Article

Impact of Penetrations of Connected and Automated Vehicles on Lane Utilization Ratio

Xiaoyuan Wang ^{1,2,*} , Shijie Liu ^{1,3}, Huili Shi ¹, Hui Xiang ¹, Yang Zhang ¹, Guowen He ¹ and Hanqing Wang ¹

¹ College of Electromechanical Engineering, Qingdao University of Science & Technology, Qingdao 266000, China; 4019030012@mails.qust.edu.cn (S.L.); shihuili@qust.edu.cn (H.S.); 2019030024@mails.qust.edu.cn (H.X.); 4019030049@mails.qust.edu.cn (Y.Z.); 4019030007@mails.qust.edu.cn (G.H.); 2019030020@mails.qust.edu.cn (H.W.)

² Collaborative Innovation Center for Intelligent Green Manufacturing Technology and Equipment of Shandong Province, Qingdao 266000, China

³ School of Transportation and Vehicle Engineering, Shandong University of Technology, Zibo 255000, China

* Correspondence: wangxiaoyuan@qust.edu.cn

Abstract: Lane Utilization Ratio (LUR), affected by lane selection behavior directly, represents the traffic distribution on different lanes of road section for a single direction. The research on LUR, especially under Penetration Conditions of Connected and Automated Vehicles (PCCAV), is not comprehensive enough. Considering the difficulty in the conduction of real vehicle experiment and data collection under PPCAV, the lane selection model based on phase-field coupling and set pair logic, which considers the full-information of lanes, was used to carry out microscopic traffic simulation. From the analysis of microsimulation results, the basic relationships between Penetration of Connected and Automated Vehicles (PCAV), traffic volume, and Lane-Changing Times, also that between PCAV, traffic volume, and LUR in the basic section of the urban expressway were studied. Moreover, the influence of driving propensity on the effect of PCAVs was also studied. The research results could enrich the traffic flow theory and provide the theoretical basis for traffic management and control.

Keywords: Connected and Automated Vehicles; Lane Utilization Ratio; microsimulation; traffic flow; lane-changing behavior

Citation: Wang, X.; Liu, S.; Shi, H.; Xiang, H.; Zhang, Y.; He, G.; Wang, H. Impact of Penetrations of Connected and Automated Vehicles on Lane Utilization Ratio. *Sustainability* **2022**, *14*, 474. <https://doi.org/10.3390/su14010474>

Academic Editors: Xiaobei Jiang, Haixiang Lin, Fei Yan, Qian Cheng and Elżbieta Macioszek

Received: 26 October 2021

Accepted: 30 December 2021

Published: 2 January 2022

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1. Introduction

The road traffic system is a complex open system, integrating the human-vehicle-environment and other subsystems, with high randomness, indeterminacy, and real-time capability. In recent years, with the rapid development of the transportation industry, the vehicle population has increased rapidly. The contradiction between humans, vehicles and the environment has become more prominent. The statistics show that nearly 100,000 people are dead, and more than 250,000 people are injured in road traffic accidents every year in China [1]. The situation of traffic safety is serious. When people enjoy the convenience of travel, traffic problems become more and more serious. Through road construction and expansion, and conventional traffic control, it is no longer possible to solve the contradiction between traffic supply and demand well. With the development of new technologies such as the Internet of Things, Artificial Intelligence, and cloud computing, the connected and automated road traffic system is gradually developing. As the critical component of the road traffic system, the vehicle has a repaid development of connection and automation technologies. The Connected and Automated Vehicle (CAV) has become the effective means to alleviate the traffic contradiction. CAV is equipped with advanced sensors, communication modules, controllers, and other devices. Compared with the Conventional Manual Vehicle (CMV), the CAV integrates modern communication and network technologies V2V/V2I technologies to realize the interaction perception and information sharing of

the human-vehicle-environment. With functions such as the perception of the complex environment and intelligent decision-making, CAV can help drivers make better choices according to rich information [2]. The development of CAV has a profound influence on driving behavior and traffic flow. CAVs will likely revolutionize the way we travel, through the use of advanced communication and computing technologies [3]. It is necessary to study the driving behavior under the variable Penetrations of Connected and Automated Vehicles (PCAV). Before realizing advanced automated driving, CAVs will form hybrid traffic with CMVs to share limited road sources. Therefore, it is of great significance to study traffic distribution and evolution law of traffic flow under different PCAV.

Many researchers have studied the impact of CAV on traffic efficiency, traffic safety, and energy. The existing research shows that CAV could improve traffic efficiency, improve traffic safety, and save energy. CAV can predict the driver's behavior, accurately quantify the angular velocity change of the target vehicle, realize smooth speed control, and improve traffic flow stability by obtaining the information of surrounding vehicles and considering the influence of surrounding vehicles on the target vehicle [4–6]. Wang et al. [7] conducted simulation experiments on the intelligent vehicle penetration of 5%, 10%, 50%, and 100%. They found that the increase in the intelligent vehicle can mitigate traffic congestion and change the transmission characteristics of the stop-and-go wave. Zou and Qu [8] studied the cooperative strategy of CAV, taking freeway work zones as the research scene. Through microscopic traffic simulation, the research results show that the proposed strategy could improve traffic efficiency and reduce emissions. Cao et al. [9] studied the impact of the lane change decision point and maximum waiting time on traffic flow. The impact of mandatory lane-changing on traffic efficiency was also evaluated in their study. The results indicate that the two factors affect travel time and failure rate of lane-changing. The optimal lane change decision point and maximum waiting time were also determined in the research. Focusing on the control of CAV, Yao et al. [10] proposed a two-level model to optimize scheduling and trajectories for CAVs in a conflict zone, which is constitute by the scheduling optimization model and trajectory optimization model. In addition, a rolling optimization framework was developed for the field application. The numerical simulation results showed that the proposed method is resulting in effective reduce of vehicle delay and fuel consumption.

