Investigating the Effects of Automated Vehicle Driving Operations on Road Emissions and Traffic Performance

by

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Abstract

Automated vehicles (AV) will inevitably have an impact on the movement of people and goods. Assessing the effects of AVs on land use, congestion and the environment have become of great interest to researchers. This study explores the effects of AVs and vehicle electrification on greenhouse gas emissions using traffic microsimulation and emissions modeling. The driving behaviour parameters of a traffic simulation package, most relevant to AVs, are tested within the ranges deemed to be representative of potential AV operations. The effects of AVs are evaluated under both uninterrupted and interrupted traffic flow operating environments, as well as under high and low traffic demand. The main findings indicate that automated vehicles can bring positive changes in terms of emission and traffic flow performance. The significance of the impacts is more evident when AVs are tuned to more aggressive driving settings and especially under high traffic conditions in uninterrupted flow operations.

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My overall experience at UofT was a memorable one with challenges that have shaped me into who I am today. All great things eventually come to an end. I now draw another chapter to a close and I am excited to see where my next endeavour will take me.

Chris Stogios, 2018

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List of Acronyms

AV	Automated Vehicle(s)
CV	Connected Vehicle(s)
CAV	Connected and Autonomous Vehicle(s)
EV	Electric Vehicle
ACC	Adaptive Cruise Control
CACC	Cooperative Adaptive Cruise Control
V2V	Vehicle to Vehicle Connectivity
VKT	Vehicle Kilometers Travelled
GHG	Greenhouse Gas Emissions (Carbon Dioxide, CO_{2eq})
opModeID	Operating Mode
VSP	Vehicle Specific Power
EF/EI	Emission Factor/ Emission Intensity

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Chapter 1
Introduction

1.1 The Future of Transportation

Technology has advanced rapidly over the past years and will continue to improve in the years to come. Improved computing power, sensors and communication / connectivity are finding their way into the automotive industry in the form of connected and automated vehicles (CAV), promising to change the characteristics of transportation and how people and goods are moved from one place to another. The evolution of automation has already begun with various automated and drive assist features already available, especially in high end vehicles (Tesla, Mercedes, BMW etc.), but now these features are becoming more mainstream (KPMG, 2015; PPSC, 2018). Vehicle manufacturers (such as Volvo, GM, BMW, Audi, Mercedes) are expected to sell autonomous vehicles by 2020 (Bierstedt et al., 2014). Various levels of automation have been tried in vehicles over the past few years, with pilot projects on fully automated vehicles being initiated by Tesla and Google. Now, the industry has reached the point where having fully automated vehicles (AV) with increased market penetration will be inevitable over the coming years, as incremental levels of automation gain acceptability by the general public (Bierstedt et al., 2014).

To a large extent, automated transportation addresses some challenges in the industry, alters others and introduces new ones. Agencies, legislative bodies, and other entities (insurance companies, technology firms, etc.) have been putting a lot of effort into creating an all-encompassing framework for the adoption and operation of AVs. This framework includes technology specifications, safety rules, legislation, business models, etc., with the expectation to address many of the challenges faced by transportation, including safety, congestion, and vehicle emissions. In Canada, all levels of government will have a key role in raising public awareness and ensuring important safety information and regulations are set in place for the deployment of AVs. Governments, including municipal, provincial and federal, need to develop and execute a framework that includes safety enforcement of the technology, vehicle licensing, insurance and any infrastructure changes that might be needed to support the deployment of AVs (PPSC, 2018). The key industry players, including vehicle manufacturers and technology firms, will also need to coordinate with government agencies to ensure that the governments are aware of the challenges of AV technology, and, on the other hand, manufacturers are aware of the safety and regulatory standards that have been put in place to ensure public interest (PPSC, 2018).

The automotive industry is in the initial stages of a paradigm shift. New business models for delivery of transportation services will be introduced and rely heavily on the automated technology (automated ride-share and taxi services, delivery services, etc.). The field of transportation and the fabric of our urban environment is rapidly changing and will continue to evolve as technology advancements and these new business models develop.

1.2 Research Motivation

Automated and connected vehicles share many technological characteristics but may function differently depending on their configuration and capabilities. Connected vehicles (including human operated ones) gather information from other vehicles and the surrounding infrastructure, without necessarily being automated. Other vehicles can be automated without being connected. AVs can be partially automated with driver assistance functions, or fully automated without the need for driver input. Fully automated vehicles can rely only on information from their on-board sensors to sense the environment and operate independently without human input (PPSC, 2018; PSC & CAR, 2017).

Automated vehicles have the potential to inflict change on the movement of people and goods within our urban environment. Equipping vehicles with automation technology brings the possibility of improving safety, changing the cost of transportation, modifying land use, affecting traffic flow, reducing congestion, as well as reducing energy consumption and pollution (Anderson et al., 2016; PSC & CAR, 2017). It is important to understand and quantify the impacts of automation technology to gather information to provide an evidence base for the development policy and legislative frameworks.

Automated vehicles have the potential to introduce capacity benefits, operating efficiencies, improved safety, and steps towards emission reduction. There is more than one aspect of how automated vehicles can affect GHG emissions. Operation efficiencies as well as improved powertrain technology of automated vehicles (electrification) are expected to yield benefits with regards to emissions. Increasing concerns about global warming makes it even more critical to explore and evaluate the effects that automation in the transportation industry may induce.

The transportation industry is responsible for 27% of GHG emissions in Canada and the United States (Statistics Canada, 2012; USEPA, 2017). With advancement in technology, there is an opportunity to reduce the environmental impacts of the transportation sector, especially considering that AVs present an opportunity to adopt concurrent advancements in powertrain technology (i.e. electrification).

The literature and available research that has been completed on the topic of connected, automated and transformative transportation covers the potential impact of this advanced technology in terms of safety, congestion, and travel behaviour, as well as some potential impacts on emissions and energy use. However, this field is still in the early stages of research and, with limited availability of the full automated technology in the market, many of the impacts that are identified in the research are still speculative in nature. With the advancement of simulation tools, opportunities are becoming available to explore the effects of automated vehicles, or various aspects of automation, well before the widespread deployment in transportation fleets. This allows for initial estimates of the environmental and transportation impacts of automated vehicles and technology. This research focuses on investigating and quantifying the impacts of fully automated vehicle technology on greenhouse gas (GHG) emissions and traffic performance.

1.3 Objectives of Study

This study is focused on three main objectives. The first is to understand and identify representative driving behaviours of AVs. The second is to investigate the effect of these driving behaviours on operating regimes (i.e. high traffic and low traffic) and with different flow characteristics (uninterrupted vs. interrupted). The third is to assess the emissions associated with the traffic performance of automated vehicles under each driving behaviour and operating regime.

The driving behavior parameters most relevant to AVs are tested within ranges that research has identified to represent potential behavior of AV operation. The parameters with most influence on emissions are identified. Since fully automated AVs are computer-controlled vehicles relying on sensor technology with the ability to react faster than humans, an extreme aggressive driving style, with shorter time gaps and safety distances, and faster accelerations are feasible. Cautious AV driving behaviour is evaluated in this study to cover the possibility of AVs initially being programmed on the conservative side of the driving style spectrum to generate user comfort and confidence.

1.4 Structure of Thesis

To carryout the investigation of automated vehicles on emissions and traffic performance, this thesis is structured into seven chapters. First, available literature is presented in a comprehensive literature review. This review includes information and recent work done on defining automated vehicles and technology, as well as their impacts on safety, traffic performance and the environment. The methodological framework adopted in this study is then described detailing information on how the traffic simulation is developed and how the emissions are estimated. The results are then described for both high and low traffic operating regimes and uninterrupted and interrupted traffic flow. Finally, the results are discussed drawing conclusions from the investigation and identifying areas for future work.

Chapter 2
Literature Review

The concept of vehicle automation and connectivity has become a popular topic in the literature over recent years. As technology continues to advance, many researchers and vehicle manufacturers have gained interest in defining this new technology and investigating its potential from an overall regional perspective, as well as the microscopic level of vehicle operations. This section presents an overview of the work that has been conducted on the topic of automated vehicles and discusses what changes researchers expect this technology to bring in terms of safety, emissions, as well as traffic flow and operations.

2.1 Evolution of Automated Vehicles in Transportation

The rate at which automated vehicles (AVs) will enter the transportation fleet will depend heavily on the advancement of the technology in terms of safety, liability, cyber security, cost and equity, and the availability of infrastructure (Bierstedt et al., 2014). There are various levels of automation that have been defined by the Society of Automotive Engineers (SAE International), that serve as a basis for understanding the transfer of driving tasks from human drivers to the system as the technology advances. The taxonomy of the five levels of automation is shown in Figure 2.1 below (SAE, 2016). Within the SAE taxonomy, levels 3 to 5 of automation can be distinguished from lower levels (levels 0, 1 and 2) simply by the fact that an automated system can perform the dynamic driving task (DDT) without the need for human control (PSC & CAR, 2017). For the case of level 1 (driver assistance systems) and level 2 (partial driving task automation), a human driver is still monitoring the driving environment and is assisted by the automated driving system (ADS) for either lateral/longitudinal control (for level 1) or both (for level 2). For level 3, conditional driving automation, the automated driving system performs all the dynamic tasks associated with driving, including monitoring the surroundings and controlling the movement. However, the human driver is required to be aware and available to take over control of the vehicle if necessary. For level 4, high driving automation, the automated system can fully control the vehicle within prescribed limits of operation without human interference (e.g. freeway operations only, or closed circuit etc.). For the final and top level of full automation, level 5, the automated driving system can operate the vehicle without intervention on all roads and driving conditions without restrictions (Milakis, Van Arem, & Van Wee, 2017; SAE, 2016).

All vehicle manufacturers with plans to release automated vehicles have already offered some level of automation in their vehicles (Greenblatt & Shaheen, 2015). It is estimated that automotive manufacturers will have high levels of autonomous vehicle technology (level 4) available by 2025, with full level 5 automation being anticipated by regional planning agencies to be available by 2040 (Bierstedt et al., 2014; Childress, Nichols, Charlton, & Coe, 2015; KPMG, 2015; Policy and Planning Support Committee (PPSC), 2018). Initially, AVs will be designed to operate with the existing transportation infrastructure and will be integrated into the transportation network incrementally over time (PPSC, 2018).

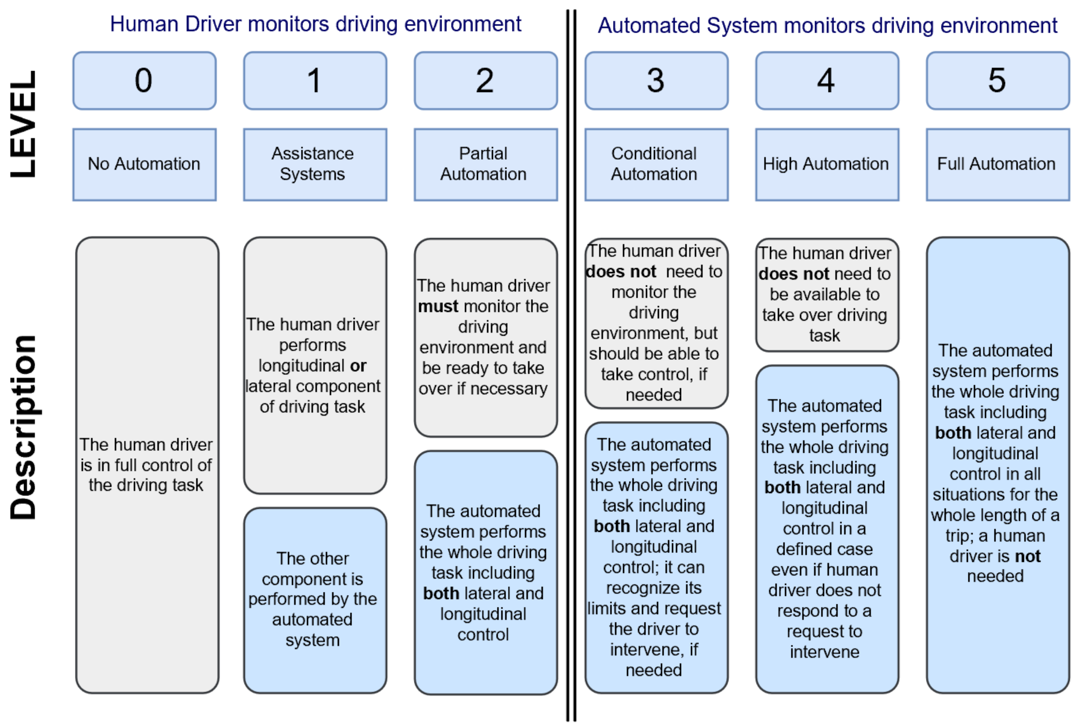

Figure 2.1: Summary of levels of automation; adapted from KPMG (2015) and SAE (2014, 2016)

It is also important to identify and distinguish the differences between the various types of automated vehicles. The literature has indicated that there is a lack of distinction between connectivity and automation with respect to this new technology of vehicles (Olia, Abdelgawad, Abdulhai, & Razavi, 2015; Olia, Razavi, Abdulhai, & Abdelgawad, 2017; Talebpour & Mahmassani, 2016). Vehicles can be considered connected and gather information from other vehicles and surrounding infrastructure, without necessarily being automated. AVs can also be further categorized into cooperative (connected) and autonomous, both of which can be driverless vehicles (Olia et al., 2017). An automated vehicle can theoretically rely only on its onboard sensors, radar, or video to sense its surrounding environment to navigate through a network without necessarily communicating with other vehicles or infrastructure. On the other hand, a cooperative/connected AV gathers information by communicating with other vehicles or infrastructure and combines it with the information it receives from its onboard sensors to navigate through a transportation network (Olia et al., 2017; PSC & CAR, 2017; Talebpour & Mahmassani, 2016).

2.2 Impacts of Automated Vehicle Driving Characteristics

Recent studies show that the adoption of automated vehicles would provide numerous benefits to transportation mobility. These benefits include an increase in traffic capacity of existing roadway infrastructure, improved fuel efficiency, improved traffic flow, improved safety, reduction in traffic congestion and, ultimately, a reduction in Greenhouse Gas (GHG) emissions (Fagnant & Kockelman, 2015; PTV AG, 2017). Fagnant and Kockelman (2015, 2014) explore the benefits associated with automated vehicles. They determine that AVs create the opportunity to improve safety on the road by reducing the human error component of driving which could result in up to a 40% reduction in vehicle crashes. Papadoulis et al. (2018) investigate connected autonomous vehicles (CAV) with respect to safety and conduct a CAV safety evaluation study. They use the External Driver Model API of PTV VISSIM microscopic simulation software to introduce the characteristics of a CAV into a transportation network. Their analysis concludes that CAVs will bring significant reductions in traffic conflicts, with up to a 94% reduction, if the CAV penetration in the network reaches 100%.

AV technology can influence vehicle operational characteristics through various mechanisms including changed accelerating and decelerating characteristics, changed longitudinal behavior when following other vehicles, changed lateral behavior and gap acceptance thresholds (Atkins, 2016). AVs have the opportunity to build platoons of closely spaced vehicles with less frequent stops and slow downs, which can improve fuel economy, but still maintain higher effective speeds and improve overall travel time (Anderson et al., 2016). Most of these operational characteristics and effects can be captured through microscopic traffic simulation models. Micro-simulation analysis considers the lowest level of traffic stream aggregation and reflects vehicle operations and driver behavior in the underlying car-following, lane-changing, and gap acceptance sub models (PTV AG, 2016).

Several AV research studies have been conducted to understand the impact of AV penetration on road capacity, emissions, traffic performance, or safety. However, these studies are limited to a conservative driving behavior range and are based on a scenario comparison approach. One study investigates the influence of AVs on traffic performance by conducting a micro-simulation of an autobahn segment including an on-ramp, an off-ramp, and a roundabout with an urban road. The study examines various penetration rates of AVs with fixed conservative driving behaviour, and concludes that AV traffic performance benefits are more significant under congested conditions (Aria, 2016; Aria, Olstam, & Schwietering, 2016). Bierstedt et al. (2014) suggests that AV will initially have no effect on highway capacity, or even degrade the capacity of the network as cautiously programmed AVs with conservative headways could lead to reduced flows and densities. Their microsimulation estimates that capacity improvements will only be present when at least 75% of the vehicles are AVs programmed to operate at intermediate levels between cautious and aggressive. Another study in Germany also conducts a traffic simulation under different AV penetration rates and concludes that conservative driving behavior has a negative impact on capacity while more aggressive behavior increases capacity by up to 30% (Hartmann, Motamedidehkordi, Krause, Hoffmann, & Vortisch, 2017). The influence of AVs on road emissions and traffic performance under variable vehicle flow is studied using a traffic simulation model, concluding that road capacity is improved and emissions are reduced at high vehicle flow, while there is a slight increase in delay and emissions in the low vehicle flow scenario (Bohm & Häger, 2015).

Bailey (2016) uses a microscopic traffic simulation to determine the changes in traffic dynamics as the penetration rate of autonomous vehicles varies. Human driven and autonomous vehicles are modelled using different behavioural models obtained from the literature in a simple network with traffic flowing through an isolated signalized intersection. With an increase in penetration of autonomous vehicles on the road, an increase in network capacity and a decrease in average delay is observed.

Songchitruksa et al. (2016), Milanes et al. (2014), Vanderwerf et al. (2001), Van Arem et al. (2006), and Arnaout et al. (2014; 2011) all explored applications of AV/CV operations in their research, specifically with respect to vehicle cruise control systems. Songchitruksa et al. (2016) develop a framework to incorporate realistic AV/CV driving behaviours into the PTV VISSIM microscopic simulation software. To demonstrate their framework, researchers conducted a case study of a simple freeway network with various penetration rates of cooperative adaptive cruise control (CACC) capable vehicles. CACC is a form of adaptive cruise control (ACC), whereby vehicles can wirelessly connect to each other (V2V communication) and follow each other with very tight spacing. The results of the case study show that the modification of a microsimulation driver model can successfully evaluate the benefits of AV/CV applications (such as CACC) with respect to traffic flow, safety, and environmental performance. Also, it is determined that higher penetration of CACC results in better traffic and emission performance. The example of the effects of CACC-equipped vehicles on congestion mitigation of a complex network is also explored in a few studies by Arnaout et al. (2014; 2011). Various penetration rates of CACC-equipped vehicles are studied in an agent-based microscopic traffic simulator. The results indicated that CACC penetration in the network resulted in higher capacity and better traffic flow performance leading to a reduction in congestion.

Vanderwerf et al. (2001) develop a car-following model for ACC- and CACC-equipped vehicles and compare their performance on freeway operations with that of manually driven vehicles. They conclude that at 100% penetration, CACC-equipped vehicles significantly increase the freeway capacity compared to ACC-equipped vehicles (which had the next highest capacity increase) and manually driven vehicles. Milanes et al. (2014) find similar results; however, they explore varying penetration rates of ACC- and CACC- equipped vehicles. They find that for ACC vehicles, the penetration rate has minimal impact on freeway capacity, while an increase in the penetration rate of CACC-equipped vehicles results in an increase in capacity.

Van Arem et al. (2006) consider a platoon of vehicles equipped with CACC at various penetration rates and compare the results to a platoon of only manually driven vehicles. They determine that the CACC-equipped vehicles exhibit smoother acceleration and deceleration. They also explore the effects of CACC vehicles on traffic flow, like the other studies, and conclude that CACC vehicles show improvements with penetration rates of 60% and above.

Much like the previous studies discussed, Ntousakis et al. (2015) conducts research that uses Aimsun to explore the effects of penetration of ACC equipped vehicles into a network with varying time gaps and under various traffic conditions, to determine their effects on traffic flow. They conclude that traffic flow performance was better at short time gaps (time headway) with high penetration of ACC vehicles, as opposed to longer time gaps and lower penetration of ACC.

Talebpour et al. (2015; 2016) conduct many studies exploring the changes that connected and autonomous vehicles (CAV) will bring to the driving environment. They identify a gap in the literature with regards to distinguishing between connectivity and automation and their different effects on driving. Their studies work towards developing a framework that uses different technology assumptions to simulate vehicles with distinctive communication capabilities at various penetration rates. At higher penetration rates, CAVs can improve vehicle throughput and the stability of a string of vehicles (Talebpour & Mahmassani, 2015, 2016). Also, they develop an integrated microscopic traffic simulation and communication network model to explore the system level impacts of vehicle connectivity and discuss the importance of considering telecommunications in addition to vehicle movements to best evaluate their effects on mobility and emissions (Talebpour et al., 2016).

Olia et al. (2015, 2017) also conduct studies with respect to AV penetration into a transportation network. They categorize AVs as cooperative (or connected) AVs and autonomous AVs and develop an analytical framework to quantify and evaluate the effects on capacities of highway systems. Both studies concluded that autonomous AVs have limited effect on highway capacity regardless of their penetration, while connected AVs have a significant effect on improving lane capacity.

2.3 Sensitivity Analysis of Driving Behaviour Parameters

Sensitivity analysis studies have also been conducted for traffic simulation driving behavior parameters to study roadway capacity, travel time or safety. However, none are focused on the impact on GHG emissions. Additionally, all these sensitivity studies are based on range variations for the driving behavior parameters that are specific for conventional vehicles only. These driving behaviour parameters are defined in detail in section 3.3.1, Table 3.1. Lownes and Machmehl (2006a, 2006b) conduct a one-at-a-time (OAT) sensitivity analysis for longitudinal driving behavior and look-back distance parameters in PTV's VISSIM simulation platform. Their research provides an understanding of the individual influence and interaction through combinations of these parameters on the capacity of simulated motorways. Their results reveal that look-back distance is the most influential parameter individually and that there is interaction between driving behavior parameters in two cases: standstill distance (CC0) and standstill acceleration (CC8), as well as headway time (CC1) and negative/positive following thresholds (CC4/CC5). Furthermore, the impact on capacity for CC8 and CC4/CC5 are dependent on the values of CC0 and CC1, respectively.

A sensitivity analysis of VISSIM driver behavior parameters was conducted using the technique of quasi-Optimized Trajectory based Elementary Effects (quasi-OTEE) to identify the most influential parameter of mostly lateral movement parameters for a transportation network (Ge, Ciuffo, & Menendez, 2014). Habtemicheal and Santos (2012) conduct an OAT sensitivity analysis based on all 10 car-following and 11 lane-changing model parameters with respect to safety and travel time. Their results reveal that headway time (CC1) and following variation (CC2) are the most influential parameters of the VISSIM Wiedemann 99 car-following model in terms of safety and performance. Additionally, the negative/positive following thresholds (CC4/CC5) are found to have a moderate effect, while time threshold for entering (CC3) and safety distance reduction factor only affect safety without any impact on traffic performance.

2.4 Environmental Impacts of Automated Vehicles

Automated vehicles could improve fuel efficiency, minimize traffic shockwave propagation and reduce GHG emissions with their ability to sense surrounding vehicles and adjust their driving cycles for smoother acceleration and braking, and form platoons (Fagnant & Kockelman, 2015; Liu, Kockelman, & Nichols, 2017). Reduced congestion, smoother traffic flows, reduced air resistance due to shorter headways, lighter vehicles (results of increased safety) and less idling from reduced delays can all translate into energy and emission benefits (Milakis et al., 2017). The AV technology can improve fuel economy by 4-10% from smoother acceleration and deceleration alone, in comparison to human drivers (Anderson et al., 2016). The improved safety and reduction in frequency of crashes could lead to the next generation of AVs to become lighter, further improving fuel efficiency, reducing pollution, and eliminating the concerns of driving range issues that are preventing the electrification of vehicles from prevailing as an alternative to vehicle power (Anderson et al., 2016). Higher levels of vehicle automation, cooperation, and market penetration of these vehicles will lead to higher reductions in GHG emissions, while the use of shared automated vehicles can lead to further reductions in Volatile Organic Compounds (VOC) and

Carbon Monoxide (CO) due to reduced number of vehicle starts (Choi & Bae, 2013; Fagnant & Kockelman, 2014; Milakis et al., 2017).

Greenblatt & Shaheen (2015) conduct a review of the history and projected trends of automated vehicles and their potential environmental impacts. They estimate that AVs have an 80% or greater reduction in energy use and GHG emissions as a result of benefits from platooning, efficient parking and traffic flow, and potential for automated ridesharing. In another study, Greenblatt and Saxena (2015) find that shared electric AVs combined with improved low-carbon electricity generation could reduce GHG emission intensities (g/km) by approximately 90% in comparison to conventional internal combustion engine vehicles.

Anderson et al. (2016) and Brown et al. (2014) both speculate that vehicle kilometers travelled (VKT) could increase dramatically as a result of AVs. It is noted that AV technology of at least level 3 automation will most likely reduce the cost of congestion (in other words reduce the value of time), since occupants can do other activities during their commute. A decrease in the cost of driving may result in an increase in VKT, which could also translate into an increase in congestion. However, it is also important to note that the automation technology has the potential to be more efficient in operations and increase throughput, therefore, the effects of AV technology on congestion can still be regarded as uncertain (Anderson et al., 2016). Furthermore, this advancement in technology can lead to use of personal vehicles by those currently unable to drive (e.g. elderly, disabled, children under 16), an increase in the number of trips, a possible shift away from public transit, and additional VKT due to self-parking trips, and longer commutes. Brown et al. (2014) and Mackenzie et al. (2014) both indicate that this increase in VKT and behavioural implications will significantly increase energy/fuel consumption and emissions. However, there seems to be a lack of consensus in the literature on the overall effect of AVs from the environmental perspective. There are opportunities where AVs and the subsequent improvements in technology will result in overall reductions in GHG emissions, and fuel/energy consumption. Yet, some of the literature argues that the overall effects are uncertain. AVs might lead to higher emissions, as a result of ancillary effects of increased VKT and increased travel demand in the long term, as well as the possibility of empty shared AVs driving continuously until the next call, or driving farther distances to reach cheaper parking facility options (Anderson et al., 2016; Brown et al., 2014; Fagnant & Kockelman, 2014; Milakis et al., 2017; Wadud, MacKenzie, & Leiby, 2016). Others argue that the overall improvements in fuel consumption, efficiency in traffic flow, and platooning that will be introduced by AVs, will result in the net effect to be a reduction in the environmental impact (Greenblatt & Saxena, 2015; Greenblatt & Shaheen, 2015).

Choi and Bae (2013) develop a model to estimate the effects that connected and automated vehicles under lane-changing conditions will have on GHG emissions. During manual driving, the human driver accelerates or decelerates accordingly in order to create a safe distance before making a lane change. They determine that automated driving makes lane-changing decisions based on the acceleration or deceleration of the preceding vehicle through vehicle-to-vehicle (V2V) communication. They use simulation to investigate the gap, safety distance and variation in speed under various Level of Service (LOS) conditions for both manual and automated driving. The conclusion of the study indicates that automated driving will result in an overall decrease in CO_2 emissions due to the smoother drive cycles and reduced variations in speed during lane-changing movements. They estimate that connected automated vehicles can bring up to 7.1% reduction in CO_2 emissions when going from a fast lane to a slower lane, while there is the possibility of up to 11.8% reduction in CO_2 through changing from a slower to a faster lane. This trend was also confirmed by other studies, which indicate that automation can lead to smoother reactions to traffic disturbances (Ioannou & Stefanovic, 2005; Milakis et al., 2017).

Olia et al. (2016) create a test-bed in a microsimulation platform for a Toronto transportation network where part of their study evaluates the effects of connected vehicles on emissions. They consider the emission factors of CO_2 to illustrate their impact. They show that connected vehicles have the potential to reduce emissions by up to 30% with emission factors dropping from 177 g/km to 124 g/km with 50% penetration of connected vehicles.

2.5 Gap in Literature

The field of automated transportation is still in the early stages of research. With limited availability of the technology on the market, much of the impacts that are identified can still be considered speculative in nature. The available research discusses the potential impacts in terms of congestion, safety, and travel behaviour, as well as some potential impacts on emissions and energy use. However, questions still remain regarding the impacts of fully automated vehicles on traffic performance and GHG emissions. With this inevitable advancement in technology, research needs to continue to focus on identifying and quantifying the potential environmental impacts on the urban fabric.

Chapter 3
Methodology

This study involves simulating the potential driving behaviour characteristics of automated vehicles to evaluate their potential impacts relative to conventional human operated vehicles under both uninterrupted and interrupted traffic flow conditions, and under low and high traffic demands levels. An overall study framework is devised to include a one-at-a-time (OAT) sensitivity analysis of the driving behaviour parameters in the traffic simulation platform PTV VISSIM 9.0, as well as a scenario analysis of automated vehicle driving behaviour.

3.1 Methodological Framework

The research framework is presented in Figure 3.1. The traffic simulation is set-up to analyze a base case with default parameters representing conventional vehicles. Then an OAT sensitivity analysis is conducted by incrementing each parameter individually and analyzing the results of the microsimulation in terms of their effects on emissions and traffic performance. This is used to determine the most influential parameters with regards to GHG emissions. In the parameter scenario analysis all parameters are set to create aggressive or cautious driving behaviour. The results of the simulation are analyzed with regards to the impacts of AV driving behaviour on network performance and GHG emissions. Each step of the framework is discussed in more detail in the subsequent sections of this chapter.

AVs are evaluated based on their impacts on GHG emissions (CO_{2eq}), as well as traffic performance indicators (e.g. traffic flow, delay, average speed, and number of stops). The United States Environmental Protection Agency MOtor Vehicle Emissions Simulator, MOVES2014a (MOVES) is used to estimate the GHG emissions under the various conditions. Electrification of the vehicle fleet, as well as market penetration rates of AVs are also considered in this study. The base case condition for both uninterrupted (urban freeway) and interrupted (urban arterial) corridors consists of default driving behaviour parameter values, representing human driven conventional vehicles and observed traffic demand. The traffic demand is also varied (either reduced or increased by 50%), in order to compare automated driving to conventional driving in both a high traffic and a low traffic volume environment.

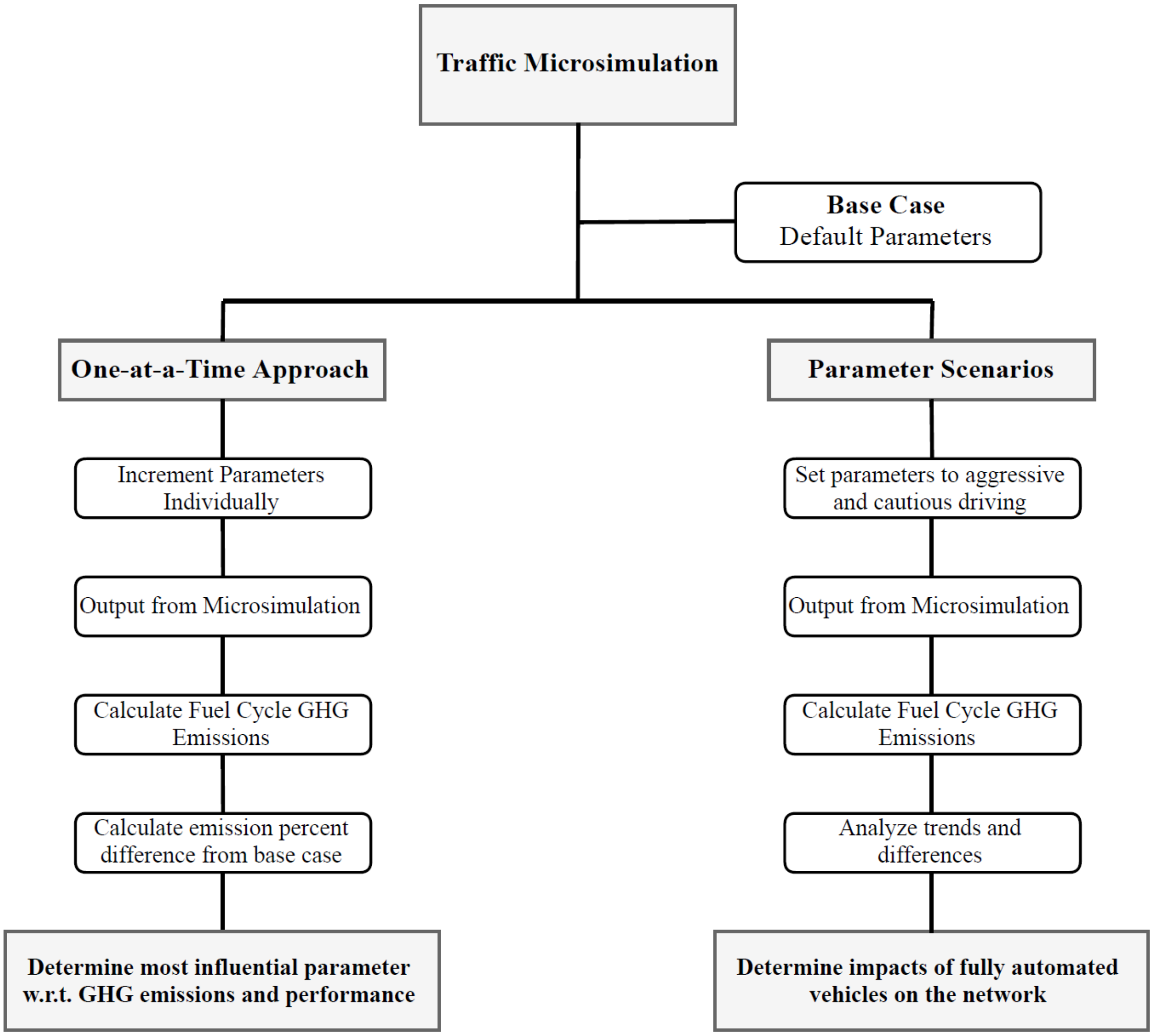

Figure 3.1: Methodology framework of the study

3.2 Study Networks and Traffic Demand

Two microsimulation models are developed using PTV's VISSIM 9.0 traffic simulation software package. To study automated vehicles under uninterrupted freeway traffic flow conditions, a microsimulation model of a section of the Gardiner Expressway in Toronto, Canada is used. A microsimulation of an urban arterial corridor, modelled after a section of College Street in Toronto, Canada, is also used to explore the effects of automated vehicles under arterial roadway interrupted flow conditions. Both simulations are completed for 4600 seconds, including a 17-minute warm up period (1000 seconds) and one-hour (3600 seconds) simulation time during which data is collected for analysis. A warm up period is used in the model to load the network with a realistic level of traffic (still under free flow conditions) before data from the simulation period with the actual demand were recorded for analysis. This is to create a fair representation of realistic traffic conditions.

