Comparative Analysis of the Performance of Conventional and Hybrid Electric Vehicles in Real-World Driving Conditions: Montréal Case Study

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ABSTRACT

Replacement of conventional gasoline passenger vehicles to more sustainable vehicle technologies (such as hybrid- or full-electric vehicles) is one of the emission-reduction strategies and the transition to electrification in the transportation sector in Canada. This research aims to investigate the performance of passenger hybrid electric vehicles (HEVs) in real-world driving conditions and in various road environments and temperature conditions. More specifically, this research is two-fold: i) to investigate the performance of HEVs in terms of fuel consumption and emissions with respect to conventional gasoline vehicles (non-HEVs) considering real-world measurements and ii) to compare the fuel consumption and emission rates between conventional HEVs and plug-in hybrid electric vehicles (PHEVs), including the impacts of ambient temperature conditions. This research is based on data collected in the City of Montréal, Canada, as a case study. The effects of different factors on the fuel consumption and emissions are analyzed.

Among the main results of this study, it was found that the HEVs reduce fuel consumption rate (FCR) by approximately 33.5% to 43.3% and carbon dioxide (CO_2) emissions rate by approximately 60.9% to 66.3%, from the statistical analysis of the experiments. After controlling for other factors, the results from the regression models reveal that by driving a HEV, FCR could decrease by approximately 25.5% and CO_2 emission rate could decrease by approximately by 55.7%, compared to conventional gasoline vehicles. This aligns with past research on the fuel economy savings (when comparing conventional gasoline vehicles to HEVs) between 20-45% and between a similar range for CO_2 reduction between 20-40%.

Key factors that affect the fuel economy and emission rates of HEVs and non-HEVs are vehicle speed, acceleration, slope, road type and ambient temperature. Of the factors, vehicle speed has the biggest influence on vehicle performance (after vehicle type). For speed, the marginal effects analysis revealed that for every unit increase in vehicle speed, the FCR increases by 25.2% for HEVs and 50.9% for non-HEVs. For CO_2 emission rate, it decreases by 5.2% for HEVs and increases by 51.3% for non-HEVs for every unit increase in speed. Acceleration has a positive but small effect on the performance, where 1% increase in acceleration increases FCR by around 0.2% and CO_2 around 0.3%. Slope also has a positive but small effect on the performance. The effect of road type is mixed from the regression models. But, from statistical analysis, it was revealed that FCR and emissions for non-HEVs are consistently higher than HEVs across all different types of road class. For non-HEVs, the emissions are higher in local streets than highways, whereas it is the opposite for HEVs.

Overall, the findings in this study provide some insights into the factors influencing the fuel consumption and CO_2 rates of HEVs and non-HEVs in real-world conditions.

RÉSUMÉ

Le remplacement des véhicules de tourisme à essence conventionnels par des technologies plus durables (telles que les véhicules hybrides ou entièrement électriques) est l'une des stratégies de réduction des émissions et de transition vers l'électrification dans le secteur des transports au Canada. Cette recherche a pour but d'étudier les performances des véhicules électriques hybrides (HEV) dans des conditions de conduite réelles et dans divers environnements routiers et conditions de température. Plus précisément, cette recherche comporte deux volets : i) étudier les performances des HEV en termes de consommation de carburant et d'émissions par rapport aux véhicules à essence conventionnels (non- HEV) en prenant des mesures en conditions réelles et ii) comparer les taux de consommation de carburant et d'émissions entre les HEV conventionnels et les véhicules électriques hybrides rechargeables (PHEV), y compris l'impact des conditions de température ambiante. Cette recherche est basée sur des données collectées dans la ville de Montréal, au Canada, en tant qu'étude de cas. Les effets de différents facteurs sur la consommation de carburant et les émissions sont analysés.

Parmi les principaux résultats de cette étude, l'analyse statistique des expériences a montré que les véhicules électriques hybrides réduisent la consommation de carburant d'environ 33,5 % à 43,3 % et les émissions de dioxyde de carbone (CO_2) d'environ 60,9 % à 66,3 %. Après prise en compte d'autres facteurs, les résultats des modèles de régression révèlent qu'en conduisant un HEV, le FCR peut diminuer d'environ 25,5 % et le taux d'émission de CO_2 d'environ 55,7 %, par rapport aux véhicules à essence conventionnels. Cela correspond aux recherches antérieures sur les économies de carburant (en comparant les véhicules à essence conventionnels aux véhicules électriques hybrides) entre 20 et 45 % et à une fourchette similaire pour la réduction du CO_2 entre 20 et 40 %.

Les principaux facteurs qui influencent la consommation de carburant et les taux d'émission des véhicules électriques hybrides et non hybrides sont la vitesse du véhicule, l'accélération, la pente, le type de route et la température ambiante. Parmi ces facteurs, c'est la vitesse du véhicule qui a la plus grande influence sur les performances du véhicule (après le type de véhicule). Pour la vitesse, l'analyse des effets marginaux a révélé que pour chaque unité d'augmentation de la vitesse du véhicule, le FCR augmente de 25,2 % pour les HEV et de 50,9 % pour les non-HEV. Quant au taux d'émission de CO_2, il diminue de 5,2 % pour les véhicules électriques hybrides et augmente de 51,3 % pour les véhicules électriques non hybrides pour chaque unité d'augmentation de la vitesse. L'accélération a un effet positif, mais faible, sur les performances : une augmentation de 1 % de l'accélération accroît le FCR d'environ 0,2 % et le CO_2 d'environ 0,3 %. La pente a également un effet positif mais faible sur les performances. L'effet du type de route est mitigé dans le modèle de régression. Mais l'analyse statistique a révélé que le coefficient de réduction de la consommation et les émissions des véhicules autres que les HEV sont systématiquement plus élevés que ceux des HEV, quel que soit le type de route. Pour les véhicules autres que les VHE, les émissions sont plus élevées dans les rues locales que sur les autoroutes, alors que c'est l'inverse pour les HEV.

Dans l'ensemble, les résultats de cette étude permettent de mieux comprendre les facteurs qui influencent la consommation de carburant et les taux de CO_2 des véhicules électriques hybrides et des véhicules électriques non hybrides dans des conditions réelles.

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CONTRIBUTION OF AUTHORS

My contributions to this thesis include data collection, data processing, data analysis, models and framework building and manuscript writing (all the chapters). My supervisor, Prof. Luis Miranda-Moreno, provided guidance on the approach and methodology, as well as comments and revisions of the manuscripts.

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1. INTRODUCTION

1.1. Context

Transportation sector is one of the fourth largest contributors of greenhouse gas (GHG) emissions in the world, accounting for 25% of worldwide GHGs (International Energy Agency, 2022). In Canada, the transport sector emitted 159.2 megatonnes of carbon dioxide equivalent (CO_2e) in 2020, accounting for approximately 23.7% of the total GHG emitted in the country, making it the second largest emitter after the oil and gas sector where it emitted 178.8 megatonnes of CO_2e (26.6% of the total GHG) (Environment and Climate Change Canada, 2022). The emissions in the transport sector come from the following categories: passenger (cars, light trucks, motorcycles, bus, rail and aviation), freight (heavy duty trucks, rail, aviation and marine) and other categories (recreational, commercial and residential use). Taking a closer look at emissions from passenger cars, where this study is focused on, passenger cars emitted 26 megatonnes of CO_2e in 2020 in Canada, accounting for 16.3% among the categories included in the transport sector. Even though there was an approximately 22.6% reduction from passenger cars during the COVID-19 pandemic, the levels of traffic and the emissions are back to the pre-COVID years (Environment and Climate Change Canada, 2023b). The transport sector is responsible for 28% of global energy consumption (IPCC, 2014), 40% of the transport energy is used by urban transportation, including passenger cars. Quebec is one of the top three provinces in Canada that emit the most GHG emissions (Environment and Climate Change Canada, 2023b). Of which, transportation sector is the biggest GHG emitter in the province, accounting for 40% of overall emissions (Ministère de l’Environnement, 2023). This is a huge source of GHG emissions. The transport sector is quite broad and there are many areas where emission reduction efforts could be focused.

To combat climate change, many countries around the world have committed to reducing GHG emissions in the Paris Agreement and to achieving net zero emissions through policies and legislation, including the European Union and the Government of Canada where the *Canadian Net-Zero Emissions Accountability* Act became law in June 2021 for achieving net-zero emission by 2050 (Government of Canada, 2023). Of which, transportation electrification was one of the strategies. Canada has committed to at least 20% of the new vehicles sold to be zero emissions by 2026, 60% by 2030 and 100% by 2035, having hybrid vehicles as the transition (Environment and Climate Change Canada, 2021).

The GHG emissions, specifically CO_2 emissions, from vehicles in the sector account for a significant proportion of the total emissions (Seo et al., 2016). It is imperative to target the transport sector for the reduction of CO_2 emissions. In addition to CO_2, tailpipe emissions also include other GHGs such as methane, nitrous oxides and hydrofluorocarbons. This study assumes the other GHG emissions are negligible because past research have shown that CO_2 emissions account for approximately 95-99% of the total tailpipe GHG emissions (U.S. Environmental Protection Agency, 2023).

In literature, many studies have examined the impacts of HEVs, PHEVs and battery electric vehicle technologies. In these studies, the general consensus is that reduction in GHG emissions is achieved by employing these technologies. In general, HEVs or PHEVs can reduce the energy consumption and emissions in the range of 20% to 40% approximately, depending on the parameters of the study. More specifically, there are also studies that looked at the amount of reduction from converting fossil-fuel powered vehicle fleets. One study showed that if 25% of the vehicle fleet converts to HEVs, there could be a 10% decrease in GHG emissions (Chan et al., 2013). HEVs can serve as transitional vehicles where they provide higher acceptability than full electric vehicles, are perceived as more reliable and they are the more economical option than conventional gasoline vehicles.

1.2. Limitations and Research Gaps

Because hybrid electric vehicles (HEVs) and plug-in hybrid electric vehicles (PHEVs) are still considered to be novel technologies that are still being improved, they are not as well-studied (Sarlioglu et al., 2016). When manufacturers report the fuel economy or the estimated GHG emissions, they are performed in laboratory setting or estimated (Suttakul et al., 2022). This is a big limitation because vehicle performance is highly influenced by other factors such as driving ranges, road geometry, road condition, ambient temperature, weather and driving behaviour (Suttakul et al., 2022). Real-world driving tests can incorporate some of these possible impacts. There is a lack of real-world driving data from HEVs and PHEVs which this research fills by conducting data collection.

In addition, HEVs and PHEVs are considered to be the transitional vehicles between the conventional gasoline vehicles (with internal combustion engine) and battery electric vehicles (100% electrification). The general public is still slightly skeptical about its performance, reliability and fuel savings claimed by manufactures. From the accessibility perspective, the HEV market is geared towards households with higher income, post-secondary education and those living in dense neighbourhoods with access to transit and services (Dimatulac & Maoh, 2017). For PHEVs specifically, where they have the option to fuel electricity directly from the grid, the emission intensities for electricity production vary greatly from different geographic locations. Across provinces and territories within Canada for example, the electricity carbon intensities are 900, 40 and 1.7 grams of GHG/kWh in Alberta, Ontario and Quebec, respectively

(Canada Energy Regulator, 2018). There is currently a lack of electric modelling approaches that are fully scalable to large transportation network applications or to consider the actual on-road vehicle operating conditions (Xu et al., 2020).

1.3. Objectives

The general objective of this thesis is to evaluate the performance of passenger (sedans, hatchbacks and SUVs) hybrid electric vehicles, with respect to fuel consumption and CO_2 emissions, and the impacts of environment and road conditions on its performance.

The specific objectives are as follows:

1. To compare the fuel consumption rate and CO_2 emission rate between hybrid electric vehicles and conventional gasoline vehicles based on real-world driving in Montréal, Canada. The impacts of various driving, environmental and road conditions are evaluated against the fuel economy and emissions. The variables studied include vehicle class (hatchback, sedan or SUV), vehicle speed, acceleration, engine speed, slope, road class (local streets, collectors, main arterials, secondary arterials and motorways), speed limit, number of lanes and annual average daily traffic.
2. To compare the fuel consumption rate and CO_2 emission rate between conventional hybrid electric vehicles and plug-in hybrid electric vehicles. The impacts of ambient temperature are evaluated against the performance of the different powertrain types of vehicles (conventional gasoline vehicles, hybrid electric vehicles and plug-in hybrid electric vehicles).

1.4. Contributions

Based on the gaps identified in the literature, the unique contributions of this work are as follows:

- To generate a dataset on vehicle performance and emissions from hybrid electric vehicles using Portable Emissions Measurement System (PEMS) based on real-world driving experiments, to add more data to the database. The data could be used for further modelling, analysis and for helping with decision making with policy and guidelines (such as carbon tax or incentives).
- To evaluate the performance of hybrid electric vehicles (both conventional HEVs and plug-in HEVs) in different urban road conditions using the City of Montréal in Canada as a case study.
- To better understand how hybrid electric vehicle characteristics, driving behaviour, weather conditions, road and traffic conditions affect fuel consumption rate and greenhouse gas emissions.

1.5. Organization

This research is organized in the following manner:

- Chapter 2 is a review of the existing literature surrounding the topics of hybrid electric vehicles, plug-in hybrid electric vehicles, its associated fuel consumption, efficiency, and emissions. In addition, a general overview was conducted on the factors influencing the performance of HEVs such as driving behaviour (i.e. vehicle speed and acceleration), environmental conditions (i.e. ambient temperature) and road and traffic conditions (i.e. road type and slope). Some literature review was done on vehicle specific power, which is an important outcome when evaluating and estimating a vehicle’s performance.

Previous studies on comparing real-world driving to laboratory testing was researched. For data analysis purposes, previous modelling approaches used for similar research were also studied.

- Chapter 3 details the methodology and experimental design for the entire study. It covers the on-road experiments including vehicle selection process, equipment selection and set-up and the study area. In addition, it also covers the process for data preparation, cleaning, processing and analysis.
- Chapter 4 comprises the complete results and research findings from this study and has two parts. Part 1 is results from Objective 1 and Part 2 is results from Objective 2.
- Chapter 5 is the discussion where it focuses on the implications and interpretations of the results, the overall limitations, uncertainties and assumptions. Further, it also discusses the contributions and policy implications from this study.
- Chapter 6 concludes this research by summarizing all the relevant findings, evaluating the limitations, strengths and weaknesses of this research and suggesting the topics and gaps for future studies.

2. LITERATURE REVIEW

2.1. Hybrid Electric Technologies

The hybrid electric vehicle (HEV) system works by combining a conventional internal combustion engine and an electric motor, where the electric motor is engaged depending on the vehicle speed and acceleration (Fontaras et al., 2008). With the addition of an electric motor, the powertrain of a HEV distributes power to the engine and motor based on considerations such as the driver's request, engine status, battery status and vehicle driving information through the hybrid control unit (Choi et al., 2021). There are generally two types of hybrid drivetrains: parallel and series configurations.

Past studies have shown the environmental benefits of HEVs including reducing the impacts of internal combustion engines on air pollution and greenhouse gas emissions (Li et al., 2021). Not surprisingly, the purchase of HEVs are becoming more popular and affordable, being projected to make up of 23% of global sales by 2025 (Robinson & Holmén, 2020).

The designs for the hybrid electric systems comprise of parallel and series hybrid propulsion configurations, depending on the power flow from the sources of energy (fuel and energy storage system to the transmission) (M. Sabri et al., 2016). In parallel hybrid propulsion, both the electric motor and the internal combustion engine work together to power the vehicle, where the electric motor recaptures energy during deceleration to provide power for the auxiliary systems (Zhai et al., 2011). Whereas in the series hybrid propulsion, the electric motor is solely responsible for powering the vehicle, converting mechanical output into electricity using a generator (Zhai et al., 2011).

HEVs reduce pollution and energy consumption by combining at least one electric motor with internal combustion engine to power the vehicle; regenerative braking is captured by the system, using recuperated kinetic energy and stored as electric energy (Emadi et al., 2008) (Alvarez & Weilenmann, 2012). Because of this, HEVs do not need external charging (Ahmad et al., 2022). The hybrid system also turns off the engine when the vehicle stops and it allows the internal combustion engine to operate at a more constant and efficient speed (Amjad et al., 2010). Regenerative braking is crucial because it has the potential to have significant energy recovery, especially in a downhill urban setting (Prati et al., 2021).

Plug-in hybrid electric vehicles (PHEVs), similar to HEVs, have two engines, one conventional internal combustion engine and one electric engine. HEVs can only be fueled by gasoline directly, which then charges a battery then to be used to drive on electric drivetrain (in addition to charging through regenerative braking). Unlike HEVs, in addition to fueling only with gasoline, PHEVs can be connected and charged directly to the electricity grid and it can also run solely on electric power. PHEV is an in-between vehicle between a conventional HEV and full battery-electric vehicle. PHEV has an internal combustion engine and a larger and more powerful battery pack than HEV where it can be recharged by connecting to the electric grid directly (Boschert, 2006). PHEVs typically have greater margin of efficiency improvement than HEVs (Martinez et al., 2017) and they have the benefits of operating for longer distances using only electric power (Boschert, 2006). Once the electric power is depleted to a certain state of charge, the vehicle would switch over to hybrid (Amjad et al., 2010).

In this study, for comparing between conventional gasoline vehicles and HEVs, the PHEVs would be encompassed in the broader HEV group for comparisons.

2.2. Fuel Efficiency of HEVs

Many studies have shown that the fuel consumption and efficiency for hybrid electric vehicles are lower by approximately 20% to 49% (depending on the study) in comparison to their comparable conventional vehicles (with internal combustion engine) counterparts, with certain nuances in all the studies that were conducted (Huang et al., 2019; Robinson & Holmén, 2020; Wang et al., 2022; Zahabi et al., 2014). The fuel consumption reduction range provided here has a large variation. The low and high ends of the ranges were taken from different studies. Each study may vary in terms of experimental designs, methodology, parameters and assumptions, resulting in the large variation. In one of the studies reviewed, the average fuel consumption rate for HEV is 9.18L/100km and for non-HEV is 16.85 L/100km, which is around 45.5% lower in HEV than non-HEV (Zahabi et al., 2014). For PHEVs more specifically, depending on factors such as geographic location, usage and charging behaviour, the fuel consumption rate is between 2.1 and 7.5 L/100km (Plötz et al., 2021).

The performance of HEVs have been under scrutiny under different circumstances as many studies have been undertaken in order to understand HEVs better in different aspects with respect to their performance and the potential variables that influence their performance. There are many other factors that are found to be significant for fuel consumption such as eco-driving training, city size, cold start and vehicle type (Zahabi et al., 2014). In order to quantify the fuel economy savings from hybrids, tests have been conducted to compare performance HEVs and different types of HEVs (i.e. HEV sedan, HEV hatchback or HEV SUV) to its comparable gasoline vehicles under different conditions such as driving, environmental and road conditions.

Within all the different vehicle class in HEVs, the fuel efficiency differs. Fuel consumption is the lowest in hatchbacks, followed by sedans, then SUVs. The fuel consumption rates are approximately 40% and 35% lower for hatchbacks hybrids and sedans hybrids, respectively, compared to SUV hybrids (Zahabi et al., 2014). Plug-in hybrids should theoretically have a better fuel economy compared to conventional hybrids. However, the fuel consumption for PHEV would depend on the distance driven between battery charge and how frequent it is plugged in to charge and its fuel economy may be around the same as a similar HEV (Prati et al., 2021).

2.3. Emissions Reductions from HEVs

The emissions from vehicle tailpipes comprise of other GHG emissions, but CO_2 emission accounts for 95-99% of the GHG emissions (Ou et al., 2010). Although this study focuses only on CO_2, there have been past literature on other GHGs and air pollutants that are worth noting for background information. There is a general consensus that HEVs can reduce CO_2, carbon monoxide (CO) and nitrogen oxides (NO_x) emissions in comparison to non-HEVs, but it also depends on other factors such as the environment and the weather. In a real-world driving test conducted in Toronto, it was found that the estimated emission reductions from HEVs, in comparison to non-HEVs, were 21.6%, 31.3% and 53.0% for CO_2, CO and NO_x, respectively, whereas the emission reduction potentials were higher in Beijing for the same vehicles (Wang et al., 2022). In this study, there is more aggressive driving in Toronto than in Beijing. When there is more aggressive driving and higher power demand vehicle operations, the benefits of HEV have been shown to be smaller. This shows the importance of testing in real-world conditions where other factors are also considered in order to get more representative values.

The average CO_2 emission factor for a HEV in urban driving environment is 117.4 g/km, whereas it is 150.9 g/km in highway driving (O'Driscoll et al., 2018). The emission factor from

HEVs in highway driving is similar to the average for a conventional gasoline vehicle, implying that there is not much fuel economy savings from HEV driving on highways (O'Driscoll et al., 2018). The CO_2 emission from HEVs is approximately 30-40% less than conventional gasoline vehicles, as a range generally (Wang et al., 2022). In a study conducted in Macao, the average CO_2 emission factor from HEV was reduced by 35% compared to conventional gasoline vehicle (Wu et al., 2015). On the higher end, HEVs can reduce CO_2 by up to 60% compared to gasoline vehicle, driving at an average speed of 15 km/hr (Wu et al., 2015).

Literature has shown that PHEVs has a high variability as it heavily depends on other factors. From a study that analyzed real-world fuel consumption data of PHEVs, over 2000 PHEVs of five different models were tested, it showed a range of 29 g CO_2 emissions /km to 106 g/km (Plötz et al., 2018). Of which, Toyota Prius was 95 (+/-17) g CO_2 emissions per kilometer (it is one of the vehicles that was tested in this study in Montréal). In comparison to conventional gasoline vehicles, PHEVs could result in approximately 15 to 55% less CO_2 emissions (Plötz et al., 2020). And as expected, decreasing the power of combustion engine while increasing in electric-range aids emission reduction.

To summarize, the emission reduction from HEV can have a range from 30% to 60% from past research (Plötz et al., 2020; Wang et al., 2022; Wu et al., 2015). This may also be unique to each city and different driving conditions.

The NO_x emissions are expected to be lower in HEVs because the electric motor produces less power output of the hybrid engine than a conventional vehicle so the in-cylinder combustion temperature is reduced (Wang et al., 2020). The level of NO_x emissions is in the order of 0.6 g/km (Kousoulidou et al., 2013). In comparison to the gasoline vehicles, the HEVs can reduce NO_x emission by up to 90% (Wu et al., 2015). In the Macao case study, it was shown that NO_x emissions from HEVs decreased as the average speed became lower, which is an indication of environmental benefits and energy savings in congested driving conditions, whereas CO_2 is less sensitive to speed changes (Wu et al., 2015).

2.4. Factors Influencing the Performance of HEVs

There are many external factors that influence the performance of vehicles that include the driving behaviour, environmental and road conditions. Driving behaviour or driving style is how one operates the vehicle and has shown to be one of the important factors in influencing vehicle performance (Alessandrini et al., 2012). Driving behaviour includes a combination of vehicle speed and acceleration, where an example for eco-driving driving concept is adopting an anticipatory driving style to avoid unnecessary acceleration and braking. Using the engine as efficiently as possible is another example of eco-driving concept where the efficiency increases with decreasing engine speed (Alessandrini et al., 2012).

Some examples of environmental conditions include ambient temperature, humidity, pressure and precipitation. Seasonal changes have been one of the factors of interest when evaluating the performance of HEVs and that these environmental factors influence the vehicle performance (Ng et al., 2021).

The road conditions include factors such as slope, road class, speed limit, number of lanes and average daily traffic which also influence the vehicle performance (Carrese et al., 2013; Faria et al., 2019; Harantová et al., 2022; Panis et al., 2006; Zahabi et al., 2014).

From the literature review, there are more information and data on fuel consumption than GHG emissions. There were analyses conducted to study the relationship between fuel consumption and emission (Hien & Kor, 2022; Nguyen & Gonzalez, 2021). It was found that the CO_2 emitted is directly related to fuel consumption, with linear correlation (Mickūnaitis et al., 2007). Burning one litre of regular gasoline generates approximately 2.29 kg of CO_2 (Gao &

Checkel, 2007). Therefore, where there is no information on emissions, it is assumed that the general trend for emissions is similar (Hien & Kor, 2022).

2.4.1. Driving Behaviour

The relationship between fuel consumption and speed generally follows an U-shaped curve where fuel consumption decreases slightly from 0km/hr to 60km/hr and gradually increases from 60km/hr and above (Fontaras et al., 2008). Toyota Prius II, a hybrid vehicle as an example, is found to have a fuel economy of 38 g/km, 58 g/km and 82 g/km at average speeds of 17 km/hr, 60km/hr and 95km/hr, respectively (Fontaras et al., 2008). In comparison, a gasoline Euro 3 vehicle (<1400 cm^3) has a fuel economy of 83 g/km, 80 g/km and 82 g/km at the same speeds. At a driving speed of 95km/hr, the fuel economy is the same for the hybrid and gasoline vehicles. It has been shown in other studies that HEVs start to use the gasoline engine between 40 to 60 km/hr and that as the vehicle speed increases, the fuel economy saving becomes lower compared to conventional gasoline vehicles (Zahabi et al., 2014). Hence, HEVs are more fuel efficient at lower speeds, while they are not as efficient at higher speeds. This could have implications on further promoting driving HEVs in local driving where lower speeds are generally observed. This also ties in with the road type.

How acceleration impacts the fuel economy is connected with the vehicle speed. Acceleration and speed together could also be a proxy for the drive cycle aggressiveness (Alessandrini et al., 2012). In a study, vehicles were tested by scaling up and down the speed. It was shown that scaling up the speed is linked with aggressive acceleration which increases inertial force and that increases the fuel consumed (Sharer et al., 2007). The fuel consumption can increase between 5% to 14% for aggressive driving (hard acceleration when there is an opportunity) for speed lower than 20km/hr and the increase can be between 11% to 21% for speeds greater than 80km/hr (Thomas et al., 2017).

Engine speed is an internal engine variable that is readily available information in ECU or through OBD-II logger. It measures the iterative combustion process in the engine. Generally, the relationship between engine speed is linear with fuel consumption, given the same torque requirement (Manzie et al., 2007). However, in another study, it was found that the relationship between engine speed and fuel consumption follows a parabolic shape (Rakha et al., 2011). As engine speed increases, the specific fuel consumption rate decreases to a minimum value ranging between 2000 and 3500 RPM, then increases again for higher engine speed. Engines are typically developed to have the highest efficiency between this range.

2.4.2. Environmental Conditions

The environmental conditions, particularly changes in ambient temperature (and seasonal changes), affect the fuel consumption. In a study conducted by Lee et al., it illustrates the theoretical relationship between temperature and energy consumption. The relationship follows a V-shaped graph where the energy consumption decreases as temperature increases (where heating demand is required), then it reaches the minimum at the base temperature (temperature that does not require heating or cooling demand to maintain a comfortable condition), from there, energy consumption increases as temperature increases (where cooling demand is required (Figure 1) (Lee et al., 2014). It is further supported by another study where the U- or V-shaped pattern is observed for multiple HEVs where both fuel consumption and emissions follow similar curves and they are at the lowest around 5ºC and much higher at lower temperature (Alvarez & Weilenmann, 2012).

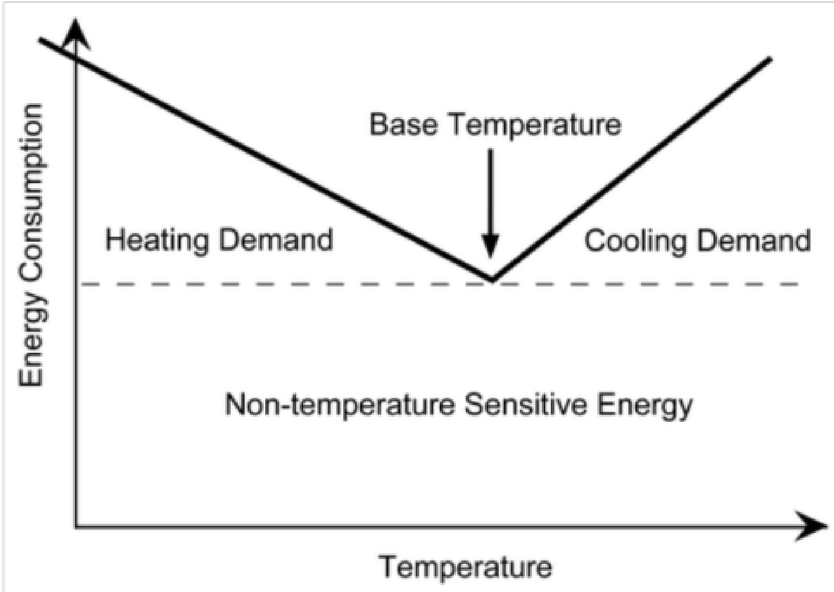


Figure 1. Theoretical relationship between ambient temperature and energy consumption.

Note: The figure is extracted from a study done by Lee et al., 2014.

In the winter, the fuel efficiency of HEVs is about 20% lower compared to summer, particularly at low speeds (Zahabi et al., 2014). When the ambient temperature is below 0ºC, the fuel consumption for HEV can even be 12% greater than a conventional gasoline vehicle (Zahabi et al., 2014). The fuel consumption for HEVs is significantly impacted on colder days because the battery capacity is reduced (Fontaras et al., 2017). This may have an implication on how much fuel economy savings are actually benefited from HEVs in cities that experience cold winters, such as Montréal.

In a study conducted in the far north regions in Russia by Shvetsov, there is more of an extreme case of ambient temperature at -40ºC, it was shown that the fuel consumption could be increased by up to 73% comparing to operating in a more temperate or typical temperature at 20ºC (Shvetsov, 2021). At this temperature, the electric engine for HEV is not turned on, hence the fuel consumption is comparable to a conventional gasoline vehicle.

2.4.3. Road and Traffic Conditions

The road conditions also affect the fuel consumption; some of the road factors include slope, road type or class (local street or highway), speed limit, number of lanes and average daily traffic (Carrese et al., 2013; Faria et al., 2019; Harantová et al., 2022; Panis et al., 2006; Zahabi et al., 2014).

As slope increases, fuel consumption increases. One study has shown that when the slope is 0.08, the fuel consumption increases by three times (16 litres/hr) compared to a flat road (Zhang et al., 2020). And as expected, the fuel consumption decreases with decreasing slope.

Road characteristics affect the fuel efficiency. Fuel consumption for different vehicles is also affected by driving in different road types or classes, such as in local streets (urban settings) or on highways. The fuel consumption for HEVs is lower by approximately 35% in urban setting (i.e. local roads) than rural setting (i.e. highways) compared to conventional vehicles (Wang et al., 2020). On highways, the performance of HEVs are similar to the gasoline conventional vehicles (Zahabi et al., 2014).

It has also been shown that HEVs can have significant fuel savings when the traffic density is high (with high average daily traffic) (Zhang et al., 2020). However, in a free traffic flow condition, the fuel saving is not significant as the engine is already working in the most efficient area and the vehicles are running at its maximal velocity.

