

Article

Assessing Traffic-Flow Safety at Various Levels of Autonomous-Vehicle Market Penetration

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Abstract: This study analyzes the impact of autonomous-vehicle (AV) market-penetration rates on traffic-flow safety using a genetic algorithm. We set up a microscopic traffic-simulation scenario on a 640 m section of the US I-101 freeway using VISSIM, a microscopic traffic-simulation software. The results of analyzing the number of conflicts according to the introduction rate of autonomous vehicles showed that the number of conflicts increased as the introduction rate increased up to 30%, and then decreased from 40% or more. In this study, it was assumed that autonomous vehicles can avoid dangerous situations, so it is judged that this is the result of an increase in the traffic volume of autonomous vehicles and a decrease in the traffic volume of conventional vehicles. When planning an exclusive lane for autonomous vehicles, it is judged that it is desirable to install two exclusive lanes on the left side until the introduction rate of autonomous vehicles reaches 30%. When the introduction rate of autonomous vehicles is 40–90%, the risk of accidents between autonomous vehicles and conventional vehicles decreases, and the traffic volume of autonomous vehicles is higher than that of conventional vehicles. Therefore, it is judged that it is desirable to operate a mixed road where autonomous vehicles and conventional vehicles can drive together rather than operating an exclusive lane for autonomous vehicles.

Keywords: autonomous vehicles; collision; genetic algorithms; VISSIM; car-following distance



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1. Introduction

SAE International classifies autonomous vehicles into six levels based on the driver's intervention and the vehicle's capabilities. It is predicted that, by 2023, autonomous driving technology will have reached Level 2 or Level 3. With the advancement of autonomous driving technology, various studies have been conducted on the effects of introducing autonomous vehicles, including potential accident collisions [1], accident severity [2,3], economic analysis [4], and traffic-control system design [5]. Accordingly, several studies have been conducted to investigate the safety of traffic flow when autonomous vehicles are introduced using micro-traffic simulations such as VISSIM. However, there is a lack of research that analyzes the safety of traffic flow in mixed traffic that reflects the driving behavior of general-purpose vehicles.

This study analyzes the safety of traffic flow due to changes in the introduction rate of autonomous vehicles using the driving behavior of general vehicles analyzed based on actual data and the input variables of autonomous-vehicle driving behavior used in previous studies for sections that include highway grade separations and examines the operation of lanes dedicated to autonomous vehicles.

2. Related Work

To analyze traffic safety in a situation where autonomous vehicles and conventional vehicles are mixed, we implemented the driving behavior of autonomous vehicles using

the Intelligent Driving Model (IDM) and analyzed the mobility and safety of autonomous vehicles as a function of their adoption rate using VISSIM. We found that the mobility of the network improves as the adoption rate of autonomous vehicles increases, but the traffic flow becomes unstable when mixed, increasing the need for safety management [6]. Weather events or infrastructure conditions can cause problems with a vehicle's sensors or communication capabilities, and reduced sensor coverage has been shown to increase both sudden decelerations and the number of vehicle-to-vehicle collisions [7].

Recent studies using VISSIM have proposed the concept of autonomous-vehicle aggressiveness as a traffic operations management strategy to optimize the performance of the road transportation system with the introduction of autonomous vehicles, in terms of accident presence, service level, and vehicle acceptance rate [2,8], evaluated the potential safety impact of autonomous vehicles, and reported that the frequency and severity of accidents decrease with the introduction of autonomous vehicles [9–12].

Research on traffic management for vehicles has shown that genetic algorithms are highly effective for calibrating and validating networks [13,14], and genetic algorithms have been shown to be particularly effective for analyzing traffic characteristics, in terms of safety, operational efficiency, and environmental performance [15,16].

Models that can represent the driving behavior of autonomous vehicles include the Wiedemann model, the IDM, and the Optimal Velocity Model (OVM). The Wiedemann model is the default driving behavior model used in VISSIM and is based on four driving behaviors: free flow, approach, follow, and brake, while the Wiedemann 99 model is used for continuous flow. The Wiedemann 99 model is employed for simulating uninterrupted traffic flow. While the Wiedemann 74 model is typically utilized for urban road networks (interrupted flow), the Wiedemann 99 model is more suitable for freeway networks (uninterrupted flow). In contrast to the Wiedemann 74 model, which only provides two parameters for calculating average stopping distance and average distance headway, the Wiedemann 99 model allows for a more nuanced representation of car-following behavior. This is achieved through the incorporation of various parameters, including standstill distance (CC0), time headway (CC1), and following threshold (CC3), enabling a more accurate reflection of real-world driving patterns [17].

The IDM is a model designed to maintain a safe following distance based on the cognitive reaction time and acceleration of individual vehicles. While IDMs do a good job of representing differences in perceptual reaction time, they have the limitation that the speed of a particular vehicle may be negative at certain times [18].

OVM models the instability of congested traffic, where each driver reacts to the motion of the vehicle in front and controls acceleration and deceleration to maintain a safe speed, but it does not account for reaction latency [19]. However, it has the limitation of showing unrealistically high acceleration values in some situations [20].