3.2.1 Freeway Network: Gardiner Expressway

To explore automated vehicles driving on a realistic freeway network and beyond specific configuration scenarios previously used in the literature, a microsimulation model for a 5-kilometer section of the Gardiner Expressway is used for the freeway corridor test of this study (see Figure 3.2). This section of the Gardiner consists of varying configurations and geometry, including lane merging and lane drops, diverging lanes, weaving, on-ramps, and off-ramps. The number of lanes range from at least 2 lanes per direction up to at most 4 lanes per direction.

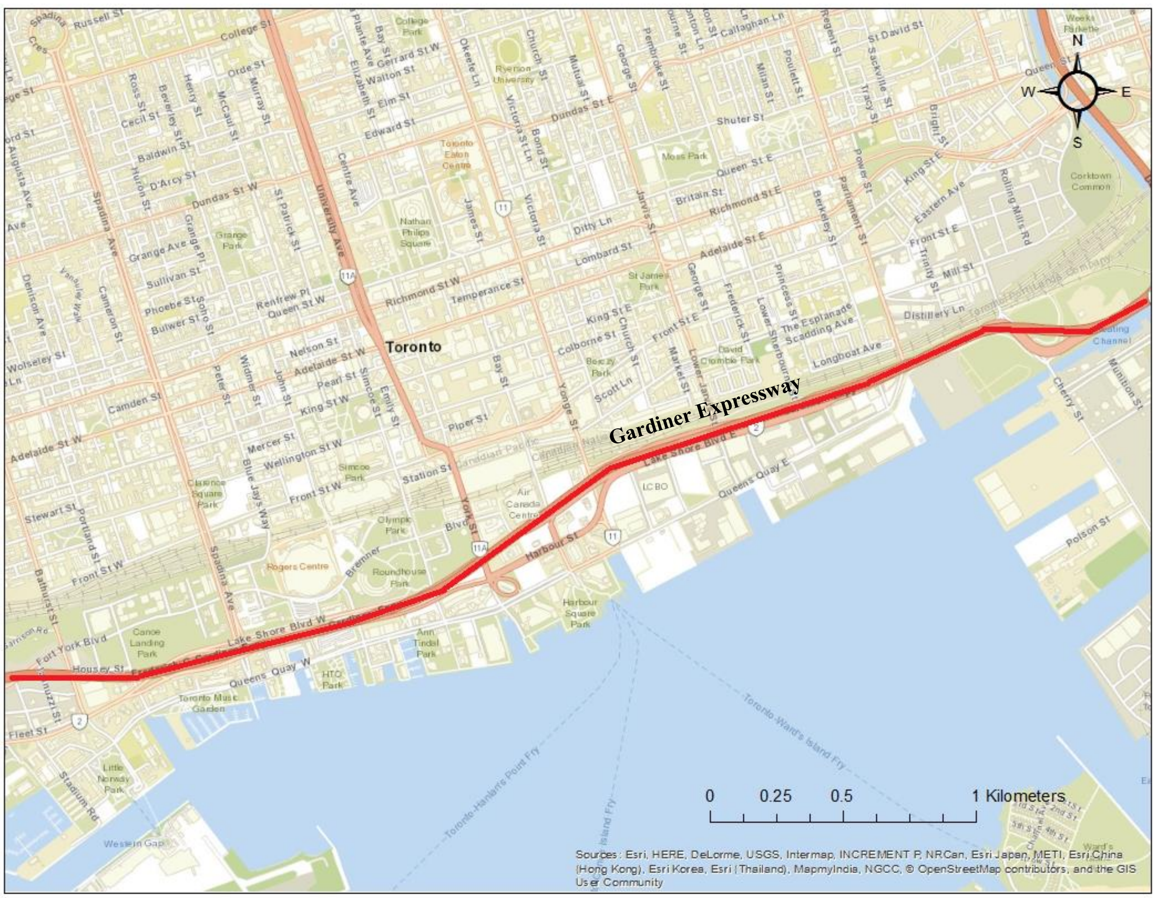

Figure 3.2: Freeway (Gardiner Expressway) study area modelled in VISSIM

The simulation model traffic demand used to load the network is based on hourly morning peak period traffic flows from a study for assessing alternative rehabilitation options for the Gardiner

East Expressway by the University of Toronto and the City of Toronto (Abdulhai, Roorda, & Miller, 2015; PWIC, 2015). The base case condition consists of these traffic flows and the microsimulation default driving behaviour parameters deemed to represent conventional vehicles, based on research and development by the vendors of the traffic simulation software (PTV AG, 2016).

The microsimulation is conducted over a one-hour (3600 seconds) weekday morning peak period in the summer with a 1000 second warm-up period. These hourly traffic demand rates are temporally distributed over the 4600 second simulation period to ensure that all the demand entered the network under the base case conditions. The traffic demand is disaggregated into smaller time periods including the 1000 second warm-up period and four 900-second (15-minute) increments. This time slicing allows the model to capture the temporal variation of the demand within the simulation period, as well as the effects on traffic operations including congestion, queue propagation and dissipation. To capture this full spectrum of traffic conditions, the simulation is set up to start and end with uncongested conditions under the conventional vehicle operations. Therefore, traffic loading profiles are developed to allow for the gradual build up and dissipation of congestion on the simulation network. This is achieved by loading the network with increasingly higher volumes of traffic demand in increments of 15 minutes until the anticipated level of congestion is reached, and then continuing the loading of the network with decreasingly lower volumes of traffic demand until the congestion dissipates fully. There is a total of four vehicle entry points in the westbound direction of the freeway, including one main line entry point, and three on-ramps. The eastbound direction consists of three entry points, including one main line entry point, and two on-ramps. The traffic loading profiles are fixed for the gradual build-up and dissipation of traffic for all seven entry points on the network. An example of a traffic profile for the westbound main line can be seen in Figure 3.3. The remaining traffic loading profiles can be found in Appendix A. These original profiles serve as the high traffic scenario in this study. An additional low traffic scenario is also considered whereby the traffic profiles are reduced by 50% to achieve a less congested traffic environment and explore the effects of automated vehicles under these conditions.

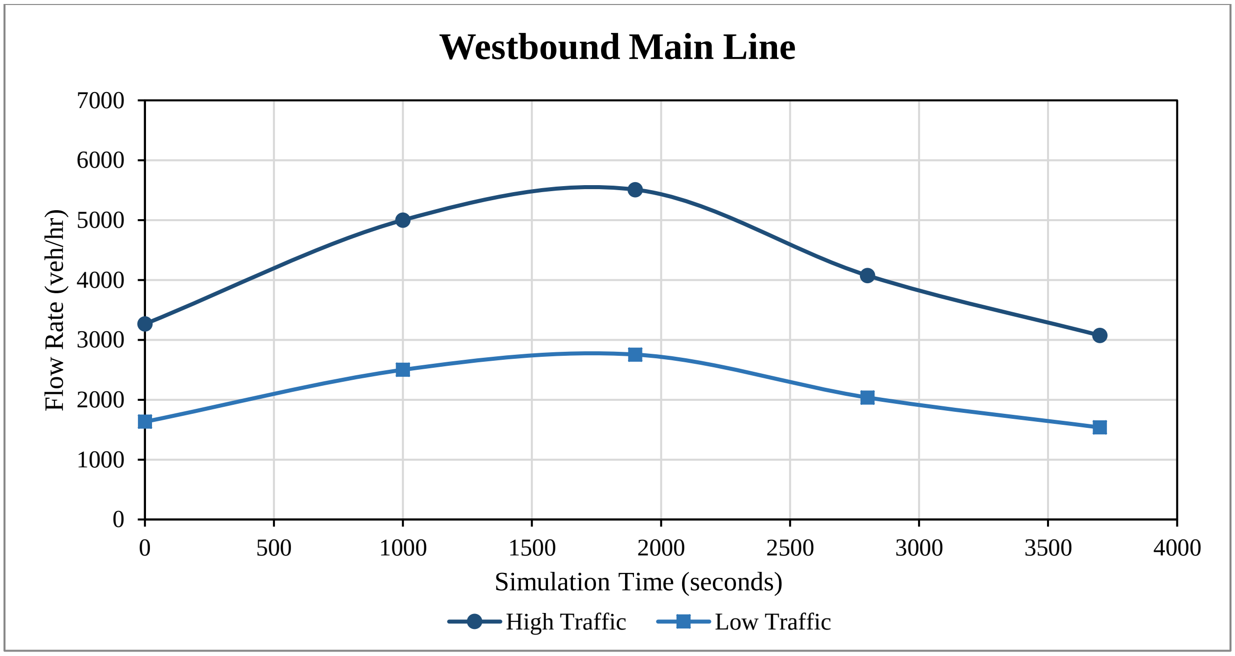

Figure 3.3: Sample traffic profile for the westbound main line of the Gardiner Expressway

3.2.2 Urban Corridor Network: College Street

A microsimulation model for a 1.1-kilometer section of College Street, a four-lane (2 lanes per direction) arterial roadway in Toronto, Canada, is used for the urban corridor test of this study (see Figure 3.4). A section with intersections is modelled carrying through traffic and turning vehicle movements. The traffic volume is based on traffic counts conducted at the intersection of College and St. George streets. Since the traffic counts were observed in 15-minute increments, it was decided that there was no need for any further temporal disaggregation of the traffic demand. These traffic counts are then loaded into the VISSIM network directly for each 15-minute increment they were observed. The microsimulation is conducted over a one-hour (3600 seconds) weekday evening peak period (5:00-6:00PM) in the summer with a 1000 seconds warm-up period. The traffic loading profiles for the College Street network can be found in Appendix B. Based on the traffic volume, the westbound direction of travel is slightly more congested in comparison to the eastbound direction of travel. These original traffic counts serve as the low traffic scenario in this study. An additional high traffic scenario is also considered whereby the traffic counts are increased by 50% to achieve more congestion and explore the effects of automated vehicles under these conditions.

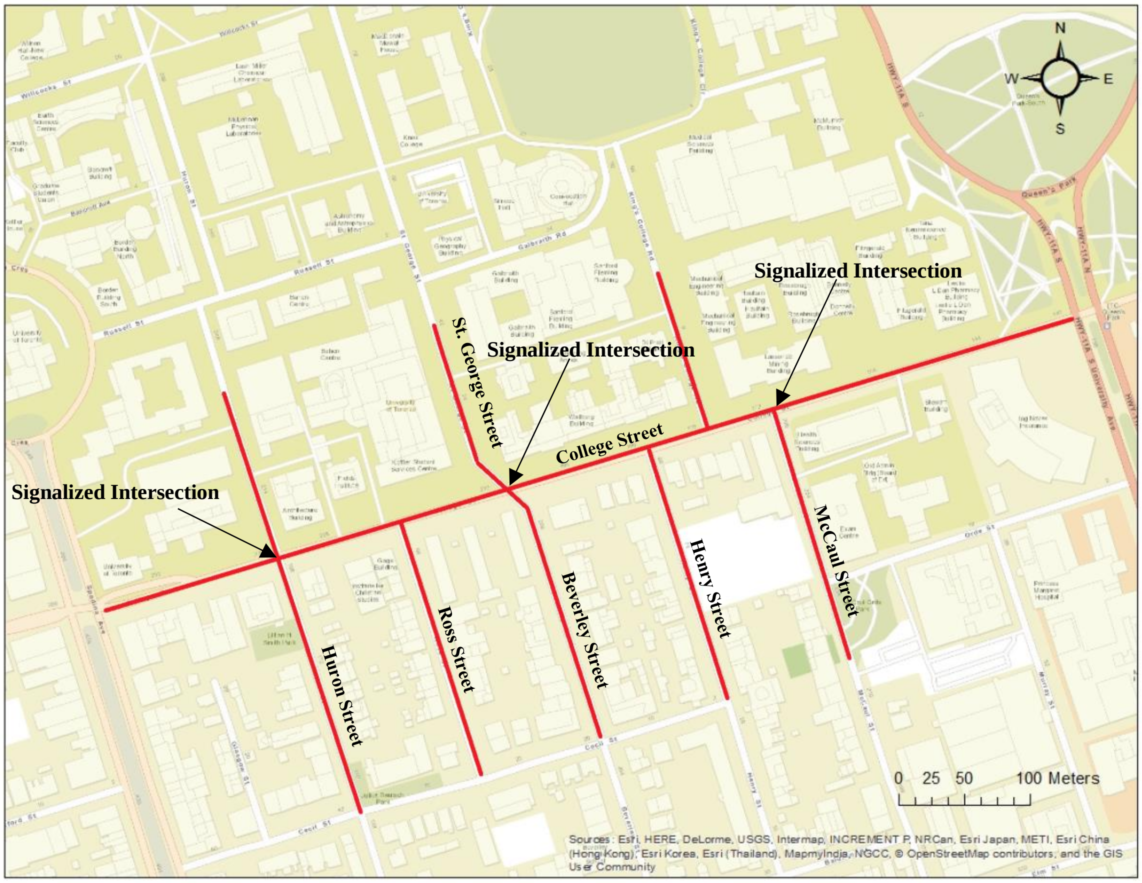

Figure 3.4: Urban Corridor (College Street) study area modelled in VISSIM

3.3 Traffic Microsimulation

There is currently limited capability for microsimulation software to model automated vehicles and, therefore, alternative approaches are used to simulate them using available software. In this study, the driving behaviour parameters of the longitudinal and lateral behaviour models of PTV VISSIM 9.0 are modified to simulate AV operations. In VISSIM, a psycho- physical car-following model is used for longitudinal driver behavior, while a rule-based lane changing model is employed for lateral behaviour (PTV AG, 2016; Songchitruksa et al., 2016).

3.3.1 Driving Behaviour Parameters

The VISSIM microsimulation platform is a stochastic time-step model that is based on the Wiedemann traffic flow model. The Wiedemann model assumes that a driver can be in one of four different driving states at any given time (Songchitruksa et al., 2016):

1. **Free Driving –** this is when no preceding vehicle is observed, and the driver attempts to maintain their desired speed

2. **Following** – this is the process by which the driver follows a preceding vehicle while maintaining a safety distance

3. **Approaching** – this is the process where a driver approaches a preceding slower vehicle and proceeds to decelerate until there is no difference in speed by the time the desired safety distance is reached

4. **Braking –** this is the process by which the distance between the driver following and the preceding vehicle falls below the desired safety distance, and the following driver/vehicle applies an appropriate deceleration rate to increase the distance from the preceding vehicle

The drivers within the simulation switch between the four different driving states as they reach certain perception thresholds related to their willingness to take risks, perception of safety, as well as speed and distance from the preceding vehicle (PTV AG, 2016). Vehicle acceleration is a function of the vehicle speed, the speed difference between preceding vehicles, as well as the distance to the preceding vehicle and various driver characteristics and perception thresholds. This study uses the existing driver behaviour parameters built into the microsimulation model to replicate the characteristics of automated driving by modifying the parameters to essentially replace the driver with driving characteristics and perception thresholds that are deemed to be feasible for computer operation.

Two car-following sub models, Wiedemann 74 and Wiedemann 99, are available to be modified within the VISSIM platform (PTV AG, 2016). Wiedemann 74 is mainly used for urban road segments, while Wiedemann 99 is traditionally used for freeway simulation (PTV AG, 2016). However, the Wiedemann 99 sub model is used for this study as it offers a higher number of parameters available to modify and, therefore, more flexibility for adjustments to consider in the AV driving behavior.

The modifiable longitudinal driving behavior parameters (labelled CC0-CC9) correspond to the driving characteristics of the four driving states described above: free driving, approaching, following, and braking (PTV AG, 2016). In addition, the traffic simulation has lane-changing parameters that could also be modified (PTV AG, 2016). The 10 parameters (8 car-following and

2 lane-changing parameters) that are assumed to be the most relevant to automated vehicle driving behavior operations are described in Table 3.1.

Table 3.1: Definition of driving behaviour parameters deemed relevant to automated vehicle driving (PTV AG, 2016; Songchitruksa et al., 2016)

Wiedemann 99 Car-following Parameters	**Description**
CC0: **Standstill distance** [m]	- The average distance between stopped vehicles (rear bumper to front bumper) - This parameter influences the jam density of a road network
CC1: **Headway Time** [s]	- The time distance which a driver wants to maintain at a certain speed - Higher values are associated with more cautious driving; this is the minimum distance a driver will maintain when in the following state - Under high volumes this headway time has a determining influence on capacity - This parameter determines the average safety distance; at a given speed v [m/s], the safety distance (dx_safe) is: dx_safe = CC0 + CC1 • v
CC3: **Threshold for entering 'Following'** [s]	- Controls the start of the deceleration process when a driver identifies/senses a preceding slower vehicle - Defines how many seconds before reaching the safety distance the driver starts to decelerate
CC4/CC5: **'Following' thresholds** [m/s]	- Controls the speed differences during the following state - Smaller values lead to more sensitive reaction to accelerations or decelerations of preceding vehicles - CC4 is for negative speed difference, and CC5 is for positive speed differences
CC7: **Oscillation Acceleration** [m/s^2]	- The fluctuations in acceleration during the acceleration process
CC8: **Standstill Acceleration** [m/s^2]	- The desired acceleration when starting from standstill (stopped position)
CC9: **Acceleration at 80 km/hr** [m/s^2]	- The desired acceleration at the speed of 80km/hr

Lane-Changing Model Parameters	Description
MinHdwy: **Minimum headway (front/rear)** [m]	- The minimum distance between two vehicles that must be available after a lane change for the lane change to take place - A greater minimum distance between vehicles might be required under normal traffic flow to maintain the speed-dependent safety distance.
SDRF: **Safety Distance Reduction Factor**	- This reduction factor is considered for each lane change - During the lane change, the safety distance is reduced to a value equal to: Safety_Distance x SDRF - This determines by how much the safety distance is reduced when carrying out a lane change and following another vehicle in the next lane - Once the lane change is complete, the original safety distance is restored

These 10 selected parameters are modified to represent driving characteristics of a potential computer operated system. The logic behind this stems from the assumption that a computer operated system, such as that of an automated vehicle, would be able to sense the environment more effectively, and with a lower reaction time to maintain perception thresholds that would allow vehicles to operate closer together and accelerate at faster rates. The test ranges for each parameter are identified based on a literature review and are shown in Table 3.2.

Table 3.2: Driving behavior parameters and the range of values used in this study based on literature review; parameters with an asterisk (*) are from the lane-changing model (Aria, 2016; Atkins, 2016; Bierstedt et al., 2014; Leyn & Vortisch, 2015; PTV AG, 2016)

Parameter	Default Value in VISSIM	Test Range
CC0: **Standstill distance** [m]	1.50	0.5 – 2.5
CC1: **Headway Time** [s]	0.9	0.5 – 2.1
CC3: **Threshold for entering 'Following'** [s]	-8.00	(-4) – (-16)
CC4: **Negative 'Following' thresholds** [m/s]	-0.35	(-0.1) – (-0.6)
CC5: **Positive 'Following' thresholds** [m/s]	0.35	0.1 – 0.6
CC7: **Oscillation Acceleration** [m/s^2]	0.25	0.05 – 0.45
CC8: **Standstill Acceleration** [m/s^2]	3.50	3.1 – 3.9
CC9: **Acceleration at 80 km/hr** [m/s^2]	1.50	1.9 – 1.1
MinHdwy: **Min. headway (front/rear)** [m] *	0.50	0.2 – 0.8
SDRF: **Safety Distance Reduction Factor** *	0.60	0.1 – 0.7

These ranges cover the driving behavior spectrum from cautious (or conservative) driving to aggressive driving based on research indicating how automated vehicles are expected to operate. It is expected that automated vehicles could operate to what is the equivalent of a very aggressive driving behaviour. However, AVs could also be programmed to operate on the conservative side of the spectrum in order to gain confidence by the public (Bierstedt et al., 2014). Both driving characteristic extremes are investigated to cover the potential driving behaviour spectrum. Each parameter is captured in the model through a statistical distribution from which stochastic values are assigned in each simulation run. In other words, vehicles within the traffic simulation are assigned driving characteristics according to these distributions (Songchitruksa et al., 2016). Each value shown in Table 3.2 is the mean of the respective parameter's distribution.

3.3.2 Outputs of Traffic Microsimulation

The microsimulation for each transportation network is set up to provide indicators of the network performance to evaluate the changes that AVs will introduce. GHG emissions and traffic performance are the key indicators that are used in this study. To estimate the GHG emissions, vehicle trajectories are required as output from the microsimulation. These trajectories provide second by second information on individual vehicle speed, vehicle type, and distance travelled throughout the road network. In addition, the microsimulation provides information from data collection and measuring points at set locations within the network. The data collected include average network delay per vehicle, average speed, number of stops per vehicle, and link segment speed, flow, and density. The average network delay is defined as the total delay normalized by the total number of vehicles that traversed the network. Average speed, network delay and speed-flow are used as performance indicators for the freeway case, while average speed, network delay and number of stops are used for evaluating the urban arterial road network.

3.4 Emission Modelling

One of the key indicators used for evaluating the performance of potential AV operations in this study is GHG emissions. The United States Environmental Protection Agency (USEPA) MOVES2014a software in coordination with an emissions calculation algorithm (discussed in subsequent sections) is used in this study to calculate the GHG (CO_{2eq}) emissions. MOVES2014a can estimate emissions based on two methods embedded in the software (USEPA, 2015):

1. **Average Speed:** The average link speed, road characteristics, meteorology, vehicle compositions, and fuel type are input into MOVES2014a, which then assigns a default drive cycle in order to determine the appropriate emission factor (EF). The total GHG emissions are then determined by multiplying the EF by the total vehicle kilometers travelled (VKT)
2. **Second-by-Second:** The second-by-second vehicle speed profiles, as well as meteorology, fuel type and vehicle compositions are input into MOVES2014a, which then calculates operating mode (opModeID) distributions of the driving cycle. Emission factors are then determined for each opModeID and the total GHG emissions are calculated.

Since this investigation is based on microsimulation, the second-by-second emissions estimation method of MOVES2014a is used. The emission model accounts for the variations in the individual vehicle driving cycles, including acceleration, deceleration, idling and cruising of each vehicle. This is important for this study as it quantifies the changes in GHG emission output as a result of changed driving behavior from AV operations. This is a computationally intensive process, but it is deemed to be the most realistic. The efficiency of the process can be improved by extracting an emission factor (EF) look up table from MOVES2014a for various operating modes, vehicle types, fuel types, and meteorology of the test area similar to the study by Xu et al. (2016). Therefore, in this study, the GHG emissions are calculated externally from the software using emission factors extracted from MOVES2014a and an algorithm that determines the operating modes (opModeID) of each vehicle based on vehicle speeds, acceleration, and vehicle-specific power (VSP).

The electrification of the vehicle fleet is also considered in this study. In order to make a fair comparison between electric vehicles (EV) and gasoline vehicles, powered by internal combustion engines, the overall fuel cycle GHG emissions are considered. The fuel cycle emissions consist of both the operational GHG emissions from the vehicles, as well as the emissions generated upstream from the production of fuel.

3.4.1 Operating Modes (opModeID)

The vehicle running emissions and energy consumption are determined by the operating mode of the vehicles. These operating modes cover the driving state spectrum from braking/deceleration, to idling, coasting and cruising (USEPA, 2015). The key concepts underlying the determination of the opModeID are vehicle speeds, acceleration, and vehicle-specific power (VSP). The VSP represents the tractive power that is exerted by a vehicle to move cargo, passengers and itself (USEPA, 2015). It is calculated using Equation 1 below:

$$P_{v,t} = \frac{Av_t + Bv_t^2 + Cv_t^3 + mv_t a_t}{m} \qquad (1)$$

$P_{v,t}$ – Vehicle Specific Power [kW/Mg]
v_t – Vehicle speed at time t [m/sec]
a_t – Vehicle acceleration define as v_t - v_{t-1} (m/sec^2)
m – Vehicle mass [Mg]
A, B, C – Track-road coefficients for rolling resistance [kW-sec/m], rotational resistance [kW-sec^2/m^2] and aerodynamic drag [kW-sec^3/m^3]

In MOVES2014a there are a total of 23 operating modes based on VSP, speed and acceleration, identified by an ID number known as an opModeID (see Table 3.3). The deceleration/braking mode is defined by the vehicle acceleration alone, while the idle mode is defined in terms of only speed. The remaining 21 modes, including coasting and cruising/acceleration, are defined in terms of VSP within broad speed classes (USEPA, 2015).

Table 3.3: Definition of MOVES2014A operating modes (in metric units) (USEPA, 2015)

opModeID	Description	VSP (kW/Mg)	Vehicle Speed (km/hr)	Acceleration (km/hr-sec)
0	Deceleration/Braking			$a_t \leq -3.2$ OR ($a_t < -1.6$ AND $a_{t-1} < -1.6$ AND $a_{t-2} < -1.6$)
1	Idle		$-1.6 \leq v_t < 1.6$	
11	Coast	VSP < 0	$-1.6 \leq v_t < 40$	
12	Cruise/Acceleration	0 ≤ VSP < 3	$-1.6 \leq v_t < 40$	
13	Cruise/Acceleration	3 ≤ VSP < 6	$-1.6 \leq v_t < 40$	
14	Cruise/Acceleration	6 ≤ VSP < 9	$-1.6 \leq v_t < 40$	
15	Cruise/Acceleration	9 ≤ VSP < 12	$-1.6 \leq v_t < 40$	
16	Cruise/Acceleration	VSP ≥ 12	$-1.6 \leq v_t < 40$	
21	Coast	VSP < 0	$40 \leq v_t < 80$	
22	Cruise/Acceleration	0 ≤ VSP < 3	$40 \leq v_t < 80$	
23	Cruise/Acceleration	3 ≤ VSP < 6	$40 \leq v_t < 80$	
24	Cruise/Acceleration	6 ≤ VSP < 9	$40 \leq v_t < 80$	
25	Cruise/Acceleration	9 ≤ VSP < 12	$40 \leq v_t < 80$	
27	Cruise/Acceleration	12 ≤ VSP < 18	$40 \leq v_t < 80$	
28	Cruise/Acceleration	18 ≤ VSP < 24	$40 \leq v_t < 80$	
29	Cruise/Acceleration	24 ≤ VSP < 30	$40 \leq v_t < 80$	
30	Cruise/Acceleration	VSP ≥ 30	$40 \leq v_t < 80$	
33	Cruise/Acceleration	VSP < 6	$v_t \geq 80$	
35	Cruise/Acceleration	6 ≤ VSP < 12	$v_t \geq 80$	
37	Cruise/Acceleration	12 ≤ VSP < 18	$v_t \geq 80$	
38	Cruise/Acceleration	18 ≤ VSP < 24	$v_t \geq 80$	
39	Cruise/Acceleration	24 ≤ VSP < 30	$v_t \geq 80$	
40	Cruise/Acceleration	VSP ≥ 30	$v_t \geq 80$	

3.4.2 Vehicle Composition

The vehicle composition and age distribution are also key components in estimating emissions from vehicles. This study considers passenger cars and passenger trucks; however, the age of the vehicles is converted to model year 2016 for both AVs and conventional vehicles. This is the newest vehicle model available in the database for Ontario passenger cars and trucks obtained from the Ministry of Transportation of Ontario (MTO) 2016 Statistics and Management Reporting database (Ontario Ministry of Transportation, 2017). Model year 2016 is selected to acknowledge the fact that AVs, when introduced, will have the most recent vehicle technology available in terms of fuel efficiency and emissions performance. Conventional vehicles were also estimated as model year 2016 vehicles for the purposes of strictly testing for AV driving behavior with respect to the base case (default parameter values) and removing the effects of newer and more fuel-efficient technology on GHG emissions. The proportion of passenger cars and passenger trucks remain consistent with the 2016 MTO database, with 45.6% of the fleet being passenger cars and 54.4% being passenger trucks.

3.4.3 Gasoline Vehicle Emission Calculations

Gasoline vehicle emissions are estimated through the algorithm developed to calculate emissions using MOVES2014a emission factors and operating modes. This study consists of a microsimulation of AVs, therefore, vehicle trajectories extracted from the simulation model are used to calculate emissions. These vehicle trajectories include information on individual vehicle speed, acceleration, vehicle type, distance traveled throughout the road network, as well as time spent on the network. As can be seen in Figure 3.5, the emission estimation algorithm requires inputs of MOVES2014a emission factors, vehicle composition and age distribution, as well as the vehicle trajectories from the microsimulation. A CO_{2eq} operating emission factor look up table, in units of grams/second, is extracted from the MOVES2014a software for all 23 operating modes, specific to the vehicle age distribution of Ontario, fuel type and for the meteorology of a June day in Toronto, Canada.

Additionally, the upstream GHG emissions generated from the production of the gasoline fuel is also considered. This is important, as the fuel cycle GHG emissions are needed in order to make a fair comparison with electric vehicles, which only have GHG emissions from energy production, and no operating emissions. These upstream GHG emissions are determined from "well to pump" (WTP) emission factors generated by the fuel cycle model of Greenhouse gases, Regulated Emissions, and Energy use in Transportation (GREET) (Argonne National Laboratory, 2017). These WTP emission factors are quantified by grams of CO_{2eq} per unit energy consumed. The upstream GHG emission factors are calculated by multiplying the WTP emission factors with the energy consumed based on the vehicle's operating mode.

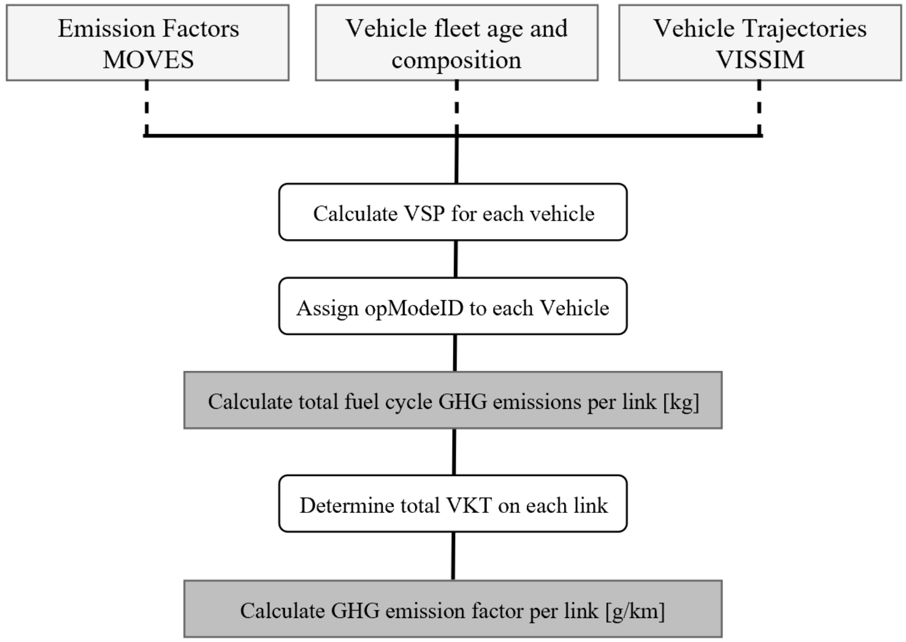

Figure 3.5: The emission estimation calculation process

The emission estimation algorithm uses the second by second vehicle trajectory file from the microsimulation to calculate the VSP for each vehicle that entered the network during the simulation. Based on the provided vehicle age distribution and composition (passenger car and passenger truck ratios), the algorithm assigns an opModeID to each vehicle based on the criteria outlined in Table 3.3. From the opModeID, the emission factor (grams/second) associated with each vehicle's operation is then determined and the total GHG emission, on a per link basis, is calculated for both vehicle operation and fuel production. For comparison purposes between conventional vehicles and the two AV scenarios, it is important to normalize the GHG emissions by vehicle kilometers travelled (VKT), as the distance travelled by a vehicle on the network is indicative of the traffic conditions of the network (i.e., a more congested network would result in reduced VKTs). Therefore, the emissions algorithm calculates an emission factor, in units of grams/kilometer, for each link on the network.

The fuel cycle emission factors associated with each opModeID can be seen in Figure 3.6 for both operating emissions (from MOVES2014a) and for upstream fuel production emissions (converted from energy consumption). The emission factors are combined for model year 2016 passenger cars and passenger trucks based on the 45.6% and 54.4% ratios.

