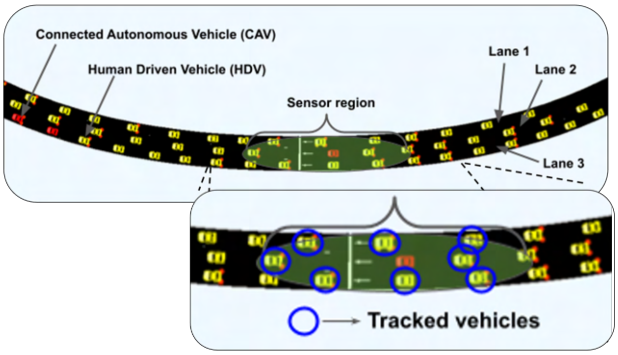


Fig. 1: Modeling CAV sensing capabilities in a mixed-traffic multi-lane highway.

lane change controller is also implemented to ensure that control is applied evenly across all lanes. Even in low CAV penetration levels, the CAVs are able to act proactively in a way that affects the traffic behavior of the entire network of human-driven cars, such that the stop and go phenomenon is mitigated. We stress that, unlike most existing methods, the CAVs are able to timely detect a shock-wave via local information and inter-communication, and are influencing the traffic flow by both velocity control and lane changing decisions. We compare against baseline approaches to show that the proposed method leads to improved shock wave dissipation on a multi lane highway. Further tests also show that, even with very low CAV penetration levels, effective shock wave dissipation can be achieved, while the choice of the CAV controller can depend on design parameters such as safety requirements and the aggressiveness of the driving behavior allowed.

II. Modeling CAV Sensors and Dynamics

We consider a general multi-lane highway stretch in a mixed-traffic setting, as shown in Fig. 1. The structure of the highway stretch (e.g., ring loop), its length, the number of lanes, and the number of HDVs and CAVs, are all design parameters that are subject to change depending on the problem at hand (see Section V). In this section, we model the sensors, actuators, and dynamics of the CAVs.

A. Autonomous Vehicle Sensors

Regarding the sensing capabilities of the CAVs, it is assumed that each CAV can detect the positions and velocities of its surrounding vehicles within a realistic sensor range. We assume that the CAV can track the positions of up to eight adjacent non-occluded vehicles as shown in Fig. 1.

Regarding the vehicle-to-vehicle (V2V) communication capabilities of each CAV, we assume that the CAVs communicate using a combination of IEEE 802.11p and 5G networks. We also assume real-time communication and as such do not consider network conditions such as delay and packet loss.

B. CAV Dynamics

The system created for shock wave detection and dissipation acts as a high-level control system which computes a target control velocity command for each CAV on the highway. It is assumed that each CAV has its own low-level controller capable of computing actuation commands in order to safely reach this target longitudinal velocity command while ensuring that the vehicle stays within its allocated lane.

For our high-level controller, we define the longitudinal vehicle dynamics by a velocity control scheme:

$$\begin{aligned} \dot{s_i} &= v_i \\ v_i(t) &= u_i(t) \end{aligned} \tag{1}$$

where $s_i(t)$, $v_i(t)$, and $u_i(t)$ denote the position, velocity and applied target control of each vehicle i respectively, for $i \in \{1, \dots, n\}$. Here, n represents the number of CAVs on the highway.

An integer variable $b^i \in \{1, , \dots, m\}$ is assigned to each CAV i, to represent the CAV's current lane. Here, m represents the number of lanes. The CAV's length, maximum acceleration and maximum braking is represented by l^i, a_{max} and a_{min} respectively. Therefore, each CAV has the following state:

$$x_i(t) = [s_i(t), v_i(t), b^i, l^i, a^i_{max}, a^i_{min}]^{\mathrm{T}} \tag{2}$$

for $i \in \{1, \dots, n\}$.

