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Traffic Operational Analysis from Sensor Application of Electric Autonomous Vehicles and Internal Combustion Engine Autonomous Vehicles Focusing on Difference in Acceleration Profile

Chae-Rin Lee,[1] Sung-Ha Kim,[1] Ki-Han Song,[2]
Sabeur Elkosantini,[3] Seongkwan Mark Lee,[4] and Wonho Suh[1*]

[1]Department of Smart City Engineering, Hanyang University ERICA Campus,
55 Hanyangdaehak-Ro, Sangnok-Gu, Ansan 15588, Republic of Korea
[2]Department of Civil Engineering, Seoul National University of Science and Technology,
232 Gongneung-ro, Nowon-gu, Seoul 01811, Republic of Korea
[3]Faculty of Economics and Management, University of Carthage,
Sidi Bou Said, Av. de la République, Carthage 1054, Tunisia
[4]Kunsan National University, 558 Daehak-ro, Gunsan-si, Jeollabuk-do 54150, Republic of Korea

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With the development of sensor technology in the autonomous and electric vehicle industry, more vehicles are expected to be electric and have autonomous driving capability. It is believed that electric vehicles allow for the simpler integration of advanced sensor application technologies required for the cleaner and safer operation of autonomous vehicles. Although electric autonomous vehicles have many advantages over their gasoline-powered counterparts, not all autonomous vehicles are manufactured as electric vehicles. Therefore, it is expected that they will be operated in a mixed environment. Even though autonomous vehicles operate without human inputs, electric and internal-combustion-engine autonomous vehicles would operate differently owing to their respective characteristics including acceleration profiles. Their different acceleration profiles would lead to differences in traffic operation characteristics. From the data acquired from sensors, in this study, we investigate the traffic operational characteristics of electric and internal-combustion-engine autonomous vehicles in a fully autonomous driving environment. Acceleration potential curves for electric and internal-combustion-engine autonomous vehicles are modeled in a simple traffic network in a microscopic traffic simulation model. It is demonstrated that more vehicles can pass a signalized intersection when there are electric autonomous vehicles than when there are internal-combustion-engine autonomous vehicles. Also, the impacts of different speed limits and market penetration rates are investigated.

[*]Corresponding author: e-mail: wonhosuh@hanyang.ac.kr
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1. Introduction

Sensors and communication technologies have been developed and widely utilized as indispensable components to improve efficiency and safety in transportation applications.(1–7) Sensors collect traffic data on highways and vehicle operational data from vehicles. Integrating these onboard and roadside sensor data has potential applications in monitoring traffic operations and increasing traffic operational efficiency.(1–5) As a result, this integration will help us understand traffic operations and mitigate traffic congestion and associated problems in our society.(8–10) With the recent development of autonomous and electric vehicle technologies, more vehicles are expected to be electric and have autonomous driving capability, and sensor applications are providing crucial information used to analyze system efficiency in the areas of tranffic operation.

In this paper, the operational efficiency of different types of autonomous vehicle technologies is investigated for the integration of the advanced sensor application technologies required for the operation of autonomous vehicles.

2. Related Works

In 2019, the Korean government announced the ‘Future Vehicle Industry Development Strategy 2030’.(11) Its goal is to commercialize Level 4 autonomous vehicles on major roads nationwide by 2027 and to make 33% of domestic new car sales be electric and hydrogen vehicles by 2030. While the market for electric vehicles and autonomous vehicles is expected to grow rapidly, not all autonomous vehicles are manufactured as electric vehicles. Therefore, it is expected that electric and internal-combustion-engine autonomous vehicles will be operated in a mixed environment. Currently, internal-combustion-engine and electric autonomous vehicles are in operation in autonomous vehicle pilot areas in the Republic of Korea. As of 2022, among the 30 autonomous vehicles operated in five autonomous vehicle pilot areas in the Republic of Korea, eleven were internal-combustion-engine autonomous vehicles and 11 were electric autonomous vehicles.