2.5. Vehicle Specific Power (VSP)

Vehicle specific power (VSP) represents the instantaneous vehicle engine power, it is used as the basis for modelling emissions and is deemed a crucial factor when estimating the emission and energy consumption of vehicle operating condition that are dependent on speed, roadway grade, acceleration and deceleration (Sullivan & Sentoff, 2020; Yao et al., 2013; Zhai et al., 2011). The mathematical equation of VSP was first developed by J.L Jiménez in 1999 that describes VSP as power (kinetic and potential energies, rolling resistance, aerodynamic drag and internal friction and acceleration), divided by the mass of the vehicle (Yao et al., 2013). This can be simplified using coefficient values. For a typical light-duty vehicle, Equation (1) can be used to calculate the VSP value (Duarte et al., 2014).

$$VSP = v \times (a + 9.81 \times \text{grade} + \psi) + \zeta \times v^3 \tag{1}$$

Where v is the vehicle speed in m/s, a is the vehicle acceleration in m/s^2, grade is the vehicle vertical rise divided by the horizontal run, in percentage, ψ is the rolling resistance coefficient in m/s/s and ζ is the draft coefficient (reciprocal metres).

On-road vehicle measurements, using the Portable Emissions Measurement System, implements the VSP approach to assess energy and environmental characterization of the vehicles (Duarte et al., 2016). The average VSP during acceleration is around 8.9 kW/t and 3.4 kW/t during cruising mode (Tu et al., 2022). When VSP is greater than 13 kW/t, HEV demonstrates benefits over the conventional gasoline vehicle, which is around 1.72 greater on average (Robinson & Holmén, 2020). Higher VSP corresponds to higher emissions of CO_2, CO and NO_x (Yao et al., 2013). At lower VSP ranges, HEV can be powered by the electric motor. However, when the power demand is high, gasoline is consumed, leading to higher fuel consumption and emissions (Tu et al., 2022).

The second-by-second VSP is typically calculated based on the corresponding vehicle operating parameters, as it is an outcome variable (Moradi, 2021). Using a combination of calculated VSPs and vehicle speed, another calculation process can often find the appropriate operating modes from an operating mode bin table, as defined by the Motor Vehicle Emission Simulator by the U.S. Environmental Protection Agency (United States Environmental Protection Agency, 2005). VSP is a crucial concept, but because it is outside of the scope of this study, it was not analyzed.

2.6. On-Road Measurements vs Laboratory Testing

In previous studies, it has been shown that there are discrepancies in fuel consumption and emissions between on-road collected data and specifications provided by car manufacturers (Emadi et al., 2008; Kousoulidou et al., 2013; Moradi, 2021; Zahabi et al., 2014). Tests that are conducted in a lab setting usually overestimates the emission reduction potentials (Karabasoglu & Michalek, 2013; Tansini et al., 2022). Even standards like WLTC (Worldwide Harmonized Light Vehicles Test Cycles) do not align to local tests such as the one done in China in 2019: China Light-Duty Vehicle Test Cycle (Wang et al., 2020). The methodology for real-world driving experiments would follow similarly in the research done by Moradi (Moradi, 2021).

There are drastic variations in air pollutant emissions, some even show that HEV can possibly generate more emissions under certain conditions (Emadi et al., 2008). Emissions such as CO and CO_2 are strongly influenced by the road grade where the energy consumption is about four times when going from a flat road to uphill (Prati et al., 2021). In a real driving emission test comparing the emission reduction of HEV to conventional vehicle, CO emission is actually higher by 13% and NO_x emission is lower by 5% in HEV (Bagheri et al., 2021). Many factors could affect the emissions from hybrids. In one of the studies, it was found that frequent re-start time, warm-up time and high engine speed in hybrids increase lead to higher CO emission than conventional vehicles (Wang et al., 2020). PHEVs have shown to be more sensitive to many other factors such as mileage, usage, electric-range, availability of charging stations and charging behaviour (Plötz et al., 2020; Plötz et al., 2021). In a study related to PHEVs, it was found that the gap between the real-world and official type-approved CO_2 emissions for PHEVs is attributed to the share of electric driving: less frequent charging than anticipated, and also driving at different ambient temperatures while using heating or air-conditioning (Dornoff, 2021). This highlights the importance of conducting real world driving tests, rather than just laboratory tests. Furthermore, the measurements from vehicles could be specific to macro-level conditions.

2.7. Modelling Approaches

Log-linear mixed effect technique has been used to establish the link between fuel consumption and various factors (Zahabi et al., 2014). The random effect in that case study is observation from the same driver as this is correlated. The equation for the model will be outlined in the methodology section. This is not the only study that used the log-linear model for analysis related to fuel consumption and emissions for vehicles. In another study that studied the impact of climate change on passenger vehicle consumption, it also employed a simple log-linear model (Jeon, 2019). The log-linear approach was also used in another analysis on fuel economy and ambient temperature on hybrid vehicles (Henning et al., 2019). In addition to the log-linear regression analysis, there are also other approaches and models that could be employed, comparing to other similar studies. In a study to analyze the impacts of built environment on vehicular distance travelled and their GHG emissions, a latent class regression modelling framework is implemented (Zahabi et al., 2015). The dependent variable in the study, GHG emission, has been taken by natural logarithm. Another example is a study using data from real-world driving to predict total and instantaneous fuel consumption (Çapraz et al., 2016). The study compares the outcomes from the following models and approaches: Support Vector Machine, Artificial Neural Network and Multiple Linear Regression. The results shows that Support Vector Machine performs the best, even though the outcomes vary depending on the correlation between instantaneous and total fuel consumption.

For analysis on ambient temperature, some literature have suggested using piecewise linear regression (Alvarez & Weilenmann, 2012; Henning et al., 2019) as the relationship between energy consumption and ambient temperature usually follows an U- or V-shaped curve. However, it has already been established that relationship between fuel economy or emissions to other factors are typically non-linear and that a polynomial model will be used to assess ambient temperature in this study (Saerens et al., 2013).

2.8. Research Gaps

Many studies on estimating the performance of HEVs do not take into consideration of driving behaviours, weather, road characteristics and other external or environmental conditions (Huang et al., 2019). Therefore, it is crucial to conduct data collection in real-world driving conditions and environment, instead of conducting lab testing which is what most car manufacturers do. Conducting real-world driving tests captures vehicle performance that is more realistic and representative of the real-world conditions. Recommendations can be made based on specific situations and could be location dependent.

Many past research mainly focused on just fuel economy or consumption, and not as much on emissions. Although fuel consumption and emissions are related (combustion of fuel is directly linked to the emissions produced at the tailpipe), it is beneficial to measure the tailpipe emissions in order to confirm this. In line with a lack of real-world driving tests, very few studies that analyzed emissions took into considerations of the real-world conditions. Most emissions are estimated based on models or measured in a laboratory setting. Real-world driving tests where emissions are measured directly from vehicle tailpipes emerged more recently and commonly.

Even though the measurements across the studies differ slightly, the general consensus is that HEVs still demonstrate to be the competitive technology to mitigate GHG emissions and to reduce the fuel consumed. From literature review, it still appears that there is a lack of real-world driving tests where external factors such as driving behaviour, environmental and road and traffic conditions are considered. Therefore, conducting and collecting more real-world observations from metropolitan cities (such as Montréal, especially in a city that experiences cold winters) could fill in some of the gaps at the macroscopic level and provide some insights in the Canadian context.

3. METHODOLOGY

3.1. On-Road Experiment

On-road experiments from conventional gasoline vehicles were collected in July to November 2019 and the data from HEV were collected from June to November, 2022 and March 2023 in Montréal, Quebec, Canada. The data from gasoline vehicles are needed in order to serve as the baseline to compare with the HEV data. Data from the two HEVs were collected in March to investigate the impacts of colder ambient temperature on the performance of HEVs, in comparison to the warmer months.

Summer months are considered to be from June to August; fall months are from September to November; winter months are from December to February; and spring months are from March to May, with slight variations depending on the temperature. The mean temperature for the experiments conducted during the summer months was 21ºC for both gasoline vehicles and HEVs. The mean temperatures for experiments conducted during the fall months were 7ºC and 10ºC for the gasoline vehicles and HEVs, respectively. The mean temperature for experiments conducted during the spring months was -0.7ºC for HEVs (collected in March 2023). These mean temperatures were taken from the daily reports based in the weather station at Montréal Pierre Elliott Trudeau International Airport from Meteorological Services of Canada (Environment and Climate Change Canada, 2023a). The methodology for equipment set-up and protocols are detailed in Section 3.1.2 to ensure consistency and quality on equipment performance and data collected. This includes ensuring the sensor for measuring the emissions sensors was warmed to the same internal temperature (between 32ºC to 38ºC) before starting the experiments.

In order to investigate the performance of individual vehicle, the ideal set-up is to keep all variables constant (i.e. same driver hence same driving behaviours, routes and weather condition in each season) with each unique vehicle. However, this is not always realistic or feasible. This study involved two drivers, assuming similar driving behaviours, driving in an urban setting in Montréal. There were no cold-starts in any experiment and the weather conditions were similar in each season.

One of the logistical constraints for on-road experiments is that testing cannot be conducted during heavy rainfall or snowfall events and that the exhaust pipes cannot come into contact with water. Therefore, during winter where there is snow on the road that could splash into the exhaust pipes, results could be affected and become unreliable. Potential solutions will need to be discovered for real-world driving testing in the winter in the future to overcome the challenges.

3.1.1. Vehicle Selection

A total of eleven unique vehicles were selected in this study: four hybrid electric vehicles (two conventional HEVs and two PHEVs) and seven conventional gasoline vehicles. A total of thirteen trips were included as one of the same HEV (Toyota Prius C) and PHEV (Ford C-Max Energi) had two trips each in total (one trip during the warmer months and one during the colder months). The vehicles were selected based on some of the popular vehicles of choice in Quebec and in Canada in general. It was also based on availabilities of the vehicles at time of rental and rental sites. Because the HEVs were rented during high season in the summer through early fall, the selection was slightly limited. The conventional gasoline vehicles were selected to match as closely as possible to the HEVs based on vehicle class and specifications, in order to have a fair comparison. Due to time constraints and vehicle availabilities, the exact equivalent gasoline vehicles were not available to match the HEVs selected. The specifications of the selected vehicles are summarized in Table 1.

Table 1. Vehicle characteristics and manufacturer specifications for all the selected vehicles for this study.

Powertrain Type	Manufacturer	Model	Manufacture Year	Vehicle Class	Engine Size (L)	Curb Weight (kg)
Plug-in hybrid	Ford	C-Max Energi	2016	Compact Hatchback	2	1750
Plug-in hybrid	Toyota	Prius Prime	2020	Compact Sedan	1.8	1288
Hybrid	Toyota	Prius C	2019	Subcompact Hatchback	1.5	1148
Hybrid	Toyota	RAV4 Hybrid XSE	2021	Compact SUV	2.5	1703
Gasoline	Honda	Civic	2014	Compact Sedan	1.8	1230
Gasoline	Kia	Optima	2012	Midsize Sedan	2.4	1461
Gasoline	Kia	Rio	2013	Subcompact Hatchback	1.6	1126
Gasoline	Mazda	6	2009	Midsize Sedan	2.5	1500
Gasoline	Mazda	3	2016	Compact Sedan	2	1329
Gasoline	Toyota	RAV4	2016	Compact SUV	2.5	1619
Gasoline	Toyota	Yaris	2015	Subcompact Hatchback	1.5	1059

3.1.2. Equipment Selection and Set-Up

3.1.2.1. On-Board Diagnostics Loggers

The On-Board Diagnostics loggers (OBD-II) (Figure 2), were installed on all the vehicles to collect engine-state parameters. The measurements from engine control unit were captured in real-time wirelessly to the “OBD Fusion” application on the tablet. The OBD-II logger, along with the OBD Fusion application on the tablet, can log a wide range of vehicle and engine variables (from accelerometer, gyroscope, magnetometer), but not all vehicles report the full range of variables. The OBD Fusion application also performs some calculations and generates some new variables based on OBD readings. OBD-II loggers were set to log variables at 1Hz frequency (one measurement per second). Some of the parameters include vehicle speed reported by Engine Control Unit (km/hr), acceleration (m/s^2), engine speed (revolutions per minute), GPS latitude and longitude, altitude (m), intake manifold absolute pressure (kPa), intake air temperature (ºC), mass air flow rate (g/s), absolute throttle position (%), barometric pressure (kPa) and fuel-air equivalence ratio. Most variables can be used directly, whereas some variables are used for calculations of fuel rate (mass air flow rate and fuel-air commanded equivalence ratio) and emissions (barometric pressure and intake air temperature).

(a) (b) (c)

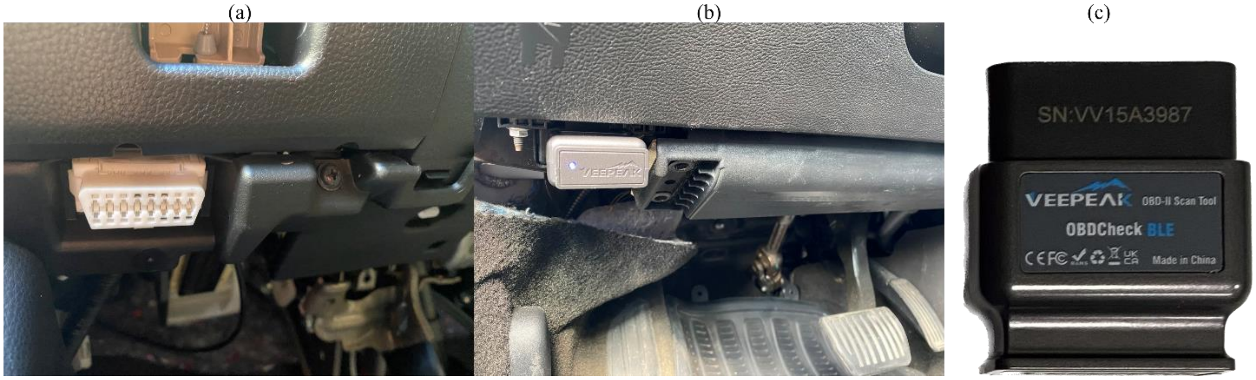


Figure 2. OBD-II logger.
Note: (a) OBD-II port under the steering wheel; (b) OBD-II port under the steering wheel with the OBD-II logger plugged in and . (c) Wireless OBD-II logger/ scanner

3.1.2.2. Portable Emissions Measurement System

Portable Emissions Measurement System (PEMS) was used for on-road vehicle monitoring to measure second-by-second characterization of the trip while the vehicle was operating. PEMS is a recent state-of-the-art technology that measures emissions and the sensor is light-weight, small-size and portable. This equipment has been used in previous studies on collecting emissions data and has been becoming more popular in emission measurement (Emadi et al., 2008).

PEMS monitors the instantaneous CO_2, CO, NO, NO_2 and particulate matter (PM) concentrations. CO_2 is measured by using non-dispersive infra-red (NDIR) absorption technology with a measurement range of 0-20% and an accuracy of +/- 70ppm. NO_x is measured by using 3-electrode electrochemical sensors with a measurement up to 500ppm for NO and 300pm for NO_2. The measurement resolution is 1-5ppm and 0.1ppm for NO and NO_2, respectively. PM is measured by undiluted emissions through the response of three dissimilar particulate sensors. Since only the CO_2 emissions are of interest in this study, the other emissions were not used but saved for other future studies. GoPro Hero10 Camera was used to capture video data in order to analyze road characteristics and environmental conditions in other future studies.

Figure 3 shows the PEMS set-up for the data collection. The tailpipe probe (6) is inserted and clamped in the tailpipe to collect the exhaust gas samples at a 2.5 litres/minute rate. There is no dilution and therefore extrapolating sensor values to full concentration is not needed. The probe is first connected with the intake hose (5) to transport it to the Condensate Unit for Batch Emissions (CUBE) or the chiller (2) which condenses and removes the water vapour present in the exhaust. The water trap (3) further collects condensation that forms within the tailpipe sample line before it sends the gas sample to the sensor module (1). The sensor module is the main measurement unit for reading the sample. After passing through all the sensors, the exhaust sample gasses continue to flow out to a particulate filter, flow pump and an exhaust outlet (4). The sensor is wirelessly connected to a 3DATX computer and it run on the parSYNC software.

Figure 3. The PEMS set-up.
Note: The Portable Emissions Measurement System (PEMS) set-up on a test vehicle with the following parts: 1. Sensor Module 2. Chiller 3. Water Trap 4. Exhaust Outlet 5. Intake Hose 6. Tailpipe probe 7. Laptop

On test day, the temperature setting on PEMS is set to 38ºC to allow it to pre-condition for at least one hour where the chiller is set to 5ºC. The target internal sensor temperature is typically between 32ºC to 38ºC, depending on the ambient temperature. The parSYNC software is then connected with the devices. The zeroing procedure is conducted first to calibrate with a true zero air cylinder, sampling with clean ambient air. The measurement of the ambient conditions is completed in 60 seconds, this is also to ensure internal temperature is stable and operating between the 32ºC to 38ºC range. Once this step is done and the system has been setup, the data collection can begin. At the end of the test cycle, the engine is turned off and data collection is stopped. The zeroing procedure is conducted at the end of the cycle again to measure the ambient conditions. The internal temperature of the PEMS unit could change drastically in the middle of the experiment and measurements of emissions concentrations would be affected. The measurements from the zeroing procedures at the start and end of experiments can help adjust the data should this happen. After data logging is stopped, the sample lines are disconnected, water traps are drained, both the PEMS unit and chiller are turned off and the output files are saved and exported for processing.

3.1.3. Study Area and Route Selection

Figure 4 shows the aggregated views of GPS trajectory for all of the vehicle experiments for HEVs and conventional gasoline vehicles conducted in Montréal, Quebec, Canada, respectively, in 2022 and 2019. The colours indicate the frequency each link is travelled. Every GPS data point is linked to an unique link ID which has link characteristics information such as road class, speed limit, annual average daily traffic and number of lanes, sourced from the GeoBase database.

The objectives of this study are to evaluate how the fuel economy or fuel consumption and GHG emissions are impacted by different conditions. One of these conditions is the road conditions. The routes selected included a diversity of different road conditions. A mix of slopes was considered including uphill and downhill, dedicating approximately 10% of the trip for going uphill. Different road types or classes were tested, with a mix of urban driving and highway driving. The predetermined percentage of driving on highway was set to approximately

10% of the trip, where permissible. Some trips may have less highway driving than others. With every road link that was covered, it also has a variety of speed limits, number of lanes and average daily traffic which may be correlated with the road class.

The following corridors in Montréal were pre-selected and driven by most tests in order to obtain data for the same road sections using different vehicles: Parc Avenue, Sherbrooke Street, Chemin de la Côte de Neiges, Chemin de la Côte-Sainte-Catherine and sections of Highway 40. These corridors were chosen as they are major streets in the city and of interest.

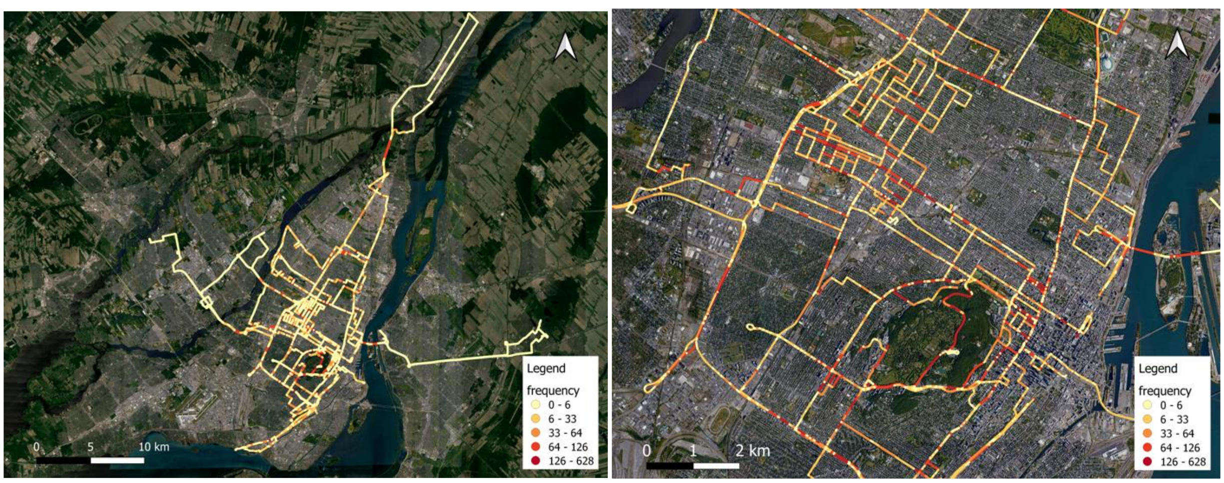


Figure 4. Study Area.
Note: GPS trajectory for all HEVs and conventional vehicles experiments conducted in Montréal, Quebec, Canada, based on the frequency of routes taken, with a zoom-in of the downtown Montréal area on the right.

3.1.3.1. Road Geometry Variables

The following road geometry or characteristics were chosen for analysis as they are common traits to characterize a segment of the road. The source of the GeoBase data (including road geometry data) was provided by the City of Montréal. The GeoBase database (Ville de Montréal, 2023) is presented as a filamentary network of straight line segments with which the digitization is generally done in the centre of the street. Each road segment has an unique ID, containing location information such as GPS and altitude, as well as all the road characteristics listed below that were included in this study. Each unique ID represents a portion of the road with homogeneous characteristics described mainly by the following attributes: an official and current toponym, address ranges and a reference to administrative boundaries (i.e. boroughs, municipal boundaries, neighbourhoods).

From the real-world driving experiments, GPS data were collected, which were used to link with the unique ID in the GeoBase database. The driving tests measured the second-by-second data (1 Hz) on fuel consumption and emissions.

- Slope: Slope is presented as a numeric value. It is calculated from LiDAR elevation data in the digitized direction. This information may not always be accurate. As a result, for this study, slope is calculated separately in R using the Haversine distance of two geospatial points in the Geosphere package. It uses information on longitude, latitude and altitude to calculate slope.
- Road type or class: The classes included are local streets, collectors, secondary arterials, main arterials and motorways. The classes are listed in order of the road hierarchy according to their functions and capacities, with local streets having the highest access to property but lowest speed limits and capacities to motorways having the lowest access to property but highest speed limits and capacities. This indicator gives a general idea of the potential of vehicle type, average speed and traffic volume.
- Speed limit: The speed limit in the segment of the road. It further reinforces the type of the road. It ranges from 30 km/hr to 50 km/hr within the city and municipal streets, up to maximum of 70 km/hr on gravel roads and up to maximum of 100 km/hr on highway.
- Number of lanes: Number of the lanes per direction was obtained from the macroscopic model of the City of Montréal (built in the Aimsun software).

- Average daily traffic (ADT): This indicator is a count of number of vehicles that pass through the link. The traffic volume was chosen as proxy for traffic conditions.

3.2. Data Preparation, Cleaning and Processing

Both the OBD-II logger and PEMS measure the second-by-second data at the micro-scale level, the output raw files were both in the comma-separated values (CSV) format. Both sensors log a wide range of variables but only a number of them were used for this study. The description of the variables that are included are listed in Table 2.

Table 2. Variables from OBD-II logger and PEMS

Variable	Description	Unit	Source
Time	Date and time of when the data points are logged		App
Latitude	GPS latitude	deg	GPS
Longitude	GPS longitude	deg	GPS
Altitude	GPS altitude (alternatively, elevations from GIS or GoogleMaps API could be used)	m	GPS
GPS Speed	Vehicle speed based on distance calculated using GPS coordinates	km/h	GPS
Wheel speed	Vehicle speed reported by ECU	km/h	OBD
Acceleration	Calculated acceleration based on speed	m/s2	App
Trip Distance	Distance traveled since the start of the trip	km	App
Trip Duration	Duration of trip since the start	min	App
Intake manifold absolute pressure (MAP)	Pressure of intake air which is used by MAP sensor to define proper air and fuel quantities required for ignition in cylinders	kPa	OBD
Engine speed	Rate of engine revolutions in unit of time	RPM	OBD
Intake air temperature	Temperature of the air entering cylinders through the intake manifold	ºC	OBD
Mass air flow rate (MAF)	Mass rate of air entering cylinders through the intake manifold	g/s	OBD
Barometric pressure	Ambient air pressure	kPa	OBD
Fuel/Air commanded equivalence ratio	This is equal to current fuel-to-air mixture ratio over stoichiometric fuel-to-air mixture ratio	-	OBD
Ambient air temperature	Temperature of the air entering the cylinders	ºC	OBD
A/F Commanded	Air-to-fuel mixture ratio commanded by ECU to injection system (retrieved from the hardcoded calibration parameters based on readings from MAF, MAP, and throttle, Crank, and Cam position sensors)	-	OBD
A/F Actual *	Air-to-fuel mixture ratio that actually occurs (could be different from the commanded value)	-	OBD
CO_2	Carbon dioxide (GHG) concentration measurement (V is the analog electrical measurement of NDIR CO2 sensor)	V, Vraw, ppm	PEMS

After filtering for the variables desired for the study, a new file was generated and used for continuity check algorithmically using the timestamp column to ensure there were no interruptions during the logging process and there is data for every second. The data from both equipment units were then combined using the unique time stamp.

For cleaning the data, every column in all the files was checked for missing values or outliers. If there were missing value, the data was augmented using the neighbour values and controlling for the technically accepted ranges. If there were outliers, the values were adjusted based on basic visualization and descriptive statistics. In addition, a number of new variables were generated based on the OBD Fusion and PEMS output files, most notably, the fuel consumption rate (FCR) in grams per second and all the emissions data to grams per second (taking into account of the internal PEMS temperature, barometric pressure and mass air flow rate).

For fuel consumption rate in Equation (2) the air-to-fuel mixture ratio at the stoichiometric level used was 14.7 grams, which means that for every 1 gram of fuel, 14.7 grams of air are required (Al-Arkawazi, 2019). The equation also takes into account of the volume correction factors to 15ºC for use with all grades of gasoline and gasoline ethanol blends (15% maximum ethanol) (Measurement Canada, 2018):

$$FCR_t = \frac{MAF_t}{\lambda \times AFR_{stoich}} \tag{2}$$

Where FCR_t is the fuel consumption rate at time t in g/s, MAFt is the mass air flow rate at time t in g/s, λ is the ratio of the actual air-to-fuel ratio (AFR), AFR_{stoich} is the stoichiometric air-to-fuel mixture ratio which is 14.7g.

From the PEMS unit, particulate matter is reported in μg/m^3, NO_2 and NO are reported in parts per million and CO_2 concentration is reported in percentage. For this study, the main emission focus is on CO_2 and the calculation is shown in Equation (3) converting CO_2 in percentage to grams per second (3DATX Corporation, 2022):

$$CO2_t = CO2_{\%} \times \frac{M_{CO2}}{V_m} \times \frac{273}{T_t} \times \frac{p_t}{p_o} \times \frac{MAF_t}{\rho_m} \times 10^{-2} \tag{3}$$

Where CO_{2t} is the concentration of CO_2 at time t in g/s, $CO_{2\%}$ is the concentration of CO_2 at time t, measured by the PEMS unit in percentage, M_{CO2} is the molar mass of CO_2 which is 44.01 g/mol, V_m is the molar volume of ideal gas at standard temperature and pressure which is 22.4 L/mol, T_t is the internal temperature of the PEMS unit at time t in Kelvin, p_t is the barometric pressure at time t, measured by the PEMS unit in kPa, p_o is the standard atmospheric pressure which is 101.3 kPa, MAF_t is the mass air flow rate at time t in g/s and ρ_m is the density of gas mixture which is approximately 1.2929 kg/m^3.

The final component of the input data is road segment data and its characteristics from the GeoBase database. Each road segment has an unique link identification number, GPS coordinate points, along with the road geometry variables listed in Section 3.1.3.1. A map matching process is conducted using this input layer of GeoBase information and the collected vehicle data. This process is conducted using QGIS to join the two input files together based on geographic locations. The processing tool called “Join Attributes by Nearest” is used, specifying a maximum distance of 10m, so only features that are closer than this distance would be matched. “Join Attributes by Nearest” is an algorithm that uses Cartesian calculations for distance (QGIS Documentation, 2023). The tool takes an input vector layer (vehicle data) and creates a new vector layer that is an extended version of the input one, with additional attributes in its attribute table. The additional attributes and their values are taken from the second layer (the GeoBase layer). The features are joined by finding the closest features from each layer. Once joined, the output layer would contain vehicle data that is linked with all the road geometry variables including road class, number of lanes and so on.

For each trip per vehicle, there is an output CSV file that contains all the joined information (collected from the experiment on vehicle data and on link information) for every second. All the output files from all vehicles are then combined into one output file for analysis.

3.3. Data Analysis

3.3.1. Time-Based and Distance-Based Rates

The collected vehicle data are recorded for every one second. Hence, the fuel consumption rate and CO_2 emission rate are in grams per second, the time-based units. This captures the instantaneous readings on all the variables. Because there could be some noise in the sensor when recording the second-by-second data, those outliers have been removed before proceeding with statistical analysis. These outliers are eliminated by first calculating the factor of emission divided by fuel, since emission and fuel are correlated. The interquartile range for the factor is then computed. Those values that fall below the 25% quartile with the interquartile range were considered to be outliers and removed (no more than 10% of the total combined data). This would be the main dataset that is used for analysis.

Another potential aggregation of data is by distance travelled in order to get the distance-based rates for fuel consumption rate and CO_2 emissions rate, in L/100km and g/km, respectively. These units are more commonly used in industry standards, hence easier for direct comparisons. They are also computed and used as a reference and comparison to using the time-based dataset. These rates are calculated in two-folds.

First, the rates for every trip (by each vehicle) are calculated by summing the total fuel consumed (in grams) and total CO_2 emitted (in grams) for the entire duration of the trip. Then, the fuel economy and emission rates were calculated by dividing the total fuel consumed or emissions by the total distance travelled. Information on a trip level is aggregated to obtain a general sense of each vehicle's performance.

Second, the data were aggregated to calculate the distance-based fuel consumption and emission rates. This was done by summing the fuel consumed and emissions for every 50 meters travelled for each trip from the instantaneous readings. Then, the total fuel consumed and CO_2 emitted are summed, then divided by 50 meters, for each trip. Therefore, each observation represents an average rate for distance travelled. The distance of 50 meters was selected as this covers around half a block in an urban setting. This distance is likely to still have the same road class and to cover from one stop to the next to get a representative picture of vehicle performance.

All the dependent and independent variables that are being considered for analysis are listed in Table 3. The categorical independent variables that were included in the study were converted to "dummy variables" when using R to analyze the data. All the data analysis is conducted using RStudio (Version 2023.03.0+386). In the subsequent analysis, not all of the independent variables would be kept as correlation would be checked first to see if any of the independent variables are correlated with one another.

Table 3. All the variables considered in the data analysis.