A review of previous studies shows that many studies have been conducted to analyze the safety of traffic flow by the introduction rate of autonomous vehicles in a mixed situation of autonomous vehicles and conventional vehicles using VISSIM, a microscopic traffic simulation, and various models, such as the Wiedemann 99 model, IDM, OVM, etc., have been used to implement the driving behavior of autonomous vehicles. However, in most of the previous studies, the driving behavior of conventional cars was not implemented to reflect the vehicle motion in the analysis section.

Therefore, in this study, we implemented the driving behavior of a regular car and an autonomous vehicle using the Wiedemann 99 model, which can apply different levels of autonomous vehicle to reflect the driver's awareness, safety, and attention, and can analyze the safety impact of autonomous vehicles in different scenarios by allowing collisions of vehicles out of longitudinal control [21]. In addition, we used a genetic algorithm to implement the driving behavior of a regular car similar to the actual driving behavior of the analysis section and, then, analyzed the safety of introducing autonomous vehicles.

3. Methodology

3.1. Research Scope

This study utilized data collected from the US I-101 highway in the United States, made publicly available by the US Department of Transportation. The data, sourced from the Next Generation Simulation (NGSIM) program, encompasses a 640 m section of the highway, comprising five main lanes and one auxiliary lane. Measurements were taken at 15 min intervals from 7:50 AM to 8:35 AM on 15 June 2005.

The dataset provides vehicle information at 0.1 s intervals for all vehicles traveling on the road. We selected the US I-101 highway data for this study as it includes an auxiliary lane that allows for frequent lane changes, making it suitable for research on the longitudinal behavior control of autonomous vehicles [22] (The data can be accessed at <http://doi.org/10.21949/1504477>, accessed on 23 May 2023). Figure 1 shows the spatial scope of the data used in this study.

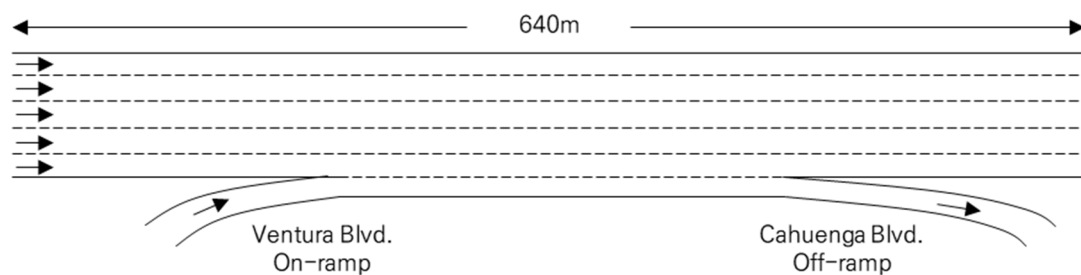


Figure 1. Spatial scope of the study.

3.2. Analysis Design

In the experimental design, we introduced the analysis simulation environment and analysis scenarios and described how to set the input variables for the driving behavior of conventional and autonomous vehicles. The simulation environment of this study is the same as that of the NGSIM data. The analysis network is a straight, continuous-flow road consisting of a five-lane main road section with a total length of 640 m and a single-lane auxiliary lane between the exit and entrance intersections.

After basic data pre-processing, such as removing outliers in speed and acceleration values, the traffic volume and spatial average speed were calculated, and it was found that 4824 vehicles were traveling during the analysis period, with a spatial average speed of 34.24 km/h. Based on the analysis results, the desired speed of the network was set at 30–50 km/h, considering the traffic conditions on the road, and the driving speed was allowed to change according to the traffic conditions. To avoid distorting the analysis results, the first 600 s of the total simulation time of 3300 s were not included in the analysis, and only the last 2700 s were analyzed.

The analysis scenarios consisted of nine scenarios, with market penetration rates (MPR) ranging from 10% to 90% in 10% increments, and five simulations were run for each scenario.

3.3. Simulation Calibration

Microscopic simulation is a realistic representation of the individual movements of vehicles in a road network and has been used for purposes such as traffic assessment. Previous researchers using microscopic simulation have conducted various studies to accurately represent the behavior of vehicles, and one of the most important steps is the calibration of the microscopic simulation model. Calibration refers to the process of calibrating the input variables of the simulation software to increase the accuracy and reliability of the microscopic simulation.

In this study, VISSIM is used as the microscopic simulation tool, and in order to increase the reliability of the simulation, the model calibration is performed in two steps. In the first step, the input variables of a regular car were estimated to derive the input

variables of an autonomous vehicle in VISSIM. The input variables and range values were determined by reviewing previous studies, and the input variables were optimized using a genetic algorithm. The second step was to configure the input parameters of an autonomous vehicle. Since the collected data were based on a regular car, this calibration process ensured that the driving behavior of the autonomous vehicle was as accurate as possible.

3.4. Human-Driving Vehicles (HDVs) Input Variable Estimation

3.4.1. VISSIM Input Variable and Range Setting

To simulate the driving behavior of a car, it is necessary to adjust various input variables, but it is difficult to derive the optimal values of all variables. Therefore, in this study, after reviewing the existing studies that calibrated the input variables of general vehicles using VISSIM, the main input variables that have the greatest influence on the driving behavior of a vehicle and the minimum and maximum values of each variable were selected as shown in Table 1. The range values of the input variables were selected within the range of the minimum and maximum values of each input variable in the existing studies.

Table 1. Driving behavior parameter range for VISSIM calibration.