Even though autonomous vehicles operate without human inputs, electric and internal-combustion-engine autonomous vehicles would follow their respective characteristics including acceleration profiles.(12–14) Their different acceleration profiles would lead to differences in traffic operation characteristics at signal intersections.(15) Because internal-combustion-engine vehicles (ICEVs) use an engine as a power source, they must exceed a certain speed to reach the maximum torque. However, electric vehicles (EVs) use an electric motor as a power source, and the maximum torque develops from the start of driving, enabling rapid acceleration (Fig. 1).(16,17) Additionally, since ICEVs have multiple gears, there are moments when power transmission is interrupted during the gear-shifting process. However, since EVs are usually composed of only one gear, there is no gear-shifting process; thus, power can be maintained continuously.(18–20) As such, ICEVs and EVs exhibit different acceleration characteristics.(21,22) Owing to differences in acceleration characteristics between ICEVs and EVs, it is expected that differences in traffic operation characteristics will occur at signalized intersections.

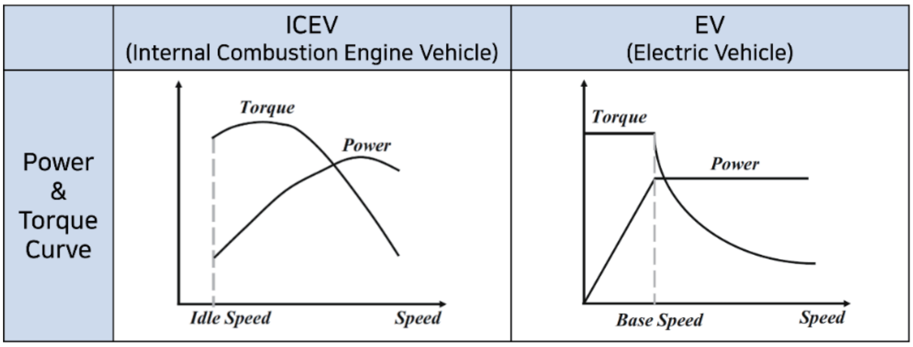

Fig. 1. (Color online) Examples of power and torque curves.

However, studies that quantitatively analyze the effect of these acceleration characteristics on traffic operation are limited. In this study, we aim to analyze the traffic operation characteristics according to the acceleration characteristics of ICEVs and EVs at a signalized intersection in a fully autonomous driving environment. The flow of this study is shown in Fig. 2.

The literature regarding the acceleration profiles of ICEVs and EVs and the driving behavior of autonomous vehicles was reviewed. The literature shows that the ‘acceleration potential curve’ represents the acceleration profile that a vehicle can achieve at a specific speed.

Makridis *et al.* proposed a microsimulation free-flow acceleration (MFC) model that models the dynamic characteristics of ICEVs. The model represents an acceleration potential curve demonstrating the acceleration of an ICEV at a specific speed.(23) The MFC model was verified and calculated using chassis dynamometer and real-driving data. The data suggest that the ICEV’s following behavior in a microscopic traffic simulation can be more precisely simulated using the MFC model. The MFC model of an ICEV presents an acceleration potential curve according to the driver’s gear-shifting behavior and driving behavior (Aggressive, Normal, Timid). Figure 3 shows the acceleration potential curve of an ICEV. It can be seen that the maximum acceleration varies depending on the driver’s driving behavior and acceleration drops significantly during gear shifting.

He *et al.* proposed an MFC model that reflects the dynamic characteristics of EVs including an acceleration potential curve.(24) The MFC model of an EV presents an acceleration potential curve according to the driver’s driving behavior (Aggressive, Normal, Timid). Figure 4 shows the acceleration potential curve of an EV. The maximum acceleration varies depending on the driver’s driving behavior. Unlike the acceleration potential curve of an ICEV, acceleration does not drop since there is no gear-shifting process. Additionally, it can be seen that an EV reaches the maximum acceleration from the start.

CoEXist(25,26) was a European project conducted from May 2017 to April 2020 aimed at preparing the transition phase during which automated and conventional vehicles will co-exist on city roads. CoEXist presents a framework for traffic simulation to analyze the impact of the introduction of autonomous vehicles on traffic flow. CoEXist defines the concept for each autonomous driving level and provides parameter values accordingly. It presents four categories according to the level of autonomous driving: Rail-safe, Cautious, Normal, and All-knowing. Figure 5 shows the autonomous driving levels and explanations presented by CoEXist.

