IMPACT OF OPERATIONAL SPEED CHARACTERISTICS OF HEAVY VEHICLES ON HIGH-SPEED HIGHWAYS

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ABSTRACT

This thesis explores the safety impact of differential speed limit (DSL) strategy by considering gross vehicle weight (GVW) combined with average speed enforcement (ASE) for heavy vehicles. The study used one-year of Weigh-in-Motion (WIM) data (2014) and one-month of Global Positioning System (GPS) data (Mar 2016) collected from along the Trans-Canada Highway 1 in British Columbia.

The research consisted of a data-driven analysis and a two-part simulation analysis. As the DSL investigated was based on GVW, a Modified-Federal Highway Administration (M-FHWA) classification that explicitly considered GVW was tested alongside the FHWA classification regarding average speed and GVW. The simulation analysis assessed the DSL strategy associated with M-FHWA classification and ASE strategy's impact on the safety of heavy vehicles.

In general, the analyses showed that DSL adopted with M-FHWA classes combined with ASE would be effective in reducing heavy vehicle speed and improving highway safety.

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LIST OF ACRONYMS AND ABBREVIATIONS

AADT	Average Annual Daily Traffic
ASE	Average Speed Enforcement
DOT	Department of Transportation
DSL	Differential Speed Limit
FHWA	Federal Highway Administration
GIS	Geographic Information System
GPS	Global Positioning System
GVW	Gross Vehicle Weight
QQ plot	Quantile-Quantile plot
SSE	Spot Speed Enforcement
USL	Uniform Speed Limit
VSL	Variable Speed Limit
WIM	Weigh-in-Motion

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Chapter 1 Introduction

1.1 Problem Statement

Heavy vehicle collisions on high-speed rural highways are largely due to human errors such as speeding, impaired driving and fatigued driving. Speeding, which is defined in police reports as "driving in excess of the posted speed limit" or "driving too fast for environmental conditions," is considered as a major contributing factor for collisions involving heavy vehicles on high-speed highways (NHTSA, 2008). The mass and speed of heavy vehicles, contribute to the often severe heavy vehicle collisions that occur on roadways, particularly high-speed highways.

The 2018 Humboldt Broncos collision between a bus and a semi-trailer truck at an intersection on HWY 35 in Saskatchewan, Canada resulted in 16 fatalities and 13 serious injuries and can be viewed as a representative example of the disastrous consequences that may be associated with a heavy vehicle collision (CBC News, 2018). In British Columbia, Canada, statistics from 2013 to 2017 show an average of 14,000 heavy vehicle collisions/year involving an average of 56 fatalities/year and 3,300 injuries/year (ICBC, 2018).

Numerous engineering safety countermeasures are already deployed on rural highways in North America to reduce the number and severity of collisions involving heavy vehicles. Countermeasures include speed limits, medians, transverse marking, transverse rumble strips, and speed feedback information (FHWA, 2009; Jonah et al., 2009). Speed limits have been applied in various ways and may be enforced through manual or automatic speed measurements, and probably have the longest history of scientific and non-scientific debate of any countermeasure regarding the impact on safety.

In North America, the most common type of speed limit is the maximum speed limit (sometimes combined with a minimum speed limit). A speed limit that applies to all vehicles equally is known as a uniform speed limit (USL). Some high-speed highways have separate speed limits for passenger cars and heavy vehicles. These speed limits are known as differential speed limits (DSL) and may be regulated differently depending on the specific by-laws of different jurisdictions (Forbes et al., 2012). DSL is used mainly to reduce the severity of collisions involving heavy vehicles (Johnson and Pawar, 2005; Saccomanno et al., 2009).

Seven of the fifty-two States in the United States operate a DSL for passenger cars and heavy vehicles on selected highways (J.Gates et al., 2016). Gross Vehicle Weight (GVW) is one of the key criteria used to differentiate speed limits for passenger cars and heavy vehicles. In Indiana, the speed limits for vehicles with a GVW of greater than 26,000 lbs are lowered by 10 to 20 mph on rural interstate highways (J.Gates et al., 2016; NHTSA, 2012). California, Michigan and Washington use 10,000 lbs as the GVW criterion for differentiating speed limits on rural interstate highways (J.Gates et al., 2016; NHTSA, 2012). Most states with DSLs have only a very generic rationale based on the longer braking distances and less flexible lane-changing and/or overtaking maneuverability of heavy vehicles compared with passenger cars.

Canada does not apply DSLs to heavy vehicles, but two Canadian provinces (Ontario and Quebec) have mandated the use of an advanced Electronic Control Module (ECM) known as a heavy vehicle speed limiter which mechanically limits the maximum traveling speed of heavy vehicles to 105 km/h on highways where the maximum speed limit is 100 km/h (Spoerri et al., 2008). As it is known that passenger cars typically travel at 10 to 20 km/h faster than the posted maximum speed limit, the effect of ECM on traffic flow on highways in Ontario and Quebec could be similar to the effect of a DSL. Saccomanno et al. reported that mandatory speed limiters can produce safety benefits under various traffic conditions tested using microsimulation (Saccomanno et al., 2009).

In the United Kingdom, which mandated the installation of speed limiters for heavy vehicles in 1992, the number of collisions involving a heavy vehicle declined by 26 % from 1993 to 2005 (European Commission, 2009; Transport Canada, 2008).

In general, it seems possible that well-organized speed enforcement tactics/techniques will maximize the effect of speed limits on heavy vehicles' travel speed, and a lack of actual and/or perceived law enforcement will reduce the effect of such limits. Various types of speed enforcement are currently applied by jurisdictions across North America (D. Soole et al., 2014). Enforcement ranges from manual speed enforcement by field police officers to sophisticated automatic speed enforcement systems (ASES). Both approaches usually use some kind of radar detection system with/without automatic license plate readers to detect and record vehicles' speed limit violations. Neither approach can take into account the GVW of specific vehicles. Heavy vehicle speed enforcement simply relies on surrogate weight measures such as the vehicle's size, length, classification, and/or number of axles, and sometimes relies on field police officers' subjective judgment.

Regular, frequent and efficient speed limit law enforcement on high speed highways is greatly hampered by adverse weather conditions (e.g., snow, rain, wind, and extreme temperatures), low traffic levels, and the vast distances of many high speed highways in rural areas. It is particularly challenging for field officers to enforce speed limits and judge the weight of a vehicle on fast moving highways especially at night or when visibility is poor. Weigh-in-motion (WIM) scale facilities on high speed highways are designed primarily to measure the weight of heavy vehicles and have potential as a tool for heavy vehicle speed enforcement (IRD, 2017b). WIM scale technologies have advanced dramatically and can now provide a vast amount of additional traffic information. For each individual vehicle, the systems can record travel speed, length (via wheelbase), class (via axle spacing) and, axle load and GVW (Jacob et al., 2010). The systems can also collect vehicle count data, and measure the time gap and headway between moving vehicles. WIM scale facilities can even identify and access detailed information such as the commercial vehicle identification number, the company owning the commercial vehicle, profiles of commercial vehicle drivers, etc. (IRD, 2014a). Also, WIM scale facilities were used in the United States to monitor traffic and provide real-time traffic volume, occupancy and speed data for passenger cars and heavy vehicles during the evacuation for hurricane Irma in 2017 (IRD. 2017).

Saifizul et al. (2011) developed a framework based on a data-driven empirical approach for determining appropriate DSLs for heavy vehicles. In 2013, Transport Scotland reported a pilot study that examined the speed limit violation rate for heavy vehicles and used data from WIM scale facilities to screen vehicles above a certain weight (7.5 tons $\approx$ 16,500 lbs) (A9 Safety Group, 2013). It is clear that modern WIM scale facilities have evolved into highly sophisticated devices with many potential additional applications.

Vehicle speed may be measured in different ways. All North American jurisdictions currently enforce speed limits by measuring the spot speed of the vehicle. In Europe, many countries (e.g., Austria, Netherland, England, Scotland, Ireland, Switzerland, Norway, the Czech Republic, Italy, France, and Spain) have adopted a new and stricter approach to speed limit enforcement known as average speed enforcement (ASE), and it is also named point-to-point enforcement, or section speed enforcement (Soole et al., 2013; Soole et al., 2014). ASE measures the average speeds of vehicles traveling from one point to another on a section of highway and allows authorities to manage vehicle speed along whole roadway sections rather than only at selected locations (Soole et al, 2013). Montella et al. (2012) reported a 31% reduction in the number of collisions (all collision types/severities) after applying ASE on Italian Motorway A1 Milan-Naples. The 31% collision reduction was much higher than the 16.2% collision reduction reported for a study of automated spot speed enforcement (SSE) on 14 corridors with a high number of collisions in the City of Charlotte, North Carolina (Moon and Hummer, 2010).

1.2 Research Goal and Objectives

The goal of the thesis is to explore the safety impacts of a differential speed limit (DSL) for different type of heavy vehicles based on GVW combined with average speed enforcement (ASE) to improve highway safety for freight transportation. The specific objectives of this research are to:

1. Propose a Modified-Federal Highway Administration (M-FHWA) classification with a more precise consideration of GVW compared to Federal Highway Administration (FHWA) class;
2. Investigate the empirical relationship between heavy vehicles' average speed, GVW, FHWA class and M-FHWA class;
3. Compare traffic performance of heavy vehicles under two different speed limit strategies, USL and DSL.
4. Compare traffic performance of heavy vehicles under two different speed enforcement strategies, SSE and ASE.

1.3 Scope

The scope of this study is limited to exploring the safety impact of applying DSL based on GVW combined with ASE for heavy vehicles. The research obtained data from two WIM stations on the British Columbia Highway 5 and Trans-Canada Highway 1 from Laidlaw to Golden in British Columbia, The Two WIM stations are installed around 548 km apart from each other. The study also used GPS traffic data collected from the same highway segment.

The research proposed a M-FHWA class including a more precise consideration of GVW. The study conducted a statistical analysis of the empirical relationships between heavy vehicles' average speed, GVW, FHWA vehicle classification and M-FHWA class using the integrated dataset developed by combing WIM data and GPS data.

The study employed a simulation approach using PTV VISSIM as a tool for microscopic simulation analysis. No field study was conducted to either calibrate or validate the study results. The VISSIM model was used to understand the potential traffic impact of DSL based on GVW combined with ASE for heavy vehicles along the study corridor. Three traffic performance indicators were evaluated: 1) the longitudinal 85th percentile speed profile, 2) standard deviation of speed, and 3) the speed violation rate. The 85th percentile speed is widely used by highway agencies to describe operating speeds and to establish speed zones, and speed standard deviation and speed violation rate are the important potential contributing factor for collisions on highways and has been widely used to evaluate the safety effectiveness of different types of speed limits and speed enforcement.

1.4 Thesis Organisation

Chapter 2 is an extensive review of the literature. The topics cover different speed limit strategies, speed enforcement strategies, speed data collection methods, and microscopic simulation.

Chapter 3 describes the field data collected from the WIM stations and the GPS data collected from the study corridor.

Chapter 4 presents the statistical methods used to analyze various aspects of the collected traffic data. The methods include analysis of variance (ANOVA) test, Quantile-Quantile (QQ) plot, linear regression model, Monte Carlo data fusion method and correlation tests. The Chapter also discusses the microscopic simulation approach used to evaluate the traffic performance of heavy vehicles including the longitudinal speed profile, the speed violation rate and the speed standard deviation.

Chapter 5 introduces M-FHWA class that takes GVW into account used in this study. The Chapter presents the study's data fusion analysis conducted to amalgamate WIM data and GPS data in order to develop an integrated dataset. The Chapter also discusses the statistical relationship between heavy vehicle speed, GVW, the FHWA vehicle classification, and the proposed M-FHWA classification.

Chapter 6 describes using VISSIM simulation to analyze the traffic impact of USL and DSL strategies and the traffic impact of SSE and ASE strategies.

Chapter 7 presents to a summary, the conclusions of the research and recommendations for future studies.

Chapter 2 Literature Review

Historically, speed limits designed to reduce vehicle speeds on a section of highway are the most popular countermeasure used to improve traffic safety (Kirk & Co. Consulting Ltd. et al., 2014; Montella et al., 2012). In order for a speed limit to be effective in reducing vehicle speeds, enforcement tactics need to be implemented properly.

This Chapter reviews three speed limit strategies:1) uniform speed limit (USL), 2) variable speed limit (VSL) and 3) differential speed limit (DSL). Two speed enforcement strategies, SSE and ASE, are also reviewed. A microsimulation using VISSIM is also described in terms of its varied applications for evaluating safety and operational performance.

2.1 Speed Limit

Speeding has been recognized as the most important contributing factor for vehicle collisions involving heavy vehicles (Monsere et al., 2017; Paton et al., 2018).The most effective speeding control strategy, with a long history of application, is the speed limit. In this Chapter, we review three particular forms of speed limit: 1) uniform speed limit (USL), 2) variable speed limit (VSL), and 3) differential speed limit (DSL).

2.1.1 Uniform Speed Limit

The most common type of speed limit is the USL (also known as a fixed speed limit). USL is currently applied on most highways in the world. Many researches have conducted studies to understand the effectiveness of USL (Al-Ghamdi, 1998; Keall et al., 2001; Monsere et al., 2017). However, the USL does not eliminate collisions. For example, nine fatalities on highway A56, an urban motorway with an 80 km/h USL and a total length of 20.2 km in Naples, Italy. This was the highest number of fatalities on the motorway (in terms of the number of collisions per kilometer) in Italy in 2008 (Punzo et al., 2010). Neuman et al. (2009) reported that USL was applied on the A56 with little consideration of potentially important factors that may influence travel speed and safety. They overlooked some key characteristics of the A56 that influence speed such as traffic, roadway design and environmental characteristics. They concluded that USL might not be the most suitable form of speed limit for A56.

Similarly, a speed limit of 72.4 km/h (45 miles per hour) has been associated with considerable delay and a large number of crashes due to high traffic demand during the peak periods. An example is a 47-km bi-direction freeway corridor on Interstate 880 in California (Li et al., 2016). In this case, a simulation model was used to develop a VSL strategy designed to reduce both the number and severity of highway collisions. The results of simulation analyses showed that a VSL could reduce the number of collisions by up to 25.88% and reduce the number of injury collisions by up to 14.7%.

2.1.2 Variable Speed Limit

VSL is designed to take traffic and highway environmental factors into account. VSL can apply show variable speed limits appropriate to the traffic and environmental conditions of the highway considered.

For some highways in Europe, Asia and North America, VSL has been implemented in response to the adverse weather conditions (Choi and Oh, 2016; Saha at al 2015; Li et al., 2014). Saha et al. (2015) investigated the effectiveness of VSL systems and the effect of grades and sharp horizontal curves on collision frequency in adverse weather conditions (snow, ice, frost, wind). A negative binomial (NB) regression model was employed for modeling collision occurrence to determine the effectiveness of a VSL system for reducing crash frequencies. The data was collected from multiple sources including crash data, weather data, roadway geometrics and traffic data on four Interstate-80 VSL corridors in Wyoming from 2007 to 2012. The simulation model estimated that 29 collisions could be avoided each year. The model also found that horizontal curves had no impact on crashes, but was significant under certain weather conditions. VSL had a significant effect of reducing collisions for steep grades. Similarly, VSL was also reported to help reduce the number of collisions on geometrically challenging corridors (e.g., sharp horizontal curves and steep grades through mountain terrain). VSL could also help to reduce the number of highway collision on less challenging corridors.

Although VSL is a popular form of speed limit in many countries, it is still relatively rare in Canada (Ludwar, 2017). The Ministry of British Columbia (B.C.) has installed VSL systems on three major highway sections, the Coquihalla Highway 5 through Snowshed Hill (40km), Highway 99 between Squamish and Whistler (30km), and Highway 1 from Perry River to Revelstoke (30km) (Ludwar, 2017). The VSL systems display varying speed limit according to the rapidly changing weather conditions as these corridors include high elevation mountain passes with highly changeable environments subject to a diverse range of weather that can change very rapidly especially in winter. A set of sensors that can instantly detect changes in various traffic, pavement and visibility conditions was installed on the target highway sections. The sensors provide operational staff with recommended speeds allowing staff to continuously monitor the various changes on the highway sections and manually adjust the digital display of the variable message signs accordingly. For example, British Columbia had heavy snow during Dec 2016 and the speed sign on Highway1 was reduced to 60 km/h from 100 km/h. The 85th percentile speed on the corridor was recorded as 59 km/h.

VSL has also been implemented in response to highway work zones with high levels of congestion and potential safety problems. A work zone along a highway section (I-494) near Minneapolis-Saint Paul, Minnesota, had a VSL system installed and operated for three weeks (Kwon et al., 2007) . Speed data showed a 25 % to 35% reduction in average speed during morning peak hours (6:00 to 8: 00 a.m.) and a 7% increase in total throughput traffic volumes during evening peak periods.

Yang et al. (2017) conducted a study to show the operational and safety impact of a VSL system installed in 2011 on a work zone along highway (I-495) near Silver Spring, Maryland. They used VISSIM to develop a simulation network covering upstream and downstream from the work zone area. The results showed that the VSL system could reduce speed in the upstream to downstream congestion and improves the operation efficiency at the work-zone area. The study also compared a no-VSL scenario with a VSL-control scenario. The results showed that VSL system could smooth speed reduction and prevent a sudden speed drop within one to two segments. The speed change rate was 31 km/h in the no-VSL scenario and 14 km/h in the VSL-control scenario.

VSL has also been expected to bring potential safety benefits on non work zone highway sections. The benefits include reducing the number of highway collisions (Li et al., 2016; Guebert et al., 2012), reducing speed variation which decreased the probability of collisions (Khondaker and Kattan, 2015), and reducing the speeding violation rate (Hellinga et al. 2011).

However, some studies have shown inconclusive and inconsistent results for VSL applications on highways and in work zones. An early study investigated a VSL system on a work zone on highway I-495 in Minnesota. The highway had heavy congestion due to high traffic (Fudala and Fontaine, 2010a; Fudala and Fontaine, 2010b). The VSL evaluation study showed inconclusive results perhaps because of the site conditions and issues such as inconsistent use of the VSL due to control algorithm problems. The researchers conducted a simulation study to understand the impact of VSL. The results showed that VSL was not recommended for highway sections where traffic demand is far above capacity. The study did not consider safety benefits of VSL for work zones and also did not look into possible benefits during uncongested hours.

Nissan and Koutsopoulosb (2011) evaluated the impact of a VSL system on the E4 motorway in Stockholm, Sweden. The results indicated that there was no significant impact on changes in traffic volume and density, both immediately after VSL installation and again several months later.

Kianfar et al. (2015) evaluated the impact of VSL systems on eight different locations on the I-270 in Missouri. The study used two separate approaches to analyze traffic conditions before and after VSL installation: the nonparametric two-dimensional Kolmogorov-Smirnov Test, and parametric flow-occupancy curve fitting. Because the impact of traffic control affected the highway traffic conditions at the different sites, the effect of VSL was inconsistent. After VSL installation, the study found that maximum traffic flow before breakdown decreased at four locations, but increased at the rest of four locations. The study also found the maximum flow after breakdown decreased at three locations and increased at five locations. In addition, the average duration of congestion decreased at five locations, but increased at three locations.

2.1.3 Differential Speed Limit

DSL is another commonly used speed limit. Many jurisdictions in North America have introduced lower speed limits for heavy vehicles than for passenger cars (Misaghi and Hassan, 2005; Transport Canada, 2008; Korkut et al., 2010; Gates et al., 2016; Monsere et al., 2017). DSL is used mainly to reduce the severity of collisions involving heavy vehicles (Johnson and Pawar, 2005; Saccomanno et al., 2009).

The DSL is usually based on different maximum speeds for different classifications of vehicle (NHTSA, 2012), but some jurisdictions use different criteria such as a vehicle's size and weight, and some DSL approaches are based on weather or other roadway conditions such as nighttime speed limits, work zone speed limits, transition zone speed limits, and seasonal speed limits (Forbes et al., 2012). DSL does not require the complex speed control algorithms and extra cost of purchasing equipment and/or installation and maintenance fees associated with VSL systems.

A typical DSL is set at a maximum speed limit that is around 10-20 km/h lower for heavy vehicles than for passenger vehicles (Ghods et al. 2012). As an example, the speed limit for passenger cars and motorcycles is typically between 80 km/h to 90 km/h on expressways in Singapore and 60 or 70 km/h for heavy vehicles (Yeung et al. 2015). In Malaysia, the speed limits on expressways are 110 km/h for passenger cars and 80-90 km/h for heavy vehicles. Federal and State Routes in In Malaysia have a speed limit of 90 km/h for passenger vehicles and 70-80 km/h for heavy vehicles (Saifizul et al. 2011). The rationale for the lower speed limit for heavy vehicles include 1) heavy vehicles require longer braking distance, 2) heavy vehicles are less flexible in lane-changing and/or overtaking maneuverability compared with passenger cars, and 3) collisions involving heavy vehicles often result in serious fatalities (Montella at al. 2011; Montella et al., 2015).

Saifizul et al. (2011) proposed a new approach to DSL based on the vehicles' GVW rather than the vehicles' classification or size. The approach was based on an observation that there was a higher correlation between vehicles' travel speed and gross vehicle weight (GVW) than between vehicle speed and vehicle classification or size.

In the United States, seven states currently operate a DSL system based on vehicle GVW. Washington, California and Montana use a 15 mph differential between passenger vehicles and heavy vehicles. Michigan and Oregon use a 10 mph differential, and Indiana uses a 5 mph differential (Gates et al. 2016). Indiana uses 26,000 lbs as the GVW threshold to differentiate the speed limit while California, Michigan, and Washington use 10,000 lbs (NHTSA, 2012) (Gates et al. 2016).

In Italy, the maximum speed limit on motorway and expressways is 80 km/h for heavy vehicles weighing more than 12 tonnes and 100 km/h for heavy vehicles weighing less than 12 tonnes (Montella at al. 2011; Montella et al., 2015).

Some European countries, such as the United Kingdom, Denmark, Finland, and Italy, also mandate the use of an advanced speed control device in the form of an electronic control module. The device is connected to the truck's diesel engine and limits the truck's maximum speed according to the vehicle's GVW (European Commission, 2009). European Council Directive EU-Directive 92/24/EEC and its recent adaptation (Council Directive 2004/11/EEC) mandated a speed limiter on heavy vehicles over 3.5 tonnes and on all vehicles weighing more than 10 tonnes including buses/coaches with more than nine seats (European Commission, 2009; Montella et al., 2015). It is believed that speed limiters have contributed to improving road safety. In the United Kingdom, which mandated the installation of speed limiters for heavy vehicles in 1992, the number of collisions involving a heavy vehicle declined by 26 % from 1993 to 2005 (European Commission, 2009; Transport Canada, 2008).

In Canada, Ontario and Quebec have mandated the use of truck speed limiters in heavy vehicles with a GVW greater than 11,794 kg. The maximum speed is set up as 105 km/h (Saccomanno et al., 2008; Saccomanno et al., 2009). Saccomanno et al. reported that mandatory speed limiters can produce safety benefits under various traffic conditions tested using microsimulation (Saccomanno et al., 2009).

DSL and speed limiters reduce travel speed and the number of collisions involving heavy vehicles, and can also improve service reliability and efficiency for backhauls. Most European countries, e.g., Italy, Bulgaria, the Netherlands, Estonia, Finland, and Austria, have 20 and 25 % of heavy vehicles' vehicle-kilometers (VKM) running empty (McKinnon, 2010). In Canada between 2000 and 2009, it is estimated that approximately 14 % of all heavy vehicles' VKM travelled empty (Natural Resources Canada, 2009).

Some studies have reported that DSL has little impact on highway capacity and traffic safety (Neeley et al., 2011; Ghods et al., 2012; Davis et al., 2015; Ghods and Saccomanno, 2016), and some have reported that DSL and truck speed limiters may have an adverse impact on traffic flow conditions by increasing travel time (Ghods and Saccomanno, 2016) and increasing speed variation between vehicles (Ghods and Saccomanno, 2016; Gates et al., 2016; Russo et al., 2017). These negative impacts are expected to apply mainly to two-lane highways (Gates et al., 2016; Ghods and Saccomanno, 2016; Russo et al., 2017).

2.2 Speed Enforcement

Speeding is recognized as possibly the most important collision contributing factor, particularly for fatal collisions (Montella et al., 2015). Speed management can improve traffic safety and is therefore important. Effective speed management techniques include the various types of speed limits outlines in Section 2.1 and law enforcement. Governing agencies have dedicated significant resources to developing and implementing various speed enforcement tactics designed to reduce the number of collisions.

Section 2.2 chapter reviews two speed enforcement tactics: spot speed enforcement (SSE), and average speed enforcement (ASE).

2.2.1 Spot Speed Enforcement

All North American jurisdictions currently enforce speed by measuring a vehicle's spot speed. Indeed, this conventional method is the most common method for controlling traffic speed around the world. A vehicle's traveling speed is measured as the target vehicle passes a very short section of highway (spot). The speed may be measured manually, by handheld radar guns, or by automatic enforcement devices such as photo radar coupled with CCTV and license plate readers. Many studies have shown the effectiveness of conventional speed enforcement tactics.

Liu et al. (2011), for instance, analyzed the effect of automated (fixed) speed camera enforcement in Nanjing, China. Speed data was collected from April 2010 to June 2010 at seven sites. Three sites were rural highways with a speed limit of 60 km/h, and two sites were located on Ningli highway and S341 highway that have employed automated speed cameras for at least two years. The third site was the control site located on Ningli highway which did not have speed cameras. The left four sites were rural highways with a speed limit of 80 km/h, and three of them were located on G104 highway and Ningli highway that have employed automated speed cameras for at least two years. The forth site was the control site located on G104 highway which did not have speed cameras. Liu et al. (2011) reported that the cameras decreased mean travel speed by 12 km/h to 16 km/h and decreased the 85th percentile travel speed by 12 km/h to 22.3 km/h. The study also reported that the proportion of speeding vehicles (defined as traveling at 10% or more higher than the speed limit) was reduced by 41 % to 58 % for the study sections with the 60 km/h and 80 km/h speed limit respectively.

Liu et al. (2011)stressed that spot speed enforcement is, unfortunately, not a very effective tool for reducing vehicles' traveling speeds beyond the area of influence of the speed enforcement installation. They observed that drivers usually reduce travel speed from 300 m - 400 m upstream of the speed camera location and then recover their vehicle speed at 300 m - 400 m downstream of the speed camera location. As a result, the influence area of the speed camera was less than 1 km.

In Belgium, Pauw et al. (2014b) looked into the effect of a fixed camera on speed on two sections of motorways where the speed limit was 120 km/h. The first section was in Brasschaat on the direction of Antwerp on the E19, a two-lane motorway. The second section was in Boutersem on the E40 in the direction of Liege, a three-lane motorway. The speed cameras were employed in Nov 2011. At the Brasschaat location, Pauw et al. collected 13 months of before data (from October 2010) and 10 months of after data (to September 2012). At the Boutersem location, they collected 11 months of before data (from Dec 2010) before and 18 months of after data (to May 2013).

Pauw et al. (2014b) reported that the installation of the speed cameras resulted in an average speed decrease of 6.4 km/h at the two locations. The proportion of drivers exceeding the speed limit decreased by 80 %, and the proportion of drivers exceeding the speed limit 120 km/h by 10% or more decreased by 86%. Like Liu et al. (2011), Pauw et al. reported that the area of reduced speed was limited. A clear V-shaped speed distribution along both highway sections was observed as drivers avoided enforcement near the point of speed detection by suddenly reducing, but then recovering speed shortly after passing the detector.

Shim et al. (2015) also reported that drivers usually reduce speed near the speed cameras, but increase their speeds shortly after passing the cameras. Shim et al. collected traffic data from GPS equipped taxis and inductive loop detectors for the month of May, 2013. The study sites were selected according to data availability for 259 taxis in Daegu, South Korea. The study used geographic information system (GIS) to spatially match the trajectory data with the automated speed enforcement locations. Trajectory data was collected from four locations around Taegu. Two of them were on Korean Expressways and two of them were on Gyeongbu Expressway. Inductive loop detectors data was collected from three sites along Gyeongbu Expressway. The study was divided into segments and the researchers conducted a comparative analysis using the Empirical Bayes method for each segment before and after the speed camera installation. The results of the comparison showed that total crashes decreased by 7.6%, but collision occurrences increased by 11% at 1500-m and 500-m segments upstream of the speed cameras due to drivers suddenly reducing speed as they approached the location of enforcement. These findings are similar to those of previous studies (Liu et al., 2011; Pauw et al., 2014b). In the study segments, the magnitude of the positive effect of the spot speed enforcement cameras on overall traffic safety was small compared to the negative effect.

Interestingly, a few studies have found that speed enforcement cameras can affect road safety adversely by increasing the number of collisions because the cameras increase speed variability along the affected highway sections (Quddus, 2013; Shim et al., 2015; Soole et al., 2012). These studies found, for example, that some drivers tried to avoid a speeding ticket by suddenly decelerating upstream of speed enforcement cameras leading to an unprepared following rear ending the leading vehicle. Such problems suggest that SSE may not be suitable for reducing vehicle speed. It has also been found that increases in acceleration and deceleration associated with spot speed enforcement lead to increases in fuel consumption and pollutant emissions (e.g., CO2, CO, NOx, pm10) (Punzo at al., 2010; Soole et al., 2012).

2.2.2 Average Speed Enforcement

ASE presents an improved speed control strategy that overcomes spot speed enforcement issues and is gaining in popularity. ASE is described differently in different jurisdictions. It is known as ASE in the United Kingdom, South Africa and China (Velden, 2017; Akpa et al., 2015; Speed Check Services, 2007), as point-to-point speed enforcement in Australia and New Zealand, (Soole et al., 2012; Montella et al., 2015) and as section speed enforcement in Italy and Belgium (Pauw et al., 2014a; Cascetta et al., 2011).

Unlike conventional spot speed enforcement, ASE uses the average speed estimated between two points of interest along a section of highway as the justification for speed enforcement (Soole et al., 2012; Soole et al., 2013). The length of ASE applied in various regions varies widely. ASE on Tower Bridge in London (United Kingdom) is for a section of only 300 m, the shortest section where ASE is implemented. The Tower Bridge speed limit is 60 km/h (Speed Check Services, 2007). The longest ASE application is in the Aberdeen direction on a 71.7 km section of the R61 route between Beaufort West and the Eastern Cape border in South Africa. This installation was introduced by the Western Cape government in 2011 starting with a pilot project (Velden, 2017).

Many studies conducted from various countries have safety benefits from ASE. The benefits include reductions in average travel speed, the 85th percentile travel speed, the number of speeding violations, and speed variability and reductions in vehicle emissions (Soole et al., 2013).

The first successful ASE application was in Netherlands in 1997. Average travel speed was reduced by from 115 km to106 km/h, and the speeding violation rate was reduced by 90% (Soole et al., 2012). There was also a reduction in the 85th percentile speeds and speed violation rate for both passenger vehicles and heavy vehicles. The Netherlands currently has 11 ASE systems operating on sections of various highways such as the A2 motorway (between Amsterdam and Utrecht) and the A13 motorway (between Rotterdam and the Hague) (Wegman and Goldenbeld, 2006; Soole et al., 2012).

The United Kingdom installed an ASE system in 1999 as a pilot project. The speeding violation rate was reduced by 30% (Soole et al., 2012). The ASE is now widely used in the United Kingdom . In addition to the benefit of reducing speeding, ASE also reduced the number of collisions (Soole et al., 2013; Soole et al., 2012). For instance, an ASE system was installed in January, 2012 on a section of the A614 near Nottingham This section had a significant history of severe collisions with 289 people killed or injured in a five year period. The study compared speed data before the installation of the ASE in January, 2012 and for the 23 months after the installation ending in Dec 2013. The study found a 52% reduction in the number of total collisions and a 40% reduction in the number of serious injury collisions. No fatalities was reported (Collins and Hurt, 2014).

Owen et al. (2016) evaluated the impact of ASE using 15 years of traffic and collision data (2000 to 2015) in the United Kingdom. ASE cameras were installed at 25 sites covering 294 km of road. The study found a 36.4% reduction in the mean rate of fatal and serious collisions in the after-installation period. Personal injury collisions of all severities decreased by 16%. Collins and Hurt (2014) reported that ASE helped reduce speed standard deviation that contributed to reducing the number of collisions. The reduced speed standard deviation also contributed to achieving a more homogeneous traffic flow than before the ASE installation and increasing highway capacity as well as reducing congestion (Collins and Hurt, 2014; Soole et al., 2012).

In Italy, the first ASE system was introduced in 2006 and by 2015, 320 motorway sections with 2,900 km of roadway had ASE installed (Montella et al., 2015). In 2009, Punzo et al. (2010) conducted a before-after study to evaluate the safety impact of the ASE installed on the A56 motorway near Naples. The section's speed limit was 80 km/h. The researchers reported a 9.1 km/h reduction in average speed, from 80.8 km/h to 71.7 km/h, and a decreased percentage of speed violations, from 51.6% to 17.4%. Speed variability was reduced from 18.1 km/h to 12.1 km/h (Soole et al., 2012; Punzo et al., 2010). The study found that the ASE system significantly reduced travel speed and speed variance leading to homogeneous traffic flow conditions.

In 2015, Montella et al. (2015) evaluated ASE associated with DSL on two motorways in Italy, the A56 (an urban motorway) and the A3 (a rural motorway). The speed limits for heavy and light vehicles were 70 km/h and 80 km/h respectively on the A56 and 80 km/h and 100 km/h respectively on the A3,. The study reported that the ASE systems on the A56 urban motorway resulted in a 84% and 77% reduction respectively in the number of light and heavy vehicles exceeding the speed limits by more than 20 km/h, and that the ASE systems also reduced the standard deviation of the speed of light vehicles (by 26%) and heavy vehicles (by 20%). The ASE safety improvements on the A3 motorway were less significant than those achieved on the A56 motorway. The researchers concluded that this was due to the lack of public education and public involvement about the ASE on the A3 motorway where approximately 25% of drivers did not know how the ASE systems work and 22% on the A56. The percentage of people unaware of the presence of ASE was 35% on A3 and 26% on A56.

In Scotland, Summersgill and Neil (2012) found that ASE combined with DSL could improve traffic safety by changing drivers' operational behaviours especially for vehicles in excess of 7.5 tonnes by increasing the speed limit from 40 mph to 1) 50 mph and 2) 60 mph. The study involved the development of an S-Paramics microsimulation model to simulate the route between Dalwhinnie and Moy. The results indicated that the ASE with an increased speed limit for heavy vehicles would result in a reduction of 3 mph average speed for all vehicles, a reduction of approximately 13% in the desire to overtake on single carriageway sections, and a reduction of speed variance of approximately 35%.

In Canada, few public agencies have endorsed the use of ASE on Canadian highways (Plant and Perry, 2018; Coulter, 2018; Fletcher, 2018; Kendall and Young, 2014; Antweiler, 2016). The Traffic Safety Commission of the Capital Regional District has proposed and recommended that ASE be installed on the Malahat highway, a high traffic corridor in British Columbia (Plant and Perry, 2018). Local politicians in Squamish and Lion Bay in British Columbia have recommended considering ASE as a way to reduce speeding violations on Highway 99 (Coulter, 2018). Similarly, municipal officials in the vicinity of the Sea to Sky Highway and the Coquihalla Highway in British Columbia have discussed the possible implementation of ASE on these highways (Fletcher, 2018; Kendall and Young, 2014; Antweiler, 2016). Although many local jurisdictions in Canada, especially in British Columbia, have discussed the potential use of ASE as a speed enforcement tactic, ASE has not been introduced officially in Canada.

2.3 Microsimulation

In recent years, transportation engineers and researchers have used different microsimulation models to analyze the performance of heavy vehicles (F. Saccomanno et al., 2008;

Summersgill and Neil, 2012; Llorca et al., 2015). A popular microsimulation tool is PTV VISSIM (PTV VISSIM, 2011). VISSIM can simulate traffic performance by considering speed, density, travel time, weight, vehicle type, and other related parameters.

Wang and Wang (2011) used VISSIM to evaluate the impact of various speed limits targeting different sections of rural highways in China. In Scotland, Transport Scotland developed a microsimulation traffic model to understand the impact of ASE for heavy vehicles (Summersgill and Neil, 2012).

In Canada, VISSIM simulation has been applied to evaluate truck speed limiters on highways in Ontario and Quebec. Saccomanno et al. (2008) have also used VISSIM in Ministry of Transportation of Ontario (MTO) research designed to evaluate the safety impact of speed limiters for heavy vehicle with GVW greater than 11,794 kg. The analysis of the safety impact included the expected the number and severity of collisions involving heavy vehicles under different traffic scenarios and speed control strategies, and included 1) various geometric configurations (straight segments, off-ramp segments, and on-ramp segment), 2) various traffic conditions (traffic volume, heavy vehicle percentage, and rates of speed limiter compliance) and 3) different speed control strategies (105 km/h and 110 km/h). The results of the simulation found that speed limiters set to 105 km/h would increase safety on uncongested roadways for all types of geometry highway configuration, that the safety impact of the 105 km/h speed limiter would be reduced when traffic volume and the percentage of heavy vehicles increased, and that the safety gains of speed limiters would be reduced as vehicle compliance increased.

Microscopic simulation has also been used to evaluate the safety aspects of differential speed limits on a Canadian highway. Lee et al. (2006) applied a PARAMICS microsimulation model to understand the impact of various speed limits on the Gardiner Expressway in Toronto.

The study showed that variable speed limits could substantially reduce collision potential, i.e., by 5% to 17% depending on time of day (peak/off-peak and morning/ afternoon.

Some studies have developed microsimulation models to show the impact of various intelligent transportation system (ITS) such as WIM systems and GPS-based detecting devices. Gu (2005) developed a simulation model using VISSIM to compare the performance of two WIM threshold strategies regarding traffic volume, weight distribution, and WIM accuracy and static scale service time. The two types of threshold strategies were the fixed-threshold algorithm, mainly focusing on weight limit and WIM accuracy, and the floating-threshold algorithm which also considered traffic volume, heavy vehicle weight distribution, and static service time. The simulation results showed that the floating-threshold algorithms resulted in a more effective performance than did the fixed-threshold algorithm, and that the floating-threshold algorithm was more effective than the fixed-threshold algorithm for WIM systems regarding weight enforcement and reducing delay.

It is worth noting that the development of a traffic simulation model requires proper calibration of the model. The calibration is aimed at finding the appropriate combination of various input parameters to reduce the size of the errors between observed and simulated measures of performance (e.g., travel time, speed and traffic volume) to assure the accuracy and reliability, in this case, the VISSIM microsimulation model (Appiah et al., 2012).

An approach to calibrating a microsimulation model is to use a genetic algorithm (GA) which is a stochastic algorithm that can maximize the goodness-of-fit values (Yu et al., 2011; Appiah et al., 2012; Fan et al., 2013). Appiah et al. (2012) applied a GA to a VISSIM model and compared the average speed estimation of the calibrated and uncalibrated models. The researchers found that the calibrated model errors ranged from 10% to 16% while the uncalibrated model errors ranged from 15% to 35%.

