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Research article

Evaluating the environmental impact on connected vehicles during freeway accidents using VISSIM with probe vehicle data

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Abstract: We evaluated emissions as an environmental effect resulting from connected vehicles (CVs) during freeway accidents. The CVs were used to determine the CV driving characteristics, whose values were used to implement the CV driving pattern using a microscopic traffic simulation. The environmental effect of implementation of CV was evaluated using the vehicle trajectory data derived from the simulation results. Implementation of CV effectively minimized the vehicle emissions regardless of the market penetration rate (MPR). In terms of vehicle type, the emissions reduction rate of passenger cars was the highest at a maximum of 33.4%. In the case of pollutants, the reduction rate of CO based on all vehicles was the highest at a maximum of 28.8%. Overall, we found that the implementation of CV positively affected vehicle emissions reductions, and an MPR of 60% could maximize the vehicle emissions reduction effect.

Keywords: connected vehicle; traffic simulation; vehicle emissions; traffic accidents; probe vehicle data

1. Introduction

A connected vehicle (CV) is a vehicle that is capable of wireless connection communication with the inside and outside environment of the vehicle through vehicle-to-X (V2X) interaction and includes applications and technologies [1]. CV technology is developing worldwide, and related services include warnings/notifications of forward danger, speed limits, road work zones, weather information, and accident danger zones. Many studies have analyzed the impact of CV services, which can be broadly categorized into safety, mobility, and environment. Most researchers have focused on analyzing the effects of safety and mobility while providing forward safety information. However, the environmental aspects of CV services have received limited scholarly attention.

Studies on the transportation environment have focused on fuel consumption and emissions. To estimate vehicle fuel consumption, a platoon-level optimal signal control strategy was implemented to minimize the fuel consumption of a CV or connected autonomous vehicle (CAV) in the case of interrupted flow [2–4]. Li et al. proposed a non-signalized intersection passing control model for V2V communication based on deep reinforcement learning [5]. For continuous flows, Apostolakis et al. discussed the effects of applying adaptive cruise control (ACC) to CAVs on freeways [6]. The implementation of CV or CAV effectively reduces the fuel consumption for interrupted and uninterrupted flows. However, this effect is offset in proportion to the closeness of the market penetration rate (MPR) of CV or CAV to 100%.

To increase the operational efficiency of the intersection within interrupted flows, studies based on vehicle emissions have analyzed the effects of introducing connected vehicle- or platoon-based intersection management systems [7–9]. Other studies have estimated vehicle emissions reductions by installing intelligent intersections or controlling signals [10–13]. Studies have also analyzed vehicle emissions from a vehicle behavior perspective, basing their analyses on vehicle movement when providing information regarding upcoming traffic conditions or optimal speeds to drivers [14–19]. Some of these studies analyzed vehicle emissions by considering the CV MPR [18,19]. Various studies have proposed real-time optimal lanes and routes to maintain speed [20,21]. For uninterrupted flow, vehicle emissions were estimated on freeways by investigating optimal lanes and variable speeds according to the upcoming traffic conditions and providing forward hazard warnings [22–24]. Technical aspects, such as the appropriate number of CV connections and roadside unit (RSU) placement, have also been analyzed [25,26]. Based on the implementation of CV, emissions were analyzed depending on the road type, such as freeway, residential area, commercial area, or freeway, urban, and rural area [27,28]. Similar to the results of previous research on fuel consumption, the emissions reduction effect increased and before decreasing with increasing MPR.

Most researchers have analyzed vehicle emissions by considering CV-based traffic operation techniques, whereas congested traffic flows and traffic congestion caused by accidents have received limited scholarly attention. Freeway incident management is essential because the accidents temporarily reduce the freeway capacity, cause congestion, and increase vehicle emissions [29]. Ahn analyzed emissions from freeway accidents using the cases of a one-lane freeway accident and route conversion from a freeway, with regular vehicles (RVs), to the main road [30]. We primarily analyzed the effect of vehicle emissions by considering the CV MPR during a freeway accident. For the analysis, we extracted the driving characteristics of the CV when providing the collision prevention service from actual CV driving data to reflect driving behavior similar to that seen in reality.

This study is organized as follows: The next section describes the analysis methodology. Section 2 presents the results of simulation analyses for each scenario. Section 3 discusses the analysis results, and the final section presents the conclusions.

2. Methodology

The CV driving characteristics were defined by analyzing the probe vehicle data (PVD), which were collected depending on whether V2V-based collision prevention services were provided to the

CVs. These characteristics were implemented in VISSIM [31], a microscopic traffic simulation, to reflect driving patterns. Based on the simulation results, the environmental effects with respect to variations in the CV MPR were evaluated using a MOVES, which is motor vehicle emission simulator (MOVES) [32]. The overall evaluation procedure is illustrated in Figure 1.

Figure 1. Overall research procedure.

2.1. Scenario

In this study, PVD collected from vehicles receiving CV services on freeways were used to reflect the driving patterns of CVs. PVD refers to vehicle status, location, and driving information collected in a wireless communication environment [33]. Among the services provided in the freeway C-ITS implementation project by Korea Expressway Corporation, we analyzed the effect of the V2V-based collision prevention service that most closely matches the purpose of the CV service (i.e., traffic safety and mobility enhancement) [34]. A total of 22 scenarios were created considering accident severity and the MPR of CV to evaluate the environmental improvement effect of providing a V2V-based crash prevention service. The accident severity was divided into one blocked lane and two blocked lanes according to the occurrence of the accident. Scenarios were set by dividing the MPR from 0 to 100% in 10% increments.

Table 1. Scenario setting.

Accident severity	One blocked lane										
Scenario no.	1	2	3	4	5	6	7	8	9	10	11
MPR of CV	MPR 0% (Baseline)	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Accident severity	Two blocked lanes										
Scenario no.	12	13	14	15	16	17	18	19	20	21	22
MPR of CV	MPR 0% (Baseline)	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%

2.2. Defining CV driving characteristics

An individual CV that receives warning information about dangerous situations ahead performs avoidance behaviors, such as decelerating, increasing the inter-vehicle distance, and increasing the headway time. In addition, a CV that receives V2V-based warning information shows improved driving behaviors, such as observing the speed limit, reducing sudden acceleration and deceleration, and performing lane changes in advance, compared to a regular vehicle (RV) that does not receive warning information. In this study, we defined the change in behavior of an individual vehicle and the effect of improving driving behavior resulting from providing warning information as driving characteristics of CV. The behavioral changes and driving behavior improvement effects of CV were used as the basis for adjusting the driving behavior parameters in microscopic traffic simulation. As shown in Figure 2, we explored which driving behavior parameters in microscopic traffic simulation can be adjusted in order to change CV behaviors and improve driving behaviors.

