Capacity Analysis and Cooperative Lane Changing for Connected and Automated Vehicles: Entropy-Based Assessment Method

Yunpeng Shi¹, Qing He²,³, and Zhitong Huang⁴

Abstract

Connected and automated vehicles (CAVs) are poised to transform how we manage and control the existing traffic. CAVs can provide accurate distance sensing and adaptive cruise control which make shorter headway possible, and will eventually increase the roadway throughput or capacity. The vehicle-to-vehicle (V2V) communication technology equipment on CAVs allows vehicles to exchange information and form platoons more efficiently. This paper uses the intelligent driver model (IDM) as the behavior model to simulate CAVs in mixed traffic conditions with both CAVs and human-driven vehicles (HDVs) under different CAV penetration rates. A cooperative CAV lane-changing model is introduced to build more CAV platoons. The model develops two lane-changing algorithms. Partial CAV lane change (PAL) is applied at low CAV percentages, whereas full CAV lane change (FAL) is used at high CAV percentages. In addition, block entropy is employed as a performance measure for lane-changing results. The simulation experiments show that capacity will increase as the CAV percentage grows, and the peak growth rates occur in medium CAV percentage between 40% and 70%. The cooperative CAV lane-changing algorithm is found to decrease HDV–CAV conflicts remarkably by 37% as well as to marginally increase capacity by 2.5% under all CAV percentages. The simulation performance suggests that the threshold of CAV penetration rate for switching PAL to FAL is approximately 55%. Furthermore, it is demonstrated that block entropy can measure CAV lane-changing performance efficiently and represent capacity changes to some extent.

Connected and automated vehicle (CAV) research has been the focal point of current transportation studies for a while. Accurate distance sensing allows shorter headways and shorter reaction time, which brings great potential for improving traffic efficiency, stability, and safety (1). Many studies have been done on the CAV capacity analysis and intersection management in the CAV-only environment (2–4). Some research, such as reservation-based and priority-based intersection management, intends to remove intersection signals to increase traffic throughput. However, before reaching that ideal state, the long transition period from mixed driving environments with both CAVs and human-driven vehicles (HDVs) to a CAV-only environment is also worth studying (5). These studies assume that infrastructure will remain the same in the transition period althoughtraveling rules and policies on lane configurations can be modified for better efficiency. Because some human drivers might overreact when driving close to CAVs, setting HDV-only and CAV-only lanes needs to be possible to ensure safety. In addition, when CAV penetration rate, that is, the percentage of CAVs in the traffic system, is higher than a certain amount, the capacity can be significantly increased. However, the past studies have paid less attention to the medium and lower range of CAV penetration rates, which could be prevalent especially at the beginning of the transition period.

Among the various CAV technologies, vehicle-to-vehicle (V2V) communication is critical to the reorganizing and platooning of CAVs. CAV platoons allow small

¹Department of Civil, Structural and Environmental Engineering, University at Buffalo, The State University of New York, Buffalo, NY
²Key Laboratory of High-Speed Railway Engineering in Ministry of Education, School of Civil Engineering, Southwest Jiaotong University, Chengdu, China
³Department of Industrial and Systems Engineering and Department of Civil, Structural and Environmental Engineering, University at Buffalo, The State University of New York, Buffalo, NY
⁴Leidos Inc., Saxton Transportation Operations Laboratory, McLean, VA

Corresponding Author:
Address correspondence to Qing He: qinghe@buffalo.edu
time gaps between vehicles while maintaining the same velocity level and safety standards, which are essential to increase capacity (6). CAVs are electronically controlled which can avoid human errors that cause accidents, so conceptually CAV platoons can be considered as accident free. In a multilane mixed traffic environment with CAVs and HDVs, without any coordination, the two types of vehicles are randomly distributed, so CAVs led or followed by HDVs can still get involved in accidents caused by unexpected human errors. In addition, some human drivers might have concerns about driving next to CAVs. To address these problems, setting CAV-only lanes might be the best solution, although it requires some conditions such as certain CAV penetration rates and accessibilities of the roadway. When these conditions are not met, organizing more CAVs into platoons will be the best option and the number of CAV platoons can be increased through cooperative lane change. The cooperative CAV lane change requires vehicles to communicate with each other and reorganizes them into groups for purposes of safety, fuel efficiency, and capacity maximization (7).

The goal of this study is to investigate when to set CAV-only lanes and how cooperative CAV lane change would enhance traffic performance under different CAV penetration rates. To pursue this goal, first, a CAV behavior model is built on the intelligent driver model (IDM) to distinguish CAVs from HDVs in the simulation tool, VISSIM, and then a simulation-based analysis is conducted to estimate the capacity under mixed traffic conditions, as well as develop a lane allocation plan under different CAV penetration rates. Second, to platooon the CAVs, a cooperative CAV lane-changing algorithm is developed and an entropy-based evaluation method is also introduced aiming to evaluate the performance of CAV lane change. Different simulations are conducted on performance-based and capacity-based analysis to measure the algorithm's performance, and the proposed entropy-based method is then validated to be an efficient tool for measuring the CAV lane change.

