# Cooperative Car-Following and Merging: A Novel Merge Control Strategy Considering Cooperative Adaptive Cruise Control and Courtesy

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## ABSTRACT

This study focuses on how to improve the merge control prior to lane reduction points due to either accidents or constructions. A Cooperative Car-following and Merging (CCM) control strategy is proposed considering the coexistence of Automated Vehicles (AVs) and Human-Driven Vehicles (HDVs). CCM introduces a modified/generalized Cooperative Adaptive Cruise Control (CACC) for vehicle longitudinal control prior to lane reduction points. It also takes courtesy into account to ensure that AVs behave responsibly and ethically. CCM is evaluated using microscopic traffic simulation and compared with no control and CACC merge strategies. The results show that CCM consistently generates the lowest delays and highest throughputs approaching the theoretical capacity. Its safety benefits are also found to be significant based on vehicle trajectories and density maps. AVs in this study do not need to be fully automated and can be at Level-1 automation. CCM only requires automated longitudinal control such as Adaptive Cruise Control (ACC) and information sharing among vehicles, and ACC is already commercially available on many new vehicles. Also, it does not need 100% ACC penetration, presenting itself as a promising and practical solution for improving traffic operations in lane reduction transition areas such as highway work zones.


**Keywords**: Connected and Automated Vehicles, Cruise Control, Ethics, Cooperative Merge, Lane Reduction, Work Zone

## INTRODUCTION

Work zones and incidents are major reasons for non-recurring congestion that causes lane reduction and further contributes to delay and secondary incidents on highways. In the United States, work zones account for nearly 10% of all congestion (*1*), and 24% of unexpected freeway delay (*2*). This research aims to address the merge control problem in transition areas prior to lane reductions due to work zones, which has substantial impacts on safety and mobility. The proposed merge control method is based on the Cooperative Adaptive Cruise Control (CACC) technology and does not require full vehicle automation. It can also be used for incident scene traffic operations, as the transition areas generated by work zones and incidents are very similar.

Due to the significance of work zone merge control, numerous studies have been conducted and proposed a variety of strategies such as early merge (EM) and late merge (LM). It is debatable which strategy is the best based on field and simulation studies (*3–9*). There are major limitations for both control strategies. It is noted that the compliance rate of EM often drops as congestion builds up (*3*) that leads to risky driving behaviors, and EM typically generates long queues. LM can better address these issues. However, at the merging point the take-turn-to-merge rule may create both risky short gaps and inefficient large gaps that affect safety and throughput.

Connected and Autonomous Vehicles (CAVs) have attracted tremendous attention because of their potential for precise and cooperative control. CAVs can travel with much shorter gaps between vehicles compared to human drivers, since their reaction time is almost zero and they can even share accurate acceleration information with each other so that vehicles can maneuver proactively. Besides longitudinal control, more challenging lateral maneuvers such as merge control can also benefit from CAVs. There are usually two ways to control CAVs' merge behavior.

The first one is centralized control. As the name suggests, this approach takes global traffic information (e.g., speeds and locations of all CAVs) into consideration and makes decisions for every vehicle being controlled (*10–12*). For example, Schmidt et al. (*12*) proposed a heuristic two-layer rule-based approach to control on-ramp CAVs. The first layer generates the merging sequence considering the time when each vehicle reaches the merging point. Based on the sequence, the second layer calculates a constant acceleration rate for each vehicle to avoid conflicts. Raravi et al. (*11*) also developed an automatic merge control, which was formulated as an optimization problem to minimize the time for each vehicle travelling to the merging point while satisfying some safety constraints.

The second one is decentralized control, where each CAV decides its own control policy based on information perceived and received from other CAVs. For instance, Kim and Kumar (*13*) considered Model Predictive Control (MPC) to control individual CAVs. In their study, CAVs use surrounding traffic information as the input and identify optimal control policy by solving a constrained linear quadratic optimization problem. Milanés et al. (*14*) proposed a fuzzy logic controller for automated merge control. Such decentralized control strategies are more flexible, but are unlikely to generate globally optimal solutions if each vehicle behaves selfishly.

This research also adopts the decentralized control approach given its flexibility and proposes a novel *Cooperative Car-Following and Merging* (CCM) control strategy. CCM assumes some vehicles are connected and partially automated. It is developed based on the New England Merge (NEM) control method (*15*). Different from NEM, vehicle longitudinal movements in CCM are governed by a modified Adaptive Cruise Control (ACC) and consider information sharing among vehicles (i.e., Cooperative ACC). Also, CCM explicitly takes courtesy and ethics into consideration during car-following and merging. ACC is a mature technology and is already commercially available on many new vehicles. Compared to merge control methods assuming 100% CAVs, CCM is more practical and can potentially be field implemented in the near future. Also, it can be relatively easily generalized to handle lane reduction on multi-lane highways (3 or more lanes). More importantly, CCM can handle traffic situations where human drivers and partially automated vehicles coexist.

The rest of the paper is organized as follows: in the next section, a brief overview of the NEM method is provided, followed by the description of the CCM model. A thorough simulation analysis is then conducted to evaluate the proposed CCM model, and the results are described in detail. Finally, conclusions and discussion are provided.

## METHODOLOGY

### Background

As shown in Figure 1, this research considers a two-lane highway work zone with the right lane closed to introduce the proposed merge control method. Similar to the New England Merge (NEM) control (*15*), CCM divides the transition area of a work zone into a metering zone and a merging zone. Based on the NEM control, in the metering zone vehicles in both approaching lanes are required to increase their gaps to twice the length as typically needed, and merging vehicles in the right lane are instructed to adjust their longitudinal positions so that they maintain a safe gap with the two immediately neighboring vehicles in the left lane. No lane changes are permitted in this metering zone. The metering zone is intended to create a safe gap between any two vehicles if all of them are hypothetically projected into a single lane. In this way, vehicles can safely merge by the time they reach the beginning of the merging zone, forming a high-speed and high-density single-lane platoon before the lane reduction point.

