

# Flow-aware platoon formation of Connected Automated Vehicles in a mixed traffic with human-driven vehicles

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## ABSTRACT

Connected Automated Vehicles (CAVs) bring promise of increasing traffic capacity and energy efficiency by forming platoons with short headways on the road. However at low CAV penetration, the capacity gain will be small because the CAVs that randomly enter the road will be sparsely distributed, diminishing the probability of forming long platoons. Many researchers propose to solve this issue by *platoon organization* strategies, where the CAVs search for other CAVs on the road and change lanes if necessary to form longer platoons. However, the current literature does not analyze a potential risk of platoon organization in disrupting the flow and reducing the capacity by inducing more lane changes. In this research, we use driving model of Cooperative Adaptive Cruise Control (CACC) vehicles and human-driven vehicles that are validated with field experiments and find that platoon organization can indeed drop the capacity with more lane changes. But when the traffic demand is well below capacity, platoon organization forms longer CAV platoons without reducing the flow. Based on this finding, we develop the *Flow-Aware platoon organization strategy*, where the CAVs perform platoon organization conditionally on the local traffic state, i.e., a low flow and a high speed. We simulate the Flow-Aware platoon organization on a realistic freeway network and show that the CAVs successfully form longer platoons, while ensuring a maximal traffic flow.

## 1. Introduction

Cooperative Adaptive Cruise Control (CACC) is a vehicle technology that brings promise of greater road capacities and improved energy efficiency without investing on the road infrastructure, such as additional lanes or ramp metering controllers. Vehicles equipped with this technology are henceforth termed Connected Automated Vehicles, or CAVs for short. These vehicles monitor their speeds and gaps relative to their lead vehicles, and automatically adjust their motions in response. Moreover, CAVs can communicate with others of their kind nearby in real time and at high frequencies. With this communication, vehicle accelerations, lane-change maneuvers and other driving decisions can be shared across vehicles without the perception errors and reaction times associated with human drivers. These capabilities enable smaller vehicle headways than were previously possible (and thus larger road capacities) (Shladover et al., 2012) and smaller air drag, improving energy efficiency (Altinisk et al., 2015; Kaluva et al., 2020; Liu et al., 2020). Note that the present research focuses on freeway setting to study the traffic impact of CAVs forming platoons without interruptions, such as signalized intersections.

Capacity gains are likely to be small, however, when the market penetration of CAVs is low in the early stage of implementation (van Arem et al., 2006; Shladover et al., 2012; Liu et al., 2018b). The sparse distribution of CAVs that randomly enter the road diminishes the probability of a CAV immediately following another of its kind, as shown in Fig. 1. This introduces challenges

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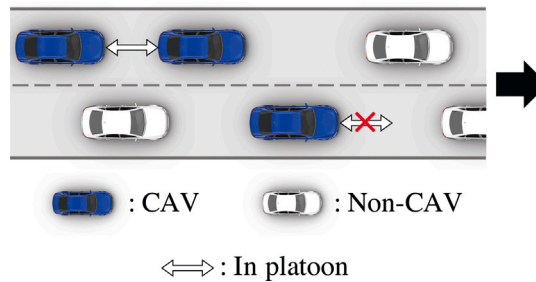


Fig. 1. Challenges of CAVs at low penetration.

when trying to form long platoons of CAVs so as to diminish the average headway in a traffic stream. To overcome this challenge, the CAVs can maneuver to organize the relative positions to each other on the road. The CAVs may have non-CAVs between them in the same lane or the CAVs may be in different lanes. A CAV can maneuver to follow another by accelerating, decelerating, or changing lanes. Then the gap between the consecutive CAVs must be reduced to form a platoon. In this present research, a term *platoon organization* is defined to describe the strategies for CAVs to maneuver on the road to form longer platoons.

Platoon organization has two potential impacts to the traffic. On the one hand, it can increase the number of CAVs in platoon, reducing the headways within the platoons and increasing the traffic capacity. On the other hand, it can induce more lane changes on the road that may disrupt the roadway flow (Laval and Daganzo, 2006; Chen and Ahn, 2018; Laval et al., 2007; Liu et al., 2020). In other words, it is possible to negate the gain in capacity from longer platoons by the flow disruption from the induced lane changes. If platoon organization worsens capacity, it will be unfair for the society to suffer a lower capacity, while the drivers in CAVs enjoy the platooning benefits, such as fuel efficiency and driver comfort (Altinisik et al., 2015; Kaluva et al., 2020; Liu et al., 2020). Unfortunately, no literature has analyzed the traffic capacity under platoon organization, considering the impact of lane changes.

Many researchers propose to promote CAVs to form longer platoons with dedicated lanes for CAVs, where only CAVs are allowed to travel in the designated lanes and increase the probability of forming a platoon. However, their results on capacity vary. Some argue that traffic capacity increases with platoon organization, but do not consider the realistic impact of lane changes (Ghiasi et al., 2017; Hua et al., 2020). Ghiasi et al. (2017) analytically calculate that the capacity increases with dedicated lanes for CAVs, using a Markov Chain model. However, they assume that the CAVs enter the road already formed in longer platoons on the dedicated lanes and do not describe the impact of lane changes in capacity analysis. Hua et al. (2020) use Cellular Automata model to show that the traffic capacity increases for all levels of CAV penetration with dedicated lanes for CAVs, however the lane change model is simple and does not model its flow disruption.

Some do not model the disruptive impact of lane changes, but still show that the capacity can drop at low CAV penetration because the dedicated lanes for CAVs are under-saturated (Talebpour et al., 2017; Chen et al., 2017; Ye and Yamamoto, 2018a; Ma and Wang, 2019). Talebpour et al. (2017) show that the throughput is smaller at low CAV penetration but higher at high CAV penetration, if the CAVs optionally use the dedicated lanes for CAVs. However, they use a game-theory based lane change model, which is to be calibrated in future research (Talebpour et al., 2015). Chen et al. (2017) analytically calculate that the capacity decreases at low penetration with dedicated lanes for CAVs, but capacity increases if the dedicated lanes are optional for the CAVs. They use a formulation derived from a single-lane capacity, recommending a future study to consider the effect of lane changes in the formulation. Ye and Yamamoto (2018a) show that throughput decreases in free-flow but increases in congestion at low CAV penetration, though their model does not describe the realistic impact of lane changes, such as the stochastic reaction of vehicles upstream of a lane-changing vehicle. Ma and Wang (2019) show that the dedicated lanes for CAVs decrease capacity at low CAV penetration but increases it over 40% CAV penetration. However, they use modified Cellular Automata with a simple assumption for the CAVs to change lanes in a 'cooperative and instantaneous' manner.

Some model the impact of lane changes realistically, however do not analyze the traffic capacity under platoon organization (Zhong and Lee, 2019; Xiao et al., 2020). Zhong and Lee (2019) use a CACC model (E-IDM) and a lane change model (MOBIL) that describe the flow disruption of lane changes. Xiao et al. (2020) implement an extensive model of lane change behavior (Xiao et al., 2017b,a) and simulate a mixed traffic of CAVs and non-CAVs on a freeway network. However, the analysis on traffic capacity is missing. At low CAV penetration, both studies report poorer traffic performance with dedicated lanes for CAVs because those lanes are under-saturated. The dedicated lanes will be more saturated at higher CAV penetration, however both studies only use the same demand for all CAV penetration levels and do not analyze the traffic flowing at capacity at high CAV penetration. Note that Xiao et al. (2020) observed speed reduction in the dedicated lanes for CAVs due to the lane changes to enter and exit the dedicated lanes.