The paper is structured as follows. The next section conducts a comprehensive literature review. The third section describes the methodology and results for capacity analysis, and the fourth introduces the cooperative CAV lane-changing algorithm and entropy calculation. The fifth section demonstrates the numerical results, and the final section concludes with the major findings and presents directions for future research.

Literature Review

Car-Following Techniques and Capacity Analysis for CAVs

Equipped with sensors and communication devices, CAVs can detect the surrounding vehicles and infrastructures automatically and deploy an efficient self-driving plan. One of the basic models in simulating is adaptive cruise control (ACC), which allows vehicles to calculate acceleration and deceleration automatically to match the target speed. ACC can follow the leading vehicle with the same speed and headway. Cooperative ACC (CACC) is a further developed model that involves V2V communication, in which CACC vehicles can adjust velocity based on the gap and behavior of the preceding vehicle. The CACC vehicle can provide a smoother, safer, and more natural response (8, 9).

ACC and CACC are the foundation of many recent models. Kesting, Treiber and Helbing proposed a car-following model as an implementation of ACC (10). This model considered most parameters from the IDM proposed by Treiber (11), but modified it with a constant acceleration heuristic to reduce overreacting IDM deceleration. To deal with the IDM's overreaction in lane changing, Zhou developed a cooperative IDM (CIDM) which added V2V interaction (12). CIDM used a lane-changing impact rule and classified two classes of lane-change types: discrete lane change and mandatory lane change. Using CAVs' advantage to improve discharging performance, Le Vine built an “assured clear distance ahead” car-following model that limits a vehicle's speed and spacing from the vehicle ahead (13). This model allows consecutive vehicles in discharge to keep smaller headway for a longer period than the traditional method to increase queue discharge efficiency.

In the majority of the previous studies on capacity involving CAVs, the assumption was CAV-only. However, there will be a long transition towards high CAV penetration (5). Therefore, some studies have focused on the transition period, and created networks containing both HDVs and CAVs with different behaviors. Zhao used different headways and detection range (6), and Mahmassani used IDM for connected vehicles, real-time headway calculation for autonomous vehicles, and Kahneman and Tversky's prospect theory (14) for HDVs (5). Furthermore, Lioris took advantage of CAV platooning, converted the reduced headway to a factor which varied by vehicle types, and simulated under different signal plans (15). All the simulations showed that CAVs could increase capacity, especially at high CAV penetration rates (5, 6, 15). And Lioris also found that platooning and increasing signal switches per cycle could improve throughput.

To investigate the mixed-usage capacity under different lane configuration plans, Chen modeled a CAV–HDV mixed-usage condition focusing on the spacing between leading vehicle and immediate follower (1). The spacing was the shortest between two CAVs. Therefore, platooning CAVs would achieve high efficiency in a single lane roadway. For multilane roadways, Chen tested...
different combinations of autonomous-only, regular-only, and mixed-usage. The autonomous-only lane was the most efficient but only worked when CAV penetration rate was greater than a certain amount.

The literature above indicates that CAVs could increase capacity and throughput. However, none of these covered all ranges of CAV penetration rates for multilane configurations.

Cooperative Lane-Changing Studies

One of the advantages of CAVs is cooperative platooning. Previous research proposed various ways of lane changing which made CAV platooning achievable in the simulation. Some researchers aimed to improve lane-changing efficiency by modifying specific behaviors. The collaborative driving system (CDS) (16) was an autonomous platooning system based on CACC. CDS optimized the splits and merges of vehicles with the centralized platoon and decentralized platoon. Centralized platoon coordination only involved the lane change and immediately following vehicles. In a decentralized platoon, however, all surrounding vehicles could respond to the lane change. CDS aimed to reduce the time headway change when splitting and merging, as well as decrease the shockwave effect (16). In the lane-changing process, lane-changing vehicles would create voids and reduce flow after leaving the original lane. Laval presented a quantitative model as a solution, in which scenarios such as lane drops and moving obstacles were considered (17). For creating the best location for CAVs to make mandatory lane changes, Cao proposed an optimization model used in urban arterials (18). First, the time required to reach safe headway was determined by considering shockwave and horizontal queueing theory. Then the optimal travel time to make the lane change was derived and used. The simulation indicated that the proposed model could save travel time especially in light or medium traffic.

Some studies improved lane-changing performance by generating new systems and rules. Simulation of Intelligent TRAnsport System (SITRAS) was introduced by Hidas as a CAV lane-changing method (19). This method determined destinations for CAVs and applied corresponding lane-changing procedures. The lane-changing requests were categorized into three urgent levels. Then the algorithm would assign “forced” or “cooperative” lane change depending on specific situations. This was efficient especially for lane changes under congested and incident traffic conditions. To further demonstrate the lane-changing algorithm, Hidas proposed a lane-changing and merging concept using the lane-changing vehicle’s gap and relative speeds with desired lane adjacent vehicles (20). In a situation in which the gap was not enough for a lane change, the required deceleration rate for the target lane following vehicle was suggested. In the cooperative-driving environment, the gap could be created by accelerating the leading vehicle and decelerating the following vehicle.