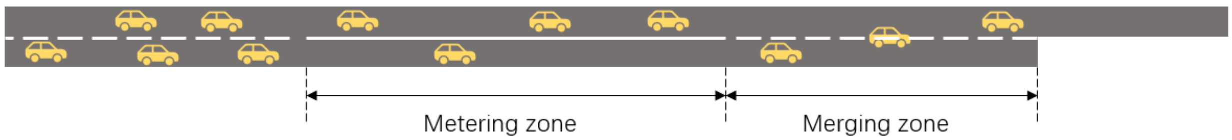



**Figure 1. Overview of the NEM control.**

In this study, CCM and other benchmark strategies are evaluated using VISSIM microscopic traffic simulation. In the metering zone, NEM uses a set of empirical rules to control vehicles, while CCM adopts a modified CACC method to control those partially automated vehicles. Human-Driven Vehicles (HDVs) in CCM are controlled by the default Wiedemann 99 car-following models in VISSIM. Since this research considers the coexistence of HDVs and CCM-controlled automated vehicles (AVs), the Wiedemann 99 car-following model (for HDVs) is briefly described below. The modified CACC (for AVs) is detailed later in this paper.

The Wiedemann 99 model mimics how human drivers react to stimulates stimulus (e.g., distance and speed differences with the lead vehicle). It categorizes car-following conditions into four states: free driving, approaching, following, and braking. In the Wiedemann 99 model (*16*), vehicles' distance keeping behavior and the related parameters and thresholds are defined in Eqs. (1) to (4).

$$d_s = L + CC0 \tag{1}$$

where $CC0$ is the standstill distance, $d_s$ is the desired distance between two stationary vehicles, and $L$ is the length of the lead vehicle.

$$d_{fl} = d_s + CC1 * v \tag{2}$$

where $d_{fl}$ is the lower bound of safe distance, $CC1$ is the desired headway time, and $v$ is the subject (following) vehicle's speed. $v$ equals the lead vehicle's speed plus some random errors if the subject vehicle is faster than the lead vehicle, otherwise it equals the subject vehicle's speed. In the following Eq. (3), $CC2$ is a variation term, and $d_{fu}$ is the upper bound of safe distance indicating the boundary between the "no reaction" and "unconscious reaction/following" states.

$$d_{fu} = d_{fl} + CC2 \tag{3}$$

When the subject vehicle enters the "unconscious reaction/following" state (i.e., distance between them is $< d_{fu}$ and $> d_{fl}$), the acceleration of the subject vehicle will oscillate around 0.

$$d_r = -\frac{\Delta x - d_{fu}}{CC3} - CC4 \quad (4)$$

$d_r$ in Eq. (4) defines the perception threshold distance between the lead and subject vehicles. It determines if the subject vehicle is in the "reaction/approaching" state. $\Delta x$ is the front bumper to front bumper distance between the two vehicles. When the subject vehicle enters the "reaction/approaching" state (i.e., distance to the lead vehicle is $< d_r$), the subject vehicle will begin to decelerate.

For the no control benchmark strategy considered in this study, the default $CC1$ (See Eq. (2)) parameter in VISSIM is used. For NEM, vehicles before and after the metering zone are also controlled using the default VISSIM $CC1$. However, for vehicles in the metering zone, a modified $CC1$ is considered to increase the gap between vehicles.

## Cooperative Car-Following and Merging (CCM)

As discussed before, the basic simulation network setup of NEM and CCM are the same. In the metering zone they both attempt to create a safe gap between vehicles in the open and closed lanes as if they were traveling in the same lane, to facilitate the lane changes in the upcoming merging zone. Unlike NEM, CCM is built upon the CACC (Cooperative Adaptive Cruise Control) for vehicle longitudinal control in the metering zone and allows the coexistence of human drivers and partially automated vehicles (i.e., only the longitudinal control is automated). The key differences between NEM and CCM are summarized in Table 1.

**TABLE 1. The difference between NEM and CCM**

| Control Strategy | Car-Following Model | Metering Zone Length | Extendibility | Human drivers' involvement |
|---|---|---|---|---|
| NEM | Wiedemann 99 | 1,520 meters | Need some effort to modify it for multilane (>=3) highway work zones | All vehicles are AVs |
| CCM | CACC/ACC | 100-200 meters | Can be relatively easily generalized for lane reduction scenarios with >= 3 travel lanes | AVs and HDVs coexist |

When simulating the CCM control using VISSIM, Human-Driven Vehicles (HDVs) still follow the Wiedemann 99 model throughout the simulation process. For those partially automated vehicles, they will drive in "*free mode*" if no other vehicles are within 100 meters downstream in all lanes, and will only follow the posted speed limit. On the other hand, if there are other vehicles within 100 meters downstream, these partially automated vehicles will drive in "*G-CACC mode*" or "*G-ACC mode*". G-CACC stands for Generalized-Cooperative Adaptive Cruise Control, while G-ACC stands for Generalized-Adaptive Cruise Control. Many CACC and ACC control logics have been proposed. In the next two subsections, the CACC and ACC modes adopted in this research are firstly introduced. The CCM control and the associated G-CACC and G-ACC modes are then described.

*CACC Mode*

The CACC control logic described in Eq. (5) is used as the basis for CCM. A brief description of this CACC control is provided here and more information can be found from the original paper (*17*).

$$u_2(t) = k_0\ddot{x}_1(t) + k_1(\dot{x}_1(t) - \dot{x}_2(t)) + k_2(r(t) - \eta - \tau_e\dot{x}_2(t)) \quad (5)$$

where,

$u_2(t)$ = acceleration of the following vehicle,
$\ddot{x}_1(t)$ = acceleration of lead vehicles,
$\dot{x}_1(t)$ = speed of lead vehicle,
$\dot{x}_2(t)$ = speed of following vehicle,
$r(t)$ = current distance between the lead and following vehicles,
$\eta$ = jam distance,
$\tau_e$ = the desired effective time-gap, and
$k_0 = 1, k_1 > 0, k_2 > 0$ = gains.

