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Environmental Implications on Energy and Emissions of the use of a Connected and Autonomous Vehicle Environment

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Connected and autonomous vehicles (CAVs) have the potential to decrease air pollutants like carbon dioxide, nitrogen oxides (NOx), and sulfur oxides (SOx) through many advanced CAV technologies such as improved fuel efficiency, better routing, and better lane changing. However, CAVs also have the other negative side to increase fuel consumption through electricity spent and negative effects such as longer travel time, and frequent acceleration for comfortable driving. This paper analyses fuel consumption effects of CAV by collecting data from a simulation within cooperative adaptive cruise control (CACC). Compared with normal vehicles (NVs), this paper found that it has significant differences between results of CAVs and NVs. though electricity spent and longer distance time can be damaged, average fuel efficiency and reduced gas emission of CAV technologies far outweigh the disadvantages of those. This paper will help to evaluate various environmental effects on CAV technologies.

1. Introduction

Most people know that an environmental impact of a vehicle is severe and needs a proper management. Energy efficiency and greenhouse gas (GHG) emissions from vehicles need a control to preserve the ecosystem. (Barth et al., 2014) Many researchers have proved the relationship between the environmental effect of vehicles and parameters related to vehicles such as vehicle kilometres travelled (VKT), and acceleration profiles. (Morrow et al., 2014) Researches have shown that long distance and frequent acceleration by people have had a significant impact on the emissions such as NOx, SOx (Barth, et al., 2014), and Cox (Casals, et al., 2016), which means that vehicles are related to the environment (Kim, et al., 2017).
Conventional vehicles cannot essentially solve the environmental problem. Many researchers raise the issues about an optimization of a negative effects of a vehicle. Optimizing engine efficiency and managing an amount of emissions is limited (Casals et al., 2016) and negative effects of human driving are hard to be eliminated because optimal control needs autonomous driving which means that vehicle drives themselves.
Considering the limitation of conventional vehicles, new vehicles are introduced. First, due to the efficiency of the engines, electronic vehicles are used. (Kim et al., 2017) Autonomous vehicles (AVs) are also introduced to optimize acceleration behaviour, which means that traffic flow can be controlled by AVs. Moreover, connected vehicles (CVs), communicating with other infrastructures or vehicles, can optimize their paths, which means that their path can be optimally assigned satisfying system optimum (SO).
Nowadays, connected and autonomous vehicles (CAVs) are mentioned as the future technologies containing two types of technologies, connected vehicles (CVs) and autonomous vehicles (AVs). CAVs can eliminate several human factors and judge themselves for improving driving efficiency and safety. Due to the introduction of CAVs, many researchers stated that future traffic flow will be more stable.
CAVs judge and drive themselves by using the vehicle and road information through the CAV environment and/or vehicle sensors. Well-known technologies are Adaptive cruise control (ACC) and cooperative adaptive cruise control (CACC), which are related to traffic stability. ACC (Jia and Ngoduy, 2016) and CACC (Milanes and Shladover, 2014) keep the time headway between an ego vehicle and a following vehicle. Therefore, the

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complexity and diversity of the information obtained by CAVs have resulted in the combination of many sensitive components. Many researchers expect that CAVs will have a significant impact on the environment (Barth et al. 2014). Improved speed and acceleration functions of CAVs make them improve their path and acceleration skills. Improved functions encourage CAVs to avoid an unnecessary driving behaviour such as abrupt acceleration or deceleration and choosing a longer path.

Meanwhile, some researchers warn that some useful functions that cause CAVs to increase in VKT. Self-driving to a parking lot is one example (Correia and Arem, 2016). Correia and Arem (2016) has studied user optimum privately owned automated vehicles assignment problem(UO-POAVAP), which means that when vehicle arrived the destination, travellers get off the vehicle and their vehicles automatically drive themselves to nearby parking lots. Though this driving strategy may charm many travellers, researchers are worried about an increase in VKT of CAVs. Air pollutants per vehicle per kilometre can be reduced due to the development of engine efficiency and proper selection of paths but an overall increase in VKT may have a chance to compensate this improvement. However, these negative impacts on the environment has not yet studied. Some researches only concentrate on positive impacts on traffic flow; while other environmental researches solely concentrate on environment analysis.