More details on this formulation can be found in our previous work [11]. The design of the shock-wave dissipation control $u_i(t)$ will be addressed in Section IV-B and is assumed independent of the lane changing decision of the vehicle. In other words, the lane changing procedures are handled by a separate low-level lane change controller.

III. Modeling Human-Driven Vehicles

Modeling human-driven vehicle behavior in large scale highway networks plays a major role in shock wave generation and simulation. A car following model determines the in-lane behavior of each vehicle, considering possible interactions with surrounding vehicles and a lane-changing model determines the lane-changing behavior of each vehicle.

A. Krauss Car-following Model

While there are many car-following models such as the Krauss model [12] and the Intelligent Driver Model (IDM) [13], we chose the Krauss model for its accuracy and simplicity. This model computes the safe following speed $v_s(t)$ by considering the impact of speed limits $\bar{v}$, vehicle acceleration capabilities a_{max}, the vehicle deceleration profile $b(v(t))$, distance gap $\Delta s(t)$ and speed $v_l(t)$ of lead vehicle, time step Δt and driver reaction time τ_r as shown in equation (3).

$$v_s(t) = \min(\bar{v}, v(t) + a_{max}\Delta t, v_l(t) + \frac{\Delta s(t) - v_l(t)\tau_r}{\frac{v(t)}{b(v(t))} + \tau_r}) \tag{3}$$

A key attribute of the Krauss model, which makes it very useful in the framework of this work, are the parameters $actionStepLength$ (τ_r) and $Sigma$ which allow modeling a diverse set of human-driving behaviors, including human reaction times and driving imperfections. These factors play a major role in shock wave research as they have been shown to be the major contributors to spontaneous shock wave generation.

B. Lane-Changing Model

The lane changing model used by the simulated human drivers is responsible for choosing the best lane to travel in and computing safe lane changing maneuvers to get to its desired lane. In simulating shock waves it is important that the HDVs behave realistically and are willing to change lane to overtake slow moving vehicles given the chance. In this research we adopt the lane-changing model developed by Erdmann [14] for the HDVs, as it has the desired driving characteristics.

IV. Shock-Wave Detection and Dissipation

In this section, we introduce our shock-wave detection algorithm, and develop a proactive control methodology to mitigate the effects of the shock-wave formation.

A. Shock-Wave Detection

The task of detecting the presence of shock wave conditions, an important prerequisite for shock wave dissipation control, requires knowledge on the traffic flow conditions at different positions on the highway. The characteristics of a traffic shock wave can be determined using the Rankine-Hugoniot condition using the throughput Q_c and density ρ_c at different points in the highway as shown in [11]. For shock wave detection, however, the most important criteria is the mean velocity V_c of vehicles at different points in the highway.

A naive approach (see, [6]) makes use of a rolling time average velocity estimate $\hat{V}_i(t)$ at position $s_i(t)$, given by $\hat{V}_i(t) = \frac{1}{k+1}\sum_{\tau=0}^{k} v_i(t-\tau)$. However, $\hat{V}_i(t)$ is often a bad estimator of a traffic state for multi-lane highways, since vehicles in different lanes may face different traffic conditions. To counteract this problem, in our prior work [11], we introduced a method to compute an accurate estimate for the multi-lane average velocity estimate $V_i^e(t)$ at the location of CAV i. We define the number of vehicles tracked as m, the maximum memory length as k and the velocity of the j^{th} tracked vehicle at time t as $v_j^i(t)$. Also let $k_j \leq k$ denote the number of time steps for which the j^{th} vehicle was tracked and $v_0^i(t)$ denote the velocity of ego CAV i. Then the average velocity estimate $V_i^e(t)$ is computed by

$$V_i^e(t) = \frac{1}{m+1}\sum_{j=0}^{m}\frac{1}{k_j+1}\sum_{\tau=0}^{k_j} v_j^i(t-\tau) \tag{4}$$

This method involves data gathered from multiple lanes, and therefore presents a more accurate representation of the average vehicle velocity.