Eq. (5) basically describes that the subject vehicle reacts without time delay to the acceleration of, position difference to and speed difference to the lead vehicle in the ***same*** lane. With properly calibrated coefficients $k_0, k_1, k_2$, a property of string stability (*18*) could be achieved. In this study, the parameters calibrated by Van Arem et al. (*17*) are used. Besides serving as a building block of CCM in our study, CACC itself is adopted as a baseline control method. In this baseline control, all vehicles are AVs. When merging, these AVs still follow human drivers' logic but with reduced time gap (see parameters in Table 2), and vehicles in the closed lane yield to vehicles in the open lane.

*ACC Mode*

If the lead vehicle is equipped with on-board devices that broadcast its acceleration and speed information, the following AV can enter the CACC mode. Otherwise, the following AV needs to rely on its own sensors such as camera and LiDAR to measure the movement information of nearby traffic, and this often comes with delay and inaccuracy. In this case, the following Adaptive Cruise Control (ACC) model in (*19*) is used to capture the following AV's longitudinal behavior.

$$u_2(t) = k_1\big(\dot{x}_1(t) - \dot{x}_2(t)\big) + k_2\big(r(t) - \eta - \tau_e\dot{x}_2(t)\big) \quad (6)$$

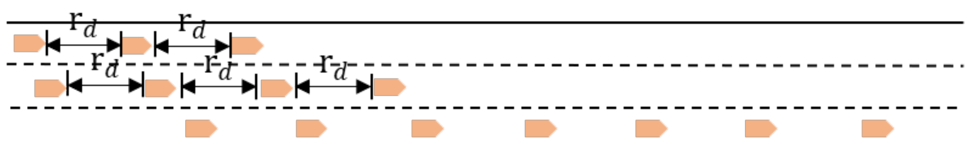
where,

$\eta$ = jam distance,
$\tau_e$ = the desired effective time-gap, and
$k_1 > 0, k_2 > 0$ = gains

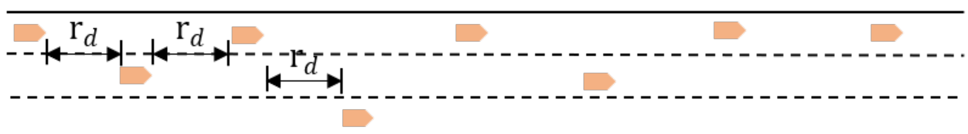
Unlike CACC, ACC is string unstable and tends to amplify the velocity change of the lead vehicle (*19*, *20*). We use the following parameters $k_1 = 0.2692\ s^{-1}, k_2 = 0.0131\ \mathrm{s}^{-2}, \tau_e = 1.6881\ s, \eta = 7.5699$ m calibrated in the original paper (*19*) .

*CCM Control and Courtesy Strategy*

The main difference between CCM and CACC/ACC is that instead of following the lead vehicle in the ***same*** lane, an AV controlled by CCM follows the nearest (in terms of longitudinal distance) downstream vehicle (we refer to this vehicle as the generalized lead vehicle, or G-lead vehicle for short) *regardless which lane it is in* as illustrated in Figure 2. With this straightforward extension of CACC/ACC, all AVs could keep a "safe" longitudinal distance with adjacent downstream vehicles in any lanes and merge smoothly before the lane closure point.




**(a) Regular CACC/ACC Control**




**(b) CCM Control**

**Figure 2. Comparison of CCM and Regular CACC/ACC**

An AV's car-following behavior in the metering and merging zoned depends on whether its G-lead vehicle is equipped with an on-board device to share real-time information. It is described mathematically in Eq. (7) below.

$$u_2(t) = \begin{cases} k_0^{CACC}\ddot{x}_1(t) + k_1^{CACC}(\dot{x}_1(t) - \dot{x}_2(t)) + k_2^{CACC}(r(t) - \eta - \tau_e\dot{x}_2(t)), & OBD = 1 \\ k_1^{ACC}(\dot{x}_1(t) - \dot{x}_2(t)) + k_2^{ACC}\left(r(t) - \eta - \tau_e\dot{x}_2(t)\right), & OBD = 0 \end{cases} \tag{7}$$

The notations in Eqs. (5) and (6) are still applicable here but are calculated based on the G-lead vehicle, not the lead vehicle in the same lane. In addition, OBD=1 (0) indicates the G-lead vehicle is (is not) equipped with an on-board device (OBD). Basically, if the G-lead vehicle has OBD to share its high-order movement information such as acceleration, the following AV will drive in the CACC mode but following the G-lead vehicle, not the lead vehicle in the same lane. To differentiate from the traditional CACC mode, we refer to this as G-CACC mode. On the other hand, if OBD is not available, the AV will drive in the G-ACC mode. Just like the CACC and G-CACC modes, the only difference between ACC and G-ACC modes is that the AV will follow the G-lead vehicle, not the lead vehicle in the same lane. Eq. (7) describes the behavior of AVs. For human-driven vehicles under the CCM control, they simply follow the Wiedemann 99 model.

Other than the G-ACC and G-CACC modes, a courtesy strategy is considered when the following condition is met: *for an AV in the open lane (left lane in Figure 1), its closest lead vehicle in the closed lane (right lane in Figure 1) is a human-driven vehicle.* Under this condition, the AV will follow the CCM control (could be either G-ACC or G-CACC mode). Beyond that, it will maintain a *larger* gap (than required by the CCM control) with the human-driven lead vehicle in the closed lane so that the human driver will feel safe and comfortable to merge in the merging zone. Note that it is possible that an HDV in the closed lane is followed by an HDV in the open lane. In this case, both HDVs are controlled by the default VISSIM traffic models and no courtesy strategy is considered.

CACC requires information sharing among vehicles and all vehicles (include HDVs) to broadcast their location, speed and acceleration information. In this research, we recognize that not all vehicles are equipped with OBD. The mixed traffic with both AVs and HDVs generates the following exhaustive combinations of merge control scenarios in Table 2.

