Shock Wave Mitigation in Multi-lane Highways using Vehicle-to-Vehicle Communication

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***Abstract*—In the presence of human driven vehicles (HDVs), traffic shock waves are a naturally occurring phenomena, which contributes to congestion and efficiency degradation in highway networks. The introduction of connected autonomous vehicles (CAVs) with advanced sensing, actuation and communication capabilities allow new approaches in control to be applied in order to solve the problem of shock waves. This work on shock wave dissipation, introduces a communication-based cooperative control method for CAVs in multi-lane highways in a mixed traffic setting. The method allows for proactive control application and exhibits good shock wave dissipation performance even with low CAV penetration levels. Results are verified on a three lane circular highway loop using realistic traffic simulation software.**

I. INTRODUCTION

Modern transportation systems are witnessing a transition from vehicles which completely rely on human drivers for decision making and control, to automated systems which perform a large range of activities without the need for human intervention. With the development of on-board sensing and communication technology in modern CAVs, research now focuses on ways in which CAVs can contribute to solving some of the persistent problems which have been plaguing road and highway infrastructure for decades. A major driving factor of this is the advent of 5G networking, which enabled vehicles to share larger amounts of data at low latency [1], from vehicle to vehicle (V2V) and from vehicle to infrastructure (V2I). Furthermore, on-board sensing technology has also seen drastic improvements. Modern vehicles often come equipped with radar sensors, vision based sensors and even lidar ranging sensors [2]. This allows vehicles to observe more of their surroundings and control algorithms can leverage this information in order to make better decisions.

This research focuses on using the communication and sensing capabilities of modern CAVs to solve the problem of stop and go waves in highway networks. Stop and go waves, also known as shock waves, are characterized by the traffic condition in which vehicles accelerate and decelerate in a periodic manner. This is a common cause of overall network efficiency degradation. Once a shock wave forms, if left unchecked, it usually resolves only when the demand (vehicles entering the highway) reduces. As such, in high density periods, shock waves can last for hours on end. Shock waves are also a major contributor to increased fuel consumption on highways, due to the large variance in velocity experienced by vehicles facing these conditions. In high traffic density highway conditions, these shock waves can easily be generated by even the simplest of triggers such as a few cars slowing down due to a distraction on the side of the road. Other common triggers for shock waves include busy highway merge junctions, disabled vehicles on the side of the road, vehicle collisions and road construction activities. The main contributing factor to shock wave generation is the latency introduced by human decision making.

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The major issue in dealing with shock waves lies in the difficulties in sensing highway conditions and subsequently actuating vehicles in a suitable manner to dissipate the shock wave. Traditionally, these were carried out by infrastructure based sensing and variable speed limits. However, with the advent of CAVs, many more options for sensing, actuation and control have opened up. Even at low percentages of CAVs to HDVs (hereafter referred to as CAV penetration levels), the CAVs can act as Lagrangian sensors, collecting local information about the state of highway traffic. This local information can thereafter be combined to obtain a global state of traffic. Furthermore, CAVs can also act as Lagrangian actuators, allowing the control of themselves and their surrounding vehicles via inter-vehicle interactions. Thus, the slowing down and speeding up of HDVs can be achieved by suitable actuation of the CAVs dispersed among the HDVs.

Literature review

The problem of traffic shock wave generation and mitigation has been studied in field experiments conducted by Sugiyama *et al.* [3] and Stern *et al.* [4]. Here, vehicles were placed in a single file loop and in [4], one ego vehicle was used to apply control for shock wave dissipation. The use of vehicle platoons to help reduce shock waves in single lane roads was studied in [5]. An optimal control approach to this problem is explored in [6] which allows for multiple ego vehicles on a single lane ring-road, but requires the assumption that ego vehicles have access to the global traffic state. While these approaches yield effective results in single lane roads, on multi-lane highways the control strategies need to be revised. The use of V2V communication for shock wave suppression is considered in [7], which explores the idea of changing driving parameters when shock waves are detected downstream.

