The Impact of Autonomous Vehicles on Highway Tunnel Work Zones

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ABSTRACT

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In the transition step to the near future where autonomous vehicles fill the highways, the autonomous vehicles' successful implementation counts on knowledge about their interaction with conventional vehicles. Due to the lack of numbers of the autonomous vehicles on roadways, many transportation professionals depend on simulations in order to examine the coexistence of both vehicle types and their interaction in the circumstance of higher market penetration rates of the autonomous vehicles. In this study, VISSIM microscopic simulator is used for inspecting the autonomous vehicles interactions and assessing their impacts on traffic stream. A case study that evaluates the effects on vehicles throughput, delay, queue length, and safety at the highway work zone merging area is investigated. The simulation was generated the proximity of the Louis-Hippolyte La Fontaine tunnel, which connects Boucherville and Montréal island. To simulate coexist periods, the autonomous vehicles were put into the simulation with different penetration rates starting at 20% and increasing 20% for each scenario until reaching 80% of the rates of the autonomous vehicles. Furthermore, the safety impact of the autonomous vehicles in the matter of conflicts was studied using the Surrogate Safety Assessment Model (SSAM). The simulation results showed that the tunnel work zone's capacity per lane was increased when CAVs were added to the simulation. The average vehicle delay did not improve a low CAV penetration rates. However, as CAVs account for more than 40% of the total passenger vehicles, the vehicle delay improved. The simulated model also showed that the average queue length increased with the increase of CAV in the traffic stream. Nonetheless, the conflict analysis results proved that CAVs can improve overall traffic safety at the work zone.

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Acronyms/Abbreviations

AADT = Annual Average Daily Traffic

ACC = Adaptive Cruise Control

ACTIVE = Alberta Cooperative Transportation Infrastructure and Vehicular Environment

ADAS = Advanced Driver Assistance Systems

AIMSUN = Advanced Interactive Microscopic Simulator for Urban and Non-urban networks

ANOVA = Analysis of Variance

ARTM = Autorité Régionale de Transport Métropolitain

AURORA = Automotive testbed for Reconfigurable and Optimized Radio Access

AV(s) = Autonomous vehicle(s) or Automated Vehicle(s)

AVAM = Autonomous Vehicle Acceptance Model

CA model= Cellular Automation model

CAV(s) = Connected and Autonomous Vehicle(s)

CV(s) or ConV(s) = Conventional Vehicle(s)

DeltaS = Maximum Speed Differential

DeltaV = Vehicle Velocity change had the event proceeded to a crash

DR = Initial Deceleration Rate

DSRC = Dedicated Short-Range Communications

FHWA = Federal Highway Administration

GA optimization = Genetic Algorithm optimization

GEH statistic = Geoffrey E. Havers statistic

GRE = Global Relative Error

HEVs = Hybrid Electric Vehicles

HGVs = Heavy-Goods Vehicles or Trucks

HV(s) or HDV(s)= Human-Driven Vehicle(s)

IDM+ = Intelligent Drivel Model

La Fontaine Tunnel = Louis-Hippolyte-La Fontaine Tunnel

LiDAR = Light Detection and Ranging

LMRS = Lane-change Model with Relaxation and Synchronization

MANE = Mean Absolute Normalized Error

MATLAB = Matrix Laboratory

MaxD = Maximum Deceleration Rate

MaxS = Maximum Speed

MOE = Measure of Effectiveness

MOPSO = Multi-Objective Particle Swarm Optimization

MPC method = Model Predictive Control method

NMA optimization = Nelder-Mead optimization

O/D = Origin/Destination

PET = Post Encroachment Time

PMAE = Point Mean Absolute Error

PMRE = Point Mean Relative Error

PSO = Particle Swarm Optimization

PTV = Planung Tansport Verkehr (German logistics software company)

SAAQ = Société de l'Assurance Automobile du Québec

SAE = Society of Automotive Engineers

SAVs = Shared Autonomous Vehicles

SMD system= Spring-Mass-Damper system

SSAM = Surrogate Safety Assessment Model

SUMO = Simulation of Urban Mobility

TS algorithm = Tabu Search algorithm

TSM = Two-state Safe-speed model

TTC = Time to Collision

UA = User Acceptance

UX = User Experience

V2I = Vehicle-to-Infrastructure

V2V = Vehicle-to-Vehicle

VISSIM = Verkehr In Städten - Simulationsmodell

WOA = Whale Optimization Algorithm

WSDOT = Washington State Department of Transportation

1. Introduction

1.1 Background

Modern cars using engine power have been used since their invention in 1886, and they now face their most challenging evolution yet, in which they become autonomous vehicles (also known as AVs, self-driving, or driverless vehicles). In the transition step to the not-so-distant future where autonomous vehicles will fill highways, a successful implementation counts on knowledge about the interaction with conventional vehicles (CVs). Due to the small number of low-level and Level 5 autonomous vehicles on roadways, many transportation professionals depend on simulations in order to examine the coexist state of both vehicle types, conventional vehicles and autonomous vehicles, and their interaction in the circumstance of higher market penetration rates of the autonomous vehicles (*1*-*7*).

The microscopic simulation platform VISSIM from PTV is one of the most frequently used simulation systems in the traffic engineering field. While it allows for external add-in programs to implement connected and autonomous vehicles (CAVs), in its recent upgrades it offers a built-in function for simulating CAVs, a feature that has been utilized by transportation professionals in many applications. Furthermore, the PTV developers used this feature for a project they participate in and has been improving its abilities through various updates (*8*).

In Canada, especially in Quebec, severe weather conditions shorten roadways' lifetime, which can be one of the reasons why there are so many work zones when the weather becomes warm. According to the *Société de l'Assurance Automobile du Québec* (SAAQ), in 2019, there were 876 people injured, and nine people were killed at work zones in Québec. Also, the government built a safety guide for the work zones and charged fines to those who don't obey speed limits, but highway maintenance, or construction work is still dangerous for workers (*9*). Not only is safety a big problem, but also capacity in highway work zones. There have been many studies examining work zone capacity drops, and methodologies in order to improve those situations (*10*-*11*).

Safety assessment of roadways generally depends on police reports; however, all of the roadways do not have statistically significant vehicle accidents and there are even needs to examine roadway facilities that are not built yet. To address these limitations, the Surrogate Safety Assessment Model (SSAM) software was developed by the Federal Highway Administration (FHWA) (*12)*. Basically, SSAM evaluates traffic safety based on vehicle trajectory data which can be obtained from four different traffic simulation programs: TEXAS, VISSIM, AIMSUN, and Paramics. Time-to-collision (TTC) and Post-Encroachment Time (PET) are the key values of conflict evaluation, as well as types of conflicts, and the total number of conflicts (*13*). Since SSAM came out, it has been widely used for evaluating transportation facilities with compatible traffic simulation software (*1-2,14-16*).

1.2 Problem Statement

Since low-level autonomous vehicles were introduced to the motorcar market, autonomous vehicles' technologies have kept progressing year after year. The CAVs are expected to ease traffic-related problems such as congestion, pollution, and accidents. However, when considering the technologies' advancement time, it is certain that there will be a long transition period where the conventional vehicles and autonomous vehicles coexist. For the successful fusion of autonomous and conventional vehicles, more studies are needed to assess the impacts of the CAVs on traffic streams under mixed conditions before more CAVs penetrate the marketplace.

Transportation facilities, including pavement, traffic lights, and markings, require maintenance efforts in order to function properly and guarantee safety. Therefore, work zones created by the maintenance work and construction of new facilities as well, cannot be avoided. Highways facilities are especially in a unique circumstance due to the fact that they demand higher speeds than arterial and local roads. The higher speeds accompanied by higher travel demands shorten highway pavement lifetimes. Moreover, severe weather conditions, and the percentage of heavy-goods vehicles also exacerbate the situation. The work zones on the highways commonly cause lane-closures and force vehicles to merge with the open lanes. To deal with the lane-closures, open highways can utilize shoulder areas as temporary lanes or for widening the lanes, but special facilities such as tunnels and bridges only have limited space.

1.3 Research Objectives

The objective of this thesis is to examine the impact of CAVs on traffic flow under mixed traffic conditions at tunnel work zone areas, and to provide an overall estimate of traffic stream for the near future where conventional vehicles and CAVs coexist. The study area used to analyze the results in this thesis was limited to a tunnel with one lane reduction. However, it could be extended to the overall merging areas because the distinctiveness of the study area is only concerned with whether shoulder areas can be utilized as a temporary lane or not. Under the limited condition of the tunnel section, this study investigates whether the CAVs can improve traffic operations as well as how much they change with respect to vehicle throughput, vehicle delay, queue length, and safety. Consequently, if autonomous vehicles can reduce the tunnel work zones' congestions and improve safety, it will mean that they are also able to somewhat enhance the open highway's work zone conditions.

1.4 Thesis Organization

The following chapters are organized as follows: Chapter 2 provides reviews of studies related to connected and autonomous vehicles, microscopic traffic simulation VISSIM, and Surrogate Safety Assessment Model; Chapter 3 presents the VISSIM driving parameter setting method, the calibration process, and SSAM analysis; Chapter 4 provides details of the simulation network and the simulation results; Lastly, Chapter 5 delivers the conclusion of the study, and provides future research subjects which can be extrapolated from this study.

2. Literature Review

2.1 Recent Studies on Connected and Autonomous Vehicles (CAVs)

Ever since the first steps for driverless vehicles were taken in 1977, technologies for car automation greatly depend on government funding. However, as vehicle automation has started getting great attention, mainstream car manufacturers now have projects in many ways for pursuing higher levels of vehicle automation (*17*).

Autonomous vehicles (AVs), also known as self-driving cars or driverless vehicles, refer to fully automated vehicles which belong to automation level-5 of SAE (Society of Automotive Engineers) standard (*18*). Sometimes AVs are distinguished from connected vehicles (or cooperative AVs) in some papers for the reason that connected AVs can interact with other vehicles (V2V) or with transportation infrastructure (V2I), whereas autonomous vehicles gather information through sensors (e.g., LiDAR, radar, video, etc.) (*12,19-20*). However, in many studies connected and autonomous vehicles (CAVs) are defined as one concept of the future automobile that can drive without human intervention.

Vehicle automation level has 6 steps from level 0, which means no automation condition, to level 5: fully automated so human intervention isn't required in any case and at any time. Moreover, they can even move on road facilities without human drivers (*21-23*). Table 1 is a criterion which were established by SAE International, and its descriptions of each levels (*18*).

Many car models sold in the market today have Level 1 automation systems. They are equipped with auto-braking, self-parking, lane correction, crash avoidance, and adaptive cruise control for assisting drivers (*24,27*). Tesla vehicle systems are considered Level 2 (*28-29*), which is not a fully autonomous step: Level 4, but have the most advanced driver assistance systems than most vehicles on the market which still stay in the Level 1 stage (*24*). Audi introduced A8 with Traffic Jam Pilot which is considered as a level 3 automation. A8 has six camaras, one Bus gateway and five LiDAR sensors that make a 360° view possible (*25*). However, due to the lack of legislation, all the features of level 3 Traffic Jam Pilot are allowed in Germany only; therefore, it is limited functionally and categorized as level 2 in the USA. For the same reason, vehicles having level 4 automation features that are in development by companies like NAVYA, Alphabet’s Waymo, Magna, and Volvo, are not able to be fully rolled out yet. They have geolocation limitations which include speed limits for a test drive: geofencing (*26*).

SAE J3016™ LEVELS OF DRIVING AUTOMATION

	SAE LEVEL 0	SAE LEVEL 1	SAE LEVEL 2	SAE LEVEL 3	SAE LEVEL 4	SAE LEVEL 5
What does the human in the driver’s seat have to do?	You are driving whenever these driver support features are engaged – even if your feet are off the pedals and you are not steering			You are not driving when these automated driving features are engaged – even if you are seated in “the driver’s seat”		
	You must constantly supervise these support features; you must steer, brake or accelerate as needed to maintain safety			When the feature requests, you must drive	These automated driving features will not require you to take over driving	
	These are driver support features			These are automated driving features		
What do these features do?	These features are limited to providing warnings and momentary assistance	These features provide steering OR brake/ acceleration support to the driver	These features provide steering AND brake/ acceleration support to the driver	These features can drive the vehicle under limited conditions and will not operate unless all required conditions are met		This feature can drive the vehicle under all conditions
Example Features	• automatic emergency braking • blind spot warning • lane departure warning	• lane centering OR • adaptive cruise control	• lane centering AND • adaptive cruise control at the same time	• traffic jam chauffeur	• local driverless taxi • pedals/ steering wheel may or may not be installed	• same as level 4, but feature can drive everywhere in all conditions

For a more complete description, please download a free copy of SAE J3016: https://www.sae.org/standards/content/J3016_201806/

Table 1 SAE autonomous vehicle level and description (18)

Narla and Stowell (*27*) pointed out the automated vehicle market was estimated to be worth \$54.23 billion in 2019. Furthermore, it is predicted that it will keep growing to a market share of \$556.67 billion by 2026 according to Allied Market Research (*30*). As evidence of the market expansion, many vehicle manufacturers are investing heavily in autonomous vehicles: Waymo is testing its driverless cars in various cities in the United States, General Motors is trying out its self-driving cars also in the States, and they are planning to start a self-driving car business in 2021. Moreover, Tesla keeps updating its automation technology, *Autopilot*, for pursuing ‘*Full Self-Driving (FSD)*’ by the end of 2020 at the earliest according to the article from 2019 (*31*). Ford has also the intention to sell automated vehicles by 2025 (*24*).

Accompanying the efforts of businesses, governments of each country are doing hard work to let higher-level autonomous vehicles drive their way on roadways: in the US, states such as Nevada, California, Florida, Michigan, and Washington DC have passed legislation for providing testbeds for driverless cars (*32*). As an example, the California Department of Motor Vehicles (California DMV) issues autonomous vehicle testing permits for providing opportunities to manufacturers for driving on roadways. The testing permits include two types: with and without a driver. Until September 1, 2020, 61 permits for a test with a driver had been issued, and as of July 17, 2020, three manufactures, Waymo LLC, Nuro inc., AutoX Technologies Inc hold the permit that makes it possible to conduct a test without the presence of a driver (*33*). Moreover, the Government of Canada has launched the Program to Advance Connectivity and Automation in the Transportation System (ACATS) to invigorate autonomous vehicle technologies, and to make jurisdictions ready for the innovations. In addition, Canada has had 21 autonomous-vehicle-related tests and research studies in various areas with great advantages regarding diverse weather, road surface conditions, and varying geographical environments (*34-35*). ACTIVE-AURORA project is one of those studies which furnishes four test beds and two laboratory test conditions: ACTIVE (Alberta Cooperative Transportation Infrastructure and Vehicular Environment) in Edmonton, and AURORA (Automotive testbed for Reconfigurable and Optimized Radio Access) is conducted in Vancouver for studying wireless communications for vehicle connectivity and performing test-driving even in severe winter conditions in Canada. The Government of Canada, academic and industry partners are involved in this project to accomplish advancement of development, researching, and testing of connected-vehicle-related technologies (*35-36).*

2.2 Future Development of CAVs

It has been said that there might be two possible futures when AVs become mainstream technology: a utopian or dystopian future (*37*). In the utopian future of the AVs, accompanied by a decrease in vehicle possession through so-called Shared Autonomous Vehicles (SAVs) like many studies predict (*38-40*), there will be fewer traffic accidents, parking problems, less traffic jams, and fossil fuel consumption (*2,24,32*). On the other hand, in the dystopian future, vehicle usage will be increased since all people can approach the vehicles without the hassle of driving manually. Therefore, it is predicted that there will be worse traffic congestion, air pollution, and more energy consumption as a result (*37*). Regardless of which future humans are going to be faced with, the problem is when the level 5 autonomous cars will be available and how they expand their market dominance.

One study predicted AVs' influence will get bigger from the 2020s onward and they will become a main transport method by the 2050s (*32*). Ye and Yamamoto (*41*) also stated that CAVs will be found in the market starting in the 2020s. In his recent study, Litman (*22*) forecasted level 5 autonomous vehicles will start their way from the 2030s when considering previous vehicle-related technologies' footsteps: automatic transmissions, airbags, hybrid vehicles and so on. The author also added its development will go along with the Innovation S-Curve (see below Figure 1) like many other technologies have done. Self-driving car technologies are put on the very first step now, Development and Testing, and he said that it will be available commercially with a high price tag, but as the market is expanded the price will be reduced and be more accessible for the public. Consequently, it is estimated that it will finally be able to reach Saturation level in the 2070s.