To the best of our knowledge, it is still unclear if and how platoon organization increases or decreases the traffic capacity in a mixed traffic of CAVs and non-CAVs. To answer this question, we must analyze the traffic capacity, considering the impact of lane changes and using a platoon organization strategy that can saturate all lanes. Finally, it is necessary to design an operation strategy for CAVs to form longer platoons, while ensuring a maximal traffic flow.

**Table 1**  
Literature on microscopic simulation of mixed traffic.

Publications	Mixed traffic of CAVs and Non-CAVs	Microscopic model	Lane change model	Calibration with CAV experiments
Ghiasi et al. (2017), Ye and Yamamoto (2018b), Chen et al. (2017), Jin et al. (2018)	✓			
Talebpour and Mahmassani (2016), Li et al. (2017)	✓	✓		
Xiao et al. (2018)	✓	✓	✓	
Liu et al. (2018b), Xiao et al. (2017a)	✓	✓	✓	✓

In this paper, we contribute to the current literature by revealing that platoon organization can reduce capacity and create congestion, by inducing lane changes that disrupt the flow. We use a driving model for CACC vehicle that is empirically verified from the real world data and conduct a sensitivity analysis on platoon organization at various traffic demands. We learn that when the demand is below capacity, platoon organization forms longer CAV platoons but does not reduce the flow. Based on this finding, we propose the *Flow-Aware strategy of platoon organization* that forms longer CAV platoons and ensures maximal traffic flow without a capacity drop. We validate the Flow-Aware strategy by simulating it on a realistic freeway network.

This paper is structured as follows. In Section 2, we describe the microscopic traffic model to evaluate the traffic performance that considers the flow disruption of lane changes. We also propose a sample strategy of platoon organization that fully saturates all lanes at capacity. In Section 3, we present a preliminary study to validate that platoon organization can drop the traffic capacity with more lane changes. The main experiments include the sensitivity analysis on platoon organization at various flow levels and the validation of the performance of the Flow-Aware Platoon organization strategy. In Section 4, we describe the sensitivity analysis method, propose the Flow-Aware platoon organization strategy, and explain how we validate the Flow-Aware strategy on a freeway network. In Section 5, we present the results of the sensitivity analysis and show that the Flow-Aware strategy produces longer platoons without flow disruption. In Section 6, we highlight the findings and discuss the shortcomings of this paper. Supplementary materials are given in the [Appendix](#).

## 2. Research approach

In this work, we will conduct experiments to evaluate the impact of CAVs under platoon organization on traffic capacity and develop an CAV operation strategy that forms longer platoons and ensures a maximal traffic flow. Although the CAVs are not readily available in real settings, their driving behavior has been modeled via small scale experiments (Nowakowski et al., 2010; Milanés et al., 2014; Milanés and Shladover, 2015; Lu et al., 2017). We will use the driving models to simulate the mixed traffic of CAVs and non-CAVs. The following describes four features of a traffic model that this research requires to emulate platoon organization in a mixed traffic with CAVs and non-CAVs. The traffic models from the current literature are classified based on the four features and we will select one model to be used in the present study. In addition, we develop a sample strategy of platoon organization that saturates all lanes at capacity at all CAV penetration rates, eliminating the factor on capacity drop from unsaturated lanes.

### 2.1. Microscopic traffic model

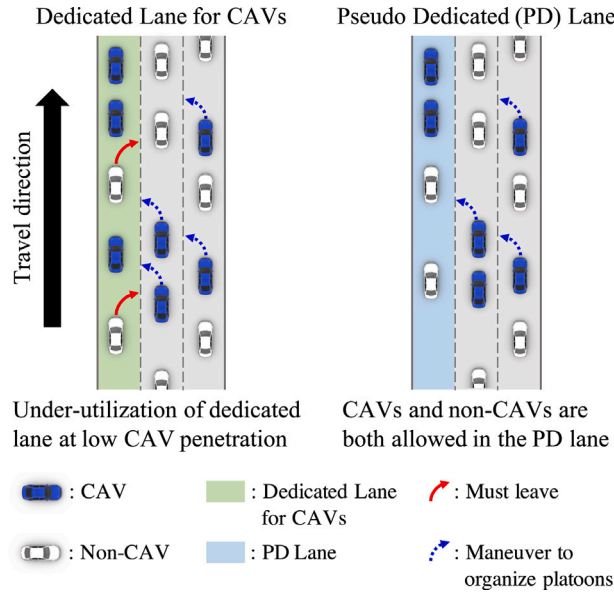
We need four features in a traffic model to emulate platoon organization. First, the model needs to describe mixed traffic composed of CAVs and non-CAVs at various penetrations of CAVs. Second, the model needs to be microscopic so as to depict the detailed operation of platoon organization, such as the number of CAVs in platoon. Third, the model needs to describe the impact of lane changes on roadway flow. Fourth, the model needs to be calibrated with experiments involving CAVs.

The current literature on traffic models for the mixed traffic is organized according to the four features in Table 1. Among them, the model in Liu et al. (2018b) and Xiao et al. (2017a) for mixed traffic satisfies the model requirements of the present study. Note that this model was calibrated for human and automated driving behaviors in Nowakowski et al. (2010) and Milanés and Shladover (2014) and the lane change model for human drivers was calibrated in Kan et al. (2019). This present work uses the model in Liu et al. (2018b) as it is an improved model from Xiao et al. (2017a). Table 2 provides a list of parameters to be used in simulations from the model in Liu et al. (2018b), used in the current study. In this paper, we simulate the traffic using Aimsun with external behavior enabled by MicroSDK.

Note that in this model, simulated drivers in CAVs change lanes manually because we assume the CAVs are equipped with CACC, which automates the car-following maneuvers but not the lane-change maneuvers. The model assumes that CAVs have a weaker motivation for discretionary lane changes than human drivers do because the CAVs prefer to stay in a platoon than to seek higher speeds. Note that when the brake is applied manually, the automatic car-following mode of a CAV is deactivated immediately and reverts to the manual driving mode. Additional description of the model is given in [Appendix A.1](#).

**Table 2**  
Microscopic driving parameters.

Parameters	Non-CAV	CAV
Average reaction time	1.2 s	0.4 s
Average headway	1.25 s	0.6–1.1 s from Nowakowski et al. (2010)
Minimum space gap	1.5 m	1.5 m
Average maximum acceleration	−4 m/s <sup>2</sup>	−4 m/s <sup>2</sup>
Average maximum deceleration	1.5 m/s <sup>2</sup>	1.5 m/s <sup>2</sup>
Vehicle length	4 m	4 m
Average of maximum desired speed	110 km/h	110 km/h
Inter-platoon gap	NA	1.5 s
Maximum number of vehicles in a platoon	NA	10



**Fig. 2.** Pseudo Dedicated (PD) lane.

## 2.2. Platoon organization strategy

We develop a platoon organization strategy called pseudo dedicated (PD) lane, to avoid under-saturating a particular lane at high flow, which occurs with dedicated lanes for CAVs at low CAV penetration. Similar strategies have been proposed in the literature that allow both CAVs and non-CAVs on particular lanes (Talebpoor et al., 2017; Chen et al., 2017). Fig. 2 explains the PD lane strategy in comparison to the dedicated lane for CAVs.

