ASSESSMENT OF TRANSPORTATION GHG MITGATING SOLUTIONS

THE POLICY-TECHNOLOGY NEXUS FOR MITGATING PASSENGER ON-ROAD TRANSPORTATION GHG EMISSIONS: E-BUS, E-RIDE-SHARE, OR OTHER ALTERNATIVES

By

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Lay Abstract

There is a dire need to evaluate the effectiveness of transportation GHG mitigation policies as alternative mobility solutions are being adopted and the pressure to respond to climate change intensifies. This work evaluates the effectiveness of policy optimization and vehicle-level simulation techniques to inform GHG mitigation decision-making.

A two-step approach is adopted herein. At the strategic level, a cost optimization model for passenger vehicle electrification policies in Ontario is calibrated to identify the optimal allocation of provincial policy to achieve a 30% GHG reduction by 2030. Next, a micro level focuses on the energy consumption of eight vehicle technologies over 450 operational scenarios is simulated and trip-level passenger emissions are estimated to reveal the environmentally beneficial mobility option, corresponding passenger thresholds, and extent of variability associated with local operating conditions.

Overall, optimization and trip-level vehicle simulation can be used to demystify optimal decision-making related to mobility solutions.

Extended Abstract

The passenger transportation sector is notoriously difficult to decarbonize. In this thesis, two distinct and novel methodologies to estimate the environmental impact of alternative and conventional transportation technologies are developed.

In Chapter 2, a provincial fleet policy-driven linear programming model is developed to minimize the cost of three passenger vehicle electrification policies in Ontario under a 30% GHG reduction target by 2030. Provincial life-cycle emissions and total-cost-of-ownership associated with policy allocation is estimated. The results highlight that electrification of on-road passenger transportation will *not* be sufficient to meet the 30% reduction target despite Ontario's low-carbon electricity grid. Instead, reductions of between 24% to 26% are forecasted at an annual cost (for ten years) of between CAD 0.29 to 0.3 billion annually indicating that additional policies are necessary to realize a 30% reduction target.

In Chapter 3, a trip-level vehicle framework is developed to determine under what operating conditions transit buses and passenger cars will be environmentally beneficial across the dimensions of technology, service mode, and power source pathway. The well-to-wheel energy consumption and GHG emissions are simulated for over 450 operating scenarios. Emissions are then normalized through passenger-trip emission thresholds to facilitate equivalent comparison across all dimensions. The results indicate that the most beneficial solution are fuel-cell electric car-share, battery electric car-share, and battery electric bus all powered by low-carbon intensity power sources at average occupancy (7.9-19.7 gCO2e passenger-service-mode-trip-km-travelled^{-1}). Furthermore, transit bus

technologies have the potential to reduce up to 2.3 times more GHG per passenger-trip than comparable ride-share passenger cars at average occupancies.

The results of Chapter 2 and 3 highlight that technology alone may not be sufficient to achieve significant GHG reductions; policy which leverage local operating data and target GHG reduction associated with passenger-trips are critical to informing under *what* conditions a mobility solution is environmentally beneficial.

Keywords:

Well-to-Wheel GHG Emissions; car-share; ride-share; transportation policy; interval programming, total-cost-of-ownership ; electric mobility; vehicle simulation

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Publications

This MA.Sc. thesis is formatted as a sandwich style submission based on the following published or submitted papers:

1. **Anastasia Soukhov,** Moataz Mohamed, Zhong Li, "Optimizing Provincial Passenger Road Transportation Emission Policies in Canada" accepted to the *Canadian Research Transport Research Forum (CTRF)* for presentation and publication in May 2021. Anastasia conceptualized, wrote the original draft, conducted the data collection and formal analysis.
2. **Anastasia Soukhov,** Moataz Mohamed, "e-Bus, e-Ride-Share or Other Alternative? Passenger-Trip Emission Thresholds for Alternative Technologies" submitted to *Transportation Research Part D: Transport and Environment* in July 2021. Anastasia significantly contributed to the conceptualization, wrote the original draft, and conducted all data collection and formal analysis.