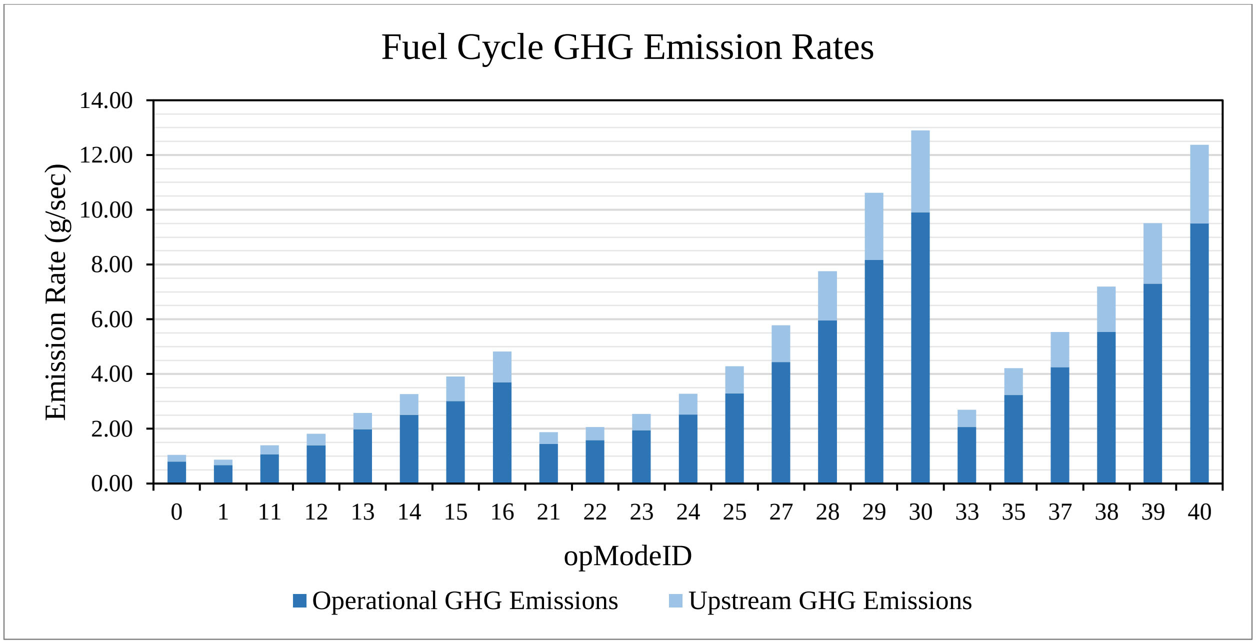

Figure 3.6: Fuel cycle GHG emission factors for each opModeID

3.4.4 Electric Vehicle Emission Calculations

The electrification of the vehicle fleet is also considered in this study in order to investigate the possibility of electricity becoming more common as an alternative energy source for vehicles. For the purposes of comparing electric vehicles to gasoline powered vehicles, the GHG emissions derived from producing the energy to generate electricity (WTP emissions) are used as the only source for fuel cycle emissions. This is under the assumption that electric vehicles have zero operating emissions. Unlike the gasoline vehicle upstream (WTP) GHG emission factors, the electric vehicles are independent of vehicle operating mode. These emission factors are calculated by first estimating the emission intensity for the generation of the electricity (in units of grams of CO_{2eq} per kilowatt-hour) and then considering the average energy consumption of an electric vehicle, in units of kilowatt-hour per vehicle kilometer travelled (Wang et al., 2018).

In Ontario, electricity is generated from a variety of energy sources. The 2016 Ontario energy mix is used consisting of 61.0% nuclear, 23.7% hydro, 8.4% natural gas, 6.2% wind, 0.3% biofuel and 0.3% solar power (IESO, 2017). The emission intensities for electricity generation are calculated by taking a weighted average of the GHG emissions generated to extract a kilowatt-hour (kWh) of energy from these sources. The average energy consumption for electric passenger cars and passenger trucks is determined to be 20.29 kWh/100 km and 23.22 kWh/100 km, respectively (Natural Resources Canada, 2017). From here, the GHG emission factor, in units of grams per kilometer is determined, considering the proportion of passenger cars and passenger trucks in the Ontario vehicle fleet. The equivalent electricity "fuel cycle" GHG emission factor, combined for passenger cars and passenger trucks, is estimated to be 13.81 g CO_{2eq}/km. This is then multiplied by the VKT of each vehicle extracted from the microsimulation vehicle trajectories to determine the total GHG emissions generated in order to power an electric vehicle on the road.

3.5 Analysis Methods

Both a sensitivity analysis and a scenario-based approach are employed to investigate automated vehicle driving operations on both an uninterrupted (freeway) and interrupted (urban arterial) traffic flow conditions. Due to the dynamic properties of traffic and its inherent variability, it is important to take this variability into account with the results. This is achieved through the execution of a series of simulation runs with varied random seeds before obtaining and averaging the results for each sensitivity and scenario-based analysis. The suitable number of replications, to consider the effect of the random seed on the results, is calculated based on Equation 2 (Hellinga, 2005; Washington DOT, 2011):

$$\boldsymbol{N_2} = \left(\boldsymbol{t_{\alpha,n-2}} \frac{\boldsymbol{S}}{\boldsymbol{\varepsilon \bar{x}}}\right) \qquad (2)$$

N_2 – number of suitable replications
ε – percentage allowable error (select around 0.5%)
$\bar{x}$ – mean of the sample from N_1 replications
S – sample standard deviation from N_1 replications
$t_{\alpha,\, n\text{-}2}$ – t-statistic at a 95% confidence interval

Equation 2 is used to calculate the number of suitable replications based on test runs conducted with N_1=5 replications. In the case when N_2 from Equation 2 is larger than the initial number of replications used (N_1), then N_2-N_1 additional replications should be done (Hellinga, 2005). In the case of this study, N_2=3 runs, which is less than the initial 5 replications, concluding no additional replications are required. Therefore, each simulation is conducted with 5 replications, incrementing the seed for random number generation by 10.

3.5.1 Sensitivity Analysis: One-at-a-time (OAT) Approach

A base case simulation of 5 replications for the default parameter values in VISSIM (Table 3.2) of the car-following and lane-changing parameters is conducted, considering this to be the driving behavior of conventional (human operated) vehicles. In each sensitivity test, one of the 10 parameters are varied within the range of potential automated vehicle operations including the minimum, maximum, median, 25th and 75th quartile values, while the rest of the parameters remain at their default value. The vehicle trajectories and traffic performance outputs for each simulation are obtained for use in subsequent analysis and comparisons. The results from the 5 replications are then averaged to obtain a more accurate picture of the network performance under the various driving operations. The percent change in GHG emissions and traffic performance with respect to the default base case is determined to effectively identify which parameters have the most influence on emissions and traffic performance as a result of various driving operations. This OAT analysis was conducted for both the freeway and urban corridor networks, as well as under high traffic and low traffic conditions.

3.5.2 Scenario Based Parameter Analysis

This scenario-based analysis consists of three different parameter settings to test the extreme ends of the driving behaviour ranges. The first parameter setting represents the automated driving operations under aggressive driving. The second parameter setting was the base case conventional driving operations using default parameter settings. The third parameter setting represents the automated driving operations under more cautious driving characteristics. The parameter settings for each scenario can be found in Table 3.4.

Table 3.4: Parameter settings for three driving operations tested

Parameter	Aggressive	Default	Cautious
CC0: **Standstill distance** [m]	0.5	1.50	2.5
CC1: **Headway Time** [s]	0.5	0.9	2.1
CC3: **Threshold for entering 'Following'** [s]	-4.00	-8.00	-16
CC4: **Negative 'Following' thresholds** [m/s]	-0.10	-0.35	-0.60
CC5: **Positive 'Following' thresholds** [m/s]	0.10	0.35	0.60
CC7: **Oscillation Acceleration** [m/s^2]	0.45	0.25	0.05
CC8: **Standstill Acceleration** [m/s^2]	3.90	3.50	3.1
CC9: **Acceleration at 80 km/hr** [m/s^2]	1.90	1.50	1.1
MinHdwy: **Min. headway (front/rear)** [m]	0.20	0.50	0.80
SDRF: **Safety Distance Reduction Factor**	0.10	0.60	0.70

The parameter settings in Table 3.4 are tested under various conditions for both the freeway and urban arterial road scenario. As can be seen in Figure 3.7, each transportation network is studied under both high traffic or low traffic conditions, as well as for gasoline and electric powered vehicles under 100% penetration of automated and conventional vehicles, respectively.

To investigate the incremental changes with increasing market penetration of automated vehicles, another set of simulations was also completed with 10%, 30%, 50%, 70%, and 90% penetration rates. This was done for gasoline powered vehicles for both network types and traffic conditions.

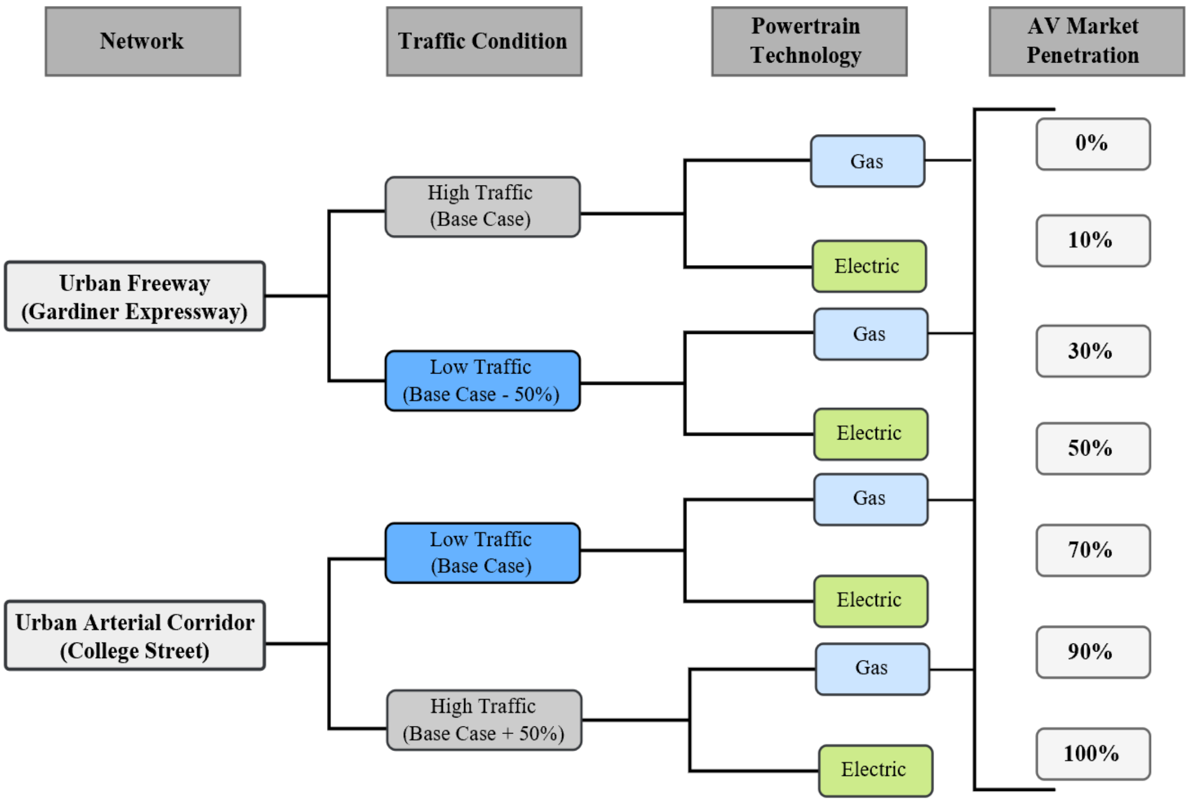

Figure 3.7: Simulation traffic conditions and powertrain technology

Chapter 4
Freeway Case Study – Gardiner Expressway

The Gardiner Expressway network (mainline and on/off-ramps) allows for the examination of vehicle operations under uninterrupted flow conditions. In other words, vehicles are free to move through the network without the need to stop due to traffic signals or signs. Any disturbance in the flow of traffic is the result of the interaction amongst vehicles as they follow and/or overtake each other and change lanes as they enter or exit the freeway. This activity, as the volume of traffic increases and/or other planned/unplanned events occur (e.g. lane closure, blockage due to construction or incidents etc.) leads to the build-up of congestion. This chapter discusses the results of both the OAT sensitivity analysis and parameter scenario analysis of potential AV operations on a full-scale freeway under both high and low traffic conditions. Varied market penetration of AVs on the network, and electrification of the vehicle fleet are also investigated for their potential effects. The automated vehicles driving parameters are evaluated based on the effects on GHG emissions and traffic performance.

4.1 One-at-a-Time Approach Analysis

Understanding the role of the individual parameters in the operation of vehicles is important to determine which parameters are most critical in inducing change on emissions and traffic performance. The results of the OAT approach provide insight into the effects of individual parameters on GHG emissions and traffic performance indicators within the anticipated driving behaviour spectrum of automated vehicles. The sensitivity analysis is conducted under both high and low traffic conditions on the Gardiner Expressway network. Each of the eight car-following and two lane-changing parameters are varied individually, while observing induced changes on fuel cycle GHG emission factors, average network speed and average network delay. The percent differences of each performance measure, with respect to the default parameter results, are calculated.

4.1.1 High Traffic Condition

The morning peak period traffic demand of the Gardiner Expressway is used to evaluate the sensitivity of emissions and performance indicators in this scenario. This provides information on which parameters are most important to the vehicle operation under more congested conditions.

When looking at the effects of the individual parameters on the fuel cycle GHG emission factors, the headway time (CC1) and safety distance reduction factor (SDRF) are identified as the two parameters that induce statistically significant changes in GHG emissions, based on a two-tailed t-statistic test with a critical t-statistic of 2.571 at 5 degrees of freedom and 95% confidence interval (see Figure 4.1). The threshold for entering 'following' (CC3) parameter induces the next most change, although at a much smaller scale. The effects of the remaining parameters are negligible. Expanding the performance indicators to include average speed and delay, it can be seen in Figure 4.2 that the headway time and safety distance reduction factor are also the leading parameters. A detailed table of the percent change in GHG emission factors, average speed and delay is provided in Appendix C.

The headway time (CC1) is a dominating parameter of the car following model embedded in the microsimulation platform. It is defined as the distance (in seconds) that a driver wants to maintain from a preceding vehicle at a certain speed (PTV AG, 2016). Lower values of this parameter translate into closer spacing between vehicles and more aggressive driving behaviour. Cautious driving behavior is associated with higher values of this parameter. CC1 has the largest impact on GHG emissions, average speed and delay relative to other parameters in this study. When evaluated at the upper end of its range (cautious driving), the largest change is observed as a 31% increase in GHG emissions from the base case. A smaller headway time between vehicles produces relatively smaller change in emissions, but still considered to be significant (based on the two-tailed t-statistic significance test performed) with the potential to reduce emissions by almost 10%.

This trend can be attributed to the platooning effect formed by automated vehicles travelling at proximity to each other. This platooning results in smoother and more uniform drive cycles amongst vehicles leading to emission reductions (Liu et al., 2017), and improved traffic flow. However, the reduction in aerodynamic drag of vehicles from platooning is not accounted for in this analysis, potentially underestimating the GHG emission reduction benefits.

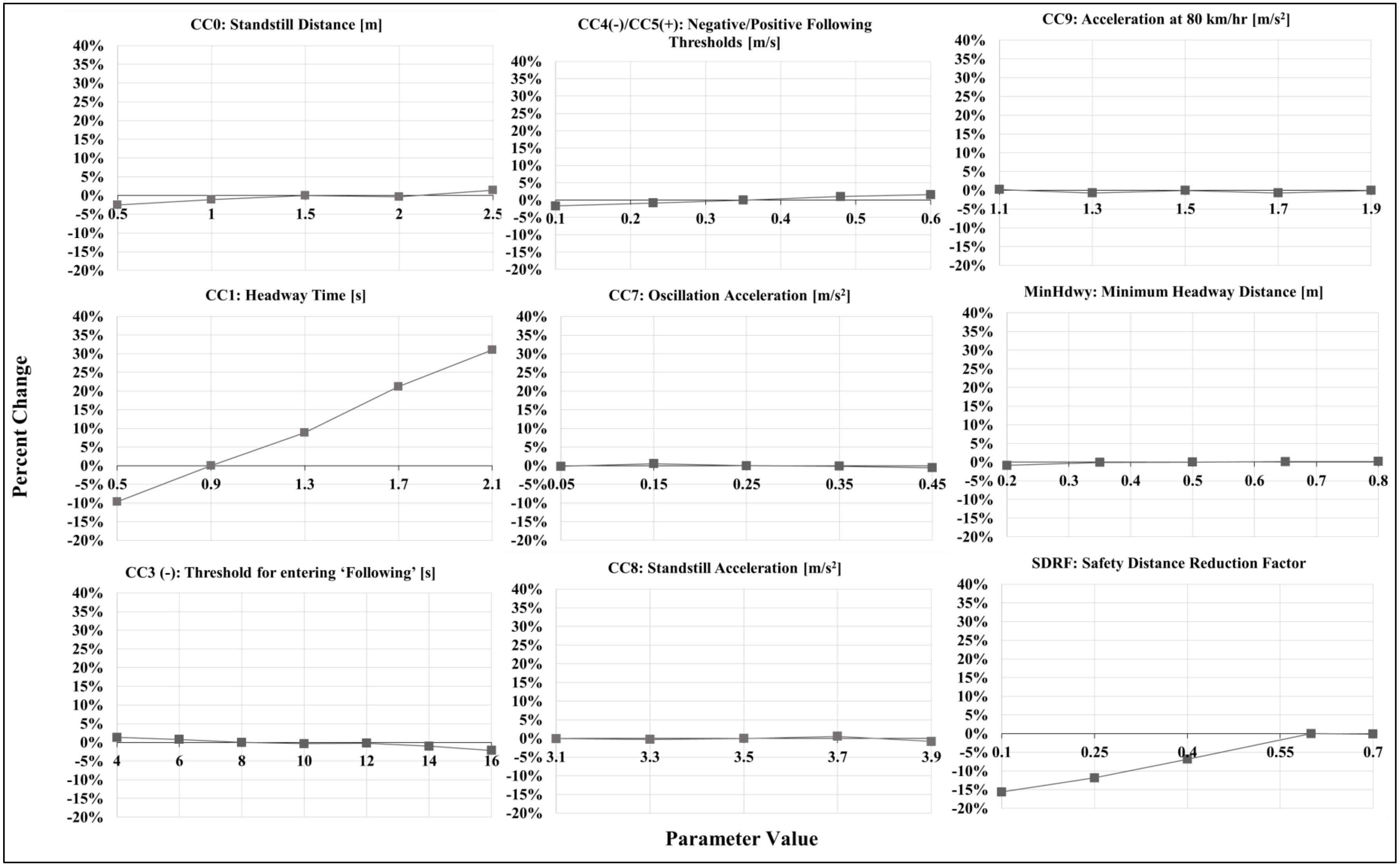

Figure 4.1: Percent change of fuel cycle GHG emission factors for high traffic case *(the y-axis is the percent change, while the x-axis is the value of the parameter)*

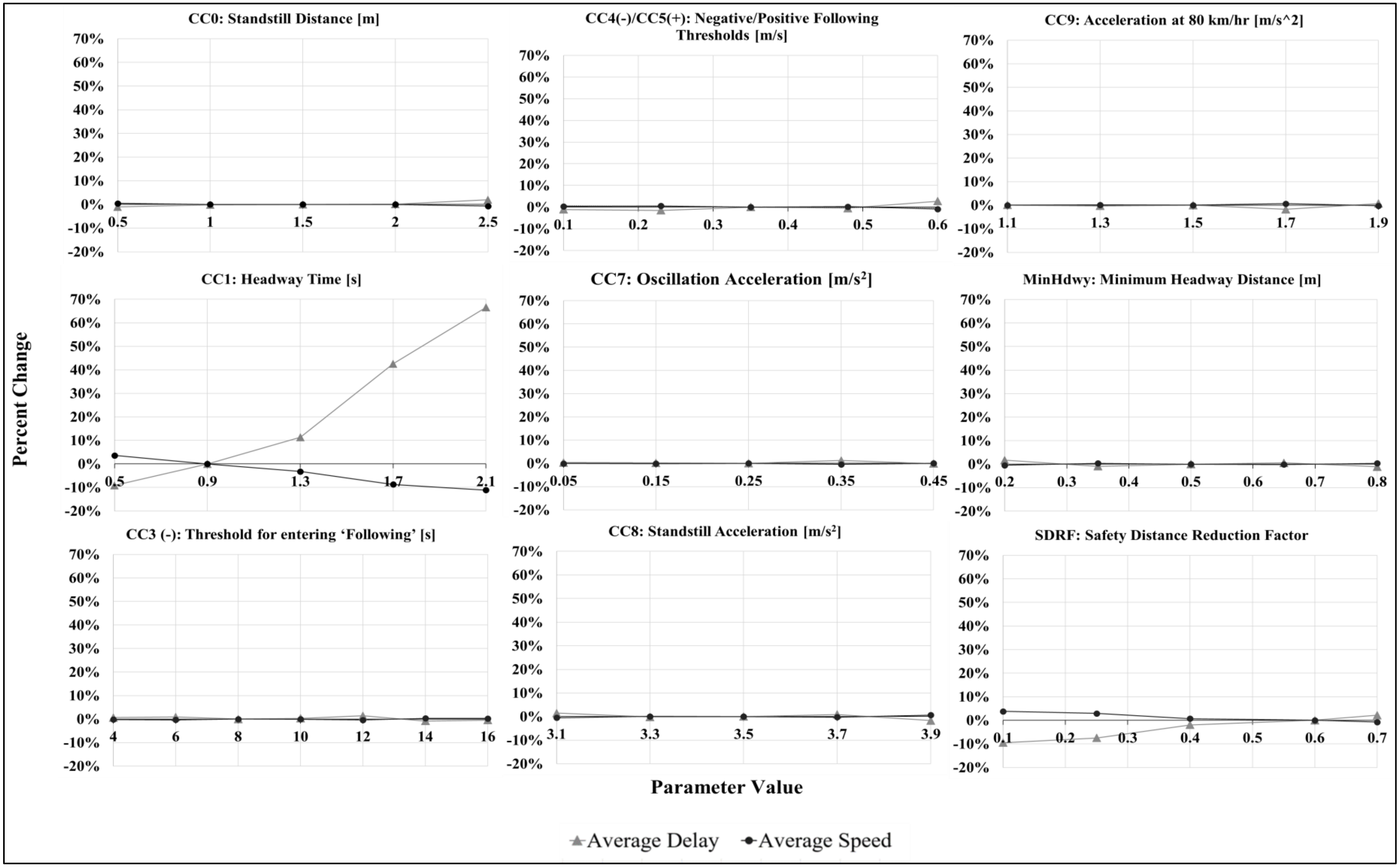

Figure 4.2: Percent change in average speed and delay for high traffic case *(the y-axis is the percent change, while the x-axis is the value of the parameter)*

In terms of traffic performance, vehicles travelling closer together can travel through the network more efficiently and uniformly. This is evident from the trend in average speed and network delay with respect to the CC1 parameter. A lower headway value reduces delay and increases average speed, indicating that vehicles could travel through the network with less interruption in their driving, which contributes to a reduction in emissions. With higher values of headway time, this uniformity in the driving behavior between the vehicles is lost and results in a breakdown of traffic flow and an increase in GHG emissions.

The safety distance reduction factor is a parameter associated with lane changing and is defined as the amount by which a vehicle reduces its safety distance with a vehicle in front when changing lanes (PTV AG, 2016). The lower the value of this parameter (<0.4), the smaller the desired safety distance is when changing lanes or entering the traffic flow from an on-ramp. This is associated with the characteristics of more aggressive driving behaviour. A 90% reduction in safety distance (SDRF value of 0.1) when changing lanes produces a 15 % reduction in emissions. This can be closely associated with the headway time parameter. When vehicles take the risk to change lanes with less space between them, the disruption on the traffic flow is minimized, similarly to short headway time gaps. The limited disruptions to the traffic flow translates into reduced emissions, as there is less braking and fewer fluctuations in acceleration/deceleration when there is more tolerance to closer distances when changing lanes. It also leads to a decrease in delays (especially in more congested conditions), and an increase in speed from the default parameter value. It is interesting to note that a more cautious SDRF value than the default resulted in almost no change in emission and performance. This can be attributed to the fact that, under high traffic conditions, the vehicles are already moving at a slow speed and taking extra space to make a lane change has a minimal and temporary affect on the traffic flow.

Parameter CC3 is the threshold for following and is defined as the time (in seconds) when the vehicle starts to decelerate before reaching the safety distance (PTV AG, 2016). A higher magnitude value of CC3 is related to cautious driving and corresponds to vehicles beginning their deceleration process farther apart from other vehicles. This parameter has shown to influence changes in the GHG emission factor, more so than on average speed and delay. The increase in CC3 values results in a decrease in the GHG emission by up to 2.16%. This trend results from vehicles reducing their operating mode to lower speed modes, which in turn have lower emissions.

By decelerating over a longer period of time, vehicles operate in lower speed categories with less emissions than those vehicles that maintain higher speeds and decelerate faster over short periods of time. In general, lower values of CC3 are better for emission reduction, but this parameter is dependent on the traffic conditions.

The remaining parameters have a much less significant impact on the performance indicators, with the percent changes remaining below 2%. This shows that on a freeway, the spacing maintained between the vehicles is what determines the performance of the traffic flow. Changes in the traffic flow, determined by the operations of the vehicles, translate into affects on GHG emissions.

4.1.2 Low Traffic Condition

The OAT analysis of the driving parameters is repeated under a low traffic loading of the Gardiner Expressway network. This is conducted to determine which parameters have the largest effect with less traffic causing fewer interactions among the vehicles.

The results from the analysis under low traffic conditions show that the induced changes by the parameters are lower order than that of the high traffic condition; however, the trends remain similar. This is consistent with the literature indicating that driving behavior parameters are more influential under congested conditions (Aria, 2016; Aria et al., 2016). The results can be seen in Figure 4.3 for fuel cycle GHG emissions and Figure 4.4 for average speed and delay. It is important to note the percent change scale difference from the high traffic scenario. From these results the headway time (CC1) and the safety distance reduction factor (SDRF) are the most significant parameters in terms of how much they affect emissions and traffic performance (see Appendix C for details on all the parameter results).

Similar to the high traffic scenario, the headway time parameter (CC1) showed to have the largest range of effect on emissions, average speed, and delay. With lower values of this parameter (aggressive driving), there is the potential to reduce emissions by 1.8% in comparison to the default parameter. Higher values of headway time (cautious driving) can lead to 3.3% increase. When considering average speed and delay, the effects of headway time are not as significant as on emissions and much less than what is seen under high traffic. There is a 0.5 % decrease in delay and a 0.5% increase in average speed in the lower end of the spectrum, with up to a 1.83% increase in delay and 1.92% decrease in average speed associated with higher values.

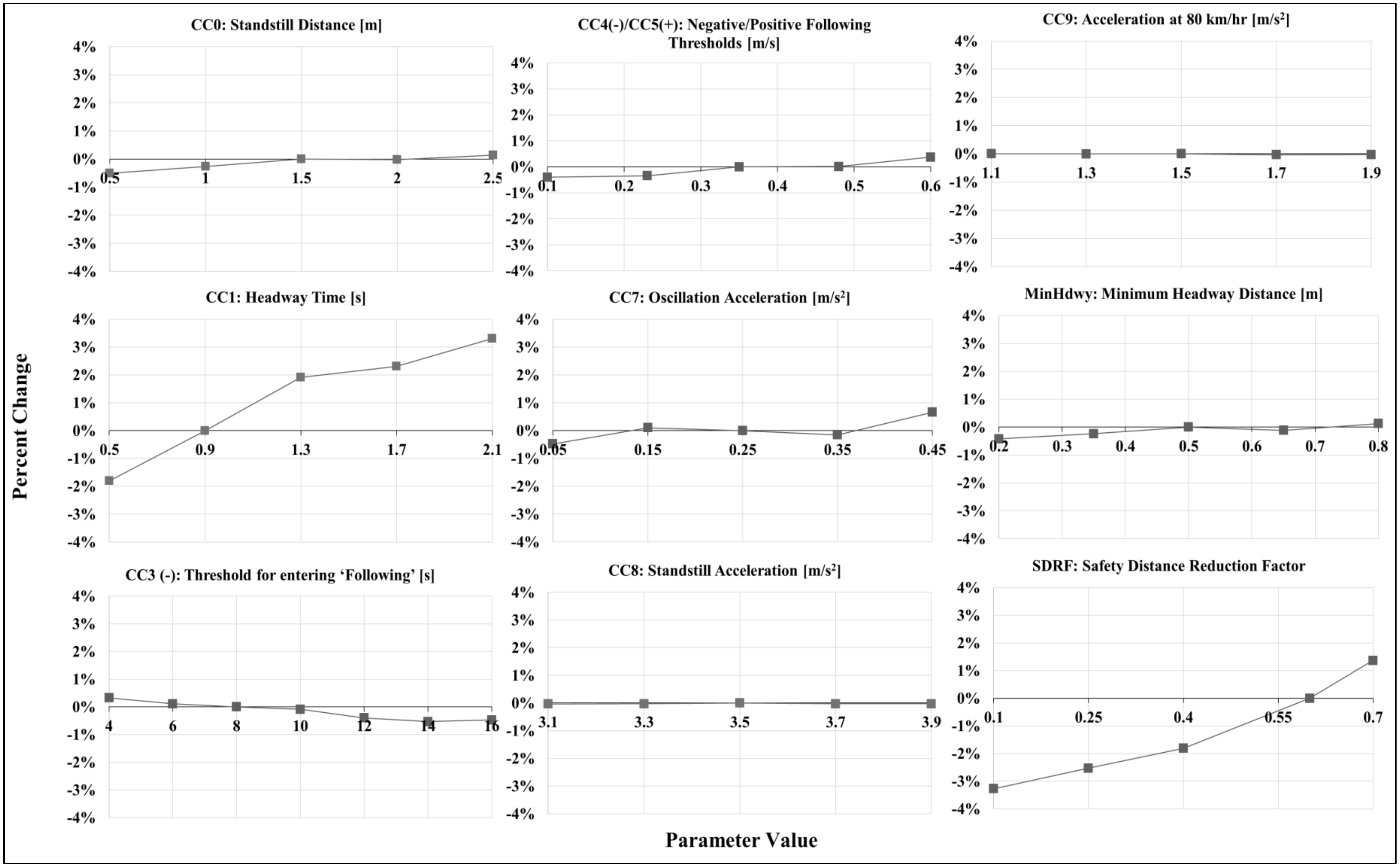

Figure 4.3: Percent change of fuel cycle GHG emission factors for low traffic case *(the y-axis is the percent change, while the x-axis is the value of the parameter)*

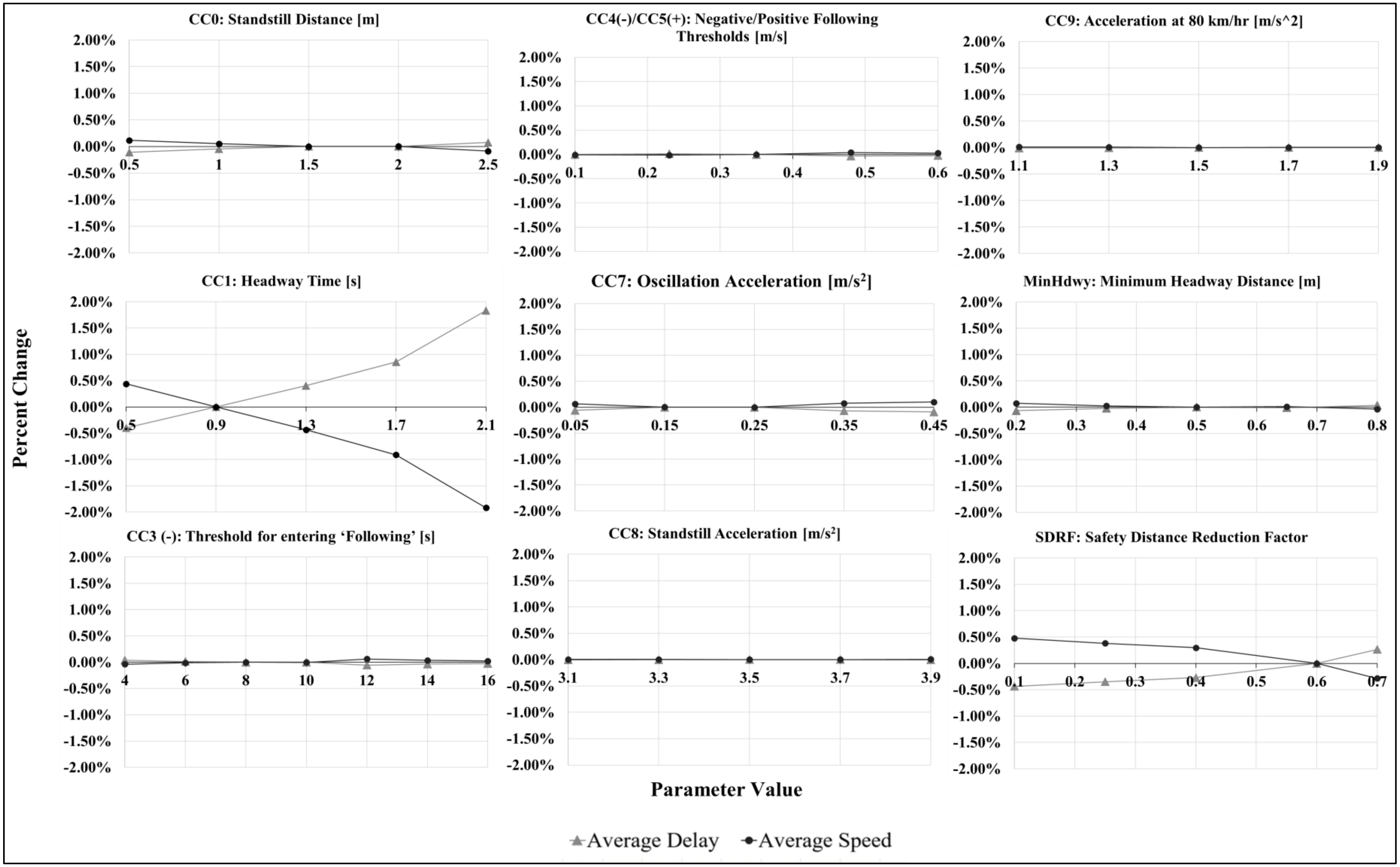

Figure 4.4: Percent change in average speed and delay for low traffic case *(the y-axis is the percent change, while the x-axis is the value of the parameter)*

The safety distance reduction factor parameter presents the same trend as the high traffic condition, but at a much lower scale. At lower values of the SDRF, resulting in a larger reduction in the safety distance during lane changes, there is up to a 3.3% reduction in the fuel cycle GHG emission. This relates to a 0.5% increase in average speed and a 0.5% reduction in delay. These reductions are due to less disruptions during lane changes allowing for more swift movements. Increasing the SDRF to have smaller reductions in the safety distance during lane changes leads to a slight increase in GHG emissions and delay, as well as a reduction in average speed. The significant reduction in the impacts of these parameters is associated with lower traffic volume on the network.