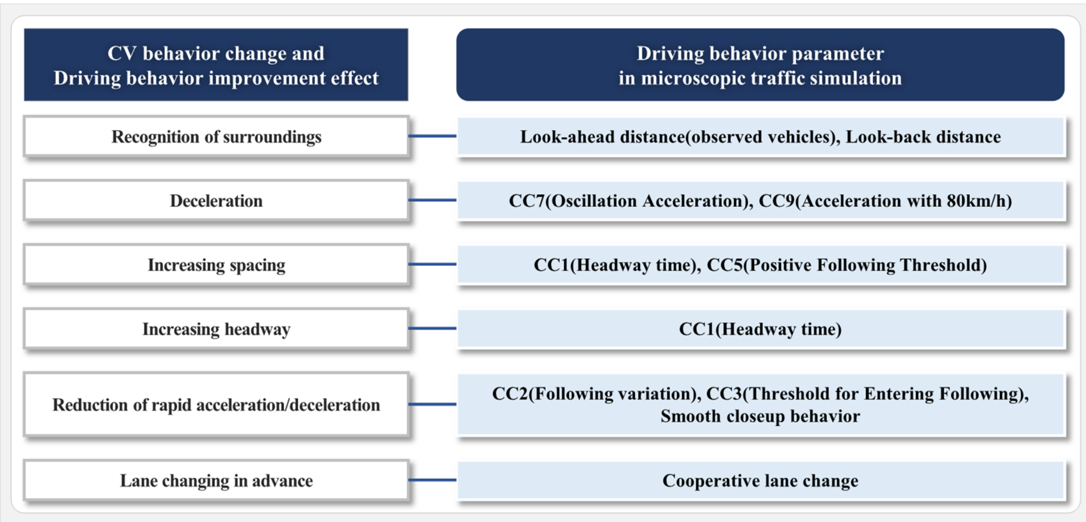


Figure 2. Selected behavior parameters to simulate driving behavior characteristics of CV using VISSIM.

To apply the conditions for providing real-time warning information, the parameters for the look-ahead (observed vehicles) and look-back distances were selected. The decrease in acceleration resulting from the delivery of warning information was incorporated by selecting CC9 (acceleration at 80 km/h), which is the preset acceleration when the vehicle approaches a speed of 80 km/h. CC5 (positive following threshold) and CC2 (following variance) were selected to account for the reduction in speed deviation and increment in vehicle spacing, respectively. CC1 (headway time) and CC3 (threshold for entering following) were selected to consider the driving characteristics with increasing headway time. CC7 (oscillation acceleration) and smooth close-up behavior options were selected to apply the reduction effect during sudden acceleration and deceleration. The cooperative lane-change feature represented the behavior of changing lanes in advance.

In this study, freeway PVD were analyzed to compare the driving behaviors of CV and RV when V2V warning information was provided. The analyzed results were reflected when adjusting the driving behavior parameters in microscopic traffic simulation to realize the driving characteristics of the CV. Among the CV services, we analyzed the effect of the V2V-based collision prevention service and reflected the results in the implementation of CV behavior. A collision prevention service provides warning information to drivers in advance based on V2V communication to induce avoidance behaviors, such as decelerating, increasing the following distance, and changing lanes in advance. When a risk of a collision occurs due to a decrease in spacing between the preceding vehicle and the following vehicle and an increase in relative speed due to a sudden stop of the preceding vehicle, the onboard unit of the following vehicle determines whether to provide information [35]. This application provides warning information based on the expected time-to-collision (TTC) [36,37], which was computed using the position and speed data of the subject vehicle along with the maneuvering behavior (MB) of the preceding vehicle. The TTC is calculated by Eq (1) [38].

$$\mathrm{TTC} = \frac{d}{v_2 - v_1} \tag{1}$$

where v_1 and v_2 are the speeds of vehicle1 and vehicle2, respectively, and d is the distance between them.

As shown in Figure 3, warning information is provided and warning information zones are categorized into the following three stages based on the risk points and vehicle position by computing the TTC: Zone 3 (caution zone), Zone 2 (warning zone), and Zone 1 (alert zone) [39].

Figure 3. Defining zones to provide warning information for collision prevention services.

The spatial range of the PVD analysis was the 85.4 km section of the Korean freeway CV pilot project, from Giheung-Dongtan Interchange (IC) to Yangjae IC on the Gyeongbu Freeway, from Sangil IC to Jonam Junction (JC) on the Sudogwon Je1sunhwan Freeway, and from Gwangju IC to Hanam JC on the Jungbu Freeway.

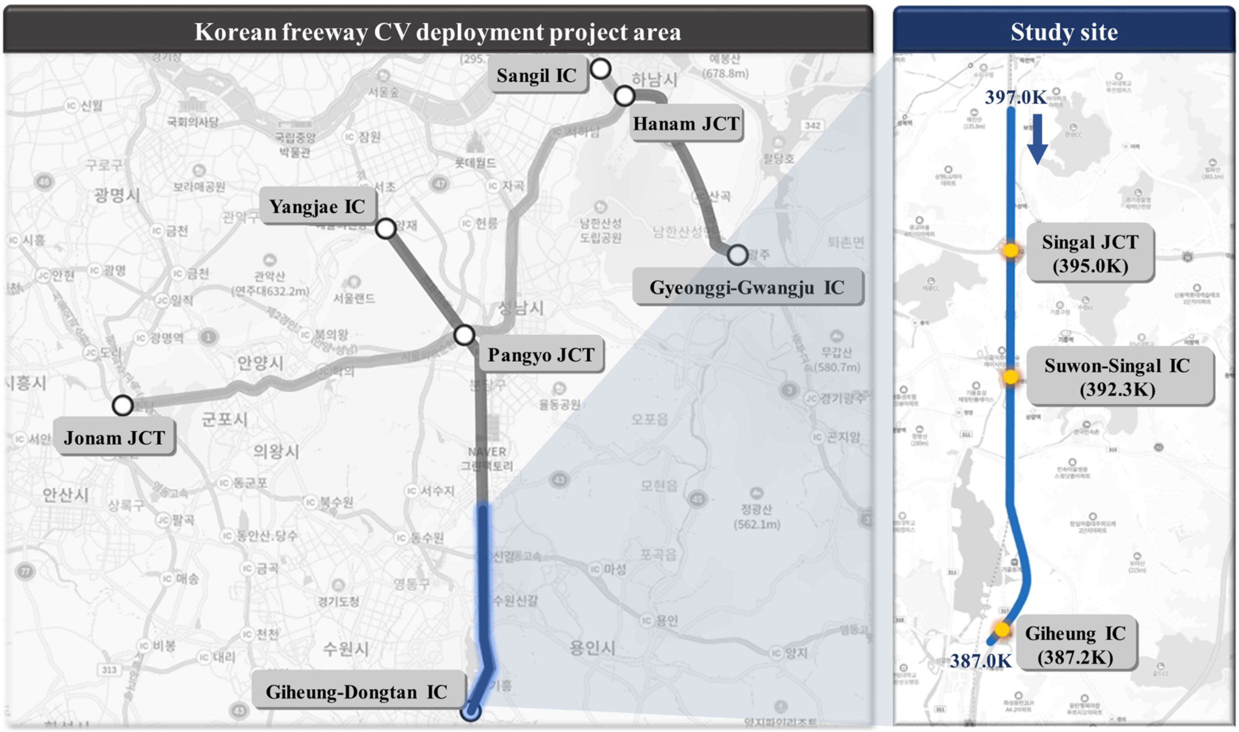


Figure 4. Study site.