Given the traffic state estimate described by (Q_c, ρ_c, V_c), where V_c is approximated by $V_i^e(t)$ based on (4), we are now in place to introduce our shock wave detection algorithm. If the CAVs do not communicate with each other (*reactive control strategy*), shock waves can only be detected by comparing the current velocity of the CAV $v_i(t)$ to its long term average velocity data $\hat{V}_i(t)$ as used in [6]. This method only allows the CAV to detect the presence of a shock wave condition after the CAV has already reached the low velocity congested region of the shock wave.

However, the detection process can be improved by taking advantage of the communication capability of the CAVs, using the following process. Each CAV carries out a shock wave detection process independently. The ego CAV i communicates with all other downstream CAVs within communication range C_i and requests for an update on the traffic conditions at their current positions. These local traffic states are then compared and the downstream CAV facing the worst case traffic conditions ($v_{det}^i(t)$) is identified as follows,

$$v_{det}^i(t) = \min_{j \in C_i} V_j^e(t) \tag{5}$$

Here, $V_j^e(t)$ is obtained from equation (4). The detection algorithm focuses on finding the worst case scenario downstream of the CAV, as we observe that the best performance is obtained by identifying this worst case scenario and adapting the control to counter this. The position $s_{det}^i(t)$ corresponding to the position of the CAV facing the worst conditions is also noted. The system then computes the relative velocity gap $v_{rel}^i(t)$ between the ego vehicle and the worst case conditions ahead of it as follows.

$$v_{rel}^i(t) = \max\{0, v_i(t) - v_{det}^i(t)\} \tag{6}$$

If $v_{rel}^i(t)$ exceeds a tunable threshold V_{sw}, a shock wave is detected, thus triggering a shock wave dissipating control strategy for CAV i, as described in Section IV-B. We note that as a result of the properties of this detection algorithm, the control strategy is *proactive*, starting to affect highway conditions upstream of the actual shock wave location.

B. Proactive Shock-Wave Dissipation Control

Once a shock wave has been detected, a control strategy should be implemented by each CAV to dissipate the effects of the shock wave as soon as possible, and with minimal control effort. It has been shown that a shock-wave mitigating controller should reduce the velocity of the CAV in an attempt to regulate traffic and avoid the stop-and-go behavior [6]. In a naive approach, a velocity control scheme for CAV (i) is computed based on the worst case minimum average velocity $v_{det}^i(t)$ in (5), as shown in equation (7) below:

$$v_i(t+1) = v_i(t) + dt\min\{\alpha_{min}^i, v_{det}^i(t) - v_i(t)\} \tag{7}$$

where it is assumed that $v_{det}^i(t) < v_i(t)$, α_{min}^i represents the maximum braking capacity of the vehicle, and dt is the timestep used which depends on the operation frequency of the controller.

While this is indeed a proactive controller that allows the ego vehicle i to react in advance to the shock wave traffic conditions, it is easy to see (see Fig. 2, case $\delta_i = 0$) that it corresponds to a largely aggressive braking profile. In designing a better controller, we have to take into account both the velocity gap $e_v = v_{det}^i(t) - v_i(t)$, and the actual distance $e_s = |s^i_{det}(t) - s_i(t)|$ between the ego vehicle and the vehicle which corresponds to the worst case minimum average velocity $v^i_{det}(t)$ ahead of ego vehicle i. In particular, the shock-wave dissipation scheme should be proportional to the velocity gap, and should be less aggressive if the distance from the shock-wave e_s is large, i.e. when the CAV has detected the shock wave in a timely manner. This contributes to reducing fuel consumption and maximizing the passenger's comfort. In addition, the controller should also be appropriately parametrized, such that it is able to model different driving behaviors, for example the aggressiveness of the CAV with respect to exogenous metrics, e.g. vehicle priority or emergency. In view of all these, we propose the following adaptive controller:

