FREIGHT MOBILITY RESEARCH INSTITUTE
College of Engineering & Computer Science
Florida Atlantic University

Project ID: Y1R2-17

ECO-DRIVING STUDY ON TRUCKS ALONG A SIGNALIZED ARTERIAL WITH SIGNIFICANT FREIGHT TRAFFIC

Final Report

by

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September, 2018

ACKNOWLEDGEMENTS

This project was funded by the Freight Mobility Research Institute (FMRI), one of the twenty TIER University Transportation Centers that were selected in this nationwide competition, by the Office of the Assistant Secretary for Research and Technology (OST-R), U.S. Department of Transportation (US DOT).

DISCLAIMER

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EXCUTIVE SUMMARY

The project starts from a literature review of the topics from these aspects: the studies of emission models, the eco-driving applications for heavy-duty vehicles (Trucks), Eco-driving and signal control, the benefits from CAVs and Simulation using MOVES and VISSIM. The research on Multiclass/heterogeneous traffic modeling is also reviewed. To define the problem, the research starts with the analysis of the influence the truck percentage has on the individual signalized intersection and on a coordinated signal corridor. The simulation results show the high percentage of heavy-duty vehicles in traffic may significantly degrade the signal control based on the concept of delay optimization mainly considering passenger cars. To solve the problem, an eco-driving strategy for freight mobility control at signalized intersections is introduced. It is by optimizing the travel time while maintaining optimal fuel consumptions and emissions. A two-level dynamic optimization is formulated. An emission weighted optimization is used to simulate vehicles passing the intersection with balanced travel time and emissions savings and compared to a baseline simulation without eco-driving consideration. A jerk penalty is added to ensure safety and comfort. Heavy-Duty Vehicles (HDVs) are the focus of this modeling effort. The emission term in the optimization used an instantaneous speed-acceleration based microscopic fuel consumption models and the results were validated by EPA's MOtor Vehicle Emission Simulator (MOVES) model. The results from this study showed that the weighting factor of the emission term in the objective function reaches an optimal at 0.5. Generally, the proposed method provided dynamic trajectories with slightly longer travel time than the baseline but reduce the emission at about 4% for Nitrogen oxide (NOx) and 7% for carbon dioxide (CO_2) for different initial conditions (different distance approaching intersection). Based on the results, an optimal weighting factor of emission term and the range of distances to apply the eco-driving strategy are recommended. A case study is performed to simulate the recommended model, with varying HDV percentages. The test results showed an overall emission reduction of 6% for NOx and 6% for CO_2 according to MOVES. To show the relationship between truck percentage and discharge rate, a multiply linear regression is conducted, and the results are shown in the appendix. The data in MOVES and the emission models used are also presented in the appendix.

1.0 INTRODUCTION

1.1 OVERVIEW

The transportation sector accounts for 70 percent of the total petroleum consumption and ranks second among atmospheric carbon emitters in the United States where on-road traffic emissions are responsible for more than 80 percent (Zlatar and Shinn, 2009) (Davis, 2002). Among all types of on-road traffic, freight traffic takes a significant share and grows fast, which is mainly composed of HDVs (heavy-duty vehicles) and produces large unit emissions. Improving the fuel efficiency and reducing the emissions of these freight traffic will lead to significant environmental and economic benefits. Options such as alternative fuels, better emit systems, vehicle platooning or alternative powertrain (electronic vehicles) have been applied towards this goal(Baker et al., 2009). Among all the solutions, eco-driving is a concept to reduce fuel consumption and greenhouse gas emissions by changing driving behaviors.

Eco-driving can reduce fuel consumption and greenhouse gas emissions by about 10% on average (Ala et al., 2016). Eco-driving can act as a policy or driving assistant equipment on existing vehicles. This literature review focuses on the technology aspect. Major causes of high emission include frequent accelerations, complete stops, excessing speeds over 60 mph and slow movements on a congested road. Therefore, some major real-time driving advice on speed limits, acceleration or deceleration, and speed alerts is necessary to reduce traffic oscillations and avoiding idling. Geometric properties, vehicle type (car or truck), signal control, and the connection of infrastructure are considered in the problem according to specific situations. Generally, an Eco-driving strategy can be developed to form freight mobility control by maintaining the travel time and optimal fuel consumptions and emissions.

Testing and modeling are two approaches to measure the benefits of fuel consumption and emissions. When considering a hypothetical experiment, an emission model is a better choice. The emission models are generally divided into inventory and instantaneous models. An inventory model concerns the emissions on a macroscopic scale while an instantaneous model measures the emission rate on a microscopic level. Some inventory emission models are MOBILE, EMFAC, COPERT, DMRB, HBEFA, VERSIT and MOVES. Some instantaneous models are CMEM, EMIT, VT-micro, PHEM, VeTESS, EMPA, and PΔP (Park et al., 2016).

The connected and autonomous vehicle (CAV) is one significant and systematic way to achieve the goal. Automation itself is an approach to reduce energy use and emissions. Therefore, to apply connected vehicle technology is a way to achieve the eco-driving purpose. Although it is not the first-stage benefit from connected vehicles, the control strategies of the connected vehicle can help to provide an environmentally friendly approach for eco-driving. What is more, with the development of connected vehicle technology, the vehicle-to-infrastructure (V-to-I, or V2I) communication enables the trucks to get real-time information such as Signal Phase & Timing (SPaT) and queuing information, which is important to assist the vehicles to make real-time driving decisions, paving ways for effective eco-driving of trucks (Kamalanathsharma and Rakha, 2014). All these technology developments show that the eco-driving control strategies specific to assist the heavy-duty vehicles (trucks) are close to reality and the related research efforts are necessary.

The goal of the study is to estimate the eco-driving benefits on emissions, specifically for HDVs, in a connected vehicle environment at intersections. The research effort starts with the literature research of the related topics in this Chapter 1. Then it is followed by analysis and evaluation of the influence the significant freight traffic has on signalized intersections (both for individual intersection and coordinated corridor) (Chapter 2). Then we develop strategies for eco-driving at a single intersection (Chapter 3) and test its performance (Chapter 4). For the methodology, a baseline case where the travel time is minimized by using the largest deceleration to arrive to and the largest acceleration to leave an intersection. Then a two-level dynamic optimization algorithm is introduced to balance the emissions and travel time. APmonitor for nonlinear optimization is used as the tool to solve the optimization problems (Hedengren et al., 2014). Not only individual optimal trajectories under different situations of emission types are obtained, but also their performances to the input parameters are analyzed. Recommendations for the parameters and suitable implementation conditions are proposed according to the results, with the assumptions of truck penetration rate, and spacing distributions, to produce aggregated level results. In the final summary part (Chapter 5), the findings will be concluded and recommendations are given accordingly. In the appendix, the relationship between the truck percentage and the discharge rate drop over a corridor is shown by multiple linear regression.

1.2 LITERATURE REVIEW

1.2.1 Some relative studies

The benefit of eco-driving, as a driving assistant, has been studied via dynamic programming, optimal control, or learning methods. Barth and Kari introduced a dynamic eco-driving by adjusting its velocity using a dynamic eco-driving velocity planning algorithm(Barth and Boriboonsomsin, 2009; Barth et al., 2011; Kari et al., 2014). The simulation showed a 12% improvement in initial fuel economy and CO2 reduction. Speed was considered to make dynamical advice using intelligent speed adaptation (ISA). Li tested traffic energy and emission reductions at signalized intersections using an alert to decelerate gently(Li et al., 2009). Rakha developed a framework to improve the vehicle fuel consumption efficiency by incorporating the microscopic fuel consumption models in the optimization function(Rakha and Kamalanathsharma, 2011). Mensing found that high acceleration rates with low and constant average speeds are important in optimal vehicle operation when doing eco-driving using numerical optimization, and fuel efficiency is tested to have an improvement of 34% (Mensing et al., 2013). Chen developed an optimization model to determine the optimal speed profile by minimizing a linear combination of emissions and travel time. The Motor Vehicle Emissions Simulator (MOVES) was used to estimate the emissions (nitrogen oxide)(Chen et al., 2014). Jiang developed an optimal control problem to speed profiles to improve fuel efficiency and maintaining mobility of traffic flow has been designed for isolated intersection under CAVs environment by solving it using Pontryagin's Minimum Principle(Jiang et al., 2017). The driving decisions of heavy-duty vehicles not only have major impacts on the emission but on the mobility to a large extent. Since heavy-duty vehicles need extra distance and time for deceleration and acceleration, taking twice or even longer compared to conventional vehicles for the same distance. This situation is further compounded on signalized arterials where deceleration, stopping, and acceleration is frequent because of traffic signals. However, few pieces of research focus specifically on the eco-driving strategies for heavy-duty vehicles on signalized corridors.

1.2.2 The studies of emission models

Some studies were conducted to find the emission given vehicle conditions and status. For example, Ahn developed a hybrid regression models to model fuel consumption and emission rates for light-duty vehicles and light-duty trucks (Ahn et al., 2002). Panis developed an instantaneous traffic emission model considering the acceleration and speed based on empirical measurements (Panis et al., 2006). The model is also selected in this project to obtain the instantaneous emission rates for heavy-duty vehicles while MOVES is selected to present its macroscopic comparison.

A comprehensive overview of fuel consumption and emission models are presented in the Figure 1 from (Wang, 2014). In the table, the fuel consumption and emission models can be categorized into a few groups, which include aggregated emission factors, average speed models, traffic situation models, traffic variable models, cycle variable models, simple modal models, statistical modal models and physical modal models.

The aggregated emission factors calculate the total emissions based on the total distance, road types (e.g. urban, rural and motorway) and vehicle classes (truck or car). The average speed models consider the average speed at different traffic conditions. Traffic situation models use traffic states such as free flow and congestion to model the emissions. The traffic variable models consider quantifiable traffic variables describing traffic conditions instead of traffic states. Cycle variable models consider cycle variables to make a calculation, such as average speed, idle time, positive kinetic energy, and number of stops. In simple modal models, emission rates are related to specific operational modes of vehicles. Statistical modal models calculate instantaneous emission rates based on the instantaneous acceleration and speed, and then the modal class is usually divided by using regression. Finally, physical modal models apply a physical model calculating the required engine load instantaneously (Cappiello et al., 2002; Smit et al., 2010; Wang, 2014).

Model class	Traffic input data	Road input data	Vehicle input data	Application range	Link to traffic models	Examples
Aggregated emission factors	Traffic volume	Road type	Vehicle class	National or regional inventory estimation	Traffic demand models (without route assignment)	NAEI
Average speed models	Traffic volume and trip-speed	Road type	Vehicle class	Regional inventory estimation	Traffic demand and supply models	COPERT, MOBILE, DMBR, EMFAC
Traffic situation models	Traffic volume and LOS	Road type	Vehicle class	Regional inventories and network level controllers assessment	Traffic demand and supply models + Traffic flow models (Macro-, meso- or micro-scopic)	HBEFA
Traffic variable models	Traffic volume and speed	Road type	Vehicle class	Link level controllers assessment	Traffic flow models (Macro-, meso- or micro-scopic)	TEE, Matzoros Model
Cycle variable models	Speed, acceleration	Road gradient	Vehicle type	Link, platoon and vehicle level controllers schemes	Microscopic flow models	VERSIT+
Simple modal models	Speed, acceleration	Road gradient	Vehicle type	Link, platoon and vehicle level controllers assessment	Microscopic flow models	UROPOL, MOVES
Statistical modal models	Speed, acceleration	-	Vehicle type	Link, platoon and vehicle level controllers assessment	Microscopic flow models	VT-Micro
Physical modal models	Speed, acceleration	Road gradient	Vehicle type	Link, platoon and vehicle level controllers assessment	Microscopic flow models	CMEM, PHEM, ARRB model

Figure 1: a collection of emission models from Wang, 2014.

1.2.3 Eco-driving for heavy-duty vehicles (Trucks)

In some research, eco-driving study is one aspect of the impact studies of ADAS (Advanced Driver Assistance Systems). in addition to the impact on emission and fuel consumption, the impact on traffic flow can also be considered. Several indicators are used to evaluate macroscopic traffic operations. The performance indicators for traffic operations can be categorized into three groups: efficiency, predictability and smoothness, safety. Capacity, total travel time and delay are the most important indicators for the efficiency. Predictability and smoothness are indicated by string and flow stability, speed and travel time variations. Safety is usually indicated by the risk of collisions.

For trucks, infrastructure and terrain variables have more effects than driving behavior variables (Walnum and Simonsen, 2015). Driving behavior becomes a more important influencing factor under challenging infrastructure conditions. Multivariate regression model is used for analysis and independent variables are selected from infrastructure conditions (engine load, use of highest gear, average speed), driving behavior (cruise control,), vehicle properties((horsepower), control variables (weight load). A predictive eco-driving assistance system (EDAS) is developed to simulate driving behavior for heavy vehicles. 6.6 % reduction of fuel consumption is observed by using EDAS. (Daun et al., 2013)

Anticipation distance of trucks determines anticipation of driver behaviors, and there is a potential improvement of anticipation without exceeding driver's acceptance (Thijssen et al., 2014). The effects of information of intermittent and continuous visual eco-driving (glance behavior) are analyzed for truck eco-drivers, from an aspect of safety (Kircher et al., 2014).

Acceleration and hybrid powertrain operation are used in an optimization problem on rolling terrain. As a result, 5.0–16.9% fuel consumptions are saved given constant speed with rule-based powertrain controller (Hu et al., 2016). An optimal controller is designed to improve fuel efficiency for vehicles equipped on rolling terrain without a preceding vehicle. Real-time optimization for vehicle dynamics and powertrain operation are obtained on fuel saving. The method can be utilized for connected vehicles (Hu et al., 2017).

Heavy-duty diesel vehicles usually refer to those who are greater than 8500 lb gross and emissions of particulate matter (PM) can include oxides of nitrogen (NOx), carbon monoxide (CO), and hydrocarbon (HC) (Yanowitz et al., 2000). Heavy-duty diesel (HDD) vehicles have a large portion in the contribution to the emissions. In the CMEM framework, there are several HDD truck sub-models, in which models correspond to different vehicle technology categories. Data are collected to calibrate HDD models. The emissions of Carbonyl group from Light-Duty and Heavy-Duty Vehicles are compared. (Grosjean et al., 2001)

EMFAC2014 is a mobile source emission used for the emission perdition. The emissions on major freight corridors in California are analyzed and it shows measured values are consist with the prediction (Quiros et al., 2016).

Emission models specific for freight transportation are reviewed and compared (Demir et al., 2011).These include:

- An instantaneous fuel consumption model. In the model, vehicle characteristics such as mass, energy, efficiency parameters, drags force and some fuel consumption components to link with aerodynamic drag and rolling resistance, so as to estimate fuel consumption per second.

- A four-mode elemental fuel consumption model. The model estimates fuel consumption in idle, cruise, acceleration and deceleration. Some factors such as initial speed, final speed and energy-related parameters are added.

- A running speed fuel consumption model. The model provides fuel consumption during a period when a vehicle is running and is in an idle mode. The model is an extension of the instantaneous model and can be viewed as an aggregation of the elemental model.