Recently, a swarm intelligence-based algorithm for CAVs was introduced by Wang (21). In this algorithm, a CAV-only environment was desired and all vehicles were communication-ready. CAVs could form platoons and drive at different speeds depending on users’ preference. When the subject vehicle was faster than the leading vehicles, the subject vehicle could pass by either changing lane or requesting the leading vehicles to change lane, whichever is more efficient. The simulation results showed that the swarm intelligence-based algorithm could increase throughput while keeping stability.

The literature had developed several lane-changing and platooning methods. However, no studies had measured the performance of CAV lane change in a mixed traffic scenario under different CAV penetration rates. Therefore, for better presenting the influence of CAV lane change, this study will introduce an entropy-based evaluating method for the performance of cooperative lane change.

Capacity Analysis

Intelligent Driver Model (IDM)

The goal of the capacity analysis is to determine how CAVs will affect the road capacity under different penetration rates. IDM (11) is used to simulate CAV behavior. IDM is frequently used as the car-following model for CAV, which reduces unnecessary hard braking and over acceleration from the HDV behavior model (Wiedemann) to provide a smoother and more efficient movement. The acceleration function in IDM is shown as

$$a_{IDM}(S, v, \Delta v) = a \left[ 1 - \left( \frac{v}{v_0} \right)^\delta - \left( \frac{S'(v, \Delta v)}{S} \right)^2 \right]$$  \hspace{1cm} (1)

$$S'(v, \Delta v) = S_0 + vT + \frac{v\Delta v}{2\sqrt{ab}}$$  \hspace{1cm} (2)

where

- $S$ is the bumper-to-bumper distance to the leading vehicle,
- $v$ is the actual speed, and
- $\Delta v$ is the velocity difference from the leading vehicle.

Parameters in the model, such as desired speed ($v_0$), can be set to different values depending on vehicle types. The specific values used in this research are:

- Maximum acceleration $a = 2 \text{ m/s}^2$;
- Maximum deceleration $b = 3 \text{ m/s}^2$;
- Desired speed \( v_0 = 15 \text{ m/s} \);
- Free acceleration component \( \delta = 4 \);
- Jam distance \( S_0 = 1.5 \text{ m} \); and
- Safe-time headway \( T = 0.6 \text{ s} \).

Parameter values are set according to previous studies \((10, 12, 22)\). Desired speed matches the simulation speed limit of 50 km/h. The maximum acceleration used for CAVs, which is 2 m/s\(^2\), is smaller than 3.5 m/s\(^2\), which is the typical value for HDVs, as it allows the CAV to start smoothly. Preliminary sensitivity tests on this parameter suggest that decreasing the maximum acceleration will affect the capacity for less than 1%, which can be neglected. CAVs can detect headway and react immediately. Therefore, safety factors of maximum deceleration, jam distance, and headway can be slightly decreased from those of HDVs.

A tutorial on using the external driver model and inputting IDM into VISSIM has been uploaded to GitHub, with the following link: https://github.com/YunpengShi/VISSIM-External-Driver-Model-DLL-Tutorial.

Simulation Settings

An urban roadway network is created in PTV VISSIM for simulation. The network contains a 1,060 m two-lane throughway with speed limit of 50 km/h. At 1,000 m downstream from the start, a traffic signal is placed to control vehicle movements. Volume input is unreachably high for the maximum vehicle output. HDVs use the built-in driving behavior model preset by VISSIM. The car-following model is Wiedemann 99 and headway is 1.5 s.

The IDM is coded into the external driver model DLL file by C++. The DLL file can extract vehicle and road information from VISSIM, run the IDM model, and return parameters back to VISSIM in each simulation step. In this case, the parameter returned is the desired acceleration calculated by IDM. Because IDM is a car-following model, it cannot stop a vehicle properly in front of the red signal. Therefore, when the first vehicle in each lane arriving at the signal is a CAV, to ensure a proper stop, that CAV will be controlled by VISSIM and act as an HDV. In this simulation, two CAVs at most will be affected as there only are two lanes.

When the simulation begins, the intersection signal is red for 2 min, allowing vehicles to stop in front of the signal in a queue. After that, the signal turns green and discharges vehicles continuously for 1 h. Hourly discharge volume is recorded as the saturation flow rate. In this study, it is denoted as the capacity for the rest of this paper. Different CAV penetration rates, or the percentages of CAVs, are simulated from 0% to 100%, with an increment of 10%. When CAV and HDV have similar volume, the changes might be critical. Therefore, CAV penetration rates of 45% and 55% are also simulated. Three random seeds are used in each penetration rate to increase accuracy.

For capacity optimization, all possible lane configurations are tested. Two mixed traffic lanes are simulated for all CAV penetration rates. For low CAV penetration rates, from 10% to 45%, because HDVs are the majority, one HDV-only lane and one CAV–HDV mixed traffic lane are set, whereas one CAV-only lane and one CAV–HDV mixed traffic lane are simulated for CAV penetration rates from 55% to 90%.

Simulation Results and Discussions

Figure 1a displays the single lane capacity under different CAV penetration rates. The capacity of an HDV lane is 1,650 vph (vehicles per hour), whereas a 100% CAV lane reaches 2,520 vph. In this sense, a CAV lane has a capacity 53% higher than an HDV lane. When the CAV penetration rate increases from 0% to 70%, the increment rate is nearly linear. However, after that, the increment rate decreases as the penetration rate increases.