$$\begin{aligned} v_i(t+1) = v_i(t) + \min\{&\alpha^i_{min}dt, \\ &a_i\gamma_i(s_i(t), s^i_{det}(t))(v^i_{det}(t) - v_i(t))dt \\ &+ b_i(v_i(t-1) - v_i(t))\} \end{aligned} \tag{8}$$

where the term $b_i(v_i(t-1) - v_i(t))$ contributes to a smooth velocity trajectory (notice also its connection to the derivative of the error $\dot{e}_v \approx \frac{v_i(t-1)-v_i(t)}{dt}$), and the position-dependent coefficient $\gamma_i(s_i(t), s^i_{det}(t))$ is given by:

$$\gamma_i(s_i(t), s^i_{det}(t)) = \frac{1}{1 + (\frac{\delta_i}{d_c})^2 |s^i_{det}(t) - s_i(t)|^2} \tag{9}$$

where d_c is the maximum communication range of the CAVs.

The parameters a_i and δ_i control the closed-loop velocity trajectory as shown in Fig. 2. We observe that for different δ_i coefficients the velocity-position (and velocity-time) profiles of the closed-loop system can vary from sub-linear, to linear, and to super-linear, while, at the end, converging to the detected worst case minimum average velocity $v^i_{det}(t)$. The case $\delta_i = 0$ corresponds to the naive control scheme (7). An increase in the parameter a_i induces larger deceleration steps, and is interpreted as a tendency to hard break (increased fuel consumption, decreased driver's comfort). On the other hand, a low value of a_i results in smaller deceleration steps, but may not result in a convergence to $v^i_{det}(t)$. A typical value is $a_i = 1$, which represents the maximum coefficient of the proportional term $(v^i_{det}(t) - v_i(t))$ of the controller.

The optimal controller parameters a_i and δ_i, are estimated from simulation data in Section V, based on exhaustive search in the parameter space aiming to minimize the objective function:

$$\begin{aligned} &\min J = \hat{V}[v] \\ &\text{s.t.} \quad \hat{E}[v] - \bar{v} > \nu \end{aligned} \tag{10}$$

where $\hat{E}[v] = \frac{1}{N}\sum_{i=1}^{N} \|v_i(T)\|^2$ represents the average velocity of the N cars in the highway section, and $\hat{V}[v] = \frac{1}{N}\sum_{i=1}^{N} \|v_i(T) - \hat{E}[v]\|^2$ the average variance of the velocity of the cars, at the end of the simulation time $t = T$. Minimizing the variance of the velocity of the cars results in mitigating the stop-and-go effect of the shock wave. The threshold ν represents how much we are willing to reduce the average velocity of the vehicles of the highway (with respect to the speed limit $\bar{v}$) to dissipate the shock wave effect. Notice that the optimization problem (10) can be alternatively written as:

$$\max J = c_1\hat{E}[v] - c_2\hat{V}[v] \tag{11}$$

which represents the scalarization method in constrained optimization, and results in different Pareto optimal solutions, depending on the values of c_1 and c_2 which can be chosen depending on the priorities given by the designer. We note that the simulation time T should represent a reasonable time frame to resolve the shock wave phenomenon. Note that the constraints placed on the vehicle by the speed limit $\bar{v}$ and each vehicles dynamics and acceleration capabilities also need to be satisfied.

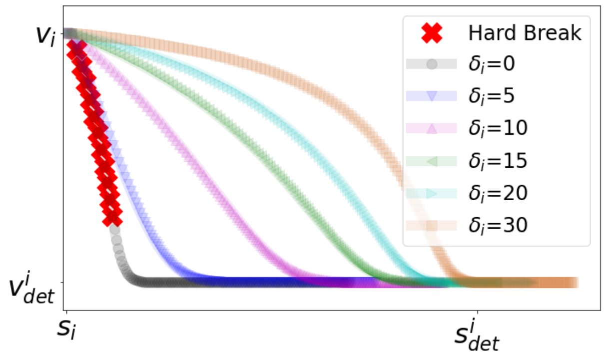


Fig. 2: Closed-loop velocity-position profiles for different parameter values $\delta_i \in [0, 5, 10, 15, 20, 30]$ ($a_i = 1$, $d_c = 300$). Here v_i, s_i, are the initial velocity and position of a CAV that detects a shock wave at a distance s^i_{det} from the worst case minimum average velocity $v^i_{det}(t)$.