The increase in PCAV can effectively reduce the risk of collision, reduce the probability of traffic accidents, improve traffic flow stability, and further improve traffic safety. National Highway Traffic Safety Administration [11] found that the increase in the proportion of CAV can effectively reduce the number of deaths and economic losses caused by road traffic accidents. Li et al. [12] found that the vehicle equipped with Adaptive Cruise Control can reduce the risk of collisions on freeways by 39.7–67.8% under the penetration of 10–100%. Rahman et al. [13] analyzed the intersection crash risk by extracting conflict numbers using Surrogate Safety Assessment Model. The segment crash risk was analyzed based on exposed time-to-collision, integrated time-to-collision, and rear-end crash risk index. The results show that CAV can reduce crash risk and guarantee the safe operation of traffic.

CAV can also reduce energy consumption. Gawron et al. [14] conducted a life cycle assessment of CAV considering the vehicle-level impacts. The results indicate that the energy consumption of CAV can reduce by about 9%, considering the energy consumption required by the additional equipment at the L4 autonomous driving stage. Rios-Torres et al. [15] studied the impact of partial penetrations of CAV and traffic volume on fuel consumption and traffic flow. The research found that a condition of 100% penetration with any traffic volume or partial penetration with low traffic volume can achieve fuel saving, and fuel consumption can be reduced by up to 63% under the condition of 60% penetration with medium traffic volume.

CAV affects driving behavior directly, which leads to the improvement of traffic efficiency, traffic safety, and energy consumption. Therefore, it is essential to study the driving behavior under Penetration Conditions of Connected and Automated Vehicles (PCCAV). Most existing research on the influence of CAV are on macroscopic characteristics

of traffic flow. However, the research on driving behavior and microscopic traffic flow characteristics are not comprehensive and sufficient. Few studies on lateral distribution of vehicles or lane distribution of traffic volume, which can be represented by Lane Utilization Ratio (LUR), are conducted under PCCAV. The model used by the existing research does not fully consider the influence of the surrounding vehicles (including the next front vehicle, next rear vehicle and next left-front vehicle) on the target vehicle, so it is unable to describe the vehicles' lateral distribution and evolution laws objectively.

Lane-changing and car-following are the most critical driving behaviors, constituting the micro traffic flow theory. Lane-changing has an important impact on traffic safety, traffic bottleneck, and traffic capacity. Lane selection, which has attracted much attention in recent years, has an essential influence on traffic flow stability, vehicle distribution, and driving safety [16]. In the early research of lane-changing [17,18], the driver's behavior is assumed to be rational, and lane selection is regarded as a process based on specific rules. The lane-changing behavior is divided into three steps: intention generating, condition detecting, and operation executing.

Some scholars build lane-changing models based on the lane-changing decision. Li et al. [19] introduced a decomposition framework to model, analyze and design the platoon system of CAV based on multi-agent consensus control. Xie et al. [20] construct a data-driven lane-changing model based on a deep belief network and long-short term memory network. Díaz-Álvarez et al. [21] built a lane-changing model based on Multilayer Perceptions and Convolutional Neural Networks by learning lane-change acceptance using feed-forward Artificial Neural Network. The driving process is a dynamic game process in essence, many scholars studied lane-changing behavior by game theory. Ali et al. [22] proposed a mandatory lane-changing with incomplete information based on non-zero-sum non-cooperative game applicable to traditional and connected environments. Wang et al. [23] built a lane selection model based on multi-player dynamic game with complete information considering vehicle group situation. The drivers' payoffs were analyzed, and the Nash equilibrium solution was solved through backward induction.

The existing lane-changing models do not fully consider the influence of PCAV, driving propensity, surrounding vehicles and other factors, nor can they represent the interaction among vehicles. However, the lane selection model based on phase-field coupling and set pair logic has comprehensively considered and analyzed the above factors. It can describe the driver's lane selection behavior objectively and realize the personification decision of CAV.

LUR, an important influential factor of traffic flow stability, represents the traffic distribution on different lanes of road section for a single direction. It is affected by the lane selection behavior directly, and closely related to traffic composition (PCAV), traffic volume, driver characteristics (driving propensity) and other factors. However, different PCAVs are challenging to realize in reality, and LUR is difficult to be collected by real vehicle experiments under different conditions.

Aiming at the issue of the previous studies, the impact of CAVs on traffic flow and driving behavior is carried out based on the microscopic traffic simulation, taking LUR as the main index. In order to simulate the lane-changing of CAVs, a lane selection model for CAVs is used in the microscopic simulation. In this research, the microscopic traffic simulation was carried out to study LUR under different PCAVs and traffic volumes in the basic section of the urban expressway. Considering the influence of driver characteristics, the influence of driving propensity on LUR under PCCAV is further studied.

Through the analysis of simulation results, it can realize that (1) an in-depth analysis of the impact of the development of CAVs on LUR and traffic flow, (2) the preliminary exploration of lane-changing behavior and traffic flow characteristics under PCCAV, (3) the improvement of the research connotation of LUR, and (4) the preliminary expansion of the traffic flow theory under PCCAV. The remainder of this paper is structured as follows. Section 2 describes the methodology using in the microscopic traffic simulation. The sim-

ulation results and the discussion are conducted in Section 3. Finally, Section 4 ends this paper with conclusions.