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List of Abbreviations and Symbols

BEB	Battery Electric Bus
BEV	Battery Electric Vehicle
CO_2e	Carbon Dioxide Equivalent
EB	Electric Bus
EV	Electric Vehicle
FCEV	Fuel Cell Electric Vehicle
GHG	Greenhouse Gas
GWP	Global Warming Potential
ICEV	Internal Combustion Engine Vehicle
LC	Life-Cycle
LCA	Life-Cycle Assessment
LDV	Light-Duty Vehicle
LNG	Liquified Natural Gas
PCF	Pan-Canadian Framework on Clean Growth and Climate Change
PHEV	Plug-in Electric Vehicle
PKT	Passenger Kilometres Travelled
PPCKT	Passenger private car-adjusted kilometres travelled
PTW	Pump-to-Wheels
SoC	State of charge
TCO	Total Cost of Ownership

VKT	Vehicle Kilometres Travelled
WTP	Well-to-Pump
WTW	Well-to-Wheels

Chapter 1. Introduction

Globally, greenhouse gas (GHG) emissions have continued to grow faster than any other energy end-use sector and doubled since 1970 reaching 7.1 GT CO2e in 2010 (Sims et al., 2014). Road vehicles account for approximately 80% of emissions and OECD (Organisation for Economic Co-operation and Development) countries are responsible for the majority of total emissions despite representing 10% of the global population (Sims et al., 2014). It is internationally agreed upon that additional policy action within the transportation sector is necessary to avoid a 2-degree global warming climate scenario (Sims et al., 2014).

Canada, as an OECD country, is no exception; the nation's road transportation emissions increased 27% from 2000 to 2018 and remains one of the largest GHG emitting sectors (NRCan, 2020). With respect to passenger transportation, efforts have been made in the Canadian context to reduce average GHG emissions intensity (CO_2e/passenger-km and CO_2e/km) through policy action that increases the uptake of low-carbon power sources, increases vehicle efficiency, and reduces vehicle kilometres travelled (VKT) (Bhardwaj et al., 2020; Hammond et al., 2020). However, despite these recent efforts, Canada is not on its way to meeting 2030 or 2050 goals as forecasted by the most recent biennial report (ECCC, 2019) and confusion exists on the associated costs of policy action and benefits of emerging technologies such as low-carbon power source and service modes such as ride-share, car-share, and transit buses.

At the fast pace of technology development and the urgent pressure to mitigate GHG emissions, policy must get it right. This thesis broadly addresses this theme through the following questions:

1. What is the environmental benefit of emerging passenger vehicle technologies?
2. Under what operational conditions, passenger occupancies, and power source pathway (energy systems) are these technologies no longer beneficial?
3. What methods can be operationalized to estimate the cost and GHG reduction potential of selected technology-adoption policies?

1.1. Thesis Outline and Objectives

The thesis is divided in the following sections and objectives:

Chapter 2 presents a linear programming model developed to estimate the minimized cost of three passenger transportation electrification policies in Ontario under a 30% GHG reduction target in 2030. This effort demonstrates the associated cost of GHG emission policies and their potential to reduce GHG emission which is missing within the Canadian context. This chapter is based on a paper that has been presented and published.

Chapter 3 simulates the energy consumption, estimates the GHG trip-level passenger thresholds for eight conventional and emerging passenger car and transit bus technologies under various service modes (transit bus, private passenger car, ride-share, and car-share). This work contributes a novel approach by which the impact of mobility solutions through the GHG emission produced by each passenger on a specific service-mode can be examined. Additionally, this effort further contributes by providing dynamically simulated energy consumption and WTW GHG emission for a variety of vehicle powertrains under a wide array of operating conditions (drive cycle, road grade, initial SoC, vehicle test weight) to the literature. It is also worth noting that this chapter is based on a paper that has been submitted for publication.

Chapter 4 provides concluding remarks about the novel contributions made within this body of work and directions for future investigation.

Chapter 2. Optimizing Provincial Passenger Road Transportation Emission Policies in Canada

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This chapter is organized as was accepted to the *Canadian Research Transport Research Forum (CTRF)* for publication in May 2021

Abstract

The passenger transportation sector is notoriously difficult to decarbonize as it is linked with individual choices and economic growth. Therefore, there is always a need to evaluate the effectiveness of Greenhouse Gas (GHG) mitigation policies while simultaneously optimizing the policy costs. In this study, we investigate Ontario's transportation electrification policy through a transparent and interpretable interval integer linear programming model. The model is developed to minimize policy costs to achieve a 30% GHG reduction target in 2030. The considered policies are; (1) incentivization of electric vehicle (EV) purchase, (2) electrification of provincial light-duty-vehicle (LDV) fleet and (3) electrification of buses. Life-cycle (LC) emissions and total-cost-of-ownership (TCO) models are estimated to account for the full extent of emission reduction and associated costs. The results highlight that electrification alone will not be sufficient to meet the 30% reduction target on a provincial level, and more progressive policies that target transportation demand management should be considered. The developed optimization approach could be used to support transportation GHG reduction policy cost analysis and inform the decision-making process at all levels of government.