4.2 Scenario-Based Parameter Analysis

In the scenario-based analysis, the three parameter settings representing aggressive AV, conventional vehicle default driving characteristics, and cautious AV driving characteristics are tested in the microsimulation package under high and low traffic conditions. These parameter settings identify the extremes that AVs could operate within, given that they will be operated by a computer and can potentially safely handle more demanding traffic conditions than what a human driver would be able to handle. These scenarios are conducted under 100% market penetration of AVs (for aggressive and cautious) and 100% conventional vehicles for the default case. The AV aggressive driving consists of setting the relevant driving behaviour parameters identified in 3.5.2, Table 3.4 to the aggressive end of the spectrum, while the cautious driving setting consists of setting the relevant parameters to the cautious end of the driving behaviour. The electrification of the vehicle fleet, as well as varied market penetration of AVs are investigated in this section as well. The results presented are normalized by VKT in order to get a full picture of the emission changes based on the vehicle operations; however, the total fuel cycle GHG emissions, as well as the total GHG emissions produced to generate energy for electric vehicles are shown in Appendix D.

4.2.1 High Traffic Condition

This scenario looks at the observed traffic conditions on the Gardiner Expressway during the morning peak period. This traffic condition, as well as the default conventional vehicle parameter setting is the base case. The potential AV driving characteristics are compared to conventional vehicles in terms of their effects on GHG emissions and overall traffic performance of the freeway.

4.2.1.1 Automated vs. Conventional Vehicle Emissions

The results of this study demonstrate that automated vehicles operating under more aggressive driving characteristics than a human driven conventional vehicle can reduce the average GHG emission factor. On the other hand, more cautiously programmed AVs result in a significant increase in GHG emissions as a result of the changes it would introduce to the freeway traffic operations. As can be seen in Figure 4.5, the automated vehicle aggressive driving setting has the potential to reduce the average fuel cycle GHG emission factor by approximately 26% from 284 g CO_{2eq}/km (standard deviation of 5.46) to 210 g CO_{2eq}/km (standard deviation of 2.41). This result is attributed to the fact that aggressive AVs have the ability to take larger risks and operate with much smaller time gaps and safety distances between vehicles, resulting in formations of platoons and less time spent on the network, which in turn, reduces emissions. It can also be seen from Figure 4.5 that the vehicle kilometers travelled (VKT) between the aggressive AV case and conventional vehicle is relatively identical, indicating that the emission reduction is purely from the improved vehicle operations. On the other hand, the cautious AV driving setting results in a significant increase of approximately 35% in the total fuel cycle emission factor, despite the VKT dropping from 41,300 km to 31,734 km. This can be attributed to the more cautious spacing between vehicles, preventing vehicles from entering the network and, thus causing congestion build up on the network.

When considering the total fuel cycle emissions, the trends are similar to the emission factor results presented in this section. The total fuel cycle emissions can be seen in Figure D.1, Appendix D. From these results it is evident (as indicated by the emission factors) that aggressive AVs have lower emissions, while the cautious AVs increase the total emissions significantly regardless of the decrease in VKT. The cautious AVs lead to traffic flow breakdowns to the point where each individual vehicle experienced increased fuel consumption and larger intensity of emissions per VKT.

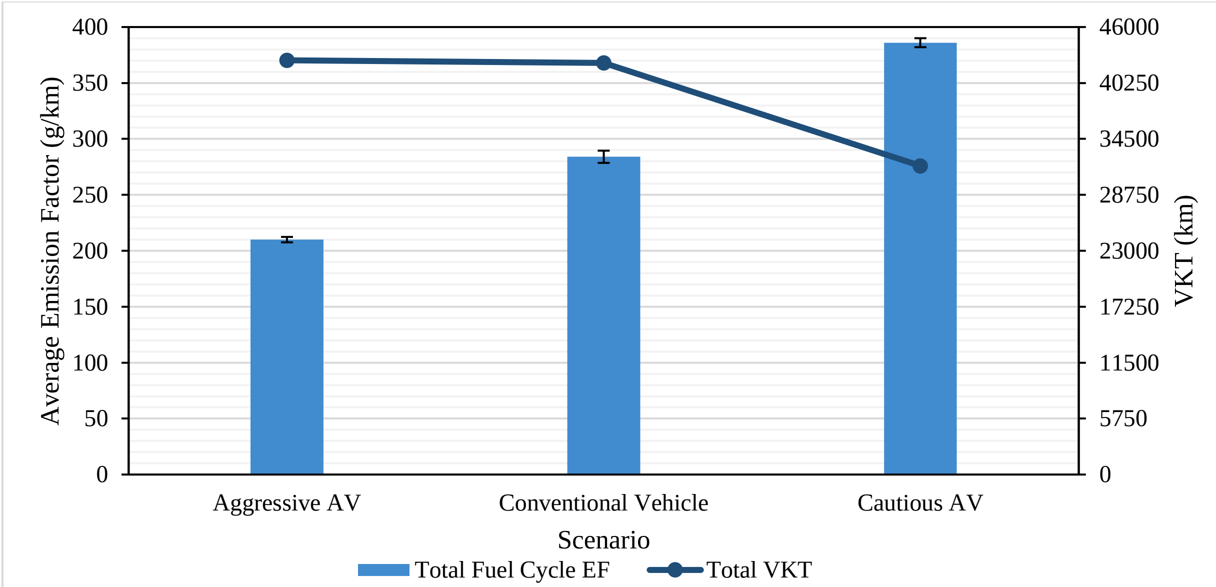

Figure 4.5: The average fuel cycle emission factor and total vehicle kilometers travelled for each parameter setting on Gardiner Expressway with high traffic *(the bars above the columns represent the standard deviation of the average fuel cycle emission factors)*

4.2.1.2 Traffic Performance

It is also important, however, to consider the traffic performance of the network while drawing conclusions about the changes in GHG emissions. As can be seen in Figure 4.6, the aggressively operated AVs are able to consistently maintain a higher average network speeds closer to the speed limit of 100 km/hr. Meanwhile, the default parameter setting maintains the freeway operations at just under 60 km/hr, and the cautious AVs significantly reduce the average network speed to around 26 km/hr. As a result of the changes in average speed, it is expected that the vehicles would also experience changes to travel time delay. The aggressively operated AVs reduce delay to 8 seconds per vehicle in comparison to the conventional vehicles (80 seconds per vehicle), while the cautious AVs significantly increase the delay to 266 seconds. The latent demand of the network is also an interesting metric to consider. The aggressive AV and conventional vehicles allow for all the demand to be accommodated in the network over the one simulation period, while the cautious AVs operations prevent almost 3,500 vehicles from entering the network. This indicates that the cautious AV driving characteristics degrade the network traffic performance.

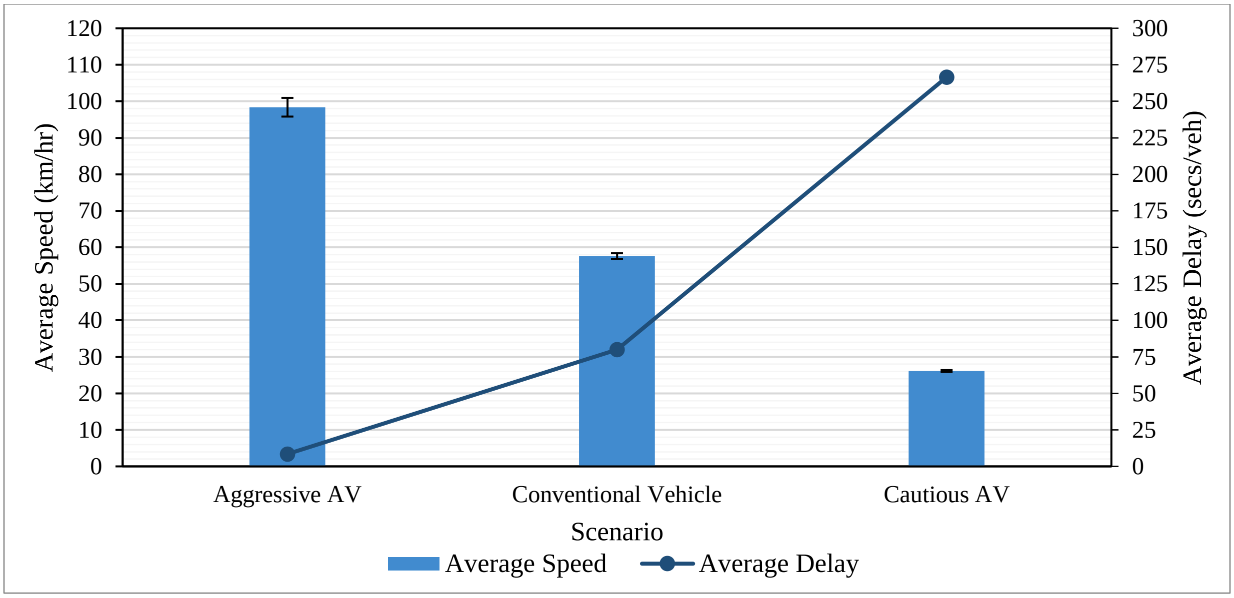

Figure 4.6: Average network speed and delay under high traffic conditions on Gardiner Expressway *(the bars above the columns represent the standard deviation of the average fuel cycle emission factors)*

Looking at the operating mode (opModeID) distributions for the three vehicle parameter settings provide insight on how the vehicles operate with respect to the traffic performance and emissions. The opModeID distribution can be seen in Figure 4.7. The aggressive AV operation has larger proportion of the vehicles in the higher operating modes, while the conventional vehicles and the cautious AVs can be found to have a larger proportion in mid to low operating modes. This also helps explain the differences in emissions between the three types of vehicles. As was shown in Figure 3.6 (fuel cycle EF by opModeID), higher speeds generate more emissions. However, even though the aggressive AVs operate at higher speeds, their emissions decreased. This can be explained by the fact that these aggressive AVs spend less time traversing the network, which essentially counteracts their high emission output due to speed. The cautious AVs and conventional vehicles, although operating at lower speeds, take longer to traverse the network and emit more GHG emissions. Extended periods of idling because of congestion build up, leads to emissions adding up, and overcoming the benefits of lower speed on emissions.

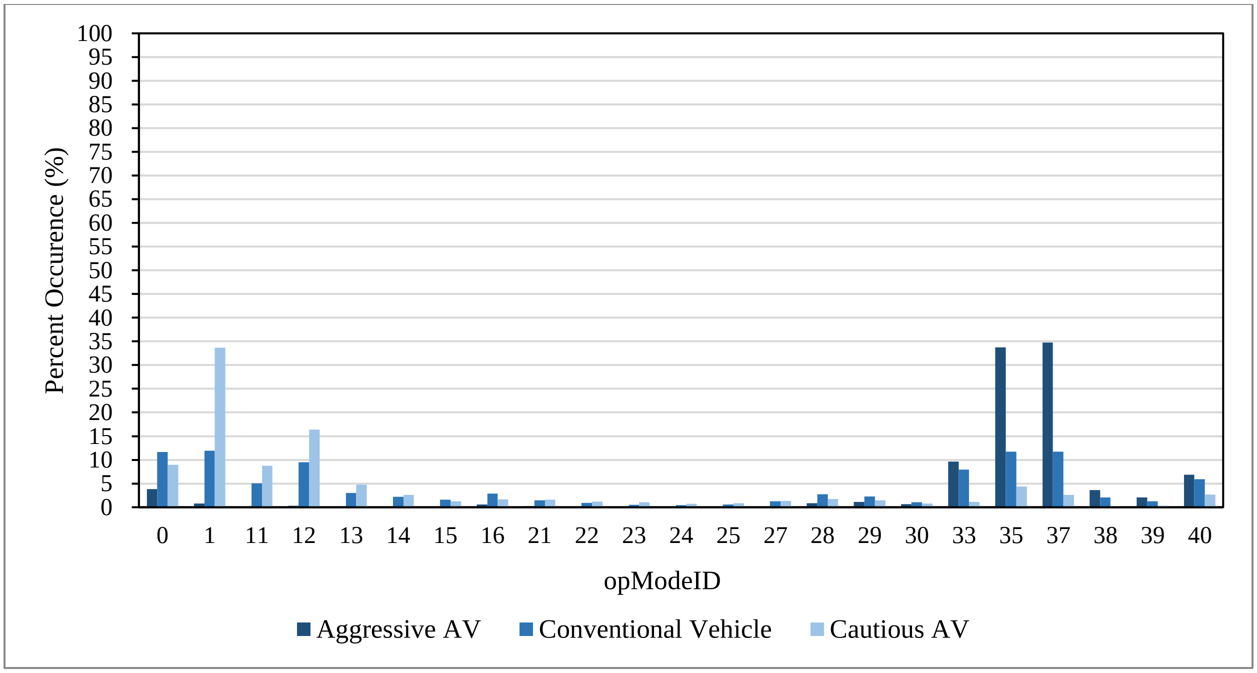

Figure 4.7: opModeID distribution under high traffic conditions on Gardiner Expressway

The speed-flow relationship of the network also indicates the effects on traffic flow of each type of vehicle operation. These relationships can be seen in Figure 4.8 and they show the capacity changes of the high traffic loaded Gardiner Expressway (the curves fitted are based on a model developed by Van Aerde and Rakha (1995)). Under the 100% conventional vehicle default parameter scenario, the network simulation speed-flow data depict both an uncongested and congested regime, with a capacity peaking around 2,300 vph/lane. When looking at the aggressively programmed AVs, the network becomes uncongested, because of the increase in capacity (close to 2,800-3,000 vph/lane), which is attributed to shorter time gaps between the vehicles.

This study, however, does not account for the increased demand that the aggressively programmed AVs will induce by reducing the congestion on the network. It is possible that a larger induced demand would also result in congestion build up, but overall, the capacity will be much higher. On the other hand, cautiously programmed AVs, through this performance measure, once again show that they have the potential to degrade the transportation network. The more cautious decisions made by the vehicles, and the larger time gaps, result in more congestion and reduce capacity to just below 1,500 vph/lane.

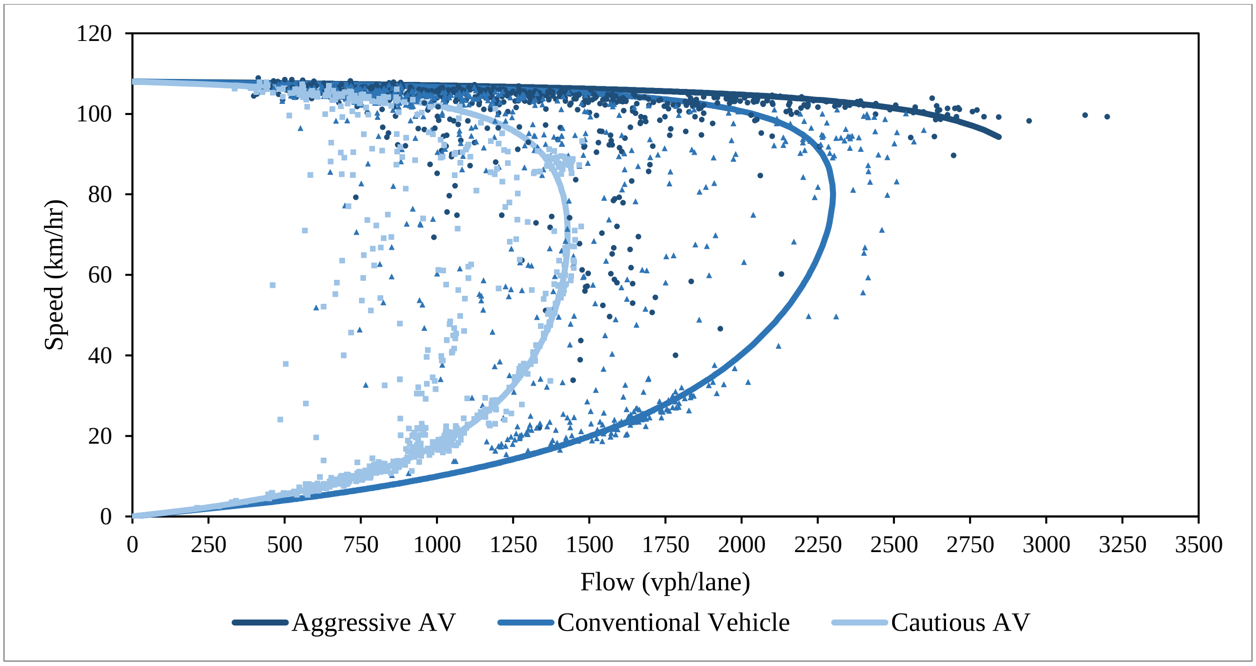

Figure 4.8: Speed-flow relationship on the Gardiner Expressway under high traffic

The effects on traffic flow, as indicated by Figure 4.8, also serve as an explanation for the changes in emissions. Aggressive AVs improve the traffic flow conditions and therefore, reduce emissions in comparison to conventional vehicles. The breakdown of the network under cautious AVs exacerbates congestion, slows traffic, and results in much more emissions to be generated.

4.2.2 Low Traffic Condition

This scenario looks at a reduced traffic condition on the Gardiner Expressway. This traffic condition is used to evaluate the driving behaviour of automated vehicles relatively to that of conventional vehicles in terms of their effects on GHG emissions and overall traffic performance of the freeway under less congestion.

4.2.2.1 Automated vs. Conventional Vehicle Emissions

The results of this study demonstrate that automated vehicles, regardless of their operation settings, do not cause any large changes to GHG emissions and traffic performance under low traffic conditions. This is consistent with the OAT analysis, where the magnitude of the change in emissions and traffic performance is greatly reduced under lower demand. As can be seen in Figure 4.9 below, the trends are like the high traffic condition case in the sense that aggressively programmed AVs provide reductions in emissions, while cautious AVs increase emissions.

However, the changes are not as large. For instance, the automated vehicle aggressive driving setting reduces the average fuel cycle GHG emission factor by only approximately 3% from 198 g CO_{2eq}/km (standard deviation of 0.95) to 190 g CO_{2eq}/km (standard deviation of 0.85). On the other hand, the cautious AV driving setting results in a slight increase of approximately 8% in the total fuel cycle emission factor to a value of 214 g CO_{2eq}/km. It can also be seen from Figure 4.9 that the VKT between the three driving settings are identical, indicating that the majority of the vehicles were served and traversed the network. When comparing this to the high traffic condition in section 4.2.1, these results indicate that the difference in operations between the vehicle settings are more obvious when there is more traffic present and, therefore, more opportunities for vehicle interactions (congestion build up on ramps and bottlenecks).

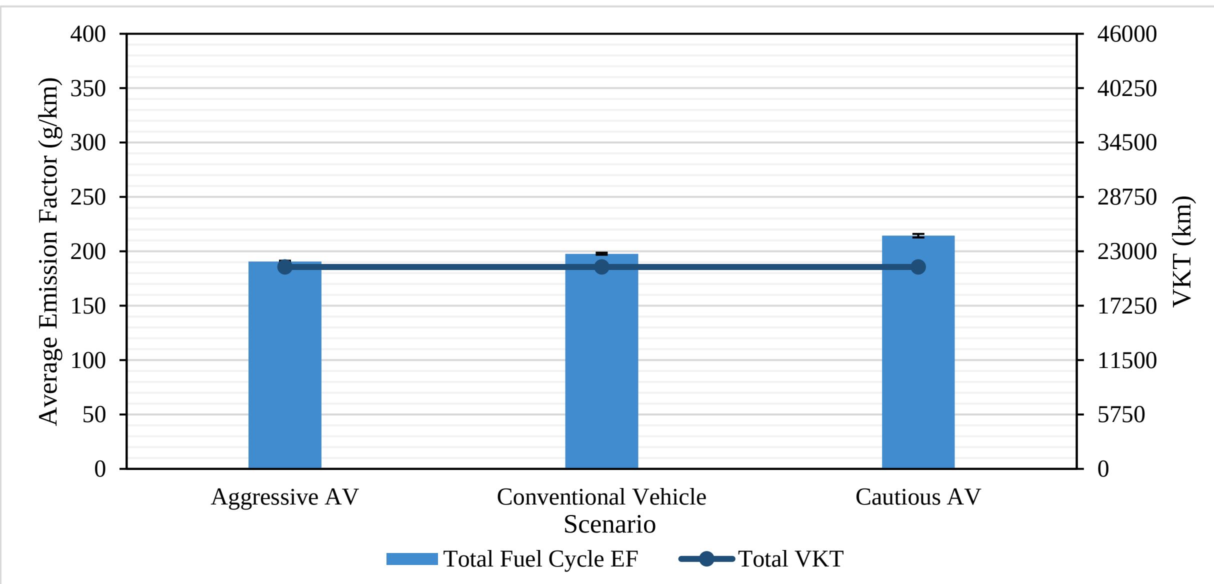

Figure 4.9: The average fuel cycle emission factor and total vehicle kilometers travelled for each parameter setting on Gardiner Expressway with low traffic *(the bars above the columns represent the standard deviation of the average fuel cycle emission factors)*

The same trend can be found in the total fuel cycle emissions as shown in Figure D.2, Appendix D. The minor changes in the emission factor between the aggressive AVs, conventional vehicles, and cautious AVs, as well as the constant VKT result in minimal differences in the total fuel cycle emissions. Aggressive AVs produce almost the same amount of emissions as conventional vehicles, while the cautious AVs have a slightly higher emission intensity per VKT, which results in a minimal increase in total emissions.

4.2.2.2 Traffic Performance

The traffic performance of the network helps confirm the GHG emission results that were discussed previously. As can be seen in Figure 4.10, the aggressively operated AVs, as well as the conventional vehicles and cautious AVs are able to consistently yield a higher average network speeds closer to the speed limit of 100 km/hr. In fact, the aggressive AVs and conventional vehicles maintain a speed of around 104-105 km/hr, while the cautious AVs are around 98 km/hr. When considering average network delay, the values remain similar regardless of vehicle operations style. This is an expected result that is consistent with the reduced demand on the network. These results indicate that during off-peak periods, with reduced demand, the advantages associated with aggressively programmed AVs, or the disadvantages associated with cautious AVs, will not have much of an effect on the traffic performance of the network.

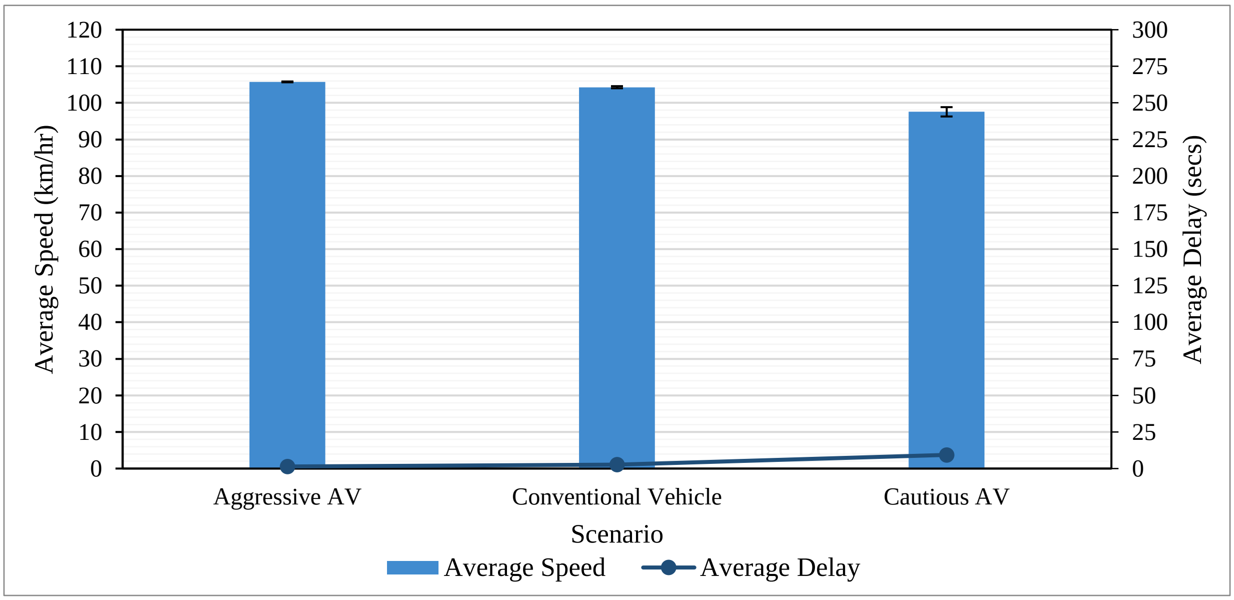

Figure 4.10: Average network speed and delay under low traffic conditions on Gardiner Expressway *(the bars above the columns represent the standard deviation of the average speed)*

The opModeID distribution for the low traffic demand can be seen in Figure 4.11. All vehicle operation types have the majority proportion of their vehicles operating within the higher speed operating states. The cautious AV operation has approximately 5% of its vehicles decelerating/braking (opModeID 0); however, this is insignificant considering the remaining 95% are in higher operating modes. The reason for this can be attributed to the fact that the cautious AVs prefer to maintain larger gaps between each other and will adjust their driving accordingly, despite the reduced traffic demand. The opModeID distribution also confirms the results of the GHG emission analysis. The majority of the operating states are consistent across the different vehicle driving characteristic parameter settings, confirming the reason why there is insignificant differences in emissions. This is in contrast to the opModeID distribution of the high traffic case, which highlighted the difference in operating states between aggressive AVs, conventional vehicles, and cautious AVs, in reaction to the increased vehicle demand and consequent increased vehicle interactions.

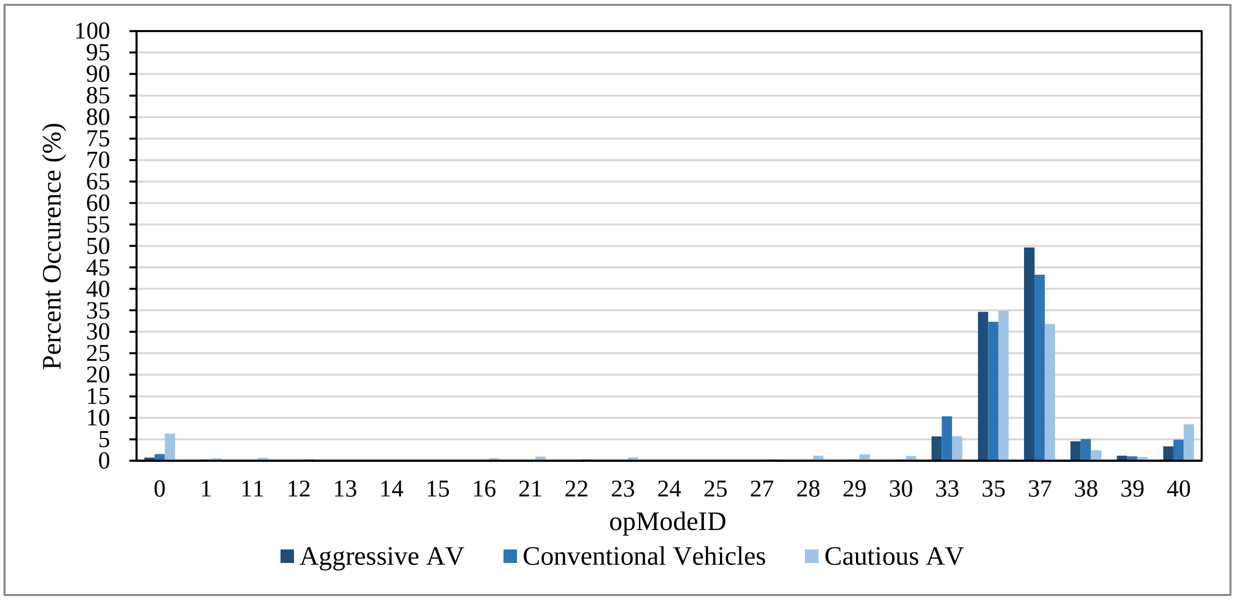

Figure 4.11: opModeID distribution under low traffic conditions on Gardiner Expressway

The speed-flow relationship of the low traffic demand Gardiner Expressway network is shown in Figure 4.12. The results show that all three driving parameter settings remain on the uncongested side of the relationship, which is consistent considering that the network was loaded with a demand 50% lower than what it would be in the morning peak hour. However, the cautious AV scenario does show early signs of degradation with instances of speeds dropping and the capacity being approached well before the conventional vehicles and aggressive AV cases.

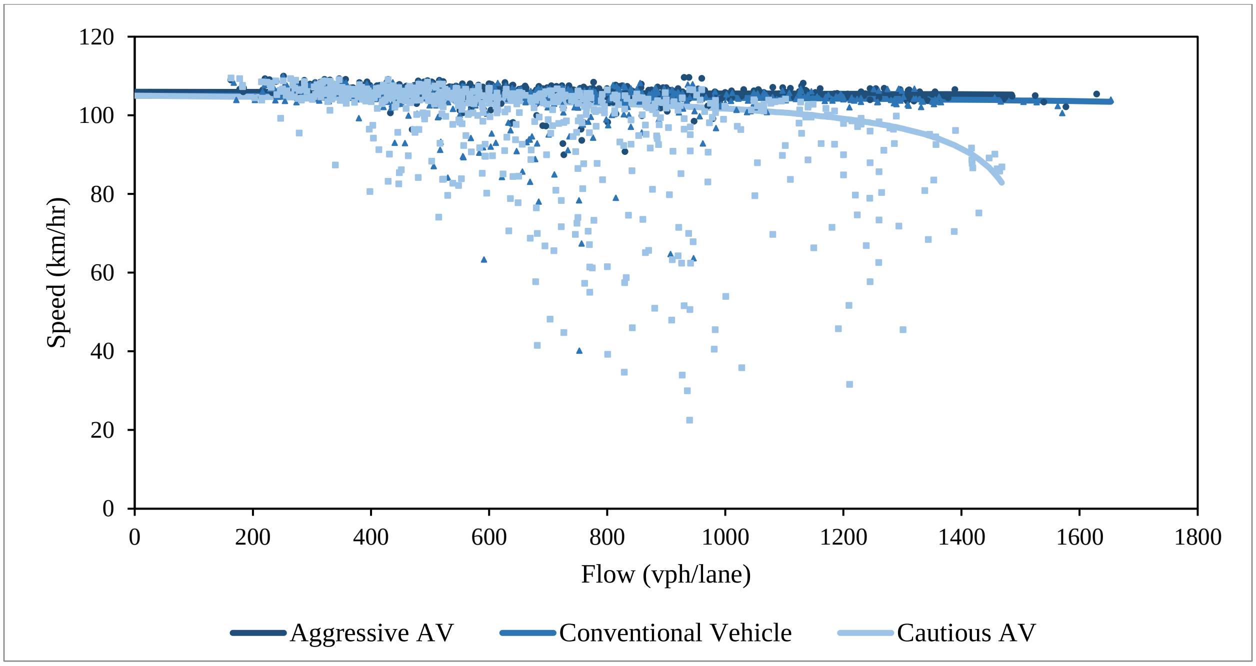

Figure 4.12: Speed-Flow relationship on the Gardiner Expressway under low traffic

Note: Curve fitted based on model developed by Van Aerde and Rakha (1995)

This relationship confirms the emissions results with slight variability between the scenarios. A low traffic condition is not sensitive to drastic changes in driving operations that could potentially be introduced by automated vehicles.

4.2.3 Varied Market Penetration of Automated Vehicles

The penetration rate of automated vehicles is considered in order to investigate the incremental effects in terms of emission benefits as the proportion of AVs on the road is increased. The literature has indicated that changes to traffic flow, capacity etc. are not evident with less than 50% penetration of automated vehicles (Bierstedt et al., 2014; Olia et al., 2016; Van Arem et al., 2006). However, based on the results of this investigation, the effects of automation are realized with relatively low penetration rates.

As shown in previous sections, aggressively programmed automated vehicles have the potential to reduce emissions and improve traffic performance by maintaining higher speeds. The emission performance and traffic performance are shown in Figure 4.13 and Figure 4.14, respectively, for AV driving settings of the Gardiner Expressway under the high and low traffic demand. From these figures, it is evident that the presence of automated vehicles (from their introduction at low penetration rates to 100% market penetration) brings incremental changes to GHG emissions and average network speed. In the case of high traffic loading on the network, the aggressively programmed AVs improve the traffic performance and reduce emissions with increased market penetration. However, under low traffic conditions, the effects of automation are not as evident from 0% to 100% penetration. This reiterates that automated vehicles will offer the most benefits under more congested conditions.