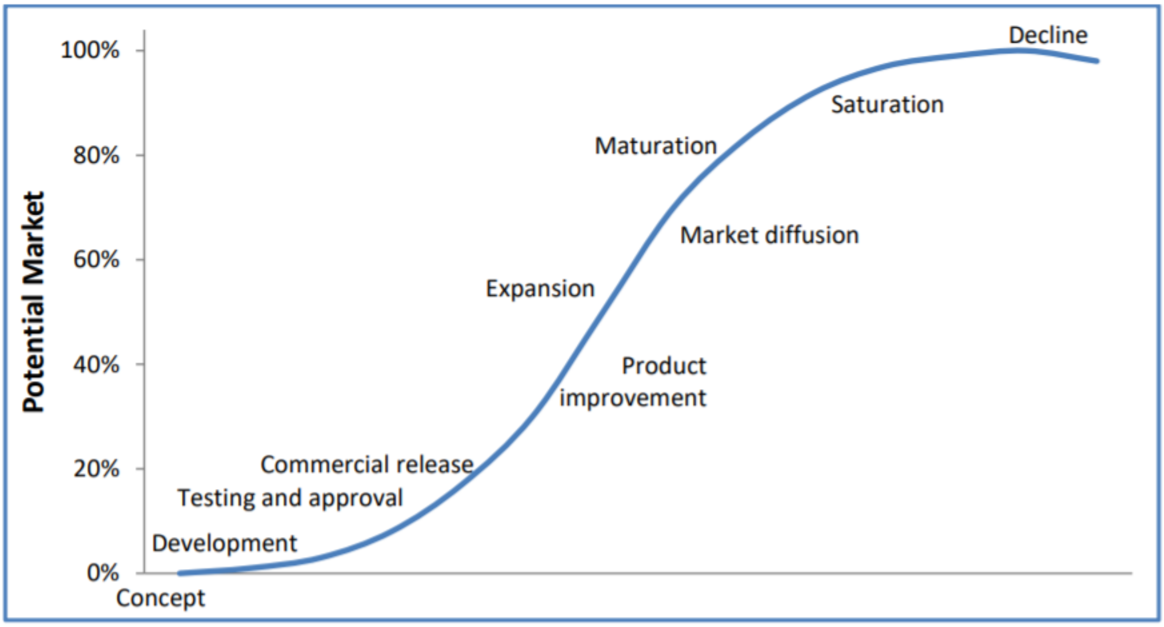

Figure 1. Innovation S-Curve (22)

Autonomous vehicles' future was predicted in a different way by building an autonomous vehicles adoption model in the USA regarding similar technologies and trends. The proposed Generalized Bass diffusion models include two main factors: the innovation factor (how people take a risk) and the imitation factor (how people depend on social status). Additionally, the price-change tendency and economic wealth were considered as external factors. In the study, deployment of the autonomous vehicles was assumed based on Hybrid Electric Vehicles (HEV)' sales data in the US compared with the same size and the same company's conventional vehicle. Not only did the authors give thought to HEVs, but also internet and cell phone adoptions as the public will obviously take the AVs in a more conservative way than those innovations. This study presumed AVs will be on the market starting in 2025 and reach the saturation level in 2059, comprising 75% of total sales (*42*).

In another study, an innovation diffusion model was established from the expectation that the driverless cars will be on the roadways in 2025 as (*42*) expected. This study examined how an individual's openness to new technology has an effect on the introduction of AVs in the market. The authors obtained the results from an online survey in the Chicago metropolitan area. The researchers presented a consistent additional price decrease of $5,000 every five years, starting from $20,000 and until it reached $5,000 in the survey choices. In addition, the respondents were asked for personal and demographic backgrounds in their responses, such as travel patterns, education level, income level, car accident experience, advanced technologies usage status. By analyzing 1013 eligible responses, they concluded that 71.3% of the Chicago metropolitan residents will ultimately possess the AVs, and significantly, people who often travel long distances, who can afford higher prices, and who have a car accident experience are more open to self-driving vehicles (*43*).

However, the future toward the higher penetration rate of self-driving cars still has a long way to go. An unknown length of coexisting period cannot be avoided until fully autonomous vehicles become the mainstream on roadways (*3,41,44*). Difficulties to invent and implement technologies for driverless cars, as well as users' unwillingness to utilize them, are the main obstructions. AVs are even referred to as having more complex systems than airplanes when thinking about interactions with surrounding transportation facilities and other vehicles as well (*22*). From potential users' point of view, examples of fatal accidents surely make people anxious about bringing CAVs into their daily lives. However, opposing examples in which existing low-level automated vehicles save drivers' lives can be commonly found so advancements of technologies do not always usher in horrifying consequences (*45*).

2.3 Evaluation of CAVs Impact on Traffic Operations and Safety

CAVs are expected to bring numerous advantages to traffic flow in many ways (i.e. capacity, safety, efficiency, stability and air pollution) (*2-3,20,46*). In addition, connected and autonomous vehicles' instant reaction time and smaller vehicle gaps maintainability, compared to human-driven vehicles, are directly led to traffic conditions (*41,47*).

Even though there have been many technological improvements to correct mistakes of human drivers, nobody can be sure about the future of self-driving cars on roadways, in and of itself, but also interaction with other transportation components, including conventional vehicles in heterogeneous traffic flow. Furthermore, level 2 autonomous vehicles are the most prevalent ones on roadways so only through traffic simulators or model frameworks mixed traffic conditions including both conventional vehicles and higher level of autonomous vehicles can it be embodied. Therefore, many traffic practitioners give assumptions based on their studies through traffic simulations and models. Some researchers predict CAVs will solve many existing problems such as traffic jams and human-error related crashes (*41,48*). Others give opinions saying they can cause worse traffic conditions in the early adaptation stage. Nevertheless, fortunately, both forecasts agree that higher penetration of autonomous vehicles will finally subdue traffic congestion (*44*).

2.3.1 Impact on Roadway Capacity

To examine autonomous vehicles' impacts on mobility, safety, emission, and fuel consumption in mixed traffic conditions, Li & Wagner (*48*) utilized SUMO, an open-source microscopic simulator, with various penetration rates of AVs. They built a simulation model using a New Zealand's 5.3-km length highway corridor with three on/off ramps and examined four different travel demands based on the traffic data: free-flow, light congestion, heavy congestion, and future demand which is three times the heavy congestion vehicle volume. The study revealed exceptional traffic stream improvement can be achieved when the penetration rate is over 70% in the light and heavily congested traffic conditions. It is in accordance with other studies saying low-penetration rate of autonomous vehicles will not bring immediate traffic ease (*44*). In addition, due to the lack of vehicle interactions there was no great enhancement under free-flow speed, and roadway safety and air pollution became worse in the future traffic demand as overall mobility was escalated.

Connectivity among autonomous vehicles was emphasized by Olia et al. (*19*) to improve highway capacity through comparing simulation results, including autonomous vehicles or cooperative AVs by utilizing PARAMICS microscopic traffic simulation. The simulation scenarios can be categorized into two big vehicle categories: regular vehicles and autonomous vehicles, or regular vehicles and cooperative AVs. As base conditions for each vehicle type, regular and autonomous vehicles have the same headway, which is 1.0s, and cooperative vehicles have 0.5s in case related vehicles are all cooperative vehicles, otherwise, they behave like the same way that autonomous vehicles do. The study results assured that cooperative AVs have a better role in improving roadway capacity as the market penetration rate becomes larger. Besides, autonomous vehicles were not able to make significant enhancements even in a situation of 100% composition rate. The authors found reasons from cooperative AVs' instant information sharing ability, and therefore, unlike autonomous vehicles they don't waste time capturing leading vehicles' speed and processing it. However, the background of this study overlooked that vehicle automation technologies consider not only autonomation but also their connectivity at once. Additionally, as the researchers recommended, if dedicated short-range communications (DSRC) can be a solution for separation, there is no need to worry about connectivity.

Dissimilar to simulation-based studies, Chen et al. (*49*) proposed a mathematical approach to compute traffic capacity in a heterogeneous traffic condition. They expanded the formulations from single-lane highways to multi-lane highways, and also took AV penetration rates, and platooning into consideration. However, it is a theoretical method, so it has limitations in terms of catching external factors.

An O/D pair nonatomic routing game was deployed by Mehr & Horowitz (*47*) to verify that it will take time to see the vehicle automation's positive aspects on total vehicle delay. The study assumed only a homogeneous state of each vehicle type; however, it still has a meaning in terms of the results confirmed that autonomous vehicles' selfish driving route choice can have a negative effect on the network equilibrium.

On the contrary, the positive effect of connected and autonomous vehicles in low penetration on capacity was checked from a study using model frameworks. The study employed a two-state safe-speed model (TSM) and a two-lane cellular automation (CA) model: the former was utilized for simulating conventional vehicles and the latter was for CAVs, with diverse penetration rates of self-driving cars. Additionally, to apply various levels of connectivity, three different values (0.5s, 0.8s, 1.1s) were used as the desired net time gap of CAVs in this study. The results said after the CAV penetration rate reaches 30%, its impact on traffic capacity is significant, and the higher the vehicle connectivity, the greater the capacity increase during coexist periods (*41*). However, this study only assessed two-vehicle connection between a leading vehicle and a following vehicle. The limitation of connectivity follows disjointedness in lane changing maneuvers, so it needs to depend on external detection of vehicle movements in an adjacent lane.

Calvert et al. (*44*) utilized an Intelligent Drive Model (IDM+) and a Lane-change Model with Relaxation and Synchronization (LMRS) for deploying both longitudinal and lateral movements of vehicles: regular manual vehicles and low-level automated vehicles having Adaptive Cruise Control (ACC) system. The simulation network contains a three-lane highway with on-ramp area to examine traffic stream change at a bottleneck, with various penetration rates of automated vehicles. It is significant that it considered not only interaction with conventional vehicles but also with trucks which generally have slower speed limits. The results indicate that more than 70% of low-level automated vehicles can improve traffic flow. However, it also shows there are no exceptional correlations to bottleneck severity or the interaction with heavy good vehicles.

2.3.2 Impact on Safety and Stability

Even autonomous vehicles have enough technologies to drive by themselves, their bright future in which they achieve dominance in the automobile market depends on users' acceptance. Some people would believe that machines drive better than men, and hence, they will implement autonomous vehicles in their lives ahead of others. However, others will take time to trust their safety and stability. Unfortunately, others would never fully credit self-driving vehicles.

Drivers' openness towards autonomous vehicles is highly related to their driving habits, sociological and demographic characteristics. König & Neumayr (*50*) figured out that people who are young, urban, males, who have experience with the present vehicles' automated features are likely to be fond of self-driving vehicles. Rödel et al. (*51*) reached a similar conclusion through an online questionnaire. The survey revealed how the levels of automation affect User Acceptance (UA) and User Experience (UX), and the result indicated drivers who are experienced with low-level vehicle automation systems, Advanced Driver Assistance Systems (ADAS), and often use vehicles are expected to accept autonomous vehicles easily. Hewitt et al. (*52*) conducted an online poll to capture potential users' viewpoints towards various autonomy levels by using the Autonomous Vehicle Acceptance Model (AVAM) they proposed. The study showed worsening safety concerns, along with an increase in anxiety, with growing vehicle automation levels.

Since these are all survey studies, they may have uncertainties in selecting a sample group, and ambiguity in its representation that decides if these studies can be widely applied. Furthermore, the public are required to conceptualize being in a driverless vehicle, and therefore, their fears come from unknown things may cause the negative judgements.

Safety

From the prospects of the aforementioned studies, it became obvious that successful employment of autonomous vehicles counts on how they appeal to inexperienced drivers in the matter of safety. Generally, self-driving vehicles are expected to have a smaller headway between surrounding vehicles. Hence, many studies have assured that roadway capacity will be improved with the presence of autonomous vehicles (*41,48*). Now, the problem is how shorter gaps have an influence on roadway safety.

Level-4 autonomous vehicles' positive impacts on safety and delay at a signalised intersection and a roundabout were checked by using traffic simulation VISSIM. Morando et al. (*2*) designed two autonomous vehicle models by modifying parameters of Wiedemann 99 driving behavior: one model, named AV-1 in this study, has aggressive acceleration but slightly higher headway time (CC1), and the AV-2 model has a longer standstill distance (CC0) and following variation (CC2) values. A number of conflicts per scenario with various penetration rates of autonomous vehicles were computed through the Surrogate Safety Assessment Model (SSAM). Moreover, conflicts between AV and AV, AV and Human-driven Vehicle (HV), and HV and HV were distinguished from vehicle IDs obtained through VISSIM results. In this study, Time to Collision (TTC) and Post Encroachment Time (PET) values were used for estimating vehicle conflicts, and the authors used a default value of PET but applied 1 second and 0.75 seconds of TTC threshold for AV-AV conflict to reflect their smaller vehicle gap. The simulation results identified that with more than 50% of the penetration rate of both AV models, the number of conflicts were significantly reduced at the signalized intersection. For the roundabout, meaningful safety improvements appeared in the 100% scenario of the AV-1 type model, and the AV-2 model required above 75% and 50% of the market penetration rate when using 1 second and 0.75-second PET values respectively. They also emphasized vehicle connectivity for better safety improvement and, the necessity of a new safety assessment technique for AVs (*2*). This study is meaningful because the researchers distinguished AV-AV, AV-HV, and HV-HV conflicts separately, and hence, it makes more precise conflict analysis possible. However, when a simulation network size gets bigger, it will not be an easy task. From a long-term point of view, what is required is an additional function that indicates conflict related vehicle types in an undemanding way.

VISSIM is also used in another study (*1*) utilized to investigate CAVs' impacts on traffic safety on a three-lane motorway stretch during weekdays with different CAV penetration rates: 0%, 25%, 50%, 75%, and 100%. However, different from Morando et al. (*2*), vehicle control algorithms for CAVs were programmed externally through C++. The programmed CAVs in this study can recognize up to twelve vehicles surrounding themselves within the range of 200m. A basic rule for the CAVs which was set by the researchers is a CAV finds a downstream CAV to form a platoon, and, if necessary, changes lanes. Plus, once it successfully detects a leading CAV it will follow them with a predefined accepted car-following time-gap: 0.6s. Additionally, vehicle inputs for human-driven vehicles (HVs) were calibrated with loop detector data, and TTC values for the HVs were adjusted with radar, camera, and GPS device data obtained from an instrumented vehicle at a testbed. The safety impacts of CAVs were examined by the total number of conflicts computed through SSAM. The authors used default TTC and PET threshold values, 1.5s and 5s each, for all scenarios. The study results stated that even a low penetration rate of CAVs can improve roadway safety, and the impact is bigger in higher travel demand conditions. Additionally, Papadoulis et al. (*1*) observed that conflict reduction between 75% penetration rate and 100% was smaller than other scenarios in all weekdays. They guessed that CAVs in the 75% penetration rate scenarios are able to find other CAVs easily and make a platoon, and therefore, they can effectively reduce the influence of HVs.

Different traffic simulator is also employed to investigate AVs' safety impact in mixed traffic conditions. Arvin et al. (*4*) employed SUMO traffic simulation and modelled a 150m intersection area. They set ten different vehicle compositions for two case studies: case 1 contains human-driven vehicles (HVs, automation level 0), level-3, and level-5 automated vehicles while the second case excludes. When considering the fact that the average vehicle lifetime is 12.88 years in Canada and 15.36 years in the U.S. (*53*), and thinking about early adopters who will bring self-driving vehicles to daily life as soon as possible, case 1 presumes the advancement of vehicle automation technologies from level-3 to level-5 will not take longer than the vehicle lifetime expectation, and it seems more realistic than case 2. The first case supposed that each driving behavior was calibrated from the Wiedemann model by having a distinguished level of cautiousness and a level of situation awareness values. The results showed that a number of conflicts were alleviated with a decrease of the HVs in the first case. Besides, the number of conflicts started to reduce when the penetration rate of the AVs on roadways exceeded 40% in the second case. In contrast, scenarios having less than 40% of the AVs have more accidents than a base case that only contains human-driven vehicles. The researchers explained these results by human drivers' slower reaction time than the AVs: they fail to stop vehicles according to the level-5 AVs' instant deceleration, so it leads to rear-end conflicts.

SUMO micro-simulator was also utilized in Li &Wagner's study (*48*) to examine impacts of automated vehicles on driving safety on a stretch of highway including three on/off ramps under four traffic conditions: free-flow traffic (≈0.5*capacity), lightly congested traffic (≈0.7*capacity), heavily congested traffic (>0.95*capacity), and estimated future traffic condition (3*heavily congested traffic vehicle volume). This study counted a number of vehicle conflicts having less than 0.5s TTC value since the surrogate safety assessment program SSAM doesn't support SUMO simulation. The simulation results specified that under the lightly and heavily congested traffic, safety improvement was notable when AVs occupied more than 70% and 90% respectively. However, in the free-flow condition, interactions between vehicles were very low so there were no remarkable differences. Conversely, the estimated future traffic demand scenarios showed worse safety circumstances over all penetration rates. They found the reason came from the extremely high traffic flow and AVs' shorter vehicle gaps.