Contribution

Many existing methods for shock wave dissipation rely on assumptions such as availability of global information or the presence of a single lane ring highway structure. Due to these assumptions, these methods are often difficult to implement and perform poorly in practical highway scenarios.

The main contribution of this work is to introduce a method which utilizes the communication capabilities of CAVs in order to provide good shock wave dissipation performance in multi-lane complex highway environments. Our cooperative control method allows each ego vehicle to take proactive control actions when compared to most methods which are reactive to the presence of shock waves. Furthermore, unlike most existing methods, the performance of our method is independent of the highway structure and the algorithm would perform identically on either a ring road or a straight road.

Our method was tested using the realistic SUMO traffic simulation system, and the results and comparisons are presented. We show that our 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 with our method.

II. Highway and vehicle models

In this section, we model the highway infrastructure used in our research, and the characteristics of the autonomous vehicles used as both sensors and actuators for shock wave dissipation. A section of the highway model is shown in Fig. 1, in which lane structure, HDVs, CAVs and CAV sensor ranges are highlighted.

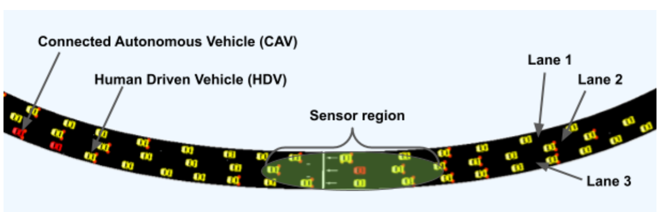


Fig. 1: Modeling a highway section including vehicles

A. Modeling the physical highway structure

The highway stretch is modeled in the form of a loop. This design decision was made in order to simulate an infinite stretch of a multi lane highway. We set the length of the highway loop to 1 km and the number of lanes to 3. The length of the loop and number of lanes are both parameters that can be modified. It should also be possible to change the number of vehicles on this highway loop as necessary. A three lane highway is selected in order to accurately represent the effects of vehicle lane changing on shock wave creation and dissipation. The resulting simulation is more realistic, highlights the effects of interactions between vehicles and provides a more accurate representation of the conditions faced by vehicles under highway shock wave conditions.

B. Vehicle Model

Two different types of vehicles are used in this research. Human driven vehicles whose motion is modeled according to section III, and CAVs modeled as follows.

For the high level controller proposed for shock wave mitigation, we find that it is unnecessary to consider the highly non-linear nature of the dynamics of real-world vehicles. In this research, we assume that the low-level control of each CAV is managed by a local controller c_i, which is also responsible for the control of lateral motion that keeps the vehicle in lane. This allows the i^{th} vehicle to be modeled as a point object moving along the center of the lane according to a non-linear differential equation:

$$\dot{s_i} = f(t, s_i, c_i), \qquad s_i(t_i^0) = s_i^0 \tag{1}$$

where t^0 is the initial time the vehicle enters the highway. Therefore, we can define the high-level longitudinal vehicle dynamics by the following velocity control scheme:

$$\begin{aligned} \dot{s_i} &= v_i \\ v_i(t) &= u_i(t) \end{aligned} \tag{2}$$

where $s_i(t)$, $v_i(t)$, and $u_i(t)$ denote the position, velocity and applied control of each vehicle i respectively, along the direction of the lane, for $i \in \{1, \dots, n\}$. n is the number of CAVs on the modeled highway stretch. Here, it is important to note that the velocity control requested by the high-level controller should be reachable by the low-level vehicle controller c_i in system (1). Additionally, as the control applied by the high level controller is independent of the lane the CAV is in, we also assume that the lane changing procedures are handled by a separate lane change controller.