- A comprehensive modal emission mode (CMEM). The model has three modules: engine power, engine speed and fuel rate. (Barth et al., 2000)

- Methodology for calculating transportation emissions and energy consumption (MEET). The methodology includes estimating functions that are primarily dependent on speed and some fixed and parameters for vehicles of weights ranging from 3.5 to 32 tones. Gradient is available in the model.

- Computer programme to calculate emissions from road transportation (COPERT) model. The model differentiates between two speed ranges for each vehicle class. Gradient is not available in the model.

1.2.4 Eco-driving and signal control

An Eco-Friendly Freight Signal Priority algorithm is proposed to improve traditional traffic signal priority by considering the reduction of fuel consumption and travel time at the same time for both freight and non-freight traffic. In the algorithm, a multi-agent systems (MAS) based freight signal priority algorithm is developed, in which the measures of effectiveness (MOEs) are selected as energy, emissions, travel delay, or any combination. The method can decrease the travel time of freight vehicles by 26% and improve systemwide fuel economy by 5%-10% (Kari et al., 2014).

For a single intersection, the traffic state is predicted by mathematical models such as model predictive control, and the optimal signal is derived from minimizing a cost index that is function of the predicted traffic states. For multiple intersections with traffic delay and emissions, model predictive control does not work. Therefore, a co-simulation optimization control approach is used to generate the traffic light sequence for priority of trucks (Zhao and Ioannou, 2016).

The actuated coordination and multi-modal priority control are coordinated by a method fulfilling multiple priority requests from different vehicles modes and pedestrians considering the vehicle actuation (He et al., 2014). The efficiency of vehicle fuel consumption at a signalized intersection has been studied according to signal phase and timing plan to form the most fuel-optimal speed profile. The research shows that the formation of the objective function and the utilization of the fuel consumption model have great effects on the final results (Rakha and Kamalanathsharma, 2011). An eco-cruise control (ECC) method is combined with a state-of-the-art car-following model to form an eco-drive system. The system has input variables such as topographic information, the distances, and desired speeds (Ahn et al., 2013).

Human-driven vehicles and autonomous vehicles are coordinated to increase traffic throughput by considering drivers and intersections as autonomous agents in a multi-agent system (Dresner and Stone, 2008). A predictive fuel efficiency driver assistance system environment is developed by using signal timing and the vehicle's power-train. The first step uses dynamic programming to compute an optimal time progression within a certain horizon of interest. The intermediate result is used in a second step to compute optimal velocity and gear shift guidance for the driver (Guan and Frey, 2013). A multi-objective driving profile optimization can optimize the speed profile and the selection of gears for heavy-duty vehicles (HDVs) considering elevation, headwind, desired terminal time, and traffic information. A parameter region is calibrated for the balance of the fuel consumption and travel time (He et al., 2016). A bi-objective optimization model is used to determine timing plans coordinating delay and the traffic emissions. A modal emission method is combined with the cell transmission model for the analysis of emission rates at different steps. A simulation-based generic algorithm is used to provide a solution (Zhang et al., 2013). A model is proposed to enhance traffic signal coordination of at intersections during the transition phase considering social costs. An ant colony algorithm was utilized (Peñabaena-Niebles et al., 2017).

1.2.5 Benefits from CAVs

Connected and Automated Vehicles (CAVs) can impact the transportation in three levels. Traffic and time cost is in the first stage while energy consumption, pollution, safety, social equity, economy, and public health are thought to be on the second and third-order stage. Market penetration rate is a main influence factor when considering the benefits from the increase of automation and cooperation (Milakis et al., 2017). Literatures are done on the approaches to coordinate CAVs with objectives of congestion mitigation and eco-driving. (Rios-Torres and Malikopoulos, 2017)

Optimizing speed profiles to improve fuel efficiency and maintaining mobility of traffic flow has been designed for isolated intersection under CAVs environment. The optimal control problem is solved using Pontryagin's Minimum Principle. Simulation shows that the market penetration rate of connected and automated vehicles and v/c ratio benefit the fuel efficiency, CO2 emission and throughput ranging from 2% to 58%, 2% to 33% and 10%. The benefit has positive relation with the market penetration of CAV until 40% (Jiang et al., 2017).

For those CAVs equipped with CACC (Cooperative Adaptive Cruise Control), on a single lane, energy saving is 19% when the penetration rate of CAVs reaches 100%. On multilane, the saving is negative when the rate is less than 30%. Other factors are proved to affect the performance, such as length of control segments, the signal phasing and timing plan, and the traffic demand levels. (Ala et al., 2016).

A longitudinal control concept is raised based on the distance between trucks. The concept contains a two-layered control structure: A nonlinear acceleration controller in the inner control loop that linearizes the nonlinearities while an outer control loop includes a robust platoon controller (Gehring and Fritz, 1997). A comprehensive literature review is conducted for truck platooning. The fuel consumption will be reduced with the increase of trucks in the platoon, but the throughput does not benefit from the increasing of numbers of truck, and too many trucks in a platoon will cause congestion. (Bhoopalam et al., 2017). The ACC-equipped vehicles are modelled and simulated by Aimsun. Results show that desired time-gap has a negative effect on capacity while MPR can improve the capacity when time-gap is smaller than normal vehicles. (Ntousakis et al., 2015).

Connected vehicle techniques can smooth the intensity and frequency of stop-and-go waves so as to increase the stability of traffic and reduce the emissions and fuel computations. There are ways to design a controller for connected vehicles. Take ACC (Autonomous cruise control) system as an example, they are: Car-following models, including state feedback algorithms such as Optimal Velocity Model (OVM) and Intelligent Driver Model (IDM), Artificial intelligence (AI) techniques, rule-based controllers and other methods such as fuzzy logic or self-learning systems. Model predictive control (MPC) method can be applied for an ACC or a CACC controller. It is called a receding horizon control and it minimizes the deviation from desired gaps. The deviations of predecessor speed, accelerations, jerk, and the desired acceleration calculated by Helly model are used. (Wang et al., 2016b). Based on MPC, an enhanced string stability strategy is proposed, considering the sensor delay and actuator lag (Wang et al., 2016c).

A rolling horizon control framework for driver assistance systems is developed. In the framework, accelerations of equipped vehicles are controlled to optimize a cost function with multiple control objectives, based on the predicted behavior of other vehicles. Among the framework, a non-linear model predictive ACC controller is developed. It presents a way of solution based on Pontryagins Minimum Principle and compare it with solutions using CARE and SQP to a linear quadratic control problem. An iterative algorithm (iPMP) is applied to find the optimal control. An application to eco-driving systems controller design is proposed by changing the objective function. Since in this context, a microscopic fuel consumption and emission models is favorable. The modal fuel consumption model from Akcelik is employed as an example in the experiment. The simulation shows that it results in similar fuel consumption in decelerating phase, but substantially less fuel consumed in the accelerating phase compared to the ACC controller. (Wang et al., 2014a).

Vehicles with driver assistance systems can share information using V2V communication to enhance the reactions to surroundings by employ a multi-anticipative controller by cooperative sensing and to achieve a coordinated control by designing a cooperative controller. The controllers are then simulated and they are compared with non-cooperative controllers. In the results, smoother behaviors are observed in accelerating and decelerating. (Wang et al., 2014b)

An optimal control using rolling horizon stochastic strategy is proposed. It is based on the constant time gap policy, the ACC and CACC are tested in the control strategy under uncertainty. The uncertainty here refers to disturbances that can happen in vehicle control systems. Sensor measurements are modeled as normal distribution in a state-space formulation. In the process of the optimization, the objective function includes terms of control efficiency and of driving comfort, in which both are over a predictive horizon to determine the acceleration. In the constrains, acceleration or deceleration collision protection is considered (Zhou et al., 2017b). A multi-objective evolutionary algorithm is developed to achieve a Cooperative Adaptive Cruise Control, which is based on evolving neural networks. In the research, a Pareto Strength approach from SPEA2 is incorporated into NEAT. The algorithm provides a set of solutions that each embody their own priorities of requirements such as speed, comfort or fuel economy (van Willigen et al., 2013). A multi-objective optimization (MOOP) for CACC is used for automated longitudinal control. It considers objectives including mobility, safety, driver comfort, and fuel consumption. (Zhong et al., 2017).

Connected cruise control (CCC) is an acceleration-based system that utilizes acceleration signals from multiple vehicles ahead via a vehicle-to-vehicle (V2V) communication. It considers various structures that includes both human-driven and CCC vehicles (Jin and Orosz, 2014). A general framework of connected cruise control (CCC) is established to allow modular and scalable design of heterogenous CV. The process is independent of the external disturbances, applied control gains, connectivity structure, and communication delays (Orosz, 2016). The issue about the stochastic delays of connected vehicles were studied by considering both the mean and covariance dynamics based on a CCC.(Qin et al., 2017)

A numerical sub-gradient-based algorithm with SH as a subroutine (NG-SH) is used to optimize the travel time, a safety measure, and the fuel consumption for traffic on a signalized highway. Parsimonious shooting heuristic (SH) method is used to solve classic kinematic wave theory under finite accelerations after separating vehicle trajectories into solvable part. In the optimization problem, traffic, environment and safety are considered. (Ma et al., 2017; Zhou et al., 2017a).

1.2.6 Simulation using MOVES and VISSIM

VISSIM is a microscopic traffic simulation model while MOVES can estimate second-by-second emissions. A software program VIMIS is developed to link VISSIM and MOVES to convert VISSIM files into MOVES files and to do analysis on the effect of major parameters on emissions. The second-by-second average speeds and volumes, link drive schedules, and operating mode distributions are concerned. The results show that speed has a large impact on CO2 emissions. (Abou-Senna et al., 2013) (Abou-Senna and Radwan, 2013)

CMEM, VISSIM, and VISGAOST are once linked to optimize fuel consumption signal timings. (Stevanovic et al., 2009). An integration is made to link VISSIM and CMEM by defining technical characteristics in VISSIM according to categories in CMEM (Kun and Lei, 2007). Vehicle-specific power (VSP) distribution is analyzed for its impact on the estimation of emissions in microscopic simulation (Song et al., 2012). Speed profiles are modeled for eco-driving strategy and models in MOVES are utilized for evaluation of emissions. A weighting factor is linearly used for balancing travel time and emission. Solutions such as enumeration method, simplex optimization, and a genetic algorithm are used to solve the optimization problem (Chen et al., 2014).

1.2.7 Multiclass/heterogeneous traffic modeling

Serge Hoogendoorn did a comprehensive literature review of traffic models from mico to macro level. The issues such as the accuracy, ability in application and generalization, and model calibration and validation are discussed (Hoogendoorn and Bovy, 2001). A multiple user-class macroscopic traffic model is presented. Velocity variance, vehicle interactions, acceleration time, reaction time, desired velocity, and vehicle lengths with regard to different vehicle class are considered (Hoogendoorn and Bovy, 2000).

Heterogeneous traffic model is conducted via a simulation way. Field data is collected in the southern part of Chennai City, India, which show some basic characteristics of different traffic mode under highly heterogenous situation. (Arasan and Koshy, 2005). An extension of LWR model considering heterogeneous drivers are developed. (Wong and Wong, 2002) A new car-following model is developed considering i-class involving both car and bus. (Tang et al., 2009) Multi-class kinematic wave modelling is done by considering class-specific densities, vehicle length, ect. The property of hyperbolicity and anisotropy is discussed. The framework to analyze the hyperbolicity and anisotropy for multi-class kinematic wave traffic flow models are developed. (van Wageningen-Kessels et al., 2013)

1.2.8 Other related work

A dynamic eco-driving algorithm with respect to real-time traffic condition is developed near traffic signals. Theoretically, maintaining a stable middle range speed can save energy. A Velocity Planning Algorithm is used to make the decision on acceleration and deceleration. Then a speed profile for acceleration or deceleration is optimized by choosing the best parameter satisfying minimal cumulative tractive power among a trigonometric family of curves. Riding comfort is also considered in the method. 12% benefits are observed in simulation for both fuel consumption and CO2 emission (Barth et al., 2011).

Vehicle Infrastructure Integration (VII) technologies provides information such as traffic signal status (TSS) to alert drivers to prevent unnecessary acceleration. The time to red (TTR) information can be calculated based on an estimation of the speed, which is combined by current speed and a normal distributed additional possible speed. When the probability of passing before red exceed a threshold, an alert will be released to drivers. The microscopic emissions model Comprehensive Modal Emissions Model (CMEM) is integrated with the traffic simulation model in PARAMICS through the use of an Application Programming Interface (API). Scenarios under different traffic conditions (v/c) are considered. Results show that the savings on fuel consumption is 8% and CO2 emissions is 7% when the traffic is in medium congestion. (Li et al., 2009).

Key variables in Eco-driving for trucks has been investigated (Díaz-Ramirez et al., 2017) according to literatures reviewed. They are: VP: vehicle parameters. VE: vehicle or engine models. Em: emissions. RC: road/route infrastructure & traffic conditions. LE: load and weight effects. DC: driving cycles/route. DP: driver profile. The scopes concerned are: DS: chassis dynamometers tests or simulations. Urb: urban or suburban. LD: long distances. The methods for analysis and results features are: LS: feedback logging systems effects. SM: statistical models/hypothesis tests. ER: empirical results. MR: managerial recommendations. Frg: freight transport. RT: real time data.

Three level of decisions are considered in eco-driving, they are: strategic (vehicle selection and maintenance), tactical (route selection and vehicle load) and operational (driving behavior) decisions (Sivak and Schoettle, 2012). Tactical decisions consider traffic and road. In the traffic part, signal control, as well as road performance, are important factors. For operational decisions, speed, idling, and acceleration(deceleration) are manipulated to make driving smooth.

Driving effectiveness are concerned though index ODE (Overall drive effectiveness) and a data mining fuel consumption prediction method regarding vehicle speed, speed and load of engine is used. (Hsu et al., 2017). In the model, the improvement of the driving effectiveness is represented by attributes and the real-time fuel consumption is predicted given driving behaviors linking to these attributes. A piecewise linear model is built as a model tree, minimizing variability in each terminal node. The model tree makes fuel consumption as a function of other vehicle attributes, in multi-regions with independent linear regression models.

Scaled tractive power (STP) as a function of speed, accretion and vehicle mass is used in MOVES for analysis for the transit bus (Xu et al., 2017). Tractive power requirements is given by : Speed is considered to make dynamical advice using intelligent speed adaptation (ISA) (Barth and Boriboonsomsin, 2009).The optimal speed profile of a real route is developed for Electric Bus, with constraints of speed and time, including driver feedback and scoring. Energy consumption is modeled from a Vehicle Dynamic equation and an optimization problem is solved for the problem. (Rios-Torres et al., 2015)

1.3 SUMMARY OF LITERATURES

The measures of effectiveness (MOEs) used for evaluating eco-driving are: energy consumption, emissions, travel delay, or any combination of them.

The main methods used to achieve an eco-driving goal are as follows:

- Speed adviser: in this kind of methods, a system will provide suggested speed to drivers. For example, driving decisions will be made from different level: tactical- signal control(priority), operational- cruise control, and then speed profile control is conducted to fulfill the decisions.