2. Methodology

In order to analyze the impact of PCAV on LUR, a microscopic traffic simulation is carried out in the basic section of urban expressway to collect the traffic data (such as LUR and LCT) under various PCAVs considering driving propensity. Due to LUR is directly affected by lane-changing behavior, a lane selection model based on phase-field coupling and set pair logic is proposed to simulate the personification decision-making of CAVs. In this simulation, a variety of factors are considered, such as traffic volume, PCAV, driving propensity and road condition.

2.1. Lane Selection Model Based on Phase-Field Coupling and Set Pair Logic

Driver's lane selection is a process of pursuing interests. The driving revenue and behavior of the target vehicle are influenced by cluster vehicles, surrounding traffic environment and driver characteristics. With the development of connection and automation technologies, this research comprehensively analyses the full-information of lanes considering driving propensity, the interaction between cluster vehicles, and information acquisition characteristics (incompleteness and uncertainty). The methods of phase-field coupling and set pair logic are used to construct a lane selection model suitable for CAV, as shown in Figure 1.

Figure 1. Basic framework of lane selection model based on phase-field coupling and set pair logic.

During lane selection, driving propensities of cluster vehicles [24,25] and vehicle cluster situation of target vehicle [26,27] should be identified first. Then the action order is determined by the location and driving propensity. The forward the position is, the higher the priority of the action order is. When the longitudinal position is too close, the action order depends on driving propensity (Radical > Common > Conservative).

According to the definition of 'force' in existing research, the lane worth is used to calculate revenue of lane-changing based on the analysis of the impact of cluster vehicles ($i = 2, 3, \dots, 7$) on the target vehicle ($i = 1$). Here, the lane worth mainly considers the safety, efficiency, comfort and operating difficulty during lane-changing.

The safety worth of lane $W_i^{1\lambda}$ refers to the effect of the vehicles in the interest region on the target vehicle after the target vehicle changes to the target lane λ ($\lambda = L, M, R$).

$$W_i^{1\lambda} = F_i^{\lambda'} = \sum_j f_i^{j\lambda'} \mu_i^{j\lambda'} (i = 1, 2, \dots, 7, j = q, h, zq, zh, yq, yh, \lambda = L, M, R) \quad (1)$$

The efficiency worth of lane $W_i^{2\lambda}$ refers to the effect of the vehicles in the front part of the interest region on the target vehicle after the target vehicle changes to the target lane.

$$W_i^{2\lambda} = F_i^{Q\lambda'} = \sum_{Qj} f_i^{Qj\lambda'} \mu_i^{Qj\lambda'} (i = 1, 2, \dots, 7, \lambda = L, M, R, Qj = zq, q, yq) \quad (2)$$

The comfort worth of lane $W_i^{3\lambda}$ refers to the effect of the vehicles in the target lane on the target vehicle after the target vehicle changes to the target lane.

$$W_i^{3\lambda} = F_i^{C\lambda'} = \sum_{Cj} f_i^{Cj\lambda'} \mu_i^{Cj\lambda'} + f_{i'}^{nCQ\lambda'} \mu_i^{nCQ\lambda'} (i = 1, 2, \dots, 7, \lambda = L, M, R, Cj = zq, zh \vee q, h \vee yq, yh, CQ = zq \vee q \vee yq) \quad (3)$$

The difficulty worth of lane $W_i^{4\lambda}$ refers to the effect of the vehicles in the target lane's rear region and the original lane's rear region on the target vehicle.

$$W_i^{4\lambda} = F_i^{H\lambda} = \sum_{Hj} (f_i^{Hj\lambda} \mu_i^{Hj\lambda} + f_{i'}^{nHj\lambda} \mu_i^{nHj\lambda}) (i = 1, 2, \dots, 7, \lambda = L, M, R, Hj = zh, h \vee h, yh \vee zh \vee h \vee yh) \quad (4)$$

In the above equations, f is the force of the vehicles in the interest region on the target vehicle, μ is the contribution rate of the target vehicle's comprehensive force from the vehicles in each subregion j ($j = q, h, zq, zh, yq, yh$), and Qj, Cj, CQ and Hj are the different sets of subregions. The specific definitions are same as [28], the specific values can refer to our previous research [26]. According to the analysis of lane worth, only the identical degree $a_{i\lambda}^k$ and discrepancy degree $b_{i\lambda}^k$ need to be considered. Based on the definition of connection number [29], the binary connection numbers $u_{i\lambda}^k = a_{i\lambda}^k + Jb_{i\lambda}^k$ of three lanes are computed, where J is the coefficient of discrepancy degree. The closeness degrees of three lanes are calculated considering the different drivers' cognition ζ_k^p of lane worth.

$$D_{i\lambda} = \sum_{k=1}^4 u_{i\lambda}^k \zeta_k^p (\lambda = L, M, R) \quad (5)$$

The gain on safety, efficiency and comfort are considered in the lane-changing revenue. The revenue is calculated by the difference between three kinds of lane worth before and after lane-changing.

$$E_i^{\lambda'} = \Delta W_i^{\lambda'} = \sum_{k=1}^3 W_i^{k\lambda'} - W_i^{k\lambda} (i = 1, 2, \dots, 7, k = 1, 2, 3, \lambda = L, M, R, \lambda' = M, L \vee R, M) \quad (6)$$

After the candidate target lane selection, the overall satisfaction needs to be evaluated. Suppose the overall satisfaction does not meet the requirement. In that case, the lane selection will be carried out again on the existing basis until the overall satisfaction meets the requirement. Lane selection affects vehicle cluster situation directly, and driving safety is greatly affected. So, the overall satisfaction is mainly conducted based on the evaluation of vehicle cluster situation after lane-changing.

$$S_i = \sum_{j=1}^6 \mu_i^{j\lambda} f_i^j (i = 1, 2, \dots, 7) \quad (7)$$

The lane selection model based on phase-field coupling and set pair logic can provide a theoretical basis for the study of CAV. This model lays a theoretical and technical basis for the simulation research of the impact of PCAV on Lane Utilization Ratio.