C. CAV's Lane-Changing Controller

The proactive shock-wave dissipation controller described in Section IV-B constituted a high-level longitudinal controller for the velocity control of CAVs once a shock wave is detected. In parallel to this controller, we also implement a lane changing controller which identifies the best lane a CAV should be in and facilitates the lane changing maneuver to achieve this. In this work, the lane-changing controller is based on maximizing the entropy of the distribution of the CAVs along the multiple-lanes, i.e., on maintaining a uniform distribution for the CAVs at any given highway segment.

In multi-lane highways when CAVs attempt to apply a forced bottleneck control, what often occurs is that the neighboring HDVs would simply move to a different lane and overtake the CAV. This reduces the corrective effect of the shock wave dissipation control applied by the CAV. In order to prevent this and maximize this correctional effect, it is important that the CAVs are evenly distributed among the lanes of the highway. To achieve this uniform distribution, each ego CAV calculates the distribution of other CAVs among lanes downstream of its location. This information is gathered via V2V communication with all CAVs within range. At this point, our high level lane-changing controller computes the lane with lowest CAV occupancy and sets this as the target lane. The system then performs a safety check to identify if the ego vehicle can safely execute a lane change maneuver in the direction of the target lane. If this safety check is passed then the this controller issues the lane change command to the low-level lane following controller for execution. For our research we adopt the low-level controller found in [14], which provides several parameters for fine tuning a vehicle's lane changing behavior.

V. Experimental Setup and Results

In order to evaluate the performance of our proposed approach, we implemented a circular multi-lane highway loop simulation on the SUMO [15] simulation platform. This simulation setup used for our testing is shown in Fig. 3. Our control algorithms communicate with the SUMO simulator using the TraCI interface. A personal computer with an Intel i7-8750H CPU and 32GB of RAM was used to run the simulations and control algorithms.

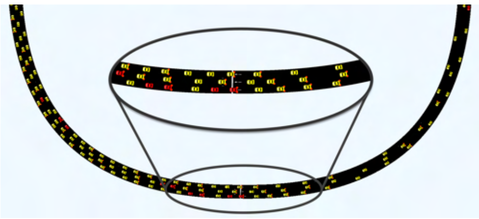


Fig. 3: Circular multi-lane highway simulation

A. Modeling the physical highway structure

The highway model used in these experiments is a 3 lane highway loop with a circumference of 1km. This is a sufficient length to accurately simulate the shock wave related behavior of $N = 200$ vehicles moving within the loop. This includes the different types of interactions among vehicles in a multi-lane highway such as forced slow downs and overtaking maneuvers. While keeping the total vehicles in the loop constant, the proportion of CAVs to HDVs (CAV penetration level) can be varied.

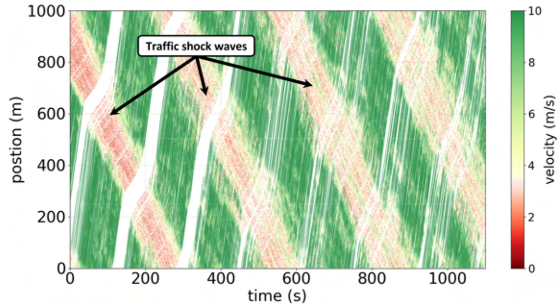
B. Parameters for shock wave generation

In order to simulate realistic human driving behaviors resulting in the natural formation of shock waves, we modify two key simulation parameters related to SUMO and the Krauss [12] car following model. The parameter $Sigma$ that governs driving imperfection is set to the maximum value (1). The parameter $actionStepLength$ that governs the decision making reaction time is set to $1sec$.