- Trajectory control: mathematic methods are utilized to design a proper trajectory for a certain type of vehicle using a certain emission model. For example, Index=f (v, acc, mass etc.). Machine learning can be utilized find value of efficient attributes.

- Optimal control: design connected vehicle controllers and solve them, incorporating object functions related to emission and fuel consumption.

For the majority of the literature, the results show that the energy saving and emission reduction is positive to PR (penetration rate) of the eco-driving vehicles. Some other concerns are in the literature, for example, geometric property and traffic conditions. VISSIM is usually applied to simulate the truck corridor and MOVES can be utilized to evaluate emissions.

2.0 ANALYSIS AND EVALUATION

2.1 INTRODUCTION

This chapter provides some simulation results to show the problems exist for signal intersections with significant freight traffic. Then based on these results, the problem our project focus is defined and positioned so as to form a structure. One aspect is chosen and then Chapter 3 gives the solution to that aspect. The influences of truck percentage have on an individual signalized intersection and on the signalized corridor are tested by simulation using VISSIM. Simulations are conducted to show how the percentage of heavy-duty vehicles or trucks fails the signal control for both cases. Besides, the speed difference between the trucks and conventional vehicles also worsen the performances.

2.2 INDIVIDUAL SIGNALIZED INTERSECTION

2.2.1 Experiment setting

In this experiment, the penetration rate of trucks on a corridor is tested, by varying the percentage of trucks and traffic (input volume from small to large).

Table 1 : experiment setting of truck percentage at an individual signalized intersection

Average speed	Car speed: 60 km/h Truck speed: 40 km/h
Lane assignment	Three-lane arterials evaluated at a 10 m segment Gradient: 0% Lane width: 3.5 m
Input volume	Eastbound , other zero volume1800-3600 veh/h
MPR	Truck 5%-50%
Simulation duration	3600s
Multi run	3 runs per scenario
g/c	70/120

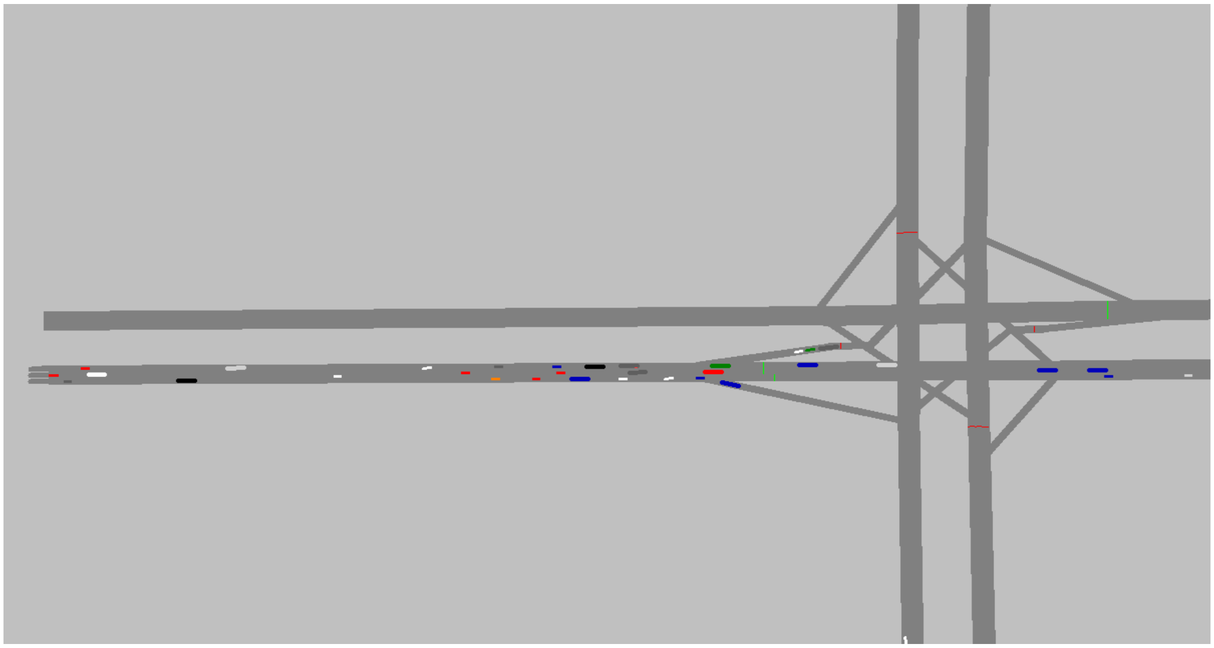
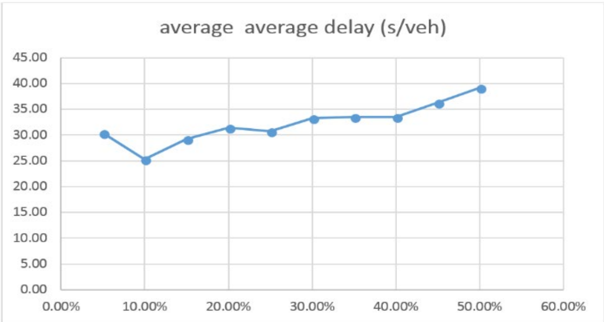
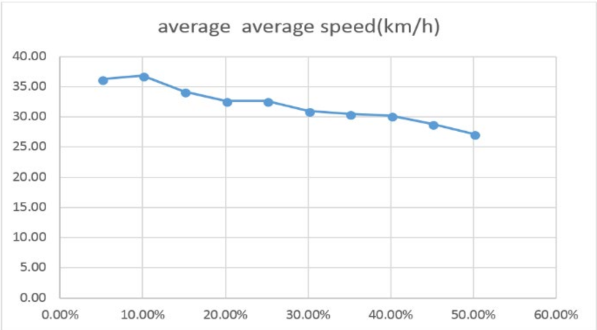


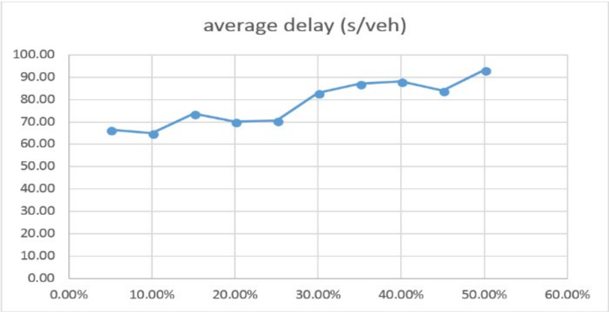
Figure 2: layout of truck percentage at an individual signalized intersection

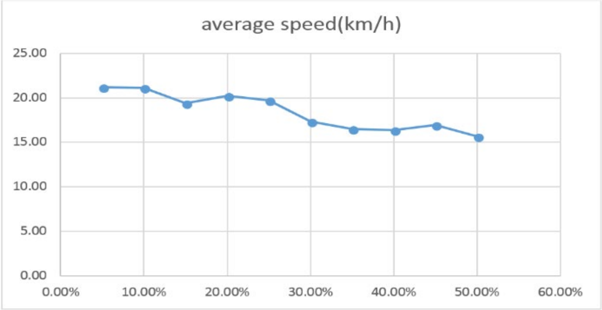
2.2.2 Results

In this analysis, the performance of the corridor is analyzed under different levels of volume for different truck PR. For each scenario (a level of volume, a truck PR), the multi-run is conducted to provide a generalized result. The generalized results are in the form of figures.









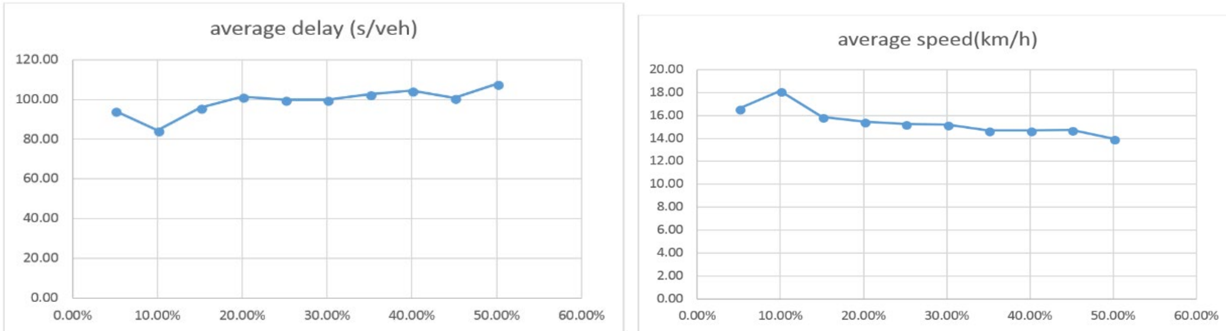


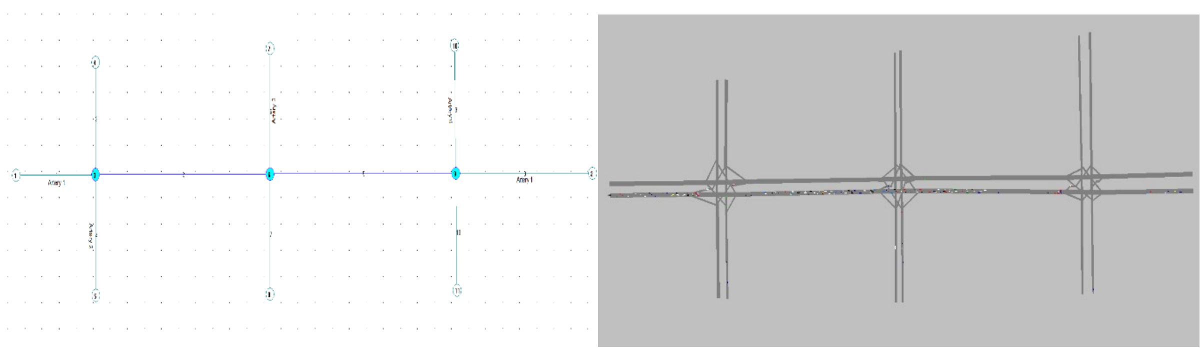
Figure 3 average delay and average speed on the corridor with low volume (from top to down 1800, 2700 and 3600 veh/h)

The results show that the average delay per vehicle increases with the increase in truck percentage, generally. Besides, the average speed decreases with the increase in truck percentage. The slope is not obvious when the volumes on the corridor are low while the slope becomes steeper at high volume levels. The relationship between average delay and truck PR shows a fluctuation when the volume is on a high level.

2.3 SIGNALIZED CORRIDOR

2.3.1 Experiment setting

In this experiment, the penetration rate of trucks on a coordinated signalized corridor is tested, by varying the percentage of trucks and traffic (input volume from small to large). Firstly, the influence on an isolated intersection is tested; secondly, a coordinated signalized arterial is tested. The aggregated influence of truck speed and its penetration rate (PR) on the performance of signalized arterial are tested for an isolated intersection and a coordinated signalized corridor. For an isolated intersection, the speed and delay are tested when trucks with PR ranges from 5%-50%. For three coordinated signalized intersections, PR ranges from 2%-60% while the speed of trucks and conventional cars are set to be either same and different. The figure 4 shows the layout of the corridor in PASSER V and corresponding signal setting.



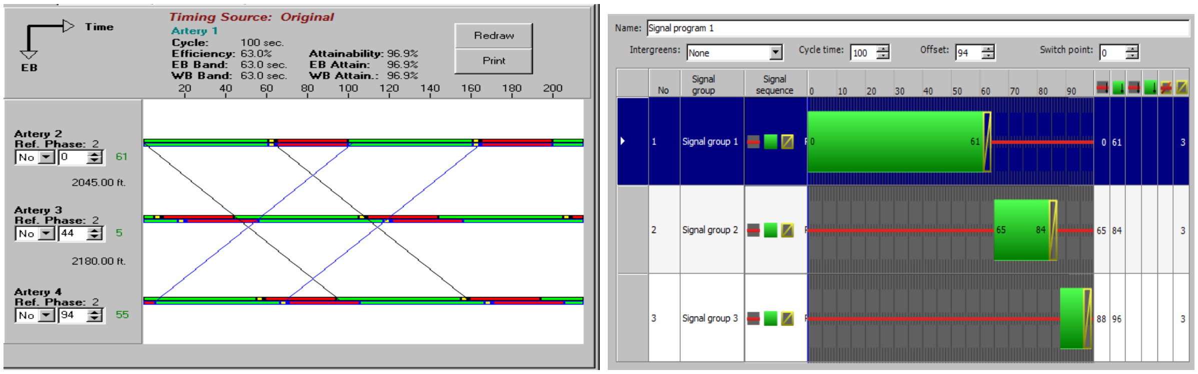


Figure 4 simulation setting using PASSER V

2.3.2 Results for average delay

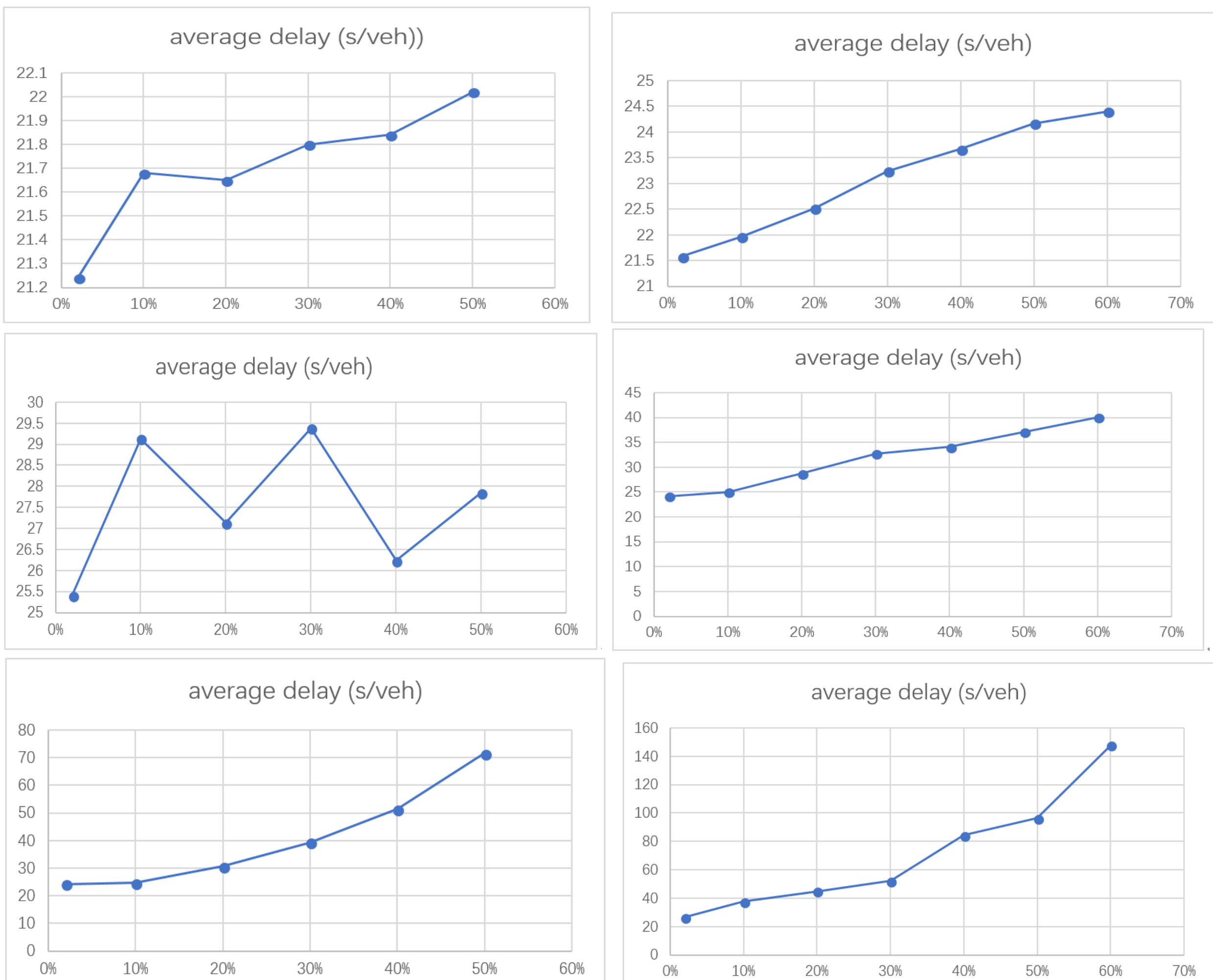


Figure 5 average delay on the corridor with low volume (800 1200 2400 veh/h) when trucks and cars are with the same speed(left) and different speeds (right)

The average delay increases with the increase of shares of trucks when the total volume is fixed. The slope is not obvious when the volumes are low. For the low volume case (800veh/h), it shows a fluctuation when the volume is at a lower level. For the case when trucks and cars are with different speeds, the average delay increases sharply with the increase of PR. The slope also becomes steeper when the total input volume has increased. Comparing the delay changes for each PR level, the increase in delay is sensitive to the amount of volume.

