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Environmental Impacts of Heavy-Duty Natural Gas Vehicle Incentives in California

DISSERTATION

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for the degree of

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in Civil and Environmental Engineering

by

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2019

DEDICATION

To

My Family

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ABSTRACT OF THE DISSERTATION

Environmental Impacts of
Heavy-Duty Natural Gas Vehicle Incentives in California

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Society has an interest in reducing pollutants emitted from the vehicles used for transporting people and goods. The main goal of heavy-duty natural gas vehicle (NGV) incentive projects is to offer upfront monetary incentives to reduce greenhouse gas emissions and the production of regulated pollutants in the state. However, these incentives are often based on vehicle weight and do not account for environmental impacts. In addition, although heavy-duty NGVs are being used in a variety of vocation types, conventional emission models only support a limited number of these vocation types. Because of this, it is challenging to assess the precise impacts of the heavy-duty NGV (HD NGV) adoption and predict the specific environmental benefits per given operational conditions and vocation type. If government agencies realize the environmental benefits of alternative fuel vehicles (AFVs), like NGVs, with respect to vocation type and operating characteristics, it would be beneficial to design cost-effective incentive structures and

implementation plans. This study primarily focused on the operational characteristics and environmental impacts of the HD NGVs incentivized in California. This study conducted pattern clustering and classification analyses to obtain drive mode compositions (DMC) over duty cycles and showed the heterogeneity of operational and emission characteristics of the vocational HD NGVs. The vocational impact analysis computed the adoption impact of 40 NGVs operating in California across ten different vocation types. The proposed evaluation framework included life-cycle nitrogen oxides (NOx) and carbon dioxide (CO2) emissions of natural gas, renewable natural gas and diesel fuel pathways and compared the lifetime NOx emission reduction potential of the considered vocation type vehicles. The resulting emission benefits of the fuel pathways were used to determine the most incentive-effective vocation types among the considered NGV applications. The multi-criteria decision-making analysis prioritized the fuel pathways based on multiple criteria which are related to an incentive effectiveness index as well as life cycle emissions. Refuse truck and transit bus pathways are likely to achieve the highest return for the total incentive granted when the vehicles are renewable natural gas (RNG)-powered. For compressed natural gas (CNG) fuel pathways, school and transit buses take the highest ranks over the various analysis scenarios. Each vocation type showed different incentive effects and emission reduction potential, which means that some vocational vehicles can play a critical role in the state's funding and emission reduction plans. The suggested decision-making tool and assessment framework can provide useful reference data to improve the performance of future alternative fuel vehicle incentive programs.

Chapter 1 Introduction

Transport activity is known to be the major contributor to the production of greenhouse gases (GHG) and criteria pollutants due to the dependency of major transportation modes on fossil fuels. Mobile sources, such as cars, trucks, and buses account for approximately 80 percent of nitrogen oxide (NOx) emissions, 90 percent of particulate matter (PM) emissions, and nearly 50 percent of GHG emissions (*1*). Heavy-duty vehicle (HDV) operations, in particular, are responsible for close to 36% of nitrogen oxides (NOx) emissions in the U.S. transportation sector, while HD and medium-duty vehicles consume 28% of petroleum and emit 26% of carbon dioxide (CO_2) emissions (*2*). This study focuses on the production of NOx and CO_2 emissions over the entire fuel life cycle. NOx is a poisonous and highly reactive gas and an ozone precursor that facilitates the production of ozone via chemical reactions in the atmosphere. When inhaled, ozone can damage the lungs and cause asthma attacks (*3*). A great deal of NOx is produced when fossil fuels are combusted at high temperatures, and motor vehicles emit 55% of NOx emissions (*4*-*5*).

The use of natural gas is more environmentally friendly than other conventional petroleum-based fuels. When internal combustion engines (ICEs) burn compressed natural gas (CNG), they emit less carbon than conventional fuels, such as gasoline and diesel. Graham et al. (*6*) and Arteconi et al. (*7*) compare emission inventories from different fuel vehicles, and the results show that natural gas can reduce CO_2 equivalent GHG emissions by 10 - 20% compared to diesel. This is because natural gas has the lowest carbon-hydrogen ratio of all stable hydrocarbon fuels. Dominguez-Faus (*8*) confirms this point by asserting, "NG combustion emits about ¼ less carbon dioxide than diesel." Melendez et al. (*9*) find that CNG is capable of reducing nitrogen-oxide emissions by 35 to 60 percent, compared to gasoline. Natural gas buses can emit 53% lower NOx emissions than conventional diesel buses (*10*). Furthermore, natural gas has been expected to become the most viable alternative fuel in the heavy-duty trucking sector, providing a significant amount of regulated pollutant reductions with cheaper pricing ranges than conventional fuels.

Spurred by increasing concerns about air quality in the State of California, the state government has set emission reduction goals, as shown in the Mobile Source Strategy (1). Government agencies offer various policy and monetary incentives to public and private entities that are interested in alternative fuel vehicle (AFV) adoption. The main goal of the vehicle incentive projects is to offer upfront monetary incentives to reduce GHG emissions and regulated pollutants from mobile sources in the state and ultimately achieve the emission abatement goals. About $2 billion of financial incentives have been distributed for heavy-duty natural gas vehicle (HD NGV) adoption (*11-15*). Although the government agencies have distributed an enormous sum of money, a limited amount of incentives is available for select customers. Therefore, financial incentives should be deployed effectively under stringent distribution plans. The AFV incentives are often based on vehicle weight and do not account for environmental impacts. In addition, conventional emission models only support a limited number of these vocation types, even though heavy-duty natural gas vehicles (HD NGVs) have been used in a variety of vocation types for past decades. Because of this, it is challenging to assess the precise impacts of the HD NGV adoption and predict the specific environmental benefits per given operational conditions and vocation type. Therefore, this study aims to assess the environmental impacts of various vocational HD NGVs and determine the incentive-effective fuel pathways in terms of lifecycle NOx and CO2 emission benefits for vehicle lifespans. This is not only the problem of NGVs but also other AFVs. If government agencies realize the environmental benefits of alternative fuel vehicles (AFVs) with respect to vocation type and operating characteristics, it would be beneficial to identify the main policy targets and design a vehicle incentive structure that maximizes emission reductions. Then, the agencies can offer different incentive values to vocation types based on the estimated environmental impacts. Accordingly, the incentive projects can be more cost-efficient by focusing on the specific fuel and vehicle application types.

This study hypothesized that vocational NGVs would have different operational characteristics and resulting environmental impacts and investigated the relationship between vocation type and operational characteristics of HD NGVs, which has been underestimated in previous studies. The vocational impacts on vehicle activity were assessed in driving mode composition (DMC) which can provide an insight into how the vehicles are operated. Based on the stated research opportunity, this study proposed an evaluation framework that estimates lifecycle emissions of various fuel pathways and prioritizes the fuel type and vehicle application scenarios in multiple aspects, such as lifetime NOx and CO_2 emission reduction potential, incentive effectiveness index, and the low-speed driving mode feature.

The revealed best combination of fuel pathways and vocation groups can be a crucial player in designing alternative fuel vehicle incentive projects because it can enable the establishment of time- and cost-efficient emission reduction strategies, ultimately contributing to more sophisticated decision-making processes for determining the most environmentally friendly fuel pathways.

1.1 Research Objectives

The objectives of this research are to:

- Evaluate the environmental impacts of various vocational HD NGVs compared to their diesel counterparts
- Assess the lifecycle NOx and CO_2 emissions of NG and diesel vehicle applications
- Evaluate the performance of NGV incentive projects in terms of environmental incentive effectiveness index (EI^2, EI-square), which indicates the lifetime NOx emission reduction potential over the incentives granted.
- Determine the most environmentally friendly fuel pathways for contributing to the state's NOx and CO_2 emission reduction goals.

1.2 Evaluation framework

The proposed evaluation framework for assessing air quality impacts of incentivized HD NGVs is presented in **Figure 1.1**. This study estimated CO_2 and NOx emissions of HD NGVs using the vehicle activity data obtained via the J1939 controller area networks (CAN) bus protocol and then calculated driving mode distributions which aim to capture operational characteristics of the NGVs.

The well-to-wheel (WTW) assessment covered NG lifecycles which include the entire NG production and consumption procedure so that the analysis results can explain the total environmental impacts of the NG fuel pathways and vehicle applications. The estimated total fuel cycle NOx and CO_2 emission rates were used to prioritize NG and diesel fuel pathways and determine cost-effective vocation type in terms of lifetime NOx emission reduction potential over incentive values granted.

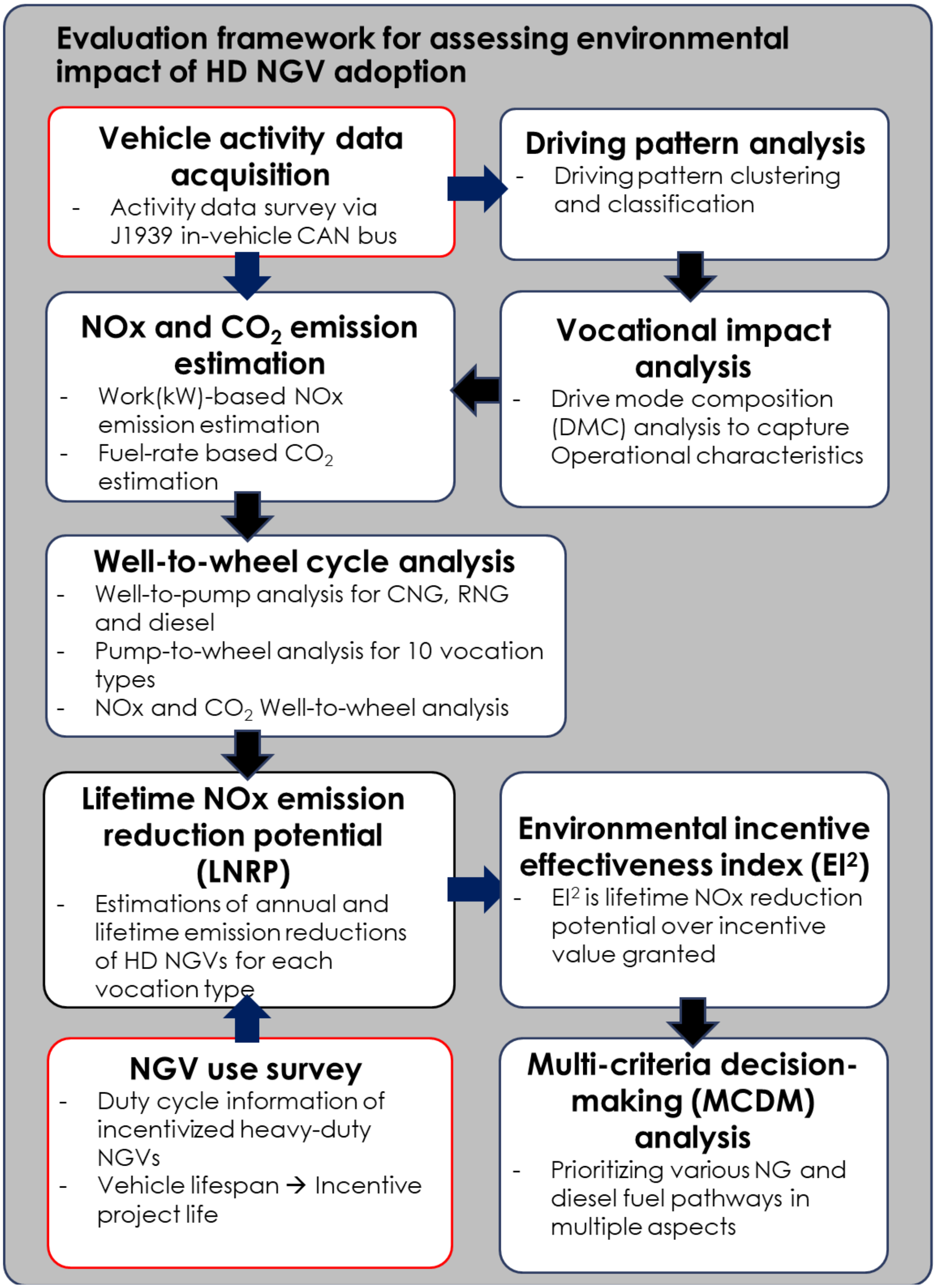

Figure 1.1. Environmental impact analysis framework of this study

1.3 Dissertation Outline

This dissertation consists of nine chapters.

Chapter 1 introduces the research background and opportunities in alternative fuel vehicle incentive projects, objectives of this dissertation, and the proposed evaluation framework.

Chapter 2 revisits the policy details of the current incentive projects and discusses the academic contributions of this dissertation compared to previous studies related to the total fuel cycle, driving pattern, and multi-criteria decision-making (MCDM) analyses.

Chapter 3 introduces the procedure of vehicle activity data survey and survey results.

Chapter 4 presents estimation procedures and results of NOx and CO_2 emissions.

Chapter 5 introduces the vocational impact analysis that captures the operational characteristics of heavy-duty NGVs and investigates causal relationships between vehicle activity patterns and emission characteristics.

Chapter 6 introduces the total fuel cycle analysis and the resulting environmental impacts of natural gas (NG), renewable natural gas (RNG), and diesel fuel pathways.

Chapter 7 presents the lifetime NOx emission reduction potential of the considered HD NGV types and predict environmental incentive effect that indicates emission reductions over the incentive values granted.

Chapter 8 presents the prioritized NG, RNG, diesel fuel pathways by considering multiple criteria.

Chapter 9 provides concluding remarks. This chapter discusses the contributions of this dissertation and potential future studies. Associated policy implications are discussed and address the anticipated contributions of the proposed incentive policy and evaluation framework.

Chapter 2 Literature Review

The proposed evaluation framework integrates various data sources and analytical methods, and this chapter discusses the academic contributions of the relevant assessments and research efforts.

2.1 Total fuel cycle analysis

Total fuel cycle analysis (TFCA), also known as Well-to-Wheel (WTW) analysis or life-cycle analysis (LCA), estimates the total emissions associated with the whole process of energy production from the fuel source ("wells"), distribution through various transportation modes to the stations ("pumps"), to consumption in vehicle engines ("wheels"). WTW analysis consists of the Well-to-Pump (WTP) cycle and the Pump-to-Wheel (PTW) cycle (*16*).

The California Energy Commission conducted a TFCA for 17 different vehicle and fuel type combinations with more than 50 fuel pathways (*17*). It was discovered that renewable natural gas (RNG) is the most environmentally favorable fuel pathway among methane-based fuels in terms of its environmental impacts. The NG WTW analysis of Cai et al. (*18*) asserted that NGVs consume less water and produce fewer NOx and PM emissions in comparison to conventionally fueled trucks. Wang et al. (*19*) conducted a full fuel cycle analysis of the energy and emissions impacts of transportation fuels produced from natural gas using the GREET1 (Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation) total fuel cycle analysis (TFCA) tool. The study considered eight fuel types produced from natural gas for five vehicle types. The GREET1 model had to be modified to estimate emissions from heavy-duty trucks because the model supports only light-duty vehicles (*8*). Wang et al. (*19-21*) later improved the GREET model and released the 2018 version with updated fuel pathways and parameters of upstream stages.

Despite these improvements, the broad focus of TFCA methods has left gaps in their sensitivity to vocational applications. These gaps motivated this study to obtain activity data from a variety of vocational vehicles in service and to estimate their environmental impact.

Many previous LCA studies have asserted that the environmental benefits of AFV adoption should be assessed in a total fuel cycle analysis (TFCA) to explain the total emissions produced during production, distribution, and consumption of energy (*16-22*). However, previous studies have aggregated key parameters for pump-to-wheel (PTW) analysis due to a lack of data sources from diverse heavy-duty vehicle types and vocations (*16*). Although these TFCA results may show the general environmental benefits of alternative energy use, the aggregation may not accurately reflect the incremental benefits of adopting AFVs making them less useful for deciding whether to adopt alternative fuel vehicles for specific vocational applications. Neither lab tests nor macroscopic emission models are capable of considering various vocation types, meaning that the emission rates used are insufficient to reflect in-use emissions produced by heavy-duty vehicles.

Furthermore, recently introduced low NOx engine models offer far lower emissions compared to conventional CNG and diesel engines. The current TFCA tools, however, do not consider the impact of such near-zero emission vehicle operations. The near-zero low NOx engines are certified to the optional NOx emission standard (*23*), which is 0.02 grams per bhp-hour, while clean diesel and most modern conventional CNG 8.9-liter engines emit approximately 0.13 grams per bhp-hour. This study compared the environmental impacts of the low NOx, conventional CNG, and diesel engine vehicles to consider the benefits of these near-zero technologies. Because the low NOx engines are more expensive than their counterparts and customers are being offered additional incentives for the low NOx engine, this study includes an environmental incentive effectiveness index in the multi-criteria decision-making (MCDM) analysis to prioritize the fuel pathways.

To estimate and compare WTP emissions rates of different fuels, this study used the California Air Resource Board's CA-GREET model (*24*). The proposed PTW analysis demonstrated how vehicle activity data could be used to customize the input parameters of the WTW analysis framework. The resulting life-cycle emission estimates were more sensitive to vocational performance differences, and this approach allowed fleet managers or policy practitioners to determine the vocation-specific adoption impacts of AFVs.

2.2 Heavy-duty vehicle activity data collection

Substantial research efforts have been made to investigate the operational characteristics of heavy-duty commercial trucks due to their significant economic and environmental impacts on emissions inventory. A joint research project in 1999 between the California Air Resources Board (CARB) and Federal Highway Administration (FHWA) aimed to analyze characteristics of heavy-duty truck travel and improve the heavy-duty truck activity data that are used in forecasting on-road emissions (*25*). The obtained GPS data was used to assess driving, trip, and start patterns of study vehicles sampled from geographic regions and weight class groups. The study mainly focused on diesel-powered commercial truck activities and a relationship between vehicle speed and emission characteristics (*26*).

Borisboonsomsin et al. (2011) conducted a heavy-duty truck activity data survey, and the obtained data includes electronic control unit (ECU) summary data and telematics-based vehicle tracking data to improve the MOtor Vehicle Emission Simulator (MOVES) which is one of the popular emission models. The study presented distributions of distance and duration per trip by operation area type, highway functional, and vehicle weight classes, which can be used as input data for MOVES *(27)*. The ECU summary data contains aggregated data and is limited to show various engine performance-related parameters.

Borisboonsomsin et al. (2016) obtained detailed ECU data via J1939 data protocol from 90 heavy-duty diesel trucks and assessed the impact of selective catalytic reduction (SCR) temperature on nitrogen oxides (NOx) emission rates (*28*). The study vehicles were sampled based on the EMFAC2011 (EMission FACtors) vehicle categories and various vocation types. The analysis results show the significant regional impacts on the variations of the ambient, engine, and Selective Catalytic Reduction (SCR) temperature. The participated commercial trucks are diesel-powered, which means that the subject trucks have different emission characteristics from NGVs. Moreover, the structure and size of the diesel truck market are quite different from those of NGVs. Thus, the analysis results were limited to explain the operational characteristics of HD NGVs.

Since the previous studies have focused on the diesel vehicle types, not many studies on the natural gas trucks and their vocation types have been conducted. The most recent cross-vocational data analysis on NGVs is done by Fleet DNA: commercial fleet vehicle operating data of the National Renewable Energy Laboratory (NREL). Due to the huge population of diesel trucks, the fleet operation data was mainly collected from diesel vehicles, and NGV data takes a relatively small portion. 4% and 5% of total trips and total travel distance respectively are provided by NGVs.

The Fleet DNA activity data includes numerous parameters derived from vehicle speed, and it helps researchers to understand the general operational characteristics of NGVs. However, GPS-based vehicle speed data is likely to have severe error data in urban areas. This study used a data collection device that is capable of obtaining ECU and GPS data simultaneously so that it was possible to analyze spatial-temporal vehicle activities in multi-dimensions of various engine parameters.

2.3 Driving pattern analysis

Considerable research efforts have been made to capture the operational characteristics of HDVs in service and investigate diverse vehicle activities. Although the reviewed papers had different research goals, a collective research task was related to the characterization and generalization of observed vehicle activities to derive meaningful findings. Many previous studies have emphasized the importance of driving pattern analysis, with a particular focus on the estimation of emission inventory, because emission rate does not linearly increase as speed increases. For example, when a vehicle is coasting, tailpipe emission rates and engine speed can be relatively lower than the other driving states. Internal combustion engine vehicles produce GHG emissions and criteria pollutants in idling status and more after the extensive idling operation due to the lowered efficiency of after-treatment systems.

2.3.1 Production of micro driving patterns

A common practice to process activity data in the previous studies is refining vehicle activity data into micro driving patterns, which are defined by successive two stopping events. Lin et al. (29) divided data into small driving patterns by assuming that a new pattern started every time the vehicle came to a stop. Liaw (30) also used a similar scheme in which the data was broken down into sequentially isolated 'driving pulses,' each representing an active driving period bounded by two adjacent stops. Dai et al. (31) also used stops to define the micro driving patterns, which they called micro-trips. Yokoi et al. (32) used a slightly different method that divides the obtained data into micro driving patterns based on the distance traveled, such as 100 meters. These approaches often found that too many short driving patterns that last 2 ~ 3 seconds and seem to be useless in pattern analyses. To exclude the meaningless driving patterns, Larsson and Ericsson (33) used a speed threshold of 2mph, which successfully improved the equality of the patterns identified. This study adopts the Ericsson's speed pattern threshold to divide the obtained speed trajectories.

2.3.2 Driving pattern analysis

Once the micro-patterns are defined, a typical data treatment is to compute summary statistics to classify the driving snippets, and then the driving pattern groups that constitute the drive cycle, representing on-road driving patterns, as shown in Larsson and Ericsson (*33)*, Wang et al. (*34*), Ericsson (*35*), Hung et al. (*36*), Lin et al. (*37*), and Brundell-Freij et al. (*38*). Typically, the summary statistics are aggregated values per pattern and include average, median, and standard deviation for speed, acceleration, and deceleration, etc. These statistics can be easily generated from speed parameters but are challenging to obtain optimal classification thresholds for whole datasets. Furthermore, they are relatively abstract pattern features that lack explanatory power compared to features capturing pattern-shape and joint-distributions (*39-40*).

Speed and Acceleration Frequency Distribution (SAFD, also known as a Watson plot) had been popularly used in previous pattern analyses because emission rate does not exhibit a linear relationship with vehicle speed and acceleration. For instance, Nesamani and Subramanian (*41*) developed a driving cycle for intra-city buses in a city of India using speed and acceleration frequency distribution. The SAFD is known to effectively address the non-linear relationship between emission rates and vehicle speed; however, the SAFD matrix is likely to have too many empty cells or zero values to be used in statistical analyses.

Another set of studies focuses on classifying micro driving patterns using thresholds for identifying operating modes. Bata et al. (*42*), Dembski et al. (*43*), Gu and Rizzoni (*44*), and Rapone et al. (*45*) set speed bins to classify driving patterns. For instance, Bata et al. (*42*) classify driving patterns into modes using an acceleration threshold of 0.03 m/s^2 to define accelerating and decelerating modes. Below those thresholds, a vehicle is considered to be in cruise mode if its speed is greater than 0.3 m/s (0.67 mph) and in idle mode, if the speed is less than 0.3 m/s. Nesamani and Subramanian (*41*) defined five operating modes as: idling (speed equals zero), cruising mode (speed > 3.1 mph (5km/h) and acceleration > 0.1 m/s2), creep mode (speed < 3.1 mph and absolute acceleration < 0.1 m/s2), accelerating mode (acceleration rate > 0.1 m/s2), and decelerating mode (acceleration rate < -0.1 m/s2). Dembski et al. (*43*) categorized driving patterns based on the average speed of the patterns. An urban driving trip is outlined for pattern mean velocities less than 20 mph, while a road driving trip is defined for the mean velocity between 20 and 35 mph (*43*). If the average speed of a driving pattern exceeds 35 mph, the driving pattern is classified as a highway driving trip.

Borisboonsomsin et al. (2*8*) calculated the operation mode (OpMode) matrix based upon computing the vehicle-specific power for MOVES (Motor Vehicle Emission Simulator) using in-vehicle CAN data from HD diesel trucks. Because the element values of the OpMode matrix tend to concentrate on a certain OpMode in a driving pattern, it is likely to have many zero values, which lack the discrimination power of the pattern feature. Most vehicle activity parameters do not follow a Gaussian distribution; therefore, it is difficult to use conventional statistical tests for comparisons of the pattern features derived from vehicle speed. Barth and Borisboonsomsin (*46*) showed that different driving pattern compositions are more tightly correlated with vehicle fuel consumption, such that total fuel consumption can be significantly reduced by practicing eco-driving behavior, involving smooth acceleration and deceleration, maintaining steady speeds, and coasting to a stop with efficient transmission gear shifts.

Prohaska et al. (*47*) and Fotouhi et al. (*48*) conducted pattern clustering analyses and then classified micro driving patterns into driving mode groups. Prohaska et al. focuses on the operational characteristics of diesel drayage trucks in port areas and used the average and maximum speed of each driving pattern to conduct the k-medoids clustering analysis. Fotouhi et al. used the k-means clustering method with average speed and idle time percentage of each micro trip to develop representative driving cycles for Tehran. The clustering method shows outstanding results for pattern classification and is useful in the visualization of the distances between the driving mode partitions.

2.4 Alternative fuel vehicle incentive programs and impact analysis studies

The California government set the emission reduction goals as 1) Reducing GHG emissions to 1990 levels by 2020, 2) Reducing GHG emissions to 40 percent below 1990 levels by 2030, 3) Reducing GHG emissions to 80 percent below 1990 levels by 2050, 4) Reducing short-lived climate pollutant emissions, such as methane, to 40 to 50 percent below 2013 levels by 2030. The transportation sector is responsible for reducing 39% of state GHG emissions (*49*). The California legislature passed Assembly Bill 118 (Núñez, Chapter 750, Statutes of 2007). This legislation created the Alternative and Renewable Fuel and Vehicle Technology Program (ARFVTP), which provides up to $100 million per year for projects that facilitate fuel transition in California through 2024 (a total of $745 million) (*12*). The California Energy Commission ARFVTP (Reference California Health and Safety Code 44270-44274.7 and California Code of Regulations, Title 13, Chapter 8.1) supports $10 million per year to Natural Gas Vehicle Incentive Program (NGVIP), and its incentive structure is presented in **Table 2.1**. The project offers $25,000 for heavy-duty NGVs that are 33,001 lbs. and greater. For the past decade, the ARFVTP has invested more than $745 million on a variety of alternative fuels and vehicle technologies. (*49*)

Table 2.1. NGVIP incentive levels

GVWR (lbs.)	Incentive amount ($)
Up to 8,500	$1,000
8,501-16,000	$6,000
16,001-26,000	$11,000
26,001-33,000	$20,000
33,001 & greater	$25,000

The HDV and off-road equipment investment (SB 1204) of Low Carbon Transportation Investments and the Air Quality Improvement Program has funded the Hybrid and Zero-Emission Truck and Bus Voucher Incentive Project (HVIP) and Low NOx Engine Incentives (*50*). HVIP provides vouchers of up to $300,000 for California purchasers and lessees of zero-emission trucks and buses, up to $30,000 for eligible hybrid trucks and buses, and up to $45,000 for low NOx engines on a first-come, first-served basis. HVIP has supported 7,114 clean vehicle adoptions with $349 million (31.2 million for NGV adoption) (*11*).

The goods movement emission reduction project (*13*) funded by the Proposition 1B program has invested $892 million and provides monetary incentives up to $200,000 for heavy heavy-duty trucks operated on California's trade corridors (*13-14*). Many other incentive programs are also available for alternative fuel light-duty vehicle adoption (*51*), such as Clean Fuel Reward Program (52), Clean Vehicle Rebate Project (*53*), Clean Vehicle Assistance Program (*54*).

Most incentive projects can be categorized into two types of incentives. The first type of incentive is monetary incentive type, and the other one is a policy incentive type. The fiscal incentive program offers upfront financial benefits, while policy incentive types provide non-monetary benefits, such as High occupancy vehicle (HOV) and high occupancy toll (HOT) exemption for clean vehicles in California (*55*).