The increment of roadway capacity under each CAV penetration rate is shown in Figure 1b. Starting off from 0% to 10%, capacity increases by 75 vph, and the increment reaches a maximum when the penetration rate increases from 60% to 70%, adding 150 vehicles into capacity. Above 80% CAV penetration rate, the capacity becomes relatively stable, illustrating that HDVs will not have significant influences slowing down the traffic when the majority are CAVs. The results are compared with some existing models in \((23)\). Because of the differences in parameter settings, this study’s simulation results have a slightly lower capacity, but the variation of capacity with CAV penetration rates shows similar trends and growth percentages.

The analysis results of lane configuration are supported by the single lane capacity in Figure 1a and increment on Figure 1b. Two-lane roadway capacities under different lane configurations versus CAV penetration rates are depicted in Figure 1c. Two mixed traffic lanes are simulated through all penetration rates. One HDV-only and one mixed traffic lane are only for low penetration rates, whereas one CAV-only and one mixed traffic lane only show in high penetration rates. The scenario with one HDV-only and one mixed traffic lane has slightly higher capacity under 45% penetration rates. The reason is that in a two-lane low CAV penetration rate situation, to achieve higher capacity, one lane needs to reach a higher CAV penetration rate up to 70% as soon as possible. For example, in 20% overall penetration rate, the capacity increment is higher for one lane with 40% CAV penetration than for two lanes with 20%.
It is worth noting that in a 50-50 situation, two mixed traffic lanes perform better than one HDV-only and one CAV-only lane. Furthermore, two mixed traffic lanes also outperform one CAV-only and one mixed traffic lane when CAV penetration rate is greater than 50%. Because the capacity increment starts to drop rapidly after 70% CAV penetration rate, keeping two lanes with relatively high CAV penetration rates will be better than one lane with extremely high CAV penetration rate (CAV-only) and the other with low CAV penetration rate. In summary, under the underlying assumption that the overall CAV penetration rate is fixed, the simulation results suggest that under low CAV penetration rates, the scenario with one HDV-only and one mixed traffic lane will have the slightly higher capacity, whereas on high penetration rates, two mixed traffic lanes will maximize the roadway capacity.

**Cooperative CAV Lane Change and Block Entropy-Based Assessment**

**Cooperative CAV Lane-Changing Algorithm**

Results from the above section show that two mixed traffic lanes have overall the best roadway capacity performance across the range of CAV penetration rates, especially for high penetration rates. Therefore, for further optimization, platooning CAVs is a good approach to organize traffic under the mixed traffic condition. The cooperative CAV lane-changing algorithm used in this study is inspired by (20), considering the physical characteristics of the subject vehicle, as well as that of the leading and following vehicles on the target lane. The goal is to guide an isolated CAV into CAV platoons. Therefore, a CAV could be recognized as the subject vehicle for lane change only when the CAV’s leading and following vehicles are both HDVs. Figure 2 shows three different scenarios in which a lane change is recommended by the algorithm. Scenario (a) is full CAV lane change (FAL), in which both the leading and following vehicles on the target lane are CAVs. Scenarios (b) and (c) are partial CAV lane change (PAL), in which either the leading or following vehicle on the target lane is CAV. FAL leads to a platoon of a minimum of three CAVs, and PAL leads to two. Thus, FAL is treated as a special case of PAL in this study. The intent is to apply FAL when the CAV penetration rate is relatively high. However, with low CAV penetration rates, some isolated CAVs will not pass by any CAV platoons during the whole simulation. To maximize the effect of lane change, PAL is developed to platoon isolated CAVs from different lanes without affecting the traffic stream. The flowchart and algorithm details are presented in Figures 3 and 4, respectively.

This algorithm is built in VISSIM using the external driver model DLL along with IDM. It detects a single CAV isolated by HDVs and guides this CAV into a platoon through cooperative lane change when possible. In FAL, there are three CAVs involved in the lane-changing process—the CAV that needs lane change (the subject vehicle) and two adjacent CAVs in the target lane—whereas PAL only can control the subject vehicle and one of the adjacent CAVs in the target lane. When the subject vehicle travels much faster or slower than the target lane vehicles, forcing a merge may cause accidents and will significantly slow down the upstream traffic flows and create a shockwave. Therefore, a maximum speed difference, ΔVmax, is created in situations when
speed difference exceeds ΔVmax, so that the subject vehicle will neglect nearby CAVs and look for a lane-changing opportunity in the downstream traffic. In the lane-changing process, sometimes gaps between the subject and target lane vehicles are insufficient, so FAL can speed up the leading vehicle or slow down the subject and following vehicles according to different types of insufficient gaps. The acceleration modifying factors \(a_{1-3}\) are used as shown in Figure 4. The value of ΔVmax and \(a_{1-3}\) will be revealed later, in the simulation results. The minimum gaps required between vehicles for lane change are shown as

\[
G_{l_{\text{min}}} = G_{0l_{\text{min}}} - v_s \Delta t + v_f \Delta t \tag{3}
\]

\[
G_{f_{\text{min}}} = G_{0f_{\text{min}}} - v_s \Delta t + v_f \Delta t \tag{4}
\]

where

\(G_{l_{\text{min}}}\) and \(G_{f_{\text{min}}}\) are the modified minimum gaps from the subject vehicle to the target lane leading and following vehicles, respectively;