The left figure shows the dedicated lane for CAVs, where only CAVs are allowed to travel on a dedicated lane. At low penetration, the dedicated lane will not be saturated and worsen capacity.<sup>1</sup> To isolate the effect of inefficient lanes in capacity estimation, the dedicated lane strategy is not used in this present study. In the pseudo dedicated (PD) lane strategy shown in the right figure, CAVs are motivated to maneuver into the PD lane for platoon organization, but non-CAVs are not banned from it. We assume that due to the higher probability of forming long platoons, the CAVs have a stronger motivation to travel in the PD lane than the non-CAVs. The CAVs will occupy the PD lane more than the other lanes and the non-CAVs will occupy the PD lane less than the other lanes. This strategy thus guards against under-utilization of the lane at low market penetration of CAVs.

Throughout this study, we define *baseline capacity*, as the traffic capacity of a given penetration rate of CAVs that do not perform platoon organization. We assume that a CAV can change a lane when it is the leader of a platoon. If a follower in a platoon were to change a lane, it must brake and split from its present platoon before the lane change. When a CAV immediately follows another CAV, it automatically starts to form a platoon. Note that we acknowledge a potential error in simulating the platoon organization with an assumption that the CAVs change lanes manually by the human drivers. The future work to improve this issue is described in Section 6 Discussion.

<sup>1</sup> The dedicated lanes for CAVs also pose an equity issue because a portion of public road is allocated only to people who can afford expensive CAVs (Zhong and Lee, 2019).

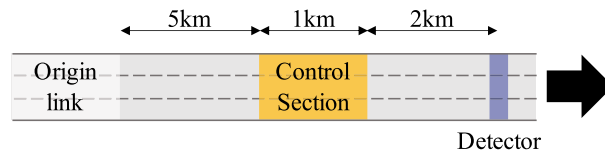


Fig. 3. Homogeneous road segment.

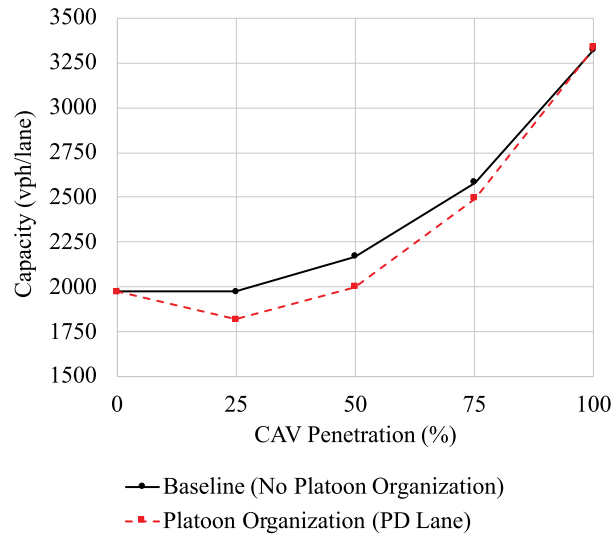


Fig. 4. Capacity for varying market penetrations of CAVs.

### 3. Preliminary study: Capacity drop with platoon organization

This section describes a preliminary study to test if platoon organization can drop capacity by inducing lane changes to disrupt the flow. We simulate the traffic on a homogeneous road segment, comparing the capacity with and without platoon organization. The results validate that when the CAVs change lanes to organize platoons, the traffic flow is reduced and the bottleneck capacity drops.

This simulation experiment uses a 3-lane homogeneous road segment; refer to Fig. 3. After the first stretch of 5 km, CAVs execute the PD lane strategy in the control section of 1 km. As the PD lane strategy allows both CAVs and non-CAVs, the PD lane is not regulated by infrastructural measures (like egress and ingress points) but by the lane targeting behavior of the CAVs. In the control section, the CAVs in short platoons change lanes to the PD lane to form longer platoons. CAV penetration levels are tested from 0 to 100% at increments of 25%. Vehicles are generated according to a Poisson process of a traffic demand rate and vehicle types are decided with Bernoulli trials with the probability of CAV type as the CAV penetration. The detector shown in Fig. 3 measures traffic flow in 30-second intervals.

The simulation procedure is as follows. First, the baseline capacity is estimated for each CAV penetration level without platoon organization. To estimate the baseline capacity, the traffic demand to the origin link as shown in Fig. 3 is increased until a queue forms in the link. The baseline capacity is measured as the maximum sustained flow discharged from the queue over a 60-minute period, at the detector downstream. Second, the capacity of a bottleneck that forms in the control section under the platoon organization strategy is estimated for each penetration level of CAVs. For one hour, an input flow that produces the baseline capacity flow is used. The first 20 min is used as a warm-up period to create a stationary flow. In the next 40 min, the PD lane strategy is implemented in the control section and a queue forms in the control section. The bottleneck capacity is measured after the warm-up period for the 40-minute period (with a total of 2 samples/minute  $\cdot$  40 min = 80 samples), as the maximum flow discharged from the queue that maintains for more than 15 min.

Fig. 4 shows the capacity with and without platoon organization as functions of CAV penetration. The baseline capacity without platoon organization is shown in a black solid line, which increases with more CAVs due to the smaller headways than the human-driven vehicles. The capacity increases slowly at low CAV penetration up to 50% and increases rapidly at higher penetration. We see that platoon organization worsens the capacity, as shown in a red dotted line. At 25% CAV penetration, the PD lane strategy produces a capacity (around 1800 vph/lane) even less than the baseline capacity at 0% penetration (around 2000 vph/lane). This means that capacity with CAVs under platoon organization can be worse than the capacity with no CAVs. At 50% CAV penetration, the PD lane results in a capacity around 2000 vph/lane, similar to the baseline capacity at 0% penetration. In other words, the PD lane can cancel the capacity improvement from having CAVs comprise half the vehicles on the road.

This negative effect of platoon organization on traffic capacity can be interpreted with the queuing theory, which describes that the output rate of a closed system is bounded by its input rate regardless of the dynamics in the system. We can define our closed system as the homogeneous road segment in Fig. 3, with one input and one output. Applying the theory to our experiment, it is impossible for the CAVs to increase the discharge flow (i.e., output rate) further than the input flow of baseline capacity (i.e., input rate), no matter how they maneuver on the road (i.e., platoon organization). Therefore, platoon organization cannot improve the capacity further than the baseline capacity. This must be true for any design of the closed system, whether it is a homogeneous road segment or a freeway network with multiple entrances and exits. Furthermore, the theory explains the capacity drop under platoon organization. When a system is at capacity, the output rate is bounded by the service rate. If the service rate decreases, the output rate decreases. Applying to our experiment, the platoon organization reduces the service rate by inducing more lane changes and inefficiently using the road. Therefore, the discharge flow (i.e., output rate) decreases. There is a need to prevent capacity drop under a naive implementation of platoon organization but still provide platooning benefits to the CAVs.

#### 4. Methodology

In this section, we describe the methodology of the two following experiments. We first conduct a sensitivity analysis on platoon organization with various levels of traffic demand, which provides the evidence in proposing the Flow-Aware strategy of platoon organization. The results provide the evidence in proposing the Flow-Aware strategy of platoon organization that ensures a maximal traffic flow and forms longer CAV platoons. Next, we validate the performance of the Flow-Aware strategy on a simulated freeway network.