As an alternative energy vehicle incentive program demands a very large budget, many studies have been conducted to assess the effectiveness of AFV incentive policies. Mersky et al. (*56*) investigated the effect of incentives on per-capita electric vehicle (EV) sales among the municipalities and regions of Norway. On both the regional and municipal levels, the number of charging stations is the most influential factor, while personal EV purchases are sensitive to median household income only on the municipal level. Lévay et al. (*57*) investigated the causal relationship between costs and sales of EVs and the impact of financial incentives, which reduce TCO and increase EV sales. The study calculated the total cost of ownership (TCO) and conducted a comparative analysis for TCO values of EVs and internal combustion engine (ICE) vehicles in eight European countries. The TCO of Norway is lower than that of ICE counterparts, while TCO values of Netherlands, France, and the UK are similar to the TCO of ICE pairs. For the rest of the countries, the TCO of EVs is higher than the corresponding ICEs.

Bjerkan et al. (*58*) attempted to investigate the role of EV incentive programs and what kind of incentive types is effective to promote battery electric vehicle (BEV) sales. 80% of all respondents declared that exemptions from purchase tax and VAT are critical for purchasing EVs. This result is consistent with Gass et al. (*59*), Jin et al. (*60*), Brand et al. (*61*), Tal and Nicholas (*62*), and David Diamond (*63*) and these papers highlighted that up-front price reduction is the most powerful incentive in increasing EV and hybrid-electric vehicle (HEV) adoptions. Tal and Nicholas (*62*), notably, argued that the incentive is critical for low-priced BEV purchases, while not crucial for high-end BEVs. It means that quite a few high-end BEV purchasers would buy the cars without fiscal support. Hardman and Tal (*64*) also support this argument. Another suggestion of Gil Tal and Michael Nicholas is that incentives should support more BEVs and PHEVs with high electric driving ranges than the vehicle types with low electric ranges. It is because the incentive is less important for the purchasers who drive PHEVs with lower electric driving ranges.

Robert Kok (*65*) assessed the impact of CO_2-based tax incentives for low-carbon light-duty cars in the Netherlands. The tax incentives provided 13 gram/km, or 11% lower average CO_2 emissions in 2013. This incentive program achieved 4.6 million tons of potential lifetime CO_2

abatement from the new light-duty cars sold between 2008 and 2013 at the cost of 30 to 50% of decreased tax revenues.

In addition to the above financial support, the seven fleet rules of the South Coast Air Quality Management District (SCAQMD) in Southern California mandate that public and private fleets are operating in a set of specific alternative fuel vehicles if their fleet size is 15 or more (*66*). Because of these rules, most conventionally powered vocational vehicle types are likely to be replaced with alternative fuel vehicles (AFVs), particularly in the public sector. In light of the potential of the NGV market, a better understanding of heavy-duty truck activities is an essential component for studies on the strategic emission abatement plan. Furthermore, it is expected that the population of AFVs will gradually increase until the current emission levels meet the state's goal with the successful implementation of the above projects.

2.5 Difference of CO_2 emission and fuel economy between diesel compression-ignition (CI) and natural gas spark-ignition (SI) engines

The CO_2 emission estimation method of this study relies on instantaneous fuel rates (liter/hour) obtained from vehicle ECU with the assumption that carbon content is maintained between pre- and post-combustion. In order to estimate CO_2 emissions of diesel vehicle scenarios, this study adjusted instantaneous horsepower values based on the difference in CO_2 emissions and fuel economy between compression-ignition (CI)and spark-ignition (SI) engines, as provided by Johnson et al. (*67*), who noted that stoichiometric SI natural gas engine would emit approximately 20% less CO_2 than diesel engines. This is because natural gas (NG), which is primarily composed of methane, contains less carbon per unit energy than diesel; therefore, the resulting tailpipe exhaust is likely to contain less CO_2. CI diesel engines, however, offer about 10 to 15 % higher thermal efficiency than SI NG engines. Consequently, the lower thermal efficiency of SI NG engines partially negates the environmental benefits from the lower carbon content of NG.

Clark et al. conducted chassis dynamometer tests for diesel and CNG transit buses. Emissions of CO_2 from the natural gas transit buses averaged 11.6% lower compared with CO_2 emissions from the diesel-fueled buses (*68*). Ayala et al. also conducted chassis dynamometer tests for diesel and CNG transit buses over various driving schedules, such as 55 mph steady-state (SS) cruise, Central Business District (CBD), Urban Dynamometer Driving Schedule (UDDS), and New York City Bus Cycle (NYBC). The CNG transit bus produced 21.2%, 7.6%, 10.5%, and 2.1% lower CO_2 emissions than diesel transit buses over the considered driving schedules, respectively (*69*). Lyford-Pike et al. measured various emission species of 12 CNG and diesel trucks over the Urban Dynamometer Driving Schedule (UDDS) and Viking drive cycles. The subject CNG vehicles emitted 7% and 6.5% lower CO_2 emissions than diesel counterparts over UDDS and Viking cycles, respectively (*70*).

Hesterberg et al. referred to numerous previous experimental studies and compared criteria pollutants and GHG emission rates of refuse trucks, school buses, and transit buses empowered by diesel fuel and CNG, respectively. For the most vehicle types, fuels, and after-treatment systems, NOx and CO_2 emission rates were similar except for diesel school buses which provide 25% higher CO_2 emission rates than the CNG buses (*71*). Lopez et al. compared GHG emissions from diesel, biodiesel, and natural gas refuse trucks, and the analysis results present 13 % less CO_2 emission production from CNG trucks compared to diesel counterparts. The study also presented that CNG SI engines operating the Otto cycle have lower thermal efficiency than diesel CI engines (*72*). Quiros et al. presented in-use CO_2 emission rates of diesel, hybrid diesel, and CNG tractor trucks and the CNG truck data shows 11.6% less carbon dioxide per mile than the five diesel vehicles (73).

Assuming that CO_2 emissions are a proxy measure of fuel consumption, this study reviewed previous studies on the comparisons of fuel economy from diesel CI and NG SI engine vehicles. Lyford-Pike et al. (*70*) found that the fuel economy penalty for NGVs was about 20% compared to diesel vehicles. Tong et al. (*74*) found that diesel engines show approximately 10% better fuel efficiency than NG engines with various vocation types, such as refuse, transit, and haulers. Dominguez-Faus (*8*) assumed that NG SI engines are 10-15% less efficient than diesel, and the resulting fuel economy of the diesel trucks is 14.2% more efficient than the study NG trucks. Based on this literature, this study followed Tong et al. and assumed that diesel compression-ignition (CI) engines consume 10% less energy than NG spark-ignition (SI) engines. As such, this study converts ECU fuel rates of the subject NGV data into therms and then reduce them by 10% to estimate CO_2 emissions for diesel vehicle scenarios.

2.6 Multi-Criteria Decision-Making Analysis

NOx and CO_2 emission species are different tailpipe exhaust types making it difficult to aggregate them into a single factor. Furthermore, the life-cycle emission rate alone is insufficient to explain the validity and feasibility of AFV adoption fully because government agencies need to consider not only the environmental benefits of AFVs but also the sustainability of the incentive programs and relevant emission reduction programs. Multi-criteria decision-making analysis (MCDM) is commonly used for situations such as these in which the goal is to identify the best alternative based upon criteria that cannot be combined into a single metric.

MCDM is an evaluation technique that compares available alternatives with various qualitative and quantitative criteria to find the best choice or strategy in the given situation. Among the numerous MCDM methods, the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is one of the most popular. Hwang and Yoon developed TOPSIS in 1981 (*75*), and Nădăban et al. (*76*), Kuo (*77*), and Krohling et al. (*78*) were helpful to understand the basic concepts and methodologies of the TOPSIS. Chen et al. (*79)* provides well-organized reviews about the variations and evolution of the TOPSIS methods.

TOPSIS identifies the best alternative by finding a solution that has the shortest geometric distance from the positive-ideal solution (PIS), and the longest geometric distance from the negative ideal solution (NIS). The PIS consists of all the best values attainable of the criteria; therefore, it minimizes the cost criteria and maximizes the benefit criteria. NIS is composed of all the worst values attainable of the criteria and maximizes the cost criteria and minimizes the benefit criteria (*76*). TOPSIS has been used in a variety of research areas, such as economic and stock market analyses (*80*), commercial product evaluations (*81*), and energy selection problem studies (*82-84*).

According to Lee and Chang (*85*), MCDM methods are popular in energy selection problems because the MCDM methods allow considering multiple and conflicting criteria. Available renewable energy sources for electricity generation in Taiwan were evaluated and ranked up based on various criteria. The analysis results show that Hydro is the best alternative for Taiwan, followed by solar. Ümran Sengül et al. (*82*) proposed a multi-criteria decision support framework for comparing renewable energy supply systems in Turkey. TOPSIS results concluded that hydropower station is the top prioritized energy supply system for Turkey, followed by Geothermal Power Station.

Kim (*84*) used the fuzzy decision-making approach to solve the optimal energy selection problem with ten energy alternatives. As a result, solar energy is the top-scored energy alternative, followed by wind and biomass. Buyukozkan and Guleryuz (*83*) used a hybrid fuzzy MCDM methodology to evaluate the sustainable energy alternatives for Turkey. The analysis result presented that nuclear energy is the highest scored alternative. As shown in Buyukozkan and Guleryuz (*83*) and Lee & Chang (*85*), the previous studies considered various kinds of criteria, such as economic, technical, social, and environmental criteria; therefore, the alternatives were assessed by considering multiple perspectives.

The decision analysis requires a set of weights for the considered criteria, and the decision analysis results can significantly vary depending on these assigned weights. This means that the weighting process is the most critical step in the MCDM analysis. Previous studies obtained weight values by conducting surveys (*84*) or using the Shannon entropy method (*82-83)(85*). This study set multiple weight value scenarios and conducted a sensitivity analysis assessing the impacts of different weight vectors. Depending on the applied weight value set, each scenario focuses on different criteria in the determination of the best alternative among the fuel and vehicle alternatives.

2.7 Summary and research opportunity

2.7.1 Total fuel cycle analysis

Numerous fuel lifecycle studies have been conducted to compare the environmental impacts of various fuel pathways. It is essential to recognize the fuel cycle emissions as well as vehicle cycle emissions because no alternative fuel type is possible to offer net zero-emissions. This study used the GREET.net of Argonne National Laboratory and CA-GREET of the California Air Resources Board to compare the environmental impacts of CNG, RNG, and diesel fuel pathways. In addition, this study demonstrated how vehicle activity data collected from standard in-vehicle controller area networks (CAN) could be used to customize input parameters of the TFCA framework, which reflect fuel consumption and emission production of the subject vehicles. The resulting life cycle emission estimates are more sensitive to vocational performance differences, which allows fleet managers or policy practitioners to determine the vocation-specific adoption impacts of AFVs using life cycle analysis.

2.7.2 Heavy-duty vehicle activity data collection

The previous activity data collection projects focused on heavy-duty diesel trucks, which are mainly being used for freight transportation; therefore, the investigated truck activity types lack diversity and the resulting emission characteristics only support diesel-powered vehicle applications. Natural gas and other alternatively fueled vehicles and their related vocations have received less attention than the leading player in the market despite the cleanness of the alternatives. Considering the vehicle population and infrastructure network scale of HD NGVs, NGV applications are the most viable fuel and vehicle technologies among the alternative fuel vehicle types. Thus, NGVs are expected to take a crucial role in emission reduction plans of the state.

2.7.3 Driving pattern analysis

Depending on the research goal, researchers should select a proper data treatment process to transform the obtained raw data into appropriate evaluation metrics. When we, for instance, compare fuel economy values of two vehicles, one of the vehicles can show a higher fuel economy than the other. The metric, fuel economy, exhibits fuel consumption of the subjects; however, it is limited to explain why it does. The reviewed vehicle activity and pattern studies demonstrate that the micro driving pattern analysis can effectively capture operational characteristics with drive mode composition (DMC), also known as drive mode distribution. DMC indicates the total amount of operating time for each driving mode; therefore, it is possible to explain the difference in fuel economy values of the two vehicles. The presented causal relationships between the drive mode composition, traffic environments, and the resulting environmental impacts of the subject vehicles are expected to show a clearer picture of emission characteristics over duty cycles.

2.7.4 Alternative fuel vehicle incentive programs and impact analysis studies

Previous incentive policy studies mainly focused on the determination of effective incentive types and influential factors for promoting alternative fuel light-duty vehicle adoption. Due to the immature clean vehicle technologies and market, it has been difficult to predict the environmental impact of emerging clean vehicles. Therefore, not many research efforts have been made to assess the effectiveness of the incentive programs and associated influential factors, such as operational conditions, business type, vehicle cost, incentive type, regional effects. The previous studies commonly concluded that up-front price reduction is the most effective in AFV adoption and a limited amount of studies have been conducted to assess the performance of incentive projects.

The HDV incentive projects offer monetary benefits based on vehicle gross vehicle weight rating (GVWR), while the light-duty vehicle incentive projects often provide different benefits according to the income level of purchasers. The incentive is to compensate for the price premium of alternative fuel vehicles. The vehicle cost, however, varies by vehicle class and vocation type. It means that HDVs can have different incentive benefits depending on vocation type, and the resulting environmental benefits cannot be consistent in the same GVWR group. This study investigated the incentivization impact of the subject NGVs by vocation type and argued that the incentive projects could be further improved by re-designing the incentive structure based on the suggested emission benefit measures.

2.7.5 Multi-Criteria Decision-Making Analysis

MCDM analysis can compare alternatives in multiple aspects; therefore, it has been popular in energy-related problems. This is the reason that this study chose the method for the prioritization of the fuel pathways. Compared to conventional MCDM analysis studies on energy problems, this study considered new criteria that reflect the impacts of incentivization and operational characteristics of the subject vehicles. This study set multiple weight value scenarios to conduct sensitivity analysis. Depending on an applied weight value set, each scenario focuses on different criteria in the determination of the best fuel pathways among the fuel and vehicle alternatives.

Chapter 3 Vehicle activity data and duty cycle information acquisition

3.1 Purpose and background

The California Energy Commission (CEC) operates a number of programs under its Alternative and Renewable Fuel and Vehicle Technology Program (ARFVTP) to reduce the upfront cost of alternative fuel vehicles, accelerate the deployment of such vehicles, improve air quality in heavily impacted regions, and strategically support alternative fuel vehicles. One of these programs is the Natural Gas Vehicle Incentive Program (NGVIP), which offers monetary incentives for the purchase of NGVs in California. The survey task focused on the collection of technology-specific deployment data from the planned use of NGVs operated by private and public entities receiving incentives. The NGVIP has involved three general classes of end-users of the incentive program:

- Freight fleet operators
- Non-freight fleet operators, which may include bus, utility, and lightweight delivery fleets
- Consumers purchasing light-duty vehicles for personal use

3.2 Survey instruments

The NGV use survey was conducted by using two survey instruments. The first instrument is ECU data loggers which are also known as On-Board Diagnostics (OBD) reader and the main device of this survey task. This survey instrument was used to collect vehicle activity data from the incentivized NGVs. The second one was designed to obtain duty cycle information for predicting annual and lifetime emission benefits of the subject vehicles. This study procured fifteen OBD-II/J1939 data loggers for the proposed survey task.

3.2.1 Instrument 1 (J1939 data collection from NGVs)

Survey participants were asked to install a Global Positioning Device (GPS) and OBD reader into their NGVs for at least two weeks. **Figure 3.1** shows an example of the data logger installed in a heavy-duty truck. The data collection period varied with the operational schedules and conditions of the survey participants. This instrument gathers high-resolution data on trajectories and engine performance characteristics of participants' vehicles to understand how vehicles are deployed in practice. The obtained datasets were used to estimate NOx and CO_2 emissions of the subject vehicles and conduct driving pattern analyses.

3.2.2 Instrument 2 ("Natural Gas Vehicle use paper survey")

In the second part of the survey, participants were asked to take a short paper survey, and the answers were used as supplement data for analyzing the obtained vehicle activity data. The survey questionnaire was designed to ask about the purchased NGV's vocation-related information. The survey sheets were included in a survey package as shown in **Figure 3.1** and sent to fleet managers. The questionnaire is presented in Appendix A.

This method depends on self-reported survey data collected from incentive recipients, such as a fleet manager, a shop manager, or an owner-operator. Each participant was asked to fill out the survey after the voucher redemption process. The data to be collected in the survey include the following information for the purchased vehicle:

- Purpose of use: commercial or personal transportation
- Information on prospective refueling station types and behaviors
- Duty-cycle and travel pattern information

- Expected vehicle miles traveled per week
- Previous vehicle and fuel types

		
J1939 CAN bus port	Example of installed data logger in a heavy-duty truck	Survey packages prepared for the data survey

Figure 3.1. Data survey instruments

3.3 NGVIP data survey procedure

The proposed survey task was carried out in a cross-sectional design. The instrument 1 is the main data survey, which was to capture the operational characteristics of the subject vehicles. The instrument 2 is to validate the instrument 1 data and a source of duty cycle information in the incentive impact analysis. Survey targets of instrument 1 were the CNG vehicles incentivized by the NGVIP and only focused on the vehicle activity, while instrument 2 was answered by fleet operators

The chronological procedure is as follows:

3.3.1 Instrument 1

a. Individuals and business representatives ("applicants") who apply for natural gas vehicle incentives were recruited for participation in the research study. Those who agreed to participate became research subjects.

b. The GPS+OBD data collection device was mailed to each survey participant with instructions on how to install the device in their vehicle.

c. Survey participants installed the data logging device in the vehicle for the data collection period (two weeks or over)

d. Survey participants returned the device to the researchers using the provided packaging.

e. Surveyors copied the electronic data from the device to a secure, encrypted electronic database.

f. Surveyors reformatted the memory of the data collection device.

g. Surveyors performed life-cycle analysis using the collected data and integrate the aggregated results into a comparative life-cycle analysis model.

h. All subject identifiers were aggregated and/or removed from the raw data after the analyses.

3.3.2 Instrument 2

a. Those subjects indicating a willingness to participate in the Instrument 2 survey were identified. Along with the data collection device (s), incentive administrators sent a paper survey (Instrument 2) to the subject to be completed at their home or place of business.

b. Following the data collection from the selected natural gas vehicles, applicant-subjects were asked to include the completed Instrument 2 with the OBD data logger return mailing.

c. The completed Instrument 2 surveys were given to the research team.

d. The surveyor encoded the data from the forms in an electronic database for analysis.

e. The surveyor performed aggregate analyses of general and annual operational characteristics of natural gas vehicles.

3.4 Obtained vehicle activity data

To support this research, vehicle activity data was obtained by using a device to read engine parameters via the in-vehicle controller area network (CAN) bus protocol. Society of Automotive Engineers standard SAE J1939 is a key protocol in CAN bus data logging and commonly used for communication and diagnostics among vehicle components. The data logging device provided accurate and high-resolution driving performance data because it is directly transmitted from the engine control unit (ECU) of the subject NGV. The ECU data is more tightly correlated with emission production than vehicle speed. Therefore, the J1939/OBD-II CAN data has a high research potential for aiding in the development of more seamless and sophisticated methodologies to alleviate the given problems.

Table 3.1. Subject CNG vehicles and specification

Service type	Bus transit		Local service			Hauling service						Utility service	
Vocation type	Urban transit	School bus	Street sweeper	Refuse truck		Long-haul truck	Short-haul truck					Utility service truck	Sewer truck
Vehicle fleet description	Urban Transit buses	School district buses	Street Sweeper in a university	Refuse trucks in San Diego	Refuse trucks in Los Angeles	Long-haul trucks	Waste transfer short-haul trucks in San Diego	Water district short-haul trucks	Waste transfer short-haul trucks in Los Angeles	Waste transfer short-haul trucks in Los Angeles	Dairy reefer trucks	Water retail crew utility trucks	Water retail sewer trucks
Group code	TB	SCHB	SWPER	RF SD	RF LA	LHT	WTSH SD	SHT	WTSH LA I	WTSH LA II	DDRT	CRWT	SWT
Model year	2016	2016 / 2017	2009	2014 / 2017	2016	2017	2014	2013/ 2014	2016	2018	2018	2011	2016
Location	Southern CA	Orange County	Orange County	San Diego County	Los Angeles County	San Francisco & Sacramento County	San Diego County	Los Angeles County	Los Angeles County	Los Angeles County	San Diego County	Orange County	Orange County
Make / Model	New flyer / XN40	Thomas / HDX & C2	Elgin broom sweeper	Autocar / ACX	Peterbilt /320	Kenworth / T680	Autocar / ACX	M2112 / Daimler	Peterbilt / 365	Kenworth / T880	Kenworth / T680	Condor / American La Frnace	Kenworth / T880
Number of vehicles in fleet	3	2	1	4	3	6	2	2	3	7	1	3	3
Data length (operation hour)	166.9	77.6	78.1	175.2	370.6	244.9	82.0	151.5	157.2	268.5	59.4	99.2	169.4
Total distance traveled (mile)	1755	1117	462	1113	3043	3405	1030	1916	3503	11670	1217	1050	4909
Average driving speed (mph)	19.29	18.63	6.69	8.57	9.51	19.65	13.25	18.06	15.38	16.60	18.01	14.78	13.48
Engine dimension (Litre)	8.9	8.9/6.7	5.9	8.9	8.9	11.9	8.9	8.9	11.9	11.9	11.9	8.9	11.9
Total working days of the group	21	14	27	24	56	58	12	66	47	58	15	104	45
Gross Vehicle Weight Rating (lbs.)	42,540	33,000	33,000	60,000	58,000	54,320	80,000	80,000	80,000	80,000	54,320	33,000	80,000
NOx emission rate (g/bhp-hour)	0.13	0.13/ 0.08	1.44	0.13 / 0.01	0.13	0.15	0.13	0.13	0.15	0.01	0.01	0.13	0.15

This study computed the adoption impact of 40 NGVs operating in California across ten different vocation types as shown in **Table 3.1,** including a street sweeper, three transit buses, six long-haul trucks, a dairy distribution reefer truck, two school buses, six retail water service trucks, twelve waste transfer short-haul trucks, two water district short-haul trucks, and seven refuse trucks. Since the operating conditions and availability of each fleet differed, this study attempted to collect as much activity data as possible from a variety of vocation types. By the end of the collection effort, this study obtained a total of 2,100 operating-hours of activity data, which is sufficient to cover the duty cycles of the subject NGVs.

3.4.1 Parameter IDs used in the assessments

Table 3.2 presents the ECU parameters obtained from the presented activity data survey. The listed parameters were primarily used to calculate vehicular emissions and recognize the driving status.

Table 3.2. ECU parameters used in the assessments

	PIDs	Purpose
Time	Time	Time detection
	Date	
Torque	Actual Maximum Available Engine - Percent Torque (%)	Torque calculation
	Actual Engine - Percent Torque (Fractional) (%)	
	Actual Engine - Percent Torque (%)	
	Driver's Demand Engine - Percent Torque (%)	
	Engine Demand ï¿½ Percent Torque (%)	
	Estimated Pumping - Percent Torque (%)	
	Nominal Friction - Percent Torque (%)	
	Estimated Engine Parasitic Losses - Percent Torque (%)	
RPM	Engine Speed (rpm)	Driving status detection
Idle time	Idle Time (s)	
Speed	Wheel-Based Vehicle Speed (kph)	
	Engine's Desired Operating Speed (rpm)	
	Desired Operating Speed Asymmetry Adjustment (Ratio)	
	Engine Percent Load At Current Speed (%)	
GPS	Latitude	Road facility type identification
	Longitude	
	Altitude	
	Velocity	
	Heading	
Pressure	Engine Fuel Delivery Pressure (kPa)	Engine diagnosis
	Engine Extended Crankcase Blow-by Pressure (kPa)	
	Engine Intake Manifold #1 Pressure (kPa)	
	Engine Intake Air Pressure (kPa)	
	Barometric Pressure (kPa)	
	After-treatment 1 DPF Intake Pressure (kPa)	
Temperature	Engine Fuel Temperature 1 (C)	Emission factor calibration
	Engine Oil Temperature 1 (C)	
	Engine Intake Air Temperature (C)	
	Engine Intercooler Temperature (C)	
	Engine Intake Manifold 1 Temperature (C)	
	Engine Exhaust Temperature (C)	

3.5 Surveyed duty cycle information

The paper-based survey obtained the following answers from fleet managers and operators. Several questions and answers are related to private information of the fleets; therefore, the questions were omitted in the tables. The following tables present answers directly written by the survey respondents.

Table 3.3. Survey ID and basic information of subject vehicles

Question number			Basic Q2	Basic Q5
Vehicle group	Survey Vehicle Number	Survey date	Model and Make	Odometer (miles)
Urban Transit buses	P002	08/30/17	XN60 / NewFlyer	32,355
	P003		XN40 / NewFlyer	45,279
	P001			33,977
Waste transfer short-haul trucks in SD	1008	10/11/17	ACXXPERH012 / Autocar	46,272
	1006		ACX / Autocar	73,153
Refuse Trucks in SD	1005	10/11/17	ACXXPERH012 / Autocar	3,197
	1007		ACX / Autocar	40,940
	1004		ACXXPERH012 / Autocar	5,925
	1009		ACXXPERH012 / Autocar	4,840
Waste transfer short-haul trucks in LA	2005	6/18/18	Peterbilt / 365	36,483
	2006			55,888
	2003			36,467
Refuse Trucks in LA	2004	6/18/18	Peterbilt / 320	27,245
	2002			29,649
	2001			24,009
Long-haul trucks	3001	5/31/18	T680 / Kenworth	14,287
	3002	6/20/18		14,837
	3003	5/31/18		13,400
	3004	6/5/18		15,395
	3005	6/27/18		93,557
	3006	6/1/18		74,587
School buses	5001	10/17/18	C2 / Thomas	19,958
	5002		HDX / Thomas	20,965
	5003		HDX / Thomas	18,978
	5004		C2 / Thomas	10,640
Water retail sewer trucks	4005	8/30/18	T880 / Kenworth	52,850 (1,510 hours)
	4006	8/30/18		62,825 (1,795 hours)
	4004	10/9/18		53,200 (1,520 hours)
	4007	8/30/18		25,760 (736 hours)
Water retail crew utility trucks	4001	10/9/18	Condor / American La France	Unknown
	4002			104,615 (2,989 hours)
	4003			54,075 (1,545 hours)
Dairy reefer trucks	6002	10/19/18	T440 / Kenworth	13689
	6001		T680 / Kenworth	10524
Short-haul trucks	8002	1/17/19	M2112 / Daimler	63763
	8003			35838
Waste transfer short-haul trucks in LA county	7001	3/18/19	T880 / Kenworth	9278
	7002			9278
	7003			9659
	7004			8568
	7005			980
	7006			8146
	7007			7165
	7008			4820

Table 3.4. Duty cycle information

Question number		A1	A2	A3	A4
Vehicle group	Survey ID	Working hours per day	Working days per week	VMT per week	Business type
Urban Transit buses	P002	15	5	950	Transit/Passenger Transportation
	P003	6.5	5	535	
	P001	10.75	5	535	
Refuse Trucks in SD	1008	10	5	640	Waste Management
	1006	10	5	400	
	1005	10	5	275	
	1007	10	5	350	
	1004	10	5	385	
	1009	10	5	220	
Waste transfer short-haul trucks in LA	2005	7	5	650	Waste Management
	2006	7	5	650	
	2003	7	5	650	
Refuse Trucks in LA	2004	6	5	268	
	2002	6	5	268	
	2001	6	5	303	
Long-haul trucks	3001	6	6	1,491	Freight trucking
	3002	6	7	1,641	
	3003	6	6	1,641	
	3004	6	6	1,491	
	3005	6	7	1,030	
	3006	7	7	1,537	
School buses	5001	6	5	307	Educational Service
	5002	9	5	265	
	5003	6	5	440	
	5004	6	5	413	
Water retail sewer trucks	4005	3.3	5	16.5 hours / 577.5 miles	Utilities
	4006	4.1	5	20 hours / 700 miles	
	4004	3.3	5	16.5 hours / 577.5 miles	
	4007	2.2	5	10 hours / 350 miles	
Water retail crew utility trucks	4001	5	4	Not reported	Public organization
	4002	5	4	9.5 hours / 332.5 miles	
	4003	6	4	7.4 hours / 259 miles	
Dairy reefer trucks	6002	8	5 (40)	1,000	Accommodation or food service
	6001	8	5 (40)	900	
Short-haul trucks	8002	8	4	783	Warehouse delivery
	8003	8	4	840	
Waste transfer short-haul trucks in LA county	7001	8	5	1,000	Refuse transfer
	7002	8	5	1,000	
	7003	8	5	1,000	
	7004	8	5	1,000	
	7005	8	5	1,000	
	7006	8	5	1,000	
	7007	8	5	1,000	
	7008	8	5	1,000	

Questions A1 to A4 ask operational schedule information of the subject vehicles. Most survey respondents provided identical values of working hours and days for their fleet vehicles.