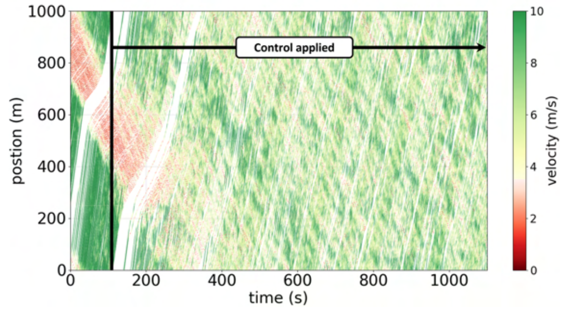
C. Performance Evaluation

The performance of the proposed approach (Section IV) which includes a proactive shock-wave dissipation controller designed using the V2V communication-based shock wave detection algorithm is compared against the baseline case where no shock wave mitigating control is applied by the CAVs. In Fig. 4 and Fig. 5, we compare the performance of the proposed approach for different control profiles, i.e., different parameters δ_i (see Section IV-B).

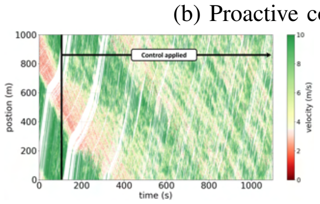
We illustrate the trajectories of the vehicles over time and their corresponding velocities over time in Fig. 4 and Fig. 5 respectively. In both these figures the presence of continuing shock waves is evident in the case in which no control was applied as indicated by the waves of red regions depicting very slow moving traffic in 4a and the continued high-low discontinuous velocity profile in 5a.



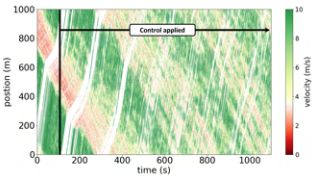
(a) No control applied



(b) Proactive control ($\delta_i = 0$)

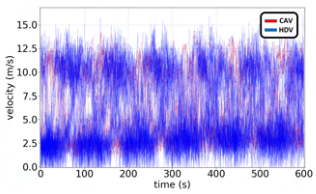


(c) Proactive control ($\delta_i = 10$)

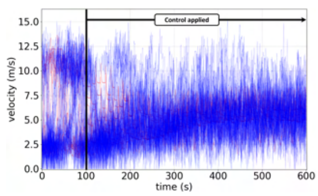


(d) Proactive control ($\delta_i = 20$)

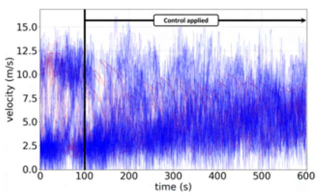
Fig. 4: Variation in trajectories of vehicles.



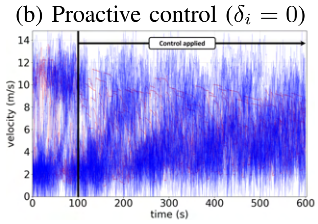
(a) No control applied



(b) Proactive control ($\delta_i = 0$)



(c) Proactive control ($\delta_i = 10$)



(d) Proactive control ($\delta_i = 20$)

Fig. 5: Variation in velocities of vehicles.

We also explore the impact of applying proactive control with varying control profiles with parameter $\delta_i = 0, 10, 20$. We find that lower values of δ_i lead to very effective shock wave dissipation but comes at the cost of requiring CAVs to perform very steep deceleration tasks, which leads to very uncomfortable conditions for passengers and also possibly hazardous conditions if the following HDVs cannot react in time. This is evident in Fig. 4b, where we observe that the shock wave is fully dissipated within 2 minutes of activating the control strategy. Higher δ_i values on the other hand result in slower shock wave dissipation but allow for smoother deceleration tasks, which is safer and more comfortable to passengers. In Fig. 4c, we observe that it takes more than 4 minutes in order to fully dissipate the shock wave. Our testing showed that a value of around $\delta_i = 4$ provided a good trade-off between shock wave dissipation performance, safety and passenger comfort.