##### 4.1. Sensitivity analysis on traffic demand

The sensitivity analysis explores how platoon organization impacts the traffic performance under various levels of traffic demands. We use the homogeneous road segment in Fig. 3, where the CAV penetration is fixed at 50% and input demands are tested at 1000, 1500, 2000, and 2500 vph/lane. The traffic is simulated for an hour. For the first 20 min, no platoon organization is implemented as a warm-up period. For the next 40 min, the PD lane strategy is implemented in the control section. The simulation results are compared in terms of the average number of lane changes, the average platoon length, the platooning probability, and the discharge flow, which are all measured after the first 20 min. We define the *platoon length*,  $L_i(\tau)$ , as the number of CAVs in a platoon that the  $i$ th CAV is a member of at time  $\tau$ . The *average platoon length*,  $\bar{L}$ , is defined as the following:

$$\bar{L} = \frac{\sum_{i=1}^{N_{\text{CAV}}} \max_{\tau} \{L_i(\tau)\}}{N_{\text{CAV}}}, \quad (1)$$

where  $N_{\text{CAV}}$  is the total number of CAVs that travel the network. The average platoon length computes the average of the maximum platoon lengths experienced by individual CAVs. Note that a CAV has  $L_i(\tau) = 1$  if it is not connected to any other CAVs at time  $\tau$ .

We also define the *platooning probability*,  $P_p$ , as the probability that a CAV is ever in a platoon with other CAVs as the following:

$$P_p = P(\max_{\tau} \{L_i(\tau)\} > 1), \quad \forall i \in [1, N_{\text{CAV}}] \quad (2)$$

We calculate the average number of lane changes as the total number of lane changes that occur in the network, divided by the total count of vehicles including CAVs and non-CAVs. The discharge flow is measured at the flow detector.

##### 4.2. Flow-aware platoon organization

We propose the *Flow-Aware strategy of platoon organization* that forms longer platoons of CAVs but ensures maximal traffic flow. The main idea is for the CAVs to execute platoon organization conditionally on the traffic state. Since the traffic demand may be difficult to monitor in practice, we use speed and count to estimate the traffic condition and determine whether platoon organization is allowed. We do not enforce a specific location or time for the CAVs to change lanes for platoon organization, which is often how the ingress and egress points of special purpose lanes are operated. Instead, we determine if the traffic can absorb the disturbance from lane changes, based on a constant flow threshold,  $\rho_q$  in the unit of vph/lane, and a constant speed threshold,  $\rho_v$  in the unit of km/h. Although the traffic density is more robust in analyzing the level of traffic congestion, common detectors can estimate it only by a surrogate measure like occupancy, calibrated with a parameter like the effective vehicle length. Moreover, we believe that there is no sufficient evidence to support that the density can be accurately estimated on the road, when a traffic flows with a substantial percentage of platooned vehicles with short headways. We therefore choose the parameters of flow and speed, which are directly measurable.

Under the Flow-Aware strategy, a CAV gathers the average flow and speed measurements from the detectors nearby, as  $\bar{q}$  and  $\bar{v}$ , respectively. The CAV evaluates a condition in Eq. (3) to check if the flow measure is lower than the threshold and the speed measure is higher than the threshold.

$$\{\bar{q} < \rho_q\} \wedge \{\bar{v} > \rho_v\} \quad (3)$$

If the condition is satisfied, we assume that the traffic can ‘handle’ the disturbances like lane changes and the CAV performs platoon organization, such as the PD lane strategy.



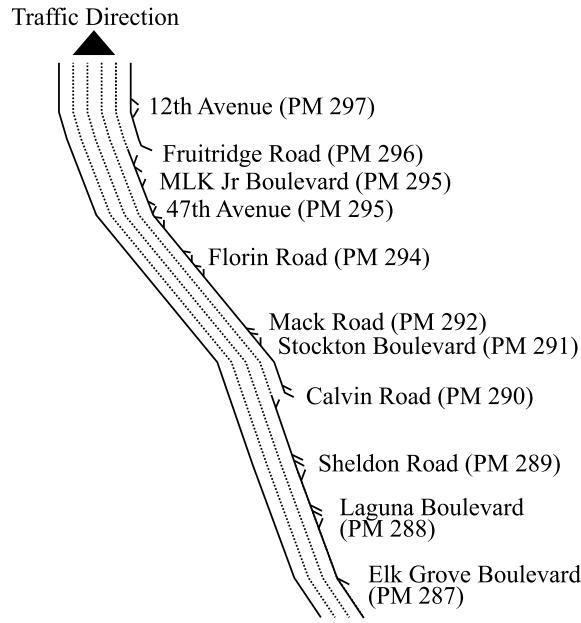


Fig. 5. Simulated State Route 99 in Sacramento, California (PM: Post-mile).

Note that when the threshold values,  $\rho_q$  and  $\rho_v$ , are poorly calibrated, the Flow-Aware strategy may induce lane changes in a traffic with high demand and create unnecessary congestion. As the CAV penetration increases, the flow threshold,  $\rho_q$ , can be increased because the capacity improves with more CAVs and traffic can absorb more shock at a given demand level. Also the threshold values must be calibrated for different road networks as their geometries and capacities vary. For the freeway network studied in this paper, we calibrated the values of  $\rho_q$  and  $\rho_v$  for each CAV penetration rate by trial and error. The calibration procedure for each rate of CAV penetration is as follows.

First, we create a baseline traffic case with no platoon organization that induces capacity flow at a given CAV penetration rate and gather the speed contour plot of the network for the entire duration of the simulation. Second, we initialize the parameters at some reasonable values that could show the traffic is at free flow. For  $\rho_q$ , we choose 80% of the capacity flow. For instance, if capacity flow is 2200 veh/h/lane at 50% CAV penetration, we initialize  $\rho_q$  at  $80\% \cdot 2200 \text{ veh/h/lane} = 1760 \text{ veh/h/lane}$ . For  $\rho_v$ , we choose 80 km/h. Third, we simulate the same traffic demand under the Flow-Aware platoon organization with the parameter values. Fourth, if the speed contour of the traffic under the Flow-Aware platoon organization shows a large reduction in speed compared to the baseline, we update the threshold values. If there has been no update on the threshold values so far or the last update has been on  $\rho_v$ , we reduce  $\rho_q$  by 5%. For instance, we try at 75% of the capacity flow. If the last update on the parameter has been on  $\rho_q$ , we update  $\rho_v$  by increasing it by 5 km/h. Fifth, we repeat the third and fourth steps until the speed contour of the traffic under Flow-Aware platoon organization shows no large reduction of speed from the baseline contour.

Note that we found that once  $\rho_v$  is over 90 km/h did not show much impact to the traffic performance under the Flow-Aware platoon organization with little or no difference to the speed contour. However, the reduction of  $\rho_q$  often improved the speed contours under the Flow-Aware platoon organization. In addition, with a higher  $\rho_q$ , the traffic under Flow-Aware strategy showed more congestion than the baseline, similarly to the traffic under the original platoon organization without flow awareness.