This may be due to trucks in a fleet having similar duty cycles or fleet managers failing to follow up the detailed operational schedule. For example, one of the refuse truck fleet managers who participated in the survey mentioned the uncertainty of operation schedules. He noted that refuse trucks occasionally failed to pick up all assigned solid waste in residential communities. Then, the vehicles visited the communities again the next day, even if it was a weekend. Since it was unpredictable and happened often, some fleet managers had difficulty characterizing duty cycle information precisely, such as VMT per week or day and working days per week. Furthermore, school buses were operated over a planned route. However, the buses were often assigned to field-trip operations which traveled significantly longer than regular operations. Because of this type of operation, school bus fleet operators also had difficulty determining exact duty cycles.

The water retail district truck data showed extensive power take-off (PTO) operations; therefore, VMT per week and odometer questions were answered in units of operating hours and VMT both. According to the fleet manager, a common conversion factor from working hours to VMT is 35 miles per hour. Due to the high-speed operations of long- and short-haul trucks, these trucks provided relatively larger values of VMT per week than the other vocational trucks, such as refuse and bus type vehicles. The fleet operator of the dairy reefer truck fleet reported that the vehicles work 40 days per week. The answer was corrected to 5 based on the confirmation from the fleet operator.

In **Table 3.5**, transmission type question (A6) is omitted because all subject vehicles were reported as automatic transmission-equipped except for the waste transfer short-haul trucks operated in Los Angeles county. Answers of question A9 are some of the most useful and meaningful information because it can be used to assess the replacement impacts of the NGV adoptions. According to the model year of the replaced vehicles, hauling trucks were replaced with new ones more often compared to the bus type vehicles. If one assumes that the average lifespan of heavy-duty trucks is either of 150,000 or 200,000 miles, the haulers are likely to reach high mileage points earlier than the other trucks which causes a higher turnover rate. From **Table 4.5**, this study found that most of the subject NGVs refuel on an everyday basis regardless of refueling infrastructure type. One of the participating fleet managers commented that his/her fleet tries to keep the fuel level of the NGVs at 50% to 60% full because of the possibility for incidents and rescue costs.

Table 3.5. Vocation type and replaced vehicle information

Question number		A5	A7	A8	A9
Vehicle group	Survey ID	Vocation	Body type	Replaced vehicle's fuel type	Replaced vehicle's information (Engine info / reference torque / MY)
Urban Transit buses	1002	Others: Public Transit	N – 05 Transit bus	Diesel	1CEX40540LAB/1100/2001
	1003			LNG	8CEXH0540LBD/980/2001
	1001				
Refuse Trucks in SD	1008	Roll-off truck	N-10 Roll off	Diesel	ISL07 Cummins/1150/ 2008
	1006	Refuse truck	N – 07 Refuse truck	Diesel	ISC 07 Cummins / 860/ 2008
	1005				
	1007				VE D7 Volvo / 800/ 2002
	1004				ISC Cummins / 800/ 2004
	1009				
Refuse transfer short-haul trucks in LA	2005	Non-drayage - short-haul tractor	N – 08 Tractor	Diesel	5CPXH0928EBK / 1850/ 2004
	2006				
	2003				
Refuse Trucks in LA	2004	Refuse truck	N – 07 Refuse truck	Diesel	2CPXH0629ERK / - / 2003
	2002				
	2001				
Long-haul trucks	3001	Short Haul	N – 08 Tractor	Diesel	9CEXH0912XAL/1850/2010
	3002				CCEXH0912XAS / 1850 / 2013
	3003				
	3004				
	3005				
	3006				
School buses	5001	School Bus	N - 03 School bus	-	No previous vehicle prior to the adoption
	5002				
	5003				
	5004				
Water retail sewer trucks	4005	Sewer Maintenance truck	N - 10 – Sewer Jeter	-	No previous vehicle before the adoption
	4006				
	4004				
	4007	Construction Excavation			
Water retail crew utility trucks	4001	Construction utility crew truck	N – 06 Service utility	-	No previous vehicle prior to the adoption
	4002				
	4003				
Dairy reefer trucks	6002	Refrigerated transport	N - 02 Single	Diesel	6NVXHQ466AEA/650/2006
	6001		N–08 Tractor		5CEXH0661MAT/1350/2005
Short-haul trucks	8002	Short-haul	N - 10 Single flat-bed	-	No previous vehicle prior to the adoption
	8003				
Waste transfer short-haul trucks in LA county	7001	Non drayage short-haul	N–08 Tractor	Diesel	4CEXH0661MAT, MY2005 KENWORTH T800 (TIER 3 DPF)
	7002				
	7003				
	7004				
	7005				
	7006				
	7007				
	7008				

Table 3.6. Refueling behavior information

Question number		B1	B2-1	B2-2	B3	B4
Vehicle group	Survey ID	Station type	Number of refueling times per week	Refueling frequency (Average tank level before refueling)	Refueling time	Refueling station type
Urban Transit buses	1002	Maintenance yard	5	Unknown	5 mins	Fast-fill
	1003					
	1001					
Refuse Trucks in SD	1008	Terminal / Depot	5	45%	6 hours 3 mins	Time-fill
	1006			25%		
	1005					
	1007					
	1004					
	1009					
Refuse transfer short-haul trucks in LA	2005	Maintenance yard	5	60%	15 mins	Fast-fill
	2006					
	2003					
Refuse Trucks in LA	2004			33%	8 mins	
	2002			33%	8 mins	
	2001			50%	15 mins	
Long-haul trucks	3001	Maintenance yard	2	55%	20 mins	Fast-fill
	3002		2			
	3003		7			
	3004					
	3005					
	3006					
School buses	5001	Maintenance yard	5	80%	7 mins	Fast-fill
	5002	Public station / Maintenance yard		75%	2 hours 30 mins	Time-fill
	5003					
	5004					
Water retail sewer trucks	4005	Public station	5	50%	20 mins	Fast-fill
	4006					
	4004					
	4007		2		30 mins	
Water retail crew utility trucks	4001	Public station	4	60%	20 mins	Fast-fill
	4002					
	4003					
Dairy reefer trucks	6002	Public station	4	40%	12 mins	Fast-fill
	6001		8	10%		
Short-haul trucks	8002	Public station	4	50%	25 mins	Fast-fill
	8003					
Waste transfer short-haul trucks in LA county	7001	Public station	5	40%	30 mins	Fast fill
	7002					
	7003					
	7004					
	7005					
	7006					
	7007					
	7008					

3.6 Summary and conclusion of vehicle activity data acquisition

This study obtained vehicle activity data and duty cycle information to assess operational and emission characteristics of the HD NGVs operating in California. 40 HD NGVs of 10 entities participated in the NGV use survey and provided the equivalent number of survey answer sheets as well as a total of 2,100 operating-hours of activity data. The survey results were used to estimate the regulated pollutants and greenhouse gas (GHG) emissions savings attributable to the incentive program assessment as well as in the development of an evaluation framework for predicting air quality impacts of NGV adoption.

According to the paper-based survey results, the HD NGVs in the same fleet are likely to have similar operating conditions, such as working days per week and operating hours per day. Overall, survey results show that each vehicle had a different average VMT per week. Inter-group differences of weekly VMT were significantly larger than intra-group differences. This provided the research motivation to investigate the heterogeneity of operational and emission characteristics of various vocation types. If VMT is the sole metric to assess the environmental impacts, long-haul trucks are likely to be the largest source of mobile source emission inventory. This study discussed the limitation of VMT-based emission factors in the driving pattern analysis and PTW analysis chapters. In addition, the survey results brought up a question about the differences between the perception of fleet operators on their vehicle operation and actual activity logs recorded via the in-vehicle CAN bus protocol. This study found that the operating time and distance information was not always consistent with the paper survey answers.

The paper-survey results can be used to design the future survey process which aims to investigate the CNGV market status and customer preference. The future survey should include economic perspective and customer experience related questions to capture a comprehensive picture of CNG commercial vehicle operating businesses. For example, refueling behavior information can be used to assess causal relationships between fuel type, vocation type, refueling behavior and environments. If the survey results can be integrated with other publicly available datasets, it would be possible to improve our understanding of the market status and enhance the capability to predict future market transformations.

Chapter 4 Estimation of nitrogen oxides (NOx) and carbon dioxide (CO_2) emission rates

4.1 Estimation of NOx emission rates using in-vehicle CAN data

EMFAC2017 (EMission FACtors) model and the MOVES (Motor Vehicle Emission Simulator) model are widely used in the estimation of vehicular emission inventory based on energy consumption, and vehicle mileage traveled (VMT) respectively (*86*). MOVES supports diverse vehicle, fuel, and activity types as well as various modeling scales ranging from project level to network level (*3*)(*86*). However, the models, including the other existing models, such as MOBILE6, VT-Micro, and CMEM, have limited emission factors for NGVs due to the lack of relevant data (*86-87*). California's EMFAC uses speed correction factors for NGVs adopted from diesel vehicle test results. The two conventional models only support CNG transit bus and refuse truck types only, even though NGVs have been used in diverse vocational applications for decades (*87*).

Depending on the driving status, vehicles produce tailpipe exhausts at different rates. VMT-based emission models are limited to estimate accurate environmental impacts because the model is in disregard of operational conditions and vehicle specifications, such as vocation type, engine model, number of stops per mile, idling time over total operation time, etc. Heavy-duty commercial vehicles in service can provide significantly different environmental impacts depending on the engine model and fuel type. With the introduction of near-zero emission engines, conventional internal combustion engines, including natural gas engines, exhibit a broader range of NOx emission factors than before.

In order to reflect the different emission factors of the heavy-duty engine families, this study adopted emission factors provided by the engine certification program of the California Air Resources Board (CARB). Because all internal combustion engines operated in California must pass the engine certification program of CARB, engine-specific emission rates can be obtained from CARB's published certifications. CARB's Heavy-Duty Certification Program tests all medium and heavy-duty commercial engines for conformity over the HD transient drive cycle and federal test procedures (FTP) (*88*). A certification sheet for each engine family shows applicable emission standards along with the engine's certified emission performance over the test cycle.

The published engine certifications express emissions factors in pollutant grams produced per brake-horsepower-hour. Revolutions Per Minute (RPM) and torque parameter values were used to calculate brake-horsepower (BHP) as shown in **Equation 1**. Specifically, actual engine percent torque (Suspect Parameter Number, SPN 513) and friction percent torque (SPN 514) were used to calculate horsepower. Because both are expressed in percentages, the maximum torque information for the specific engine was obtained from the engine specification sheet and applied to calculate instantaneous torque. Engine Speed parameter (SPN 190) provided the instantaneous engine RPM. With these values, this study was able to apply **Equation 1** to compute the instantaneous horsepower and then multiply it by the emission certification values to compute NOx emission rates in grams per second as shown in **Equation 2** (*67)(89*).

$$HP_t = \frac{RPM_t\left(Torque_t^{actual} - Torque_t^{friction}\right) \times Torque^{reference}}{5252} \qquad (1)$$

- $HP_t = Instantaneous\ power\ from\ the\ engine\ at\ time\ t$
- $RPM_t = Instantaneous\ engine\ speed\ at\ time\ t\ as\ reported\ by\ ECM\ through\ J1939\ protocol$
- $Torque_t^{actual} = Instantaneous\ engine\ actual\ torque\ (\%)\ at\ time\ t$
- $Torque_t^{friction} = Instantaneous\ engine\ friction\ torque\ (\%)\ at\ time\ t$
- $Torque_t^{reference} = Reference\ torque$

$$Instantaneous\ NOx\ emissions\ rates\ (g/sec)_t = NOx\ fac_k\ \div 3600\ \times HP_t^{adj} \quad (2)$$

- $HP_t^{adj} = adjusted\ Instantaneous\ NOx\ emission\ rate\ at\ time\ t$
- $NOx\ fac_k = Certification\ NOx\ emission\ factor\ of\ engine\ k,\ i.e.,\ 0.15\frac{grams}{bhp*hour}$

The equation relies on the statistically significant linear relationship between NOx emission rates from engine and chassis dynamometer tests (*89-91*). The estimation performance could be improved by using tailpipe emission data obtained via a portable emission measurement system (PEMS). This data resource would help to find more accurate instantaneous NOx emission rates as well as other regulated pollutant species. The PEMS data has limited availability across engine and vehicle model variations, although it is far more accurate than any other emission models. The engine certification program has no requirement for the idle NOx emission rate of NGVs. As such, this study followed McCormick et al. that assumed 0.00445 g/sec (*92*), while the idle emission rates for diesel trucks are 0.00938 g/sec, which is 33.763 g/hour (*93*).

4.2 CO_2 emission estimation methods using ECU fuel rate

The engine fuel rate (SPN 183) was converted to therm per second, and the U.S. Energy Information Administration's CO_2 emission factor was used to calculate grams of CO_2 per second. As discussed in the literature review for the difference of CO_2 emission and fuel economy between diesel compression-ignition (CI) and natural gas spark-ignition (SI) engines, this study converted ECU fuel rates of the subject NGV data into therms and then reduced them by 10% to estimate CO_2 emissions for diesel vehicle scenarios.

$$CNG\ Engine\ fuel\ rate(gallon/sec)_t = CNG\ Engine\ fuel\ rate\ (l/sec)\ \times 0.264172$$
$$CNG\ Engine\ fuel\ rate(therm/sec)_t = CNG\ Engine\ fuel\ rate\ (gallon/sec)\ \times 1.25$$

- 1.25 Therms = 1 Gasoline Gallon Equivalent (GGE) = 125,000 BTU (*94*)
- 1.39 Therms = 1 Diesel Gallon Equivalent (DGE) = 139,000 BTU (*94*)

$$Instantaneous\ CO2\ emission\ rates\ (Therm/sec)_t = Engine\ fuel\ rate\ (Therm/sec)\ \times 5307.026 \quad (3)$$

- 117.0 pounds of CO_2 per million British thermal unit (MMBtu) for natural gas (*95*)
- 161.3 pounds of CO_2 per million British thermal unit (MMBtu) for diesel (*95*)
- 1 pound = 453.592 g, 1 MMBtu = 927.8 SCF NG
- 53070.26 gCO_2 per MMBtu = 54.55413 gCO_2 per SCF (standard cubic feet) NG
- 0.054554kg CO_2 per SCF NG = 5307.026 gCO_2 per therm from NG
- 73164.39 gCO_2 per MMBtu = 7316.439 gCO_2 per therm from Diesel

4.3 Summary

The emission modeling algorithm of this dissertation relied on engine horsepower (HP) and instantaneous fuel rate parameters that were obtained from engine control units (ECUs) via SAE J1939 in-vehicle CAN bus protocol. HP was used to estimate instantaneous NOx emissions, while the fuel rate was used for CO_2 estimation. This study adopted emission factors provided by the engine certification program of the CARB; therefore, the proposed evaluation framework was able to estimate NOx emissions across all NG engine families in the market including the near-zero emission low NOx engine models.

Chapter 5 Driving pattern analysis to capture operational characteristics of HD NGVs

5.1 Production of micro driving patterns

Vehicle activity data obtained from the survey was partitioned into micro driving patterns to investigate the operational characteristics of the HD NGVs. The micro driving pattern was defined as a speed profile between two idling (stopped) events and was also called a driving trip snippet. Ericsson also defined a micro driving pulse as a driving pattern between two stops, and a stop is a driving status corresponding to vehicle speeds below two mph (*33)(35*). The driving pattern analyses in this study used the same speed threshold value of Ericsson (*33)(35*) to divide the obtained speed profile.

5.2 Driving pattern clustering and classification

Heavy-duty vehicle (HDV) engines are typically identified with a primary intended service class (PISC), which is assigned by vehicle manufacturers, and commercial HDVs usually use various names originating from vocation type, business type, or appearance. The PISC is assigned based on engine configurations, which may not be consistent with vocational operations. Therefore, the PISC is not always the same as vocation type because the PISC is for engines and a broader concept of the classification scheme, and vocation type is defined with respect to business and operation type of the fleet operator. For instance, a tractor truck, which is a PISC, can be used for long-haul, short-haul, or port drayage operations, etc. Due to the given objectives, commercial vehicles travel on assigned operation routes and schedules in order to accomplish their purpose. Hence, this study presumed that vocation type induces operating mission-related driving situations, and the vehicles typically conduct repetitive operation patterns that are associated with the given duties.

This study defined drive modes as common driving patterns that have distinct driving and emission characteristics. Drive mode composition (DMC) represents the captured behavioral features over a duty cycle and was calculated by aggregating the durations and distances of the classified driving patterns by drive mode group. Therefore, DMC shows how a vehicle is being operated in terms of time and distance. As shown in Prohaska et al. (47), a comparison of DMC can show differences in operational and emission characteristics between vocation types. For instance, if two trucks operate for the same distance but in different DMCs, emission productions of the vehicles cannot be the same because each drive mode has a different emission factor per time and distance.

The driving patterns can be classified into three drive mode groups depending on the speed attributes of patterns. For example, a short and low-speed operation, also called creeping mode (CRP), is typically shown in a turning movement or operations in truck queues. Extensive and sustained high-speed operations are usually defined as cruising mode (CRS) and observed from freeway driving data. Transient (TRS) pattern is an oscillating speed profile with a relatively shorter pattern duration than cruising mode and achieves brief high peak speeds but does not sustain these speeds. It also appears when a vehicle's operation is in a transition to another. Generally, the transient mode operation can be found in operations on urban arterials (*47)(96)*. These drive modes are included in the heavy-duty transient drive cycle, and the drive cycle is used for testing conformity of vehicle emission through chassis dynamometer tests. It means that the three drive modes are prevalent and essential in typical truck operations.

To identify these broadly defined driving modes, the entire dataset was partitioned into micro driving patterns (*33)(35*)(*36-37*) and classified into drive mode groups representing commonly observed driving pattern types. Prohaska et al. (*47*) and A. Fotouhi et al. (*48*) asserted that pattern clustering could be an effective way to obtain pattern classification thresholds, and this study applied k-means clustering to group the observed micro driving patterns and used the boundaries between clusters as thresholds for pattern classification. Montazeri-Gh et al. showed that the average and maximum speed of each pattern are highly correlated with fuel consumption and NOx emission production (*97*). The average and maximum speeds of the entire patterns were normalized and then used in the clustering analysis.

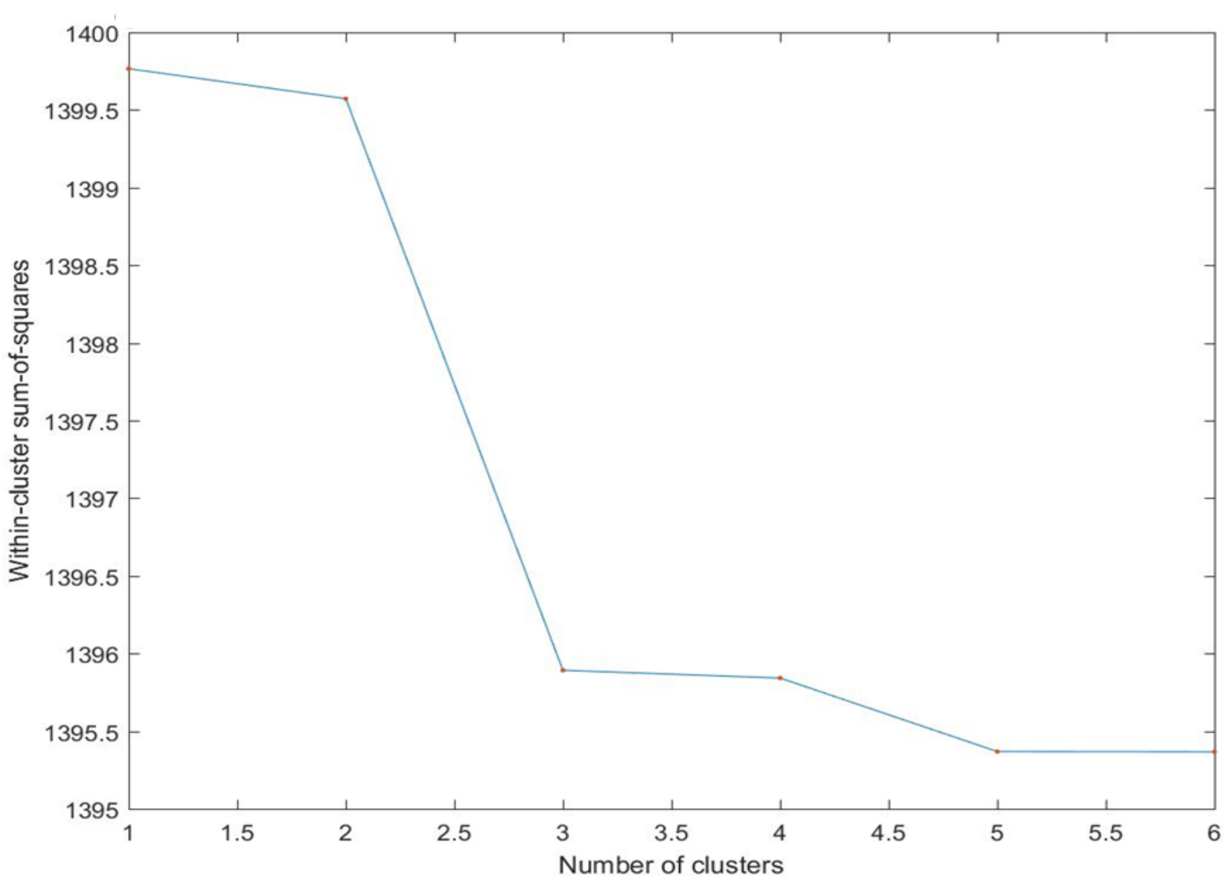

Figure 5.1. Scree plot for determining the number of clusters

The k-means clustering method requires that the analyst can predefine the number of clusters. This study determined the optimal number using the elbow method (*47*), which finds a balance point between the number of clusters and the percentage of variance explained as the sum of squared error within the clusters. The first cluster usually explains a large portion of the variance in the data and each successive cluster explains less and less of the overall variance. The results from the elbow method analysis showed that the driving patterns could be partitioned into three clusters as shown in the scree plot of **Figure 5.1**. Although this technique cannot always identify an unambiguous optimum, this study found it to be an effective heuristic in this application and obtained three clusters as the optimal using the average and maximum speed of the micro driving patterns.

In addition to the three drive modes, this study considered two additional drive modes in the pattern analysis. Since 2005, the CNG vehicle population has been steadily growing by the implementation of SCAQMD's fleet rules (*98*). Unlike conventional cargo tractor and drayage truck operations, vocational NGVs show different movement patterns that are related to their specific operational duty, such as waste collection and compaction, extensive high RPM idling for Power Take-Off (PTO) operation, and street sweeping. These special activities induced different driving engine loads and vehicle speed variations, compared to the basic three drive modes. Refuse trucks, and street sweepers conducted sustained low-speed operations, and this study designated the operations as low-speed cruising (LSC) mode. Bus and food distribution truck types presented greater portions of arterial operations than the other road-type operations. In general, bus transit operation is required to cover maximum service areas and be punctual at every bus station, while food distribution trucks travel back and forth between distribution centers and several local stores or retail customers. These vehicle types performed bell-shaped speed profiles, including frequent stops due to signalized intersections. High-speed transient (HST) mode showed high maximum speed as cruising pattern speed on freeways; however, the peak speed was not sustained. The LSC and HST modes exhibited different speed variations and micro trip pattern lengths, compared to the basic driving modes. Thus, this study used the pattern-duration feature to distinguish the LSC and HST patterns from the primary modes in the pattern classification.

Table 5.1. Thresholds for the driving pattern classification

Thresholds	Creeping (CRP)	Cruising (CRS)	Transient (TRS)	Low-speed cruising (LSC)	High-speed transient (HST)
Pattern average speed (mph)	< 11	> 18	Driving patterns that not meet the requirement for other drive mode groups	< 18	> 18
Pattern maximum speed (mph)	< 18	> 35		< 35	> 35
Pattern duration (sec)	< 30	> 205		> 145	< 205

Boundaries between clusters were determined as straight lines, which are average values of maximum and minimum of the nearest clusters, and **Table 5.1** presents the pattern classification scheme associated with the thresholds. The classified driving patterns were validated based on their drive mode groups and pattern shapes. Driving patterns in the transient drive mode usually appeared as bell-shaped curves having higher variations than the other drive modes. While the other pattern types were relatively easily identifiable at a certain speed level, transient patterns typically showed wide ranges of driving speed and pattern duration, which means that it is difficult to define a transient reference pattern precisely. Therefore, transient patterns were defined as unclassified driving patterns that could not fit in the other drive mode conditions.

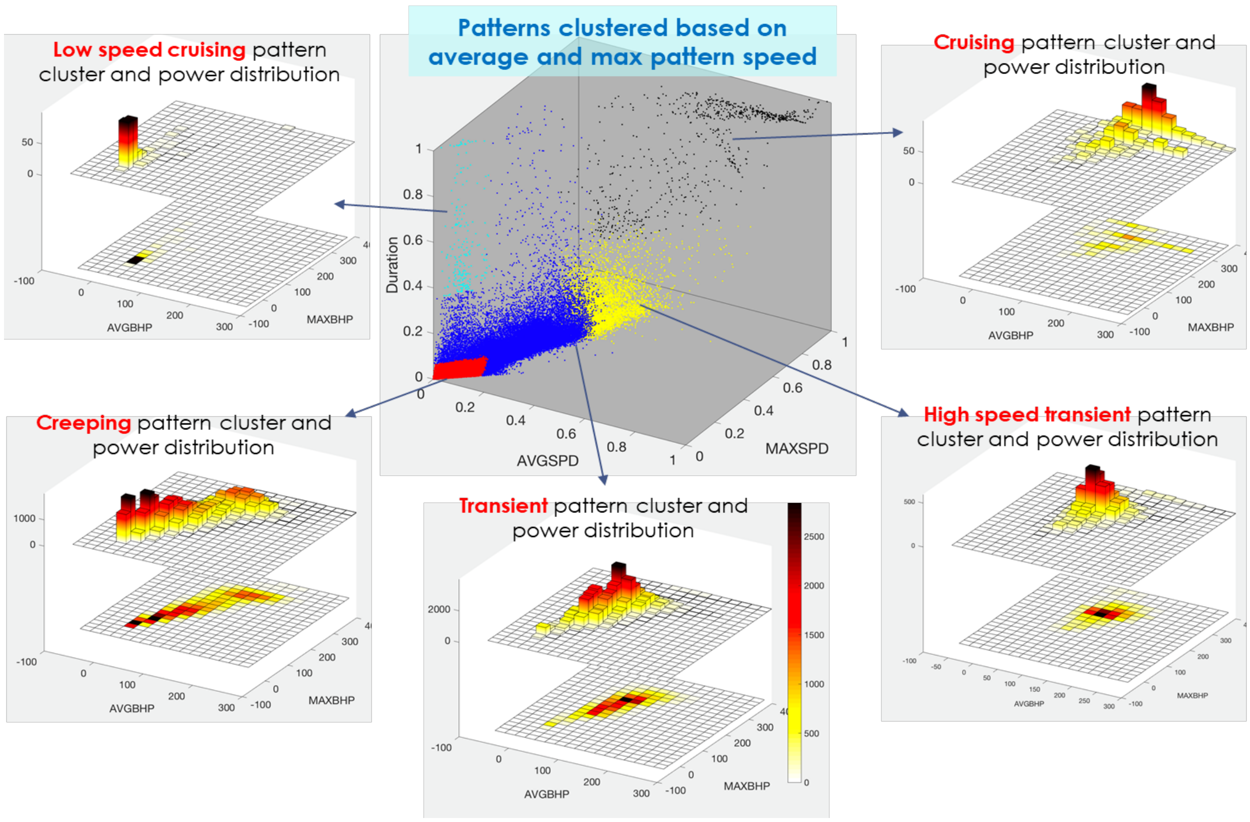

Figure 5.2. Clustered driving patterns into each drive mode

Couch and Leonard (*96*) and Prohaska et al. (*47*) noted that each drive mode possesses distinctive emission characteristics. For example, the creeping mode is regarded as a short and low-speed driving pattern, while cruising mode represents extended and high-speed driving patterns. The abstract conception on the drive modes indicated that the pattern duration could be a useful pattern feature. This study determined the duration threshold values depending on the operational characteristics of each drive mode. For instance, cruising patterns were the most common driving patterns on the freeway. Assuming that a typical ramp/intersection spacing is 2 miles (*99-100*) and a vehicle maintains average speed 35 mph on a freeway (*43*), this study computed a pattern duration threshold for cruising mode as $\frac{2\,mi}{35\,mi/hr}\frac{3600s}{1hr} \approx 206s$.