The number of vehicle conflicts in this study seems to need to be distinguished according to related vehicle types, as the default value for TTC is 1.0s in most studies. Furthermore, the bigger values are likely to be suitable if a following vehicle is a human-driven vehicle.

The aforementioned studies all come from simulation-based research. Therefore, various characteristics defining AVs' driving behavior can lead to different results. Even so, those studies are all meaningful because there are no consensus parameters for driving behavior of AVs. However, transportation practitioners need to keep in mind that simulation-based results can be different by types of simulations and parameters composing AVs' car-following and lane-changing behavior.

Instead of employing traffic simulators, Ye & Yamamoto (*54*) studied the safety impact of CAVs with various penetration rates through a mixed traffic model framework. They proposed a time-space-discrete rule-based cellular model that can capture vehicle movements per time step and location. The authors evaluated network safety with TTC value and the frequency in which conflicts may happen. They regulated the conflicts by the following three rules, and when a following vehicle fulfils requirements the following vehicle hits a leading vehicle: a vehicle collision happens. Plus, the following Figure 2 describes vehicle movement per time step.

(1) $v(i + 1, t) > 0$, indicating that vehicle $i + 1$ is moving at time step t.
(2) $v(i + 1, t + 1) = 0$, indicating that vehicle $i + 1$ will stop abruptly at time $t + 1$.
(3) $v(i, t)^2/(2 * d(i, t)) > 10$, indicating that the following vehicle i has to apply a deceleration rate beyond 10 m/s^2 in order to avoid crashing with its stopped leader.

Where time step is 1s, longitudinal space step is 0.5 m, and speed step is 0.5 m/s^2 in the simulation.

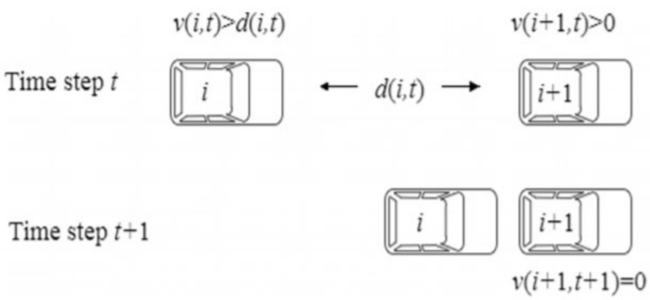

Figure 2. Schematic illustration of the rules for detecting dangerous situation (54)

Additionally, TTC value was calculated by the equation below [1]:

$$TTC\ (i,t)\ = \frac{d\ (i,t)}{v\ (i,t) - v\ (i+1,t)}\ \forall\ v\ (i,t)\ > v\ (i+1,t) \qquad [1]$$

The results demonstrated a significant impact of CAVs on traffic safety with their increasing market penetration rate. In both desired time gap scenarios, denoted T_{acc} in this study and having 0.5s and 1.1s each, positive impacts were verified. In detail, T_{acc} =0.5s scenario showed positive consequences after CAVs reaching 60% of total, but T_{acc} =1.1s generated differences even in low penetration rate. This implies larger time gap policies are more suitable for an introductory period of CAVs. Ye and Yamamoto's model framework is relevant to investigate the safety impact of CAVs, yet it only captured one consecutive vehicle set in one moment; it needs to be expanded to multi-coupled vehicle examination for practical and broad application.

Stability

Another CAVs' impact criteria on traffic flow is stability. The traffic flow stability is directly connected to maintaining capacity, safety, and other traffic conditions (*55*). Papadoulis et al. (*1*) utilized micro traffic simulation VISSIM to examine a safety improvement from employing connected and autonomous vehicles. In this research, the results offered an additional remarkable impact of CAVs on traffic flow stability enhancement regardless of different vehicle inputs per weekday. Even though Friday has more traffic than other days, travel time results remained almost the same as other weekdays in 100% of AV-penetration-rate scenarios. However, the improvement was achieved under a homogeneous traffic condition and the research was not designed for the stability impact study of CAVs. Thus, further inspection of CAVs' impact on traffic flow safety in mixed traffic composition is required.

There are several model-framework-based studies to investigate connected and autonomous vehicles' impact on traffic flow stability. Gan et al. (*55*) proposed an analytical model in heterogeneous traffic conditions containing CAV market penetration rate, size of CAV platooning, and power cooperation within coupled vehicles in mixed traffic as three key components. The results revealed that the traffic flow stability increased when the rates which CAVs occupied grew: CAVs had a greater influence on the traffic stability when CAVs filled up major vehicle types in overall traffic conditions. Zheng et al. (*56*) researched automated vehicles' effect on traffic stability and human drivers' uncertainty at a highway bottleneck area in mixed traffic streams under free-flow conditions (100 km/hr) and congested situations (60 km/hr). In this study, the traffic flow stability was assessed by variance of the mean speed of all vehicles. The authors set ten different market penetration rates of AVs from 5% to 50%, and a basic scenario has a 100% rate of HVs. The automated vehicles were distributed in traffic flow in four different ways according to their input location: randomly, front, middle, and rear of the traffic stream. The model results ascertained that a presence of AVs on stream enhances traffic stability in both free-flow (100 km/hr) and slower vehicle speed (60 km/h) conditions. The reduction of the speed variance reached up to 19% in the various autonomous vehicles penetration rates. However, it turned out that the AV-input locations do not link to the traffic stream stability from the presented model. Talebpour & Mahmassani (*20*) proposed a simulation framework for investigating string stability advancement of traffic flow caused by connected vehicles and autonomous vehicles. The authors distinguished autonomous vehicles from connected vehicles, and examined each impact in mixed traffic. In this study, three vehicle models were set up for simulation: 1. regular vehicles which have no connectivity to other vehicles and traffic infrastructure; 2. autonomous vehicles that are able to detect surrounding vehicles and react in a short time; and 3. connected vehicles with four different connectivity abilities. Before running a mixed scenario having three types of vehicles, the traffic flow stability study under regular & connected vehicles condition, and regular & autonomous vehicles network condition, was conducted. The results stated that the presence of AVs in traffic composition has more positive impacts than connected vehicles when they take the same penetration rate. However, both autonomous vehicles and connected vehicles ultimately improved the traffic flow safety with an increase of their market penetration rate more than regular vehicles' homogeneous traffic conditions. Finally, from the scenario including all three vehicle types, connected vehicles played a better role on the traffic stability at low penetration rates. Conversely, autonomous vehicles showed outstanding efficiency in high market penetration rate conditions.

The aforementioned studies all agreed that implementation of autonomous vehicles and connected vehicles in traffic composition will bring traffic flow stability amelioration. However, they all utilized different driving behaviors and parameters, and hence, it will be possible to get different outcomes by other driving mechanisms under various roadway conditions such as on/off-ramp areas, work zones, and tunnels.

2.4 Modeling CAVs in Mixed Traffic

Autonomous vehicles' movements originated in longitudinal and lateral controls of human-driven vehicles and many studies proposed its control methods. However, CAVs' control logic also needs to give thought to not only its movements but also interactions with conventional vehicles because there will be a long coexisting period. Therefore, many researchers have been paying attention to autonomous vehicle control logic in mixed traffic conditions (*3,5-7*). Building a model framework for CAVs in heterogeneous traffic would be more complex since it needs to contemplate disconnection with human-driven vehicles and adapt to various driving circumstances.

A lane-changing model framework for autonomous vehicles in heterogeneous traffic was proposed by Wang et al. (*5*), and they conducted a field test in a designated testbed. The presented model contains four steps until autonomous vehicles achieve lane-changing by being surrounded by three human-driven vehicles: a leading vehicle in a current lane, a leading vehicle, and a following vehicle in a target lane. The first step, car following (and lane-keeping), describes a situation where an autonomous vehicle follows a leading vehicle in a current lane and decides whether to perform lane-changing maneuver to an adjacent lane. During this step, the autonomous vehicle can monitor surrounding traffic situations through an equipped LiDAR (Light Detection and Ranging) sensor. Then it enters the next step, lane-changing decision, where the autonomous vehicle makes sure if the lane-changing maneuver is allowed by checking line marking. When the mark is a dashed line, it calculates the safety distance between a leading vehicle in a target lane and the following vehicle's acceleration. For smooth lane-changing performance, the authors suggested a lane-changing path algorithm based on the improved sin-function which can react to traffic environment changes. This study considered both longitudinal and lateral movement of autonomous vehicles, and therefore, as a final step to complete the lane-changing maneuver, the researchers utilized the MPC method to minimize a trajectory following error. The kinematic model below, Figure 3, described the steering wheel angle and the vehicle heading angle of the AV, denoted $\delta(t), \theta(t)\ \forall t \in \mathcal{T}$ respectively, that were used for calculating the target steering wheel angle.

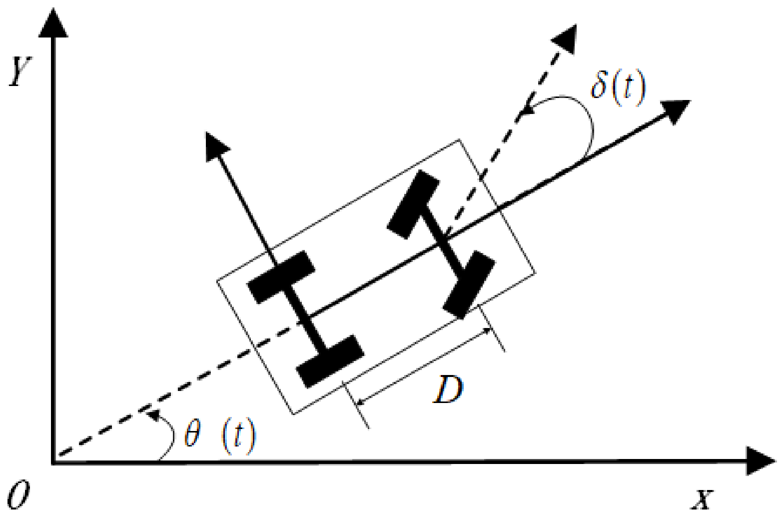

Figure 3. Steering wheel angle and vehicle heading angle of AV (5)

To check validation of the proposed model, a field test was carried out with the LiDAR equipped vehicle on a two-lane stretch of road. The authors designed two test modes: AV mode and HV mode, to inspect if there are improved outcomes obtained from the model, and four scenarios which include uncooperative behavior of the following vehicle in the adjacent lane that consequently blocks the lane-changing behavior of the autonomous vehicle. Therefore, it was possible to capture human drivers' different behaviors toward the lane-changing maneuver. The field test results revealed the proposed lane-changing model for autonomous vehicles improves driver comfortability and safety in properly designed circumstances.

However, this study only takes into account one autonomous vehicle during lane-changing behavior in the model. Furthermore, the testbed didn't include complex traffic situations such as merging and diverging. Therefore, there is a need to consider various combinations of CVs and AVs at different transportation facilities.

Another study suggested a modelling and control framework of connected and automated vehicles in mixed traffic conditions at an on-ramp merging area (*3*). The authors employed the MPC method and showed its effect through MATLAB simulation results. This study is significant as it considered CAVs not only as a merging vehicle but also as a following vehicle which provides a lag gap for cooperative merging behavior. However, unlike Wang et al.'s (*5*) work, this study didn't consider vehicles' lateral movement and steering angle for simplifying the model. The basic premise of this study is that CAVs have the ability to communicate with other vehicles (V2V) and transportation facilities (V2I), and therefore, CAVs can be aware of surrounding conditions. Additionally, the authors employed second-order dynamics for modelling CAVs, and the linear car-following Helly's model, and the linear free-flow model for embodying human-driven vehicles (HVs).

The study network supposed two on-ramp merging circumstances with different combinations of CAVs and human-driven vehicles: two CAVs and one HV, and one CAV and two HVs. The former one is Scenario A, and in this scenario a leading vehicle and a merging vehicle are CAVs, while the following vehicle is a conventional vehicle. In the latter one, Scenario B, opposingly, a leading vehicle and a merging vehicle are HVs and a follower is a CAV. In detail, each leading vehicle, a merging vehicle, and a follower are referred as V1, V2, and V3 respectively. Each scenario has three phases until completing an on-ramp merging maneuver.

In Scenario A, as phase 1, a merging vehicle V2 will attempt to merge when a gap between V1 and V3 is enough, and potential merging points can guarantee safe lead and lag gaps. The ideal merging point is half of the gap between V1 and V3 ($\frac{\triangle\chi_{1,3}(j)}{2}$). During this phase, V1 – which is a CAV – maintains the desired mainstream speed (v^{d}_{main}) and V3 keeps following it with the linear Helly's car-following model. When V2 reached the beginning point of the merging area, phase 2 started. In this phase, V3 can recognize V2, and V2 then searches if there are enough lead and lag gaps for safe merging. If V2 makes sure there are sufficient gaps, it merges into the mainstream. In this phase, the control target will be the gap between V1 and V2 because when V3 perceives V2, it will change its leader to V2 and follow it by a car-following model. Then the model starts phase 3 and now V3 follows V2, and V1 drives with the desired mainstream speed. Since V2 is also a connected and autonomous vehicle, the desired steady-state headway will be maintained through phase 3. Consequently, the control target for phase

3 is the desired steady-state headway between V1 and V2, and the desired mainstream speed. Therefore, the control target for each phase can be described as the equation [2] below:

$$Y_1^d(j) = \begin{bmatrix} \frac{\triangle x_{1,3}(j)}{2} \\ v_{main}^d \end{bmatrix},\ Y_2^d = \begin{bmatrix} g_{d,lead} \\ v_{main}^d \end{bmatrix},\ Y_3^d = \begin{bmatrix} g_{s1,2} \\ v_{main}^d \end{bmatrix} \qquad [2]$$

Where $g_{d,lead}$ means the desired acceptable lead gap, and $g_{s1,2}$ is the desired steady-state headway value between V1 and V2.

In Scenario B, the CAV has a role as a following vehicle in the mainstream and is denoted as V3. Before V3 can notice V2, it follows V1 by the same speed and maintains the desired acceptable lead gap and lag gap. As the follower can detect traffic circumstances through V2V and V2I communication, it can identify V2's movement before it enters the beginning of the merging point, and follow V2's speed as well as provide the desired lag gap for cooperative merging behavior. Before conducting a merging maneuver, the desired lead and lag gaps need to be satisfied and then V2 finally can merge into the mainstream. V1 and V2 in this scenario, conventional vehicles, utilize the linear free-flow model before the merging happens. However, after V2 completes the merging maneuver, V1 can keep using the free-flow model but V2 should change its behavior to a car-following model in case V1 becomes too close to itself. Meanwhile, V3 will follow V2 with the same speed and keep a desired steady-state distance from it. Hence, the control target for each phase can be expressed like the following equation [3]:

$$Y_1^d(j) = \begin{bmatrix} g_{d,lag} + g_{d,lead} \\ v_1(j) \end{bmatrix},\ Y_2^d(j) = \begin{bmatrix} g_{d,lag} \\ v_2(j) \end{bmatrix},\ Y_3^d(j) = \begin{bmatrix} g_{s2,3} \\ v_2(j) \end{bmatrix} \qquad [3]$$

Where $v_1(j)$is the speed of V1, and $v_2(j)$ means the speed of V2.

Before the simulation, the authors applied the MPC method to increase model reliability and set constraints for a realistic driving framework. The simulation results obtained from *fmincon* solver from MATLAB stated the proposed model can bring efficient driving conditions of CAVs in terms of acceleration and deceleration besides fulfilling the constraints.

Platooning, as one of the advantages that come from vehicle connectivity, cannot be neglected to enhance traffic characteristics in mixed traffic streams. Feng et al. (*6*) suggested a robust platoon control method in mixed traffic and checked out its efficiency in reducing disturbances. Unlike many studies that employed the MPC method to eliminate predicted uncertainties, this study utilized the tube MPC method including feedback control as well as feedforward control to minimize computational and inter-vehicular communication complexities. The tube MPC method does not require replanning each time step like the MPC method but only needs to replan in case other external disturbances happen. The researchers supposed two different scenarios: both scenarios have a predecessor CAV, which is heading a platoon, and a following CAV that becomes a tail of platoon, and n-HDVs (human-driven vehicles) between them. The only difference among scenarios is scenario 2 has one more CAV in the middle of n-HDVs. Therefore, it has an extra CAV that has a role as a leader and a follower at the same time. It is for examining the impact of not only initial disturbances (scenario 1) but also multiple external disturbances (scenario 2) on traffic stability. CAVs can communicate with each other, but they should depend on sensors to detect HDVs' speed and distance from them. In both experimental scenario results, the following CAVs succeeded in removing external disturbances and maintained safety, stability, and string stability. Furthermore, the proposed tube MPC method showed its advancement with fewer trigger numbers of feedforward control and inter-vehicular communication than the MPC method.