2.2. Microscopic Traffic Simulation

Microscopic traffic simulation can reproduce traffic flow's actual behavior under various traffic conditions. The random characteristic of a single-vehicle and driver's personal preferences can also be considered. In developing and researching Intelligent Transportation System, microscopic traffic simulation is becoming an essential means [30]. The microscopic traffic simulation in this research is carried out based on SUMO [31]. The basic simulation framework is shown in Figure 2.

Figure 2. Basic framework of microscopic traffic simulation.

2.2.1. Driving Behavior Model

Considering the characteristics of Conventional Manual Vehicle (CMV), the FVD (Full Velocity Difference) model [32] and MOBIL (Minimizing Overall Braking Induced by Lane Change) model [33] are selected to simulate the driving behavior of CMV. Furthermore, the IDM (Intelligent Driver Model) model [34,35] and lane selection model based on phase-field coupling and set pair logic are selected to simulate the driving behavior of Connected and Automated Vehicle (CAV).

For the CMV, FVD model is selected as the car-following model, and MOBIL model is selected as the lane-changing model. FVD model can describe the following behavior of the CMV better, which is widely used in the research of the following behavior of the CMV. The FVD model was further improved and calibrated the model by measured traffic data. The FVD model is,

$$\dot{v} = \kappa \left\{ v_0 \left[1 - \exp \left(-\frac{\alpha}{v_0} (s - s_0) \right) \right] - v \right\} + \frac{\vartheta}{s} \Delta v \quad (8)$$

where, κ , α and ϑ are sensitive coefficients, v_0 is the free flow speed, s_0 is the minimum stopping distance. The calibration results of the model parameter [36] are $v_0 = 33.0$ m/s, $\kappa = 0.629$ s⁻¹, $\vartheta = 4.10$ s⁻¹, $\alpha = 1.26$ s⁻¹, $s_0 = 2.46$ m.

In the MOBIL model, the safety and incentive rules are proposed, which the lane-changing decision should comply with, considering lane-changing safety and payoff. The safety rule is,

$$\tilde{a}_n \geq -b_{safe} \quad (9)$$

where, $\tilde{a}_n$ is the acceleration of the rear vehicle in the target lane after the target vehicle lane-changing, b_{safe} is the maximum safe deceleration. The incentive rule of the MOBIL model is,

$$\tilde{a}_c - a_c + p(\tilde{a}_n - a_n + \tilde{a}_0 - a_0) > \Delta a_{th} \quad (10)$$

where, a_c and $\tilde{a}_c$ are the acceleration of the target vehicle before and after lane-changing, respectively, a_n and $\tilde{a}_n$ are the acceleration of the rear vehicle in the target lane before and after the target vehicle lane-changing, respectively, a_0 and $\tilde{a}_0$ are the acceleration of the rear vehicle in the original lane before and after the target vehicle lane-changing, respectively, p is the politeness factor (the degree of altruism), Δa_{th} is the switching threshold. Some values of the MOBIL parameters are determined: $b_{safe} = 4 \text{ m/s}^2$, $\Delta a_{th} = 0.2 \text{ m/s}^2$. Moreover, the value of p is $p_{com} \in (0.35, 0.5]$ for the conservative driver, $p_{con} \in (0.15, 0.35]$ for the common driver, and $p_{rad} \in (0, 0.15]$ for the radical driver.

For CAV, IDM model is selected as the car-following model. The lane selection model based on phase-field coupling and set pair logic is taken as the lane-changing model. IDM model can represent the driving characteristics of the driver when acquiring the driving status of other vehicles. The IDM model is,

$$\dot{v} = a \left[1 - \left(\frac{v}{v_0} \right)^4 - \left(\frac{s_0 + vT - v\Delta v / (2\sqrt{ab})}{s} \right)^2 \right] \quad (11)$$

where, a is the maximum acceleration, T is the safe time headway, b is comfortable deceleration. The values of model parameters [37] are $v_0 = 33.0 \text{ m/s}$, $T = 2.0 \text{ s}$, $a = 4.0 \text{ m/s}^2$, $b = 2.0 \text{ m/s}^2$ and $s_0 = 2.0 \text{ m}$.

In the lane selection model based on phase-field coupling and set pair logic, the requirement of overall satisfaction is $\forall S_i \geq 0$, and the setting of other model parameters is shown in Table 1.

Table 1. Parameter setting of lane selection model based on phase-field coupling and set pair logic.