Prohaska et al. (*47*) characterized the creeping mode of drayage trucks as very low-speed operation; a common driving pattern in truck queues. Because creeping is a short driving pattern with varying pattern shapes and likely between two idling states, this study set the pattern duration threshold for creep as 30 seconds. Low-speed-cruising modes are typically performed by vocational trucks such as refuse trucks and street sweepers that are primarily operated in residential areas, where low-speed limits (25 mph) are predominant. As such, this study computed the pattern duration threshold for the low-speed-cruising (LSC) mode as 144 seconds based on the assumption that a vehicle drives at an average 25 mph on a typical 1-mile residential area street. It resulted in a maximum LSC pattern duration threshold of $\frac{1\,mi}{25\,mi/hr}\frac{3600s}{1hr} \approx 144s$. As a consequence, the pattern duration thresholds for transient and high-speed transient modes should be longer than maximum creep pattern duration and lower than minimum cruising pattern duration.

Internal combustion engines (ICE) consume more fuel to generate energy to propel the vehicle faster. An emission inventory is highly relevant to the power production of ICEs. Therefore, this study compared the power distributions of each drive mode group. **Figure 5.2** shows the partitions of the classified driving patterns and joint distributions of average and maximum horsepower values. The partitions shown in the figure implied that each drive mode exhibits different driving behaviors with a different speed level. The horsepower distribution of the creeping drive mode widely is spread over a joint area of average and maximum horsepower parameters, while LSC mode has a very concentrated distribution. Overall, the drive mode groups showed that each drive mode has different concentration patterns at different locations.

5.3 Drive mode composition (DMC) by vocation type

This study hypothesized that vocation type is one of the factors affecting operational and emission characteristics of HD NGVs, and DMC can explain how these vehicles are being operated in terms of driving time and travel distance. Depending on the distribution of the drive modes over the duty cycle and the emission rate of each mode, the vehicles could produce different amounts of NOx emissions for given operational conditions. **Table 5.2** shows NOx emission rates per drive mode and vocation type.

Refuse trucks and buses are known to conduct frequent stop-and-go operations. The refuse trucks had a higher value of total NOx emission rates (g/mile) than urban transit and school buses, as shown in **Table 5.2**. Since refuse trucks exhibited more idling and low power-demand driving patterns, a greater gap existed between the DMCs of the refuse trucks and the other vocation types. It illustrates the limitations of using aggregated emission rates only in comparing environmental impacts. With little thought of operational characteristics, it is difficult to understand the emission characteristics of commercial vehicles. Matt Grote et al. mentioned that notwithstanding local government authorities (LGA) are responsible for estimating accurate emission productions in their area of administration and for establishing reliable emission abatement plans. Existing contemporary emission estimation methods of LGAs are likely to provide imprecise measures due to scarce funds for air quality impact analyses and modeling studies and the difficulty of balancing the model's accuracy and complexity (*101*). Therefore, this is an essential area for current research, and driving pattern-based air quality impact analyses are expected to show more detailed emission characteristics explicitly without high computational efforts.

Table 5.2. NOx emission rates by drive mode and vocation type

Service type	Bus transit		Waste service			Hauling service						Utility service	
Vocation type	Urban transit bus (UTB)	School bus (SCHB)	Street sweeper (SWPER)	Refuse truck (RF)		Long-haul truck (LHT)	Short-haul truck (SHT)					Utility service truck (UT)	Sewer truck (SWT)
Vehicle fleet description	Urban Transit buses	School district buses	Street Sweeper in a university	Refuse trucks in San Diego	Refuse trucks in Los Angeles	Long-haul trucks	Waste transfer short-haul trucks in San Diego	Waste transfer short-haul trucks I in Los Angeles	Waste transfer short-haul trucks II in Los Angeles	Water district short-haul trucks	Dairy reefer trucks	Water retail crew utility trucks	Water retail sewer trucks
Fleet code	UTB	SCHB	SWPER	RF SD	RF LA	LHT	WTSH SD	WTSH LA I	WTSH LA II	SHT	DDRT	CRWT	SWT
TOTAL	1.193	0.602	2.528	1.646	1.509	0.305	1.002	0.660	0.283	0.497	0.123	1.690	2.400
CRP	0.430	0.180	1.684	0.566	1.122	0.332	0.675	0.352	0.034	0.222	0.046	0.328	0.490
CRS	0.279	0.161	2.323	0.159	0.334	0.263	0.323	0.386	0.026	0.200	0.029	0.271	0.427
TRS	0.374	0.218	1.893	0.288	0.563	0.257	0.506	0.450	0.046	0.207	0.048	0.367	0.532
LSC		0.171	1.376	0.117	0.595	0.189	0.542	0.474	0.024	0.222		0.280	0.444
HST	0.351	0.194	2.274	0.184	0.381	0.292	0.353	0.402	0.032	0.200	0.037	0.360	0.467

Water retail sewer trucks and street sweeper showed the highest total emission rates (g/mile) among the considered vocation types, and the values of the sewer trucks were far higher than their running exhaust emission rates. This is because the sewer trucks conducted work-zone activities that demand a power supply in idling status. Due to the extensive PTO (Power-Take-Off) operations, these vehicles produced a considerable amount of idling emissions. Regarding the high NOx emission rate of the street sweeper, it is equipped with an old engine model (MY 2009); therefore, it provided relatively higher NOx emission rates than the others.

For most vocation types considered in this study, creep (CRP) drive mode patterns showed the highest emission rates among the drive modes, followed by transient (TRS). Creep and transient patterns exhibited high engine speed variances, and these power-demanding driving patterns required relatively higher fuel rates. In dynamically transitioning traffic situations, it is difficult to maintain and control the performance of after-treatment systems, which aim to reduce criteria pollutant species in tailpipe exhausts. These results are consistent with the experimental analysis results of George Karavalakis et al. (*102-103*). According to the William H. Martin Refuse Truck Cycle (RTC), which was developed by West Virginia University, driving cycles of waste haulers consist of a transport segment, a curbside pickup segment, and a compaction segment. In the curbside pickup segments, the refuse trucks conducted numerous stop-and-go driving patterns, and the resulting CO_2 and NOx emission rates are twice as high as the emission rates in the transport segment (*102*).

The obtained vehicle activity data is one of spatial-temporal data; it can be assessed on a pattern duration-basis and distance-basis. While duration-based DMC showed the time fractions of idling mode operation, distance-based DMC neglected the idling impact. Distance-based DMC in **Figure 5.5** showed different proportions compared to duration-based DMC in **Figure 5.3**. This is mainly due to the idling mode duration and also because each drive mode has a different impact on pattern-duration and pattern-distance. For example, cruising mode exhibits high-speed operation, so it has more VMT per unit of time than the other lower speed operation modes.

Vocation type specific-DMC showed that the vocational vehicles were likely to have specific predominant drive modes, and the primary driving mode differed by vocation type. As shown in **Figure 5.3**, most vocation types commonly have portions of idling mode over the total operating time. Ironically, vehicle emission enforcement programs never specify idling emission standards for NG engines.

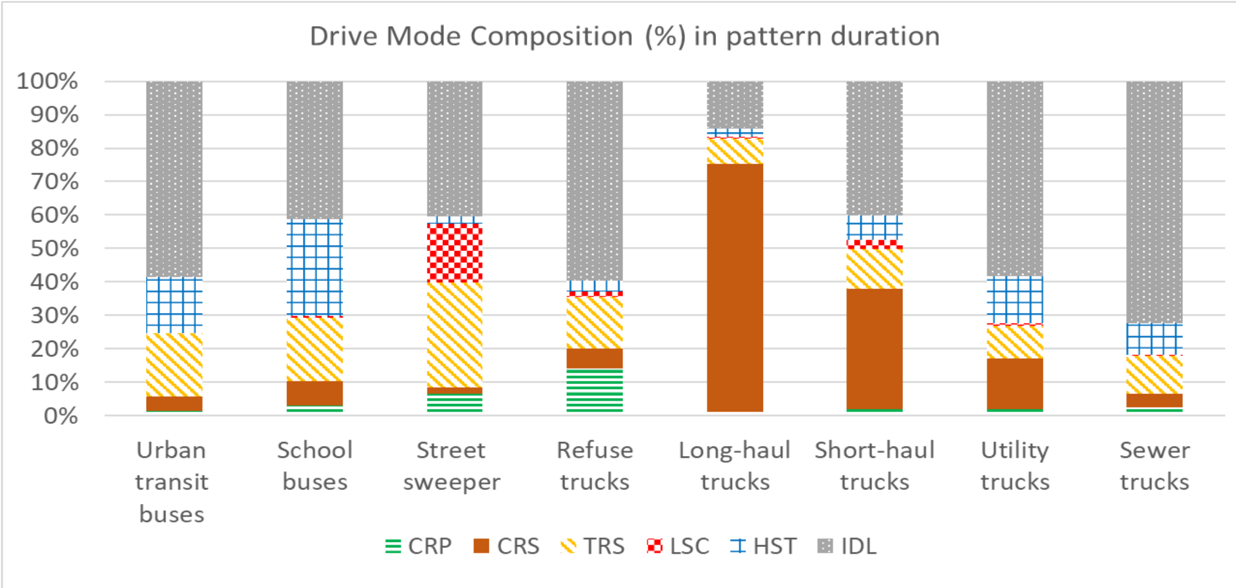

Figure 5.3. Pattern duration-based drive mode composition

The refuse trucks and street sweeper data showed a substantial amount of low-speed range operations, such as creeping and low-speed-cruising modes. The refuse truck data had the highest proportion of creeping mode to the total operation time compared to the others. The best explanation for this is that refuse trucks dropped by every waste collection point and travel in residential areas that have numerous turning and stop-and-go events. The number of stop per mile and GPS trajectories also could support the analysis results. As shown in **Table 5.3,** refuse trucks had a significantly higher number of stops per mile than other vehicle types. **Figure 5.4** shows a complicated GPS trajectory of the refuse trucks participated in the activity data survey. These results indicated that refuse trucks are likely to conduct more NOx emission-intense operations, compared to the other vocational types.

The predominant drive modes of transit and school buses were transient and high-speed transient patterns that are more common in arterial street operations, while short- and long-haul trucks were operated in the cruising mode for the most of time in their duty cycle. Also, the DMCs of transit buses and the dairy reefer truck showed no low-speed cruising operations over the entire operation schedule.

Table 5.3. Drive mode composition and number of stops per mile

Service type	Transit service		Waste service		Hauling service		Utility service	
Vocation type	Urban transit	School bus	Street sweeper	Refuse truck	Long-haul truck	Short-haul truck	Utility service truck	Sewer truck
Group code	UTB	SCHB	SWPER	RFT	LHT	SHT	UT	SWT
CRP	1.5%	3.0%	6.4%	14.2%	1.0%	2.0%	2.0%	2.4%
CRS	4.3%	7.4%	2.0%	5.9%	74.2%	35.9%	15.0%	4.2%
TRS	18.9%	18.8%	31.4%	15.5%	7.8%	11.9%	9.9%	11.3%
LSC	0.0%	0.4%	17.7%	1.4%	0.5%	2.7%	0.6%	0.2%
HST	16.8%	29.1%	2.0%	3.3%	2.4%	7.2%	14.1%	9.6%
IDLING	58.6%	41.2%	40.5%	59.7%	14.1%	40.2%	58.4%	72.3%
# of stops per mile	2.82	1.91	3.98	14.65	0.20	1.27	1.35	3.31

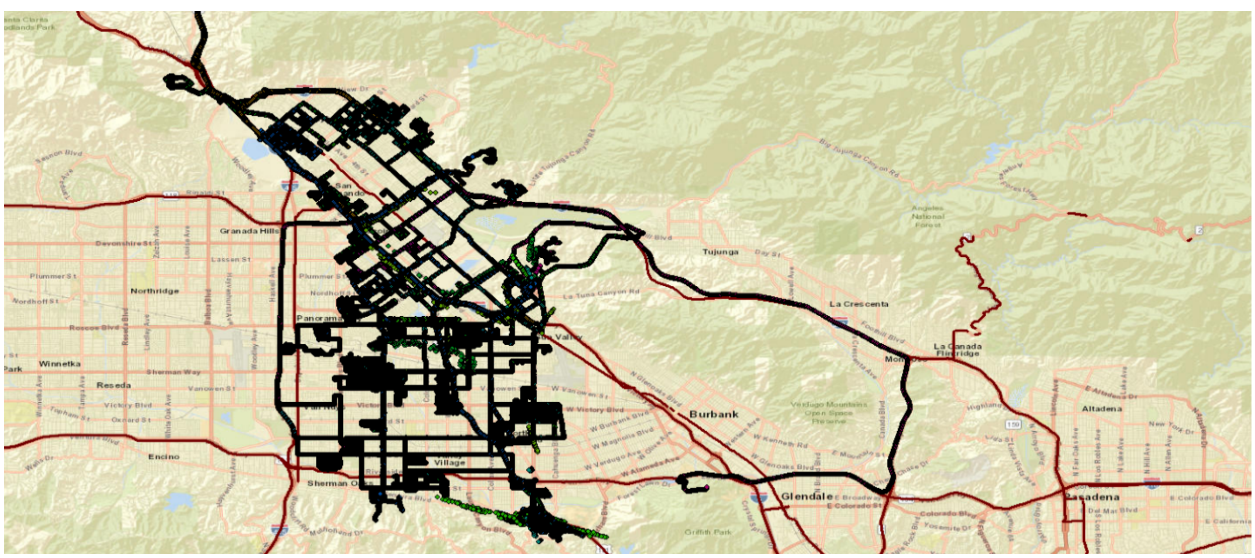

Figure 5.4. A sample GPS trajectory of the refuse truck participated in the data survey

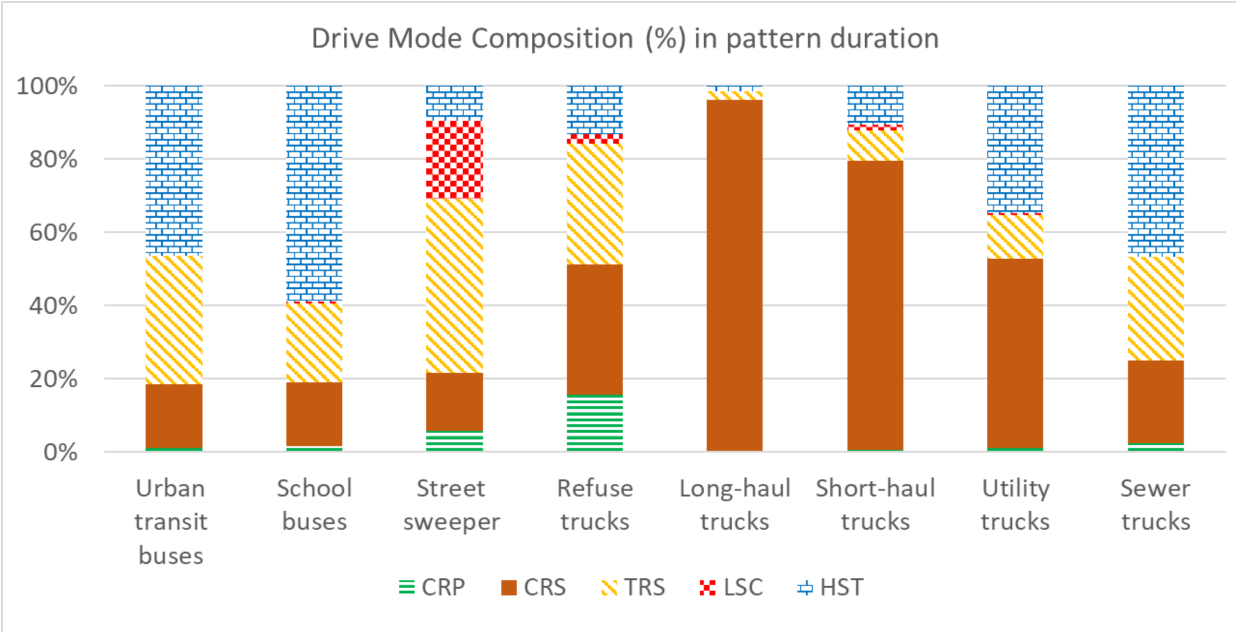

Figure 5.5. Pattern distance-based drive mode composition

Table 5.3 presents the DMCs of the considered vocation types. The long- and short-haul truck datasets provided a substantial amount of cruising mode portions, which means that the subject trucks primarily travel on freeways. These trucks have very similar drive mode distributions even though their operation areas are different from each other. This study discovered similar DMC patterns not only from the cargo truck types but also bus type vehicles. Urban transit buses and school buses showed similar concentration patterns in **Figures 5.3** and **5.5**.

Figure 5.6 presents the concentrations of the running NOx emissions by drive mode. The figure highlights drive modes that contribute to the total NOx emissions the most. It also supports the hypothesis that the vocational HD NGVs are likely to have specific predominant drive modes. Urban transit and school buses produced a significant total amount of NOx emissions in high-speed transient mode, while the majority of NOx emissions of long- and short-haul trucks were from cruising mode. Refuse trucks showed that most NOx emissions were produced in creeping and transient modes. The analysis results showed the predominant drive modes that were highly correlated with the total NOx emissions of the subject NGVs.

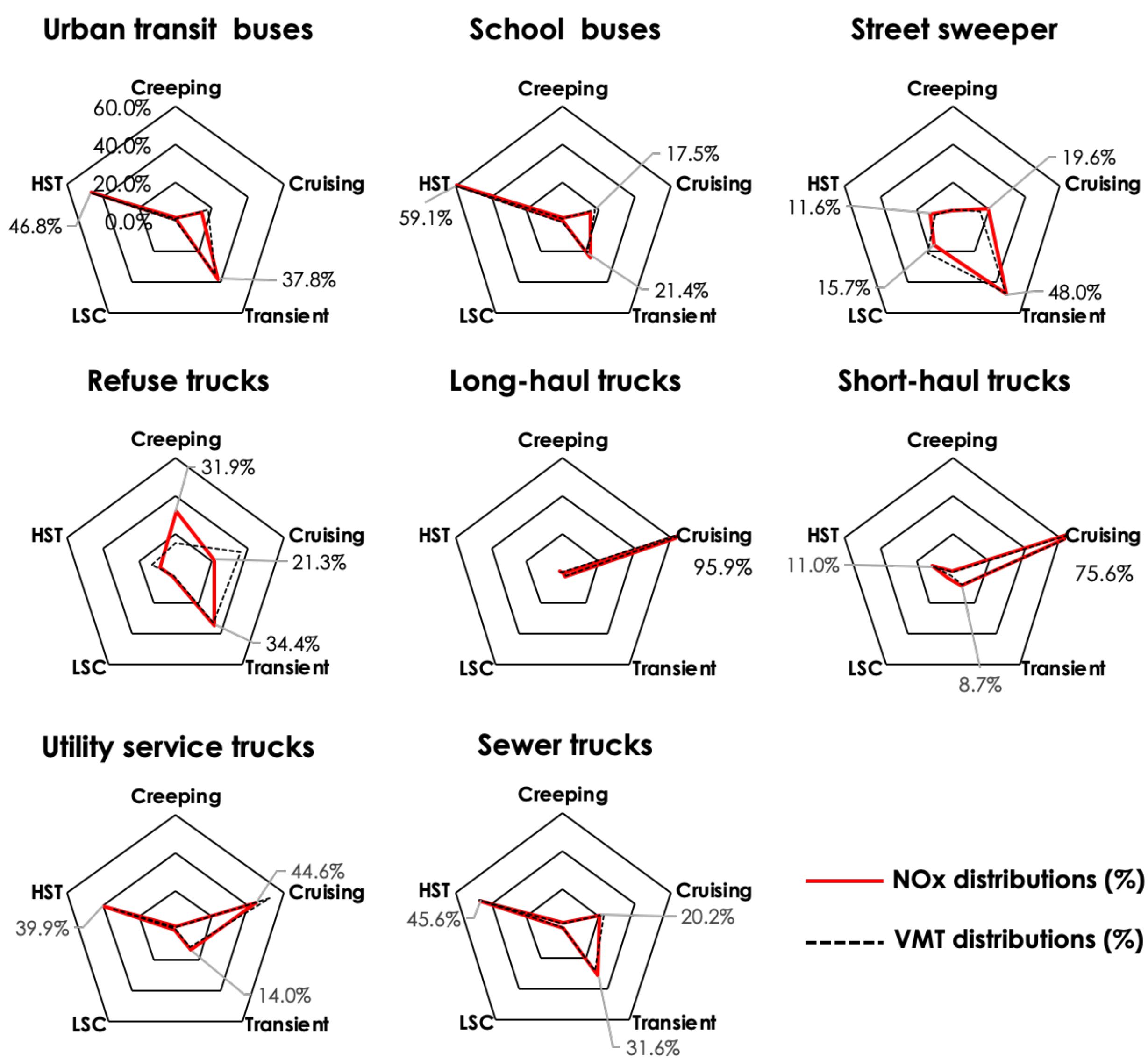

Figure 5.6. NOx and VMT distributions by drive mode

Not all the subject vehicles in the vocation type group travel on the same routes and experience the same traffic conditions. DMC can differ from vehicle to vehicle; therefore, this study presented DMCs of all subject vehicles in **Figure 5.7**. This study found that the DMCs of specific vocations were consistent across regions. In other words, inter-group differences were much more significant than intra-group differences. Refuse truck (RFT) 1, 2, and 3 in **Figure 5.7** were included in the fleet RF SD in **Table 5.3** and were operated in San Diego County, while RFT 4, 5, and 6 were from the fleet RF LA, and the corresponding activity data was obtained from an entity in Los Angeles County. The refuse trucks from different regions also presented similar DMCs. The DMC analysis results illustrated that the vocation type factor could have a very significant impact on commercial HDV operations and be more influential than the other factors. This is because vehicle activities are constrained by given operational conditions to achieve the objectives assigned by fleet operators. Although the vocation type cannot explain the entire variations of operational and emission characteristics, it is, at least, an essential factor in determining the environmental impact of the vehicles.

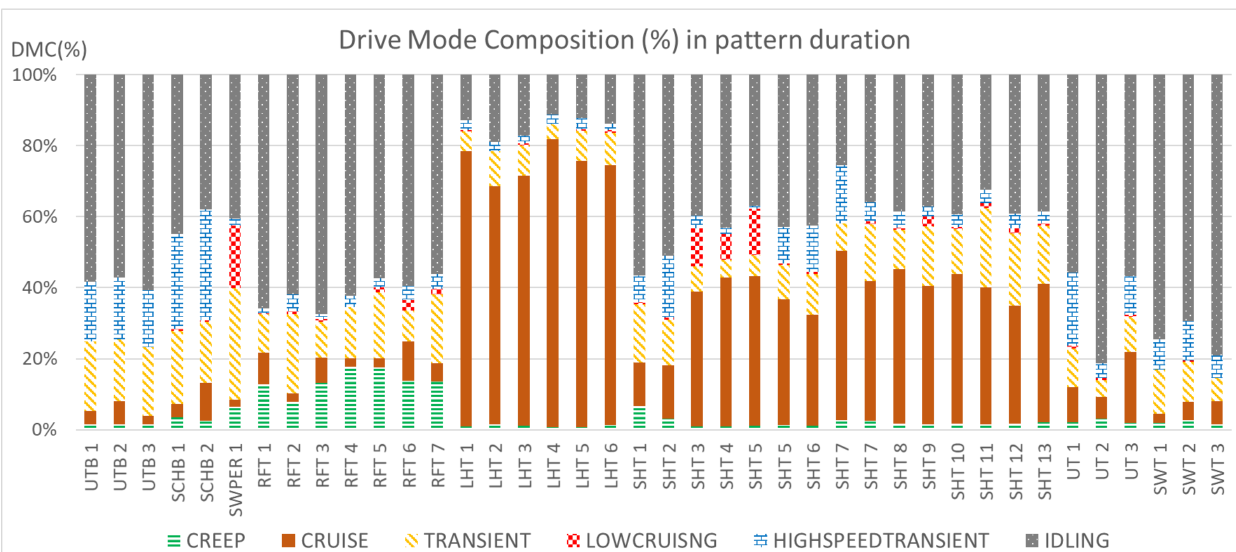

Figure 5.7. Drive mode composition in duration per vehicle

5.4 Drive mode compositions by road facility type

On-road emissions production is not uniform over time and space because a vehicle's driving status is affected by driving situations and operational conditions, although emission rates usually are expressed and compared in averages (in the unit of time or distance). The previous section showed that HD NGVs could have different environmental impacts due to vocation and business types. This section focused on the concentration of criteria pollutant emissions associated with road facility type over time and space. The DMC by road type can address the environmental impact of the subject vehicles more specifically, such as estimating the adoption impact on vulnerable communities and contributing to geofencing strategies, while aggregated emission rates may preclude these types of assessments. Hence, this study considered the influence of the transportation network and associated road conditions on vehicle performance. From the entire datasets collected, this study selected the ten activity datasets that have the least error-prone GPS data and captured GPS trajectories covering a variety of traffic and road conditions. To analyze network impacts on emissions, this study geocoded the trajectories into an open-source map and then correlated the DMCs to road facility type.

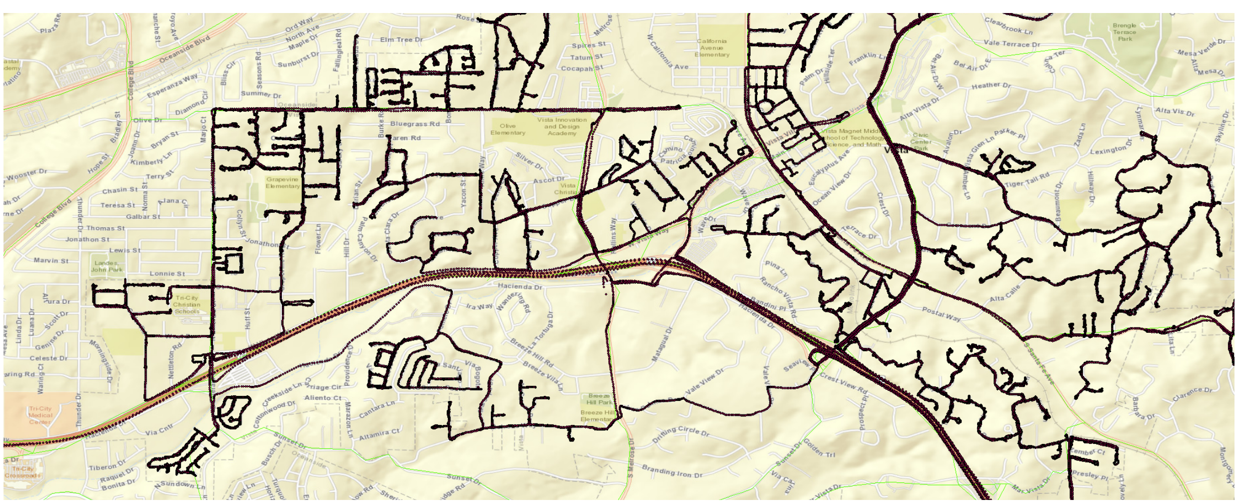

Figure 5.8. Sample of geocoded vehicle trajectories

5.4.1 Highway Functional Class

The Federal Highway Administration (FHWA) classifies road type in seven classes, such as interstate, other freeways or expressways, principal-arterial, minor-arterial, major-collector, minor-collector, and local street. This study assumed that the driving features between the similar road types are analogous. For instance, operational and emission characteristics of interstate, expressways, and freeways may not be significantly different. Accordingly, the DMCs were divided into three road facility types, such as freeway (FW), arterial (ARTE), and local street (LOC). Using the California Road System (CRS) maps and geographic information system (GIS) tools, road types on the obtained vehicle trajectories were identified, and DMC and pattern features were re-calculated based on the road type. **Figure 5.8** shows a sample of geo-mapped trajectories.