Bang & Ahn (*7*) presented a CAV platoon control framework in mixed traffic based on the spring-mass-damper (SMD) system they proposed in a previous study (*57*). The researchers investigated the impact of cut-in vehicles from on-ramp areas with a presence of human-driven vehicles in platoons. As a further step, they proposed a method to ease the cut-in impacts caused by HDVs' lower acceleration/deceleration rates compared to CAVs in a platoon, and to prevent disturbance propagation to upstream HDVs in congested traffic situations.
The SMD model explains CAVs' driving behavior in a platoon as below (*57*):

$$m_1\ddot{x}_1 = c(v_d - \dot{x}_1) \quad [4]$$

$$m_n\ddot{x}_n = k_{n-1}(x_{n-1} - x_n - \ell) + b_{n-1}(\dot{x}_{n-1} - \dot{x}_n) = k_{n-1} \triangle x_n + b_{n-1} \triangle \dot{x}_n$$

[5]

Where m_i = mass of i^{th} vehicle in platoon ($i = 1$ for lead vehicle in platoon)

$x_i, \dot{x}_i, \ddot{x}_i$ = position, speed, and acceleration, respectively, of i^{th} vehicle

v_d = desired speed of lead vehicle

c = coefficient that represents how fast lead vehicle reaches v_d

k_i, b_i = spring constant and damping coefficient, respectively, for i^{th} vehicle

ℓ = critical spacing

The equation [4] describes the behavior of a leading CAV, and [5] illustrates following CAVs in a platoon. Moreover, spring constant and damping coefficient have to satisfy the following conditions [6],[7] for fulfilling the physical environment of CAVs and achieving critical damping or over-damping conditions in which CAVs can reach an equilibrium state without oscillations respectively:

$$0 < \mathrm{k} \leq \frac{1}{\triangle x} m_n a_{max} \qquad [6]$$

$$b \geq max\left(\frac{m_n}{\tau}, \sqrt{km_n}\right) \qquad [7]$$

Where m_n = weight of n^{th} vehicle

a_{max} = maximum acceleration

τ = response time

In the simulation experiments with different CAV penetration rates, a platoon is divided into small inter-platoons under light traffic due to acceleration rate differences between CAVs and HDVs. Therefore, there are enough spaces that can be accommodated for vehicle cut-in, and it is able to absorb cut-in disturbances effectively. Moreover, the increase of CAV penetration rate leads to more cut-in behavior without disturbances. However, under near-capacity traffic, the cut-in impact cannot be eased by CAVs, and flow reduction and inter-vehicular voids after cut-in behavior caused by HDVs lower acceleration rate increased. Similarly, in congested traffic conditions, it is hard to find cut-in space due to the overall low speed. As a result, the cut-in disturbance is even amplified to upstream. To resolve these problems, the authors suggested the three-step methods to mitigate the cut-in disturbances by decreasing the spring coefficient and increasing the damping coefficient from the model. When CAVs detect the cut-in movement from an on-ramp area, they count the number of CAVs until reaching a first HDV upstream using V2V and V2I communication systems. Then, if they conclude the cut-in disturbances will propagate to the first HDV, they reduce the spring coefficient and increase the damping coefficient to cover spacing shortages regardless of default critical spacing, and block disturbance amplification. Therefore, recovery time is decreased, and the cut-in disturbances cannot reach the HDV.

The aforementioned studies only considered typical passenger vehicles as a type of CAV and HDV. As an example, heavy good vehicles (HGVs) have lower acceleration/deceleration rates and lower speed limits on highways. Their driving behaviors, such as merging and lane changing, will bring worse traffic flow degradation. Therefore, vehicle interactions including HGVs also need to be identified. Furthermore, perfect communication systems between CAVs were assumed. Hence, functional failures or communication delay times were not pointed out in these studies.

2.5 Microscopic Traffic Simulation VISSIM

Traffic simulators are utilized in many ways these days to research impacts on present or future transportation facilities, as well as to see what consequences traffic legislation changes bring to the traffic stream. Ever since the microscopic multi-modal traffic flow simulation software VISSIM was invented in 1992 (*58*), it has been loved by not only researchers but also many governments (*8*). Furthermore, calibrating methods and its comparison using VISSIM become a single research subject (*59-61*). Based on the Wiedemann car-following model, users can modify various parameters to fulfill their demands through in-simulation features or external ways such as DriverModel.dll, Driving Simulator, and COM interface.

2.5.1 VISSIM Parameters

Driving Behavior

Before the VISSIM 11 version first deployed simulation features for connected and autonomous vehicles (CAVs), there used to be five types of pre-defined driving behaviors: *Urban (motorized), Slow lane rule (motorized), Outside of city (free lane selection), Footpath (no interaction),* and *Cycle path (free overtaking)* (*62*). Therefore, users who wanted to implement CAVs in VISSIM networks had to utilize external ways like DriverModel.dll, Driving Simulator, and COM interface like Python, MATLAB, and JavaScript. Now VISSIM 11 and the later version have the internal functions for implementing CAVs, so it can be simulated in a much easier and simpler way. PTV themselves used these functions for a project they participated in, the CoEXist Project, and has been improving its role by several updates (*8,63-65*). Basically, there are three default types of automated vehicle driving behavior: *AV-cautious, AV-normal*, and *AV-aggressive*. According to the VISSIM 2020 manual (*62*), the *AV-cautious* type observes road codes, and always employs safe behavior, and the *AV-normal* is a vehicle class behaving like human drivers with an additional capacity of measuring distances and speeds of surrounding vehicles with its range of sensors. Lastly, vehicles that follow *AV-aggressive* characteristic have advanced awareness and predictive capabilities, leading mainly to smaller gaps for all maneuvers in all situations. Along with those default vehicle categories, users can adjust its driving parameters in line with their needs and create different vehicle types with different levels of automation. Moreover, VISSIM 2020, the latest version, has improved extra functions in terms of platooning for the connected vehicles (*66*).

Car-Following Model

Car-following behavior is one of crucial elements to estimate traffic simulation's precision when considering the fact that it constitutes the core of the traffic flow model. Car-following behavior shows how a pair of vehicles interact with each other (*67*). PTV VISSIM 2020 employs the Wiedemann 74 and Wiedemann 99 car-following models as a base setting. The Wiedemann car-following model is a psycho-physical model for longitudinal movement, and a rule-based algorithm for lateral movement (*16*) which has a foundation in Wiedemann, R. 's research. The Wiedemann car-following models were established upon four different driving conditions: Free driving, Approaching, Following, and Braking. In the VISSIM 2020 manual (*62*) those statements are explained:

Free driving: no influence from the leading vehicle so the driver can maintain or pursue its desired speed without obstacles.
Approaching: the following vehicle becomes close to the leading vehicle; the driver should decelerate and keep safety distance.
Following: the states in which the following vehicle drives after the leading vehicles without accelerating or decelerating.
Braking: the following vehicle is required to decelerate with high rates to keep the defined safety distance between the leading vehicle and itself.

Figure 4 is a graphical description of the Wiedemann car-following model (*68*). In the graph, the x-axis is the speed difference between a leading vehicle and a following vehicle, and the y-axis indicates distance between them.

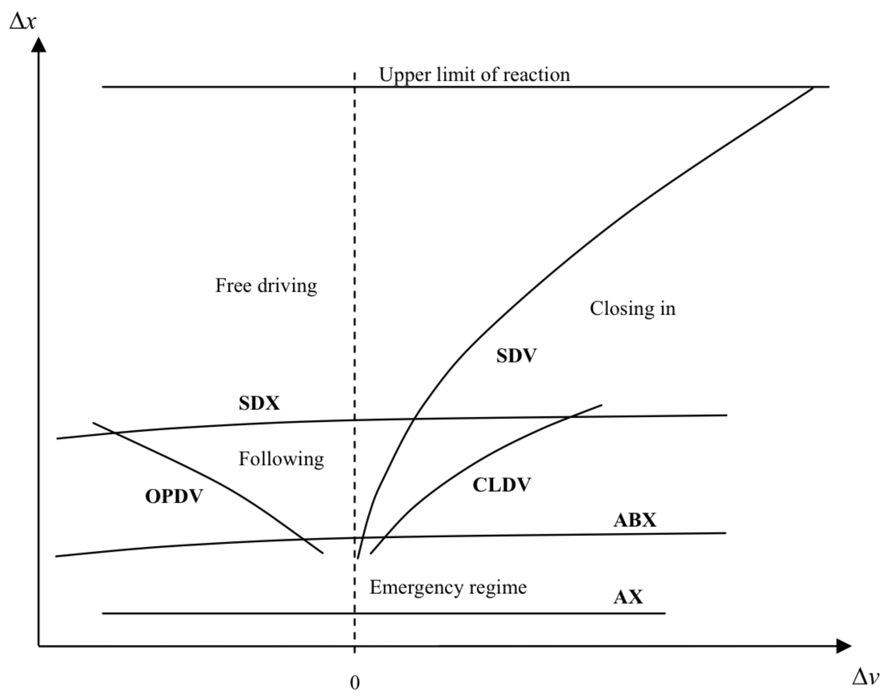

Figure 4 Wiedemann Car-following model (68)

where
AX: Desired distance between the front of paired vehicles in queue state.

ABX: Desired minimum following distance, which is a function of AX, a safety distance, and speed

SDV: Approaching point, a following vehicle's driver notices that a leading vehicle is slower than its speed. SDV increases when speed difference rises.

$OPDV$: Increasing speed difference; distance between the paired vehicles increased. The following vehicle's driver starts to accelerate to reduce a gap.

SDX: Maximum following distance, with a value between 1.5 and 2.5 times the minimum following distance, ABX.

$CLDV$: Parameter similar to SDV, being used in case a vehicle pair, separated by a short distance, has small speed differences. In VISSIM, this is ignored and considered to be equal to SDV (*67-68)*.

Commonly, the Wiedemann 74 car-following model is recommended for urban traffic flow and merging areas, and Wiedemann 99 is suitable for freeway conditions without merging areas (*62*).

The Wiedemann 74 model, as a developed version of Wiedemann's 1974 car-following model, has three parameters that the users can control: Average standstill distance (w74ax), Additive part of safety distance (w74bxAdd), and Multiplicative part of safety distance (w74bxMult). It can be expressed by the formula below for Desired distance *d*;

$$d = ax + bx \qquad [8]$$

where

$$bx = (bx_{add} + bx_{mult} * z) * \sqrt{v}$$

v = vehicle speed $[{}^{m}/{}_{s}]$, minimum value is 0.1.

z = a value of range [0.1], normally distributed around 0.5 with at standard deviation of 0.15.

The saturation flow rate, which means the number of vehicles that can drive freely on a highway segment for an hour, can be explained by the additive part of safety distance and the multiplicative part of safety distance parameters in the Wiedemann 74 car-following model (*62*). Besides, for the Wiedemann 99 car-following model, it is greatly impacted by the CC1 parameter (Headway time), and this value plays a key role in the safety distance as well.

Although the Wiedemann 99 model is suitable for freeway with no merging areas, PTV VISSIM employed it as a default setting for simulating CAVs. Moreover, P. Sukkennik, from the CoEXist project conducted by the European Union, recommends using Wiedemann 99 for implementing connected and autonomous vehicles in networks because it offers more varied options that the users can adjust according to their needs (*65*). The following Table 2 is the definition of each parameter and the default values for each automated vehicle type offered by VISSIM 2020 (*62*).

$CC0$: *Standstill Distance*
$CC1$: *Headway Time (Following Distance)*
$CC2$: *'Following' Variation (Longitudinal Oscillation)*
$CC3$: *Threshold for Entering 'Following' (Perception Threshold for Following)*
$CC4$: *Negative 'Following' Threshold (Negative Speed Difference)*
$CC5$: *Positive 'Following' Threshold (Positive Speed Difference)*
$CC6$: *Speed Dependency of Oscillation (Influence Speed on Oscillation)*
$CC7$: *Oscillation during Acceleration*
$CC8$: *Acceleration Starting from Standstill*
$CC9$: *Acceleration at 80 km/h*

		Control logic			
Model	Parameter	CVs (Freeway)	AV-cautious	AV-normal	AV-aggressive
Wiedemann 99	$CC0$ [m]	1.50	1.50	1.50	1.00
	$CC1$ [s]	0.9	1.5	0.9	0.6
	$CC2$ [m]	4.00	0.00	0.00	0.00
	$CC3$ [s]	-8.00	-10.00	-8.00	-6.00
	$CC4$ [m/s]	-0.35	-0.10	-0.10	-0.10
	$CC5$ [m/s]	0.35	0.10	0.10	0.10
	$CC6$ [1/(m·s)]	11.44	0.00	0.00	0.00
	$CC7$ [m/s^2]	0.25	0.10	0.10	0.10
	$CC8$ [m/s^2]	3.5	3.00	3.50	4.00
	$CC9$ [m/s^2]	1.5	1.20	1.50	2.00

Table 2 Definition of Each Parameter and Default Values for Each Automated Vehicle Type (62)

Furthermore, the Table 3 below illustrates general recommendations created through the CoEXist project for the Wiedemann 99 car-following behavior adjustments for each control logic (*65*):

		Control logic		
Model	Parameter	AV-cautious	AC-normal	AV-aggressive
Wiedemann 99	CC0	def	def	smaller
	CC1	def/higher	def	smaller
	CC2	def/smaller	smaller	smaller
	CC3	def/higher	def	def
	CC4	def/smaller	def/smaller	smaller
	CC5	def/smaller	def/smaller	smaller
	CC6	def/smaller	def	smaller
	CC7	def/smaller	def/smaller	smaller
	CC8	smaller	def	def
	CC9	smaller	def	def

Table 3 General recommendations for control logics (65)

Lane Change Behavior

Theoretically, automated vehicles require a smaller gap for lane-changing maneuvers than human-driven vehicles (*65*). In VISSIM 2020, lane-change behavior parameters can be adjusted in a sub-tab of the driving behavior window. There are two general behaviors – *free lane selection* and *slow lane rule* – and by changing parameters such as *advanced merging*, *cooperative lane change*, *safety distance reduction factor*, *minimum net headway (front/rear)*, and *maximum deceleration for cooperative braking* from the driving behavior setting display, the users can customize lane-change behavior for modelling different levels of vehicle automation. Among them, *safety distance reduction factor* is vital to make vehicles accept smaller gaps for lane changing. The factor is set to 0.6 as a default for CVs, and 1.0, 0.6, and 0.75 for AV-cautious, AV-normal, and AV-aggressive, respectively. In addition, *cooperative lane change* parameters allow the users to generate vehicle types with more realistic lane-change behavior. In detail, if the *cooperative lane change* function is checked; vehicle A from Figure 5 is likely to change its lane to left (the third lane) in accordance with vehicle B, which will obviously merge into its proceeding lane (the second lane). While the vehicle A is changing lanes, it behaves like it meets a connector at a long distance, and decides upon its own *maximum deceleration* as well as deceleration of vehicle C. Furthermore, the users can give values, and activate *maximum speed difference* and *maximum collision time*, which have 10.80 km/h and 10.00 s individually as the preset, and vehicles will follow the values when they are required to merge into adjacent lanes (*62*).

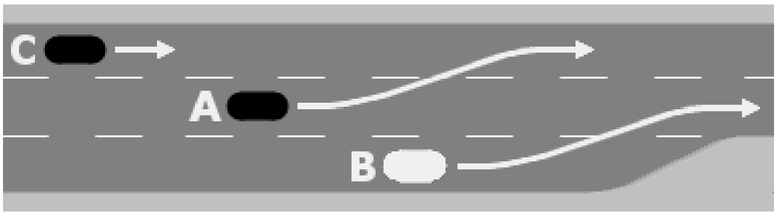

Figure 5 Cooperative lane change (62)

The CoEXist project (*65*) suggests a higher *safety distance reduction factor* for AV-cautious with the activation of *enforce absolute braking distance* function, and smaller values or default set for AV-normal and AV-aggressive vehicles.

2.5.2 Calibration and Validation of VISSIM Simulation Network

Traffic simulation models have become one of the crucial techniques to examine transportation facilities' impacts, including the present one – as well as future planning. However, using VISSIM without calibration has been pointed out because it cannot properly replicate actual traffic situations. In the study (*69*) conducted by Hellinga in 1998, model calibration is said to be the steps adjusting driving parameters, including car-following and lane-changing behaviors, to simulate traffic conditions of study sites. Also, model validation is a stage, checking similarity of two results obtained from simulation, and collected from a study area. Consequently, calibrated parameters and validated simulation networks are reliable and able to be used for analyzing roadway conditions (*70*). Therefore, many studies employ various calibration and validation methods to make their simulation networks more realistic.