When analyzing PVD, we defined "Without" as the cases where V2V-based collision prevention services were not provided and "With" as the cases where V2V-based collision prevention services were provided. The Without data collected from February 16, 2019 to March 17, 2019, and the With data collected from July 17, 2019 to July 31, 2020 were collected and used for analysis. The PVD collected from onboard units installed on 400 buses, 264 trucks, and 36 sport utility vehicles (SUVs) were analyzed. The PVD used in the analysis were a combination of raw PVD, Digital Tacho Graph (DTG) data, and Vehicle ADAS data. The ADAS data included ADAS information such as driving characteristics, service event display information, headway time, and expected collision time.

Prior to analysis, valid samples were defined to utilize the high-quality data from the collected PVD with outliers below a certain level. These samples were extracted according to the following three principles based on when the warning information was displayed: (i) No intervention from other services for 30 s prior to providing the V2V-based forward collision warning information; (ii) existence of at least 30 observed data points for 60 and 30 s before and after providing the information, respectively; and (iii) existence of at least 15 data points 30 s before and after providing the information. A valid sample was considered for analysis only if all the three conditions were satisfied, and the data obtained during the 30 s after providing the V2V-based forward collision warning information was used.

The PVD was analyzed to adjust the driving behavior parameters in a microscopic traffic simulation. Consequently, the speed standard deviation, average spacing, average acceleration, acceleration standard deviation, and average headway were analyzed according to the "Without" and "With" situations of the V2V-based collision prevention services. If a lane change was performed after the warning information was provided, the speed decreased, and the following distance increased, it was defined as a pre-lane change pattern. The number of data values showing the pre-lane change pattern were aggregated to calculate the ratio of the number of pre-lane-change data values to the total number of data values. Additionally, the increase and decrease rate was calculated for the pre-lane change and the CV driving pattern was derived. Table 2 shows the PVD analysis results based on the driving behavior parameters.

Table 2. PVD analysis results for each driving behavior parameter.

Driving behavior indicators	Actual PVD			Driving behavior parameters for VISSIM
	Without	With	Δ (change ratio)	
Std. of speed	7.09 km/h	4.50 km/h	-36.45%	CC5
Avg. of spacing	43.06 m	53.34 m	+23.85%	CC2
Avg. of acceleration	0.41 m/s²	0.39 m/s²	-5.81%	CC9
Std. of acceleration	0.39 m/s²	0.35 m/s²	-15.62%	CC7 Smooth closeup behavior
Avg. of headway time	2.26 s	2.66 s	+17.86%	CC1 CC3
Rate of early lane change	47.55%	51.15%	+7.56%	Cooperative lane change

2.3. Microscopic traffic simulation analysis

A microscopic traffic simulation was used to reproduce the traffic patterns of road users at the microscopic level. It is widely used in traffic operations and control, traffic impact, and ITS strategy application research [40]. Figure 5 shows the microscopic traffic simulation analysis.

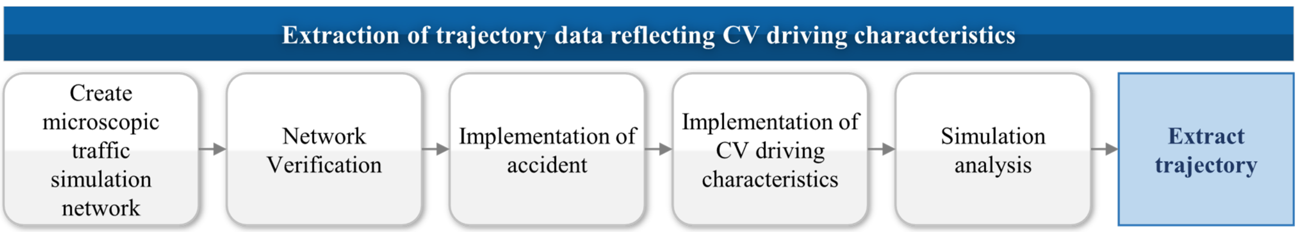


Figure 5. Vehicle trajectory extraction procedure.

A simulation network was constructed and calibrated to analyze the effect on traffic flow according to the MPR of CV. The analysis target section was the 10-km section from the Busan-direction Giheung-Dongtan IC on the Gyeongbu Line where the frequency of accidents is high and congestion often occurs among the freeway CV pilot project sections. The analysis target section is presented in Figure 4. It has four to six one-way lanes with one lane exclusively for buses and includes two ICs and one JC. The network was constructed using microscopic traffic simulation for the analysis section. After the network was constructed, calibration was performed to reflect the actual traffic flow in the section. For calibration, the vehicle class ratio, speed distribution by vehicle class, and vehicle following behavior were reflected in the parameters based on actual data. We used 12 types of vehicles provided by the Ministry of Land, Infrastructure, and Transport's traffic volume information system (http://www.road.re.kr). For convenience of analysis, 1 was classified as passenger cars, 2 as buses, and 3–12 as trucks. The vehicle class ratio reflects the vehicle class ratio of the peak time using the

VDS (Vehicle Detection System) traffic volume data and the traffic volume data by vehicle class, by direction, and by time zone. For the speed distribution by vehicle class, the VDS speed data were normalized and reflected in the desired speed distribution in microscopic traffic simulation. The vehicle following behavior was set to the Wiedemann 99 model to reflect the freeway characteristics.

In order to consider the severity of the accident, we created a situation where an accident occurred around 8 km from the network start point and consisted of either one blocked lane or two blocked lanes on the rightmost side due to the accident. The lane control situation due to the accident was set to last for 30 min out of the total simulation analysis time of 1h in a section of about 100m between Suwon-Shingal IC and Giheung IC. Traffic flow simulation was run 10 times for each scenario and the results were analyzed.

2.4. Evaluation of environmental effects

A vehicle emission model was used to estimate the emissions using vehicle trajectory data. A vehicle emission model, called the motor vehicle emission simulator (MOVES), estimated air pollutants and greenhouse gas emissions from mobile sources. In addition, it enables the analysis of emissions by vehicle class and fuel type, and the estimation of emissions at the micro level, and it is widely used in vehicle emissions estimation. In this study, we applied the vehicle trajectory data extracted from microscopic traffic simulation to vehicle emission model to estimate vehicle emissions. The emissions estimation process using vehicle emission model is shown in Figure 6.