Stakeholders	Park et al. (2006) [13]	Oh et al. (2018) [15]	Lee et al. (2023) [16]	Srikanth et al. (2017) [23]	He (2022) [24]	This Study
CC0, Standstill distance (m)	1.0~2.0	2.23~6.07	0.0~3.0	0.5~1.5	0.0~20.0	0.0~3.0
CC1, Headway time (s)	0.5~3.0	0.0~16.9	0.0~2.0	0.5~1.5	0.0~5.0	0.0~5.0
CC2, Car-following distance (m)	0.0~15.0	2.23~20.94	0.0~40.0	2.0~10.0	0.0~10.0	0.0~40.0
CC3, Threshold for entering following (s)	−30.0~0.0	-	-	-	−20.0~0.0	-
CC4, Negative following threshold (m/s)	−1.0~0.0	-	-	-	−5.0~0.0	-
CC5, Positive following threshold (m/s)	0.0~1.0	-	-	-	0.1~5.0	-
CC6, Speed dependency of oscillation (1/(m/s))	0.0~20.0	-	-	-	0.1~20.0	-
CC7, Oscillation during acceleration (m/s ²)	0.0~1.0	-	-	-	−1.0~1.0	-
CC8, Standstill acceleration (m/s ²)	1.0~8.0	-	-	-	0.0~8.0	-
CC9, Acceleration at 80 km/h (m/s ²)	0.5~3.0	-	-	-	0.0~8.0	-
Look-ahead distance	200~300	-	-	-	72~108	-
Observed vehicles	1~5	-	-	-	-	-
Accepted deceleration (m/s ²)	−3.0~0.2	-	-	-	-	-
LC4, Minimum headway (m)	0.1~0.9	-	-	-	-	-
Maximum deceleration for cooperative braking (m/s ²)	−5.0~−1.0	-	−9.0~0.0	-	-	−5.0~0.0
Safety-distance reduction factor	-	-	0.0~1.0	-	-	0.0~1.0

Among the input variables of the vehicle-following model, CC0, CC1, and CC2 were selected as the input variables that affect the longitudinal motion. Figure 2 illustrates the concepts of CC0 (standstill distance), CC1 (headway time), and CC2 (car-following distance). CC0 (standstill distance) is the minimum distance that a vehicle must maintain when stopped in order to maintain a safe distance from other vehicles. CC1 (headway time) is the amount of headway the car wants to maintain with the car in front of it. CC2 (car-following distance) is the safe following distance ($CC0 + CC1 \times \text{vehicle speed}$) plus an additional buffer.

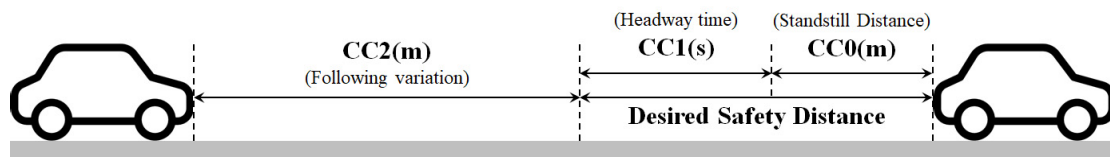


Figure 2. Example of parameter set for Wiedemann 99 model.

Maximum deceleration for cooperative braking and safety-distance reduction factor were selected as the input variables with the greatest influence on lateral movement. Maximum deceleration for cooperative braking is the maximum deceleration of the vehicle when changing lanes, and the safety-distance reduction factor is the percentage of the safety distance that is reduced when changing lanes. During the analysis, all but five of the input variables were set to their default values in VISSIM.

3.4.2. Optimizing VISSIM Input Variables with Genetic Algorithms

A genetic algorithm is an algorithm that finds a more appropriate combination of variables to satisfy an objective function and is often used to find the optimal value among a large number of cases. In this study, the process of using genetic algorithms to find the optimal values of the VISSIM input variables is shown in Figure 3.

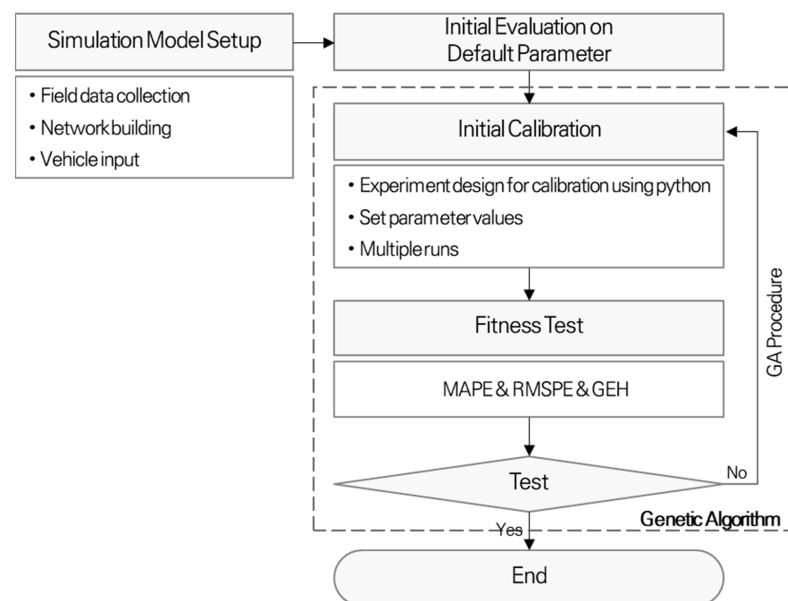


Figure 3. VISSIM input variable optimization process using genetic algorithm.