Some VISSIM calibration and validation studies were sorted out in Rredaj & Bombol's study (*59*), according to calibration methods being used in each research paper: Genetic Algorithm

(GA) optimization, Nelder-Mead (NMA) optimization algorithm, Sensitivity analysis, and Heuristic optimization search algorithms. However, most of the studies, which are introduced in this paper, utilized the GA optimization method, which finds optimum solutions through repetition, since it has great advantages in terms of flexibility and enhancement (*60*) compared to Monte-Carlo or trial-and-error methods.

Before figuring out how to calibrate simulation model and check validation, parameters need to be chosen and their influence on simulation results needs to be inspected. In the study conducted by Woody (*70*), sensitivity analysis was employed to determine which parameters have great impacts on calibrating highway transportation facility models: highway corridors, merging, diverging, and weaving area. He noted that there are two categories of parameter calibration in the simulation: (1) system and (2) operational. The former indicates basic model presumptions such as vehicle speed, geometric characteristics, travel demands, route choice, and traffic control rules; the latter deals with parameters related to specific driving behaviors suck as car-following, and lane-changing behavior. Among these two parameter calibration steps, Woody chose operation calibration parameters, including the car-following behavior, necessary lane change, and lane change distance, to decide crucial parameters that affect highway capacity. The results indicate that Vehicle headway (CC1), Following variation (CC2), and Oscillation acceleration (CC7) are the most powerful parameters that have an impact on highway corridors' capacity change, as well as Standstill distance (CC0), and car-following threshold parameters (CC4 & CC5) with a fair bit of influence on capacity increase. At merging areas, CC1 and Deceleration of merging (own) & Trailing vehicles, from car-following behavior and necessary lane-changing parameters respectively, had great impacts. Moreover, necessary lane-changing parameters, as well as lane change distance parameters, had an influence on the capacity at diverging areas. For weaving parts, needless to say, the parameters which are the most important for both merging and diverging areas – CC1 from car-following behavior, necessary lane change behavior, lane change distances – significantly affect highway capacity.

VISSIM parameters' impacts on highway capacity were also examined in the study of Nicholas & Randy (*71*) as well as deciding how big their influences is through ANOVA, one of the hypothesis tests, at the highway interchange bottleneck area. The authors developed their previous study (*72*), which looked into influences of each car-following behavior parameters, CC0 to CC9, and checked the fact that CC0 and CC1 play an important role in terms of capacity.

Based on this result, the researchers looked into interactions between the car-following parameters with various combinations. The results revealed that the interaction between CC0 and CC8, Acceleration Starting from Standstill, is remarkable with the α-level of 0.05. Moreover, they also concluded through the result analysis that CC1 is greatly related to CC4/CC5, Positive/Negative Following Thresholds.

The aforementioned studies about impacts of driving behavior parameters on highway capacity investigated not only individual parameters themselves but also their interactions between combinations of car-following parameters. However, the mutual influences of car-following and lane-changing behaviors were overlooked. Therefore, thorough inspection of the impacts of car-following parameters and lane-changing parameters on the on-ramp/off-ramp capacity will be required for improved simulation parameter settings.

As an example of applying the calibration method on a simulation network, Park & Qi presented the systematic calibration and validation procedure using the GA method and its implementation on an actuated signalized intersection with average travel time as measures of effectiveness (MOE) (*73*). Furthermore, their subsequent research showed its application on a freeway work zone (*74*). They proposed a five-step procedure including feedback routes for simulation model calibration: (1) simulation model setup, (2) initial calibration, (3) feasibility test, (4) parameter calibration using GA, and (5) evaluation of the parameter sets. Later, the authors included three more steps: Experimental Design, and Adjust Key Parameter Ranges before/after the Feasibility test step respectively, and Model Validation & Visualization as a last step (see Figure 6 below) (*74*).

From the case study at the actuated signalized intersection, the authors compared three calibration results obtained from the GA method, the default parameters, and a best guess from an engineer's perspective. The comparison using the one-way ANOVA test showed that the calibration results of the GA method matched well with the multiple field travel time data. On the other hand, the default parameters and the best-guess parameters did not correspond to the collected data from the study site.

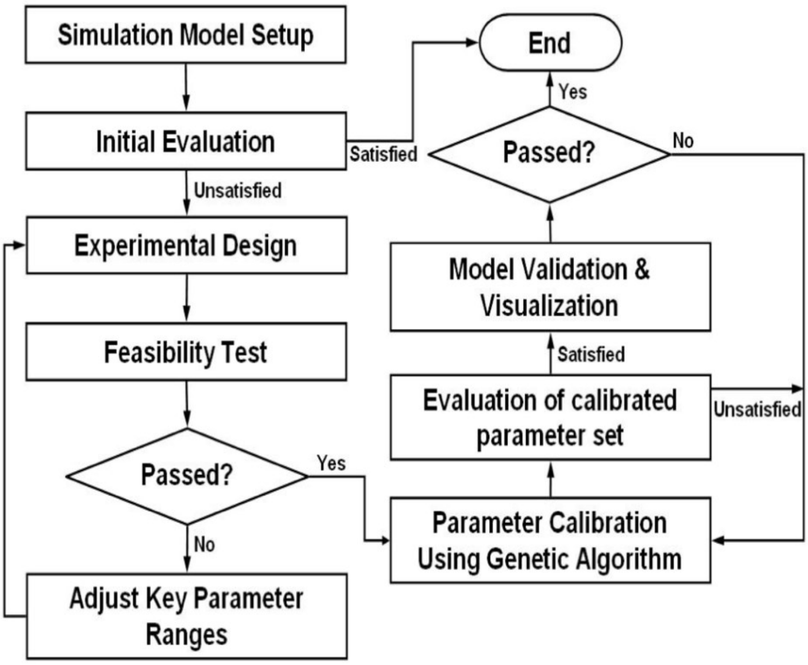

Figure 6 A Procedure for Microscopic Simulation Model Calibration and Validation (74)

In their further research, which applied the presented calibration and validation procedure to the freeway work zone, the results demonstrated that it is able to provide parameter adjustment that makes the travel time field data located among the simulation results.
However, the comparison between the GA method, the default parameters, and the best-guess obviously concluded that the GA method prevails in terms of performance. It is required to implement other metaheuristic algorithms to prove its ability.

The GA method can also be combined with the other calibration methods. As an example, Yu & Fan (*60*) employed GA and Tabu search (TS) metaheuristic algorithms in four different ways (GA, TS, and their combinations: warmed GA, and warmed TS) to match flow and speed data from simulation runs with the field data. Unlike other VISSIM calibration studies, which implemented each calibration method separately, the authors suggested combining metaheuristic algorithms based on the belief in applying two different algorithms as the warm-start method – employing another calibration method on the result which was obtained from another – would lead to enhanced results. Yu & Fan used Mean Absolute Normalized Error (MANE) based on vehicle speed and flow, as well as three additional objective functions, Global Relative Error (GRE), Point Mean Absolute Error (PMAE), and Point Mean Relative Error (PMRE), to precisely show the accuracy of the proposed methods. Through the calibration process, optimized CC0-CC5 and CC7 car-following parameters were generated. Each calibration method has all different results, and the author explained that it originated from the huge search space, so those are the local optimal solutions not global optimal. However, they also added the global optimal solution can be obtained through repetition. The results indicate that any calibration methods employed in this study show obvious improvements on default values. In addition, all objective functions – MANE, GRE, PMAE, and PMRE – demonstrated that the warmed GA and warmed TS methods were able to provide enhanced calibration more than the single GA and TS procedures.

The aforementioned study utilized the aggregated objective-function including the vehicle speed and the flow all at once. However, it isn't entirely clear whether the speed and flow aggregated objective function was proper for the multi-objective calibration process (*61*). The authors also brought up the limitation of several a priori calibration methods in dealing with the multi-objective calibration process. When it comes to multi-objective calibration problem, a priori methods carry out calibration about each objective function one after the other. Otherwise, it combines different objective functions as one equation. However, Karimi et al. explained that the step-by-step calibration process for multi-objective functions could fail to spot the influence from the previous calibration step. In addition, they added that it should be careful to combine different objective functions as one aggregated form because there might be conflicts between them and possibilities to overlook its impacts on each other. To address the shortcomings, they proposed the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm as a posteriori calibration process and compared the results with three broadly used algorithms: the GA, Whale optimization algorithm (WOA), and Particle Swarm Optimization (PSO). In the study, vehicles' longitudinal and lateral movements – vehicle headway distribution and the number of lane changes – were contemplated at the same time through the following aggregated objective function equation with the weighting coefficients which were set as the equal to reflect the researchers' determination that both are equally influential, and they don't conflict with another term.

$$Obj_{total} = w_1 Obj_1 + w_2 Obj_2$$

$$= w_1 \left[\frac{1}{n} \sum_{i=1}^{n} \frac{1}{m} \sum_{j=1}^{m} \frac{\left| h_{ij}^{Obs} - h_{ij}^{Sim} \right|}{h_{ij}^{Obs}} \right] + w_2 \left[\frac{1}{n} \sum_{i=1}^{n} \frac{1}{p} \sum_{l=1}^{p} \frac{\left| LC_{il}^{Obs} - LC_{il}^{Sim} \right|}{LC_{il}^{Sim}} \right] \quad [9]$$

where w_1, w_2 = weighting coefficients

$h_{ij}^{Obs}, h_{ij}^{Sim}$ = headway obtained from the observation – data collection –, and headway obtained from the simulation runs

$LC_{il}^{Obs}, LC_{il}^{Sim}$ = the number of lane changes counted from the observation, and the number of lane changes counted from the simulation

The calibration results comparing between three a priori methods – GA, WOA, and PSA – reveals that PSO shows better parameter adjustment in longitudinal movements, and the GA and WOA methods are more suitable for calibrating lateral-behavior-related parameters. In other words, all three methods failed to find optimal parameter set for both objective function parts (headway and the number of lane changes) all at once. However, it is confirmed, through examining the Pareto solutions found using the MOPSO algorithm, that the MOPSO calibration method is able to find optimized parameter sets for both headway and the number of lane-changes at the same time. Consequently, it is also guaranteed that the MOPSO algorithm can bring improved parameter adjustment in the multi-objective calibration process through validation which compares calibration ability with the same condition. Nevertheless, it seems necessary to have subsequent research to reveal which objective function can be aggregated without conflicts or influencing one another.

Another straightforward calibration method that can be employed is the trial-and-error method. As an example of its application, Srikanth et al. (*75*) utilized the trial-and-error calibration method in their study to adjust three car-following parameters – CC0, CC1, and CC2 – in accordance with the field data obtained from the four-lane highway. Before the calibration process, the authors had conducted sensitivity analysis to examine the impacts of CC0, CC1, and CC2 on capacity. They divided them into two groups, CC0&CC1 and CC1&CC2, and compared the simulation capacity results with different values of parameters. The results reveal that CC1 has a great impact on capacity, and CC2 also has an influence but it is smaller than CC1. Moreover, they concluded that higher values of CC1 and CC2 cause capacity drop. Based on the sensitivity analysis, they performed the calibration process using capacity as a measure of effectiveness. The researchers were able to find two optimized value sets through the MS Excel solver function among given ranges of each value, and they checked through the speed and flow curves that the values can successfully replicate the field data in terms of vehicle speed and vehicle volume, together. Furthermore, the validation process proves that the calibrated parameters can be used on the six-lane highway, as well. The flow and speed curves generated from the validation process showed that the calibrated values have a higher maximum flow rate than the default values, and well-matched result with the field data.

Through an in-depth examination of several calibration methods, the fact that selecting the calibration method depends on the researchers' preference is identified. Also, it is hard to say whether certain calibration methods are superior to others or not because it is up to study-characteristics, such as how precisely simulation networks were built, what calibration parameters were selected, and which objective functions were utilized. Moreover, there is no specific optimal parameter, so the calibration is the procedure which finds parameter sets corresponding to field data, and it can be different per algorithm. Since it is a time-consuming process, and requires repeat tasks, it is important to pick a proper and easy-to-use calibration method based on criteria such as what and how many parameters need to be calibrated.

2.6 Surrogate Safety Assessment Model (SSAM)

In their publication, the U.S. Department of Transportation Federal Highway Administration (FHWA) described conflicts as inter-vehicle interaction that may cause accidents (*76*). Moreover, they defined a traffic conflict as:

An event involving two or more road users, in which the action of one user causes the other user to make an evasive maneuver to avoid a collision.

Therefore, as conflict situations directly link to vehicle collisions and accidents,
traffic conflict analysis is a major element to understand the safety aspects of certain transportation facilities.

Traditionally, roadway safety assessment depended on crash data and required tremendous time to collect associated data (*77*). In addition, it was considered to be a difficult task due to lack of safety estimation models (*78*). By reason of necessity of a roadway safety analysis method, FHWA had put effort into it and finally presented a safety research software Surrogate Safety Assessment Model (SSAM). Consequently, it soon became a powerful tool broadly used due to the fact that it makes it possible to evaluate traffic safety without costly and time-consuming data collection. Moreover, it can also be utilized for assessing safety at not-yet-built transportation facilities or of not-yet-applied traffic regulations (*78*).

SSAM has been utilizing for examining safety and its validation at various roadway conditions including highway, signalized or non-signalized intersections, roundabouts, and so on (*1-2,79-80*). Furthermore, researchers have employed SSAM not only for vehicle conflicts but also potential conflicts between pedestrians (*81-84*) or cyclists (*85-86*) and vehicles. In case of studies which examined the interaction between vehicles and pedestrians, the researchers pointed out pedestrians should be modeled as vehicles having pedestrian-like driving behavior and physical characteristics in the VISSIM simulation because the vehicle trajectory output data only marks vehicle data. It is a bypass method using SSAM as a safety-analysis tool for pedestrian-related conflicts, and by doing so, SSAM can analyze potential conflicts between vehicles and pedestrians (*81,84*). Furthermore, pedestrians can be filtered manually by vehicle length which can make it possible to distinguish vehicles and pedestrians from an SSAM result file, which has a .csv extension, since SSAM doesn't provide conflict-related vehicle types in the "result" tab (*82*).

Safety Assessment Method

SSAM, as a post-processor, examines a vehicle trajectory file obtained from designated simulations: VISSIM, AIMSUN, Paramics, and TEXAS. The trajectory file includes the vehicles' location and dimensions around every ten seconds which are used for calculating *Minimum time-to collision (TTC)*, *Minimum post-encroachment (PET)*, *Initial deceleration rate (DR)*, *Maximum deceleration rate (MaxD*), *Maximum speed (MaxS)*, *Maximum speed differential (DeltaS)*, *Vehicle velocity change had the event proceeded to a crash (DeltaV)*, and *Conflict type* (*13*). Most studies (*1-2,14*) utilize TTC and PET for assessment of potential conflict situations and employ a number of conflicts to inspect safety at given traffic conditions.

Campisi et al. (*87*) added the explanation that conflict probability increases as those parameters decrease. Additionally, an SSAM result file categorizes conflicts as three types: Crossing, Lane change, and Rear-end as a result of vehicle trajectory file analysis (*13*).