Driving Propensity	Threshold of Lane-Changing Revenue	Weight of Lane Worth			
		Safety Worth ζ_i^1	Efficiency Worth ζ_i^2	Comfort Worth ζ_i^3	Difficulty Worth ζ_i^4
Radical	0.060	0.31	0.45	0.14	0.1
Common	0.063	0.34	0.3	0.21	0.15
Conservative	0.065	0.39	0.15	0.23	0.23

2.2.2. Simulation Scenario

The basic section of the one-way two-lane and the one-way three-lane urban expressway is taken as the simulation scenario in this research. The simulation under various traffic conditions is carried out considering the impact of different traffic conditions. Various values are designed for PCAV, traffic volume, driving propensity composition, etc. Considering the road capacity, the traffic volume is settled for [500 pcu/h, maximum service traffic volume] (4000 pcu/h for two-lane and 6000 pcu/h for three-lane). In order to explore the influence of driving propensity, the composition of driving propensity, including all conservative, all common, all radical, and various ratios, is set. The main work of this study is to explore the variation law of LUR under PCCAV. Therefore, a variety of PCAVs are set, including traffic flow of all CMVs, traffic flow of all CAVs, and the hybrid traffic of CMVs and CAVs. For the facilitate subsequent analysis, the traffic flow states are

divided into free flow, stable flow, unstable flow and forced flow according to the Level of Service. Combining the traffic capacity with the simulation scenario, the criteria of traffic flow states are given by traffic volume: for two-lane urban expressway, free flow (volume ≤ 1000 pcu/h), stable flow ($1000 \text{ pcu/h} < \text{volume} \leq 2000 \text{ pcu/h}$), unstable flow ($2000 \text{ pcu/h} < \text{volume} \leq 4000 \text{ pcu/h}$) and forced flow (volume $> 4000 \text{ pcu/h}$); for three-lane urban expressway, free flow (volume $\leq 2000 \text{ pcu/h}$), stable flow ($2000 \text{ pcu/h} < \text{volume} \leq 3500 \text{ pcu/h}$), unstable flow ($3500 \text{ pcu/h} < \text{volume} \leq 6000 \text{ pcu/h}$) and forced flow (volume $> 6000 \text{ pcu/h}$).

2.2.3. Traffic Generation

The shifted negative exponential distribution determines the time interval of vehicles arriving at the road section to generate various traffic volume conditions. According to the shifted negative exponential distribution, vehicles appear in the simulation road section based on the set traffic volume conditions:

$$h = (H - h_{\min})[-\ln(1 - R)] + H - h_{\min} \quad (12)$$

$$H = 3600/Q_{avg} \quad (13)$$

where, h is time headway, H is the expected average time headway, R is a random number in the interval $(0, 1)$, Q_{avg} is traffic volume.

2.2.4. Other Parameters Setting

The simulation section is 6 km long. The total simulation time is 1 h, and the first 5 min are the trial simulation stage. The simulation step is 1 s. Consider the impact of random factors, 3 simulation experiments were carried out under each combination of conditions, and the average data was used to reduce the influence of random factors. The settings of vehicle and driver characteristic parameters are shown in Tables 2 and 3. In simulation 1, only the impact of PCAV is considered when traffic volume changes. On the basis of simulation 1, driving propensity is considered, and the impact of PCAV and driving propensity are further studied in simulation 2.

Table 2. Setting of vehicle characteristic parameters.

Vehicle Type	Composition (%)		Geometry Size (m)					Dynamic Characteristics (m/s ²)				
			Length		Width			Maximum Acceleration		Maximum Deceleration		
Small-sized vehicle	70		$L \leq 6$		1.8			2.5		−3.5		
Middle-sized vehicle	20		$6 < L < 12$		2.5			2.5		−3.5		
Large-sized vehicle	10		$L \geq 12$		2.5			2.5		−3.5		
Vehicle Genre			Composition									
CAVs	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%	
CMVs	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%	

Table 3. Setting of driver characteristic parameters.

Driver Characteristic		Composition									
		Simulation 1					Simulation 2				
Age	Youth	60%					60%				
	Middle-age	20%					20%				
	Agedness	20%					20%				
Gender	Male	80%					80%				
	Female	20%					20%				
Driving propensity	Radical	20%	0%	0%	100%	20%	20%	60%	20%	40%	40%
	Common	60%	0%	100%	0%	20%	60%	20%	40%	20%	40%
	Conservative	20%	100%	0%	0%	60%	20%	20%	40%	40%	20%

3. Results and Discussion

LUR is affected by lane-changing behavior directly. Furthermore, the lane-changing behavior is different with various PCAVs and road traffic conditions. The Lane-Changing Times (LCT) and LUR under different PCAVs and traffic volumes are obtained through the simulation experiment. Moreover, the LCT and LUR under different PCAVs and traffic volume considering driving propensity are obtained through simulation by adjusting the driving propensity composition. This section will analyze the influence of PCAV, traffic volume, and driving propensity on LUR and LCT to explore the lane-changing characteristics under PCCAV.

3.1. Simulation 1: Considering PCAV

The simulation results of LCT and LUR under different PCAV and traffic volume conditions in the basic section of the two-lane and three-lane urban expressway are shown in Figures 3 and 4.

Figure 3. Simulation results under different PCAV and traffic volume conditions in the two-lane urban expressway.

Figure 4. Simulation results under different PCAV and traffic volume conditions in the three-lane urban expressway.

3.1.1. Two-Lane

Figure 3a is the LCT under different PCAV and traffic volume conditions in two-lane urban expressway. From the perspective of the relationship between traffic volume and LCT, the LCT is very small in the free flow state. With the increase in traffic volume, the LCT gradually increases. When the traffic volume is 2000 pcu/h, the LCT reaches the maximum and gradually decreases to have no lane-changing behavior. From the perspective of the relationship between PCAV and LCT, the LCT first increases and decreases with the increase in PCAV. When the PCAV reaches 50%, the LCT starts to decrease, the gap of LCT decreases gradually under different traffic volumes, and the stability of traffic flow gradually improves.