Some researches have argued that GA can evaluate only one measure of performance per simulation and that a large set of simulations is required to fully evaluate many performance measures. In such cases, GA is not efficient (Duong et al., 2010).

Alternative approaches have been developed for calibrating the VISSIM model. They include multi-criteria calibration and two-stage calibration (Duong et al., 2010; Fan et al., 2013). Fan et al. (2013) found that the two-stage calibration procedure could improve consistency between simulation and observation. Later, Havers of the Wisconsin DOT proposed a goodness-of-fit measure known as the GEH (for Geoffrey E. Havers) to calibrate the VISSIM simulation model and this is now the most widely used measure of performance (Ramezani et al. 2018a; Choi and Oh, 2016; Ramezani et al. 2018b). Although the GEH approach provides a good assessment of how accurately the traffic model reflects observed conditions, there were still some concerns with the approach (Wisconsin DOT, 2014). An updated calibration approach has since been proposed. This is a new goodness of fit metric called the Root Mean Square Percent Error (RMSPE) that has been endorsed by Wisconsin DOT. It can be applied to various calibration parameters including traffic volume, speed, travel time, queues, and lane use (Wisconsin DOT, 2018).

2.4 Chapter Summary

This chapter focused on reviewing three topics: 1) speed limit, 2) speed enforcement tactics, and 3) microsimulation.

The speed limit discussion reviewed three different speed limit strategies and their impact on operational and safety aspects of traffic flow condition. The conventional uniform speed limit does not differentiate the maximum speed for passenger vehicles and heavy vehicles. For the variable speed limit, the safety impact particularly for heavy vehicles was not consistent. Some studies have shown meaningful safety benefits, but others have shown inconclusive results or even no significant impact on safety. The differential speed limit has been applied in many countries with some safety gains for heavy vehicles, but it is not currently used in Canada.

The speed enforcement tactics discussion noted that conventional spot speed enforcement has a limited area of enforcement (i.e., speed is reduced near the speed enforcement location only). Possible negative impacts included an increased number of collisions, and increased fuel consumption and pollutant emissions. As an alternative, average speed enforcement is used in many countries and significant safety benefits such as significant reductions in highway speed, the number of collisions and the speed violation rate are reported, but the approach has not been used in North America.

The discussion of microsimulation concentrated on VISSIM model. These models have been applied widely to evaluate the safety and operational performance of heavy vehicles. Various approaches to model calibration are available to maximize the accuracy of VISSIM as a simulation tool for evaluating performance measures such as speed, travel time and traffic volume.

Chapter 3 Study Data

3.1 Study Location

This study obtained heavy vehicle travel speed and GVW data from the British Columbia (BC) HWY 5 and Trans-Canada HWY 1 from Laidlaw to Golden in B.C. See Figure 3-1. The corridor has two WIM stations installed about 548 km apart from each other.

We used one year (2014) of WIM data collected from the two WIM stations and one month (March, 2016) of GPS data collected from a sample of heavy vehicles travelled along the corridor.

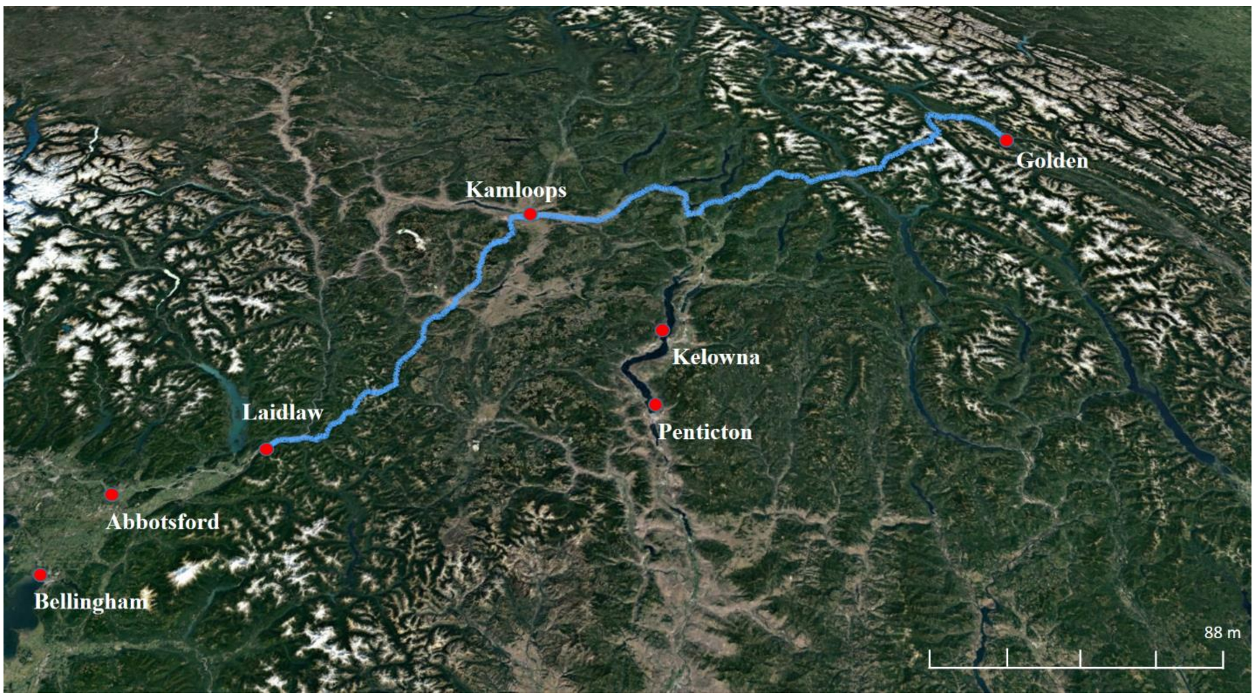


Figure 3-1: Study Corridor

3.2 Data Collection Method

3.2.1 Weigh-in-Motion

Back in the early 1950s, WIM scales were mainly used in the United States to collect data on vehicles' weight and axles (Norman and Hopkins, 1952). The information was used largely to improve pavement maintenance and design. Over the years, WIM scale technologies have advanced tremendously and can now provide a vast amount of additional traffic information. For each individual vehicle detected, the WIM system can record travel speed, length (via wheelbase), class (via axle spacing) and, of course, axle load and GVW (Jacob and Feypell-de La Beaumelle. 2010). The system can also collect vehicle count data and measure travel speed and the time gap and headways between travelling vehicles.

Some studies have explored the technical feasibility of using WIM scale facilities equipped with automatic license plate readers to enforce speed limits. Han and Hargrove (2007) used WIM scale facilities near Knoxville, TN to enforce heavy vehicle speed limits, but did not consider GVW explicitly. This study was the first such study in North America.

In Malaysia, Saifizul et al. (2010) developed a conceptual framework using speed and GVW data from WIM scale facilities for heavy vehicle speed enforcement. They expanded the framework by suggesting a data-driven empirical approach for determining appropriate differential speed limits for heavy vehicles (Saifizul et al., 2011).

In Scotland, WIM systems have been applied to collect the speed of vehicles by weight for HGVs to study speeding offence rates on single carriageway sections (Summersgill and Neil, 2012). A pilot project then examined the speed limit violation rate for heavy vehicles. The pilot used data from WIM scale facilities to screen vehicles above a certain weight (7.5 tonnes ≈ 16,500 lbs) (A9 Safety Group. 2013).

In Canada, the B.C. Ministry of Transportation proposed the Weigh2GoBC program. In Weigh2GoBC, WIM systems are equipped with automatic license plate readers and the system enforces vehicle weight limits and identifies and accesses detailed information such as the commercial vehicle identification number, the company owning the commercial. Modern WIM scale facilities are clearly a sophisticated tool for collecting traffic data with many potential applications.

In this study, we used WIM station data supplied by International Road Dynamics (IRD) Inc. (IRD, 2017a). The data provided information for selected heavy vehicles travelling from west to east in the 12 months of 2014.

The dataset we developed could be categorized into two types: 1) the single dataset, and 2) the link dataset.

The single dataset presents vehicle traffic data collected from each WIM station. The data for each vehicle includes time stamps, lane number used, vehicle speed, vehicle length, number of axles, each axle’s weight, spacing between axles and vehicle classification.

Vehicle classification was made according to the Federal Highway Administration’s (FHWA) (FHWA 2016) 13 classes which are grouped into six major classifications: 1) motorcycles (class 1), 2) passenger vehicles (classes 2 and 3), 3) buses (class 4), 4) single-unit trucks (classes 5 to 7), 5) single trailers (classes 8 to 10) and 6) multi-trailers (classes 11 to 13). Appendix A provides more detailed classification information.

As this study was interested in investigating speed enforcement for heavy vehicles, we used traffic data showing headways greater than 9 seconds and speeds between 60 and 140 km/hr. We discarded data containing any improper value originating from a WIM sensor error. We have also used data collected under favourable weather conditions. We did not use data for days with adverse weather conditions such as snow, rain, fog, wind speeds greater than 60 km/hr, and temperatures lower than -25°C.

The weather data was collected from Environment and Climate Change Canada (Government of Canada, 2014). The 2014 weather data was obtained from the two weather stations located near Golden and Laidlaw (AGASSIZ RCS and GOLDEN A). The weather data was updated three times per hour and contained temperature (in Celsius), wind speed (in km/hr), and a description of the weather condition.

Our final single dataset contained information including lane number used, vehicle speed, vehicle length, number of axles, vehicle weight, vehicle classification, day of the week, headway, time gap and weather conditions. In total, 1,337,921 vehicles passed through the Laidlaw station and 285,025 vehicles passed through the Golden station.

The link dataset was based on trip records for heavy vehicles equipped with the Automatic Vehicle Identification (AVI) electronic vehicle tag which is part of the B.C. Weigh2GoBC program (International Road Dynamics Inc., 2014a). The AVI and Weigh2GoBC program allow registered heavy vehicles to be identified at each weighing station. The vehicles in this program are only heavy vehicles with good vehicle history that can be said very conservative. As a result, we were able to use data from the two WIM stations to identify individual heavy vehicle trip records on the study corridor and generate the link dataset.

The link data for each trip included the trip time (travel from Laidlaw to Golden) down to a hundredth of a second, the lane number, the vehicle speed, the vehicle length, and GVW, and each axle’s weight and spacing. The data also included the FHWA vehicle class from class 6 to class 13. As the GPS data (described in Chapter 3.2.2) focused on heavy vehicles larger than a single unit truck, the WIM dataset excluded FHWA classes 6 and 7. FHWA class 11 was excluded due to a WIM systems error concerning vehicle types.

To evaluate the impact of the introduction of ASE on heavy vehicles on highways, we analyzed mainly the link dataset rather than the single dataset. Our final link dataset contained information including 9,363 heavy vehicle trips from the Laidlaw WIM station to the Golden WIM station in 2014. Table 3-1 shows the FHWA vehicle classification, average speed, and number and percentage of vehicles speeding. Speeding was defined as exceeding the average speed limit calculated for the 9,363 heavy vehicle trips.

Table 3-1: Average Speed and Speeding Distribution for FHWA class in Link Dataset

Vehicle Classes (FHWA)	Number of Vehicles	Average Speed (km/h)	Number of Speeding Vehicles	Percentage of Speeding Vehicles
Class 8	18	86.12	9	50%
Class 9	6429	74.13	281	4.37%
Class 10	2299	72.82	73	3.18%
Class 12	247	71.76	6	2.43%
Class 13	370	67.93	1	0.27%
Total	9363	-	370	3.95%

The average speed limit was estimated based on Equation 3-1, which was using total distance travelled divided by total travel time spent from Laidlaw to Golden:

$$\boldsymbol{Average\ Speed\ Limit} = \frac{\sum(\boldsymbol{Speed\ Limit})(\boldsymbol{Section\ Length})}{\boldsymbol{Total\ Distance}} \qquad \textbf{Equation 3-1}$$

The average speed limit was 88 km/h and 3.95% (see Table 3-1) of heavy vehicle exceeded this speed limit. These vehicles were considered to be speeding.

Table 3-2 shows interesting differences in the single dataset for all vehicles collected at each station (Laidlaw and Golden). At the Laidlaw station, 2.96 % of heavy vehicles (class 8 to class 13) and 36.90 % of all vehicles (class 1 to class 13) exceeded the local speed limit of 110 km/h. At the Golden station, the speed limit violation rate was much higher: 20.71 % of heavy vehicles (class 8 to class 13) and 56.49 % of all vehicles (class 1 to class 13) exceeded the local speed limit of 90 km/h. Passenger cars and smaller vehicles (smaller GVW) usually travel faster that would lead high speed violation rate. Heavy vehicle with large GVW travel slower and have lower speed violation rate. Also, the speed violation rate in Golden is higher then Laidlaw. It could be caused by that the speed limit in Laidlaw station is 110 km/h and the speed limit in Golden station is 90 km/h. Lower speed limit would cause higher speed violation rate and vice versa.

Table 3-2: Speeding Distribution for FHWA Class in Two Single Dataset

Vehicle Classes (FHWA)	**Number of Vehicles at Laidlaw**	**Percentage of Vehicles Speeding at Laidlaw**	**Number of Vehicles at Golden**	**Percentage of Vehicles Speeding at Golden**
Class 1- Class 13	1,337,921	36.90 %	285,025	56.49%
Class 8- Class 13	355,305	2.96 %	99,246	20.71 %

The percentage of heavy vehicles speeding at Golden single station based on spot speed is higher than the percentage of heavy vehicles speeding based on exceeding the average speed limit for heavy vehicles driving along the study corridor. This difference is due partly to the difficulty involved in tracking each heavy vehicle's travel accurately along the 548 km of study corridor.

Some heavy vehicles travelled continuously without stopping and other heavy vehicles could have made one or more stops during the trip for rest, gas, and/or loading/unloading.

To alleviate this problem, the data were categorized into two different types of trip: 1) travel without stops (nonstop), and 2) travel with stop (stopping) (s). To do this, we looked at both the total travel time and the GVW measured at the two trip ends (i.e., the WIM stations at Golden and Laidlaw).

The average travel time for heavy vehicles is 7.6 hours and the minimum travel time is 5.5 hours. We assumed that a heavy vehicle travelled without a stop if it travelled the study corridor in less than 8 hours.

We also assumed that a heavy vehicle travelled without a stop if the GVW was the same or approximately the same at both WIM stations. Static WIM systems detecting vehicles travelling at low speed can measure GVW with an accuracy of ±0.5% (IRD, 2014b). Unfortunately, dynamic WIM systems detecting vehicles travelling at high speed (up to 200 km/h) have an error tolerance of ±5% to ±15% (IRD, 2017a; Al-Qadi et al., 2016; Papagiannakis et al., 2008). This study assumed that a vehicle did not stop if the GVW difference at the two stations was within ±10%.

We removed trips that likely have extremely long travel time, more than 12 hours. The travel time between 8 hours to 12 hours was considered as heavy vehicle stopped one or more times during the trip. The study found that the GVW difference between a fully loaded truck and an unloaded truck can be up to approximately 300% for heavy combination trucks (Gardner and Merlo, 2014). The GVW changing exceeding 300% could be considered as measurement errors or erroneously large. We removed all heavy vehicles for which the change in GVW exceeded ±300%. This study assumed that the travel time was between 8 hours to 12 hours and GVW changing was between ±10% to ±300% would be travel with stop category.

Table 3-3 shows the number and percentage of nonstop and stopping heavy vehicle trips in the link dataset. More vehicles travelled nonstop than stopping: 5,525 (59%) compared with 3,838 (41%).

Table 3-3: Nonstop and Stopping Vehicle Distribution in Link Dataset

Classification (FHWA)	Number of Nonstop Vehicles	Percentage of Nonstop Vehicles	Number of Vehicles with Stops	Percentage of Vehicles with Stops
Class 8	5	27.78%	13	72.2%
Class 9	3,854	59.95%	2,575	40.05%
Class 10	1,395	60.68%	904	39.32%
Class 12	109	44.13%	138	55.87%
Class 13	162	43.78%	208	56.22%
Total	5,525	59.01%	3,838	40.99%

Existing WIM systems are not primarily used to collect and record the average travel speed of individual heavy vehicle travelling along a corridor since they can not detect whether trucks stop or rest along their journey. Global Positioning System (GPS) data, however, may provide additional insight regarding individual vehicles' travel information including speed measurement, and vehicles' stop time, rest time and re-fueling time on long-distance trips. The polling rate of a GPS makes it possible to detect moving vehicles in real-time. The higher polling rate indicate that the collected information is closer to real-time.

3.2.2 Global Positioning System

A GPS device installed in a heavy vehicle can be used to track origin and destination (OD) and other performance measures associated with freight transportation. Various studies that used

GPS data to evaluate freight movement and performance. The City of Portland, Oregon, for example, conducted a GPS analysis to investigate travel time reliability on 10 different segments of northbound Interstate 5 (Sarkar et al., 2011), and GPS data was used in Minnesota for a study evaluating heavy vehicle mobility and reliability (Liao, 2014). Such studies provided meaningful inputs for infrastructure improvement and for developing operational strategies for freight transportation.

GPS technologies can also be used to measure and monitor the travel speed of freight vehicles. In 2010, a study found that GPS data can estimate heavy vehicles' average speed along a route by measuring the vehicles' location and attached time stamp, and can also accurately estimate the vehicles' spot speed (Zhao et al., 2011). The City of Calgary, Alberta conducted a study to evaluate different variable speed limit systems by using average speed estimated from GPS devices (Kattan et al., 2015). In 2017, a GPS data was used in China to evaluate variation in vehicles' travel speed in relation to road geometry (road curvature, gradient, etc) (Dai, 2017).

It appears that GPS can play an important role in measuring and monitoring freight vehicles' travel speed. However, speed enforcement for freight vehicles is a complex problem that requires more studies to achieve a deeper understanding. For instance, GVW is a key factor affecting freight travel speed and other freight performance measures (NHTSA, 2012), but GPS does not provide information about vehicles' weight and classification.

In this study, we obtained one month (March, 2016) of GPS heavy vehicle data (defined as FHWA vehicle Classes 8 to 13) travelling in both directions along the study corridor between Laidlaw and Golden. The GPS traffic data for each trip included: 1) unique trip identification (ID), 2) start and end latitude-longitude reading for each trip, 3) stopping hours (duration that the heavy vehicle stopped), 4) total trip hours, and 5) total driving hours (total trip hours minus stopping hours). In total, there were 1,727 (raw) heavy vehicle trips from Laidlaw to Golden and 1,858 trips (raw) from Golden to Laidlaw. See Table 3-4.

The raw GPS data contained the geospatial points (i.e., the location) of the start and end points, and the stop points where the stopping duration exceeded 300 seconds (5 minutes). To geocode the GPS data to the study roadway network, shape files were developed using ArcGIS to create 5 km by 5 km square zones centered on both WIM stations to capture the start and end (Laidlaw and Golden) points of the heavy vehicle trips. A 5 km wide buffer zone was created using ArcGIS to exclude trips with stops outside the main study corridor. See Figure 3-2 which shows the raw data (a) and the adjusted data (b). We analyzed only the trips with all ping points located within the buffer zone.

a) Raw GPS Data

b) GPS Data within Buffer Zone

Figure 3-2: GPS Data Between Laidlaw to Golden

The GPS data was divided into two groups: 1) travel without stops (nonstop), and 2) travel with stop(s). The travel without stops group included no vehicles stops or the stop duration of each stop was less than 300 seconds (5 minutes) between Laidlaw and Golden. For consistency with the WIM data, we considered only the trips from Laidlaw to Golden.

Abnormal trips were also screened and excluded. Examples include trips for which the total time exceeded 24 hours or the driving time exceeded 13 hours without a stopping time of at least 8 hours (as required by Hours-of-Service regulations) (Goverment of B.C., 2012). For consistency with the WIM dataset, only trips of less than 12 hours were included in the final sample.

The final GPS traffic dataset included 1,241 vehicles of which 332 made non-stop trips and 909 made stopping. The Table 3-4 shows interesting differences compared to Table 3-3. The percentage of nonstop trip in GPS data (Table 3-4) is 27 % (73% of stopping trip). The percentage of nonstop trip in WIM data is 59 % (41 % of stopping trip). It could be caused by different criteria to differentiate nonstop and stopping trips. The detail comparison between two datasets would be discussed in Chapter 5.2

Table 3-4: GPS Traffic Data for Laidlaw to Golden Direction

Type of Data	Total Number of Vehicles	Number of Non-Stop Vehicles	Percentage of Non-Stop Vehicles	Number of Vehicles with Stops	Percentage of Vehicles with Stops
Raw Laidlaw to Golden	1,727	334	0.19	1,393	0.81
Final Laidlaw to Golden	1,241	332	0.27	909	0.73

3.3 Chapter Summary

This chapter describes the WIM and GPS study datasets. Both datasets were collected along the same study corridor.

The WIM data consisted of a single dataset and a link dataset. The datasets included data for trips made in favourable weather and traffic conditions only. The study mainly focused on processing link dataset. The average speed limit was estimated for link dataset and the speed violation rate was able to calculate for the heavy vehicles traveling from Laidlaw to Golden. The link data were also categorized into nonstop trips and stopping trips according to the total travel time less than 8 hours and the GVW measured within 10% at the two trip ends.

GPS dataset was also included to improve the accuracy of the speed estimates for this study. The GPS data excluded data for abnormal trips for processing the raw GPS data to obtain the ready-to-use GPS study data. GPS data was also categorized into nonstop trips and stopping trips based on the duration of stops less than 5 minutes for each trip.

Chapter 4 describes the detailed methodology used in the examining proposed M-FHWA class, the development of an integrated database, the investigation of relationships, the simulation model development and the model calibrations.

Chapter 4 Methods of Analysis

This chapter introduces the six methodologies used in the detailed data analysis presented in Chapter 5 and the simulation study presented in Chapter 6. The methodologies are: analysis of variance (ANOVA) test, Quantile-Quantile (QQ) plot, linear regression model, Monte Carlo data fusion method, statistical correlation tests, and a microsimulation model.

Section 4.1 discusses the statistical approaches as Figure 4-1 showing. The conventional FHWA class scheme largely depends on the configuration of vehicles. A Modified-Federal Highway Administration (M-FHWA) classification that takes GVW into account was created. First, ANOVA tests with Tukey's HSD tests were used to exam whether the average speed in each M-FHWA class was distinctive enough to suggest that setting different speed limits for each M-FHWA class would be appropriate. The study used three different approaches to develop an integrated dataset that combined WIM data with GPS data to include more accurate speed distribution with nonstop and travel with stops information. Firstly, a QQ plot was used to check whether the speed distributions of the WIM and GPS data were similar. Secondly, a linear regression model was used to estimate the linear relationship between the WIM speed data and GPS speed data. Thirdly, the Monte Carlo method was applied to develop the integrated dataset that incorporated WIM data and GPS data. The study then evaluated the FHWA heavy vehicle classification and a proposed M-FHWA classification to decide which scheme would be suitable for developing a DSL strategy based on GVW. Two types of correlation tests, Spearman and Pearson, were employed to examine the empirical relationships between heavy vehicle speed and GVW for FHWA classes and M-FHWA classes.

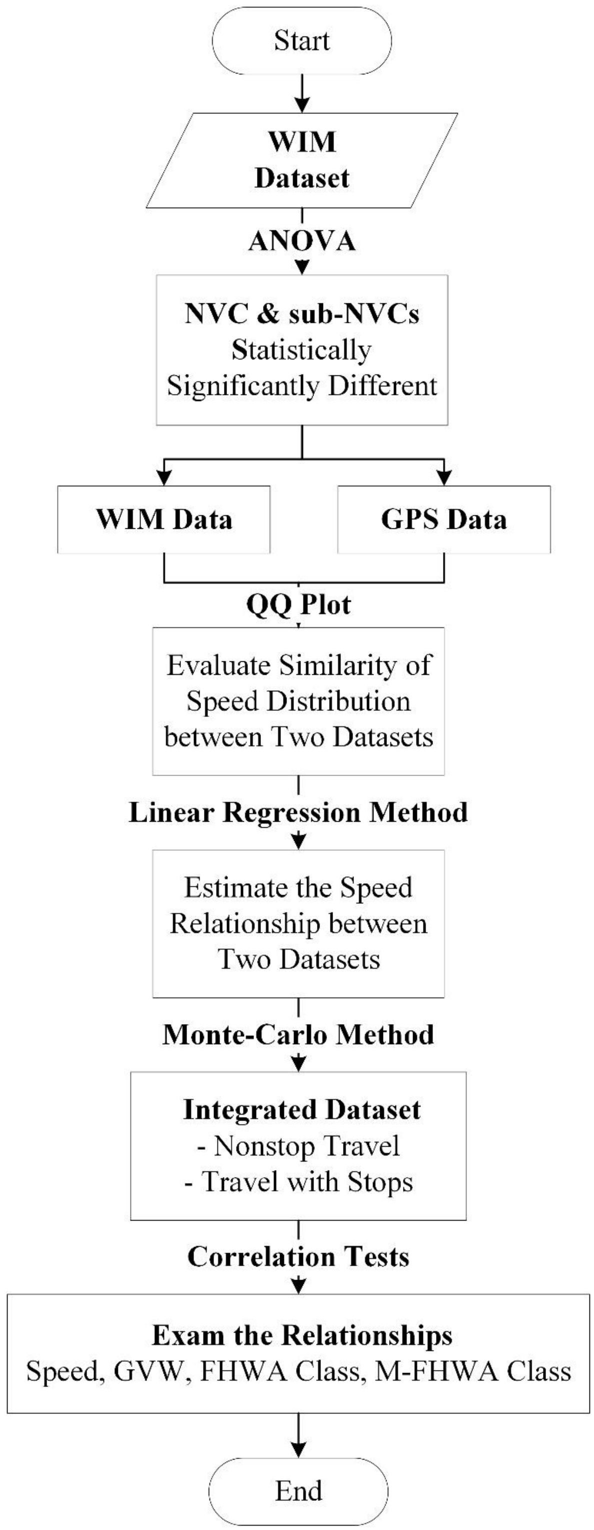


Figure 4-1: Process of Data-Driven Analysis

Section 4.2 describes the microsimulation and the two-stage calibration approach in a VISSIM environment.

To analyze and interpret the large amount of data available, we used the R statistical language (R Core Team, 2018).

4.1 Statistical Approaches

4.1.1 Analysis of Variance Tests

Analysis of variance tests (ANOVA) is a widely used statistical approach that analyzes the data by comparing the means of subsets of data. The base case is the one-way ANOVA which has one independent variable. One-way ANOVA compares the means of three or more groups and determines whether the means are significant different from each other (Williams, 2004).

The null hypothesis for the one-way ANOVA test is that the means of the different groups are equal. In other words, the null hypothesis implies that there is not enough evidence to prove the means of the group are different from others. The alternative hypothesis is that at least one sample mean is not equal to the others. In the one-way ANOVA test, an F value indicates whether the variance between the means of two groups is significant. F value is the ratio of the variability between the groups to the variability within the groups, i.e., an F value of 10 indicates that the variability between the groups is 10 times than the variability within the groups. The F-value is close to 1 if the ANOVA null hypothesis is true (Frost, 2017a).

The F value must be used together with the P value. In one-way ANOVA, F value indicates whether some group mean is significant, but the P value indicates whether the overall results are significant. If the P value is less than the significance level of 0.05 and the F value is large (larger than 1), the null hypothesis should be rejected indicating that there is a significant difference between the groups (Webb and Pajak, 2014; Frost, 2017b).

At this point, it is important to note that ANOVA tests only investigate whether the results are significant different overall. The tests do not provide deeper insights, i.e., they do not indicate which specific groups are significant statistically different from other groups (Stevens, 1999; Newsom, 2018). In our study, more than two groups needed to be compared. Specifically, there are four groups of M-FHWA classes (class 1, class 2, class 3, class 4) and 11 sub-groups that can be found in Table 5-1 of Chapter 5.1. After completing one-way ANOVA test, a Post Hoc test, also known as multiple comparisons, was needed to make all of the pairwise comparisons between groups. Different Post Hoc tests are available. For one-way ANOVA, Tukey's Honest Significant Difference test (Tukey's HSD) is a popular approach when the sample size of the groups is unequal. Tukey's HSD calculates one critical values and the differences between all possible pairs of means. Each difference is then compared to the Tukey's HSD critical value. If the absolute value of the difference between the two pairs' means is greater than or equal to the Tukey's HSD critical value which represents the P value equal to 0.05, the comparison is statistically significant (Stevens, 1999; Newsom, 2018). Equations 4-1 and 4-2 show the calculation of the critical value and the comparison:

$$\boldsymbol{HSD = q\sqrt{\frac{MSE}{n}}} \qquad \textbf{Equation 4-1}$$

$$\boldsymbol{\left|Y_i - Y_j\right| \geq Tukey's\ HSD} \qquad \textbf{Equation 4-2}$$

where:

MSE is the mean square value within a group;

n is the number of values in a group;

q is the relevant critical value obtaining from the studentized range statistic table (Stevens, 1999);

Y_1 is the mean of group i; and

Y_2 is the mean of group j.

In this study, we conducted a series of one-way ANOVA tests and Tukey's HSD tests for each M-FHWA class and sub- M-FHWA classes to check whether the average speeds estimated for each M-FHWA class and sub- M-FHWA classes are significantly different from each other. Chapter 5.1 provides details.

4.1.2 Quantile-Quantile Plot

A quantile-quantile (QQ) plot is a probability plot and a non-parametric graphical method. It can be easily constructed by the R language (Ford, 2015). Although a QQ plot is generally a more powerful approach than simply comparing histograms of the two samples, it requires skill to interpret properly.

The QQ plot is a scatterplot that plots two dataset's quantiles against one another as shown in Figure 4-2 (Perktold et al., 2019). It can be used to virtually inspect the similarity between the distributions of two datasets. If the distributions of two datasets are similar, the points in the scatterplot lie approximately on the 45-degree line (the red line in Figure 4-2). Greater departure from the 45-degree line indicates greater evidence that the distributions of the two data sets are different (Ihaka, 2007).

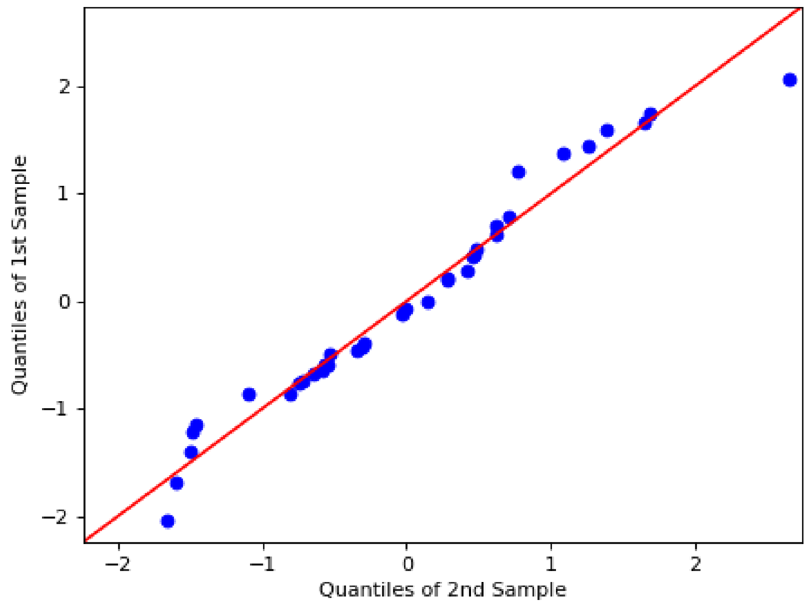


Figure 4-2: Example of Quantile-Quantile Plot (Perktold et al., 2019)

An advantage of the QQ plot is that the two datasets tested does not require the strong assumption of equal distribution. For instance, two test datasets do not both need to have a normal distribution. QQ plots can detect shifts in location, shifts in scale, changes in symmetry, and the presence of outliers. If the two data sets come from populations whose distributions differ only by a shift in location, the points should lie along a straight line that is displaced either up or down from the 45-degree line.

This study conducted QQ plotting to examine similarities in the speed distributions between the WIM and GPS speed datasets and to determine whether or not there exists a relationship between the WIM and GPS speed datasets.

4.1.3 Linear Regression Model

After examining the similarities in the speed distributions, it is time to establish whether there is a relationship between WIM speed distribution and the GPS speed distribution. Regression modeling has been widely used to estimate the relationships between one or more independent variables and dependent variables (Myers, 1990). Linear regression, the basic and commonly used type of regression model, finds the best-fitting straight line that describes the relationship between two continuous variables, an independent variable and a dependent variable. Equation 4-3 presents a linear regression model (Zou et al., 2003):

$$\boldsymbol{y = a + bx}$$ **Equation 4-3**

where:

x is the independent variable;

y is the dependent variable;

a is the intercept of the regression line; and

b is the slope of the regression line.

The equations for the intercept “a” and the slope “b” can be calculated as follows (Kutner et al., 2005):

$$\boldsymbol{a = \frac{(\sum y)(\sum x^2) - (\sum x)(\sum xy)}{n(\sum x^2) - (\sum x)^2}}$$ **Equation 4-4**

$$\boldsymbol{b = \frac{n(\sum xy) - (\sum x)(\sum y)}{n(\sum x^2) - (\sum x)^2}}$$ **Equation 4-5**

where:

a is the intercept of the regression line;

b is the slope of the regression line;

x is the independent variable;

y is the dependent variable; and

n is the number of observations.

4.1.4 Monte Carlo Data Fusion Method

After calculating the relationship between the WIM speed data and the GPS speed data using a linear regression model, we created an integrated dataset containing information such as travel speed, vehicle classifications, weight, stop pattern (non-stop trips and stopping trips) for further analysis. This data fusion process is discussed below.

As mentioned earlier, the WIM data included information such as vehicle classifications and GVW for all vehicles, but it did not include details of non-stop trips and stopping trips along the study corridor. The GPS data contained information that was not recorded in the WIM system such as stopping duration and stopping locations and for each heavy vehicle, but it did not include weight and vehicle class information.

In order to create an integrated dataset that contained all the information in the two distinct, but incomplete sources of information (WIM and GPS), this study relied on data fusion technology known as the Monte Carlo method (Reichstein and Richardson, 2011).

The Monte Carlo method is applied to create a single integrated database that maintained the distributions of the various factors inherited from the two distinct datasets. In simple terms, the integrated dataset created by the through Monte Carlo method was able to present the equivalent ratio for each important characteristic considered (e.g., vehicle class, GVW, stopping and non-stopped ratio) compared to those characteristics in each dataset.

The Monte Carlo data fusion method is a set of computational algorithms that conduct repeated random sampling to obtain desired numerical outcomes. The approach is often used to solve problems in the area of physics and mathematics and can also be found in many engineering applications (Reichstein and Richardson, 2011; Kroese et al, 2014; Trieu et al, 2014). To minimize uncertainty in the process, instead of using a single value (e.g., an average) as a representative input for a particular variable, the Monte Carlo method provides a better approach (Shapiro, 2003; Kroese et al., 2014). Figure 4-3 shows an outline of the Monte Carlo data fusion method adopted in this study.

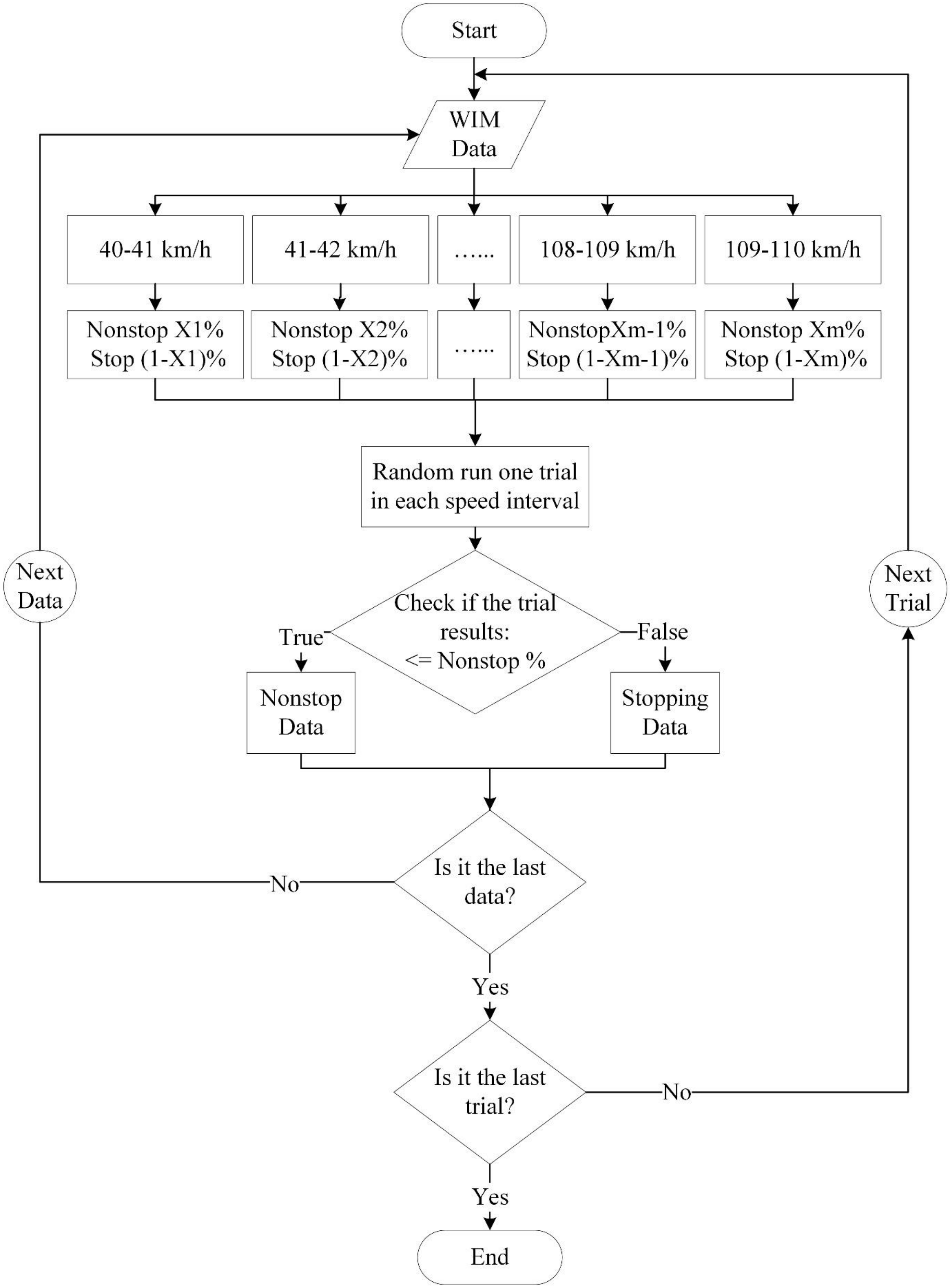


Figure 4-3: Process of Monte Carlo Data Fusion Method

Figure 4-3 shows the multiple steps of the Monte Carlo data fusion method. The method first created a multiple partitioned dataset according to the percentage of nonstop vehicles in each speed interval obtained from the GPS dataset. The percentage of nonstop vehicles in the first speed interval (40 km/h to 41 km/h) can be interpreted as X_1 %, and the percentage of stopping vehicles in the first speed interval (40 km/h to 41 km/h) can be interpreted as (1- X_1) %.The percentage of nonstop vehicles in the last speed interval (109 km/h to 110 km/h) can be interpreted as X_m %, and the percentage of stopping vehicles in the first speed interval (109 km/h to 110 km/h) can be interpreted as (1- X_m) %. The subscript letter m represents the maximum value and X_m represents the maximum speed interval.