First, VISSIM 2023 was used to build the same network as the NGSIM data and input data such as vehicles. Second, using Python (v. 3.7), the values of each input variable are randomized and entered into VISSIM, and the effectiveness measures MAPE (mean absolute percentage error), RMSPE (root mean square percentage error), and GEH statistic are calculated. Equations (1)–(3) show the formulas for these three measures of effectiveness. The third step is to examine the convergence conditions of the impact measures and select the combination of input variables that gives the best impact measure values. The convergence conditions of the impact measures are 0.05 or less for MAPE and RMSPE and 5 or less for the GEH used in traffic analysis models, and if the conditions converge, the level of simulation is considered reasonable [16]. If the convergence condition is not met, a new combination is generated and returned to the second step until the convergence condition is met.

In the genetic algorithm analysis, the unit of value for finding the optimal solution was changed to 0.01 to generate a large number of cases, and the number of generations was

set to 10 generations, 20 populations, 10% population mutation probability, and 50% gene mutation probability.

$$MAPE = \frac{1}{2} \left(\left| \frac{\hat{v} - v}{\hat{v}} \right| + \left| \frac{\hat{t} - t}{\hat{t}} \right| \right) \quad (1)$$

$$RMSPE = \sqrt{\frac{1}{2} \left[\left(\frac{\hat{v} - v}{\hat{v}} \right)^2 + \left(\frac{\hat{t} - t}{\hat{t}} \right)^2 \right]} \quad (2)$$

$$GEH = \sqrt{\frac{2(\hat{v} - v)^2}{\hat{t} + t}} \quad (3)$$

where, $\hat{v}$ = average traffic speed derived from NGSIM data, v = average traffic speed from simulation, $\hat{t}$ = traffic volume derived from NGSIM data, and t = traffic volume derived from simulation.

The results of the analysis of the optimal values for the five input variables using the genetic algorithm are shown in Table 2. The analysis resulted in a CC0 of 2.75, CC1 of 3.28, CC2 of 13.07, maximum deceleration for cooperative braking of -3.18 , and safety-distance reduction factor of 0.46. After analyzing the effectiveness measures using these input variables, the MAPE and RMSPE values are 0.002, and the GEH is 0.130, indicating that the traffic volume and average traffic speed are very similar to the actual driving behavior of the NGSIM data.

Table 2. Calibration analysis results of VISSIM parameters for HDVs.

Variation	Value	MAPE	RMSPE	GEH
CCO, Standstill distance (m)	2.75			
CC1, Headway time (s)	3.28			
CC2, car-following distance (m)	13.07	0.002	0.002	0.130
Maximum deceleration for cooperative braking (m/s^2)	-3.18			
Safety-distance reduction factor	0.46			

3.5. Setting Autonomous-Vehicles (AVs) Input Variables

In a review of studies that have implemented the driving behavior of autonomous vehicles using VISSIM, the input variables proposed in Atkins (2016) [25] have been used in many papers [8,26,27]. Since the autonomous vehicles in this study are Lv.4 or higher, we used the input variables for Lv.4 autonomous vehicles presented in Atkins (2016) [25] as shown in Table 3, and set CC2, CC4, CC5, and CC6, which reflect human behavior, to zero [28].

Table 3. Driving behavior parameter value of autonomous vehicles.

Variation	Value
CCO, Standstill distance (m)	0.5
CC1, Headway time (s)	0.6
CC2, Car-following distance (m)	0
CC4, Negative following threshold (m/s)	0
CC5, Positive following threshold (m/s)	0
CC6, Speed dependency of oscillation ($1/(m/s)$)	0
CC7, Oscillation during acceleration (m/s^2)	0.4
CC8, Standstill acceleration (m/s^2)	3.8
CC9, Acceleration at 80 km/h (m/s^2)	1.8
LC4, Minimum headway (m)	0.2
LC5, Safety-distance reduction factor	0.3
MG1, Minimum time gap (s)	2.4
MG2, Minimum headway (m)	3.5

3.6. Evaluation Indicator Selection

We used time to collision (TTC), one of the surrogate safety measures, as a metric to analyze traffic safety. TTC is the minimum time for a collision between a trailing vehicle and a leading vehicle to occur if both vehicles are traveling at the current speed at the current location, as shown in Equation (4), and the smaller the value, the higher the risk.

$$TTC_i = \frac{x_j(t) - x_i(t)}{v_j(t) - v_i(t)} \quad (4)$$

where, $x_j(t)$ = position coordinates (x,y) of car j at time t , $v_j(t)$ = vehicle j's speed at time t , $x_i(t)$ = position coordinates (x,y) of vehicle i (the following vehicle in the same lane or the lane-changing lane closest to vehicle j) at time t , and $v_i(t)$ = the speed of vehicle i (the following vehicle in the same lane or the lane-changing lane closest to vehicle j) at time t .

In this study, we set the threshold of 0.9 s [29] or less to be considered as a high risk of accident and affect road safety and used the Surrogate Safety Assessment Model (SSAM) program for analysis. We also assumed that autonomous vehicles can avoid dangerous situations, so we only considered cases where a regular car is the trailing vehicle in the analysis.