This paper analyses an environmental implication considering CAVs' new technologies. This paper selects new CAVs' technology, Cooperative adaptive cruise control (CACC), experimented by Milanes and Shladover (2014). Through aggregated speed and acceleration profiles as a result of a microscopic simulation, this paper simulates two technologies and calculate vehicle's direct and indirect fuel consumption and emissions. This paper will help a decision maker determine when CAVs will be introduced, and what technologies of CAVs will be preceded. The remainder of the paper is organized as follows: Section 2 explains the methodology of this paper; Section 3 specifically defines the simulation scenario setup; Section 4 analyses the result of microscopic impact and environmental impact; Section 5 concludes this paper.

2. Methodology

2.1 Two microscopic models – Human driver model (HDM) and Intelligent driver model (IDM) with CACC

NVs and CAVs are based on a same microscopic car following model, Intelligent driver model (IDM) for the performance of technologies to simulate the results (Treiber and Kesting, 2017), which is most commonly used for realistic acceleration model (Treiber and Kesting, 2013). Eq(1) depicts its model (Treiber and Kesting, 2013). It contains ratio of vehicle speed to desired speed and ratio of desired space gap to real space gap. In this Eq(1), a is the maximum acceleration of a vehicle(m/s^2), v_0 is the desired speed of a vehicle(m/s), δ is the free acceleration exponent, $s(t)$ is the space gap(m) at time t, s_0 is jam distance(m), T is desired time gap(s), and $\Delta\mathrm{t}$ is the simulation time step(s).

$$a_{IDM}^{free}(v,t) = a\left[1-\left(\frac{v(t)}{v_0}\right)^{\delta}-\left(\frac{s_0+\max\left[0,v(t)T+\frac{v(t)\Delta v(t)}{2\sqrt{ab}}\right]}{s(t)}\right)^2\right] \tag{1}$$

In this paper, normal vehicles (NVs) and CAVs are introduced and carefully defined. Abilities among NVs needed by a microscopic simulation are similar. Only engine powers or weights of vehicle are different; while abilities among CAVs expect to be totally different by technologies so this paper sets up vehicle technologies.

NVs have four human factors including perception-reaction time, imperfect driving, temporal anticipation, and perception error (Treiber and Kesting, 2013). Perception-reaction time (T_r) is simulated on the discrete-time model using interpolation method. In this paper, perception-reaction time follows lognormal distribution, location parameter (λ) as 0.17, and scale parameter (ξ) as 0.44 (Gartner et al., 1997); while previous studies fixed a constant perception-reaction time, 1 s (Treiber and Kesting, 2013). 1st, 2nd, and 3rd formula of Eq(2) explain perception-reaction time (Treiber and Kesting, 2017). Speed of ego vehicle is described as $v_i(t)$, revised speed of ego vehicle and leading vehicle calculated by the HDM is defined as $v_i^{rev}(t)$, and $v_l^{rev}(t)$. Error of the driver's reaction causes the acceleration noises which follows white-noise process. 4th formula of Eq(2) explains imperfect driving factor, σ_a as a standard deviation of imperfect driving, and η_a as a white noise process which follows a standard normal distribution (mean of the distribution as 0, standard deviation of the distribution as 1). Due to the anticipation of experienced drivers, drivers anticipate ego vehicle's position, speed and space gap considering perception-reaction time. It compensates human driver's imperfection. 2nd, 3rd, and 4th formula of Eq(2) explain temporal anticipation. Difference between perception-reaction time makes estimated leading vehicle's speed (v_l^{est}) and gap (s^{est}) be modified as revised speed (v_l^{rev}) and gap (s^{rev}). 5th, 6th, and 7th formula of Eq(2) explain perception error. Difference between human driver caused real values of the space gap (s) and leading vehicle's speed (v_l) to be substituted as estimated gap (s^{est}) and estimated leading vehicle's speed (v_l^{est}). Its equations are relevant to the certain persistence which is modelled by Wiener process (w_i), a stochastic process which has individual acceleration by initializing drivers' acceleration and space gap properties.