Figure 3b is the LUR under different PCAV and traffic volume conditions in two-lane urban expressway. On the whole, vehicles mainly drive in the outer lane under the condition of low traffic volume. With the increase in traffic volume, the LUR of the inner lane gradually increases. After the traffic volume exceeds 2000 pcu/h, the LUR tends to be stable, presenting a phenomenon that the LUR of the inner lane is slightly higher than the LUR of the outer lane. With the increase in PCAV, the distribution of vehicles in each lane tends to be stable under different traffic volumes. When the PCAV exceeds 70%, the LUR of the inner lane is slightly higher than the LUR of the outer lane, even under low traffic volume conditions.

When the PCAV is low, the driving environment is good in the free flow state. Vehicles can drive in the nearby outer lane without changing lanes to find better driving conditions, manifested as fewer LCT and higher LUR of the outer lane. With the increase in traffic volume, the driving condition deteriorates gradually. To obtain a better driving environment, the LCT increases. The gap between the LUR of the inner and outer lanes decreases with the vehicles choosing to drive in the inner lane. At 2000 pcu/h, the traffic flow reaches an unstable flow state and becomes saturated gradually; the driving environment further deteriorates. Even though the expectation of better driving conditions through

lane-changing still exists, due to the increase of traffic density and the reduction of merging headway, the opportunities of lane-changing and LCT reduced gradually. The LUR of the inner lane is slightly higher than that of the outer lane since the inner lane is disturbed less. When the traffic volume is close to the maximum service traffic volume, the traffic flow is about to reach the forced flow state (the speed decreases, the traffic density increase, the merging headway reduced further, vehicles queue up, and the difference of driving conditions between the inner and outer lane is slight). At this time, the chance of lane-changing decreases, the LCT decreases, and the gap of different lanes' LUR is reduced and stabilized by keeping the LUR of the inner lane slightly higher than that of the outer lane.

The increase in PCAV makes the information acquired more abundant, which plays a positive role in the stability of traffic flow and traffic efficiency. Under the low PCAV, the number of CAVs is small, and the distribution is random. The improvement in the richness of information is limited, but drivers' operation is freer than without CAVs. The restrictions of lane-changing are relatively relaxed, and the LCT is increased. Affected by the number and distribution, CAV is easily degraded due to the influence of surrounding CMVs. CAV's advantages are difficult to play a full role, and the effect of improving traffic operation is not apparent. The increase in PCAV can enhance the coordination ability between vehicles and improve the vehicle's speed indirectly, which has a more obvious effect on the small-sized vehicle. The traffic flow is gradually divided according to speed, some vehicles with higher speed drive in the inner lane. The LUR of the inner lane increases, the LCT decreases gradually, and the utilization of different lanes is balanced. The effect of PCAV on improving traffic flow stability increases gradually with the increase of PCAV; especially after PCAV exceeds 70%, the improvement effect is significant. The improvement effect of PCAV on traffic flow is also affected by traffic volume. The increase of PCAV has a more obvious improvement effect on traffic flow in the steady flow state and unstable flow state.

3.1.2. Three-Lane

Figure 4a is the LCT under different PCAV and traffic volume conditions in the three-lane urban expressway. From the relationship between traffic volume and LCT, the LCT increases with the increase of traffic volume until 3000 pcu/h and decreases. From the relationship between PCAV and LCT, with the increase of PCAV, the LCT under different traffic volumes has shown a trend of first increasing and then decreasing (at 50% in PCAV) with varying degrees of decline.

Figure 4b is the LUR under different PCAV and traffic volume conditions in the three-lane urban expressway. In the free flow state, vehicles mainly drive in the outer lane. As the increase in traffic volume, vehicles gradually change to the middle and inner lanes. The LUR of the inner lane increases gradually, and the LUR of the middle lane fluctuates. When the traffic volume exceeds 3500 pcu/h, the LUR stabilizes, showing a gradual decline of LUR from the inner lane to the outer lane. With the increase of PCAV, the distribution of vehicles in each lane tends to be balanced, and the influence of traffic volume on LUR is reduced gradually. When the PCAV exceeds 60%, the LUR remains relatively stable, and the phenomenon of decreasing from inside to outside is shown under various traffic volume conditions.

The change law of LCT in the three-lane environment with different PCAV and traffic volume is similar to that in the two-lane environment, but the corresponding key traffic volumes increase due to the increase in road capacity caused by road conditions. The change in LUR in the three-lane road is similar to that in the two-lane road, and crucial traffic volumes are also improved. Affected by the complicated traffic conditions of the three-lane road compared with the two-lane road, the improvement of PCAV on traffic flow is obvious, and the key PCAVs are reduced. The change in the middle lane's LUR is notable. The LUR of the middle lane presents a fluctuation change affected by the inner lane and the outer lane at the same time. Under the high traffic volume or PCAV, the LUR of the three-lane environment is similar to the two-lane environment, which shows that the

LUR decreases from the inner lane to the outer lane with a small gap. In the three-lane, the degradation of CAV also exists under the low PCAV, and its advantages are difficult to play a full role.

3.1.3. Discussion

The effect of the improvement in PCAV on LUR and LCT is affected by the traffic environment's complexity. There are some differences between the two-lane and three-lane environments. However, both show that the LCT increases first and then decreases with the increase in PCAV. The LUR is gradually balanced and stable with the slightly higher LUR of the inner lane than the outer lane. PCAV and traffic volume affect each other and act together on traffic flow. The impact of PCAV on traffic flow is not significant under the condition of low traffic volume. The effect of traffic volume reduces under the condition of high PCAV. The traffic condition of the three-lane is more complex than the two-lane, showing poor traffic flow stability and obvious fluctuations of traffic flow in the middle lane.