2.3.3 Results for average speed

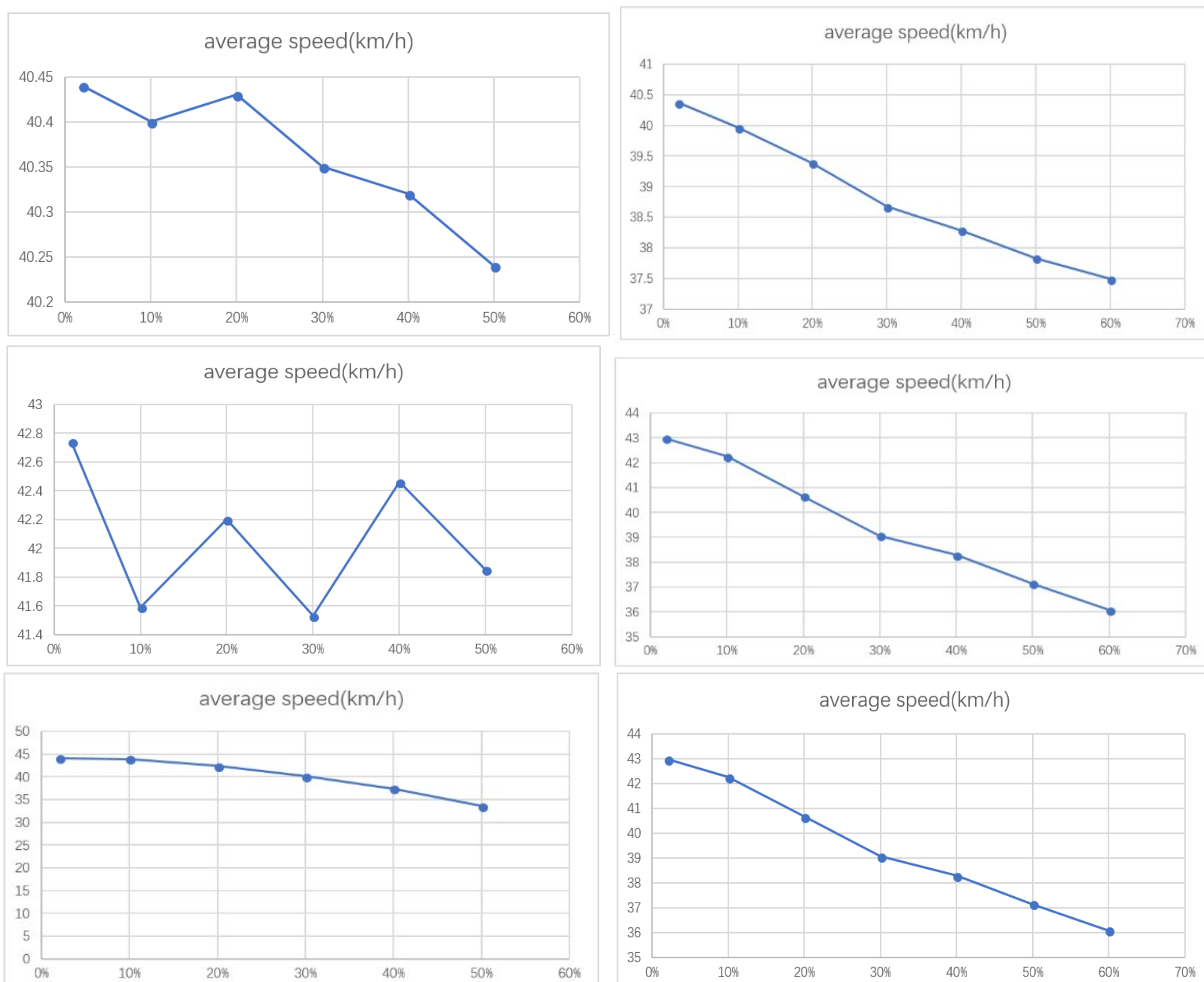


Figure 6 average delay on the corridor with volume (800 , 1200 and 2400 veh/h) when trucks and cars are with the same speed(left) and different speeds (right)

In summary, the average speed decreases with the increase of shares of trucks. For the homogeneous speed case, the average delay only changes when the volume is at 2400 veh/h – it changes from 45 km/h to 35 km/h. For varied speed case, the decreasing slope becomes steeper. Though the increasing percentage of the trucks means more share of low speed vehicles, excluding this influence, the performance of the arterial is still decreasing. Comparing the values under different volumes for a level of PR, the sensitivity of the average speed of the arterial to the volume is not as large as the average delay, in percentage.

2.4 CONCLUSIONS AND PROBLEM POSITION

For both individual and coordinated signals, the more percentage of the heavy-duty vehicles (trucks) are in a traffic, the worse the performance is (more delay and less average speed). The situation is worse when there is a different average speed between the different vehicle classes. Some solutions are necessary to handle the problem. A comprehensive structure to solve the problem is formulated as in the following figure (Figure 7). In this structure, the problem is solved by optimization while adjusting controller in proper ways, while inputs should be real data, microscopic traffic model should be utilized and simulations are assistants. However, we cannot cover all of them in this project. Thus, one of the possible directions is to start with looking at the relationship between individual vehicles and individual signal intersections. This research then starts from the microscopic level by looking at an individual signal intersection and tries to find optimal trajectories for heavy-duty vehicles to pass with good mobility and low emissions. The algorithms are presented in Chapter 3. Besides, to reveal some relationships needed for modelling from a macroscopic aspect, some statistical works are shown in the appendix.

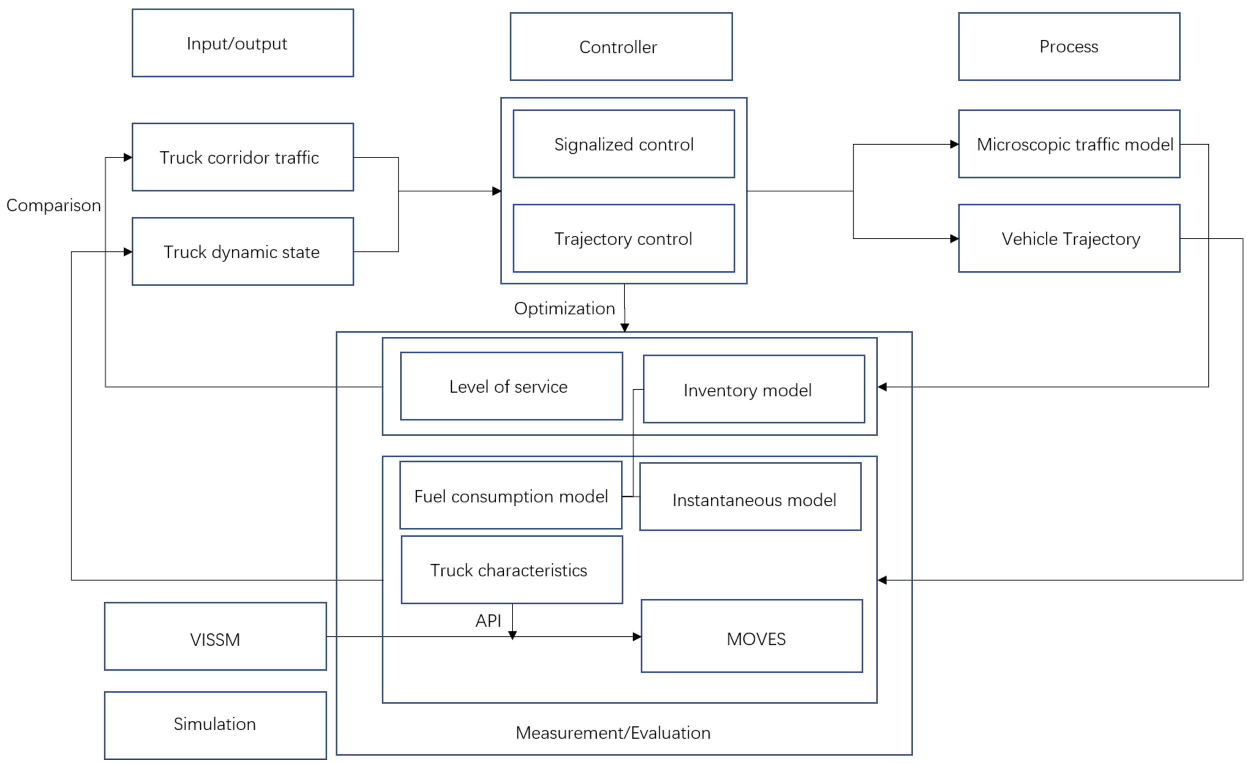


Figure 7 A structure that shows how to solve the problem

3.0 METHODOLOGY

3.1 INTRODUCTION

The experiment uses an algorithm by formulating a two-level dynamic optimization model for individual vehicles. Firstly, basic assumptions in terms of the early arrival and late arrival conditions are defined given a signal timing and initial vehicle conditions. Given the conditions, a baseline case is developed with the shortest travel time. Secondly, a two-level dynamic optimization model is developed for individual vehicles. At the first level, a minimal possible emission is calculated. Then on the second level, a weighted cost is set for time and emissions. All optimizations are based on given initial conditions, whose information is assumed to be known via V2I communications. Such information includes Signal Phase & Timing (SPaT), the initial distance, queue discharge time. The results from the two-level dynamic optimization model is compared to the results from baseline. The following figure 8 shows the structure of the method

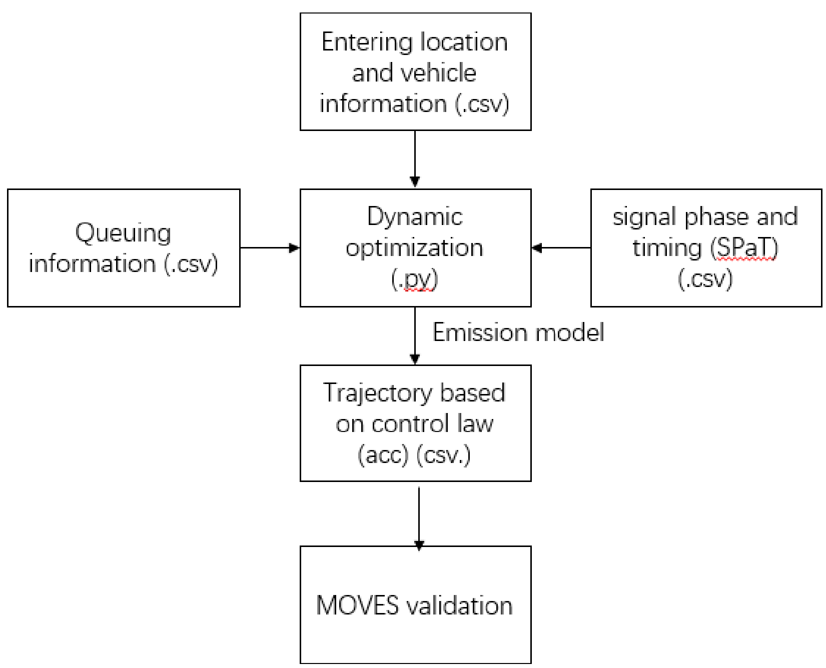


Figure 8 the flow chart of trajectory optimization strategy.

3.2 BASIC ASSUMPTIONS

This section covers the basic assumptions in this study, including arrival conditions, parameters in baseline scenarios and eco-driving scenarios.

3.2.1 Arrival Conditions

If a vehicle can maintain its speed at the speed limit and pass the signalized intersection before the signal turns red, or the vehicle cannot stop behind the intersection stop-bar with maximum deceleration, this situation is denoted as an early arrival. This vehicle is excluded from Eco-driving consideration. Conditions for a vehicle that is not early arrival is:

$$\boldsymbol{T_e \leq \frac{S-S_d}{v(0)}} \tag{1}$$

$$\boldsymbol{S_d > \frac{v^2(0)}{2|a|}\ (a < 0)} \tag{2}$$

Where,
T_e is the green left at the last cycle,
S stands for distance to an intersection when starting eco-driving,
S_d is the distance for deceleration,
$v(0)$ is the initial speed, and
a is the deceleration of the vehicle.

Conversely, if a vehicle drives at the speed limit and decelerate at the maximum deceleration, it still enters the intersection when the signal has turned green in the next signal cycle, then this situation is denoted as a late arrival. This vehicle is also excluded from Eco-driving consideration. The conditions between the early arrival and later arrival are considered in this experiment for eco-driving optimization. Conditions for a vehicle that is not late arrival is:

$$T_n + T_d = \frac{S-S_d}{v(0)} + \frac{v(0)}{a} \leq T_e + R \tag{3}$$

$$S_d > \frac{v^2(0)}{2|a|}\ (a < 0) \tag{4}$$

Where,
T_n is the duration when the vehicle is driving at a normal speed (speed limit).
T_d is the duration of deceleration, and
R is the duration of red signal.