$$
\begin{aligned}
a_i(t+\Delta t) &= a_{IDM}^{free}(v_i,t) + \sigma_a\eta_a(t) \\
v_i^{rev}(t) &= v_i(t-T_r) + T_r a_i(t-T_r) \\
v_l^{rev}(t) &= v_l^{est}(t-T_r) \\
s^{rev}(t) &= s^{est} - T_r \Delta v^{est}(t-T_r) \\
\sigma_a &= 0.1,\ \eta_a \sim WN(0,1) \\
s^{est} &= s \times e^{V_s w_s(t)} \\
v_l^{est} &= v_l - s\sigma_r w_l(t) \\
w_i &= e^{-\frac{\Delta t}{\tilde{\tau}}} w_{i-1} + \sqrt{\frac{2\Delta t}{\tilde{\tau}}}\eta_i\ , \eta_a \sim WN(0,1)
\end{aligned} \tag{2}
$$

This paper uses cooperative adaptive cruise control (CACC) as the result of an experiment at the real field test of PATH program (Milanes and Shladover, 2014). While in a platoon which members are all CAVs, they use CACC that following vehicles update their own speed by compared with the leading vehicle using speed transfer function. They use the first order model to the speed transfer function resulting in goodness of fit as 95 %. Table 1 shows the result of speed transfer functions. Their speed transfer functions are inversely proportional to the space gap.

Table 1: Vehicle transfer function for CACC model (Milanes and Shladover, 2014)

Vehicle index	Speed transfer function between a leading and following vehicle
2nd vehicle	$\frac{v_2}{v_1} = \frac{1}{1.31s} + 1$
3rd vehicle	$\frac{v_3}{v_1} = \frac{1}{2.11s}$+1
4th vehicle	$\frac{v_4}{v_1} = \frac{1}{2.47s}$+1

Figure 1 explains overall microscopic model algorithm. CAV model considers the presence and formulation of CACC using speed transfer function as described at Table 1 by Milanes and Shladover (2014). In this discrete-time traffic simulation, CAV model gets space gaps between a preceding vehicle and ego vehicle and uses them to simulate CACC. For each simulation time step (Set 0.5 s), CAV model considers CAV condition, CACC condition (within 300 m), and a packet error rate (1 %). All platoon members should be CAV within radio communication ranges (V2V case: within 300 m) to formulate a platoon in a CAV environment.

2.2 Evaluation of gas emission and electricity consumption

Gas emission and electricity consumption is a significant factor for environmental analysis on road. This paper selects six pollutants, CO, VOC, NO_x, CO_2, particulate matter less than 10μm (PM_{10}), and particulate matter less than 2.5 μm ($PM_{2.5}$).

$$\mathrm{TE} = (\mathrm{TEP} \circ \mathrm{FC})^{\mathrm{T}} \cdot \mathrm{UC} \tag{3}$$

TE means emission costs by air pollutants per vehicle (g/km), expressed by (j x 1) vector. TEP is defined as an air pollution emission coefficient, expressed by (m x j) matrix. FC is average fuel consumption matrix with (m x j) and UC is the unit cost of air pollution vector with (m x 1). Expression ○ means the Hadamard product between two matrices, it directly multiplies between two matrices' components. The number of types of vehicles are j, and the types of air pollutants are m = 6.