3.2. Simulation 2: Considering PCAV and Driving Propensity

Driving propensity has an important influence on driving behavior. This research further studies the influence of driving propensity on the effect of PCAV. The LCT and LUR considering PCAV and driving propensity are collected from simulation, which takes values of driving propensity at an interval of 10%. The results are shown in Figures 5 and 6, taking three kinds of single driving propensity as an example.

Figure 5. Simulation results under different PCAV, driving propensity and traffic volume conditions in two-lane urban expressway.

Figure 6. Simulation results under different PCAV, driving propensity and traffic volume conditions in three-lane urban expressway.

3.2.1. Two-Lane

Figure 5 shows the LCT and LUR under different PCAV, driving propensity and traffic volume conditions in the two-lane urban expressway. Regardless of driving propensity, the LCT increases first and then decreases as the traffic volume increases. Under the driving propensity of all conservative or all common, the LCT increases at first and decreases at last with the increase of PCAV. The LCT rapidly drops to a low level as the traffic volume is close to the maximum service traffic volume. Under all radical driving propensity conditions, the LCT shows a special process of increasing first, then decreasing and increasing at last as the increasing of PCAV. When PCAV is 70%, LCT changes from decrease to increase. In some traffic volume conditions, lane-changing is the most frequent when PCAV is 100%.

From driving propensity-LUR, the balance degree of inner and outer LUR of conservative, common and radical decreases in turn. With the increase of PCAV or traffic volume, the changing speed and range of LUR of conservative, common and radical are successively reduced.

Under the condition that all drivers' driving propensities are common in traffic flow: From the perspective of traffic volume-LUR, when PCAV is low, there is a large gap in LUR of inner and outer lanes in the free flow state, and vehicles mainly travel in the outer lane.

With the increase in traffic volume, the LUR gap decreases gradually. The final performance is that the LUR of the inner lane is slightly higher than the LUR of the outer lane. From the PCAV-LUR point of view, with the increase of PCAV, the LUR gap between inner and outer lane decreases under different traffic volume, the lane distribution of vehicles tends to be stable, and the influence of traffic volume reduces. As PCAV is 70%, the LUR of the inner lane is higher than the LUR of the outer lane in the free flow state.

Under the condition that all drivers' driving propensities are conservative in traffic flow: The variations of traffic volume-LUR and PCAV-LUR are similar to those of common driving propensity. However, the LUR gap between the inner lane and outer lane is smaller than that of the common type under the condition of high PCAV or large traffic volume, while the LUR of inner and outer lanes are basically the same under the higher PCAV.

Under the condition that all drivers' driving propensities are radical in traffic flow: Traffic volume-LUR and PCAV-LUR do not show a significant change law. In most cases, the LUR gap between inner and outer lanes gradually decreases with the increase in traffic volume, and the gap is larger than that of the common type. PCAV-LUR mostly shows that as PCAV increases, the LUR gap reduces. When PCAV is 70%, the LUR of the inner lane is slightly higher than the LUR of the outer lane in the free flow state. However, with the further increase of PCAV, the LUR of the inner lane continues to improve, and the LUR gap is gradually increasing. The chaotic phenomena of traffic flow composed of radical drivers are pronounced, and it is difficult to avoid under high PCAV.

3.2.2. Three-Lane

Figure 6 is the LCT and LUR under different PCAV, driving propensity and traffic volume conditions in the three-lane urban expressway. The change of LCT in three-lane is similar to that in two-lane. No matter what kind of driving propensity, LCT increases first and decreases last with increased traffic volume. Under the driving propensity condition of all common or all conservative, LCT first increases and then decreases as increased PCAV; when the traffic volume reaches the maximum service traffic volume, LCT decreases rapidly. Under all radical driving propensity, LCT first increases, then decreases, and increases last with the increase of PCAV. The changing amplitude of LCT does not show an obvious rule. The LCT turns from decrease to increase at PCAV of 70%. There is also the highest LCT when PCAV is 100% under some traffic volume conditions. The relationship between driving propensity and LCT in three-lane is similar to that in two-lane, and radical drivers show a higher frequency of lane-changing.

The traffic flow is entirely composed of drivers of the common type. In terms of traffic volume-LUR, the LUR of the inner lane is higher in the free flow state. With the increase of traffic volume, vehicles move to other lanes, resulting in the gradual narrowing of the LUR gap between three lanes, and the LUR is decreasing from the inner to the outer lane. From PCAV-LUR, the distribution of vehicles in each lane is balanced as the PCAV increases. After PCAV reaches 60%, LUR is relatively stable and is less affected by traffic volume.

The traffic flow is entirely composed of drivers of the conservative type. In terms of traffic volume-LUR, the LUR of the inner lane is relatively low under low PCAV conditions and gradually increases with traffic volume. With the increasing traffic volume, the LUR gap of three lanes is reduced and keeps the state that the LUR of the inner lane is slightly higher than the LUR of the middle and outer lanes. The relationship of PCAV-LUR is similar to that of the common type. The LUR gap is smaller than that of the common type. Compared with the common type, the LUR of three lanes reaches a balanced and stable state faster with the increase in PCAV and traffic volume.