Each CAV i, is assigned an integer variable $b^i \in \{1, , \dots, m\}$ which signifies which lane it is on, with m denoting the number of lanes. It also has a length l^i parameter, and bounded acceleration capabilities characterized by its maximum acceleration a_{max} and maximum braking a_{min} capability. Therefore, all the CAVs are completely defined by the state vectors:

$$x_i(t) = [s_i(t), v_i(t), b^i, l^i, a^i_{max}, a^i_{min}]^{\mathrm{T}} \tag{3}$$

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

With regards to the sensing capabilities of the CAVs, each CAV is assumed to have the minimum required on-board sensing capabilities to detect the positions and velocities of surrounding vehicles within a realistic sensor range. Each CAV can track the positions of up to eight adjacent non-occluded vehicles surrounding it. The surrounding vehicles that a CAV could track are highlighted in Fig. 2. In practice the actual number of vehicles tracked may be lower due to factors such as the density level and the lane the CAV occupies.

When considering the V2V communication capabilities of each vehicle, we assume that the CAVs communicate using a combination of IEEE 802.11p and 5G networks. In this work we do not consider network delay and packet loss during transmission. Vehicles within a realistic communication range

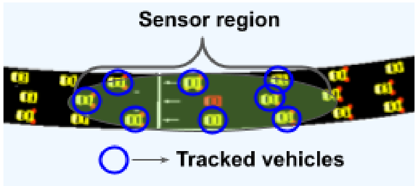


Fig. 2: Modeling sensing capability of CAVs

of each other are assumed to communicate shared information in real time.

III. Microscopic traffic models

The process of modeling vehicle behavior in large scale highway networks usually involves two separate models. A car following model, used to define the longitudinal movement of a vehicle, considering both its interactions with a lead vehicle and safety parameters. A lane change model, used to determine the appropriate choice of lane, and the parameters necessary for a safe lane change maneuver in multi-lane highways. Some of the widely accepted car-following models adopted in traffic modeling and simulation include the Krauss model [8], the Wiedemann model [9] and the Intelligent Driver Model (IDM) [10]. In this research, we opt to use the Krauss model due to the simplicity of the model, its accuracy, and the ease in which parameters relating to human reaction speed can be adjusted.

A. Krauss Car-following Model

The Krauss model [8] developed in 1997, enables the direct computation of the target control velocity needed to achieve safe car following behavior. The behavior of the vehicle in this model depends on if it is in free motion or interacting motion. In free motion, there is no lead vehicle affecting the ego vehicle and the command velocity $u(t)$ is governed by the road speed limits $\bar{v}$ as shown in equation (4). Additionally, $u(t)$ is also constrained by the acceleration capabilities of the ego vehicle, characterized by its maximum acceleration a_{max} and maximum braking a_{min} capabilities as shown in equation (5). Here $v(t)$ represents the current velocity of the ego vehicle and Δt is the time step.

$$0 \leq u(t) \leq \bar{v} \tag{4}$$

$$a_{min}\Delta t \leq u(t) - v(t) \leq a_{max}\Delta t \tag{5}$$

In the case of interacting motion, the ego vehicle is affected by the behavior of the lead vehicle. Therefore, in addition to the constraints in equations (4) and (5), a safe velocity $v_s(t)$ is computed considering the lead vehicle velocity $v_l(t)$, gap to lead vehicle $\Delta s(t)$ and the driver reaction time τ_r as shown in equation (6). Here, $b(v(t))$ represents the deceleration function.

$$v_s(t) = v_l(t) + \frac{\Delta s(t) - v_l(t)\tau_r}{\frac{v(t)}{b(v(t))} + \tau_r} \tag{6}$$

Therefore, the desired command velocity $v_d(t)$ is computed as the minimum of the speed limit, acceleration bound and safe following velocity as shown in:

$$v_d(t) = min(\bar{v}, v(t) + a_{max}\Delta t, v_s(t)) \tag{7}$$

Finally, the command velocity $u(t)$ is set by considering the random perturbations η that occur due to both the imperfection in human drivers and vehicle actuation as shown in:

$$u(t) = max(0, v_d(t) - \eta) \tag{8}$$

A key factor for the choice of the Krauss model in this research, is the accessibility of parameters τ_r and η which allow the overall modeling of human driving imperfections and reaction time. These factors are essential in shock wave research as they are usually the major contributors to spontaneous shock wave generation.