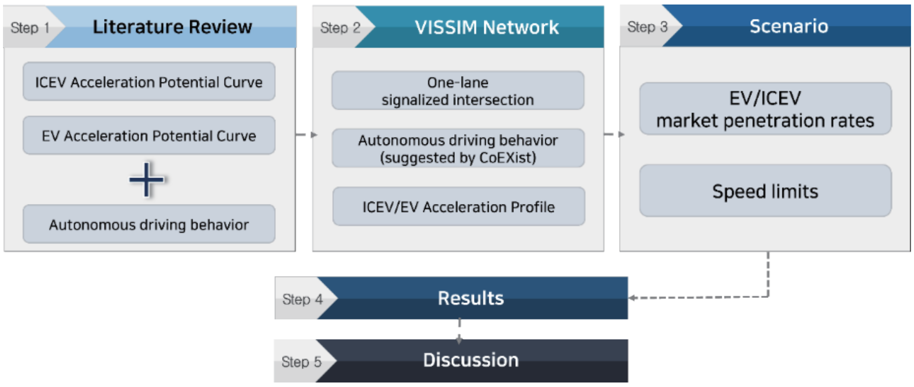

Fig. 2. (Color online) Research flow.

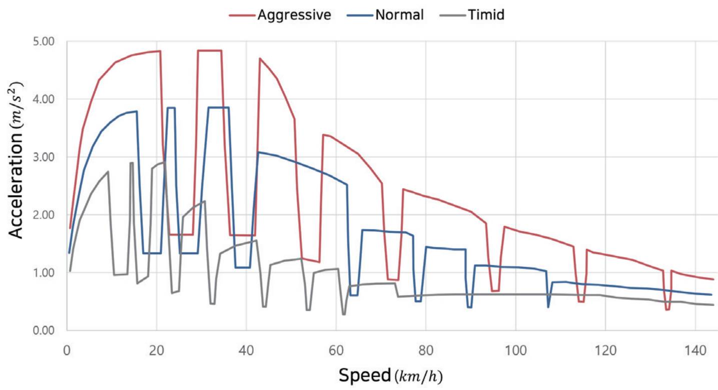

Fig. 3. (Color online) ICEV acceleration potential curve.

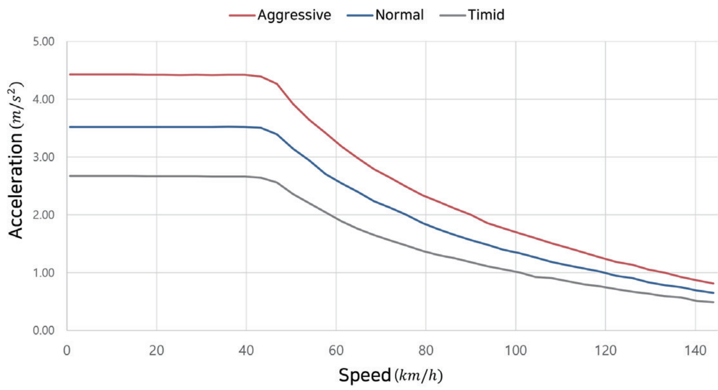

Fig. 4. (Color online) EV acceleration potential curve.

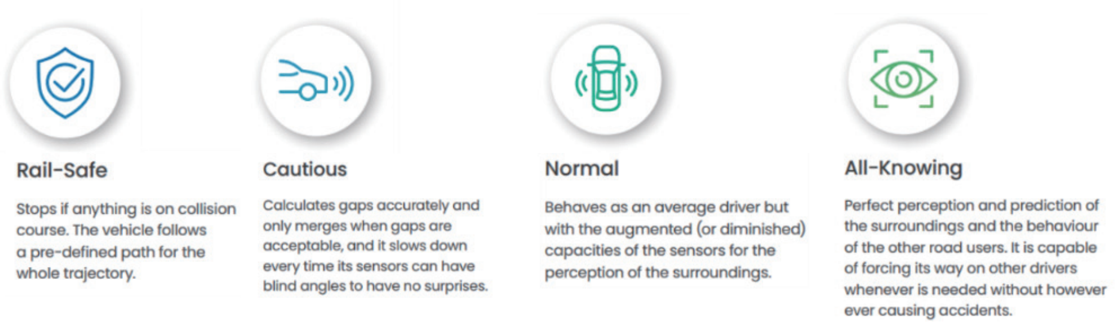

Fig. 5. (Color online) CoEXist's autonomous driving level.[15,16]

Additionally, CoEXist presents parameter values for the Car-following, Lane-change, Lateral, and Signal-control models depending on the autonomous driving level.

