Dedicated Lane for Connected and Automated Vehicle: How Much Does A Homogeneous Traffic Flow Contribute?

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Abstract—Dedicated lanes for connected and automated vehicles (CAVs) can not only provide the technological accommodation, but also the desired market incentive for road user to adapt CAVs. Thus far, the majority of the impact assessment of CAV focused on the network-wide benefits. In this paper, we investigate the change of the traffic flow characteristic with two configurations of dedicated CAV lane across levels of market penetration. The traffic flow characteristics are quantified from the perspectives of headway distribution, communication density, and speed-flow diagram. The results highlight the contributions of the CAV lane. First, CAV lanes significantly improves the speed-flow characteristics by extending the stable region of the speed-flow curve and yielding a greater optimum flow. The highest value of optimum flow is 3400 vehicle per lane per hour at 90% MPR with one CAV lane.

Furthermore, the concentration of CAVs at a lane results a narrower headway distribution (with smaller standard deviation), even with partial market penetration. Moreover, the CAV lane creates a more consistent CAV density which maintains the communication density level at a predictable level, hence decreasing the probability of packet drop.

Index Terms—CAV Lane, Managed Lane, Connected and Automated Vehicle, Cooperative Adaptive Cruise Control, Microscopic Traffic Simulation, Traffic Flow Characteristics

I. INTRODUCTION

Since its inception in early 2000s, connected and automated vehicle (CAV) technology is expected to revolutionize the way a vehicle is operated. CAV has been identified as one of the thrust areas by government agencies, industries, and academia all around the world in improving mobility, environment, and more importantly safety. Despite policy encouragement from government agencies and the progress made in academic research, large-scale field deployment is still considered premature at the current stage in terms of safety, technological, and budgetary concerns. Simulation is one of the best approaches to bridge the gap between prototyping CAV technologies to evaluating network-level impact by providing a virtual environment.

In this paper, we assess the improvements of the traffic flow characteristics brought by the use of CAV lanes. It is the consensus that CAV could fundamentally change our transportation system. However, limited studies have performed the characterization of the flow enhancements for a CAV lane, especially when CAVs coexist with human-driven vehicles (HVs) under different market penetration rates (MPRs).

II. RELATED WORKS

Due to the distinctive operational characteristic of CAV, knowledge learned from traditional managed lane may not be directly transferable to CAV, despite that managed lane (ML) has been widely applied to highway operation with great success. CAV lane is one type of ML and the concept is typically referred as CAV-ML. Most of the CAV studies did not focus on operation policy of CAVs in mixed traffic condition. Therefore, limited studies on CAV-ML had been reported thus far.

A multi-resolution modeling was proposed in [1] to study the mobility impact of CAV lanes. Traffic flow-based static traffic assignment and the mesoscopic simulation-based dynamic traffic assignment were adapted in the bi-level framework. The former yielded the MPR-based trends, whereas the latter refined the trend based on traffic congestion. The results indicated that it was not beneficial to provide toll incentive for CAVs at lower MPR due to the marginal increase in highway capacity.

In [2], the performance of the ML and general propose lane (GPL) was compared based on average speed, throughput, and travel time. The results indicated that the speed improvement of a ML was significant compared to that of GPL. With 20% MPR, the latent demand (the demand that cannot enter the simulation network due to congestion) decreased to zero. Inspired by the fluid approximation of traffic, [3] proposed an algorithm for simulating the weaving activity at the interface of a ML and the adjacent GPL at a macroscopic scale.

A time-dependent deployment framework was proposed in [4], which was formulated with a network equilibrium model and a diffusion model (for modeling adoption of a new product...
in a population). With the constraint of a given set of candidate lanes which corresponds to the field condition, the social cost was minimized with the consideration of levels of MPR.

The introduction of CAV lane a signalized corridor was reported in [5]. Two configurations of dedicated CAV lane, along with other managed lane, were evaluated. Due to the turning nature of the arterial, buffer zones where HVs were allowed to temporarily use the CAV lane for turning movements was implemented. The CAV-ML in freeway setting can be found in [6], [7], where a 30% minimal MPR was recommended to avoid lane use imbalance that could degrade the performance.

In [8], an analytical capacity model for mixed traffic was proposed. The model relied on the Markov chain representation of spatial distribution of heterogeneous and stochastic headway. With the sufficient and necessary condition of capacity increase proven, the authors emphasized the importance of quantitative analysis of the actual headway setting.

An analytical modeling framework for assessing the benefits of CAV operations was proposed in [9]. The overall results indicated that CAV improved network mobility performance, when the MPR was low, even in the absence of ML policies. Throughput without managed lane increased by 4%, 10%, and 16% at market penetration rate of 10%, 20%, and 30%, respectively. It was also discovered that managed lane policy facilitates homogeneous CAV traffic flow that yielded more consistent and stable network output.