Dependent Variables		
	Unit	Description
FCR	g/s	The fuel consumption rate in grams per second.
	L/100km	The fuel consumption rate in litres for every 100km, averaged by every 50m of the trip.
CO_2	g/s	The CO_2 emission rate in grams per second.
	g/km	The CO_2 or greenhouse gas emission rate in grams for every kilometer, averaged by every 50m of the trip
Independent Variables		
	Unit	Description
Vehicle Type		For the general analysis and comparison between gasoline vehicles and hybrids, conventional HEVs and PHEVs have been lumped together under HEVs.
Vehicle class		
Hatchback		The vehicle class for the vehicle of the experiment
Sedan		
SUVs		
Speed	km/hr	
Acceleration	m/s^2	
Engine speed	Revolutions per minute	
Slope		
Average daily traffic		Average of the count of the number of vehicles per link
Road Type		
Local street		The road type of the link in Montréal. Highway is the reference in all of the models.
Collector		
Secondary arterial		
Main arterial		This can also be divided into local/urban setting (combining local street, collector, secondary and main arterials into one category) and highway setting.
Highway		
Speed Limit		
30 km/hr		
40 km/hr		The posted speed limit of the link in Montréal. Speed limit of 70km/hr is the reference in all of the models.
50 km/hr		
60 km/hr		
70 km/hr		
Number of lanes		
1		
2		The number of lanes of the link in Montréal. Five lanes is the reference in all of the models.
3		
4		
5		
Ambient temperature	Degrees Celsius	The ambient temperature recorded for the day of the experiment

Note: For the distance-based dataset, if the independent variables are continuous, then an average value is taken for every 50 meters travelled.

3.3.2. Exploratory Data Analysis

The dependent variables for this research are fuel consumption rate and CO_2 emission rate. The relationships between FCR and CO_2 and different factors (from Table 3) were explored.

In addition to the variables from Table 3, other combined factors or factors split into different categories were explored. For example, combining speed and acceleration can create a factor called the driving state or operation. The driving operations are segmented into four states (idling, cruising, acceleration and deceleration) and they are defined as follows (Tu et al., 2022):

- Idling: When speed $v < 1.6$ km/hr and absolute value of acceleration $|a| < 0.14$ m/s^2
- Cruising: When $v \geq 1.6$ km/hr and $|a| < 0.14$ m/s^2
- Acceleration: When $a > 0.14$ m/s^2
- Deceleration: When $a < -0.14$ m/s^2

The speed of 1.6 km/hr threshold is based on the definition of idling in the emission model in Motor Vehicles Emissions Simulator (United States Environmental Protection Agency, 2020) and the acceleration and deceleration threshold of 0.14 m/s^2 is based a study on local driving cycle comparisons (Yang et al., 2020).

Another factor that has been categorized is ambient temperature. The threshold for when ambient temperature is considered to be “warm” is 7ºC or higher, otherwise, the temperature is considered to be “cold”. This definition is from Natural Resources Canada (Natural Resources Canada, 2018).

The exploratory data analysis was conducted using R, generating the following: correlation matrix, descriptive statistics and a variety of graphs such as box plots, bar graphs of mean FCR and CO_2 for each vehicle included in this study, FCR-speed curves and CO_2-speed curves.

3.3.3. Regression Analysis

In order to examine and investigate the relationships between factors of interest listed in Table 3 with fuel consumption and CO_2, a couple of regression analysis and models were considered and explored, based on past studies and research (Zahabi et al., 2014). The following models were explored: multiple linear regression, polynomial regression, mixed-effect regression modelling and random-effect log-linear regression.

Linear regression is chosen as it is one of the base ones to start and explore. A simple linear regression model provides an initial overview of the potential relationships between the independent variables with the dependent variables (FCR or CO_2). This is indicated by the coefficients, whether it is positively or negatively associated with the dependent variables. The p-values for the coefficients indicate whether theses relationships are statistically significant (if p-value is less than 0.05).

Polynomial regression is chosen because of polynomial terms of speed, potential relationships with vehicle specific power which has speed to the power of three and interaction terms between speed with acceleration and speed with slope.

Because the dataset includes multiple effects with engine parameters, environmental conditions and random effects such as the different vehicles that were tested, mixed-effect regression seems appropriate.

Random-effect log-linear regression model is a type of generalized linear mixed model that allows for random variation in the intercepts of slopes of the model, with the random variation being the unique vehicle selection. This linear mixed-effect model fits the data by using maximum likelihood. The approach of random-effect log-linear regression was used in previous research (Henning et al., 2019; Zahabi et al., 2014).

Similar to rationales for using mixed-effect modelling, relationships with response variables (FCR and emission rates) and different factors are explored along with a random effect component within. The random effect log-linear regression is selected as the modelling method for this research because it has one of the better model performances and is also used and referenced in past research. The model evaluation is discussed in the next section.

The log-linear model allows for fixed effect (such as speed, acceleration, slope, road type and ambient temperature), and random effect, which is applied on the unique vehicle on the response variables of fuel consumption and CO_2 emission. Mathematically, the random-effect log-linear model follows Equation (4).

$$ln(Y_{it}) = X_{it}\beta + (u_i + v_{it}) \tag{4}$$

Where $\ln(Y_{it})$ is the natural logarithm of fuel consumption or CO_2 emission by vehicle i in segment t, β is the vector of model parameters ($\beta_o, \ldots\ \beta_k$), X_{it} is the vector of factors associated with FCR or CO_2 (such as speed, acceleration, road type), u_i is the normally distributed random effect for each vehicle i and v_{it} is the random independent error term, normally distributed for vehicle i and segment t.

The log-linear approach was used for both Objective 1 and 2. However, for Objective 2, to evaluate the impacts of ambient temperature on the different powertrain types of vehicles, a log-linear model with ambient temperature as a quadratic term was also tested.

In addition to testing the different model approaches, other sensitivity analyses were also conducted. FCR and CO_2 emissions are not normally distributed and has many zero values, hence a natural logarithm is applied to it. Because there are many zeros, a constant value needs to be added to the natural logarithm. The constant, c, tested in ln(y+c), include the values of 0.01, 0.1, 0.5 and 1. And the variable y being the dependent variable, either FCR or CO_2.

The results from both the time-based and distance-based rates were tested and compared as well.

3.3.4. Model Performance Evaluation

Many log-linear models were explored and tested in order to determine which combinations of the predictors had the best model performance. The performances of the models were evaluated based on several metrics such log-likelihood, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and coefficient of determination (R-squared). Each model was built for fuel consumption and CO_2 emissions separately.

The approach was to first incorporate all the viable potential predictors into all of the models. Then, by using k-fold cross-validation method, where the number of folds (k) is 5. Cross-validation is used to assess the models' ability to generalize to new data by splitting the data into training and testing sets and evaluating on the testing set. The dataset is split into 80% training dataset and 20% testing dataset. The performance models were then evaluated based on the performance metrics.

The models that were tested had a combination of reduced set of predictors. The important variables identified using statistical analysis were used as reference. The model performances were evaluated for all the tested models by using the same approach of k-fold validation with the same training and testing data and performance metrics on test data.

The marginal effects analysis for each model was also evaluated. In addition, elasticities were estimated for the models in order to see how sensitive the dependent variable is to changes in each independent variable. In a log-linear model, the elasticities also provide an indication of the percent change in the dependent variables for the one independent variable, while keeping other variables constant. The calculations for elasticities are as follows (which differ if the variable is continuous or if it is categorical).

When X is a continuous independent variable, the elasticity of dependent variable Y with respect to X_k in a log-linear model is $\beta_k \times \bar{X}_k$ where β_k measures the relative change in Y due to the change in X_k by one unit and X_k is the mean of X_k (Holmes et al., 2022; Schmidheiny, 2022).

When X is a categorical independent variable, the elasticity of dependent variable Y with respect to X_k in a log-linear model is $\exp(\beta_k) - 1$ (Holmes et al., 2022; Schmidheiny, 2022).

4. RESULTS

4.1. Comparative Analysis: Gasoline Vehicles vs Hybrid Electric Vehicles

This section presents the results from comparing the vehicle performance, namely fuel consumption rates (FCR) and CO_2 emission rates, of hybrid electric vehicles (including plug-in electric vehicles) (HEVs) with conventional gasoline vehicles (non-HEVs) under real-world driving conditions in Montréal, Canada. The section includes plots and graphs to compare two vehicle types under different conditions such as driving speed, driving state (acceleration or deceleration) and driving condition (local roads versus motorways or highways) based on the observed data.

4.1.1. Summary of Individual Trips

From the experiments, data were collected from a total of thirteen trips and from eleven unique vehicles (seven gasoline vehicles, two hybrid electric vehicles and two plug-in hybrid electric vehicles). Each trip is summarized to calculate the average fuel consumption rate (L/100 km) and average emissions (CO_2) rate (g/km) (Figure 5) to gain a general understanding of the characteristics of each individual vehicle. The gasoline vehicles have both higher FCR and CO_2 emissions than HEVs and PHEVs, as expected. However, PHEVs do not necessarily have lower FCR or CO_2 rate.

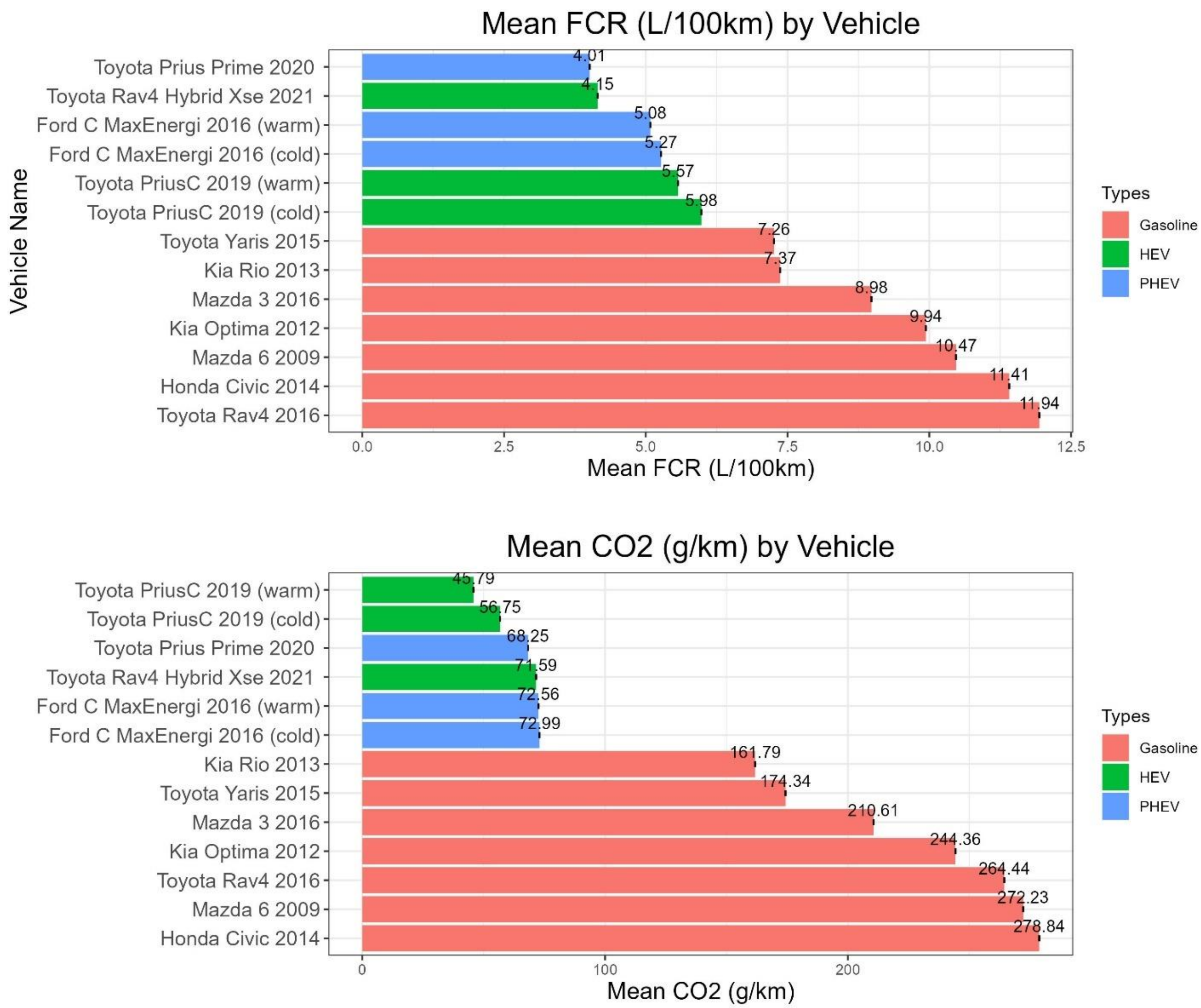


Figure 5. Average fuel consumption rate and CO_2 emission rate by vehicle.

Note: If the same vehicle has taken more than one trip, both are shown, indicated by the parenthesis: (warm) and (cold). For example, one trip is during warmer condition (warm) and the other is during colder condition (cold).

Table 4 shows the complete result of the number of observations, total fuel consumed, total CO_2 emitted, total distance travelled, average CO_2 in grams per second and grams per kilometer, FCR in grams per second and liter per kilometer and percent of driving on the highway for each vehicle included in the study. Two Welch two-sample t-tests were conducted. One was to compare the fuel consumption between gasoline vehicles and HEVs. The other one was to compare the CO_2 emissions between gasoline vehicles and HEVs. The analysis revealed that there were significant differences in means between the two vehicle groups (t = 60.826, df = 13414, p-value < 2.2e-16 for FCR; t = 106.93, df = 11049, p-value < 2.2e-16 for CO_2).

Table 4. Summary of all the vehicles included in the experiments.

Vehicle	Type	Season	Mean Temp (°C)	Time Travelled (hr)	Distance Travelled (km)	% Highway Driving	Mean FCR (L/ 100 km)	SD FCR	Mean CO_2 (g/ km)	SD CO_2
Toyota Rav4 2016	Gas	Summer	23.8	2.4	42.12	11.65	11.94	0.28	264.44	0.85
Honda Civic 2014	Gas	Fall	-2.2	1.17	17.47	0	11.41	0.26	278.84	0.93
Mazda 6 2009	Gas	Fall	-3.6	1.31	24.57	0.11	10.47	0.34	272.23	1.21
Kia Optima 2012	Gas	Fall	12.7	2.53	55.28	2.09	9.94	0.31	244.36	1.03
Mazda 3 2016	Gas	Summer	20.1	3.36	60.67	1.64	8.98	0.30	210.61	0.95
Kia Rio 2013	Gas	Fall	12.6	1.83	47.77	3.39	7.37	0.26	161.79	0.81
Toyota Yaris 2015	Gas	Fall	15.4	1.96	38.35	1.42	7.26	0.29	174.34	0.95
Toyota PriusC 2019 (Trip 2)	HEV	Spring	-1.9	4.08	77.34	10.47	5.98	0.48	56.75	0.88
Toyota PriusC 2019 (Trip 1)	HEV	Summer	19.2	4.44	77.35	13.18	5.57	0.34	45.79	0.63
Ford C MaxEnergi 2016 (Trip 2)	PHEV	Spring	0.5	4.44	90.04	10.88	5.27	0.48	72.99	1.01
Ford C MaxEnergi 2016 (Trip 1)	PHEV	Fall	10	4.64	85.28	11.71	5.08	0.46	72.56	0.97
Toyota Rav4 Hybrid Xse 2021	HEV	Fall	8.2	3.59	69.72	8.42	4.15	0.41	71.59	1.03
Toyota Prius Prime 2020	PHEV	Summer	18.2	2.04	59.75	13.01	4.01	0.43	68.25	1.15

Note: The trip summary includes the season the trip was taken, mean temperature, total time travelled, total distance travelled, percentage the trip was driven on highway, mean fuel consumption rate and mean CO2 emission rate and their standard deviations.

The fuel consumption and CO_2 emission rates collected from the experiments in this study are also compared with other sources and the values provided by the car manufacturers (Table 5). It is revealed that real-world driving data from this study are not all higher than those reported from the other sources.

The information extracted from Canada Energy Regulator is specific for Quebec in terms of the GHG intensity. It is revealed that estimates from CER are consistently lower for both fuel economy and GHG emissions compared to the manufacturers' estimates. This could potentially be due to the specific conditions tested under the Canadian context and because the electricity consumption carbon intensity in Quebec is lower (for vehicles like PHEVs that could be charged directly to the electricity grid). The estimates obtained from this study vary between being higher or lower compared to the other sources. The experiments conducted for this study potentially have more noise and variations. It could also be due to the nature of data collection or noise from the equipment. The equipment performance could be affected by lower ambient temperatures, presence of water or snow on the road surface and condensation build-up in the sensors.

Table 5. The fuel consumption rate and CO_2 emission rate of vehicles from this study.

	FCR (L/100km)				CO_2 (g/km)			
Vehicle	**Study***	**US DoE****	**CER-QC*****	**Car Emi Site********	**Study**	**US DoE**	**CER-QC**	**Car Emi Site**
Honda Civic 2014	11.41	6.12	6.53	5.5	278.84	171.5	149.6	132.9
Kia Optima 2012	9.94	8.7		5.4	244.36	204.4		140.9
Kia Rio 2013	7.37	7.53		4.7	161.79	180.8		114.5
Mazda 3 2016	8.98	7.06		4.8	210.61	165.3		116.6
Mazda 6 2009	10.47	9.88		6.4	272.23	229.9		158.1
Toyota Rav4 2016	11.94	9.41		5.5	264.44	216.9		131.5
Toyota Yaris 2015	7.26	7.29		4.4	174.34	172.7		102.6
Toyota Prius C 2019 (cold)	5.98	5.17		4.7	56.75	119.9		100
Toyota Prius C 2019 (warm)	5.57	5.17		4.7	45.79	119.9		100
Toyota Rav4 Hybrid Xse 2021	4.15	5.88		5.7	71.59	138.6		129.6
Ford C MaxEnergi 2016 (cold)	5.27	6.12	6.05	4.8	72.99	80.2	0.4	118
Ford C MaxEnergi 2016 (warm)	5.08	6.12	6.05	4.8	72.56	80.2	0.4	118
Toyota Prius Prime 2020	4.01	4.47	4.32	3.2	68.25	48.5	0.3	21.6

*Study = Collected from the real-world driving experiments
**US DoE = United States Department of Energy (Holmes et al., 2022; U.S. Department of Energy, 2023b),
***CER-QC = Canadian Energy Regulator, for Quebec specifically, where there is information applicable (Canada Energy Regulator, 2018)
****Car Emi Site = Values obtained from the Car Emissions Website (Car Emissions, 2023).

4.1.2. Overall Comparisons

To gain general insights on how the different vehicle drivetrains perform, the vehicles were first aggregated based on the following three groups: gasoline vehicles, HEVs or PHEVs. Then, for subsequent analysis, PHEVs are aggregated with HEVs under the HEVs group to see how the combined fleets perform in comparison to the conventional gasoline vehicles.

The average fuel consumption rates and average emissions rate for each vehicle type are illustrated using boxplots (Figure 6). The distance-based dataset is used where data is aggregated by every 50 meters, in order for easier comparisons with industry numbers.

Fuel consumption rates for gasoline vehicles, HEVs and PHEVs are 7.1 L/100km, 4.7 L/100km and 4.3 L/100km, respectively. The percent reductions using the time-based dataset were also calculated to get a range. FCR is reduced by approximately 33.5% to 38.6% in HEVs and 38.7% to 43.3% in PHEVs from gasoline vehicles, where the higher reduction potentials are from the time-based dataset.

The carbon dioxide emission rate for gasoline vehicles, HEVs and PHEVs are 167.1 g/km, 59.9 g/km and 65.4 g/km, respectively. CO_2 rate is reduced by approximately 64.2% to 66.3% in HEVs and 60.9% to 64.2% in PHEVs from gasoline vehicles.

The expected reduction range for FCR and emission should be similar. In this study, there are some differences between the reduction range. In real-world driving tests, FCR and emission are measured through two different devices. The PEMS, sensor for emissions, can have quite a bit of noise and it is sensitive to any presence of water or condensation, which can affect the readings.

As expected, FCR and CO_2 are both the highest in gasoline vehicles. The expectation was that the next highest would be HEVs then PHEVs which was true for FCR. However, for CO_2 emission rate, PHEVs are actually around 6.2% to 9.3% higher than HEVs. It also shows that the distribution for emission is skewed as the mean is higher than the medians for HEV and PHEV. It could potentially be due to underestimation and measurement from the sensors. There are also many values that are zeros.

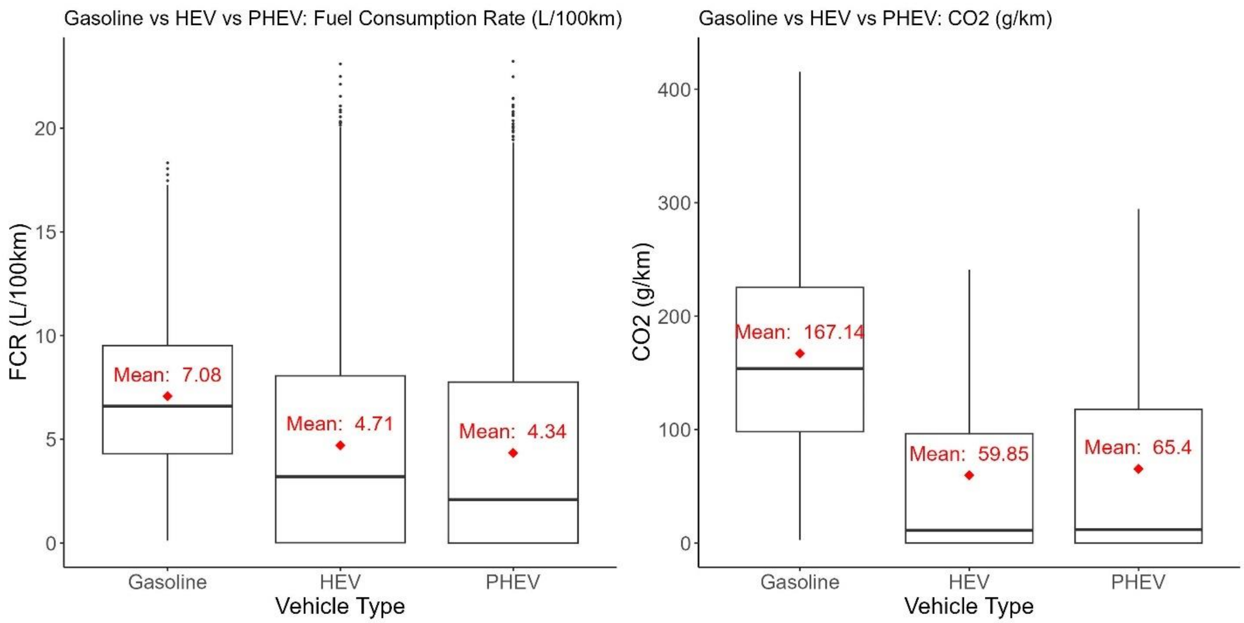


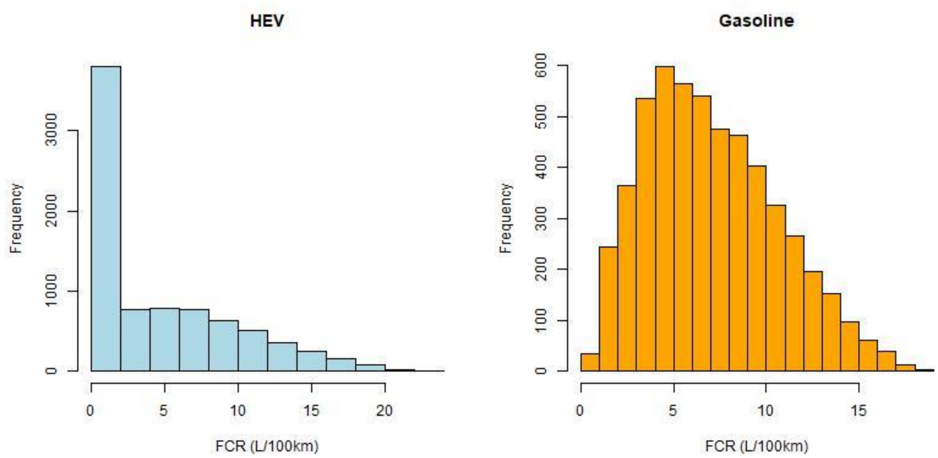
Figure 6. Boxplots of the means of FCR and CO_2.
Note: Fuel consumption rate (L/100km) (left) and CO_2 emission rate (g/km) (right) by vehicle type (with a further breakdown of gasoline vehicles, HEVs and PHEVs) based on trip data for every 50m for each individual vehicle.

In addition to the boxplots, summary statistics are also presented to show the standard deviation, variance, median, minimum, maximum and the spread of the mean values for FCR and CO_2. PHEVs and HEVs have been aggregated together in the summary statistics. The histograms are also displayed to show the distribution. Both the summary statistics and distribution histograms serve as complementary to the boxplots (Table 6 and Table 7).

Table 6. Descriptive statistics of FCR for HEV and non-HEV.

Vehicle Type	Number of Observations	**Mean**	**Standard Deviation**	Median	Min	Max	Q1	Q3	IQR	CI
Gasoline	5368	7.08	3.55	6.60	0.12	18.32	4.31	9.52	5.21	0.09
HEV	8111	4.51	5.10	2.65	0.00	23.22	0.00	7.91	7.91	0.11

Distribution of FCR in HEVs and Gasoline Vehicles

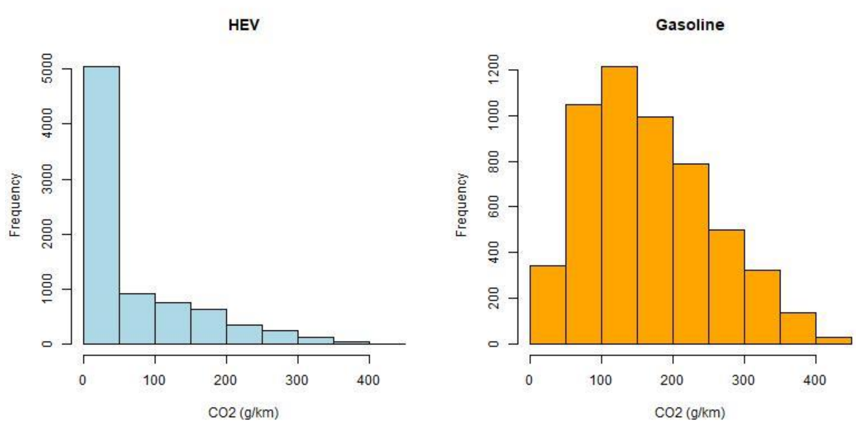


Note: Fuel consumption rate is in L/100km for HEV (left) and non-HEV (right).

Table 7. Descriptive statistics of CO_2 for HEV and non-HEV.

Vehicle Type	Number of Observations	**Mean**	**Standard Deviation**	Median	Min	Max	Q1	Q3	IQR	CI
Gasoline	5368	167.14	87.78	153.82	2.75	424.75	98.24	225.36	127.12	2.35
HEV	8111	62.87	86.73	11.44	0.00	422.50	0.00	107.75	107.75	1.89

Distribution of CO_2 Emission Rate in HEVs and Gasoline Vehicles



Note: CO_2 emission rate is in g/km for HEV (left) and non-HEV (right).

4.1.3. Comparisons Based on Speed, Road Types and Driving States

Table 8 presents the summary statistics table for gasoline vehicles and HEVs with all the tested variables (including average speed, acceleration, engine speed, proportion of highway driving, proportion of summer driving and average ambient temperature). This was from the vehicle data during the experiments, then using the distance-based dataset that is aggregated by every 50 meters.

Table 8. Summary statistics of FCR and CO_2 for gasoline vehicles and HEVs and their tested variables.

Description	**Unit**	**Mean**		**SD**	
		Gasoline	HEV	Gasoline	HEV
Number of observations		5368	8111	-	-
Fuel consumption rate	L/100km	7.08	4.51	3.55	5.1
CO_2 emission rate	g/km	167.14	62.87	87.78	86.73
Average speed for every 50m travelled	km/hr	32.66	42.87	13.9	22.11
Average acceleration for every 50 m travelled	m/s^2	0.1	0.08	0.45	0.38
Average engine speed for every 50m travelled	Revolutions per minute	1329.92	701.93	270.36	756.15
Proportion of Highway Driving		0.08	0.26	0.28	0.44
Proportion of Summer Driving		0.37	0.25	0.48	0.43
Average ambient temperature	ºC	14.01	7.74	8.17	7.7

Speed was identified as one of the factors in determining FCR and CO_2 in past research. Figure 7 shows the FCR and CO_2 with their corresponding speed profiles for gasoline vehicles and HEVs. The patterns of the curve for FCR and CO_2 exhibit similar patterns for each type of vehicle and both are non-linear. For HEVs, the rates start out lower at lower speed, then there is a slight increase to around 35km/hr, stabilizes and increases slightly at higher speed. For gasoline vehicles, the rates start out higher at lower speed and gradually decreases with increase in speed.

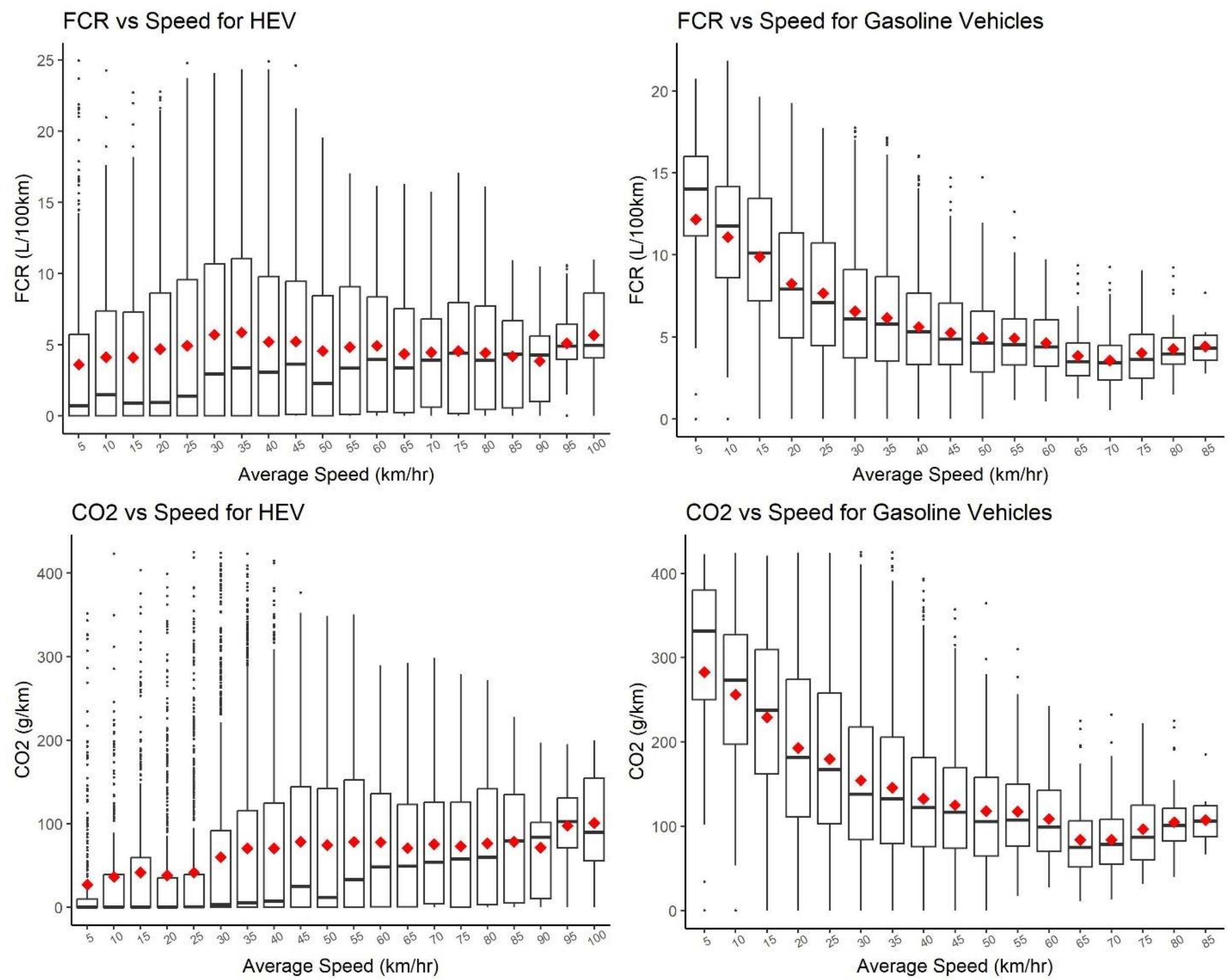


Figure 7. Average speed profiles with their corresponding FCR and CO_2 for gasoline vehicles and HEVs. Note: Plots also show the distribution of the variables at different speeds. The red dots are the mean values at each speed.