B. Lane change model

When we consider a large scale simulation of a multi-lane highway, the modeling of lane change behavior also plays an important role. This model involves the computation of speed adjustments necessary to change lane, the choice of the best lane to change to and the safety criteria in choosing suitable gaps for a lane change maneuver. Lane change can be necessitated by strategic requirements such as taking the next off ramp, speed gain requirements or cooperative requirements which involve changing lanes to allow other vehicles to pass. In this research we use the model developed by Erdmann [11], as it provides many parameters for fine tuning each vehicle's lane changing behavior. This model carries out the tasks of selecting the best lane in order to maximize vehicle requirements, choosing when to merge depending on certain safety criteria, and the execution of the actual lane change maneuver. It is also capable of ensuring that traffic rules such as always overtaking on the left are followed.

IV. Methods and Procedures

The first step in designing a control algorithm for shock wave dissipation involves the detection of the presence of a shock wave condition. The accurate detection of shock wave conditions require a decent estimate of the traffic conditions at various locations on the highway.

A. Traffic state estimation

We define the traffic state as the aggregate state over all lanes and not the state of a single lane. The main desired components of the traffic state are the density, throughput and mean velocity of vehicles along the length of the highway. Traditionally, data for traffic state estimation had to be gathered from static, sparsely located infrastructure nodes. Therefore, unless a large number of sensors were used, the resulting state estimation would be quite inaccurate. However, with the presence of Lagrangian sensors in the form of CAVs interspersed among the HDVs, we can now obtain a far more accurate depiction of the state of traffic on a highway link. Here, accuracy is defined as the similarity between the estimated traffic state and the ground truth value. As expected, in estimating the traffic state using CAVs, we observe that the accuracy of state prediction achieved increases with the number of CAVs present on the highway.

While density and throughput can be computed based on the number of vehicles in a highway section at each time instance, it is more difficult to compute the average velocity of vehicles at a specific point on a highway section. The estimation methods presented, try to compute the average vehicle velocity at the CAV's location on the highway. In this research we consider two separate methods for highway state reconstruction. CAVs could gather data based on its own internal state or based on the cumulative information it gathers about surrounding vehicles and itself.

1) Estimation based on ego vehicle data: Here, we assume each CAV maintains a memory of its own past k velocities, where k is a parameter defining the length of the memory needed. Then the average velocity estimate $V_i^e(t)$ at position $s_i(t)$ of CAV i is computed by a rolling time average as follows,

$$V_i^e(t) = \frac{1}{k+1} \sum_{\tau=0}^{k} v_i(t-\tau) \tag{9}$$

2) Estimation based on surrounding vehicle data: The average velocity estimate $V_i^e(t)$ computed in equation (9) may often not be accurate in the case of a multi-lane highway, since the lane containing the CAV may be moving slower or faster than its surrounding lanes. In order to address this issue, we leverage the advanced sensor suite on-board modern CAVs to collect data regarding the vehicles surrounding the CAV. The sensor range and tracked vehicles are discussed in Section II-B. Let the number of vehicles tracked be m, the maximum length of memory be k and $v_j^i(t)$ represent the velocity at time t of the j^{th} vehicle tracked by CAV i. Also let $k_j \leq k$ be the number of time steps the j^{th} vehicle is tracked. Then the average velocity estimate $V_i^e(t)$ at position $s_i(t)$ of CAV i is computed by a rolling time average considering all tracked vehicles as follows,

$$V_i^e(t) = \frac{1}{m+1} \sum_{j=0}^{m} \frac{1}{k_j+1} \sum_{\tau=0}^{k_j} v_j^i(t-\tau) \tag{10}$$

Here, $v_0^i(t)$ represents the velocity of the CAV under consideration i, at time t. As data is gathered from multiple lanes, this method leads to a far more accurate representation of the average vehicle velocity at any given position and time $s_i(t)$, on a multi lane highway. It is important to note that, k_j for every tracked vehicle j will vary depending on how long it stays within the field of view of CAV i.