3.3 STRATEGIES

3.3.1 Baseline Scenario

When vehicles pass through an intersection, the travel time is the key index to measure the mobility performance. The baseline scenario is developed based on an algorithm with the shortest time. In the baseline case, a truck will decelerate at the max deceleration $u_{min,}$ and stop before queue or at the stop line, pass the intersection and then accelerate back to the original speed at its max acceleration u_{max}. Queue length is assumed as physical constraints, and for safety concerns, the moving speed of the queue is assumed to be no smaller than the vehicles'. The acceleration of truck should be smaller than conventional vehicles. The average max acceleration is around 1m/s^2. Therefore, in this experiment, the range of acceleration is chosen as [-1,1] m/s^2. The basic parameters in this scenario are following the rules from equation 5 to equation 7.

$$T_r = T_e + max(R, T_q) - T_n - T_d \tag{5}$$

$$a = \begin{cases} u_{min,} \ a < 0 \\ u_{max}, a > 0 \end{cases} \tag{6}$$

$$S_e + S_q = \frac{v^2(0)}{2u_{max}} \tag{7}$$

Where,
T_r is time stopped by red or queue,
a is the acceleration, and
S_e is The distance after passing the intersection to accelerate back to the original speed.
S_q is The queue length where the vehicles stop if there is a queue.

3.3.2 Eco-driving Scenario

An eco-driving scenario is formulated by a two-level dynamic optimization based on a minimal final time problem. The objective function of the eco-driving is to optimize the travel time while maintaining the minimal emissions:

$$\min_{u(t),t_f} J = \left(w\frac{(t_f - t_{g_s})}{t_{g_s}} + (1-w)\frac{(\int_0^{t_f} \dot{E}dt - E_0)}{E_0} + (\frac{\dot{u}(t) - \dot{u}_{max}}{\dot{u}_{max}})^2\right) \tag{8}$$

Where,
$u(t)$ and t_f are the control variable acceleration and the final time.
t_{g_s} is the time point when the next green start, which is also the minimal possible travel time,
$\dot{E}$ is an instantaneous emission rate,
E_0 is the total emission when only considers emission, it is used as a base reference to evaluate how low the emission can possibly be along the distance,
w is a weighting factor that balances the travel time to sacrifice and the relative emissions to save,
$\dot{u}(t)$ is instantaneous jerk term, and
J is the total cost.

In the first level optimization, the objective function shown as equation 9, which is subjective to spacing constraints (equation 10) and speed constraints (equation 12). The total travel time t_{f_0} is bounded by starting time t_{g_s} and ending time t_{g_e} of the next green or the estimated time of queuing discharge t_{q_e}. Besides, extra time should be spent after the intersection and it is larger than the time to reach final speed using the max acceleration as equation 11 shows.

$$E_0 = \min_{u_0(t), t_{f_0}} (\int_0^{t_{f_0}} \dot{E}\, dt) \tag{9}$$

$$\int_0^{t_{f_0}} v\, dt = S + S_e \tag{10}$$

$$max(t_{g_s}, t_{q_e}) \le t_f - \frac{v^2(t_{f_0})}{2u_{max}} \le t_{g_e} \tag{11}$$

$$v(t_{f_0}) = v(0) \tag{12}$$

Then the second level optimization is carried out using results from the first level and subjective to the constraints from equation 13 to equation 18. Spacing constraints in equation 13 determine the vehicles to pass the intersection reaching the same distance as the baseline case. The range of speed, acceleration, and jerk is considered for trucks for comfort and safety reasons in equation 14 15 and 16. Since a too sharp change of acceleration of a truck is dangerous. The jerk scaling in the objective function references to the maximal change of acceleration. In the experiment speed limit is 20 m/s^2,the range of acceleration is chosen as [-1,1] m/s^2 and jerk is chosen as [-1,1] m/s^3. Travel time constraints in equation 17 is similar to travel time constraint in equation 11 and final speed constraints in equation 18 are similar to that in 12.

$$\int_0^{t_f} v\, dt = S + S_e \tag{13}$$

$$0 \leq v \leq v_{limit} \tag{14}$$

$$u_{min} \leq u(t), u_0(t) \leq u_{max} \tag{15}$$

$$\dot{u}_{min} \leq \dot{u}(t) \leq \dot{u}_{max} \tag{16}$$

$$max(t_{g_s}, t_{q_e}) \leq t_f - \frac{v^2(tf)}{2u_{max}} \leq t_{g_e} \tag{17}$$

$$v(t_f) = v(0) \tag{18}$$

4.0 EXPERIMENTS AND RESULTS

4.1 EXPERIMENT DEVELOPMENT

Case studies are conducted to evaluate the difference between eco-driving model and baseline model in emission quantities. The results are then validated by the emission outputs from MOVES. In this section, the results are presented as follows.

- Individual trajectories of all cases with different initial distance S and weighting factor w values.
- Emission results of each individual trajectory and the comparison with the outputs from MOVES.
- Aggregated emission benefit by comparison between the baseline algorithm and eco-driving algorithm at low volume traffic condition with different HDV (truck) penetration rates.

Emission model

Based on the arrival assumption, two different simulation cases are developed. The baseline scenario is developed with a shortest time algorithm. The eco-driving scenario is developed with an eco-driving algorithm. In this study, the instantaneous emission rate is assumed as equation 19 (Panis et al). The parameters for CO2 and NOX are listed in Table 1.

$$\dot{E} = max(E_0, f_1 + f_2 v(t) + f_3 v^2(t) + f_4 v(t) + f_5 u^2(t) + f_6 v(t) u(t))$$

Table 2 : emission model parameters (from Panis, L. I. et al.).

pollutant	type	E_0	f_1	f_2	f_3	f_4	f_5	f_6
CO2	**HDV**	0	1.52e+00	1.88e+00	−6.95e−02	4.71e+00	5.88e+00	2.09e+00
	Car (Petrol)	0	5.53e−01	1.61e−01	−2.89e−03	2.66e−01	5.11e−01	1.83e−01
NOx	**HDV**	0	3.56e−02	9.71e−03	−2.40e−04	3.26e−02	1.33e−02	1.15e−02
	Car (Petrol)	0	6.19e−04	8.00e−05	−4.03e−06	−4.13e−04	3.80e−04	1.77e−04

Intersection Setup

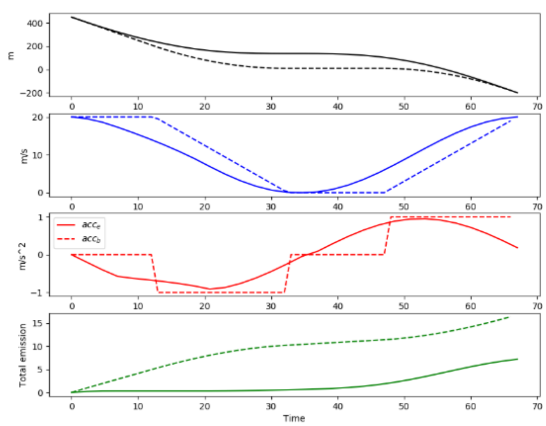
The signal timing plan of the intersection is set as Table 2. Red and Green show a normal timing plan and time left of last green T_e can make the vehicles starting from a distance S ranging from 250 m to 700 m can all satisfy the conditions in basic assumptions. Initial speed is selected as a normal speed limit, while initial acceleration is 0, the queue discharge time is assumed to be 20 secs after the vehicle starts, this information should be derived from V2I communications.

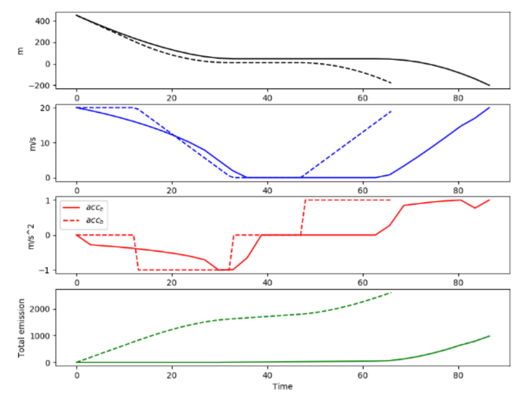
Table 3 Experiment setting

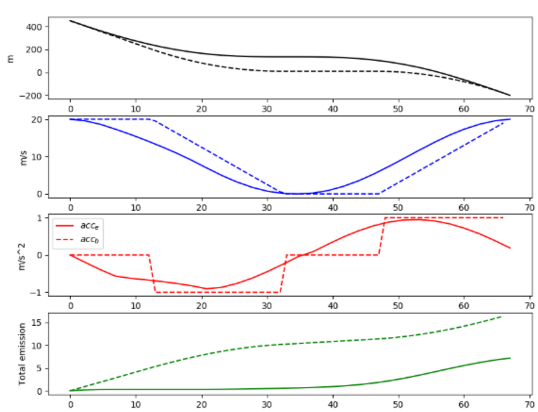
#	distance S (m)	Initial speed v(0) (m/s)	Initial acc u(0)	Estimated queue discharge time point (t_(q_e))
0-9	250-700 in 50 intervals	20	0	20

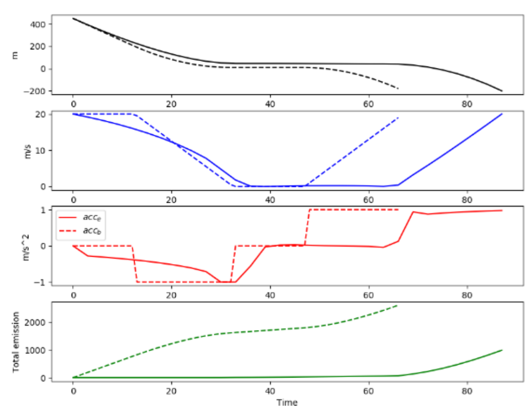
4.2 ACTIVITY RESULTS OF INDIVIDUAL VEHICLE TRAJECTORIES

One case (S=400m) is presented to show how trajectories of travel distance (black), instantaneous speed(blue), instantaneous acceleration (red) and incremental emission (green) change under baseline scenario (dashed lines) and eco-driving scenario (solid line) for individual vehicles. Weighting factor w =0.1 0.5 and 0.9 are applied respectively.









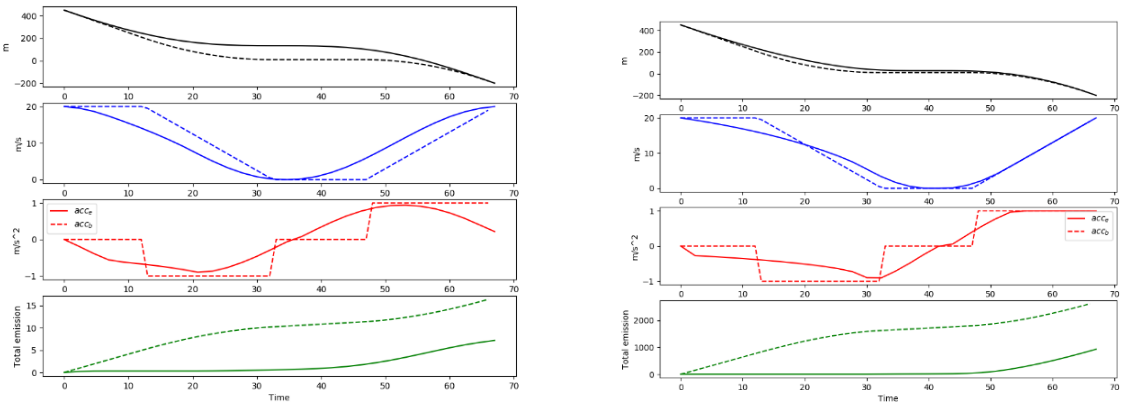


Figure 9 Case (S=400m) The eco-driving trajectories for NOx (left) and CO2 (right); w= 0.1, 0.5, 0.9 (from up to down)

For the trajectories that concern NOx, their travel time values are almost the same as that of the baseline cases, while their emissions are largely reduced. For trajectories that concern CO2, their travel time values decrease when the weighting factor increases, but when weighting factor is larger than 0.5, the travel time values become almost the same as that of baseline cases. The acceleration trajectories (solid red line) represent the control laws for acceleration variables in the objective function. Compared to baseline cases, they are smoother, which is reasonable. Since an aggressive driving strategy with the largest acceleration may lead to large emissions, and an incremental acceleration may save fuel and emissions, which makes sense theoretically and empirically.

4.3 EMISSION RESULTS OF INDIVIDUAL VEHICLE TRAJECTORIES

To validate the results, the trajectories are inputted to MOVES. Table 3 and Table 4 show the average performances of individual vehicles. Average travel time and emissions from the proposed model, and average emissions from MOVES are listed. Their relative benefits compared to baseline case are presented.

Table 4 average travel time and emission NOx saving and their corresponding MOVES results

	Baseline	W=0.1	W= 0.5	W=0.9
Ave Travel time (sec)	67	68.83	68.83	68.83
Travel time scarification (%)	/	2.73%	2.73%	2.73%
Average emission (g)	16.77	7.33	7.37	7.33
Average emission saving (%)	/	56.29%	56.05%	56.29%
Average emission from MOVES (g)	11.47	11.46	11.01	11.09
Average emission saving (%) from MOVES	/	0.09%	4.01%	3.31%

Table 5 average travel time and emission CO2 saving and their corresponding MOVES results

	Baseline	W=0.1	W= 0.5	W=0.9
Ave Travel time (sec)	67	76.49	74.56	76.67
Travel time scarification (%)	/	14.16%	11.28%	14.43%
Average emission (g)	2674.20	1064.79	1076.00	1044.76
Average emission saving (%)	/	60.18%	59.76%	60.93%
Average emission from MOVES (g)	1210.531	1124.231	1140.486	1114.318
Average emission saving (%) from MOVES	/	7.13%	5.79%	7.95%

The average results show that the model reduces emissions while sacrifices travel time no matter applying which weighting factor. However, the saving of emissions is not necessarily decreasing with the increasing of the weighting factor w and the time scarification is not necessarily decreasing with the increase of the weighting factor w. This is because of the two-level structure of the model, which starts with a final value problem, and the final time is a variable as well as a part of the objective function. Therefore, the weighting factor can vary to help to find the optimal cases but not necessarily dominate the results in shaping their travel time or emissions. What is more, the proposed model exaggerated the effect of emission reductions compared to MOVES results. This is because that the proposed model uses an instantaneous emission model that only considers acceleration and speeds and is calibrated from other data. Therefore, it may provide a trend rather than specific accurate values. To make it more convincing, only the emissions from MOVES are used for validation in the following contents.

When comparing the results for NOx and CO2, the results using indicator NOx consume less travel time (3%) but reduce fewer emissions (3%); while the results concerning CO2 shows less time saving (11%) but more emission reduction (6%). For some trajectories, the method can maintain almost the same travel time while decreasing the total emission. The conditions for these trajectories are concerned. A weight of about 0.5 can perform well when considering both travel time and emission.

The MOVES emissions of trajectories from are listed in Figure 2 (NOx) and Figure 3(CO2) according to their starting distances to the intersection, from 250 m to 700 m in an interval of 50 m. For each distance, input trajectories are the baseline case, and the proposed methods using weighting factor w=0.1,0.5,0.9.