Engine speed (revolutions per minute) is speculated to be correlated with FCR and CO_2, they are plotted to illustrate the changes in the response variables at different engine speed. In Figure 8, it is seen that for HEVs, it is a steady, relatively linear increase in CO_2 and FCR (until higher engine speed when it drops a bit) as engine speed increases. In non-HEVs, the FCR and CO_2 both have higher fluctuations.

Both the speed and engine speed are expected to have a U-shaped curve in relation to FCR and CO_2.

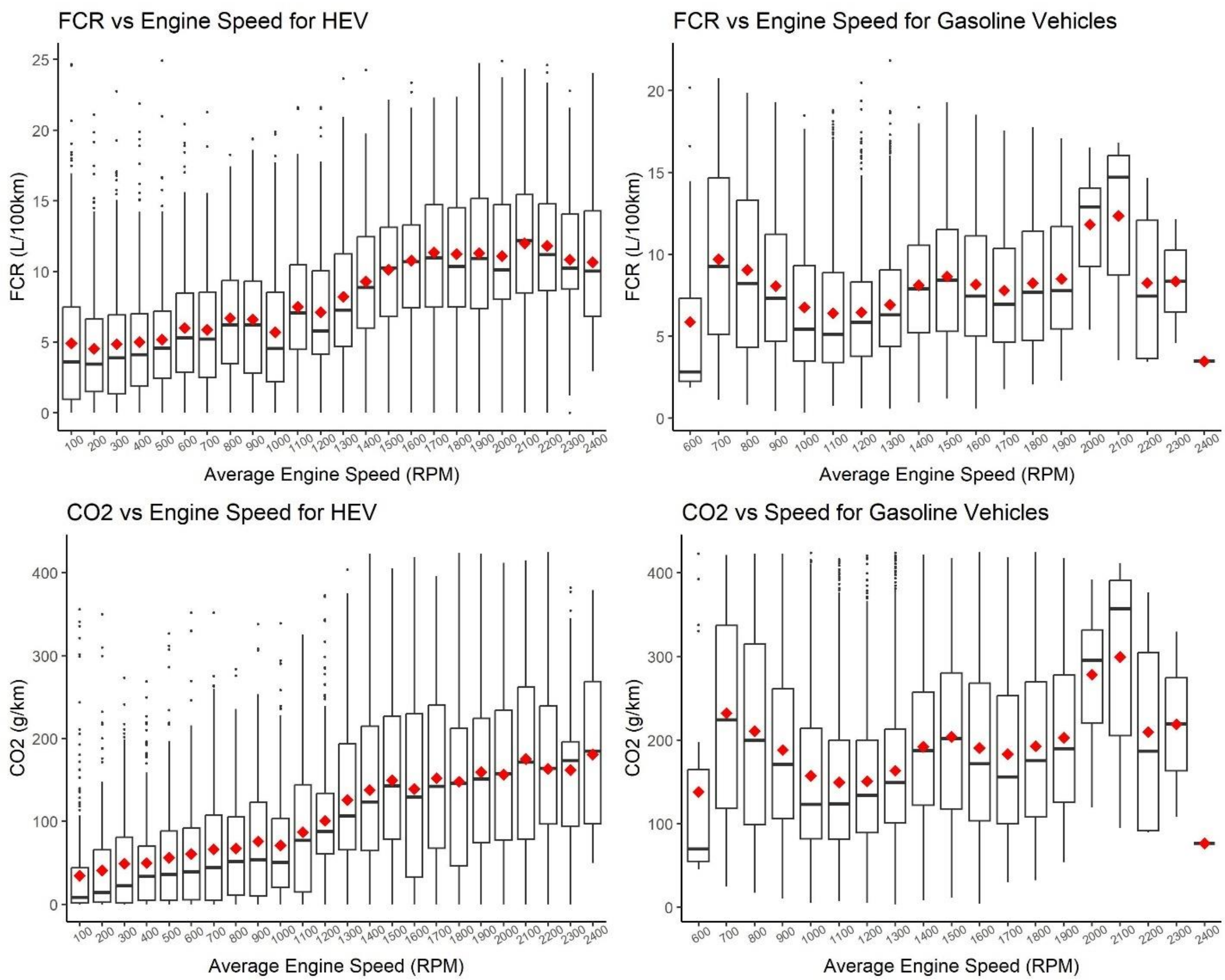


Figure 8. Average engine speed (RPM) profiles with their corresponding FCR and CO_2 for gasoline vehicles and HEVs.
Note: Plots also show the distribution of the variables at different engine speeds. The red dots are the mean values at each engine speed.

From the boxplots of driving state (acceleration, cruising or deceleration) (Figure 9), gasoline vehicles are seen to have higher average FCR and CO_2 than the HEVs in all driving states. There seems to be a huge difference in the deceleration phase, especially. It is also noticed that there is a higher variability in HEV measurements, especially for CO_2 measurements.

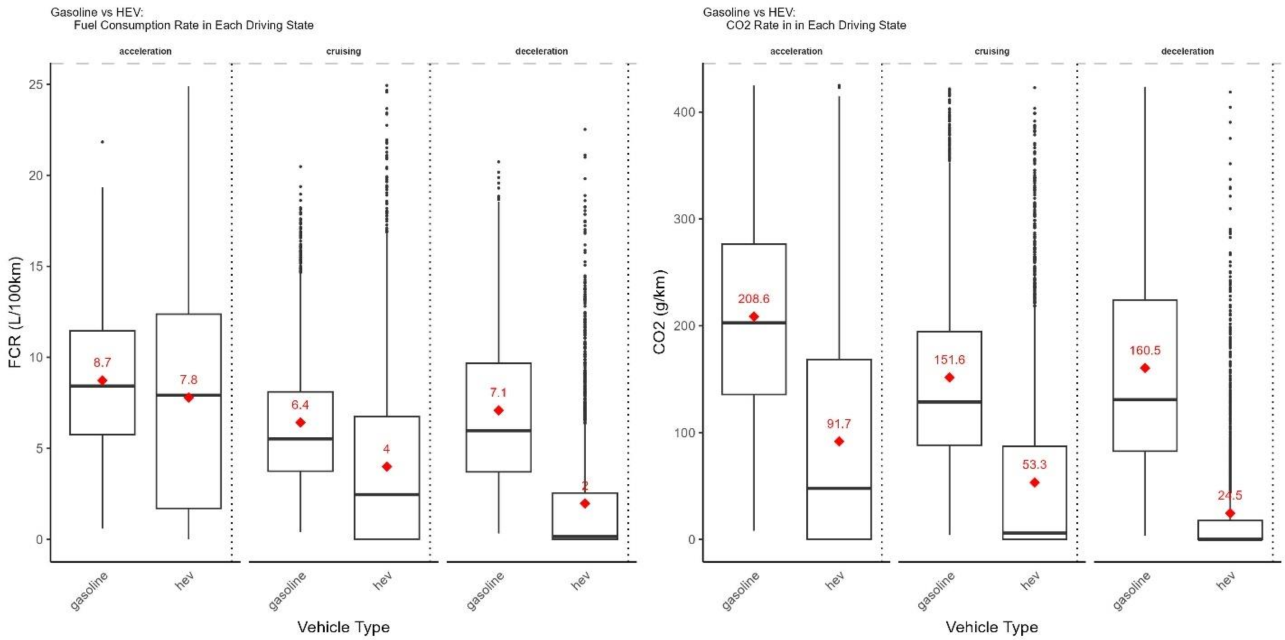


Figure 9. Boxplots of FCR and CO_2 in different driving states for gasoline vehicles and HEVs.
Note: Fuel consumption rate is in L/100km (left) and CO_2 emission rate in g/km. The different driving states are: acceleration, cruising and deceleration.

In terms of road conditions, both the slope and different road types are of interest. As slope increases, FCR and CO_2 both increases, as expected. However, for gasoline vehicles, the mean consumption at the steepest road segments actually dips a little, but has a higher variability.

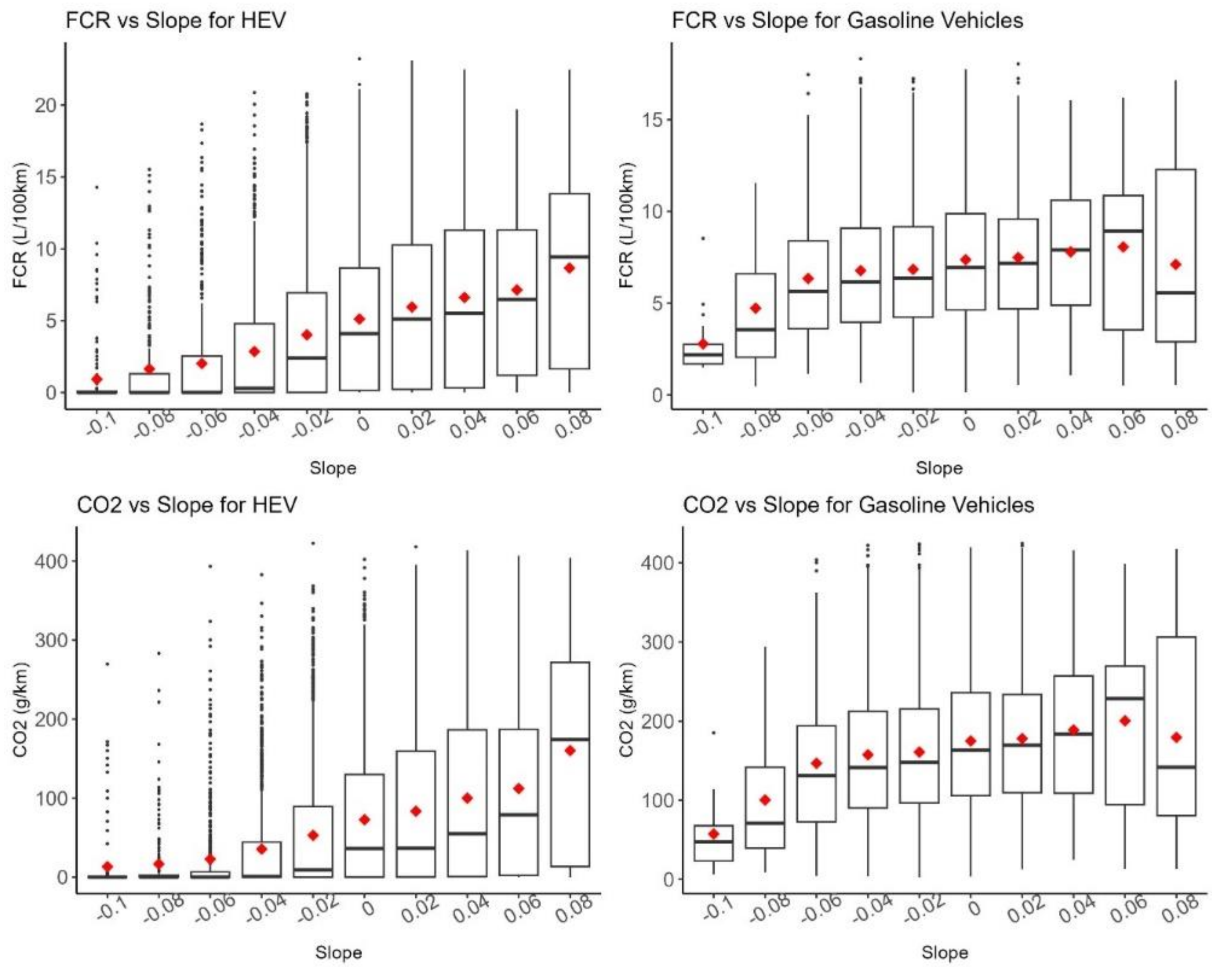


Figure 10. Slope profiles with their corresponding FCR and CO_2 for gasoline vehicles and HEVs.
Note: The plots also show the distribution of the variables at different slopes. The red dots are the mean values at each slope.

One part of the research question is to investigate the FCR and CO_2 emissions across the various different road types. In the boxplots with a breakdown of the different road classes (in increasing traffic volume order from left to right- from local street on the left to motorway on the right) (Figure 11), the FCR and CO_2 emissions are consistently lower in HEVs than gasoline vehicles in all road types. It is also interesting to note that within HEVs, the emission is the highest in highway, which aligns with what literature showed. And for conventional gasoline vehicles, the emission is the highest in local streets.

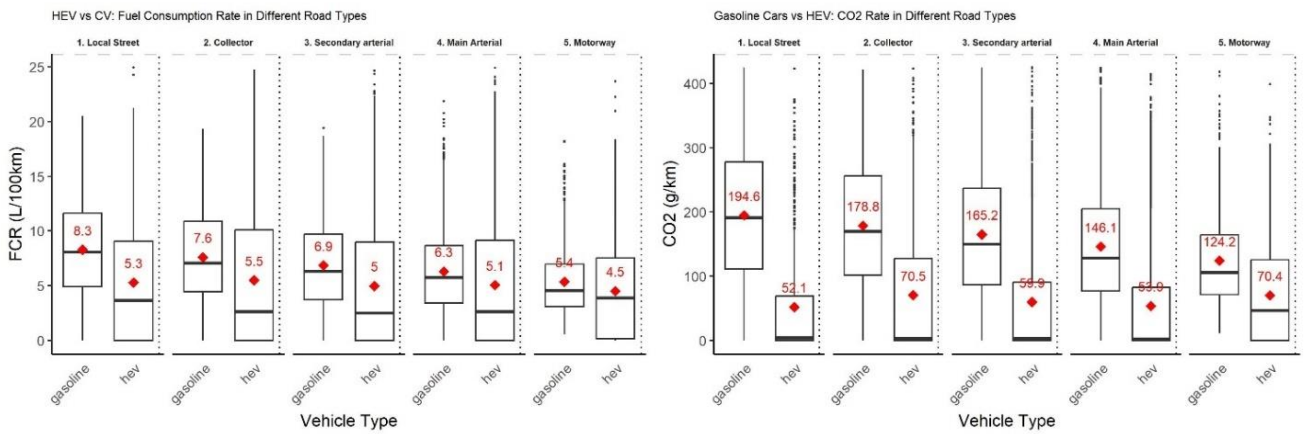


Figure 11. Boxplots of FCR and CO_2 in different road types for gasoline vehicles and HEVs.
Note: Fuel consumption rate is in L/100km (left) and CO_2 emission rate in g/km. The different road types are: local street, collector, secondary arterial, main arterial and motorway/highway.

4.1.4. Correlation Analysis

Before conducting statistical analyses, all the continuous independent variables were examined to determine if they are correlated with the dependent (or response) variables of interest (fuel consumption and CO_2). With all variables, some variables such as ambient temperature is shown to have a weak correlation with the dependent variables, whereas some are shown to high a strong correlation.

During data collection, two vehicle speeds were recorded- one speed was derived from the GPS data and the other speed was wheel speed reported by the engine control unit from the OBD-II logger. A comparison of the two speeds (GPS speed and wheel speed) indicated that both units provide similar speed estimates, as shown in Figure 12. Therefore, only speed from GPS is kept as a variable for the analysis, as this was also done in a previous research.

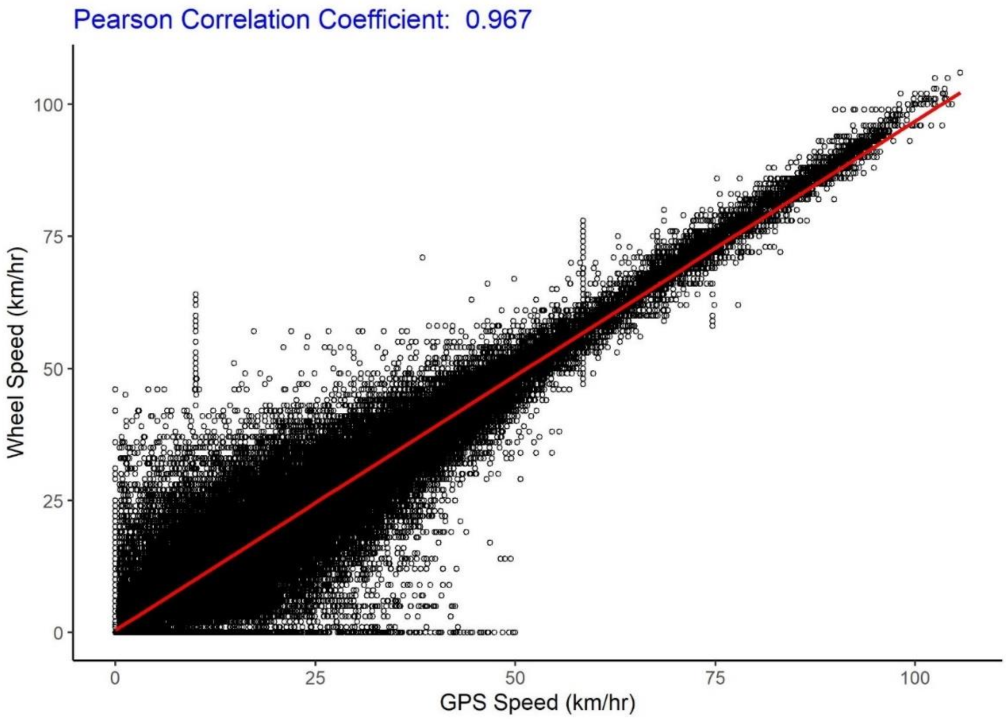


Figure 12. Comparison between GPS and OBD speed data.
Note: The solid line is the reference line where y=x.

The correlation matrix, shown in Figure 13, was used to see if any of the continuous independent variables were correlated with one another and to examine if any of the independent variables were correlated (with coefficients higher than 0.4) with the dependent variables of fuel consumption and CO_2. The Pearson correlation coefficients between engine speed in revolutions per minute and GPS speed is 0.46 which is considered to be high, therefore, one of it should be removed from analysis. The independent variables that have correlation matrix greater than 0.4 would be considered to be removed. The variable that are being kept in the subsequent analysis and models would be the ones that have higher correlation with the dependent variables of interest (FCR and CO_2).

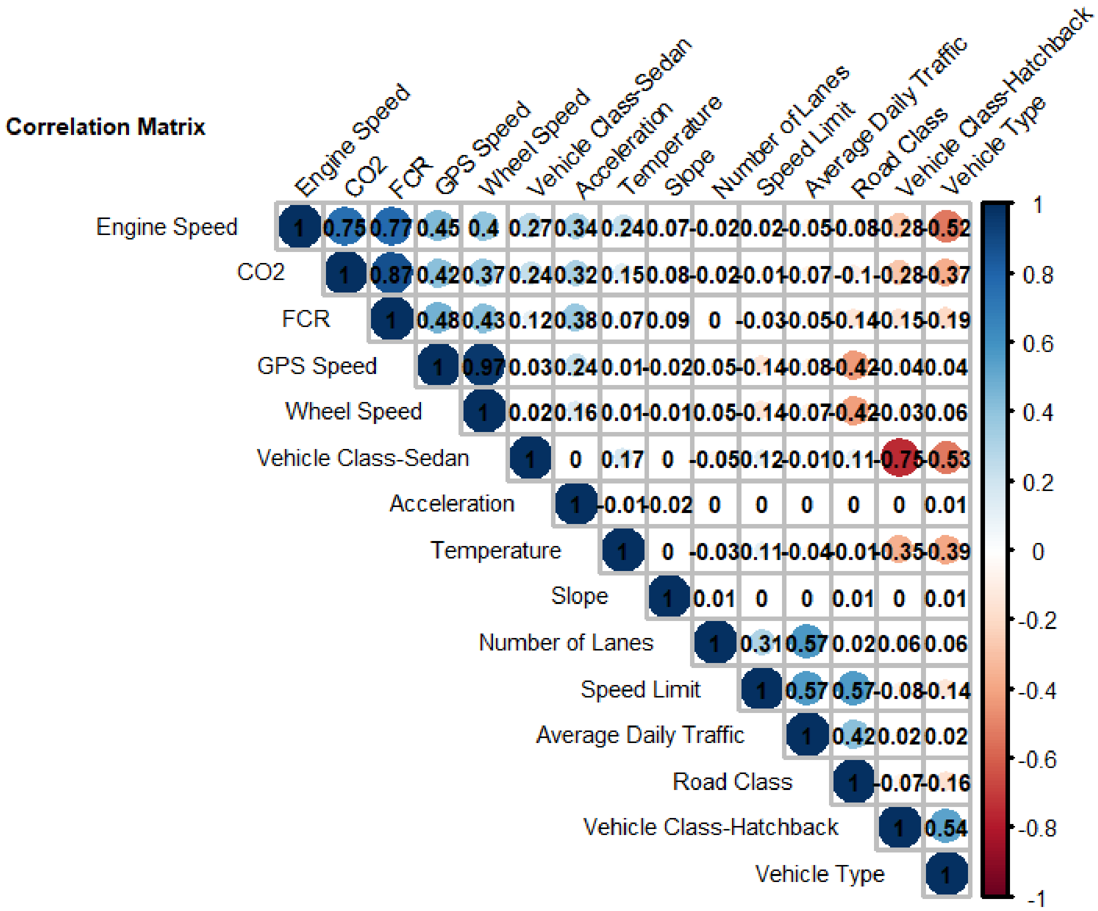


Figure 13. Correlation matrix.
Note: This includes all the independent variables and dependent variables (FCR and CO2).

From the correlation matrix, the following independent variables are kept: vehicle type (whether it is conventional gasoline vehicle or HEV), GPS vehicle speed, acceleration, slope, road class or road type (whether it is local driving or highway driving) and the ambient temperature. Even though some of the selected variables (such as slope and ambient temperature) have relatively lower correlation coefficients against the dependent variables, they are included in analysis as they have shown to be significant variables in past literature. In addition, from a simple linear regression, these variables are significant, even though the coefficients are relatively small.

4.1.5. Linear Regression Analysis

The results from linear regression analysis were analyzed first and presented in this section. The result outputs include the estimated coefficient, standard error, t-value and p-value. The estimated coefficient is the average increase or decrease in the dependent variable with every one unit increase in the independent variable, assuming all other independent variables are held constant. The standard error of the coefficient measures the uncertainty in the estimate. The t-value or t-statistic is the coefficient divided by the standard error. The p-value, which corresponds to the t-value, indicates significance. If the p-value is less than 0.05, the independent variable is statistically significant.

Two linear regression analyses were done, one for response variable as fuel consumption rate, the other as emissions rate. Both of the response variables are in original units, not in the logarithmic function. The dataset used was the time-based data for every one second. The following output tables for FCR (Table 9**Error! Reference source not found.**) and CO_2 emission (Table 10) as response variables are presented as examples to show the coefficient estimate and significance for each predictor.

In the FCR output, it suggests that all of the included variables are statistically significant in determining FCR, as all of the p-values are less than 0.05. From the coefficients of the predictor variables, the FCR is less when the vehicle type is a HEV and the ambient temperature is negatively associated with FCR. Other variables are all positively associated with FCR.

Table 9. Linear regression analysis for fuel consumption rate.

		FCR			
Predictor		Coef.	Std. err	t-value	p-value
Vehicle Type	HEV	-0.177	0.002	-85.411	0
	Non-HEV	Base	---	---	---
Speed		0.009	0.00005	160.781	0
Acceleration		0.215	0.002	118.736	0
Slope		0.921	0.021	43.822	0
Road Type	Urban	0.00817	0.004	2.166	0.03
	Highway	Base	---	---	---
Ambient Temperature		-0.0006	0.0001	-5.213	0
		R^2= 0.356 Degrees of freedom: 122862 Residual standard error: 0.326 F-statistic: 1.131e+04 p-value: < 2.2e-16			

Note: The variables vehicle type and road type are considered to be dummy variables. In vehicle type, 1 is for HEV and 0 is for non-HEV. In road type, 1 is for urban road and 0 is for highway.

In the CO_2 emission output, it suggests that all of the included variables play important roles in determining the emissions, except for the road type. The signs of the coefficients (positive or negative) align with the FCR output for vehicle type and ambient temperature.

Table 10. Linear regression analysis for CO_2 emission rate.

		CO_2 Emission Rate			
Predictor		Coef.	Std. err	t-value	p-value
Vehicle Type	HEV	-0.832	0.005	-155.737	0
	Non-HEV	Base	---	---	---
Speed		0.020	0.0001	148.003	0
Acceleration		0.475	0.005	101.750	0
Slope		2.204	0.054	40.745	0
Road Type	Urban	0.002	0.009	0.232	0.816
	Highway	Base	---	---	---
Ambient Temperature		-0.0007	0.0003	-2.318	0.021
		R^2= 0.382 Degrees of freedom: 122862 Residual standard error: 0.84 F-statistic: 1.267e+04 p-value: < 2.2e-16			

From the linear regression results, in general, increasing in speed, acceleration and slope would result in an increase in FCR and emissions. From driving a HEV and on a warmer day, this would result in a decrease in FCR and emissions. However, this alone may not provide the complexity of the relationships among the variable and further regression analysis would be conducted.

4.1.6. Regression Analysis

This section evaluates the effects of the potential predictors (independent variables) on fuel consumption rate and CO_2 emission rate using log-linear mixed-effect model.

The random effect in these models is the unique vehicle. The main dataset used in the regression model is the time-based data for every one second.

The models were fitted by using the combined data (with all vehicle data) and two separate subsets of vehicle type or vehicle technology where the combined data was partitioned into: hybrid electric vehicle (HEV) or non-HEV (conventional gasoline vehicles) datasets. The response variables (FCR and CO_2) have been normalized for this type of regression by taking a natural logarithm. Because there are many zeros in FCR and CO_2, a constant is added to the variables before taking a natural logarithm. The different constants, ranging from 0.01 to 1, were tested for sensitivity. The constant 0.5 was selected because the constant should ideally be less than 1 and the estimated fuel and emission reduction using 0.5 resemble the reductions from the collected data.

Different model settings were explored and tested with a combination of different predictors implemented, along with the two response variables separately and using two different datasets. The primary dataset used where results from regression analysis would present is the time-based dataset for every 1 second. The second dataset used (for exploring and testing) is the distance-based dataset for every 50 meters travelled.

There are a total of six different models as outcomes to showcase how the two response variables (FCR and CO_2) behave in the combined dataset (with all vehicle data), in the HEV group and in the non-HEV group. The different models tested included a combination of the predictors identified as significant from the correlation matrix analysis and statistical analysis. The following are the fixed effects in the models in this section: vehicle type (HEV or non-HEV, for the combined dataset), speed, acceleration, slope and road type. Ambient temperature is evaluated in Section 4.2. The random effect is the individual unique vehicle.

The performances of the models are evaluated using 5-fold cross validation technique to assess the model's predictive accuracy on testing data. The performance metrics used to compare the models are log-likelihood, R^2, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) (AIC and BIC are not shown). The metrics were used to evaluate the goodness-of-fit of the models and were used to select the model and their predictors that performed the best. The correlations between variables were verified to avoid collinearity and multicollinearity issues. The assumptions of the modelling technique were also checked.

4.1.6.1. Fuel Consumption and CO_2 Models for All Vehicles

Using the combined data (with all vehicle data from both HEVs and non-HEVs), the log-linear model output is shown in Table 11. All of the variables included in the model are statistically significant except for road type for the emission model. However, the models perform the best in comparison to the other tested models with the listed variables included. The signs (positive or negative) on the coefficients or the average marginal effects reveal the general trend of relationship between the variable with the dependent variables, fuel consumption rate (FCR) and or CO_2 emission rate.

Table 11. Log-linear models outcomes of fuel consumption rate and CO_2 emission rate (combined data).

		FCR				CO_2			
Predictor		Coef.	Std. err	P-value	Elasticity (%)	Coef.	Std. err	P-value	Elasticity (%)
Vehicle Type	HEV	-0.294	0.029	0	-25.455	-0.815	0.053	0	-55.725
	Non-HEV	Base	---	---	---	---	---	---	---
Speed		0.009	0	0	16.986	0.013	0	0	24.137
Acceleration		0.209	0.002	0	0.22	0.253	0.003	0	0.267
Slope		0.891	0.02	0	0.036	1.325	0.031	0	0.054
Road Types	Urban	0.025	0.004	0	2.566	-0.001	0.006	0.906	-0.066
	Highway	Base	---	---	---	---	---	---	---
		R^2= 0.42 Log-likelihood= 27945.79				R^2= 0.54 Log-likelihood= 19937.61			

Note: Elasticities are calculated at the mean values for continuous variables.

By driving a HEV, the fuel consumption rate could be reduced by 25.5% and emission rate reduced by 55.7%, in the base case, according these specific log-linear models, which is what the elasticities reveal. The elasticity is the highest for vehicle type in both models, indicating that whether the vehicle is a HEV or non-HEV has the strongest influence on FCR and emissions.

For speed, the marginal effects analysis revealed that for every unit increase in vehicle speed, holding other variables constant, the FCR increases by 25.2% for HEVs and 50.9% for non-HEVs. For CO_2 emission rate, it decreases by 5.2% for HEVs and increases by 51.3% for non-HEVs for every unit increase in speed. The elasticities for speed are the highest after the vehicle type, implying that speed is an important factor that influences FCR and emissions. With 1% increase in speed, the FCR increases by approximately 17% and CO_2 emission increases by approximately 24.1%, at the mean of vehicle speed (19.2 km/hr), holding everything constant, in the base scenario. The fuel consumption is slightly more sensitive to changes in speed with elasticity of 24.1% whereas the elasticity for CO_2 rate is 17.0%.