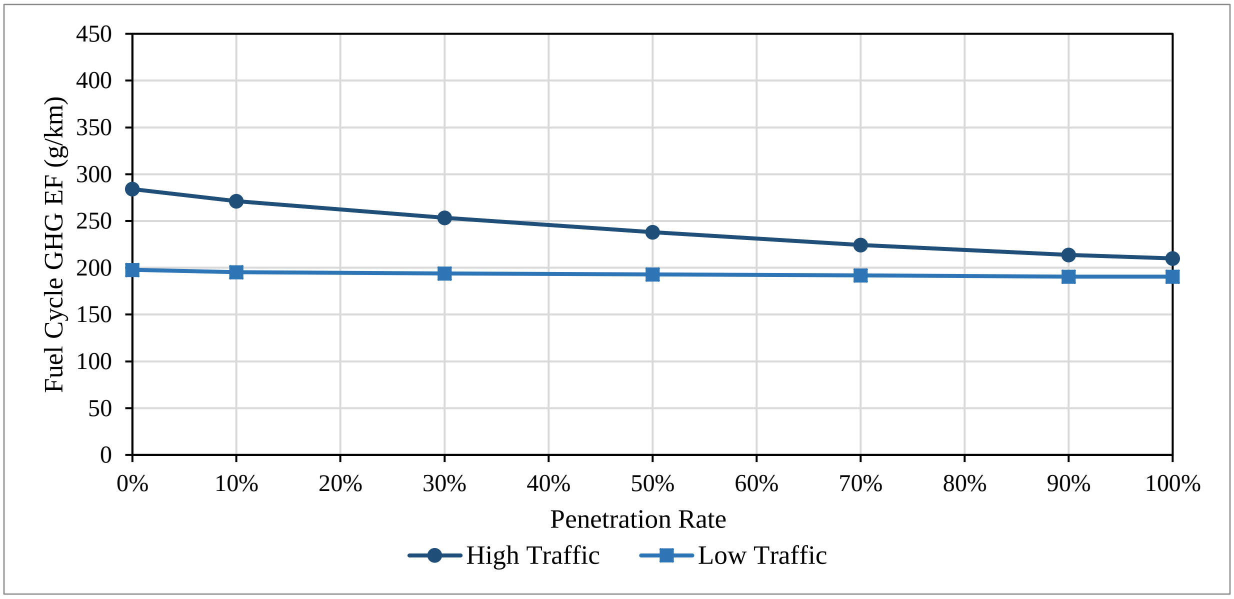

Figure 4.13: Effects of penetration of aggressive AVs on fuel cycle GHG emission factors

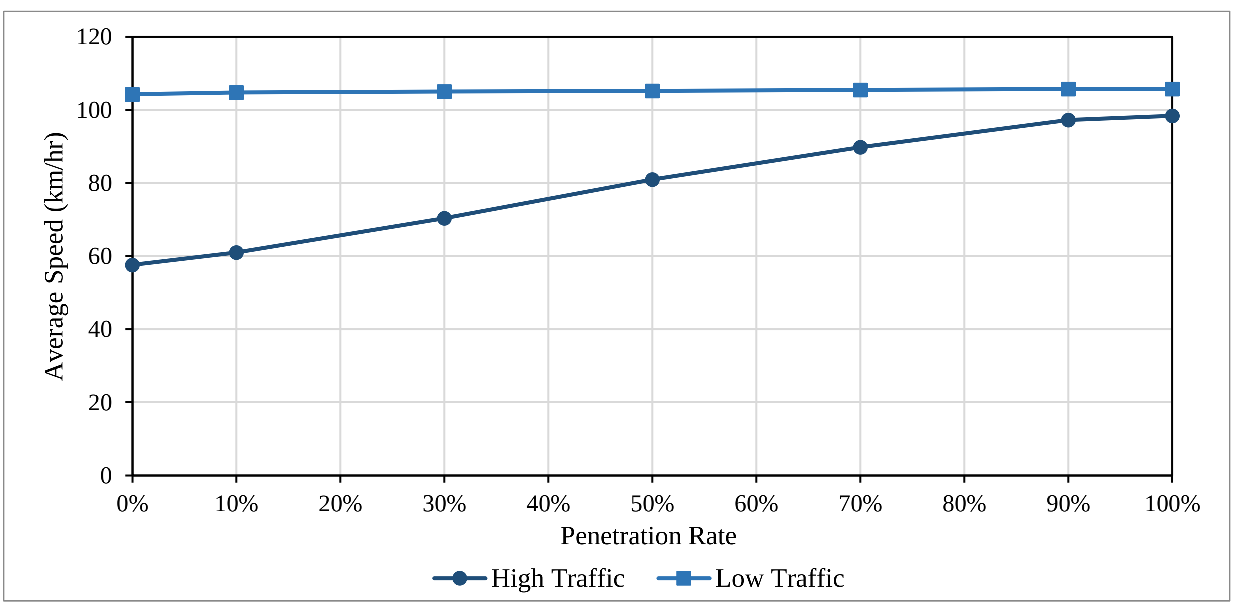

Figure 4.14: Effects of penetration of aggressive AVs on average network speed

4.2.4 Electrification of the Vehicles

As discussed earlier, the electrification of vehicles is likely to advance in step with the automation of vehicles. As such, this study considers the effects of electrification as an added element to this investigation of automated vehicles. When considering converting the vehicles to operate on electricity, the subsequent GHG emissions can be reduced significantly. Electric vehicles (EV) introduce the opportunity to essentially eliminate the operating emissions that would otherwise be emitted from the exhaust of gasoline vehicles. Instead, all the associated GHG emissions are attributed to the generation of energy to power the EVs. The cleaner sources used for energy generation, along with the zero operating emissions makes EVs particularly attractive in reducing the GHG emission output from transportation. In Figure 4.15, the electric vehicle emissions are added and compared to the total fuel cycle emissions shown in the previous sections for gasoline powered vehicles under high and low traffic conditions. The equivalent emission factor for the energy generation of electric vehicles, based on average energy consumption values, is estimated to be 13.81g CO_{2eq}/km regardless of operating mode or driving style (automated vs. conventional). This is an average of 94% reduction in emissions from conventional gasoline powered vehicles, under high and low traffic conditions.

In this study, the electric vehicle GHG emission estimate is based on the VKT. Therefore, since aggressive AVs and conventional vehicles lead to the same VKT values, under the electrification of the vehicle fleet, there is no added benefit from the introduction of automated vehicle operations. This leads to the conclusion that for the goal of reducing emissions from transportation, the focus should shift towards vehicle electrification. Even if a direct relationship between operating modes of electric vehicles and energy production emissions generated is used to estimate the emission impacts of EVs, it is still expected to be significantly less than what gasoline vehicles would produce. In this case, the added benefit of automated vehicle operations with electrification could potentially show further emission reductions.

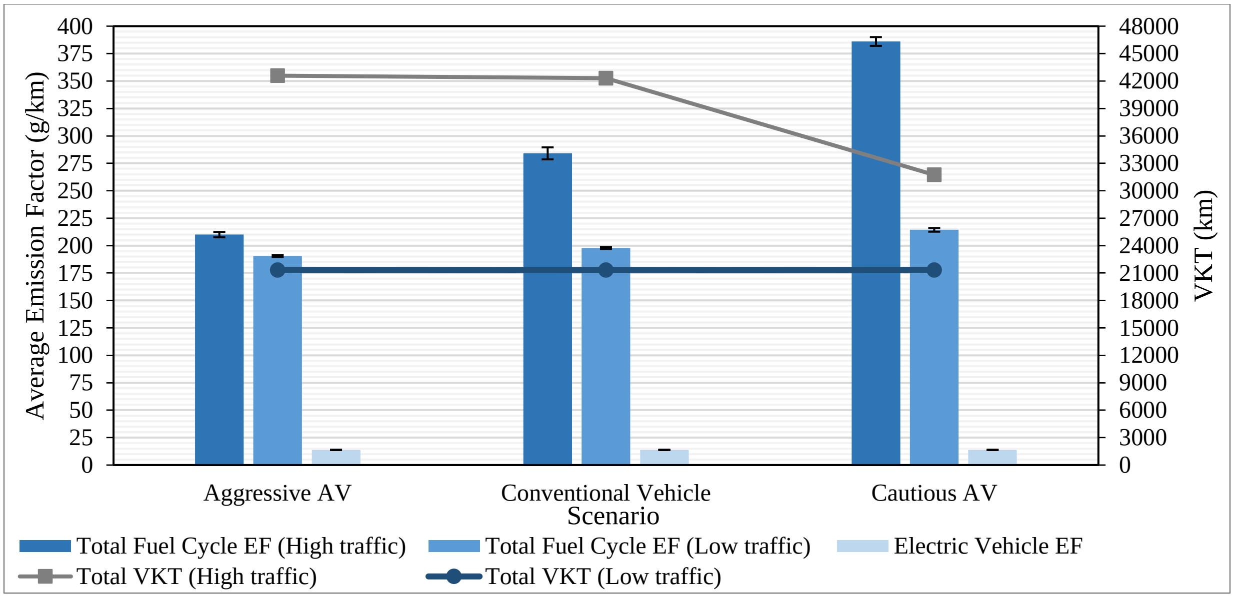

Figure 4.15: Comparison of GHG emission factors between gasoline vehicles and electric vehicles under high and low traffic conditions on the Gardiner Expressway *(the bars above the columns represent the standard deviation of the average fuel cycle emission factors)*

The total amount of GHG emissions produced to generate energy for electric vehicles can be found in Figure D.3 and Figure D.4 of Appendix D. These show the significant emission reductions that electric vehicles can introduce. However, it is important to note that the cautious AV under the high traffic regime results in a lower GHG emission output by electric vehicles since the total VKT is reduced in comparison to the aggressive AVs and conventional vehicles. The overall traffic condition is worsened, in this case, and is not considered a favourable improvement in the overall performance of the network.

Chapter 5
Urban Corridor Case Study – College Street

The College Street network allows for the examination of vehicle operations under interrupted flow conditions, given the signalized intersections that are included in the network. The vehicles have to react to congestion build up, in addition to frequent stops made for signalized intersections. This chapter discusses the results of both the OAT sensitivity analysis and parameter scenario analysis of potential AV operations on an urban corridor under both high and low traffic conditions. Varied market penetration of AVs on the network, as well as electrification of the vehicle fleet are also investigated for their potential effects. The automated vehicles are evaluated based on their effects they have on GHG emissions and traffic performance.

5.1 One-at-a-Time Approach Analysis

Understanding the role of the individual parameters in the operation of vehicles through a network with signalized intersections is important to determine which parameters are most critical in inducing change on emissions and traffic performance. The results of the OAT approach provide insight on the effects of individual parameters on GHG emissions and traffic performance indicators within the anticipated driving behaviour spectrum of automated vehicles. The sensitivity analysis is conducted under both high and low traffic conditions on the College Street network. Each of the eight car-following and two lane-changing parameters are varied individually observing induced changes on fuel cycle GHG emission factors, average network speed and average network delay. The percent differences of each performance indicator, with respect to the default parameter value results, are calculated to measure the changes induced by the parameter changes.

5.1.1 Low Traffic Condition

The observed traffic counts are used for the low traffic loading of the College Street network to evaluate the sensitivity of emissions and performance indicators in this scenario. The network is not fully congested during this time and, therefore, this traffic loading is serving as the low traffic condition for this analysis.

Figure 5.1 and Figure 5.2 show the degree of influence of each driving behavior parameter on GHG emissions and traffic performance indicators, respectively. Overall, the impacts of the parameters are seen to be minimal on both emissions and traffic performance. The impact on average speed is in fact negligible (less than 0.5%) for all the parameters. On the other hand, only a specific set of parameters influence GHG emissions. A detailed table of the percent change in fuel cycle GHG emission factors, average speed and average delay can be seen in Appendix E.

With the intent of identifying effects on GHG emissions, Figure 5.1 shows that the headway time gap (CC1) is the parameter that induces the most change from the default value. Additionally, standstill distance (CC0), threshold for entering 'following' (CC3), the safety distance reduction factor (SDRF), oscillation acceleration (CC7), and the negative/positive following thresholds (CC4/CC5) also show changes in the emission factor beyond 0.50%. However, it should be noted, that these changes are too small to be considered meaningful.

Expanding the indicators to include delay, only the headway time parameter seems to create the largest changes, yet these are still considered to be too small to be meaningful. It can be seen from these results that traffic performance under interrupted traffic flow conditions is not sensitive to changes in the parameters. The remaining parameters: CC8, CC9 and MinHdwy have negligible effect on the GHG emission factor and the traffic performance indicators.

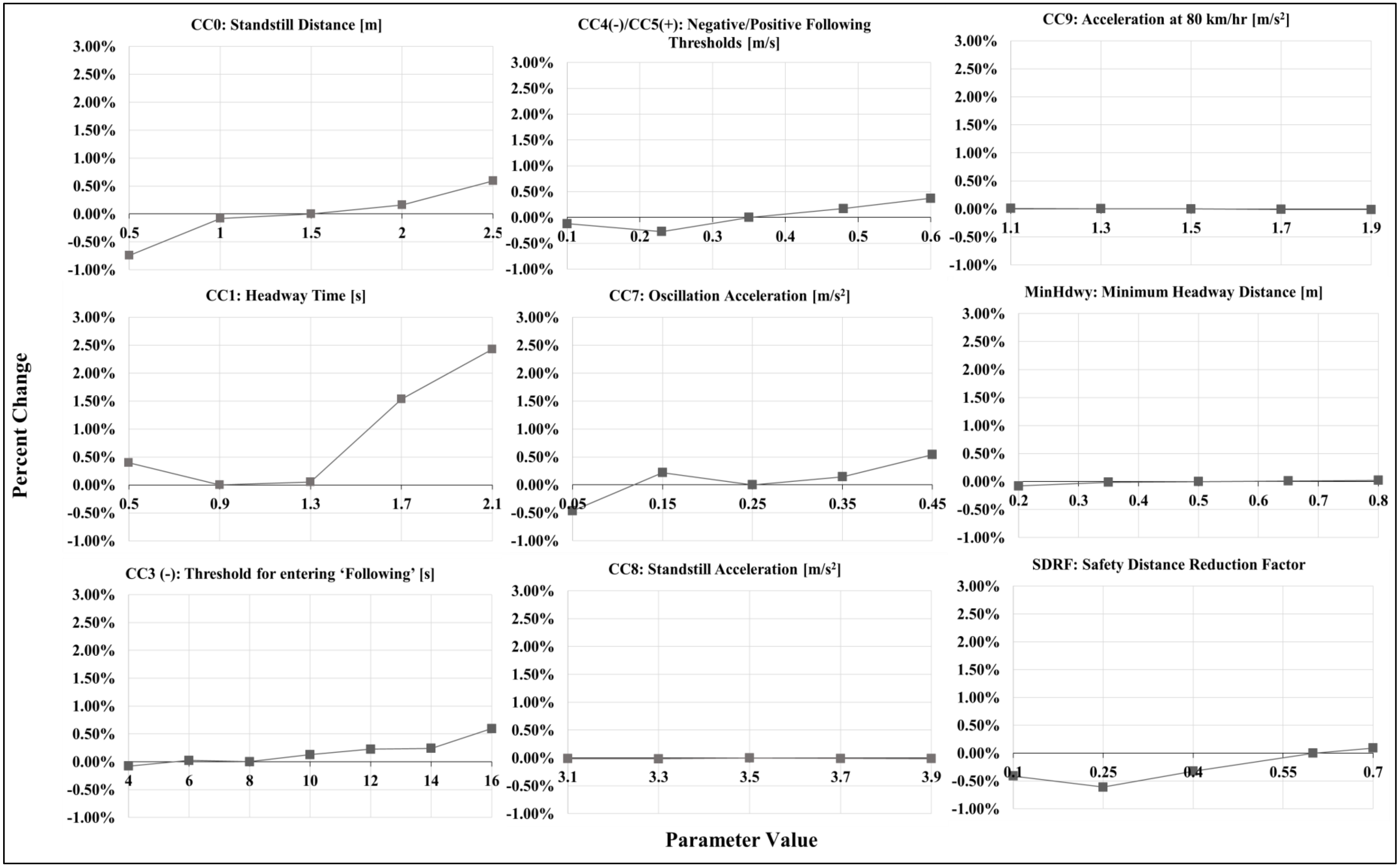

Figure 5.1: Percent change in fuel cycle GHG emission factors for low traffic case *(the y-axis is the percent change, while the x-axis is the value of the parameter)*

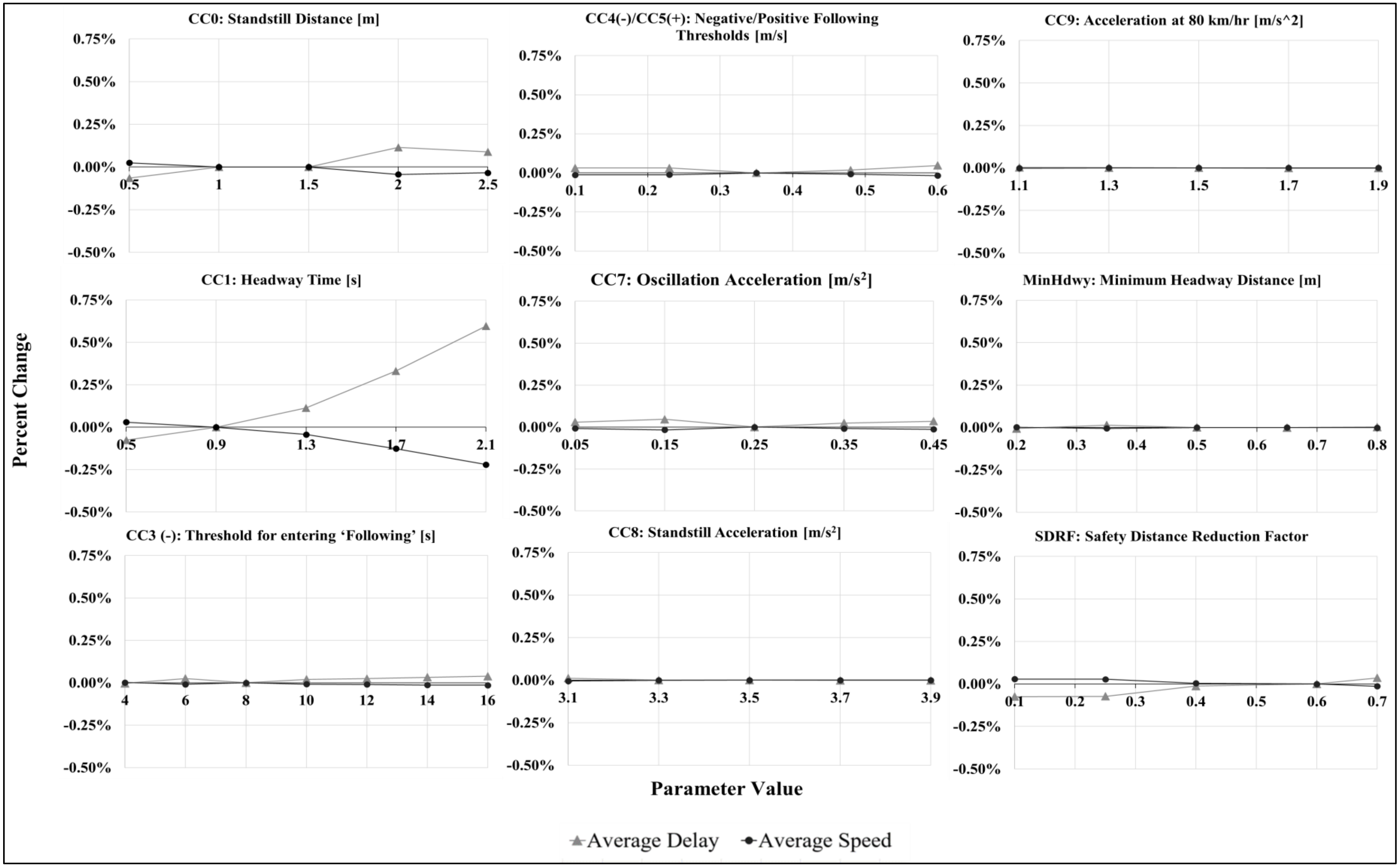

Figure 5.2: Percent change in average speed and delay for low traffic case *(the y-axis is the percent change, while the x-axis is the value of the parameter)*

Parameter CC1 is the headway time and is defined as the distance (in seconds) that a driver wants to maintain from a vehicle in front at a certain speed (PTV AG, 2016). Cautious driving behavior is associated with higher values of this parameter. CC1 has the largest impact on GHG emissions and delay relative to other parameters in this study. When evaluated at the upper end of its range (cautious driving), the largest change is observed as a 2.43% increase in GHG emissions from the default parameter setting. A smaller headway time between vehicles also produces a very small increase of 0.40% in the emission factor. This trend can be attributed to the fact that the traffic flow on the College Street network is frequently interrupted by the changes in signals at the intersections. Therefore, changing the headway time to the extreme aggressive and cautious ends of the spectrum seems to further aggravate the conditions and result in additional emissions. Driving close together (aggressive driving) with frequent interruptions due to intersections or driving far apart and trying to maintain a distance (cautious driving) results in unstable driving behaviour, producing more emissions. Vehicles traveling closer together can travel through the network more efficiently and uniformly, thus reducing the number of vehicles stopping at the intersections and creating idling emissions. This is evident from the trend in delay with respect to the CC1 parameter, as a lower headway value reduces delay, indicating that vehicles could travel through the network faster. With higher values of headway time, this uniformity in the driving behavior between the vehicles is lost and results in a breakdown of traffic flow and an increase in GHG emissions.

Parameter CC0 is standstill distance [m] and is defined as the desired distance between stopped vehicles (PTV AG, 2016). For this parameter, cautious driving is associated with higher values of standstill distance, while more aggressive behavior is associated with shorter distances. The shorter desired standstill distance of a vehicle (~0.5m) is associated with a reduction of 0.74% in the GHG emission factor from the default value, while higher desired standstill distances (~2.5m) results in a 0.59% increase in the GHG emission factor. This can be attributed to the deceleration and stopping behavior to achieve the desired standstill distance. In the case where the desired distance is small, the deceleration process can be much smoother, because there is less of a need for abrupt braking to achieve the larger spacing. The vehicle can gradually reduce its speed and coast to a halt over longer distance, which translates to lower emissions. This also translates to reduced delay, since it implies vehicles are traveling closer together with fewer vehicles stopping at the intersections, which further reduces GHG emissions due to idling.

Parameter CC3, the threshold for entering 'following', is defined as the time (in seconds) when the vehicle starts to decelerate before reaching the safety distance (PTV AG, 2016). A higher magnitude value of CC3 corresponds to vehicles beginning their deceleration process farther apart from other vehicles. In the upper end of this parameter, there is the potential for an increase of 0.59% in the GHG emission factor, while the lower end of the spectrum produces a negligible reduction of 0.08% in the emission factor. It can also be seen that the changes in CC3 values have no impact on average speed and network delay. This can be explained by the fact that in uncongested conditions, the safety distance is not fully used, as there is extra spacing already and therefore, the higher values of CC3 disrupt the traffic flow causing more abrupt accelerations and, decelerations to accommodate cautious vehicle driving. In general, lower values of CC3 are better for emission reduction, but this parameter is dependent on the traffic conditions.

Parameter SDRF, the Safety Distance Reduction Factor, is defined as the amount by which a vehicle reduces its safety distance with a vehicle in front when changing lanes (PTV AG, 2016). Lower values of this parameter (<0.4) are associated with greater reductions in the safety distance and more aggressive driving. This results in a decrease in delays and an emission factor reduction of 0.4% in the most aggressive end of the spectrum, as there is less braking and fewer fluctuations in acceleration/deceleration when there is more tolerance to closer distances for lane changing.

Parameter CC7 is the oscillation acceleration [m/s^2] of the vehicle (PTV AG, 2016). Cautious driving is associated with lower values of acceleration, while more aggressive behavior is associated with higher acceleration rates. The literature has indicated that CC7 has limited effects on traffic performance indicators (Lownes & Machemehl, 2006a, 2006b). However, acceleration is known to have relevance to vehicle emissions. Lower rates of acceleration can be related to smoother and steadier driving with less abrupt increases in speed, leading to a reduction in emissions. Accelerations at the lower end of the range (~$0.05 m/s^2$) lead to a reduction of almost 0.5% in GHG emission factor from the base case, while accelerations at the higher end of the range (~$0.45\ m/s^2$) lead to an increase of 0.5% in emissions.

Parameters CC4/CC5 are the negative/positive following thresholds and are defined as the speed differences [m/s] during the following state, with smaller values resulting in a more sensitive reaction of drivers to accelerations or decelerations of the preceding car (PTV AG, 2016). For smaller values (aggressive behavior), the decrease in GHG emissions, despite an increase in delay and decrease in average speed, can be explained by a reduced amount of acceleration/deceleration due to the higher sensitivity to the movement of preceding vehicles. This results in smoother, more uniform driving and indication of uniform motion among AVs.

Parameters CC8 and CC9 are the acceleration from standstill and desired acceleration at a speed of 80km/hr, respectively (PTV AG, 2016). These parameters have negligible effect on GHG emissions and traffic performance based on this study. Similarly, MinHdwy, which is the minimum distance that must be available between vehicles after a lane change (PTV AG, 2016), has almost no effect on GHG emissions.

5.1.2 High Traffic Condition

The traffic demand for the College Street network is increased to resemble more congested conditions. This allows for the investigation of the sensitivity of emissions and traffic performance to vehicle operations under more congested conditions in an interrupted flow operating environment.

The degree of influence of each driving behavior parameter on GHG emissions and traffic performance indicators are shown in Figure 5.3 and Figure 5.4, respectively. Overall, the impacts of the parameters are seen to be minimal on both emissions and traffic performance; however, the induced changes are of a higher magnitude than the low traffic condition. The impact on average speed remains negligible (less than 0.5%) for almost all the parameters. A detailed table of the percent change in fuel cycle GHG emission factors, average speed and average delay can be seen in Appendix E.

With the intent of identifying effects on GHG emissions, Figure 5.3 shows that the headway time gap (CC1) is the parameter that induces the most change from the default value. Additionally, standstill distance (CC0), threshold for entering ‘following’ (CC3), the safety distance reduction factor (SDRF), and the negative/positive following thresholds (CC4/CC5) also show changes in the emission factor of at least 1% or more.

When considering average speed and delay, only the headway time parameter seems to yield large changes. It can be seen from these results that traffic performance is not sensitive to changes in the parameters under interrupted traffic flow conditions, even with more congested traffic conditions. The remaining parameters: CC7, CC8, CC9 and MinHdwy have negligible effect on the GHG emission factor and the traffic performance indicators.

Parameter CC1, the headway time has the largest impact on GHG emissions, average speed, and average delay relative to other parameters under this high traffic condition. When evaluated at the upper end of its range (cautious driving), the largest change is observed as a 10.42% increase in GHG emissions from the default parameter setting. A smaller headway time between vehicles produces a very small decrease of 0.64% in the emission factor. This trend can be attributed to the platooning effect formed by automated vehicles traveling at close proximities to each other. This platooning results in smoother and more uniform drive cycles, as well as improved traffic flow. Vehicles travelling closer together can travel through the network more efficiently and uniformly, thus reducing the number of vehicles stopping at the intersections and creating idling emissions. This is evident from the trend in delay with respect to the CC1 parameter, as a lower headway value also reduces delay, indicating that vehicles could travel through the network with less interruption in their driving, which contributes to a reduction in emissions. With higher values of headway time, this uniformity in the driving behavior between the vehicles is lost and results in a breakdown of traffic flow and an increase in GHG emissions.

Standstill distance (CC0) is another parameter that shows a varied range of effects under high traffic interrupted flow conditions. The shorter desired standstill distance of a vehicle is associated with a reduction of 1.62% from the default value in the GHG emission factor, while higher desired standstill distances lead to a 1.26% increase in the GHG emission factor. This can be attributed to the deceleration and stopping behavior to achieve the desired standstill distance. Higher traffic makes the impact of this parameter more noticeable, as spacing between vehicles often determines how the vehicles interact. With more vehicles on the road, the larger desired standstill distance leads to more sensitivity to acceleration/deceleration to maintain the desired distances between vehicles. This, in turn, increases average network delay, reduces average network speed, and, consequently increasing GHG emissions. On the other hand, smaller desired distances at standstill allows vehicles to gradually reduce their speed and coast to a halt over longer distance, translating to lower emissions. This translates to vehicles traveling closer together with fewer vehicles stopping at the intersections, which reduces GHG emissions due to idling.

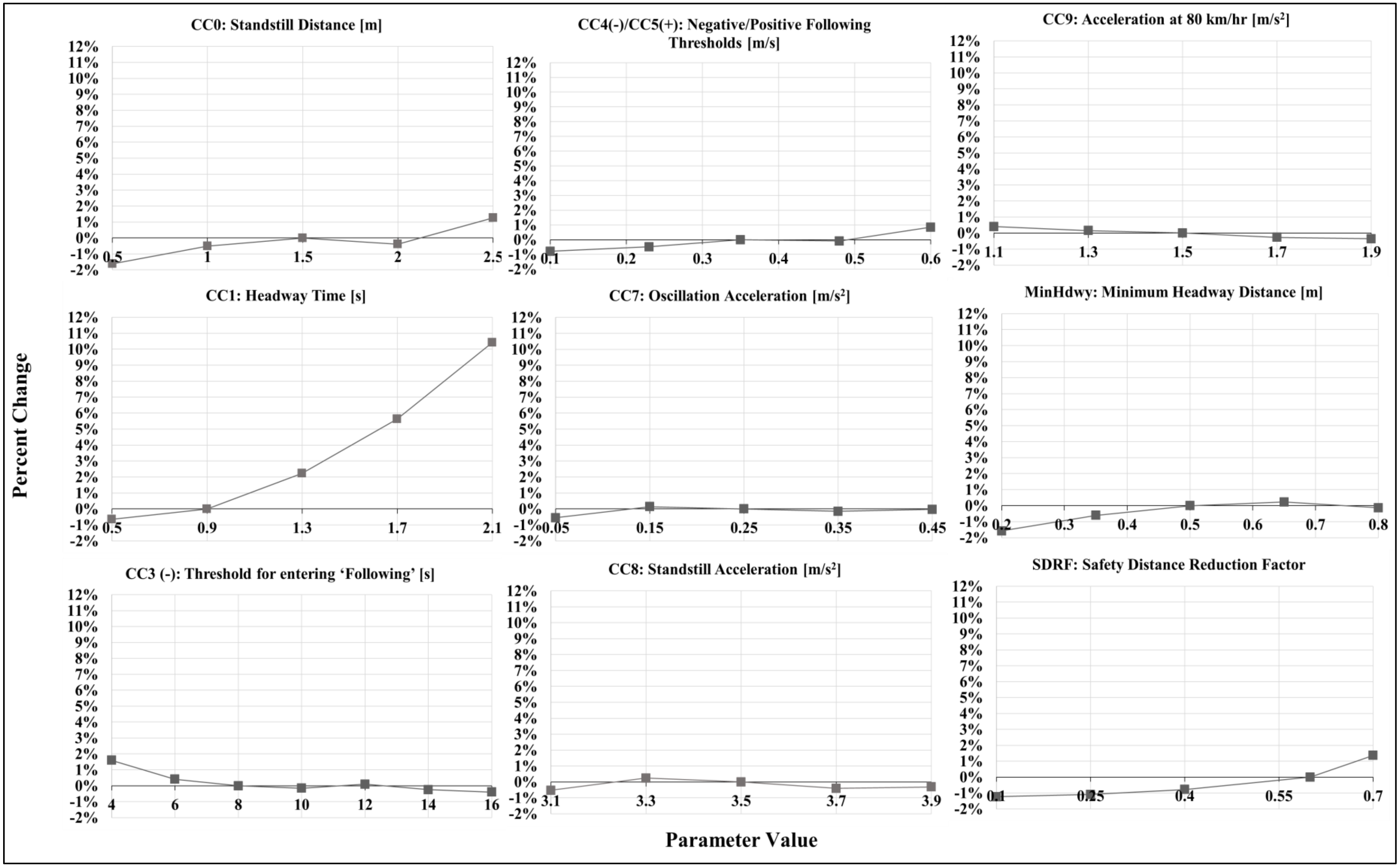

Figure 5.3: Percent change in fuel cycle GHG emission factors for high traffic case *(the y-axis is the percent change, while the x-axis is the value of the parameter)*

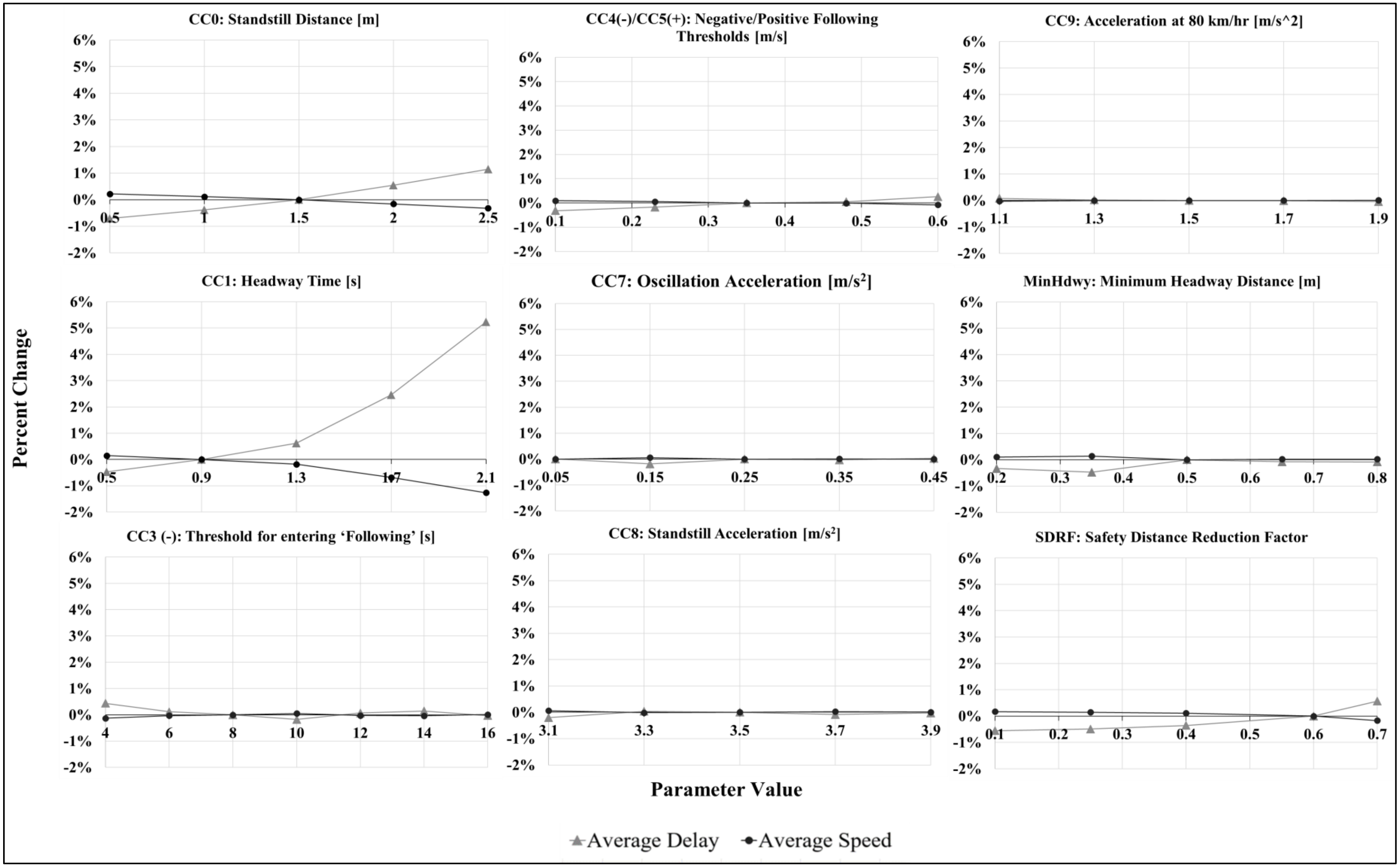

Figure 5.4: Percent change in average speed and delay for high traffic case *(the y-axis is the percent change, while the x-axis is the value of the parameter)*

Parameter CC3, the threshold for entering ‘following’, shows a relatively larger effect on the performance indicators under high traffic conditions. There is a different pattern on its effect of GHG emission factors under higher traffic than under lower traffic condition. In this case, a higher magnitude value of CC3 led to a slight decrease of 0.39% in the GHG emission factor, while the lower end of the spectrum produces a relatively larger increase of 1.60% in the emission factor. This can be explained by the fact that under more traffic, initiating the deceleration process earlier results in a smoother reduction in speed, which translates to a reduction in emissions. It can also be seen that the changes in CC3 values have negligible impact on average speed and network delay.