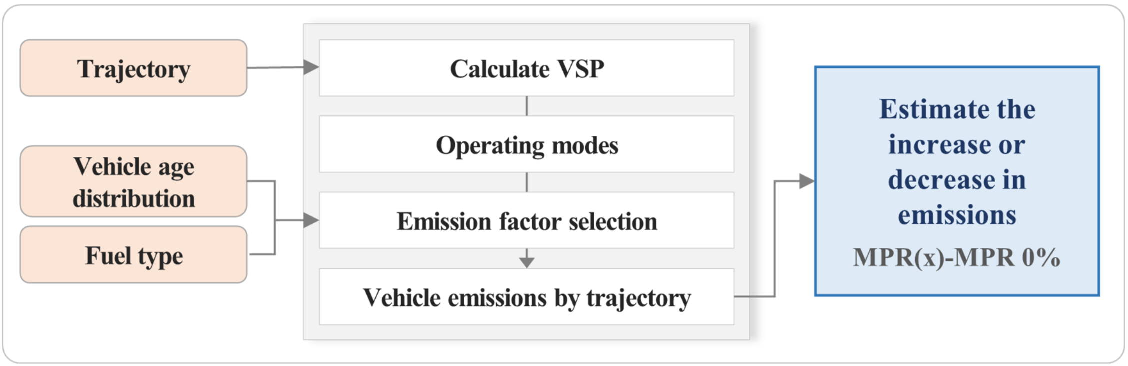


Figure 6. Vehicle emissions estimation procedure using a vehicle emission model.

The vehicle emission model uses a method that considers vehicle specific power (VSP) and speed. VSP represents the effect of vehicle driving conditions, and the calculation formula is shown in Eq (2) [41]. A, B and C in Eq (2) have different values for each vehicle class.

$$VSP_{v,t} = \frac{(A*V_t+B*v_t^2+C*V_t^3+m*v_t*a_t)}{m} \tag{2}$$

where $VSP_{v,t}$ is the VSP (kw/tonne) for vehicle V at time t, t is the time (s); V_t is the speed (m/s); a_t is the acceleration (m/s²); and m is the weight (tonne).

To evaluate the environmental effect of MPR when providing V2V-based collision prevention services, we applied the operating mode (OpMode) approach, which classifies the driving behavior by the trajectory data. Emissions are estimated by finding an OpMode that matches the vehicle's speed and VSP range and applying the corresponding emission factors. There are 23 OpModes in total, and OpModes according to VSP and vehicle speed are shown in Table 3 [41].

Table 3. List of operating modes.

OpMode ID	Operating mode description		OpMode ID	Operating mode description	
0	Braking	-	25	9 ≤ VSP < 12	25 ≤ Speed < 50
1	Idling	-	27	12 ≤ VSP < 18	25 ≤ Speed < 50
11	VSP < 0	1 ≤ Speed < 25	28	18 ≤ VSP < 24	25 ≤ Speed < 50
12	0 ≤ VSP < 3	1 ≤ Speed < 25	29	24 ≤ VSP < 30	25 ≤ Speed < 50
13	3 ≤ VSP < 6	1 ≤ Speed < 25	30	30 ≤ VSP	25 ≤ Speed < 50
14	6 ≤ VSP < 9	1 ≤ Speed < 25	33	VSP < 6	50 ≤ Speed
15	9 ≤ VSP < 12	1 ≤ Speed < 25	35	6 ≤ VSP < 12	50 ≤ Speed
16	12 ≤ VSP	1 ≤ Speed < 25	37	12 ≤ VSP < 18	50 ≤ Speed
21	VSP < 0	25 ≤ Speed < 50	38	18 ≤ VSP < 24	50 ≤ Speed
22	0 ≤ VSP < 3	25 ≤ Speed < 50	39	24 ≤ VSP < 30	50 ≤ Speed
23	3 ≤ VSP < 6	25 ≤ Speed < 50	40	30 ≤ VSP	50 ≤ Speed
24	6 ≤ VSP < 9	25 ≤ Speed < 50	(blank)		

Emission factors for each vehicle class and driving mode are values corresponding to US road conditions and need to be updated to suit domestic road conditions. In this study, the emission factors for each operating mode were updated by reflecting the distribution by vehicle age, size, and fuel type provided by the Korean Ministry of Land, Infrastructure, and Transport [42]. Table 4 lists the values used to update the emission factors.

Table 4. Distribution by vehicle class and fuel type.

Veh type	Fuel type	Ratio (%)	Veh type	Fuel type	Ratio (%)	Veh type	Fuel type	Ratio (%)
	Gasoline	47.309		Gasoline	0.021		Gasoline	0.043
	Diesel	25.338		Diesel	3.539		Diesel	13.650
PC	LPG	6.841	Bus	LPG	0.421	Truck	LPG	0.726
	CNG	0.029		CNG	0.137		CNG	0.002
	Others	1.609		Others	0.056		Others	0.280

3. Analysis results

3.1. Network calibration and verification

The network was calibrated by adjusting the simulation parameters such that it can accurately represent the actual driving environment conditions [43]. Accurate simulation models provide more accurate predictions of the effects on traffic flow and driver driving behavior when the driving environment or traffic policies change [44]. Accordingly, numerous studies have performed calibrations by adjusting the driver behavior parameters [44–48]. In this study, the results of a previously performed PVD analysis were used to implement the CV driving pattern. Table 5 lists the parameter adjustment results.

Table 5. Adjusted parameters based on the PVD analysis.

Driving behavior indicators	VISSIM driving parameters	Regular vehicle (default)	Connected vehicle
Std. of speed	CC5	0.35 km/h	0.22 km/h
Avg. of spacing	CC2	4.00 m	4.95 m
Avg. of acceleration	CC9	1.50 m/s²	1.41 m/s²
Std. of acceleration	CC7	1.5 m/s²	1.27 m/s²
	Smooth closeup behavior	-	Check
Avg. of headway time	CC1	0.90 s	1.06 s
	CC3	-8.00 s	-9.43 s
Rate of early lane change	Cooperative lane change	-	Check

Verification was performed based on the network calibration results. We used U-Value, which uses speed as an effect measure for verification. The U-Value calculation formula is presented in Eq (3). A U-Value closer to 0 indicates similarity between the real and simulated data. Typically, when the U-Value is less than 0.1, the simulated data are judged to be consistent with the actual data [49].

$$U = \frac{\sqrt{\sum_{i=1}^{N}(V_i - \hat{V}_i)^2}}{\sqrt{\sum_{i=1}^{N} V_i^2} + \sqrt{\sum_{i=1}^{N} \hat{V}_i^2}} \tag{3}$$

where i is the iteration; V_i is the actual speed(km/h); and $\hat{V}_i$ is the simulation speed (km/h).

Table 6 shows that the average U-Values derived from 10 iterations of the simulation are all below 0.1, so it can be concluded that the roads in the VISSIM network constructed for this study reflect the traffic flow on actual roads.

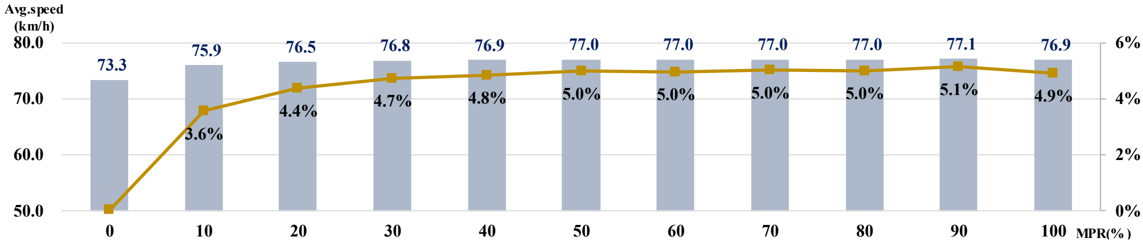
Table 6. Comparison of u-values between field data and simulated VDS data.