Nearly all of the previous studies evaluated the benefits of CAV at a aggregated level with the emphasis of the overall improvement. In this paper, we further the impact analysis to a traffic flow level, aiming to investigate the traffic flow characteristic with the presence of CAV lanes.

III. SIMULATION

A. Simulation Framework

Managed lane has a proven track record in promoting new technology or travel patterns (e.g., HOV lane, low-emission electric vehicle lane). When it comes to CAV, a CAV lane can be adopted to create a homogeneous traffic flow to better harness the benefits of the technology. A dedicated lane can also cluster the CAVs on designated lane to create a local high market-penetration region in the early deployment phase with low MPR. However, it is nearly impossible and to conduct a network level field experiment at current stage. In addition, small scale result may not be directly extrapolated to network level. Simulation could provide valuable insights in a cost-effective way for evaluating ML policies.

1) Vehicle Behavioral Models: Two types of car-following behaviors are used for the analysis: 1) a calibrated Wiedemann car-following model (the default model in Vissim) for HVs; and 2) the Enhanced Intelligent Driver Model (E-IDM) [10]. As an improvement from the collision-free IDM, the E-IDM deals with CAV longitudinal maneuver and it was implemented using Vissims external driver model (EDM) application programming interface (API). Three cases of CAV lanes, as shown in TABLE I, are implemented on the network: i) mixed traffic without CAV lane, ii) CAV lane at the most left lane, and iii) two CAV lanes at the leftmost and the 2nd leftmost lane.

2) Wireless Communication Model: An packet-level communication module was implemented into Vissims EDM API. The analytical model [11] was developed from ns-2, an empirical packet-level network simulator, and it returns the probability of one-hop broadcast reception under IEEE 802.11p, an approved amendment tailored to wireless access in vehicular environment (WAVE) in the 802.11 family protocol. The model uses the concept of communication density level, which is a metric representing channel load in vehicular communication in the form of the sensible transmission per unit of time and per unit of road [12].

3) Model Parameters: The E-IDM is selected as the longitudinal control for the CAVs. All the parameters remain the same as those originally specified in [10], with the exception of the desired time gap (DTG), which is defined with two values: 0.6 s and 1.2 s. The former DTG is used when the communication between a preceding CAV and the subject CAV is successful, whereas the latter one is in effect when the communication failure occurs. The updating frequency for the E-IDM model in Vissim is 10Hz. The density of CAVs which is used to calculated the communication activity is updated at a 2-Hz frequency to reflect the traffic dynamic. Each transmission is assumed to have maximum five attempts. At least one successful attempt is required for a transmission to be considered successful, upon which the DTG is determined.

B. Simulation Network

A 9.3-km 4-lane hypothetic network was constructed in Vissim with two interchanges located at mile marker 2 (km) and 6 (km) respectively. An abstract geometry of the network along with vehicle demand of the origins and destination is shown in Fig. 1. The calibrated parameters for the Wiedemann car-following model is the same as in [13]. Note that the demand originated on the mainline is deliberately set higher than usual to create a congested network.

IV. RESULTS

Five replications are run for each combination of ML polices and MPRs. Aggregated data was collection with a 5-min interval and the raw data was collected at each simulation time step. Speed-flow curve, headway distribution, and throughput were selected to measure the performance. Communication density for each CAV and the probability of successfully communication is presented as well.

A. Traffic Flow Characteristic

By overlaying the sample points of various scenarios, Fig. 2 demonstrates the change of traffic flow characteristics in
TABLE I: Managed Lane Evaluation Plan

| Policy               | ID   | 1st Lane | 2nd Lane | 3rd Lane | 4th Lane | MPR     |
|----------------------|------|----------|----------|----------|----------|---------|
| No Managed Lane      | NDL  | HV + CAV | HV + CAV | HV + CAV | HV + CAV | 0% - 100%|
| Managed Lane 1       | CAV-1| HV + CAV | HV + CAV | HV + CAV | CAV      | 30%～100%|
| Managed Lane 2       | CAV-2| HV + CAV | HV + CAV | CAV      | CAV      | 40%～100%|

speed-flow diagram. Being a fundamental diagram, Speed-flow diagram is comprised of a stable region and a congested region, separated by the optimum (maximum) flow. Several distinctive patterns can be observed. First, the speed-flow curves shift leftward as the MPR of CA V increases, which is an indication of greater optimum flow with the same speed. Second, under the same MPR, the presence of CA V lane facilitates the shifting further. For example, note the comparison of NDL and CA V-1 at 70% and 90% MPR respectively. Third, congested flow is not shown with the presence of CA V lane at 70%, whereas the sample points from congested flow are shown for the “NDL-70%” case. Lastly, agreeing with previous studies, the traffic flow improvement is observed even at 30% MPR in the absence of a CA V lane (see “NDL-30%” curve).