These days, various kinds of fuels are used for a car. According to the number of cars (Ministry of Land, Infrastructure and Transport in Korea, 2017), There are three kinds of fuels based on the passenger car, Diesel (47.0 %), Gasoline (43.4 %), and LPG (9.5 %). It is obvious that an amount of air pollutants depends on several types of engines. This paper uses results of 2015 by National Institute of Environmental Research (NIER) whose results are based on 2012 (NIER, 2015). NIER uses real-field gas emission data by the vehicle's speed. Different regression methods are used to improve the power of explanation. Table 2 explains the result of air pollutant coefficient considering three types of engines. PM_{10}, and $PM_{2.5}$ which is proportional to the PM_{10} are only emitted from the gasoline engine.

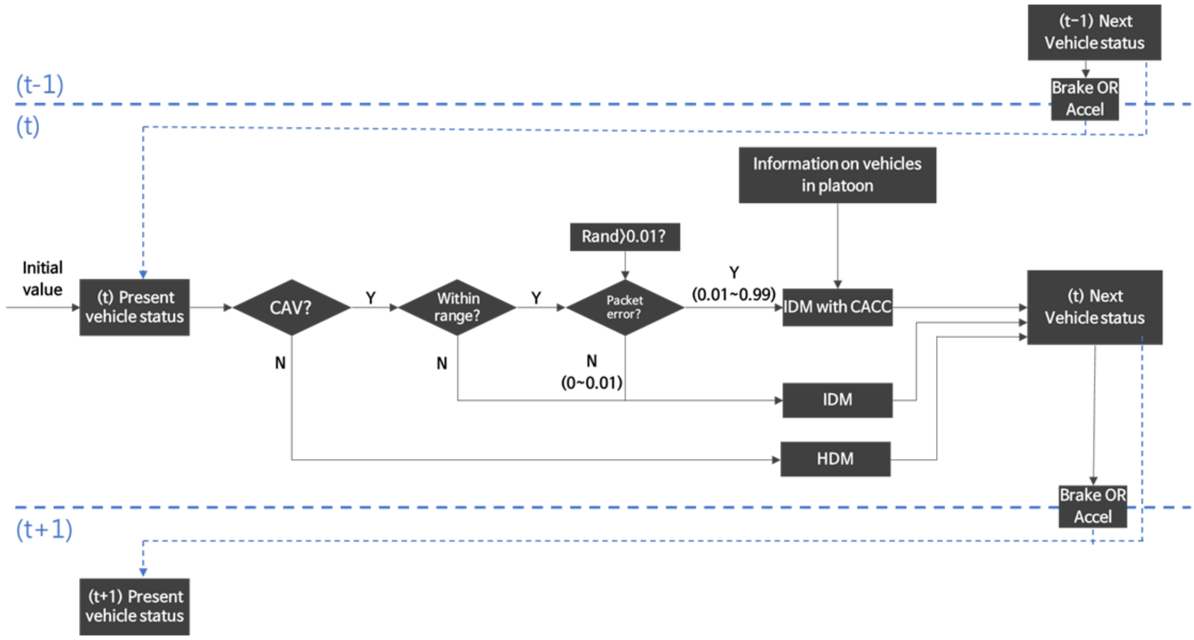

Figure 1: Flowchart of microscopic model algorithm

Table 2: Emission coefficients considering types of engines by air pollutants (NIER, 2015)

Air pollutants (g/km)	Diesel (47.0 %)	Gasoline (43.4 %)	LPG (9.5 %)
CO	$Y = 0.0001V^2 - 0.0071V + 0.2245$	$Y = 0.5775 \times V^{-0.7524}$	$Y = 39.362 \times V^{-1.0085}$
VOC	$V \leq 65.4km/h: Y = 0.0633 \times V^{-1.0484}$ $V > 65.4km/h: Y = 1.32 \times 10^{-6} \times V^2 - 0.000188V + 0.0077$	$Y = 0.0825 \times V^{-0.6848}$	$Y = 2.8981 \times V^{-1.3927}$
NO_x	$Y = (-3.5 \times 10^{-6})V^2 + 0.00033V + 0.0112$	$V \leq 65km/h: Y = 1.1849 \times V^{-0.5476}$ $V > 65km/h: Y = -4 \times 10^{-5} \times V^2 + 0.0021V - 0.0110$	$Y = 1.8419 \times V^{-0.7864}$
CO_2	$Y = 1313.7V^{-0.6}$	$Y = 1113.1V^{-0.587}$	$Y = 1447.3V^{-0.5933}$
PM_{10}	-	$Y = 0.0420V^{-0.3420}$	-
$PM_{2.5}$	-	$Y = 0.92 \times 0.0420V^{-0.3420}$	-