\(G_{0l_{\text{min}}}\) and \(G_{0f_{\text{min}}}\) are the constant minimum leading and following gaps, which are 7 m and 9 m, respectively (the following gap is larger because vehicles would need a greater reaction time to obstacles in front);

\(V_s, v_s, v_f\) are the speeds of subject, target lane leading and following vehicles, respectively; and

\(\Delta t\) is the time difference between each simulation steps.

In this case, it is set as 0.2 s which matches VISSIM’s time step per simulation second.

In scenario (b), a part of PAL, when gaps between subject vehicle and V4 are not enough, V4 will not decelerate to create enough space. However, in scenario (c), V3 is able to accelerate with the same rate as FAL because this will not slow down the traffic. The negative side of using PAL is that it decreases the chance of isolated CAVs being able to join larger CAV platoons. Therefore, using PAL for high CAV penetration rates may reduce the efficiency of CAV lane change. A decision is added to the algorithm that when CAV penetration rate is lower than \(P^*\), PAL is used; Otherwise, FAL will apply. \(P^*\) is the threshold based on lane-changing performance results which will be revealed after the simulations, in the results section. The determination logic is

**Cooperative Lane – changing Algorithm Determination :**

\[
\begin{cases}
\text{FAL if } C_{\text{FAL}}(P^*) > C_{\text{PAL}}(P^*), \text{low } P^* \\
\text{PAL if } C_{\text{PAL}}(P^*) > C_{\text{FAL}}(P^*), \text{high } P^*
\end{cases}
\]

where \(C\) is the lane-changing performance measure such as capacity or block entropy.

The cooperative CAV lane-changing algorithm checks all CAVs once in each time step, and then send back to VISSIM with modified accelerations and lane-changing orders for CAVs that need lane change. With regard to other CAVs, only IDM acceleration will be sent back.

**Block Entropy Calculation**

Entropy, or information entropy, is the average amount of information produced by a stochastic source of data...
(24). It has been applied in lots of areas including transportation in, for example, freight logistics (25) and transportation optimization problems (26). In this study, entropy is used to measure the lane-changing performance of a spatial queue that consists of both CAVs and HDVs. In standard entropy calculation, a CAV-only or an HDV-only lane will result in an entropy of 0 because there is only one type of vehicle and there is no randomness involved. A lane with 50% HDV and 50% CAV will have an entropy of 1, which is the maximum. Entropy \( H \) can be calculated as

\[
H(X) = - \sum_{i=1}^{n} P_i \log_2 P_i
\]

where \( n \) is the number of variables, which in this case represents the types of vehicles, and \( P \) is the probability of each variable being chosen, which represents the percentages of each type of vehicles.

\[\text{Figure 3. The flowchart of cooperative CAV lane-changing algorithm.}\]
However, standard entropy only considers the total number of vehicles in each type as a whole, ignoring the vehicle orders. To measure the sequence and the effect of cooperative lane change, the concept of block entropy (27) is introduced. Block entropy calculation shares the same equation as standard entropy but adds a concept of an evaluation block with various block lengths. In this study, a block is a group of consecutive vehicles that is recorded by vehicle types and will be evaluated as a whole. Therefore, a block can be seen as a stream of vehicles, and block length is the number of vehicles in the block. The number of possible vehicle type combinations in a block is \( n \) in Equation 6, and the probability of each combination’s occurrence is \( P \) which is calculated as

\[
P_i = \frac{C_i}{C_1 + C_2 + \ldots + C_n} \tag{7}
\]

where \( C_i \) represents the \( i \)th combination of a platoon, and \( n \) is the total number of possible combinations. For example, as shown in Figure 5, when block length is 1, which is the case of standard entropy, the two possible combinations are CAV and HDV. Thus, \( n = 2 \). For a block length of 2, there are four possible combinations (\( n = 4 \)): CAV–CAV, CAV–HDV, HDV–CAV, and HDV–HDV. Increasing block length by 1 will double \( n \) because there will be two vehicle types, HDV and CAV.

Before the calculation begins, all vehicles in the same lane are recorded in order as a vector of numbers that indicates the corresponding vehicle types. Then the block moves down the vector one vehicle by one vehicle after evaluating, and the corresponding combination is \( C_i = C_i + 1 \). After reaching the end of the vector, the probability \( P_i \) is calculated for each combination \( C_i \) using Equation 7 and inputs to Equation 6 for block entropy calculation.