The TTC is the minimum time for a collision to occur if both vehicles are traveling at the current speed at the current location, and a TTC of 0 s versus 0.9 s is the difference in the probability of avoiding a collision. The probability of avoiding a collision with a pedestrian based on the TTC value is as follows [30]. In this study, these criteria are used to categorize vehicles from one to four, which we define as conflict risk (Table 4).

Table 4. Conflict Risk Classification.

Category	Range	Conflict Risk Level
TTC 1	$0 \leq TTC \leq 0.3$ s	It is impossible to avoid the collision.
TTC 2	$0.3 \leq TTC \leq 0.5$ s	A collision can be avoided by swerving while braking.
TTC 3	$0.5 \leq TTC \leq 0.7$ s	Collision can be avoided by swerving only.
TTC 4	$0.7 \leq TTC \leq 2.0$ s	Collision can be avoided only by braking.

4. Results

4.1. Operational Efficiency Analysis

In this study, we analyzed nine scenarios with MPRs ranging from 10 to 90% in 10% increments, and the results are presented in Table 5.

Table 5. Average speed and traffic volume by MPR.

MPR (%)	Average Speed (km/h)	Average Traffic Volume (veh/h)
10	41.96	4643
20	41.48	4958
30	41.01	5305
40	40.50	5526
50	39.98	5785
60	39.47	6139
70	38.97	6408
80	38.48	6415
90	37.98	6418

Before analyzing the number of conflicts under the TTC, we analyzed the through-traffic volume and average travel speed by MPR. It was found that, as the MPR of autonomous vehicles increases, the through-traffic volume increases and the average speed decreases. This is due to the fact that autonomous vehicles have a shorter safety distance and following distance than conventional vehicles, so there are more vehicles on the road.

4.2. Traffic Safety Analysis Results

4.2.1. Number of Conflicts Analysis

As shown in Table 6, when analyzing the number of collisions per case, we found that the overall number of collisions increases until the adoption rate of autonomous vehicles reaches 20%, while the number of collisions between conventional vehicles and autonomous vehicles increases until the adoption rate of autonomous vehicles reaches 30%. This is similar to previous studies [31], which have shown that the number of collisions between autonomous vehicles and conventional vehicles increases up to a TTC threshold of 25%, and then decreases above 25%.

Table 6. Number of conflicts by case (unit: times).

Case	HDV-HDV Conflicts			HDV-AV Conflicts				Total			
	Side	Rear	Sum	HDV-AV		AV-HDV		Sum	Side	Rear	Sum
				Side	Rear	Sum	Side				
MPR 10%	55.4	113.8	169.2	0.8	4.6	5.4	43.6	49.0	99.8	118.4	218.2
MPR 20%	137.8	541.6	679.4	19.2	129.2	148.4	36.8	185.2	193.8	670.8	864.6
MPR 30%	57.6	81.0	138.6	7.4	19.0	26.4	174.0	200.4	239.0	100.0	339.0
MPR 40%	3.4	42.8	46.2	1.2	21.8	23.0	48.6	71.6	53.2	64.6	117.8
MPR 50%	2.2	35.0	37.2	0.8	24.6	25.4	32.2	57.6	35.2	59.6	94.8
MPR 60%	0.2	17.6	17.8	0.2	27.2	27.4	11.6	39.0	12.0	44.8	56.8
MPR 70%	0.2	11.2	11.4	0.0	22.2	22.2	7.4	29.6	7.6	33.4	41.0
MPR 80%	0.0	5.2	5.2	0.0	17.4	17.4	3.6	21.0	3.6	22.6	26.2
MPR 90%	0.0	2.0	2.0	0.0	10.4	10.4	1.2	11.6	1.2	12.4	13.6

4.2.2. Conflict Risk Analysis

Conflict risk analysis analyzes how dangerous each case is, and in this study, we analyzed the risk level according to the TTC value. As detailed in Table 7, the results of analyzing the number of conflicts between autonomous vehicles and conventional vehicles by conflict risk level showed that conflicts with conflict risk level 1 accounted for about 50.5–100.0% of the total number of conflicts per case in all cases, indicating a very high probability of accidents. In addition, the number of conflicts with conflict risk level 1 decreased steadily as the adoption rate of autonomous vehicles increased after 20%.

Table 7. Conflict risk analysis results by case (HDV-HDV) (unit: times).

Case	Side Collision				Rear Collision				Total			
	TTC 1	TTC 2	TTC 3	TTC 4	TTC 1	TTC 2	TTC 3	TTC 4	TTC 1	TTC 2	TTC 3	TTC 4
MPR 10%	45.4	4.6	4.2	1.2	105.4	3.0	2.8	2.6	150.8	7.6	7.0	3.8
MPR 20%	80.6	21.4	22.8	13.0	262.6	35.4	85.6	158.0	343.2	56.8	108.4	171.0
MPR 30%	42.8	6.2	5.8	2.8	72.8	1.8	4.6	1.8	115.6	8.0	10.4	4.6
MPR 40%	2.0	0.6	0.4	0.4	38.6	1.0	0.6	2.6	40.6	1.6	1.0	3.0
MPR 50%	1.4	0.4	0.2	0.2	31.8	1.2	1.4	0.6	33.2	1.6	1.6	0.8
MPR 60%	0.2	0.0	0.0	0.0	16.6	0.6	0.2	0.2	16.8	0.6	0.2	0.2
MPR 70%	0.0	0.2	0.0	0.0	10.2	0.4	0.2	0.4	10.2	0.6	0.2	0.4
MPR 80%	0.0	0.0	0.0	0.0	4.8	0.0	0.2	0.2	4.8	0.0	0.2	0.2
MPR 90%	0.0	0.0	0.0	0.0	2.0	0.0	0.0	0.0	2.0	0.0	0.0	0.0