* V: speed of car(km/h), Y: Air pollutant coefficient(g/km)

Meanwhile, CAVs does not directly emit the any harmful gases because CAVs use an electricity as an engine power stored in the battery. Instead, when power plants generate electricity, power plants emit harmful gases, which means that CAVs emit harmful gases indirectly by electricity. To compare the impact on introduction of CAVs, this paper considers harmful gases by power plants as harmful gases by CAV. Table 3 shows the power plant's emission coefficients which is not updated. (Korea power exchange, 2011) This paper assumes that fuel consumption per d of an electricity vehicle as 5.7 km/kWh (commonly used in 2014), time for recharging batteries as 4 h (Seoul City Hall, 2014).

Table 3: GHG emission factor in electric power sector (by KPR)

Year		t CO_2/MWh	kg CH_4/MWh	kg N_2O/MWh
2011	Produce based	0.4415	0.0050	0.0038
	Use based	0.4585	0.0052	0.0040

3. Simulation scenario setup

This paper sets up one single lane highway scenario, which a microscopic simulation is hard to depict a large scenario. This scenario is expressed by Figure 2. Lane changing behaviour is omitted in this paper. It is useful to express the stop-and-go wave by abrupt speed reduction. First vehicle reduces the speed abruptly to 10 km/h at 500~680 s (for 3 min) due to the rock fall on a road. Following vehicles also reduce the speed and after first vehicle recover their speed, they will recover their speed. After simulating this scenario, vehicle information is calculated such as vehicle speed, position, and acceleration profile. Summary of data is used as a parameter of environmental analysis.

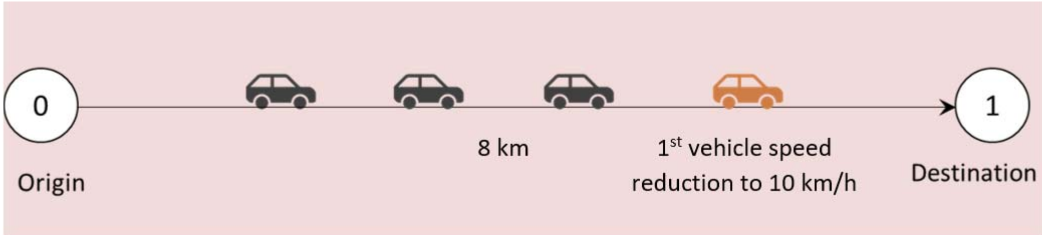

Figure 2: Single lane highway – abrupt speed reduction scenario

4. Result analysis

4.1 Microscopic simulation results

Figure 3 depicts time-position between NVs and CAVs. Black lines mean a NV while red lines mean a CAV. Time-position graph depicts its shockwave length and period. Speed reduction of first vehicle occurred at the 500~680s. Due to the human driver model, stop-and-go wave occurred longer as time increases. Unlike NV, CAV absorbed the stop-and-go waves as time increases. After the reduction, following vehicles suffer from this speed reduction simultaneously at a NV scenario while others suffer from some vehicles only and disappeared at a CAV scenario.