Keywords: transportation GHG emission reduction policy cost estimation, interval programming, life-cycle (LC) emissions, total-cost-of-ownership (TCO)

2.1. Introduction

In April 2016, alongside 175 other counties, Canada committed to reducing its greenhouse gas (GHG) emissions as part of the Paris Agreement, which acknowledged the urgent need to address climate change (ECCC, 2019). Canada's most recent Biennial Report submitted to the United Nations Framework Convention on Climate Change (UNFCCC) outlines the continued implementation of the national plan (the *Pan-Canadian Framework on Clean Growth and Climate Change,* also referred to as the PCF) and the estimated progress towards the 2030 target (30% below 2005 levels). The PCF includes policy actions that focus on the reduction of GHG emissions across all sectors; namely carbon pollution pricing strategy, complementary actions to reduce emissions, adaptive and resilience measures, and support for clean technology. Despite these measures, the most current GHG reduction projections indicate that under the reference and best-case scenarios, emissions will only decrease between 8% to 17% below 2005 levels, respectively (ECCC, 2019).

Canada has one of the least carbon-intense energy systems in the world due to a high proportion of renewable electricity production (Hughes, 2018; Kennedy, 2015). As such, significant short-term reductions can be realized by switching to more energy-efficient technology (Hughes, 2018) without significantly changing behaviour. However, despite the short-term scope, significant uncertainties associated with policy costs and GHG reductions are still present in complementary GHG abatement analysis (Rissman et al., 2018). To this end, this paper develops an interpretable and transparent inexact linear programming model to support GHG reduction policy decision making. The model optimizes the total cost of energy-efficient-oriented policies under an achievable GHG reduction target, considering GHG emissions and cost uncertainties.

The developed model is formulated for the passenger transportation sub-sector in Ontario and minimizes the policy costs associated with passenger vehicle electrification policies (i.e., electric vehicle (EV) subsidies, EV replacement, and electric transit bus (EB) replacement) under a GHG reduction target for the year 2030. The model incorporates life-cycle (LC) GHG emissions and interval programming techniques to account for some of the uncertainties associated with total-cost-of-ownership (TCO). Through best/worst case scenario analysis, three solutions are generated to represent do-nothing, upper bound, and lower bound scenarios. To the author's knowledge, this is the first study that applies optimization techniques to both modes of passenger transportation (private vehicle and public transit) with the aim of optimizing expenditure related to GHG reduction policy.

2.2. Literature Review

Optimization approaches, namely deterministic and inexact, have been used in literature to support decision-making processes and quantify uncertainties associated GHG mitigation, energy system planning, and policy costs at different scales.

Mustapa and Bekhet (2016) developed a deterministic linear programming model for the Malaysian transportation sector, which estimated the composition of the vehicle fleet that minimizes GHG emissions under fuel price and travel demand constraints. It demonstrated that the removal of existing fuel price subsidies would encourage the uptake of enough fuel-efficient vehicles to enable Malaysia to reach its national 2020 GHG reduction target. Hashim et al. (2005) developed a deterministic mixed-integer linear programming model to optimize the extent of fuel balancing and fuel switching, which in turn minimize the GHG emissions produced by Ontario fossil-fuel electricity generation plants under cost, production, supply, operational, and capacity constraints. Sen et al. (2019) developed a Pareto optimal modelling approach to determine the optimal fleet mix of heavy-duty-trucks (electric, hybrid, and/or fossil-fuel/biofuel) in five U.S. economic sectors based on their LC environmental, economic, and social impacts. The model results showed that the 30% reduction target is infeasible under existing techno-economic circumstances but in the future may be possible with reductions in energy-system carbon intensity. Although the deterministic models developed in these studies have high interpretability, they do not reflect the uncertainties associated with LC GHG emissions, energy system planning, and associated policy cost.

In contrast to deterministic approaches, inexact optimization approaches model the parameters and/or coefficients in objective functions and constraints as non-deterministic, namely through a combination of stochastic, interval, and/or fuzzy-based approaches.

Stochastic approaches are appropriate when decision parameters could be expressed as a probability (chance-constrained) and/or there are multiple stages where the decision made in the previous stage impacts the possible decision in the current stage. For instance, Karan et al., (2016) and (Cristóbal et al., 2013) use stochastic optimization approaches to address uncertainty in GHG emissions and optimal policies in a solar power generation and carbon capture system contexts respectively. Interval approaches can be applied when upper and lower bound solutions are appropriate to derive optimistic and pessimistic solutions (Zeng et al., 2011). Chen et al., (2018) and Li et al., (2011) applied interval programming approaches to optimize energy systems in terms of costs and GHG emissions under a range of policy scenarios. Fuzzy-based approaches are often applied to model the uncertainty when precise data is not available or variable (Rommelfanger, 1996). Tan et al., (2008, 2009) and Martinsen & Krey, (2008) used fuzzy approaches in conjunction with a LC assessment model and a Computable General Equilibrium (CGE) model, respectively, to estimate optimal energy system configurations under flexible (and sometimes contradictory) national environmental targets.