5.4.2 Drive mode composition by road facility type

DMCs by facility type provides a broad picture of the operational conditions of the HD NGVs. When the road type changes along a vehicle trajectory, the corresponding road segment is identified as a road-facility trip. This study calculated the drive mode composition and driving statistics for each road-facility trip segment identified, including the number of stops, speed, travel distance, power consumption, and idling time. DMCs by road facility type in **Figure 5.9** showed that the HD NGVs used a specific road facility type during their duty cycles. This implies that some specific drive modes were highly correlated with road type, and the vocational vehicles had their specific areas of operation. Referring to the DMC bar graph shown in **Figure 5.9**, it was possible to envision the operational environments of the buses. Bus type vehicles were operated predominantly on major-arterials and, as expected, the arterial road type is responsible for most NOx productions from the buses in service. While transit bus operations primarily focused on arterials, school buses presented slightly different facility type DMCs. In addition to the substantial amounts of high-speed transient mode operations on arterials, the school bus type showed significant transient mode operations in local streets, which could be explained by student pick-up and drop-off behaviors.

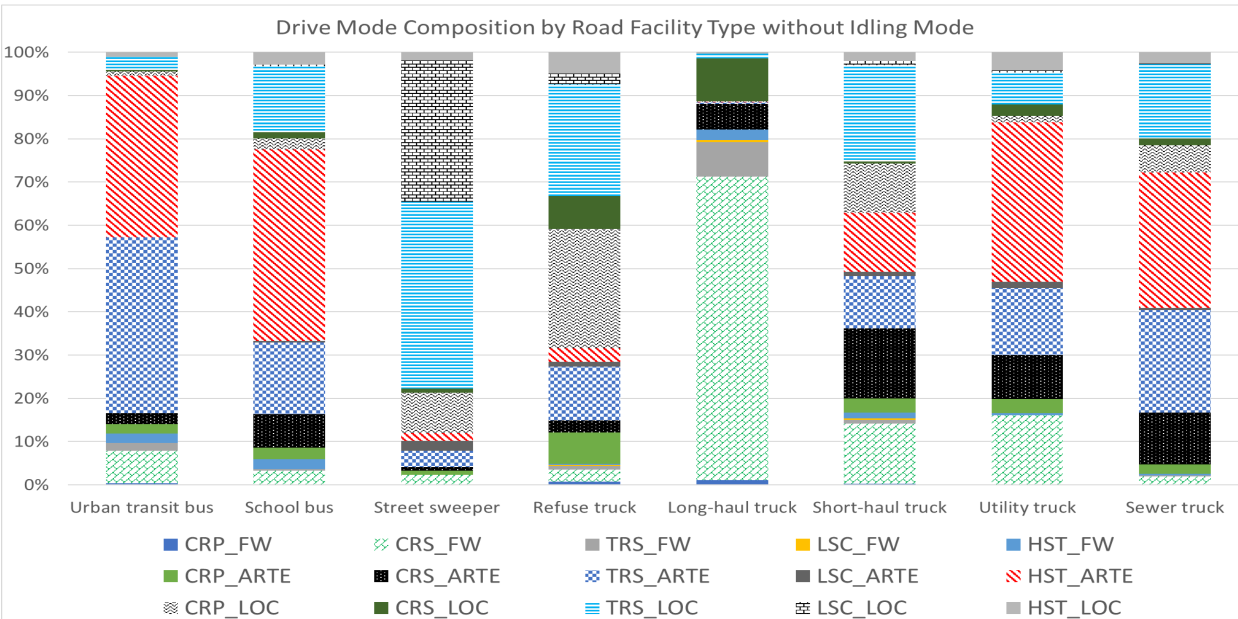

Figure 5.9. Drive mode composition without idling mode by road facility type

Similarly, most operations of long-haul trucks were conducted on freeways in cruising mode. The street sweeper had significant portions of creep, transient, and LSC patterns on local streets due to its special duty. Refuse trucks had the largest portions of creeping mode among the considered vocation types, and they operated creeping mode mainly on local streets and transient mode on arterials. It implies that sweepers and refuse trucks are partially responsible for the air quality of residential and business areas. If a government agency wants to reduce emissions in residential areas, these vehicle types can be the main policy targets that the agency needs to focus on. Short-haul trucks presented a variety of predominant drive modes that have similar portions, while road type-specific DMCs of refuse and long-haul truck types were primarily focused on local streets and freeways, respectively. Short-haul trucks were likely to experience very diverse traffic environments over their duty cycles. It implies that each vocation type can have different driving difficultness, which is highly related to system requirements for automated vehicles. For instance, the short-haul trucks are likely to require the highest autonomous level because of their various driving mode distributions and diverse road conditions over drive cycles.

Utility service and sewer trucks mainly traveled on arterials. Utility trucks had slightly more freeway cruising operations, while sewer trucks had relatively more transient model portions. The two vehicle types showed similar DMCs by road type to those of bus type vehicles. The trucks traveled mainly in the high-speed driving modes across all road types and had substantial fractions of idling time in the arterial and local streets. It is possible to summarize the vehicle activities of the utility and sewer trucks as the vehicles quickly moved to work-zones and conducted extensive PTO operations.

Figure 5.10 illustrates road type compositions (RTC) and demonstrates that the HD NGVs have primary road facility types associated with their operations. The figure also shows the variability of intra- and inter-group RTCs. Urban bus, school bus, crew trucks, and sewer trucks mainly traveled in arterials (ARTE in the figure). Refuse trucks and street sweepers usually operated on local streets (LOCAL), presumably residential areas. Long-haul trucks and waste dumpsters focused on freeway (FW) operations. The vocation types in each partition can be grouped as vehicle classes that exhibit similar activity patterns.

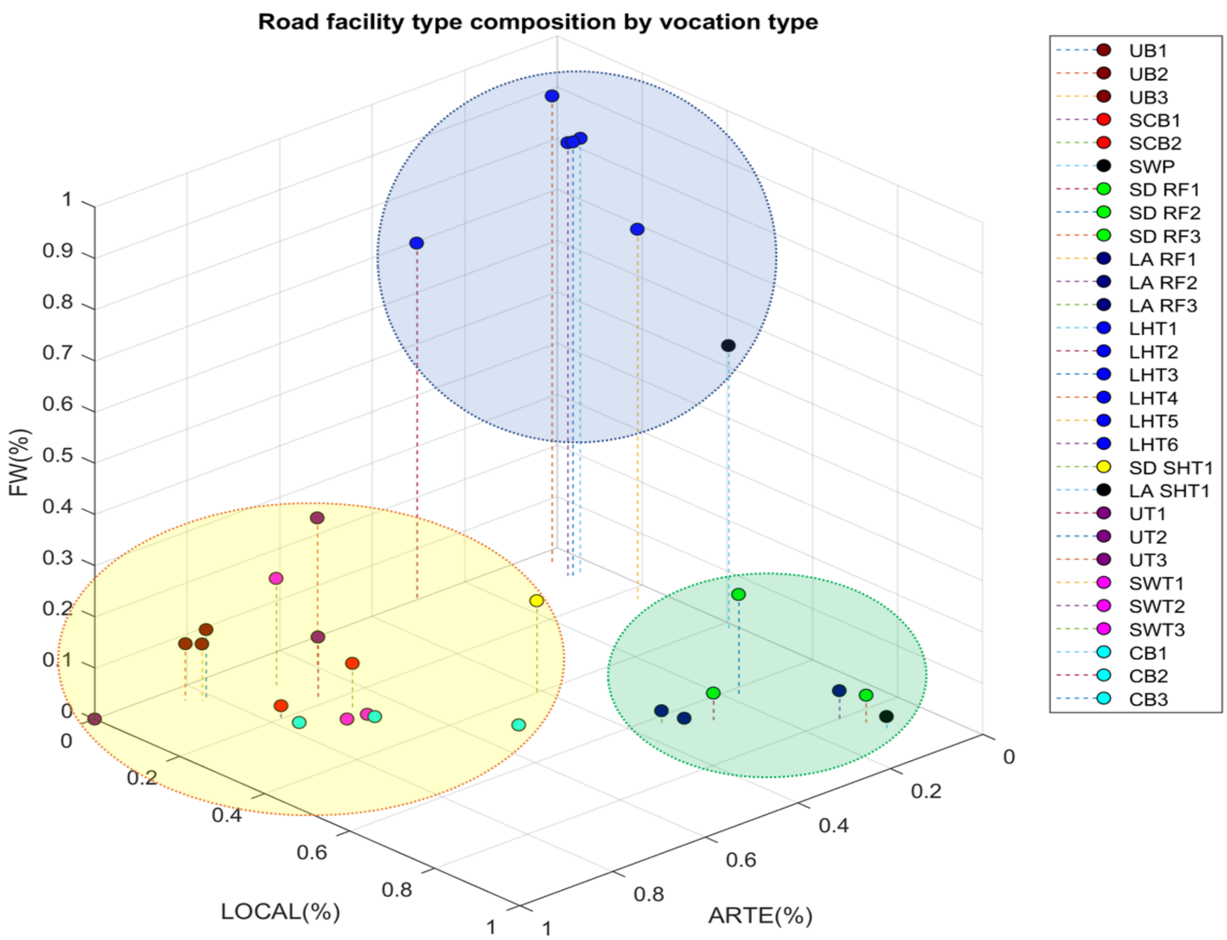

Figure 5.10. Road facility type compositions of the subject vehicles

For instance, some vocation types can be merged into newly defined vehicle groups, and the new group can represent emission production potential of the included subject vehicles. With an underlying assumption that air pollutant exposure rates for humans differ by road type due to different population concentration in residential and freeway areas, it is possible to argue that the refuse truck and sweeper group can provide higher fuel transition impact than the other vehicle groups.

5.5 Analysis of the variability of environmental impacts with possible drive mode compositions

The observed activity patterns are limited to explain the duty cycles of the entire vocational NGV population in California. Although activity patterns are similar between the same vocation type vehicles, drive mode compositions (DMCs) can differ depending on given operational and traffic conditions, such as traffic conditions, duty cycle, geographical features over an assigned operation route. This study assumed that DMCs of HD NGVs could differ by ±10% and ±20% from the observed DMCs and estimated the variations of NOx emission rates of the considered vocation types.

This study generated 2,000 synthetic DMCs for each vocation type that are randomly produced within the allowed variation range of ±10% and ±20% from the observed DMCs. The sum of durations of drive modes should be equal to 100%, which is the total operation time of the vehicles. This study calculated NOx emission rates for each synthetic DMC generated. **Figure 5.11** shows the histograms of NOx emission rates of the vocation types considered in this study under the allowed 10% variations of DMCs. The range of each distribution indicates the variability of NOx emission productions of each vocation type.

Long-haul trucks showed the lowest NOx emission rates and were expected to provide very consistent emission benefits. School buses and short-haul trucks with 8.9-liter engines had an overlapped area, which means that school buses could provide better emission benefits in some DMCs than short-haul trucks with 8.9-liter engines and vice versa. The distribution of NOx emission rates of sewer trucks was substantially far from the other vocation groups. At a glance, the vocational vehicles can have the presented ranges of NOx emission rates in **Figure 5.11** under the assumption that the obtained activity data is not significantly different from the operational characteristics of the entire NGV population.

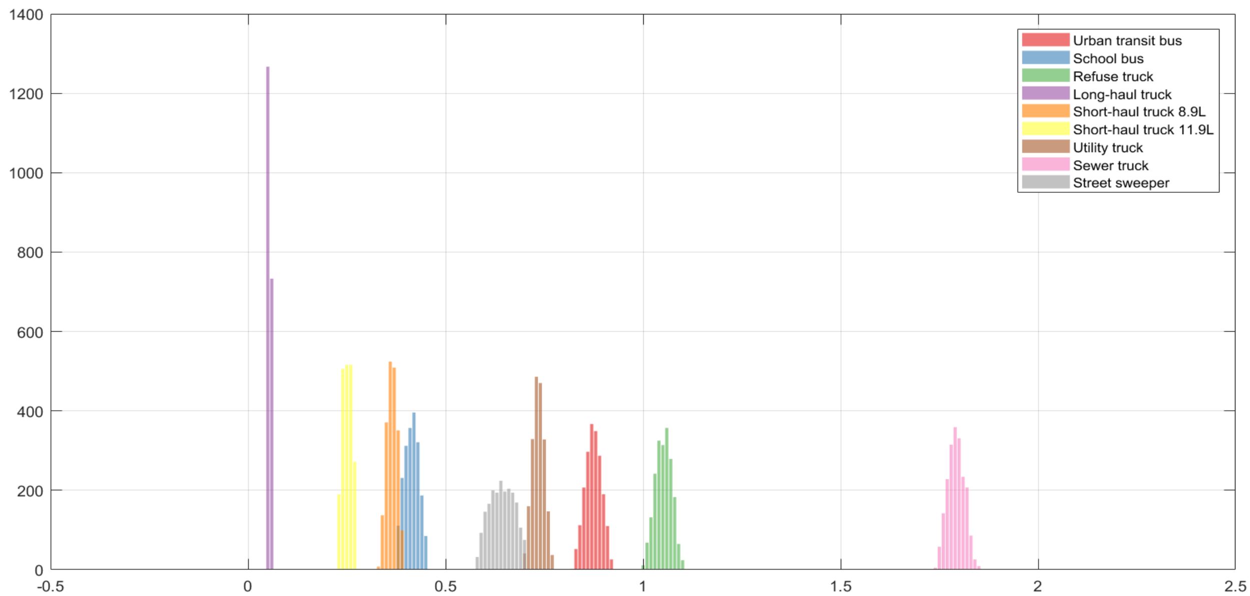

Figure 5.11. Distributions of NOx emission rates with 10% of allowed DMC variability

A higher variation of DMC provided larger overlapped spaces between the distributions, as shown in **Figure 5.12**. The consecutive order of the vocation types from the left side of the figure presented the environmental friendliness, and it can be regarded as a priority in public health-related policy design such as vehicle incentive projects. In addition, the extent of the overlapped area indicated that the two involved vocation types could be used to determine their priorities. Hence, the rightmost side of each distribution showed the tipping point where the vocation type loses the superiority of emission benefits compared to the adjacent vocation type to its right.

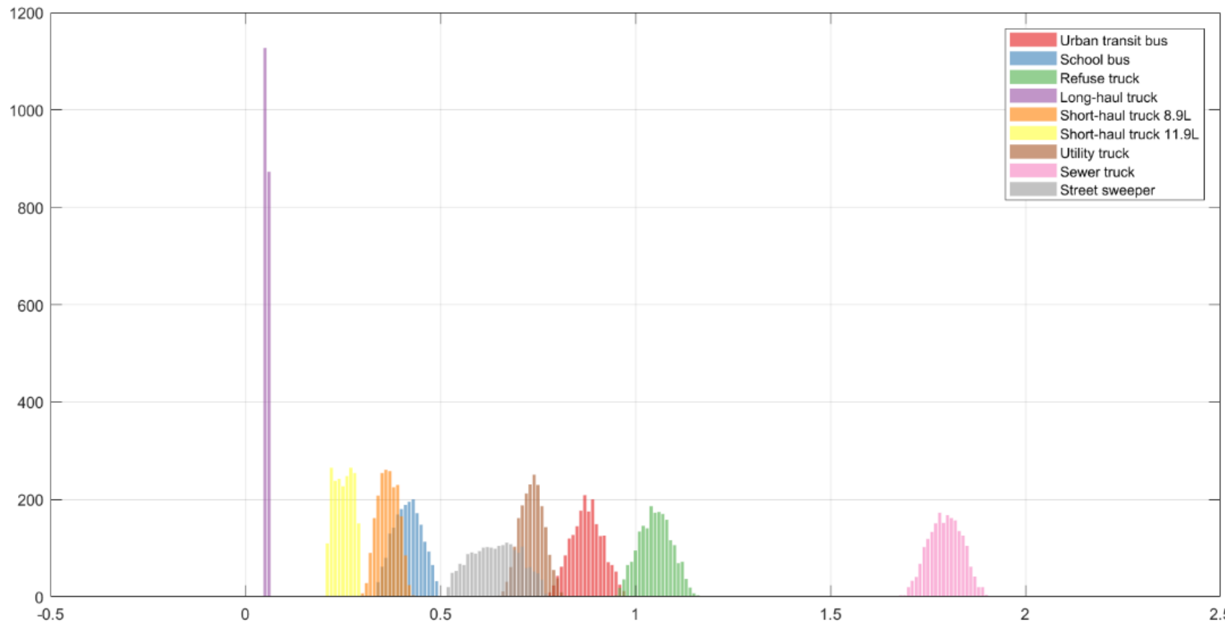

Figure 5.12. Distributions of NOx emission rates with 20% of allowed DMC variability

5.6 Summary

In this chapter, various driving pattern analyses were conducted to define common driving patterns per vocation type and capture operational characteristics of the subject NGVs. The obtained activity data was processed into micro driving patterns and used to conduct k-means pattern clustering analysis. The pattern classification thresholds obtained from the clustering analysis were used to categorize the micro driving patterns into the five drive mode groups, including creep, transient, cruising, low-speed cruising, and high-speed transient. The resulting drive mode composition (DMC) of each vehicle exhibited the operational characteristics of the subject NGV types. This study demonstrated that the operational characteristics captured by DMC are correlated with emission production patterns over duty cycles because each drive mode has different NOx and CO_2 emission rates.

Vocation type specific-DMC showed that the vocational vehicles are likely to have specific predominant drive modes, and the primary driving mode differs by vocation type. This indicated that the vocation type is one of the influential factors affecting the operational and emission characteristics of HD NGVs. The refuse trucks and street sweeper data showed a substantial amount of low-speed range operations, such as creeping and low-speed-cruising modes. The refuse truck data had the highest proportion of creeping mode to the total operation time compared to the others, while most operations of hauling service groups were conducted in cruising mode. This study found that inter-group differences are much more significant than intra-group differences. The refuse trucks from different regions presented similar DMCs. This result supported the argument that vocation type factor can have a very significant impact on commercial HDV operations and be more influential than the other factors. DMCs by facility type provided a broad picture of operational conditions of the HD NGVs. DMCs by road facility type showed that the HD NGVs use a specific road facility type during their duty cycles.

Chapter 6 Total fuel cycle (Well-to-Wheel) analysis on NGVs

6.1 Well-to-Pump (WTP) analysis

Battery-electric and fuel cell vehicles produce zero emissions on the roads, and this is reasonably true when we only account for the vehicle cycle (Pump-to-Wheel) emissions. Since no natural source of electricity and hydrogen exist yet, it is necessary to construct stationary power plants and applications to produce hydrogen and electricity and store them in stable and reliable forms. Given the entire process of energy production and consumption, vehicle electrification does not offer zero-emission production. This is the reason that alternative fuel vehicles should be compared in total fuel cycle analysis. **Table 6.1** and **Table 6.2** present Well-to-Pump emission rates of NG, RNG, and diesel fuel pathways.

While NGVs provides significant regulated pollutant and GHG emission reductions compared to diesel vehicles (DVs), RNG powered NGVs offer much more environmental benefits than fossil-fueled NGVs and DVs. Argonne National Laboratory's GREET.net version and California Air Resources Board's CA-GREET version provide slightly different CO_2 emission rates for the conventional CNG fuel pathway. This is because the CA-GREET uses different assumptions of fuel consumption and emission characteristics that reflect the operational conditions of California. The RNG pathway can provide different environmental impacts depending on how the vehicles are refueled. If NGVs perform on-site RNG refueling, the expected emission benefits are incredible and likely to negate the partial vehicle cycle emissions. Due to the limited number of RNG facilities, the emission benefits are disappeared in the off-site RNG refueling scenario of the recently released CA-GREET 3.0 version. The emission rates of off-site refueling scenario are higher than the other pathways; therefore, the fuel pathway was excluded in the well-to-wheel analysis.

For the WTP diesel emissions, this study referred to the fuel economy values of diesel vehicles in the GREET.net model (*22-24*). Overall, emission rates of the CA-GREET 3.0 version were higher than those of the default GREET.net. Because the subject vehicles were being operated in CA, the CA-GREET estimates were coupled with vehicular emissions in the WTW analysis. Notably, conventional and California Ultra-Low-Sulfur (ULS) diesel WTP CO_2 emission rates were nearly 10% higher and 10% lower respectively than the CNG WTP CO_2 emission rates, respectively. In addition, WTP NOx emission rates of diesel fuel types were 80% lower than CNG WTP NOx emission rates. Considering the PTW CO_2 and NOx emission rates of the CA-GREET 3.0, it was found that the total carbon intensity (CI) of diesel fuel pathways exceeds the total CI of the conventional CNG fuel pathway.

6.2 Well-to-Pump analysis results

WTP emission rates can be expressed in either gram per mile or grams per Megajoule. **Table 6.1** and **6.2** show the WTP CO_2 and NOx emission rates estimated with the HD NGV fuel economy assumptions of GREET.net and CA-GREET. For WTW analysis, this study used the CI of each WTP pathway and horsepower of the subject NGVs to estimate NOx and CO_2 fuel cycle emissions because the subject NGVs had different fuel economy from the assumption of the GREET models. If this study uses distance-based fuel cycle emission rates (g/mile) to estimate the WTW emissions of the subject vehicles, NOx and CO_2 emissions of long- and short-haul trucks will be over-estimated, compared to other vocational trucks. This is because the long-distance traveling vehicles, which are primarily operated on freeways, are likely to have higher VMT than the other vocational vehicles. Therefore, this study used the emission rates in grams per Megajoule in the WTW analysis.

Table 6.1. WTP CO_2 emission rates of the fuel cycles of NG, RNG, and diesel (g/mile)

Fuel pathway	GREET.net diesel	CA-GREET Conventional diesel	CA-GREET CA ULS diesel	GREET.net CNG	CA-GREET CNG	CA-GREET RNG (off-site refueling)	CA-GREET RNG (on-site refueling)
Heavy-duty intercity Buses	310	525.7	450.0	220	449.5	662.8	-1171.4
Heavy-duty school Buses	260	450.6	385.7	200	407.9	601.5	-1063.2
Heavy-duty transit Buses	480	846.2	724.4	370	739.7	1090.9	-1927.9
Heavy-duty long-haul trucks	300	475.3	406.9	220	442.1	651.9	-1152.2
Heavy-duty short-haul trucks	300	468.9	401.3	220	435.0	641.4	-1133.6
Medium heavy-duty vocational vehicles	98.91	418.0	357.9	64.11	380.7	561.4	-992.3
Heavy heavy-duty vocational vehicles	300	468.9	401.3	220	442.1	651.9	-1152.2
Heavy-duty Refuse trucks	380	608.7	521.1	300	594.9	877.2	-1550.4

Table 6.2. WTP NOx emission rates of the fuel cycles of NG, RNG and diesel (g/mile)

Fuel pathway	GREET.net diesel	CA-GREET Conventional diesel	CA-GREET CA ULS diesel	GREET.net CNG	CA-GREET CNG	CA-GREET RNG (off-site refueling)	CA-GREET RNG (on-site refueling)
Heavy-duty intercity Buses	0.640	0.302	0.326	1.070	1.331	5.234	-0.204
Heavy-duty school Buses	0.540	0.259	0.279	0.970	1.208	4.750	-0.185
Heavy-duty transit Buses	0.990	0.486	0.525	1.760	2.191	8.614	-0.336
Heavy-duty long-haul trucks	0.630	0.273	0.295	1.050	1.309	5.148	-0.201
Heavy-duty short-haul trucks	0.620	0.269	0.291	1.030	1.288	5.065	-0.198
Medium heavy-duty vocational vehicles	0.210	0.240	0.259	0.310	1.128	4.433	-0.173
Heavy heavy-duty vocational vehicles	0.630	0.269	0.291	1.050	1.309	5.148	-0.201
Heavy-duty Refuse trucks	0.790	0.349	0.377	1.410	1.762	6.927	-0.270

Table 6.3. WTP CO_2 and NOx emission rates in grams per Megajoule (g/MJ)

WTP fuel pathway	California Conventional CNG	California RNG (off-site refueling)	California RNG (on-site refueling)	California Conventional Diesel	California Ultra-Low-Sulfur-Diesel
Carbon Dioxide	17.765	26.198	-46.302	25.396	21.740
Nitrogen Oxides	0.049	0.207	-0.008	0.015	0.016

6.3 Pump-to-Wheel (PTW) analysis

Pump-to-wheel (PTW) cycle NOx and CO_2 emissions were compared between NGV and diesel vehicle (DV) type scenarios as presented in **Table 6.4**. The base scenarios showed the emission rates of the subject vehicles, while low NOx and diesel vehicle scenarios were included in the analysis as counterparts of the base scenarios. The low NOx engines are the cleanest engine models currently on the market and conform to the optional criterion of the NOx emission standard of less than 0.02 g/bhp-hr. This study determined the diesel counterparts based on the Primary Intended Service Class (PISC), model year (MY) and engine dimension of the subject vehicles. Among the 2017 and 2018 MY diesel engines with comparable engine dimensions, this study selected the diesel counterparts that have the lowest NOx emission rate.

Table 6.4. PTW analysis scenarios

PTW scenario ID	Service type	Vocation group	Group code	Model year (MY)	Location	Engine dimension (liter)	Engine family [NOx emission rate (g/bhp-hr)]		
							Base scenario - Subject vehicles	Low NOx engine scenario	Diesel counterpart scenario
1	Transit service	Urban transit bus	UTB	2016	South California	8.9	GCEXH0540LBG [0.13]	HCEXH0540LBK [0.01]	GCEXH0540LAV [0.19]
2		School bus	SCB	2016	Orange County	8.9	GCEXH0540LBF / HCEXH0408BBA [0.13 / 0.08]	HCEXH0540LBK [0.01]	HCEXH0540LAX [0.16]
3	Waste service	Street sweeper	SWP	2009	Orange County	5.9	9CEXH0359BBG [1.44]	FGKTE06.8FM1 [0.01]	HCEXH0408BAT [0.14]
4		Refuse truck	RFT SD	2014 / 2017	San Diego County	8.9	ECEXH0540LBH / HCEXH0540LBK [0.13 / 0.01]	HCEXH0540LBK [0.01]	HCEXH0540LAX [0.16]
5		Refuse truck	RFT LA	2016	Los Angeles County	8.9	FCEXH0540LBH / GCEXH0540LBF [0.13]	HCEXH0540LBK [0.01]	GCEXH0540LAV [0.19]
6	Hauling service	Waste transfer short-haul truck	WTSH SD	2014	San Diego County	11.9	ECEXH0540LBH / FCEXH0540LBH [0.13]	JCEXH0729XBC [0.01]	HCEXH0540LAX [0.16]
7		Waste transfer short-haul truck	WTSH LA I	2016	Los Angeles County	11.9	GCEXH0729XBA [0.15]	JCEXH0729XBC [0.01]	GCEXH0729XAE [0.19]
8		Waste transfer short-haul truck	WTSH LA II	2018	Los Angeles County	11.9	JCEXH0729XBC [0.01]	JCEXH0729XBC [0.01]	GCEXH0729XAE [0.19]
9		Long-haul truck	LHT	2017	San Francisco and Sacramento County	11.9	HCEXH0729XBA [0.15]	JCEXH0729XBC [0.01]	HCEXH0729XAE [0.19]
10		Short-haul truck	SHT	2013 / 2014	Los Angeles County	8.9	DCEXH0540LBH ECEXH0540LBH [0.13]	HCEXH0540LBK [0.01]	HCEXH0540LAX [0.16]
11		Dairy reefer truck	DRT	2018	San Diego County	11.9	JCEXH0729XBC [0.01]	JCEXH0729XBC [0.01]	HCEXH0729XAE [0.19]
11	Utility service	Water retail crew utility trucks	CUT	2011	Orange County	8.9	BCEXH0540LBH [0.13]	HCEXH0540LBK [0.01]	GCEXH0729XBA [0.15]
12		Water retail sewer trucks	SWT	2016	Orange County	11.9	GCEXH0729XBA [0.15]	JCEXH0729XBC [0.01]	HCEXH0729XAE [0.19]

6.4 Pump-to-Wheel (PTW) analysis results

PTW NOx and CO_2 emission rates of the NGV and diesel vehicle scenarios were presented in **Table 6.5**, **Figure 6.1**, and **Figure 6.2**. Because the street sweeper was equipped with a relatively older engine model (MY 2009) than the other subjects, it showed higher NOx emission rates than the 2018 diesel engine models and did not provide the fuel rate parameter used for estimating CO_2. Thus, the total fuel cycle analysis excluded the street sweeper data, but its operating characteristics were unique and showed high emission reduction potential (ERP) due to the extensive amount of low-speed operations as shown in **Figure 6.3**.