Remark 1: Fig. 4 and Fig. 5 plot only 50 of the total 200 vehicles (6 CAVs and 44 HDVs) in order to provide less cluttered graphs. In the experiments, the CAV penetration level is set as 7.5% and control application is initiated at time $t = 100s$. With safety being built into all algorithms, no collisions were observed.

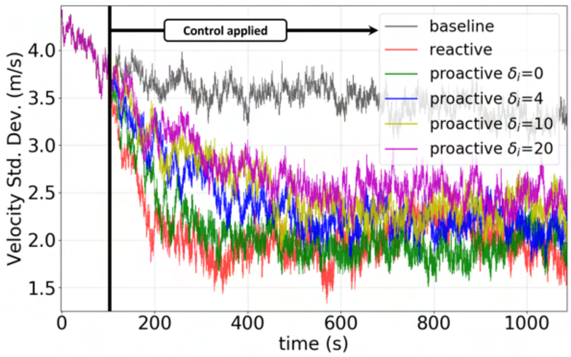


Fig. 6: Velocity Standard Deviation for different methods.

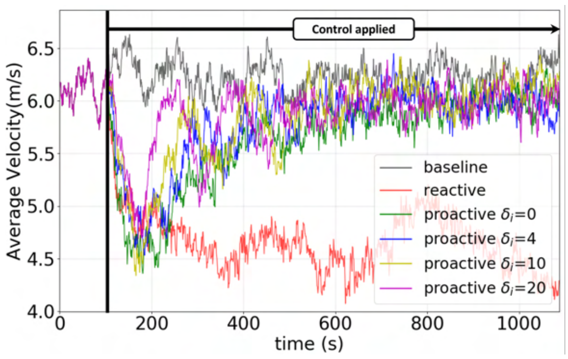


Fig. 7: Average velocity comparison for different methods.

In Fig. 6 and Fig. 7, the proposed approach (hereby referred to as "proactive" control method) is compared against the baseline case (no shock wave dissipation control) and an independent method (hereby referred to as "reactive" control method) which applies a control which does not consider cooperation among CAVs, similar to that used in [6], in terms of optimizing the objective function mentioned in (10) and (11). In other words, we are investigating the performance of the different control strategies with respect to the average velocity achieved (higher average velocity corresponds to higher overall throughput) and the average variation of the velocities of each vehicle (low variation corresponds to dissipation of the shock wave). A good control scheme should be able to reduce the velocity variation within a short time-span without affecting the overall system throughput. It is also important to stress on the connection between shock wave dissipation and fuel consumption. As the variations in velocities reduce, this implies that there are much less acceleration and breaking tasks leading to reduced fuel consumption.

As the performance of our proactive control approach can be tuned based on the control parameter δ_i, to get a better understanding on the impact of this parameter we plot the performance in terms of average velocity (Fig. 7) and velocity standard deviation (Fig. 6) with varying control parameter values of $\delta_i = 0, 4, 10, 20$. The standard deviation in velocities is a key indicator of the smoothness of traffic flow in the highway. Fig. 6 shows the rate and level of reduction in standard deviation across the different control strategies in contrast to a baseline approach where no control is applied. This figure needs to be analyzed along with the average velocity of vehicles on the highway which is a measure of the overall throughput and is depicted in Fig. 7. From these two figures we observe that all the proactive control strategies have a strong effect in reducing the velocity standard deviation while ensuring that the average velocity is not impacted in the long run. We find that the strategies using lower δ_i values result in overall faster shock wave dissipation and the ability to reach lower values of standard deviation in a shorter time. However this comes at the cost of passenger comfort and safe breaking behavior. Therefore in practice it would be more suitable to use a control profile with slightly higher δ_i values (eg. $\delta_i = 4$) which would provide a balance between these factors.