From literature, speed is associated with FCR and emission non-linearly. In addition to log-linear model, different combinations of polynomial models with respect to speed were also tested (combination of speed, speed^2 and speed^3), though not shown here. Some of the preliminary sensitivity analysis results show that with every 1% increase at the average vehicle speed, FCR increases around 16.9% and 17.3% and CO_2 emission rate increases around 23.3% and 23.5% (from tested models with different combinations of polynomial speed terms). The elasticities are similar to the log-linear models presented here.

Acceleration has relatively small elasticities in comparison, implying that the influence of acceleration on FCR and emission is small, but it is a statistically significant variable and is correlated positively with the dependent variables. At the mean of acceleration (average acceleration of -0.011 m/s^2) in the base scenario, FCR increases by 0.22% and emission increases by 0.27% for every 1% increase in acceleration. The elasticities for acceleration are extremely small because the elasticities are computed at the mean and acceleration has a small absolute mean value.

Slope, similar to acceleration, also has relatively small elasticities in comparison. It is a statistically significant variable and correlated positively with the dependent variables. At the mean of slope (average road grade or slope of 0.04%) in the base scenario, FCR increases by 0.036% and emission increases by 0.054% for every 1% increase in acceleration. The elasticities for slope are extremely small for the same reason as acceleration.

By driving in an urban setting or in local streets, the FCR is increased by approximately 2.6% and emission is decreased by approximately 0.07%, in the base scenario, for non-HEVs. For HEVs driving in an urban setting, holding other variables constant, FCR and emission are reduced by 23.5% and 55.8%, respectively (in comparison to highways with reductions of 25.5% in FCR and 55.7% in emissions). The effect of road class is small. The response variables, FCR and emission, are not sensitive to changes to the different road types.

The road class, according to past literature, should have reduced FCR and emission in an urban setting (local streets), more so for HEVs. The CO_2 model aligns with theory where by driving in an urban setting, the emission is slightly further reduced for HEVs. However, for fuel consumption, it revealed a positive correlation with driving in urban setting. Even though FCR and emission should be correlated, the real-world driving experiments do not always align with this, especially for HEVs.

In addition, when driving in a metropolitan city such as Montréal, the highways can sometimes get congested. Therefore, a data point could be labeled as a highway but behaves like a local street. This could also be due to modelling parameters. The small elasticities provide an indication that road class is not an extremely important variable in these specific models. The p-value for road class in the CO_2 model is greater than 0.05, indicating insignificance, even though the model performance overall is better with this variable.

4.1.6.2. HEVs vs non-HEVs: FCR Model

This subsection discusses the model outputs for FCR for HEV and gasoline vehicles (non-HEVs) (Table 12), separately, in order to observe if there are any differences from the overall models (from Section 4.1.6.1, using the dataset with all types of vehicles) and further investigate the differences between HEV and non-HEV more specifically. All the predictor variables in the model are statistically significant (p-value < 0.05). All of the predictors are positively correlated with FCR, meaning increasing in the variables would increase the FCR.

Table 12. FCR log-linear models outcomes for HEV and non-HEV.

FCR		HEV				Non-HEV			
Predictor		Coef.	Std. err	P-value	Elasticity (%)	Coef.	Std. err	P-value	Elasticity (%)
Speed		0.009	0	0	18.558	0.007	0	0	13.337
Acceleration		0.294	0.003	0	0.224	0.152	0.002	0	0.220
Slope		1.806	0.035	0	0.119	0.191	0.02	0	0.001
Road Types	Urban	0.016	0.005	0.001	1.639	0.087	0.006	0	9.100
	Highway	Base	---	---	---	---	---	---	---
		R^2= 0.38 Log-likelihood= 14246.82				R^2= 0.38 Log-likelihood= 12840.85			

Note: Elasticities are at the mean values for continuous variables.

The elasticities for speed are 18.6% and 13.3% for HEVs and non-HEVs, respectively, which is around the same range as the combined models. In other words, for every 1% increase in vehicle speed, at the mean (19.9 km/hr for the HEV model and 18.2 km/hr for the non-HEV model) in the base case, the FCR increases by around 18.6% for HEVs and 13.3% for non-HEVs. It also implies that HEVs are more sensitive to changes due to speed than non-HEVs. Similar note to the previous section where speed has a non-linear relationship with FCR, though the elasticities are quite similar to the log-linear models.

Acceleration has a small positive effect on FCR and it is not as sensitive to change due to changes in acceleration with the small elasticities. For every 1% increase in acceleration, at the mean (-0.0076 m/s^2 for HEVs and -0.014 m/s^2 for non-HEVs) in the base case, the FCR increases by around 0.22% for both types of vehicles. The elasticities are small for acceleration for similar reasons that elasticities are calculated at the mean and the mean of acceleration is small.

Slope has a small positive effect on FCR. The elasticities are higher in HEVs than non-HEVs, implying that HEVs are more sensitive to changes in slope. And that increasing in slope could increase FCR more in HEVs. More specifically, for every 1% increase in slope, FCR increases by around 0.12% and 0.001% for HEVs and non-HEVs, respectively, at the mean of slope (0.066% for HEVs and 0.0066% for non-HEVs) in the base case. Once again, the elasticities are extremely small because of the small mean of slope values. The observations were mainly from flat roads.

In theory, driving in non-highway roads lowers the FCR, meaning the fuel economy is usually higher on highways than in city driving for HEVs. In these models, it is revealed that FCR increases by approximately 1.6% for HEVs and 9.1% for non-HEVs by driving in an urban setting. This implies that FCR for non-HEVs are more sensitive to change based on the road type. For conventional gasoline vehicles, the fuel economy is generally better in highway than city driving.

4.1.6.3. HEVs vs non-HEVs: CO_2 model

This subsection discusses the model outputs for CO_2 emission rate for HEV and gasoline vehicles (non-HEVs) in Table 13. All the predictor variables in the model are statistically significant (p-value < 0.05). All of the predictors are positively correlated with CO_2, meaning increasing in the variables would increase the CO_2, with the exception of road type for HEV.

Table 13. CO_2 log-linear models outcomes for HEV and non-HEV.

CO_2		**HEV**				**Non-HEV**			
Predictor		Coef.	Std. err	P-value	Elasticity (%)	Coef.	Std. err	P-value	Elasticity (%)
Speed		0.013	0	0	26.0	0.011	0	0	20.688
Acceleration		0.267	0.005	0	0.204	0.251	0.003	0	0.361
Slope		2.55	0.052	0	0.168	0.367	0.032	0	0.002
Road Types	Urban	-0.023	0.007	0.001	-2.284	0.134	0.01	0	14.376
	Highway	Base	---	---	---	---	---	---	---
		R^2= 0.31 Log-likelihood= 11830.90				R^2= 0.38 Log-likelihood= 7747.23			

Note: Elasticities are at the mean values for continuous variables.

For speed, the elasticities are higher for both types of vehicles in comparison to the FCR models. It once again implies that HEVs are more sensitive to changes due to speed than non-

HEVs (26% and 20.7% for HEV and non-HEV, respectively). The elasticities also indicate the change in emission based on changes from speed. In other words, CO_2 emission rate increases by 26% and 20.7% for HEVs and non-HEVs, respectively, for every 1% increase in speed, at the mean speed in base scenario. From both the FCR and CO_2 models, they imply that vehicle performance is sensitive to change due to change in speed and it is also more sensitive for HEVs.

Acceleration has a positive but small effect on CO_2. From the sensitivity analysis, it was revealed that emission rate increases by 0.20% and 0.36% for HEVs and non-HEVs, respectively, for every 1% increase in acceleration, at the mean acceleration in base scenario. Emission is not as sensitive to change due to changes in acceleration. The acceleration factor in this model for the types of vehicles do not show much difference.

Slope, like acceleration, also has a positive but small effect on CO_2. Results from slope is consistent with that of the FCR model where HEVs are more sensitive to changes in slope than non-HEVs (0.17% versus 0.002% of elasticity). In other words, emission rate increases by 0.17% and 0.002% for HEVs and non-HEVs, respectively, for every 1% increase in slope, at the mean slope in base scenario. And that increasing in slope could increase CO_2 more in HEVs.

Road type (driving in either urban setting or highway) is a statistically significant variable for both types of vehicles. However, it has opposite effects on the types of vehicles. Driving in urban setting decreases CO_2 emission rate by average of 2.3% for HEVs, while it increases the rate by 14.4 % for non-HEVs. From the sensitivity analysis, it is also shown that emission from conventional gasoline vehicles is sensitive to different road types.

4.2. Effect of Ambient Temperature on Performance of Hybrids

This section first evaluates the impacts of ambient temperature using a quadratic function for all types of the vehicles first (HEVs versus non-HEVs), presenting statistical analysis and regression analysis.

The models used in the previous section (Section 4.1) was Equation (4). As explained in the methodology and previous literature, a quadratic term would be added to the log-linear models in attempt to develop models to estimate for vehicle performance based on the ambient temperature. All the variables used in the previous section would be kept in these models.

Then, using data from only HEVs and PHEVs, the remainder of the section investigates specifically on only HEVs and PHEVs where it goes into a deeper dive of comparisons between the vehicles with different potential factors. Two sets of statistical and regression analyses would be conducted for HEVs and PHEVs only. The first set is similar to the previous section where log-linear model would be used and not including ambient temperature as a factor. The second set, using the quadratic function for modelling where ambient temperature is considered, would be conducted. The data for this part is a subset of data from only HEVs and PHEVs.

4.2.1. Effect of Ambient Temperature on All Vehicles

This section evaluates the effects of ambient temperature on temperature on fuel consumption rate and CO_2 for all vehicles first to get a general overview, before focusing in on just the hybrids.

From the analysis of variance, it has been shown that all of the variables are significant, including the vehicle type, speed, acceleration, slope, road class (only significant for the FCR model), ambient temperature and quadratic term of ambient temperature (raised to the power of two).

Using the log-linear model in the previous section, ambient temperature was shown to be not statistically significant. For analyzing the effects of ambient temperature, quadratic function is utilized in this section, keeping the same variables from previous sections.

Table 14 shows the model results for fuel consumption rate and emission rate for all vehicle types. The road class has been removed in these models as it is not statistically significant in this model. Both ambient temperature and ambient temperature to the power of two (quadratic term) are shown to be statistically significant.

Table 14. Log-linear model outcomes with quadratic term for FCR and CO_2 emission rate.

		FCR				CO_2			
Predictor		Coef.	Std. err	P-value	Elasticity (%)	Coef.	Std. err	P-value	Elasticity (%)
(Intercept)		-0.3382	0	0	---	0.1633	0	0	---
Vehicle Type	HEV	-0.2812	0	0	-24.509	-0.8031	0	0	-55.206
	Non-HEV	Base	---	---	---	Base	---	---	---
Speed		0.0087	0	0	16.774	0.0127	0	0	24.443
Acceleration		0.2083	0	0	0.219	0.2495	0	0	0.263
Slope		0.8929	0.02	0	0.0362	1.3263	0.03	0	0.0538
Ambient Temperature		-0.0061	0	0	1.000	-0.0028	0	0	1.564
(Ambient Temperature)^2		4.00E-04	0	0	---	2.00E-04	0	0	---
		R^2= 0.42 Log-likelihood= -33690.83				R^2= 0.52 Log-likelihood= -85161.99			

Note: Elasticities are calculated at the mean values for continuous variables.

As expected, the coefficients for HEV are both negative, indicating a reduction in response variables by driving a HEV. In these models, including the quadratic term of ambient temperature, the FCR could be reduced by approximately 28.7% by driving a HEV and CO_2 emission rate could be reduced by approximately 55.2% by driving a HEV.

The ambient temperature, in first degree, has negative coefficient and ambient temperature raised to the power two is positive for both models. This implies that the general shape of the estimated curves would be U-shaped.

From the marginal effects analysis, it is revealed that the FCR could increase by 25.1% and 49.4% for HEVs and non-HEVs, respectively, for every unit increase in ambient temperature. The CO_2 emission rate could decrease by 5.3% for HEVs and increase by 49.7% for non-HEVs, for every unit increase in temperature. These differences are generated mostly from the vehicle type and not as much from the ambient temperature variable. As seen further from the sensitivity analysis, with every 1% increase in ambient temperature, both the FCR and CO_2 emission increase by approximately 1.0%, at the mean of ambient temperature (10ºC), holding everything constant, in the base scenario. This also implies that even though ambient temperature has an overall average positive effect on the response variables, the effect is small and the response variables are not sensitive to changes to ambient temperature from these models.

The relationship between FCR and CO_2 emission rate with ambient temperature from these specific models are illustrated in Figure 14 and Figure 15, respectively. Both exhibit the U-shaped curves, though the temperature effects are quite small.

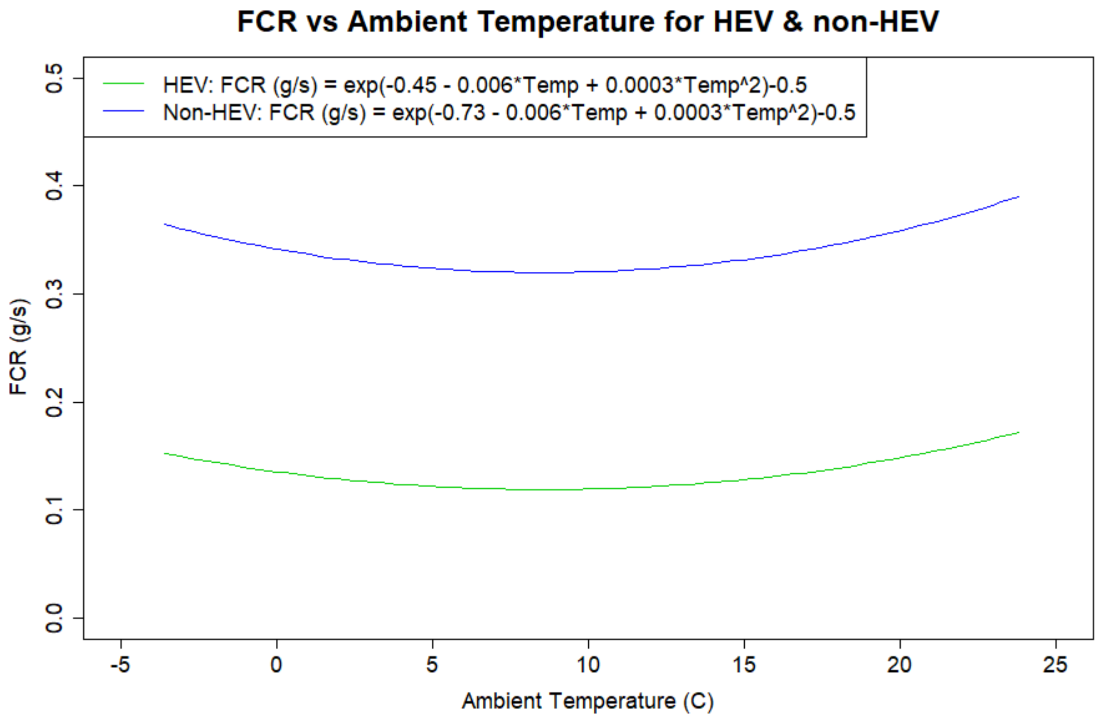


Figure 14. Effect of ambient temperature on FCR.

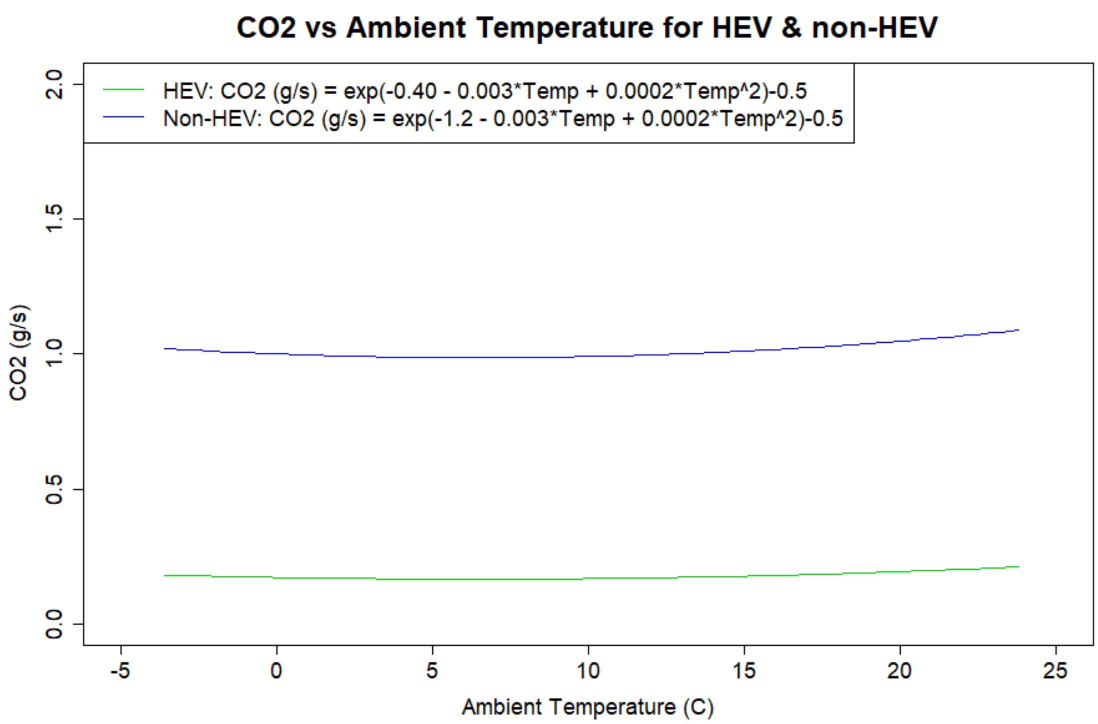


Figure 15. Effect of ambient temperature on CO_2 emission rate.

4.2.2. Comparisons Between HEVs and PHEVs

This section presents comparisons of fuel consumption rate and CO_2 emission rate between HEVs and PHEVs based on speed profiles, different road types and driving states.

Based on data from experiments, fuel consumption rate is approximately 7.8% lower in plug-in HEVs compared to conventional HEVs, with the mean FCR being 4.7 L/100km and 4.3 L/100km for HEV and PHEV, respectively.

However, the emissions rate is actually higher in PHEV than conventional HEV by approximately 9.26%. The mean CO_2 based on collected data from experiments is approximately 59.9 g/km and 65.4 g/km for HEV and PHEV, respectively. Table 15 and Table 16 detail summary statistic of FCR and CO_2, respectively, on HEV and PHEV, along with the histograms to show their data distribution. The data distribution for HEVs and PHEVs have very similar pattern, with similar standard deviation, maximum and ranges. The observations are quite skewed as there are many zero values in the observations, which is expected given the data points could be on electric engine mode for the hybrids.

Table 15. Descriptive statistics of FCR in L/100km for HEVs and PHEVs.

Vehicle Type	Number of Observations	**Mean**	**Standard Deviation**	Median	Min	Max	Q1	Q3	IQR	CI
HEV	3691	4.71	5.05	3.20	0	23.09	0.02	8.06	8.04	0.16
PHEV	4420	4.34	5.14	2.10	0	23.22	0.00	7.76	7.76	0.15

Distribution Fuel Consumption Rate in HEVs and PHEVs

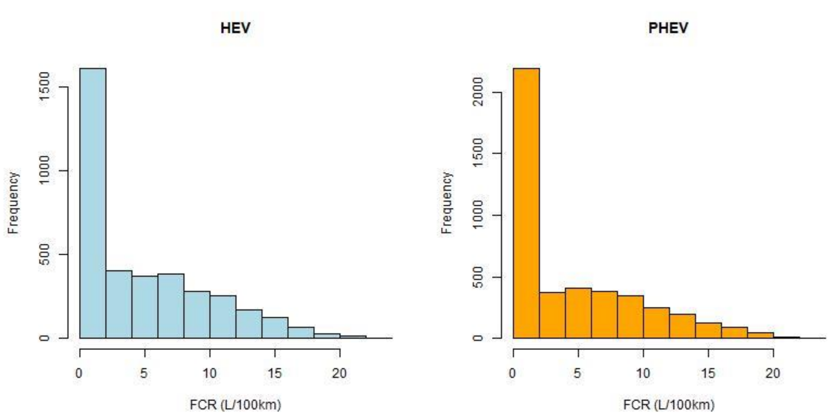


Table 16. Descriptive statistics of CO_2 emissions rate in g/km for HEVs and PHEVs.

Vehicle Type	Number of Observations	**Mean**	**Standard Deviation**	Median	Min	Max	Q1	Q3	IQR	CI
HEV	3691	59.85	84.62	11.26	0	422.50	0.13	96.55	96.42	2.73
PHEV	4420	65.40	88.38	11.87	0	406.08	0.00	117.91	117.91	2.61

Distribution of CO_2 Emission Rate in HEVs and PHEVs

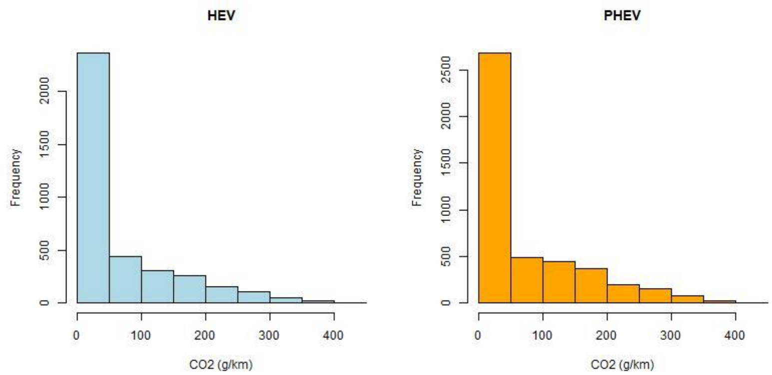


Table 17 is another summary statistics table to summarize HEV and PHEV with other tested variables (including average speed, acceleration, engine speed, proportion of highway driving, proportion of summer driving and average ambient temperature).

Table 17. Summary statistics of FCR and CO_2 emission rate (g/km) for HEVs and PHEVs and their tested variables.

Description	**Unit**	**Mean**		**SD**	
		HEV	PHEV	HEV	PHEV
Number of observations		3691	4420	-	-
Fuel consumption rate	L/100km	4.71	4.34	5.05	5.14
CO2 emission rate	g/km	59.85	65.4	84.62	88.38
Average speed for every 50m travelled	km/hr	37.39	47.44	18.43	23.83
Average acceleration for every 50 m travelled	m/s2	0.08	0.08	0.39	0.37
Average engine speed for every 50m travelled	Revolutions per minute	674.03	725.23	678.02	815.02
Proportion of Highway Driving		0.18	0.34	0.39	0.47
Proportion of Summer Driving		0.26	0.24	0.44	0.43
Average ambient temperature	ºC	7.09	8.28	8.44	6.98

Figure 16 shows the FCR and CO_2 with their corresponding speed profiles for HEVs and PHEVs. The patterns of the curve for FCR and CO_2 exhibit similar patterns for both types of vehicles and both are non-linear. For both HEVs and PHEVs, the rates start out lower at lower speed, then there is a gradual increase from low speed to around 35 km/hr to 60 km/hr, stabilizes and increases slightly at higher speeds.

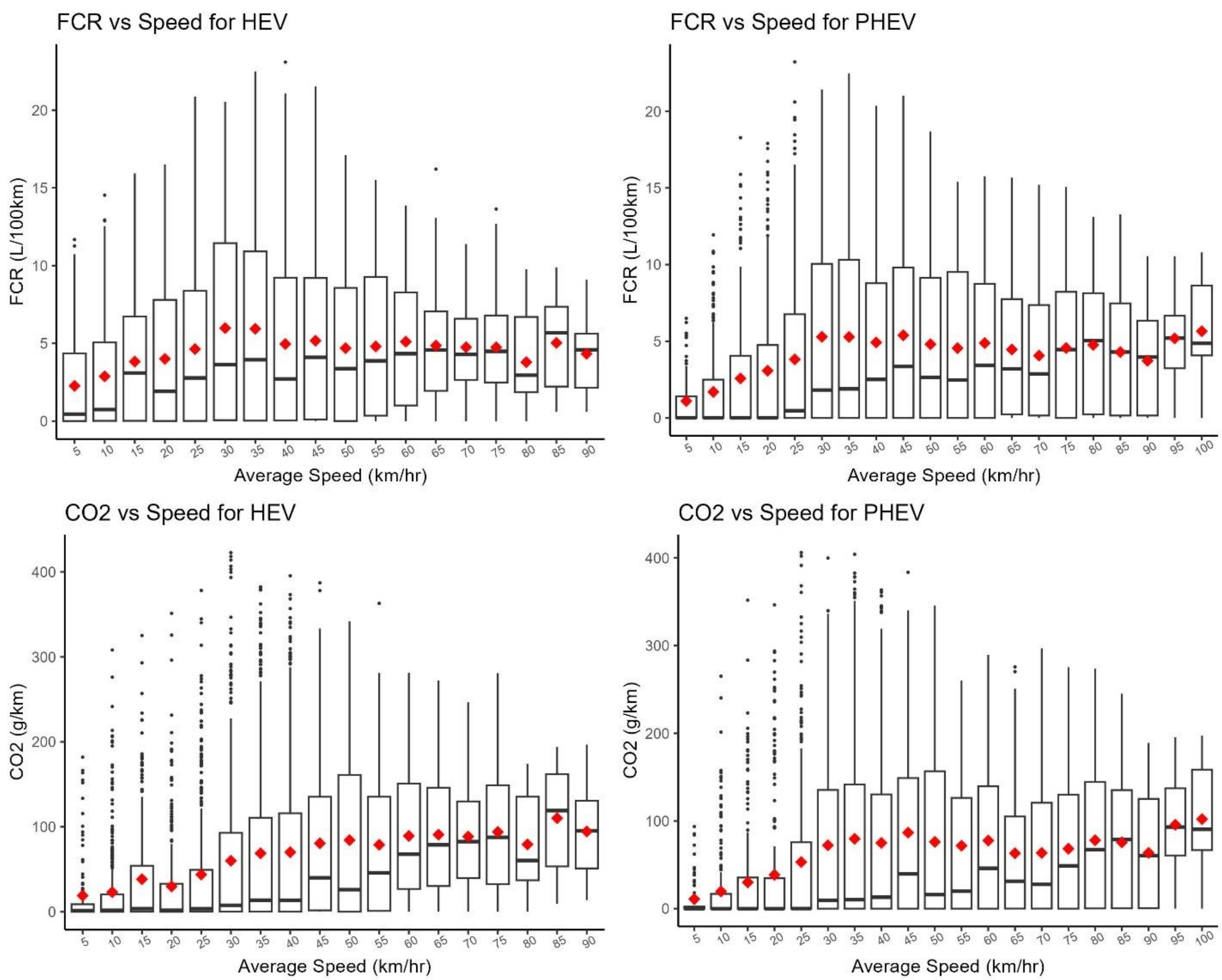


Figure 16. Average speed profiles with their corresponding FCR and CO_2 for HEVs and PHEVs.
Note: The plots also show the distribution of the variables at different speeds. The red dots are the mean values at each speed.

The boxplots of fuel consumption rate (Figure 17) and CO_2 emissions (Figure 18) show that the averages do not fluctuate much among the different road types. The spread of the data also seem quite consistent for both conventional HEV and PHEV. However, there seem to be long tails on the boxplots. The variabiltiy in HEV and PHEVs, as seen in previouss sections as well, are larger than regular gasoline vehicles. It is also observed that PHEVs actually have higher average emissions in certain road types (such as local roads) compared to conventional HEVs. Range of emissions from PHEVs are quite consistent across different road types whereas the emissions from highway are the highest on average for HEVs.

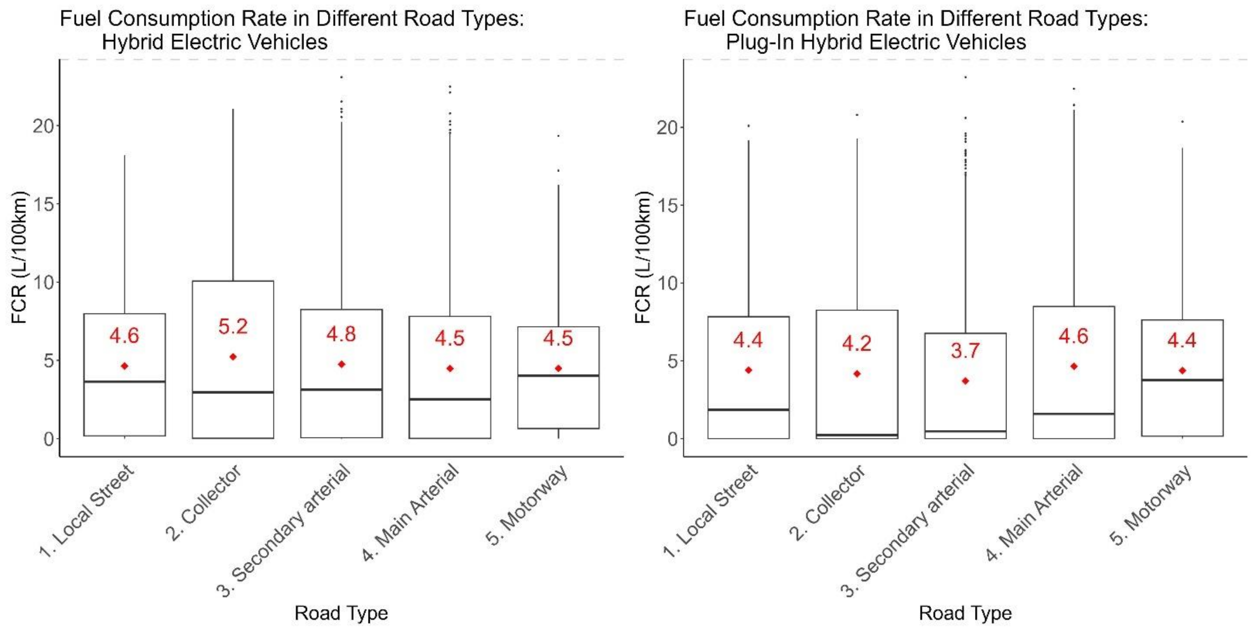


Figure 17. Boxplots of FCR for HEVs (left) and PHEVs (right), grouped by the different types of roads.