B. Shock wave detection

Shock waves are characterized by a sudden change in the traffic state on a highway. These shock waves propagate either upstream or downstream on the highway in the form a wave. The rate at which the shock wave moves V_λ, can be computed using the Rankine-Hugoniot condition which guarantees the conservation of mass of traffic flow as follows,

$$V_\lambda = \frac{Q_c - Q_f}{\rho_c - \rho_f} \tag{11}$$

Here, density and throughput are given by Q_c and ρ_c for the congested region at the shock wave, and Q_f and ρ_f for the free-flow region outside the shock wave. While this parameter characterizes the shock wave, the actual detection process is carried out by the evaluation of the estimated traffic state near each of the CAVs on the highway. In the case where CAVs do not communicate with each other, shock waves are detected by comparing the current velocity of the CAV to its long term average velocity data $V_i^e(t)$. This method only enables the CAV to estimate whether or not it is currently facing a shock wave scenario. This process is vastly improved when communication among CAVs is considered. A CAV can compare its own current and temporal average velocity with the velocities communicated to it from downstream CAVs within communication range. This allows CAVs to not only detect the presence of the shock wave in advance, but also the exact location of the shock wave on the highway. This then paves the way for the use of proactive control algorithms, which begin affecting highway conditions upstream of the actual shock wave location. This is shown to have a strong impact on the shock wave dissipation process.

The process of shock wave detection and the subsequent application of a suitable control, is carried out by every CAV present on the highway. The first step of the algorithm for shock wave detection using V2V communication involves gathering local traffic state data, as discussed in Section IV-A, from all downstream CAVs within communication range C_i of the ego vehicle i. The ego vehicle then builds up an estimate of the traffic conditions in front of it and selects the worst case scenario as shown in equations (12) and (13). We observe that the best performance is obtained by identifying the worst case scenario downstream of the CAV and adapting the control to suit this.

$$v_{det}^i(t) = \min_{j \in C_i} V_j^e(t) \tag{12}$$

$$v_{rel}^i(t) = \max\{0, v_i(t) - v_{det}^i(t)\} \tag{13}$$

Here, $V_j^e(t)$ is obtained from either equation (9) or (10) depending on whether data is collected from surrounding vehicles. The algorithm also takes note of the position $s_j^i(t)$ of the vehicle j which corresponds to the worst case minimum average velocity $v_{det}^i(t)$ ahead of ego vehicle i. Here, $v_{rel}^i(t)$ is the relative velocity gap between the ego vehicle and the worst case velocity downstream of it. When the value of $v_{rel}^i(t)$ exceeds a tunable threshold value V_{sw}, a shock wave is considered detected, and control will then be applied to CAV i for shock wave dissipation.

C. Control for shock wave dissipation

The control algorithms defined in this section aim to dissipate shock waves as soon as possible with minimal control effort. While our proposed method focuses on cooperative control and information sharing, for comparison we also implement a control algorithm (*independent method*) for the case of no cooperation, similar to the method in [4].

The output desired target velocity $v_d^i(t)$ generated for ego vehicle i will be based on the type of control algorithm used.

1) Independent control method: For the simple case (*independent method*) that does not consider information sharing among vehicles, $v_d^i(t)$ is computed based on a rolling average of the velocity of vehicle i as shown in equation (14). Here, m represents the length of memory used and needs to be set to a high value ($m >> k$) to achieve suitable results.

$$v_d^i(t) = \frac{1}{m+1} \sum_{\tau=0}^{m} v_i(t-\tau) \tag{14}$$

2) Communication based control method: In contrast, for the cooperative control approach (*our method*) with V2V information sharing, when a shock wave is detected downstream, we set the value of $v_d^i(t)$ based on $v_{det}^i(t)$ obtained from equation (12). This allows the ego vehicle i to react in advance to the shock wave traffic conditions ahead of it. Note that this control will only be applied until the CAV reaches the position $s_j^i(t)$, detected as the worst case conditions ahead of the CAV. However, the CAV can always adapt its control if traffic conditions worsen ahead of it. The process of setting the target velocity $v_d^i(t)$ is explained in Algorithm 1.