For the same vector of vehicles, each block length will result in a block entropy value and a longer block length will have a higher block entropy. Because increasing block length by 1 will double the number of combinations and the entropy calculation formula uses log base

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**Figure 4.** Cooperative CAV lane-changing algorithm.
2, increasing block length by 1 will increase the maximum entropy by 1 as well. For example, the maximum block entropy for block length 5 is 5 when there are 50% HDVs and 50% CAVs that are randomly distributed. In this case, all the possible vehicle type combinations have the same probability of occurrence. For any CAV penetration rates other than 50%, the maximum entropy will not be reached because the probabilities for CAVs and HDVs appearing are not even. Therefore, the comparison is only meaningful between entropies with the same CAV penetration rates and the same block length. The purpose of using block entropy is to measure the performance of the cooperative CAV lane-changing algorithm. Therefore, comparisons will be done between block entropy with or without using the algorithm. If more CAVs are in platoons, some vehicle type combinations with consecutive CAVs or HDVs will occur more frequently. As a result, the block entropy will decrease as a sign of the algorithm’s performance. In this study, block entropy is calculated for each simulation up to block length 6. Because the algorithm aims to platoon single and isolated CAVs, evaluation block of six vehicles should be sufficient to measure the performance. This block entropy evaluation method contains some bias in that the first and last vehicle in the vector are evaluated only once, whereas in the middle of the vector, the vehicles can be evaluated as many times as the value of block length. However, because each simulation produces a string with more than 2,000 vehicles and a maximum of 10 vehicles will cause the bias with block length 6, the error will have very little influence on the result and can be neglected.

**Numerical Examples**

**Model Simulation**

The cooperative CAV lane-changing algorithm is implemented in VISSIM and tested on a hypothetical roadway network. This network is modified from the one used in capacity analysis by extending the road to 2,000 m to create more opportunities for lane change. Following the previous model in the capacity analysis, the HDV’s behavior remains unchanged (this is preset by VISSIM), whereas the CAV still uses IDM with the same specifications as given previously in the description of the IDM. In addition, the cooperative CAV lane-changing algorithm is built in IDM in the same file with FAL and PAL separately. The network has two lanes, and CAVs can change from either lane to the other to form a platoon. The simulation contains two parts. The goal of the first part is to measure the performance of the algorithm. The input volume is set to be 2,000 vphpl (vehicles per hour per lane) to create a relatively dense traffic scenario. CAV penetration rates from 10% to 90% are investigated in the test, with an interval of 10%. And each penetration rate is simulated with 10 different random seeds to mitigate randomness and to be more accurate. The second part is to test the influence of the algorithm on roadway capacity. Thus, the input volume is unreachable high. All penetration rates are simulated with five different random seeds. For each set of penetration rate and random seed, two simulation runs are done using different external driver model files; one uses the combination of the cooperative CAV lane-changing algorithm and IDM, whereas the other only uses IDM to identify the influence of the algorithm.

Raw data are obtained from VISSIM for further analysis. To calculate block entropy, the sequence of all vehicles by vehicle type is required. Then the block entropy calculation method is coded using a Microsoft Visual Basic macro. With the input of vehicle sequences, the macro will calculate block entropy from block length 1 to 6, as well as the capacity. FAL and PAL will be simulated separately and compared.

**Simulation Results**

After very many simulation experiments, the maximum speed difference $\Delta V_{\text{max}}$ mentioned previously is set as
7 km/h. This value matches the study conducted by Hidas (19). The acceleration modifying factors \( a_1, a_2, \) and \( a_3 \) are also tested through simulations to ensure as little influence to the downstream traffic as possible; the values are 0.75 m/s\(^2\), 1 m/s\(^2\), and 1.5 m/s\(^2\), respectively. The factors are also supported by Hidas.

Table 1 gives the result for part one of the simulation, with the input volume of 2,000 vphpl; it displays the block entropy for simulations from CAV penetration rates of 10% to 90%. The simulation runs using FAL are colored red, whereas PAL runs are green. Blue cells with “no CAV lane change” represent the simulation runs using only IDM, for which vehicle sequence remains the same after releasing unless HDVs receive a lane-changing order from VISSIM. As previously explained, block entropy indicates the randomness of vehicle sequences in relation to vehicle types or the biased level of possible vehicle type combinations. Therefore, lower entropy shows that vehicle distribution is more ordered, and vice versa. This comparison is representative only when the comparison is conducted within the same block length because, for the same sample, block entropy always increases with the increase of block length.

The “no CAV lane change” columns in the table show entropies for the scenario without lane change, in which vehicles are discharged by VISSIM randomly based on CAV penetration rate, representing a well-mixed traffic environment. For validation, entropies for the most random situation, CAV penetration rate of 50%, can be a good sample; as explained in the previous sections, the maximum entropy for each block length equals the value of that block length. In Table 1, entropies for 50% penetration with “no CAV lane change” are very close to the corresponding value of block length (5.986 under block 6), which means the simulation without using the cooperative CAV lane-changing algorithm has the maximum randomness. Table 1 also illustrates that within any block length, starting from 10%, increasing CAV penetration rate will also increase entropy until 50% which results in the maximum entropy among all CAV penetration rates. After that, entropy starts to decrease with the increase of CAV penetration rates. This makes sense because increasing CAV penetration rate means changing the initial randomness of the system. Before 50% penetration, it decreases the dominance of HDV which brings an increase of randomness, so entropy will be increased. Conversely, when CAV takes up at least half of the volume, increasing CAV penetration rate will strengthen the CAV dominance, thus reducing randomness and decreasing entropy. Furthermore, entropies resulting from the same CAV and HDV penetration rates are similar—for example, 30% CAV penetration rate and 30% HDV penetration rate (70% CAV) share similar values for entropies.