Detector	Iterations										Average
	1	2	3	4	5	6	7	8	9	10	
Detector 1	0.064	0.067	0.063	0.071	0.062	0.063	0.080	0.065	0.065	0.067	0.067
Detector 2	0.061	0.061	0.066	0.066	0.063	0.063	0.065	0.066	0.064	0.066	0.064
Detector 3	0.055	0.056	0.055	0.054	0.056	0.061	0.055	0.055	0.056	0.056	0.056
Detector 4	0.067	0.067	0.067	0.066	0.068	0.067	0.069	0.067	0.067	0.066	0.067

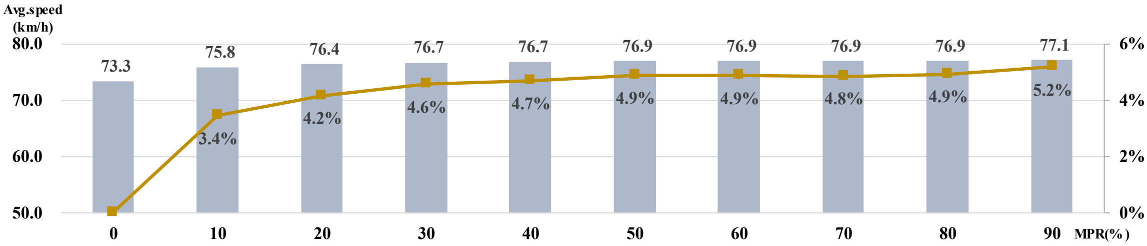
3.2. Estimation of vehicle emissions

Microscopic traffic simulation analysis was performed based on 22 analysis scenarios. MOVES was used to estimate the vehicle emissions using the vehicle trajectory data. Based on the extracted vehicle trajectory data, we set CV MPR of 0% as the baseline and estimated the difference in emissions for each MPR. Emissions per vehicle (g/vehicle) were used to compensate for the difference in the total number of vehicles for each simulation. The environmental effects of implementing CV were evaluated by vehicle type (CV, RV), vehicle class (passenger cars, trucks), and pollutant (CO_2, CO, NOx, and $PM_{2.5}$). Among the vehicle classes, buses were excluded from this study because they use dedicated lanes and are considered to have less impact on traffic flow.

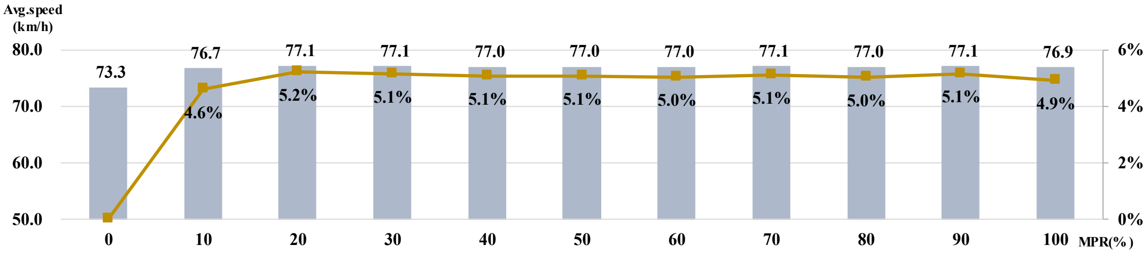
3.2.1. One blocked lane scenario



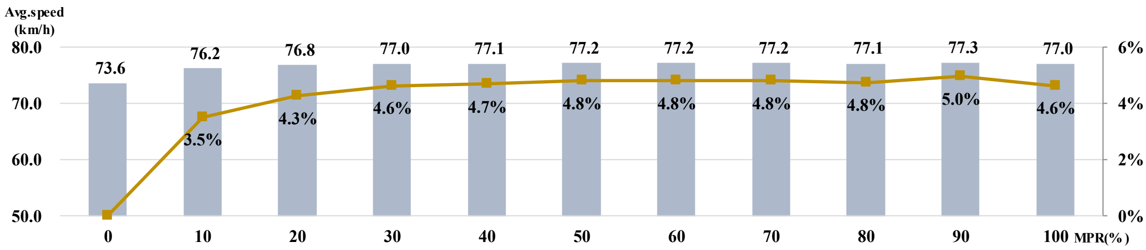
(a) Total (RV + CV, Passenger cars + trucks)



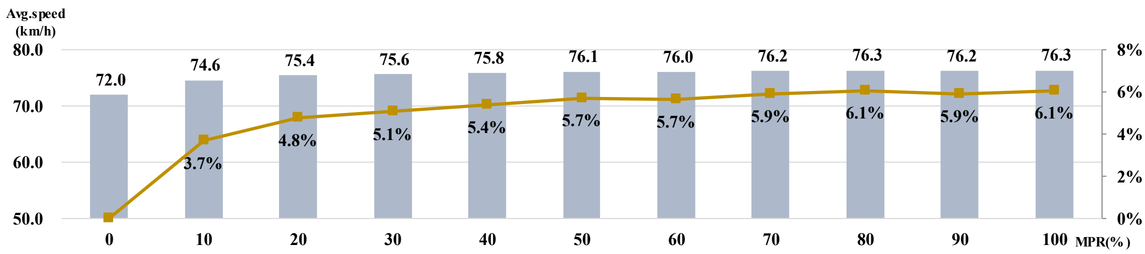
(b) RV



€ CV



(d) Passenger cars



(e) Trucks

Figure 7. Speed and increase rate by MPR (one blocked lane).

Emissions were estimated according to the MPR of CV when one lane was blocked due to an accident. Before confirming the changes in vehicle emissions, we reviewed the speed variations in Figure 7. The speed showed the highest increase rate of 5.1% compared to the baseline at MPR 90%

based on all vehicles. RV and CV showed the highest speed increase rate at MPR 90% and MPR 20%, respectively. MPR 100% for RV means that no RV exists, so the analysis was performed for MPRs from 0 to 90%. On the other hand, MPR 0% for CV used the emissions from traffic consisting of only RV because there was no CV. The highest speed increase rate by vehicle class was MPR 90% for passenger cars and MPR 100% for trucks.

Table 7. Emissions increase/decrease rate by MPR (all, RV, CV) - one blocked lane.