#### 4.3. Validation of flow-aware platoon organization on freeway

We test the Flow-Aware platoon organization strategy proposed in Section 4.2 by simulating it on a realistic freeway network and evaluating if the strategy ensures a maximal traffic flow and forms longer CAV platoons. We use a freeway network shown in Fig. 5. This freeway network is the State Route 99 in Sacramento, California, covering the North-bound 10-mile (approximately 16-km) corridor. It starts at the Elk Grove Boulevard and ends at the 12th Avenue, including 16 on-ramps and 11 off-ramps. The network originally includes High-Occupancy Vehicle lanes, however we exclude them in this paper to isolate their effect on the capacity analysis. The traffic is simulated from 5 AM to 9 AM as the morning peak typically lasts from 6:30 AM to 9 AM. Bottlenecks recurrently form in the network, including one downstream of Elk Grove Boulevard due to high traffic demand. The free flow speed is around 105 km/h for the freeway.

We assume that on the freeway network, detectors are installed around 50 m upstream of all on-ramps and off-ramps, as well as around 50 m downstream of all on-ramps. The detectors aggregate data in 5-minute intervals and broadcast the latest information on the vehicle count and speed. The CAVs can gather information from detectors located within 1 to 2 km range. This allows the CAVs under the Flow-Aware strategy to evaluate the local traffic condition with Eq. (3) and perform platoon organization accordingly.

**Table 3**

Platoon organization at various traffic demands (Homogeneous road in Fig. 3, CAV penetration of 50%).

Traffic demand (vph/lane)	Average number of lane changes (count/veh) <sup>b</sup>		Average platoon length, $\bar{L}$ , (CAV count)		Platooning probability, $P_p$ <sup>c</sup>		Discharge flow (vph/lane)		
	B	PO	B	PO	B	PO	$Q_B$	$Q_{PO}$	$\frac{Q_{PO} - Q_B}{Q_B}$
1000	0.05	0.49	2.6	5.0	0.73	0.89	1006.3	1006.7	0.04%
1500	0.07	0.51	3.0	5.1	0.74	0.89	1483.4	1478.3	-0.34%
2000	0.05	0.53	2.8	5.1	0.74	0.89	1961.7	1924.6	-1.89%
2500	0.04	0.56	3.3	5.4	0.78	0.91	2260.6	2045.0	-9.54%

<sup>a</sup> B: Baseline, PO: Platoon Organization,  $Q_B$ : Baseline discharge flow,  $Q_{PO}$ : Discharge flow under PO.<sup>b</sup>Note that the number of lane changes increase both for CAVs and non-CAVs.<sup>c</sup>Note that the platooning probability  $P_p$  around 0.75 in the baseline makes sense for the baseline traffic of 50% CAV penetration. Here is a simple explanation. Denote the CAV penetration rate as  $P_{CAV}$ . Then the platooning probability,  $P_p$  can be expressed as the probability that given the subject vehicle is a CAV, its leader and/or follower vehicle is a CAV, i.e.,  $P_p = 1 - (1 - P_{CAV})^2$ . For  $P_{CAV} = 0.5$ ,  $P_p = 0.75$ . The simulation well approximates this probability.

We also assume detectors to be installed at the end of each exit of the freeway, including the off-ramps and the main lanes after 12th Avenue, to collect the total discharge flow of the freeway network.

We test the CAV penetration from 0 to 100% at increments of 20%. At each entrance to the freeway, vehicles are generated according to the Poisson process of a traffic demand rate. At each exit of the freeway, vehicles depart the freeway as Bernoulli trials with a departure rate of the exit. We simulate three cases — the traffic without platoon organization as a baseline, the traffic with the PD lane strategy from Section 2.2 with no consideration to the traffic condition, and the traffic with Flow-Aware strategy from Section 5.1 with PD lane.

There is no rigidly defined sections of ingress and egress to the PD lane because the PD lane allows both CAVs and non-CAVs. In the original PD lane strategy, the CAVs consider the leftmost lane of entire freeway as the PD lane. This strategy is an example of a naive platooning operation of the CAVs. In the Flow-Aware PD lane strategy, the traffic condition in Eq. (3) flexibly limits the execution of platooning maneuvers of CAVs. This strategy is an example of a platooning operation that controls the CAVs with awareness to the traffic flow.

The simulation procedure is as follows. First, we find the baseline demand for each CAV penetration level. We increase the network demand by scaling it with a constant factor, which we call *demand scale*, until the speed contour shows the recurrent bottlenecks of the freeway network. Second, we simulate the baseline demand traffic under the PD lane strategy and the Flow-Aware PD lane strategy. The results are compared in terms of the network discharge flow, average number of lane changes, and average platoon length. The network discharge flow is measured as the sum of discharge flows measured at the detectors on the end of each freeway exit.

## 5. Results

In this section, we find that at a low demand the CAVs can form longer platoons without reducing the discharge flow under platoon organization. Therefore, the Flow-Aware strategy conditions the CAVs to perform platoon organization only under a low demand condition so that the output flow does not drop with the induced lane changes. We confirm the performance of the Flow-Aware strategy of platoon organization by simulating the traffic on a realistic freeway network. We show that the Flow-Aware strategy ensures a maximal traffic flow and enhance CAV platooning performance.

### 5.1. Sensitivity analysis on traffic demand

We analyze the traffic performance at various traffic demands under the PD lane strategy on a homogeneous road segment at CAV penetration of 50%. Table 3 presents the average numbers of lane changes, average platoon lengths, platooning probability, and the discharge flows at various traffic demands. Note that without platoon organization, a demand of 2000 vph/lane results in a high but free flow. Without platoon organization, a demand at 2500 vph/lane results in the capacity flow. We see that at all demand levels, platoon organization induces more lane changes (with higher average numbers of lane changes in the third column) and enhances platooning performance (with higher average platoon lengths in the fifth column and higher platooning probability in the seventh column). However, platoon organization affects the discharge flow very differently depending on the traffic demand; refer to the last column of Table 3.

At low demands (1000 to 1500 vph/lane), more lane changes under platoon organization do not change the discharge flow significantly. At moderately high demand (2000 vph/lane), the lane changes under platoon organization breaks down the traffic and reduces the discharge flow by 1.89%. At a high demand (2500 vph/lane), the discharge flow reduces significantly by 9.5%. Therefore, platoon organization can be used when there is low demand, where the disturbance from lane changes can be absorbed easily. At a moderately high demand (2000 vph/lane), platoon organization can also break down the traffic and cause a bottleneck. At a high demand, platoon organization is ill-advised. The Flow-Aware platoon organization is designed with this mechanism by estimating the traffic demand based on speed and count measurements and elongating the platoon lengths without flow disruption.