As an extension of previous efforts on the topic of energy planning, GHG mitigation, and policy cost minimization, this study aims to develop an interval integer linear optimization model to estimate the policy cost associated with meeting a GHG reduction target. To the author's knowledge, there is a gap in the literature that applies optimization methods to the cost estimation and policy allocation of EV-related policies within Ontario's passenger transportation sub-sector. This study offers the following two novel contributions:

- Firstly, the costs associated with vehicle fleet efficiency policies are optimized on a per policy unit basis under a fixed GHG emission reduction target.
- Secondly, the uncertainty in policy costs and GHG emission reductions due to TCO, LC emissions and EV sales scenarios are incorporated.

2.3. Methodology

2.3.1. Data Sources: Policy Selection

The study considers four provincial policies, four federal policies, and their respective ten-year costs as listed in Table 2-1**.** In terms of provincial policies, four policies that encourage the uptake of clean technology through different actions are considered in the model: 1) *Battery Electric Vehicle (BEV) incentives* and 2*) Plug-in Hybrid Electric Vehicle (PHEV) incentives* financially encouraging a shift in consumer purchase behaviour, and the 3) *government Battery Electric Vehicle (BEV) replacement* and the 4) *government Battery Electric Bus (BEB) replacement* replace conventional internal combustion vehicles with battery electric vehicles. Additionally, four federal policies that are currently implemented or planned are considered as background emissions reductions. It is assumed that the federal policies come at no cost to the province, and thus only their emissions reduction impact is considered in the model.

The provincial policies represent actions that have been in place or are currently in place in jurisdictions within the province. For instance, Ontario recently cancelled EV incentives in 2018 (Ontario, 2010, 2018), and municipalities have pledged to electrify their municipal light-duty vehicles (LDV) fleets and bus fleets (City of Kingston, 2020; City of Ottawa, 2020; City of Toronto, 2019; Greater Sudbury, 2020).

Table 2-1: Provincial policies, costs, and GHG reduction outcomes and background ongoing federal policies

Provincial Policies				**Background Federal Policies (no associated provincial cost)**		
Policy	Cost	Assumed Outcome	Source	Policy	Assumed Outcome	Source
1. BEV incentive	$3,000 point-of-purchase incentive per BEV	An increase in one BEV and a reduction in one conventional gasoline LDV	(British Columbia, 2019)	1. Carbon price	An increase in the proportion of EV sold and reduction in conventional vehicles use as a result of increased fossil fuel price	(ECCC, 2019)
2. PHEV incentive	$1,500 point-of-purchase incentive per PHEV	An increase in one PHEV and a reduction in one conventional gasoline LDV	(British Columbia, 2019)	2. EV purchase incentives	Additional point-of-purchase incentives will further increase the proportion of EV sold and reduction in gasoline LDV	(ECCC, 2019)
3. Government BEV Replacement	Between $9,000 to $3,000 saved per BEV (compared to conventional gasoline LDV) depending on TCO1	Retire conventional gasoline LDV and replace with BEV	(Lutsey & Nicholas, 2019; Plug'n Drive, 2020)	3.Passenger Automobile and Light Truck Greenhouse Gas Emission Regulations	Incremental reduction in operational emission intensity of gasoline LDV (Model year 2011 to 2025)	(ECCC, 2019)
4.Government BEB Replacement	Between $0 to $76,000 per BEB (compared to conventional diesel bus) depending on TCO2	Retire conventional bus and replace with BEB	(Mohamed et al., 2018; Quarles et al., 2020)	4. Clean Fuel Standard	Incremental reduction in emission intensity of fossil fuel combustion	(ECCC, 2019)

1 includes the price of one charging station
2 includes the price of overnight charging stations (1:2 buses) and on-route charging stations (3:10 buses)
3 includes the total lifetime operation costs ($356k annual salary for operational staff) of an additional bus in addition to the lifetime cost difference between BEB and D.Bus
*** all prices in 2020 CAD**

2.3.2. Data Sources: 2020 and 2030 Vehicle Fleet GHG Emissions

LC GHG emissions associated with the average vehicle in 2020 and 2030 are extracted from Canada's vehicle LC emissions software GHGenius (S&T Squared Consultants Inc., 2018). The model considers LDV and transit buses, as they represent the majority of passenger vehicles on the road (ECCC, 2017). Three vehicle powertrains that reflect dominant and emerging powertrain technologies and energy sources are considered: 1) a conventional option (gasoline for LDV (G.LDV) and diesel for Bus (D.Bus)), 2) a reduced emission option (plug-in hybrid electric vehicle (PHEV) for LDV), and 3) an emerging power sources option (battery electric vehicle (BEV) for LDV and bus (BEB)).