MPR	Total				RV				CV			
	CO_2 (%)	CO (%)	NOx (%)	$PM_{2.5}$ (%)	CO_2 (%)	CO (%)	NOx (%)	$PM_{2.5}$ (%)	CO_2 (%)	CO (%)	NOx (%)	$PM_{2.5}$ (%)
MPR 10%	-2.2	-7.0	-2.9	-4.7	-2.0	-5.6	-2.6	-4.4	-3.9	-19.9	-5.7	-7.6
MPR 20%	-3.1	-10.0	-4.6	-7.6	-2.7	-8.1	-3.9	-6.6	-4.4	-17.6	-7.3	-11.4
MPR 30%	-3.4	-11.7	-5.3	-8.3	-3.1	-9.7	-4.5	-7.3	-4.2	-16.4	-7.1	-10.7
MPR 40%	-3.2	-12.4	-4.9	-8.0	-2.8	-10.1	-4.0	-7.2	-3.9	-15.9	-6.2	-9.3
MPR 50%	-3.7	-13.4	-5.3	-7.9	-3.2	-11.3	-4.1	-6.5	-4.2	-15.6	-6.5	-9.4
MPR 60%	-6.4	-28.0	-10.5	-11.4	-5.9	-27.2	-10.0	-11.3	-6.8	-28.5	-10.9	-11.6
MPR 70%	-6.2	-28.2	-9.9	-10.7	-5.8	-27.6	-9.7	-11.1	-6.4	-28.4	-9.9	-10.5
MPR 80%	-6.0	-28.0	-9.3	-9.7	-5.4	-27.7	-8.6	-9.4	-6.1	-28.1	-9.4	-9.8
MPR 90%	-6.3	-28.8	-10.1	-11.0	-6.1	-29.3	-10.3	-11.8	-6.3	-28.7	-10.1	-10.9
MPR 100%	-3.8	-15.1	-5.7	-8.3	-	-	-	-	-3.8	-15.1	-5.7	-8.3

Table 8. Emissions increase/decrease rate by MPR (passenger cars, trucks) - one blocked lane.

MPR	Passenger Cars				Trucks			
	CO_2 (%)	CO (%)	NOx (%)	$PM_{2.5}$ (%)	CO_2 (%)	CO (%)	NOx (%)	$PM_{2.5}$ (%)
MPR 10%	-2.1	-7.7	-3.2	-7.4	-1.8	-3.8	-1.6	-2.9
MPR 20%	-2.7	-10.9	-4.6	-10.6	-3.3	-6.0	-3.1	-4.9
MPR 30%	-3.2	-12.7	-5.5	-12.4	-3.5	-6.8	-3.7	-5.8
MPR 40%	-3.2	-13.8	-5.7	-13.6	-2.6	-6.0	-2.4	-4.5
MPR 50%	-3.7	-14.9	-6.6	-14.4	-3.6	-7.2	-3.7	-5.9
MPR 60%	-6.9	-32.4	-15.1	-26.5	-4.4	-8.3	-4.8	-6.1
MPR 70%	-6.8	-32.7	-15.0	-27.1	-4.1	-8.0	-4.2	-5.7
MPR 80%	-6.7	-32.6	-14.9	-27.0	-3.9	-7.9	-3.8	-5.3
MPR 90%	-7.0	-33.4	-15.4	-27.9	-4.2	-8.3	-4.4	-5.9
MPR 100%	-3.9	-16.9	-7.6	-16.4	-3.5	-7.1	-3.7	-5.9

Emissions of pollutants were analyzed by vehicle type in Tables 7 and 8. The pollutant that showed the highest reduction rate compared to the baseline in all vehicles was CO, which decreased by 28.8% from MPR 90%. CO_2, NOx, and $PM_{2.5}$ decreased by 6.4, 10.5, and 11.4%, respectively, at MPR 60%. RV had the highest emissions reductions for all pollutants at MPR 90%. CO_2 decreased by 6.1%, CO by 29.3%, NOx by 10.3%, and $PM_{2.5}$ by 11.8%. In the case of CV, CO emissions decreased the most by 28.7% when the MPR was 90%. Emissions of CO_2, NOx, and $PM_{2.5}$ were the lowest when the MPR was 60%, and they decreased by 6.8, 10.9 and 11.6%, respectively. In terms of vehicle class, it was found that passenger cars had the greatest effect in reducing emissions with an MPR of 90%. Emissions of passenger cars decreased by 7.0% for CO_2, 33.4% for CO, 15.4% for NOx, and 27.9% for $PM_{2.5}$ compared to the baseline. In the case of trucks, CO showed the highest reduction of 8.3% at MPR 90%, and CO_2, NOx, and $PM_{2.5}$ decreased by 4.4, 4.8 and 6.1% at MPR 60%, respectively.

The implementation of CV in one blocked lane due to an accident was found to have a positive environmental impact compared to existing traffic with only RV. In the case of vehicle class, the emissions reduction rate of CV was higher than that of RV. In terms of vehicle class, we found that passenger cars had a greater reduction in emissions than trucks. In the case of pollutants, CO and $PM_{2.5}$ emissions reductions were high, and the emissions reduction effect was remarkable in passenger cars. It was confirmed that receiving warning information about accidents occurring ahead was helpful in improving driving behaviors such as acceleration and deceleration.