From the precise speed interval, first speed interval (minimum speed interval from 40 km/h to 41 km/h) to the last speed interval (maximum speed interval from 109 km/h to 110 km/h), the percentage of nonstop vehicles in each speed interval can be interpreted from X_1 % to X_m % and the percentage of stopping vehicles in each speed interval is from (1- X_1) % to (1- X_m) %. Based on the precise speed interval, we obtained the precise percentage of nonstop and stopping vehicles in each speed interval from GPS dataset. Then, the partitioned dataset was used as criteria to re-categorize WIM dataset. The detail was explained as below.

The method used randomly sampling to obtain the percentage of nonstop and stopping vehicles in each speed interval for WIM dataset (all trips in WIM dataset) and compared the random sample results of all trips in WIM dataset with the partitioned dataset obtained in the first step for each speed interval from GPS dataset. If the sampling value of the trip in WIM dataset was smaller than the percentage value of the GPS dataset for the same speed interval, the iteration output (the trip in WIM dataset) moved on to the nonstop trips group. If the sampling value of the trip in WIM dataset was bigger than the percentage value of the GPS dataset for the same speed interval, the iteration output moved on to the stopping trips group. The iterations continued until we obtained the numerical results for each speed interval and all speed intervals were exhausted. (See Figure 4-3) After the first iteration, the simulation iterated an additional nine times until completed ten times.

Each trip in WIM dataset contained the detail travel information including average speed, GVW and vehicle classification. When all the trips in WIM dataset were randomly sampled and re-distributed into nonstop and stopping categories after integrating the dataset through this resampling process, the distribution of vehicle speed, GVW and classification were also re-distributed and signed into nonstop and stopping categories. Finally, we had a set of non-stop trips information and a set of stopping trips information.

4.1.5 Correlation Analysis

The degree of linear relationship between variables can be measured by correlation analysis. There are different types of correlation analysis. The two most popular types, Pearson correlation and Spearman correlation, were used in this study (Statistics Solutions, 2019).

Spearman's rank-order correlation (Spearman Correlation)

Spearman correlation is a non-parametric correlation test used to measure the degree of ranking association between two variables. Unlike the Pearson correlation, this analysis does not assume a linear relationship between the variables. It also does not assume any distribution for the variables tested. The equation for the Spearman correlation is shown in Equation 4-6 (Mukaka, 2012):

$$\boldsymbol{\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)}} \qquad \textbf{Equation 4-6}$$

where:

d_i is the difference between rank xi and rank yi; and n is the number of data.

Spearman's coefficient will be close to 1 if the relative position (rank) of each observation from the two variables is positively and strongly associated. Spearman's coefficient will be close to -1 if the relative position (rank) of each observation rank from the two variables is negatively and strongly associated (Hauke and Kossowski, 2011; Statistics Solutions, 2019).

Pearson product moment correlation (Pearson correlation)

Pearson correlation is the most widely used method. Both variables should be normally distributed. The correlation coefficient ranges from -1 to +1 and indicates the strength of the monotonic relationship between the two variables. A monotonic relationship is a relationship that does one of the following: 1) as the value of one variable increases, so does the value of the other variable; or 2) as the value of one variable increases, the other variable value decreases. The equation for calculating the Pearson correlation is shown in Equation 4-7 (Mukaka, 2012):

$$\boldsymbol{r} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\left[\sum_{i=1}^{n}(x_i-\bar{x})^2\right]\left[\sum_{i=1}^{n}(y_i-\bar{y})^2\right]}} \qquad \textbf{Equation 4-7}$$

where:

R is the correlation coefficient between variable x and variable y;

$\bar{x}$ is mean of variable x;

$\bar{y}$ is the mean of variable y;

x_i is the value of variable x in a sample;

y_i is the value of variable y in a sample; and

n is the number of data in a sample.

A correlation coefficient of around +1 implies a strong positive monotonic association, and a correlation coefficient of around -1 implies a strong negative association. A coefficient value of zero implies no monotonic association (Hauke and Kossowski, 2011; Statistics Solutions, 2019).

4.2 Microsimulation Approach

The use of microsimulation models in traffic operations, traffic safety, transportation design and planning is becoming popular due to the increased need for transportation engineers to solve complex transportation problems. Some real world problems cannot be easily answered using a data-driven empirical data analysis that requires observing vast amounts of real world data (Appiah et al., 2012).

This study used VISSIM simulation to understand the potential safety impact of DSL for different type of M-FHWA classes combined with ASE. The simulation study investigated the safety impact by comparing two speed limit strategies (USL and DSL) and two speed enforcement strategies (SSE and ASE). We selected three traffic performance indicators to help evaluate the safety impact in the simulation study: 1) the longitudinal 85^{th} percentile speed profile, 2) standard deviation of speed, and 3) the speed violation rate. The framework of the VISSIM model is shown in Figure 4-4.

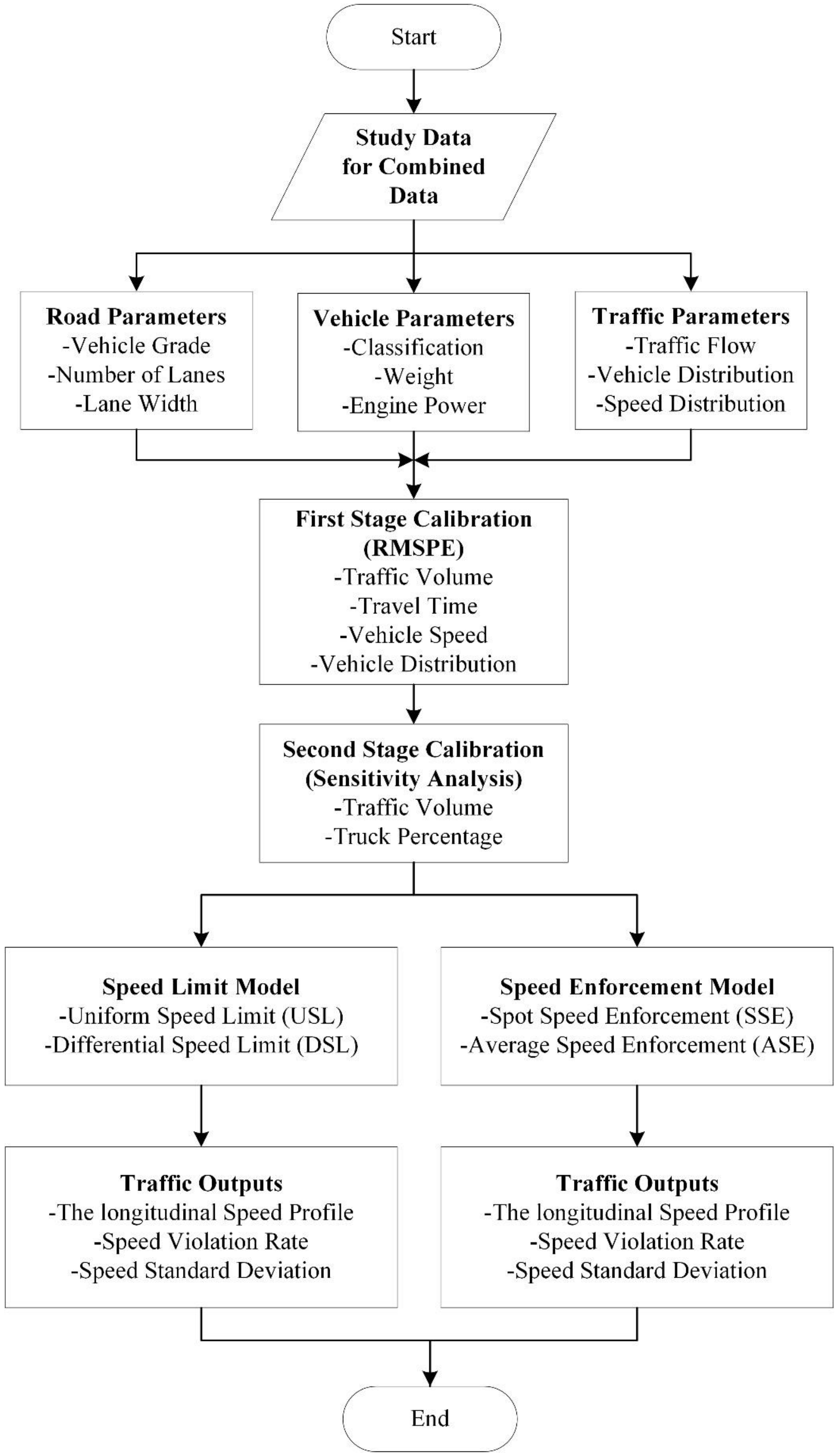


Figure 4-4: Process of VISSIM Simulation

The input parameters for the VISSIM model required three types of traffic data. The first was road parameters which includes road geometry and the number and width of lanes. The second was vehicle parameters such as vehicle classification, vehicle weight, and engine power of different types of heavy vehicles. The third was traffic parameters which includes traffic volume, vehicle distribution, and travel speed. The detail input parameters for simulation model would be described in Chapter 6.1.

The VISSIM model was calibrated to mimic existing traffic conditions as closely as possible. The terms "calibration" and "validation" are used to differentiate phases of the process used to ensure that the model accurately represents real-world traffic conditions, but for simplicity the word "calibration" is used throughout this study as recommended by Wisconsin DOT (2018). We used a two-stage calibration procedure.

In the first stage, we used integrated dataset to calibrate traffic volume, travel time and average speed to check whether the traffic volume, travel time and travel speed outputs from the simulation model represented input traffic conditions accurately. For that, the goodness-of-fit (GOF) endorsed by Wisconsin DOT (Wisconsin DOT, 2018) were used.

The GOF tests were conducted in two steps: test 1 and test 2 (Wisconsin DOT, 2018). If the model passed the test 1, a global calibration test, it was not necessary to perform test 2 which is a local test for the same metric. In test 1 (global) tests, the Root Mean Square Percentage Error (RMSPE) was used as the primary calibration metric. RMSPE is defined in Equation 4-8 (Wisconsin DOT, 2018):

$$\boldsymbol{RMSPE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{M_i - O_i}{O_i}\right)^2} \qquad \textbf{Equation 4-8}$$

where:

M is simulated data;

O is input data;

N is total number of data points in the dataset; and

i is data point i.

The RMSPE threshold was 5% for traffic volume, 10% for travel time, and 10% for vehicle speed that were endorsed by Wisconsin DOT. If all the RMSPE values for the different parameters are smaller than the threshold values, the model works well and can provide reasonable and reliable simulation results (Wisconsin DOT, 2018).

However, the integrated dataset only included heavy vehicle (FHWA class 8 to class 12 vehicles) and did not have completed traffic volume information (FHWA class 1 to class 7 vehicles). Therefore, the traffic volume information was used in the first stage calibration was estimated based on three years (2010, 2013 and 2016) of Annual Average Daily Traffic (AADT) data provided by the British Columbia Ministry of Transportation and Infrastructure (BC MTI, 2019). The data was collected around 4 km downstream of the simulation segment. We used a linear interpolation method to estimate the traffic volume and Appendix G provides details of the method used to estimate traffic volume.

In the second-stage, we focused on finding suitable values for two traffic parameters, traffic volume and heavy vehicle percentage, for our base scenario. These two parameters had significant influence on heavy vehicle speed, but could not be evaluated from the integrated data directly. A sensitivity analysis was conducted to examine different levels of traffic volume and different heavy vehicle percentage to determine suitable values of the two input parameters for the base scenario. After examining different combinations of traffic volume and heavy vehicle percentage, speed distribution was used as rationale to compare the calibration results and integrated data and find the most appropriate values for traffic volume and heavy vehicle percentage for base scenario.

Once the model accurately estimated traffic parameters such as travel speed, various mixtures of heavy vehicle classes and various traffic volumes, the model could be used to evaluate different scenarios. These included the comparison of USL and DSL and the comparison between SSE and ASE to assess the potential safety impact of heavy vehicles on highway by evaluating the three traffic performance indicators, i.e., 1) longitudinal speed distribution, 2) standard deviation of speed, and 3) speed violation rate.

4.3 Chapter Summary

This Chapter discussed the six methodologies used in the study: 1) ANOVA, 2) QQ plot, 3) linear regression model, 4) Monte Carlo data fusion method, 5) two correlation tests, and 6) a microsimulation model. One-way ANOVA tests with Tukey's HSD tests for each M-FHWA class and sub- M-FHWA classes were used to check that the average speeds estimated for each M-FHWA class and sub- M-FHWA classes were statistically significantly different. The QQ plot was used to check differences in the speed distributions obtained from the WIM and GPS datasets. A linear regression model was applied to estimate the speed relationship between the WIM and GPS speed datasets. The Monte Carlo data fusion method was applied to develop a more accurate and integrated nonstop and stopping trips dataset. The study then applied Pearson and Spearman correlation tests to examine the statistical relationship between the heavy vehicles' speed, GVW, FHWA vehicle classification and M-FHWA classification in our integrated traffic dataset. The general aspects of the VISSIM simulation model and the two-stage model calibration process were also included.

Chapter 5 Data-Driven Analysis

This Chapter discusses three empirical data analyses. Firstly, this Chapter proposes a Modified-Federal Highway Administration (M-FHWA) classification that explicitly considered heavy GVW. Secondly, this Chapter discusses the development of the integrated dataset using the data fusion process discussed in Chapter 4.1.4 to amalgamate WIM data and GPS data. Lastly, this Chapter evaluated the FHWA heavy vehicle classification and a proposed M-FHWA classification to decide which scheme would be suitable for developing a DSL strategy based on GVW. The study examined the empirical relationships between heavy vehicle speed and GVW for FHWA classes and M-FHWA classes.

5.1 Proposed Vehicle Classification

As one of the purposes of this study was to investigate the possibility of setting a new differential speed limit by considering GVW in detail, an in depth analysis was conducted to develop a new heavy vehicle classification scheme which differs from the FHWA vehicle classification because it includes a more precise consideration of heavy vehicle weights.

Figure 5-1 showed the existing FHWA vehicle classification scheme including motorcycles (class 1), passenger cars (class 2 and 3), buses (class 4), single-unit truck (class 5 to 7) and multi-unit trucks (class 8 to class 13). FHWA classification largely depends on the configuration of vehicles, for example, the presence or absence of trailers and/or the number of axles (FHWA, 2013). This means that the GVW of heavy vehicles belonging to a particular FHWA class can have widely different GVWs. The FHWA classification is not the most suitable classification to be used for DSL associated with GVW.

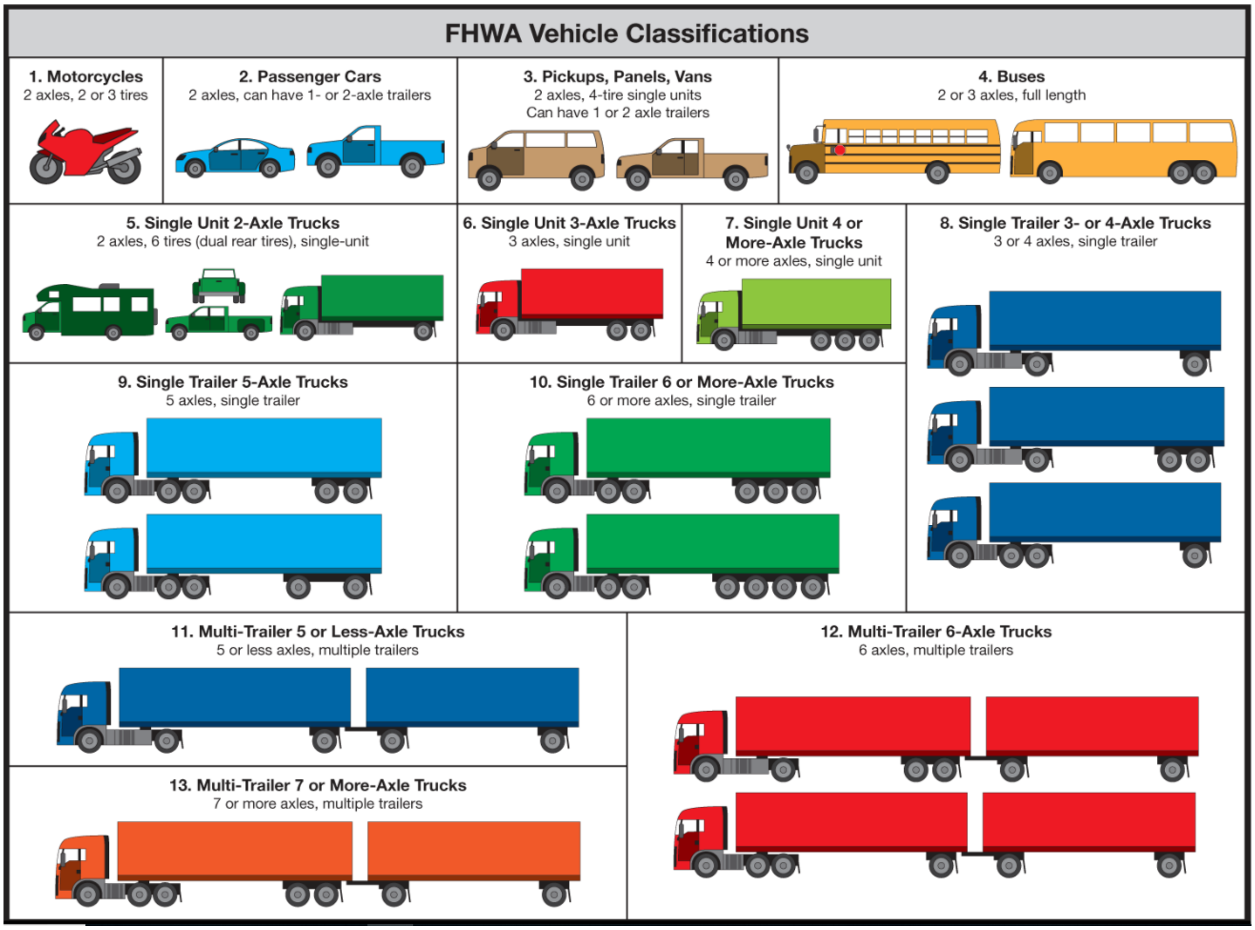


Figure 5-1: FHWA 13 Vehicle Classification Scheme (FHWA, 2013)

A different heavy vehicle classification scheme was also presented by U.S. Environmental Protection Agency with consideration of vehicle GVW as Appendix A showing (EPA, 2017). The main criterion of the EPA classification was GVW, and the maximum GVW threshold suggested in the classification is 60,000 lb (27,200 kg). However, the current classification was not precise enough for this study's objectives. Specifically, about 64 % of heavy vehicles in our sample had a GVW of more than 27,200 kg, while the average GVW for vehicles travelling in our study corridor was 31,045 kg with the highest GVW as 67,020 kg.

Thus, we proposed a Modified-Federal Highway Administration (M-FHWA) classification based on the current conventional FHWA classification. We considered one important threshold value of GVW, 27,200 kg which was the maximum GVW threshold suggested by EPA classification. Another higher threshold(s) of GVW for vehicles exceeding 27,200 kg should be considered. The threshold of GVW was selected to ensure that the speed distribution of the category created was distinctive (avoiding overlapping where possible) and that there was a sufficient number of vehicles in each category. When we tried GVW values from 30,000 kg to 60,000 kg with an increment for every 5,000 kg, we found that the speed distributions of each group overlapped when the threshold value was less than 45,000 kg and that the number of vehicles in the groups was not sufficient when the threshold value was higher than 45,000 kg. There were 3 % (372 vehicles) of heavy vehicles with GVW higher than 45,000 kg. There were 2.50 % (234 vehicles) of heavy vehicles with GVW higher than 50,000 kg, 2.10 % (196 vehicles) of heavy vehicles with GVW higher than 55,000 kg and 1.1% (103 vehicles) of heavy vehicles with GVW higher than 60,000 kg. Therefore, 45,000 kg was considered as the second threshold value of GVW to categorize heavy vehicles. Appendix B provides more details.

Based on the three criteria, GVW, FHWA class and average speed, we developed four main classes with a total of 11 sub-M-FHWA classes. We then conducted a series of ANOVA tests and Tukey's HSD tests for each M-FHWA class and sub-M-FHWA class to check whether the average speeds were statistically significantly different. Table 5-1 presents the proposed M-FHWA class and its relationship with the other criteria used to create the M-FHWA class. Total, there are four categories in M-FHWA classification scheme: class 1, class 2, class 3 and class 4 from lightest heavy vehicles to heaviest heavy vehicles according their GVWs.

Table 5-1: Number of Vehicle and Speed Distribution for Proposed Four M-FHWA Class

M-FHWA Class	Average Speed (km/h)	Sub-Class	FHWA Class	GVW (kg)	Number of Vehicles	Average Speed (km/h)
Class 1	86.12	1-8	8	<27,200	18	86.12
Class 2	75.35	2-9	9	<27,200	2,973	75.20
		2-10	10	<27,200	311	76.62
		2-12	12	<27,200	49	76.92
Class 3	72.84	3-9	9	27,200-45,000	3,456	73.22
		3-10	10	27,200-45,000	1,895	72.41
		3-12	12	27,200-45,000	185	70.76
		3-13	13	<45,000	104	71.87
Class 4	66.92	4-10	10	>= 45,000	93	68.51
		4-12	12	>= 45,000	13	66.37
		4-13	13	>= 45,000	266	66.39

If we compare the M-FHWA classification with the FHWA classification, as shown in Table 5-1, M-FHWA class 1 included FHWA Class 8 only. The GVW in this class was less than 27,200 kg and the average speed (87.40 km/h) was substantially higher than that of other M-FHWA classes. M-FHWA class 2 included FHWA Classes 9, 10 and 12 and the GVW for each sub-class was less than 27,200 kg. The average speed for M-FHWA class 2 was 76.51 km/h. M-FHWA class 3 included FHWA classes 9, 10, 12, and 13 with GVW ranging from 27,200 kg to 45,000 kg. The average speed ranged from 70.76 km/h to 73.22 km/h. M-FHWA class 4 included FHWA Classes 10, 12 and 13. The GVW was more than 45,000 kg and the average speed ranged from 66.37 km/h to 68.51 km/h.

Table 5-2 summarizes the results of the ANOVA test for the four M-FHWA classes. If the ANOVA null hypothesis is true (i.e., if the F-value is close to 1 and the P-value is more than 5%), the speed means between the M-FHWA classes were not statistically significantly different. In Table 5-2, the F-value was 117.5 and the P-value was 0, so we rejected the null hypothesis at the 5% significance level and concluded that there was a statistically significant difference in vehicle speeds between M-FHWA class 1, M-FHWA class 2, M-FHWA class 3 and M-FHWA class 4.

Table 5-2: ANOVA Test for the Four M-FHWA Classes

Source	Degrees of Freedom	Sum of Squares	Mean Square	F-Value	P-Value
Type	3	33,150	11,050	117.5	0
Residuals	9,361	880,286	94	-	-

The ANOVA test results in Table 5-3 indicate that the average speed differences between the four M-FHWA classes are statistically significant, but the results did not indicate exactly which classes had statistically different mean speeds. We applied Tukey's Post Hoc test to investigate. This test was used to compare all possible pairs of average speeds between the four M-FHWA classes. Table 5-3 shows the results. The analysis showed that the four M-FHWA classes were statistically significantly different at the 5% level of significance.

Table 5-3: Tukey Post Hoc Test for Four M-FHWA Classes

M-FHWA Class Pair	Mean Difference	Lower Bound	Upper Bound	Adjusted P-Value
Class 2 - Class 1	-10.74	-16.63	-4.85	0.0000
Class 3 - Class 1	-13.28	-19.16	-7.40	0.0000
Class 4 – Class 1	-19.20	-25.21	-13.19	0.0000
Class 3 - Class 2	-2.53	-3.08	-1.99	0.0000
Class 4 - Class 2	-8.46	-9.82	-7.10	0.0000
Class 4 - Class 3	-5.92	-7.26	-4.59	0.0000

Additional Tukey's Post Hoc tests were conducted for each pair of sub- M-FHWA classes (see Appendix B for details). The result showed that some sub- M-FHWA classes that were not statistically significantly different from each other. This implies that the four M-FHWA classes may be adequate for developing a new differential speed limit and that 11 sub-M-FHWA classes may be too many for this purpose.

5.2 Development of an Integrated Dataset Using WIM and GPS Datasets

This section discussed the development of the integrated WIM and GPS dataset. Section 5.3 discusses the relationships between heavy vehicles' travel speed, GVW, FHWA classification, and M-FHWA classification based on integrated dataset.

The WIM system could not detect whether a heavy vehicle keeps continuously travelling or stopped at somewhere for rest or refuel. To overcome this problem and reduce possible bias due to the lack of stop duration information, we considered GPS data which included information such as speed, rest locations and stop times along the study corridor to combine with WIM data and develop an integrated dataset including more accurate nonstop and stopping information.

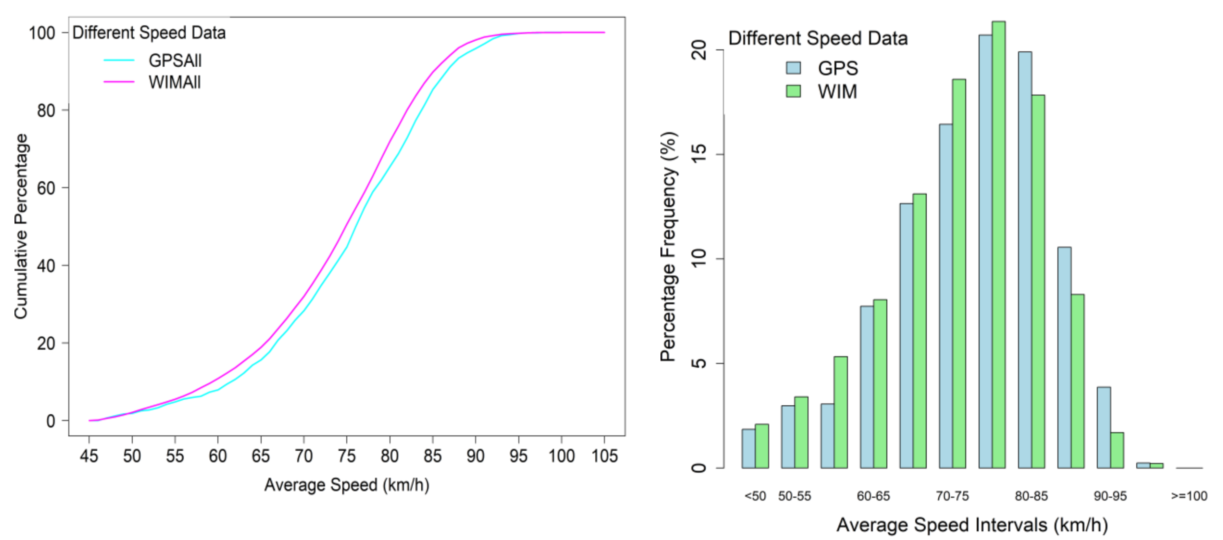
Table 5-4 show the speed violation rate for the all trips, nonstop trips and stopping trips for GPS data. We used 5 minutes as the threshold for defining a stop and separating nonstop trips from stopping trips. The speed violation rate (i.e., average travel speed faster than 88 km/h) for nonstop trips was 20% and stopping trips was 2%. The speed violation rate for all vehicles travelling along the study corridor was 7%.

Table 5-4: Speed Limit Violation Rate Distribution for GPS Data

GPS Data	All Vehicle	Nonstop Vehicles	Stopping Vehicles
Number of Vehicle	1,241	332	909
Speed Limit Violation Rate	7 %	20 %	2 %

While the average speed information from GPS is acknowledgeable, it did not contain information about the weight and classification of heavy vehicles. WIM system provided such information, we decided to combine both WIM and GPS dataset through a series of data fusion process as discussed in Chapter 4.

Before starting the data fusion process, we checked similarities in the WIM and GPS data distributions to check whether data integration through a data fusion process was feasible. Figure 5-2 confirms that the WIM and GPS data have very similar speed distributions. (Appendix D shows additional sets of data comparison between the WIM and GPS datasets.)



a) Cumulative Percent Frequency of Average Speed

b) Percent Frequency of Average Speed

Figure 5-2: Speed Data Comparison between GPS and WIM

Figure 5-3 shows the quantile-quantile (QQ) plot developed to examine the relationship between the WIM and GPS datasets. Each black point (x,y) in Figure 5-3 is a plot of GPS average speed distribution along the vertical axis against the corresponding WIM average speed distribution along the horizontal axis.

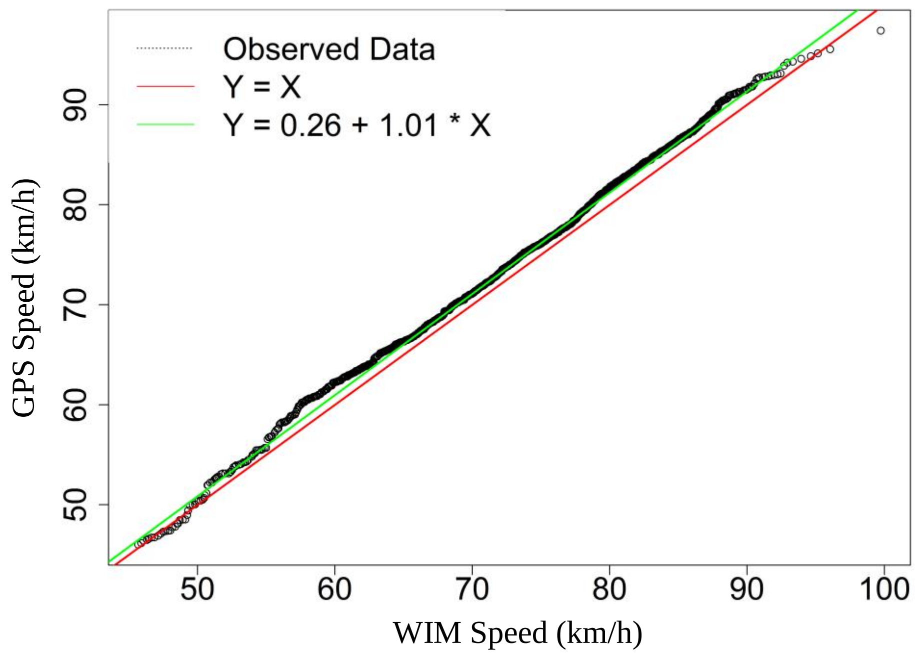


Figure 5-3: QQ Plot between WIM Data and GPS Data

The red line in Figure 5-3 is the 45-degree line with slope as 1. Points along this line indicate that the distribution of the GPS average speed perfectly equals the distribution of the WIM average speed. Figure 5-3 shows that the black points are close to the red line, but not exactly on the red line. Points above the red line indicate that the distribution of GPS average speed is slightly higher than the distribution of WIM average speed.

From Figure 5-3, it is reasonable to infer that the WIM and GPS speed distributions are very similar in shape and differ only slightly in location and scale. We developed a linear regression line (Equation 5-1) to show the relationship between the two datasets quantitatively:

$$\boldsymbol{y = a + b\,x} \qquad \textbf{Equation 5-1}$$

where

x is the speed of WIM data;

y is the speed of GPS data;

a is 0.26; and

b is 1.01.

Using the statistical relationship between the WIM and GPS data (Equation 5-1), the speed in WIM speed was updated. After updating the speed for integrated dataset, we applied the Monte Carlo data fusion method to create two distinct datasets including speed, GVW and vehicle classification, one for nonstop trips and one for stopping trips as discussed in Chapter 4.

Monte Carlo data fusion method considered the distribution of vehicle speed, class and GVW and generated simulations using random dawning of WIM data based on the partitioned dataset from GPS data instead of using a single value, such as the average value. The outcome of simulation allows us to compute the distribution of vehicle speed, class and GVW for nonstop and stopping trips. To check the minimum number of simulations required for a proper Monte Carlo data fusion method analysis, we investigated the average speed distribution for 10 simulations and 100 simulations (see Appendix E). As the results were statistically identical, we used 10 simulations to integrate the speed, class and weight distributions for nonstop trips and stopping trips.

We compared the integrated dataset (Table 5-5) with the original WIM dataset (Table 5-6) and GPS data (Table 5-7). In Table 5-5, the total number of vehicles in each vehicle class from integrated data is the same as the total number of vehicles in each class from the WIM dataset (Table 5-6). There is a total of 9,363 heavy vehicles with 18 vehicles in Class 8, 6,429 in

Class 9, 2,299 numbers in Class 10, 247 in Class 12, and 370 in Class 13. This is to be expected as the integrated data was derived from the WIM data.

The percentage of nonstop trips (26.75%) and stopping trips (73.25%) in the integrated data is the same as the percentage of nonstop and stopping trips in the GPS data (Table 5-7). This is to be expected as the integrated data was derived from the GPS data.

These findings show that the Monte Carlo data fusion method successfully incorporated the class and weight information from the WIM dataset, and the nonstop and stopping trips from the GPS dataset into integrated data.

Table 5-5: Frequency and Speed Distribution for Integrated Dataset

	Type of Vehicle Trip					Average Speed (km/h)		
Vehicle Class	**All**	**Nonstop Trips**	**Percentage of Nonstop Trips**	**Stopping Trips**	**Percentage of Stopping Trips**	**All**	**Nonstop Trips**	**Stopping Trips**
Class 8	18	9	0.10%	9	0.10%	87.41	91.12	83.41
Class 9	6,429	1,827	19.51%	4,602	49.15%	75.28	82.44	72.56
Class 10	2,299	558	5.96%	1,741	18.59%	73.95	81.21	71.68
Class 12	247	55	0.59%	192	2.05%	72.87	80.40	70.86
Class 13	370	56	0.60%	314	3.35%	69.00	74.47	68.17
Total	9,363	2,505	26.75%	6,858	73.25%	74.92	82.53	72.14

Table 5-6: Frequency and Speed Distribution for WIM Dataset

Vehicle Class	Number of Vehicles	Average Speed (km/h)
Class 8	18	86.12
Class 9	6,429	74.14
Class 10	2,299	72.84
Class 12	247	71.76
Class 13	370	67.93
Total	9,363	73.53

Table 5-7: Frequency and Speed Distribution for GPS Dataset

Type of Vehicle Trip						Average Speed (km/h)		
Vehicle Class	All	Nonstop Trips	Percentage of Nonstop Trips	Stopping Trips	Percentage of Stopping Trips	All	Nonstop Trips	Stopping Trips
8-13	1,241	332	26.75%	909	73.25%	74.92	82.53	72.14

5.3 Analysis of the Integrated Dataset

Using the integrated dataset, we explored the statistical relationships among heavy vehicles' speeds, GVW for FHWA classification and M-FHWA class. The first step was to undertake Spearman and Pearson correlation analyses (discussed in Chapter 4.1) to examine whether the relationships were statistically significant.

Table 5-8 shows the test results of the Spearman test at the 5% significance level. There are three major findings that need to be noted 1) Average speed has a strong negative correlation with GVW (-0.98), M-FHWA class (-1) and FHWA class (-1), 2) GVW has relatively stronger positive correlation with M-FHWA class (1) than FHWA class (0.98), and 3) FHWA class has a moderate positive correlation with M-FHWA class (0.41).

Table 5-9 shows that the results of the Pearson test are similar to the Spearman results. All three variable (GVW, FHWA class and M-FHWA class) have strong negative correlation with speed. GVW has relatively stronger positive correlation with M-FHWA class (0.97) than FHWA class (0.93), and FHWA class has a moderate positive correlation with M-FHWA class (0.46).

Tables 5-8 and 5-9 show that the M-FHWA class/speed and M-FHWA class/GVW correlations are stronger than the FHWA class/speed and FHWA class/ GVW correlations. These results suggest that the M-FHWA class would be more appropriate vehicle classification scheme than FHWA class when considering a DSL associated with GVW for heavy vehicles. (Appendix F provides a detailed scatter plot of these results.)

Table 5-8: Spearman Correlation Test Result

Variables	Average Speed	GVW	FHWA Class	M-FHWA Class
Average Speed	1.00			
GVW	-0.98**	1.00		
FHWA Class	-1.00**	0.98**	1.00	
M-FHWA Class	-1.00**	1.00**	0.41**	1.00

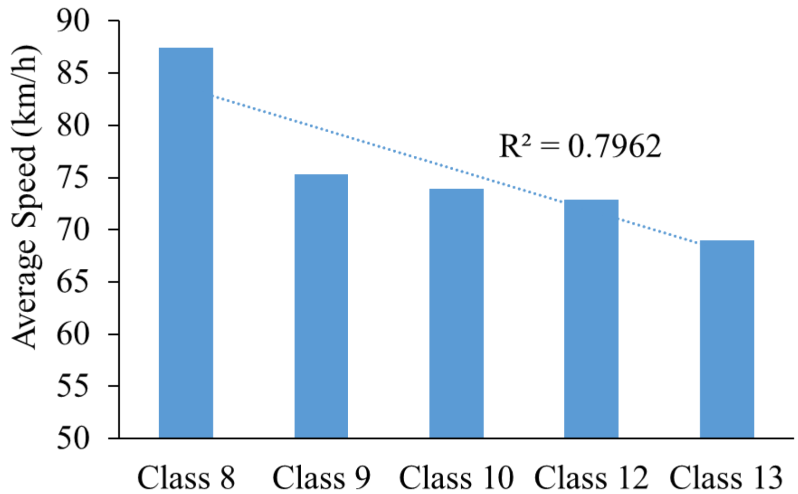
Table 5-9: Pearson Correlation Test Result

Variables	Average Speed	GVW	FHWA Class	M-FHWA Class
Average Speed	1.00			
GVW	-0.96**	1.00		
FHWA Class	-0.92**	0.93**	1.00	
M-FHWA Class	-0.94**	0.97**	0.46**	1.00

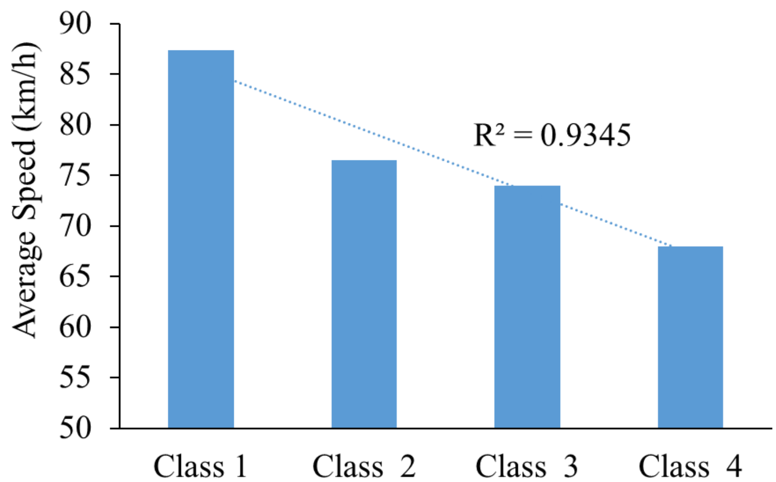
** significant at 0.05 level

Figure 5-4 shows the coefficient of determination (R^2) between average speed and FHWA Class, M-FHWA class and GVW. A value of R^2 that is close to 1.0 indicates a strong linear relationship between two variables (Dufour, 2011). It is clear that FHWA Class, M-FHWA class and GVW all have a very strong decreasing linear relationships with average speed.