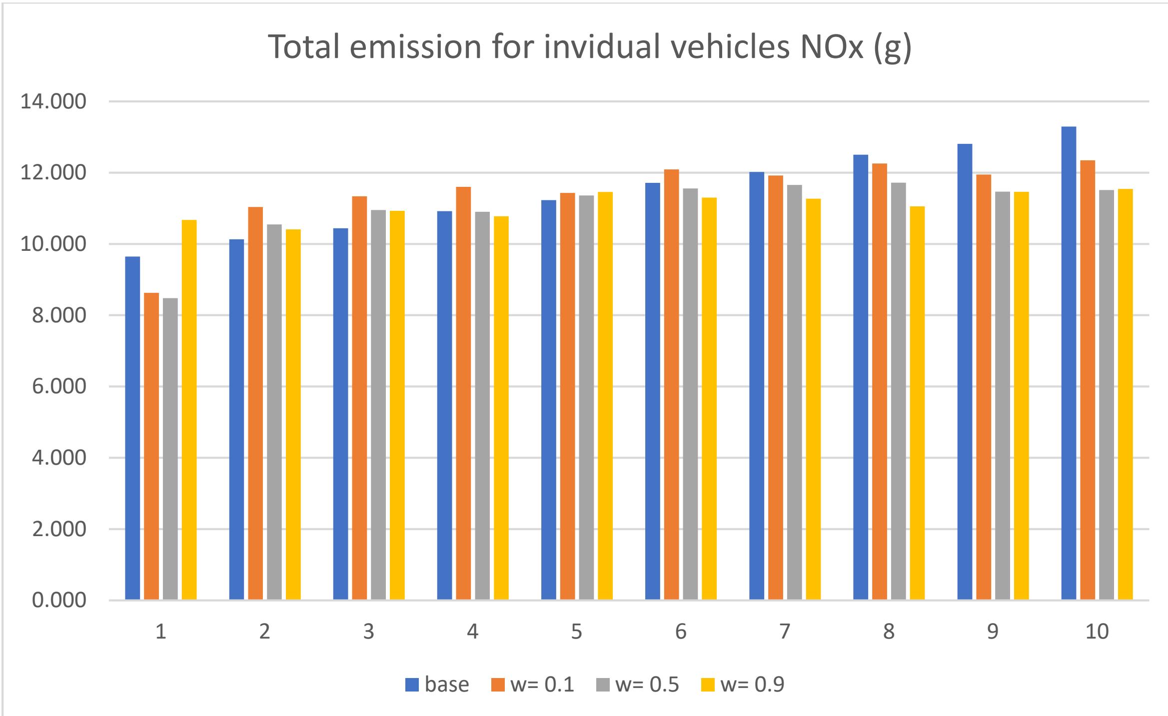


Figure 10 NOx emissions: The MOVES emission results

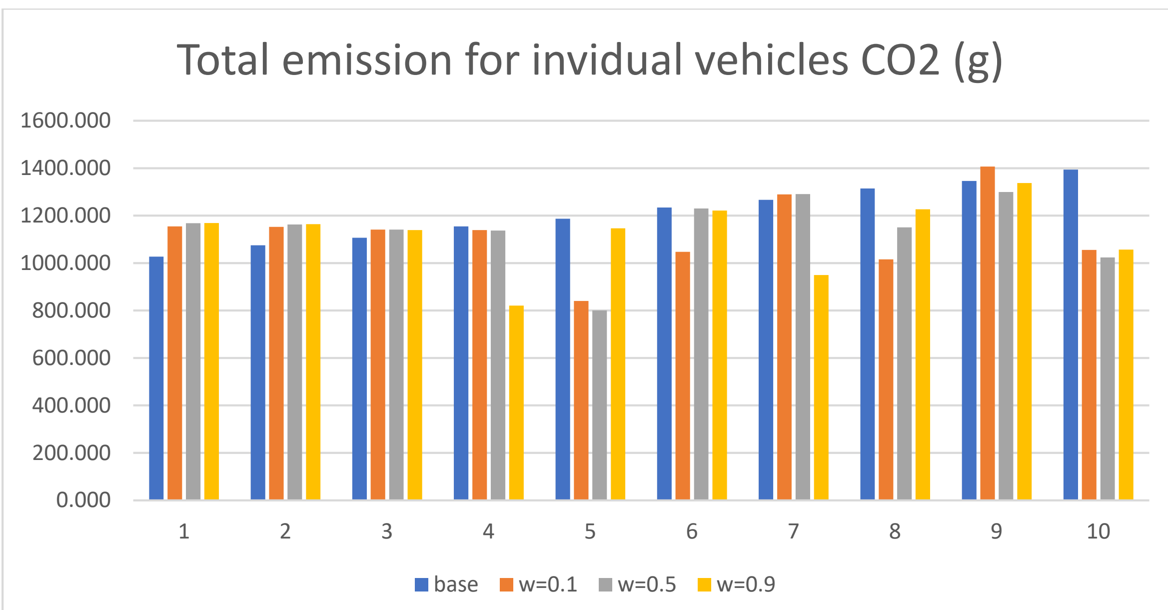


Figure 11 CO2 emissions: The MOVES emission results

For both indicators, the shorter the distance S is towards the intersection, the smaller the difference between results of the baseline and the proposed method. For some trajectories with distance S less than 400 m, baseline trajectories even produce fewer emissions. The outputs show that heavy-duty vehicles require a long distance to take actions ahead of the intersection. If vehicles start eco-driving earlier using the proposed method, the emission can be saved to a larger portion (see the performance when distance S=700m). The results give a hint that the eco-driving should start at least 400 m away from the intersection to maintain a good performance.

4.4 AGGREGATED LEVEL RESULTS

The results with a weighting factor of 0.5 have stable performances for different individual trajectories. Therefore, w=0.5 is chosen as an optimal parameter to produce aggregated level results. A traffic condition with low-density is assumed (with a flow rate of 800 veh/h) to decrease the possible interactions among trajectories of vehicles. The number of heavy-duty vehicles starting eco-driving is assumed to be uniformed distribution along its range. The portions of heavy-duty vehicles that satisfy the base assumptions calculated according to these assumptions and simulation a run based on the portions.

In the first case, the distance vehicles approaching intersections ranges from 250 m to 700 m. Their aggregated simulation results are as follows in Table 5 and Table 6. Based on the results that the further distance has better performance from individual vehicle trajectories, the second simulation case choose distance ranging from 500 to 700 m, Their aggregated simulation results are as follows in Table 7 and Table 8.

Table 6 Aggregated results case 1: S range is 250m-700m NOx unit: g, 800 vph, 1 hour

HDV %	5%	10%	15%	20%	30%	40%
baseline	635.5	1085.0	1534.4	1983.9	2882.9	3781.9
eco-driving	619.5	1052.9	1486.4	1919.8	2786.8	3653.7
saving	2.52%	2.95%	3.13%	3.23%	3.33%	3.39%

Table 7 Aggregated results case 1: S range is 250m-700m CO2 unit: g, 800 vph, 1 hour

HDV %	5%	10%	15%	20%	30%	40%
baseline	181426.3	222847.2	264268.2	305689.2	388531.2	471373.1
eco-driving	178664.3	217323.3	255982.3	294641.4	371959.4	449277.4
saving	1.52%	2.48%	3.14%	3.61%	4.27%	4.69%

Table 8 Aggregated results case 2: S range is 500m-700m NOx unit: g, 800 vph, 1 hour

HDV %	5%	10%	15%	20%	30%	40%
baseline	685.3	1174.1	1662.9	2151.7	3129.4	4107.0
eco-driving	652.5	1108.5	1564.6	2020.6	2932.7	3844.8
saving	4.78%	5.58%	5.91%	6.09%	6.29%	6.39%

Table 9 Aggregated results case 2: S range is 500m-700m CO2: unit: g, 800 vph, 1 hour

HDV %	5%	10%	15%	20%	30%	40%
baseline	193547.4	238563.4	283579.4	328595.5	418627.5	508659.5
eco-driving	189246.3	229961.1	270676.0	311390.9	392820.7	474250.5
saving	2.22%	3.61%	4.55%	5.24%	6.16%	6.76%

For case 1, the results show that the emission reductions range from 2.5% (truck penetration rate 5%) to 3.4% (truck penetration rate 40%) for NOx, and from 1.5% (truck penetration rate 5%) to 4.7% (truck penetration rate 40%) for CO2. For case 2, the emission saving has doubled. Since an optimal range of distances is selected in the simulation. The emission reductions range from 4.8% (truck penetration rate 5%) to 6.3% (truck penetration rate 40%) for NOx and from 2.2% (truck penetration rate 5%) to 6.3% (truck penetration rate 40%) for CO2. For both cases, with the increase in truck penetration rate, more emissions are saved but the increasing rate is not sensitive to the increase of the truck penetration rate. This is because the portions of the heavy vehicle that satisfy the base conditions are certain.

5.0 SUMMARY

5.1 GENERAL SUMMARY

The literature review is presented in Chapter 1 by covering the topics of: the studies of emission model, the eco-driving applications for heavy-duty vehicles (Trucks), Eco-driving and signal control, the benefits from CAVs and Simulation works using MOVES and VISSIM, and multiclass/ heterogeneous traffic modeling. Next, a simulation platform is established to define the problem in Chapter 2. It starts with the analysis of the influence truck percentage has on the individual signalized intersection and a coordinated signal corridor. The simulation results show the high percentage of heavy-duty vehicles in traffic may degrade the signal control by causing large delays. To solve the problem, an eco-driving strategy for freight mobility control at signalized intersections is introduced in Chapter 3. It is by optimizing the travel time while maintaining optimal fuel consumptions and emissions. A two-level dynamic optimization is formulated. An emission weighted optimization is used to simulate vehicles passing the intersection with balanced travel time and emissions savings and compared to a baseline simulation without eco-driving consideration. The emission term in the optimization used an instantaneous speed-acceleration based microscopic fuel consumption models and the results were validated by EPA's MOtor Vehicle Emission Simulator (MOVES) model. Some other candidate emission models tested are shown in appendix A3. In Chapter 4, the results using the eco-driving strategy is shown. To show the relationship between truck percentage and discharge rate, a multiple linear regression is conducted, and the results are shown in the appendix. The data in MOVES and the emission models used are also presented in appendix part A3. The performances of the proposed strategy are summarized in the next part.

5.2 SUMMARY OF PERFORMANCE OF ECO-APPROACHING STRATEGY AT INTERSECTION

The experiment introduced an eco-driving strategy to optimize the driving behaviors of heavy-duty vehicles (trucks) at a signalized corridor. The results show that the model reduces emissions while slightly sacrifices travel time but the saving of emissions or time is not necessarily decreasing with the increase of the weighting factor w. This is due to that the two-level optimization model has considered the final time as a variable and a part of the objective function at the same time. The weighting factor can vary to help to find the optimal results. The activity behavior of individual vehicles shows that heavy-duty vehicles require a longer distance to take actions ahead of the intersection. For NOx, the average reduction ranges from 0.1% to 4%, and for CO_2, the reduction ranges from 5% to 7%. The average travel time increases 3% and 11% respectively in the experiments. Based on analytical results from the individual trajectories, the weighting factor of 0.5 is chosen. Some trajectories can maintain almost the same travel time as the baseline and save more than 5% in emissions. The distance ranging from 500 m to 700 m can provide better performance using the method. These are considered an optimal solution and these optimal parameters are used in the model to produce aggregated level results on different truck percentage levels. The emission reductions range from 4.8% (truck penetration rate 5%) to 6.3%

(truck penetration rate 40%) for NOx and from 2.2% (truck penetration rate 5%) to 6.3% (truck penetration rate 40%) for CO2.

Some limitations are listed: concerning the results, the proposed model has somehow exaggerated the emission saving compared to MOVES outputs. Besides, with regard to assumptions, although the experiment considers the queue information via a V2I communication, the queue discharge time is hard to obtain sometimes. Although the aggregated simulation in the experiment assumes a low-density traffic condition to avoid the possible interactions between vehicles, in the reality, the interactions still exist.

For future work, an iterative process of the weighting factor will be developed to calibrate the best weighting factor. Besides, other calibrated emission models are being tested to make a comparison. The interactions between vehicles can be considered to produce performance under both low density and high-density situations. The average computation time is around 1 sec for one individual truck. The computation time can be shortened to within one second, in which case the method can be implemented in a real-time case. The authors are currently developing an iterative optimization process.

6.0 APPENDIX

6.1 A1 RELATION BETWEEN PERCENTAGE OF HEAVY-DUTY VEHICLES AND DISCHARGE RATE DROP OF COORDINATED SIGNAL CORRIDOR

Assumptions are made that the equivalent volumes along the coordinated intersections are related to heavy vehicles ratios, average speed, and speed variations. A regression tool is used to confirm the second assumption. According to the definition of the heavy factor, the PCE values can be represented by the heavy factor:

$$PCE = 1 + \left(\frac{1-f_{hv}}{f_{hv}}\right) * \frac{1}{P_{hv}} \tag{19}$$

where the heavy vehicle factor is the ratio of saturation flow rate over base saturation flow with 0% heavy vehicles. The baseline saturation flow is defined as s_b and the actual saturation flow rate s is assumed to be related to not only truck penetration rate PR, but also the average speed V and the average speed difference between trucks and conventional cars DV.

$$f_{hv} = \frac{c(PR,V,DV)}{c_b} = \frac{s(PR,V,DV)}{s_b} \tag{20}$$

Since the saturation rate $\boldsymbol{s}$ is divide by

$$s = \frac{c}{(\frac{g}{C})} \tag{21}$$

Where c is the discharge rate given a green time share in a cycle length. Under the condition of a truck penetration rate and with an average different speed between trucks and conventional cars. It can be obtained by simulation, and the decrease rate dc between the base discharge rate and the actual discharge rate is obtained.

$$ds(PR,V,DV) \quad = 1 - \frac{s(PR,V,DV)}{s(PR=0\%,V=v_{limit},DV=0)} \tag{22}$$

$$ds(PR,V,DV) = \beta_0 + \beta_1 * \Delta PR + \beta_2 \Delta V + \beta_3 * \Delta DV \tag{23}$$

The calibrated model then is used to predict the discharge rate under different conditions. A significant relation is found. Therefore, the assumption 2 can be confirmed. Then the saturation flow rates are calculated to get different PCEs.

A linear regression is firstly conducted for each parameter to visualize the relationship between the discharge difference and each variable individually.