Table 6.5. NOx and CO_2 emission rates and the number of stop-per-mile

Service type	Vocation group	Number of stops per mile	CO_2 emission rates in grams per mile		NOx emission rates in grams per mile		
			Base CNG scenario	Diesel counterpart scenario	Base CNG scenario	Low NOx engine scenario	Diesel counterpart scenario
Transit service	Urban transit bus	2.82	1822	2261	1.193	0.875	2.274
	School bus	1.91	1332	1653	0.602	0.428	1.110
Waste service	Street sweeper	5.79	-	-	2.528	0.643	1.574
	Refuse truck in SD	15.48	3589	4453	1.646	1.384	3.469
	Refuse truck in LA	13.82	3726	4623	1.509	0.959	2.795
Hauling service	Waste transfer short-haul truck in SD	3.74	1642	2037	1.002	0.637	1.716
	Waste transfer short-haul truck in LA I	0.54	1789	2220	0.660	0.288	1.130
	Waste transfer short-haul truck in LA II	0.87	1927	2391	0.283	0.283	1.094
	Long-haul truck	0.20	1078	1338	0.305	0.057	0.431
	Short-haul truck	0.64	1056	1310	0.497	0.311	0.883
	Dairy reefer truck	0.56	1704	2114	0.123	0.123	0.807
Utility service	Water retail crew utility trucks	1.35	2048	2541	1.690	1.397	3.284
	Water retail sewer trucks	3.31	4262	5288	2.400	1.939	4.793

The NGV operations provided approximately 20% lower CO_2 emissions compared to diesel scenarios. NOx emissions were reduced respectively about 42% and 67% in the base and low NOx engine scenarios. If a government agency offers the same value of incentives to the vocational heavy-duty vehicles, the anticipated emission reduction potential would be between

42% and 67% depending on the market penetrations. However, **Table 5.2** shows that each vocational NGV group provided different environmental impacts. This implies that an incentive policy can be re-designed to maximize emissions reductions by focusing on the crucial vocation types.

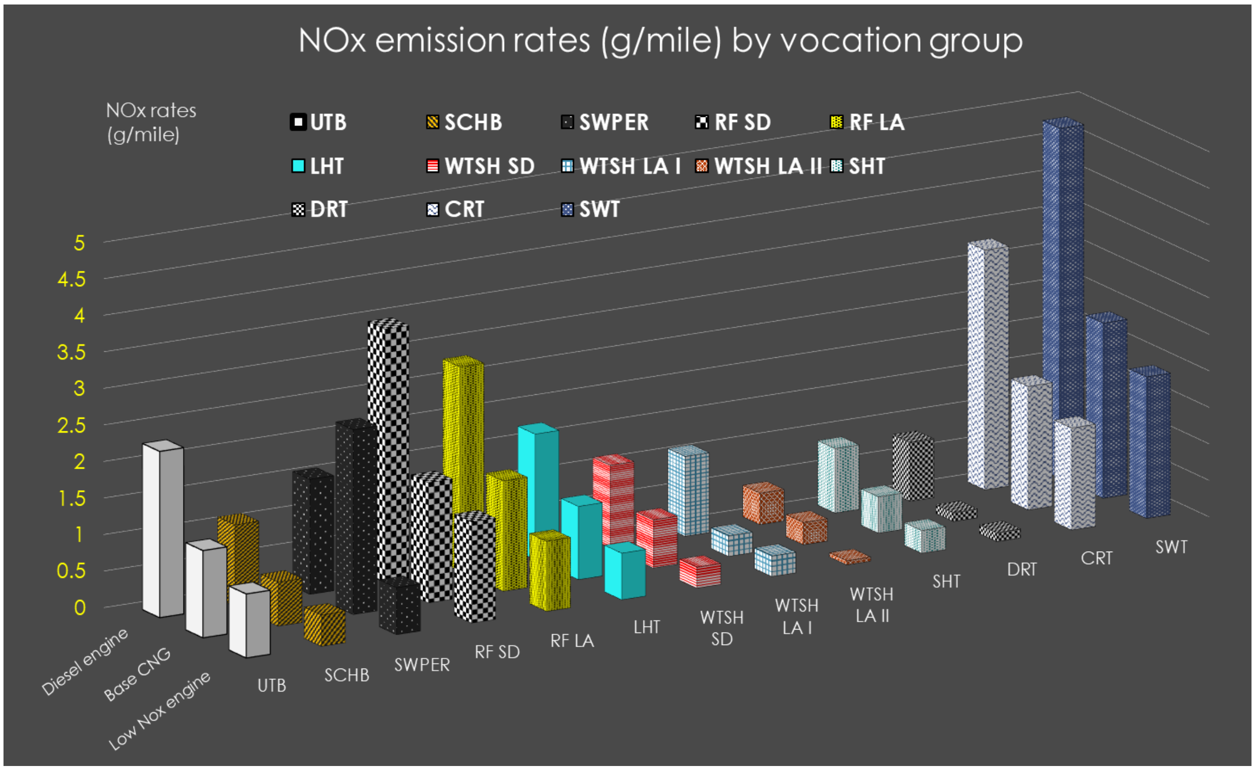

Figure 6.1. NOx emission rates of the vocation groups

The water retail sewer trucks presented the second-highest average NOx emission rate, followed by crew utility and refuse trucks. These vocational vehicles exhibited significant idling time for power take-off (PTO) operations, as shown in **Figure 6.3**. PTO operations maintain high engine RPM to supply power source for the unique activity of the vehicle type. Thus, a common practice to measure the lifespan of these vocational trucks takes account of accumulated operating time rather than using VMT. For reference, this study used engine horsepower parameters to calculate the NOx emission rates; therefore, the emission estimates reflect the impact of the PTO operations.

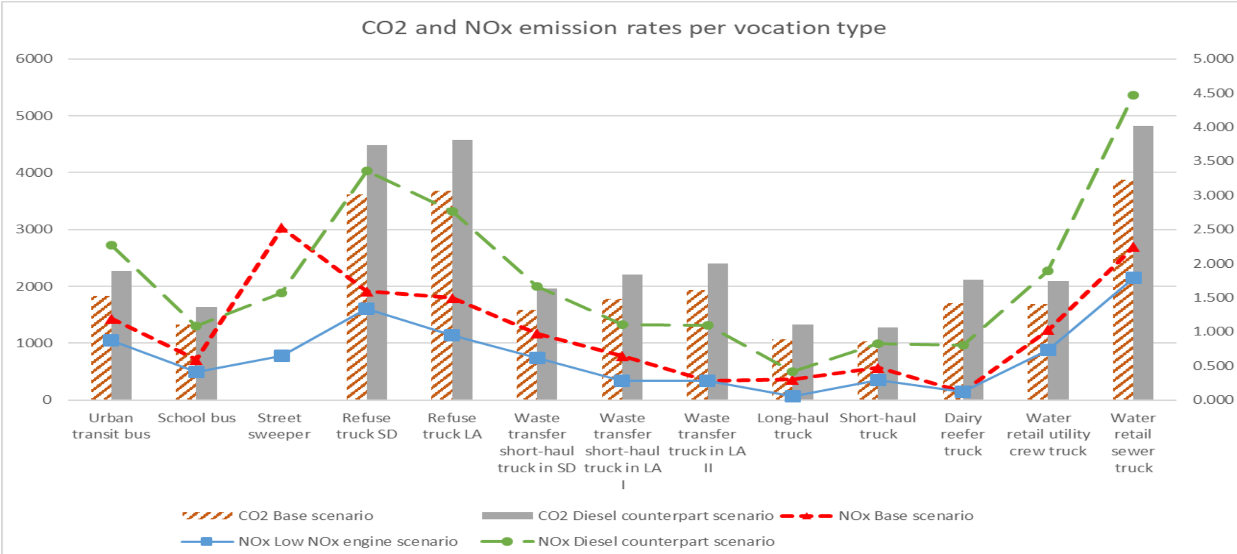

Figure 6.2. NOx and CO_2 emission rates of NGV and diesel counterpart scenarios

Urban transit buses and refuse trucks showed higher NOx emission rates than hauling service truck groups. **Figure 6.3** shows that refuse trucks and transit buses had substantial durations of creeping and transient mode operations. In particular, refuse trucks exhibited a high number of stops-per-mile as shown in **Table 5.3**, and their total NOx emission rates were also higher than the other groups. The waste collection activity included frequent stop-and-go operations, and this caused higher emission rates in grams per second. The dairy reefer truck is a low NOx engine equipped vehicle; therefore, it has the same emission rate for the base and low NOx engine scenarios. Overall, the PTW analysis results showed that conventional NG and low NOx NG engines provide significant environmental benefits in terms of both NOx and CO_2.

According to California Department of Motor Vehicles data, refuse trucks take a significant market share in the heavy-duty CNG vehicle market. This research compared the environmental benefits and incentive effect of the subject vehicles based on those of refuse trucks. Hauling service trucks showed lower emissions compared to other vocation groups. Hauling truck groups including short- and long-haul and dairy reefer trucks showed an average of 76% lower emission rates than average NOx emission rates of refuse truck groups in the CNG low NOx engine scenario. Sewer trucks showed an average of 52% and 65% higher NOx emission rates than refuse truck groups in the default CNG engine and low NOx engine scenarios, respectively. The DMC analysis results suggested that low-speed operations and frequent stop-and-go driving patterns are correlated with high emission rates. Although the activity datasets of the vocation groups were obtained from different regions, bus groups, refuse truck groups, and hauling truck groups showed similar DMCs and emission rates across regions, respectively.

6.5 Well-to-Wheel (WTW) analysis results of NG fuel pathways and NGV applications

The WTW analysis considered a total of 56 fuel pathways which consist of WTP cycles for diesel, NG, and RNG and PTW cycles for 13 vehicle groups with conventional NG, diesel, and low NOx NG engine variations. The corresponding CO_2 and NOx emission rates of the WTP and PTW cycles were respectively summed up to WTW emission rates of each fuel pathway. Then, this study prioritized the fuel pathways based on WTW CO_2 and NOx emission rates. An underlying assumption of the WTW analysis was that the CO_2 production of conventional NG and low NOx NG engines are not significantly different because the CO_2 emission estimation method relies on the ECU fuel rate.

Table 6.6 shows net CO_2 and NOx emission rates for the entire fuel cycles and the resulting rank order of the fuel pathways considered. The fuel pathway scenarios had different ranks depending on what emission species was prioritized. For instance, RNG-powered long-haul trucks equipped with a low NOx engine offered the lowest NOx emissions per mile if the fuel pathways are prioritized by NOx emission reduction benefits. Furthermore, RNG-powered urban transit buses can potentially be the best fuel pathway in terms of CO_2 emission reduction.

Since the analysis was sensitive to the focus of the emissions, some mechanism was required for considering the trade-offs. In this case, CO_2 is one of the representative GHG emission species, while NOx is a regulated pollutant. They affect our environment in different ways and therefore, cannot easily be combined into a single factor. However, public health-related policymakers and legislators are required to consider multiple aspects of fuel pathways to determine the performance of emission reduction plans precisely. Thus, this study proposed combining a multiple-criteria decision-making (MCDM) method and the emissions evaluation framework described above to compare WTW scenarios and to prioritize them.

Table 6.6. Ranked fuel pathway scenarios based on WTW NOx and CO_2 emission rates

Fuel pathway	Vocation type	Engine technology	WTW NOx emission rate (g/mile)	NOx Scenario rank order	WTW CO_2 emission rate (g/mile)	CO_2 Scenario rank order
CNG	Urban transit bus	Conventional NG engine	1.593	39	1967	31
CNG	Urban transit bus	Low NOx NG engine	1.275	34		
CNG	School bus	Conventional NG engine	0.822	23	1412	14
CNG	School bus	Low NOx NG engine	0.648	17		
CNG	Refuse truck SD	Conventional NG engine	2.534	50	3910	48
CNG	Refuse truck SD	Low NOx NG engine	2.272	47		
CNG	Refuse truck LA	Conventional NG engine	2.423	49	4057	50
CNG	Refuse truck LA	Low NOx NG engine	1.873	44		
CNG	Waste transfer short-haul truck SD	Conventional NG engine	1.506	38	1825	26
CNG	Waste transfer short-haul truck SD	Low NOx NG engine	1.141	29		
CNG	Waste transfer short-haul truck LA I	Conventional NG engine	1.055	27	1932	29
CNG	Waste transfer short-haul truck LA I	Low NOx NG engine	0.683	18		
CNG	Long-haul truck	Conventional NG engine	0.567	14	1173	11
CNG	Long-haul truck	Low NOx NG engine	0.319	7		
CNG	Short-haul truck	Conventional NG engine	0.733	20	1142	7
CNG	Short-haul truck	Low NOx NG engine	0.547	11		
CNG	Dairy reefer truck	Low NOx NG engine	0.597	16		
CNG	Crew utility truck	Conventional NG engine	2.129	45	2207	34
CNG	Crew utility truck	Low NOx NG engine	1.836	42		
CNG	Sewer truck	Conventional NG engine	3.208	53	4554	52
CNG	Sewer truck	Low NOx NG engine	2.746	51		
CNG	Waste transfer short-haul truck LA II	Low NOx NG engine	0.713	19		
DSL	Urban transit bus	Diesel engine	2.402	48	2468	39
DSL	School bus	Diesel engine	1.186	30	1766	25
DSL	Refuse truck SD	Diesel engine	3.748	55	4912	54
DSL	Refuse truck LA	Diesel engine	3.067	52	5096	55
DSL	Waste transfer short-haul truck SD	Diesel engine	1.866	43	2299	36
DSL	Waste transfer short-haul truck LA I	Diesel engine	1.264	33	2424	38
DSL	Long-haul truck	Diesel engine	0.520	10	1473	21
DSL	Short-haul truck	Diesel engine	0.966	25	1433	18
DSL	Dairy reefer truck	Diesel engine	0.968	26	2359	37
DSL	Crew utility truck	Diesel engine	3.414	54	2768	43
DSL	Sewer truck	Diesel engine	5.095	56	5706	56
DSL	Waste transfer short-haul truck LA II	Diesel engine	1.241	32	2614	40
RNG	Urban transit bus	Conventional NG engine	1.127	28	1445	19
RNG	Urban transit bus	Low NOx NG engine	0.809	22		
RNG	School bus	Conventional NG engine	0.566	13	1125	5
RNG	School bus	Low NOx NG engine	0.392	**8**		
RNG	Refuse truck SD	Conventional NG engine	1.500	37	2751	41
RNG	Refuse truck SD	Low NOx NG engine	1.238	31		
RNG	Refuse truck LA	Conventional NG engine	1.359	36	2864	44
RNG	Refuse truck LA	Low NOx NG engine	0.809	21		
RNG	Waste transfer short-haul truck SD	Conventional NG engine	0.919	24	1166	9
RNG	Waste transfer short-haul truck SD	Low NOx NG engine	0.554	12		
RNG	Waste transfer short-haul truck LA I	Conventional NG engine	0.595	15	1417	16
RNG	Waste transfer short-haul truck LA I	Low NOx NG engine	0.223	**4**		
RNG	Long-haul truck	Conventional NG engine	0.262	**5**	832	1
RNG	Long-haul truck	Low NOx NG engine	0.014	**1**		
RNG	Short-haul truck	Conventional NG engine	0.458	**9**	833	3
RNG	Short-haul truck	Low NOx NG engine	0.272	**6**		
RNG	Dairy reefer truck	Low NOx NG engine	0.045	**2**		
RNG	Crew utility truck	Conventional NG engine	1.618	40	1633	23
RNG	Crew utility truck	Low NOx NG engine	1.324	35		
RNG	Sewer truck	Conventional NG engine	2.268	46	3500	46
RNG	Sewer truck	Low NOx NG engine	1.806	41		
RNG	Waste transfer short-haul truck LA II	Low NOx NG engine	0.212	**3**		

6.6 Summary

As no zero-emission vehicle in terms of fuel lifecycle emissions exists, total fuel cycle analysis is an essential component of solving energy-related problems. This chapter presented well-to-pump (WTP) cycle emissions of conventional natural gas, renewable natural gas, and conventional diesel fuel pathways calculated by using Argonne National Laboratory's GREET.net model and California Air Resources Board's CA-GREET model.

Using the obtained vehicle activity data, this study estimated pump-to-wheel (PTW) cycle emissions of various heavy-duty NG and diesel vehicles. Waste, transit and utility service vehicle groups showed relatively higher emission rates than hauling service truck groups. Particularly, refuse trucks and urban transit buses commonly had a considerable number of stop-and-go driving patterns which caused higher NOx emissions per time and distance. Activity data obtained from utility service truck groups showed extensive PTO (Power-Take-Off) operations; therefore, these vehicles produced a significant amount of idling emissions. The water retail sewer trucks presented the second-highest average NOx emission rate, followed by crew utility and refuse trucks. Hauling truck groups including short- and long-haul and dairy reefer trucks showed an average of 76% lower emission rates than average NOx emission rates of refuse truck groups in the CNG low NOx engine scenario. Sewer trucks showed an average of 52% and 65% higher NOx emission rates than refuse truck groups in the default CNG engine and low NOx engine scenarios, respectively.

Well-to-wheel (WTW) analysis results showed net CO_2 and NOx emission rates for the entire fuel cycles and the resulting rank order of the fuel pathways considered. The fuel pathway scenarios have different ranks depending on what emission species is prioritized on. CO_2 is one of the representative GHG emission species, while NOx is a regulated pollutant. They affect our environment in different ways and therefore, cannot easily be combined into a single factor. This was the research motivation to conduct multiple-criteria decision-making analyses on the various fuel pathways.

Chapter 7 NOx emission reduction potential and environmental incentive effectiveness index

Emission rates in grams per mile or seconds were insufficient to explain the entire environmental impacts of NGV adoption because vocational HD NGVs had different operational conditions and duty cycles which cause different lifetime emissions in the unit of time and distance. Using the surveyed duty cycle information of the subject NGVs, this study extrapolated the total NOx emissions during the data collection period to annual NOx emission projections and predicted annual NOx emission reduction potential (ANRP) of the NGVs compared to diesel counterpart scenarios. VMT during the data survey period was converted to daily and annual average VMT values based on the obtained duty cycle information which is presented in **Table 7.1**.

Table 7.1. Duty cycle information of the subject NGVs

Data source		NGV use paper survey			J1939 data survey	
Vocational vehicle groups	Number of vehicles	Average daily operating hour per veh. (hour)	Average operating days per week per veh. (days)	Average daily VMT per veh. (mile)	Average daily VMT per veh. (mile)	Sum of effective working days for the survey period per fleet group (days)
Urban transit buses	3	10.8	5.7	129.7	85.1	21
School buses	2	7.5	5.0	70.5	79.8	14
Refuse trucks	7	8.3	5.0	59.1	50.1	80
Short-haul trucks - 8.9 liter	4	9.0	4.5	153.4	68.7	78
Short-haul trucks - 11.9 liter	10	7.7	5.0	179.0	88.8	105
Long-haul trucks	6	6.2	6.5	226.2	194.4	58
Dairy reefer trucks	1	8.0	5.0	180.0	127.7	15
Water district vocational trucks	6	4.3	4.5	92.8	17.1	149

The diesel counterpart engines were determined based on PISC, model year (MY) and engine dimension of the subject vehicles. Among the 2017 and 2018 MY diesel engines with comparable engine dimensions, this study selected the diesel counterparts that have the least NOx emission rate. The vehicle groups with the same vocation types, such as refuse and short-haul truck types, were merged into one group, and short-haul trucks separated into two groups based upon engine size (8.9-liter, and 11.9-liter).

7.1 Annual and lifetime NOx reductions of the HD NGVs

Per day per vehicle NOx emissions were extrapolated to the annual NOx emission projections based on the duty cycle information and the number of official working days excluding national holidays, summer, winter, and spring breaks. An assumption on this process was that every target year (TY) has the same total active working days for the project life period. **Equation 4** and **Equation 5** present the calculation processes of daily NOx emissions and annual NOx projection, and the resulting annual WTW NOx emission projections in kg/year/vehicle were presented in **Table 7.2**.

NOx emission reduction potential (NRP) represents the anticipated amount of NOx emissions reductions that can be achieved by adopting the subject HD NGV against conventional diesel vehicle applications. AFV adoption offers NOx emission reductions in the fuel cycle (Well-to-Pump) as well as the vehicle cycle (Pump-to-Wheel) because an introduction of clean vehicle technology is accompanied by expansions of the corresponding fuel supply system and refueling infrastructure. Therefore, NRP was predicted in terms of total NOx emission reductions of full NG and diesel fuel lifecycle.

$$Daily\ NOx\ emission\ production_v^{VT}(g) = Total\ NOx\ prod._v^T \div\ Eff.working\ days_v^T \quad (4)$$

- $Daily\ NOx\ emission\ production_v^{VT} =$
  $Daily\ NOx\ emission\ production\ of\ vehicle\ v\ in\ vocation\ type\ group\ VT$
- $Total\ NOx\ prod._v^T = Total\ NOx\ production\ of\ the\ vehicle\ v\ for\ the\ data\ collection\ period\ T$
- $Eff.workign\ days._v^T = Effective\ working\ days\ of\ the\ vehicle\ v\ for\ the\ data\ collection\ period\ T$

$$Annual\ NOx\ emission\ projection_{TY}^{FT}(kg) = \ Daily\ NOx\ emission\ prod._{v}^{VT} \times Working\ days_{v}^{TY} \quad (5)$$

- $Annual\ NOx\ emission\ projection_{TY}^{FT}(kg) =$
  $Projected\ NOx\ emission\ production\ of\ fuel\ type\ FT\ for\ the\ target\ year(TY)$
- $Working\ days_{v}^{TY} = Number\ of\ working\ days\ of\ vehicle\ v\ in\ target\ year(TY)$

Annual NOx emission reduction potential (ANRP) is a metric of expected NOx emission reductions per year of HD NGV adoption and calculated by using **Equation 6**. This study calculated the ANRP of each subject individually because the vehicles had slightly different operating conditions and schedules. An underlying assumption of ANRP was that the vehicle fleets maintain duty cycle and operational conditions throughout a year regardless of fuel type and pathway.

$$ANRP_{FT,VG}\ (kg/year/veh) = Annual\ NOx\ emi.projection_{TY}^{Diesel,VG} - Annual\ NOx\ emi.projection_{TY}^{NG,VG} \quad (6)$$

- $ANRP_{\ FT,VG} =$
  $Annual\ NOx\ emission\ reduction\ potentials\ of\ vehicle\ group\ VG\ of\ fuel\ type\ FT\ for\ target\ year\ (TY)$
- $Annual\ NOx\ emission\ projection_{TY}^{Diesel,VG} =$
  $NOx\ emission\ production\ of\ diesel\ vehicle\ group\ VG\ for\ TY$
- $Annual\ NOx\ emission\ projection_{TY}^{NG,VG} = NOx\ emission\ production\ of\ NG\ vehicle\ group\ VG\ for\ TY$

Table 7.2. Annual NOx projections and project life estimates based on annual VMT

Vocational vehicle groups	Activity data-based average annual VMT	Survey-based average annual VMT	Activity data VMT based project life	Survey VMT based project life	Annual WTW NOx emission projection				
					Diesel scenario	CNG scenario	CNG w/low NOx engine scenario	RNG scenario	RNG w/low NOx engine scenario
Unit	(miles/vehicle)		(years/180,000 miles)		(kg/year/veh.)				
Urban transit buses	24,026	37,443	7	5	57.69	38.44	30.69	27.09	19.34
School buses	20,035	17,696	9	10	23.23	16.28	12.75	11.10	7.57
Refuse trucks	12,584	14,838	14	12	42.25	30.67	25.68	17.66	12.68
Long-haul trucks	15,901	33,238	11	5	24.16	19.34	14.57	11.82	7.05
Short-haul trucks – 8.9 liter	22,283	44,929	8	4	27.50	17.51	15.63	6.46	4.58
Short-haul trucks – 11.9 liter	64,310	74,500	3	2	32.91	36.03	20.20	16.61	0.78
Dairy reefer trucks	32,058	45,180	6	4	31.05	19.14	19.14	1.45	1.45
Water district vocational trucks	4,001	21,278	15	8	15.80	10.13	8.50	7.14	5.51

7.2 Project life (PL) of NGV incentives

HDVs may emit different amounts of emissions for vehicle lifespan depending on vocation type due to their different VMT variations. This was also shown as the average annual VMT in **Table 7.2**. The lifespan factor was included in the incentive impact analysis to predict the lifetime emission reduction potential (LNRP) of the incentivized NGVs as shown in **Equation 7**. This study adopted various average lifespan values of HDVs from multiple sources (*50)*(*105-108*) and defined project life (PL) as the time it takes to reach 180,000 miles for each vocational group according to the vehicle replacement guidelines of South Florida Water Management District (*107*).

The survey results showed that the two survey instruments obtained different average daily VMT values from the subject NGVs and fleet operators. Thus, LNRP was calculated under multiple lifespan assumptions, such as 10 years, 15 years, activity data-based project life (ABPL) for 180k miles, and survey data-based project life (SBPL) for 180k miles. ABPL was calculated by dividing 180k miles by annual average VMT obtained from ECU data, while SBPL was obtained by dividing 180k miles by annual average of survey VMT.

According to the funding plan for clean transportation incentives, the California Air Resources Board predicts the effectiveness of the incentives by assuming 250 working days per year and a 15-year lifespan as a conservative estimate for all heavy-duty vehicle classes, and grams per mile emission estimates (*50*). Furthermore, low-speed operating vehicles, such as sweepers, utility service, sewer trucks, had significantly lower lifetime VMT than the other vocation type vehicles. The low mileages will result in unrealistic project life for the 180k miles operating condition; therefore, the project life (PL) estimates are limited up to 15 years. The calculated PL values of the two survey instruments are presented in **Table 7.2**.

$$LNRP_{VG,i}^{FT}(kg \,/\, veh) = ANRP_{FT,VG} \times Project\ life_i\ (years) \quad (7)$$

- $Lifetime\ NOx\ emission\ reduction\ potential\ _{TY}^{FT}(LNRP) =$ $NOx\ emission\ reduction\ potential\ of\ fuel\ type\ FT\ of\ vehicle\ group\ VG\ for\ project\ life\ type\ i$
- $Project\ life_i\ (years) =$ *Active period of the incentivized vehicle, i.e., 10 years*

7.3 Lifetime NOx emission reduction potential

Annual NRP of the vehicle groups was presented in **Figure 7.1**, and each vehicle group in the figure represents a combination of fuel and vocation type and engine family. Overall, RNG-powered NGV applications offered a significant amount of NOx emission reductions compared to conventional NG and diesel vehicle applications. Urban transit bus groups showed the highest NRP among the CNG-powered applications, while low NOx engine equipped long-haul truck, waste collection vehicle, dairy reefer truck, and transit bus groups presented the highest NRP among the RNG-powered applications.

Annual NRP in kg/year/vehicle can differ by a total of the active period of the subject vehicles, and vocational NGVs can have different annual VMT due to their operational schedule and conditions. Lifetime NRP (LNRP) was estimated under various project life assumptions and presented in **Table 7.3** and **Table 7.4**.