**TABLE 2. All possible scenarios in CCM**

| Scenario | Follower | G-lead vehicle type | Car-following model | Key parameters' setting |
|---|---|---|---|---|
| 1 | HDV in *any* lane | HDV/AV in *any* lane | Wiedemann 99 | $CC0 = 1.5$, $CC1 = 2$, $CC2 = 4$, $CC3 = -8$, $CC4 = -0.35$ |
| 2 | AV in *any* lane | AV/HDV *with* OBD in *any* lane | CCM (G-CACC) | $k_0^{CACC}$=*1.0*, $k_1^{CACC}$=*0.58*, $k_2^{CACC}$=*0.1*, $\eta = 2.0$, $\tau_e = 1.0s$ |
| 3 | AV in *any* lane | HDV *without* OBD in *any* lane | CCM (G-ACC) | $k_1^{ACC} = 0.2692$, $k_2^{ACC} = 0.0131$, $\eta = 7.5699$, $\tau_e = 1.6881s$ |
| 4 | AV in *open* lane | HDV *with* OBD in *closed* lane | CCM (G-CACC) | $k_0^{CACC}$=1.0, $k_1^{CACC}$=0.58, $k_2^{CACC}$=0.1, $\eta = 2.0$, $\tau_e = 2.0s$ |
| 5 | AV in *open* lane | HDV *without* OBD in *closed* lane | CCM (G-ACC) | $k_1^{ACC} = 0.2692\ s^{-1}$, $k_2^{ACC} = 0.0131$ $\eta = 7.5699$, $\tau_e = 2.0s$ |

*Note: Scenario #4 is a sub-case for Scenario #2. They all follow G-CACC. However, if the condition for Scenario #4 is met, the follower would adopt Scenario #4's key parameters instead of Scenario #2's. This priority rule also applies to Scenario #5, which is a special sub-case of Scenario #3.*

## SIMULATION ANALYSIS

As shown in Figure 1, a work zone on a two-lane highway with the right lane closed is considered as the testing network. For this work zone, the input traffic volume varies from 1,200 vph to 2,000 vph with an increment of 400 vph. CCM is implemented using VISSIM's DriverModel API, and compared with NEM (*15*), no control, and two CACC merge controls based on VISSIM microscopic simulation under various input traffic volumes. The CACC merge controls are similar to no control other than that the default VISSIM car-following logic is replaced by the CACC mode. Unlike NEM and CCM controls, no control and CACC controls do not require vehicles to be cooperative or courteous. Vehicles do not consider their neighbors in adjacent lanes and only follow vehicles in front of them. On the other hand, NEM and CCM all have built-in mechanisms (e.g., G-CACC) to create safe gaps before the merging point.

Note that in Table 3, two sets of CACC and CCM control are considered. One set adopts a reduced headway of 1 second, since AVs in both CACC and CCM can follow other vehicles at shorter time gaps. The other set uses a regular headway of 1.7 seconds. Considering these two headways is to separate the impacts of headway on model performance from other factors (e.g., creating gaps ahead of the merging point, following vehicles in adjacent lanes or G-CACC). Also, no mixed autonomy traffic is considered in Table 3, as NEM can only model 100% AVs. The impacts of mixed autonomy traffic are reported later in Table 4 and Figure 5.

## Overall Mobility Performance

**TABLE 3. Performance comparison of different control strategies**

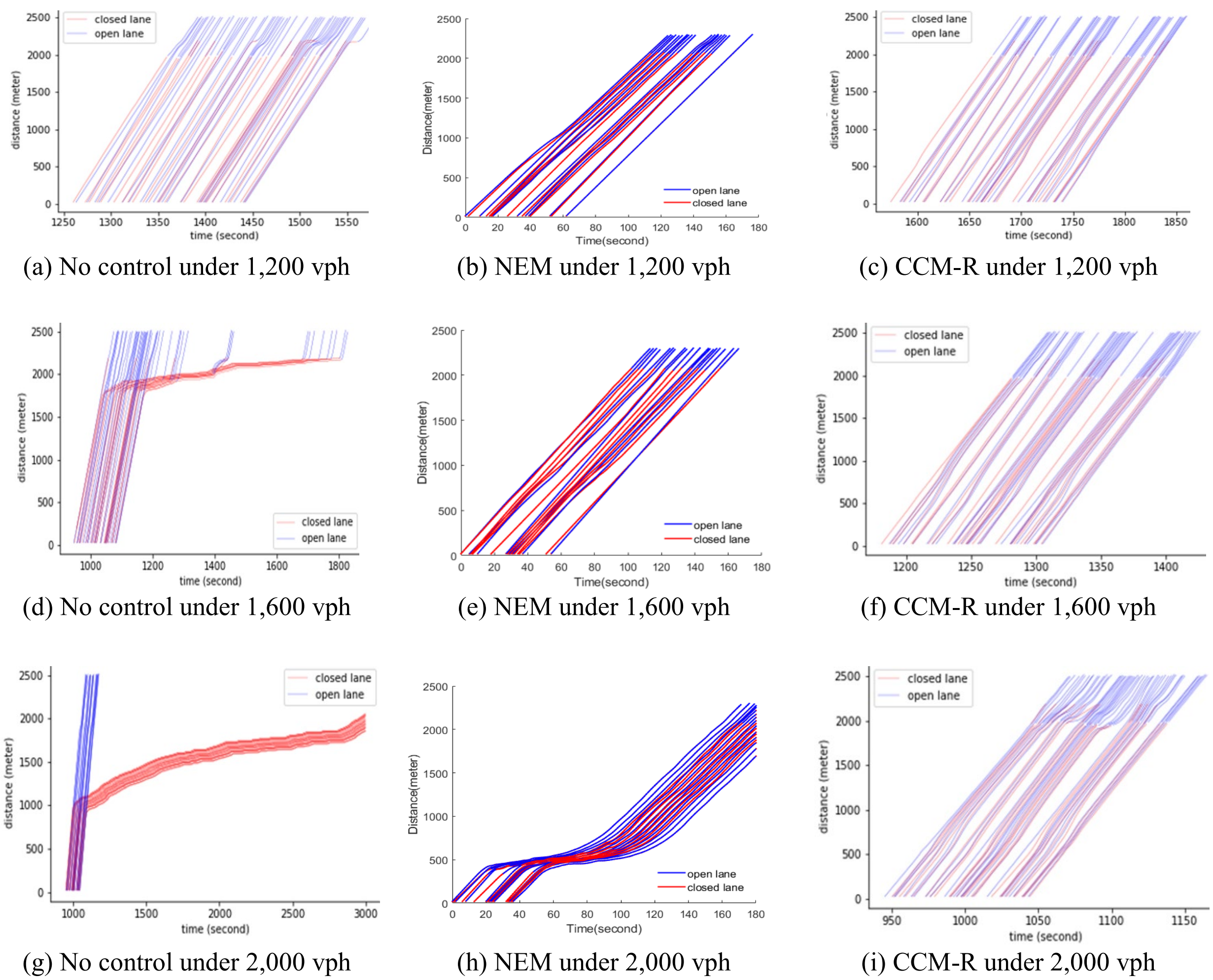
| Performance Measure | Control Strategy | | | | | |
|---|---|---|---|---|---|---|
| | 100% HDV | 100% AV | | | | |
| | No control | CACC | CACC-R (Reduced headway) | NEM | CCM | CCM-R (Reduced headway) |
| | Volume Input 1,200 vph | | | | | |
| Ave. Delay (s/veh) | 1.9 | 1.6 | 0.2 | 5.5 | 0.7 | 0.0 |
| Throughput (vph) | 1203 | 1203 | 1203 | 1197 | 1204 | 1199 |
| | Volume Input 1,600 vph | | | | | |
| Ave. Delay (s/veh) | 24.9 | 21.8 | 1.5 | 9.7 | 11.5 | 0.0 |
| Throughput (vph) | 1595 | 1594 | 1598 | 1591 | 1548 | 1598 |
| | Volume Input 2,000 vph | | | | | |
| Ave. Delay (s/veh) | 374.9 | 396.7 | 80.3 | 80.9 | 11.7 | 0.0 |
| Throughput (vph) | 1754 | 1665 | 1964 | 1915 | 1944 | 1980 |