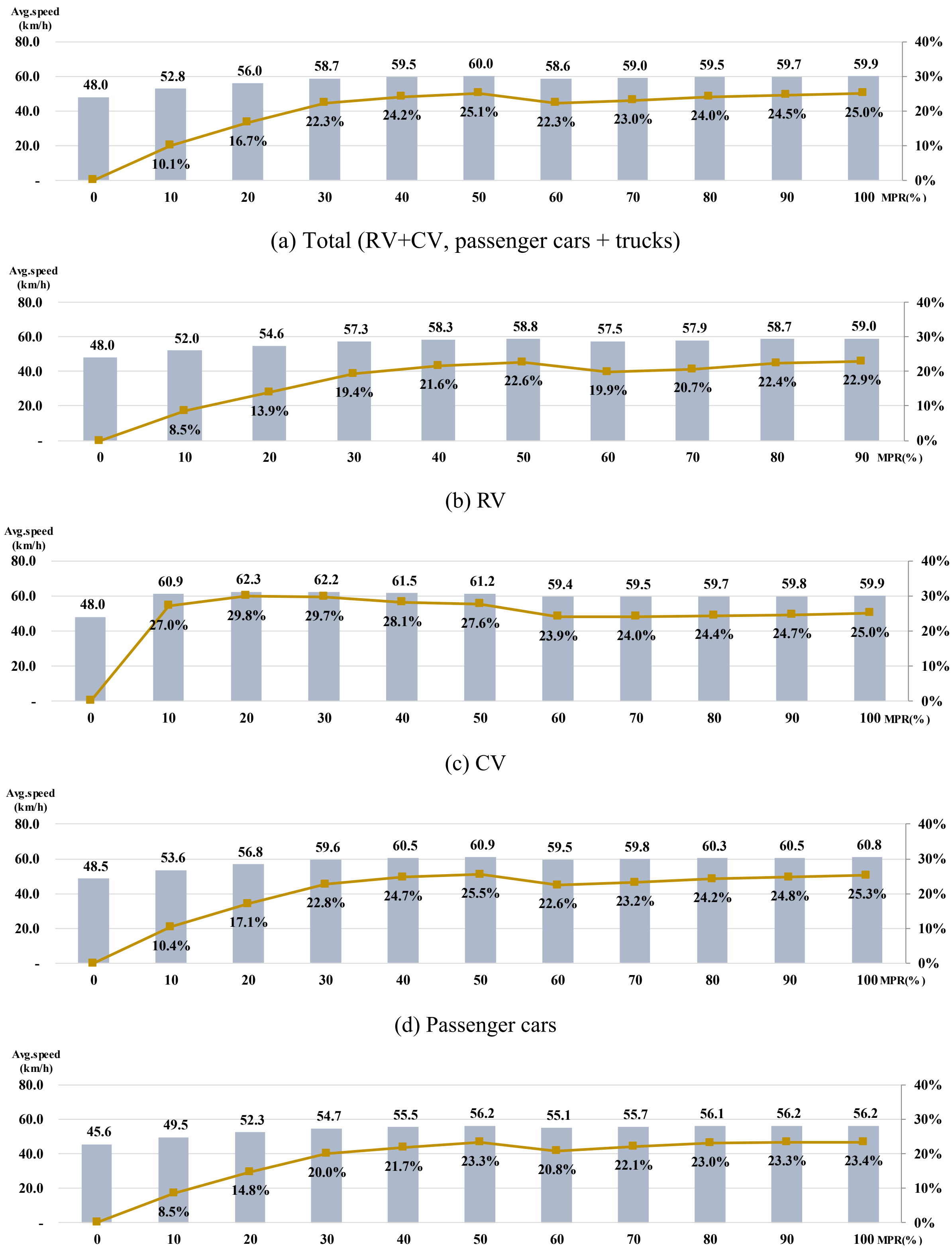
3.2.2. Two blocked lanes scenario

Emissions were estimated according to the MPR of CV when two lanes were blocked due to an accident. The highest speed increase rate of 25.1% compared to the baseline was shown at MPR 50% based on all vehicles in Figure 8. RV and CV showed the highest speed increase rate at MPR 90% and MPR 20%, respectively. The highest speed increase rate by vehicle class was shown at MPR 50% for passenger cars and MPR 100% for trucks.

Table 9. Emissions increase/decrease rate by MPR (all, RV, CV) - two blocked lanes.

MPR	Total				RV				CV			
	CO_2 (%)	CO (%)	NOx (%)	$PM_{2.5}$ (%)	CO_2 (%)	CO (%)	NOx (%)	$PM_{2.5}$ (%)	CO_2 (%)	CO (%)	NOx (%)	$PM_{2.5}$ (%)
MPR 10%	-3.7	-5.5	-2.7	-4.4	-2.9	-3.6	-1.9	-3.5	-10.8	-22.6	-9.2	-12.9
MPR 20%	-6.2	-9.4	-4.7	-7.6	-4.8	-6.8	-3.3	-5.6	-11.5	-19.8	-10.2	-15.3
MPR 30%	-7.9	-11.3	-5.5	-8.6	-6.6	-8.7	-3.9	-6.5	-10.9	-17.5	-9.0	-13.4
MPR 40%	-8.4	-11.9	-5.7	-8.8	-7.4	-9.5	-4.6	-7.3	-10.0	-15.6	-7.4	-11.2
MPR 50%	-8.8	-13.1	-5.8	-8.6	-7.9	-10.9	-5.0	-7.7	-9.7	-15.2	-6.5	-9.5
MPR 60%	-10.2	-24.5	-9.7	-10.6	-9.4	-23.6	-9.3	-10.5	-10.8	-25.0	-9.9	-10.7
MPR 70%	-10.7	-24.7	-10.0	-10.9	-9.8	-24.2	-10.0	-11.4	-11.1	-24.9	-10.0	-10.7
MPR 80%	-10.8	-24.8	-9.5	-9.9	-10.3	-25.2	-9.6	-10.2	-10.9	-24.7	-9.5	-9.8
MPR 90%	-10.8	-24.1	-9.9	-11.0	-10.4	-25.2	-10.8	-13.3	-10.9	-23.9	-9.8	-10.7
MPR 100%	-9.1	-14.8	-6.6	-8.9	-	-	-	-	-9.1	-14.8	-6.6	-8.9

The vehicle emissions were analyzed by vehicle type and pollutant, as shown in Tables 9 and 10, respectively. The pollutant that showed the highest emissions reduction rate compared to the baseline in all vehicles was CO. CO decreased by 24.8% at MPR 80%. CO_2 and $PM_{2.5}$ decreased by 10.8 and 11.0%, respectively, at MPR 90%, and NOx decreased by 10.0% at MPR 70%. In the case of RV, the emissions of all pollutants decreased the most at MPR 90%. CO_2, CO, NOx, and $PM_{2.5}$ decreased by 10.4, 25.2, 10.8, and 13.3%, respectively. On the other hand, in the case of CV, CO decreased the most at MPR 60% by 25.0%. CO_2, NOx, and $PM_{2.5}$ decreased by 11.5, 10.2 and 15.3%, respectively, at 20% MPR. In the case of vehicle class, passenger cars showed a large reduction in the emissions of all pollutants compared to the baseline at MPR 80%. CO_2, CO, NOx, and $PM_{2.5}$ decreased by 11.7, 28.0, 13.6, and 23.8%, respectively. In the case of trucks, CO showed the highest reduction of 12.6% at MPR 70%, and CO_2, NOx, and $PM_{2.5}$ decreased by 8.6, 6.4 and 7.4%, respectively, at MPR 90%.



(a) Total (RV+CV, passenger cars + trucks)

(b) RV

(c) CV

(d) Passenger cars

(e) Trucks

Figure 8. Speed and increase rate by MPR (two blocked lanes).

Table 10. Emissions increase/decrease rate by MPR (passenger cars, trucks) - two blocked lanes.

	Passenger Cars				Trucks			
MPR	CO_2 (%)	CO (%)	NOx (%)	$PM_{2.5}$ (%)	CO_2 (%)	CO (%)	NOx (%)	$PM_{2.5}$ (%)
MPR 10%	-3.7	-5.6	-2.2	-4.8	-3.0	-4.8	-2.1	-3.1
MPR 20%	-6.1	-9.6	-4.0	-9.0	-5.5	-8.3	-3.7	-5.1
MPR 30%	-7.9	-11.4	-4.7	-10.6	-7.1	-10.5	-4.8	-6.5
MPR 40%	-8.6	-12.2	-5.2	-11.5	-7.0	-10.5	-4.6	-6.1
MPR 50%	-9.0	-13.4	-5.8	-12.8	-8.0	-11.6	-5.4	-7.0
MPR 60%	-11.0	-27.6	-12.9	-23.0	-7.6	-11.7	-5.5	-6.1
MPR 70%	-11.5	-27.7	-13.4	-23.2	-8.3	-12.6	-6.2	-7.2
MPR 80%	-11.7	-28.0	-13.6	-23.8	-8.1	-12.3	-5.7	-6.5
MPR 90%	-11.5	-26.9	-13.1	-23.0	-8.6	-12.5	-6.4	-7.4
MPR 100%	-9.6	-15.7	-7.8	-15.1	-7.7	-11.2	-5.3	-7.1

When two lanes were blocked due to an accident, the implementation of CV had the same effect of reducing emissions as the one blocked lane scenario. The CV emissions reduction effect was greater than that of RV, and passenger cars had a greater emissions reduction effect than trucks for all pollutants. As a result, it was concluded that the CV collision prevention service had an emissions reduction effect regardless of the MPR.