Parameter SDRF, the Safety Distance Reduction Factor, shows a similar pattern under high traffic, as it did under low traffic conditions. Lower values of this parameter lead to a decrease in delays and an emission factor reduction of 1.24%, while higher, more cautious values lead to a 1.36% increase in the emission factor value and an increase in delay. This result stems from the reduced disruptions to the traffic flow during lane changing when the safety distance is reduced more. Similar to the SDRF, the minimum headway distance parameter (MinHdwy) is another lane changing model parameter that has shown more influence under high traffic than it did in the low traffic case. MinHdwy is defined as the minimum distance [m] that must be available between vehicles after a lane change (PTV AG, 2016). Lower values of this parameter correspond to more aggressive driving and leads to 1.59% reduction in the GHG emission factor, as well as a decrease in the delay. This result is related to the tolerance of vehicles to have smaller distances between them after lane changes, leading to reduced disruptions on the traffic flow.

The negative/positive following thresholds (CC4/CC5), as well as the oscillation acceleration (CC7) also show a similar trend under high traffic when compared to the low traffic case, but, in comparison to the other parameters noted above, their effect was less than 1% and was deemed to be minimal. Parameters CC8, CC9, and MinHdwy have negligible effect on GHG emissions and traffic performance based on this study.

5.2 Scenario-Based Parameter Analysis

In the scenario-based analysis, the three parameter settings representing aggressive AV, conventional vehicle default and cautious AV driving characteristics are tested in the microsimulation package under high and low traffic conditions in the interrupted traffic flow operating environment of an urban corridor. The investigated scenarios include 100% market penetration of AVs (for aggressive and cautious) and 100% conventional vehicles for the default case. The AV aggressive driving setting consists of all the relevant driving behaviour parameters set to the aggressive end of the spectrum, while the cautious parameter setting consists of all the parameters set to the cautious end of the spectrum. The electrification of the vehicle fleet, as well as varied market penetration of AVs are also investigated in this section.

5.2.1 Low Traffic Condition

This scenario considers observed low traffic volumes on College Street. This traffic condition as well as the default conventional vehicle parameter setting form the base case scenario. The potential AV driving characteristics are compared to conventional vehicles in terms of their effects on GHG emissions and overall traffic performance of the urban corridor, including average network speed, average network delay and average number of stops per vehicle.

5.2.1.1 Automated vs. Conventional Vehicle Emissions

Based on the results from this study, it is shown that under interrupted traffic flow, such as an urban corridor with signalized intersections, there is minimal difference in the resulting GHG emission factor between automated vehicles (both aggressively and cautiously programmed) and human driven conventional vehicles. As can be seen in Figure 5.5 below, the automated vehicle aggressive driving setting has the potential to reduce the average fuel cycle GHG emission factor by only 0.95% from 355 g CO_{2eq}/km (standard deviation of 4.12) to 352 g CO_{2eq}/km (standard deviation of 4.16). On the other end of the spectrum, cautiously programmed automated vehicles lead to a relatively larger change in the emission factor with a 2.71% increase to 365 g CO_{2eq}/km (standard deviation of 6.21). It can also be seen from Figure 5.5 that the VKT between all three cases are identical, indicating that all simulated vehicles are able to enter the network under each driving parameter setting scenario. These results show fairly insignificant changes as a result of the different driving settings. The frequent interruptions in the traffic flow from the signalized intersections interfere with the vehicle operations and prevents the realization of any benefits from automated vehicle operations. This shows that, under interrupted flow conditions, changes due to the different driving settings are more or less indiscernible. Regardless of the driving style, the vehicles need to stop and go frequently to adhere to traffic signals. This is consistent with the OAT sensitivity analysis, which found that there is very minimal sensitivity to changes in the parameters.

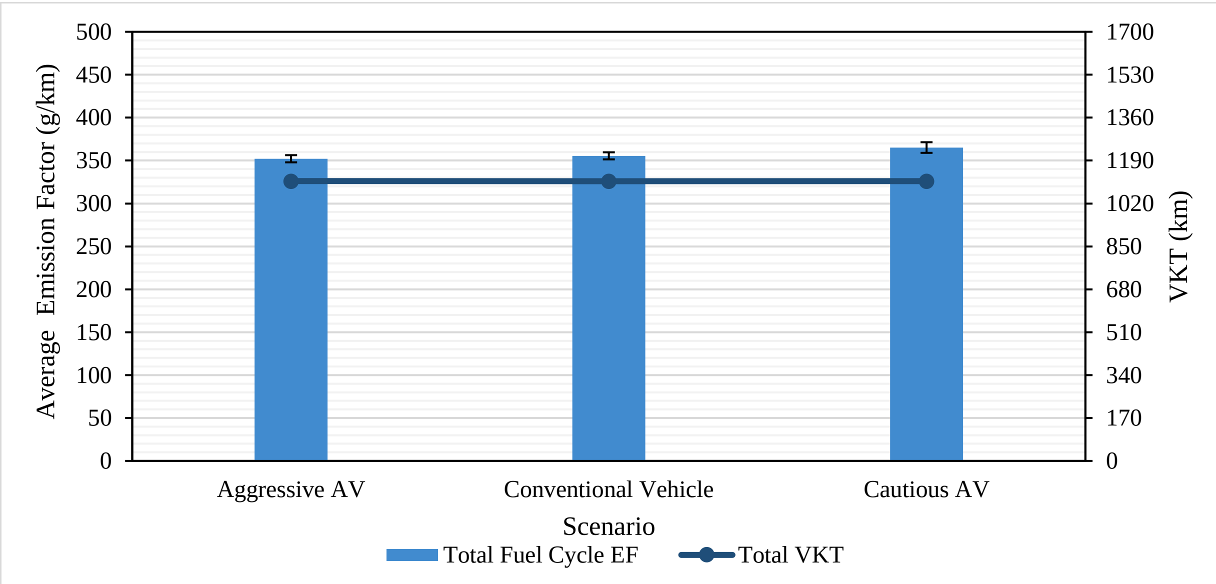

Figure 5.5: The average fuel cycle emission factor and total vehicle kilometers travelled for each parameter setting on College Street with low traffic *(the bars above the columns represent the standard deviation of the average fuel cycle emission factors)*

The total fuel cycle emissions are shown in Figure F.1, Appendix F and, as expected, show the same trends as the emission factors normalized by VKT. No changes in VKT and minimal changes in the emission factors between the three vehicle parameter settings result in a slight increase in the total fuel cycle GHG emissions for the cautious AVs, while aggressive AVs produce slightly less emissions than conventional vehicles.

5.2.1.2 Traffic Performance

When drawing conclusion about the changes in GHG emissions, it is also important to consider traffic performance. To evaluate the traffic performance between automated vehicle and conventional vehicle driving characteristics, average network speed, average network delay per vehicle and average number of stops per vehicle are used. These are the most relevant parameters for an interrupted flow operating environment, such as College Street.

As can be seen in Figure 5.6, the average speed remains constant between the three different driving settings with a difference of ±0.5km/hr. This is a result of interrupted flow from stopping at traffic lights at the intersections in the network. However, the network delay shows greater variability amongst the different driving settings. The aggressive AVs and conventional vehicle presented no difference in delay and it was maintained at 34 seconds. The cautious AV driving settings resulted in a slight increase in delay to a total of 37 seconds. This increase in delay is expected to be a result of larger spacing between the vehicles; however, the difference is quite minimal. These small changes are a result of the low traffic demand on the network, as well as the signalized intersections obscuring the differences in driving characteristics.

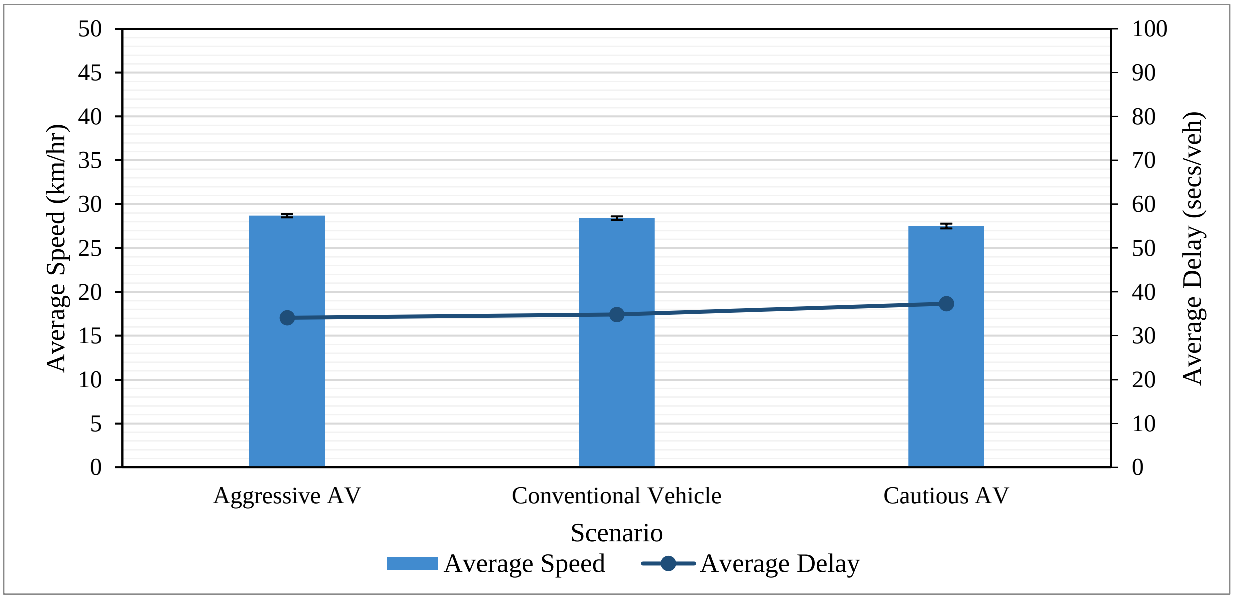

Figure 5.6: Average network speed and delay under low traffic conditions of College Street *(the bars above the columns represent the standard deviation for the average speed)*

The operating mode distribution can be seen in Figure 5.7. The three driving settings have an equal distribution of operating modes, with the majority of the proportion being in the low speed, braking/decelerating and idling categories. This also helps explain the minimal differences in emissions between the three types of vehicle settings. Lower speeds supposedly generate less emissions; however, when a vehicle spends more time on the road, it generates more emissions. Therefore, despite the lower speeds, the vehicles for all three parameter settings need to adjust their driving to stop at intersections, spending more time on the road and increasing their emission factor/intensity. Extended periods of idling because of stop and go traffic and interruptions to the traffic flow lead to emissions adding up and offsetting the benefits of lower speed on emissions.

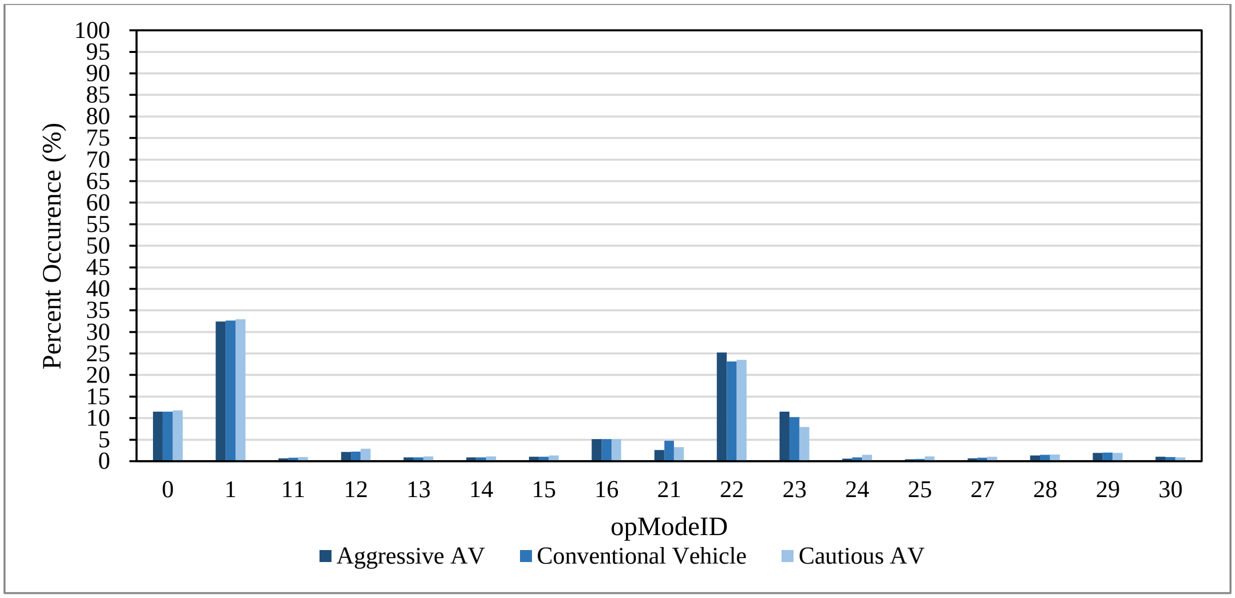

Figure 5.7: opModeID distribution under low traffic conditions on College Street

Another traffic performance indicator that is most relevant to interrupted flow conditions, such as the ones observed in the College Street network, is the average number of stops per vehicle. This metric is defined as the total number of stops divided by the total number of vehicles on the network. It can be seen from Figure 5.8 that the three parameter settings of aggressive AV, conventional vehicle, and cautious AV are within the standard deviation of each other. There is no significant difference between the scenarios. This is inherent of the low traffic demand, and the fact that the vehicle operations have remained consistent between the scenarios.

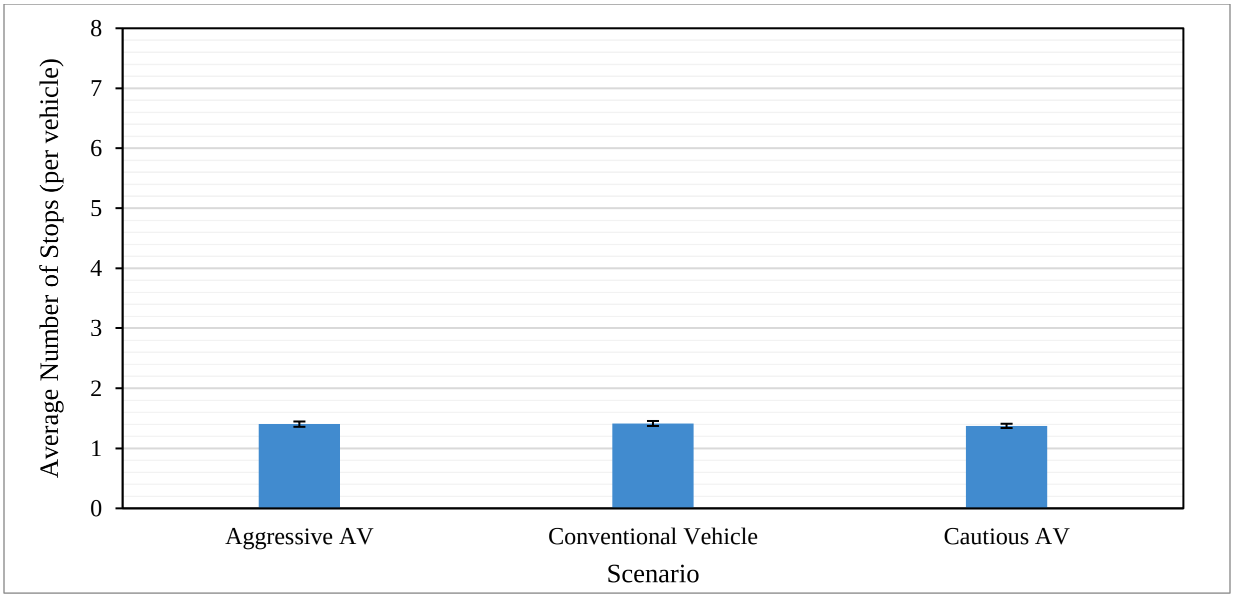

Figure 5.8: Average number of stops under low traffic conditions on College Street *(the bars above the columns represent the standard deviation for the average number of stops)*

5.2.2 High Traffic Condition

In this part of the study, the traffic demand on the College Street network is increased to reflect more congested conditions. This allows for the evaluation of automated vehicle operations, in comparison to conventional vehicle operations, under more congested interrupted flow conditions. Once again, the scenarios are evaluated for changes in GHG emissions and traffic performance (speed, delay, and number of stops).

5.2.2.1 Automated vs. Conventional Vehicle Emissions

High traffic demand on the interrupted traffic flow urban corridor highlights some of the distinct differences between the automated vehicle driving operations and the conventional vehicle. As can be seen in Figure 5.9, the automated vehicle aggressive driving setting has the potential to reduce the average fuel cycle GHG emission factor by 3.44% from 393 g CO_{2eq}/km (standard deviation of 14.09) to 380 g CO_{2eq}/km (standard deviation of 10.76). This still is a small difference, as there is a slight overlap of the potential error ranges. On the other end of the spectrum, cautiously programmed automated vehicles lead to a larger change in the emission factor with a 19.62% increase to 470 g CO_{2eq}/km (standard deviation of 20.37). It can also be seen from Figure 5.9 that there is some variability in VKT among the aggressive AV, the conventional vehicle, and the cautious AV scenarios. There is no significant difference between the VKT of the aggressive

AV scenario and the default conventional vehicle scenario (difference of 1 km more for AV). However, the cautious AV scenario resulted in a slight decrease in VKT from 1655.8 km to 1602.5 km. This indicates the difference in the resulting traffic condition between the vehicle operating scenarios. The cautious AVs deteriorate the network to the point where a latent demand is created (approximately 43 vehicles left out of the network). As a result, vehicles are backing up and the emission factor increases, reflecting the increase in emissions. On the other hand, the aggressive AVs show an improvement. This is attributed to the smoother operations and less time that the vehicles spend on the network when they travel closer together forming platoons and moving more efficiently. These results are more significant than what was shown in the OAT analysis, as the combined effect of the parameters (all of them being set to the aggressive or cautious extreme) results in the inducement of more change.

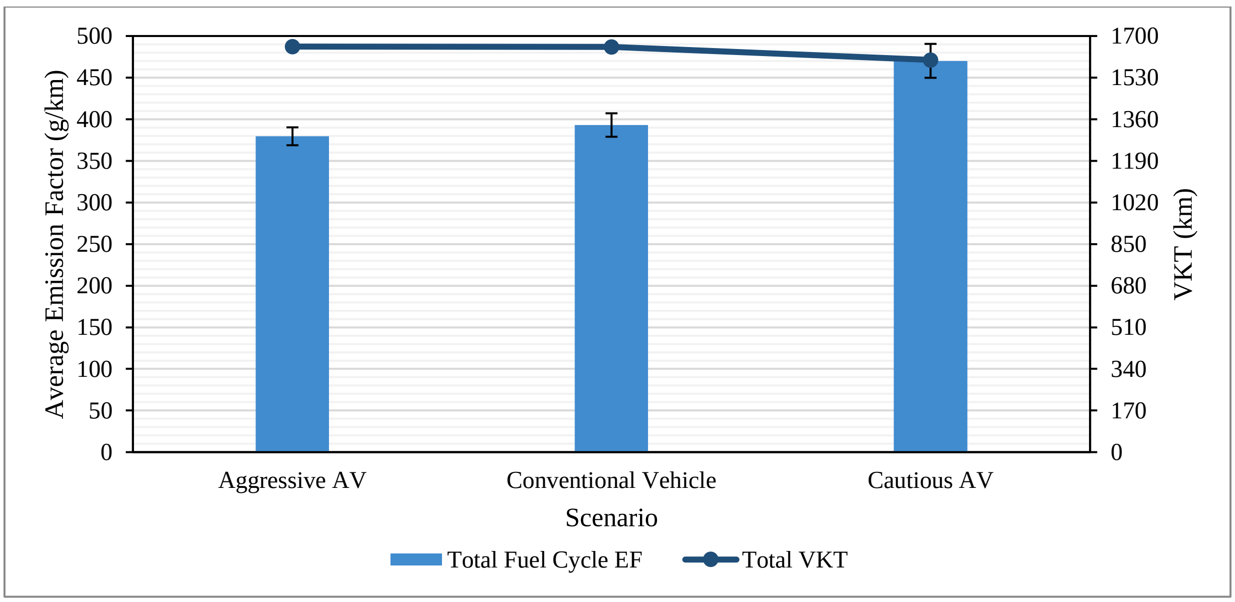

Figure 5.9: The average fuel cycle emission factor and total vehicle kilometers travelled for each parameter setting on College Street with high traffic *(the bars above the columns represent the standard deviation of the average fuel cycle emission factors)*

When considering the total fuel cycle GHG emissions, similar trends as the emissions factors are found in the results. As can be seen in Figure F.2, Appendix F, the aggressive AVs reduce the total emissions in comparison to conventional vehicles, while cautious AVs lead to a significantly higher fuel cycle emissions output, despite the decrease in VKT. This result is attributed to the increased emission intensity per VKT due to the worsening conditions on the network leading to more idling.

5.2.2.2 Traffic Performance

Consideration of traffic performance for the high traffic demand on the College Street network is useful in understanding the changes between the driving operations and their GHG emission impact. As can be seen in Figure 5.10, the average network speed varies between aggressive AV, conventional vehicles, and cautious AVs. The average speed increases slightly from 25 km/hr to 27 km/hr when only aggressive AVs are on the network, stemming from the shorter time gaps and reduced safety distance. At the other extreme, cautious operating AVs degrade the performance of the network, resulting in a large decrease of the average speed to around 15 km/hr. The increased demand on the network, paired with the large gaps between vehicles and cautious performance exacerbated the stress put on the network. This led to more cars ending up waiting at intersections, as well as a back log of vehicles increasing the time it takes to traverse the network. These results are also confirmed by the changes in delay. Figure 5.10 also shows the average network delay decreases slightly for aggressive AVs and increases significantly from 45 seconds (conventional vehicles) to 96 seconds for cautious AVs.

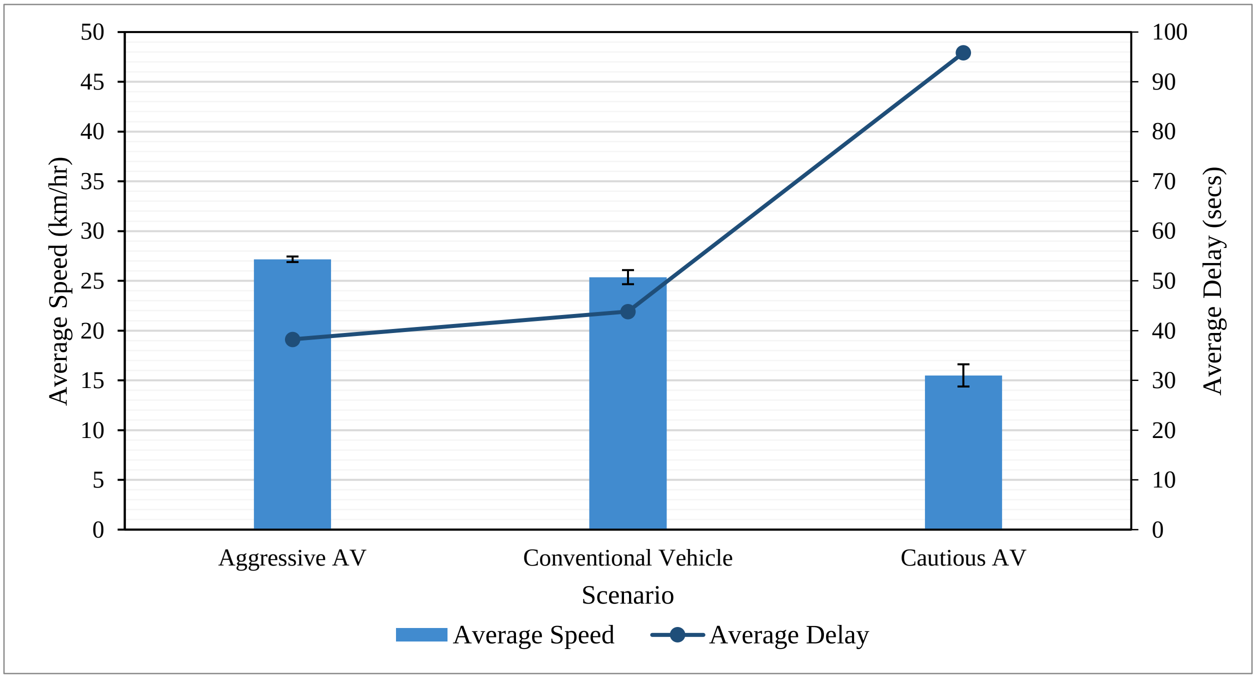

Figure 5.10: Average network speed and delay under low traffic conditions on College Street *(the bars above the columns represent the standard deviation for the average speed)*

The operating mode distribution can be seen in Figure 5.11. The aggressive AV and conventional vehicle driving settings have very similar distribution in operating modes with a large proportion

(58-60%) being in the lower speed categories (idling to 40 km/hr), but still 39-41% being in the over 40 km/hr speed categories. On the other hand, the cautious AVs have a significant larger proportion in the low speed and idling operating modes. This is helps explain the increase in delay, as well as the increase in emissions. The cautious vehicles spend more time traversing the network, and more vehicles get caught waiting at intersections, due to the larger spacing between the vehicles and the disruptions in the traffic flow to maintain larger safety distances. Lower speeds generally generate less emissions; however, when a vehicle spends more time on the road it generates more emissions. Therefore, despite the lower speeds, the vehicles end up stopping at intersections, spending more time on the road, and increasing their emission intensity. Extended periods of idling because of stop and go traffic and interruptions to the traffic flow, lead to emissions adding up.

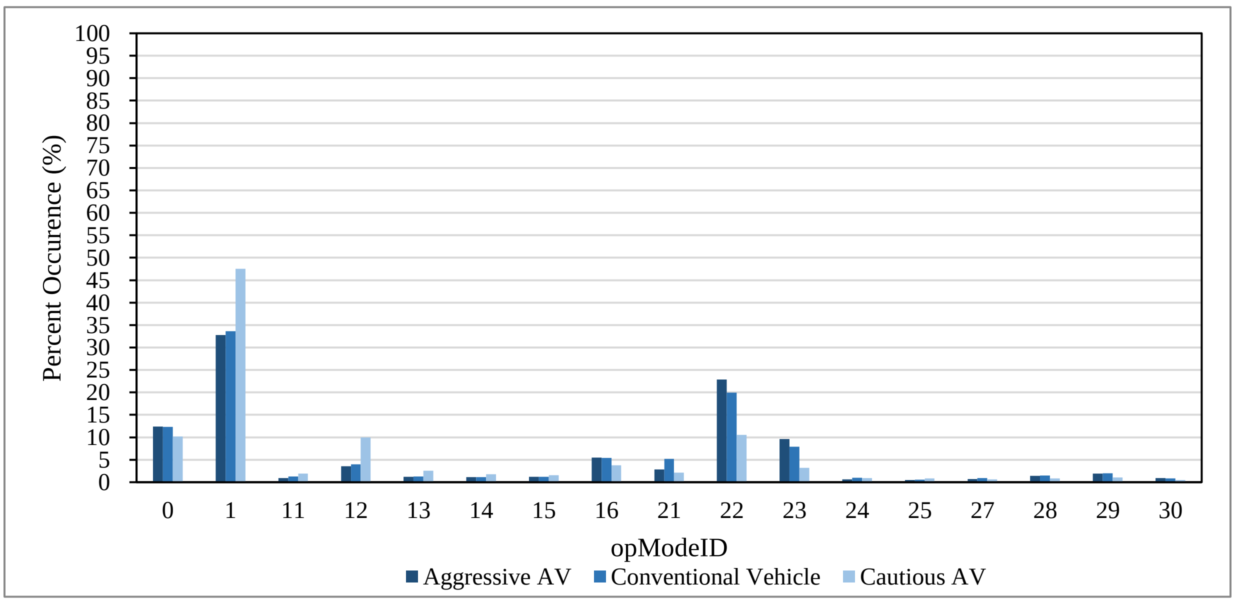

Figure 5.11: opModeID distribution under high traffic conditions on College Street

When looking at the average number of stops per vehicle, the trends are similar to the results from the previous performance indicators. As can be seen in Figure 5.12, the tighter operations of the aggressive AV lead to a very minimal reduction in the average number of stops a given vehicle has to make while travelling through the network. The insignificant change is attributed to the interrupted flow preventing the AVs from realizing their full potential. However, the increased number of stops per vehicle also indicate the breakdown of the performance caused by cautious AVs. Indeed, there is a significant increase from 2.20 to around 6.32 stops per vehicle under the cautious AV operation. This matches with the increased average network delay, reduction in average speed and increase in emission factor. The larger gaps and overly cautious decisions lead to a breakdown in the network performance of the network, exacerbating the conditions and difficulties arising from an increased demand.

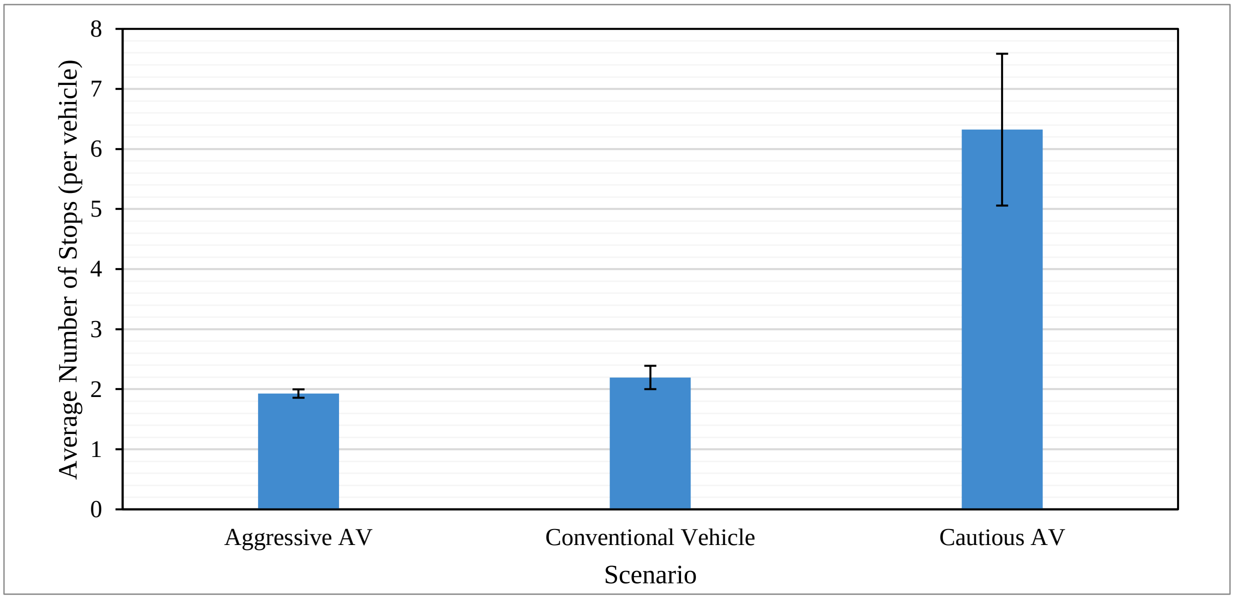

Figure 5.12: Average number of stops under high traffic conditions on College Street *(the bars above the columns represent the standard deviation of the average number of stops)*

5.2.3 Varied Market Penetration of Automated Vehicles

In this section, the incremental impact of varied penetration of automated vehicles is also considered in assessing the effects on emissions and traffic performance as the proportion of AVs on the road is increased. As shown in previous sections, aggressively programmed automated vehicles on an interrupted flow urban arterial corridor have limited impacts on emissions. The effects on the emission factor and average number of stops per vehicle are shown in Figure 5.13 and Figure 5.14, respectively, for AV operations on the high and low traffic loading of the College Street. From these figures, it is evident that the presence of automated vehicles, (from their introduction at low penetration rates to 100% market penetration) under high traffic, brings slight incremental changes to GHG emission factors and number of stops per vehicle. The aggressively programmed AVs reduce the average number of stops and reduce emissions with increased market penetration. However, under low traffic conditions, the effects of automation are not as evident from 0% to 100% penetration. This reiterates that automated vehicles will offer the most benefits under more congested conditions.