Considering a 100% penetration rate of AVs, the mobility performances of different control strategies under three input traffic levels are presented in Table 3. Under light traffic input (1,200 vph), there is not much delay (all under 10 seconds/vehicle) for all control strategies and their throughputs are almost the same. Note that at this input demand level, CCM-R with a reduced headway of 1 second is able to eliminate delay.

Under moderate traffic (1,600 vph), the performance gaps among different control strategies become clearer. NEM works well and is able to significantly reduce delay compared to no control and CACC. However, its improvements are not comparable to those generated by CACC-R and CCM-R. These two models lead to negligible delays due to reduced headway. CCM, CCM-R, and NEM all require vehicles in the open lane to create gaps for vehicles in the right (closed) lane, while no control, CACC, and CACC-R do not. The later three methods often lead to continuous high-speed flow in the open lane but stopped traffic in the closed lane in VISSM simulation, which does not occur often in practice, as the stopped vehicles in the closed lane will become increasingly aggressive and interrupt the continuous flow in the left (open) lane. Therefore, the high throughput values (as a result of the high-speed flow in the open lane) should be interpreted with caution. For CACC-R under moderate traffic flow (1,600 vph), it has a much lower average delay compared to CACC. This probably is because CACC-R generates more and larger gaps than CACC due to the reduced headway, which make it easier for vehicles in the closed lane to merge.

When more traffic (2,000 vph) is added into the network, CCM and CCM-R demonstrate clear advantages over all other methods. NEM and CACC-R have about the same delay and throughput performance. However, CACC-R considers a much smaller headway than NEM. Overall, the results suggest that it is beneficial for vehicles to follow their downstream vehicles in adjacent lanes as well (not just in their own lanes), such as NEM, CCM, and CCM-R, and create safe gaps ahead of the upcoming merging point. It is worth noting that CCM-R can still eliminate traffic delay under high traffic input. For all three input demand levels, CCM and CCM-R leads to the lowest average delays and higher throughputs. As the input demand increases, the benefits of adopting CCM and CCM-R seem to become more obvious.

## Vehicle Trajectory Diagram




(a) No control under 1,200 vph (b) NEM under 1,200 vph (c) CCM-R under 1,200 vph

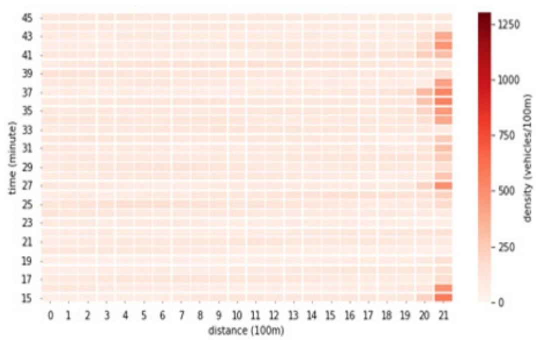
(d) No control under 1,600 vph (e) NEM under 1,600 vph (f) CCM-R under 1,600 vph

(g) No control under 2,000 vph (h) NEM under 2,000 vph (i) CCM-R under 2,000 vph

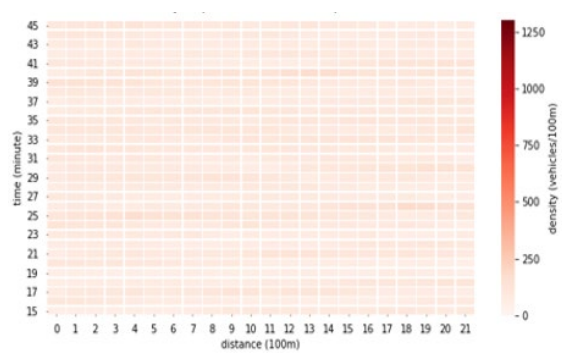
**Figure 3. Trajectory Diagrams for No control, NEM, and CCM-R**