Table 1. Block Entropy for Simulations With and Without Cooperative CAV Lane-Changing Algorithm

<table>
<thead>
<tr>
<th>Block length</th>
<th>No CAV lane change</th>
<th>FAL</th>
<th>PAL</th>
</tr>
</thead>
<tbody>
<tr>
<td>10%</td>
<td>0.462</td>
<td>0.470</td>
<td>0.461</td>
</tr>
<tr>
<td>20%</td>
<td>0.720</td>
<td>0.723</td>
<td>0.720</td>
</tr>
<tr>
<td>30%</td>
<td>0.921</td>
<td>0.922</td>
<td>0.921</td>
</tr>
<tr>
<td>40%</td>
<td>0.970</td>
<td>0.972</td>
<td>0.970</td>
</tr>
<tr>
<td>50%</td>
<td>1.000</td>
<td>1.000</td>
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<tr>
<td>60%</td>
<td>0.973</td>
<td>0.973</td>
<td>0.973</td>
</tr>
<tr>
<td>70%</td>
<td>0.887</td>
<td>0.887</td>
<td>0.887</td>
</tr>
<tr>
<td>80%</td>
<td>0.723</td>
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<td>0.723</td>
</tr>
<tr>
<td>90%</td>
<td>0.464</td>
<td>0.460</td>
<td>0.464</td>
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</tbody>
</table>

Note: CAV = connected and automated vehicles; PAL = partial CAV lane change; FAL = full CAV lane change.
The performance of the cooperative CAV lane-changing algorithm can be well indicated by the difference between “FAL,” “PAL,” and “no CAV lane change” entropies. Listing from Table 1, entropies with the algorithm are always lower than entropies with no CAV lane change which means that vehicle sequences are organized to be more ordered by the lane-changing algorithm. The exception is block length 1, for which “FAL” and “PAL” entropies are slightly higher than “no CAV lane change” under some CAV penetration rates. As explained previously, entropy with block length 1 reflects the vehicle type composition (how many HDVs and CAVs are distributed during the simulation run), which depends on VISSIM’s vehicle output. Therefore, entropies of block length 1 do not include any information about sequences. For entropies with block length larger than 1, entropy differences between “FAL,” “PAL,” and “no CAV lane change” simulations increase with the increase of block length. For better analysis, entropy difference charts are made and shown in Figure 6, a and b for “FAL” and “PAL,” respectively.

Figure 6, a and b illustrates the entropy differences between simulations without and with the cooperative CAV lane-changing algorithm. Different lines represent different CAV penetration rates, and the entropy difference is entropy of “no CAV lane change” minus FAL’s or PAL’s. The entropy differences can be seen as a measurement of traffic flow improvement, a larger entropy difference meaning that the vehicle sequence becomes more ordered with respect to vehicle types, which also indicates that more isolated CAVs form platoons using the lane-changing algorithm. Comparing FAL with PAL, PAL has larger differences on more lines than FAL, which means that PAL has better performance on more CAV penetration rates. Because the entropy difference increases linearly with the block length, larger block length can magnify the difference without affecting the accuracy. Figure 6c shows the entropy difference of all CAV penetration rates of block length 6, which clearly shows the trend of entropy reduction at different penetration rates. A CAV penetration rate of 60% has the highest difference for both FAL and PAL, followed by 50%, 70%, and 40%, which makes sense because when the numbers of two types of vehicles are comparable, there are more opportunities for lane change. However, as CAV penetration rate grows even higher, the influence of the lane-changing algorithm will decrease because there will be fewer isolated CAVs that require lane change. At the other end, low CAV penetration rates result in the lowest entropy differences. In these scenarios, because most of the vehicles are HDVs, there will be plenty of isolated CAVs waiting for lane change, but the problem is to find another CAV in the target lane. This is the reason for using PAL, as shown, in low CAV penetration rates. As one can see, PAL has much larger differences than FAL until a CAV penetration rate of 50%, then they get closer. And FAL exceeds PAL when CAV penetration rate is slightly over 70%.