A forecasted LDV (F.LDV) and bus (F.BUS) emission factor is calculated for the vehicle fleet in 2020 and 2030 based on the assumed proportion of vehicle types (i.e. percentage of conventional vehicles and EV). The composition of the F.LDV fleet is forecasted from the historic growth in registered LDV in Ontario and annual EV sales in British Columbia between 2009 to 2019. During this period in British Columbia, only provincial EV purchase incentives were offered and they were similar in value as those currently offered federally (British Columbia, 2019; ECCC, 2019). As such, the level of EV growth under federal incentives in Ontario ('no-provincial-action') is estimated to result in 8% of the LDV fleet being electric by 2030 with 5% being BEV and 3% being PHEV based on historic sales proportions (Statistics Canada, 2019a)). Similarly, the F.BEB is estimated assuming 10% of the conventional bus fleet is replaced with BEB by 2030. LC emissions for all vehicles in 2020 and 2030 are presented in the second column of Table 2-2.

The total number of vehicles in 2030 (FNV) and the number of vehicles sold between 2020 and 2030 (FNS) is forecasted assuming historic growth of registered LDV and LDV sales respectively (Statistics Canada, 2019b, 2019a). The number of government LDV in 2030 is extrapolated from the number of municipal LDV owned in Toronto relative to Ontario's population (City of Toronto, 2020). Similarly, the number of forecasted buses in 2030 is extrapolated from the historic growth of the federal urban bus stock and the proportion of the population in Ontario relative to the national population (Statistics Canada, 2018). FNV, FNS, and associated assumptions are presented in the third and fourth columns of Table 2-2**.**

Lastly, the average VKT for each vehicle type is retrieved from the U.S. Department of Energy and assumed constant for the ten year period (USDOE, 2020). These values are presented in fifth column of Table 2-2**.**

Table 2-2: LC GHG emissions factors, number of vehicles in the fleet, and vehicle kilometres travelled (VKT) in 2020 and 2030

Vehicle Type	***Total LC emissions (EF) (CO_2e g/km)***		**The forecasted number of vehicles in 2030 (*FNV*)**	**The forecasted number of vehicles sales from 2020 to 2030 (*FNS*)**	**Vehicle kilometres travelled (*VKT*) each year**
	2020	*2030*			
G.LDV	-	177.5 [1]	10,300,000 LDV of which 19,000 are government owned [2]	8,760,000 [3]	14,500 [4]
EV	-	45.7 [1]			
PHEV	-	82.4 [1]			
F.LDV	223.7 [1]	168.33 [5]			
D.Bus	-	1768.8 [6]	9,000 Buses [8]	-	43,647 [4]
BEB	-	185.9 [6]			
F.BUS	1794.0 [6]	1610.51 [7]			

[1] GHGenius output for Ontario, target year 2020 and 2030, Gasoline low sulphur LDV, Battery Electric LDV, and PHEV - EV50/Gasoline50km LDV (S&T Squared Consultants Inc, 2018)
[2] Forecasted assuming ten-year historical 16% growth in registered LDV (as seen in 1999-2009 and 2009-2019 (Statistics Canada, 2019b) and extrapolating from the number of municipal light-duty vehicles owned in Toronto (3,800) and its proportional population (20%) compared to Ontario's population (City of Toronto, 2020).
[3] Forecasted from new LDV sales data from 2015-2017 (Statistics Canada, 2019a)**.**
[4] Average VKT driven by bus (USDOE, 2020)
[5] Composition of 'provincial do nothing' fleet in 2030 forecast from historic annual EV sales in BC (2009 – 2019) and federal action estimates (British Columbia, 2019; ECCC, 2019). It assumes that the proportion of EV will grow from 3% annual sales (in 2020) to 15% annual sales in 2030. In 2030, assuming a linear growth in proportional EV sales results in 8% of the vehicle fleet being electric assuming a LC of ten years (i.e. 5% will be EV and 3% will be PHEV based on historic sales proportion, and the remaining are 92% gasoline).
[6] GHGenius output for Canada, target year 2020 and 2030, Gasoline Diesel Bus, and Battery Electric Bus (S&T Squared Consultants Inc, 2018)
[7] Assumed by authors; 10% of conventional buses will be replaced with BEB by 2030
[8] Forecasted from Canada-wide historic urban transit bus stock growth from 2008-2018 assuming number of buses is proportion to the population in Ontario (i.e. 40% of Canada's population) (Statistics Canada, 2018)