TTC/PET Values-definition & studies (values for CAVs)

According to the SSAM user manual (*12*) published by FHWA, the definition of TTC is the *minimum time-to-collision* value obtained from conflicts, and it is estimated based on current locations, speeds, and trajectories of two vehicles at a given point in time. TTC can be calculated from the equation below and the following Figure 7 elucidates a conflict situation (*2,88*):

$$TTC = \begin{cases} \frac{d_2}{v_2} & if \frac{d_1}{v_1} < \frac{d_2}{v_2} < \frac{d_1+l_1+w_2}{v_1} \ (side) \\ \frac{d_1}{v_1} & if \frac{d_2}{v_2} < \frac{d_1}{v_1} < \frac{d_2+l_2+w_1}{v_2} \ (side) \\ \frac{X_1-X_2-l_1}{v_2-v_1} & if\, v_2 > v_1 (rear\ end) \\ \frac{X_1-X_2}{v_1+v_2} & (head\ on) \end{cases} \qquad [10]$$

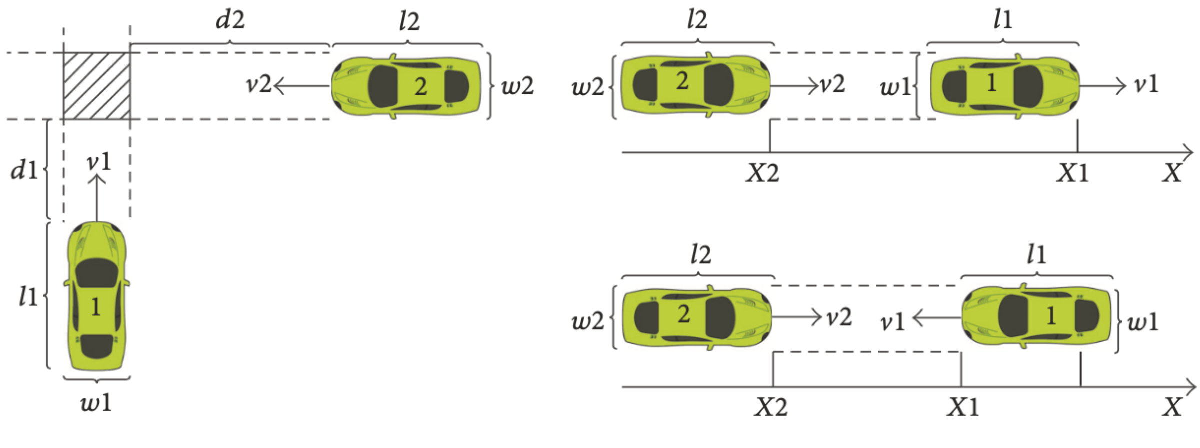

Figure 7 Time to Collision (TTC) (2)

where v_n is vehicle speed, l_n is vehicle length, w_n is vehicle width, X_n is vehicle position, and d_n is the distance to conflict areas.

Accompanied by the TTC value, PET is used as a key element for determining conflicts. PET, *minimum post-encroachment time*, is observed during conflicts. It describes the time difference that is measured until the second vehicle occupies the first vehicle's certain positions (see Figure 8) so, 0 indicates a complete overlap between two vehicles, and it is not likely to happen practically (*2,12*). For this reason, Habtemichael & Picado-Santos (*16*) considered 0 PET value as hypothetical crashes caused by simulation error and excluded it during results analysis.

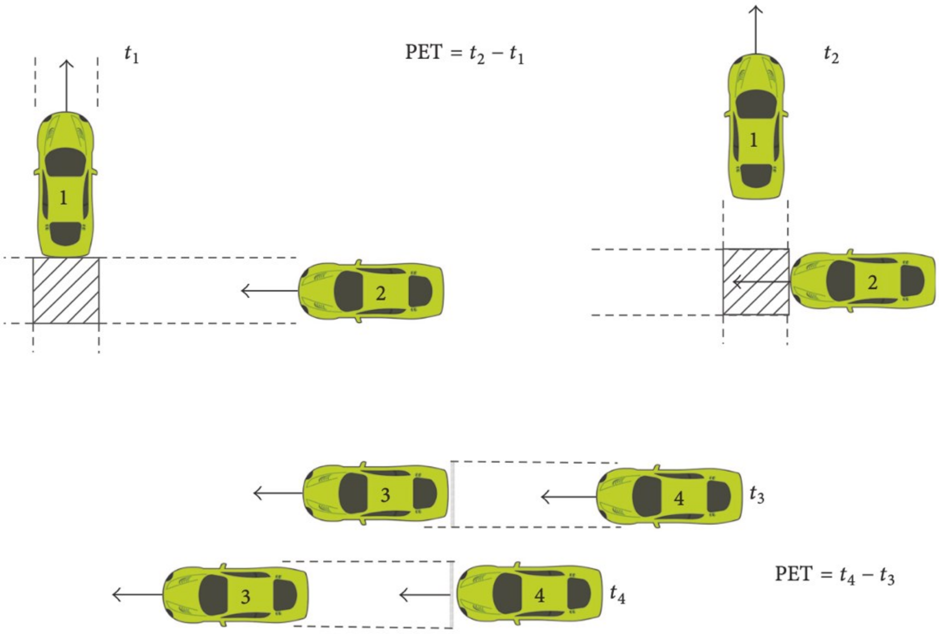

Figure 8 Post-encroachment Time (PET) (2)

A report from FHWA (*13*) suggested the default value for TTC and PET is 1.5s and 5.0s respectively based on conflict analysis research papers in 1994 and 1972 for TTC values (*89-90*) and Hyden's study (*91*) for PET parameters. Those values can be modified in the starting interface of SSAM, and when calculated TTC and PET values equal to or smaller than the given default value, it is noted as vehicle conflicts (*2*).

As connected and autonomous vehicles emerge, the default parameters need to be modified to match CAVs' advanced features. Nonetheless, some studies (*92-94*) still employ the default value of TTC for autonomous vehicles safety assessment. However, CAVs are evaluated having smaller vehicle gaps and instant reaction time, and therefore, it is possible to be assessed as a conflict situation in spite of normal driving circumstances. Accordingly, several studies conducted sensitivity analysis to see how different TTC values change the number of conflicts.

Morando et al. (*2*) applied 1s and 0.75s TTC values for investigating the number of inter-AVs conflicts. SSAM has no vehicle type indication feature yet when it processes trajectory files. However, the authors employed VISSIM traffic simulation. Thus, they extracted vehicle IDs from the simulation and compared it with conflict-related vehicle IDs. Comparing the number of conflicts which applied 1s and 0.75s as TTC values, a reduction in the number of conflicts became bigger with the increase of the AV penetration rate when using a TTC threshold of 0.75s. This is because interactions between AVs grew in accordance with its larger penetration rate.

Likewise, different TTC and PET values for CAVs were applied in Virdi et al.'s research (*14*) as it was possible to distinguish vehicle types from a vehicle IDs result. In this study, CAVs were given TTC and PET values that were one-third of the defaults. The authors explained the reason for the reduction by adjustments of standstill and following distance for CAVs: they have one-third values from conventional vehicles' parameters.

In the study of Papadoulis et al. (*1*) a need for a proper TTC value guideline for CAVs was pointed out. Additionally, the authors conducted a sensitivity analysis for TTC values of 1.0, 1.5, 2.0, 2.5 and 3s with five different CAV market penetration rates:0, 25, 50, 75, 100%, and checked no remarkable conflicts lessening. However, it is unclear why they used bigger thresholds even with the presence of connected and autonomous vehicles with abilities to maintain smaller gaps and to react to external circumstances instantly.

<u>*Conflict Types*</u>

Each conflict type is characterized by conflict angle (θ) among conflict-related vehicles. Pu & Joshi (*12*) explain the conflict-type decision method through the threshold angle as illustrated in Figure 9. The conflict angle is an estimated angle that is formed between two vehicles in a hypothetical collision state and has a range from -180° to +180°. The conflict angle is measured from the rear of the first vehicle, and increased positively in a counterclockwise direction, and the driving direction of the vehicle becomes 180°; when a second vehicle comes from the left side of the first vehicle, the conflict angle has a minus sign. If two vehicles approach each other with ‖ConflictAngle‖ $< 30°$, it categorized as a rear-end conflict, and also the vehicle approach with ‖ConflictAngle‖ $> 85°$ is defined as a crossing conflict. Otherwise, vehicle conflicts which are not included in either of them are identified as lane-change conflicts.

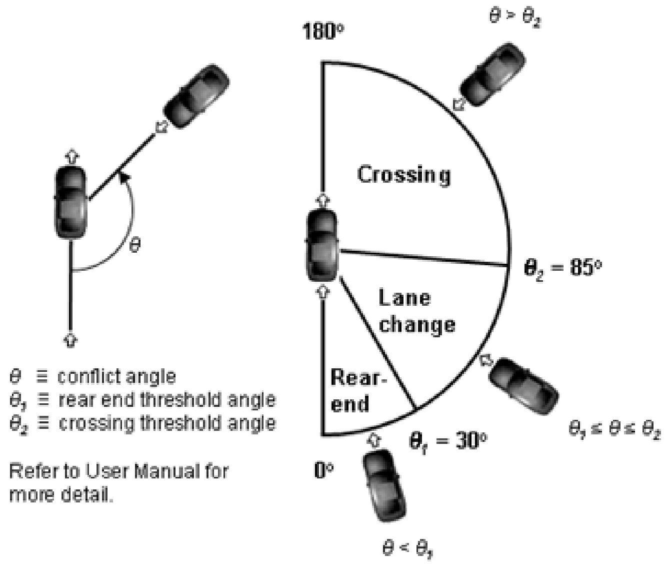

Figure 9 Conflict threshold angle (12)

2.7 Conclusion

Through the literature review, the following facts were validated: the CAV market penetration rate keeps growing with the technological improvements from the cooperation of researchers, companies, and public corporations. As a result, it is estimated that a higher level of autonomous vehicles will appear on roadways from the 2030s. The presence of CAVs with their advanced abilities in roadways will bring capacity increase, safer and much stable traffic conditions. However, during the coexist period where the conventional vehicles and CAVs share roadways, disturbance and even worse situations could happen. These can be overcome with increased CAV rates, and research studies covered in the literature review demonstrate that connected and autonomous vehicles will finally bring ameliorated traffic conditions, through various simulations and model frameworks that consider different driving behaviors and roadway circumstances.

In the following chapter, CAVs' impact on the tunnel work zone will be examined using microscopic traffic simulation VISSIM, and SSAM will be utilized for analyzing potential conflicts at the work zone merging area.

3. Methodology

3.1 VISSIM Driving Behavior

The driving behavior in the VISSIM simulation is captured through various vehicle driving characteristics: *following, car-following model, lane change, lateral, signal control, autonomous driving,* and *driver errors*. However, for vehicle types utilized in this study – conventional vehicles and CAVs – *following, car-following model,* and *lane change* parameters have differences. In addition, throughout this study, CAVs and autonomous vehicles are used interchangeably.

3.1.1 Following

Following behavior defines the *look ahead/back distance*, the *behavior during recovery from speed breakdown* parameters, and the *standstill distance* for static obstacles. For example, conventional vehicles in the simulation have an ability to perceive the look ahead distance within a maximum range of 250 m. Furthermore, they can detect two objects on the downstream road segment and seven vehicles ahead or on adjacent lanes. On the other hand, the CAVs are setup to identify a maximum of ten objects and to detect eight vehicles each within a range of 300 m ahead. Both vehicle types can spot situations behind them from 0 m to 150 m, and other following parameters are the same. The fact that the CAVs can detect more objects and vehicles ahead of them also means that they have advanced features in V2V and V2I connectivity. This doesn't imply that they have an ability to share information with other vehicles or transportation facilities, but they can at least notice more vehicles and objects than the conventional vehicles in the simulation networks.

3.1.2 Car-Following Behavior

In this study, to simulate conventional vehicles, freeway driving behavior mode was utilized. This means vehicles are controlled by the Wiedemann 99 car-following model. For implementing fully automated vehicles, the CAVs vehicles employed the default *AV-aggressive* driving behavior, which is also based on the Wiedemann 99 car-following model, but they are set to use have different parameters' values for advanced driving abilities. These set of values are defined in the PTV VISSIM 2020 and are based on the results of the CoEXist project. However, self-driving vehicles without a driver, which stands for level-5 automation, was not considered because the occupancy was not counted in the network nor used for results analysis.

3.1.3 Lane Change

Lane change parameters control a vehicle's lateral movements when they proceed to the adjacent lanes. Similar to other parameters, the connected and autonomous vehicles have more rigorously selected values compared to conventional vehicles. The CAVs have *slow lane rule* as *general behavior*. Furthermore, the CAVs' parameters for *cooperative lane change* were activated, and employed the default values: 10.80 km/h for *maximum speed difference* and 10.00s *maximum collision time*. Besides these parameters, CAVs have larger *maximum deceleration for cooperative braking*, smaller *safety distance reduction factor* which make them accept a smaller gap, and they are also allowed to have shorter *minimum headway* value, 0.5 m, when they change lanes. Also, CAVs have half of the $-1m/s^2$ *per distance* value, 100.00 m, compare to conventional vehicles. The Figure 10 below illustrates the default lane change parameters for the conventional vehicles.

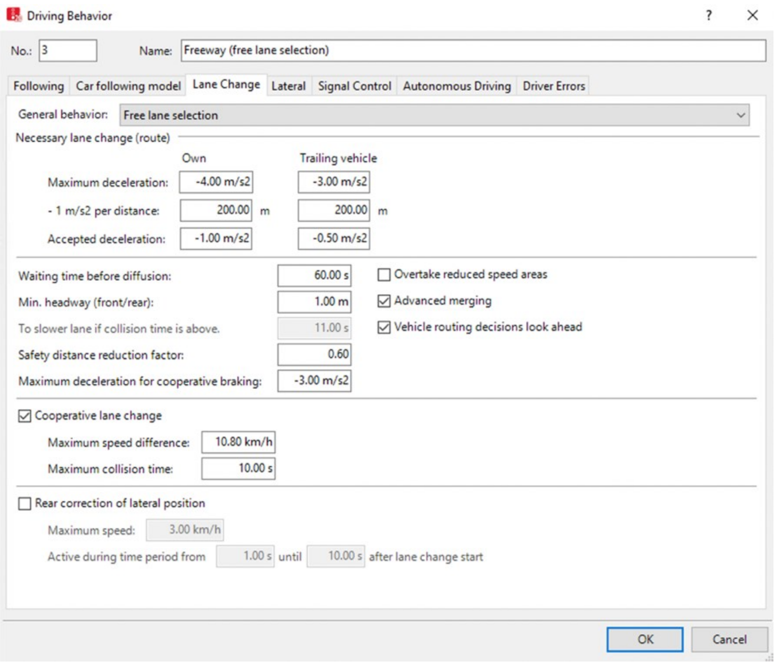

Figure 10 Default Parameters for Conventional Vehicles

3.2 Calibration

Calibration is the process of finding the parameter set values that can bring simulation results in accordance with field data. There are many methods for the calibration process, but the essential part is the iteration of simulation runs with different parameter combinations until errors between the simulation result and the field data are reduced, and the optimal values are found. The selection of the calibration method should consider the number of parameters which will be adjusted during the calibration process.

In this study, CC0, CC1, and CC2 parameters, which represent *standstill distance*, *headway time,* and *'following' variation* respectively, from the Wiedemann 99 car-following model, were chosen. The VISSIM manual (62) defines *standstill distance* as the desired standstill distance between two vehicles, *headway time* as the distance in seconds which a driver wants to maintain at a certain speed, and *'following' variation* as the distance difference between two vehicles when one vehicle follows another. According to the reviewed literature these parameters have a great influence on road capacity and are normally adjusted through the calibration process. Since there are only three parameters, the trial-and-error method was employed, instead of a systematic optimization method. The detailed calibration process was demonstrated as Figure 11 below:

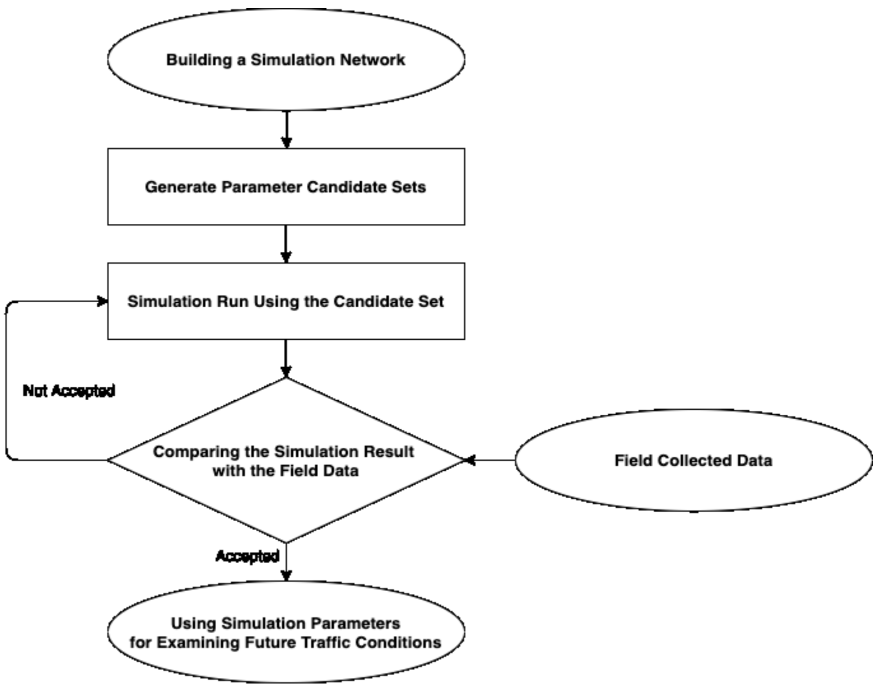

Figure 11 Calibration Process

Each parameter has the upper and lower limits to replicate vehicle movements in the real world. The following Table 4 illustrates the Wiedemann 99 car-following parameters' ranges according to roadway characteristics, and the default values.