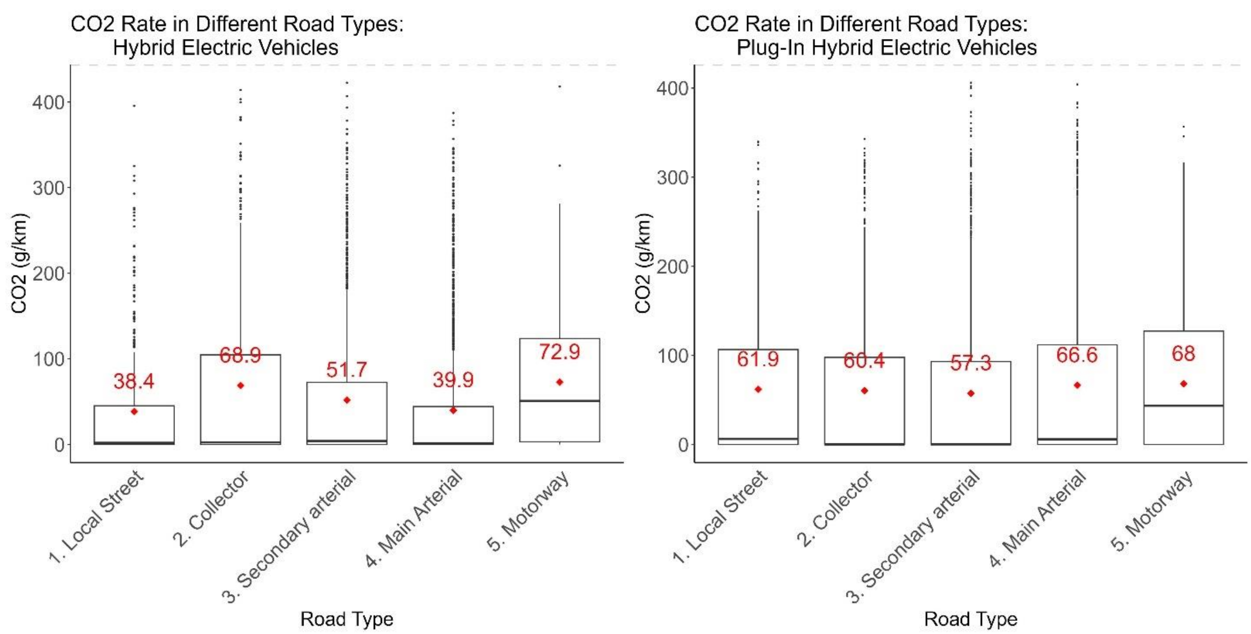


Figure 18. Boxplots of CO_2 for HEVs (left) and PHEVs (right), grouped by the different types of roads.

In the boxplots comparing the driving states (acceleration, cruising or deceleration), it is revealed that there is more fuel consumed during acceleration, following by cruising, then deceleration, with PHEV's FCR being less (Figure 19). FCR is only lower in the acceleration and deceleration phases, by 4.2% and 22.2%, respectively, for PHEVs than HEVs.

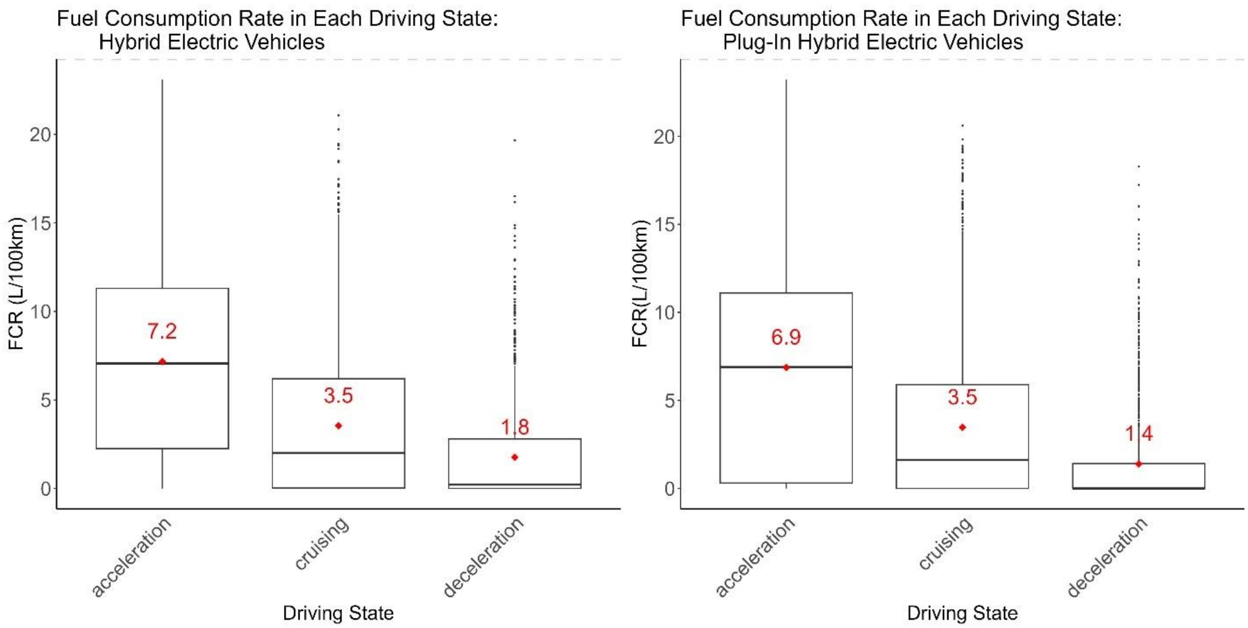


Figure 19. Boxplots of FCR for HEVs (left) and PHEVs (right), grouped by driving states.
Note: The driving states include: acceleration, cruising or deceleration.

In CO_2 emissions rate, it is as expected and following very similar trend to FCR where acceleration is the highest and deceleration is the lowest. However, for CO_2, it is revealed that the mean emissions for PHEVs are actually higher than HEVs during acceleration and acceleration phases. The CO_2 rate is only lower in the deceleration phase in PHEV by approximately 14.8% than HEVs.

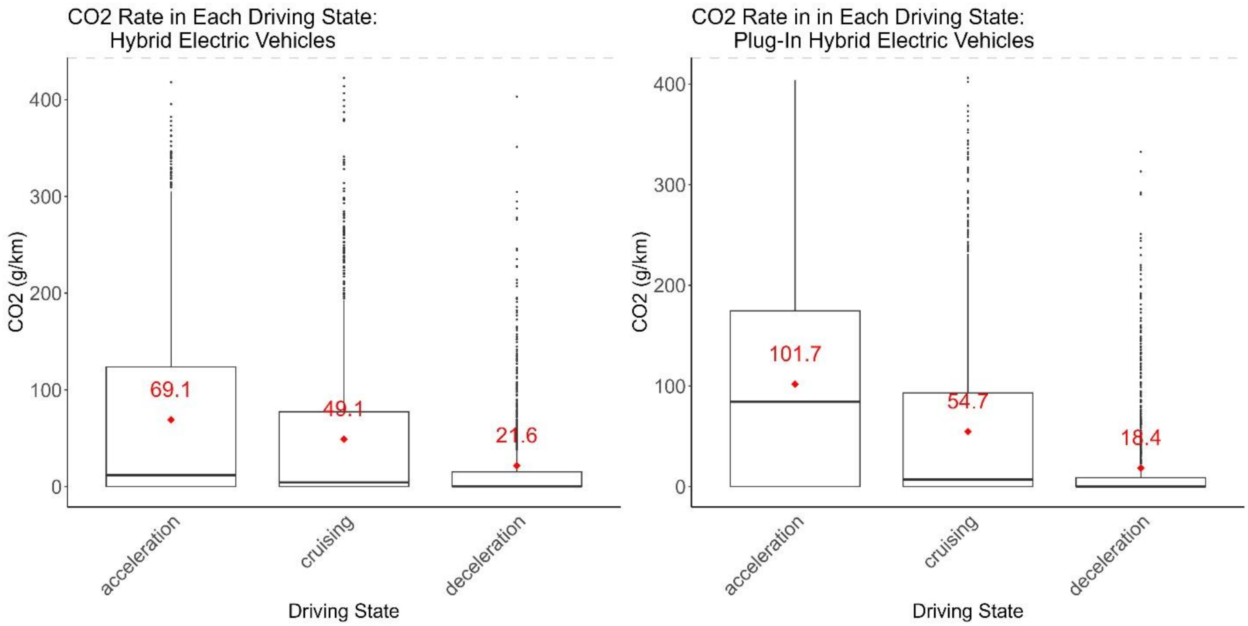


Figure 20. Boxplots of CO_2 emissions for HEVs (left) and PHEVs (right), grouped by driving states.
Note: The driving states include: acceleration, cruising or deceleration

4.2.3. Colder vs Warmer Ambient Temperature: Between Same Vehicles

There were two trips that were conducted in the colder month using the same two vehicles that were tested during the warmer months. The two vehicles are Ford C-Max Energi and Toyota Prius C. The fuel consumption rate and CO_2 emission rate are compared between the same vehicle for one trip conducted in warmer temperature and the other in colder temperature.

The experiments conducted in the colder month had the intention to only change the environmental condition (i.e. warmer versus colder ambient temperature) while keeping all other variables constant or as similar as possible: same vehicle, same driver, similar driving routes, conditions, etc.

Figure 21 shows the boxplots of FCR and CO_2 for each trip when ambient temperature is colder versus when it was warmer.

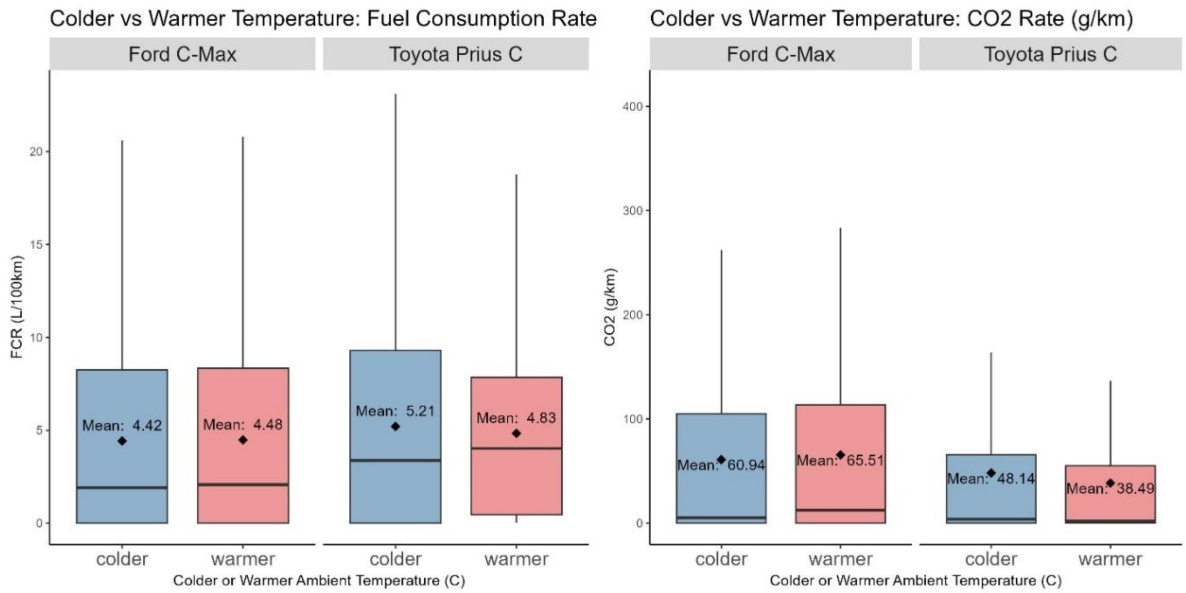


Figure 21. Boxplots of FCR in L/100km (left) and CO_2 in g/km (right) for Ford C-Max Energi (PHEV) and Toyota Prius C (conventional HEV) when ambient temperature was colder and when it was warmer.

The average ambient temperature for the colder months is -0.7 ºC and the average ambient temperature for the warmer months is 14.6 ºC for these tested vehicles. The hypothesis is that the fuel economy would be less efficient when ambient temperature is lower compared to higher temperature. However, there does not seem to be a huge difference based on the boxplots. One potential reason is that the ambient temperature difference is not huge enough to generate differences in vehicle performance. The summary statistics for the four trips is summarized in Table 18.

Table 18. Summary statistics of all four trips made by Ford C-Max Energi (PHEV) and Toyota Prius C (HEV) during a warmer ambient temperature versus colder.

	Ford C-Max Energi 2016 (PHEV)				**Toyota Prius C 2019 (HEV)**			
	Warmer		Colder		Warmer		Colder	
n	1564		1702		1465		1464	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
FCR (L/100km)	5.04	5.99	4.75	5.82	5.66	4.97	5.77	6.13
CO_2(g/km)	71.47	96.18	63.1	91.93	40.84	70.23	51.24	82.32
Speed (km/hr)	43.51	23.31	46.2	23.39	31.59	16.73	35.84	18.44
Acceleration (m/s^2)	0.07	0.38	0.08	0.36	0.11	0.37	0.11	0.4
Engine Speed (RPM)	703.15	826.8	729.7	833.84	804.91	736.28	640.79	704.63
Proportion of Highway Driving	0.32	0.47	0.33	0.47	0.14	0.35	0.14	0.34
Ambient Temp (C)	10	---	0.5	---	19.2	---	-1.9	---

Assessing the boxplots of FCR and CO_2 rate based on each driving state (acceleration, cruising and deceleration) (Figure 22), there are no noticeable huge differences between the ambient temperature variation. But, the pattern of fuel consumption and CO_2 emissions were as expected, where acceleration is the highest, following by cruising, then deceleration.

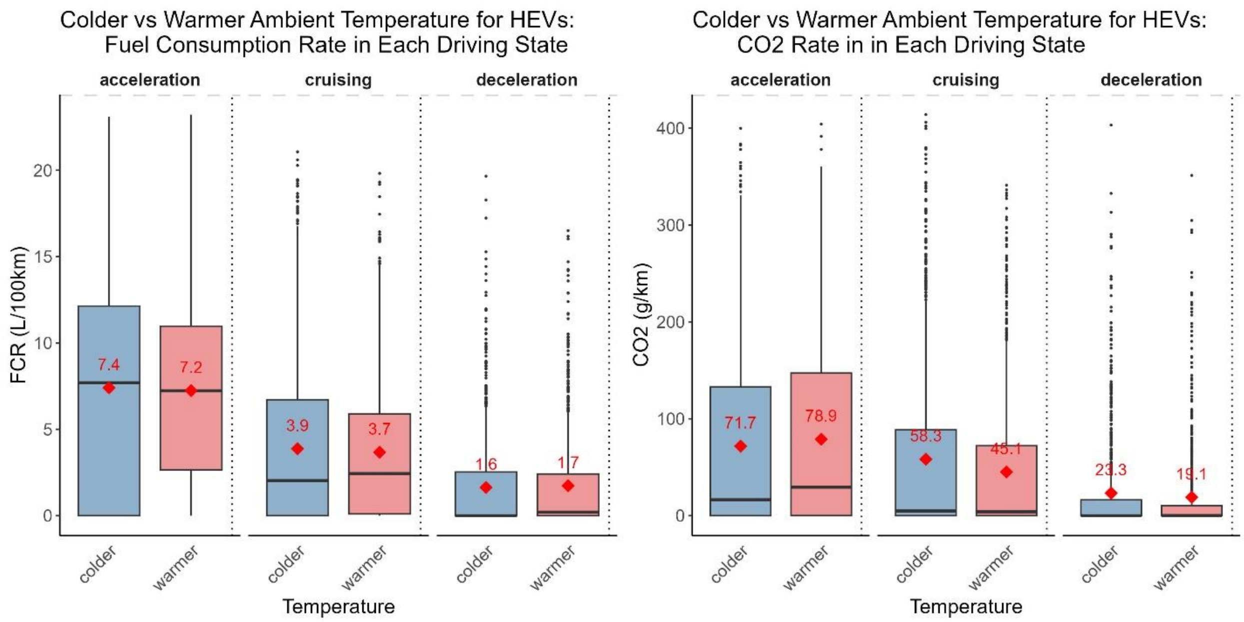


Figure 22. Boxplots of FCR (left) and CO_2 (right) for different ambient temperature variation under different driving states.
Note: FCR in L/100km (left) and CO2 in g/km (right) for different ambient temperature variations (colder versus warmer temperature) for the four trips (HEVs and PHEVs) in different driving states: acceleration, cruising or deceleration.

4.2.4. Regression Analysis: HEV vs PHEV

The predictor variables or the factors remain the same: vehicle type, speed, acceleration, slope and road type. Regression analysis was conducted where all of the potential predictors (without ambient temperature) were evaluated using the log-linear model. Then, ambient temperature is added to the analysis with the other predictors. The analysis is done using quadratic function.

4.2.4.1. Models Without Temperature

In evaluating to see how much reduction potentials PHEVs have, the analysis can provide insights into whether all hybrids are made equally and how well PHEVs perform in comparison to conventional HEVs. The log-linear models were once again conducted here for both fuel consumption rate and CO_2 emission rate with the predictors (without temperature) on HEVs and PHEVs, summarized in Table 19.

For the FCR model, the goodness of fit, R^2, is 0.31 in the FCR model and 0.37 in the CO_2 model. The relationships between each predictor with the dependent variables all follow similar trends to the previous section. The F-statistic of 8441 with a very small p-value (< 2.2e-16) indicates that the overall model is highly significant, suggesting that at least one of the independent variables has a significant relationship with the dependent variable.

Table 19. Log-linear models outcomes of fuel consumption rate and CO_2 emission rate for PHEVs and HEVs.

		FCR				**CO_2**			
Predictor		Coef.	Std. err	P-value	Elasticity (%)	Coef.	Std. err	P-value	Elasticity (%)
Vehicle Type	PHEV	-0.04	0.003	0	-3.943	-0.016	0.004	0	-1.569
	HEV	Base	---	---	---	---	---	---	---
Speed		0.009	0	0	18.409	0.013	0	0	26.156
Acceleration		0.292	0.003	0	0.223	0.264	0.005	0	0.201
Slope		1.81	0.035	0	0.119	2.567	0.052	0	0.169
Road Types	Urban	0.012	0.005	0.013	1.167	-0.027	0.007	0	-2.709
	Highway	Base	---	---	---	---	---	---	---
		R^2= 0.31 Log-likelihood= -56372.53				R^2= 0.37 Log-likelihood= -27883.48			

Note: Elasticities are at the mean values for continuous variables.

From this model, it revealed that by driving a PHEV, the FCR reduction could be 3.9% and emission reduction could be 1.6%, in comparison to a conventional HEV. In the collected data, PHEVs had higher emissions. However, in the models, after accounting for other factors, PHEVs, in fact, do show emission reductions.

From the marginal effects analysis, it is revealed that the fuel consumption increases by 46.9% for PHEVs and 50.9% for HEVs for every unit increase in vehicle speed, holding other variables constant. For CO_2 emission rate, it increases by 49.7% for PHEVs and increases by 51.3% for HEVs for every unit increase in speed. The elasticities for speed are the highest after the vehicle type, implying that speed is an important factor that influences FCR and emissions. With every 1% increase in speed, the FCR increases by approximately 18.4% and CO_2 emission increases by approximately 26.2%, at the mean of vehicle speed (19.9 km/hr), holding everything constant, in the base scenario. From the elasticities, the dependent variables in these models show that they are sensitive to changes in speed. The CO_2 emission rate is more sensitive to changes in speed than FCR.

At the mean of acceleration (average acceleration of -0.0076 m/s^2) in the base scenario, FCR increases by 0.22% and emission increases by 0.20% for every 1% increase in acceleration. Acceleration has relatively small elasticities in comparison, implying that the influence of acceleration on FCR and emission is small, but is correlated positively with the dependent variables. The elasticities for acceleration are extremely small because the elasticities are computed at the mean and acceleration has a small absolute mean value, consistent with all the other models.

For slope, FCR increases by 0.12% and emission increases by 0.17% for every 1% increase in acceleration, at the mean of slope in the base scenario (average road grade or slope of 0.066%). Slope also has relatively small elasticities in comparison but correlated positively with the dependent variables. The elasticities for acceleration are extremely small for the same reason as acceleration.

Similar to previous models, the effect of road type is opposite in the FCR model than the emission model. By driving in an urban setting or in local streets, the FCR is increased by approximately 1.2% and emission is reduced by approximately 2.7%, in the base scenario, for conventional HEV. For PHEVs driving in an urban setting, holding other variables constant, FCR and emission are reduced by 2.8% and 4.2%, respectively (in comparison to highways with reductions of 3.9% in FCR and 1.6% in emissions). The relatively small elasticities indicate that road class is not an extremely important variable in these specific models and that the dependent variables are not sensitive to changes in road class in these models.

The general trend with increasing speed is increase in FCR and emission. As mentioned previously, the relationship between speed and the dependent variables is non-linear. These models with polynomial terms were tested, but require further investigation. These models do not capture the nuances of when the gasoline engine starts to work in hybrid vehicles. Other models could be further explored to find an even better fit. Even though driving in an urban setting increases the FCR slightly, it is not a huge difference. And even in the emission model, the reduction in driving in an urban setting is not significant.

4.2.4.2. Models With Temperature

Then, models were generated with the same predictors, this time including the ambient temperature as one of the variables. These log-linear models include a quadratic term for ambient temperature (raising to the power of two), in addition to just ambient temperature.

The overall goodness of fit for the FCR model including ambient temperature and ambient temperature to the power of two has R^2 of 0.38, F-statistic of 6053 and a p-value of $< 2.2e-16$ which shows an overall good fit of the model. All of the variables are statistically significant with p-values of less than 0.05. Table 20 summarizes the model outcomes incorporating a quadratic function of ambient temperature.

Table 20. Log-linear model outcomes with quadratic term for FCR and CO_2 emission rate.

		FCR				CO_2			
Predictor		Coef.	Std. err	P-value	Elasticity (%)	Coef.	Std. err	P-value	Elasticity (%)
(Intercept)		-0.6334	0.01	0	---	-0.6435	0.01	0	---
Vehicle Type	PHEV	-0.0303	0	0	-2.982	-0.0296	0	0	-2.912
	HEV	Base	---	---	---	Base	---	---	---
Speed		0.0092	0	0	18.368	0.0131	0	0	26.042
Acceleration		0.2935	0	0	0.224	0.2659	0	0	0.203
Slope		1.8057	0.03	0	0.118	2.5603	0.05	0	0.169
Road Class	Urban	0.0131	0	0.01	1.322	-0.0232	0.01	0	-2.295
	Highway	Base	---	---	---	Base	---	---	---
Ambient Temperature		-0.0034	0	0	0.264	0.009	0	0	3.86
$(\text{Ambient Temperature})^2$		3.00E-04	0	0	---	-3.00E-04	0	0	---
		R^2= 0.38 Log-likelihood= -27831.91				R^2= 0.31 Log-likelihood= -56194.64			

Note: Elasticities are calculated at the mean values for continuous variables.

In these models, by driving a PHEV, it could reduce both the FCR and CO_2 emission rate by around 2.9%, in comparison to driving a HEV, controlling all other factors. From the sensitivity analysis, the vehicle type (whether the vehicle is PHEV and HEV) is not the variable that influences the dependent variables the most, unlike the models comparing HEV to non-HEV.

For speed, the marginal effects analysis revealed that for every unit increase in vehicle speed, holding other variables constant, the FCR increases by 47.9% for PHEVs and 50.9% for HEVs. For CO_2 emission rate, it increases by 48.4% for PHEVs and 51.3% for HEVs for every unit increase in speed. Speed has the highest elasticities in both models, implying that FCR and emission are the most sensitive to changes in speed, with elasticities of 18.4% and 26.0%, respectively. Speed is an important variable in determining the response variables in the HEVs ad PHEVs.

Acceleration and slope both exhibit similar results to all the other models. The dependent variables positively correlate with these two variables, but the effects are small. Further, the dependent variables are not very sensitive to changes due to changes in acceleration and slope.

Driving in an urban setting or local streets is expected to have higher reductions. This is the case for the CO_2 emission model, but not for the FCR model.

For ambient temperature, the marginal effects analysis revealed that for every one unit increase in ambient temperature, holding other variables constant, the FCR increases by 46.7% for PHEVs and 49.7% for HEVs. For CO_2 emission rate, it increases by 47.9% for PHEVs and 50.9% for HEVs for every unit increase in temperature. With every 1% increase in ambient temperature, the FCR increases by approximately 0.3 % and CO_2 emission increases by approximately 3.9%, at the mean (7.1 ºC), holding everything constant, in the base scenario. From the elasticities, the CO_2 emission rate is more sensitive to changes in temperature than FCR.

The ambient temperature in the FCR model seems to follow the U-shaped curve, whereas the emission model seems to have it the other way around in these models.

For FCR, the general trend with increasing temperature is a U-shaped curve. In this emission model, CO_2 is observed to be the opposite than FCR. Other models could be further explored to find an even better fit, or incorporating additional variables to improve performance. Even though driving in an urban setting increases the FCR slightly, it is not a huge difference. And even in the emission model, the reduction in driving in an urban setting is not significant.

5. DISCUSSION

5.1. Fuel Economy and GHG Emission for Vehicles from Different Sources

The vehicle performance for this study was evaluated based on the tested vehicles' fuel consumption rates or fuel economy and CO_2 emission rates. These are common metrics when comparing across different vehicle technologies.

The fuel economy and emissions information from the manufacturers or from the government where they have compiled these sources (Canada Energy Regulator, 2018; U.S. Department of Energy, 2023a) were also compared with the values obtained from this study. It was found that the fuel consumption rate and emission rate for conventional gasoline vehicles in this study are consistently higher than what the manufacturers reported. In other words, these conventional gasoline vehicles are less efficient than what the manufacturers claim. This aligns with one of key outcomes from past research where manufacturers often underestimate the FCR and emission rate (Bagheri et al., 2021; Wang et al., 2022). This also emphasizes the importance of collecting data from local real-world driving conditions as car manufacturers often overestimate the vehicle performance. However, for some HEVs and PHEVs, the FCR and emission rate are lower in this study than those reported by car manufacturers.

The experiments conducted in this study, especially for HEVs and PHEVs, have shown to have more noise and variations than conventional gasoline vehicles. There are several factors that influence the FCR and emission including driving behaviour and the local driving conditions. The tests were only conducted in Montréal; therefore, it is more specific to local conditions. It could also be due to the nature of data collection or noise from the equipment. The equipment performance could be affected by lower ambient temperatures, presence of water or snow on the road surface and condensation build-up in the sensors. This should be further investigated by checking the equipment used and by collecting more data.

5.2. Comparisons Between HEVs and Non-HEVs

From all of the statistical and regression analysis, the findings emphasize on the importance of controlling for factors influencing FCR and emissions outcomes such as vehicle characteristics (vehicle type), driving behaviour (vehicle speed and acceleration), road and environmental conditions (slope, road type and ambient temperature) when analyzing fuel consumption rate and CO_2 emissions. All the log-linear regression models provide valuable information on the effects of the factors mentioned above (whether it positively or negatively impacts the response variables based on the coefficients) and the magnitude of changes in response variables based on changes in the factors.

From the basic statistical analysis from the experiments, HEVs (including PHEVs) reduce FCR by approximately 33.5% to 43.3% and CO_2 emissions rate by approximately 60.9% to 66.3%. After controlling for other factors, the results from the regression models reveal that by driving a hybrid electric vehicle, FCR could decrease by approximately 25.5% and CO_2 emissions could decrease by approximately by 55.7%, compared to conventional gasoline vehicles. This aligns with past research on the fuel economy savings (when comparing conventional gasoline vehicles to HEVs) between 20-45% (Huang et al., 2019; Robinson & Holmén, 2020; Wang et al., 2022). For CO_2 reduction, past research has shown a reduction between 20-40% (Wang et al., 2022; Wu et al., 2015). The reduction ranges were taken from various studies. From this study, the reductions are slightly higher. This could potentially be attributed to the noise from the equipment and modelling approaches, which should be further investigated in future studies.

5.2.1. Vehicle Speed

Vehicle speed is one of the main predictors that have been studied quite extensively in the past. From this study, the model results showed that speed is positively associated with both the FCR and CO_2 emissions.

Vehicle speed has the highest elasticities after the vehicle type variable (HEV vs non-HEV). This implies that vehicle speed is one of the most important variables in the models in determining the outcomes of FCR and CO_2 emissions.

From the sensitivity analysis, (at the mean of vehicle speed, holding everything else constant), one percent increase in speed results in an increase of approximately 17.0% in FCR in the model with both HEV and non-HEVs. A one percent increase in speed would increase FCR by around 18.6% and 13.3% in the model with only HEV observations and only non-HEV observations, respectively. The emissions have slightly higher elasticities from the effect of speed. One percent increase in speed would increase CO_2 emission rate by 24.1%, 26.0% and 20.7% for the model with all vehicles, model with only HEV observations and model with only non-HEV observations. This also implies that performance of HEVs is more sensitive to changes in vehicle speed, given the higher elasticities.

From literature, the expected relationship between the response variables and vehicle speed is non-linear and should follow a U-shaped curve. The FCR or emission rate slowly decreases as the speed increases to a certain point, then the rates gradually increase as the speed continues to increase. For HEVs more specifically, the rates should peak somewhere in the 40 km/hr to 60 km/hr range where the electric motor stops and switches to the usage of normal gasoline engine and causes an increase in CO_2 (Fontaras et al., 2017; Zahabi et al., 2014).

When looking at the experimental data, the fuel consumption did have a slight peak around 30-45km/hr which aligns with the concept that HEVs start using their gasoline engine at speeds around the 40-60 km/hr range which results in more fuel consumption (Fontaras et al., 2008; Zahabi et al., 2014).

The regression models presented in this study did not show the polynomial relationship between speed and the response variables. In the vehicle specific power concept, speed is considered in association with acceleration, with slope and also raised to the power three. These models were also attempted, although not shown. When incorporating the polynomial terms, variable such as the road type becomes statistically insignificant (p-value of more than 0.05). And similar trend was observed of increasing speed increases the response variables. In the attempted model where the terms of speed to the power of two and speed to the power three were both included in addition to just speed, the coefficient for speed was positive, speed to the power of two was negative and speed to the power three was positive. This suggests a curve shape where the response variable increases first, then decreases to a certain point, then increases again. However, the coefficients are too small to observe a clear trend. The preliminary result from these polynomial models showed that the elasticities of speed are similar to the log-linear models presented in the results. Further modelling approaches and more advanced methodology could be explored in future studies.

Observing the relationships between the response variables (FCR and CO_2) and average vehicle speed in HEVs and non-HEVs from the collected data, the patterns are similar to what past literature remarked (see Figure 7 in Section 4). In HEVs, the FCR and emissions start out low at low speed, then as speed increases to around 35 km/hr to 60 km/hr, the rates peak, then they decrease back down, then increases again after 80 km/hr. In non-HEVs, the FCR and emissions start out high at low speed as the inertia initially powers the vehicle, then the rates gradually decrease. The tests did not have any observations of speeds greater than 87 km/hr for non-HEVs, otherwise, it is expected to see the rates rise back up at higher speeds.

5.2.2. Vehicle Acceleration

The magnitude of effect of acceleration differs depending on the model. However, across all the models, with increase in acceleration, both the fuel consumption rate and the CO_2 emission rate increase for all types of vehicles.