Figure 3 shows the trajectories of a platoon of entering vehicles generated by no control, NEM and CCM-R to further compare their operational performances. In this figure, red lines are for vehicles in the closed lane and blue lines are for vehicles in the open lane. It can be seen that under no control human drivers start to form a long queue at 1,600 vph (Figure 3d), while NEM and CCM can well handle this input demand level (Figures 3e and 3f). When traffic volume reaches 2,000 vph, some human drivers can get stuck in the closed lane for a very long period under no control (Figure 3g). NEM in this case also generates some queues at the beginning of the metering zone, but the delay is evenly distributed among the open and closed lanes and is manageable (Figure 3h). For CCM-R, the trajectories in Figure 3i show that most vehicles in the closed lane can successfully merge into the open lane without delay, although occasionally some vehicles cannot manage to find a safe gap and have to slow down.

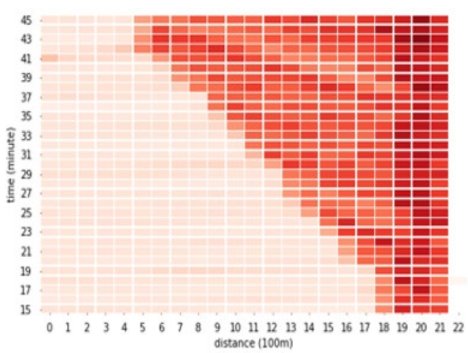
## Density Map



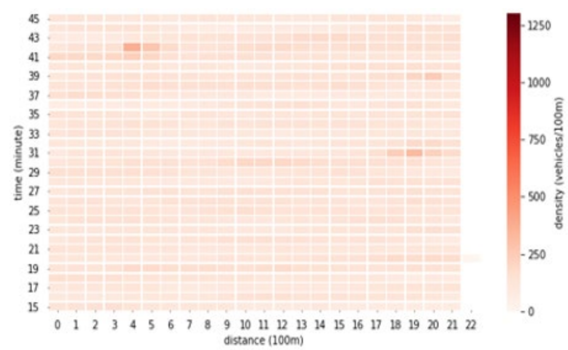

(a) No control under 1,200 vph



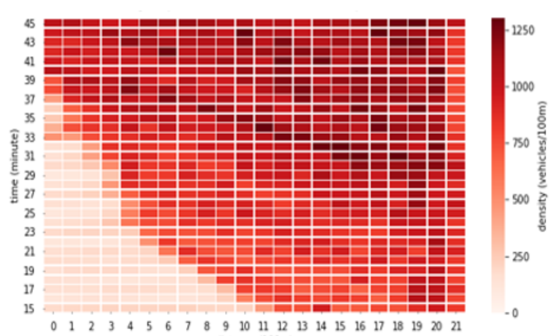

(b) CCM-R under 1,200 vph



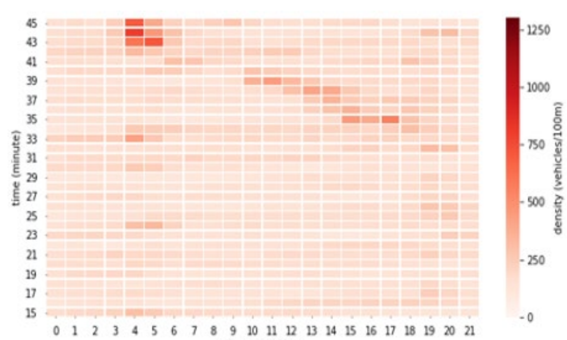

(c) No control under 1,600 vph




(d) CCM-R under 1,600 vph




(e) No control under 2,000 vph




(f) CCM-R under 2,000 vph

**Figure 4. Density maps for no control and CCM-R**

Figure 4 shows the density maps for the no control and CCM-R strategies at three input traffic levels, where the vertical axis is for time and the horizontal axis is for distance. Each cell represents a 100-meter segment and a one-minute interval. A distance of 0 refers to the point 400 meters upstream of the metering zone. Larger horizontal axis values are for locations further downstream in the network. A distance of 4 is for the beginning of the metering zone. Also, darker colors are for higher densities.

The density maps for no control suggest that it can handle the 1,200 vph volume without much trouble. As the input volume increases, queues grow rapidly as evidenced by the slopes of the high-density area boundaries in Figures 4(c) and 4(e). On the other hand, the throughput provided by CCM-R is much higher than no control. CCM-R can well handle the 2,000 vph demand level as shown in Figure 4(f).

When the traffic input is at 2,000 vph, some high-density areas also form under the CCM-R control as shown in Figure 4(f). These high-density areas for CCM-R mostly occur near the beginning of the metering zone (with horizontal axis value being 4). This is because CCM-R controlled AVs there start to follow their G-lead vehicles, and this may cause them to slow down. A relatively high-density area also occurs at 35 minutes and 1700 meters. It propagates backwards to 1000 meters and disappears there. Overall, such high-density areas do not stay for a long time and get cleared quickly. Their densities are much lower compared to those in Figure 4(e) for no control.

For CCM-R control, the density downstream of the metering zone start point can be regulated by modifying the CCM-R algorithm. For example, increasing the headway between AVs and their G-lead vehicles may reduce downstream density and increase system reliability. However, this may affect system performance (i.e., throughput) and increase the chance for forming high-density areas prior to the metering zone.

**Coexistence of AVs and HDVs**

The previous sections consider the mobility benefits of CCM with 100% AVs. This section investigates the benefits of CCM when AVs and HDVs coexist, and some HDVs are equipped with OBD to share information. In this case, AVs could be in either G-CACC or G-ACC mode depending on whether its G-lead vehicle is an AV (or HDV with OBD). The results for various AV penetration rates are presented in Figure 5, in which all HDVs are assumed to have OBD. Although there is a vertical offset between the delay curves for 2,000 vph and 2,400 vph, the general trends and the turning points for these two curves are approximately the same.