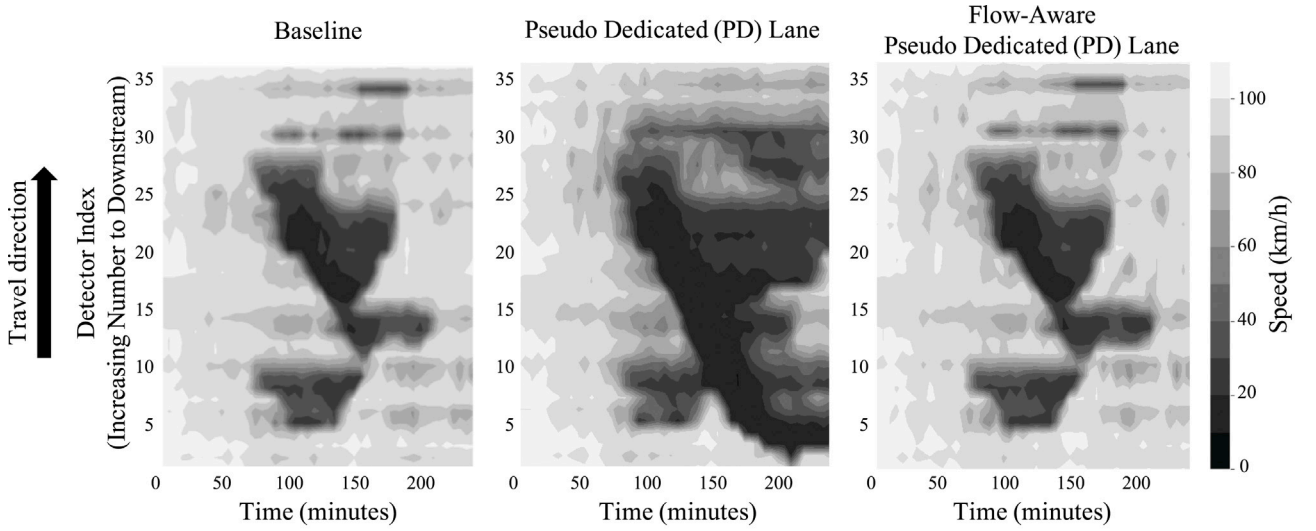


Fig. 6. Speed contours (freeway network in Fig. 5, CAV penetration of 40%): the PD lane strategy reduces the speed significantly from the baseline, whereas the Flow-Aware strategy with PD lane does not.

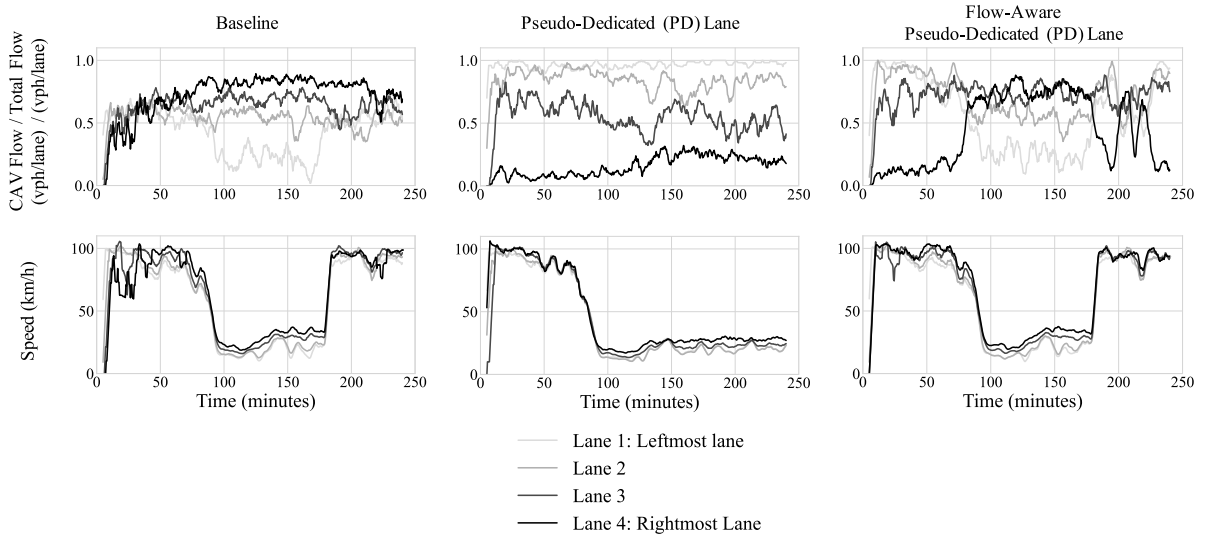


Fig. 7. Ratio of CAV flow to total flow (freeway network in Fig. 5, CAV penetration of 40%): the PD lane strategy distributes the CAVs to the leftmost PD lane regardless of the traffic condition, whereas the Flow-Aware strategy with PD lane only does so in a free flow.

## 5.2. Flow-aware platoon organization on a freeway network

We emulate the traffic on a freeway network to validate the strategy of Flow-Aware platoon organization. We assume that the CAVs perform PD lane strategy when the condition in Eq. (3) is met at any post-mile of the freeway. We first validate the traffic simulation with Fig. 6, which shows three speed contours for the baseline, the PD lane strategy, and the Flow-Aware PD lane strategy at 40% CAV penetration. The simulation time is on the  $x$ -axis and space on the  $y$ -axis with detector index of an increasing number downstream. We observe that bottlenecks form in the baseline due to traffic demand larger than the network capacity. The PD lane strategy induces lane changes of CAVs regardless of the traffic condition and reduces speed significantly compared to the baseline. However, the Flow-Aware PD lane strategy results in a speed contour very similar to the baseline, indicating that the speed is not reduced significantly due to the platoon organization.

We also observe the distribution of CAVs across the lanes under platoon organization with Fig. 7 to validate the simulation further. The figure describes the traffic with 40% CAVs in the section immediately upstream of the second on-ramp at Florin Road (shown in Fig. 5) or around the detector index 22 (shown in Fig. 6), where a bottleneck queue reduces the speed significantly. In

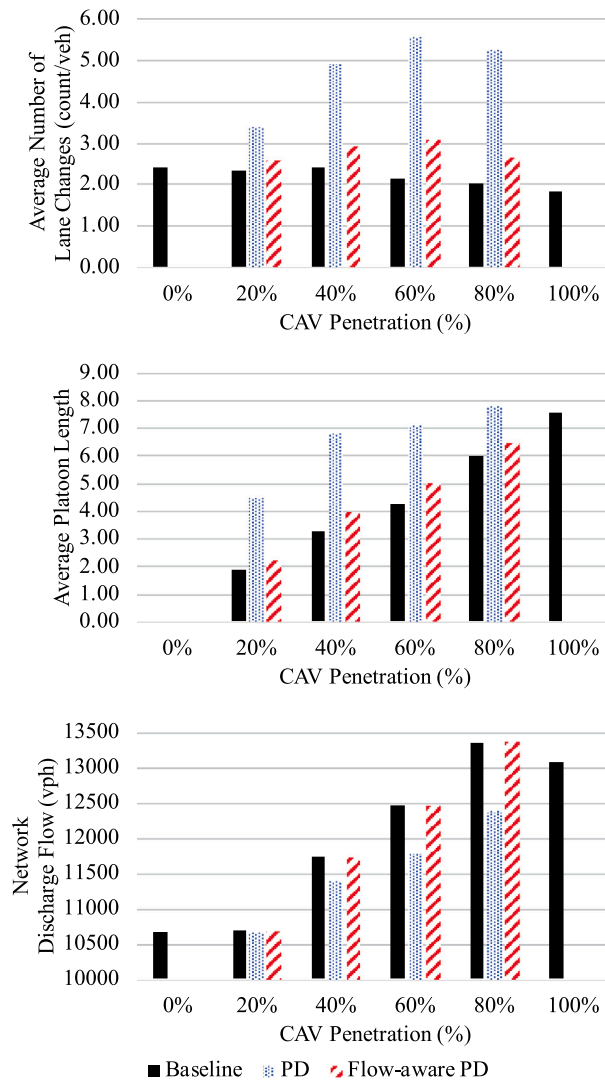


Fig. 8. Increase of lane changes and platoon lengths without flow disruption under flow-aware platoon organization.