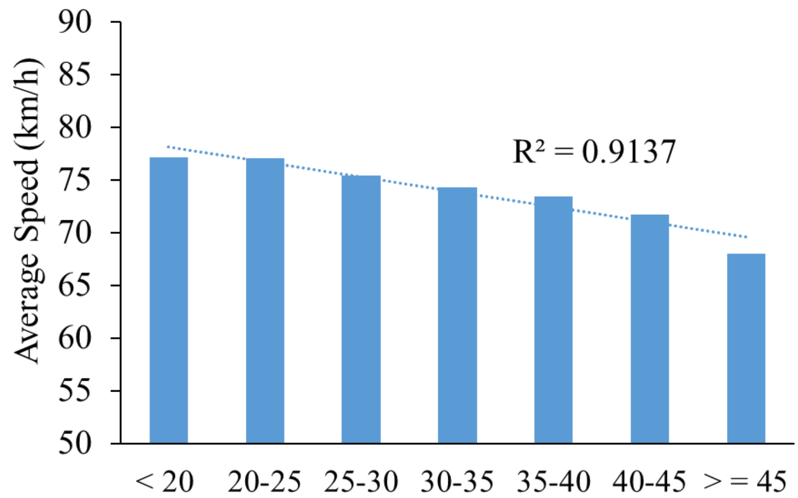
The R^2 value for FHWA class in Figure 5-4 (a) is 0.80 which is smaller than the 0.93 R^2 value for M-FHWA class in Figure 5-4 (b). Both the Spearman and Pearson tests showed that the M-FHWA class/speed relationship was stronger than the FHWA class/speed relationship. The R^2 value for GVW in Figure 5-4 (c) (0.91) shows that GVW also has a very strong decreasing linear relationship, a finding that also reflects the results of the Pearson and Spearman tests. Figure 5-4 also suggests that M-FHWA class is a reasonable classification scheme to use for setting DSL by considering precise GVW for heavy vehicles.



a) FHWA Class



b) M-FHWA Class

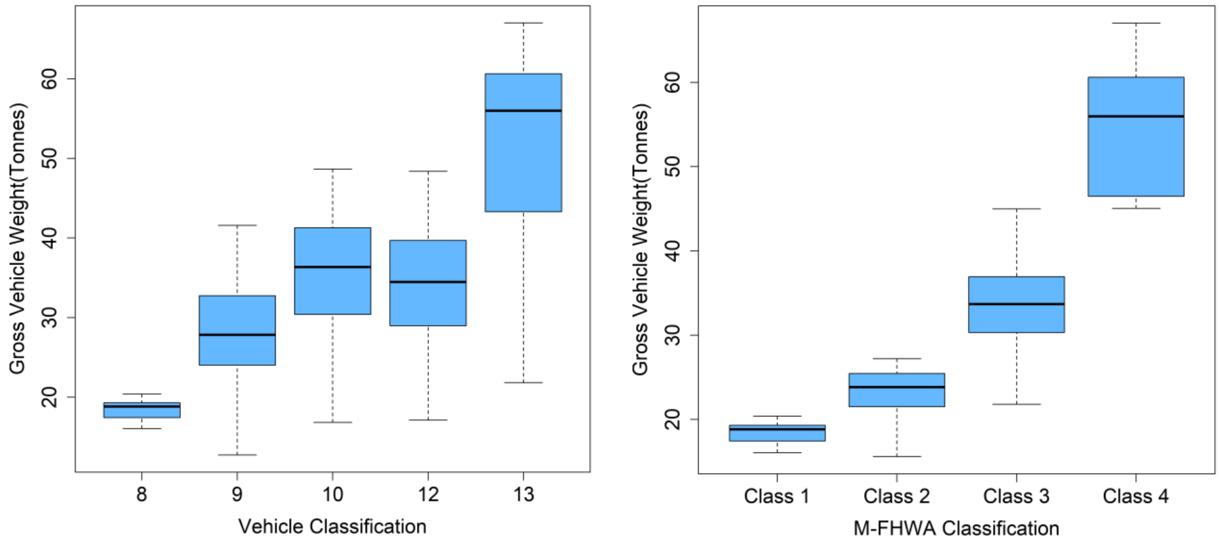


c) GVW (tonnes)

Figure 5-4: Average Speed Distribution for FHWA Class, M-FHWA Class and GVW

Figure 5-5 shows two boxplots. Figure 5-5 (a) shows the relationship between GVW and FHWA Class, and Figure 5-5 (b) shows the relationship between GVW and M-FHWA class.

Figure 5-5 (a) and (b) show that higher vehicle classes (FHWA classes and M-FHWA class) clearly have higher GVW and greater variance in GVW. FHWA class is less clearly associated with GVW (see Figure 5-5 (a)). There is more GVW variation in the FHWA classes and the GVW variation show overlap between class 9, class 10 and class 12. Figure 5-5 (b) shows the GVWs in each M-FHWA class is clearly differentiated and the variance of GVW is smaller for each M-FHWA class. The findings also suggest that M-FHWA class is a more suitable classification scheme than FHWA class for setting DSL based on GVW for heavy vehicles.



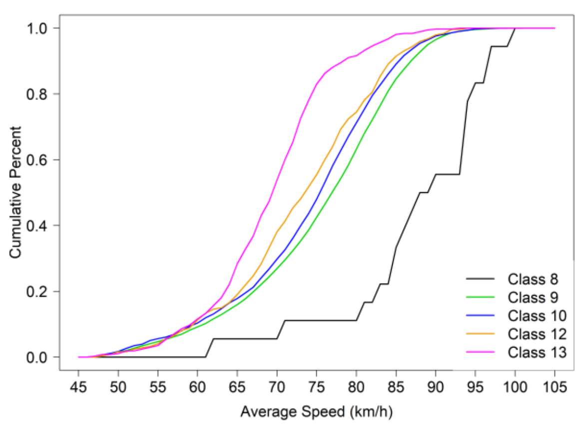
a) FHWA Class **b) M-FHWA Class**

Figure 5-5: Boxplot of GVW Distribution for Different Classifications

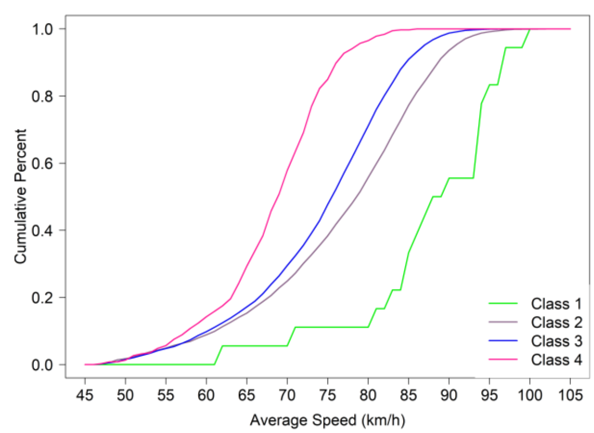
Figure 5-6 (a) shows the cumulative percentile distribution of average speed for each FHWA heavy vehicle class, and Figure 5-6 (b) shows the distribution for each M-FHWA class. In general, vehicles belonging to a lower vehicle class have a higher speed distribution than do vehicles in a higher vehicle class. It is clear, for example, that FHWA Class 8 and M-FHWA class 1 (the same group of vehicles and the lightest) have the highest average speed distribution, and FHWA class 13 and M-FHWA class 4 (the heaviest) have the lowest average speed distribution.

The speed distributions for FHWA classes 9,10 and 12 (Figure 5-6 (a)) are very close to each other: the speed distributions are very crowded at the 85th percentile speed values (the horizontal red dash line). This is because the GVW of these three FHWA classes includes overlap due to the large variance in the classes. This finding is consistent with a previous finding suggesting that vehicle weight is the primary factor affecting travel speeds of heavy vehicles (Saifizul et al., 2011).

The speed distributions for the M-FHWA class (Figure 5-6 (b)) are more clearly separated, and the 85th percentile speed values (the red dash line in Figure 5-6 (b)) are distinctive. This is a major finding that 1) supports the idea that GVW is the primary factor affecting the travel speed of heavy vehicles, and 2) shows that FHWA heavy vehicle classes (classes 8-13) have a large variation in GVW (especially classes 10 and 12) that leads to overlapping in the travel speed of each class. (See Appendix G for more details of the integrated data analysis including the frequency distributions for vehicle class, GVW intervals and average speed distribution for vehicle class and GVW).



a) Speed Percentile Distribution for FHWA Classes 8 to 13



b) Speed Percentile Distribution for M-FHWA Class

Figure 5-6: Cumulative Speed Distribution for FHWA Classes and M-FHWA Class

Based on the previous evaluations, we found both vehicle average speed and GVW had stronger monotonic relationships with M-FHWA classes than conventional FHWA classes. The GVW variance in each M-FHWA class was smaller and differentiated from each class, and the

GVW variance in each FHWA class was bigger and overlapped with each other. Additionally, the speed distribution in each M-FHWA class was clearly separated compared with the speed distributions of FHWA classes. Also, we found that GVW was an important factor to affect heavy vehicle travel speed, and lighter vehicles (smaller GVW) usually travel faster and heavier vehicles (large GVW) travel slowly. It would be more reasonable to set higher speed limit for M-FHWA class 1 (small GVW) and lower speed limit for M-FHWA class 4 (higher GVW). Therefore, the findings here demonstrated that the proposed M-FHWA classification is a more appropriate vehicle classification scheme than FHWA classification to be used for setting a differential speed limits by considering GVW.

5.4 Chapter Summary

This chapter proposed a new heavy vehicle classification (M-FHWA) with a more precise consideration of GVW than FHWA class. M-FHWA class was created by considering three criteria: 1) two GVW threshold values (27,200 kg, 45,000 kg), 2) FHWA class, and 3) the average speed of heavy vehicles in each class. The ANOVA test was conducted for the four M-FHWA classes and showed that the difference in average travel speed associated with each M-FHWA class was statistically significant.

The chapter also developed the integrated dataset from WIM and GPS data by employing QQ plot, linear regression model and Monte Carlo data fusion methods. The QQ plot was employed to find the speed distribution of WIM data was similar to the speed distribution of GPS data. A linear regression line was used to help find the existed speed relationship between WIM data and GPS speed data. Then, Monte Carlo data fusion method was used to successfully incorporate the class and weight information from WIM data and the nonstop and stopping information from GPS into integrated dataset.

After developed the integrated dataset, evaluated the FHWA heavy vehicle classification and a proposed M-FHWA classification to decide which scheme would be suitable for developing a DSL strategy based on GVW. Firstly, we inspected the relationship between heavy vehicle speed, GVW between FHWA class and M-FHWA class using two type of correlation tests, Spearman and Pearson. We found that vehicle average speed and GVW both had stronger monotonic relationships with M-FHWA class than FHWA class. Secondly, we compared the speed distributions between M-FHWA class with FHWA class. The histograms also showed that average speed had a stronger relationship with M-FHWA classes than the FHWA classes. Thirdly, we examined the relationship between vehicle classification and GVW. The boxplots showed that GVW in each M-FHWA class was differentiated with each other, and the GVW variance was smaller in each M-FHWA class compared with each FHWA class. GVW in each FHWA class was overlapped together, especially between class 9 to class 12, and GVW variance was quite large in each FHWA class compared with the GVW variance in each M-FHWA classes, especially for heavy vehicles with large GVW (class 12 and class 13). Then, we examined the cumulative speed distributions between M-FHWA class than FHWA class. The speed distribution for each M-FHWA class was clear and separated, while the speed distribution for each FHWA class was overlapping, especially for class 10 and 12. All the evaluations suggested that M-FHWA class scheme with differentiated GVW variance and separated speed distribution in each class is a more suitable vehicle classification scheme than the FHWA classification when setting a differential speed limit by considering GVW.

Chapter 6 Microsimulation Analysis

This study relied on VISSIM simulation to understand the potential safety impact of various speed limit and speed enforcement strategies. As illustrated in Figure 4-3, the VISSIM simulation adopted in this study consist of four procedural steps: 1) Specification of traffic performance indicators; 2) selection of input parameters; 3) calibration of input parameters; 4) comparing two speed limit strategies (USL and DSL) and two speed enforcement strategies (SSE and ASE) to assess the strategies' impact on the safety of heavy vehicles.

6.1 Overview of Simulation

6.1.1 Traffic Performance Indicators

The first step in this simulation model was to determine appropriate performance indicators to study the safety impact of different speed limit and speed enforcement strategies, three traffic performance indicators are selected: the longitudinal 85^{th} percentile speed profile, standard deviation of speed, and the speed violation rate.

The longitudinal speed distribution of speed reflects the amount of speed fluctuation when different types of heavy vehicle travel along a simulation segment and provides a good indication of the effects of SSE and ASE speed enforcement. The 85^{th} percentile heavy vehicle speed profile for the simulated section of highway was selected as the first performance indicator. The 85^{th} percentile speed is widely used by highway agencies to describe operating speeds and to establish speed zones. The 85^{th} percentile is adopted to include most vehicles travelling at or below the speed limit that help to reduce speed differences and minimize vehicle contacts and create harmonized traffic flow (Neuman et al., 2009).

The second performance indicator was the standard deviation of speed. Different speed limit and enforcement strategies may affect not only 85th percentile speed, but also the standard deviation of speed. The standard deviation of speed is often represented by the difference between the 85th and 50th percentile travel speed. Many studies have observed that the standard deviation of speed, which partly measures the interaction among vehicles, is an important potential contributing factor for collisions on highways (Montella et al., 2011; Summersgill and Neil, 2012; Pauw et al, 2014b; Shim et al., 2015). A large standard deviation in travel speed has generally been shown to be associated with higher crash rates (Russo et al., 2017).

The third performance indicator was the speed violation rate. A high rate of speed violations is also known to be associated with an adverse impact on the safety of both speeding and non-speeding vehicles. In 2017, speeding was a contributing factor in 26% of all traffic fatalities (NHTFA, 2019). The speed violation rate is especially important for collisions involving heavy vehicles as these collisions often have severe consequences (Monsere et al., 2017). The speed violation rate has been widely used to evaluate the safety effectiveness of different types of speed limits. Johnson and Murray (2010), for example, found that the safety implications of DSL were significantly affected by the speed violation rate.

6.1.2 Model Overview

The input parameters for the base scenario were estimated from the integrated dataset. As the integrated dataset was composed of data collected for the single uniform speed limit used from two existed WIM stations that could be assumed as the average speed enforcement on the 548 km of study corridor (see Chapter 3-1 for details), the base scenario was used to evaluate the USL strategy (Chapter 6.3.1) and the ASE strategy (Chapter 6.4.2).

As it is not reasonable to apply average speed enforcement to 548 km of roadway, a shorter segment was considered in the simulation exercises. The total simulation segment was 10 km of Trans-Canada HWY 1 to the east of Kamloops, BC. The first kilometer and the last kilometer of the simulation segment were considered warm-up and cool-down zones used to check that each vehicle (each record) traveled the completed length of the 8 km segment of interest. The warm-up and cool-down zones were not included in the simulation results. The corridor used for simulation was 8 km of uninterrupted free flow highway as shown in Figure 6-1.

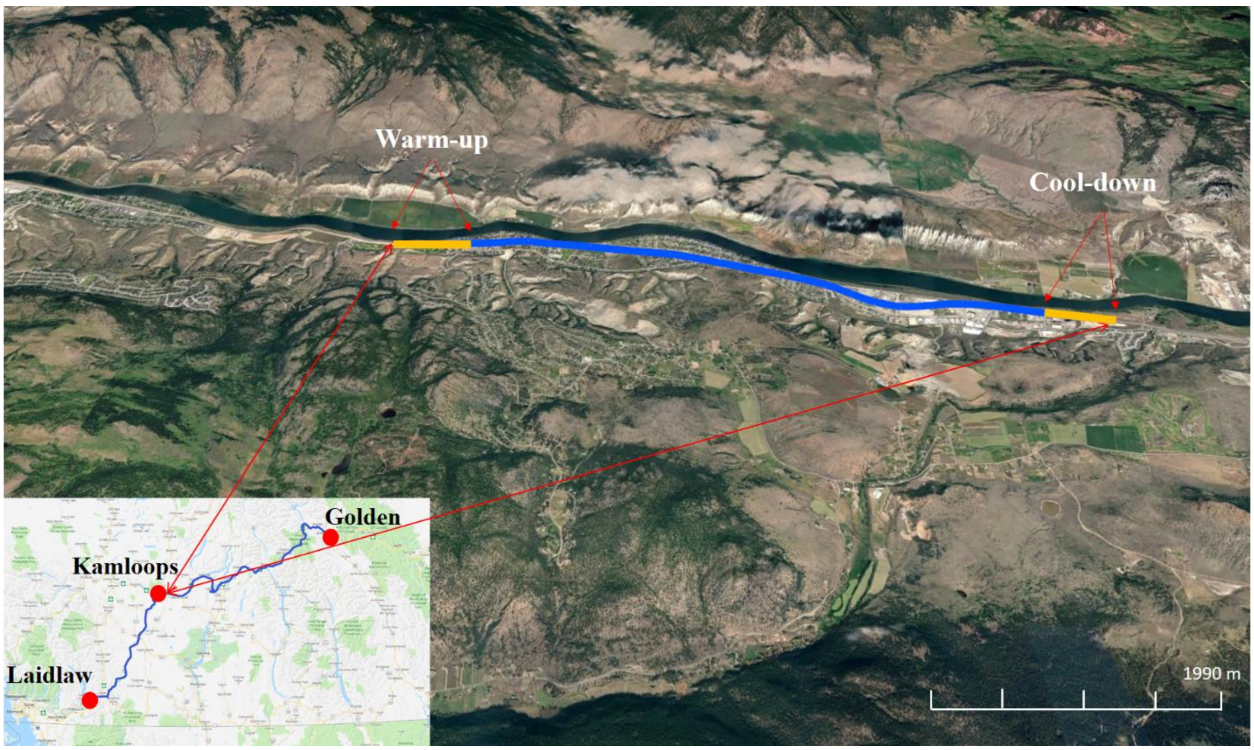


Figure 6-1: Location of Simulation Segment

The simulation period was 1.5 hours. This included 15 minutes of warm-up and 15 minutes of cool-down to allow the slowest vehicles to travel through the completed segment of the model.

The warm-up and cool-down periods were disregarded in the analysis giving and effective simulation period of 1 hour. On average, 10 runs were carried out for each speed limit and enforcement strategy with different random seeds. The random seed values were dependent on the number of runs. For 10 runs, the first random seed value was 199 with an increment of 210 for each subsequent run (Wisconsin DOT, 2018).

6.1.3 Selected Input Parameters

VISSIM includes a number of input parameters that allow the user to fine-tune the model to match existing traffic conditions. This study included only parameters that affected the three safety performance indicators (see Chapter 6.1.1 for details) under freeway conditions. These parameters can be categorized into three components: roadway parameters, vehicle parameters and traffic parameters.

In the case of the roadway input parameters, the highway segment is an undivided highway with two-lanes in each direction. The measured lane width is 3.7 m (7.4 m for two lanes). We simulated only eastbound direction traffic because we had WIM traffic data for Laidlaw (west) to Golden (east). The average slope in the simulation segment was ±1.1% which can be ignored. The segment grades were assumed to be level (0%).

The vehicle input parameters included the horsepower of different types of heavy vehicle, the GVW distribution for different types of heavy vehicles, and the vehicle classifications. Abanotu (1999) and Yoon (2005) estimated the distribution of horsepower of heavy vehicles and identified two distinct groups of heavy vehicles. For FHWA Class 8 vehicles, the average horsepower was estimated as 216 kw. For FHWA Class 9 to FHWA Class 13, the average horsepower was estimated as 272 kw. See Table 6-1.

Table 6-1: Horsepower Distribution of Heavy Vehicles (Abanotu, 1999; Yoon, 2005)

Cumulative Percentile	Class 8 (kw)	Class 9 - Class 13 (kw)
0	128.71	165.00
20	160.16	225.84
40	195.77	258.48
50	215.50	272.00
60	223.97	273.32
80	240.29	292.61
100	312.59	349.00

Vehicle GVW distribution was estimated from the integrated dataset. The study used two heavy vehicle classifications in the simulation. Our proposed Modified-Federal Highway Administration (M-FHWA) classification was used to understand the safety impact of adopting a differential speed limit strategy. The FHWA classification was used to understand the safety impact of speed enforcement strategy.

The traffic input parameters considered mainly speed distribution, traffic volume, detail heavy vehicle composition and total heavy vehicle percentage in traffic volume. Speed distribution was obtained from the integrated dataset. The detail heavy vehicle composition was described in Chapter 6.1.4. Chapter 6.2.2 investigates the suitable values for traffic volume and total heavy vehicle percentage in traffic volume using sensitivity analysis in the second stage calibration.

It should be emphasized that some traffic input parameters, such as driving behaviour and car following model, that do not have a significant impact on the safety performance under free flow traffic conditions were based on default or recommended values provided in the relevant simulation manuals or in the literature. The VISSIM default values for headway and other driving behaviour parameters were adopted. (See Table 6-2.) When traffic is very low with no congestion, there is little difference in vehicle headways for different types of vehicle (e.g., passengers cars and heavy vehicles) (Ye and Zhang, 2009). The VISSIM simulation focused on speed rather than driving behaviour and car following model. In the case of the car following model, and the Wiedemann 90 default values were adopted. Table 6-2 provides a summary of the input parameters.

Table 6-2: Selected Simulation Parameters

Input Parameters	**Values**
Road Grade	0 (Level)
Number of Lanes	2 lanes (West to East Direction)
Lane Width	3.7 m
Horsepower	Table 6-1
GVW Distribution	Calculate from Integrated Data
Speed Distribution	Calculate from Integrated Data
Vehicle Classification	M-FHWA and FHWA Classes
Traffic Volume	Unknown
Heavy Vehicle Percentage	Unknown
Car Following Model Wiedemann 99	
CCO: Standstill Distance	1.5 meters
CC1: Time Headway	0.9 second
CC2: Following Variation	4 meters
CC3: Threshold Entering Following	-8

6.1.4 Detail Heavy Vehicle Composition

As mentioned before, the input parameters of the base scenario were mainly estimated from the integrated dataset. The integrated dataset was developed by combining WIM and GPS traffic data, and it included detail nonstop and travel with stops information for different types of heavy vehicles (See Table 5-5). However, if we assume that total heavy vehicle percentage was 25% (with the remaining 75% being passenger cars) and traffic volume was 600 vehicles per hour as the second stage calibration showing (see details in Chapter 6.2.2), the VISSIM model can not obtain the detail simulation results for some types of vehicles. Specifically, when the total heavy vehicle percentage was 25% and traffic volume was 600 vehicles per hour as the Table 6-3 showing, the both number of nonstop and stopped Class 8 vehicle would be 0. Thus, the simulation model was not able to obtain the completed nonstop and stopped information for all types of heavy vehicles, especially for Class 8.

Table 6-3: Detail Vehicle Compositions for Nonstop and Stopped Travel Information in Integrated Dataset

Vehicle Types	Estimated Percent of Vehicle	Estimated Number of Vehicle
Passenger Cars	75%	450
Nonstop Class 8	0.02%	0
Nonstop Class 9	4.88%	29
Nonstop Class 10	1.49%	9
Nonstop Class 12	0.15%	1
Nonstop Class 13	0.15%	1
Stop Class 8	0.02%	0
Stop Class 9	12.29%	74
Stop Class 10	4.65%	28
Stop Class 12	0.51%	3
Stop Class 13	0.84%	5
Total	100%	600

Therefore, this simulation analysis would only focus on the completed integrated dataset without the consideration of the non-stop or travel with stops categories. Moreover, in order to meet the minimum input value of the VISSIM simulation model for each class of vehicles, an adjusted vehicle composition was estimated from the average vehicle composition between the two single WIM stations, Laidlaw and Golden as shown in Table 6-4. With these modifications, the input parameters for VISSIM simulation are feasible for further data analysis.

Table 6-4: Adjusted Detail Vehicle Composition for Integrated Dataset

Classification	**Percentage of Vehicle**			**Number of Vehicle**		
Vehicle Types	Laidlaw	Golden	Average	Laidlaw	Golden	Average
Passenger Cars	0.75	0.75	0.75	450	450	450
Class 8	1.85%	1.50%	1.67%	11	9	10
Class 9	10.71%	12.71%	11.71%	64	76	70
Class 10	7.28%	7.36%	7.32%	44	44	44
Class 12	1.39%	0.96%	1.18%	8	6	7
Class 13	3.77%	2.47%	3.12%	23	15	19

Chapter 6.2 discussed the two-stage calibration process. The second stage calibration is the sensitivity analysis used to select appropriate values for two of the traffic parameters in the base scenario.

6.2 Model Calibration

The calibration process is essential for any microsimulation to mimic local traffic conditions properly. The VISSIM model developed in this study started with default values for many input parameters. The model was then calibrated with different values for some parameters to achieve a more accurate representation of the real traffic conditions (Wisconsin DOT, 2018).

Proper calibration of the microsimulation model was essential before using the model to explore the effects of changes in the input parameters and/or the introduction of a differential speed limit strategies and the average speed enforcement.

As discussed in Chapter 4, this study employed a two-stage calibration process. The first stage evaluated traffic volume, travel time, travel speed and vehicle composition to check the accuracy of the model developed. The second stage employed a sensitivity analysis to select suitable values for traffic volume and vehicle percentage in the base scenario.

6.2.1 First Stage Calibration

In the first stage, the VISSIM simulation models were calibrated to check whether the traffic volume, travel time and travel speed outputs from the simulation model represented input traffic conditions accurately. For that, goodness-of-fit (GOF) measures were used (i.e., Root Mean Square Percent Error (RMSPE)) as described in Chapter 4.2.

As the total calibration time of 1.5 hour included a 15 -minute warm-up and a 15-minute cool-down period, the effective calibration period was 1 hour. The basic input parameters can be found in Tables 6-1 and 6-2.

For heavy vehicle percentage, we used the average proportion of heavy vehicles for the two single WIM datasets. The average heavy vehicle percentage was 22.7% for the Laidlaw WIM and 28.2% for the Golden WIM. On average, the traffic consisted of approximately 75% passenger cars and 25% heavy vehicles.

For traffic volume, we used three years (2010, 2013 and 2016) of Annual Average Daily Traffic (AADT) data provided by the British Columbia Ministry of Transportation and Infrastructure (BC MTI, 2019). The data was collected around 4 km downstream of the simulation segment. We used a linear interpolation method to estimate traffic volume which was found to be 700 vehicles per hour. Appendix G provides details of the method used to estimate traffic volume.

Table 6-5 shows the calibration results for hourly traffic volume. The Root Mean Square Percent Error (RMSPE) for traffic volume calibration was 0.04% which is much lower than the 5% threshold.

Table 6-5 also showed the calibration results for travel time. The RMSPE for travel time was 2% which is much smaller than the 10% threshold.

Table 6-5: Calibration Results for Traffic Volume and Travel Time

Parameter	Calibration Parameter	Value
Traffic Volume (veh/h)	Input	700.00
	Simulation (Start Point)	699.83
	Simulation (End Point)	700.33
	RMSPE	0.04%
	Threshold RMSPE	< 5.00 %
Travel Time (Seconds)	Input	60
	Simulation	61
	RMSPE	1.64%
	Threshold RMSPE	< 10%

Table 6-6 shows the calibration results for speed and vehicle composition. The RMSPE for speed was smaller than the 10% threshold for each type of vehicle, and the RMSPE for vehicle composition was within the 5% threshold for each type of vehicle. The results of the calibration showed that the estimated values are acceptable and that the VISSIM model provided a reasonable and reliable simulation result.

Table 6-6: Calibration Results of Speed and Vehicle Distributions

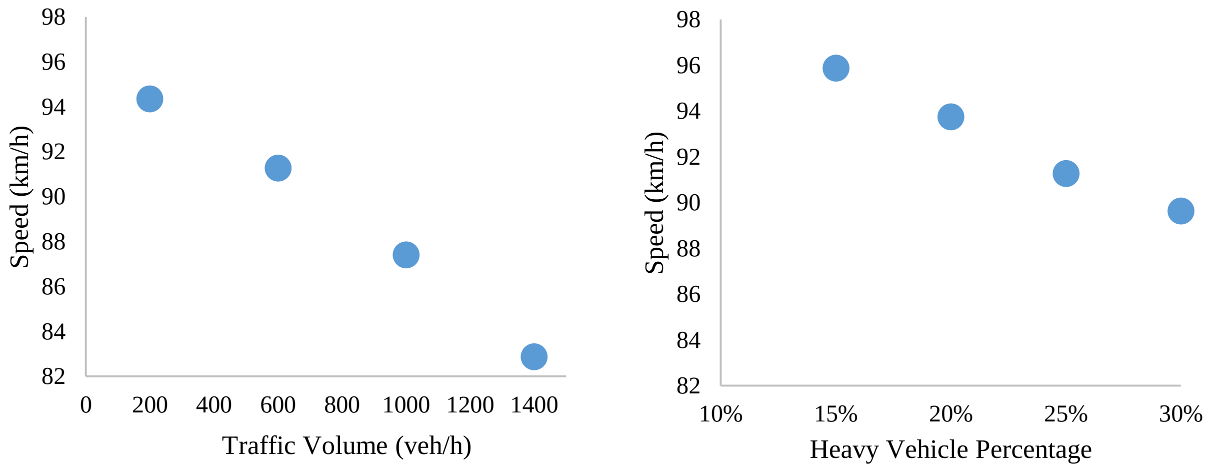
Parameters	Calibration Parameters	Cars	Class 8	Class 9	Class 10	Class 12	Class 13
Vehicle Speed (km/h)	Input	103.78	87.41	75.28	73.95	72.87	69.00
	Simulation	98.35	84.85	72.73	71.60	70.12	67.07
	RMSPE	5.23%	2.93%	3.39%	3.17%	3.78%	2.80%
	RMSPE	< 10.00 %					
Vehicle Composition	Input	525	12	82	51	8	22
	Simulation	527	12	81	51	8	22
	RMSPE	0.38%	1.18%	1.59%	0.12%	1.18%	1.54%
	RMSPE	< 5.00 %					

6.2.2 Second Stage Calibration

The second stage of the calibration focused on two parameters, traffic volume and heavy vehicle percentage. These parameters had significant influence on heavy vehicle speed, but could not be evaluated from the integrated data. A sensitivity analysis was conducted to determine suitable values for the two input parameters in the base scenario.

In the first stage of the calibration, a traffic volume of 700 vehicles per hour was used to calibrate the accuracy of model. However, this volume was based on traffic data collected from a location near the study corridor and did not represent real traffic conditions exactly. In the sensitivity analysis, we assumed four different levels of traffic volume, i.e., 200, 600, 1,000, and 1,400 vehicles per hour, to find the appropriate value for traffic volume. The truck percentages (for class 8 to class 13) obtained from the two WIM datasets were 22.7 % and 28.2 % respectively. However, the link WIM data, GPS data and integrated data were only obtained for heavy vehicles (vehicle classes 8, 9 ,10, 12 and 13). The study used five truck percentages, i.e., 15%, 20%, 25%, and 30%, to test different traffic compositions.

Figure 6-2 shows that heavy vehicle speed decreased with increased traffic volume and with increased truck percentage.

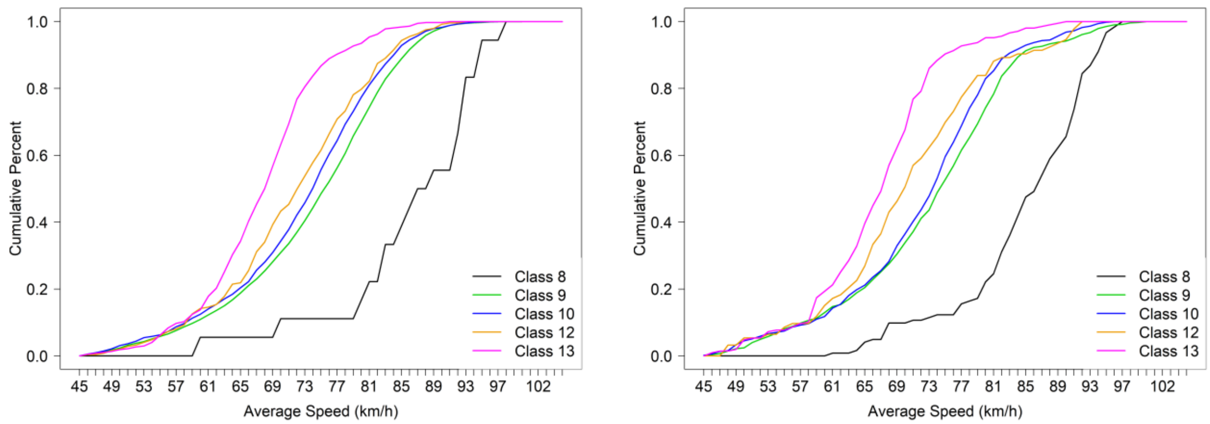


a) Traffic Volume **b) Heavy Vehicle Percentage**

Figure 6-2: Impact of Traffic Volume and Truck Percentage on Travel Speed

After examining different combinations of traffic volume and heavy vehicle percentage, the speed distributions for different classes of heavy vehicles were calculated and used to find the most appropriate values for traffic volume and heavy vehicle percentage.

The study compared different cumulative speed distributions for different combinations of traffic volume and heavy vehicle percentage (see Appendix H). Figure 6-3 clearly shows that the simulated cumulative speed distribution (Figure 6-3 b)) was a good match with the integrated dataset's observed speed distribution when traffic volume was 600 vehicles/hour/direction and heavy vehicle percentage was 25%. This combination of traffic volume and heavy vehicle percentage was therefore selected as the most appropriate source for the input parameters in the base scenario. We then used this base scenario to evaluate the differential speed limit and speed enforcement strategies. Appendix H provided result of the sensitivity analysis when traffic volume was 600 vehicles per hour and heavy vehicle percentage was 25%.



a) Integrated Data **b) Simulation Results**

Figure 6-3: Cumulative Speed Distribution of FHWA Class for Traffic Volume of 600 Vehicles per Hour with 25 Heavy Vehicle Percentage

6.3 Comparison of Different Speed Limit Strategies

The Chapter 6.3 described the two speed limit strategies (USL and DSL) and their impact on heavy vehicle travel. The proposed Modified-Federal Highway Administration (M-FHWA) classifications was used for this exercise. A data-driven empirical study was conducted to analyze operational performance again using three traffic performance measures: the longitudinal 85th percentile speed profile, standard deviation of speed, and the speed violation rate.

6.3.1 Uniform Speed Limit Strategy

As mentioned in Chapter 6.1.2, a base scenario was used to evaluate USL strategy. Therefore, most of the input parameters required for the USL strategy were the same as those for the base scenario (see Tables 6-1 and 6-2). Traffic volume was 600 vehicles per hour with 25 percent heavy vehicles. The average speed limit was 88 km/h (see Chapter 3.2.1 for the calculations), but the local speed limit in the SSE scenario (see Chapter 6.4) was 90 km/h. A rounded speed limit of 90 km/h was used in all the simulation studies to ensure a consistent and realistic value. The evaluation was based on the M-FHWA classification for heavy vehicles proposed in Chapter 5, and the vehicle speed distribution and vehicle weight distribution were calculated using the M-FHWA classification (see details in Appendix I).

6.3.2 Differential Speed Limit Strategy

The basic input parameters for the DSL strategy were the same as the input parameters used for the USL strategy, but the speed limit and speed distribution were different. We proposed a new differential speed limit for heavy vehicles based on the M-FHWA classification proposed in Chapter 5.

This study proposes a differential speed limits for the different M-FHWA classes. The 85^{th} percentile speed is currently the critical speed for posting speed limits. Much traffic engineering work dealing with speed zoning or the installation of traffic control devices specifies the 85^{th} percentile speed as the primary indicator of the prevailing speed for considering the establishment of speed zones (Agent et al., 1998) (Al-Ghamdi S., 1998). The 85^{th} percentile speed for each M-FHWA class was calculated using the integrated dataset (USL scenario) and used to suggest the differential speed limit for each M-FHWA class. Table 6-7 shows the results.

Table 6-7: Speed limit Table for M-FHWA Classes

M-FHWA classification	Class 1	Class 2	Class 3	Class 4
Uniform Speed Limit (km/h)	90	90	90	90
85^{th}-Percentile Speed (km/h)	95	87	83	75
Proposed Differential Speed Limit (km/h)	95	85	80	75

The second row of Table 6-7 shows that the 85^{th} percentile speed for M-FHWA class 1 was 95 km/h, 87 km/h for M-FHWA class 2, 83 km/h for M-FHWA class 3, and 75 km/h for M-FHWA class 4. The current uniform speed limit of 90 km/h is noticeably higher than the operational speeds (85^{th} percentile speed) for M-FHWA classes 3 and 4, and the current USL is clearly not satisfactory, because the higher USL could be increasing the frequency and severity of road collisions rather than promoting a safer driving environment.

The third row of Table 6-7 shows the speed limit proposed for each of the four M-FHWA classes. The proposed new speed limit for M-FHWA class 1 was 95 km/h in accordance, the same as the estimated 85^{th}-percentile speed and 5 km/h higher than the existing USL of 90 km/h. The proposed speed limits for M-FHWA classes 2, 3 and 4 were 85, 80 and 75 km/h respectively. These values considered the 85^{th} percentile speed, but use rounded values. They are 5 km/h, 10 km/h and 15 km/h lower than the existing USL respectively.

It is important to recognize that changing the speed limits also affects the average speed and the standard deviation and therefore affects the input information required to develop the DSL strategy in the simulation model. It is necessary to explored how much the average speeds and standard deviations would change due to the introduction of a DSL based on the M-FHWA class.

Table 6-8 provides a summary of the speed characteristics associated with the USL and DSL in various North American jurisdictions. The average speed and standard deviation for all vehicles, passenger cars and heavy vehicles were collected from a range of studies (Johnson and Pawar, 2005; Russo et al., 2015; Ghods and Saccomanno, 2016; Gates et al., 2016). For example, Gates et al. (2016) compared speed data under DSL (113 km/h and 97 km/h) on two-lane rural highways in Montana with speed data under USL (105 km/h) on two-lane rural highways in neighbouring states including Idaho, North Dakota, South Dakota, and Wyoming. Analysis of truck speed data shown that a DSL with a lower speed limit (97 km/h) for trucks had a smaller speed standard deviation (7.93) and lower average speed (97.46 km/h) than the corresponding values for a USL (9.48 and 99.75).