Parameter	Range	Default
CC0	Basic segment: 1.2-1.7 Weaving/Merge/Diverge: > 1.5	1.5
CC1	Basic segment: 0.7 – 2.0 Weaving/Merge/Diverge: 0.9 to 3.0	0.9
CC2	Basic segment: 2-7 Weaving/Merge/Diverge: 4-12	4

Table 4 Wiedemann 99 Car-Following Parameter Ranges

Therefore, among the accepted ranges, different parameter combinations were generated, and simulations were run with the parameter sets. Finally, the vehicle throughput results obtained from the simulation runs were examined if they were within the expected range using the GEH statistic below:

$$GEH = \sqrt{\frac{2(M-C)^2}{M+C}} \qquad [11]$$

where

M = hourly traffic volume from the simulation

C = hourly traffic volume from the field

The GEH statistic is more adequate when traffic volumes are proportionately high. Consequently, following the traffic modeling guidelines from Transport for London (*93*), the parameter set of the simulation which shows the GEH value less than 5 and the relative difference between the simulation and the field flow less than or equal to 10% will be utilized in this study.

3.3 Surrogate Safety Assessment, SSAM

SSAM was utilized to analysis the simulation networks' safety through the number of conflicts that might have happened in the network. To collect the data, Sections were applied through the on-ramp and the tunnel area. From the Sections results, SSAM recognizes each circumstance as conflict when the calculated TTC value is less than the given TTC threshold. In this study, sensitivity analysis was conducted using 1.5s, 1.0s, and 0.75s of TTC value according to the second vehicle's type among conflict-related vehicles. It is obvious that CAVs show a better reaction time when decelerating, and they require additional caution in the case of sharing roadways with conventional vehicles and trucks. Therefore, through comparing the SSAM conflict analysis results and travel time raw data from the VISSIM simulation, conflict-related vehicle types were able to be distinguished, and in the case the following vehicle (the second vehicle) is CAVs, three different TTC values were applied.

In addition, SSAM results provide not only the number of potential conflicts but also severity. It can also be found in the Map tab, but it causes delay if the simulation results used for the analysis are sizable.

3.4 Conclusion

In this chapter, the VISSIM driving parameters that can be adjusted for simulating CAVs were investigated. These parameters pertain to following, car-following, and lane change movements models. In addition, the values that will be used for the case study were presented. Moreover, the calibration process using the trial-and-error method was introduced, and the flow chart was provided. To check the accuracy of the calibrated process, the GEH statistic will be utilized with two conditions: checking if the GEH value is less than five, and the relative error between the simulation and the field flow is less than 10%. Finally, three different TTC thresholds for CAVs were presented. In detail, 1.5s, 1.0s, and 0.75s of TTC thresholds will be employed for the conflicts that the following (the second) vehicle is CAVs.

4. Case Study

4.1 Study Area

The simulation network was generated at Louis-Hippolyte La Fontaine Tunnel (henceforth on referred to as La Fontaine Tunnel) which connects Boucherville and Montréal island. The La Fontaine Tunnel was constructed in 1967 with three lanes in each direction (*95*). As a junction where Highway 20 meets Highway 25, the tunnel is a key route not only for the public moving from Longueuil, Boucherville to Montréal island and vice-versa but also for commercial and construction trucks operating between those cities. Due to the fact that tunnels have less freedom than open highway corridors to utilize shoulder areas as temporary driving roads, it would be more suitable to research work zone impacts with limited shoulder space.

This study focuses on the Northbound vehicles moving (See Figure 12) into the Montréal island, as well as merging volumes from Highway 132.

Figure 12 L.H. La Fontaine Tunnel Simulation Network

4.2 Vehicle Input Volumes and Percentage of Trucks

In this study, Northbound vehicle volumes driving through Highway 20, vehicles heading to the Southern entrance of the tunnel where Highway 25 starts, were included as well as merging vehicle volumes from Highway 132 both Northbound and Eastbound. More specifically, vehicle volumes which originated from the South approach and heading to the island of Montréal, obtained from the traffic volume measured in 2018, were considered as a study traffic volume.

However, while conducting the calibration process, the vehicle inputs needed to be adjusted due to the limit of increasing or decreasing traffic volumes at the merging area. The aforementioned traffic data indicates Annual Average Daily Traffic (AADT), and hence, the peak hour's volumes are not explicitly included in this data. Therefore, vehicle inputs based on this data were adjusted through the calibration process as shown in Table 5 without changing the total vehicle numbers heading to the tunnel entrance. The number of Highway 132 Westbound approach were set as having higher vehicle inputs because the route has merging volumes before the on-ramp, while the Eastbound vehicles do not. The same vehicle volumes were distributed per 15-minutes time interval.

Input Point	Vehicle Input Volume (veh/15-minutes time interval)
Highway 20	2350
Highway 132 Westbound	1050
Highway 132 Eastbound	908

Table 5 Vehicle Input Volumes

The networks in this study were built for simulating 2033's travel demands. This year was selected because some studies estimated that level 5 automated vehicle's implementation would be made available to the general public *(22)*. To estimate the travel demand growth the ARTM (*Autorité Régionale de Transport Métropolitain*) report on Longueuil's five years population growth factor in 2018 of 10% was used (*96)*. Hence, assuming the same growth rate the estimated 2033's volumes, V_{2033}, which are 15 years after from 2018, can be derived from the following equation [13]:

$$V_{2033} = V_{2018}(1 + 0.1)^3 \qquad [13]$$

Through the calculation, volumes of three vehicle input points are described as below:

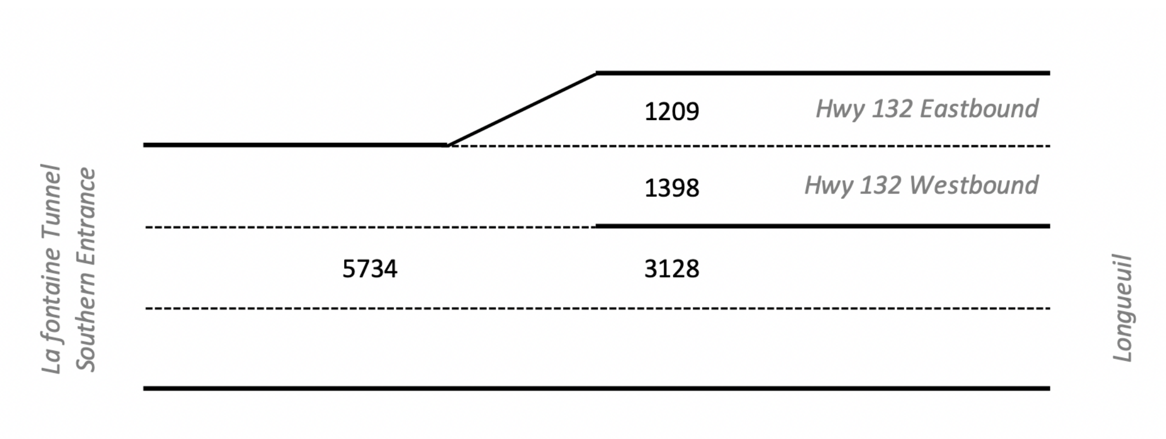

Figure 13 Vehicle Input Scheme

To make sure all the input vehicles pass through the tunnel without loss, vehicle routes were applied on each of the three input points.

The volumes of trucks travelling through the tunnel cannot be ignored, because according to the document prepared by the *Ministère des Transports* in 2017 (*97*), it says that trucks take up 13% of the total daily vehicle volume. In this study it was assumed that there will be an increase in freight traffic at the same rate as the general traffic, maintaining the same proportion of the total traffic at 13%. Consequently, all vehicle input points have 13% of the trucks and 87% of the passenger vehicles of the total vehicle volumes.

4.3 Simulation Time

The time periods when highways are most crowded are the morning and the evening peak hours. TomTom analyses of traffic data from Montréal and the result indicates the morning peak hours of the Montréal region are from 7:00 am to 9:00 am during weekdays (*98*). To reflect this time period, the simulation network was built from 7:00 am to 8:30 am with six, 15-minute time intervals. For each time interval, the same amount of vehicle inputs was employed as it was described above.

4.4 Simulation Runs

Stochastic traffic microsimulation models do not lead to the same results in every run, and the average results of multiple runs have to be analyzed to capture realistic traffic conditions (*99-100*). VISSIM 2020 generates random seeds for each simulation run to perform vehicles behavior and interactions, so it is also required to perform several times to achieve an average statistically representative output.
The VISSIM user manual (*62*) recommends 5-20 runs considering each case, and it also mentions that more than 20 runs will be proper for dynamic assignment to get reliable results. Within the range of the running time that the manual suggested, a report from the Washington State Department of Transportation (WSDOT) (*100*) proposed to carry out a minimum of 11 simulation runs because the odd number is much more beneficial to recognize median condition than an even number. Moreover, they presented the formula for calculating the required number of runs in their report. Other studies (*99,101*) also introduced the different formula to determine the number of runs. In this study, to fulfil the abovementioned recommendation, the simulation was run 15 times per scenario, and results gathered from each run were combined for analysis.

4.5 Desired Speed Decision and Reduced Speed Areas

The highway corridors heading to the southern entrance of the tunnel have 70 km/h speed limits. However, the field data, which was collected at the merging area where Highway 132 meets Highway 20, shows an 85th percentile of 90.7 km/h and a median speed of 79.5 km/h at the mainstream traffic, and an 85th percentile of 60.1 km/h and a median speed of 57.8 km/h at the on-ramp area. Therefore, the speed limit at the mainstream lanes was adjusted as 100 ± 10 km/h to cover the field data's range. In accordance with the passenger vehicles' speed limits, trucks also have a wider range of speed limits − 70 ± 10 km/h −, and it had to be slower than the passenger vehicles due to safety issues. It is because the calibration process only utilized the vehicle counts and speed data under the free-flow conditions - vehicles have a less than or equal to 20 % occupancy rate. Generally, vehicles are able to drive at their desired maximum speed within the speed limits under the free-flow conditions. Moreover, the field data shows drivers actually travel at higher speeds above the given speed limits. Also, the on-ramp area has a small radius spiral arc shape, and it imposes slower speeds for merging vehicles. Accordingly, in VISSIM *reduced speed areas* were defined, which limit to 50 km/h the speed for all vehicle types. These were applied to the on-ramp merging lanes so the simulation data could be more representative of the observed field conditions. In addition, *desired speed decision* was located at the merging lane after the *reduced speed areas* to make vehicles accelerate in accordance with the mainstream roads' speed limits.

4.6 Work Zone and Lane Restriction

In the simulation network, the work zone was applied to the first lane (the rightmost lane) during the tunnel section as described in the following Figure 14. There are no functions for work zones in VISSIM 2020, so lane restriction was utilized at first. The first lane where the work zone was located was prohibited to all types of vehicles. However, some vehicles which could not change lanes before they met the lane restriction proceeded to the work-zone area due to the fact that lane-changing maneuvers inside of the tunnel were blocked. For this reason, there was a need for a new method to be employed at the work zone. Hence, the lane-reduction method was devised: the first lane in the tunnel area was eliminated, and the first lane before the tunnel entrance was connected to the second lane inside of the tunnel with the connector.

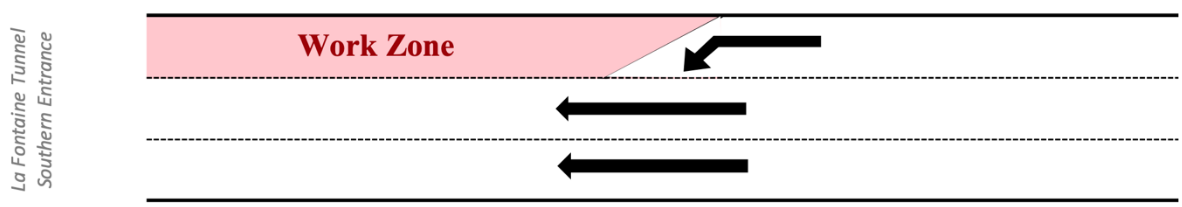

Figure 14 Tunnel Lane Closure

Consequently, since the first lane is closing all the vehicles have to drive through the remaining two lanes in the tunnel.

In the La Fontaine tunnel, there is truck-lane restriction on the third lane. When the work zone was applied, eliminating the truck-lane restriction was considered. However, this measure was considered to generate safety issues with respect the passenger vehicles using the same lanes as the trucks while significant speed differentials were observed, and it was concluded to maintain the truck-lane restriction. Therefore, the blockage was preserved so trucks can only run through the second lane with the late-merged passenger cars, and allowing only passenger cars on the third lane.

4.7 Merging Areas (Conflict Areas) and Lane-change Behavior

There are two merging areas in the evaluated case study: one is the on-ramp area merging from Highway 132, and the other one is the work zone area where the vehicles in the first lane have to change to the second lane. The type of these conflict areas in the simulation were set as *passive* to simulate a cooperative merging behavior, where none of the two approaches merging have priority, but rather the merging maneuvers are performed on first-come-first-served basis. Moreover, those merging behaviors in the work zone surely causes lane-change behaviors. Therefore, an advanced parameter set for CAVs – smaller $-1m/s^2$ *per distance* and *minimum headway* values, and activated *cooperative lane change* function – allows them to show better lane-change maneuvers.

4.8 Scenario Management

To examine CAV's impacts on various market penetration rates under coexist conditions, five different vehicle compositions were deployed. The base-case scenario has only conventional vehicles, including 13% of truck volumes from the total, and its proportion decreased 20% per scenario. On the other hand, CAVs account for zero percent in the basic scenario, but increased by 20% in each of the following scenarios. Consequently, in scenario 5, level-4 automated vehicles account for 80% of the total passenger vehicles.

Furthermore, to investigate the work zone's impact and how the presence of the CAVs can improve traffic conditions, the same scenarios were run without the work zone on the first lane (See the Table 6 below). Therefore, not only the CAVs' influence according to their increased market penetration rate, but also their impact on traffic flow with the lane-closure was analyzed.

	proportions (%)			
	without work zone		with work zone	
Scenario #	Conventional Vehicle	Autonomous Vehicle	Conventional Vehicle	Autonomous Vehicle
1 (Base-case)	100	0	100	0
2	80	20	80	20
3	60	40	60	40
4	40	60	40	60
5	20	80	20	80

Table 6 Simulation Scenarios

The above table indicates that the sum of each vehicle type is 100%, but it should be noted they are the proportions from the passenger vehicle rates, 87%, and the heavy-goods vehicles, account for the remaining 13% of the total vehicle input volumes.

4.9 Calibration

For the calibration process, the data which was collected from February to May in 2018 was used. After comparing the data's weekday peak-hour volume from 6:00 to 9:00 AM, it was decided the morning peak-hour of the data is from 6:45 to 7:45 AM. In addition, to provide similar traffic and external conditions such as temperature, only April and May traffic data was utilized. Also, holidays or weekdays that show abnormally lower traffics than others were eliminated.

Among the available model parameters values' ranges, the combinations, including the default set, which are the candidate sets for the calibration process were generated. Each candidate set was run 20 times, and the 15-minute vehicle throughput and speed at the merging area were collected. The results were divided into two traffic streams: the mainstream and the on-ramp merging traffic. Through comparing steps that use vehicle volumes as an objective function, the parameter set that had the GEH value smaller than 5, and relative errors smaller than or equal to 10% at the mainstream and the on-ramp merging traffic at the same time, was selected as the optimal set. Finally, the parameter set which shows similar dispersion on a scatter plot can be found: CC0 = 1.3m, CC1 = 1.1s, and CC2 = 5.5m.

4.10 Data Collection Points and Analyze

Four different simulation results were analyzed to examine the effect of the automated vehicles in mixed traffic conditions: vehicle throughput, vehicle delay, queue length, and number of conflicts.

The vehicle throughput was collected at the southern entrance of the tunnel using VISSIM specifically defined *data collection points*, and the data from the two open lanes was combined as one throughput result. The vehicle delay data was recorded through VISSIM defined *vehicle travel time measurement point*. The data were collected at the southern entrance of the tunnel right before the work zone for the scenarios with the work zone, and at the same position for the without-work-zone scenarios.

Similarly, the queue length was measured at the entrance of the tunnel and the average queue length results were utilized for analysis. Additionally, vehicle location data was recorded through several *sections* along the road. These *sections* were designated upstream of the southern entrance for a distance of 1.6 km; therefore, the impact of the work zone on the tunnel merging area's safety was able to be examined.

4.11 Result Analysis

After running simulations 15 times for each scenario, the results obtained from the *data collection points*, *vehicle travel time measurement points*, *queue counters*, and *sections* were assembled. Vehicle throughput, travel time, and vehicle delay results were collected by 15-minute time intervals, and queue length results have 5-minute intervals since queue formation and dissipation are time-sensitive. In addition, only simulation results from 900s to 4500s, which excluded the first and the last time intervals, were utilized for the result analysis to stand by until the simulation-stabilization period and to eliminate the impact of the remaining vehicle from the last time interval.