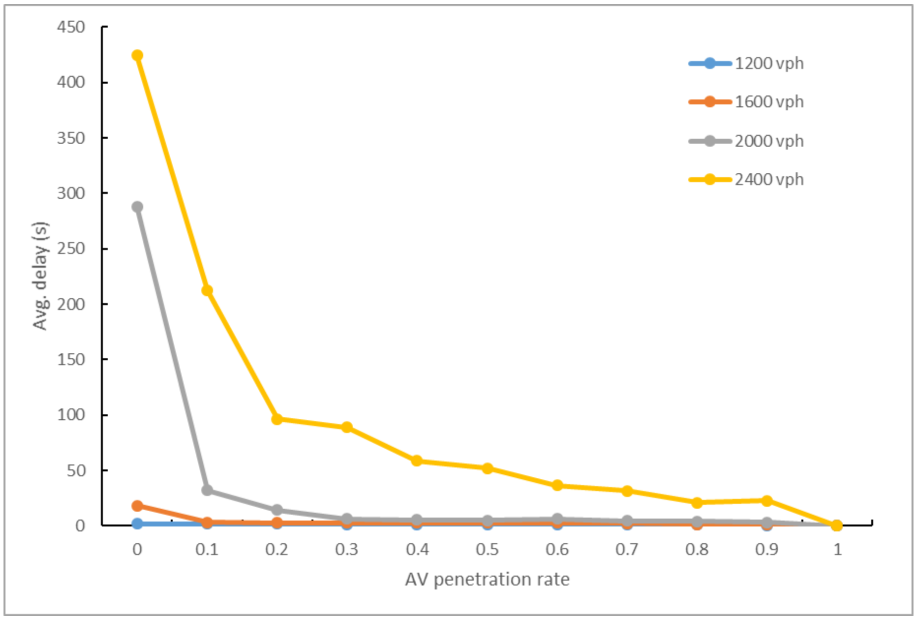



**Figure 5. Performance of CCM in a mixed autonomy traffic**

The curves suggest that there are two stages as more CCM-controlled AVs are added into the network. The first one is the “dropping stage”, where the average delay continues to decrease rapidly (0–20% AVs). The second stage is the “gradually decreasing stage” (20–100% AVs). In this stage, the system performance stabilizes gradually and improves slightly as more AVs are introduced.

Some additional insights can be obtained from Figure 5. Compared to low-volume traffic (e.g., 1,200 vph), high-volume traffic (e.g., 2,400 vph) requires much higher AV penetration rates to achieve significant delay reductions. Also, the diagram suggests that it may not be cost-effective to convert all vehicles into AVs at low traffic volumes, and a mixed fleet of HDVs and AVs with a low AV penetration rate can provide the same level of delay reduction benefits as a fleet of 100% AVs.

The analysis in Figure 5 assumes that all HDVs are equipped with OBD. The following Table 4 further illustrates how the OBD penetration rate may affect average delay at the 2,400 vph traffic input. In addition to considering various levels of OBD penetration rate, three levels of AV penetration rates are considered, which are 20%, 50%, and 80%. Also, all AVs are assumed to be equipped with OBD and share traffic information with surrounding vehicles.

**TABLE 4. Average delay for various OBD and AV penetration rates (seconds/vehicle)**

| AV Penetration Rate | % of HDVs with OBD | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | **0** | **10** | **20** | **30** | **40** | **50** | **60** | **70** | **80** | **90** | **100** |
| 20% | 359 | 350 | 317 | 284 | 243 | 207 | 164 | 140 | 133 | 105 | 99 |
| 50% | 69 | 59 | 60 | 55 | 55 | 55 | 53 | 53 | 53 | 52 | 54 |
| 80% | 24 | 24 | 24 | 23 | 23 | 22 | 23 | 23 | 23 | 23 | 23 |

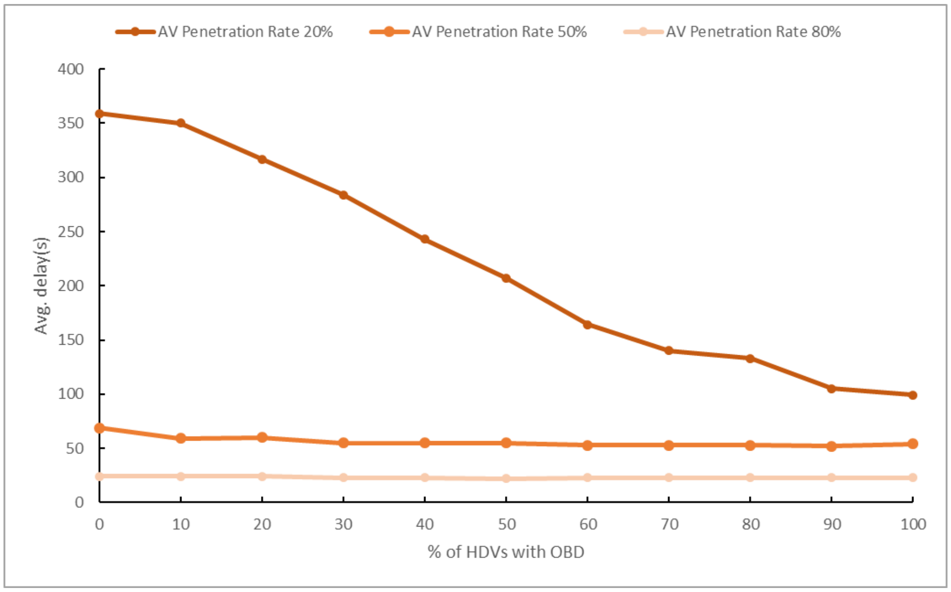



**Figure 5. Average delay for various OBD and AV penetration rates (seconds/vehicle)**

Overall, increasing the OBD penetration rate among HDVs leads to decreased average delay. However, the marginal benefits are different for various AV penetration rates. At low AV penetration rates (e.g., 20%), the average delay reduction is significant as the OBD penetration rate increases. But for higher AV penetration rates such as 50% and 80%, the corresponding average delay reductions due to increase in OBD penetration rate are much smaller.  This trend makes sense as more vehicles are automated, the impacts of whether or not HDVs are equipped with OBD are less significant.