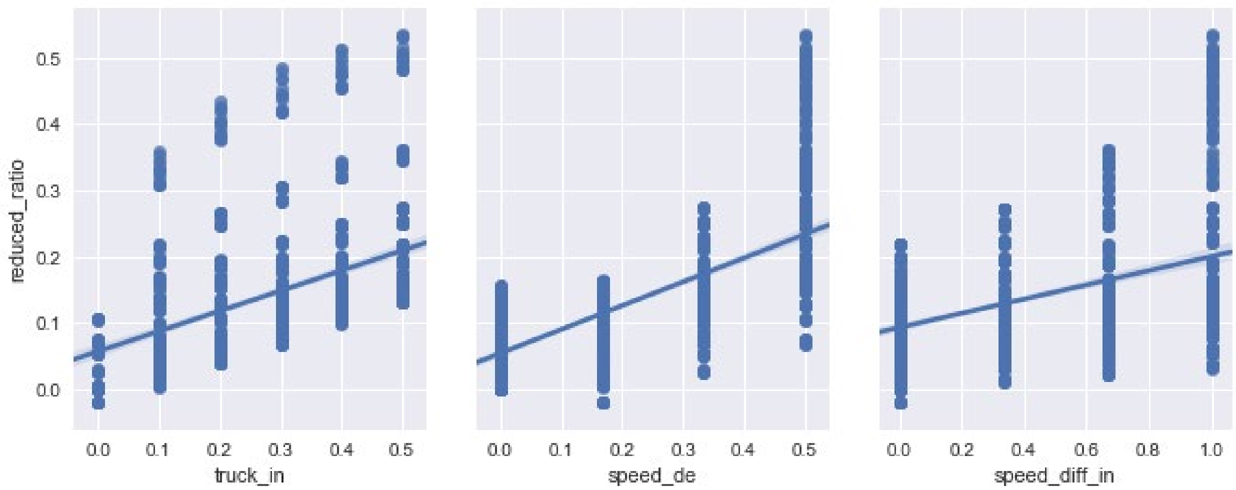


Figure 12 The relations between the discharge rate and truck penetration rate, speed, and speed difference of trucks and cars respectively.

10 runs are made by different random seeds and an average value is chosen. Then the results the calibrated regression model is:

$$ds(MPR, V, DV) = -0.0679 + 0.2715 * \Delta MPR - 0.3573 * \Delta V + 0.091 * DV$$

A prediction is conducted using the parameters calibrated to compare with 300 data points and the results are as the following figure. The R-square is 0.74 and the RMSE is 0.13.

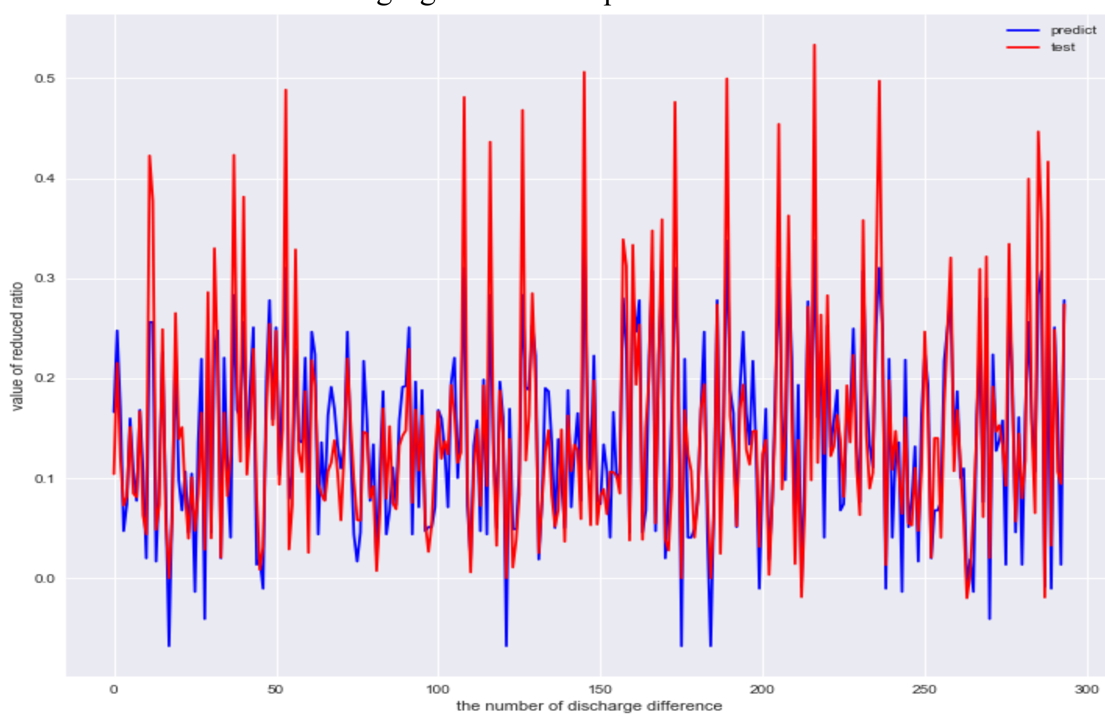


Figure 13 The prediction of discharge rate difference along a coordinated signal.

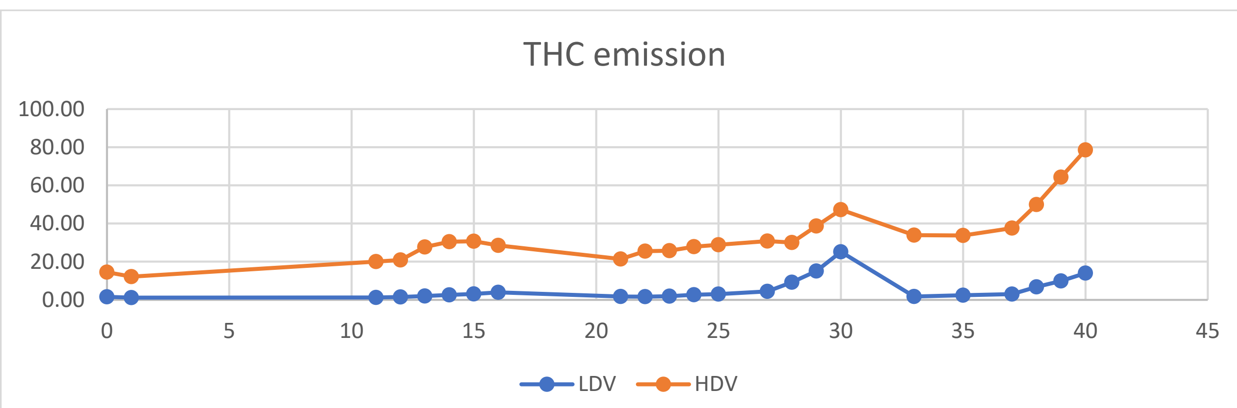
The results show that, from a macroscopic perspective, the discharge rate of coordinated signalized intersections have a negative relation with: percentage of the trucks and the speed difference between trucks and cars.

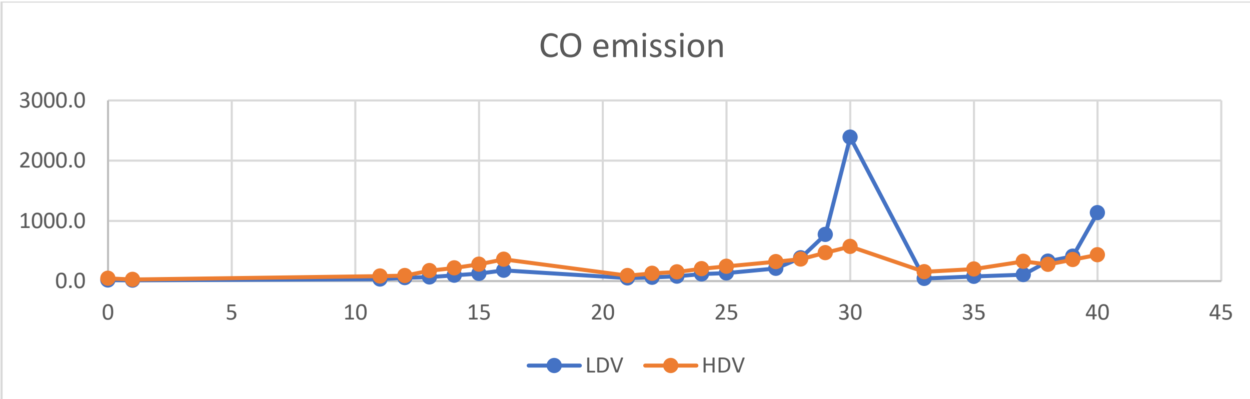
6.2 A2 MOVES MODEL USED IN THE RESEARCH

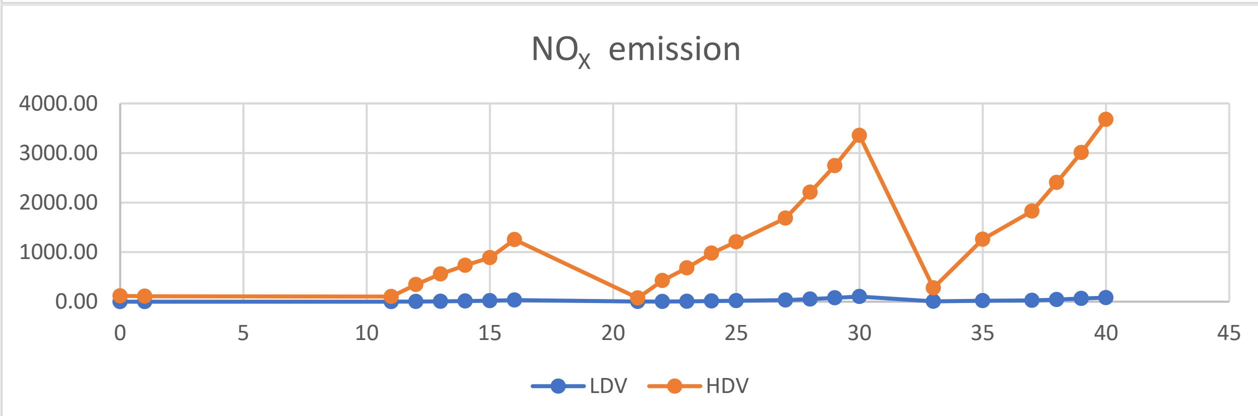
The data used in MOVES for calculation VSP and emissions are presented as following table and figures.

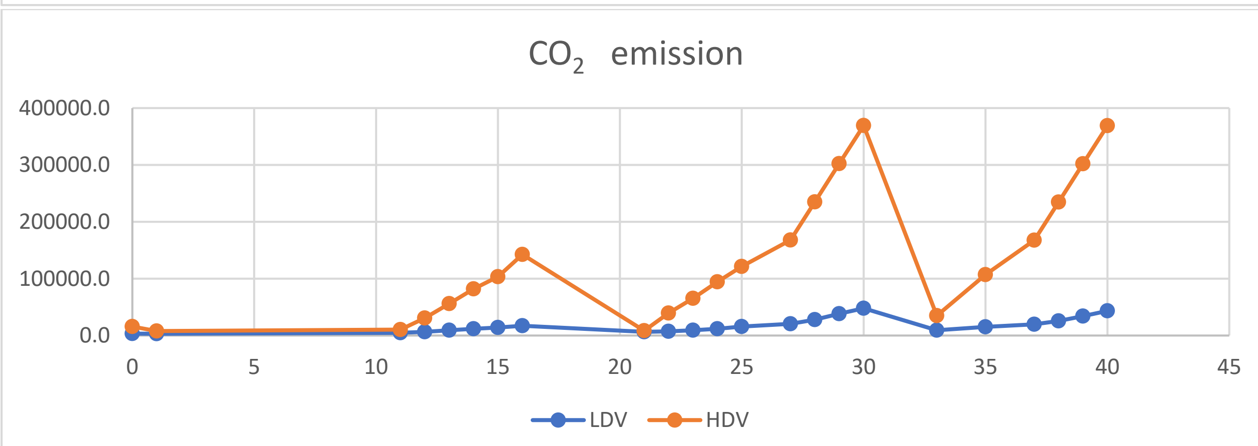
Table 10 the mode setting in MOVES

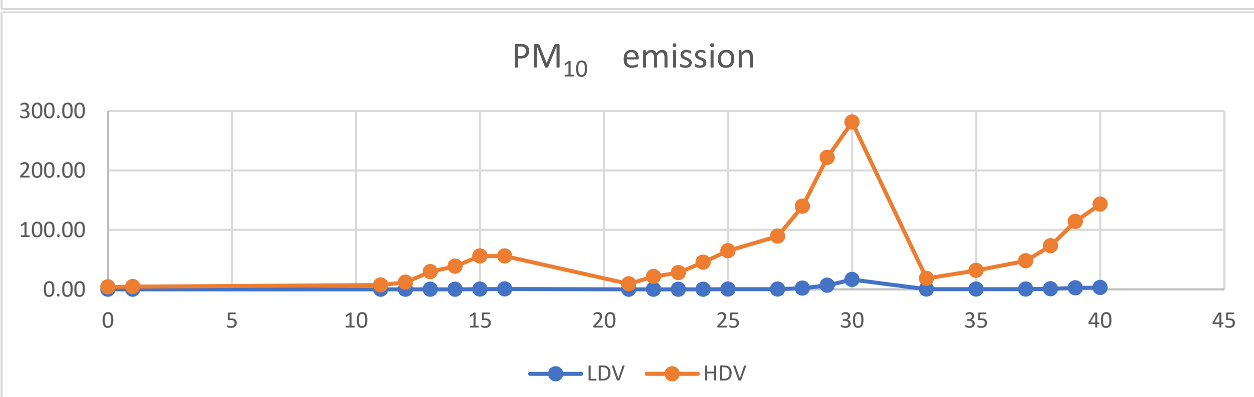
opModeID	opModeName
0	Braking
1	Idling
11	Low Speed Coasting; VSP< 0; 1<=Speed<25
12	Cruise/Acceleration; 0<=VSP< 3; 1<= Speed<25
13	Cruise/Acceleration; 3<=VSP< 6; 1<=Speed<25
14	Cruise/Acceleration; 6<=VSP< 9; 1<=Speed<25
15	Cruise/Acceleration; 9<=VSP<12; 1<=Speed<25
16	Cruise/Acceleration; 12<=VSP; 1<=Speed<25
21	Moderate Speed Coasting; VSP< 0; 25<=Speed<50
22	Cruise/Acceleration; 0<=VSP< 3; 25<=Speed<50
23	Cruise/Acceleration; 3<=VSP< 6; 25<=Speed<50
24	Cruise/Acceleration; 6<=VSP< 9; 25<=Speed<50
25	Cruise/Acceleration; 9<=VSP<12; 25<=Speed<50
33	Cruise/Acceleration; VSP< 6; 50<=Speed
35	Cruise/Acceleration; 6<=VSP<12; 50<=Speed
27	Cruise/Acceleration; 12<=VSP<18; 25<=Speed<50
28	Cruise/Acceleration; 18<=VSP<24; 25<=Speed<50
29	Cruise/Acceleration; 24<=VSP<30; 25<=Speed<50
30	Cruise/Acceleration; 30<=VSP; 25<=Speed<50
37	Cruise/Acceleration; 12<=VSP<18; 50<=Speed
38	Cruise/Acceleration; 18<=VSP<24; 50<=Speed
39	Cruise/Acceleration; 24<=VSP<30; 50<=Speed
40	Cruise/Acceleration; 30<=VSP; 50<=Speed




CO emission
3000.0
2000.0
1000.0
0.0
0
5
10
15
20
25
30
35
40
45
LDV
HDV


NO_X emission
4000.00
3000.00
2000.00
1000.00
0.00
0
5
10
15
20
25
30
35
40
45
LDV
HDV


CO_2 emission
400000.0
300000.0
200000.0
100000.0
0.0
0
5
10
15
20
25
30
35
40
45
LDV
HDV


PM_{10} emission
300.00
200.00
100.00
0.00
0
5
10
15
20
25
30
35
40
45
LDV
HDV

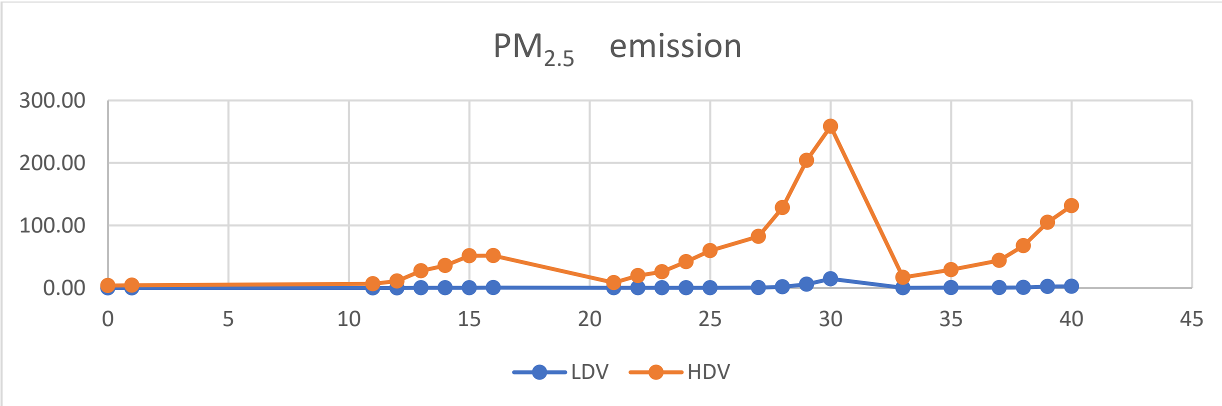


Figure 14 The emission rate of LDV and HDV with regarding to mode type for different emissions

In our report, only the emission CO2 and NOx are used for calibration and validation cases.