B. Headway Distribution

The simulation collects raw data from the data collector, an equivalent of real-world detectors (e.g., loop detectors, video cameras, microwave sensors). By analyzing the high-resolution raw data (collected every 0.1 s), the headway distribution of the CA V lane could be obtained. Fig. 3 shows the comparison on the leftmost lane among three ML scenarios under different MPRs. At 40% to 70% MPR range, it is shown that implementing ML for CA Vs clearly shifts the distribution to the left-hand side, which represents smaller headway. The distributions of headway collected for either CA V-1 or CA V-2 become “narrower” (with less standard deviation), as the MPR increases from 40% to 70%. The highest bins in the histogram for both CA V-1 and CA V-2 are between 1 s and 1.2 s when MPR is below 50%. On the other hand, the highest bin of the histogram shifts to between 0.8 s and 1 s once MPR reaches higher than 50%. In comparison, the NDL case does not exhibit such concentration pattern as the MPR increases, which indicates a homogeneous traffic flow comprised of only CA Vs could maximize the short-headway benefits of CA V.

C. Wireless Communication

Fig. 4(a) shows the maximum and the average density for instances of V2V communication among three ML polices. While the transmission density increases as the MPR increases, the maximum density in NDL is higher than CA V-1 and CA V-2, because the CA V platoons were broken down by certain HVs which are susceptible to shockwave. As such, the traffic flow is compressed, producing a higher traffic density and thus higher transmission density. The fact that the average density among three ML policies is within 20 veh/km range further supports the claim of the aforementioned localized shockwave impact. The probability of successful reception of BSM from a leading vehicle to subject vehicle is shown in Fig.4(b). The probability curves of CA V-1 and CA V-2 are in close proximity of each other and they are showing the same trend. The maximum difference between these two curves is 0.04 at 90% MPR. The probability of successful communication of NDL at high MPR range (60% to 90%) is consistently lower than those of CA V-1 and CA V-2. This is caused by the compression of traffic flow by localized shockwave. The overall trend of the probability decreases as the MPR increases.

![Fig. 4: V2V communication performance measure](image-url)
D. Network Throughput

While the network-wide performance measure is not of the focus of this study, the network throughput is provided here as a reference. The throughput represents the total number of vehicles that have arrived at their destinations and it is shown in Fig. 5. As mentioned before, the network was configured with higher demand than the usual. With 10,000-vehicle per hour (vph) demand, the network was only able to meet 6500 vph in the absence of CAVs. As the MPR of CAVs increase, so does the network throughput. Then the throughput remains the same at 40% and 50% MPR for approximately 8000 vph. However, at 60%, the throughput increase resumes, reaching up to 9168 vph. The throughput maintains at the same level at 9600 vph when MPR is above 70%. The throughput begins to outperform the NDL case at MPR 50% and keeps increasing to 9700 vph at 70% MPR, where the throughput starts leveling despite the increase in MPR. For the CAV-2 policy, the system throughput only reaches the same level of the two counterparts at 70% MPR.

V. Conclusion

A simulation study regarding the impact of CAV lanes is presented to demonstrate the change of traffic flow characteristics. Results show that the introduction of CAVs could increase the throughput of the overall system, even when no ML policy is in place. The simulation also demonstrates the effectiveness of CAV lanes by comparing headway distributions. The denser the CAV flow on the ML, the more consistent the distribution approaches to the pre-defined desired headway collectively. With the add-on DSRC communication model, the performance of V2V communication is collected at the simulation run-time. The success of the packet transmission influences subsequent behaviors of CAVs during the simulation. The probability of successful communication decreases as the MPR increases, because of the additional load imposed to the communication channel. The results quantify the effectiveness of CAV lane in enhancing the traffic flow characteristics.

The future research for the on-going study is highlighted as follows: i) to test the effectiveness of CAV lane with clustering strategy for CAVs where a free-agent CAV actively seeks opportunity to form vehicle platoons, ii) to investigate the potential impact to non-CAVs (HVs) due to induced lane change activity in the presence of CAV lane, which is typically local in the leftmost travel lane, iii) to increase the understand of the impact of CAV at individual trajectory level by analyzing high-resolution vehicle trajectory data collected in simulation, and iv) to implement more sophisticated CACC algorithm.
Fig. 3: Headway distributions

(a) 40% MPR

(b) 50% MPR

(c) 60% MPR

(d) 70% MPR

Fig. 5: Network throughput

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