Additionally, it is important to ensure that safety constraints are considered when choosing a control for the vehicle. Therefore, we compute the maximum safe following velocity of vehicle i denoted by $v_s^i(t)$, using the Krauss car following model described in Section III-A. This method uses information pertaining to the distance gap to lead vehicle $\Delta s(t)$ and the lead vehicle velocity $v_l(t)$ which are measured using the on board sensors of the CAV. Note that the constraints in equations (4) and (5) also need to be satisfied.

Algorithm 1: Communication based control

Result: Obtain control $u_i(t)$
if $v_{rel}^i(T) > V_{sw}$ *(Shock wave detected at $t = T$)* **then**
  $detPos = s_j^i(T)$;
  $v_d^i(t) = v_{det}^i(T)$;
  if $s_i(t) < detPos$ **then**
    if $v_{rel}^i(T') > v_{rel}^i(T)$ *(New det. at $t = T'$)* **then**
      $T = T'$;
      $detPos = s_j^i(T')$;
      $v_d^i(t) = v_{det}^i(T')$;
    end
    Compute $v_s^i(t)$;
    $u_i(t) = \max(0, \min(v_s^i(t), v_d^i(t)))$;
  end
end

V. Experimental Setup and Results

The performance of the proposed approach is evaluated on a circular three lane highway loop simulation, implemented on the SUMO [12] traffic simulation platform. The simulation setup for the highway loop is shown in Fig. 3. The controller communicates with the simulator using the TraCI traffic controller interface. All simulations and control algorithms are run on a personal computer with an Intel i7-8750H CPU and 32GB of RAM.

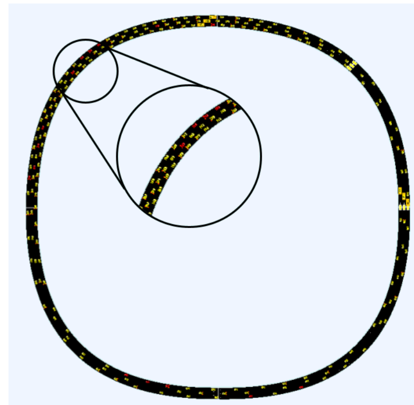


Fig. 3: Circular multi-lane highway loop simulation

The length of the circular three lane highway loop simulated is 1 km long and all tests were carried out with a density of 200 vehicles in the loop. The vehicles used were a mix of CAVs and HDVs at varying proportions (CAV penetration levels).

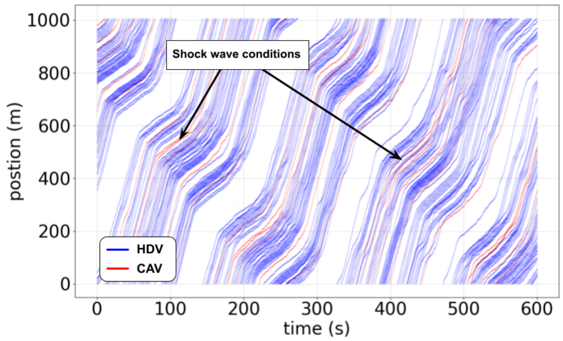
A. Parameters for shock wave generation

Two simulation parameters play a major role in simulating realistic driving behavior which results in the natural formation of shock waves. $Sigma$ is a parameter that allows the specification of driver imperfection and is set to its maximum value of 1. The parameter $actionStepLength$ which handles the reaction time involved in the decision making process of HDVs is set to $1sec$. These parameters lead to natural traffic shock wave formation over time, similar to that observed in human driving data.