2.3.3. Model Configuration

An interval pure-integer programming model is developed to estimate the optimal provincial policy spending to achieve the 30% GHG reduction target within the passenger road transportation sub-sector between 2020 and 2030. The decision variables ($x_1 \dots x_4$) represent integer units of transportation policy: Policy x_1 and x_2 correspond with the units of EV vehicle incentive rebate and policy x_3 and x_4 correspond to the units of EV and BEB the government purchases. The decision variables x_i, their upper and lower cost $C_i^{\pm}$, and the corresponding justification are summarized in Table 2-3**.** The interval linear objective function is shown in Equation 2-1. It should be noted that the model only considers one ten-year time period, from 2020 to 2030.

Table 2-3: Provincial policy actions (decision variables) and associated costs per unit policy

Decision Variable	**Policy cost per unit**		**Justification**	**Data source**
	C_i^-	C_i^+		
x_1= **BEV incentive**	$3,000		British Columbia EV incentive offering	(British Columbia, 2019)
x_2= **PHEV incentive**	$1,500			
x_3 **= Government BEV Replacement**	-$9,000	-$3,000	The difference in TCO between conventional G.LDV and BEV.	(Lutsey & Nicholas, 2019; Plug'n Drive, 2020)
x_4 **= BEB Replacement**	$0	$76,000	The difference in TCO between D.Bus and BEB. Range associated with fuel price, maintenance, and market price uncertainty.	(Mohamed et al., 2018; Quarles et al., 2020)

$$Min\ f^{\pm} = \sum_{i=1}^{4} C_i^{\pm} x_i^{\pm} \quad (2\text{-}1)$$

where f represents the total costs of the four policy over a ten year period, $x_i^{\pm} = \{x_i | x_i^- \leq x_i \leq x_i^+\}$ is the interval decision variable representing the number of unit of policy *i* purchased, i = 1,2,3,4 is the policy index, and $C_i^{\pm}$ is the unit cost of policy i .

The optimization model is subject to the following three groups of constraints:

First, the model is optimized assuming the number of EV purchased over ten years (equivalent to the number of incentives distributed) cannot exceed a target proportion of total new LDV sales. The constraint is simplified in Equation 2-2 to reflect that both the federal and provincial incentives (i.e. the upfront price of the EV is reduced through the federal incentive and an additional $1,500 to $3,000 through the provincial incentive) will result in all registered LDV consisting of 11% (lower bound) to 16% (upper bound) EV in year 2030. These EV proportions are forecasted assuming a linear growth from 3% EV sales in 2020 for both lower and upper bound solutions to 20% and 30% respectively (Statistics Canada, 2019a). The upper bound annual sales proportion represents the 2030 federal target (ECCC, 2019). Additionally, it is assumed that the number of BEV sold in the ten-year period should be double the PHEV sold based on historic consumer vehicle performance (Statistics Canada, 2019a) as summarized in Equation 2-2a.

$$\sum_{i=1}^{3} x_i \leq [11\%, 16\%] * FNS_{LDV} \quad (2\text{-}2)$$

$$x_1 - 2 * x_2 = 0 \quad (2\text{-}2a)$$

where FNS_{LDV} is the forecasted number of LDV sold in the ten-year period (see Table 2-2 for values)

Second, the conversion of the government LDV and bus fleets are assumed not to exceed 80% as represented in Equation 2-3.

$$x_3 \leq 80\% * FNV_{LDV} \quad (2\text{-}3a)$$

$$x_4 \leq 80\% * FNV_{Bus} \quad (2\text{-}3b)$$

where FNV is the forecasted number of vehicles on road in 2030 for LDV and Bus.