From the sensitivity analysis, (at the mean of acceleration, holding everything else constant), one percent increase in acceleration results in an increase of approximately 0.22% in FCR and around 0.20% to 0.36% in emission. The elasticities are relatively small for acceleration because the average acceleration is -0.011 m/s^2 for all the trips combined (-0.0076 m/s^2 for HEV-only trips and -0.014 m/s^2 for non-HEV-only trips). This implies that there is barely any acceleration on average during any trip. Though statistically significant, the effect of acceleration is small and the response variables (FCR and CO_2 emission rate) are not as sensitive to changes in acceleration.

It is intuitive that when there is acceleration, especially sudden acceleration, which is a proxy for aggressive driving, that would generate more consumption or emissions. This was also seen in a case study comparing driving behaviour in Toronto versus Beijing (Wang et al., 2022). More specifically, at lower speed, with higher acceleration (i.e. more aggressive driving), the FCR can increase between 5% to 14% and between 11% to 21% at higher speeds (Thomas et al., 2017). It is also assumed that the CO_2 increase would be approximately the same. In this study, the increase in FCR and emission are a lot smaller in comparison to past studies. This also may not be a fair comparison as there was not as much data on higher acceleration or aggressive driving.

5.2.3. Slope

Slope exhibited as a statistically significant variable (p-value of less than 0.05) in all of the models. From the coefficients in the model, the effect of slope is consistent that with increase in slope, both the FCR and emissions increase.

The sensitivity analysis for slope revealed that fuel economy and emissions from HEVs are more sensitive to changes in slope. From the sensitivity analysis, for every 1% increase in slope at the mean, FCR increases by approximately 0.036%, in the base case (non-HEV in highway). In the model with only HEV data, the FCR increases by around 0.12% for every 1% increase in slope and 0.001% in the model with only non-HEV observations. The elasticities for slope are extremely small across all models, indicating that response variables are not sensitive to changes in slope.

While the elasticities of slope for the CO_2 model are 0.054%, 0.17% and 0.002% for models with both HEV and non-HEV observations, model with only HEVs and model with only non-HEV observations, respectively. In comparing the sensitivities of the slope variable among the models, HEVs are more sensitive to changes in slope than non-HEVs, but the effects are still very small.

The average road grade or slope is 0.041% for all the trips combined (0.066% for HEV-only trips and 0.0066% for non-HEV-only trips). In the experimental design, the aim was dedicating around 10% of the trip driving uphill. Even then, on average, the routes taken in this study were mostly on flat ground. The diversity of observations with steeper slopes are lacking.

Because the elasticities are considered at the mean of the variable, they are extremely small for slope. Even though slope is a significant variable, the magnitude of effect is very small. This implies that slope may not be an important variable in determining the FCR and emissions in these models specifically.

In one of the previous studies, it was revealed that in a steep road (slope of 8%), the fuel consumption could increase by up to three times in comparison to a flat road (Zhang et al., 2020). And as expected, the fuel consumption decreases with decreasing slope. In this study, because there were not many data points on steep roads, this trend was not observed.

5.2.4. Road Type

Road type or the link type is another predictor that has appeared in past research for studying the potential impacts on the response variables.

In past research, it was shown that HEVs are approximately 35% lower in FCR than conventional in urban setting or driving in local roads. Whereas in rural areas or on highways, the HEVs actually have a higher FCR because of heavier vehicle mass (Wang et al., 2020). HEVs from another study even showed upwards of 40-60% reduction in fuel economy by driving in urban condition (Fontaras et al., 2008). This was one of supporting argument for encouraging more HEV driving in metropolitan cities such as Montréal.

From the statistical analysis of this study, the general trend aligns with literature where the emission for HEV is lower in local streets than on highways. For non-HEVs, the opposite is true where emission is higher in local streets than on highways. This supports the argument where HEVs may benefit more in an urban setting (i.e. shorter trips) than on highway setting (Zahabi et al., 2014).

However, from the regression models in this study, after controlling for other factors, driving in an urban setting showed mixed results. From the sensitivity analysis, the elasticities also vary quite a bit among the models. Generally, the elasticities for road class are relatively small, implying that road class does not have a huge influence on determining both FCR and CO_2 emissions, The CO_2 model aligns with theory where by driving in an urban setting, the emission could be reduced by 0.07% for non-HEVs and 55.8% for HEVs where the effect is mostly from the vehicle type. In the model with only HEV data, the emission could also be reduced by around 2.3%. However, for fuel consumption, it revealed a positive correlation with driving in urban setting, where FCR could actually be increased by 2.6% (model with both types of vehicles), 1.6% for HEVs and 9.1% for non-HEVs.

Conventional gasoline vehicles appear to result in higher FCR and emission in driving in local streets than HEVs. This could imply that non-HEVs perform better on highways than local streets. The effect of road class, overall, is still relatively small.

This is an unexpected result as the effect of road class is not consistent across all regression models. It could be due to similar reasons as speed where other predictors in the model may have influenced the output. In addition, there could be road segments that are characterized or labeled as highway but due to congestion, the road type becomes more like a local street. Another attempt could be to use a different modelling approach or to use a different aggregation method for the dataset used (i.e. aggregated by every 50 meters travelled).

5.2.5. Vehicle Class

Vehicle class was not included as one of the variables as it showed a strong correlation with other independent variables. However, it is an important factor to consider when selecting the vehicles to be included in studies as such.

One of the aims as part of the experimental design was to include a variety of vehicle fleets, including vehicles with different classes (a mix of hatchbacks, sedans, and SUVs). However, ideally, the number of different vehicles included in the study should be higher. The results may be slightly biased as there is only one hybrid SUV and one gasoline SUV included in the study, which may not be as representative of the vehicle class as a whole.

However, this factor is also important to note and consider as vehicle class is a predictor that encompass the main vehicle characteristics. It determines the vehicle mass and capacity that would affect the vehicle performance. Not surprisingly, in one of the studies, it was shown that hatchbacks and sedans have a significantly lower fuel consumption rate compared to SUV hybrid vehicles by 40% and 35%, respectively (Zahabi et al., 2014). It is expected as hatchbacks and sedans are typically lighter in weight, more compact and smaller than SUVs. As for differences with plug-in HEVs, the fuel consumption is more dependent on the distance driven and battery charging frequency, but the fuel economy would be around the same to a HEV similar in size (Prati et al., 2021). It is assumed that the emissions would follow similar trends to that of the fuel consumption.

5.2.6. Other Effects

There are some factors that were not included as one of the variables in the analysis, but still important to note their potential effects on the dependent variables.

Engine speed is considered to be an important engine parameter. For this study, engine speed was removed as one of the factors as it has high correlation with speed. The range of engine speed for HEV is between 0 and 3,160 revolutions per minute (RPM). For non-HEVs, the range is between 628 to 2444 RPM. Average daily traffic is a driving environment parameter. The variable is an estimate. Therefore, it may not be an extremely accurate representation of traffic volume or potential proxy for level of congestion. Average daily traffic was not included in the analysis as it has high correlation with several other factors.

Vehicle specific power is another important concept that should be further explored as a response variable. VSP is a variable that represents the instantaneous vehicle engine power to show the impact of vehicle operating conditions on fuel consumption and emissions (Yao et al., 2013). Past research has shown the importance of considering VSP in estimating both fuel consumption and emissions (Yao et al., 2013; Zhai et al., 2011). There was not sufficient and complete data to compute VSP for this study. However, the components in the VSP were analyzed in this study: speed, slope and acceleration, in addition to the concept of VSP (i.e. polynomial terms).

5.3. Comparisons Between HEVs and PHEVs

This study also had some analysis more focused in on just the conventional HEVs and PHEVs. As these types of vehicles become more common and widely acceptable, it would be interesting to determine if all hybrid vehicles are made equally and what variables are important in determining the fuel economy and emissions and if they have the same effect.

As expected, PHEVs do perform better in terms of fuel consumption rate and CO_2 emission rate, according to the log-linear models, without taking into account of the ambient temperature. However, it is also known that the performance of hybrids, especially PHEVs, highly depend on other factors such as mileage, usage, electric-range, availability of charging stations and charging behaviour (Plötz et al., 2020; Plötz et al., 2021).

In this study, by driving a PHEV, the fuel consumption could be reduced by 3.9% and emission could be reduced by 1.6%, after controlling for the other factors. Speed remains one of the important factors that influence the outcomes of FCR and emissions. There could be additional emission reduction by driving a PHEV in an urban setting. Similar to the other models, the other factors, acceleration and slope, have relatively small effects on determining the FCR and emission rate.

5.4. Effects of Ambient Temperature on Non-HEVs, HEVs and PHEVs

Ambient temperature has been shown in past research to be an important factor in estimating fuel consumption and emissions. In theory, as temperature increases, energy consumption decreases due to heating demand until the base temperature (where the energy consumption is at a minimum), then energy consumption increases as temperature continues to increase due to cooling demand, illustrated in a study by Henning et al. (Henning et al., 2019).

And in other studies, the curve resembles an exponential decay curve where the CO_2 emissions and FCR gradually decrease as temperature increases (Andrews et al., 2004; Chainikov et al., 2016).

In this study, ambient temperature was evaluated in quadratic models for comparing across different types of vehicles (HEVs with non-HEVs and HEVs with PHEVs). Some of the key findings are as follows:

- The range of ambient temperature when the vehicles were tested ranged between -3.6ºC and 23.8ºC.
- From the first part of analysis, log-linear models are used to compare conventional gasoline vehicles with HEVs, it is found that ambient temperature was statistically insignificant in those models.
- In another approach, quadratic formula is used to raise ambient temperature to the power of two.

- Ambient temperature becomes a significant variable in all the models with the quadratic function.
- The curves estimated from the models do resemble and align with literature where it is a slight U-shaped curve.
- The relationship shows that the response variables (FCR and emissions) are slightly higher when the ambient temperature is on the lower end and on the higher end, where it may require heating and cooling demands, respectively. Both demands would result in increase in rates.
- Comparing between conventional HEVs and PHEVs, the FCR model follows the expected patter of a U-shaped curve.
- According to the average marginal effects, FCR and CO_2 are both reduced by approximately 3% by driving a PHEV compared to driving a conventional HEV, with every unit increase in ambient temperature.
- However, another consideration and limitation for this study is that the coldest ambient temperature was only -3.6ºC. No data were collected in the actual winter in Montréal and the lowest ambient temperature in this study is not representative of a cold winter driving condition.

5.5. Overall Limitations, Uncertainties and Assumptions

Even though experiments through real-world driving have its benefits of accounting for external factors such as different driving behaviour, environmental conditions and road conditions, it also has many challenges. The equipment and the sensors for collecting data are susceptible of noise or human errors that were not accounted for, resulting in variations and potentially slight inaccuracies in measurements. The PEMS unit, in particular, appeared to have some sensitivities during data collection, as it was measured on 1Hz. There could potentially be slight lag at times and huge jumps in fluctuations.

The methodology could also be improved to potentially yield better results. The number of unique vehicles that were included in this study was only eleven due to time constraints and vehicle availability. More vehicles should be tested and included in similar studies in the future. In this study, the gasoline vehicles were tested under a different time period than the HEVs. In order to have a more comparable analysis between HEVs and gasoline vehicles, the method of convoy-style driving should be employed (Huang et al., 2019). Convoy mode would require two separate PEMS unit installed on two vehicles (HEV and its conventional gasoline counterpart) that would be driving simultaneously side-by-side. Under this methodology, multiple uncontrollable effects could be eliminated for performance comparisons for real-world driving tests. The effects include vehicle configurations, driving behaviour, road condition (level of congestion) and driving environment (ambient temperature, humidity, pressure). The routes taken can be exactly the same for the convoy vehicles. Even if this cannot be achieved, route planning should be planned out in detail instead of just planning for approximate proportions to be spent in each road type. Driving in other cities with more diverse road conditions should also be considered and explored. In this real-world driving study, there was a lack of diversity and variation on the acceleration and deceleration modes and terrain (the city is mostly flat). In addition, the highways can become congested at times. Therefore, a road segment could be labeled as a highway, yet it behaves like a local street with slow speed and congestion.

For data analysis, there are several ways to process and aggregate the data. The main approach chosen for this study was using second-by-second and also tested using dataset that aggregates data for every 50 meters travelled. However, other aggregation methods could be explored. In addition, other more modelling approaches or more advanced machine learning could be explored and determine if the results perform better. Because having an accurate prediction model was not part of objectives of this study, other more advanced modelling and machine learning models were not considered.

Another limitation is access to the vehicle fleet. In this study, vehicles were rented from car sharing platforms, which means it is challenging to obtain the exact same vehicle if experiments need to be repeated on the same one.

Future considerations in the study could include the state of the vehicle such as state of charge, age, mileage and how they have been maintained. This could potentially have an impact on the vehicle performance if these factors differ even though it is exactly the same make and model of the vehicle.

Cold-start was not considered in this study to keep it consistent as the method that was followed for the gasoline vehicles that were collected in the past. However, many past research have shown that cold-start is an important variable in determining the response variables (Alvarez & Weilenmann, 2012; Zahabi et al., 2014).

In order to gain an even better insight on the effect of ambient temperature on GHG emissions and fuel consumption in cities with extreme cold winters like Montréal and many other Canadian cities, real-world driving experiments should be conducted in actual winter time when the ambient temperature is below -15ºC, for example. There are practical challenges associated with this because if the snow on the ground gets into the tailpipe, the PEMS measurements would not be accurate at all. However, if this barrier could be mitigated and overcame, experiments should be conducted.

5.6. Contributions and Policy Implications

Real-world driving experiments have been shown to have a better representation of the true vehicle performance, especially for macro-mobility, city-specific planning as it takes into account of the driving conditions. This study collected real-world driving data in a metropolitan city in Montréal. This helps build a catalogue of vehicle data on both vehicle information, engine parameters and emissions. The data could be used for further modelling, simulations and for informing decision making and helping with policy and guideline developments at both the micro and macro levels.

With models like the ones developed in this study, as also seen from past research before, can be transferred and applied into micro- or macroscopic models such as urban planning and planning for intelligent transportation systems (Ahn et al., 2002).

Another potential application could be to inform on carbon tax or any future guidelines on incentives and rebates when it comes to the purchase of HEVs or PHEVs. From the results, it is observed that there are reductions by using HEVs and PHEVs. On the provincial or city level, the usage of HEVs and PHEVs can be encouraged, after other modes of transportation have been considered (such as public transportation or active mobility like walking and biking). It could also benefit programs to encourage or incentivize the purchase or use of HEVs or PHEVs such as car sharing or ride sharing platforms, food deliveries, last-mile deliveries or taxi services. Especially for existing car sharing platforms, converting current conventional gasoline fleets to HEVs and PHEVs could result in reductions and savings.

6. FINAL CONCLUSION AND SUMMARY

This research introduced a methodology to evaluate the performance of hybrid electric vehicles with respect to conventional gasoline vehicles using real-world driving measurements. It also contributed by generating a real-world driving dataset which can also be used for further investigations.

6.1. Main Results and Final Remarks

From the real-world driving experiments conducted in Montréal on gasoline vehicles, hybrid electric vehicles and plug-in hybrid electric vehicles, HEVs have better performance than non-HEVs. The fleets included in the study encompass different vehicle class: sedans, hatchbacks and SUVs. From the basic statistical analysis from the experiments, HEVs reduce FCR by approximately 33.5% to 43.3% and CO_2 emissions rate by approximately 60.9% to 66.3%. After controlling for other factors, the results from the models reveal that by driving a hybrid electric vehicle, FCR could decrease by approximately 25.5% and CO_2 emissions could decrease by approximately by 55.7%, compared to conventional gasoline vehicles. Moreover, the variables that resulted statistically significant (associated to FCR and emissions) in the regression analysis are the vehicle type (whether it is HEV or non-HEV), speed, acceleration, slope, road type (whether it is urban driving or highway driving) and ambient temperature, from the variables that were attainable and feasible in this study. From the sensitivity analysis, it was revealed that speed is one of the most important factors in influencing FCR and emissions (after vehicle type).

In a second analysis to compare conventional HEVs and PHEVs, it was found that PHEVs can reduce FCR by approximately 7.5% and 7.8%, in comparison to conventional HEVs, using the statistical analysis from the experiments. For CO_2 emissions using the statistical analysis, PHEVs are higher by approximately 6.2% and 9.2%.

Using the log-linear regression models, after controlling for other factors, it was found that FCR decreases by approximately 3.9 % and CO_2 emission rate decreases by approximately by 1.6 % from driving a PHEV compared with a conventional HEV. These differences are relatively small between HEVs and PHEVs, though the factor of vehicle type is statistically significant in the model with p-value of less than 0.05.

The effect of ambient temperature also plays a role in determining the fuel consumption and GHG emissions, even though the models in this study do not show a large effect. By including ambient temperature in the model, having a quadratic effect on temperature, the reduction from driving a HEV comparing to a non-HEV is approximately 24.5% for FCR and 55.2% for emissions. The reduction from driving a HEV depends on the specific value of temperature and the coefficients for temperature and temperature raised to the power of two.

For every unit increase in ambient temperature, FCR could increase by 25.1% and 49.4% for HEVs and non-HEVs, respectively. And the CO_2 emission rate could decrease by 5.3% for HEVs and increase by 49.7% for non-HEVs. Comparing PHEVs with HEVs, FCR and emission rate are both reduced by approximately 3% in the models that consider ambient temperature as a quadratic term, in the base scenario. The effect of temperature is small, according to the models, for all vehicles, as seen from the relatively small coefficients for temperature (in the range of 10^{-3} to 10^{-4}).

Overall, these findings provide valuable insights into the factors influencing CO_2 emissions and FCR in HEVs and non-HEVs. The key factors include speed, acceleration, slope, road type and ambient temperature. As expected, this research found that there is a significant reduction of FCR and emissions in HEVs compared to conventional gasoline vehicles for all vehicle class (sedans, hatchbacks and SUVs). However, a huge variability is observed among the HEVs and PHEVs, especially for emissions. The benefits of HEV technologies are affected by different factors such as road class, slopes and ambient temperature. The results emphasized the importance of considering vehicle characteristics, driving behavior, environmental conditions, ambient temperature, and their interactions when analyzing vehicle performance.

These findings provide insights as to how the HEVs and PHEVs perform in comparison to conventional gasoline vehicles. These data from the real-world driving tests could be further investigated. Then, it could further be used to inform decision making and develop strategies and plans related to greenhouse gas emission reductions and transitioning to electrification of the transport sector. Some of the results from this study and future studies building on this and other existing ones could help with policy and guideline developments, ranging from urban planning, conversion of fleets to vehicle incentives and rebates and carbon tax. Overall, the results provide valuable insights for policymakers and stakeholders in developing strategies to mitigate the environmental impacts of vehicles and promote sustainable transportation practices.

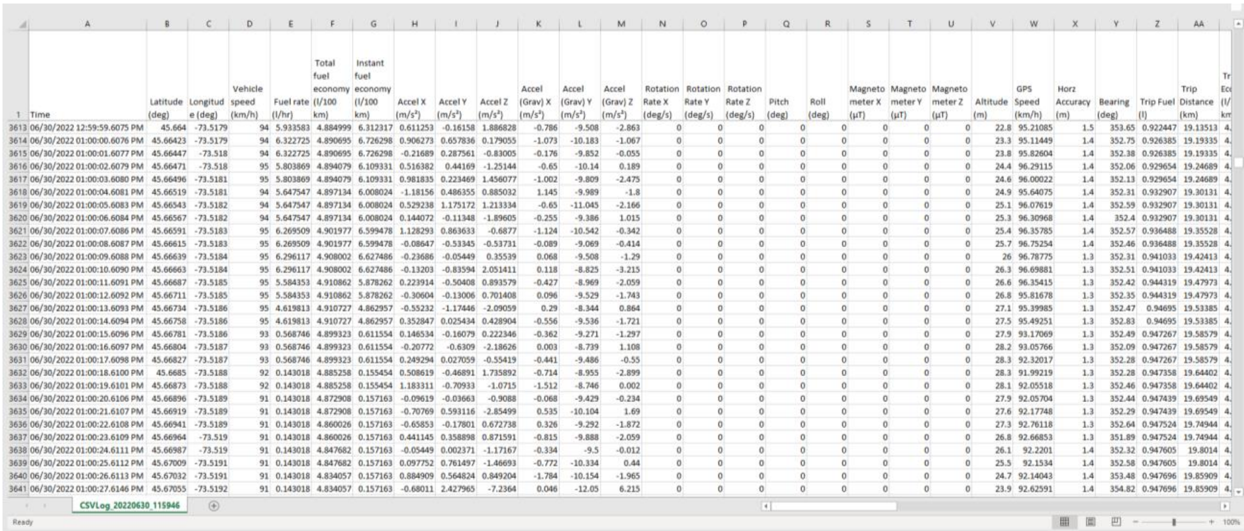
6.2. Future Studies

As addressed previously, the methodology for real-world driving could be improved. There were several challenges and limitations encountered during the data collection process. The sensors used posed some uncertainty as to its accuracy in its readings and the potential errors obtained during the experiments.

One of the improvements could start from experimental designs. Some examples include to systematically select the testing routes, obtain a variety of drivers and vehicles and conduct a convoy-style (driving both a HEV and non-HEV side by side at the same time). The convoy style methodology was unfortunately not feasible during this study. There are several other factors that could be considered in order to see how significant they are in determining vehicles' performance. Some of these include state of charge (or initial state of charge) of the hybrids, cold-starts and state of vehicles (age and mileage of the vehicles could be proxies for their conditions). In addition, more data should be collected in different seasons, especially on extreme cold days. Another unresolved challenge for this research is the inability to collect data when there is heavy precipitation, especially when there is snow on the ground. It would be more representative to collect data in winter where the temperature is consistently below -10ºC to -15ºC.

Another area of improvement is to continue to validate the measurements to identify the huge variations in data, especially the observations from HEVs. This could be done by determining a proper data aggregation method (by time or distance) and also the use of more advanced analytical modelling, techniques or machine learning for measuring performance, instead of just regression models.

APPENDIX

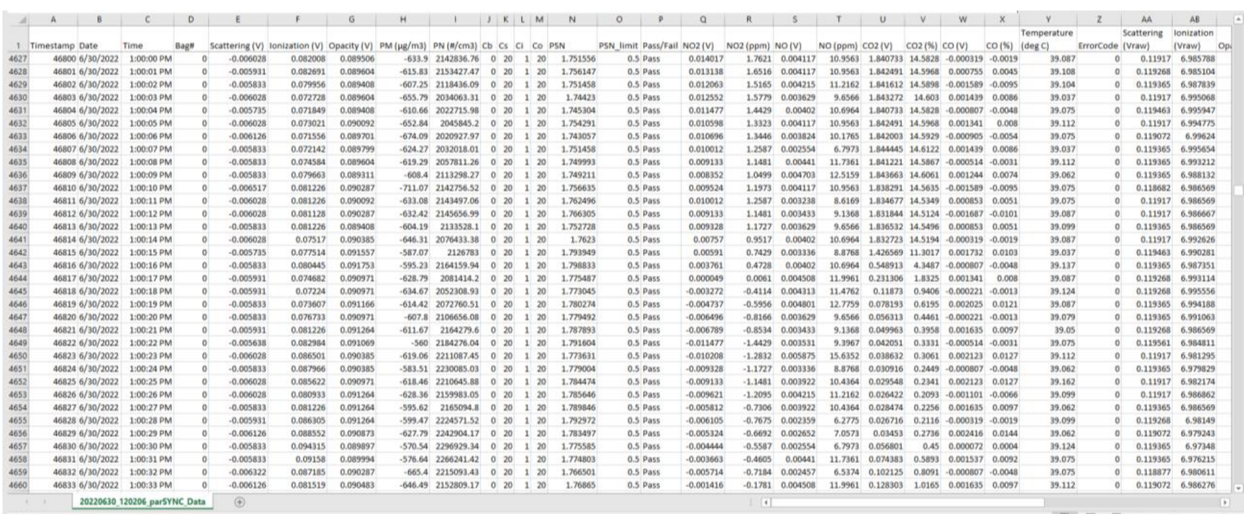


	Time	Latitude (deg)	Longitude (deg)	Vehicle speed (km/h)	Fuel rate (l/hr)	Total fuel economy (l/100 km)	Instant fuel economy (l/100 km)	Accel X (m/s²)	Accel Y (m/s²)	Accel Z (m/s²)	Accel (Grav) X (m/s²)	Accel (Grav) Y (m/s²)	Accel (Grav) Z (m/s²)
3613	06/30/2022 12:59:59.6075 PM	45.664	-73.5179	94	5.933583	4.884999	6.312317	0.611253	-0.16158	1.886828	-0.786	-9.508	-2.863
3614	06/30/2022 01:00:00.6076 PM	45.66423	-73.5179	94	6.322725	4.890695	6.726298	0.906273	0.657836	0.179055	-1.073	-10.183	-1.067
3615	06/30/2022 01:00:01.6077 PM	45.66447	-73.518	94	6.322725	4.890695	6.726298	-0.21689	0.287561	-0.83005	-0.176	-9.852	-0.055
3616	06/30/2022 01:00:02.6079 PM	45.66471	-73.518	95	5.803869	4.894079	6.109331	0.516382	0.44169	-1.25144	-0.65	-10.14	0.189
3617	06/30/2022 01:00:03.6080 PM	45.66496	-73.5181	95	5.803869	4.894079	6.109331	0.981835	0.223469	1.456077	-1.002	-9.809	-2.475
3618	06/30/2022 01:00:04.6081 PM	45.66519	-73.5181	94	5.647547	4.897134	6.008024	-1.18156	0.486355	0.885032	1.145	-9.989	-1.8
3619	06/30/2022 01:00:05.6083 PM	45.66543	-73.5182	94	5.647547	4.897134	6.008024	0.529238	1.175172	1.213334	-0.65	-11.045	-2.166
3620	06/30/2022 01:00:06.6084 PM	45.66567	-73.5182	94	5.647547	4.897134	6.008024	0.144072	-0.11348	-1.89605	-0.255	-9.386	1.015
3621	06/30/2022 01:00:07.6086 PM	45.66591	-73.5183	95	6.269509	4.901977	6.599478	1.128293	0.863633	-0.6877	-1.124	-10.542	-0.342
3622	06/30/2022 01:00:08.6087 PM	45.66615	-73.5183	95	6.269509	4.901977	6.599478	-0.08647	-0.53345	-0.53731	-0.089	-9.069	-0.414
3623	06/30/2022 01:00:09.6088 PM	45.66639	-73.5184	95	6.296117	4.908002	6.627486	-0.23686	-0.05449	0.35539	0.068	-9.508	-1.29
3624	06/30/2022 01:00:10.6090 PM	45.66663	-73.5184	95	6.296117	4.908002	6.627486	-0.13203	-0.83594	2.051411	0.118	-8.825	-3.215
3625	06/30/2022 01:00:11.6091 PM	45.66687	-73.5185	95	5.584353	4.910862	5.878262	0.223914	-0.50408	0.893579	-0.427	-8.969	-2.059
3626	06/30/2022 01:00:12.6092 PM	45.66711	-73.5185	95	5.584353	4.910862	5.878262	-0.30604	-0.13006	0.701408	0.096	-9.529	-1.743
3627	06/30/2022 01:00:13.6093 PM	45.66734	-73.5186	95	4.619813	4.910727	4.862957	-0.55232	-1.17446	-2.09059	0.29	-8.344	0.864
3628	06/30/2022 01:00:14.6094 PM	45.66758	-73.5186	95	4.619813	4.910727	4.862957	0.352847	0.025434	0.428904	-0.556	-9.536	-1.721
3629	06/30/2022 01:00:15.6096 PM	45.66781	-73.5186	93	0.568746	4.899323	0.611554	0.146534	-0.16079	0.222346	-0.362	-9.271	-1.297
3630	06/30/2022 01:00:16.6097 PM	45.66804	-73.5187	93	0.568746	4.899323	0.611554	-0.20772	-0.6309	-2.18626	0.003	-8.739	1.108
3631	06/30/2022 01:00:17.6098 PM	45.66827	-73.5187	93	0.568746	4.899323	0.611554	0.249294	0.027059	-0.55419	-0.441	-9.486	-0.55
3632	06/30/2022 01:00:18.6100 PM	45.6685	-73.5188	92	0.143018	4.885258	0.155454	0.508619	-0.46891	1.735892	-0.714	-8.955	-2.899
3633	06/30/2022 01:00:19.6101 PM	45.66873	-73.5188	92	0.143018	4.885258	0.155454	1.183311	-0.70933	-1.0715	-1.512	-8.746	0.002
3634	06/30/2022 01:00:20.6106 PM	45.66896	-73.5189	91	0.143018	4.872908	0.157163	-0.09619	-0.03663	-0.9088	-0.068	-9.429	-0.234
3635	06/30/2022 01:00:21.6107 PM	45.66919	-73.5189	91	0.143018	4.872908	0.157163	-0.70769	0.593116	-2.85499	0.535	-10.104	1.69
3636	06/30/2022 01:00:22.6108 PM	45.66941	-73.5189	91	0.143018	4.860026	0.157163	-0.65853	-0.17801	0.672738	0.326	-9.292	-1.872
3637	06/30/2022 01:00:23.6109 PM	45.66964	-73.519	91	0.143018	4.860026	0.157163	0.441145	0.358898	0.871591	-0.815	-9.888	-2.059
3638	06/30/2022 01:00:24.6111 PM	45.66987	-73.519	91	0.143018	4.847682	0.157163	-0.05449	0.002371	-1.17167	-0.334	-9.5	-0.012
3639	06/30/2022 01:00:25.6112 PM	45.67009	-73.5191	91	0.143018	4.847682	0.157163	0.097752	0.761497	-1.46693	-0.772	-10.334	0.44
3640	06/30/2022 01:00:26.6113 PM	45.67032	-73.5191	91	0.143018	4.834057	0.157163	0.884909	0.564824	0.849204	-1.784	-10.154	-1.965
3641	06/30/2022 01:00:27.6146 PM	45.67055	-73.5192	91	0.143018	4.834057	0.157163	-0.68011	2.427965	-7.2364	0.046	-12.05	6.215

	Rotation Rate X (deg/s)	Rotation Rate Y (deg/s)	Rotation Rate Z (deg/s)	Pitch (deg)	Roll (deg)	Magnetometer X (µT)	Magnetometer Y (µT)	Magnetometer Z (µT)	Altitude (m)	GPS Speed (km/h)	Horz Accuracy (m)	Bearing (deg)	Trip Fuel (l)	Trip Distance (km)	Tr Ec (l/ km
3613	0	0	0	0	0	0	0	0	22.8	95.21085	1.5	353.65	0.922447	19.13513	4.
3614	0	0	0	0	0	0	0	0	23.3	95.11449	1.4	352.75	0.926385	19.19335	4.
3615	0	0	0	0	0	0	0	0	23.8	95.82604	1.4	352.38	0.926385	19.19335	4.
3616	0	0	0	0	0	0	0	0	24.4	96.29115	1.4	352.06	0.929654	19.24689	4.
3617	0	0	0	0	0	0	0	0	24.6	96.00022	1.4	352.13	0.929654	19.24689	4.
3618	0	0	0	0	0	0	0	0	24.9	95.64075	1.4	352.31	0.932907	19.30131	4.
3619	0	0	0	0	0	0	0	0	25.1	96.07619	1.4	352.59	0.932907	19.30131	4.
3620	0	0	0	0	0	0	0	0	25.3	96.30968	1.4	352.4	0.932907	19.30131	4.
3621	0	0	0	0	0	0	0	0	25.4	96.35785	1.4	352.57	0.936488	19.35528	4.
3622	0	0	0	0	0	0	0	0	25.7	96.75254	1.4	352.46	0.936488	19.35528	4.
3623	0	0	0	0	0	0	0	0	26	96.78775	1.3	352.31	0.941033	19.42413	4.
3624	0	0	0	0	0	0	0	0	26.3	96.69881	1.3	352.51	0.941033	19.42413	4.
3625	0	0	0	0	0	0	0	0	26.6	96.35415	1.3	352.42	0.944319	19.47973	4.
3626	0	0	0	0	0	0	0	0	26.8	95.81678	1.3	352.35	0.944319	19.47973	4.
3627	0	0	0	0	0	0	0	0	27.1	95.39985	1.3	352.47	0.94695	19.53385	4.
3628	0	0	0	0	0	0	0	0	27.5	95.49251	1.3	352.83	0.94695	19.53385	4.
3629	0	0	0	0	0	0	0	0	27.9	93.17069	1.3	352.49	0.947267	19.58579	4.
3630	0	0	0	0	0	0	0	0	28.2	93.05766	1.3	352.09	0.947267	19.58579	4.
3631	0	0	0	0	0	0	0	0	28.3	92.32017	1.3	352.28	0.947267	19.58579	4.
3632	0	0	0	0	0	0	0	0	28.3	91.99219	1.3	352.28	0.947358	19.64402	4.
3633	0	0	0	0	0	0	0	0	28.1	92.05518	1.3	352.46	0.947358	19.64402	4.
3634	0	0	0	0	0	0	0	0	27.9	92.05704	1.3	352.44	0.947439	19.69549	4.
3635	0	0	0	0	0	0	0	0	27.6	92.17748	1.3	352.29	0.947439	19.69549	4.
3636	0	0	0	0	0	0	0	0	27.3	92.76118	1.3	352.64	0.947524	19.74944	4.
3637	0	0	0	0	0	0	0	0	26.8	92.66853	1.3	351.89	0.947524	19.74944	4.
3638	0	0	0	0	0	0	0	0	26.1	92.2201	1.4	352.32	0.947605	19.8014	4.
3639	0	0	0	0	0	0	0	0	25.5	92.1534	1.4	352.58	0.947605	19.8014	4.
3640	0	0	0	0	0	0	0	0	24.7	92.14043	1.4	353.48	0.947696	19.85909	4.
3641	0	0	0	0	0	0	0	0	23.9	92.62591	1.4	354.82	0.947696	19.85909	4.