As shown in Table 8, when analyzing the number of conflicts between autonomous vehicles and conventional vehicles by conflict risk level, it was found that conflicts with conflict risk level 1 accounted for approximately 49.4 to 93.3% of the total number of conflicts per case in all cases. In addition, when analyzing the number of conflicts with conflict risk level 1, it was found that the number of conflicts with conflict risk level 1 increased steadily until the adoption rate of autonomous vehicles increased to 30%, in contrast to the results of the analysis of conflicts between conventional vehicles.

Table 8. Conflict risk analysis results by case (HDV-AV) (unit: times).

Case	Side Collision				Rear Collision				Total			
	TTC 1	TTC 2	TTC 3	TTC 4	TTC 1	TTC 2	TTC 3	TTC 4	TTC 1	TTC 2	TTC 3	TTC 4
MPR 10%	19.8	7.0	11.0	6.6	4.4	0.0	0.0	0.2	24.2	7.0	11.0	6.8
MPR 20%	29.0	10.0	10.8	6.2	66.8	9.0	17.4	36.0	95.8	19.0	28.2	42.2
MPR 30%	89.6	26.4	38.2	27.2	17.4	0.2	1.0	0.4	107.0	26.6	39.2	27.6
MPR 40%	30.2	6.2	8.8	4.6	20.8	0.6	0.2	0.2	51.0	6.8	9.0	4.8
MPR 50%	19.4	5.0	4.8	3.8	23.4	0.6	0.2	0.4	42.8	5.6	5.0	4.2
MPR 60%	6.8	1.4	1.8	1.8	24.4	1.2	0.6	1.0	31.2	2.6	2.4	2.8
MPR 70%	5.0	1.4	0.8	0.2	20.4	0.6	0.8	0.4	25.4	2.0	1.6	0.6
MPR 80%	2.6	0.0	1.0	0.0	17.0	0.0	0.0	0.4	19.6	0.0	1.0	0.4
MPR 90%	0.6	0.4	0.2	0.0	10.0	0.0	0.0	0.4	10.6	0.4	0.2	0.4

4.3. Design of Exclusive Lane for AVs

An analysis of mixed traffic safety on a 640 m stretch of the I-101 highway in the United States found that, as the adoption rate of autonomous vehicles increases, through traffic increases and the number of conflicts decreases. However, when analyzing conflicts between conventional vehicles and autonomous vehicles, the number of conflicts increases as the adoption rate increases until the adoption rate of autonomous vehicles reaches 30%.

When the adoption rate of autonomous vehicles is 20%, it is necessary to reduce the risk of rear-end collisions between conventional vehicles and autonomous vehicles and side collisions when the leading vehicle is an autonomous vehicle and the trailing vehicle is a conventional vehicle. When the adoption rate of autonomous vehicles is 30%, it is necessary to reduce the risk of side collisions when the leading vehicle is a conventional vehicle and the trailing vehicle is an autonomous vehicle.

Therefore, until the adoption rate of autonomous vehicles reaches 30%, it was determined that it is necessary to operate an autonomous vehicle lane that separates conventional vehicles from autonomous vehicles in order to minimize conflicts between conventional vehicles and autonomous vehicles. As presented in Table 9, based on the results of the operational efficiency analysis, we calculated the traffic volume of autonomous vehicles according to the adoption rate of autonomous vehicles using the passing traffic volume and, then, calculated the traffic volume according to the number of lanes in the autonomous-vehicle lane. The number of lanes for autonomous-vehicle lanes was also examined until the ratio of traffic per lane for general vehicles and autonomous-vehicle lanes was 1:1.

Table 9. Design exclusive lanes for AVs (unit: veh/lane).

Case	Mixed-Flow Road	Operate 1 Exclusive Lane for AV		Operate 2 Exclusive Lanes for AV	
		HDV Lane	Ex. Lane for AV	HDV Lane	Ex. Lane for AV
MPR 10%	929	1045	464	1393	232
MPR 20%	992	992	992	1322	496
MPR 30%	1061	928	1592	1238	796

Finally, the operational options to be considered when establishing the operational plan for the autonomous-vehicle lane for the spatial scope of this study are illustrated in Figure 4. These options include one and two lanes, if the autonomous vehicle lane is on the left, and one and two lanes if the autonomous vehicle lane is on the right.