In terms of the average velocity achieved, as shown in Fig. 7 all the proactive strategies achieve similar overall velocities in the long run. Here, the initial reduction in average velocity when control is applied ($t = 100s$) is due to vehicles in the zones outside the shock wave being preemptively slowed down in anticipation of downstream shock wave conditions. Overall we see that all the proposed proactive control strategies once activated lead to around a 50% improvement in standard deviation while leaving the overall average velocity unchanged. In comparison we observe that while the *reactive method* appears to show the same improvement in standard deviation this comes at the cost of greatly reduced average velocities. Applying this type of reactive non-cooperative control in multi-lane highways can therefore lead to all the vehicles being forced to slow down thus severely impacting overall highway throughput. This does not solve the shock wave problem and can often lead to increased congestion.

Remark 2: The *reactive method* requires a circular ring highway structure due to each vehicle needing to face shock wave conditions multiple times before control can begin to be applied. The proposed *proactive method* applies control based on downstream conditions and is therefore independent of the highway structure.

D. Impact of CAV penetration levels

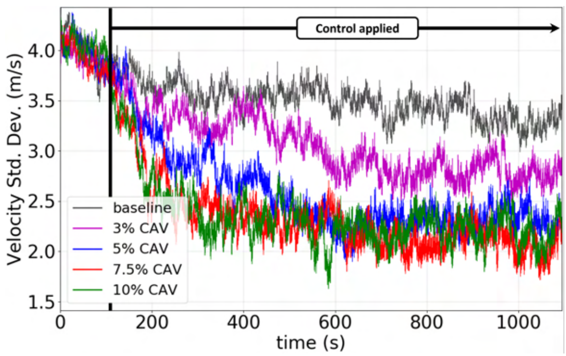


Fig. 8: Velocity std. dev. for varying CAV penetration levels.

The CAV penetration level plays an important role in shock wave mitigation performance. Since shock waves are created in the presence of human drivers, reducing the proportion of HDVs naturally has a positive impact on preventing shock wave formation. Secondly, since the proposed method is based on communication between CAVs, it requires a minimum CAV penetration level to function well. However, this required minimum level is very low. As shown in Fig. 8, penetration levels above 3% begin to show consistent improvements to shock wave dissipation. The number of lanes on the highway is also linked to the the CAV penetration level needed for good performance. This is mainly due to the fact that in a multi-lane highway, other vehicles will simply overtake the sparsely distributed CAVs attempting to apply control. We find that in our experiments on a three lane highway, around 5% or higher CAV penetration leads to effective shock wave dissipation in a timely manner. However increasing the CAV penetration level above 10% will have diminishing returns and provide the same level of performance as slightly lower CAV penetration levels. This is due to the fact that reducing the percentage of HDVs beyond a certain threshold removes the factor causing the shock waves in the first place.

VI. Conclusion

We propose the use of V2V communication among CAVs to design a proactive traffic shock wave detection and dissipation controller for multi-lane highways. This cooperation-based controller is evaluated using a multi-lane simulation on the SUMO platform with a focus on finding the best control parameters which lead to a balance between shock wave dissipation performance and passenger comfort and safety. The included lane changing controller also ensured that the CAVs are distributed uniformly among the lanes leading to better performance. We demonstrate that our proactive control method is capable of mitigating shock wave formation more effectively than other methods while ensuring safe deceleration levels in affected vehicles. We show that even a 3% CAV penetration levels can have a strong positive effect on shock wave dissipation, and the use of suitable control parameters along with higher CAV penetration levels can result in the complete elimination of shock waves within minutes of control application. Future work in this area would involve the exploration of combining V2V communication with learning based approaches for shock wave mitigation.

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