Fig. 7, the  $x$ -axis is the simulation time, the  $y$ -axes for the top figures show the CAV flow ratio, i.e., the ratio of the flow of CAVs to the flow of all vehicle types, and the  $y$ -axes for the bottom figures show the speed per lane. The lanes are differentiated by the shade, where the lightest line corresponds to the leftmost (or PD) lane. The baseline, the PD lane strategy, and the Flow-Aware PD lane strategy are shown on the left, the center, and the right, respectively.

The baseline results on the left column show that when this section is in a bottleneck queue from around 80 min to 170 min, the CAVs are more concentrated on the right lanes than the left lanes. The CAVs make up about 80% in the rightmost lane, whereas they make up about 20% in the leftmost lane. This is possibly because the human driven vehicles have moved toward the leftmost lanes to avoid the conflict with the on-ramp merging flow.

The results under PD lane strategy on the center column show an opposite distribution of CAVs across lanes to the baseline results. The CAVs are highly concentrated in the leftmost PD lane all throughout the simulation. With the naive implementation of the PD lane strategy, the CAVs join the PD lane regardless of the traffic condition. This cause a longer duration of congestion.

The results under the flow-aware PD on the right column are interesting, as the distribution of CAVs are similar to the PD lane during free flow, but similar to the baseline during congestion. During free flow (when speed is around 100 km/h), the CAVs concentrate on the leftmost PD lane as the traffic condition in Eq. (3) is met and their maneuvers do not disrupt the flow. During congestion (from around 80 min to 170 min), the CAVs refrain from platoon organization because the condition in Eq. (3) is not satisfied. The CAVs concentrate higher in the right lanes like in the baseline case. Because of the restricted lane changes to the PD lane under congestion, the queue is dissipated at a similar time to the baseline.

We evaluate the traffic performance under the Flow-Aware platoon organization in comparison to the baseline and the PD lane strategy with Fig. 8. The detailed values for the figure are found in Table 4 in the Appendix A.2. Three figures present the average

number of lane changes, average platoon length, and the network discharge flow, as functions of CAV penetration rates. At each penetration rate, the solid black bar shows the baseline result, the blue dotted bar shows the PD lane result with no condition on traffic, and the red dashed bar shows the result of Flow-Aware strategy with PD lane. Note that there is no result for the PD lane strategy and the Flow-Aware PD lane strategy for 0% and 100% CAV penetration rates because no CAV needs to be organized for longer platoons. The average platoon length is not applicable at 0% CAV penetration. The demand scales are 100%, 100%, 110%, 117%, 125%, and 127% for CAV penetration rates of 0%, 20%, 40%, 60%, 80%, and 100%, respectively.

The top figure in Fig. 8 shows that more lane changes are induced under both PD lane strategy and the Flow-Aware PD lane strategy, compared to the baseline. The PD lane strategy naively induces more lane changes than the Flow-Aware strategy, without checking on the flow conditions. The middle figure in Fig. 8 shows the PD lane strategy increases the platoon length the most, but the Flow-Aware PD lane strategy also significantly increases the average platoon length (by 8 to 20% as shown in Table 4).

The bottom figure in Fig. 8 shows the network discharge flow. Compared to the baseline, the PD lane strategy significantly reduces the network flow (up to 7% at 80% as shown in Table 4). However, the Flow-Aware PD lane strategy does not decrease the network flow significantly (only up to 0.1% as shown in Table 4). The Flow-Aware PD lane strategy successfully forms longer platoons while ensuring the maximum level of traffic flow. In other words, the CAVs can form longer platoons without trading off the level of traffic flow. Agreeing with the preliminary analysis in Section 3, platoon organization does increase the network flow further than the baseline.

Note that the network discharge flow in the baseline is lower at 100% than at 80%. Under the current simulation settings, the CAVs form and remain in a platoon if possible. The preference of CAV drivers to choose between forming a platoon and traveling in a faster lane is not well modeled or calibrated in this study; please refer to the future work in Section 6) Discussion. At full CAV penetration, the CAVs form platoons soon after entering from the on-ramps because they find other CAVs immediately and stay in platoon on the right main lanes. So the highly dense traffic on the right lanes create conflicts with other merging flows downstream, resulting in a lower discharge flow than 80% CAV penetration. This issue is out of scope for the current study, as we compare the baseline at each CAV penetration rate, not across different penetration rates. However, please refer to Liu et al. (2018a) for further investigation on the need for a merging assistance system for a mixed traffic with CAVs and non-CAVs.

## 6. Discussion

In this paper, we examine the potential problem of disrupting the traffic flow and causing unnecessary congestion with a naive platooning operation of CAVs. At low penetration, the CAVs will not deliver a large gain in the traffic capacity and the fuel economy because they are likely to form only few, short platoons. The CAVs can operate under a *platoon organization* strategy, where they can maneuver to follow other CAVs on the road by changing lanes and form longer platoons. However, a poorly designed strategy of platoon organization can deteriorate the traffic capacity by inducing lane changes that disrupt the flow. We explore this issue by implementing the realistic driving models of CACC and human-driven vehicles, which are validated by field experiments and model the disruptive effects of lane changes. The key findings from this research are as below.

- CAVs can form longer platoons by platoon organization, but may induce more lane changes on the road. At low traffic demand, the induced lane changes do not affect the traffic performance significantly as the traffic flows below capacity. However at high traffic demand, the induced lane changes can drop the capacity and create unnecessary traffic congestion.
- We propose the *Flow-Aware strategy of platoon organization* as a solution to enhance CAV platooning without degrading the traffic performance. Under the strategy, we estimate if the traffic can absorb the disturbances from additional lane changes by measuring the local flow and speed. If flow is below and speed is above the given thresholds, the CAVs execute platoon organization. If not, the CAVs refrain from platoon organization and avoid traffic disruption. We simulate the Flow-Aware strategy of platoon organization on a realistic freeway network (State Route 99 in California) and show that CAVs under this strategy indeed form longer platoons with no disruption to the traffic flow.
- The traffic capacity cannot increase further by forming longer CAV platoons on the road and reducing the headways within the platoons. Based on the queuing theory, an output flow is bounded by the input flow in a closed system. However, the input flow is composed of CAV platoons that are not longer, as platoon organization is yet to be performed. Therefore, the output flow is bounded by the input flow, i.e., the capacity cannot increase further by the maneuvers of CAVs on the road.

The CAVs may be motivated to form longer CAV platoons regardless of the capacity increase, due to the energy efficiency improvement (Muratori et al., 2017). There is an ongoing research to validate the improvement of energy efficiency in passenger vehicles by driving in platoons. For instance, Altinisik et al. experimented with a platoon of two passenger cars and found a significant reduction in air drag in the leading vehicle (Altinisik et al., 2015). Kaluva et al. computed that a longer platoon reduced the average air drag coefficient of the platoon, saving energy (Kaluva et al., 2020). Also, Liu et al. show that vehicles driving in connectivity can improve traffic stability and fuel efficiency (Liu et al., 2020). To facilitate the formation of long CAV platoons in a mixed traffic, we advocate for the Flow-Aware strategy of platoon organization to be implemented.