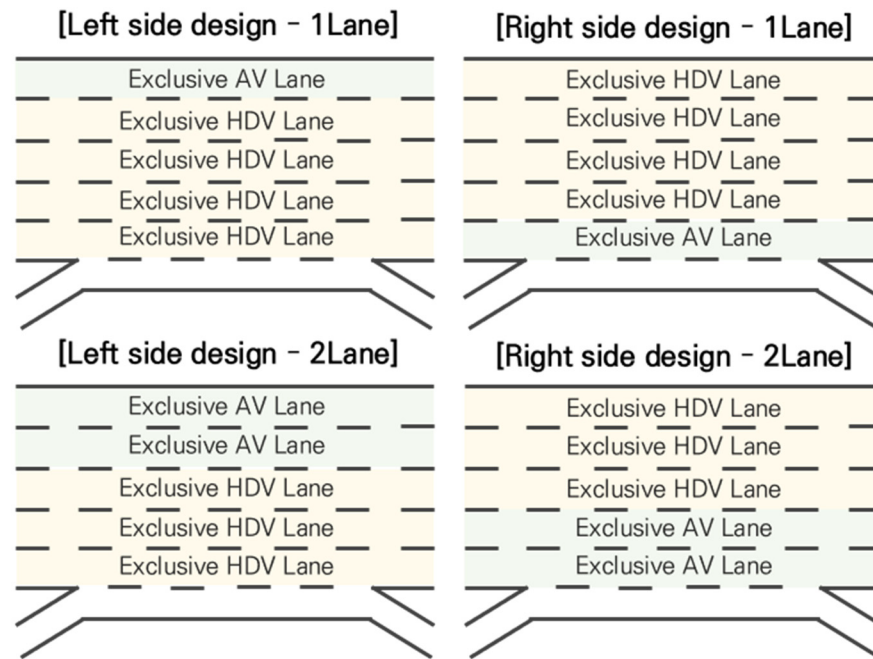


Figure 4. Design of exclusive lane for AVs.

When the number of conflicts was analyzed for the four autonomous-vehicle lane design options, as presented in Table 10, the lowest number of conflicts was found when the autonomous-vehicle lane was installed with two lanes on the left side. In addition, the number of conflicts was lower when the autonomous-vehicle lane was designed on the left side than when it was designed on the right side, and the number of conflicts was higher when the autonomous-vehicle lane was designed on the right side than when the autonomous vehicle lane was designed on the left side.

Table 10. Safety assessment results by exclusive AV lane operation plan (unit: times).

Case	Mixed Flow			1 Lane (Left)			2 Lanes (Left)			1 Lane (Right)			2 Lanes (Right)		
	HDV-HDV	HDV-AV	Sum	HDV-HDV	HDV-AV	Sum	HDV-HDV	HDV-AV	Sum	HDV-HDV	HDV-AV	Sum	HDV-HDV	HDV-AV	Sum
MPR 10%	169.2	49.0	218.2	153.6	4.2	157.8	133.8	3.6	137.4	132.0	83.2	215.2	265.0	75.4	340.4
MPR 20%	679.3	185.2	864.6	141.0	21.8	162.8	117.4	9.2	126.6	120.2	194.8	315.0	203.0	118.4	321.4
MPR 30%	138.6	200.4	339.0	126.0	44.2	170.2	100.0	17.4	117.4	107.2	268.0	375.2	115.2	136.6	251.8

Designing a dedicated lane on the right side of the road resulted in fewer conflicts for one lane of autonomous vehicles than for two lanes of autonomous vehicles until the adoption rate of autonomous vehicles reached 20%. This is likely due to the fact that the on-ramp is located on the right side, which requires more vehicles to change lanes from the main road to the on-ramp or from the on-ramp to the main road compared to a lane dedicated to autonomous vehicles on the left side or a mixed-use road. In addition, when comparing the two right-lane options, the number of HDV-AV conflicts was higher when the adoption rate of autonomous vehicles was 10% than when the right lane was two lanes. This is because when the adoption rate of autonomous vehicles is 20% or higher, the traffic volume per lane is analyzed, and it is relatively difficult for entering and exiting vehicles to change lanes due to the higher traffic volume in the lane dedicated to autonomous vehicles compared to the lane dedicated to regular vehicles, which causes more rear-end conflicts when the trailing vehicle is a regular vehicle.

Therefore, in the spatial scope of this study, it is recommended to install two lanes on the left side of the autonomous-vehicle lane until the adoption rate of autonomous vehicles reaches 30%.

To analyze the traffic aspect, we analyzed the average traffic speed of the main road for each autonomous-vehicle lane operation plan, as presented in Table 11. We found that the average traffic speed is similar at about 40.43 km/h regardless of the autonomous-vehicle lane operation plan. This indicates that the lane change of entering and exiting vehicles does not have a significant impact on traffic.

Table 11. Operational efficiency evaluation results by exclusive AV lane operation plan (Unit: km/h).

Case	Mixed-Flow	1 Lane (Left)	2 Lanes (Left)	1 Lane (Right)	2 Lanes (Right)
MPR 10%	40.44	40.45	40.45	40.45	40.46
MPR 20%	40.45	40.41	40.40	40.43	40.44
MPR 30%	40.44	40.42	40.42	40.43	40.44

Dedicated lanes for autonomous vehicles have the potential to enhance road safety while maintaining average travel speeds comparable to those on mixed-flow roads. Consequently, until the adoption rate of autonomous vehicles reaches 30%, and there exists a high risk of conflict between AVs and regular vehicles, implementing dedicated autonomous-vehicle lanes emerges as a favorable road management strategy.

In other words, as illustrated in Figure 5, when the adoption rate of autonomous vehicles is between 40 and 90 percent, the risk of accidents between autonomous vehicles and regular cars will be reduced, and the traffic volume of autonomous vehicles will be higher than that of regular cars. So, it may be preferable to operate mixed-use roads so that autonomous vehicles and regular cars can drive together, rather than operating lanes for autonomous vehicles.