3. Sensor Data and Methods

Acceleration potential curves for electric and internal-combustion-engine autonomous vehicles are modeled in a simple traffic network with an intersection in Vissim, a microscopic traffic simulation model. First, the autonomous vehicle driving parameters suggested by CoEXist were applied to reflect the autonomous driving behavior.[27] In addition, on the basis of the acceleration potential curves, the acceleration profiles of ICEVs and EVs in an autonomous driving environment were modeled.

Out of the total simulation time of 7200 s, the number of passing vehicles for 3600 s was calculated after 3600 s of the initialization time. The simulation was replicated 10 times with different random seed numbers. A total of 15 scenarios were performed at different market penetration rates of EVs and ICEVs (0, 25, 50, 75, and 100%) and speed limits (70, 50, and 30 km/h).

To implement an autonomous driving environment in Vissim, the parameters presented by CoEXist were applied, and the variable values are as shown in Tables 1–3.[28] In Vissim, Wiedemann 74 is suitable for urban traffic and merging areas, whereas Wiedemann 99 is recommended for freeway traffic with no merging areas. Since a signalized intersection is modeled in this study, Wiedemann 74 is recommended.[29] However, CoEXist states that "it is recommended to use Wiedemann 99 to simulate automated vehicles because of more options to control the behavior through the driving parameters."[30] Therefore, Wiedemann 99 was utilized in this study.[31–33] Unlike human drivers who behave stochastically, autonomous vehicles act deterministically, so it was assumed that there would be no speed or acceleration deviation. In addition, in this study, we applied the 'Aggressive' acceleration potential curve, where there is a clear difference in acceleration behavior between ICEVs and EVs. Since this acceleration behavior is similar to the behavior of the highest autonomous driving level in CoEXist, 'All-knowing' was applied in this study.[27,32] Tables 1–3 show autonomous driving parameters of Vissim Default and All-knowing.

Table 1
Car-following model parameters.

Parameters	Description	Vissim default	All-knowing
CC0	Standstill distance	1.5 m	1.0 m
CC1	Gap time distribution	0.9 s	0.6 s
CC2	'Following' distance oscillation	4 m	0 m
CC3	Threshold for entering 'Following'	−8.0	−6.0
CC4	Negative speed difference	−0.35	−0.1
CC5	Positive speed difference	0.35	0.1
CC6	Distance dependence of oscillation	11.44	0
CC7	Oscillation acceleration	0.25 m/s^2	0.1 m/s^2
CC8	Acceleration from standstill	3.5 m/s^2	4.0 m/s^2
CC9	Acceleration at 80 km/h	1.5 m/s^2	2.0 m/s^2

Table 2
Lane-change model parameters.

<table>
<tr><th rowspan="2">Element</th><th rowspan="2">Description</th><th colspan="2">Vissim default</th><th colspan="2">All-knowing</th></tr>
<tr><th>Own</th><th>Trailing vehicle</th><th>Own</th><th>Trailing vehicle</th></tr>
<tr><td rowspan="3">Parameter for necessary lane change</td><td>Maximum deceleration (m/s^2)</td><td>−4</td><td>−3</td><td>−4</td><td>−4</td></tr>
<tr><td>−1 m/s^2 per distance (m)</td><td>100</td><td>100</td><td>100</td><td>100</td></tr>
<tr><td>Accepted deceleration (m/s^2)</td><td>−1</td><td>−1</td><td>−1</td><td>−1.5</td></tr>
<tr><td rowspan="5">Behavior functionality</td><td>Advanced merging</td><td colspan="2">On</td><td colspan="2">On</td></tr>
<tr><td>Cooperative lane change</td><td colspan="2">Off</td><td colspan="2">On</td></tr>
<tr><td>Safety distance reduction factor</td><td colspan="2">0.6</td><td colspan="2">0.5</td></tr>
<tr><td>Min. headway (front/rear) (m)</td><td colspan="2">0.5</td><td colspan="2">0.5</td></tr>
<tr><td>Max. deceleration for cooperative braking (m/s^2)</td><td colspan="2">−3</td><td colspan="2">−6</td></tr>
</table>

Table 3
Signal-control model parameters.