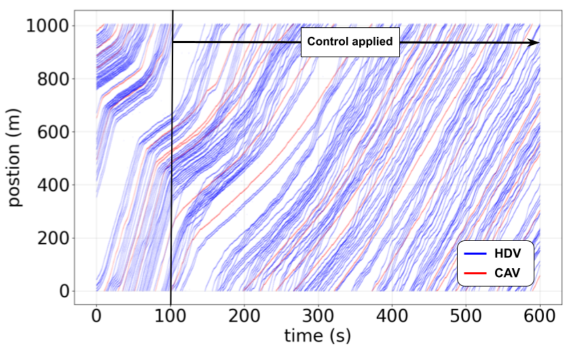
B. Proposed method performance

In this section, we discuss the performance achieved by the proposed V2V communication-based method (*our method*) which allows cooperative information sharing among CAVs to achieve better shock wave dissipation performance. The presence of continuing shock waves is evident in the case in which no control was applied as seen in Fig. 4a and Fig. 5a. While the vehicle trajectories showcase repeating shock waves, from the velocity curves we observe that the majority of vehicles constantly switch between higher velocities and very low velocities which is characteristic of a traffic shock wave.

Note that while the experiment contains 200 vehicles, Fig. 4 and Fig. 5 plot only the information of 50 vehicles (6 CAVs and 44 HDVs). This results in clearer less cluttered graphs which showcase information representative of the traffic state in the overall simulation. In these experiments, the CAV

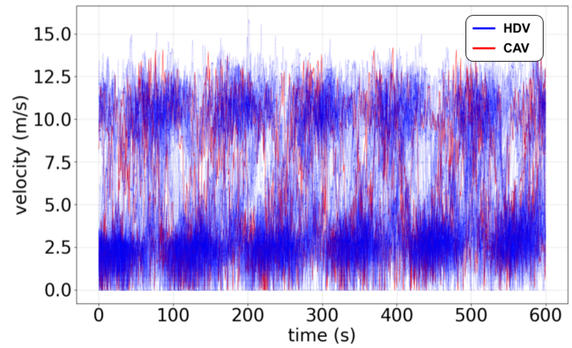


(a) No control applied

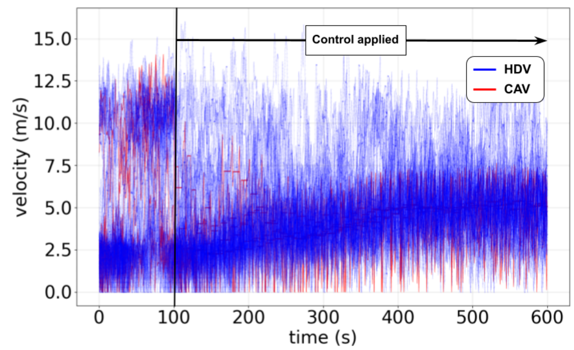


(b) Proposed method control

Fig. 4: Variation in trajectories of vehicles



(a) No control applied



(b) Proposed method control

Fig. 5: Variation in velocities of vehicles

penetration level is set as 7.5%. Furthermore, control is applied to CAVs starting at time $t = 100s$ in all experiments.

In Fig. 4b, based on vehicle trajectories, we observe that the shock wave is fully dissipated within 2 minutes of activating the control strategy. From Fig. 5b, we observe that the velocities of all vehicles converge to a common average value and note that this average value gradually increases with time. Additionally, as safety was a critical component built into all control algorithms used, no collisions were observed in any of the experiments.

Remark 1: In Fig. 4, trajectories of individual vehicles occasionally cross one another. Due to the fact that we simulate a multi-lane highway system, it is understood that these intersections represent a vehicle being overtaken by vehicles in other lanes.

C. Comparison between methods

The shock wave dissipation performance of *our method* is compared to two other methods. We use a baseline case (*baseline method*), which does not apply any shock wave dissipation control to the CAVs. We also implement a method (*independent method*) which applies a control similar to that used in [4], to each CAV on the highway independently. In the *independent method*, vehicles do not communicate and control is computed based on equation (14).

The main performance indicator in evaluating different control schemes for shock wave dissipation is the variation in the velocities of the vehicles involved. A good control scheme should be able to reduce this variation within a short time-span without affecting the overall system throughput. The change in the standard deviation in vehicle velocities for the different methods is shown in Fig. 6. We observe that the proposed V2V communication based method results in a 40% lower standard deviation in velocity than the independent control method.