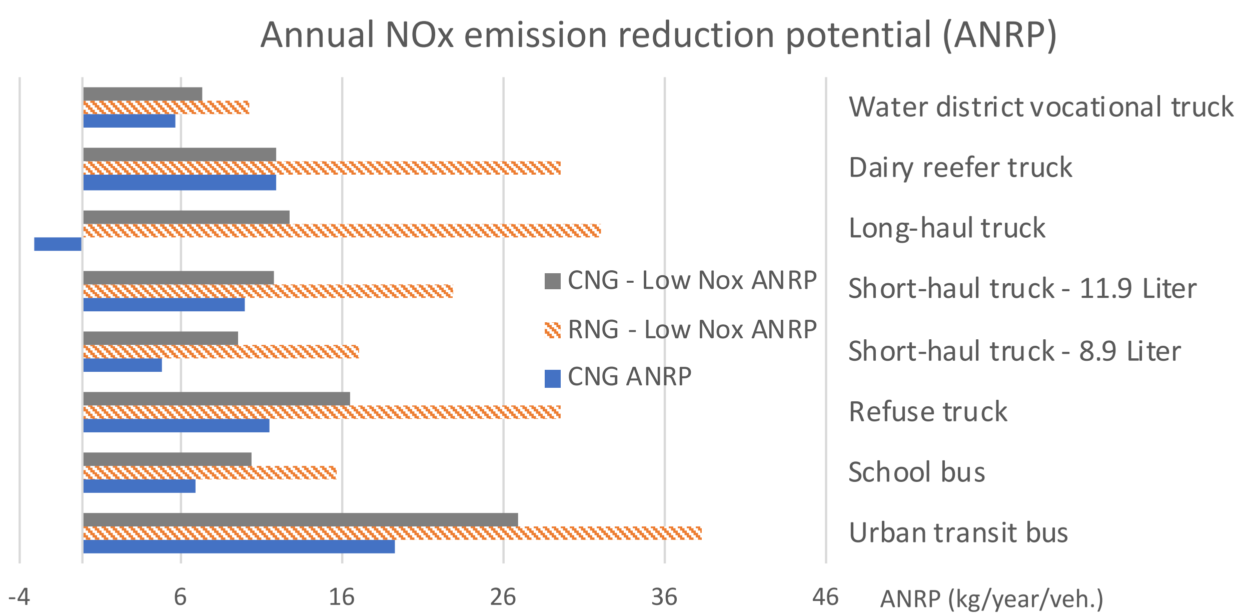

Figure 7.1. Annual NOx emission reduction potential of the HD NGVs

Table 7.3. Annual and lifetime NOx emission reduction potentials under 10- and 15-years project life assumptions

Project life	1 year				10 years				15 years			
NRP scenario (NOx emission reduction potential)	CNG ANRP	CNG & Low NOx ANRP	RNG ANRP	RNG & Low NOx ANRP	CNG LNRP	CNG & Low NOx LNRP	RNG LNRP	RNG & Low NOx LNRP	CNG LNRP	CNG & Low NOx LNRP	RNG LNRP	RNG & Low NOx LNRP
Vehicle group / Unit	(kg/year/veh)				(kg/10years/veh)				(kg/15yrs/veh)			
Urban transit buses (UTB)	19.2	27.0	30.6	38.3	192.5	270.0	306.0	383.5	288.7	405.0	458.9	575.2
School buses (SCHB)	7.0	10.5	12.1	15.7	69.5	104.8	121.3	156.6	104.3	157.2	182.0	234.9
Refuse trucks (RFT)	11.6	16.6	24.6	29.6	115.8	165.7	245.8	295.7	173.7	248.5	368.8	443.6
Long-haul trucks (LHT)	4.8	9.6	12.3	17.1	48.3	96.0	123.4	171.1	72.4	143.9	185.1	256.6
Short-haul trucks – 8.9 liter (SHT8.9)	10.0	11.9	21.0	22.9	99.9	118.7	210.4	229.2	149.8	178.0	315.6	343.8
Short-haul trucks – 11.9 liter (SHT11.9)	-3.1	12.7	16.3	32.1	-31.2	127.1	163.0	321.3	-46.7	190.6	244.6	481.9
Dairy reefer trucks (DRT)	11.9	11.9	29.6	29.6	119.0	119.0	295.9	295.9	178.5	178.5	443.9	443.9
Water district vocational trucks (WTVT)	5.7	7.3	8.7	10.3	56.7	72.9	86.6	102.9	85.0	109.4	129.9	154.3

Figure 7.2 shows lifetime NOx emission reduction potential which was calculated based on activity data VMT. LNRP presented slightly different trends compared to ANRP. Waste collection vehicle groups showed outstanding lifetime NRP among the vehicle groups, followed by transit bus and short-haul truck groups in the CNG, CNG-low NOx, and RNG-low NOx scenarios.

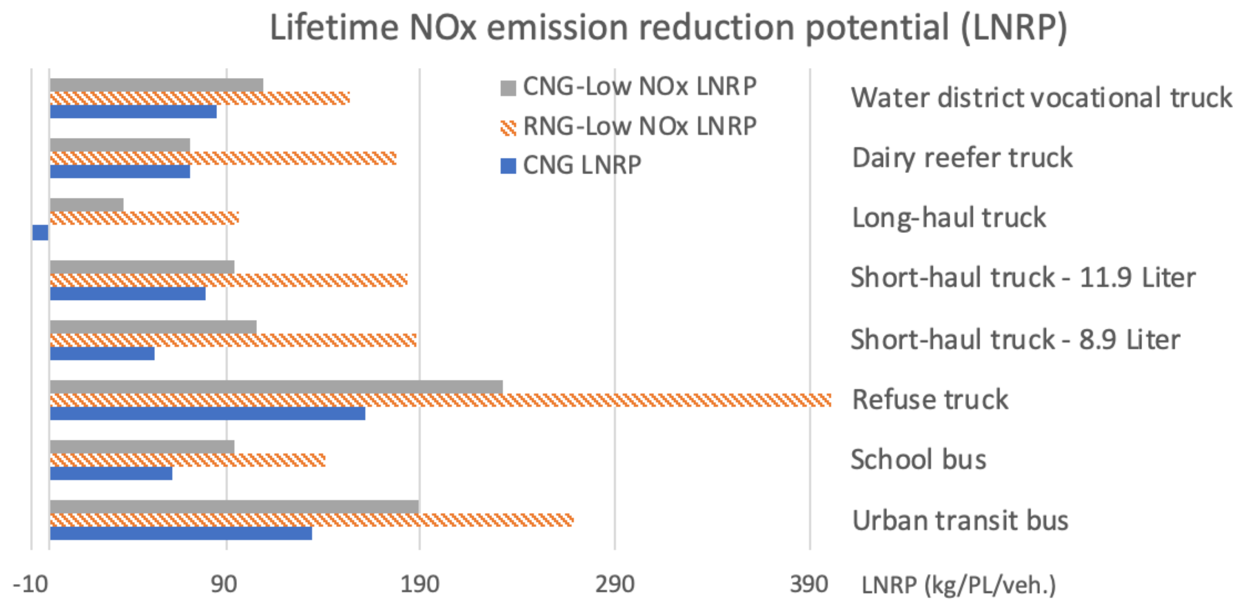

Figure 7.2. Lifetime NOx emission reduction potential of the HD NGVs

Table 7.4. lifetime NOx emission reduction potentials under activity data VMT and survey VMT based project life assumptions

Project life	Activity data VMT based project life				Survey VMT based project life			
Vehicle group	CNG LNRP	CNG & Low NOx LNRP	RNG LNRP	RNG & Low NOx LNRP	CNG LNRP	CNG & Low NOx LNRP	RNG LNRP	RNG & Low NOx LNRP
	(kg/ABPL/veh)				(kg/SBPL/veh)			
Urban transit buses (UTB)	134.75	188.99	214.18	268.42	96.2	135.0	153.0	191.7
School buses (SCHB)	62.57	94.32	109.21	140.96	69.5	104.8	121.3	156.6
Refuse trucks (RFT)	162.10	231.95	344.18	414.03	138.9	198.8	295.0	354.9
Long-haul trucks (LHT)	53.10	105.56	135.73	188.19	24.1	48.0	61.7	85.5
Short-haul trucks – 8.9 liter (SHT8.9)	79.91	94.94	168.33	183.36	40.0	47.5	84.2	91.7
Short-haul trucks – 11.9 liter (SHT11.9)	-9.35	38.12	48.91	96.38	-6.2	25.4	32.6	64.3
Dairy reefer trucks (DRT)	71.41	71.41	177.55	177.55	47.6	47.6	118.4	118.4
Water district vocational trucks (WTVT)	84.99	109.40	129.88	154.29	45.3	58.3	69.3	82.3

The proposed evaluation framework can determine the most incentive-effective vocation types in terms of NOx emission reduction. With a limited amount of funding, the incentive policy should be designed to maximize the incentive impact, which aims to contribute to the state's emission abatement goals. The incentivization effect was calculated based on NOx reduction because reducing the regulated pollutant species is the primary purpose of NGV adoption.

7.4 Environmental Incentive Effectiveness Index (EI^2)

The Environmental Incentive Effectiveness Index (EI^2) aims to assess the NRP of the NGVs in the financial perspective. EI^2 is an indicator of the effectiveness of an incentive project and defined as the reduced NOx emissions in grams for the estimated lifespan of the vehicles over the granted incentive value as calculated by using **Equation 8**. The subject vehicles are heavy-duty class vehicles that weigh 33,000 lbs. or greater and eligible for $25,000 from the Natural Gas Vehicle Incentive Project (NGVIP) of the California Energy Commission. The California Hybrid and Zero-Emission Truck and Bus Voucher Incentive Project (HVIP) also provides $40,000 to some of the qualified heavy-duty refuse and transfer NGVs which are equipped with low NOx engine and expected to replace diesel vehicles. From 2019 and later adoption, HVIP offers $45,000 per vehicle.

The $1 billion California Proposition 1B: Goods Movement Emission Reduction Program (*13)(109*) also provides monetary incentives up to $200,000 for heavy heavy-duty trucks operated on California's trade corridors (*14*). **Equation 8** shows the process of EI^2 calculation per vehicle group. **Table 7.5** shows the EI^2 of each vehicle group based on two incentivization scenarios. The street sweeper's operation was mainly focused on a sweeping activity in a boundary of a college campus. As a result, it had a low annual mileage compared to the other vehicle types; therefore, the vehicle showed the same value of EI^2 for the considered project life assumptions.

$$Environmental\ incentive\ effectiveness\ index_v^{VG} = LNRP_{VG,i}^{FT} \div TING^{VG} \quad (8)$$

- $Environmental\ incentive\ effectiveness\ index_v^{VG} =$ $Dollar\ value\ of\ reduced\ grams\ of\ NOx\ emissions\ per\ vehicle\ group$
- $TING^{VG}$ = *The amount of total incentive granted for NGVIP vehicle group* VG

Table 7.5. Environmental Incentive Effectiveness Index (EI²) with 10 years and 15 years project life assumptions (g/$)

Project life	10 years				Activity data VMT based project life			
Vehicle group	Total CNG EI²	Total CNG & Low NOx EI²	Total RNG EI²	Total RNG & Low NOx EI²	Total CNG EI²	Total CNG & Low NOx EI²	Total RNG EI²	Total RNG & Low NOx EI²
	(g/$)							
Urban transit buses (UTB)	7.70	10.80	12.24	15.34	11.55	16.20	18.36	23.01
School buses (SCHB)	2.78	4.19	4.85	6.26	4.17	6.29	7.28	9.40
Refuse trucks (RFT)	4.63	6.63	9.83	11.83	6.95	9.94	14.75	17.74
Long-haul trucks (LHT)	1.93	3.84	4.94	6.84	2.90	5.76	7.40	10.26
Short-haul trucks – 8.9 liter (SHT8.9)	1.54	1.83	3.24	3.53	5.99	7.12	12.62	13.75
Short-haul trucks – 11.9 liter (SHT11.9)	-0.35	1.41	1.81	3.57	-1.87	7.62	9.78	19.28
Dairy reefer trucks (DRT)	0.95	0.95	2.37	2.37	7.14	7.14	17.76	17.76
Water district vocational trucks (WTVT)	2.27	2.92	3.46	4.11	3.40	4.38	5.20	6.17

Table 7.6. Environmental Incentive Effectiveness Index (EI²) with ABPL and SBPL project life assumptions (g/$)

Project life	Activity data VMT based project life				Survey data VMT based project life			
Vehicle group	Total CNG EI²	Total CNG & Low NOx EI²	Total RNG EI²	Total RNG & Low NOx EI²	Total CNG EI²	Total CNG & Low NOx EI²	Total RNG EI²	Total RNG & Low NOx EI²
	(g/$)							
Urban transit buses (UTB)	5.39	7.56	8.57	10.74	3.85	5.40	6.12	7.67
School buses (SCHB)	2.50	3.77	4.37	5.64	2.78	4.19	4.85	6.26
Refuse trucks (RFT)	6.48	9.28	13.77	16.56	5.56	7.95	11.80	14.20
Long-haul trucks (LHT)	2.12	4.22	5.43	7.53	0.97	1.92	2.47	3.42
Short-haul trucks – 8.9 liter (SHT8.9)	3.20	3.80	6.73	7.33	0.61	0.73	1.29	1.41
Short-haul trucks – 11.9 liter (SHT11.9)	-0.37	1.52	1.96	3.86	-0.07	0.28	0.36	0.71
Dairy reefer trucks (DRT)	2.86	2.86	7.10	7.10	0.38	0.38	0.95	0.95
Water district vocational trucks (WTVT)	3.40	4.38	5.20	6.17	1.81	2.33	2.77	3.29

Refuse trucks showed that the highest EI^2 followed by transit buses and 8.9L engine short-haul trucks in ABPL and SBPL scenarios. The average $EI^2$of all vocation type was respectively 58%, 57%, and 61% lower than the refuse trucks' EI^2 in CNG, CNG-Low NOx engine, and RNG-low NOx engine scenarios. Hauling truck groups except for short-haul 8.9L NGVs provided substantially lower NOx emission benefits than waste and transit service NGVs. As shown in **Table 7.5**, the refuse and hauling service truck groups had considerable gaps in EI^2. In particular, RNG fuel pathway scenarios presented more distinct results between the considered vehicle groups, as shown in **Figure 7.3**.

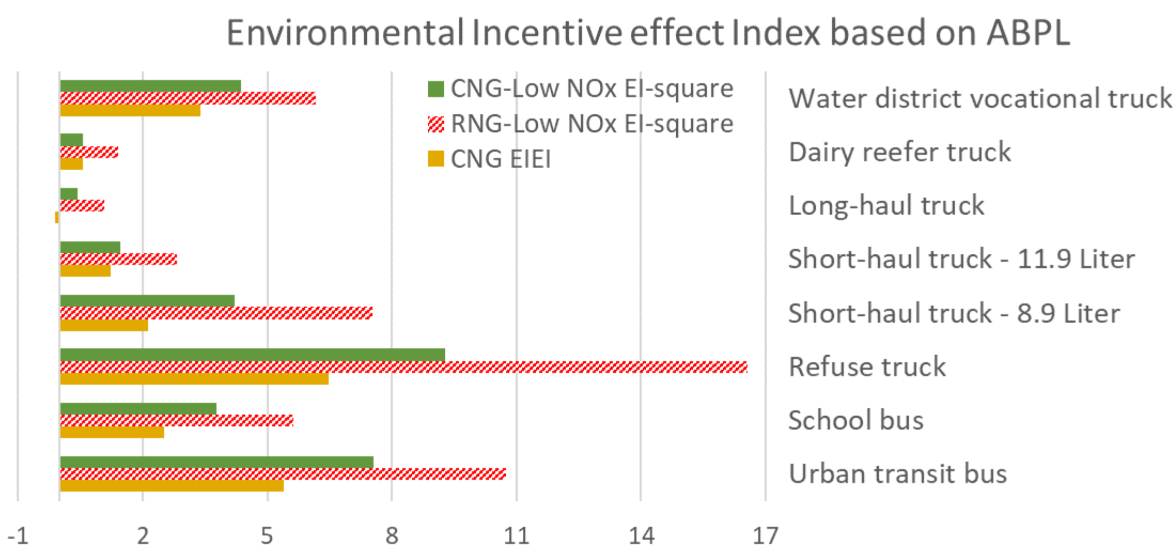

Figure 7.3. Activity data VMT based lifetime NOx EI^2 (g/USD)

According to the LNRP and EI^2 values of the NGVs, the large EI^2 value groups can be a crucial factor in the design of vehicle incentive programs. If a government agency can allocate more funding to specific vocation types, the vehicle incentive programs can achieve the emission reduction goals time- and cost-efficiently with the same amount of budget. As shown in the DMC analysis results, the two top EI^2 groups, refuse trucks and transit buses, were likely to experience dynamically changing traffic conditions and conducted more stop-and-go driving patterns than the other groups. Low-speed and high-engine-demand driving patterns, such as creeping and transient, exhibit higher emission rates (*102-104*). Moreover, these NGV types were being operated in the vicinity of residential areas so that the environmental benefits will be more effective in terms of exposure rate.

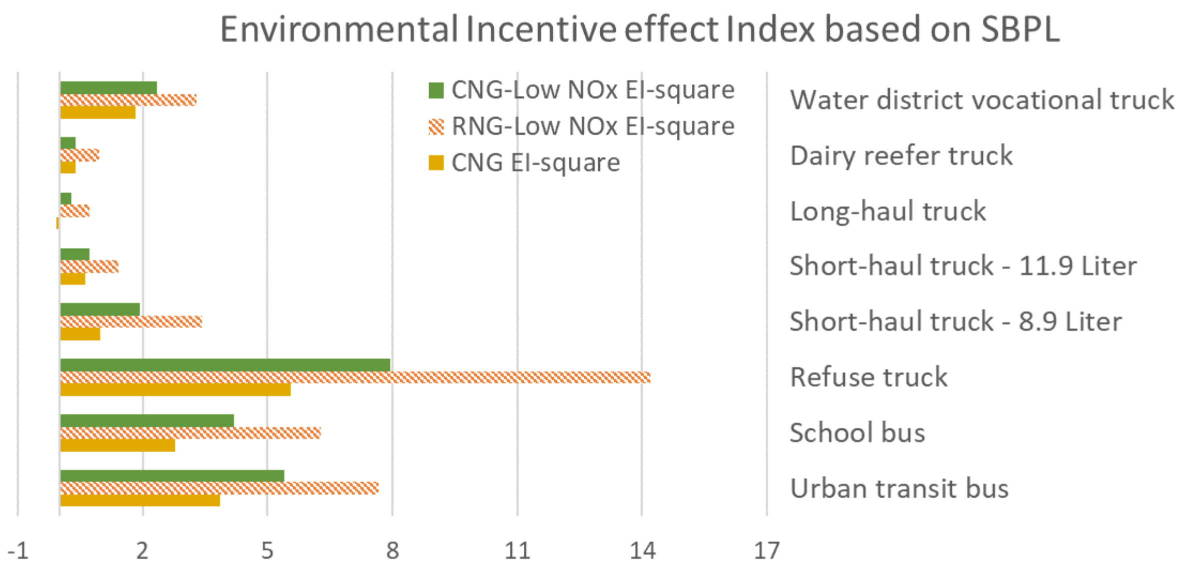

Figure 7.4. Survey VMT based lifetime NOx EI^2 (g/USD)

The water district vocational truck group showed similar annual NOx reduction potential with hauling truck groups in Figure 8.1 and Figure 8.2. However, EI^2 indicated that the truck group showed significantly higher incentive-effectiveness than the haulers in all scenarios. 8.9L Short-haul and water district vocational trucks had slightly higher EI^2 values than school buses in the ABPL scenario, while the SBPL scenario showed that the school bus group provides significantly higher EI^2 than those truck groups.

7.5 Variations of difference of environmental benefits between refuse trucks and other vocation types

A series of comparative analyses in this study determined the best fuel pathways and vehicle applications based on various evaluation metrics. **Table 7.6** shows the percentage change of evaluation metrics between refuse trucks and the other vocation types in the low NOx CNG engine scenario. This study explored whether the difference is consistent in the successive analyses presented in the WTW cycle and incentive impact analysis sections. Percentage error always have positive values; therefore, it is limited to show which vocation type has lower environmental impacts than the other. Therefore, this study used percentage change and negative percentage value in **Table 7.6** indicates that the vocation type has lower value than refuse trucks. For the pump-to-wheel cycle, NOx emission rates of hauling trucks were 76% lower than that of refuse trucks. It means hauling trucks offer significantly higher emission benefits in terms of vehicle cycle emissions. Unlike PTW, WTW emission rates and ANP values, high ANRP and EI^2 values indicate high environmental benefits. Refuse trucks provided the highest EI^2 value, while transit buses had the 63% higher ANRP than refuse trucks.

Table 7.7. Ranked fuel pathway and vehicle application scenarios by each weight scenario

Metric	**PTW NOx emission rate**	**WTW NOx emission rate**	**Annual NOx emission projection (ANP)**	**Annual NOx emission reduction potential (ANRP)**	**Environmental incentive effectiveness index (EI^2)**
Unit	gram per mile	gram per mile	gram per year per vehicle	gram per year per vehicle	gram per U.S. dollar
Urban transit bus	-25%	-38%	24%	63%	-18%
School bus	-63%	-69%	-48%	-37%	-59%
Hauling trucks	-76%	-68%	-31%	-33%	-80%
Vocational trucks	42%	11%	-67%	-56%	-53%

Compared with the gaps in the PTW cycle, the difference between refuse trucks and the vocational truck group in the WTW cycle was reduced, while other vocation types showed similar values between the two cycles. The annual NOx emission projection considered the duty cycle information of each vocational vehicles. Therefore, the differences in annual emissions showed apparent inconsistency with the assessments of the g/mile-based NOx emission estimates in PTW and WTW cycles. The resulting environmental impact of the vocational truck groups became lower than refuse trucks, while the urban transit bus group showed higher annual NOx emissions compared to the refuse truck group.

ANRP indicated the estimated NOx reductions of NGV operations compared to diesel counterparts. The urban transit bus group showed significantly higher NOx reduction potential than refuse trucks, while the other vocation types remain relatively similar in value. In terms of annual NOx reduction contribution, urban transit buses can be regarded as the most crucial promising player in the emission abatement plans.

EI^2 reflected financial incentive impacts in addition to the LNRP. The refuse truck group was not the most environmentally friendly vocation type according to the results of PTW and WTW cycle analyses and duty cycle information-specific annual emissions projections. However, the refuse truck group became the most incentive-effective vocation type considering the total fuel cycle, duty cycle information, and granted incentive values. This result implies that properly defined metrics should be used in comparisons of the emission characteristics between various vehicle and fuel types.

7.6 Summary

Emission rates in grams per mile or seconds are limited to explain the entire environmental impacts of NGV adoption because vocational HD NGVs have different operational conditions and duty cycles which cause different lifetime emissions. In this chapter, the lifecycle NOx and CO_2 emissions of the fuel pathways were extrapolated to annual NOx and CO_2 emission projections by referring to the surveyed duty cycle information of the subject NGVs. Then, this study predicted the lifetime NOx emission reduction potential of the NGVs compared to diesel counterpart scenarios.

The Environmental Incentive Effectiveness Index (EI^2) is an indicator of the effectiveness of the NGV incentive project and was defined as the reduced NOx emissions in grams for the estimated lifespan of the vehicles over the granted incentive value. Refuse trucks showed that the highest EI^2 followed by transit buses and 8.9L engine short-haul trucks. The average EI^2 of all vocation type was respectively 58%, 57%, and 61% lower than the refuse trucks' EI^2 in CNG, CNG-Low NOx engine, and RNG-low NOx engine scenarios. Hauling truck groups except for short-haul 8.9L NGVs provided substantially lower NOx emission benefits than waste and transit service NGVs. The water district vocational truck group showed similar annual NOx reduction potential with hauling truck groups. However, EI^2 indicated that the truck group showed significantly higher incentive-effectiveness than the haulers in all scenarios.

According to the LNRP and EI^2 values of the NGVs, the large EI^2 value groups can be a crucial factor in the design of vehicle incentive programs. If a government agency can allocate more funding to specific vocation types, the vehicle incentive programs can achieve the emission reduction goals time- and cost-efficiently with the same amount of budget.

Chapter 8 Prioritization of fuel pathways using multi-criteria decision-making analysis

It is not difficult to access general information on natural gas vehicles, such as the Environmental Protection Agency (EPA) certified fuel economy, engine performance, vehicle weight, and price. However, the expectation of new customers based on this well-known and wide-spread general information will often be out of the ballpark from in-use experiences. This is because commercial HDV types have different operational and emission characteristics depending on the operating conditions, such as vocation type, working schedule, geographical, and road conditions. In addition, prospective customers may be wondering which fuel and vehicle types are adequate for their business type.

If government agencies, policy-makers, legislators and researchers can access to more specific information regarding the adoption benefits of alternative fuel vehicles (AFVs), they will be more likely to make bold decisions for AFV adoption and to create reciprocal incentive policies. The gap between willingness of people to purchase NGVs and the corresponding cost will likely decrease if an emphasis is placed on the environmental friendliness of natural gas vehicles (NGVs), if more information about the advantages and disadvantages of these vehicles, and if customers have an accessibility to more specific and detail information and insight on their operating patterns. Furthermore, emerging new alternative fuel, drivetrain, and emission control technologies allow customers more choices, and government agencies have to make amendments to emission abatement strategies that consider the new technologies.

The WTW analysis results showed that the rank order of the considered fuel pathways could differ by an emission species that the analysis focuses on. Therefore, this study adopted multi-criteria decision making (MCDM) techniques, which are gaining popularity in energy selection problem studies (*81-83*). MCDM is known as an evaluation technique that compares available alternatives with various qualitative and quantitative criteria to find the best choice or strategy in the given situation (*110*). This study used the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) to evaluate the considered scenarios. The detailed steps of TOPSIS are explained in the previous studies (*81-83)(110*). The criteria used in the analysis included not only fuel and vehicle cycle emission factors but also a newly developed environmental incentive effectiveness index (EI^2).

The decision analysis method considered three types of criteria, including impacts of environmental and operational characteristics and incentivization. The environmental impact criteria consisted of fuel and vehicle cycle NOx and CO_2 emission rates. The operational characteristic factor was low-speed operation DMC, which is a driving pattern-related feature. The incentive effectiveness factor was LNRP over incentive value granted which is expressed in grams per dollar.

Weighing criteria is the most critical component in decision analysis. A criteria weight vector indicated the importance of each criterion in the analysis, and each fuel pathway and vocation type scenario had a different rank order depending on the weight vector used in the analysis. This study presumed that the importance of the considered criteria could differ by region or local conditions. For instance, urban areas where vehicles exhibit many stop-and-go driving patterns will show higher regulated pollutant concentrations than rural areas. Such an air quality impact analysis for urban areas could put more weight on the regulated air pollutants than neither incentive effect nor GHG emissions. On the other hand, an incentive policy designer will be interested in the sustainability and performance of the incentive program so incentive effectiveness can be the most crucial criterion. This study conducted scenario analyses with various weight value sets that represent different research interests.

The vehicle groups were merged into similar vocation types, such as haulers, refuse trucks, transit buses, school buses, and vocational trucks. Fuel pathway variations were CNG, RNG, and diesel, while vehicle applications had default (DEF) engine and low NOx engine variations.

8.1 Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

The TOPSIS involves the following seven steps.

Step 1. Definition of analysis variables. A MCDM problem with m alternatives $\{A_1, A_2, \dots, A_m\}$ which should be assessed by applying n criteria $\{C_1, C_2, \dots, C_n\}$ can be expressed by the decision matrix D.

$$D = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix}$$

x_{ij} is numeric data which represents the value of the i^{th} alternative with respect to the i^{th} criterion. The importance (or weight) of the criterion C_j to the decision is denoted by w_j. A set of weights can be expressed as W = $\{w_1, w_2, \dots, w_n\}$ and satisfy w_j > 0 and $\sum_{j=1}^{n} w_j = 1$ where w_j denotes the weight of the criteria C_j.

Step 2. Normalization of the decision matrix. Given the decision matrix, the normalized value y_{ij} is calculated as

$$y_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}}, \mathrm{i} = 1,2, \dots, \mathrm{m}; \; \mathrm{j} = 1,2, \dots, \mathrm{n}.$$

Step 3. Computation of the weighted normalized decision matrix.

$$z_{ij} = w_j y_{ij}, \mathrm{i} = 1,2, \dots, \mathrm{m}; \; \mathrm{j} = 1,2, \dots, \mathrm{n}.$$

Step 4. Determination of the positive ideal solution (PIS), A^+(benefits), and the negative ideal solution (NIS). A^- (costs).

$$A^+ = (P_1^+, P_2^+, \dots, P_m^+,)$$
$$A^- = (P_1^-, P_2^-, \dots, P_m^-,)$$

Where

$$P_j^+ = (\max_i P_{ij}, \mathrm{j} \in J_1, \min_i P_{ij}, \mathrm{j} \in J_2)$$
$$P_j^- = (\min_i P_{ij}, \mathrm{j} \in J_1, \max_i P_{ij}, \mathrm{j} \in J_2)$$

Where J_1 and J_2 represent the set of benefit criteria and the set of cost criteria, respectively.