Third, the model is optimized under the right-hand side constraint of 24% and 26% GHG reduction targets relative to 2005 levels (i.e. 76% and 74% of 2005 levels respectively). These are the largest possible reduction levels which yield feasible solutions under the lower bound EV sales and upper bound EV sales scenarios, demonstrating that additional policy measures would need to be considered for the sub-sector to reach or exceed the federal 30% GHG reduction target. The right-hand side represents the difference between the annual GHG emissions of the total forecasted vehicle fleet in 2030

(GHG_1) and the lower emission vehicle fleet in 2030 as a result of policy action (GHG_2). The constraint was simplified under the following assumptions and is presented in Equation 2-4:

- GHG_1 represents the forecasted vehicle fleet size and emissions in 2030 as a result of no provincial action (only federal action).
- GHG_2 represents the reduced GHG emissions in 2030 as a result of EV incentives; one EV incentive equals one new EV purchased in lieu of a new G.LDV.
- It is assumed that all policy spending decisions (provincial and federal action) are consistently applied for the full ten-year time period. All coefficients in GHG_1 and GHG_2 are listed in Table 2-2**.**

$$GHG_1 - GHG_2 \leq [74\%, 76\%] * 2005\ CO2\ eq\ Levels \quad (2\text{-}4)$$

$$GHG_1 = EF_{F.LDV} FNV_{LDV} VKT_{LDV} + EF_{F.BUS} FNV_{BUS} VKT_{BUS} \quad (2\text{-}4a)$$

$$GHG_2 = (\textstyle\sum_{i=1}^{3} EF_{G.LDV} x_i VKT_{LDV}) + EF_{D.BUS} x_4 VKT_{BUS} - (\textstyle\sum_{i=1}^{4} EF_i x_i VKT_i) \quad (2\text{-}4b)$$

Where:

$EF =$ average LC emission factor (CO_2e kg/km) for F.LDV, F.Bus, G.LDV, and D.Bus as a result of policy spending *i;*

$FNV =$ forecasted number of vehicles on the road in 2030 for LDV and Bus;

$VKT =$ average kilometres travelled in a year for LDV and Bus.

2.4. Results

The interval integer linear optimization model described in section 2.3 is solved using the best-worst case analysis, and interval solutions to the optimal provincial policies are obtained. The estimated GHG reduction in Ontario's passenger road transportation subsector under 1) provincial actions and 2) no provincial actions are shown in Figure 2-1. Federal actions (described in section 2.3) are considered in both scenarios, and as such, in the scenario with no provincial action, the policy costs are zero for the province.

In the first scenario, the grey bars indicate the most optimal provincial policy allocations considering upper and lower bound EV sales. The model estimated that GHG emissions would be reduced by between 24% to 26% below 2005 levels by 2030 as a result of the four provincial policies considered. In the second scenario, the blue bars indicate that if no provincial policy is implemented (only federal action), the province will only realize a 17% reduction of GHG emissions below 2005 levels in 2030 at no cost to the province.

In both scenarios, achieving the 30% GHG reduction of 2005 levels by 2030 target is infeasible. Results suggest that additional policies and their associated costs and GHG reduction potential should be considered to achieve the GHG reduction target.

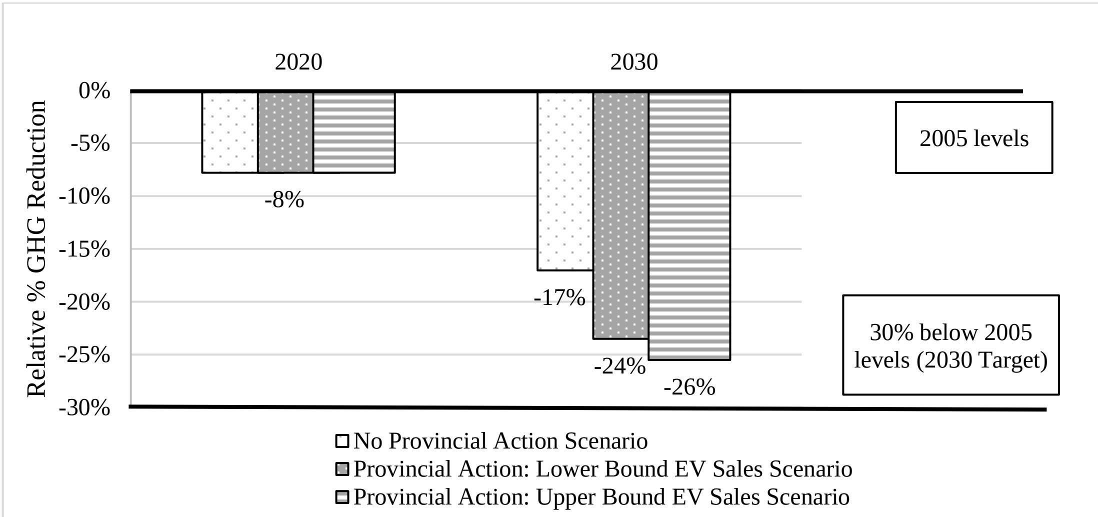

Figure 2-1: Estimated GHG emission reduction in 2030 relative to 2005 levels under policy scenarios

The breakdown of the optimized policy costs and the associated number of policy units that correspond to achieving the 24% to 26% GHG reduction by 2030 is shown in Figure 2-2 . Four scenarios are presented, each corresponding to a combination of upper and lower bound EV sales and TCO as outlined in section 2.3.1.