Similarly, other studies in Table 6-8 showed that lower speed limits were associated with lower standard deviations and lower average speeds. The standard deviation for heavy vehicle speed appeared to depart from Lave's theory (1985) that the standard deviation decreases as the speed limit and average speed increase. One explanation for this is that the Lave’s theory was used to describe passenger cars. Most researchers did not consider detailed circumstances such as traffic interactions between different types of heavy vehicle with a differential speed limit (Dixon et al., 2012; Savolainen et al., 2014). For large heavy vehicles, travel performance is governed largely by the vehicles’ mechanical characteristics. Heavy vehicles with a range of GVW and travelling on a roadway with a high USL would contribute to creating widely different travel speeds since each heavy vehicle’s acceleration/deceleration capability and each heavy vehicle’s weight-to-power ratio can be very different. As a result, higher speed limits may show a larger standard deviation. Another reason for the pattern in Table 6-8 could be the fact that many heavy vehicles in the United States are equipped with speed limiters and cannot travel at higher speeds. Higher speed limits would allow heavy vehicles without speed limiters to travel at a higher speed and could result in the higher standard deviation of speed (Johnson and Pawar, 2005).

Table 6-8: Summary od Speed Characteristics of USL and DSL

Year	States	Approach	Speed Limit Strategy	Vehicle Type	Speed limit	Average Speed	Standard Deviation
2016	Montana	Compare USL and DSL in Different Locations	USL	All	105	102.58	8.16
				Car	105	103.87	7.90
				Truck	105	99.75	9.48
			DSL	All	113/97	104.49	6.31
				Car	113	105.88	6.66
				Truck	97	97.46	7.39
2016	NA	Before and After Study	USL	All	90/90	-	-
				Car	90	90.00	10.80
				Truck	90	85.00	10.20
			DSL	All	90/80	-	-
				Car	90	90.00	10.80
				Truck	80	80.00	9.60
2015	Indiana, Michigan and Ohio	Compare USL and DSL in Different Locations	USL	All	113/113	115.23	8.69
				Car	113	117.96	6.44
				Truck	113	105.57	8.69
			DSL	All	113/97	115.39	11.10
				Car	113	118.29	7.56
				Truck	97	100.10	5.15
2005	Arkansas and Illinois	Compare USL and DSL in Different Locations	USL	All	113/113	115.07	8.30
				Car	113	116.84	7.97
				Truck	113	110.40	7.32
			DSL	All	113/105	114.91	8.35
				Car	113	118.29	6.95
				Truck	105	107.34	5.94

Table 6-8 implies that there could be a relationship between speed limit, average speed and standard deviation for heavy vehicles and that this relationship appears to be somewhat different than Lave's theory (1985). We developed linear regression models to evaluate the relationships.

Firstly, we used Equation 6-1 to evaluate the relationship between the speed limit and average speed of heavy vehicles under USL and DSL using data from the four studies shown in Table 6-8:

$$\bar{Y} = \sum_{i=1}^{4} \frac{\frac{(R_d - R_u)}{R_u}}{L_u - L_d} \qquad \textbf{Equation 6-1}$$

where:

R_d is the ratio between heavy vehicles' average speed and heavy vehicles' speed limit under a DSL strategy;

R_u is the ratio between heavy vehicles' average speed and heavy vehicles' speed limit under a USL strategy;

Lu is the uniform speed limit;

L_d is the differential speed limit;

Y is the indicator that measures how the ratio of average speed and speed limit changes when USL changes to DSL; and

$\bar{Y}$ represents the average of all Y values estimated in four studies reported in the literature (Table 6-8).

After obtaining the $\bar{Y}$ value from Equation 6-1, the ratio (R_d) of each M-FHWA class can be calculated for the integrated dataset. The parameters L_u, L_d and R_u for each M-FHWA class could be obtained directly from the integrated dataset. The ratio (R_d) for each M-FHWA class can be calculated using Equation 6-2, and the average speed (A_d) for each M-FHWA class under a DSL strategy can be calculated from Equation 6-3:

$$\boldsymbol{R_d = [(L_u - L_d) \times \bar{Y} + 1] \times R_u} \qquad \textbf{Equation 6-2}$$

$$\boldsymbol{A_d = R_d \times L_d} \qquad \textbf{Equation 6-3}$$

After obtaining the average speeds under a DSL strategy, the standard deviations of the speeds were obtained when the speed limit changed from a USL to a DSL. See Equation 6-4:

$$\bar{Z} = \sum_{i=1}^{4} \frac{\frac{SD_d - SD_u}{SD_u}}{A_d - A_u} \qquad \textbf{Equation 6-4}$$

where:

SD_d is the standard deviation of heavy vehicle speed in a DSL strategy;

SD_u is the standard deviation of heavy vehicle speed in a USL strategy;

A_d is the average speed of heavy vehicles in a DSL strategy;

A_u is the average speed of heavy vehicles in a USL strategy;

Z is the indicator that measures how the standard deviations of heavy vehicle speeds change from USL to DSL when the average speed changes from a USL to a DSL; and

$\bar{Z}$ represents the average of all Z values estimated in the four Table 6-8 studies.

Parameters A_u and SD_u were estimated directly from the integrated dataset. The standard deviation (SD_d) for each M-FHWA class under a DSL strategy was calculated using Equation 6-5:

$$SD_d = [(A_d - A_u) \times \bar{Z} + 1] \times SD_u \qquad \textbf{Equation 6-5}$$

Table 6-9 presents the results of the estimated average speeds and standard deviations for the M-FHWA classes. When the speed limit of M-FHWA class 1 was increased from 90 km/h (USL) to 95 km/h (DSL), the average speed and standard deviation increased from 87.41 km/h to 89.95 km/h and from 9.54 to 11.02 respectively. For M-FHWA classes 2 to 4, a decrease in the speed limit was associated with decreases in vehicle average speed and standard deviation. After estimating the speed limit, average speed and standard deviation of each M-FHWA class for DSL strategy, it was possible to develop the DSL scenario.

Table 6-9: Speed Comparisons under USL and DSL for M-FHWA Classes

Parameters	Class 1	Class 2	Class 3	Class 4
USL (km/h)	90	90	90	90
DSL (km/h)	95	85	80	75
USL Average Speed (km/h)	87.41	76.51	73.97	67.98
DSL Average Speed (km/h)	89.95	75.39	70.84	62.96
USL Standard Deviation	9.54	10.67	9.40	7.15
DSL Standard Deviation	11.02	9.94	7.60	4.96

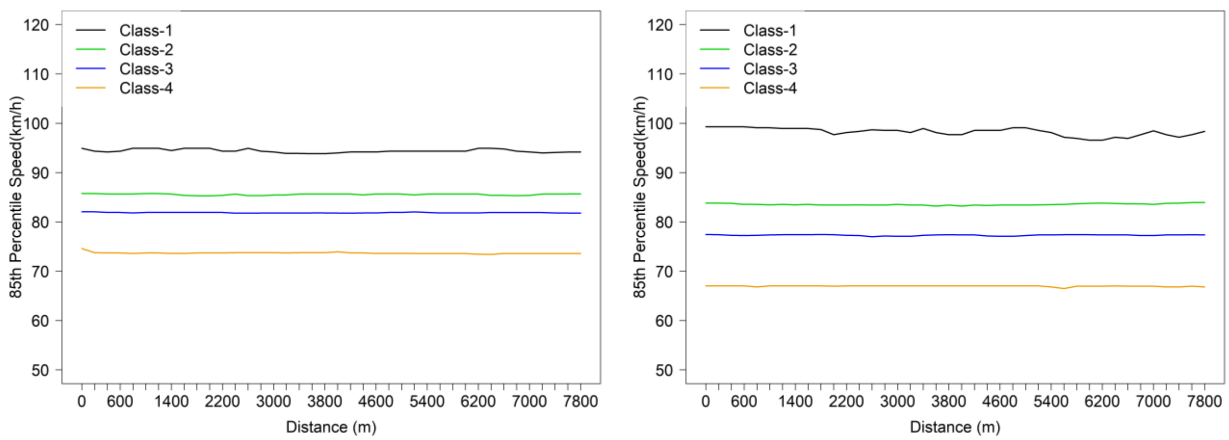
6.3.3 Discussion and Analysis

The simulation results for two speed limit strategies (USL and DSL) are based on the assumptions discussed previously. We showed the impact of these speed limit strategies on the four M-FHWA classes, using three performance indicators: 1) the longitudinal 85th percentile speed profile, 2) standard deviation of speed, and 3) the speed violation rate.

Firstly, we focused on the simulation results for the travel patterns of the two speed limit strategies, and considered the 85th percentile speed profile along the 8 km study segment. We calculated the 85th percentile speed for each M-FHWA class at each meter. As the speed profiles for every meter fluctuated too much for useful visualization, we aggregated the speed information for every 200 m segment to smooth the speed profile.

Figure 6-4 shows the 85th percentile speed profile distribution for the two speed limit strategies. The different colours represent the different M-FHWA classes.

The patterns for the M-FHWA classes under USL and DSL were similar. M-FHWA class 1 had the highest 85th percentile speed profile and M-FHWA class 4 had the lowest. Appendix J presents the detailed results.



a) Uniform Speed Limit **b) Differential Speed limit**

Figure 6-4: 85th-Percentile Speed Profile Distribution for Each M-FHWA Class

In Figure 6-4 a) (USL), the 85th percentile speed for M-FHWA class 1 was about 5 km/h higher than the 90 km/h speed limit. The 85th percentile speeds for M-FHWA classes 2, 3 and 4 were about 3 km/h, 7 km/h and 15 km/h lower than the 90 km/h speed limit respectively.

Figure 6-4 b) (DSL) shows the profiles for the DSL strategy. The pattern was as expected. The 85th percentile speeds for M-FHWA classes 2, 3 and 4 were all lower than the speed distributions in Figure 6-4 a) (USL). The 85th percentile speeds for M-FHWA classes 2, 3 and 4 in Figure 6-6(b) were also lower than the DSL speed limits of 85 km/h, 80 km/h and 75 km/h respectively.

However, M-FHWA class 1 had a different result. The 85th percentile speed for M-FHWA class 1 was 5 km/h higher than its DSL speed limit of 95 km/h. The higher speed could have several causes. Firstly, the original speed of M-FHWA class 1 under USL (Figure 6-4 a)) was 5 km/h higher than the uniform speed limit of 90 km/h (Table 6-7). Using the assumptions for the DSL strategy described in Chapter 6.3.2, the speed limit was increased from 90 km/h to 95 km/h for M-FHWA class 1. The 85th percentile speed of M-FHWA class 1 was also increased from 95 km/h to 99 km/h. Another reason for higher 85th percentile speed of M-FHWA class 1 could be that the simulation results for the travel patterns under the DSL strategy were based on the assumptions. Under a future DSL strategy with proper speed enforcement strategy, the speed limit for M-FHWA class 1 should be reduced to below the current posted speed limit (95 km/h) with fine penalties imposed for exceeding the DSL.

In general, the results were as expected: lighter vehicles travelled at faster speeds and heavier vehicles travelled at slower speeds. When the speed limit was decreased from 90 km/h to

85 km/h for M-FHWA class 2, to 80 km/h for M-FHWA class 3, and to 75 km/h for M-FHWA class 4, the 85th percentile speed profiles decreased. The DSL speed profiles for the M-FHWA classes (Figure 6-4 b)) were more widely spread than the USL speed distributions (Figure 6-4 a)).

Table 6-10 summarizes the results of the USL and DSL strategies. It compares the speed limit, 85th percentile speed, average speed, and standard deviation of speed for all heavy vehicles and for each M-FHWA class under the USL and DSL strategies. The 85th percentile speed for each M-FHWA class was estimated from the average 85th percentile of each relevant vehicle's speed of along the 8 km corridor. The average speed for each M-FHWA class was estimated from the average of each relevant vehicle's mean speed along the 8 km corridor. The standard deviation for each type of M-FHWA class was estimated from the average speed of each relevant vehicle along the 8 km corridor.

In Table 6-10, the 85th-percentile speed for all heavy vehicles was 84.39 km/h under USL and 82.09 km/h under DSL, a reduction of 2.72 % under DSL. The average speed was 74.36 km/h under USL and 71.55 km/h under DSL, a reduction of 3.77% under DSL. The standard deviation of speed for all heavy vehicles was 10.79 under USL and 10.44 under DSL, a reduction of 3.19 % under DSL.

Similar reductions occurred for M-FHWA classes 2, 3 and 4 with the biggest reductions being for M-FHWA class 4 (8.99 % reduction in 85th percentile speed, 7.52 % reduction in average speed, and 20.39 % reduction in standard deviation). For M-FHWA class 1, the 85th-percentile speed increased by 3.07 km/h when the speed limit increased from 90 km/h to 95 km/h.

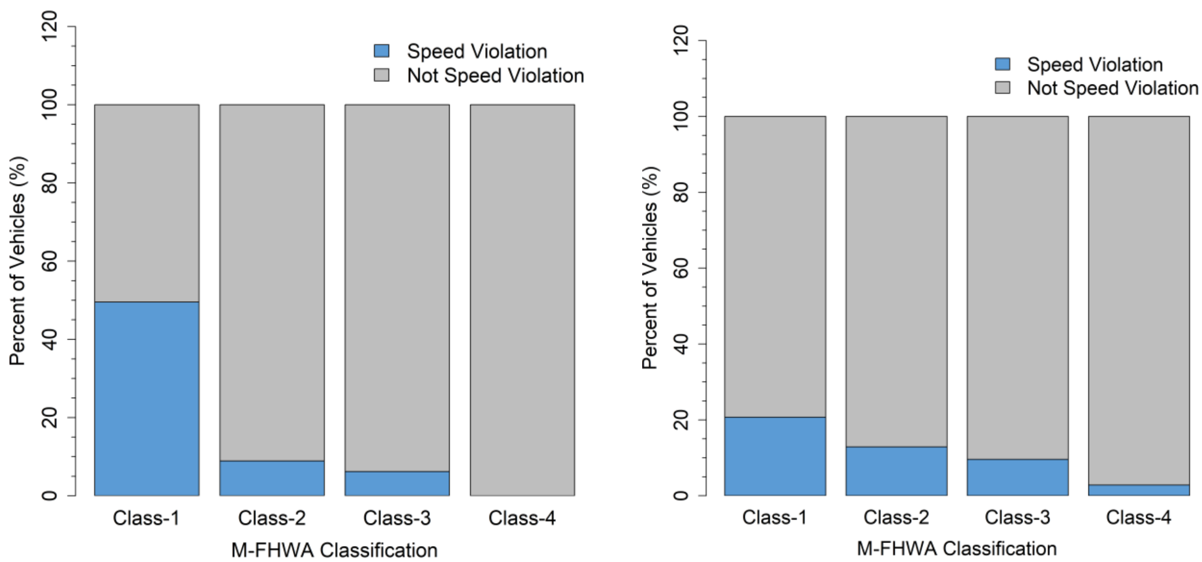
The findings were consistent with Table 6-8 and the findings of Dixon at al. (2012), but differ from Lave's (1985) theory that as the speed increases, the standard deviation of speed decreases as discussed in Chapter 6.3.2. The difference could be caused by the different approach to estimating the standard deviation used in this study. The standard deviation for each M-FHWA class was obtained by estimating the average speed of each vehicle over the simulation corridor (8 km) for each M-FHWA class rather than by estimating the standard deviation of spot speeds for each vehicle type.

Table 6-10: Comparison of Speed Characteristics between USL and DSL

Speed Limit Strategies	Parameters	All Heavy Vehicles	M-FHWA Class 1	M-FHWA Class 2	M-FHWA Class 3	M-FHWA Class 4
USL	Speed Limit (km/h)	90	90	90	90	90
	85th Percentile (km/h)	84.39	94.16	85.80	82.48	73.65
	Average Speed (km/h)	74.36	86.54	75.60	73.50	67.65
	Standard Deviation	10.79	8.07	11.47	9.90	7.48
DSL	Speed Limit (km/h)	-	95.00	85.00	80.00	75.00
	85th Percentile (km/h)	82.09	97.23	84.05	77.86	67.03
	Average Speed (km/h)	71.55	86.89	73.95	70.18	62.56
	Standard Deviation	10.44	9.61	10.66	8.54	5.96
Percentage Change	85th Percentile	-2.72%	+3.26%	-2.04%	-5.60%	-8.99%
	Average Speed	-3.77%	+0.40%	-2.18%	-4.52%	-7.52%
	Standard Deviation	-3.19%	+19.00%	-7.10%	-13.68%	-20.39%

Finally, we examined the speed violation rate under USL and DSL. Speed violation was defined as an average speed that exceeded the proposed speed limit for the vehicle’s proposed M-

FHWA class. Figure 6-5 shows the speed violation rate for each M-FHWA class under the USL and DSL strategies.



a) Uniform Speed Limit **b) Differential Speed Limit**

Figure 6-5: Speed Violation Rate for M-FHWA class

The results shown in Figure 6-5 were similar to those of the previous analyses. M-FHWA class 1 had the highest speed violation rate and the rate decreased for higher M-FHWA classes. The overall speed violation rate was 9.4% under USL and 10.54 % under DSL. The speed violation rate for M-FHWA class 1 decreased from 50.45% under USL to 20.72% under DSL (see Appendix J for details). The violation rate for M-FHWA classes 2, 3 and 4 slightly increased when DSL was adopted as the speed limits for M-FHWA classes 2, 3 and 4 decreased from 90 km/h to 85 km/h, 80 km/h and 75 km/h respectively.

Compared with Figure 6-4 b), it was noted that the 85th percentile speed profiles for M-FHWA classes 2, 3 and 4 were all lower than the DSL profiles. Figure 6-5 b), however, shows speed violations for M-FHWA classes 2, 3 and 4 and especially for M-FHWA class 4 where the 85th percentile speed was approximately 7 km/h lower than the speed limit of 75 km/h (Figure 6-4 b), but there was a 2.84% speed violation rate (Appendix J). This situation may be due to the different approaches used for creating the two figures. In Figure 6-4 b), the 85th percentile speed for each M-FHWA class was estimated at each 200 meters, but the average speed for some vehicles along the 8 km corridor might be higher than the DSL. Hence, it is reasonable to expect that although some vehicles had an average speed than was higher than the speed limit for its M-FHWA class, the overall 85th percentile speed distribution for each M-FHWA class was lower than the speed limit. Additional speed violation rate analysis, such as the number of speed violations for each M-FHWA class under USL and DSL, can be found in Appendix J.

The comparison of the two speed limit strategies in terms of the three traffic performance indicators found that a DSL strategy produced more separated and relatively lower 85th percentile speed profiles than did the USL strategy. The DSL strategy also reduced the 85th percentile speed, average speed and standard deviation of speed for each M-FHWA class compared to the USL strategy. The DSL strategy designed for the M-FHWA classes would increase heavy vehicle safety on high-speed free flow highways as a smaller standard deviation of speed is expected to reduce the probability of vehicle interactions and therefore reduce the risk of highway collisions. Russo et al. found that a reduction in average speed and the speed standard deviation reduced the fatality rate (Russo et al., 2017).

The next section introduces two speed enforcement strategies and compare the traffic performance by considering the same performance indicators.

6.4 Comparison of Two Speed Enforcement Strategies

This section discusses the two speed enforcement strategies, spot speed enforcement (SSE) and average speed enforcement (ASE), and uses a set of performance indicators to compare their effect on heavy vehicles' speed. It is useful to investigated the possibility of using a WIM system installed on a section of highway as a speed enforcement tool. As a typical WIM system can classify vehicle types and collect the spot speed of passing vehicles, it may be possible to use the system as a speed enforcement device. If a pair of WIM systems are installed on a section of highway, it may be possible to add a speed enforcement system based on measuring each vehicle's average travel speed on the segment.

We used three performance measures: the longitudinal 85th percentile speed profile, standard deviation of speed, and the speed violation rate to show differences between SSE enforcement and ASE enforcement. We used the FHWA classification in the SSE and ASE simulations as previous studies have based their model calibration and assumptions on FHWA class (see Chapter 6.2).

6.4.1 Input Parameters for Spot Speed Enforcement

For the SSE scenario, Tables 6-1 and 6-2 supplied most of the data. For example, traffic volume was 600 vehicles per hour and the heavy vehicle percentage was 25%. However, vehicle travel speed and GVW were changed. The speed and GVW of heavy vehicles were estimated from a single dataset collected at the Golden WIM station. The speed data collected at the Golden WIM was spot speed, and the local speed limit is 90 km/h which was close to the calculated average speed limit of 88 km/h (see Chapter 3.2). As mentioned in Chapter 6.3.1, the study used a speed limit of 90 km/h in all the simulation studies as this provided consistency and 90 km/h was a convenient rounded value.

A spot speed enforcement system using photo radar or speed camera usually includes upstream warning signs to warn drivers of the possible speed enforcement ahead. Drivers travelling past a highway location with fixed photo radar typically reduce their travel speed just before reaching the enforcement location and then speed up later (Shim et al., 2015). The two WIM systems installed on our study corridor provided spot speed data, but have never been used for real speed enforcement. As a result, the speed data unfortunately does not show the temporary change in speed. To simulate the impact of a speed enforcement device properly, it is necessary to reflect the speed fluctuation phenomenon before and after the speed enforcement location. We made some few assumptions, such as the degree of speed reduction. The assumptions were based on findings from previous research and were adopted to reflect the speed fluctuation phenomenon to make our simulation more realistic.

Shim et al. (2015) conducted their study by collecting traffic data from GPS equipped taxis and inductive loop detectors. The study did not consider heavy vehicles. The study sites were selected according to the availability of taxi driving records and included data for 259 taxis in Daegu, South Korea for every day in May, 2013. The study found that speed enforcement significantly reduced average speed (by 6.7% to 7.0%) for passenger cars driving on the Gyeongbu Expressway which has a 110 km/h speed limit. Drivers reduced speed around 700 m upstream of the speed enforcement system and then recovered speed shortly after passing the system.

Pauw et al. (2014b) showed similar results for passenger cars. The study did not consider heavy vehicles. The researchers found that fixed speed cameras reduced passenger car vehicle speeds by an average speed of 4.6% to 5.6 %. The data showed that drivers started braking between 250 m and 700 m upstream of the speed enforcement location and returned to their normal speed after driving 1,000 m downstream from the location.

Similar findings were also reported by Liu et al. (2011) who investigated the effect of spot speed enforcement between 1 km upstream and 1 km downstream of the speed enforcement location. Liu et al. observed that speed reduction started about 300 m to 400 m upstream of the enforcement location and recovered to the initial speed at 300 m to 400 m downstream.

The literature review suggested that passenger cars reduce speed by 4% to 7% under spot speed enforcement. The studies were based on higher local speed limits (110 km/h to 120 km/h) than our speed limit (90 km/h) (Pauw et al., 2014b; Shim et al., 2015). The area of influence for fixed speed devices was generally less than 1,000 m (Liu et al., 2011).

Truck performance regarding acceleration and deceleration at fixed speed detecting devices is less flexible than passenger car performance due to the heavy weight and longer brake distance required (Abanotu, 1999; Yang et al., 2016; Ramezani et al, 2018). We assumed that heavy vehicles would reduce travel speed by an average of 4% at the enforcement location. We also assumed that a warning sign was located 750 m upstream of the enforcement detector, that speed reduction would start 750 m before the enforcement location, and that speed recovery would occur 750 m after the enforcement location making the total area of influence 1.5 km.

To investigate whether the heavy vehicles could meet our speed reduction and recovery assumptions within 1.5 km, we first evaluated heavy vehicle weight-to-power ratio (w/p). W/p is a measurement of a heavy vehicle's maximum acceleration and deceleration rate. Using the estimated w/p ratio and current speed, we could find the typical maximum acceleration rate and deceleration rate from the Traffic Engineering Handbook (Institute of Traffic Engineers, 1999). Then, we estimated the acceleration and deceleration required by the assumption of 4% of a speed reduction with recovery within 1.5 km. Then, we compared the estimated acceleration and deceleration values with the typical acceleration and deceleration values in the Handbook to check whether the assumptions made met the requirements.

Firstly, we estimated w/p for different types of heavy vehicle. A heavy vehicle's w/p has an important effect on the heavy vehicle's ability to maintain speed control as the vehicle reaches and maintains a certain travel speed. The weight of the heavy vehicles was calculated using data from the Golden WIM system. Appendix I shows the detailed weight estimation for five vehicle classes (Classes 8, 9, 10, 12 and 13). Table 6-1 shows the horsepower. According to Harwood et al. (2003), the 85th percentile w/p is appropriate for a loaded truck on a freeway especially when a heavy vehicle is partially loaded. Table 6-11 shows the 85th-percentile w/p for the five classes heavy vehicle represented in the Golden dataset. A lower w/p is associated with better truck performance on any grade and a greater final crawl speed. Class 13 vehicles had the highest w/p which means either that they had low power or that they were heavily loaded as they were passed the Golden WIM station. Using the value of the w/p ratio in the Traffic Engineering Handbook (Institute of Traffic Engineers, 1999), the w/p ratio for different types of heavy vehicle can be categorized into three groups. Class 8 was categorized as 100 lb/hp, Classes 9 to Class 12 were categorized as 200 lb/hp, and Class 13 was categorized as 300 lb/hp.

Table 6-11: Weight-to-Power Ratio of Golden Dataset

Weight-to-Power Ratio (lb/hp)	Class 8	Class 9	Class 10	Class 12	Class 13
85th Percentile	131.59	187.58	226.34	221.98	322.51
Weight to power ratio Group	100	200	200	200	300

Based on the estimated w/p ratio and the current travel speed of different types of heavy vehicle, the typical maximum acceleration rates of different classes of heavy vehicle can be found in Table 6-12 (ITE, 1999). For example, for speeds of greater than 50 miles per hour (mph), maximum acceleration for Classes 8, 9, 10 and 12 was 0.12 m/s^2. For class 13, maximum acceleration was 0.09 m/s^2 (G. Yang et al., 2016; Ramezani et al., 2018).

Table 6-12: Typical Maximum Acceleration Rate on Level Road (ITE, 1999)

Vehicle Type	Class 8	Class 9	Class 10	Class 12	Class 13
w/p Group	100	200	200	200	300
Speed Range (mph)	>50	>50	>50	>50	>50
Max Acceleration (m/s^2)	0.18	0.12	0.12	0.12	0.09

Table 6-13 shows the deceleration rate and brake distance of heavy vehicles recorded by Harwood et al. (2003). The worst and best performance represents the efficiency of the driver in modulating the brake to obtain optimum braking performance. The worst performance requires a longer brake distance and the best performance requires a shorter brake distance (Harwood et al., 2003). When speed was around 50 mph, the deceleration rates were between 1.57 m/s^2 and 2.45 m/s^2 for the worst and best performance respectively. These rates refer to empty heavy vehicles on a wet pavement. Ramezani et al. (2018) estimated a smaller average value of 1.77 m/s^2 for maximum deceleration for a loaded heavy vehicle. The lower value implies that a driver may avoid using higher deceleration rates when making smooth speed changes. This study considered the same approach as Ramezani et al. (2018) used and estimated a maximum deceleration rate for loaded heavy vehicles of 1.79 m/s^2 at 50 mph and 1.77 m/s^2 at 60 mph. The brake distances were 476.5 ft. and 659.4 ft. at 50 mph and 60 mph respectively. See Table 6-13.

Table 6-13: Maximum Deceleration Rate Table (Harwood et al., 2003)

Parameters	**Speed Range (mph)**	**50**	**60**
Deceleration Rate (m/s^2)	Worst-Performance	1.57	1.57
	Best Performance	2.45	2.55
	Average for Empty Truck	2.01	2.06
	Average for Loaded Truck	1.75	1.77
Brake Distance (ft)	Worst-Performance	538	744
	Best Performance	333	462
	Average for Empty Truck	435.50	603.00
	Average for Loaded Truck	476.50	659.40

After finding the typical maximum acceleration and deceleration from the guidelines available, it was possible to estimate acceleration and deceleration for heavy vehicles in the Golden WIM dataset. The deceleration rates were calculated using Equation 6-6 (Barth at al., 2001):

$$\boldsymbol{a} = \frac{\boldsymbol{V_F}^2 - \boldsymbol{V_S}^2}{2 \times \boldsymbol{S}} \qquad \textbf{Equation 6-6}$$

Where:

a represents the deceleration;

V_F is the travel speed at the end of deceleration that was collected at WIM system;

V_S is the initial speed before deceleration started which was assumed at 750 m upstream of WIM system; and

S is the distance travelled during deceleration.

Acceleration can be estimated using the same Equation 6-6.

Table 6-14 shows the maximum acceleration or deceleration required for the different heavy vehicle classes to reduce and recover speed by 4 % within 1.5 km of enforcement location. The estimated maximum acceleration and deceleration of class 8 was 0.04 m/s^2, which was smaller than the typical maximum acceleration (0.18 m/s^2) and deceleration (1.75 m/s^2) according to the Traffic Engineering Handbook (ITE, 1999) and Harwood et al. (2003).

The estimated maximum acceleration and deceleration of classes 9 to 12 was 0.03 m/s^2, and all the values were smaller than the typical maximum acceleration (0.12 m/s^2) and deceleration (1.75 m/s^2) given in the Traffic Engineering Handbook (ITE, 1999) and Harwood et al. (2003). The estimated acceleration and deceleration for class 13 (0.03 m/s^2) was also smaller than the typical maximum acceleration (0.06 m/s^2) and deceleration (1.75 m/s^2). The assumption of brake distance of 750 m was longer than the typical brake distance of 145.24 m (476.50 ft.) to 200.99 m (659.40 ft.) provided by Harwood et al. (2003).

Overall, the estimated acceleration, deceleration and brake distance estimated using this study's assumptions were smaller than the maximum acceleration or deceleration rates provided in the Traffic Engineering Handbook (ITE, 1999) and Harwood et al. (2003). Therefore, the assumption that speed changed and recovered on average by 4 percent within 1.5 km is reasonable.

Table 6-14: Estimated Acceleration/Deceleration for Different Classes in Golden Dataset

Parameters	**Percentile**	**Class 8**	**Class 9**	**Class 10**	**Class 12**	**Class 13**
Initial Speed (V_S) (m/s)	85th Percentile	26.73	24.44	24.19	24.70	24.19
Final Speed (V_F) (m/s)	85th Percentile	28.06	25.56	25.28	25.83	25.28
Acceleration/Deceleration (m/s^2)	85th Percentile	0.04	0.03	0.03	0.03	0.03

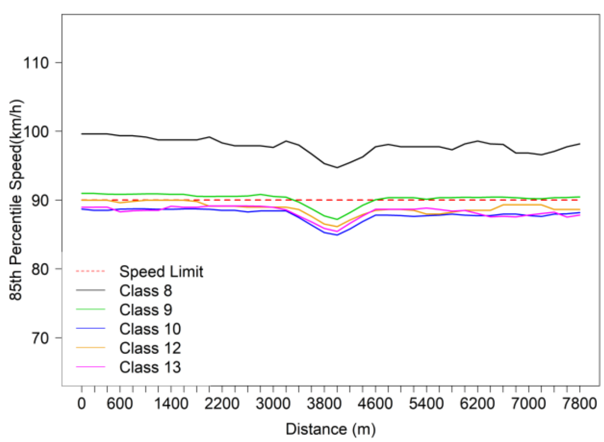
6.4.2 Input Parameters for Average Speed Enforcement

The input parameters for the ASE scenario were the same as for the base scenario (see Tables 6-1 and 6-2): traffic volume was 600 vehicles per hour, the heavy vehicle percentage was 25 %, the average speed limit was 90 km/h, and the analysis used the FHWA classification of heavy vehicles. The ASE analysis used different vehicle speed and GVW distribution. Vehicle speed and GVW in the ASE scenario were estimated from the integrated dataset. In the ASE scenario, it was assumed that all heavy vehicle speeds are monitored by a pair of WIM systems on the section of highway, and that no spot speed detection system was required on the travel corridor. We did not consider any assumptions regarding speed fluctuations including weight-power ratio, and acceleration and deceleration estimation.

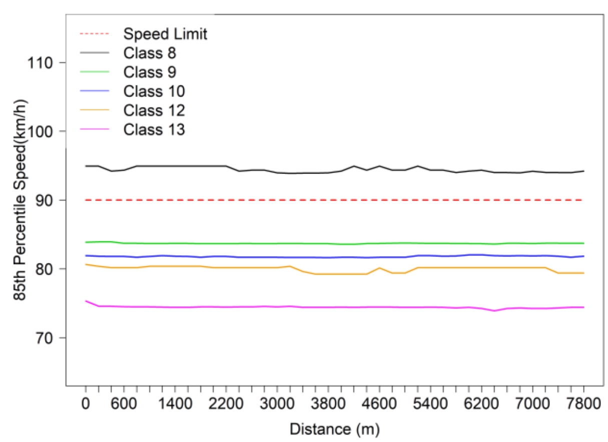
6.4.3 *Analysis of Speed Enforcement*

The first step in the ASE simulation was an analysis of the speed profile (longitudinal speed distribution) along the 8 km of study section. We used VISSIM to collect each vehicle's speed data for each meter along the 8 km corridor and evaluate the 85th speed percentile for each FHWA class for each meter. As the speed profiles for every meter fluctuated too much for useful visualization, we aggregated the speed information for every 200 m segment to smooth the speed profile.

Figure 6-6 shows the simulated longitudinal speed profile for SSE (a) and ASE (b). The different colours represent the different heavy vehicle classes.



a) Spot Speed Enforcement



b) Average Speed Enforcement

Figure 6-6: 85th-Percentile Speed Profile Distribution for Each FHWA Class (8-13)

Figures 6-6 a) and b) show that the SSE 85th percentile speed profiles were higher and less smooth than the profile were the ASE profiles. The speed profiles for SSE were also mostly closely spaced whereas the ASE speed profiles were far more widely separated. There were several interesting details.

The profile for Class 8 vehicles was much higher than for other vehicle classes. As Class 8 vehicles usually had a lower GVW than Class 9, 10, 12 and 13, they were expected to have faster travel speeds.

Figure 6-4 a) (SSE) showed that operating speed of Class 8 vehicles was 10 km/hr higher than the speeds of other vehicle classes. The speed profile was also 9 km higher than the speed limit of 90 km/h. The speed profiles for Classes 9 to 13 were all around the speed limit of 90 km/h.

In Figure 6-6 a) (SSE), the results show the result expected from the assumptions we made. All classes started to reduce operating speed approximately 750 m upstream of the speed enforcement location. The lowest speeds were observed at the location where the speed enforcement device was assumed to be installed. After passing the enforcement location, vehicles started to accelerate. They recovered their initial speed 750 m downstream of the enforcement location. The Figure showed a clear V-shaped speed profile for this 1,500 m segment of roadway for all heavy vehicle classes. Interestingly, Class 8 vehicle speeds fluctuated more than the other vehicle classes. One reason could be that the speeds collected for Class 8 were much higher than the speeds for other classes (see Table 3-1 in Chapter 3.2.1). Another reason could be that the small sample of Class 8 vehicles in the integrated dataset (only 18 vehicles) might not give an accurate indication of Class 8 travel speed.

Figure 6-6 b) (ASE) shows that all the speed profiles were smooth and widely distributed and that the Classes 9, 10, 12, and 13 speed distributions were significantly lower than the SSE speed profiles over the entire 8-km-length section. The 85th percentile speeds for Classes 9, 10 12, and 13 were lower than the speed limit of 90 km/h by about 6 km/h, 7 km/h, 9 km/h and 15 km/h respectively, but Class 8 vehicles maintained their higher speed profile and their average speed was above the speed limit (90 km/h). However, in the real world, Class 8 vehicles would be expected to reduce their speeds to under the posted speed limit to avoid fines under ASE.

Figures 6-6 a) and b) show that both SSE and ASE contributed to reducing vehicles' operating speed, but for SSE, the speed reduction effect appeared to be very localized around the point of enforcement. ASE contributed to reducing vehicles' operating speed consistently and substantially along the entire study segment. Appendix J shows the speed profiles for all heavy vehicles, the speed profiles for every 1,000 m segment, and the 50th percentile speed profiles.

Table 6-15 summarizes the analysis of speed characteristics for the SSE and ASE strategies. It shows the speed limits, 85th percentile speed, average speed and standard deviation of speed for each FHWA class. For all heavy vehicles combined, the ASE reduced the 85th percentile speed, average speed and standard deviation by 6.97 %, 8.07 % and 9.56 % respectively.

Table 6-15: Comparison of Speed Characteristics between SSE and ASE

Scenario	FHWA Class	All	Class 8	Class 9	Class 10	Class 12	Class 13
Spot Speed Enforcement	85th Percentile (km/h)	90.86	97.36	90.82	88.74	89.22	88.58
	Average Speed (km/h)	80.76	88.66	80.65	79.82	80.93	78.71
	Standard Deviation	11.91	12.13	11.98	11.20	12.61	11.10
Average Speed Enforcement	85th Percentile (km/h)	84.52	94.23	84.12	82.64	80.46	74.49
	Average Speed (km/h)	74.24	86.36	74.64	73.62	71.75	68.19
	Standard Deviation	10.77	8.29	10.74	10.04	10.00	8.12
Percent Change	85th Percentile	-6.97%	-3.21%	-7.39%	-6.88%	-9.82%	-15.90%
	Average Speed	-8.07%	-2.60%	-7.45%	-7.77%	-11.34%	-13.37%
	Standard Deviation	-9.56%	-31.65%	-10.40%	-10.37%	-20.70%	-26.88%

The Table 6-15 shows that vehicles in Class 13 had lower 85th percentile speeds, average speeds and standard deviations. Vehicles in the lowest class (Class 8) had a lower GVW and could travel at higher speeds.

The largest differences between ASE and SSE were for class 13 vehicles for which average speed reduced from 78.71 km/h to 68.19 km/h, and standard deviation reduced from 11.1 to 8.12 under ASE. SSE introduced a larger speed standard deviation compared to ASE.

(a) Spot Speed Enforcement **(b) Average Speed Enforcement**

Figure 6-7: Speed Violation Rate for FHWA Class

The speed violation rate for the two speed enforcement strategies was also analyzed for a 90-km/h average speed limit. The overall speed violation rate was 23 % for SSE and 9 % for ASE. Appendix K provides details of speed violation rates

For SSE, the speed violation rate for each vehicle class is shown in Figure 6-7 (a). The highest speed violation rate occurred for class 8 vehicles, around 59 %. The rate generally decreased for higher vehicle classes (with the exception of Class 12) and Class 13 vehicles had the lowest speed violation rate (about 16 %).

For ASE, the speed violation rate for each vehicle class is shown in Figure 6-7 (b). The pattern is similar with Class 8 vehicles having the highest speeding violation rate.