Element	Vissim default	All-knowing
Behavior at amber signal	Continuous check	One decision
Behavior at red/amber signal	Go	Stop
Reaction time distribution	—	—
Reduced safety distance factor	0.6	1
Reduced safety start upstream of stop line (m)	100	100
Reduced safety end upstream of stop line (m)	100	100

3.1 Acceleration profile

The acceleration and deceleration profiles of a vehicle can be implemented with the desired acceleration, maximum acceleration, desired deceleration, and maximum deceleration functions in Vissim. The desired acceleration function defines the target acceleration for each speed, and the maximum acceleration function sets the maximum acceleration physically possible. In this study, the acceleration potential curve of an aggressive driver was applied representing the 'All-knowing' aggressive autonomous driving behavior.

3.2 Network

A simple one-lane four-way signalized intersection with 100% through traffic flow was modeled in this study. To eliminate other influencing factors, only passenger vehicles are considered in this study. A Data Collection Point was set up at the stop line location following the definition of saturation flow rate presented in the Korea Road Capacity Manual, which is 'the maximum traffic volume that allows a vehicle stopped at a signalized intersection to pass the stop line.' The cycle length was 120 s with 55 s green time, 3 s yellow time, and 62 s red time. Of the total simulation time of 7200 s, the number of vehicles passing was counted for the latter 3600 s excluding the initial warm-up time of 3600 s. A total of 10 iterations were performed by changing the random seed, and the average number of passing vehicles was analyzed.

To investigate the impacts of different speed limits and market penetration rates of electric and internal-combustion-engine autonomous vehicles, scenarios with different speed limits and market penetration rates were designed. The numbers of vehicles passing the intersection with different market penetration rates of EVs/ICEVs, which were 0% EVs (100% ICEVs), 25% EVs (75% ICEVs), 50% EVs (50% ICEVs), 75% EVs (25% ICEVs), and 100% EVs (0% ICEVs) at a signalized intersection in a fully autonomous driving environment, were analyzed.

4. Results

In this study, traffic operational characteristics were investigated on the basis of different acceleration profiles of electric and internal-combustion-engine autonomous vehicles at a signalized intersection in a fully autonomous driving environment. Nonparametric statistical analysis was performed to quantitatively confirm the difference in results by market penetration rates.[34–37]

Figure 6 shows the numbers of vehicles passing the intersection over 3600 s at speed limits of 70 and 30 km/h. On average, 1704 vehicles passed when the EVs were 0%, 1701 when they were 25%, 1735 when they were 50%, 1769 when they were 75%, and 1800 when they were 100%. As can be seen in Fig. 7, as the market penetration rate of EVs increases, the number of vehicles