Step 5. Calculation of Euclidean distances from the PIS, A^+, and the NIS, A^- of each alternative A_j, respectively, as follows:

$$d_i^+ = \sqrt{\sum_{j=1}^{n} (d_{ij}^+)^2}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} (d_{ij}^-)^2}$$

Where

$$d_{ij}^+ = P_j^+ - P_{ij}, i = 1, \dots, m$$
$$d_{ij}^- = P_j^- - P_{ij}, i = 1, \dots, m$$

Step 6. Calculation of the relative closeness CC_i for each alternative A_i with respect to PIS as given by:

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-}$$

Here, $0 \leq CC_i \leq 1$, $i = 1,2, \dots, m$.

CC_i is also known as a composite performance score of an alternative A_i.

Step 7. Rank the alternatives according to the relative closeness. The best alternatives have higher value CC_i because the values are closer to the PIS than the other alternatives.

8.2 Weight vector scenarios and analysis criteria

This study conducted MCDM analyses for seven weight scenarios that have different weight distributions to the considered criteria shown in **Table 8.1**.

Weight scenario 1 is to prioritize the alternatives with equally allocated weights, which means the importance of the criteria is equally treated. For scenario 2 to 7, this study added some variations in the weight vectors. The DMC analysis results exhibited that low-speed operations were highly correlated with high emission rates; therefore, weight scenario 2 included a driving pattern criterion, which is defined as the sum of low-speed driving mode durations. The low-speed driving mode durations included pattern durations of creeping, transient, and low-speed cruising modes. Weight scenario 3 and 5 mainly focused on life-cycle NOx and CO_2 emission rates, respectively, while the scenario 4 and 6 were more balanced weight allocation than weight scenario 3 and 5.

The Environmental incentive effectiveness index (EI^2) was also included in the decision analysis, and it contributed to putting more weight on cost-effective vocation types. Since EI^2 considered environmental benefits for project life and lifecycle of the fuel types, it is expected to help decision-makers and policy-designers consider the sustainability and performance of incentive projects.

Table 8.1. Weight vector scenarios

Criteria	WTP NOx emission rates	PTW NOx emission rates	WTP CO_2 emission rates	PTW CO_2 emission rates	Low-speed operation DMC	Incentive effectiveness index	Note
Weight scenario 1	20%	20%	20%	20%	0%	20%	Equal weight allocation except for driving pattern criterion
Weight scenario 2	15%	20%	15%	20%	15%	15%	Including driving pattern criterion and more weights on PTW emissions
Weight scenario 3	20%	40%	0%	0%	0%	40%	Focusing on NOx emission rates and EI^2
Weight scenario 4	20%	40%	10%	10%	0%	20%	Slightly more focusing on NOx rates than scenario 3
Weight scenario 5	0%	0%	20%	40%	0%	40%	Focusing on CO_2 emission rates and EI^2
Weight scenario 6	10%	10%	20%	40%	0%	20%	Slightly more focusing on CO_2 rates than scenario 5
Weight scenario 7	15%	30%	10%	20%	5%	20%	Arbitrarily allocated weight values

8.3 MCDM analysis results

Table 8.2 shows the ranked fuel pathways, including vocation type and engine family configurations. Overall, RNG pathways were high-ranked, and diesel pathways were low-ranked. The ranking results showed that RNG-powered refuse truck scenarios are the best alternative, followed by RNG-powered transit bus scenarios. However, refuse trucks were not high-ranked in the CNG fuel pathway scenarios because CNG transit and school bus scenarios showed higher ranks than CNG-powered refuse truck scenarios. If the refuse truck type was diesel-powered, the vehicle type could be the lowest or the second lowest-ranked in all weight scenarios. The ranking results for weight scenario 2 presented the driving pattern criterion has an insignificant effect on the rank order in comparison to weight scenario 1.

Diesel school bus scenarios were placed in the highest rank among the diesel scenarios except for weight scenario 3. For weight scenario 3, the diesel hauler scenario took the highest rank, followed by diesel school bus. Moreover, CNG-powered school bus pathways were also the highest-ranked scenarios among the CNG pathway scenarios. Diesel school bus scenarios were ranked higher than several CNG-powered applications, such as haulers and vocational trucks in most of the weight scenarios. This indicated that engine family and fuel pathway have significant effects on net environmental benefits of NGV operations.

Table 8.2. Ranked fuel pathway and vehicle application scenarios for each weight scenario

Rank	Weight scenario 1	Weight scenario 2	Weight scenario 3	Weight scenario 4	Weight scenario 5	Weight scenario 6	Weight scenario 7
1	RNG-Refuse truck-Low Nox	RNG-Refuse truck-Low Nox	RNG-Refuse truck-Low Nox	RNG-Refuse truck-Low Nox	RNG-Refuse truck-Low Nox	RNG-Refuse truck-Low Nox	RNG-Refuse truck-Low Nox
2	RNG-Refuse truck-DEF	**RNG-Transit bus-Low Nox**	RNG-Refuse truck-DEF	**RNG-Transit bus-Low Nox**	RNG-Refuse truck-DEF	**RNG-Transit bus-Low Nox**	**RNG-Transit bus-Low Nox**
3	**RNG-Transit bus-Low Nox**	RNG-Refuse truck-DEF	**RNG-Transit bus-Low Nox**	RNG-Refuse truck-DEF	**RNG-Transit bus-Low Nox**	RNG-Refuse truck-DEF	RNG-Refuse truck-DEF
4	**RNG-Transit bus-DEF**	**RNG-Transit bus-DEF**	**RNG-Transit bus-DEF**	RNG-School bus-Low Nox	**RNG-Transit bus-DEF**	**RNG-Transit bus-DEF**	**RNG-Transit bus-DEF**
5	RNG-Vocational truck-Low Nox	RNG-Haulers-Low Nox	RNG-School bus-Low Nox	**RNG-Transit bus-DEF**	RNG-Vocational truck-Low Nox	RNG-Haulers-Low Nox	RNG-School bus-Low Nox
6	RNG-Vocational truck-DEF	RNG-Vocational truck-Low Nox	**CNG-Transit bus-Low Nox**	RNG-Haulers-Low Nox	RNG-School bus-Low Nox	RNG-Vocational truck-Low Nox	RNG-Haulers-Low Nox
7	RNG-Haulers-Low Nox	RNG-School bus-Low Nox	RNG-School bus-DEF	RNG-School bus-DEF	RNG-Vocational truck-DEF	RNG-School bus-Low Nox	RNG-School bus-DEF
8	RNG-School bus-Low Nox	RNG-Haulers-DEF	RNG-Haulers-Low Nox	RNG-Haulers-DEF	**CNG-Transit bus-Low Nox**	RNG-Haulers-DEF	RNG-Haulers-DEF
9	RNG-Haulers-DEF	RNG-School bus-DEF	CNG-School bus-Low Nox	CNG-School bus-Low Nox	RNG-School bus-DEF	RNG-Vocational truck-DEF	CNG-School bus-Low Nox
10	RNG-School bus-DEF	RNG-Vocational truck-DEF	RNG-Vocational truck-Low Nox	RNG-Vocational truck-Low Nox	RNG-Haulers-Low Nox	RNG-School bus-DEF	RNG-Vocational truck-Low Nox
11	CNG-School bus-Low Nox	CNG-School bus-Low Nox	RNG-Haulers-DEF	CNG-School bus-DEF	RNG-Haulers-DEF	CNG-School bus-Low Nox	**CNG-Transit bus-Low Nox**
12	CNG-School bus-DEF	CNG-School bus-DEF	CNG-Refuse truck-Low Nox	**CNG-Transit bus-Low Nox**	CNG-Refuse truck-Low Nox	CNG-School bus-DEF	CNG-School bus-DEF
13	**CNG-Transit bus-Low Nox**	**CNG-Transit bus-Low Nox**	CNG-School bus-DEF	CNG-Haulers-Low Nox	**CNG-Transit bus-DEF**	**CNG-Transit bus-Low Nox**	CNG-Haulers-Low Nox
14	DSL-School bus-DEF	CNG-Haulers-Low Nox	**CNG-Transit bus-DEF**	CNG-Haulers-DEF	CNG-School bus-Low Nox	**CNG-Transit bus-DEF**	RNG-Vocational truck-DEF
15	CNG-Haulers-Low Nox	DSL-School bus-DEF	CNG-Haulers-Low Nox	DSL-School bus-DEF	CNG-School bus-DEF	CNG-Haulers-DEF	CNG-Haulers-DEF
16	CNG-Haulers-DEF	CNG-Haulers-DEF	RNG-Vocational truck-DEF	DSL-Haulers-DEF	CNG-Haulers-Low Nox	CNG-Haulers-Low Nox	**CNG-Transit bus-DEF**
17	DSL-Haulers-DEF	DSL-Haulers-DEF	CNG-Haulers-DEF	RNG-Vocational truck-DEF	CNG-Haulers-DEF	DSL-School bus-DEF	DSL-School bus-DEF
18	**CNG-Transit bus-DEF**	**CNG-Transit bus-DEF**	DSL-Haulers-DEF	**CNG-Transit bus-DEF**	CNG-Refuse truck-DEF	DSL-Haulers-DEF	DSL-Haulers-DEF
19	DSL-Transit bus-DEF	DSL-Transit bus-DEF	DSL-School bus-DEF	CNG-Refuse truck-Low Nox	DSL-School bus-DEF	DSL-Transit bus-DEF	CNG-Refuse truck-Low Nox
20	CNG-Refuse truck-Low Nox	CNG-Refuse truck-Low Nox	CNG-Refuse truck-DEF	CNG-Vocational truck-Low Nox	CNG-Vocational truck-Low Nox	CNG-Refuse truck-Low Nox	CNG-Vocational truck-Low Nox
21	CNG-Vocational truck-Low Nox	CNG-Vocational truck-Low Nox	CNG-Vocational truck-Low Nox	CNG-Refuse truck-DEF	DSL-Haulers-DEF	CNG-Vocational truck-Low Nox	CNG-Refuse truck-DEF
22	CNG-Vocational truck-DEF	CNG-Vocational truck-DEF	CNG-Vocational truck-DEF	DSL-Transit bus-DEF	DSL-Transit bus-DEF	CNG-Vocational truck-DEF	DSL-Transit bus-DEF
23	CNG-Refuse truck-DEF	CNG-Refuse truck-DEF	DSL-Transit bus-DEF	CNG-Vocational truck-DEF	CNG-Vocational truck-DEF	CNG-Refuse truck-DEF	CNG-Vocational truck-DEF
24	DSL-Vocational truck-DEF	DSL-Vocational truck-DEF	DSL-Refuse truck-DEF	DSL-Refuse truck-DEF	DSL-Vocational truck-DEF	DSL-Vocational truck-DEF	DSL-Refuse truck-DEF
25	DSL-Refuse truck-DEF	DSL-Refuse truck-DEF	DSL-Vocational truck-DEF	DSL-Vocational truck-DEF	DSL-Refuse truck-DEF	DSL-Refuse truck-DEF	DSL-Vocational truck-DEF

As shown in the EI^2 analysis results, refuse trucks, transit buses, and sewer trucks had substantial NOx emissions reduction potential for the project life. The MCDM analysis also demonstrated that refuse truck and transit bus types are the vehicle groups that can provide the highest returns with the same amount of financial incentive. Refuse trucks and transit buses conducted a number of stop-and-go driving patterns, and it caused higher power consumption in unit time and distance. Thus, if these vehicle types are converted to cleaner fuel type vehicles, the replacement effect can be significant compared to other vocation types.

8.4 Summary

The WTW analysis results showed that the rank order of the fuel pathways could differ by an emission species that the analysis focuses on. This study adopted a multi-criteria decision making (MCDM) technique, TOPSIS, to prioritize the alternatives according to the weight vector scenarios.

RNG-powered vehicle applications were generally high-ranked, while diesel-powered vehicle pathways were low-ranked. RNG-powered refuse truck scenarios were the best alternative, followed by RNG-powered transit bus scenarios. However, refuse trucks were not high-ranked in the CNG fuel pathway scenarios because CNG transit and school bus scenarios showed higher ranks than CNG refuse scenarios. If the refuse truck type was diesel-powered, the vehicle type could be the lowest or the second lowest-ranked in all weight scenarios.

Diesel school bus scenarios were placed in the highest rank among the diesel scenarios except for weight scenario 3. For weight scenario 3, the diesel hauler scenario took the highest rank, followed by diesel school bus. Moreover, CNG-powered school bus pathways were also the highest-ranked scenarios among the CNG pathway scenarios. Diesel school bus scenarios were ranked higher than several CNG-powered applications, such as haulers and vocational trucks in most of the weight scenarios. This indicated that engine family and fuel pathway have significant effects on net environmental benefits of NGV operations. If the high-ranked pathways are converted to cleaner fuel type vehicles, the replacement effect can be significant compared to other vocation types.

Chapter 9 Conclusion and Future research

9.1 Conclusion

Vehicular emissions are of great interest because they are one of the primary sources of air pollution. Compared to commonly used gas and diesel engines, natural gas engines have relatively lower emission rates while offering higher total cost of ownership. Federal and state governments have offered various monetary and policy incentives to promote alternative fuel vehicles (AFVs) that are expected to reduce greenhouse gases and criteria pollutants significantly. The vehicle incentives are often distributed based on vehicle weight and do not account for the environmental impacts of AFVs. This study recognized the research opportunity to improve incentive structures and policies.

To improve the cost-effectiveness of vehicle incentive programs, this study assessed the adoption impact of various heavy-duty NGVs and predicted the emission reduction potential of the vehicle incentive programs. The environmental benefits of HD NGV operations were assessed by using in-use vehicle activity data and surveyed duty cycle information obtained from the proposed NGV use survey. The evaluation framework included fuel life-cycle assessments (LCA) and multi-criteria decision-making (MCDM) analyses; therefore, it was able to estimate lifecycle NOx and CO_2 emissions of CNG, RNG, and diesel fuel pathways and compare the fuel pathways in multiple aspects, such as lifetime emission reduction potential, incentive effect index, and total fuel cycle emission rates.

This dissertation provided evidence that there is a causal relationship between operational characteristics and environmental impacts. The driving pattern analysis for various HD NGVs across a number of vocation types showed that each vocation type has discernable differences in its drive mode composition. Particularly, low-speed and high-engine-load driving patterns had a significant relationship with high environmental impacts in the unit of time. Moreover, vehicles with the same or similar vocation types from different regions showed analogous DMCs. This supported an argument that the vocational impact is an influential factor affecting vehicle activity patterns. If this pattern is consistent across the broader population, it implies that the vocation type is one of the influential factors determining vehicle activity and associated environmental impact. The observed heterogeneity in vehicle operation and NOx and CO_2 emission factors per drive mode demonstrated that criteria pollutants and greenhouse gas emissions are also different among the considered vocation types.

The well-to-pump (WTP) analysis results showed that methane-based fuel pathways could provide significant emission reductions in the fuel cycle compared to the conventional diesel pathway. In particular, the RNG pathway provided negative emission rates for WTP cycles, which means significantly positive environmental impacts. The well-to-wheel (WTW) analysis showed that WTP and pump-to-wheel (PTW) emissions exert discernible influences on total emission production for each fuel pathway. This implies that alternative and conventional fuels should be compared in the total fuel cycle to see their undistorted environmental impacts.

The revealed relationships between vocation types, network characteristics, and resulting environmental impact of NGVs can potentially offer avenues for designing or improving current public health-related policies with respect to HDV operations. The lifetime NOx emission reduction potential (LNRP) values of the refuse trucks were twice as high as the average LNRP of all vocation types. Refuse trucks showed that the highest EI^2, followed by transit buses, and the average EI^2 of all vocation type was approximately 58% lower than the refuse truck EI^2 in all fuel pathway scenarios. The vocation type groups showed different EI^2, and this suggests that incentive structures based upon gross vehicle weight (GVW) may not incentivize the most environmentally beneficial fueling options. Furthermore, some vocational vehicles can play a critical role in achieving the state's emission abatement goals. The analysis result can be used to re-design the current incentive structure to focus on 'the bang for the emission reduction (buck)' vocation types.

The environmental impacts of AFVs could differ by evaluation metrics used in the analyses. For example, the incentive effectiveness analysis results are not consistent with the WTW analysis results because of the different duty cycles and operational conditions of the NGV types. This study examined the percentage difference of various evaluation metrics between refuse trucks and other vocation types, such as PTW and WTW NOx rates, annual NOx projection, LNRP, and EI^2. A series of analyses, which used different metrics, provided the different cleanest and dirtiest sets of fuel and vocation types. The findings implied that the evaluation metrics should be explicitly defined and properly selected to reflect emission characteristics of study vehicles.

The MCDM analysis was conducted to compare given alternatives with multiple criteria and determine the best-investment-alternatives. The criteria included in the MCDM are lifecycle NOx and CO_2 emission rates, low-speed driving mode distribution, and incentive effectiveness index. The analysis results indicated that refuse truck and transit bus pathways are likely to achieve the highest return for the total incentives granted when the vehicles are RNG-powered.

This dissertation focused on the improvement of incentive policy and structure, which can contribute to achieving societal emission reduction goals in a time- and cost-efficient way. The findings of this study can provide useful information to energy decision-makers and serve as a reference for energy policy design. By assessing the emission rates of criteria pollutants from various vocational trucks, it should be possible to identify the effects of vehicle vocation on emission production more closely. Such findings could help shape the incentive policy of AFVs to be more effectively targeted to vehicle vocations by analyzing their distinct duty cycles and identifying the best matches between the available technologies to achieve societal goals.

9.2 Dissertation Contributions

This dissertation proposed the following unique academic contributions.

- Natural gas and diesel fuel pathways were evaluated by a novel evaluation framework that integrates a variety of analytic research works, such as total fuel cycle analysis, driving pattern analysis, vehicular NOx and CO_2 emission estimations, incentive impact analysis, and multi-criteria decision-making (MCDM) analysis. The assessment framework suggest not only a new incentive structure that maximizes total emission reductions of HD NGV adoption, but also a decision-making tool that effectively compares various fuel pathways in multiple aspects. The tool can be used by government agencies, policymakers, legislators, and researchers who are involved with the design and assessment of vehicle incentive projects.

- This study investigated the vocational impact on heavy-duty natural gas vehicle activity patterns. Driving pattern analysis showed the heterogeneity of operational characteristics of various HD NGV types. The resulting drive mode composition (DMC) demonstrated that vocational impact is significant in heavy-duty natural gas vehicle activity patterns, and it resulted in different emission characteristics for each vocation type. Each vocation type had predominant driving modes over its driving cycle. DMCs by road facility type showed the relationship between road type and operational characteristics. The proposed DMC analysis method could be used to understand the operational characteristics of new vocation type vehicles and predict its environmental impacts.
- The estimated environmental benefits were derived from total fuel cycle analyses and used to predict lifetime emission reduction potential based on the in-use operating conditions. AFV adoption impacts should be assessed by considering lifecycle emissions because vehicle cycle emission rates were insufficient to explain the entire environmental impacts of AFV adoption (*16-22*). This study used various project life values obtained from surveyed duty cycle information and vehicle activity data obtained via the J1939/OBD-II CAN bus protocol, rather than assuming homogeneous project life per vocation type.
- Environmental Incentive Effectiveness Index (EI^2) analysis demonstrated the determination of the best policy targets in the market based on the recognized operational characteristics. The revealed cost-effective vocation types are expected to play a crucial role in the alternative fuel vehicle incentive programs. Compared to the current incentive structure, the suggested incentivization strategy can achieve more emission reductions with the same amount of monetary incentives.

- The proposed emission model was able to estimate the NOx and CO_2 emission inventories of all internal combustion engine families in the market because the method relied on engine control units (ECUs) data and the emission factors provided by the engine certification program. Therefore, this study was able to estimate the environmental impacts of a variety of vocation types and provide more accurate emission estimates than the GPS- and vehicle speed-based emission models.

9.3 Future research

The evaluation framework was designed to be readily transferable to environmental benefit assessments of other alternative fuel vehicles or vocation types. It can be used to evaluate the suitability of newly introduced alternative fuel vocational trucks based on given operational conditions and vehicle specifications. It means that the evaluation framework is not necessarily limited to natural gas, though further research is necessary. Rapidly growing electric and hybrid vehicle markets show that numerous prospective clean vehicle users are looking for an environmentally friendly vehicle as a next car. Although this study focused on commercial vehicle activity, the proposed analysis framework fits perfectly in the needs of prospective customers who want to know that their driving cycle is suitable for zero-emission vehicles. The predominant driving modes over the personal driving cycle will help understand future benefits and costs of alternative fuel vehicle adoption.

Another research opportunity extended from this study is vehicular emission modeling based on vocational vehicle activity and network characteristics. Rosqvist (*15*), Brundell-Freij and Ericsson (*38*) assessed influences of network characteristics on emissions using a linear regression method. Borisboonsomsin and Barth (*27*) investigated the impact of road grade on CO_2 emission and fuel consumption. Based on previous research, subsequent studies from this research work can find other relevant and influential factors affecting driving mode composition and emissions. The DMCs, facility trip information, and related emission characteristics can be used to predict future NOx emissions and identifying NOx-intensive driving segments. The model can contribute to design pollutant intensity-based geofencing strategies, such as in highly polluted areas or children protection zones.

NOx reduction is the main reason for the NGV adoption program. The estimated incentive impact in this study is limited to explain the full environmental benefits of the NGV adoption in the real world because the proposed evaluation framework considered NOx and CO_2 reductions only. Better emission modeling can provide more detailed and specific air quality impacts of AFV adoption. In-use emission data collected by using Portable Emission Measurement System (PEMS) can be an excellent way to improve the accuracy of estimates of a variety of criteria pollutant species and GHG emission inventories. Due to the limited budget and time, it, however, is impossible to measure all kinds of emission rates of varying vehicle types associated with various engine types, fuel types, model years, so forth. Conversely, macroscopic emission models estimate emission inventory based on VMT. This study tackled the limitation of VMT-based emission rates (grams/mile) that emissions can differ by operational characteristics and DMC. For these reasons, it was very worth putting more research efforts into developing a more accurate emission estimation model.

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APPENDIX A: Survey Questionnaire Sample

2019 CALIFORNIA NATURAL GAS VEHICLE USE SURVEY

The Natural Gas Vehicle Use Survey (NGVUS) is part of the Natural Gas Vehicle Incentive Project (NGVIP) in California. The purpose of the NGVUS is to obtain recent data on the operational characteristics of natural gas vehicles in California. The results of this survey will be used to provide necessary inputs for improving our understanding of the environmental impacts of natural gas vehicle adoption.

The survey is being conducted in conjuction with a provided in-vehicle in-vehicle data logger. Please note that the logger ID of this survey sheet must be matched with the ID written on the top of the provided logger. After the data collection period, please return this survey sheet and the logger to the Institute of Transportation Studies at University of California, Irvine. Please read the provided introductory letter before taking this survey.

Respondent privacy is of our utmost concern. All information collected will be held in strict confidentiality and be used only to obtain recent data on the operational characteristics of natural gas vehicles operating in California.

☺ **START HERE**

- **Please indicate the date this survey is completed.**

____ / ____ / _____

MM / DD / YYYY

- Use blue or black ink or pencil
- Please center numbers in their respective boxes

Example:

0 1 2 3 4 5 6 7 8 9 A E

▶ **Survey ID**

7 0 0 1

▶ **All of the following questions refer to the NGVIP-incentivized vehicle specified in the table belo**

Each survey answer sheet and the collected data will be identified based on the given logger ID

Logger ID	Vehicle Identification Number (Last 6 Digits)	Odometer reading (ex) 118,625)
1540		START: ________ / END: ________
Engine Serial Number (ESN)	**Vehicle Model / Manufacturer (e.g., ACX64 / Autocar)**	**Surveyee's title (ex) Shop manager or fleet manager**
	/	

A. Vehicle information

A1. **How many hours does <u>this vehicle</u> operate during a typical working day?**

hour(s) per day

A2. **How many days does <u>this vehicle</u> operate during a typical working week?**

day(s) per week

A3. **How many miles does <u>this vehicle</u> travel during a typical working week?**

Vehicle Miles Traveled (VMT) per week ··········→ , Miles

A4. **Which of the following best describes the business in which this vehicle is most often use**
*Mark **ONE** box only.*

- ☐ Waste management
- ☐ Transit/Passenger Transportation
- ☐ Vehicle leasing or rental
- ☐ Construction
- ☐ Retail trade
- ☐ Accommodation or food services
- ☐ Street sweeping
- ☐ Freight trucking
- ☐ Educational services
- ☐ Utilities (e.g. Water, Natural Gas)
- ☐ Manufacturing
- ☐ Wholesale trade
- ☐ Public organization
- ☐ Others: ______________________

A5. **Which of the following best describes the vocation (vehicle purpose) for which this vehicl most often used?** *Mark **ONE** box only.*

※ In this survey, short-haul truck driving is defined as within a daily operating radius of 200 miles, and lo over 200 miles.

- ☐ Drayage - short haul tractor
- ☐ Long-haul tractor
- ☐ Refuse truck
- ☐ Shuttle service bus
- ☐ Service utility van
- ☐ Step van
- ☐ Electric bucket truck
- ☐ Non-drayage - short-haul tractor
- ☐ Street sweeper
- ☐ Roll-off truck
- ☐ School bus
- ☐ Single body truck / enclosed
- ☐ Pick-up truck
- ☐ Others: ________________________

A6. **What type of transmission does this vehicle have?** *Mark **ONE** box only.*

- ☐ Automatic
- ☐ Manual
- ☐ Other – Please specify in the box

Please specify here

A. Vehicle information

A1. **Please enter the number for the body type that best matches this vehicle?**

, Other – Please specify in the box

01 Pick-up	02 Single body Truck / Enclosed	03 School Bus	04 Shuttle Bus	05 Transit Bus
				
06 Service Utility	**07 Refuse Truck**	**08 Tractor**	**09 Street Sweeper**	**10 Other**
				**? (None of the above vehicle types)**

A2. **If this vehicle replaced a vehicle that was already in service, please indicate the type of fuel used by your <u>previous</u> vehicle.** *Mark **<u>ONE</u>** box only.*

Type of Fuel

- ☐ Gasoline
- ☐ Diesel
- ☐ CNG
- ☐ LNG
- ☐ Hybrid
- ☐ Electricity
- ☐ Propane (LPG)
- ☐ Plug-in hybrid
- ☐ Ethanol
- ☐ Biodiesel
- ☐ Other

☐ This vehicle is ***not*** replacing a vehicle already in service → *You can skip question A9.*

A3. **If this vehicle replaced a vehicle already in service, please provide the following informatio about the vehicle that was replaced.** *Please provide as much information as you can.*

Fuel type	Engine type (Engine family)	Engine reference torque	Vehicle Model Year
ex) Diesel	ex) 9CEXH0359BBG	500 ft-lb	ex) 2005
		_______ foot pounds	
		_______ foot pounds	
		_______ foot pounds	

A. Refueling Behavior

A1. **Please describe the refueling location(s) used by this vehicle.** *Mark **All** that apply.*

- ☐ Public station
- ☐ Maintenance yard
- ☐ Terminal / Depot
- ☐ Private residence (home, farm, etc.)
- ☐ Other – Please specify in the box →

Please specify here

A2. **On average, how many times do you fuel this vehicle and what is the typical tank level bef refueling?**

Once every ___ days

Average tank level before refueling ___ %

A3. **How long does it usually take to refuel your natural gas vehicle?**

___ Hour(s) ___ Min(s) on average

A4. **Please select the refueling station type.**

- ☐ Time-fill
- ☐ Fast-fill

B. Operational Information

B1. **Please describe any additional features of your natural gas vehicle operations (positive or negative) that you would like to share.** ***This question is optional, but*** *any information or expe could be valuable to our understanding of your unique operations.*

Keywords: Engine reliability, Maintenance, Fuel cost, Operational area type (i.e., Residential vs. Ind area), Commodity type and weight, Refueling, Flexibility in the operating schedule, Driving perform Emissions (i.e., Near Zero CNG Engine), Equipment standards.