By comparing the traffic performance indicators for SSE and ASE, we found that the ASE 85th percentile speed profiles were lower, smoother and more separated than the speed profiles for

SSE. ASE can monitor vehicle travel along a whole section encouraging drivers to maintain an average travel speed below the speed limit for the whole of the monitored section. This result suggest that ASE is a more effective speed reduction strategy than SSE. SSE showed a very clear V-profile indicating its limited area of speed enforcement. The speed violation rate in each FHWA class was also reduced under the ASE strategy compared to the SSE strategy. The introduction of ASE can be expected to reduce vehicle speeds more substantially and more effectively than can a SSE strategy.

The 85th percentile speed, average speed, standard deviation of speed, and speed violation rate for each FHWA class under the ASE strategy were also reduced compared to the USL strategy. A lower speed standard deviation is associated with a reduced likelihood of crashes due to the similarity in vehicle speeds. An ASE strategy can also, therefore, be expected to lead to more steady speed and homogenized traffic flows and fewer collisions than can a SSE strategy.

6.5 Chapter Summary

This chapter compared heavy vehicle traffic performance under two speed limit strategies and two speed enforcement strategies. The analyses used VISSIM as the traffic simulation tool. We selected three traffic performance indicators: 1) the longitudinal 85th percentile speed profile, 2) standard deviation of speed, and 3) the speed violation rate to evaluate the safety impacts of the two speed limit strategies and two speed enforcement strategies. Two-stage calibration was carried out to improve the accuracy of the VISSIM simulation. In the first stage, we calibrated parameters such as traffic volume, travel time, travel speed and vehicle composition. The outputs were all within an acceptable error level. The second stage used sensitivity analysis to establish appropriate values for traffic volume and the percentage of heavy vehicles as this information was not available from the observed conditions. Traffic volume of 600 vehicles per hour with 25 percentage of heavy vehicle were found to match observed conditions and were the values used for the base scenario analysis. The sensitivity analysis also showed that speed decreased with increases in traffic volume and/or heavy vehicle percentage.

The first simulation model compared USL to DSL using the three performance indicators. The study's objectives included setting four different speed limits associated with the four proposed M-FHWA classes used in the simulation analysis.

The new differential speed limits for each M-FHWA class were based on the 85th percentile speed for each M-FHWA class under USL. For each M-FHWA class, a new average speed and standard deviation of speed were estimated as input for the DSL scenario.

The 85th percentile speed profiles for DSL showed the results expected from the way we designed the DSL strategy. The 85th percentile speed profiles for M-FHWA classes 2, 3 and 4 were lower than their DSL speed limits of 85 km/h, 80 km/h and 75 km/h respectively. M-FHWA class 1 was different: the 85th percentile speed profile for M-FHWA class 1 was 5 km/h higher than the class's DSL speed limit of 95 km/h. This result could be because the original M-FHWA class 1 85th percentile speed in the integrated dataset (USL scenario) was 5 km/h higher than the uniform speed limit of 90 km/h. The result could also be due to the simulation assumptions made for the DSL strategy, for example, the assumption that M-FHWA class 1 vehicles would reduce their driving speed to below the posted speed limit (95 km/h) to avoid fines.

The analysis of the standard deviation of speed compared the USL and DSL strategies. The DSL simulation found that DSL reduced 85th percentile speed by 2.72 %, average speed by 3.77 %, and standard deviation by 3.19 % for all heavy vehicles and for each M-FHWA class except M-FHWA class 1. The biggest speed reduction occurred for M-FHWA class 4 vehicles which showed an 8.99% reduction in 85th percentile speed. The average speed reduction was 7.52 % and the standard deviation reduction was 20.39 %. As the speed limit increased, the 85th percentile speed, average speed and standard deviation all increased and vice versa.

The analysis of the speed violation rate showed that the speed violation rate for all heavy vehicles was slightly increased in the DSL strategy. This overall increase was due to decreased speed limits for M-FHWA class 2, 3 and 4. In general, the DSL travel speed of each M-FHWA class for considerably less than the USL travel speed.

The results suggest that the introduction of a DSL strategy associated with the M-FHWA class would increase heavy vehicle safety on high-speed free flow highways by reducing travel speeds and speeding violation rates and thereby reducing the number and severity of highway collisions involving heavy vehicles. The reduction in the standard deviation of speed would be expected to reduce the probability of vehicle interactions and lead to reduced risk of highway collisions.

The second simulation model compared SSE with ASE using the same three traffic performance indicators. The assumption of a 4% speed change (in acceleration and deceleration) within 1,500 m of the speed enforcement location was shown to give a reasonable simulation of the speed fluctuations typical of a SSE strategy.

The 85th percentile speed profiles for SSE and ASE were compared. Compared to SSE, ASE produced a steadier traffic speed with a more homogenized traffic flow. This result was evident in the ASE's lower, smoother and more separated 85th percentile speed profiles. Compared to SSE, ASE reduced speed substantially and effectively because ASE monitors vehicle travel along a whole section encouraging drivers to keep their average travel speed below the speed limit for the whole monitoring section. The SSE 85th percentile speed profiles were as expected given the assumption of a clear V-shaped reduction in speed near the speed enforcement location indicating a very limited area of speed enforcement. SSE also produced 85th percentile speed profiles around 90 km/h and very close profiles for Classes 9, 10, 12 and 13.

The analysis of the standard deviation of speed for the SSE and ASE strategies found that, compared to USL, ASE reduced the 85th percentile speed by 6.97%, average speed by 8.07 %, and the speed standard deviation by 9.56 % for all heavy vehicles. Lower speed standard deviation reflects more homogenized vehicle speeds and can be expected to reduce the likelihood of crashes suggesting that an ASE strategy would lead to fewer collisions than the current SSE strategy.

The analysis of the speed violation rate showed that the ASE speed violation rate in each FHWA class was lower than the SSE rate. It appears that ASE would be more effective in enforcing vehicle speed on high-speed highways than conventional SSE.

Overall, the simulation exercise showed that DSL associated with the proposed M-FHWA classification combined with ASE would substantially and effectively reduce heavy vehicle travel speeds and produce smoother and more harmonized travel speeds that can be expected to reduce the number and severity of highway collisions involving heavy vehicles, improving safety for the freight transportation sector.

Chapter 7 Conclusions

This Chapter summarizes the study, presents the conclusions, and proposes recommendations for future research.

7.1 Summary

The research consisted of two technical components, a data-driven analysis and a simulation analysis. The simulation analysis consisted of two studies.

The conventional FHWA class scheme largely depends on the configuration of vehicles. Within a particular FHWA class, e.g., class12, the vehicles may have widely different GVWs. This range in the GVW means that the FHWA classification is not well suited for a DSL strategy that is associated with the GVW.

A Modified-Federal Highway Administration (M-FHWA) classification that takes GVW into account was created. The proposed classification has four M-FHWA classes for heavy vehicles. The classes are based mainly on GVW, but they also consider the FHWA class and the average speed of the vehicles as measured in the study sample. The classification was designed to ensure that the speed distribution within each class was distinctive (avoiding overlapping where possible) and that there was a sufficient number of vehicles in each category. ANOVA tests with Tukey's HSD tests were used to exam whether the average speed in each M-FHWA class was distinctive enough to suggest that setting different speed limits for each M-FHWA class would be appropriate. The test results showed that average speed in each proposed M-FHWA class was statistically significantly different.

The study used three different approaches to develop an integrated dataset that combined WIM data with GPS data to include more accurate speed distribution with nonstop and travel with stops information. Firstly, a QQ plot was used to check that the speed distributions of the WIM and GPS data were similar. Secondly, a linear regression model was used to estimate the linear relationship between the WIM speed data and GPS speed data. Thirdly, the Monte Carlo method was applied to develop the integrated dataset that incorporated WIM data and GPS data.

The study then evaluated the FHWA heavy vehicle classification and a proposed M-FHWA classification to decide which scheme would be suitable for developing a DSL strategy based on GVW. The study examined the empirical relationships between heavy vehicle speed and GVW for FHWA classes and M-FHWA classes. The results showed that the M-FHWA classes had a stronger correlation with speed and GVW than did the FHWA classes. Each M-FHWA class had less variance in GVW, less overlapping of GVW between M-FHWA classes, and more clearly distinctive speed distributions than did the FHWA classes. These results suggested that the M-FHWA classification would be the more appropriate classification scheme for assessing a DSL strategy that includes consideration of GVW.

The study proposed the new speed limit strategy (DSL) and the new speed enforcement strategy (ASE). The simulation analysis conducted two comparison studies: 1) to compare the traditional speed limit strategy (USL) with a new speed limit strategy (DSL); and 2) to compare the traditional speed enforcement strategy (SSE) with a new speed enforcement strategy (ASE).

Three traffic performance indicators, the longitudinal 85th percentile speed profile, standard deviation of speed, and the speed violation rate, were used to evaluate the safety impact of the different speed limit and speed enforcement strategies. As it is not reasonable to apply ASE on 548 km of highway, an 8 km highway section was selected as the simulation study segment.

VISSIM was used to conduct the simulation analysis. Two stages of calibration improved the accuracy of the simulation model. The first stage calibration evaluated traffic volume, travel time, travel speed, and vehicle composition to check the accuracy of the model. All the calibration results were under the threshold values. The second stage calibration was a sensitivity analysis conducted to help determine suitable values for traffic volume and heavy vehicle percentage for the base scenario. The sensitivity analysis found that appropriate values for the base scenario were: traffic volume of 600 vehicles per hour per direction, and heavy vehicle percentage of 25 %.

In the first comparison simulation analysis, new speed limits were created for the four M-FHWA classes. The four new speed limits were selected based on the 85th percentile speeds in USL strategy. The comparison of the two speed limit strategies was based on the three traffic performance indicators. The results showed that DSL generally performed better than USL: DSL produced more separated and relatively lower 85th percentile speed profiles, larger reductions in the 85th percentile speed, average speed and standard deviation of speed for each M-FHWA, and smaller standard deviations in speed. The findings suggest that DSL would reduce the probability of vehicle interactions thereby reducing the risk of highway collisions. In addition, reductions in average speed and speed standard deviation have been associated with a reduced fatality rate (Russo et al., 2017). Although the DSL speed violation rates in M-FHWA classes 2, 3 and 4 were slightly increased, the travel speeds for M-FHWA classes 2, 3 and 4 under DSL were generally reduced compared to USL.

In general, the DSL strategy associated with the M-FHWA classification appeared to be an effective speed limit strategy with the potential for bringing significant improvements to heavy vehicle highway safety.

In the second comparison simulation analysis, which used the three traffic performance indictors to compare SSE and ASE, we found that ASE generally performed better than SSE: ASE produced lower, smoother and more separated 85th percentile speed profiles. An ASE strategy can monitor vehicle travel along a whole section encouraging drivers to ensure that their average travel speed remains below the speed limit for the whole monitoring section whereas SSE reduces vehicle speeds for only a very localized section of highway around the speed enforcement location leading to drivers changing speed over a relatively short distance to avoid a speeding ticket. Compared to SSE, ASE also effectively reduced the speed violation rate for each FHWA class. Also, the 85th percentile speed, average speed, standard deviation of speed and speed violation rate for each FHWA class in ASE strategy was reduced compared to USL strategy. Lower speed standard deviation created more consolidated speeds between vehicles that reduced the likelihood of crashes. Therefore, ASE strategy would lead to more steady speed with homogenized traffic flow and less collisions than SSE strategy.

In general, it appears that ASE is more effective than SSE as ASE is expected to bring about substantial reductions in heavy vehicle speed.

In summary, the two comparison simulation studies demonstrated that introducing differential speed limits associated with a Modified-Federal Highway Administration classification combined with average speed enforcement has clear potential for enhancing highway safety for heavy vehicles. Benefits include substantially reducing heavy vehicle travel speeds and producing the smoother, the more harmonized travel speeds associated which would reduce the number and severity of highway collisions involving heavy vehicles.

7.2 Recommendations

Although this study shows that the safety of heavy vehicles is likely to be improved by the introduction of DSL associated with GVW and ASE, there are still considerable opportunities for future research.

1. The data fusion method was employed to develop an integrated dataset that included accurate information on nonstop and stopping heavy vehicle trips, but the simulation model has the limitation of obtaining the detail simulation results for different vehicle classification when the percent of heavy vehicle is small (i.e. 0.04%). Future research could focus on nonstop-travel heavy vehicles and explore the safety impact of speed limit and enforcement strategies under free flow traffic conditions.
2. The speed limit strategy analysis used the proposed M-FHWA classification, but the speed enforcement analysis used the standard FHWA classification. This was to allow the speed enforcement analysis to make use of previous model calibrations and the assumption that a speed fluctuation is typical of SSE which was based mainly on studies that used FHWA

class. It would be useful to explore the traffic performance of DSL combined with ASE with a consistent vehicle classification scheme.

3. The DSL model was built using assumptions based on previous studies all of which considered only two levels of differential speed limits, one for passenger cars and one for trucks. Future research could investigate a range of DSL strategies with more detailed and precise speed limit levels.
4. The SSE model was developed with a number of assumptions. One assumption was that the speed fluctuation phenomenon before and after the spot speed enforcement location should be simulated. The related assumptions assumed that heavy vehicles would reduce travel speed by an average of 4%, and that speed would recover within 1.5 km. Another assumption concerned the weight-to-power ratio and its effect on heavy vehicle acceleration and deceleration capabilities. In this case, our assumptions were based on ITE (1999) and we used conservative estimates, but heavy vehicle braking systems have improved over time. Future research could explore more recent guidelines regarding heavy vehicle engine and mechanical capabilities.
5. Also, future research could consider collecting field data from spot speed enforcement devices to develop a more accurate and realistic understanding of drivers' speed fluctuation behaviour.
6. The location for the ASE simulation was a selected 10 km of highway, but the actual traffic data used in the simulation was collected from 548 km of highway. Future research could consider collecting the data from a shorter segment, e.g., 20 km or 50 km of highway.

7. This study was conducted for a highway corridor in British Columbia. Future research could explore other types of roadway, other jurisdictions, and different weather conditions to check whether this study's findings apply under other circumstances.

8. Future research could be also investigating the application of DSL and ASE strategies for connected autonomous vehicles (CAV) and heavy vehicle platooning (HVP). As mentioned earlier, heavy vehicles' operating speed vary greatly depending on the GVW. Relatively precise GVW information is especially important for heavy vehicles to form HVP is unlikely to be created in reality as it would place the slowest moving vehicle (presumably the heaviest vehicle) in the lead with an inevitable loss of travel time and fuel savings. If a fast-moving vehicle leads the convoy, the platoon may break up on steep segments reducing fuel savings and creating undesirable safety challenges from cars cutting in between supposedly platooning vehicles. One of our findings has shown that heavy vehicle speed variance would be reduced within each M-FHWA class if they follow the proposed DSL (Chapter 6.3). Setting DSL based on GVW allow heavy vehicles with similar GVW to follow the same speed limit and be able to travel as a group and form a platoon with tight gaps and harmonized speeds even on steep grades without creating the issues of concern raised above. Setting differential speed limits associated with GVW would become important for the formation of proper HVPs. It would be useful to explore whether these concepts would work in a traffic environment when CAV/platooning is widely available in our public highway.

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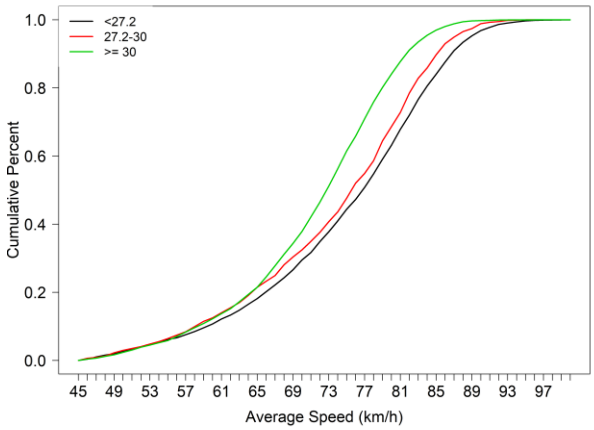
Appendix

Appendix A: FHWA Vehicle Classification Scheme

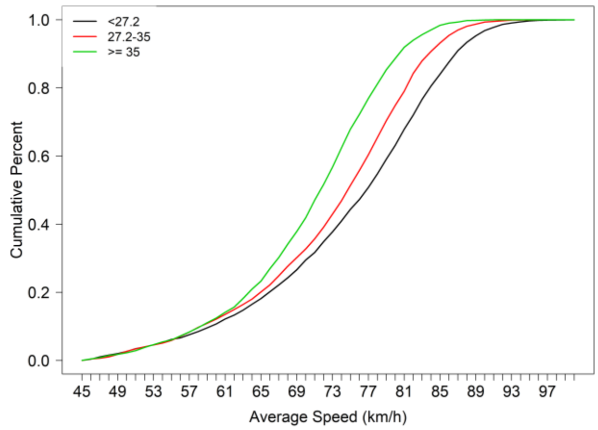
Table A-1: Vehicle Distribution based on EPA Emission Classification (EPA, 2017)

Gross Vehicle Weight Group	Average GWV Intervals (lb)	Average GWV Intervals (kg)	Number of Vehicles	Average Speed (km/h)
Light Duty Trucks	<6000	<2700	0	-
	6000-8500	2700-3850	0	-
Medium Duty	8500-10000	3850-4500	0	-
	1000-14000	4500-6350	0	-
	14000-16000	6350-7250	0	-
	16000-19500	7250-8850	0	-
Heavy Duty	19500-26000	8850-11800	0	-
	26000-33000	11800-15000	11	71.93
	33000-60000	15000-27200	3354	75.44
	>=60000	>=27200	6000	72.47

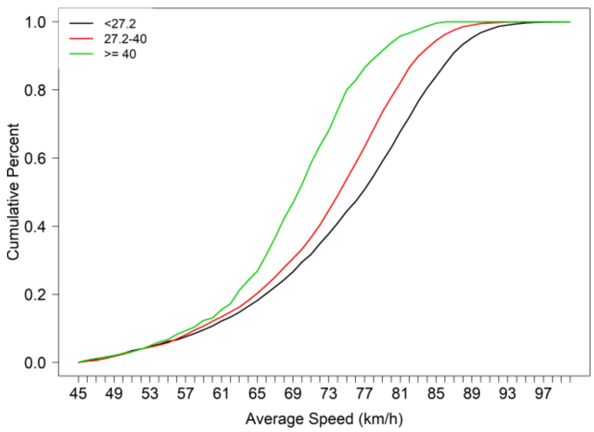
Appendix B: M-FHWA Classification Selection and Evaluation



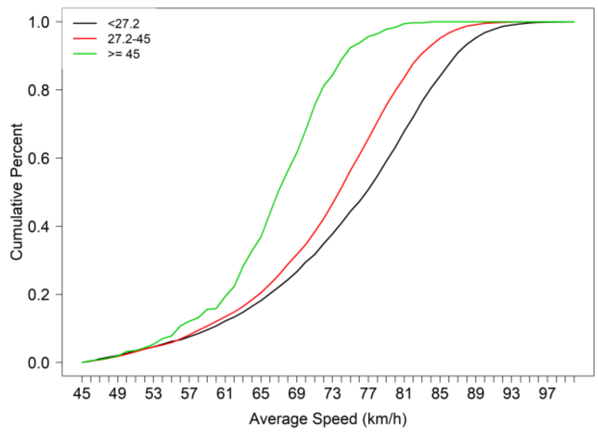
a) 30 Tonnes



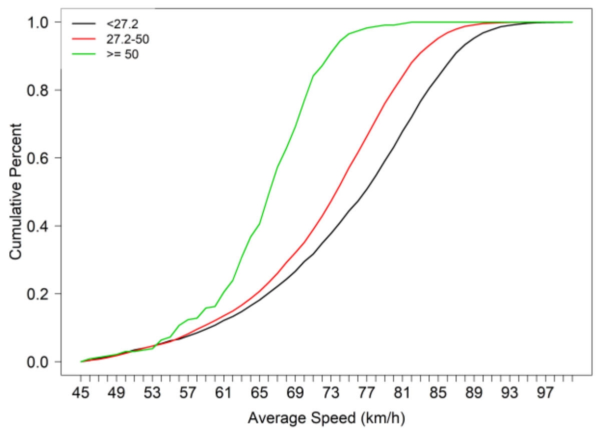
b) 35 Tonnes



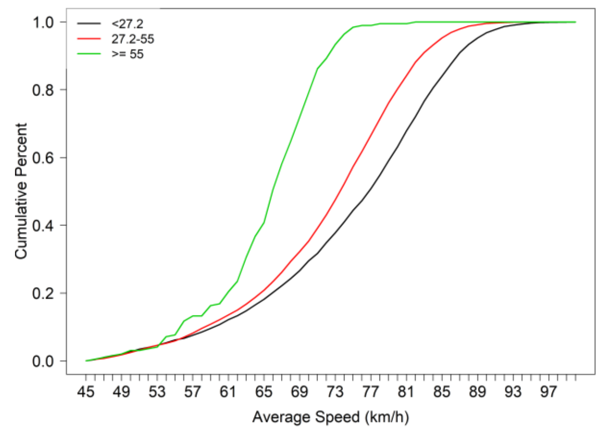
c) 40 Tonnes



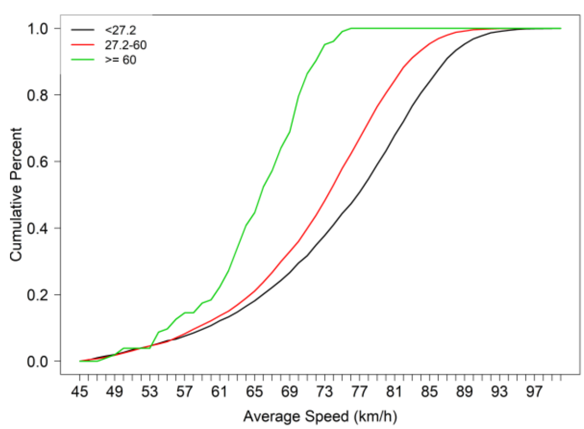
d) 45 Tonnes



e) 50 Tonnes



f) 55 Tonnes



g) 60 Tonnes

Figure B-1: Speed Distributions for Different GVW Thresholds

Table B-1: Number of Vehicle, Average Speed and 85th Percentile Speed Distributions for Different GVW Thresholds

Different GVW Threshold Combinations			
GVW Groups	**<27,200**	**27,200 - 30,000**	**≥ 30,000**
Number of Vehicles	3363.00	1247.00	4753.00
Average Speed (km/h)	75.41	74.16	72.03
85th Percentile Speed (km/h)	85.95	84.46	80.86
	<27,200	**27,200 - 35,000**	**≥ 35,000**
Number of Vehicles	3363.00	3384.00	2616.00
Average Speed (km/h)	75.41	73.53	71.10
85th Percentile Speed (km/h)	85.95	82.88	79.59
	<27,200	**27,200 - 40,000**	**≥ 40,000**
Number of Vehicles	3363.00	4898.00	1102.00
Average Speed (km/h)	75.41	73.17	69.39
85th Percentile Speed (km/h)	85.95	82.27	77.29
	<27,200	**27,200 - 45,000**	**≥ 45,000**
Number of Vehicles	3363.00	5628.00	372.00
Average Speed (km/h)	75.41	72.84	66.92
85th Percentile Speed (km/h)	85.95	81.99	73.85
	<27,200	**27,200 - 50,000**	**≥ 50,000**
Number of Vehicles	3363.00	5766.00	234.00
Average Speed (km/h)	75.41	72.73	66.03
85th Percentile Speed (km/h)	85.95	81.89	71.92
	<27,200	**27,200 - 55,000**	**≥ 55,000**
Number of Vehicles	3363.00	5804.00	196.00
Average Speed (km/h)	75.41	72.70	65.76
85th Percentile Speed (km/h)	85.95	81.87	71.50
	<27,200	**27,200 - 60,000**	**≥ 60,000**
Number of Vehicles	3363.00	5897.00	103.00
Average Speed (km/h)	75.41	72.60	65.43
85th Percentile Speed (km/h)	85.95	81.84	71.41

Table B-2: ANOVA Test for M-FHWA Classification (11 Sub-Group)

Source	Degree of Freedom	Sum of Squares	Mean Square	F-Value	P-Value
Type	10	36006	3601	38.38	≪0
Residuals	9354	877430	94	-	-

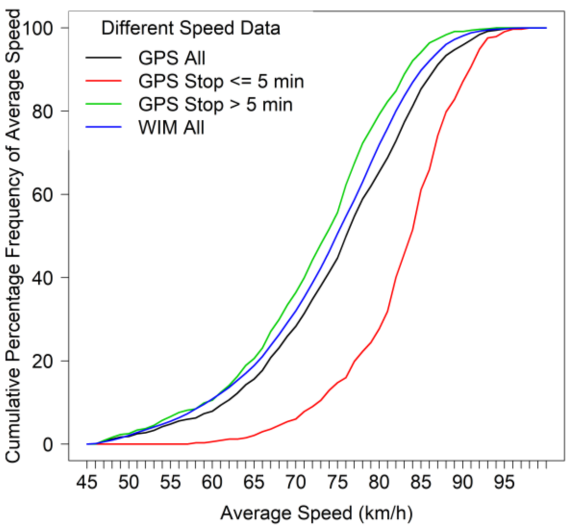
Table B-3: Tukey Post Hoc Test for M-FHWA Classification (11 Sub-Group)

Groups	Means Difference	Lower Bound	Upper Bound	Adjusted P-Value
Class2-9 - Class1-8	-10.91	-18.28	-3.54	0.0001
Class3-9 - Class1-8	-12.90	-20.27	-5.53	0.0000
Class2-10 - Class1-8	-9.37	-16.93	-1.81	0.0032
Class3-10 - Class1-8	-13.71	-21.10	-6.33	0.0000
Class4-10 - Class1-8	-17.61	-25.64	-9.58	0.0000
Class2-12 - Class1-8	-9.19	-17.79	-0.60	0.0243
Class3-12 - Class1-8	-15.35	-23.05	-7.66	0.0000
Class4-12 - Class1-8	-19.75	-31.10	-8.40	0.0000
Class3-13 - Class1-8	-14.25	-22.21	-6.29	0.0000
Class4-13 - Class1-8	-19.73	-27.32	-12.13	0.0000
Class3-9 - Class2-9	-1.99	-2.77	-1.21	0.0000
Class2-10 - Class2-9	1.55	-0.31	3.40	**0.2075**
Class3-10 - Class2-9	-2.80	-3.71	-1.88	0.0000
Class4-10 - Class2-9	-6.70	-9.98	-3.42	0.0000
Class2-12 - Class2-9	1.72	-2.77	6.21	**0.9789**
Class3-12 - Class2-9	-4.44	-6.80	-2.08	0.0000

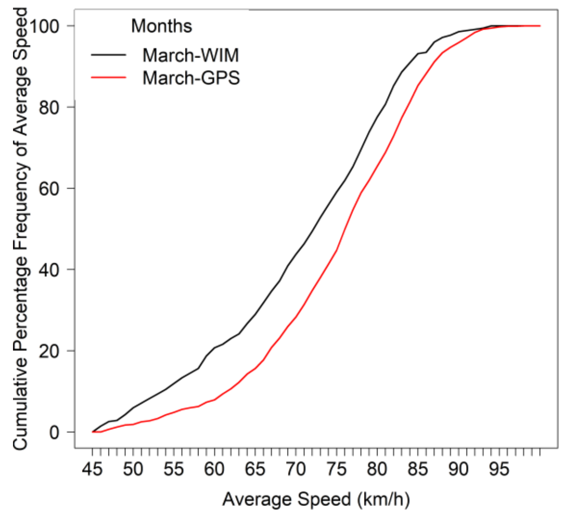
Groups	Means Difference	Lower Bound	Upper Bound	Adjusted P-Value
Class4-12 - Class2-9	-8.84	-17.50	-0.17	0.0412
Class3-13 - Class2-9	-3.34	-6.45	-0.23	0.0234
Class4-13 - Class2-9	-8.82	-10.81	-6.82	0.0000
Class2-10 - Class3-9	3.53	1.69	5.38	0.0000
Class3-10 - Class3-9	-0.81	-1.70	0.08	0.1123
Class4-10 - Class3-9	-4.71	-7.99	-1.44	0.0002
Class2-12 - Class3-9	3.70	-0.78	8.19	0.2190
Class3-12 - Class3-9	-2.46	-4.81	-0.10	0.3321
Class4-12 - Class3-9	-6.85	-15.51	1.81	0.2784
Class3-13 - Class3-9	-1.35	-4.46	1.75	0.9478
Class4-13 - Class3-9	-6.83	-8.81	-4.85	0.0000
Class3-10 - Class2-10	-4.34	-6.25	-2.44	0.0000
Class4-10 - Class2-10	-8.25	-11.93	-4.56	0.0000
Class2-12 - Class2-10	0.17	-4.62	4.96	1.0000
Class3-12 - Class2-10	-5.99	-8.88	-3.09	0.0000
Class4-12 - Class2-10	-10.38	-19.21	-1.56	0.0072
Class3-13 - Class2-10	-4.89	-8.42	-1.36	0.0004
Class4-13 - Class2-10	-10.36	-12.96	-7.76	0.0000
Class4-10 - Class3-10	-3.90	-7.21	-0.59	0.0070
Class2-12 - Class3-10	4.52	0.01	9.03	0.0494
Class3-12 - Class3-10	-1.64	-4.05	0.76	0.5028
Class4-12 - Class3-10	-6.04	-14.71	2.64	0.4763
Class3-13 - Class3-10	-0.54	-3.68	2.60	1.0000
Class4-13 - Class3-10	-6.02	-8.06	-3.98	0.0000
Class2-12 - Class4-10	8.42	2.92	13.92	0.0000
Class3-12 - Class4-10	2.26	-1.70	6.22	0.7593
Class4-12 - Class4-10	-2.13	-11.37	7.10	0.9997
Class3-13 - Class4-10	3.36	-1.09	7.81	0.3461

Groups	Means Difference	Lower Bound	Upper Bound	Adjusted P-Value
Class4-13 - Class4-10	-2.11	-5.87	1.64	0.7731
Class3-12 - Class2-12	-6.16	-11.17	-1.15	0.0037
Class4-12 - Class2-12	-10.55	-20.28	-0.83	0.0206
Class3-13 - Class2-12	-5.06	-10.46	0.34	0.0907
Class4-13 - Class2-12	-10.53	-15.38	-5.69	0.0000
Class4-12 - Class3-12	-4.39	-13.34	4.55	0.8906
Class3-13 - Class3-12	1.10	-2.72	4.92	0.9977
Class4-13 - Class3-12	-4.37	-7.36	-1.39	0.0001
Class3-13 - Class4-12	5.50	-3.68	14.67	0.6981
Class4-13 - Class4-12	0.02	-8.84	8.88	1.0000
Class4-13 - Class3-13	-5.48	-9.08	-1.87	0.0001

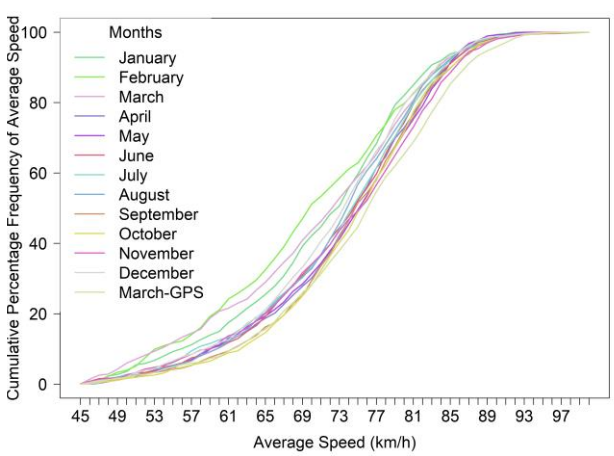
Appendix C: Comparison Analysis between WIM Speed Data and GPS Speed Data



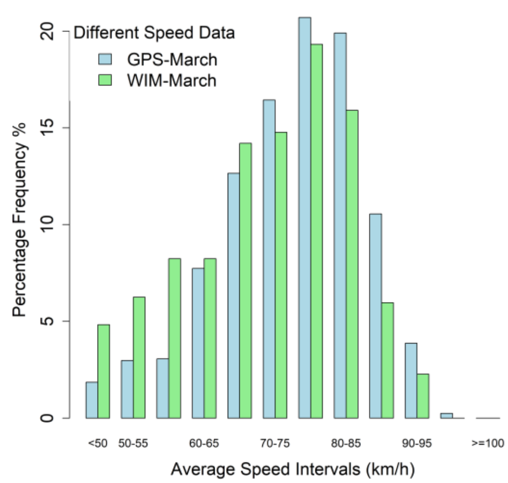
a) All WIM and Detail GPS



b) March of WIM and March of GPS



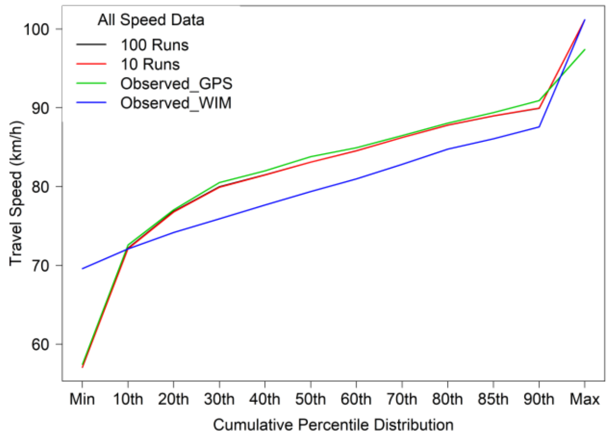
c) Twelve Months of WIM and March of GPS

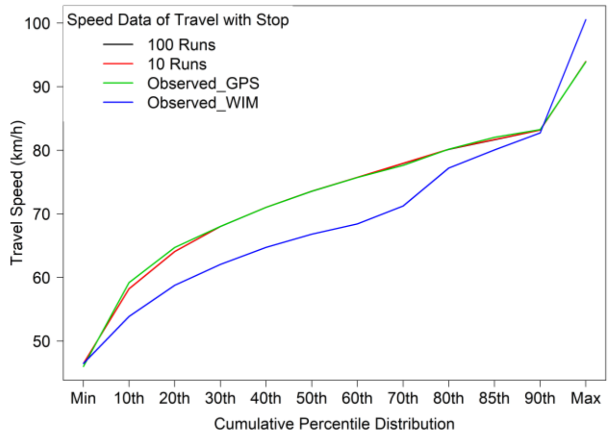


d) March of WIM and March of GPS (Bar Plot)

Figure C-1: Comparison between WIM Speed Data and GPS Speed Data

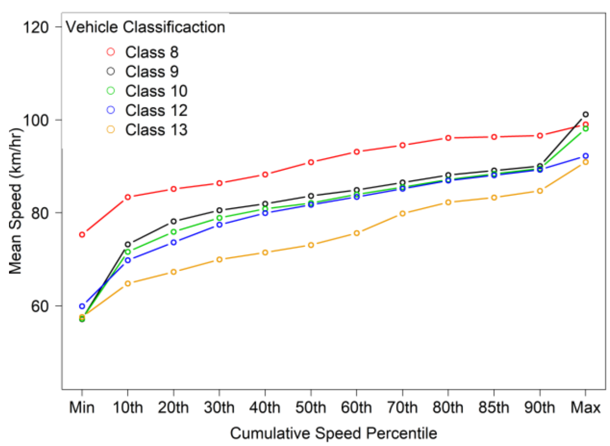
Appendix D: Speed Distribution of Monte Carlo Data Fusion Simulation Results

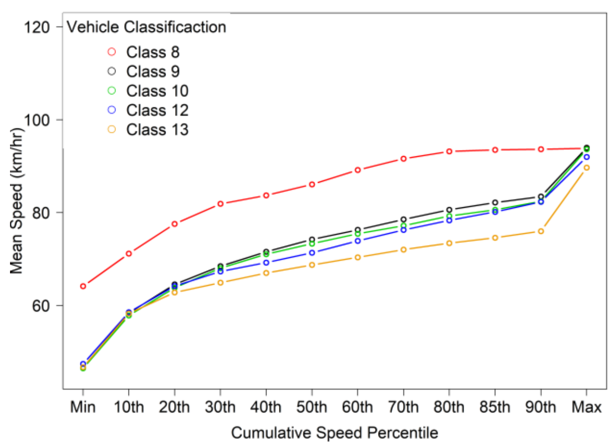




a) Nonstop Speed **b) Speed of Travel with Stops**

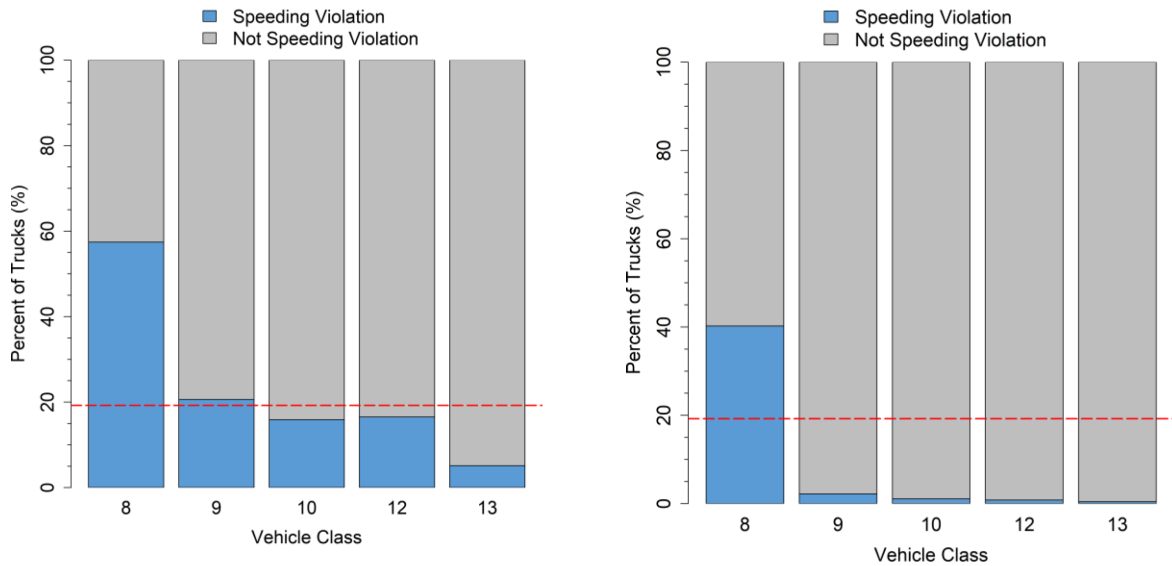
Figure D-1: Comparison of Simulated Speed of 10 Runs and 100 Runs with Observed Speed





a) Nonstop Speed **b) Speed of Travel with Stops**

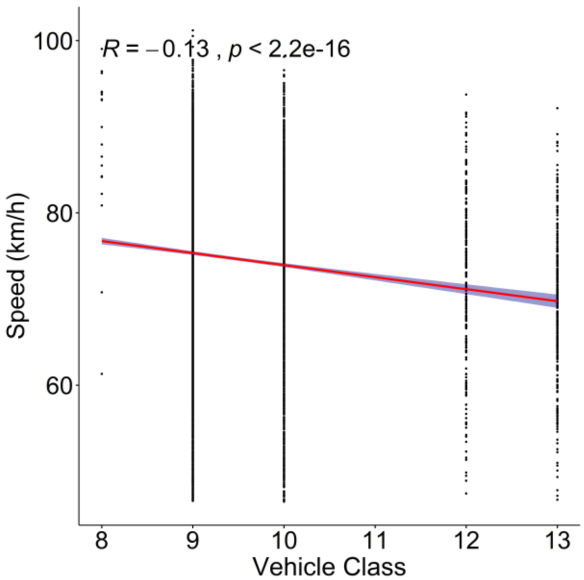
Figure D-2: Cumulative Speed Distribution of Monte Carlo Data Fusion Method