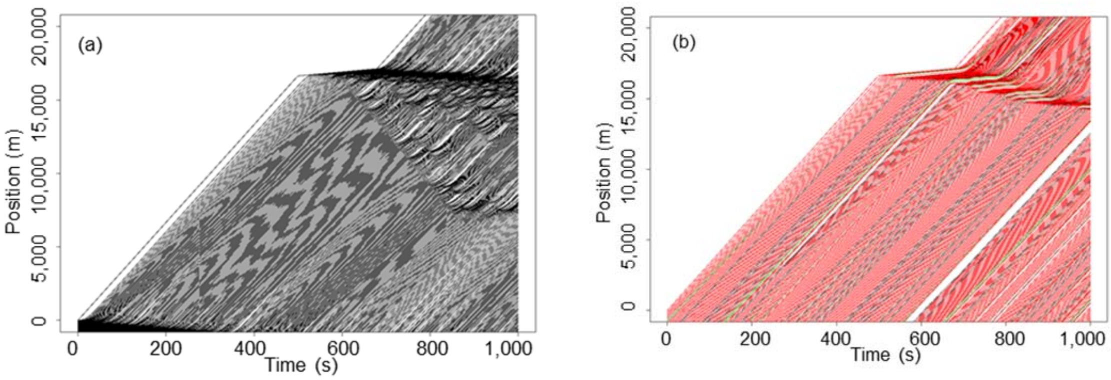

Figure 3: Time-position graph (a) NVs; (b) CAVs

Table 4, and Table 5 depicts throughput, average density, average gap, and average shockwave length. By introduction of CAVs, throughput and average density increases. Average gap and average shockwave length decreases. Throughput and average gap, average density means that for 1,000 s, their road efficiency increases. Many researchers questioned the relationship between average space gap and average shockwave lengths. In fact, many researchers found that shockwave happened at the high speed, and high density (low space gap) cases. However, formulation of stable CAV platoon makes traffic flow stable even though traffic density and average gap decreases with a similar speed.

Table 4: Throughput, the number of perturbation, and average perturbation length by two scenarios

	Throughput (veh)	The number of perturbation by one vehicle (perturbation/veh)				Average Perturbation length(s/veh)
		1	2	3	4	
Normal vehicles	144	1,811	341	151	22	380.2
CAVs	238	2,008	165	64	6	131.7

Table 5: Average gap, speed, density, traffic volume, and vehicle kilometres travelled by two scenarios

	Average gap (m)	Average speed (km/h)	Average density (veh/km)	Daily traffic volume (veh/d)	VKT (thousand veh ・ km/d)
Normal vehicles	65.24	96.20	15.33	35,400	283.2
CAVs	38.90	101.07	25.71	62,352	498.8

Through estimation results shown in Table 6, it dramatically decreases through all kinds of air pollutants. These results are due to the dramatic environmental effect of CAVs, efficiency of fuel consumption, and reduction of energy loss.

Table 6: Estimation results of Emission and air pollutant (Unit: kg)

	CO	VOC	NO_x	CO_2	PM_{10}	$PM_{2.5}$	CH_4
Normal vehicles	132,144	1,449.8	10,927.7	40,970,030	1,907.3	1,754.8	-
CAVs	-	-	332.5	38,636.3	-	-	455.1

5. Conclusion

This paper has analyzed an environmental impact considering CAVs' new technologies. This paper selects new CAVs' technology, Cooperative adaptive cruise control (CACC). Through aggregated speed and acceleration profiles as a result of a microscopic simulation such as VKT, this paper simulated two scenarios and calculated vehicle's direct and indirect fuel consumption and emissions. Estimation results have shown that it dramatically decreases through all kinds of emission and air pollutants. These results are due to the dramatic environmental effect of CAVs, efficiency of fuel consumption, and reduction of energy loss. This paper will help a decision maker to determine when CAVs will be introduced, and what technologies of CAVs will be preceded. If further study are done on lane changing behavior, radio communication network, improved algorithm of CAV and so on, these traffic flows can be simulated more realistically and acquire more realistic results of CAV.

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