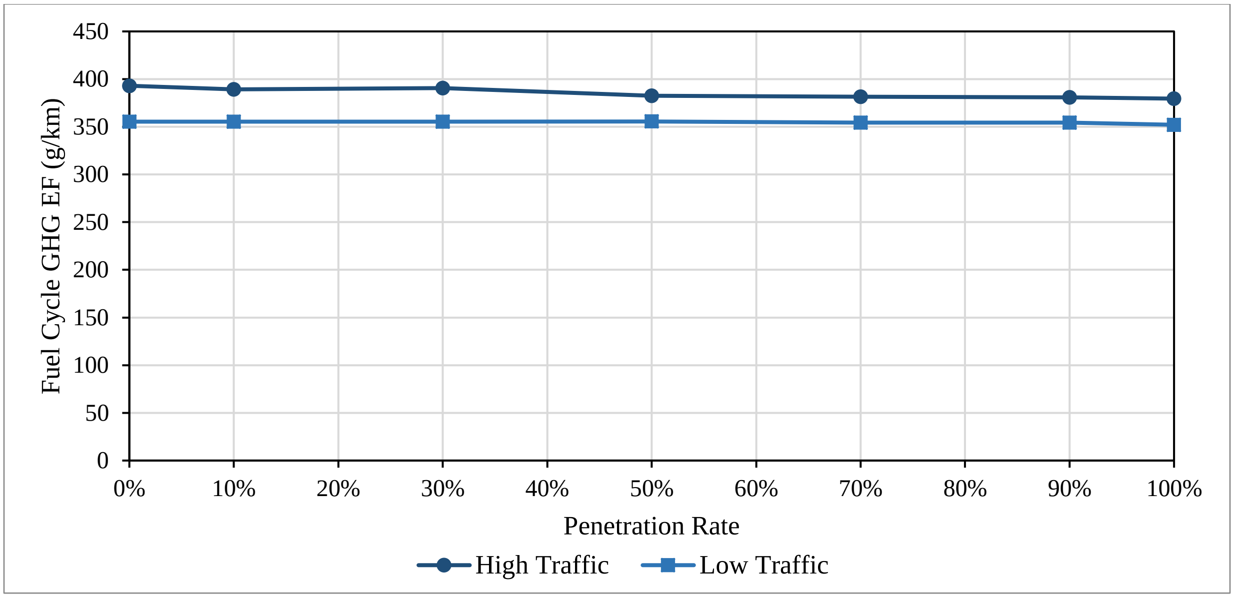

Figure 5.13: Effects of penetration of aggressive AVs on fuel cycle GHG emission factors

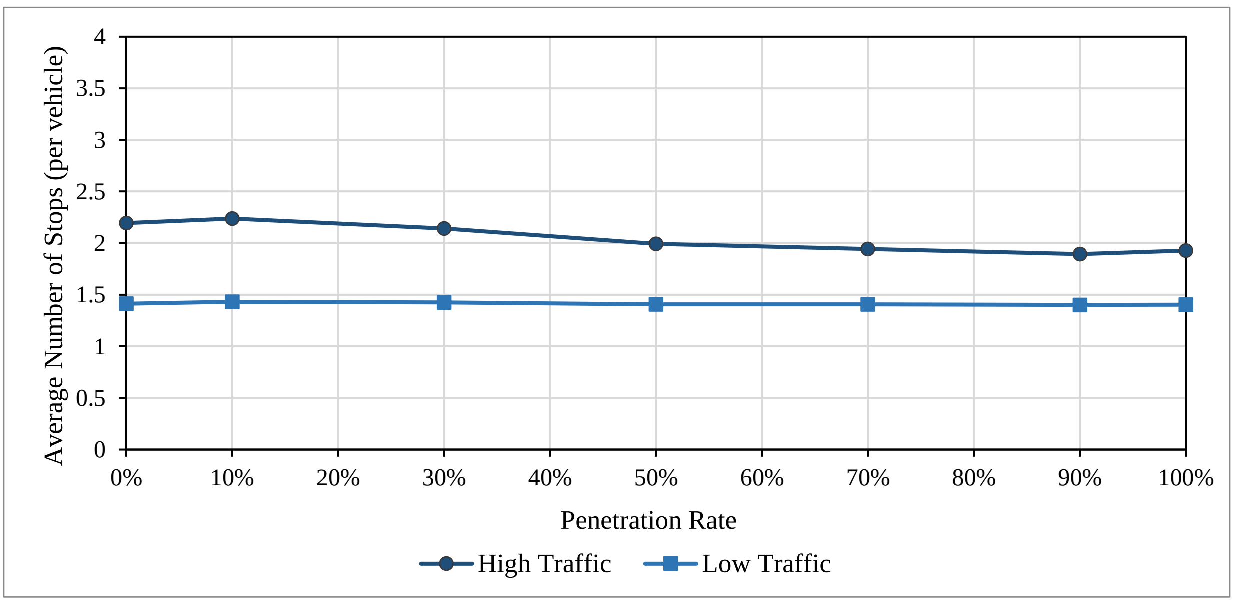

Figure 5.14: Effects of penetration of aggressive AVs on average number of stops

5.2.4 Electrification of the Vehicles

When considering converting the vehicles to operate on electricity, the consequent GHG emissions can be reduced significantly. Electric vehicles essentially eliminate the operating emissions that would otherwise be emitted from the exhaust of gasoline vehicles. In Figure 5.15, the electric vehicle emissions are added and compared to the total fuel cycle emissions shown in the previous sections for gasoline powered vehicles under high and low traffic conditions on College Street.

The equivalent emission factor for the energy generation of electric vehicles is estimated to be 13.81g CO_{2eq}/km regardless of operating mode or driving style (automated vs. conventional). This results in a 96% reduction in emissions from conventional gasoline powered vehicles, under high and low traffic conditions. In this study, the electric vehicle GHG emission estimate is based on the VKT. Therefore, since aggressive AVs and conventional vehicles lead to the same VKT values, under the electrification of the vehicle fleet, there is no added benefit from automated vehicle operations. This leads to the conclusion that, for the goal of reducing emissions from transportation, the focus should shift towards vehicle electrification. The total GHG emissions produced by the energy generation for electric vehicles can be seen in Figure F.3 and Figure F.4 of Appendix F. These show the significant emission reductions that electric vehicles can introduce. However, the cautious AV under the high traffic regime results in a lower GHG emission output by electric vehicles due to the fact that the total VKT is reduced in comparison to the aggressive AVs and conventional vehicles.

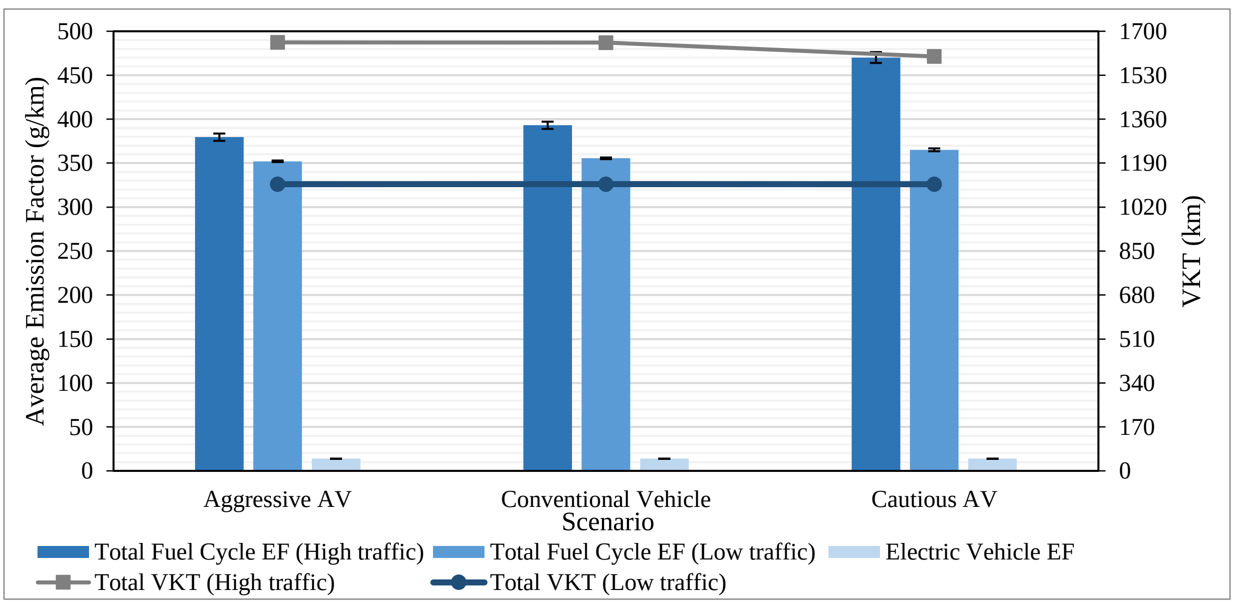

Figure 5.15: Comparison of GHG emission factors between gasoline vehicles and electric vehicles under high and low traffic conditions on College Street *(the bars above the columns represent the standard deviation of the average fuel cycle emission factors)*

Chapter 6
Key Findings and Implications for Future Work

The effects on GHG emissions and traffic performance associated with operations of automated and conventional vehicles are investigated in both uninterrupted (Gardiner Expressway) and interrupted traffic flow (College Street) operating environments, as well as under both high and low traffic demand conditions. This chapter identifies the key findings between the two operating environment case studies and discusses differences in results. The limitations and ways to expand this study in future work are also identified.

6.1 Key Findings

The one-at-a-time sensitivity analysis and the parameter scenario analysis provide an understanding of driving characteristics within the range of possible automated driving behaviour. The findings are summarized in matrix format in Table 6.1 portraying all dimensions of the analytical framework of this study. These findings are further discussed in the rest of this section.

In both uninterrupted and interrupted flow operating environments (whether under high or low traffic conditions), the headway time has proven to be the dominating parameter distinguishing automated vehicles (both aggressively and cautiously programmed) from conventional human operated vehicles. The largest effects on GHG emissions and traffic performance have stemmed from changes in the headway time gap between the vehicles. Aggressive automated vehicles can operate with small safety distances and much closer together at higher speeds. The cautious automated vehicles are programmed to operate with larger gaps and safety distances. Furthermore, the results in terms of GHG emissions and traffic performance differ when considering uninterrupted flow (Gardiner Expressway) in comparison to interrupted flow (College Street).

The uninterrupted flow on the Gardiner Expressway allows vehicles to traverse the network without any external interruptions, such as those introduced by signalized intersections and turning movements. On the other hand, the flow on the College Street network is interrupted by the signalized intersections forcing vehicles to stop for traffic control purposes. As well, it is known that, typically, traffic performance and GHG emissions benefit more under free-flowing conditions. Therefore, the impacts of automated vehicle driving settings on GHG emissions and traffic performance are more noticeable and of a larger magnitude under freeway conditions.

On the Gardiner Expressway, the aggressively operating automated vehicles improve the traffic conditions on the network and result in capacity increases, as well as reduced emissions by large margin. The aggressively programmed AVs have the potential to decongest an otherwise congested network under conventional vehicle operations (assuming no additional demand is induced from the improvement). These findings are consistent with the literature that states that automated vehicles will lead to increase in lane capacity, as well as an improvement in emissions (Bierstedt et al., 2014; Bohm & Häger, 2015; Fagnant & Kockelman, 2015; Liu et al., 2017; Olia et al., 2015, 2017). The cautiously programmed AVs, used to evaluate the possibility of AVs operating more cautiously for user comfort, result in a breakdown of the network, a reduction in capacity, build up of congestion, and an increase in emissions. When there is a higher demand on the network, the impacts of the different driving operations are amplified. The increased demand creates more opportunity for interactions between the vehicles, thus exploiting the different driving characteristics (between cautious or aggressive driving AVs and conventional vehicles) and magnifying their effects.

On the College Street network, the effects of the automated vehicle driving operations are not as evident as on the Gardiner Expressway. The flow is interrupted by turning movements and signalized intersections leading to similar driving operations between aggressive AVs, conventional vehicles, and cautious AVs. This results in minimal changes in GHG emissions, average network speed, average network delay, and average number of stops between the parameter setting scenarios. When there is a higher traffic demand on the network, although the changes were still minimal, these changes were more evident. The aggressive AVs lead to a slight reduction in GHG emissions and number of stops in comparison to conventional vehicles, indicating that the AVs have an improved efficiency in traversing the network. The cautious AVs worsened the traffic condition with increased delays and number of stops, leading to a further increase in the intensity of the emissions.

The difference in the influence of automated vehicle operations between uninterrupted flow on an urban freeway and interrupted flow on an urban arterial street is evident from the results of this study. There is a larger difference between automated vehicles and conventional vehicles in terms of emissions and traffic performance on the Gardiner Expressway case study than what was recorded on the College Street network. The Gardiner Expressway has a 26% reduction in the emission factor from 284 g CO_{2eq}/km (conventional) to 210 g CO_{2eq}/km (aggressive AV driving) under high traffic demand. On the other hand, the College street network only has a 3.44% reduction from 393 g CO_{2eq}/km (conventional) to 380 g CO_{2eq}/km (aggressive AV). It is also interesting to note that the emission intensity on the Gardiner Expressway is lower than that on the College Street network, indicating that vehicles on an urban corridor have a larger fuel consumption and, therefore, an increased emission intensity per kilometer. This is an expected difference, as vehicles travelling at lower speeds with frequent stops consume more fuel. The main reason for this is due to the characteristic differences of freeways and urban arterials. The freedom of movement on a freeway, without the external interference of traffic signals to interrupt the traffic flow frequently, allows for the benefits of more aggressively programmed automated vehicles to be better realized. A higher demand on the network allowed for greater interactions between vehicles, highlighting the influences in the parameter differences between the vehicle operating styles. This is also consistent with the literature, which states that AV traffic performance benefits are more significant under congested conditions (Aria, 2016; Aria et al., 2016). The presence of automation, with aggressive driving operations, on the network resulted in improvements to be recorded even with low market penetration. The trends on the influences of the different driving styles remained similar between the Gardiner Expressway and College Street network. Higher traffic demand led to relatively larger differences in the results yielded by the different vehicle parameter settings on both uninterrupted and interrupted flow networks, while lower demand obscured any operational differences.

When considering the electrification of the vehicle fleet, significant emission reductions are expected. The source of emissions for EVs stem purely from the energy sources, which are much cleaner than that for gasoline, as identified in section 3.4.4. Based on this study, the emission intensity decreases by over 90% to 13.81 g CO_{2eq}/km. It is important to note, however, that the energy consumption of an electric AV and an electric conventional vehicle was assumed to be the same, resulting in the same emission intensity for both. This leads to the conclusion that electrification of the vehicles, in this study, would result in the same emission output, given that aggressive AVs and conventional vehicles are found to have very similar VKT when no latent demand is considered. Despite this, the emission estimate is still valid and highlights that a shift to vehicle electrification is a direction worth pursuing, in addition to automation (with aggressive driving), to cut down the emissions impacts of vehicles.

Table 6.1: Summary of key findings from study for both Gardiner Expressway and College Street case studies

<table>
<tr><th rowspan="2">Network</th><th colspan="2">OAT Analysis</th><th colspan="2">Parameter Scenario Analysis</th></tr>
<tr><th>High Traffic</th><th>Low Traffic</th><th>High Traffic</th><th>Low Traffic</th></tr>
<tr><td>Uninterrupted Flow (Gardiner Expressway)</td><td>• Headway time parameter (CC1) induces the largest change in emission factor, average speed, and delay
• Safety Distance Reduction Factor is the next most relevant parameter</td><td>• Headway time parameter (CC1) and Safety Distance Reduction Factor induce the largest changes in performance
• Magnitude of the changes are not as significant as under high traffic</td><td>• Aggressive AVs reduce emission factor by 26%, increase average speed, reduce delay, and increase capacity to reduce network congestion
• Cautious AVs increase emissions by 35%, reduce average speed, increase delay, and exclude vehicles from the network with a reduction in capacity (congestion build up)</td><td>• Aggressive AVs reduce emissions, increase average speed, and reduce delay but at smaller scale than high traffic condition
• Cautious AVs increase emissions, reduce average speed, and increase delay, but differences were on a smaller scale than high traffic</td></tr>
<tr><td>Interrupted Flow (College Street)</td><td>• Headway time parameter (CC1), Standstill Distance (CC0), Threshold for Entering ‘Following’ (CC3) and Safety Distance Reduction Factor induce largest changes in emission factor and average delay
• Average speed was insensitive to parameter changes</td><td>• Headway time parameter (CC1), Standstill Distance (CC0), Threshold for Entering ‘Following’ (CC3) and Safety Distance Reduction Factor induce largest changes in emission factor and average delay</td><td>• Aggressive AVs reduce emission factor by only 3.44%, increase average speed and reduce delay
• Cautious AVs increase emissions by larger margin (19.62%), reduce average speed and increase average delay</td><td>• Both cautious and aggressive AVs result in minimal changes in emissions, speed, and delay
• Aggressive AVs lead to only 0.95% reduction in the emission factor, while cautious AVs lead to only 2.71% increase in the emission factor</td></tr>
</table>

6.2 Future Work

Future research work on the topic of automated vehicle technology can benefit from improvements in the following areas: methodological improvements and scenario building, analytical and traffic simulation advancements, as well as better definition of automated vehicle settings.

This study, like many others in the literature, is an initial step in estimating the effects of automated vehicles on our transportation networks. Further improvements to the methodology and additional scenarios can be considered to better investigate any implications of vehicle automation.

Developing improved car-following and lane-changing simulation models more representative of automated vehicle operations is another added improvement that could lead to more accurate estimates of changes introduced by vehicle automation. However, the lack of understanding and research on how AVs will operate is a barrier to developing accurate models.

Considering the effects of vehicle connectivity and the additional benefits they may present to vehicle operations and corresponding emission output is a next step that should be considered in future research. But, it is also possible to reverse the process. In other words, future work could include designing an automated vehicle operation setting using simulation to optimize transportation performance and emission reduction and use this as a reference for advising car manufacturers on the design of future automated vehicles.

This study also did not consider any infrastructure changes that will inevitably be in place by the time there is 100% penetration on the network. The effects on interrupted flow urban arterial corridors were observed to be negligible due to restriction on flow; however, future work could include exploiting the communication benefits of connected and automated vehicles (CAV) and create a scenario where signalized intersection coordinate with the movement of the vehicles. This would allow for less restriction on the traffic flow and potentially lead to similar efficiencies that are present on uninterrupted flow freeways.

Finally, this study identified the benefits of electrification on emissions. Further exploring this as a method of emissions control and how to better integrate EVs in our urban environments (i.e., power stations, etc.) should be considered in future research.

Chapter 7
Conclusions

Automated vehicle operations are investigated with respect to the potential changes they can introduce to transportation networks relative to human operated conventional vehicles. The complete spectrum of automated vehicles is covered ranging from aggressive driving to cautious driving, with the default human driving style in the middle. Both uninterrupted flow on a freeway and interrupted flow on an urban arterial corridor are investigated using a microsimulation of the Gardiner Expressway and College Street in Toronto, Canada.

Automated vehicles will introduce changes to the transportation networks that range from improvements (in the case of aggressive AVs) to a breakdown of traffic conditions (in the case of cautious AVs). The degree of influence is dependent on the type of network that the vehicles operate. When considering a freeway network (uninterrupted flow operating environment), such as a section of the Gardiner Expressway, aggressively programmed AVs lead to more efficient traffic flow, increased average speed, increased capacity, reduced delays and ultimately a reduction to the emission intensity of the vehicles. A reduction in the traffic demand on the network offsets the effects of automated vehicle operations. Considering an urban arterial corridor (interrupted flow operating environment), such as a section of College Street with signalized intersections, the differences in the operating styles of automated vehicles and conventional vehicles is not as apparent. The traffic flow is interrupted frequently preventing any changes in driving style from being fully exploited in the analysis. Minimal changes between the parameter setting scenarios, however, indicate the trend of improved emission and traffic performance with aggressive AVs. The electrification of the vehicle fleet results in the largest emission reduction, as expected. A shift towards making EVs a larger portion of the vehicle fleet is worth considering, as their benefits in emissions can exceed the benefits presented by vehicle automation alone.

Overall, there is potential for a reduction in emissions and improvement in traffic performance with the introduction of automated vehicles into transportation networks. They will transform the way people and goods are moved around and will introduce behavioural shifts in urban environments. Their full effects on the environment will become noticeable when all possible impacts of AVs are put together and considered as a whole.

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Appendices

Appendix A: Gardiner Expressway traffic profiles

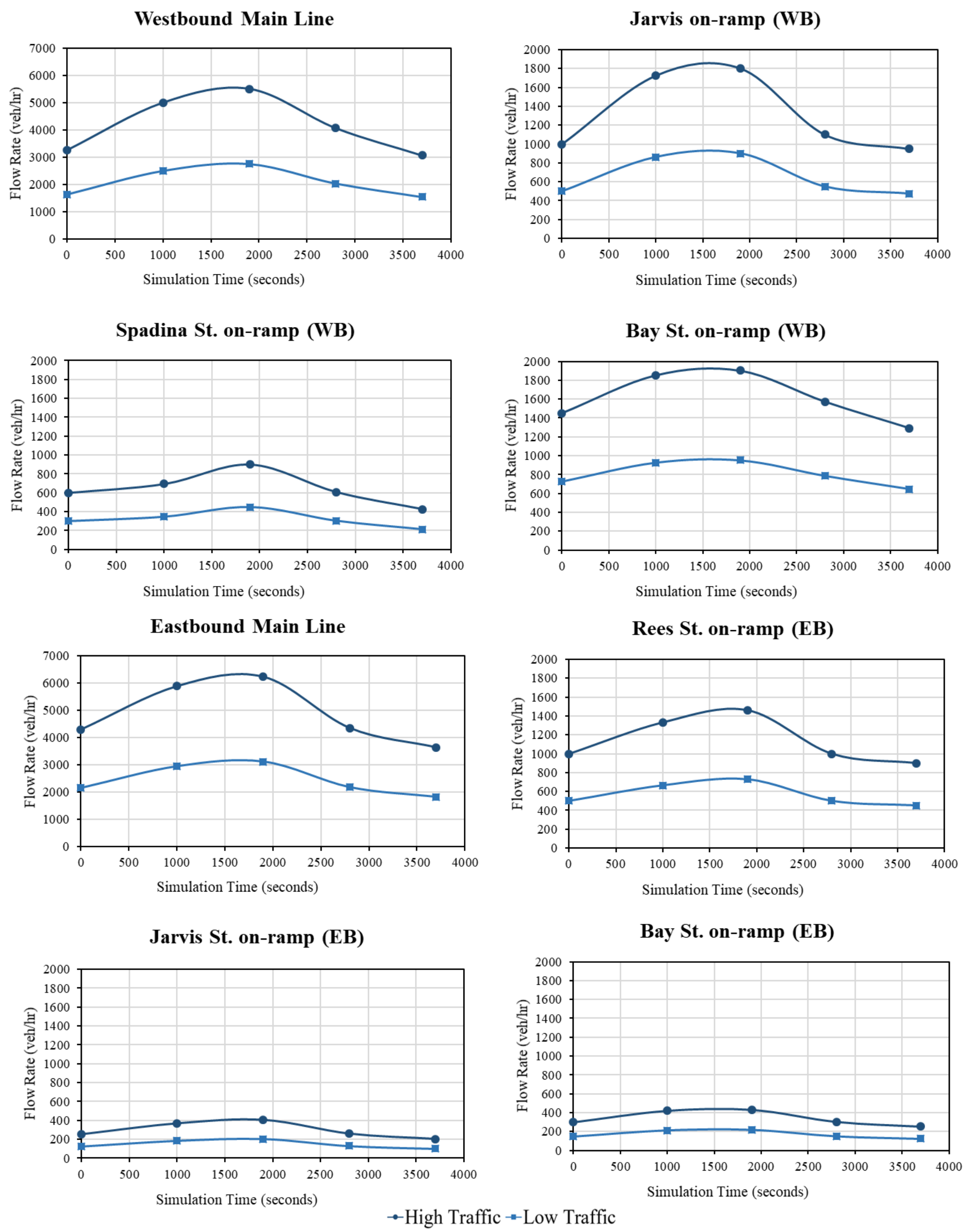

Figure A.1: High traffic and low traffic regime demand profiles (Gardiner network)

Appendix B: College Street traffic profiles

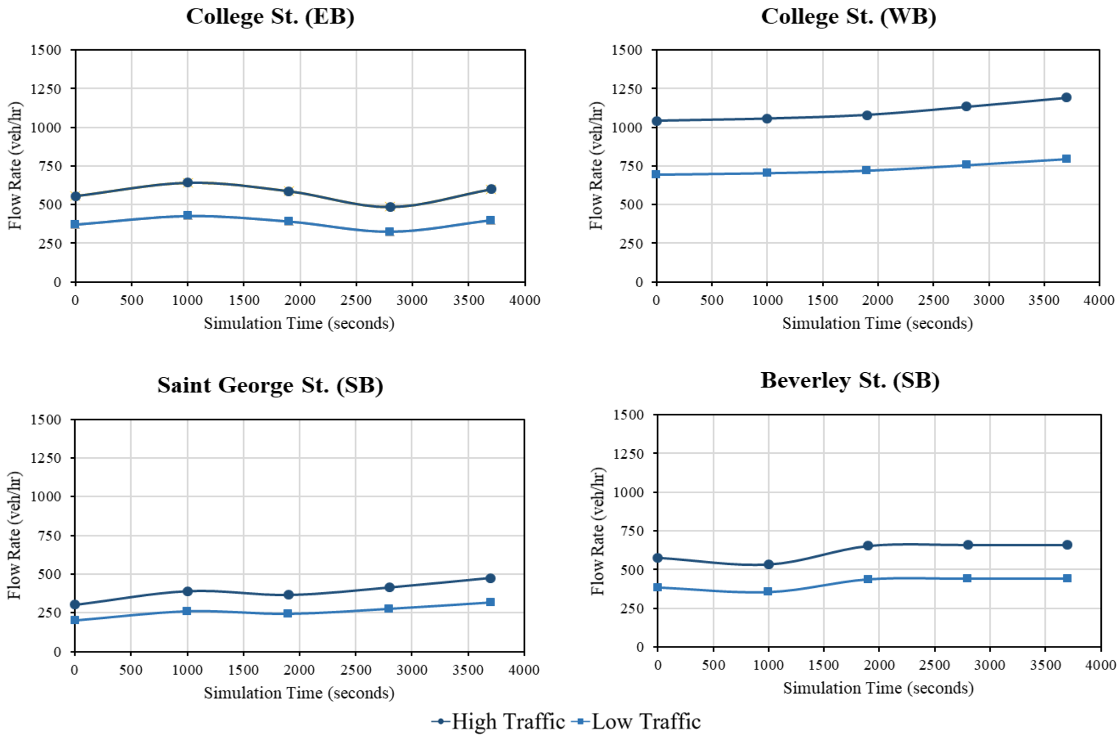

Figure B.1: High traffic and low traffic regime demand profiles (College St. network)

Appendix C: OAT sensitivity analysis results for Gardiner Expressway

Table C.1: OAT results for high traffic regime

		GHG Emission Factor (g/km)		Delay (s)		Average Speed	
		Result	% Difference	Result	% Difference	Result	% Difference
Default		284.04	--	79.96	--	57.62	--
CC0	0.5	276.89	-2.52%	77.13	-0.99%	58.81	0.42%
	1	280.82	-1.14%	79.70	-0.09%	57.72	0.03%
	1.5	284.04	0.00%	79.96	0.00%	57.62	0.00%
	2	283.14	-0.32%	80.17	0.07%	57.57	-0.02%
	2.5	288.08	1.42%	85.57	1.98%	55.68	-0.68%
CC1	0.5	256.51	-9.69%	54.21	-9.07%	67.90	3.62%
	0.9	284.04	0.00%	79.96	0.00%	57.62	0.00%
	1.3	309.13	8.83%	112.27	11.38%	48.45	-3.23%
	1.7	344.17	21.17%	200.98	42.61%	32.92	-8.70%
	2.1	372.09	31.00%	269.12	66.60%	25.98	-11.14%
CC3 (-)	4	287.78	1.32%	81.73	0.62%	57.00	-0.22%
	6	286.24	0.77%	82.38	0.85%	56.81	-0.29%
	8	284.04	0.00%	79.96	0.00%	57.62	0.00%
	10	283.05	-0.35%	80.81	0.30%	57.41	-0.08%
	12	283.41	-0.22%	83.83	1.36%	56.47	-0.41%
	14	281.13	-1.02%	77.58	-0.84%	58.52	0.31%
	16	277.89	-2.16%	78.69	-0.45%	58.35	0.25%
CC4(-)/CC5(+)	0.1	279.28	-1.68%	76.82	-1.10%	58.61	0.35%
	0.23	281.63	-0.85%	75.72	-1.49%	59.23	0.56%
	0.35	284.04	0.00%	79.96	0.00%	57.62	0.00%
	0.48	286.91	1.01%	78.61	-0.47%	58.17	0.19%
	0.6	288.48	1.56%	87.83	2.77%	55.21	-0.85%
CC7	0.05	283.56	-0.17%	80.90	0.33%	57.54	-0.03%
	0.15	285.51	0.52%	80.63	0.24%	57.36	-0.09%
	0.25	284.04	0.00%	79.96	0.00%	57.62	0.00%
	0.35	283.69	-0.12%	83.56	1.27%	56.44	-0.42%
	0.45	282.42	-0.57%	79.72	-0.08%	57.73	0.04%
CC8	3.1	283.88	-0.06%	84.08	1.45%	56.29	-0.47%
	3.3	283.31	-0.26%	79.45	-0.18%	57.83	0.07%
	3.5	284.04	0.00%	79.96	0.00%	57.62	0.00%
	3.7	285.63	0.56%	82.50	0.89%	56.97	-0.23%
	3.9	281.70	-0.82%	75.23	-1.66%	59.41	0.63%
CC9	1.1	284.72	0.24%	80.21	0.09%	57.58	-0.01%
	1.3	282.05	-0.70%	79.12	-0.30%	57.97	0.12%
	1.5	284.04	0.00%	79.96	0.00%	57.62	0.00%
	1.7	282.08	-0.69%	74.91	-1.78%	59.43	0.64%
	1.9	283.98	-0.02%	82.03	0.73%	56.94	-0.24%
MinHdwy	0.2	281.53	-0.88%	84.68	1.66%	56.25	-0.48%
	0.35	283.87	-0.06%	77.41	-0.90%	58.66	0.37%
	0.5	284.04	0.00%	79.96	0.00%	57.62	0.00%
	0.65	284.48	0.16%	81.54	0.56%	57.19	-0.15%
	0.8	284.58	0.19%	76.80	-1.11%	58.71	0.38%
SDRF	0.1	239.72	-15.60%	53.04	-9.48%	68.47	3.82%
	0.25	250.44	-11.83%	58.65	-7.50%	65.94	2.93%
	0.4	264.61	-6.84%	74.56	-1.90%	59.67	0.72%
	0.6	284.04	0.00%	79.96	0.00%	57.62	0.00%
	0.7	283.72	-0.11%	86.03	2.14%	55.48	-0.76%

Table C.2: OAT results for low traffic regime

		GHG Emission Factor (g/km)		Delay (s)		Average Speed	
		Result	% Difference	Result	% Difference	Result	% Difference
Default		197.81	--	2.71	--	104.28	--
CC0	0.5	196.80	-0.51%	2.50	-0.11%	104.51	0.12%
	1	197.29	-0.27%	2.61	-0.05%	104.38	0.05%
	1.5	197.81	0.00%	2.71	0.00%	104.28	0.00%
	2	197.78	-0.02%	2.71	0.00%	104.28	0.00%
	2.5	198.09	0.14%	2.86	0.08%	104.11	-0.09%
CC1	0.5	194.25	-1.80%	1.92	-0.40%	105.14	0.44%
	0.9	197.81	0.00%	2.71	0.00%	104.28	0.00%
	1.3	201.59	1.91%	3.51	0.40%	103.42	-0.43%
	1.7	202.38	2.31%	4.40	0.85%	102.47	-0.91%
	2.1	204.36	3.31%	6.34	1.83%	100.48	-1.92%
CC3 (-)	4	198.46	0.33%	2.78	0.04%	104.20	-0.04%
	6	198.03	0.11%	2.74	0.02%	104.25	-0.01%
	8	197.81	0.00%	2.71	0.00%	104.28	0.00%
	10	197.64	-0.09%	2.71	0.00%	104.27	0.00%
	12	197.03	-0.40%	2.60	-0.06%	104.40	0.06%
	14	196.77	-0.53%	2.64	-0.03%	104.34	0.03%
	16	196.87	-0.47%	2.66	-0.03%	104.33	0.03%
CC4(-)/CC5(+)	0.1	197.03	-0.40%	2.71	0.00%	104.26	-0.01%
	0.23	197.14	-0.34%	2.74	0.01%	104.25	-0.02%
	0.35	197.81	0.00%	2.71	0.00%	104.28	0.00%
	0.48	197.84	0.01%	2.64	-0.03%	104.36	0.04%
	0.6	198.55	0.37%	2.66	-0.02%	104.33	0.03%
CC7	0.05	196.87	-0.48%	2.59	-0.06%	104.40	0.06%
	0.15	198.01	0.10%	2.71	0.00%	104.28	0.00%
	0.25	197.81	0.00%	2.71	0.00%	104.28	0.00%
	0.35	197.51	-0.15%	2.57	-0.07%	104.43	0.08%
	0.45	199.12	0.66%	2.53	-0.09%	104.47	0.10%
CC8	3.1	197.74	-0.04%	2.70	0.00%	104.28	0.00%
	3.3	197.76	-0.03%	2.70	0.00%	104.28	0.00%
	3.5	197.81	0.00%	2.71	0.00%	104.28	0.00%
	3.7	197.76	-0.03%	2.71	0.00%	104.28	0.00%
	3.9	197.76	-0.03%	2.70	0.00%	104.29	0.01%
CC9	1.1	197.81	0.00%	2.69	-0.01%	104.30	0.01%
	1.3	197.81	0.00%	2.69	-0.01%	104.29	0.01%
	1.5	197.81	0.00%	2.71	0.00%	104.28	0.00%
	1.7	197.75	-0.03%	2.70	0.00%	104.28	0.00%
	1.9	197.76	-0.03%	2.70	0.00%	104.28	0.00%
MinHdwy	0.2	196.98	-0.42%	2.58	-0.07%	104.42	0.07%
	0.35	197.34	-0.24%	2.66	-0.02%	104.32	0.02%
	0.5	197.81	0.00%	2.71	0.00%	104.28	0.00%
	0.65	197.59	-0.12%	2.69	-0.01%	104.30	0.01%
	0.8	198.07	0.13%	2.78	0.04%	104.20	-0.04%
SDRF	0.1	191.35	-3.27%	1.85	-0.44%	105.22	0.48%
	0.25	192.82	-2.53%	2.02	-0.35%	105.03	0.38%
	0.4	194.24	-1.81%	2.17	-0.27%	104.86	0.30%
	0.6	197.81	0.00%	2.71	0.00%	104.28	0.00%
	0.7	200.52	1.37%	3.23	0.26%	103.72	-0.28%