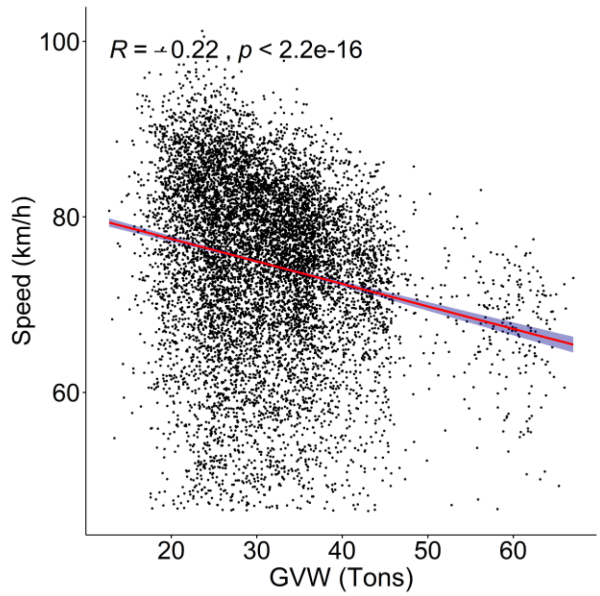
a) Nonstop **b) Travel with Stop**

Figure D-3: Speeding Violation Rate of Monte Carlo Data Fusion Method

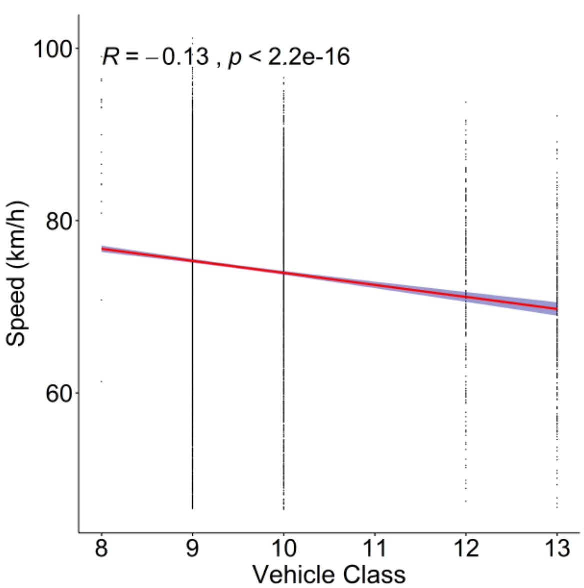
Appendix E: Scatter Plots of Correlation Tests



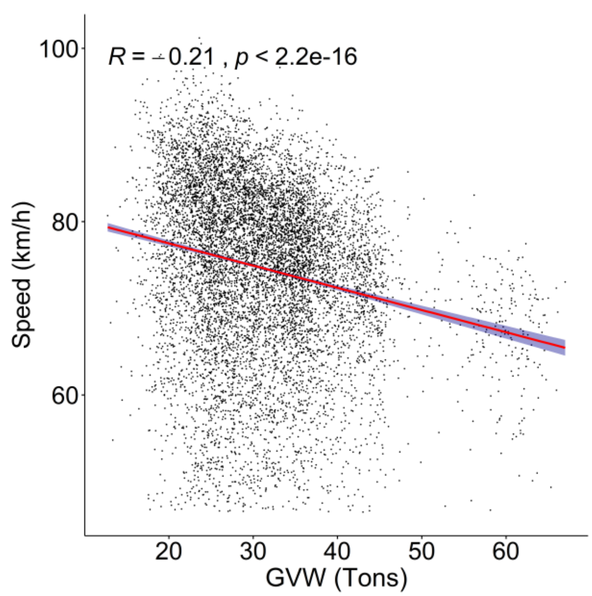
a) Spearman Test of Speed and Class



b) Spearman Test of Speed and GVW

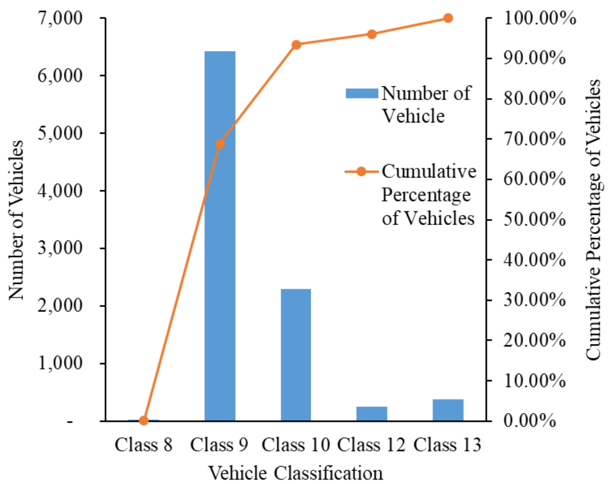


c) Pearson Test of Speed and Class

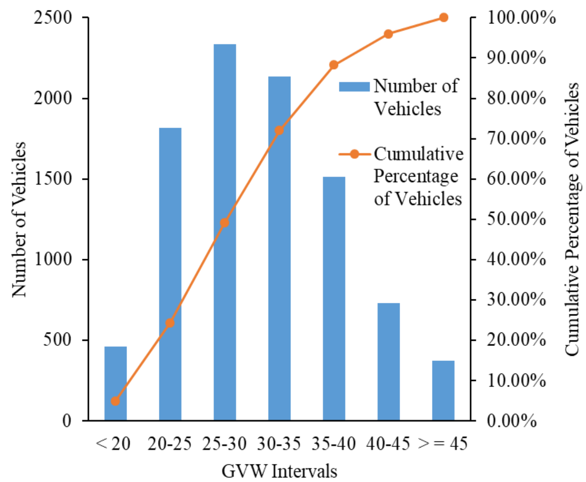


d) Pearson Test of Speed and GVW

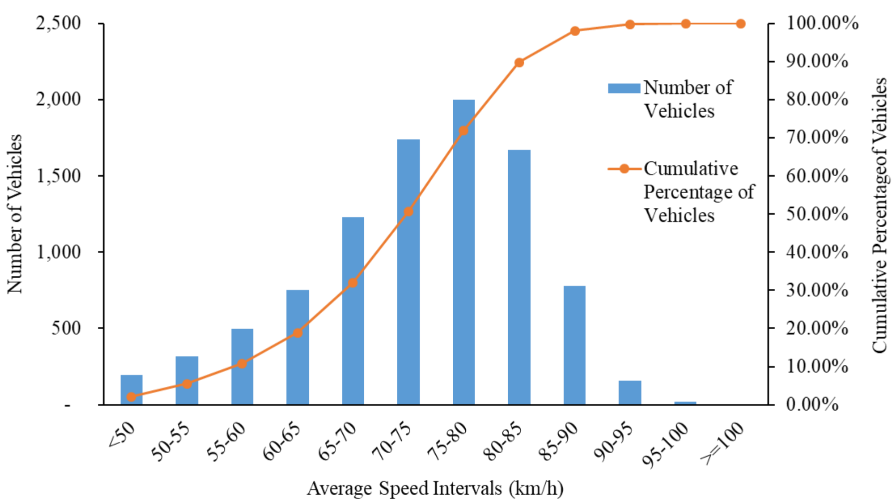
Appendix F: Average Speed, GVW and Vehicle Class Analysis for Combined Traffic Data



a) FHWA Classes

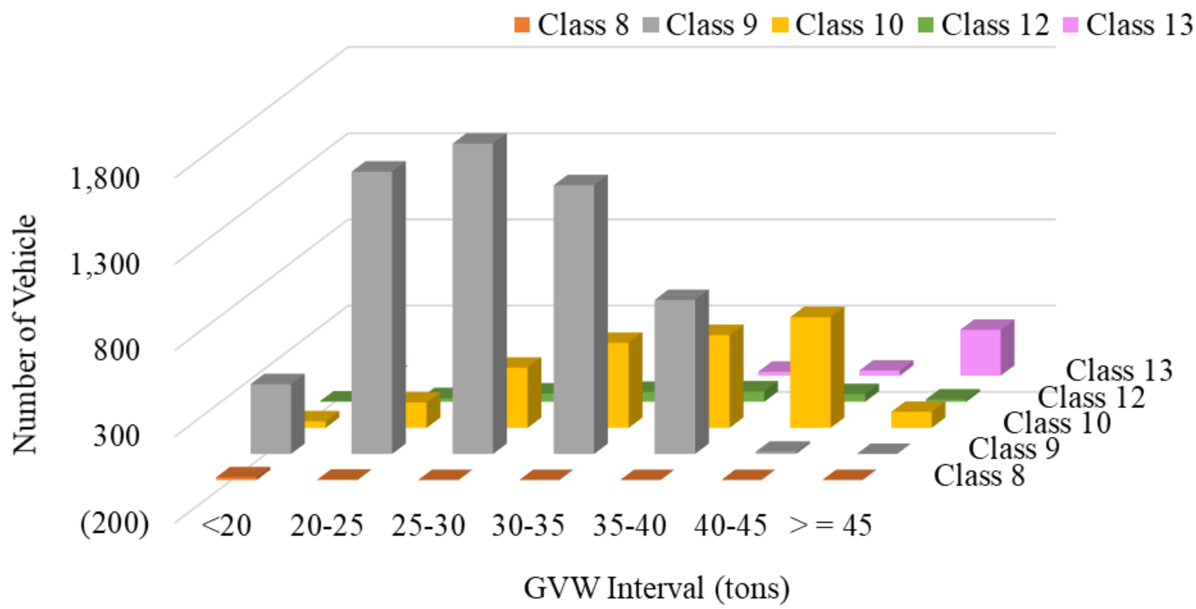


b) GVW Intervals

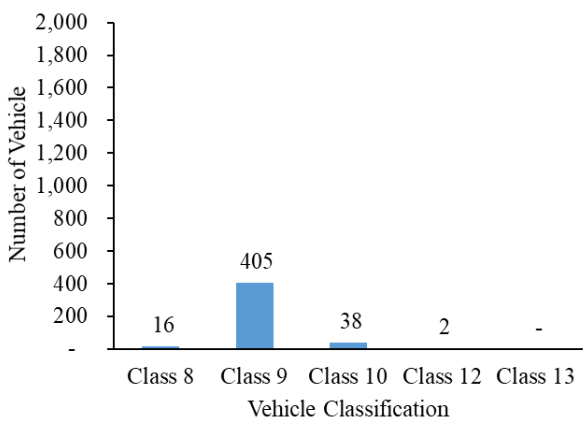


c) Average Speed Intervals

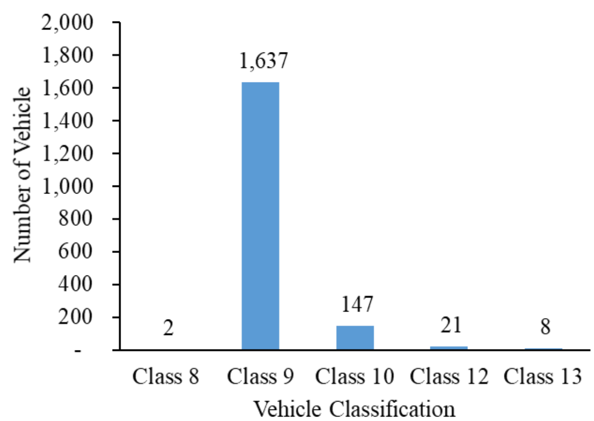
Figure F-1: Frequency Distribution for Vehicle Class, GVW and Average Speed



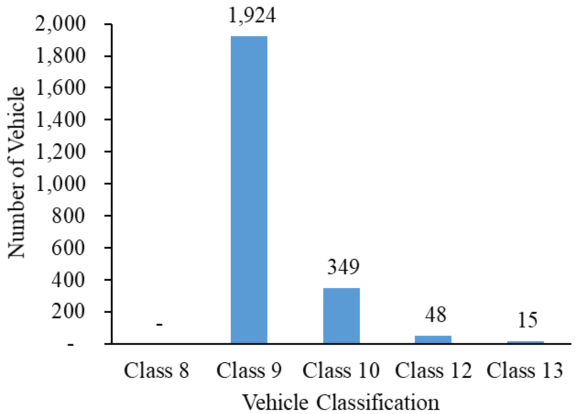
a) Overall Frequency Distribution

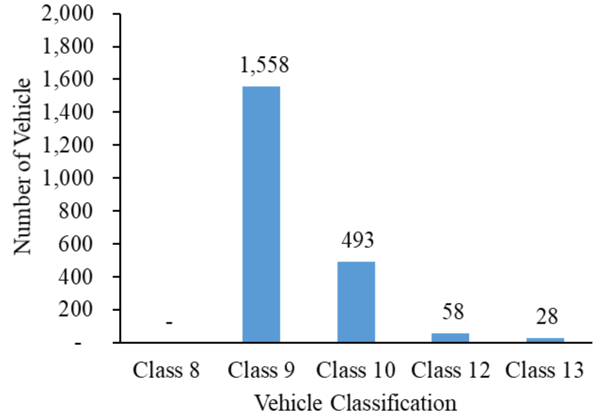


b) GVW < 20 tons



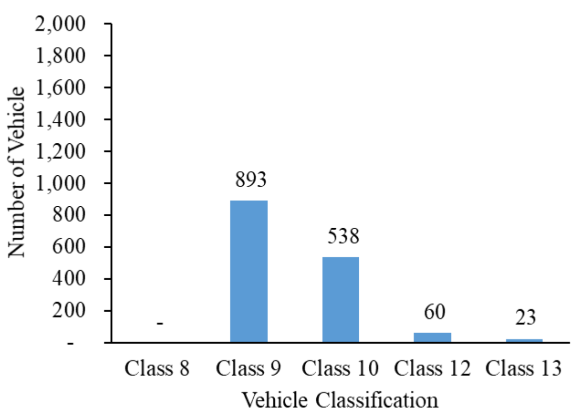
c) 20 tons - 25 tons

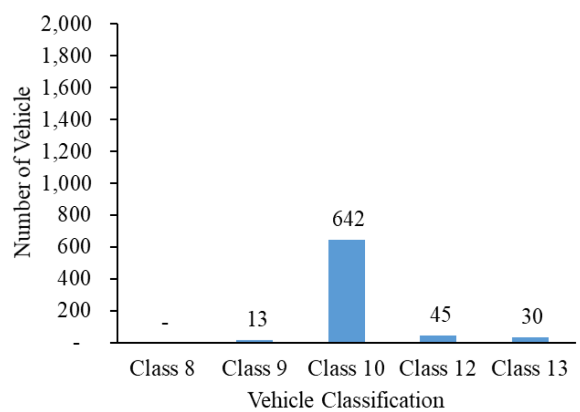




d) 25 tons - 30 tons

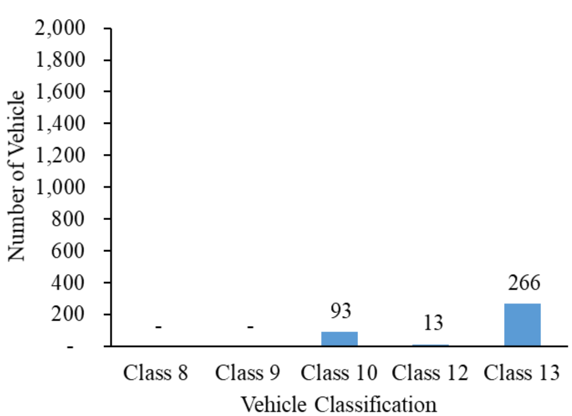
e) 30 tons - 35 tons

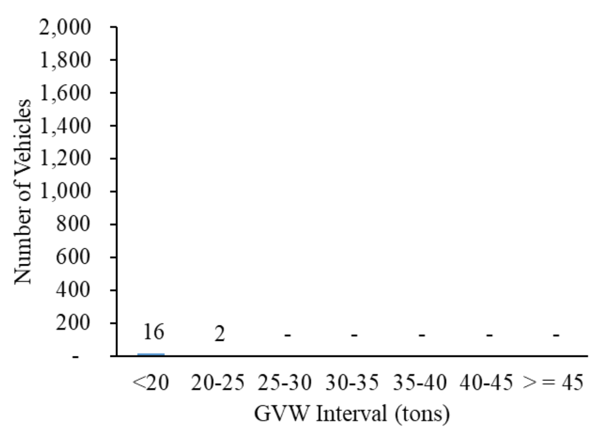




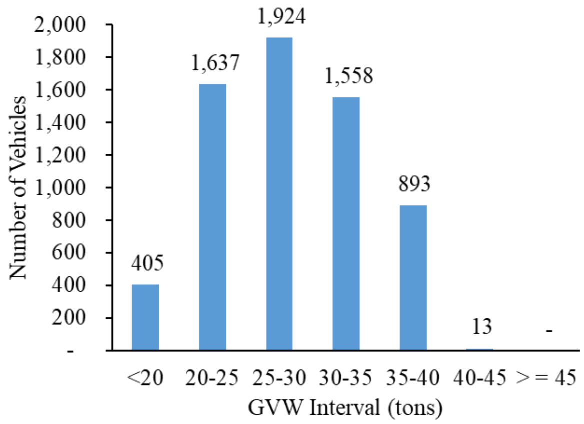
f) 35 tons - 40 tons

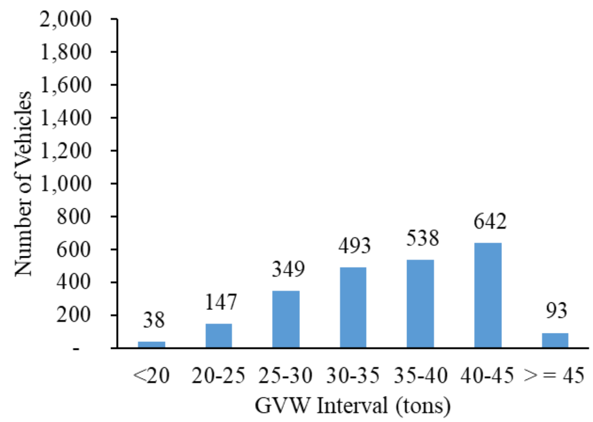
g) 40 tons - 45 tons



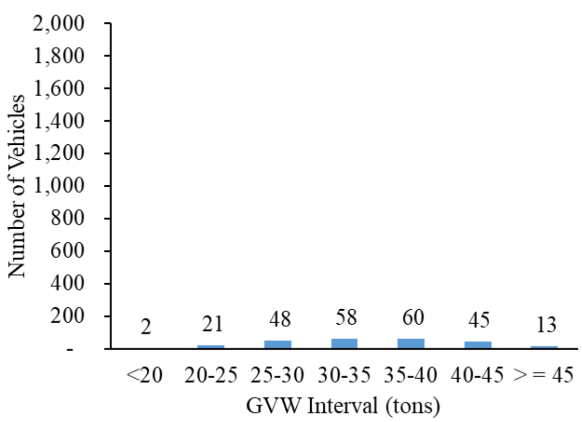


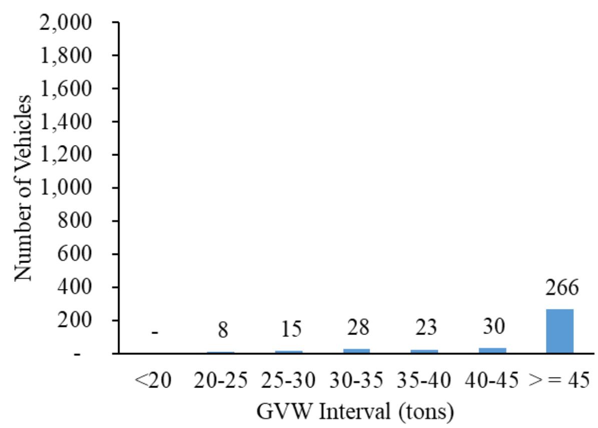
h) GVW ≥ 45 tons **i) Class 8**





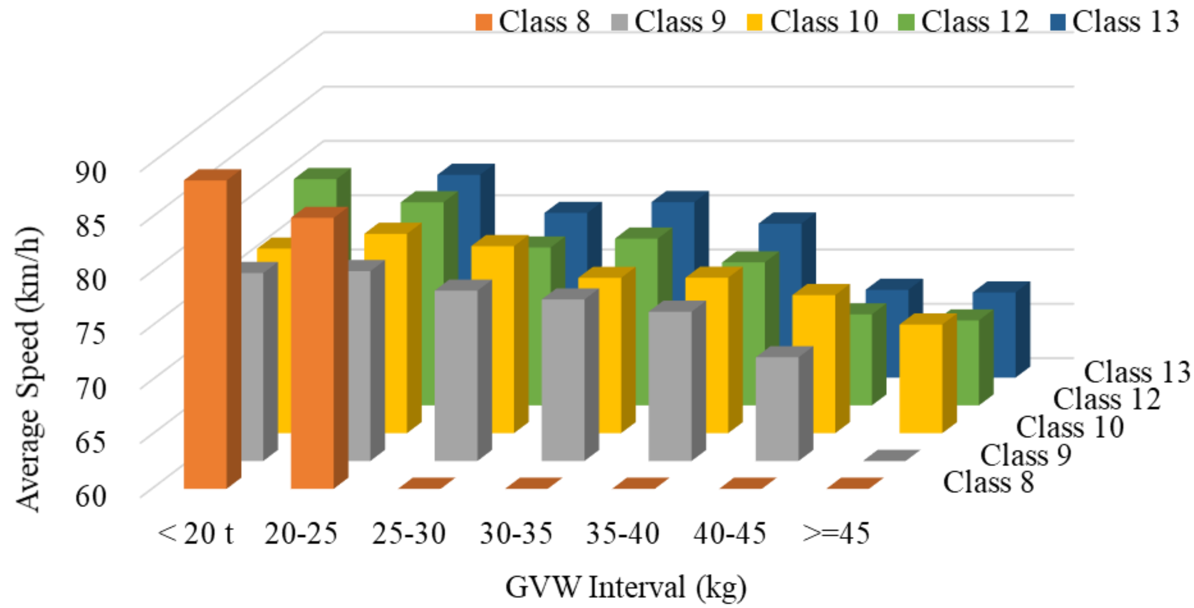
j) Class 9 **k) Class 10**



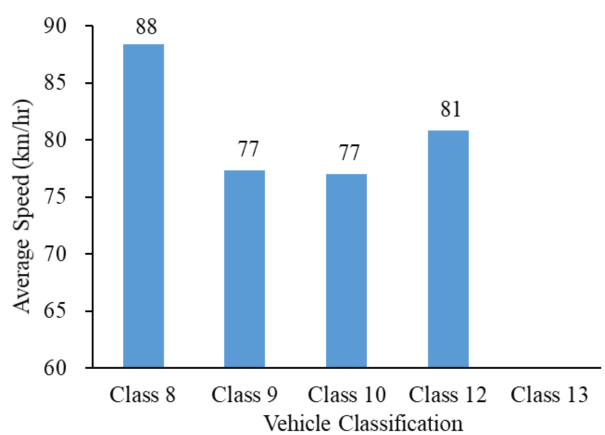


l) Class 12 **m) Class 13**

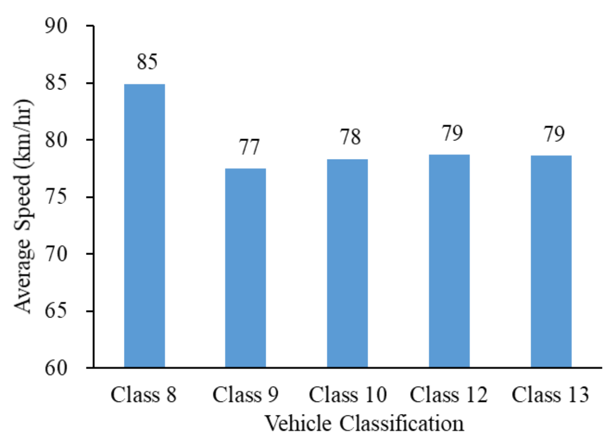
Figure F-2: Frequency Distribution for FHWA Class and GVW Intervals



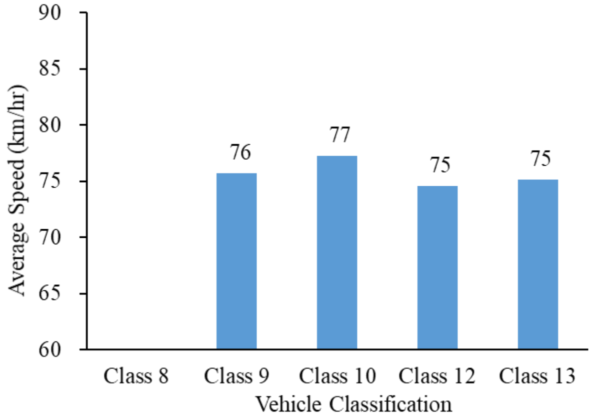
a) Overall Average Speed Distribution

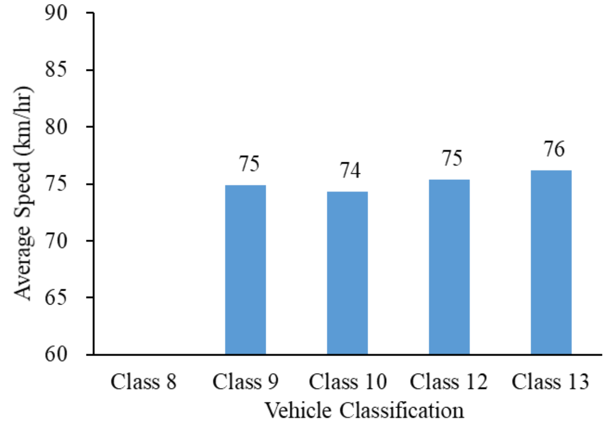


b) GVW < 20 tons



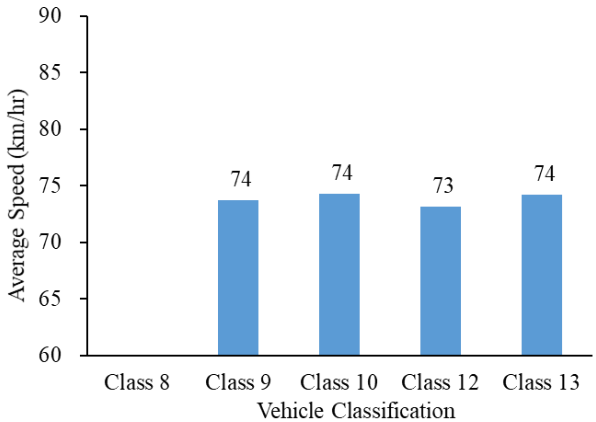
c) 20 tons - 25 tons

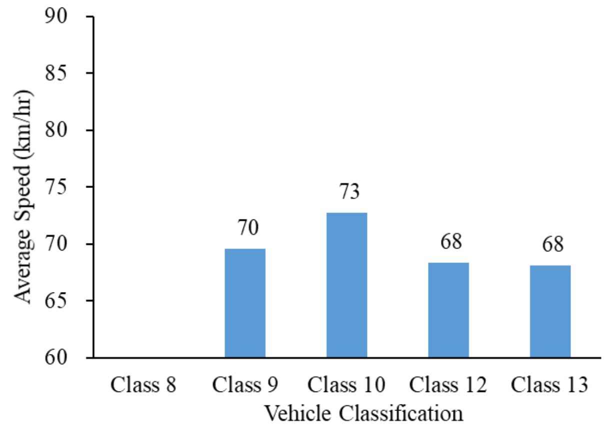




d) 25 tons - 30 tons

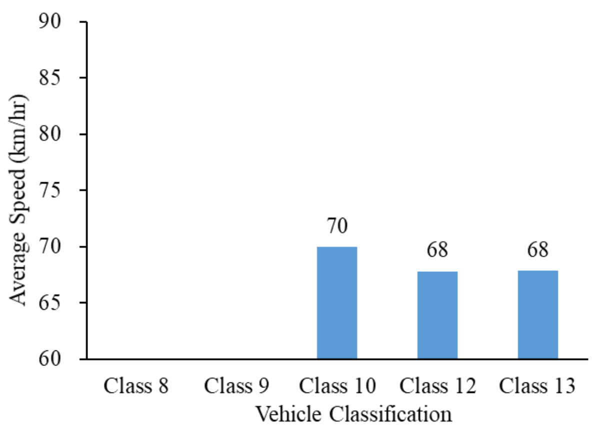
e) 30 tons - 35 tons

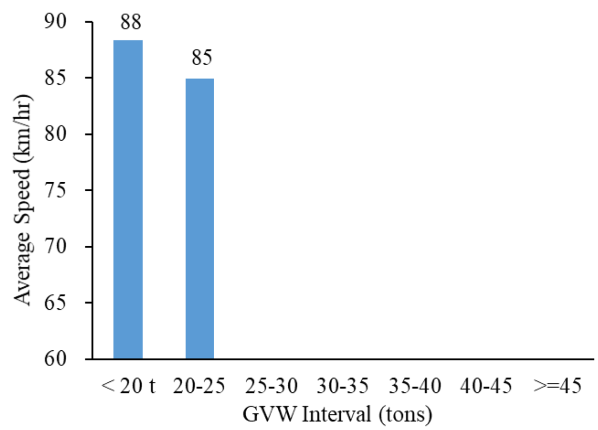




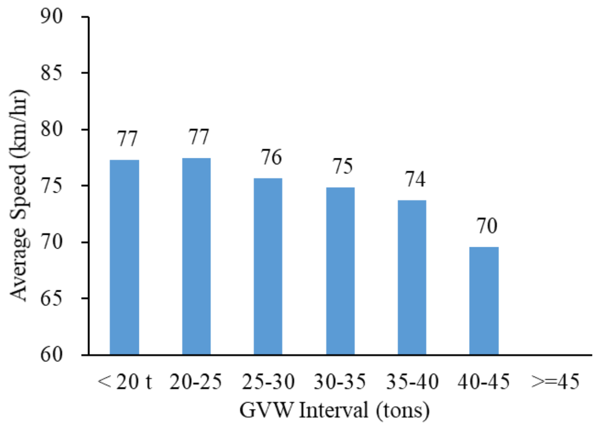
f) 35 tons - 40 tons

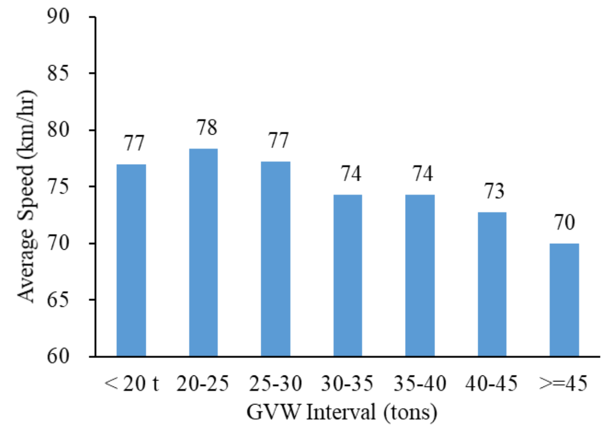
g) 40 tons - 45 tons



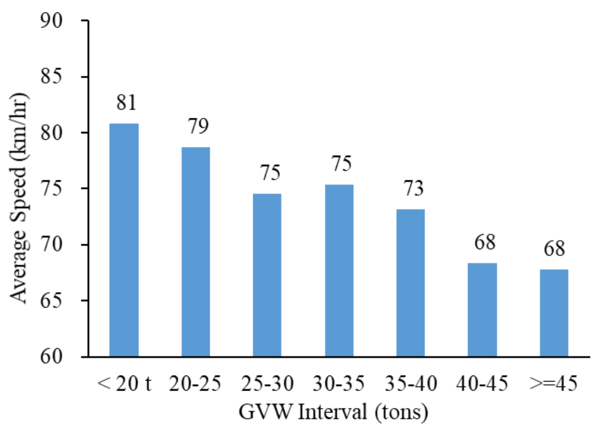


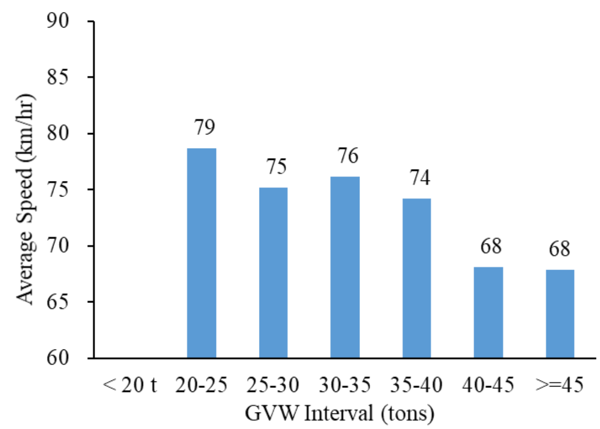
h) GVW ≥ 45 tons **i) Class 8**





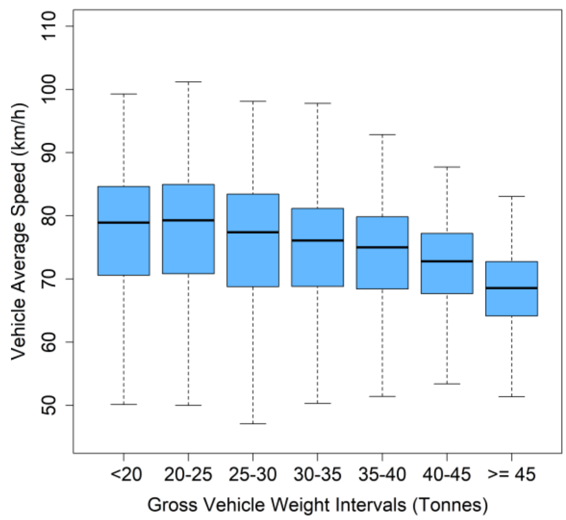
j) Class 9 **k) Class 10**



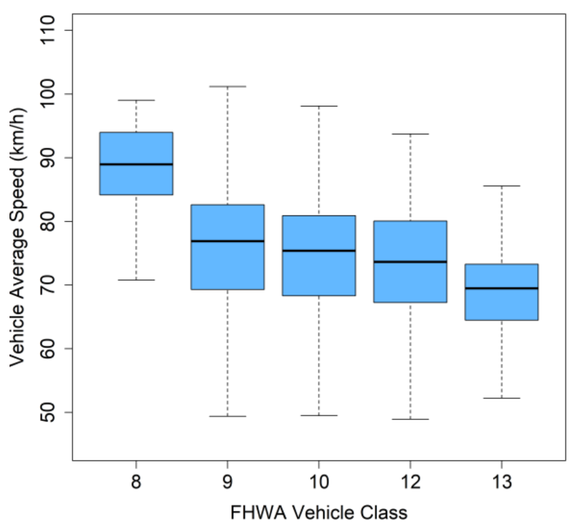


l) Class 12 **m) Class 13**

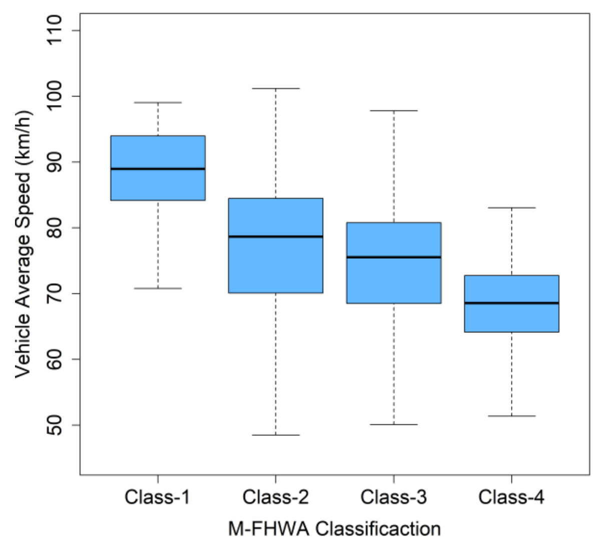
Figure F-3: Speed Distribution for FHWA Class and GVW Intervals



a) GVW Intervals

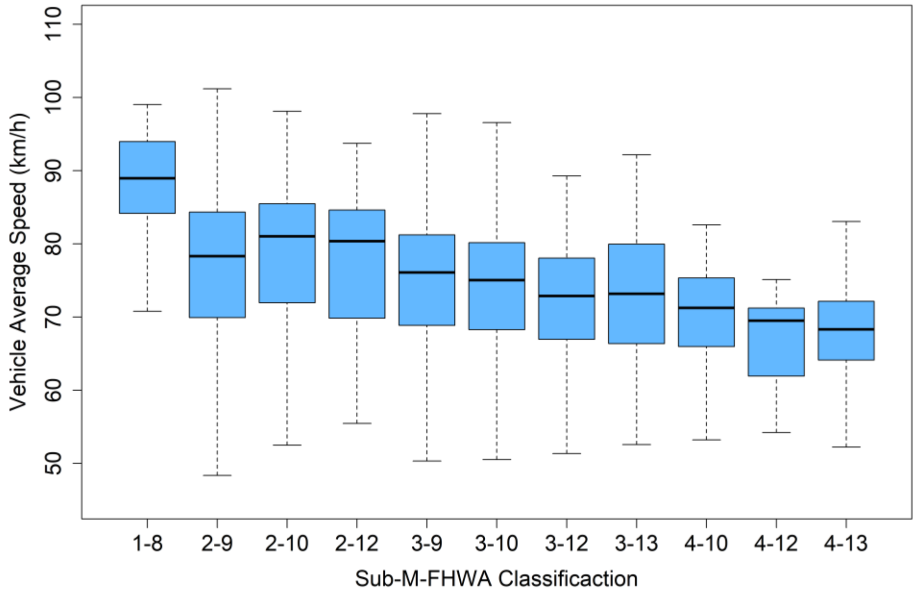


b) FHWA Class

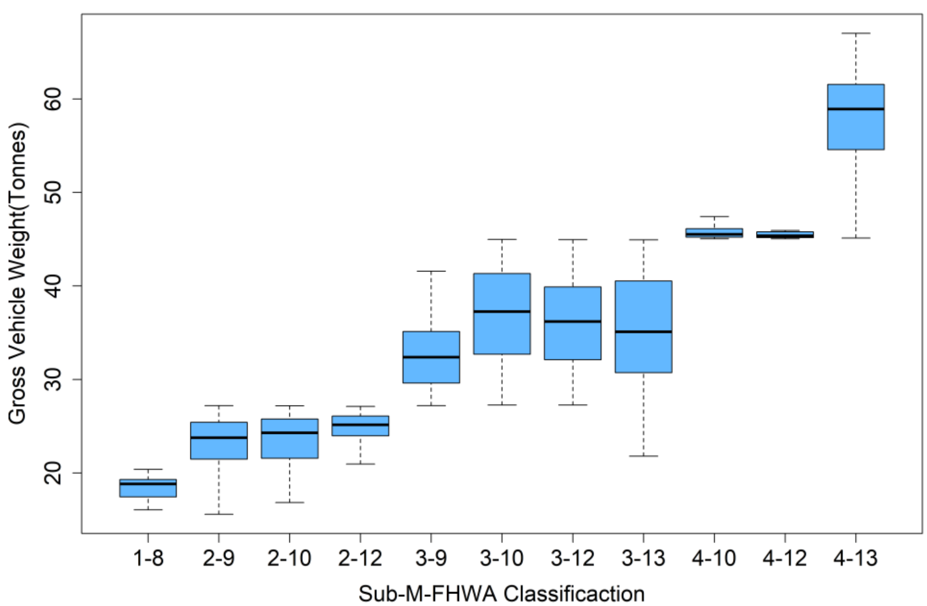


c) M-FHWA Class

Figure F-4: Average Speed Distribution for GVW Intervals, FHWA Class and Weight Class