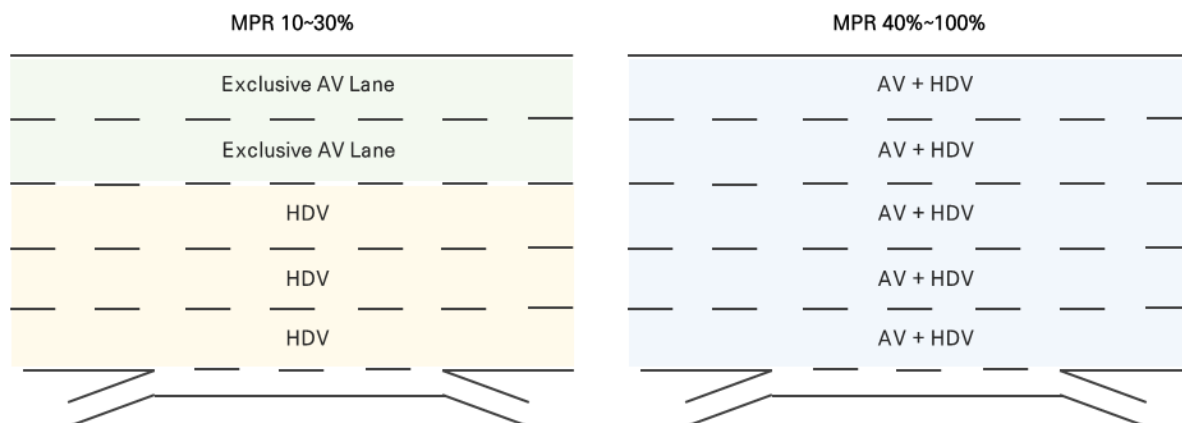


Figure 5. How to operate autonomous-vehicle lanes on US I-101 highway.

5. Conclusions

In this study, we analyzed the safety of traffic flow according to the introduction rate of autonomous vehicles using micro-traffic simulation on a 640 m section of the US I-101 highway. In the implementation of VISSIM, the input variables of regular cars were implemented similarly to the actual driving behavior using a genetic algorithm, and the driving behavior of autonomous vehicles was implemented by deriving the input-variable values by reviewing previous studies. The analysis was repeated five times for a total of nine scenarios according to the change in the MPR of autonomous vehicles.

When analyzing the number of conflicts between regular cars and autonomous vehicles, we found that the total number of conflicts increased with the adoption rate until the adoption rate of autonomous vehicles reached 30%. But, after 40%, the number of conflicts continuously decreased, as the adoption rate of autonomous vehicles increased. This is likely due to the assumption that autonomous vehicles are able to avoid dangerous situations, so as autonomous-vehicle traffic increases, conventional vehicle traffic decreases.

When analyzing the number of side collision conflicts when the lead vehicle is a conventional vehicle and the autonomous vehicle is a trailing vehicle, the total number of conflicts increased as the adoption rate of autonomous vehicles increased up to 30%. But, after 40%, the number of conflicts continuously decreased as the adoption rate of autonomous vehicles increased. However, when the lead vehicle was an autonomous vehicle, the number of rear-end collisions increased between 30 and 60 percent of autonomous-vehicle adoption. This is likely due to the fact that autonomous vehicles allow for faster acceleration and faster acceleration from a stop compared to conventional vehicles, and these rapid changes in behavior may affect the collision with the trailing conventional vehicle.

Furthermore, when analyzing the risk level according to the TTC value, it was found that the number of conflicts between autonomous vehicles and conventional vehicles with a risk level of one accounted for about 49.493.3% of the total number of conflicts, indicating a very high accident risk, and the number of conflicts with a risk level of one continued to increase until the adoption rate of autonomous vehicles reached 30%. Therefore, when the adoption rate of autonomous vehicles is 10–30%, it is considered necessary to consider the implementation of autonomous lanes that separate autonomous vehicles from conventional vehicles.

Accordingly, the number of conflicts was analyzed for a total of four autonomous lane design options, and it was found that the number of conflicts was lowest when the autonomous lane was installed with two lanes on the left until the adoption rate of autonomous vehicles reached 30%. Therefore, in the spatial scope of this study, it is recommended to install two lanes on the left until the adoption rate of autonomous vehicles is 30%. When the adoption rate of autonomous vehicles is between 40 and 90 percent, the risk of accidents between autonomous vehicles and conventional vehicles decreases, and the traffic volume of autonomous vehicles is higher than that of conventional vehicles. So, it is recommended to operate mixed-use roads so that autonomous vehicles and conventional vehicles can drive together, instead of operating lanes for autonomous vehicles.

This study has the following limitations. First, the driving behavior of autonomous vehicles is based on the results in the existing literature, which do not fully represent the actual driving behavior of autonomous vehicles. Therefore, future studies should reflect the actual driving behavior of autonomous vehicles. Second, the spatial scope of this study is limited to the US I-101 highway, which does not simulate the driving behavior and traffic volume of general vehicles on different road types. Future studies should utilize diverse datasets, such as LevelXData, which provides driving-trajectory data for various road types, and conduct sensitivity analyses under different scenarios and geometric conditions to reflect real-world driving behavior and enhance the generalizability of the findings.

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