Appendix D: Total GHG emissions results for Gardiner Expressway

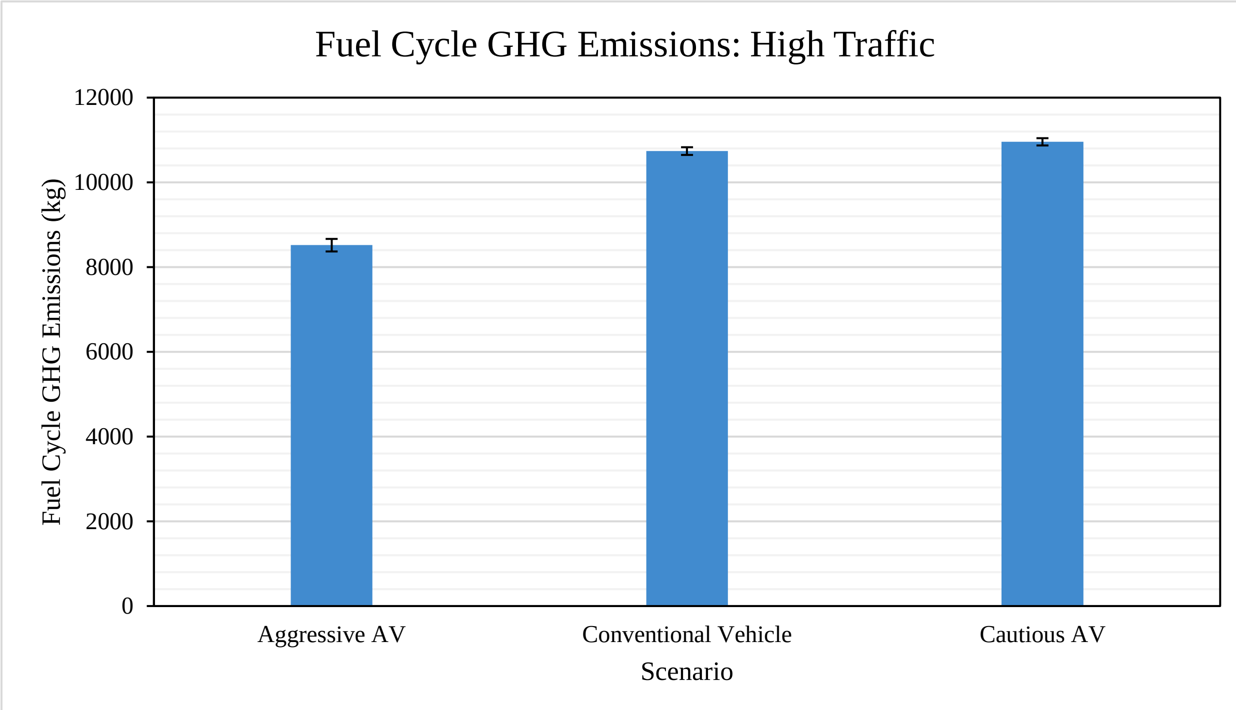

Figure D.1: Total fuel cycle GHG emissions for Gardiner Expressway, high traffic

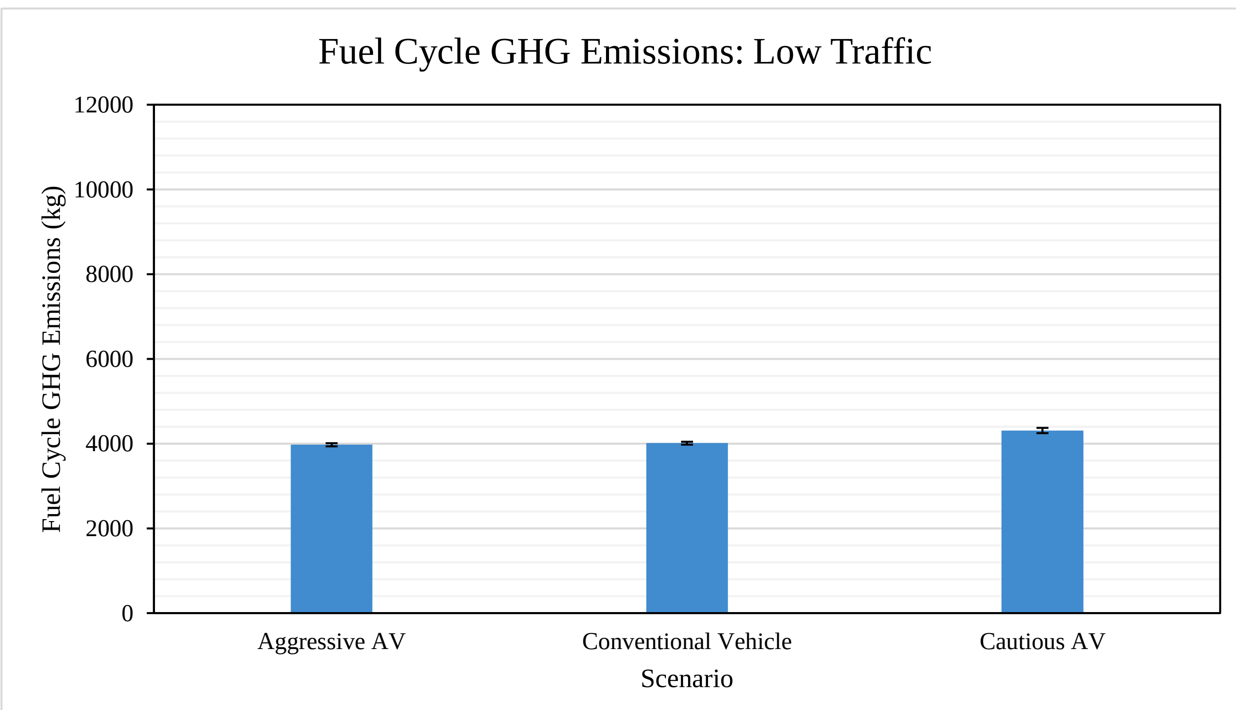

Figure D.2: Total fuel cycle GHG emissions for Gardiner Expressway, low traffic

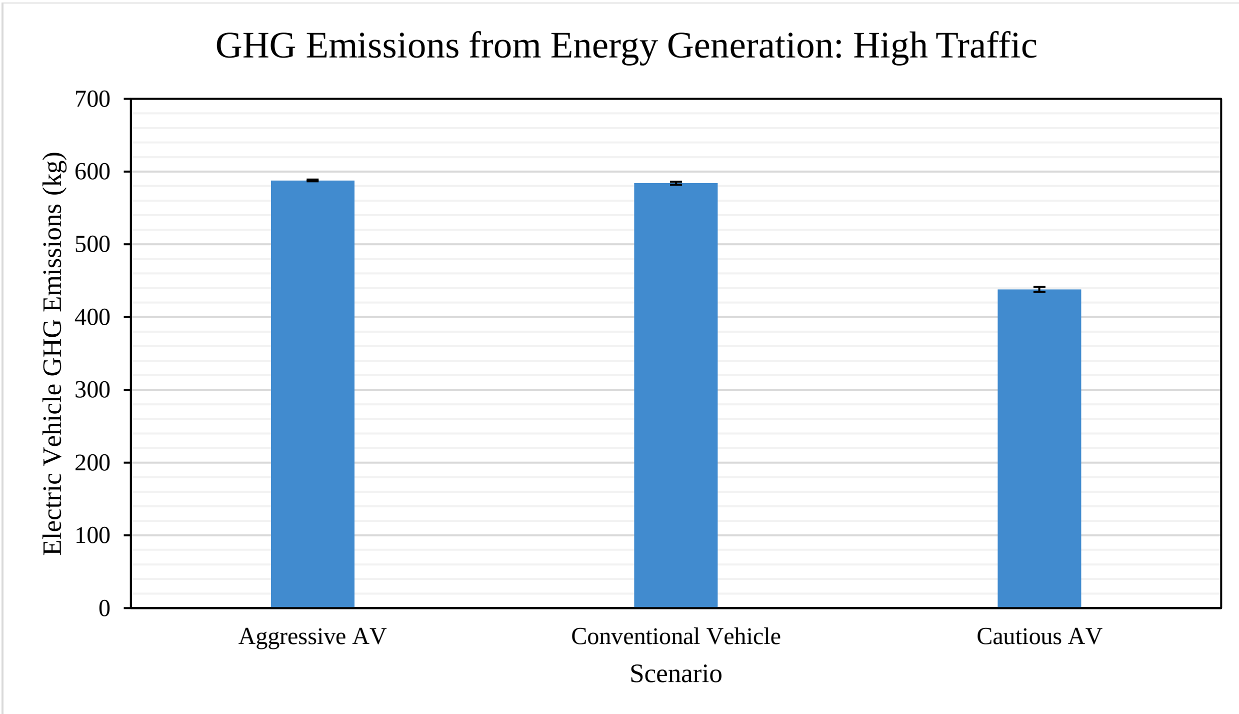

Figure D.3: Total energy generation GHG emissions for Gardiner Expressway, high traffic

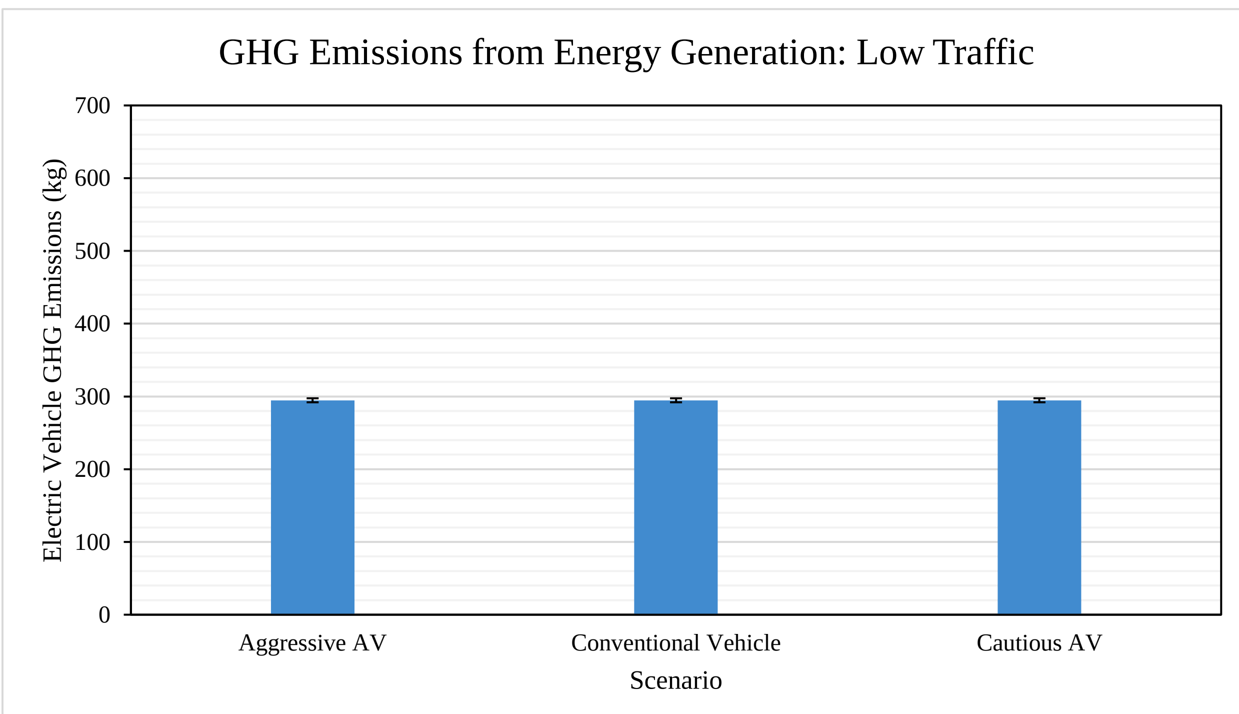

Figure D.4: Total energy generation GHG emissions for Gardiner Expressway, low traffic

Appendix E: OAT sensitivity analysis results for College Street

Table E.1: OAT results for low traffic regime

		GHG Emission Factor (g/km)		Delay (s)		Average Speed	
		Result	% Difference	Result	% Difference	Result	% Difference
Default		355.50	--	34.87	--	28.40	--
CC0	0.5	352.86	-0.74%	34.64	-0.06%	28.48	0.02%
	1	355.21	-0.08%	34.87	0.00%	28.40	0.00%
	1.5	355.50	0.00%	34.87	0.00%	28.40	0.00%
	2	356.07	0.16%	35.28	0.12%	28.24	-0.04%
	2.5	357.61	0.59%	35.18	0.09%	28.28	-0.03%
CC1	0.5	356.91	0.40%	34.60	-0.08%	28.50	0.03%
	0.9	355.50	0.00%	34.87	0.00%	28.40	0.00%
	1.3	355.68	0.05%	35.27	0.11%	28.24	-0.04%
	1.7	360.96	1.54%	36.05	0.33%	27.95	-0.13%
	2.1	364.12	2.43%	36.99	0.60%	27.61	-0.22%
CC3 (-)	4	355.23	-0.08%	34.85	0.00%	28.40	0.00%
	6	355.58	0.02%	34.96	0.03%	28.36	-0.01%
	8	355.50	0.00%	34.87	0.00%	28.40	0.00%
	10	355.95	0.13%	34.94	0.02%	28.37	-0.01%
	12	356.30	0.23%	34.95	0.02%	28.36	-0.01%
	14	356.35	0.24%	34.98	0.03%	28.35	-0.01%
	16	357.61	0.59%	35.00	0.04%	28.35	-0.01%
CC4(-)/CC5(+)	0.1	355.07	-0.12%	34.98	0.03%	28.35	-0.01%
	0.23	354.53	-0.27%	34.98	0.03%	28.36	-0.01%
	0.35	355.50	0.00%	34.87	0.00%	28.40	0.00%
	0.48	356.11	0.17%	34.93	0.02%	28.37	-0.01%
	0.6	356.82	0.37%	35.04	0.05%	28.34	-0.02%
CC7	0.05	353.85	-0.46%	34.97	0.03%	28.37	-0.01%
	0.15	356.28	0.22%	35.03	0.05%	28.34	-0.02%
	0.25	355.50	0.00%	34.87	0.00%	28.40	0.00%
	0.35	356.01	0.14%	34.95	0.02%	28.36	-0.01%
	0.45	357.43	0.54%	34.99	0.03%	28.35	-0.01%
CC8	3.1	355.45	-0.01%	34.91	0.01%	28.38	-0.01%
	3.3	355.44	-0.02%	34.87	0.00%	28.39	0.00%
	3.5	355.50	0.00%	34.87	0.00%	28.40	0.00%
	3.7	355.46	-0.01%	34.86	0.00%	28.40	0.00%
	3.9	355.45	-0.01%	34.86	0.00%	28.40	0.00%
CC9	1.1	355.52	0.01%	34.88	0.00%	28.39	0.00%
	1.3	355.51	0.00%	34.87	0.00%	28.40	0.00%
	1.5	355.50	0.00%	34.87	0.00%	28.40	0.00%
	1.7	355.46	-0.01%	34.86	0.00%	28.40	0.00%
	1.9	355.45	-0.01%	34.86	0.00%	28.40	0.00%
MinHdwy	0.2	355.22	-0.08%	34.84	-0.01%	28.40	0.00%
	0.35	355.45	-0.01%	34.92	0.01%	28.38	-0.01%
	0.5	355.50	0.00%	34.87	0.00%	28.40	0.00%
	0.65	355.53	0.01%	34.86	0.00%	28.40	0.00%
	0.8	355.57	0.02%	34.88	0.00%	28.39	0.00%
SDRF	0.1	354.03	-0.41%	34.60	-0.07%	28.50	0.03%
	0.25	353.33	-0.61%	34.61	-0.07%	28.49	0.03%
	0.4	354.34	-0.33%	34.82	-0.01%	28.41	0.00%
	0.6	355.50	0.00%	34.87	0.00%	28.40	0.00%
	0.7	355.82	0.09%	34.99	0.04%	28.35	-0.01%

Table E.2: OAT results for high traffic regime

		GHG Emission Factor (g/km)		Delay (s)		Average Speed	
		Result	% Difference	Result	% Difference	Result	% Difference
Default		393.04	--	43.80	--	25.37	--
CC0	0.5	386.65	-1.62%	41.03	-0.70%	26.23	0.22%
	1	391.05	-0.51%	42.32	-0.38%	25.83	0.12%
	1.5	393.04	0.00%	43.80	0.00%	25.37	0.00%
	2	391.54	-0.38%	45.93	0.54%	24.75	-0.16%
	2.5	397.98	1.26%	48.31	1.15%	24.11	-0.32%
CC1	0.5	390.53	-0.64%	41.94	-0.47%	25.96	0.15%
	0.9	393.04	0.00%	43.80	0.00%	25.37	0.00%
	1.3	401.80	2.23%	46.22	0.62%	24.65	-0.18%
	1.7	415.19	5.63%	53.48	2.46%	22.69	-0.68%
	2.1	434.01	10.42%	64.37	5.23%	20.40	-1.26%
CC3 (-)	4	399.34	1.60%	45.52	0.44%	24.87	-0.13%
	6	394.67	0.41%	44.25	0.11%	25.25	-0.03%
	8	393.04	0.00%	43.80	0.00%	25.37	0.00%
	10	392.45	-0.15%	43.11	-0.18%	25.57	0.05%
	12	393.44	0.10%	44.07	0.07%	25.28	-0.02%
	14	392.08	-0.25%	44.38	0.15%	25.23	-0.04%
	16	391.49	-0.39%	43.69	-0.03%	25.40	0.01%
CC4(-)/CC5(+)	0.1	389.94	-0.79%	42.55	-0.32%	25.75	0.10%
	0.23	391.16	-0.48%	43.13	-0.17%	25.58	0.05%
	0.35	393.04	0.00%	43.80	0.00%	25.37	0.00%
	0.48	392.67	-0.09%	44.01	0.05%	25.34	-0.01%
	0.6	396.38	0.85%	44.84	0.26%	25.08	-0.07%
CC7	0.05	390.85	-0.56%	43.82	0.00%	25.36	0.00%
	0.15	393.59	0.14%	43.07	-0.19%	25.59	0.05%
	0.25	393.04	0.00%	43.80	0.00%	25.37	0.00%
	0.35	392.44	-0.15%	43.68	-0.03%	25.40	0.01%
	0.45	392.92	-0.03%	43.90	0.03%	25.36	0.00%
CC8	3.1	390.99	-0.52%	43.00	-0.20%	25.60	0.06%
	3.3	393.97	0.24%	43.95	0.04%	25.30	-0.02%
	3.5	393.04	0.00%	43.80	0.00%	25.37	0.00%
	3.7	391.44	-0.41%	43.47	-0.09%	25.47	0.03%
	3.9	391.80	-0.32%	43.69	-0.03%	25.40	0.01%
CC9	1.1	394.65	0.41%	44.12	0.08%	25.27	-0.03%
	1.3	393.63	0.15%	43.88	0.02%	25.36	0.00%
	1.5	393.04	0.00%	43.80	0.00%	25.37	0.00%
	1.7	391.97	-0.27%	43.78	0.00%	25.38	0.00%
	1.9	391.63	-0.36%	43.64	-0.04%	25.42	0.01%
MinHdwy	0.2	386.81	-1.59%	42.48	-0.34%	25.78	0.10%
	0.35	390.65	-0.61%	41.93	-0.48%	25.93	0.14%
	0.5	393.04	0.00%	43.80	0.00%	25.37	0.00%
	0.65	393.92	0.22%	43.49	-0.08%	25.45	0.02%
	0.8	392.51	-0.14%	43.49	-0.08%	25.45	0.02%
SDRF	0.1	388.19	-1.24%	41.63	-0.55%	26.05	0.17%
	0.25	388.72	-1.10%	41.88	-0.49%	25.95	0.15%
	0.4	389.95	-0.79%	42.40	-0.36%	25.80	0.11%
	0.6	393.04	0.00%	43.80	0.00%	25.37	0.00%
	0.7	398.40	1.36%	46.04	0.57%	24.71	-0.17%

Appendix F: Total GHG emissions results for College Street

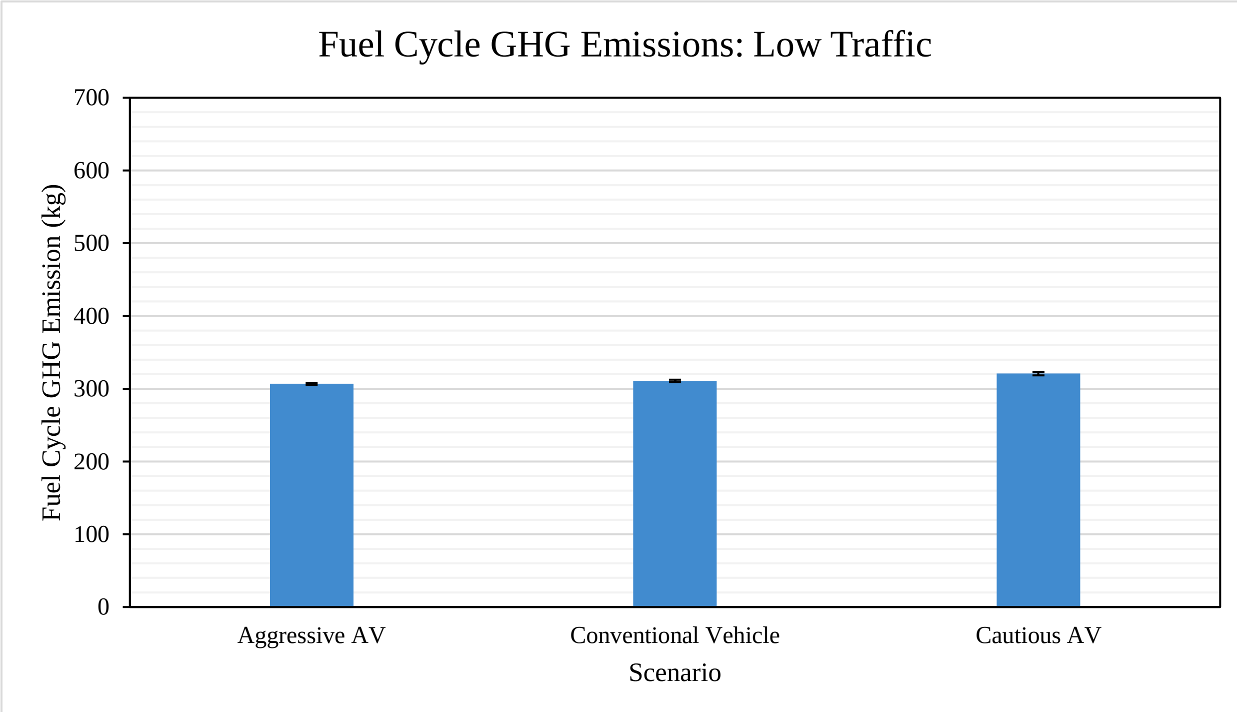

Figure F.1: Total fuel cycle GHG emissions for College Street, low traffic

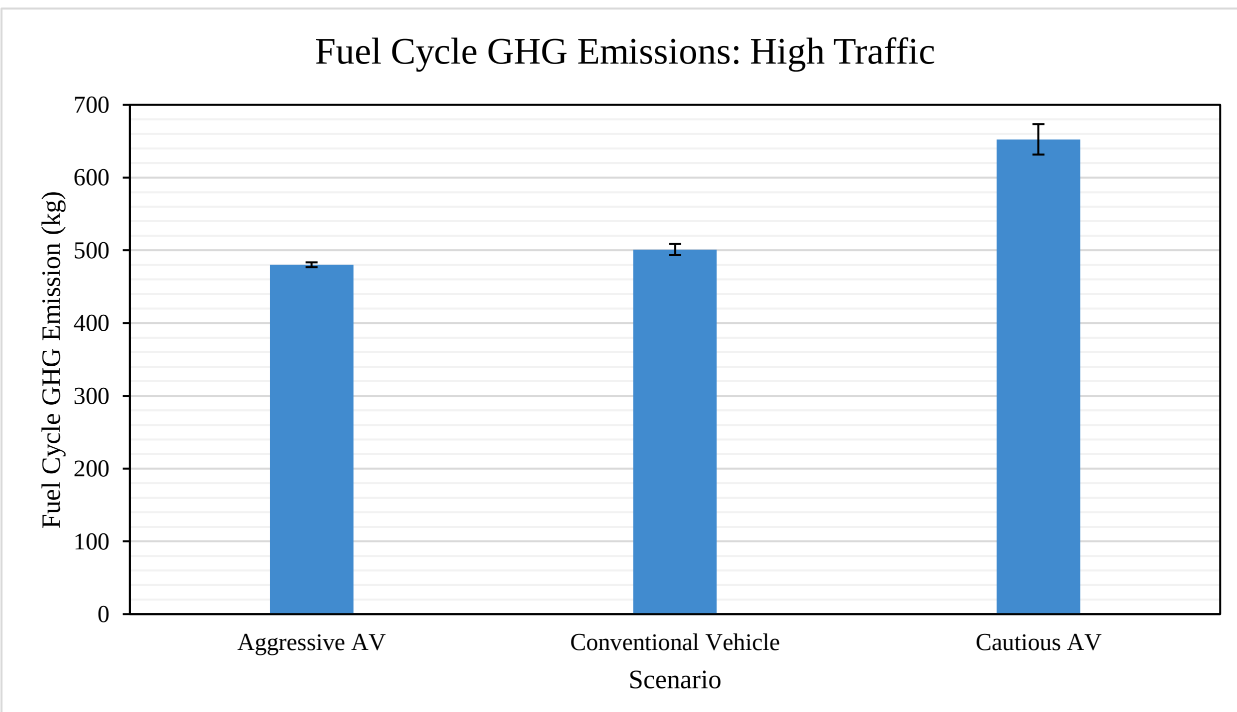

Figure F.2: Total fuel cycle GHG emissions for College Street, high traffic

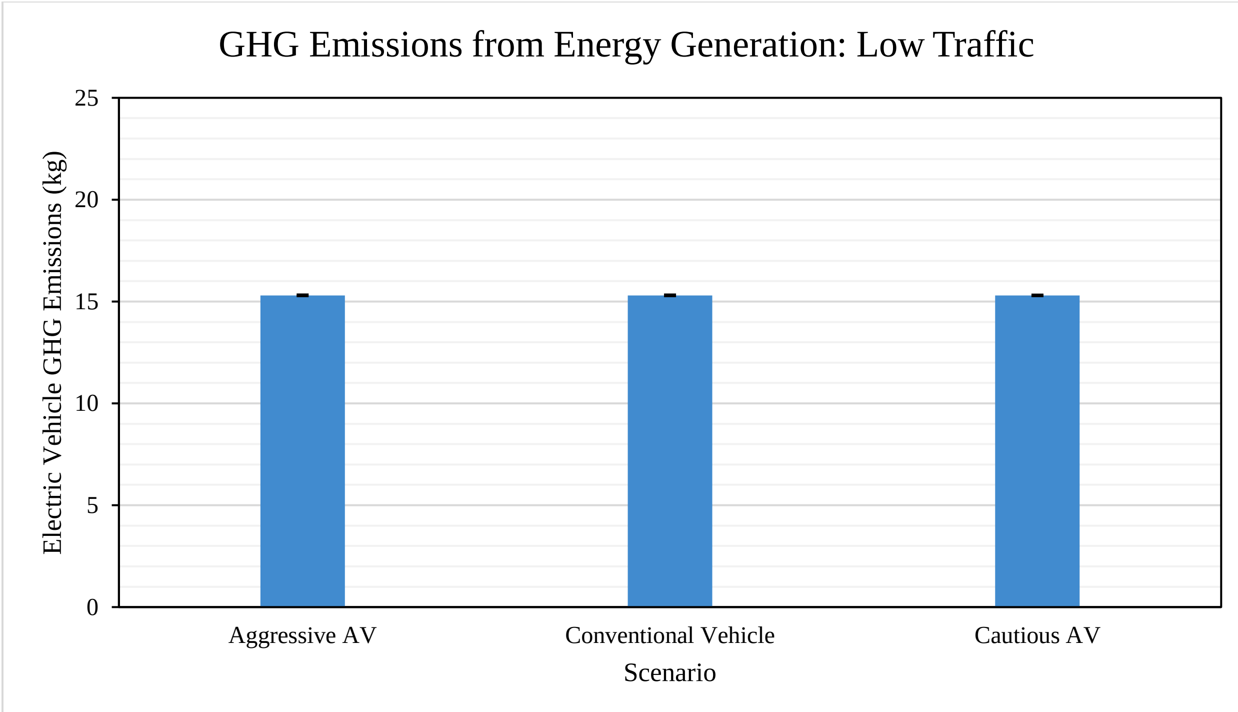

Figure F.3: Total energy generation GHG emissions for College Street, low traffic

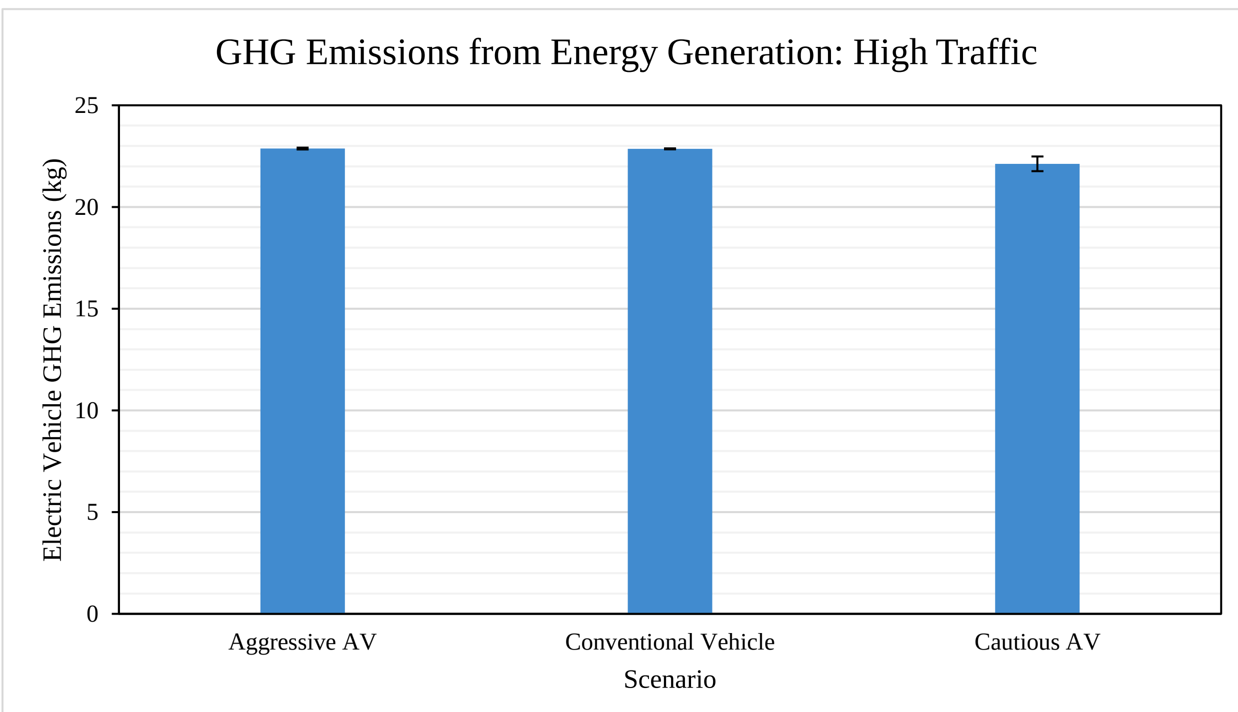

Figure F.4: Total energy generation GHG emissions for College Street, high traffic

Conference Paper Acknowledgments

Sections of this thesis are based on research modified from a paper presented at the 97th Annual Meeting of the Transportation Research Board. The reference is as follows:

Stogios, C., Saleh, M., Ganji, A., Tu, R., Xu, J., Roorda, M.J., Hatzopoulou, M. (2017). *Determining the Effects of Automated Vehicle Driving Behaviour on Vehicle Emissions and Performance of an Urban Corridor*. Presented at the 97th Annual Meeting of the Transportation Research Board, Washington D.C., January 2018

All other sources used are referenced throughout the document.