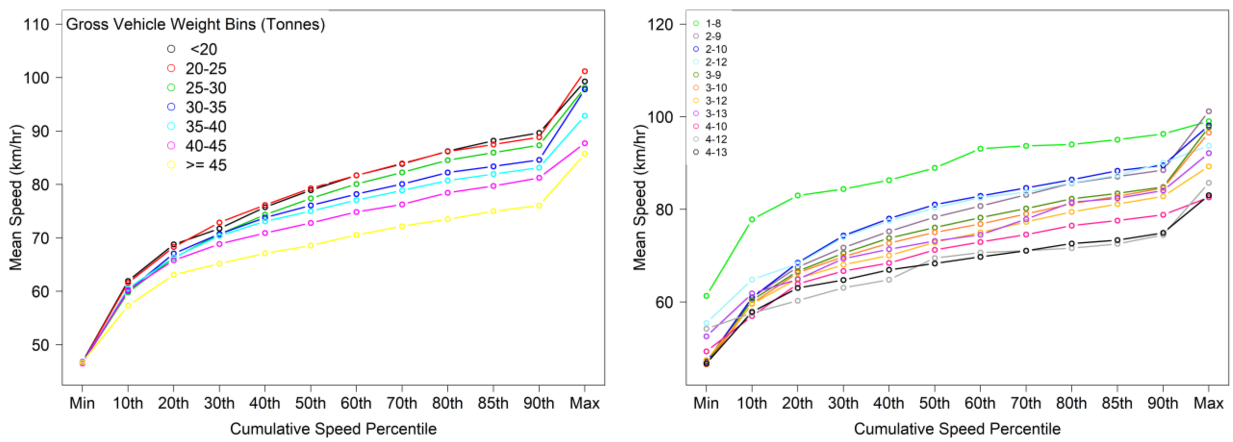


a) Speed Distribution



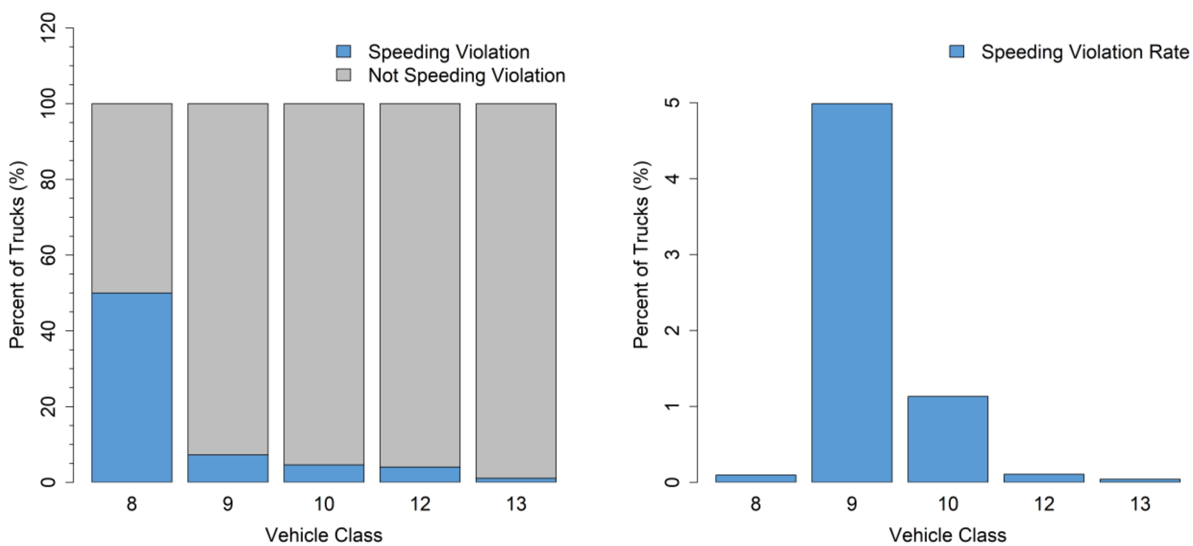
b) GVW Distribution

Figure F-5: Speed and GVW Distribution for Detail Vehicle Weight Class



a) GVW Intervals **b) Sub-M-FHWA Classification**

Figure F-6: Cumulative Speed Distribution for GVW Interval and Detail Vehicle Weight Class



a) Relative Speeding Violation Rate of FHWA Class **b) Speeding Violation Rate Distribution in FHWA Class**

Figure F-7: Speeding Violation Rate for FHWA Class

Appendix G: Traffic Data Calculation for Simulation Corridor

Table G-1: Traffic Volume Table of Simulation Corridor

Year	2010	2011	2012	2013	2014	2015	2016
Annual Average Daily Traffic (AADT)	6324	6073	5821	5570	5939	6307	6676
Summer Average Daily Traffic (SADT)	8551	8214	7878	7541	8099	8658	9216
Directional Hour Demand Volume (DDHV)	734	704	675	646	689	732	774

Equations of Traffic Volume Calculation:

$$AADT_{2014} = AADT_{2013} + (AADT_{2016} - AADT_{2013})/3$$

$$DDHV = AADT_{2014} \times K \times D$$

$$K = 0.116$$

$$D = 1$$

Where:

the traffic data of 2010, 2013 and 2016 were provided by BC Ministry of Transportation and Infrastructure (2019);

K is the proportional of AADT occurring during the peak hour and average K-factor was 0.116 AADT is between 1000 to 20000 (TRB, 2010); and

D is the proportion of peal-hour volume traveling in the peak direction and average D is 1 when the study only considered west to east one direction (TRB, 2010).

Appendix H: Sensitivity Analysis Results

Table H-1: Impact of Traffic Volume and Truck Percentage on Average Travel Speed

Parameters	Group	All	Cars	Class 8	Class 9	Class 10	Class 12	Class 13
Truck Percentage: 25%	200	94.36	103.57	89.48	72.60	72.97	73.06	67.24
	600	91.27	99.30	85.46	73.15	72.31	71.74	67.20
	1000	87.41	93.99	82.81	72.18	70.97	69.88	67.40
	1400	82.87	88.07	79.46	70.81	69.43	68.78	66.08
Traffic Volume: 600 veh/h	15%	95.87	101.15	85.88	73.56	73.10	72.35	67.59
	20%	93.74	100.43	85.77	73.19	72.82	69.97	67.57
	25%	91.27	99.30	85.46	73.15	72.31	71.74	67.20
	30%	89.63	99.03	86.69	72.67	72.00	72.33	67.20

Appendix I: Vehicle Speed and GVW Distributions for All Classes

Table I-1: Travel Speed Distribution for M-FHWA Classes

Speed (km/h)	Class 8	Class 9	Class 10	Class 12	Class 13
Min Speed	60.33	45.76	45.68	46.61	45.90
10 Percentile	76.67	59.81	58.65	58.61	58.34
20 Percentile	81.76	66.01	65.26	64.07	62.35
30 Percentile	83.13	70.11	68.98	67.06	64.39
40 Percentile	85.05	73.20	71.88	69.52	66.41
50 Percentile	87.65	75.73	74.24	72.52	68.40
60 Percentile	91.76	78.12	76.15	74.95	69.89
70 Percentile	92.34	80.25	78.44	76.94	71.43
80 Percentile	92.67	82.52	80.87	80.35	73.22
85 Percentile	93.67	83.90	82.54	81.63	74.53
90 Percentile	94.90	85.59	84.22	83.29	77.02
Max GVW	97.61	99.74	96.70	92.38	90.82

Table I-2: GVW Distribution for M-FHWA Classes

GVW (Tonnes)	Class 1	Class 2	Class 3	Class 4
Min GVW	13.81	12.74	21.80	45.04
10 Percentile	16.36	19.45	28.41	45.32
20 Percentile	17.34	20.86	29.73	45.73
30 Percentile	17.51	22.07	30.97	47.42
40 Percentile	18.29	23.05	32.39	51.73
50 Percentile	18.83	23.83	33.68	55.96
60 Percentile	19.00	24.52	34.97	58.16
70 Percentile	19.17	25.15	36.22	59.51
80 Percentile	19.40	25.79	38.05	61.16
85 Percentile	19.65	26.18	39.31	61.92
90 Percentile	20.02	26.45	40.99	62.75
Max GVW	24.04	27.20	44.99	67.02

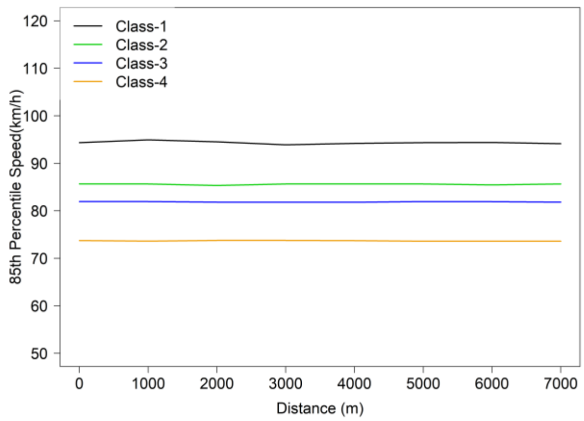
Table I-3: Travel Speed Distribution for FHWA Classes

Speed (km/h)	Class 1	Class 2	Class 3	Class 4
Min Speed	60.33	45.76	45.68	45.90
10 Percentile	76.67	60.09	59.21	56.39
20 Percentile	81.76	66.62	65.42	62.08
30 Percentile	83.13	70.85	69.06	64.15
40 Percentile	85.05	74.37	72.09	66.07
50 Percentile	87.65	77.48	74.38	67.50
60 Percentile	91.76	79.82	76.48	69.48
70 Percentile	92.34	82.08	78.53	71.07
80 Percentile	92.67	84.51	80.76	72.37
85 Percentile	93.67	85.90	82.00	73.85
90 Percentile	94.90	87.31	83.40	74.89
Max GVW	97.61	99.74	96.37	84.47

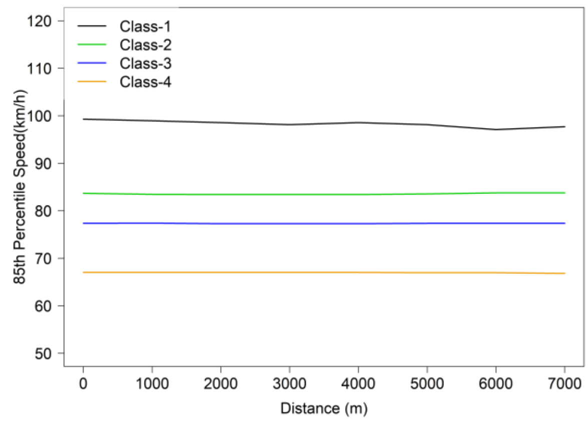
Table I-4: GVW Distribution for FHWA Classes

GVW (Tonnes)	Class 8	Class 9	Class 10	Class 12	Class 13
Min GVW	13.81	12.74	16.84	17.11	21.80
10 Percentile	16.36	21.05	25.64	25.22	32.31
20 Percentile	17.34	23.23	29.14	27.28	40.04
30 Percentile	17.51	24.76	31.95	30.46	46.06
40 Percentile	18.29	26.24	34.04	32.60	52.01
50 Percentile	18.83	27.83	36.36	34.47	55.99
60 Percentile	19.00	29.69	38.50	36.87	58.16
70 Percentile	19.17	31.66	40.40	39.16	59.53
80 Percentile	19.40	33.79	42.09	40.74	61.18
85 Percentile	19.65	34.81	42.90	42.58	61.92
90 Percentile	20.02	35.77	43.69	44.00	62.76
Max GVW	24.04	41.58	48.65	48.37	67.02

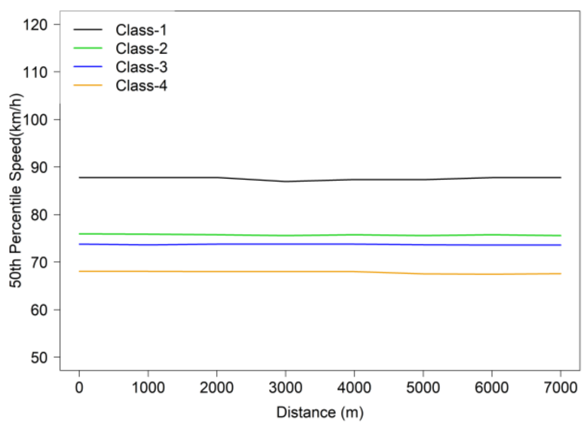
Appendix J: Comparison of Uniform Speed Limit and Differential Speed Limit



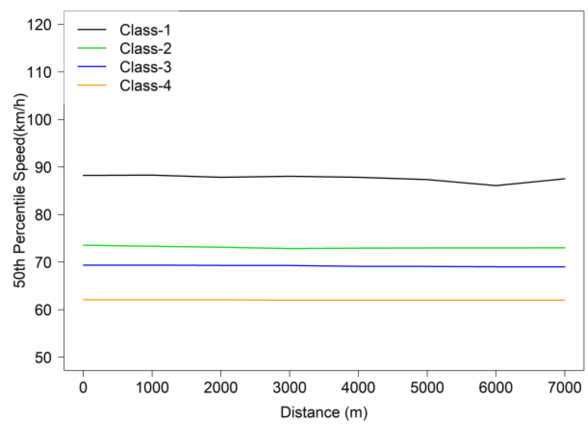
a) 85th Percentile Speed of Different Classes based on 1000-Meters Segments (USL)



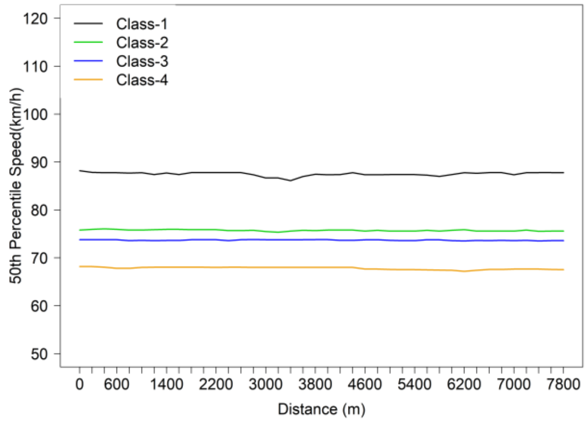
b) 85th Percentile Speed of Different Classes based on 1000-Meters Segments (DSL)

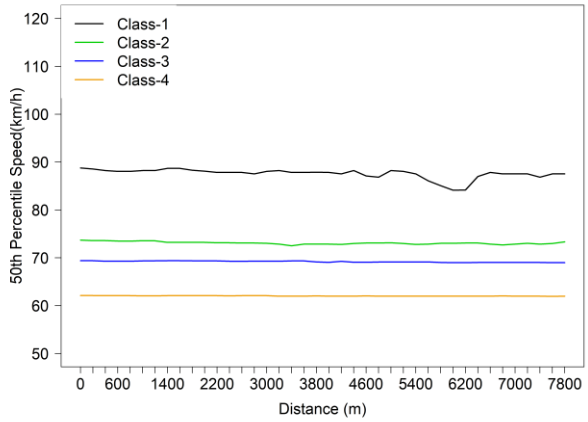


c) 50th Percentile Speed of Different Classes based on 1000-Meters Segments (USL)



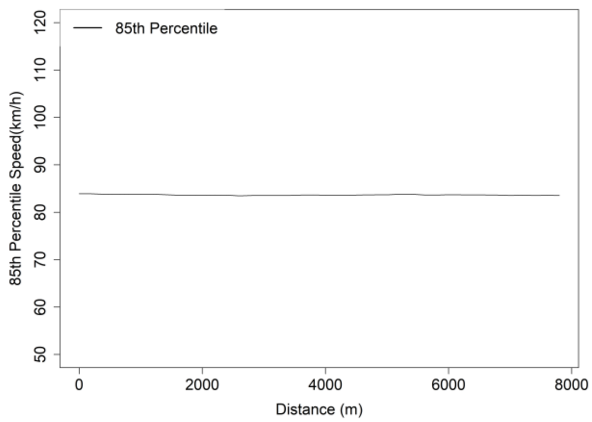
d) 50th Percentile Speed of Different Classes based on 1000-Meters Segments (DSL)

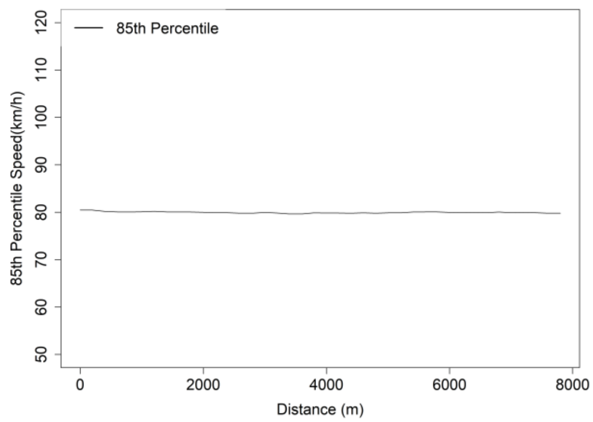




e) 50th Percentile Speed of Different Classes based on 200-Meters Segments (USL)

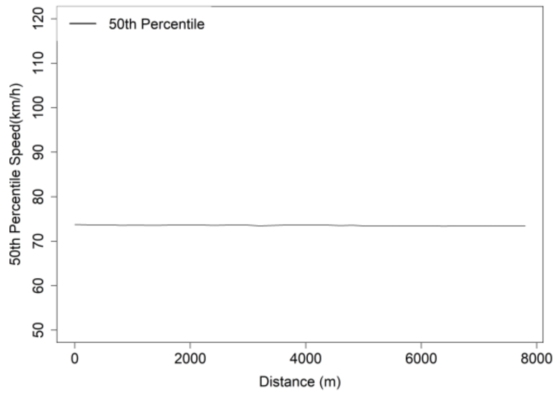
f) 50th Percentile Speed of Different Classes based on 200-Meters Segments (DSL)



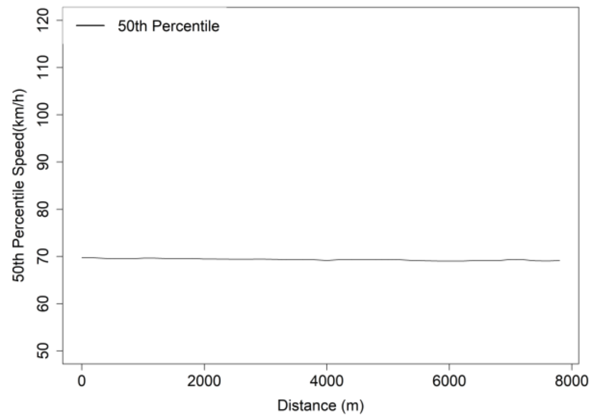


g) 85th Percentile Speed for All Classes based on 200-Meters Segments (USL)

h) 85th Percentile Speed for All Classes based on 200-Meters Segments (DSL)



i) **50th Percentile Speed for All Classes based on 200-Meters Segments (USL)**

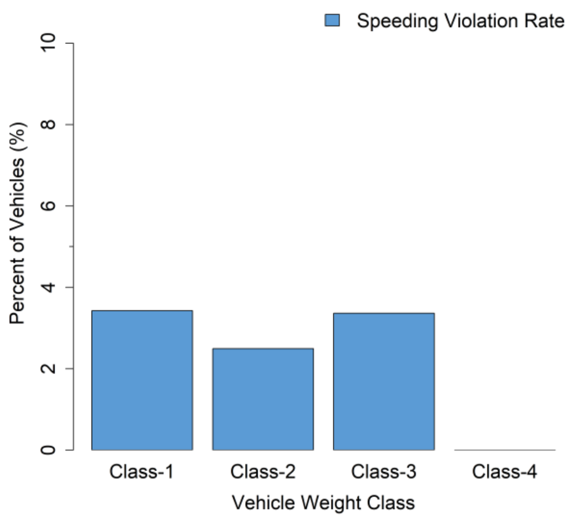


j) **50th Percentile Speed for All Classes based on 200-Meters Segments (DSL)**

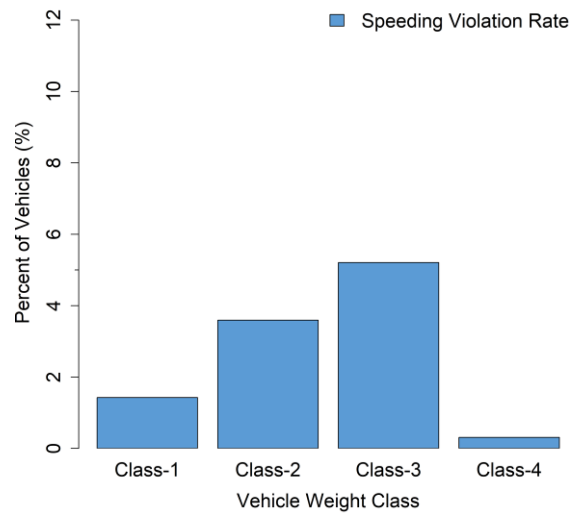
Figure J-1: Speed along the Distance for Two Speed Limit Strategies

Table J-1: Speed Violation Rate for Each M-FHWA Class for Two Speed Limit Strategies

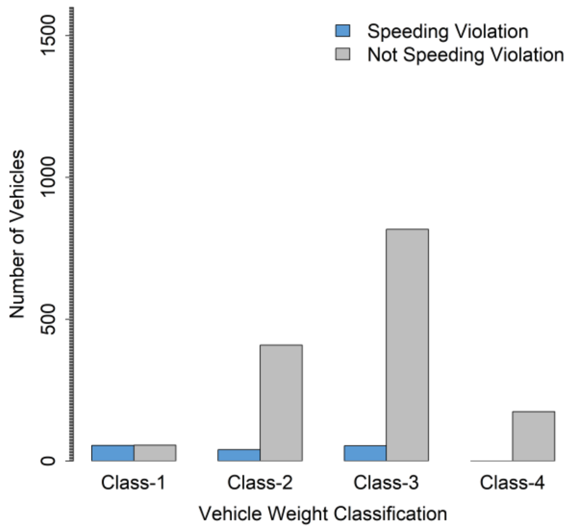
Groups	Parameters	Class 1	Class 2	Class 3	Class 4
USL	Percent Speeding	49.55	8.91	6.20	0.00
	Percent None-Speeding	50.45	91.09	93.80	100.00
DSL	Percent Speeding	20.72	12.89	9.59	2.84
	Percent None-Speeding	79.28	87.11	90.41	97.16



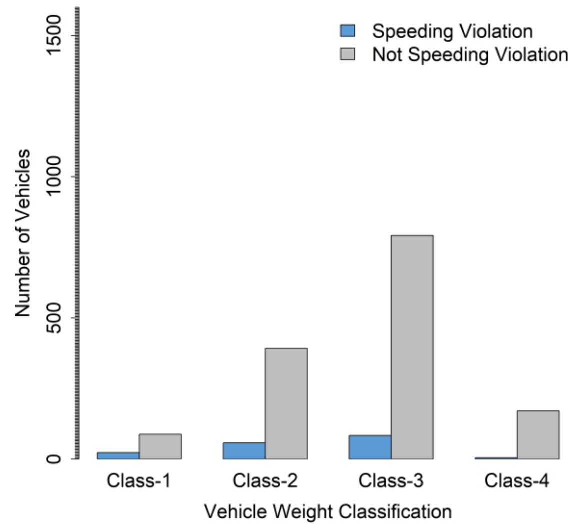
a) **Speed Violation Rate for USL**



b) **Speed Violation Rate for DSL**



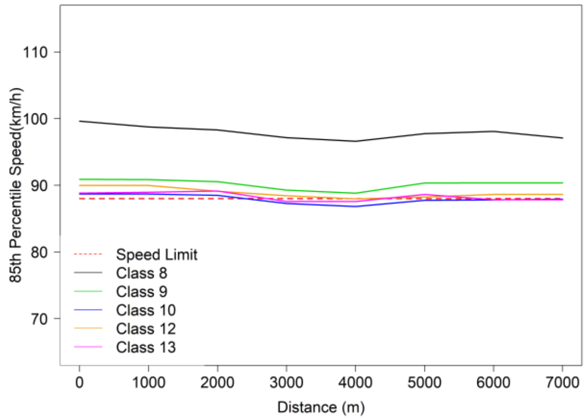
c) **Number of Speed Violation for USL**



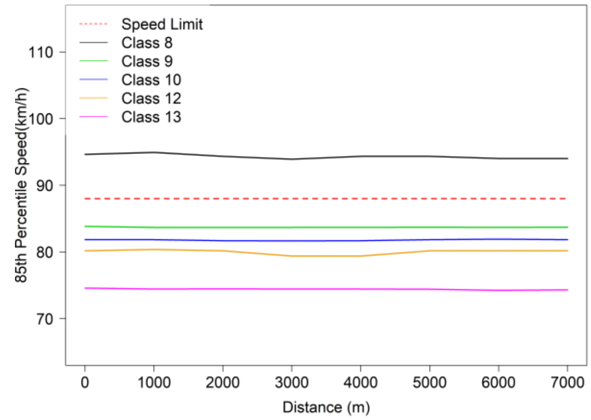
d) **Number of Speed Violation for DSL**

Figure J-2: Speed Violation Rate of M-FHWA classes for Two Speed Limit Strategies

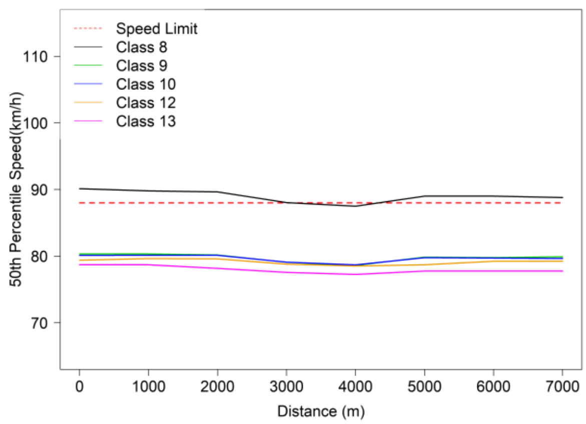
Appendix K: Comparison of Spot Speed Enforcement and Average Speed Enforcement



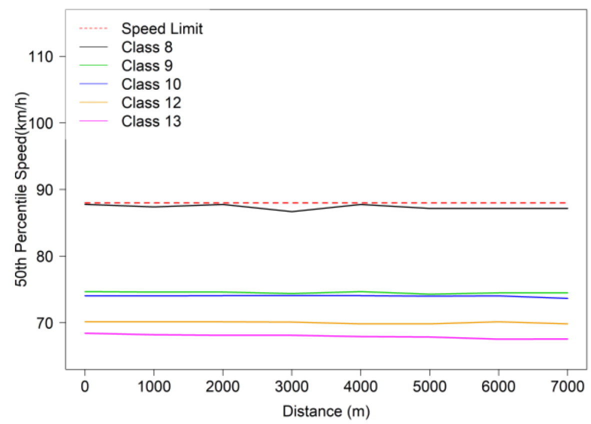
a) 85th Percentile Speed of Different Classes based on 1000-Meters Segments (SSE)



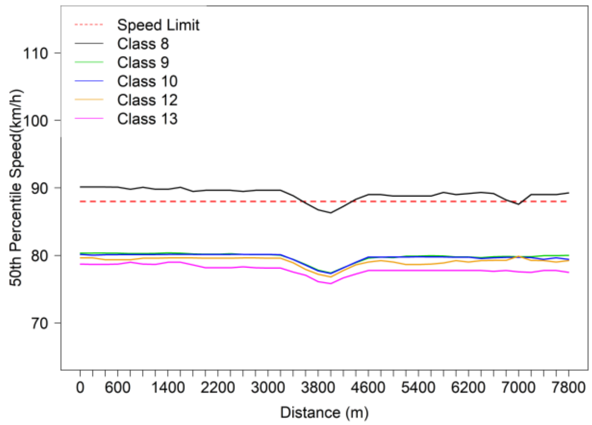
b) 85th Percentile Speed of Different Classes based on 1000-Meters Segments (ASE)



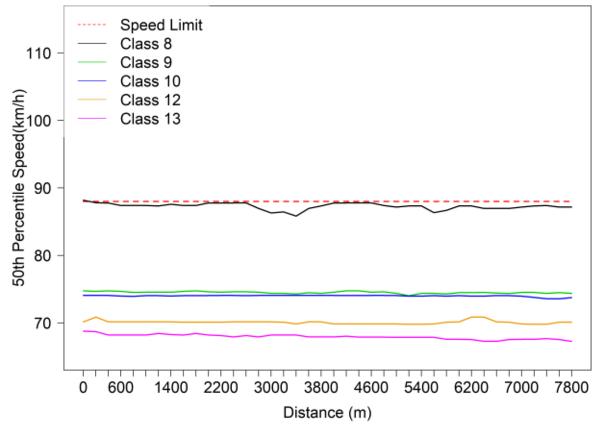
c) 50th Percentile Speed of Different Classes based on 1000-Meters Segments (SSE)



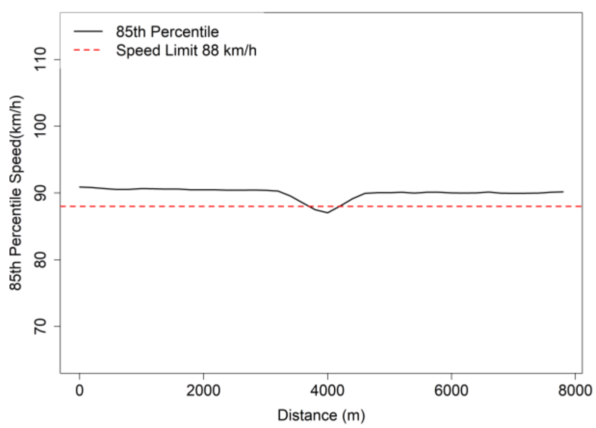
d) 50th Percentile Speed of Different Classes based on 1000-Meters Segments (ASE)



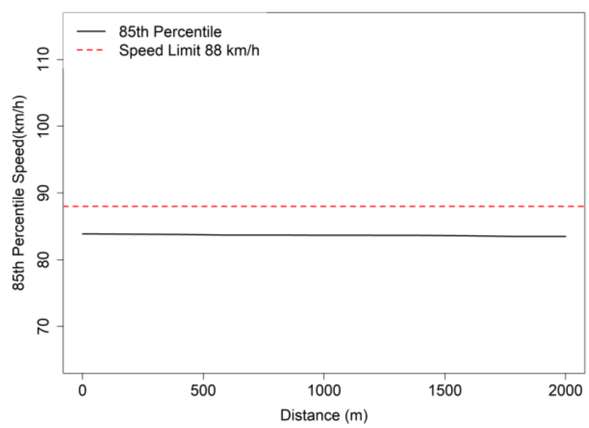
e) **50th Percentile Speed of Different Classes based on 200-Meters Segments (SSE)**



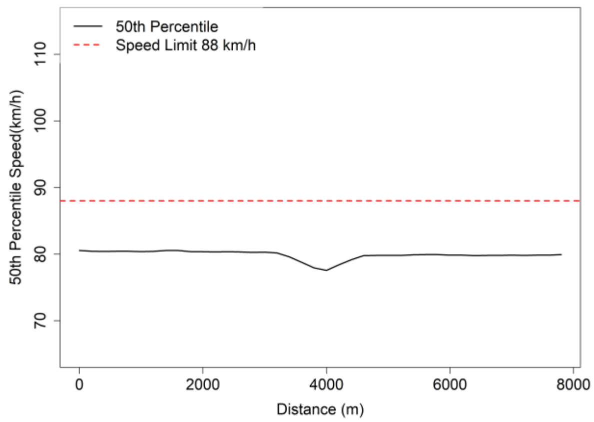
f) **50th Percentile Speed of Different Classes based on 200-Meters Segments (ASE)**



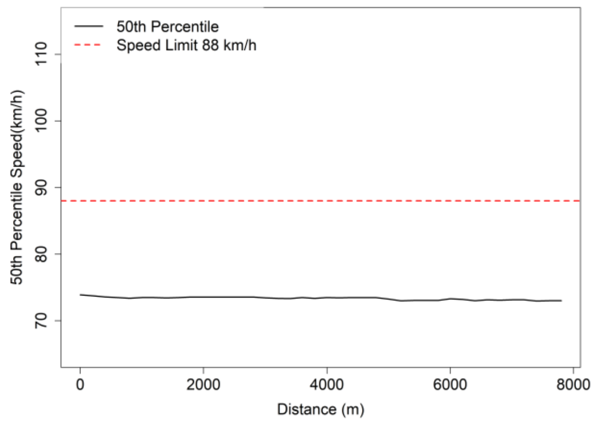
g) **85th Percentile Speed for All Classes based on 200-Meters Segments (SSE)**



h) **85th Percentile Speed for All Classes based on 200-Meters Segments (ASE)**



i) 50th Percentile Speed for All Classes based on 200-Meters Segments (SSE)

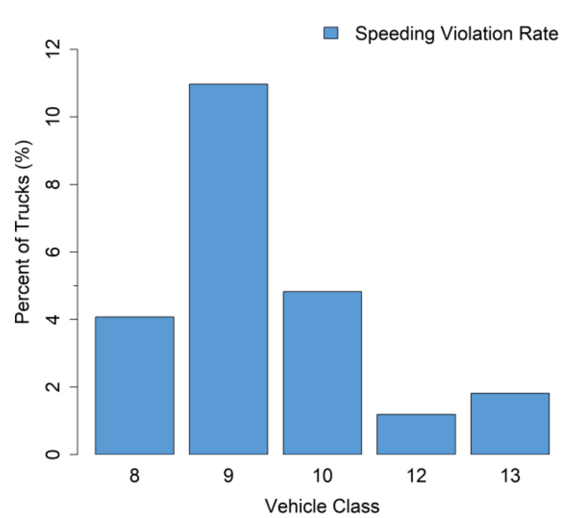


j) 50th Percentile Speed for All Classes based on 200-Meters Segments (ASE)

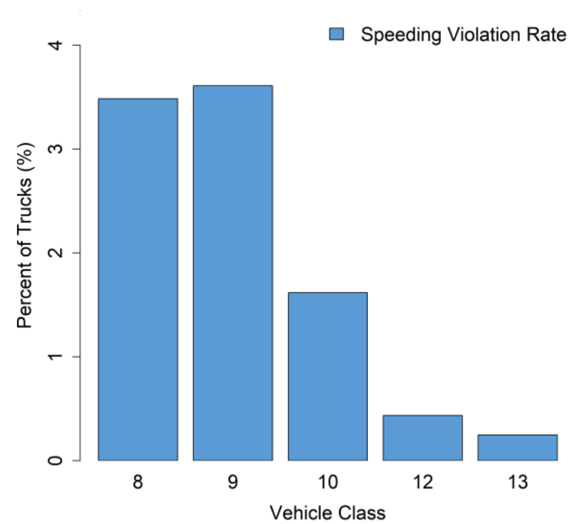
Figure K-1: Speed along the Distance for Two Speed Enforcement Strategies

Table K-1: Speed Violation Rate for each FHWA Class for Two Speed Enforcement Strategies

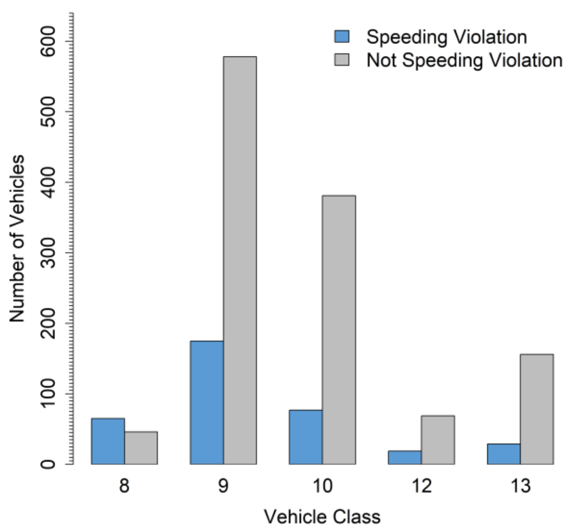
Groups	Parameters	8	9	10	12	13
SSE	Percent Speeding	58.56	23.24	16.81	21.59	15.68
	Percent None-Speeding	41.44	76.76	83.19	78.41	84.32
ASE	Percent Speeding	50.45	7.65	5.63	7.95	2.13
	Percent None-Speeding	49.55	92.35	94.37	92.05	97.87



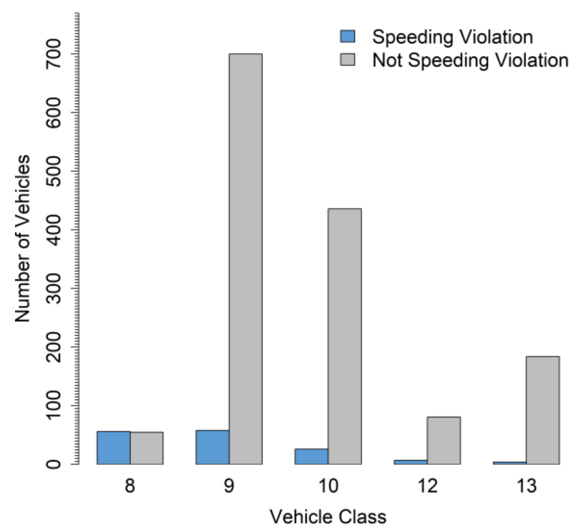
a) Speeding Violation Rate for SSE



b) Speeding Violation Rate for ASE



c) Number of Speeding Violation for SSE



d) Number of Speeding Violation for ASE

Figure K-2: Speed Violation Rate of FHWA classes for Two Speed Enforcement Strategies