To validate the performance of block entropy, a less conceptual term, HDV–CAV conflict, is introduced. In traffic safety studies, there are several types of conflicts that could cause an accident. Rear-end conflict is one of the most frequently occurring types which usually occur as a rear-end crash (28). In this study, because CAVs are able to detect adjacent vehicles and obstacles, and react to any situation immediately, it is reasonable to assume...
that CAVs are accident free. Therefore, the only condition for CAVs involving accidents is when they are next to HDVs because of the unpredictable behavior of the human driver. This condition is measured by HDV–CAV conflicts, when a CAV follows or is followed by an HDV, as shown in Figure 7. In the study simulation, the counting detector is placed at the end of the roadway for maximum performance of the lane-changing algorithm. The cooperative CAV lane-changing algorithm can reduce HDV–CAV conflicts to enhance safety. Figure 8a shows the HDV–CAV conflicts for the simulation. In all penetration rates, the algorithm helps to reduce HDV–CAV conflicts, and the maximum reductions occur in the middle where two types of vehicles have similar penetration rates. Toward the two sides, the reduction becomes smaller because of the fewer opportunities for CAV lane change. For better illustration, the percentage of reduction is shown in Figure 8b. FAL has the maximum reduction percentage on 60% CAV penetration rate at which point the HDV–CAV conflicts are reduced by 37%, whereas PAL has the maximum reduction percentage on 50% CAV penetration rate with a similar value. The trends of HDV–CAV conflict reduction are similar to that of the block entropy reduction, but FAL performance exceeds PAL’s when CAV penetration rate is 55%. This shows that if there are more CAVs than HDVs, most isolated CAVs are able to pass by a CAV platoon and join. Moreover, because FAL is safer in that no HDVs are involved in the lane-changing process, FAL should be used when CAV penetration rate is above 55%.

The second part of this simulation focuses on the influence of the cooperative CAV lane-changing algorithm on capacity. The combined results are shown in Figure 9a. At a low CAV penetration rate, there is little influence on the capacity for using the algorithm. Then the capacity increases smoothly at medium penetration rates. And towards a high penetration rate, the increase maintains a relatively constant level. The performances of FAL and PAL are very close.

Figure 9b shows the percentages of capacity increase for using the cooperative CAV lane-changing algorithm. The trends are mostly similar to the block entropy reduction trend except at extremely high CAV penetration rate, for which the capacity increases more instead of less. The maximum increase of 2.5% for FAL occurs when there are 60% CAVs. And PAL has the peak at 50% CAVs, with 2.5% capacity increase. As for the HDV–CAV conflicts, FAL performs better than PAL after 55% CAV penetration rate.

Based on the simulation results, the cooperative CAV lane-changing algorithm not only enhances safety for the network without interfering with the throughput but also has the potential to further increase roadway capacity. The algorithm brings the most benefit when the numbers of HDVs and CAVs are close. And the threshold $P^*$ can finally be determined as 55%. Therefore, the cooperative CAV lane-changing algorithm should apply PAL when the CAV penetration rate is below 55% and FAL above that rate. In addition, the concept of block entropy is able to measure the sequence of vehicles and represent the changes in functionalities such as safety and capacity efficiently to some extent.

**Conclusion and Future Research**

This study aims to study how lane configuration and cooperative CAV lane change affect the roadway performance under different CAV penetration rates, as well as...
prove the functionality of entropy as a performance measure. At first, CAV simulated by the IDM model can increase the capacity by 53% from HDVs. In a two-lane thoroughway scenario, to maximize capacity within a low CAV penetration rate range, one lane should reach 70% penetration as fast as possible, so one HDV and one mixed traffic lane perform the best. Under the underlying assumption that the overall CAV penetration rate is fixed, for high CAV penetration, keeping both lanes with relatively high penetration is better than one lane with 100% penetration and the other with relatively low penetration. Therefore, two mixed traffic lanes are the best lane configuration when more than half of the vehicles are CAV. In sum, using two mixed traffic lanes has the best overall performance, and the cooperative CAV lane-changing algorithm is created for further optimizing capacity and safety.

The cooperative CAV lane-changing algorithm performs well in platooning the isolated CAVs. PAL should be used under 55% CAVs, and FAL works better above that percentage. The result shows that HDV–CAV conflicts are reduced at all CAV penetration rates, and the most significant range is from 40% to 70% CAV penetration rate, for which, at maximum, the number of conflicts is decreased by 37%. Moreover, the algorithm also has some marginal increase in capacity, from 0.7% to 2.5% depending on CAV penetration rates. After comparing the block entropy results with the safety and capacity features, block entropy can represent the safety and lane-changing performance, but it also can represent the capacity change to a certain level.

In future, the study can be expanded from two lanes to multiples lanes with left or right turns, scenarios in which the situation is more complicated. The consideration then will not be limited to the lane-changing process, but also the exit place, lane-changing timing, and lane-changing opportunity in nonadjacent lanes. A more efficient heuristic/metaheuristic search method shall be developed for optimization. In this study, the threshold \( P^* \) for switching between FAL and PAL is roughly estimated using the simulation results. However, one can be formulated as an optimization problem, and an entropy minimization can be used to increase the accuracy for \( P^* \) in the future. Furthermore, the CAV behavior model can be modified so that the first CAV reaching a signal can stop properly before the red light without switching to an HDV behavior model. Moreover, a CAV’s headways can be made different when following different types of vehicles to enhance the platooning effect. The lane-changing behavior also has the potential to be smoother and have a smaller influence on the traffic stream.

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**Author Contributions**

The authors confirm contribution to the paper as follows: study conception and design: YS, QH, ZH; data collection: YS; analysis and interpretation of results: YS, QH, ZH; draft manuscript preparation: YS. All authors reviewed the results and approved the final version of the manuscript.

**References**

Traffic States in Empirical Observations and Microscopic
Transportation Research Record: Journal of the Transportation Research Board, 2013. 2381: 81–90.
5. Mahmassani, H. S. 50th Anniversary Invited Article—

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