CSVLog_20220630_115946

Figure 23. Sample raw data from OBD-II logger.

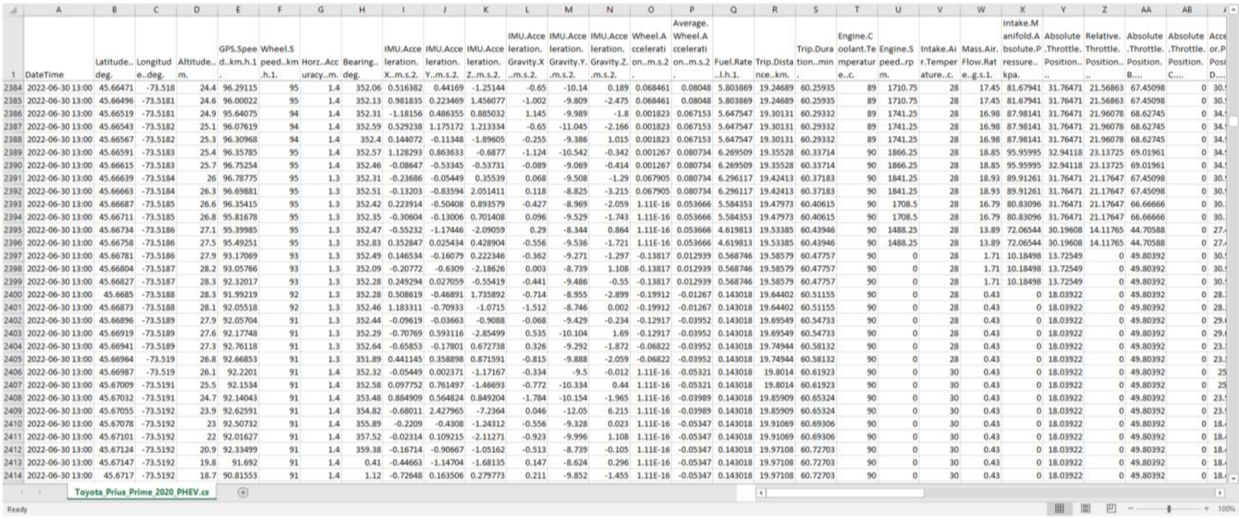


	Timestamp	Date	Time	Bag#	Scattering (V)	Ionization (V)	Opacity (V)	PM (µg/m3)	PN (#/cm3)	Cb	Cs	Ci	Co	PSN
4627	46800	6/30/2022	1:00:00 PM	0	-0.006028	0.082008	0.089506	-633.9	2142836.76	0	20	1	20	1.751556
4628	46801	6/30/2022	1:00:01 PM	0	-0.005931	0.082691	0.089604	-615.83	2153427.47	0	20	1	20	1.756147
4629	46802	6/30/2022	1:00:02 PM	0	-0.005833	0.079956	0.089408	-607.25	2118436.09	0	20	1	20	1.751458
4630	46803	6/30/2022	1:00:03 PM	0	-0.006028	0.072728	0.089604	-655.79	2034063.31	0	20	1	20	1.74423
4631	46804	6/30/2022	1:00:04 PM	0	-0.005735	0.071849	0.089408	-610.66	2022715.98	0	20	1	20	1.745304
4632	46805	6/30/2022	1:00:05 PM	0	-0.006028	0.073021	0.090092	-652.84	2045845.2	0	20	1	20	1.754291
4633	46806	6/30/2022	1:00:06 PM	0	-0.006126	0.071556	0.089701	-674.09	2020927.97	0	20	1	20	1.743057
4634	46807	6/30/2022	1:00:07 PM	0	-0.005833	0.072142	0.089799	-624.27	2032018.01	0	20	1	20	1.751458
4635	46808	6/30/2022	1:00:08 PM	0	-0.005833	0.074584	0.089604	-619.29	2057811.26	0	20	1	20	1.749993
4636	46809	6/30/2022	1:00:09 PM	0	-0.005833	0.079663	0.089311	-608.4	2113298.27	0	20	1	20	1.749211
4637	46810	6/30/2022	1:00:10 PM	0	-0.006517	0.081226	0.090287	-711.07	2142756.52	0	20	1	20	1.756635
4638	46811	6/30/2022	1:00:11 PM	0	-0.006028	0.081226	0.090092	-633.08	2143497.06	0	20	1	20	1.762496
4639	46812	6/30/2022	1:00:12 PM	0	-0.006028	0.081128	0.090287	-632.42	2145656.99	0	20	1	20	1.766305
4640	46813	6/30/2022	1:00:13 PM	0	-0.005833	0.081226	0.089408	-604.19	2133528.1	0	20	1	20	1.752728
4641	46814	6/30/2022	1:00:14 PM	0	-0.006028	0.07517	0.090385	-646.31	2076433.38	0	20	1	20	1.7623
4642	46815	6/30/2022	1:00:15 PM	0	-0.005735	0.077514	0.091557	-587.07	2126783	0	20	1	20	1.793949
4643	46816	6/30/2022	1:00:16 PM	0	-0.005833	0.080445	0.091753	-595.23	2164159.94	0	20	1	20	1.798833
4644	46817	6/30/2022	1:00:17 PM	0	-0.005931	0.074682	0.090971	-628.79	2081414.2	0	20	1	20	1.775487
4645	46818	6/30/2022	1:00:18 PM	0	-0.005931	0.07224	0.090971	-634.67	2052308.93	0	20	1	20	1.773045
4646	46819	6/30/2022	1:00:19 PM	0	-0.005833	0.073607	0.091166	-614.42	2072760.51	0	20	1	20	1.780274
4647	46820	6/30/2022	1:00:20 PM	0	-0.005833	0.076733	0.090971	-607.8	2106656.08	0	20	1	20	1.779492
4648	46821	6/30/2022	1:00:21 PM	0	-0.005931	0.081226	0.091264	-611.67	2164279.6	0	20	1	20	1.787893
4649	46822	6/30/2022	1:00:22 PM	0	-0.005638	0.082984	0.091069	-560	2184276.04	0	20	1	20	1.791604
4650	46823	6/30/2022	1:00:23 PM	0	-0.006028	0.086501	0.090385	-619.06	2211087.45	0	20	1	20	1.773631
4651	46824	6/30/2022	1:00:24 PM	0	-0.005833	0.087966	0.090385	-583.51	2230085.03	0	20	1	20	1.779004
4652	46825	6/30/2022	1:00:25 PM	0	-0.006028	0.085622	0.090971	-618.46	2210645.88	0	20	1	20	1.784474
4653	46826	6/30/2022	1:00:26 PM	0	-0.006028	0.080933	0.091264	-628.36	2159983.05	0	20	1	20	1.785646
4654	46827	6/30/2022	1:00:27 PM	0	-0.005833	0.081226	0.091264	-595.62	2165094.8	0	20	1	20	1.789846
4655	46828	6/30/2022	1:00:28 PM	0	-0.005931	0.086305	0.091264	-599.47	2224571.52	0	20	1	20	1.792972
4656	46829	6/30/2022	1:00:29 PM	0	-0.006126	0.088552	0.090873	-627.79	2242904.17	0	20	1	20	1.783497
4657	46830	6/30/2022	1:00:30 PM	0	-0.005833	0.094315	0.089897	-570.54	2296929.34	0	20	1	20	1.775585
4658	46831	6/30/2022	1:00:31 PM	0	-0.005833	0.09158	0.089994	-576.64	2266241.42	0	20	1	20	1.774803
4659	46832	6/30/2022	1:00:32 PM	0	-0.006322	0.087185	0.090287	-665.4	2215093.43	0	20	1	20	1.766501
4660	46833	6/30/2022	1:00:33 PM	0	-0.006126	0.081519	0.090483	-646.49	2152809.17	0	20	1	20	1.76865

	PSN_limit	Pass/Fail	NO2 (V)	NO2 (ppm)	NO (V)	NO (ppm)	CO2 (V)	CO2 (%)	CO (V)	CO (%)	Temperature (deg C)	ErrorCode	Scattering (Vraw)	Ionization (Vraw)	Op
4627	0.5	Pass	0.014017	1.7621	0.004117	10.9563	1.840733	14.5828	-0.000319	-0.0019	39.087	0	0.11917	6.985788	
4628	0.5	Pass	0.013138	1.6516	0.004117	10.9563	1.842491	14.5968	0.000755	0.0045	39.108	0	0.119268	6.985104	
4629	0.5	Pass	0.012063	1.5165	0.004215	11.2162	1.841612	14.5898	-0.001589	-0.0095	39.104	0	0.119365	6.987839	
4630	0.5	Pass	0.012552	1.5779	0.003629	9.6566	1.843272	14.603	0.001439	0.0086	39.037	0	0.11917	6.995068	
4631	0.5	Pass	0.011477	1.4429	0.00402	10.6964	1.840733	14.5828	-0.000807	-0.0048	39.075	0	0.119463	6.995947	
4632	0.5	Pass	0.010598	1.3323	0.004117	10.9563	1.842491	14.5968	0.001341	0.008	39.112	0	0.11917	6.994775	
4633	0.5	Pass	0.010696	1.3446	0.003824	10.1765	1.842003	14.5929	-0.000905	-0.0054	39.075	0	0.119072	6.99624	
4634	0.5	Pass	0.010012	1.2587	0.002554	6.7973	1.844445	14.6122	0.001439	0.0086	39.037	0	0.119365	6.995654	
4635	0.5	Pass	0.009133	1.1481	0.00441	11.7361	1.841221	14.5867	-0.000514	-0.0031	39.112	0	0.119365	6.993212	
4636	0.5	Pass	0.008352	1.0499	0.004703	12.5159	1.843663	14.6061	0.001244	0.0074	39.062	0	0.119365	6.988132	
4637	0.5	Pass	0.009524	1.1973	0.004117	10.9563	1.838291	14.5635	-0.001589	-0.0095	39.075	0	0.118682	6.986569	
4638	0.5	Pass	0.010012	1.2587	0.003238	8.6169	1.834677	14.5349	0.000853	0.0051	39.075	0	0.11917	6.986569	
4639	0.5	Pass	0.009133	1.1481	0.003433	9.1368	1.831844	14.5124	-0.001687	-0.0101	39.087	0	0.11917	6.986667	
4640	0.5	Pass	0.009328	1.1727	0.003629	9.6566	1.836532	14.5496	0.000853	0.0051	39.099	0	0.119365	6.986569	
4641	0.5	Pass	0.00757	0.9517	0.00402	10.6964	1.832723	14.5194	-0.000319	-0.0019	39.087	0	0.11917	6.992626	
4642	0.5	Pass	0.00591	0.7429	0.003336	8.8768	1.426569	11.3017	0.001732	0.0103	39.037	0	0.119463	6.990281	
4643	0.5	Pass	0.003761	0.4728	0.00402	10.6964	0.548913	4.3487	-0.000807	-0.0048	39.137	0	0.119365	6.987351	
4644	0.5	Pass	0.000049	0.0061	0.004508	11.9961	0.231306	1.8325	0.001341	0.008	39.087	0	0.119268	6.993114	
4645	0.5	Pass	-0.003272	-0.4114	0.004313	11.4762	0.11873	0.9406	-0.000221	-0.0013	39.124	0	0.119268	6.995556	
4646	0.5	Pass	-0.004737	-0.5956	0.004801	12.7759	0.078193	0.6195	0.002025	0.0121	39.087	0	0.119365	6.994188	
4647	0.5	Pass	-0.006496	-0.8166	0.003629	9.6566	0.056313	0.4461	-0.000221	-0.0013	39.079	0	0.119365	6.991063	
4648	0.5	Pass	-0.006789	-0.8534	0.003433	9.1368	0.049963	0.3958	0.001635	0.0097	39.05	0	0.119268	6.986569	
4649	0.5	Pass	-0.011477	-1.4429	0.003531	9.3967	0.042051	0.3331	-0.000514	-0.0031	39.075	0	0.119561	6.984811	
4650	0.5	Pass	-0.010208	-1.2832	0.005875	15.6352	0.038632	0.3061	0.002123	0.0127	39.112	0	0.11917	6.981295	
4651	0.5	Pass	-0.009328	-1.1727	0.003336	8.8768	0.030916	0.2449	-0.000807	-0.0048	39.062	0	0.119365	6.979829	
4652	0.5	Pass	-0.009133	-1.1481	0.003922	10.4364	0.029548	0.2341	0.002123	0.0127	39.162	0	0.11917	6.982174	
4653	0.5	Pass	-0.009621	-1.2095	0.004215	11.2162	0.026422	0.2093	-0.001101	-0.0066	39.099	0	0.11917	6.986862	
4654	0.5	Pass	-0.005812	-0.7306	0.003922	10.4364	0.028474	0.2256	0.001635	0.0097	39.062	0	0.119365	6.986569	
4655	0.5	Pass	-0.006105	-0.7675	0.002359	6.2775	0.026716	0.2116	-0.000319	-0.0019	39.099	0	0.119268	6.98149	
4656	0.5	Pass	-0.005324	-0.6692	0.002652	7.0573	0.03453	0.2736	0.002416	0.0144	39.062	0	0.119072	6.979243	
4657	0.5	Pass	-0.004444	-0.5587	0.002554	6.7973	0.056801	0.45	0.000072	0.0004	39.124	0	0.119365	6.97348	
4658	0.5	Pass	-0.003663	-0.4605	0.00441	11.7361	0.074383	0.5893	0.001537	0.0092	39.075	0	0.119365	6.976215	
4659	0.5	Pass	-0.005714	-0.7184	0.002457	6.5374	0.102125	0.8091	-0.000807	-0.0048	39.075	0	0.118877	6.980611	
4660	0.5	Pass	-0.001416	-0.1781	0.004508	11.9961	0.128303	1.0165	0.001635	0.0097	39.112	0	0.119072	6.986276	

20220630_120206_parSYNC_Data

Figure 24. Sample raw data from PEMS.



	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	DateTime	Latitude..deg.	Longitude..deg.	Altitude..m.	GPS.Speed..km.h.1.	Wheel.Speed..km.h.1.	Horz..Accuracy..m.	Bearing..deg.	IMU.Acceleration.X..m.s.2.	IMU.Acceleration.Y..m.s.2.	IMU.Acceleration.Z..m.s.2.	IMU.Acceleration.Gravity.X..m.s.2.	IMU.Acceleration.Gravity.Y..m.s.2.	IMU.Acceleration.Gravity.Z..m.s.2.
2384	2022-06-30 13:00	45.66471	-73.518	24.4	96.29115	95	1.4	352.06	0.516382	0.44169	-1.25144	-0.65	-10.14	0.189
2385	2022-06-30 13:00	45.66496	-73.5181	24.6	96.00022	95	1.4	352.13	0.981835	0.223469	1.456077	-1.002	-9.809	-2.475
2386	2022-06-30 13:00	45.66519	-73.5181	24.9	95.64075	94	1.4	352.31	-1.18156	0.486355	0.885032	1.145	-9.989	-1.8
2387	2022-06-30 13:00	45.66543	-73.5182	25.1	96.07619	94	1.4	352.59	0.529238	1.175172	1.213334	-0.65	-11.045	-2.166
2388	2022-06-30 13:00	45.66567	-73.5182	25.3	96.30968	94	1.4	352.4	0.144072	-0.11348	-1.89605	-0.255	-9.386	1.015
2389	2022-06-30 13:00	45.66591	-73.5183	25.4	96.35785	95	1.4	352.57	1.128293	0.863633	-0.6877	-1.124	-10.542	-0.342
2390	2022-06-30 13:00	45.66615	-73.5183	25.7	96.75254	95	1.4	352.46	-0.08647	-0.53345	-0.53731	-0.089	-9.069	-0.414
2391	2022-06-30 13:00	45.66639	-73.5184	26	96.78775	95	1.3	352.31	-0.23686	-0.05449	0.35539	0.068	-9.508	-1.29
2392	2022-06-30 13:00	45.66663	-73.5184	26.3	96.69881	95	1.3	352.51	-0.13203	-0.83594	2.051411	0.118	-8.825	-3.215
2393	2022-06-30 13:00	45.66687	-73.5185	26.6	96.35415	95	1.3	352.42	0.223914	-0.50408	0.893579	-0.427	-8.969	-2.059
2394	2022-06-30 13:00	45.66711	-73.5185	26.8	95.81678	95	1.3	352.35	-0.30604	-0.13006	0.701408	0.096	-9.529	-1.743
2395	2022-06-30 13:00	45.66734	-73.5186	27.1	95.39985	95	1.3	352.47	-0.55232	-1.17446	-2.09059	0.29	-8.344	0.864
2396	2022-06-30 13:00	45.66758	-73.5186	27.5	95.49251	95	1.3	352.83	0.352847	0.025434	0.428904	-0.556	-9.536	-1.721
2397	2022-06-30 13:00	45.66781	-73.5186	27.9	93.17069	93	1.3	352.49	0.146534	-0.16079	0.222346	-0.362	-9.271	-1.297
2398	2022-06-30 13:00	45.66804	-73.5187	28.2	93.05766	93	1.3	352.09	-0.20772	-0.6309	-2.18626	0.003	-8.739	1.108
2399	2022-06-30 13:00	45.66827	-73.5187	28.3	92.32017	93	1.3	352.28	0.249294	0.027059	-0.55419	-0.441	-9.486	-0.55
2400	2022-06-30 13:00	45.6685	-73.5188	28.3	91.99219	92	1.3	352.28	0.508619	-0.46891	1.735892	-0.714	-8.955	-2.899
2401	2022-06-30 13:00	45.66873	-73.5188	28.1	92.05518	92	1.3	352.46	1.183311	-0.70933	-1.0715	-1.512	-8.746	0.002
2402	2022-06-30 13:00	45.66896	-73.5189	27.9	92.05704	91	1.3	352.44	-0.09619	-0.03663	-0.9088	-0.068	-9.429	-0.234
2403	2022-06-30 13:00	45.66919	-73.5189	27.6	92.17748	91	1.3	352.29	-0.70769	0.593116	-2.85499	0.535	-10.104	1.69
2404	2022-06-30 13:00	45.66941	-73.5189	27.3	92.76118	91	1.3	352.64	-0.65853	-0.17801	0.672738	0.326	-9.292	-1.872
2405	2022-06-30 13:00	45.66964	-73.519	26.8	92.66853	91	1.3	351.89	0.441145	0.358898	0.871591	-0.815	-9.888	-2.059
2406	2022-06-30 13:00	45.66987	-73.519	26.1	92.2201	91	1.4	352.32	-0.05449	0.002371	-1.17167	-0.334	-9.5	-0.012
2407	2022-06-30 13:00	45.67009	-73.5191	25.5	92.1534	91	1.4	352.58	0.097752	0.761497	-1.46693	-0.772	-10.334	0.44
2408	2022-06-30 13:00	45.67032	-73.5191	24.7	92.14043	91	1.4	353.48	0.884909	0.564824	0.849204	-1.784	-10.154	-1.965
2409	2022-06-30 13:00	45.67055	-73.5192	23.9	92.62591	91	1.4	354.82	-0.68011	2.427965	-7.2364	0.046	-12.05	6.215
2410	2022-06-30 13:00	45.67078	-73.5192	23	92.50732	91	1.4	355.89	-0.2209	-0.4308	-1.24312	-0.556	-9.328	0.023
2411	2022-06-30 13:00	45.67101	-73.5192	22	92.01627	91	1.4	357.52	-0.02314	0.109215	-2.11271	-0.923	-9.996	1.108
2412	2022-06-30 13:00	45.67124	-73.5192	20.9	92.33499	91	1.4	359.38	-0.16714	-0.90667	-1.05162	-0.513	-8.739	-0.105
2413	2022-06-30 13:00	45.67147	-73.5192	19.8	91.692	91	1.4	0.41	-0.44663	-1.14704	-1.68135	0.147	-8.624	0.296
2414	2022-06-30 13:00	45.6717	-73.5192	18.7	90.81553	91	1.4	1.12	-0.72648	0.163506	0.279773	0.211	-9.852	-1.455

	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	A…
1	Wheel.Acceleration..m.s.2.	Average.Wheel.Acceleration..m.s.2.	Fuel.Rate..l.h.1.	Trip.Distance..km.	Trip.Duration..min.	Engine.Coolant.Temperature..c.	Engine.Speed..rpm.	Intake.Air.Temperature..c.	Mass.Air.Flow.Rate..g.s.1.	Intake.Manifold.Absolute.Pressure..kpa.	Absolute.Throttle.Position....	Relative.Throttle.Position....	Absolute.Throttle.Position.B....	Absolute.Throttle.Position.C....	Acce…or.P… Posi… D....
2384	0.068461	0.08048	5.803869	19.24689	60.25935	89	1710.75	28	17.45	81.67941	31.76471	21.56863	67.45098	0	30.
2385	0.068461	0.08048	5.803869	19.24689	60.25935	89	1710.75	28	17.45	81.67941	31.76471	21.56863	67.45098	0	30.
2386	0.001823	0.067153	5.647547	19.30131	60.29332	89	1741.25	28	16.98	87.98141	31.76471	21.96078	68.62745	0	34.
2387	0.001823	0.067153	5.647547	19.30131	60.29332	89	1741.25	28	16.98	87.98141	31.76471	21.96078	68.62745	0	34.
2388	0.001823	0.067153	5.647547	19.30131	60.29332	89	1741.25	28	16.98	87.98141	31.76471	21.96078	68.62745	0	34.
2389	0.001267	0.080734	6.269509	19.35528	60.33714	90	1866.25	28	18.85	95.95995	32.94118	23.13725	69.01961	0	34.
2390	0.001267	0.080734	6.269509	19.35528	60.33714	90	1866.25	28	18.85	95.95995	32.94118	23.13725	69.01961	0	34.
2391	0.067905	0.080734	6.296117	19.42413	60.37183	90	1841.25	28	18.93	89.91261	31.76471	21.17647	67.45098	0	30.
2392	0.067905	0.080734	6.296117	19.42413	60.37183	90	1841.25	28	18.93	89.91261	31.76471	21.17647	67.45098	0	30.
2393	1.11E-16	0.053666	5.584353	19.47973	60.40615	90	1708.5	28	16.79	80.83096	31.76471	21.17647	66.66666	0	30.
2394	1.11E-16	0.053666	5.584353	19.47973	60.40615	90	1708.5	28	16.79	80.83096	31.76471	21.17647	66.66666	0	30.
2395	1.11E-16	0.053666	4.619813	19.53385	60.43946	90	1488.25	28	13.89	72.06544	30.19608	14.11765	44.70588	0	27.
2396	1.11E-16	0.053666	4.619813	19.53385	60.43946	90	1488.25	28	13.89	72.06544	30.19608	14.11765	44.70588	0	27.
2397	-0.13817	0.012939	0.568746	19.58579	60.47757	90	0	28	1.71	10.18498	13.72549	0	49.80392	0	30.
2398	-0.13817	0.012939	0.568746	19.58579	60.47757	90	0	28	1.71	10.18498	13.72549	0	49.80392	0	30.
2399	-0.13817	0.012939	0.568746	19.58579	60.47757	90	0	28	1.71	10.18498	13.72549	0	49.80392	0	30.
2400	-0.19912	-0.01267	0.143018	19.64402	60.51155	90	0	28	0.43	0	18.03922	0	49.80392	0	28.
2401	-0.19912	-0.01267	0.143018	19.64402	60.51155	90	0	28	0.43	0	18.03922	0	49.80392	0	28.
2402	-0.12917	-0.03952	0.143018	19.69549	60.54733	90	0	28	0.43	0	18.03922	0	49.80392	0	29.
2403	-0.12917	-0.03952	0.143018	19.69549	60.54733	90	0	28	0.43	0	18.03922	0	49.80392	0	29.
2404	-0.06822	-0.03952	0.143018	19.74944	60.58132	90	0	28	0.43	0	18.03922	0	49.80392	0	23.
2405	-0.06822	-0.03952	0.143018	19.74944	60.58132	90	0	28	0.43	0	18.03922	0	49.80392	0	23.
2406	1.11E-16	-0.05321	0.143018	19.8014	60.61923	90	0	30	0.43	0	18.03922	0	49.80392	0	25
2407	1.11E-16	-0.05321	0.143018	19.8014	60.61923	90	0	30	0.43	0	18.03922	0	49.80392	0	25
2408	1.11E-16	-0.03989	0.143018	19.85909	60.65324	90	0	30	0.43	0	18.03922	0	49.80392	0	23.
2409	1.11E-16	-0.03989	0.143018	19.85909	60.65324	90	0	30	0.43	0	18.03922	0	49.80392	0	23.
2410	1.11E-16	-0.05347	0.143018	19.91069	60.69306	90	0	30	0.43	0	18.03922	0	49.80392	0	18.
2411	1.11E-16	-0.05347	0.143018	19.91069	60.69306	90	0	30	0.43	0	18.03922	0	49.80392	0	18.
2412	1.11E-16	-0.05347	0.143018	19.97108	60.72703	90	0	30	0.43	0	18.03922	0	49.80392	0	18.
2413	1.11E-16	-0.05347	0.143018	19.97108	60.72703	90	0	30	0.43	0	18.03922	0	49.80392	0	18.
2414	1.11E-16	-0.05347	0.143018	19.97108	60.72703	90	0	30	0.43	0	18.03922	0	49.80392	0	18.

Toyota_Prius_Prime_2020_PHEV.cs

Ready

Figure 25. Sample combined data (OBD and PEMS).

The regression model results shown in Section 4 use the second-by-second data. Many different combinations of models were tested. Of which, the same log-linear mixed effect models were conducted for FCR and CO_2, using the dataset that aggregates by every 50 meters of data. The results are shown in Table 21, along with the performance metrics results summary in Table 22.

Table 21. Log-linear models outcomes of fuel consumption rate and CO_2 emission rate for all vehicle types.

		FCR				**CO_2**			
Predictor		Coef.	Std. err	P-value	Elasticity (%)	Coef.	Std. err	P-value	Elasticity (%)
Vehicle Type	HEV	-1.048	0.087	0	-64.922	-2.895	0.179	0	-94.469
	Non-HEV	Base	---	---	---	Base	---	---	---
Speed		0.003	0.001	0	11.609	0.019	0.001	0	74.017
Acceleration		0.97	0.02	0	8.538	1.319	0.037	0	11.611
Slope		0.100	0.279	0	0.068	18.542	0.512	0	0.125
Road Types	Urban	-0.121	0.029	0	-11.408	-0.09	0.053	0.09	-8.612
	Highway	Base	---	---	---	---	---	---	---
		R^2= 0.37 Log-likelihood= -882.12				R^2= 0.45 Log-likelihood= -2371.39			

Note: Elasticities are at the mean values for continuous variables.

Table 22. Performance metrics for the models.

	R^2	Log-likelihood
FCR Model: Every 1 Second Dataset	0.42	27945.79
FCR Model: Every 50 Meter Dataset	0.37	-882.12
CO_2 Model: Every 1 Second Dataset	0.54	19937.61
CO_2 Model: Every 50 Meter Dataset	0.45	-2371.39

Note: The models here are all log-linear mixed effect models.

In addition, from the collected data, it was observed that vehicle speed exhibits in a quadratic manner. Therefore, quadratic functions of speed are also tested (where speed and speed^2 are both included in the log-linear models for estimating FCR and CO_2 emission). The model results are presented in Table 23.

Table 23. Quadratic function of speed in log-linear models for FCR and CO2.

		FCR				CO_2			
Predictor		Coef.	Std. err	P-value	Elasticity (%)	Coef.	Std. err	P-value	Elasticity (%)
Vehicle Type	HEV	-0.292	0.019	0	-25.348	-0.818	0.054	0	-55.846
	Non-HEV	Base	---	---	---	---	---	---	---
Speed		9.42e-3	1.19e-4	0	17.299	0.012	1.79e-4	0	23.539
Speed^2		-1.05e-5	1.98e-6	0	n/a	2.02e-5	2.98e-6	0	n/a
Acceleration		0.207	0.002	0	-0.218	0.256	0.003	0	-0.269
Slope		0.891	0.020	0	0.0362	1.326	0.031	0	0.0538
Road Types	Urban	0.016	0.004	0	1.628	0.017	0.006	0	1.704
	Highway	Base	---	---	---	---	---	---	---
		R^2= 0.42 Log-likelihood= 27973.22				R^2= 0.53 Log-likelihood= 20195.17			

Note: Elasticities are calculated at the mean values for continuous variables.

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