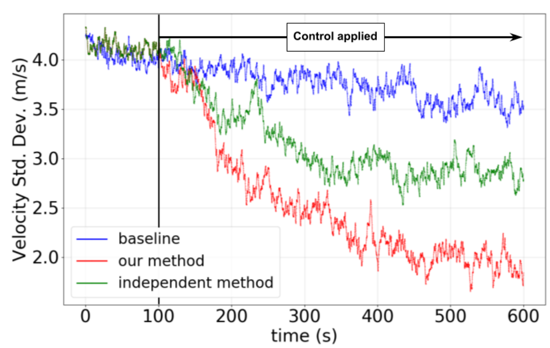


Fig. 6: Velocity Standard Deviation for different methods

In Fig. 7, we observe a greater reduction in the average velocity of vehicles when control is activated in the proposed method. This highlights how fast the proposed algorithm begins to clear up the shock wave when compared to other methods. The reduction in average velocity is due to vehicles in the zones outside the shock wave being preemptively slowed down in anticipation of downstream shock wave conditions. We see that by the 10 minute ($600sec$) mark all methods reach an average velocity close to $6m/s$, but the standard deviation in these velocities is drastically lower in the proposed method.

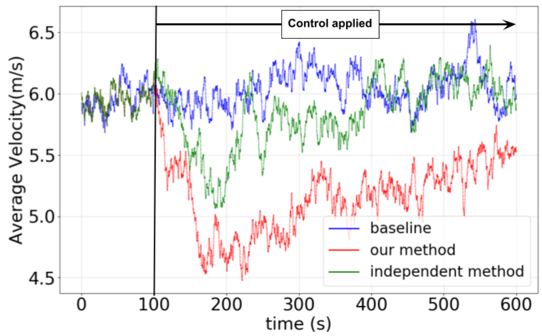


Fig. 7: Average velocity comparison for different methods

Remark 2: It is important to note that the performance of the *independent method* is quite dependent on the circular ring highway structure. This is due to each vehicle needing to collect adequate information about shock wave conditions before control can be applied. The proposed method does not have this limitation and is therefore independent of the highway structure.

D. Impact of CAV penetration levels

In this section, we explore the impact of different CAV penetration levels on the performance of the proposed method. In Fig. 8, we see that very low penetration levels like 1% and 2% have a minimal impact on shock wave mitigation. This is mainly due to the fact that in a multi-lane highway, other vehicles will simply overtake the few CAVs attempting to apply control. As the number of lanes increases, the penetration level needed for good performance also increases. For our experiments in a 3 lane highway, we observe that around 7.5% or higher CAV penetration leads to effective shock wave dissipation in a timely manner. However, even at lower penetration levels there is still a positive impact in overall shock wave dissipation, even though full dissipation will require a longer duration of time.

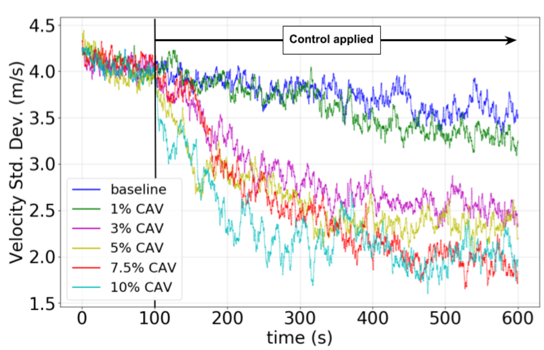


Fig. 8: Velocity std. dev. for varying CAV penetration levels

VI. Conclusion

We propose a traffic shock wave dissipation method for multi-lane highways, involving V2V communication-based cooperative control of CAVs. The performance of this method is evaluated using the SUMO platform and we demonstrate that this method is capable of proactively mitigating shock wave formation faster and more effectively than other methods. We find that when using this method, even very low CAV penetration levels have a strong positive effect on shock wave dissipation. Future work in this area could involve collaborative decision making among CAVs, improved state estimation based on information sharing and exploration of learning based approaches to control for shock wave mitigation.

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