We believe our work can improve. In this study, we assume that lane changes are executed manually by human drivers in CAVs. It may be difficult for human drivers to implement the Flow-Aware strategy of platoon organization, which is based on the measurement of the local traffic condition. Because we do not know how well the human drivers will execute the platoon organization strategy, the estimated traffic performance may be biased. This bias can be overcome by assuming that the lane changes will be automated in the future and applying a model for the automated lane changing to execute the platoon organizations

strategy. There is an on-going research on the lateral controller for automated vehicles. Although most works focus on safety and efficiency (Wang et al., 2019), some develop automated lane change controllers that consider the traffic flow. For instance, Wang et al. (2016) propose a centralized controller for cooperative lane changes that explicitly models the movement of vehicle upstream in the target lane. Their controller reduces the braking and waiting times of upstream vehicles following the lane-changing vehicle. The model for automated lane changing can replace the human-driving model for lane changing and better estimate the traffic impact of platoon organization.

Also, we lack the model to capture the preference of CAV drivers in choosing between traveling in a long CAV platoon or traveling in a faster lane without a platoon. It is possible that the adjacent lane of a CAV presents a higher probability of forming longer platoons, but flows at a lower speed than the current lane. It is also possible that the adjacent lane of a CAV flows faster than the current lane, but the CAV is traveling in a platoon already. In this paper, we assume that under the PD lane strategy, the CAVs change lanes to reach the PD lane regardless of the speed difference between the current lane and the target lanes (although if the target lane is very crowded, the CAV is less likely to succeed in joining the target lane). A proper model of the CAV behavior in choosing between driving in a platoon and driving faster will better estimate the induction of lane changes under platoon organization. However, we would like to note that the Flow-Aware PD lane strategy is designed with a condition of the local speed in Eq. (3). A CAV performs platoon organization only when all lanes have a very high speed (above 90 km/h in this paper). Therefore, the lack of a preference model between a longer platoon and a faster speed plays an insignificant role in the validation results of the Flow-Aware strategy.

There are many ways to improve the Flow-Aware strategy of platoon organization. First, we calibrated the threshold values,  $\rho_q$  and  $\rho_v$ , in Eq. (3) by trial and error. We used only one value of flow threshold (vph/lane) for the entire network at a given CAV penetration, though the shock of lane changes may be absorbed differently at locations with various road geometries. The future research can design methods to calibrate the thresholds in a systematic manner that can be applied to various roads geometries.

Second, we assumed the availability of local measurements on vehicle count and speed and used these data to evaluate the condition in Eq. (3). In practice, such data may not be available so that the CAVs need to use other sources of data to find if local traffic can absorb the shock of more lane changes. It is also possible that more sophisticated data will be available, such as individual vehicle data like gap, acceleration, and desired lane to travel. Different sources of data can be used to represent the traffic state for the Flow-Aware strategy of platoon organization with improved formulation of the condition in Eq. (3).

Third, we can add sophistication to the Flow-Aware strategy, for instance by developing a learning controller that better models the complex dynamics of how a lane change can impact the traffic flow. The algorithm can model the traffic flow outcome of a lane change given various states measured by the sensors in CAVs, such as current gap, speed, acceleration, lane, and platoon length. This controller can replace the heuristic condition developed in Eq. (3) and perhaps allow a longer platoon length than the Flow-Aware PD lane strategy. A useful resource is 'Flow', an open-source deep learning platform developed in University of California, Berkeley, which supports microscopic traffic simulation as an environment (Wu et al., 2017).

In addition, the evaluation of the energy efficiency with platoon organization is missing in this paper. It is possible that platoon organization will improve the energy efficiency of individual CAVs, while they systematically deteriorate the energy efficiency by creating congestion. If so, the Flow-Aware strategy must be implemented not only to ensure maximal traffic flow but also to avoid energy inefficiency as a whole. The future research must investigate the energy efficiency trade-off between individual vehicles and the traffic system under various operation scenarios of CAVs.

## CRedit authorship contribution statement

**Soomin Woo:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Alexander Skabardonis:** Resources, Writing – review & editing, Supervision.

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## Appendix

### A.1. The microscopic traffic model

This section briefly describes the microscopic traffic model from Liu et al. (2018b) used in this study. The model has car-following algorithms and the lane-change algorithms. The car-following algorithms are defined separately for human driving and automated driving with CACC. The algorithm for human drivers calculates the desired acceleration as the minimum of three values — acceleration from Newell's simplified car following model (Newell, 2002), Intelligent Driver Model's free flow acceleration (Treiber et al., 2000), and Gipps acceleration with safe distance (Ciuffo et al., 2012). The algorithm for automated vehicles calculates the acceleration from a model calibrated with experimental data of production vehicles instrumented with CACC (Milanés and Shladover, 2014).

**Table 4**  
Increase of lane changes and platoon lengths without flow disruption under flow-aware platoon organization (Supplementary result to Fig. 8).

CAV penetration in %	Network demand scale factor	Platoon organization	Network discharge flow in vph <sup>a</sup>	Average number of lane changes in count/veh <sup>a</sup>	Average platoon length, $\bar{L}$ , in CAV count <sup>a</sup>
0	100%	Baseline	10,675.8	2.40	NA
20	100%	Baseline	10,687.3	2.35	1.87
		PD	10,675.8 (−0.1%)	3.40 (+45.0%)	4.47 (+138.9%)
		Flow-Aware PD	10,687.8 (+0.0%)	2.58 (+9.7%)	2.25 (+20.0%)
40	110%	Baseline	11,739.8	2.40	3.28
		PD	11,402.0 (−2.9%)	4.90 (+103.9%)	6.81 (+107.2%)
		Flow-Aware PD	11,733.8 (−0.1%)	2.93 (+22.0%)	3.94 (+20.0%)
60	117%	Baseline	12,449.3	2.15	4.27
		PD	11,780.3 (−5.4%)	5.55 (+157.6%)	7.12 (+66.6%)
		Flow-Aware PD	12,446.8 (−0.0%)	3.06 (+42.2%)	4.98 (+16.6%)
80	125%	Baseline	13,347.0	2.03	5.97
		PD	12,378.8 (−7.3%)	5.24 (+157.9%)	7.78 (+30.4%)
		Flow-Aware PD	13,356.8 (+0.1%)	2.66 (+30.9%)	6.47 (+8.5%)
100	127%	Baseline	13,069.0	1.82	7.55

<sup>a</sup>In parenthesis is the percentage difference to the baseline result, i.e., (Current result — Baseline)/Baseline · 100%.

The lane-change algorithms in this model are similar for human driving and automated driving with CACC because the CACC does not provide automation for lane-changing task. In other words, human drivers in both CACC and non-CACC vehicles perform lane-change movements manually. However, the motivation for discretionary lane changes are different between the human driver and the CACC vehicles. The CACC vehicles is assumed to have a stronger motivation to stay in a platoon than to seek for higher speeds. In addition, the algorithms can emulate the complex lane-change behaviors, such as anticipatory lane changes in response to a slow speed downstream, cooperative behaviors to slow down to increase a gap for the lane-changers, and recovery responses after letting in a lane-changer with smaller reaction times and headway.

## A.2. Supplementary results on flow-aware platoon organization

Table 4 presents the detailed results visualized in Fig. 8. PD indicates the PD lane strategy without considering the traffic state. Flow-Aware PD indicates the Flow-Aware strategy of PD lane that considers the traffic state by condition in Eq. (3).

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