4. Discussion

We explored the speed and emissions according to the MPR of CV when lanes were blocked due to an accident. CV improved speed and reduced emissions in all scenarios compared to the baseline. CV was more effective at improving speed when the severity of the accident was higher. Increasing the amount of time and distance available to respond to forward-risk situations not only improved mobility but also significantly contributed to reducing emissions. The effect of vehicle emissions reductions differed based on the severity of accident, vehicle type, and pollutant type.

The emissions decreased in the MPRs of all CVs independent of the accident severity. The pollutants were different despite the similarity of emissions reduction patterns between one and two blocked lanes. In the case of one blocked lane, the emissions reduction effects of CO, NOx and $PM_{2.5}$ was high, whereas that of CO_2 was high in the case of two blocked lanes. CO_2 emission increase with higher speeds and more idling. Vehicle congestion occurs when the severity of the accident is high, and idling occurs at this time. Providing information on upcoming traffic conditions was determined to have a positive effect on reducing emissions by avoiding and mitigating vehicle congestion.

By vehicle type, emissions reductions were better for CV than RV. Emissions increase when the vehicle's driving speed rapidly increases or decreases [50]. CV can improve emissions compared to RV by allowing drivers to recognize the traffic situation in front of them through provided services and proactively change lanes, inducing gradual acceleration and deceleration.

By vehicle class, emissions reductions were higher for passenger cars than for trucks. In Korea, 15.2% of passenger car drivers and 7.2% of truck drivers drive at high speed, and rapid acceleration occurs frequently [51]. The driving patterns of passenger cars and trucks suggest that those of passenger cars are more likely to be improved than those of trucks, resulting in a higher emissions reduction effect.

In the case of pollutants, CO_2, CO, NOx, and $PM_{2.5}$ all decreased compared to the baseline. The emissions reduction effect of CO was the greatest, and it was larger when the severity of the accident was low. CO emission increase when driving at low speeds or with frequent acceleration and deceleration [52]. The implementation of CV reduces emissions by increasing driving speed and reducing the frequency of acceleration and deceleration through V2X-based information exchange. However, in severe congestion, the emissions reduction effect was relatively small due to continuous low-speed driving and repeated stop and go. The emission reduction effect of CO_2 was found to be greater when the severity of the accident was high. NOx and $PM_{2.5}$ showed similar emissions reduction effects regardless of accident severity.

The analysis indicates that implementing CV has a positive impact on emissions reductions regardless of MPR. The effectiveness of emissions reduction increased up to an MPR of 60%, but above this, it converged to a certain value. However, when the MPR was at 100%, the emissions reduction effect was offset. Therefore, an MPR of 60–90% is recommended to maximize the impact of CV from an environmental perspective.

Additionally, we analyzed the coefficient of variation for speed. A smaller coefficient of variation indicates less change in speed. The coefficient of variation for each scenario was 0.1 or less, indicating that the speed change of the vehicle according to the CV ratio was not large. It was inferred that the acceleration and deceleration behavior of vehicles decreased due to the implementation of CV, and it was determined that the improvement in driving behavior contributed to the reduction of emissions.

Table 11. Coefficient of variation by scenario.

Scenario	Coefficient of variation				
	Total	RV	CV	Passenger cars	Trucks
One blocked lane	0.014	0.014	0.014	0.013	0.016
Two blocked lanes	0.063	0.061	0.064	0.064	0.061

5. Conclusions

The Ministry of Land, Infrastructure, and Transport of Korea announced the Intelligent Transport System (ITS) Basic Plan 2030 and proposed a plan to construct digital road infrastructure. The main content is the construction of CV communication infrastructure on major roads in preparation for the commercialization of full autonomous driving (Lv4) in 2027. The ratio of CV will increase in the future. Thus, it is essential to evaluate the impact of CV implementation. In this study, we evaluated the environmental impact of implementing CV in freeway accidents. The evaluation was conducted by defining the driving characteristics of CV based on PVD collected from driving vehicles that received CV services and then performing simulations. The requirements for simulation analysis were as follows:

1) Road driving environment similar to reality (traffic volume, speed distribution, etc.)
2) Implementation of accidental situations based on accident severity
3) Settings for CV MPR
4) Implementation of CV driving patterns

Additionally, the limitations of simulation analysis are as follows:

■ In the case of CV, the driving characteristics were analyzed based on the PVD data and the vehicle behavior was implemented in the simulation. Contrastingly, in the case of general vehicles, default values of parameters were used in the simulation owing to limitations in data collection.

The simulation results confirmed that the implementation of CV reduces emissions. The major results of this study are as follows:

- CV introduction is effective for improving speed and reducing emissions.
- CV introduction improves the speed when the severity of an accident is high.
- Based on vehicle type, passenger cars exhibited a greater emissions reduction effect compared to trucks.
- Among pollutants, CO emission exhibited the greatest reduction effect.
- Emissions reduction effect was maximum when CV MPR was in the range 60–90%.

The analysis showed that the implementation of CV was found to be effective in terms of speed and emissions. Speed increased by up to 25.1% over the baseline, with higher incident severity leading to greater speed improvements. In the case of emissions, they decreased regardless of accident severity and differed by vehicle type and class and pollutant. By vehicle type, CV had a higher reduction than RV, and by vehicle class, passenger cars had a higher reduction than trucks. Emissions of CO_2, CO, NOx, and $PM_{2.5}$ were all reduced compared to the baseline, and the emissions reduction effect of CO was the greatest. At all MPRs, emissions were reduced compared to the baseline, but the effect of reducing emissions was more significant when the MPR of CV was 60–90%. However, the effect decreased when the MPR was 100%, suggesting that a large amount of V2X information can cause confusion in driving. To maximize the environmental impact of implementing CV, MPR should be at least 60%.

Several studies have been conducted to measure the environmental impact of providing CV services in the CV environment. This study is significant in that we used data collected from CV driving on Korean freeways and analyzed accident situations that have been insufficiently researched. The results of the study can be used as a basis for expanding the implementation of CV and are expected to be used as basic data when preparing policy to reduce emissions in the transportation sector. For the analysis, data of the collision accident prevention service, which had a high number of service provisions among the PVD collected on a specific freeway, were used. It is expected that the characteristics of each freeway line are different and the impact on vehicle driving behavior is different for each CV service. However, due to limitations in data collection, the analysis was conducted for specific services and spatial ranges. We believe that precisely implementing the behavior of CV based on accumulated data through continuous PVD collection and conducting additional analysis for each service, such as forward speed recommendations and lane change guidance, in the future will help to improve the CV environment and services. Additionally, research from the perspective of CAVs and connected EVs is required. Therefore, the MPRs of AV and EV are expected to increase. Automation of vehicles can contribute to reducing carbon emissions, and the introduction of EVs has the environmental benefit of decarbonizing transportation for vehicle powertrains [53,54]. Compared with CVs, a greater emissions reduction can be achieved by incorporating the connected technology in each vehicle.

Use of AI tools declaration

The authors declare that have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare that there are no conflicts of interest.

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