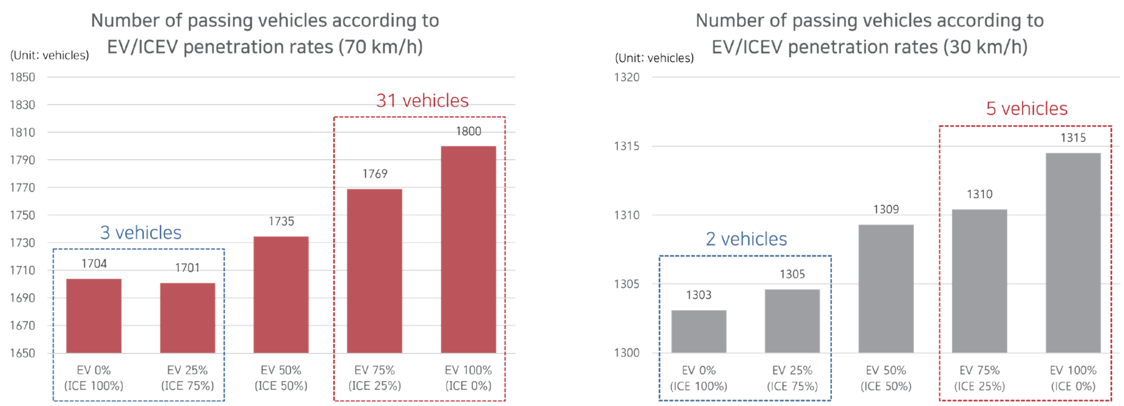

Fig. 6. (Color online) Numbers of passing vehicles.

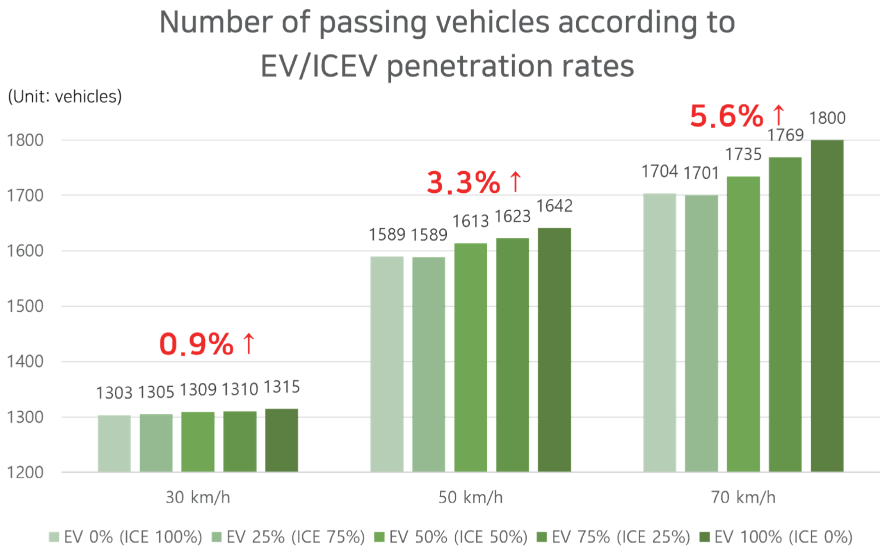

Fig. 7. (Color online) Numbers of passing vehicles at different EV/ICEV penetration rates.

passing the intersection tends to increase. The number of vehicles passing the intersection increases by 31 vehicles when the EVs increase from 75 to 100%. As seen in the case of a 70 km/h speed limit, the number of passing vehicles increases with EV market penetration rate. However, the increase is not as significant as in the case of the 70 km/h speed limit.

The total number of vehicles passing the intersection was compared at different market penetration rates of EVs/ICEVs and speed limits. When the market penetration rates of EVs/ICEVs changed from 0%/100% to 100%/0% at the 30 km/h speed limit, the number of vehicles passing the intersection increased by 0.9% from 1303 to 1315 vehicles. However, the increase went up to 5.6% when the speed limit was 70 km/h. Also, they are expected outcomes since differences in acceleration profiles between EVs and ICEVs are more significant at a higher speed limit.

When the market penetration rates of EVs/ICEVs changed from 0%/100% to 25%/75% at the 70 km/h speed limit, the number of vehicles passing the intersection differed by 0.18% from 1704 to 1701 vehicles. However, the difference becomes larger at higher market penetration rates of EVs and lower penetration rates of ICEVs. The increase is not linear as seen in Fig. 7.

5. Discussion

There are multiple ways of estimating the traffic operational characteristics based on different acceleration profiles. Field experiments with actual electric and internal-combustion-engine autonomous vehicles would be ideal in the calculation. However, this method would be time-consuming and labor-intensive. Also, it would require significant cost and permission from local governments with potential safety issues if it is tested on public roads. For these reasons, traffic simulation was utilized to measure the differences in this study. Traffic simulation programs can regenerate traffic conditions with good precision and are considered an alternative method with significantly low cost and time.