Each result has one chart to show graphical change according to the increase of CAV volumes. As a reference, the results of *without work-zone* scenarios were treated in some part of the result analysis to assist in showing traffic condition changes in the case of lane-closure.

Vehicle Throughput

Vehicle throughput results collected at the tunnel entrance were compared to the basic scenarios: 100% of conventional vehicles, referred to as 3_CAV0-CV100 for the *without work zone* scenario, and 2_CAV0-CV100 for the *with work zone* scenario (where, CAV and CV, stand for connected-autonomous vehicles, and conventional vehicles, respectively). In the *with work zone* scenarios, the absolute total vehicle throughputs are apparently lower than the *without work zone* scenarios. However, when dividing the total vehicle throughputs into the number of lanes, the *with work zone* scenarios have higher capacities per lane. (See Table 7).

	Capacity per Lane [veh/h]	
Scenario	Without Work Zone	With Work Zone
CAV0-CV100	1742	1844
CAV20-CV80	1778	1980
CAV40-CV60	1828	2075
CAV60-CV40	1881	2148
CAV80-CV20	1917	2159

Table 7 Capacity per Lane

Furthermore, compared to the basic scenario, the results analysis of the *without work zone* case (see Figure 15) shows smaller rates of increase than the *with work zone* scenarios (see Figure 16). These results reveal that higher percentages of CAVs can bring better improvement in traffic capacity in the case of poor roadway conditions such as lane-closure.

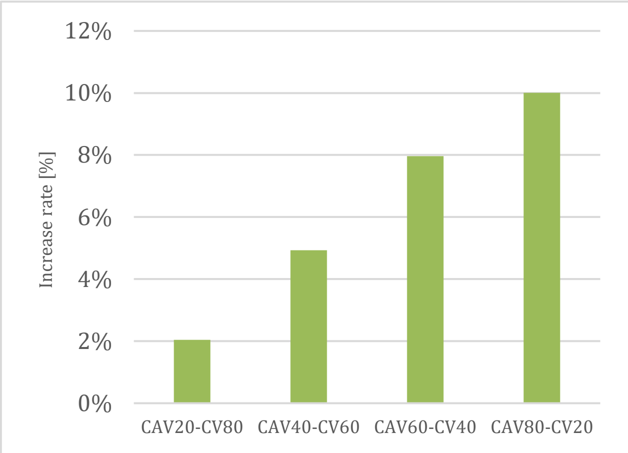

Figure 15 Vehicle Throughput Result (without work zone)

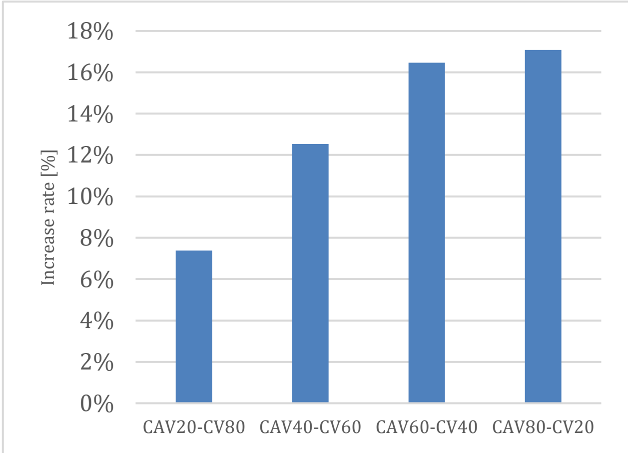

Figure 16 Vehicle Throughput result (with work zone)

In detail, the *with work zone* scenarios have 7% of the vehicle-through-increase rate for the 20% of CAVs scenario and continue to increase until 17% of increase rate, for the 80% of CAVs scenario. Comparing these scenarios to each other, the 40% CAV rate shows a 6% increase in vehicle throughput over the 20% CAV rate.

<u>*Vehicle delay*</u>

In Figure 17 it is shown that the average vehicle delay decreases with an increase of CAV rates in the *without work zone* scenarios. However, in the *with work zone* scenarios (see Figure 18), the presence of CAVs is able to reduce the average vehicle delay when they represent at least 40% of the total vehicles. Not only that, 20% of CAVs from the total passenger vehicle volume even make vehicle delays longer than the 100%-conventional-vehicle scenario. Moreover, even the highest decrease rate, which comes from the 80% of CAVs rate *with work zone* scenario, is lower than all the *without work zone* scenarios. The increased vehicle delay result of the 20% of CAVs scenario can be possible explained by the fact that a low penetration rates of connected and autonomous vehicles are not very effective in improving the vehicle interactions as well as the ability of the current models to represent realistically the actual driving behaviors still need adjustments. In addition, the calibration process was conducted at the on-ramp area, not at the work zone. As a result, there might be limitations that couldn't be caught during calibration to properly implement car-following behaviors for the work zone simulation. However, the results also reveal that even under the work zone condition, CAVs can reduce vehicle delay as they fill a higher percentage of the total passenger vehicles, and pass the initial transition period.

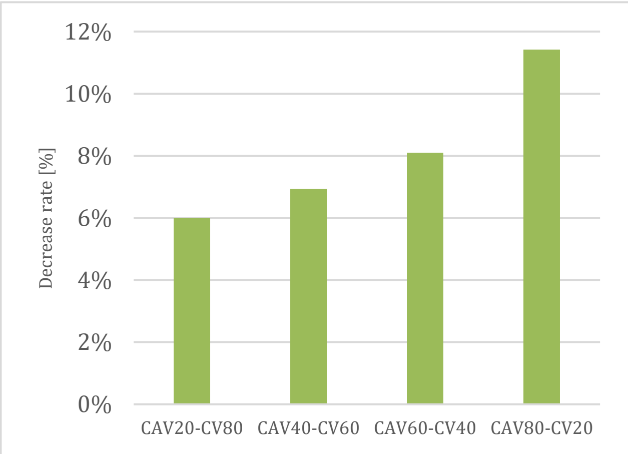

Figure 17 Relative Change in Vehicle Delay (without work zone)

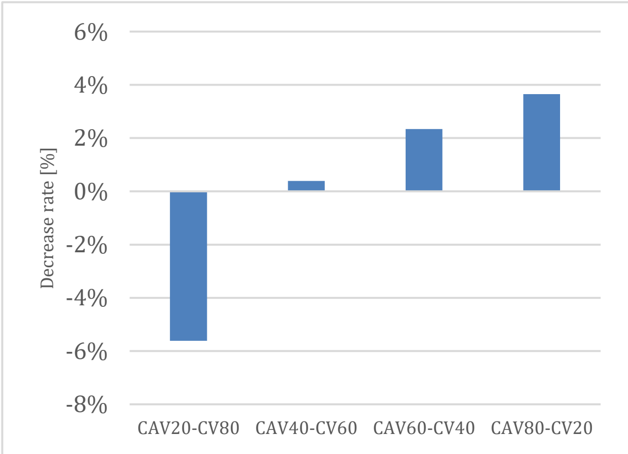

Figure 18 Relative Change in Vehicle Delay (with work zone)

Queue Length

In the *without work zone* scenarios, there are no queues because all three lanes can be utilized, and vehicles don't need to change lanes which may cause unnecessary disruption on traffic streams. By contrast, at the entrance of the tunnel where the first lane is closed for the work zone, average queue length results show the best benefit when the CAV penetration rate is low (see Figure 19). Vehicles in the *with work zone* scenarios have to wait longer to find suitable gaps to change lanes at the point where the first lane is closed, and to merge into the second lane. At this point, the waiting vehicles in the first lane are counted as queuing because they have relatively slower speeds, so they don't reach the merging point. Moreover, the vehicle throughput results described that the scenarios having the higher CAV rates shows the larger capacity per lane. As a result, more vehicles are accumulated at the merging points, and it makes the average queue length longer with the increase of CAV rates.

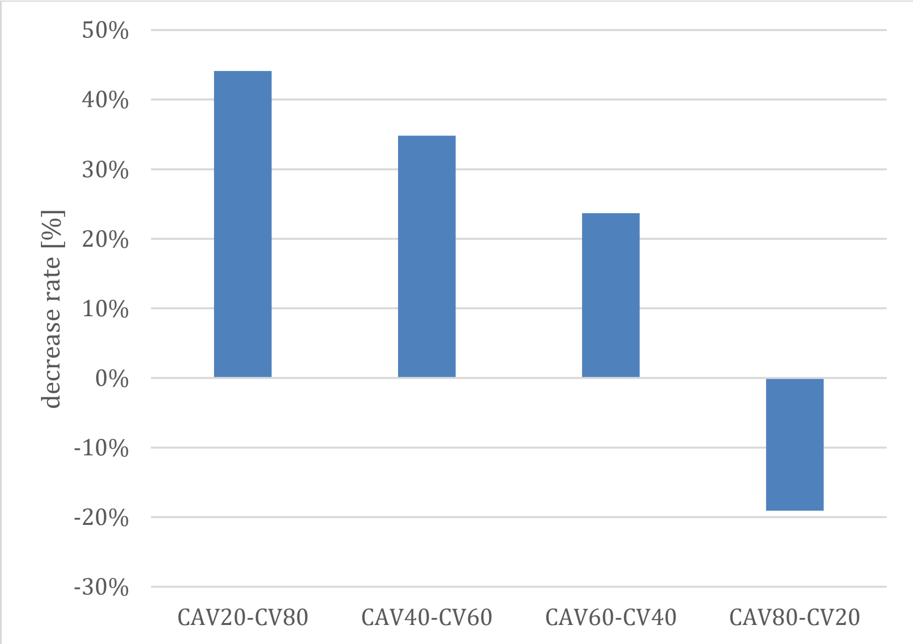

Figure 19 Average Queue Length Decrease Rates (with work zone)

<u>*Number of Conflicts (Safety)*</u>

The number of conflicts were examined using vehicle location information gathered at the work zone. Each conflict analysis results, which were obtained from SSAM, except the 2_CAV0-CV100 scenario, were divided into two groups according to the second vehicle's type, CAV or CV. In the case that the second vehicle is a CAV, three different TTC thresholds were utilized. Table 8 presents the number of conflicts per scenario, vehicle type, TTC threshold, and conflict type, as well as the total number of conflicts. When lower TTC thresholds are adapted the number of vehicle conflicts when the following-vehicle type is CAV decreases.

Under the coexisting conditions, the total number of conflicts, including rear-end and lane-change conflicts, are reduced in accordance with the increased CAV rates. Correspondingly, the analysis results using the 0.75 threshold from each scenario have the lowest potential conflicts. Specifically, the 2_CAV0-CV100 scenario has a total 1331 conflicts, while the 2_CAV40-CV60 has a total 1213 conflicts when applying the 1.5 TTC threshold, and 1178 and 858 conflicts when using the 1.0 and 0.75 TTC values, respectively. The overall decreasing trend is continued for all scenarios, and the 2_CAV80-CV20 scenario has 346 conflicts, when employing 0.75 TTC threshold, which mean a 74% reduction in the total conflicts comparing to the basic scenario.

* HGVs account for 13% of the total vehicle volume

			Conflicts per Vehicle Type		Total Conflicts	
Scenario	Vehicle Type	TTC	Conflict Type		Conflict Type	
			Rear-end	Lane Change	Rear-end	Lane change
CAV0-CV100	CVs&HGVs*	0 <TTC≤ 1.5	-	-	1313	18
CAV20-CV80	CAVs	0 <TTC≤ 1.5	534	5	1180	33
		0 <TTC≤ 1.0	500	5	1145	33
		0 <TTC≤ 0.75	182	3	827	31
	CVs&HGVs	0 <TTC≤ 1.5	645	28	-	-
CAV40-CV60	CAVs	0 <TTC≤ 1.5	848	11	1232	36
		0 <TTC≤ 1.0	769	10	1153	35
		0 <TTC≤ 0.75	256	8	639	33
	CVs&HGVs	0 <TTC≤ 1.5	384	25	-	-
CAV60-CV40	CAVs	0 <TTC≤ 1.5	823	12	1022	31
		0 <TTC≤ 1.0	704	11	902	30
		0 <TTC≤ 0.75	202	10	400	29
	CVs&HGVs	0 <TTC≤ 1.5	198	19	-	-
CAV80-CV20	CAVs	0 <TTC≤ 1.5	623	14	752	28
		0 <TTC≤ 1.0	519	13	648	27
		0 <TTC≤ 0.75	192	11	321	25
	CVs&HGVs	0 <TTC≤ 1.5	130	14	-	-

Table 8 Number of Conflicts at the Work Zone

4.12 Conclusion

Through the case study at the La Fontaine tunnel area under the lane-closure conditions, it was verified that the CAVs can improve roadways' capacity per lane, and enhancement even can be enlarged with the higher percentages. Moreover, the capacity improvements of the *with work zone* scenarios were greater than the *without work zone* scenarios. Therefore, it was proved that the higher CAV rates have bigger influences in lane-closure situations. However, the delay results fail to fulfill the reasonable expectation that the more CAVs market penetration rates will instantly bring the shorter vehicle delay. Nonetheless, the vehicle delay results were started decreasing when the CAVs accounts for more than 40% of the total passenger vehicle. In addition to the vehicle delay results, the average queue length results deteriorated when more CAVs had added to the simulation network. The exacerbations of the vehicle delay and queue length results could be explicated by four possible reasons: First, when CAVs have lower percentages, they couldn't function with their maximum ability. Second, non-automated trucks account for 13% of the total volume for all scenarios. Therefore, they impede CAVs and overall traffic flow conditions. Third, the increased capacity per lane could be a reason for the longer queue length results. Fourth, the limitation during the calibration process might be a factor that makes conventional vehicles' parameters fail to simulate the work zone driving behavior in reality. On the other hand, the conflict analysis results which were conducted to examine the safety aspect demonstrated the higher CAV rates reduced the probability of conflicts.

In consequence, CAVs during the coexist period can improve the work zone's capacity, safety as well as vehicle delay if they take more than 40% of traffic flow. However, increased capacity per lane, and non-automated HGVs may cause longer average queue length at the work zone merging area. Moreover, from the perspective of the simulation parameters, it is expected that better results are able to be achieved if the model's calibration is conducted with work zone data, instead of a nearby merging ramp.

5. Concluding Remarks and Future Work

This study examined the impact of connected and autonomous vehicles on traffic streams for mixed traffic conditions. A simulation network was built at the at Louis-Hippolyte La Fontaine Tunnel with and without a work zone deployed on the first lane. Therefore, the vehicle-merging maneuver was simulated at the entrance of the tunnel. The estimated traffic volume for 2033 was calculated based on 2018's spring morning peak travel demands. This 15-year long-term horizon was selected based on the available studies predicting that the 2030's will be the starting decade of autonomous vehicles on roadways. Vehicle throughput, delay, and queue length were measured at the tunnel entrance and the on-ramp area, where vehicles merge from Highway 132. Vehicular conflicts were analyzed using SSAM in order to investigate traffic safety improvements due to deployment of autonomous vehicles. The TTC values 1.5s, 1.0s, and 0.75s were used for the autonomous vehicles, and sensitivity analysis was conducted. This was done because while CAVs are able to maintain shorter space headways, there no guidelines for CAVs safety assessment parameters. The calibration process was conducted using the trial-and-error method to adjust car-following parameters - CC0, CC1, and CC2. The calibration was performed for conventional vehicles with the field vehicle counts data which was collected at the merging area in the spring of 2018. The calibration performance measure was the GEH statistics. The parameter set which has the GEH value less than five, and relative error less than or equal to 10% was utilized for the case study assessment.

The simulation results showed that the tunnel work zone's capacity per lane increases with the increase in the CAV penetration rates. It also found that the average vehicle delay improved at higher CAV penetration rates. However, the queue length deteriorated with the increase in the CAV rates. This could be explained by several reasons: the impact of trucks that are not modeled as CAVs, the increased capacity per lane at the work zone, and the limitation of the calibration process. Nonetheless, the conflict analysis results proved that CAVs can improve overall traffic safety and some traffic operations performance measures at a work zone.

As future study, automated trucks and different percentages of trucks can be considered. Moreover, platooning in the VISSIM simulation is also able to be employed for implementing inter-vehicle connectivity. In this study, the work zone was only located in the first lane, but it can be in the second or third lanes in the further study. Also, how various lane closure designs have an influence on traffic streams can be examined too. In addition, more in-depth analysis of the impact of CAVs not only under the different lane closure conditions, but also at intersections, weaving, or diverging areas is suggested.

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