6.3 A3 ATTEMPTS USING OTHER EMISSION MODELS

During the research process, some other emission models are selected and tested, although they are not selected to be involved into the model at last, some intermediate results are presented here.

VT-Micro model

VT-micro is an instantaneous emission rate model. Although it is not specific for heavy-duty vehicles, the parameters are assumed and tested:

P=1, acceleration mode,

$$MOE_e = e^{\sum_{i=0}^{3}\sum_{j=0}^{3}(L^e{}_{i,j}v^i a^i)} \tag{24}$$

P=0, deceleration mode,

$$MOE_e = e^{\sum_{i=0}^{3}\sum_{j=0}^{3}(M^e{}_{i,j}v^i a^i)} \tag{25}$$

$L^e{}_{i,j}$: model regression coefficient for MOE_e at speed power i and acceleration power j for deceleration

$M^e{}_{i,j}$: model regression coefficient for MOE_e at speed power i and acceleration power j for Deceleration

v: instantaneous vehicle speed

a: instantaneous vehicle acceleration

Since they should reach the minimal and maximal value at the same time while the log can be expressed as polynomials. Thus, we have the polynomial

$$In(MOE_e) = \sum_{i=0}^{3}\sum_{j=0}^{3}\left(L^e{}_{i,j}v^i a^i\right) \tag{26}$$

A sample relation according to the VT-micro mode is as follows: (a log-transferred)

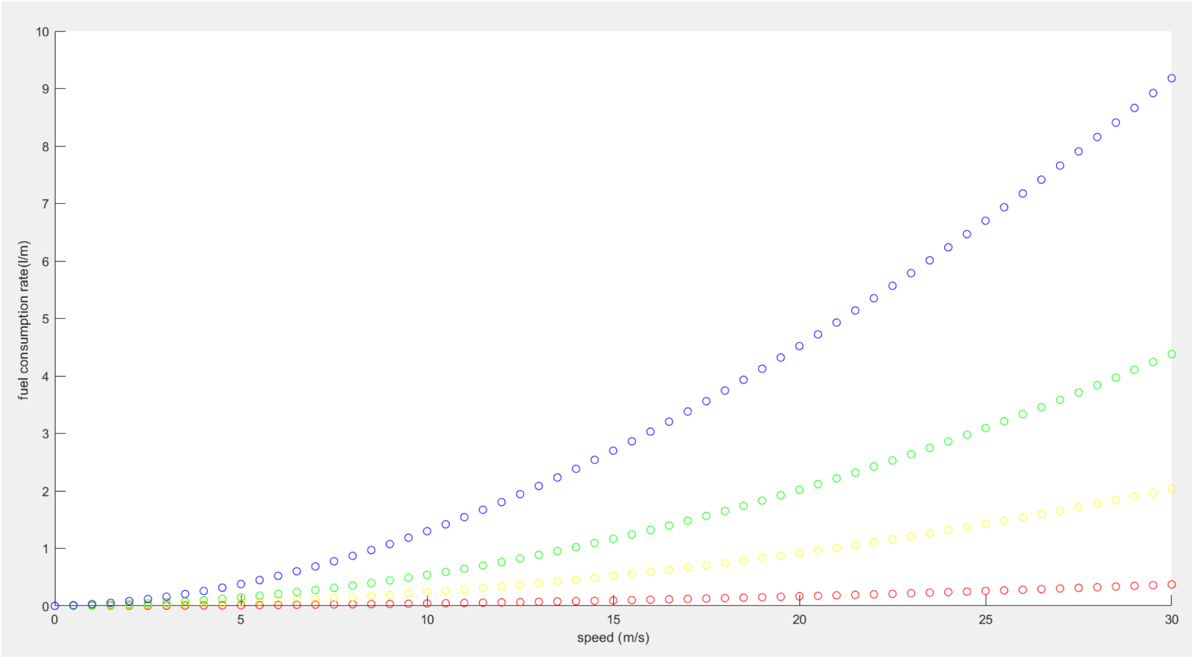


Figure 15 a sample VT-micro model (a log-transferred) accerlation: blue,green, yellow,red: 2 m/s^2, 1 m/s^2, 0.5 m/s^2, 0.1 m/s^2 for speed from 0 to 30 m/s

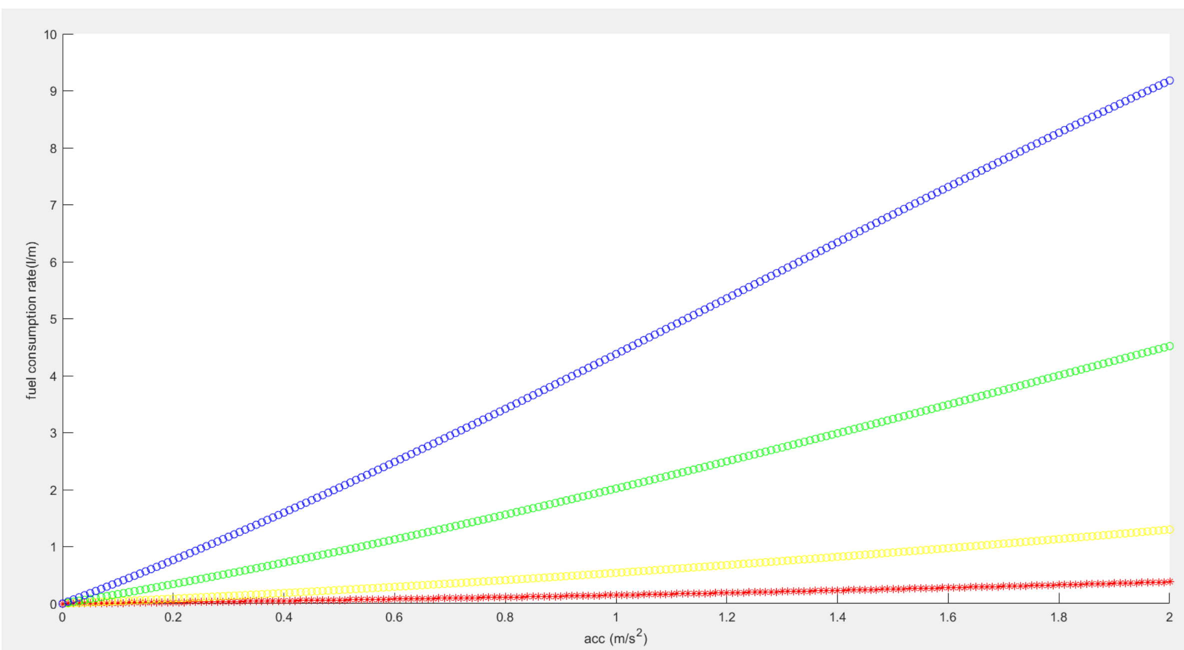


Figure 16 a sample VT-micro model (a log-transferred) speed: blue,green, yellow,red: 30 m/s , 20 m/s, 10 m/s, 5 m/s for acc from 0 to 2 m/s^2

A proposed emission model

A proposed emission model is developed so that it can describe the acceleration and deceleration mode in one model:

$$E = C_1 v^2 e^a + C_2 \tag{27}$$

$$MOE_e = \dot{E} = 2C_1 e^a v \tag{28}$$

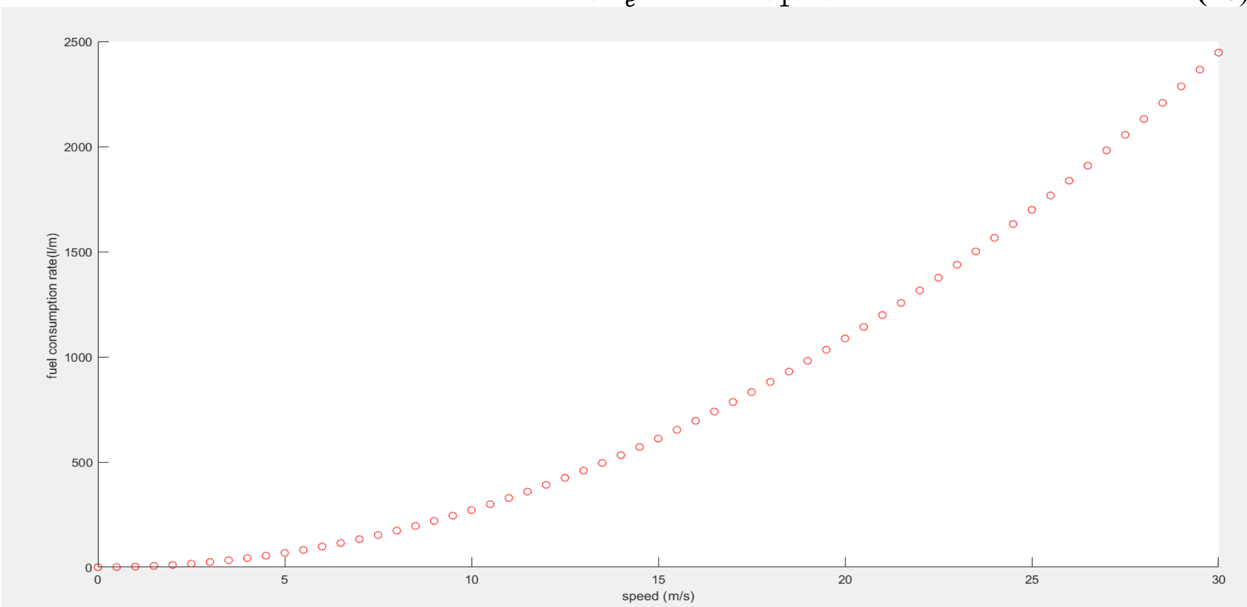


Figure 17 a sample proposed model (a log-transferred) with a=2 m/s^2 v=0-30m/s

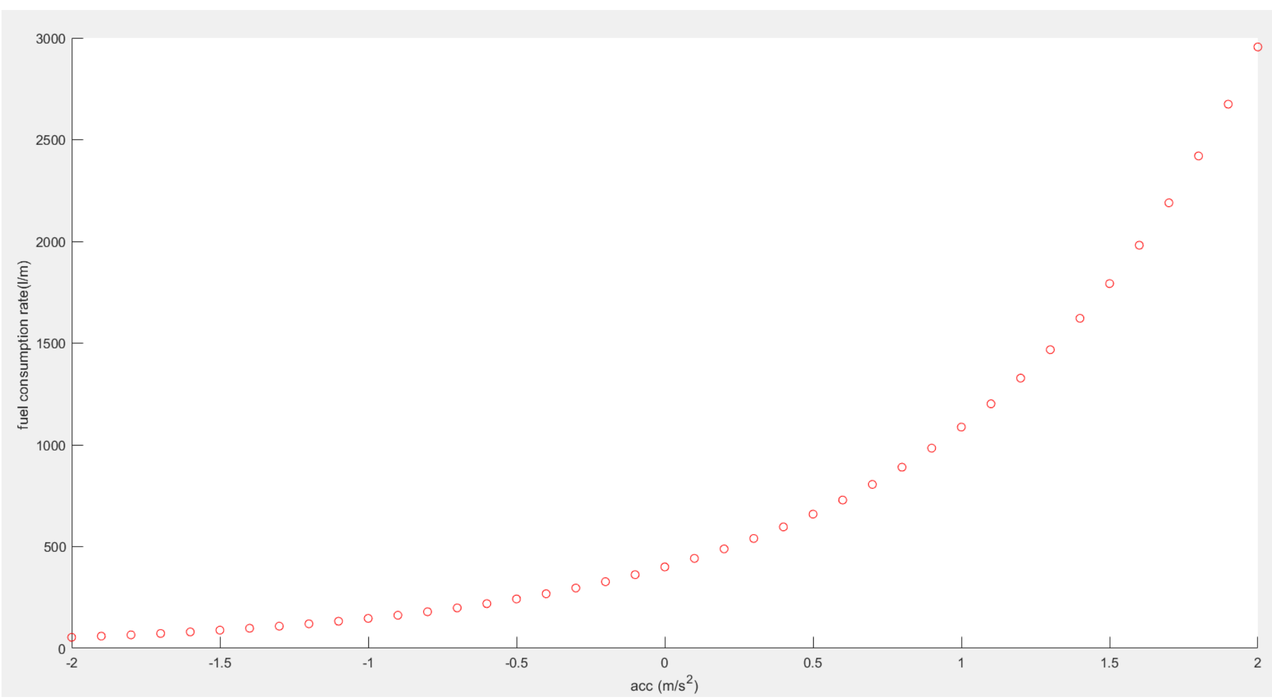


Figure 18 a sample proposed model (a log-transferred) with v=20 m/s a from -2 m/s^2 to 2 m/s^2

It can be seen that, when fixing acceleration, the total emission increase with the increase of speed. On the other hand, for a certain speed, acceleration will cause shaper increase of emission while there will be no emission (or basic emission) when decelerating (with zero or negative acceleration).

The reason why VT-micro model is not chosen is that the parameters can found in papers are not specific for heavy-duty vehicles. the reason why the proposed model is not chosen is that the calibration requires a lot of heavy vehicle data, which are not available. Therefore, the calibrated emission model specific for heavy-duty vehicles in the method we used is a reasonable choice.

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