Acceleration potential curves for electric and internal-combustion-engine autonomous vehicles were identified and modeled in a simple traffic network with an intersection in Vissim, a microscopic traffic simulation model. In this study, no human drivers were considered to simplify the scenarios and eliminate outside factors other than different acceleration profiles of electric and internal-combustion-engine autonomous vehicles. Understandably, this assumption is one of the limitations of this analysis. It was expected that the difference would be less apparent with the inclusion of human drivers in the analysis. Including human drivers in the analysis would also require a significant assumption of what the human driver behavior would be. Also, the interaction between human drivers and autonomous vehicles would create differences in the analysis depending on the assumption.

On the basis of the assumption, this study demonstrated that more vehicles could pass a signalized intersection when there are electric autonomous vehicles than when there are internal-combustion-engine autonomous vehicles. Also, the impacts of different speed limits and market penetration rates of electric and internal-combustion-engine autonomous vehicles were investigated. As expected, the impacts of different acceleration profiles of electric and internal-combustion-engine autonomous vehicles were observed at the higher speed limit since more gear changes are needed under these traffic conditions.

It is anticipated that other factors would also impact traffic capacity in autonomous vehicle environments. Those other factors would include human driving behavior, human drivers' interaction with autonomous vehicles, the number of vehicles with other acceleration profiles (for example, trucks and buses) in the traffic stream, and the driving logics of autonomous vehicles. These factors should be investigated as future research topics.

6. Conclusions

Sensor technologies have been widely utilized as indispensable components to improve efficiency and safety in transportation applications. Integrating onboard and roadside sensor data has potential applications in monitoring traffic operations and increasing traffic operational efficiency. As a result, this integration will help us understand traffic operations and mitigate traffic congestion and associated problems in our society. In this study, the operational efficiency of different types of autonomous vehicle technology was investigated for the integration of advanced sensor application technologies required for the operation of autonomous vehicles. With the development of sensor technology in the autonomous and electric vehicle industry, more vehicles are expected to be electric and have autonomous driving capability. It is believed that electric vehicles allow for the simpler integration of the advanced sensor application technologies required for the cleaner and safer operation of autonomous vehicles. Although electric autonomous vehicles have many advantages over their gasoline-powered counterparts, not all autonomous vehicles are manufactured as electric vehicles. Therefore, it is expected that electric and internal-combustion-engine autonomous vehicles will be operated in a mixed environment. Even though autonomous vehicles operate with their operating logic without human inputs, electric and internal-combustion-engine autonomous vehicles will follow their respective characteristics including acceleration profiles. The differences in their acceleration profiles would lead to differences in traffic operation characteristics where acceleration is involved, especially at signal intersections.

In this study, we investigated the traffic operational characteristics on the basis of different acceleration profiles of electric vehicles and ICEVs at a signalized intersection in a fully autonomous driving environment. Statistical analysis results demonstrated that statistically insignificant differences were found at lower market penetration rates of EVs and higher market penetration rates of ICEVs, whereas the differences were found to be significant at higher market penetration rates of EVs and lower market penetration rates of ICEVs. These outcomes are expected since a small increase in the number of ICEVs in groups with the majority of EVs will make a significant impact on the traffic flow, whereas even a relatively significant increase in the number of ICEVs in groups with the majority of ICEVs will not create significant operational differences. It was recognized that the number of vehicles passing the intersection increased with market penetration rates of EVs since EVs have acceleration profiles without gear shifting. Also, it was found that there was a significant difference in the number of vehicles passing the intersection when the market penetration rates of EVs were relatively higher. It is believed that the acceleration of a trailing vehicle is limited by the preceding vehicle. For example, if the trailing vehicle is an EV and the preceding vehicle is an ICEV, the trailing vehicle cannot accelerate with its own EV acceleration profile since it has to maintain the same acceleration as the preceding vehicle while keeping a safe distance from the preceding vehicle even though it has a higher initial acceleration capability. Additionally, the number of vehicles passing the intersection increases at a higher speed limit, since the differences in acceleration profiles between EVs and ICEVs are more significant at a higher speed limit. The findings in this study are expected to provide more insights into the operational differences between autonomous EVs and ICEVs.

Acknowledgments

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