The traffic flow is entirely composed of drivers of the radical type. Similar to the two-lane, the traffic volume-LUR and PCAV-LUR do not show obvious regular changes. Overall, the LUR gap of the three lanes is larger than that of the common type and conservative type. For traffic volume-LUR, in the free flow state, vehicles mostly drive in the inner lane. In most cases, the LUR gap decreases with the increased traffic volume. However, there are still some cases where the LUR gap increases with traffic volume. The relationship between

PCAV and LUR is similar to the relationship between traffic volume and LUR (an obvious phenomenon that the LUR gap increases). When PCAV is about 80%, the LUR gap enlarges significantly. In the three-lane, the chaotic phenomenon of traffic flow composed entirely of the radical driver is more intense.

3.2.3. Discussion

There are some differences in the personality, driving ability, and driving preference of drivers with different driving propensity. Radical drivers are lively, active, responding rapidly, agile, likely to drive at high speed and overtaking, and pursue driving efficiency. Conservative drivers are calm, cautious, relatively slow in response, relatively slow in action, prone to drive at low speed and less overtaking, in pursuit of driving safety. Common drivers are resourceful and energetic, strictly observing the rules and driving smoothly, and taking into account driving efficiency and safety. The effects of PCAV on drivers with different driving propensities under different traffic environment conditions are various.

The sensitivities of drivers with different propensities to the change of traffic volume and PCAV are different (radical > common > conservative). In the three-lane, traffic flow composed entirely of radical drivers focuses on the inner lane even in the free flow state, while the traffic flows composed entirely of common or conservative drivers behave similarly in the two-lane and three-lane. The traffic flow composed entirely of radical drivers does not show the obvious changing law of LUR. The results show that the improvement of PCAV has a limited effect on the operating efficiency and stability of traffic flow composed entirely of a single driving propensity. The traffic flow tends to develop to extreme conditions, and the chaotic phenomenon is more likely to be highlighted. In some cases, the traffic flow composed of only conservative or radical drivers even deteriorates. Under high PCAV, the LUR gap of each lane of radical traffic flow could widen, and the utilization efficiency of road resources is low.

4. Conclusions

This research analyzes the Lane Utilization Ratio considering the impact of CAVs on driving behavior and traffic flow. The lane selection model based on phase-field coupling and set pair logic, which considers the factors such as full-information of lane and driving propensity, was used to simulate the lane-changing behavior of CAVs. From the microscopic traffic simulation, the Lane Utilization Ratio and Lane-Changing Times under PCCAV can be collected to analyze the impact of CAVs on LUR and traffic flow. The following conclusions are drawn by analyzing the simulation results.

- (1) There is a positive effect of CAV on the stability of traffic flow and the efficiency of traffic operation.
- (2) The effect of different PCAV is different. In the case of low PCAV, CAV is prone to degradation due to the influence of surrounding CMVs, and the improvement in traffic operation is not obvious. In most cases, the higher the PCAV is, the more obvious the improvement of traffic operation will be.
- (3) The impact of CAV on LUR and traffic flow is different under different traffic volumes. The driving conditions in the free flow state are good, where the improvement of PCAV has less effect on LCT and an obvious effect on LUR. With the increase in traffic volume and penetrations, the impact of CAV gradually becomes obvious. However, the effect of CAV on LCT and LUR gradually decreases when the traffic volume is close to saturation.
- (4) The driving requirements and goals of drivers with different driving propensities are various, which lead to different improvement effects of CAV on traffic flow under different driving propensity conditions. The sensitivity of radical, common, and conservative drivers to the change of traffic volume and PCAV decrease in turn.
- (5) The improvement of PCAV has a limited effect on the operating efficiency and stability of traffic flow composed entirely of a single driving propensity, especially the conservative and radical types (the chaotic phenomenon of traffic flow is obvious).

This study in-depth analyzes the Lane-Changing Times and Lane Utilization Ratio considering the PCAV and driving propensity through microscopic traffic simulation. The characteristics of lane-changing behavior and traffic flow under PCCAV are preliminarily analyzed, and some results have been obtained. The model can objectively represent the traffic flow characteristics and lane selection process under PCCAV, in which the development of CAVs is fully considered. The multi-source traffic information is analyzed comprehensively, such as vehicle cluster situation (including the full information of lane) and characteristics of driver (including driving propensity). In this study, Lane Utilization Ratio's research is carried out through this model, which further enriches the connotation of lane distribution of traffic volume and promotes in-depth research on the traffic flow theory and driving behavior under PCCAV.

This research could provide a theoretical basis for traffic management and control, and transportation infrastructure planning and construction in the development of CAVs. This study can also promote the development of intelligent transportation systems, autonomous driving, and other advanced transportation technologies.

Author Contributions: Conceptualization, X.W. and S.L.; methodology, X.W. and S.L.; validation, H.S. and S.L.; investigation, S.L., H.S. and H.X.; data curation, H.X. and Y.Z.; writing—original draft preparation, S.L., H.X. and G.H.; writing—review and editing, X.W., H.S., Y.Z. and H.W.; visualization, G.H., H.W. and S.L.; supervision, X.W.; project administration, X.W.; funding acquisition, X.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Natural Science Foundation of Shandong Province, grant number ZR2020MF082; the Collaborative Innovation Center for Intelligent Green Manufacturing Technology and Equipment of Shandong Province, grant number IGSD-2020-012; the Qingdao Top Talent Program of Entrepreneurship and Innovation, grant number 19-3-2-11-zhc; the Joint Laboratory for Internet of Vehicles, Ministry of Education-China Mobile Communications Corporation, grant number ICV-KF2018-03; the National Key Research and Development Program, grant numbers 2018YFB1601500.

Data Availability Statement: Data will be made available from the corresponding author on reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

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