To further understand the average delay reduction trends in Table 4, the marginal effects of increase in "% of HDVs with OBD" on delay reduction are approximated and plotted in Figure 6. The method to approximate the marginal effects at i% of HDVs with OBD is to use the delays at its neighbors (i.e., (i-10)% and (i+10)%) and calculate the delay reduction rate.

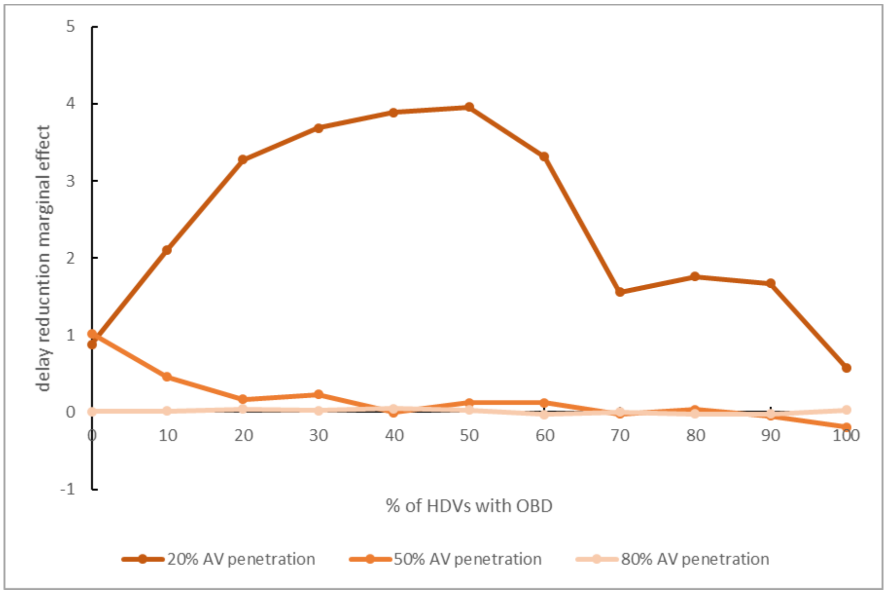



Figure 6. Marginal effect of increase in "% of HDVs with OBD"
(unit: seconds/vehicle for every 1% increase in HDVs with OBD)

The trends in Figure 6 show that when the AV penetration rate is high (e.g., 80%), the marginal impacts of % of HDVs with OBD on delay in general is negligible. When the AV penetration rate is medium (e.g., 50%), having a few HDVs with OBD can be helpful in reducing delay. However, increasing the % of HDVs with OBD beyond 20% will not bring much additional benefits. For low AV penetration rate (e.g., 10%), the marginal delay reduction benefit peaks when the % of HDVs with OBD is around 40%-50%. These results reveal an important message: it would be more cost-effective/rewarding to equip HDVs with OBD when the AV penetration rate is relatively low.

## CONCLUSIONS AND DISCUSSION

In this study, an innovative control strategy, Cooperative Car-Following and Merging (CCM), is proposed for merge control at lane reduction sites due to either construction activities or incidents. The proposed CCM extends the New England Merge (NEM) control by incorporating a modified Cooperative Adaptive Cruise Control (CACC) for vehicle longitudinal control prior to lane reduction points, and can model scenarios with both Human-Driven Vehicles (HDVs) and partially Automated Vehicles (AVs). Compared to no control, NEM, and CACC merge control, CCM demonstrates promising delay, throughput and safety performance based on VISSIM microscopic simulations.

As a decentralized merge control system, CCM offers several advantages: 1) compared to other centralized system, it requires much less computation power and its control logic is straightforward; 2) it is very flexible and does not require 100% AV penetration; 3) it is able to generate throughput close to the theoretical maximum capacity; and 4) it could be relatively easily generalized to scenarios where there are >=3 lanes or multiple lanes have been closed. Additionally, CCM only requires longitudinal control be automated and ACC technology is already mature and is commercially available on many new vehicles. It is a straightforward, efficient and practical merge control and may potentially be deployed in the near future.

The proposed CCM also explicitly takes courtesy into consideration by requiring AVs in the open lane to yield to (i.e., increase gap size) HDVs in the closed lane. The modeling results suggest that such a cooperative behavior is important for improving overall system performance. Individual AVs can make optimal yet selfish decisions, which may not lead to overall system optimal solutions. This study suggests that it is important to consider cooperation among AVs, so that they can behave responsibly and ethically.

The proposed CCM method essentially projects all vehicles into a virtual lane and apply the G-CACC/G-ACC logic to this virtual lane to ensure safe gaps among all vehicles. For multi-lane work zone control problems (e.g., 3-lane highway with the right-most lane closed), the proposed G-CACC and G-ACC strategies may generate unnecessary large gaps, since it requires each CCM-controlled vehicle to maintain a safe gap with all downstream vehicles regardless of their lanes. For future research, multiple virtual lanes may be created so that safe gaps are only required for vehicles assigned to the same virtual lane. In this case, optimal lane assignment algorithms need to be developed so that the numbers of vehicles assigned to each virtual lane are balanced and the roadway capacity is fully utilized. Additionally, human drivers may behave differently in a mixed traffic environment with both HDVs and AVs. This behavior change may not be accurately reflected by any existing microscopic simulation tools. Therefore, we would recommend that field data or data generated by driving simulator be collected in the future to develop accurate behavior models for human drivers (or HDVs) in a mixed traffic environment.

## AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: Liming Jiang, Yuanchang Xie; data collection: Liming Jiang, Yuanchang Xie; analysis and interpretation of results: Liming Jiang, Yuanchang Xie, Xiao Wen, Nicholas G Evans; draft manuscript preparation: Liming Jiang, Yuanchang Xie, Xiao Wen, Nicholas G Evans. All authors reviewed the results and approved the final version of the manuscript.

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