The two lower bound EV sales scenarios (hatched fill), which refer to lower and upper bound TCO, result in a GHG reduction of 24% by 2030. The two upper bound EV sales solutions (dotted fill), similarly referring to lower and upper bound TCO, achieve a maximum GHG reduction of 26% by 2030. The cost associated with BEV and PHEV incentives does not vary across scenarios as the TCO does not impact the unit cost of incentive offerings nor the number of EV incentives purchased. The TCO differs for the government LDV and bus fleet replacement policies, and as such, the ten-year cost for all four policies considered is between $2.86 and $3.11 billion.

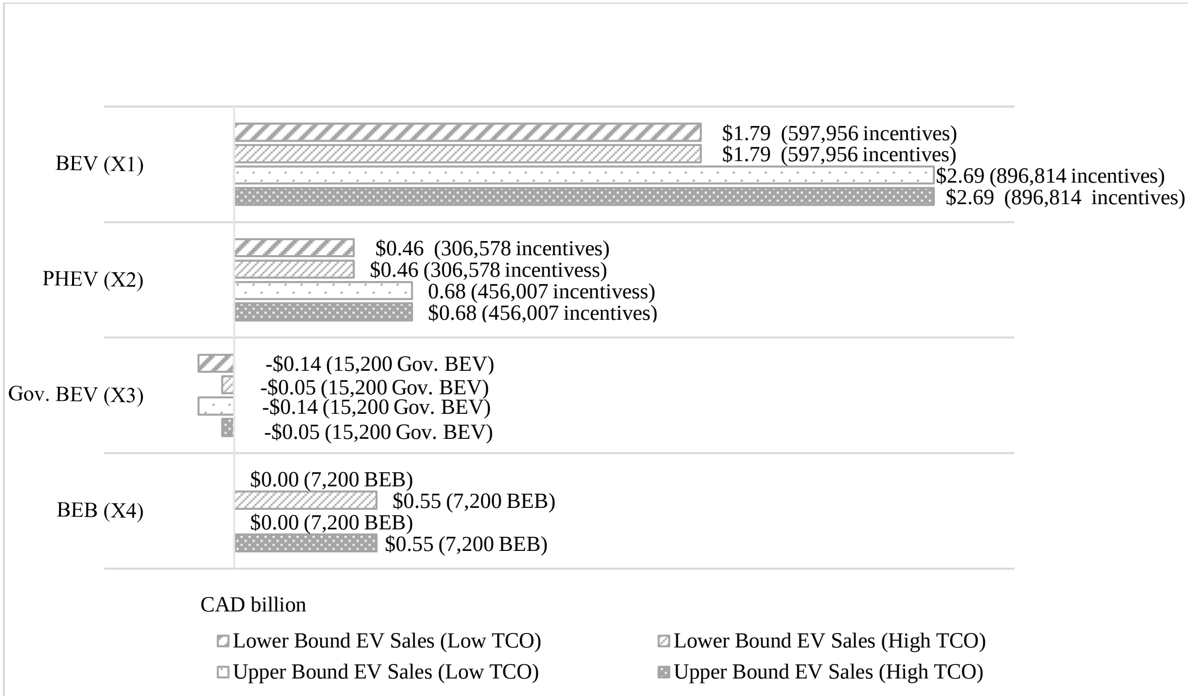

Figure 2-2: Optimized ten year costs, savings, and allocation of GHG reduction policies for all policy scenarios

A summary of the optimized policy units and costs alongside the resulting GHG abatement for all scenarios is presented in Table 2-4. The GHG abatement for the four provincial policies ranges between -$4,709 to $1,088 per tonne of CO_2e reduced. The negative and positive values correspond to the savings and costs per tonne of CO_2e reduced, respectively, for each policy.

As indicated by the GHG abatement values, the least cost-effective policies across all scenarios are BEV and PHEV incentives. The policy cost for each BEV and PHEV incentive is $3,000 and $1,500, respectively. For each incentive, one BEV or PHEV is purchased, and one new conventional gasoline LDV is not purchased; as such, a 74% and 54% reduction in g CO_2e per km results for each BEV and PHEV incentive, respectively.

Consequently, PHEV incentives are 1.4 times more cost-effective than BEV incentives; as model constraints based on historical sales assume that the proportion of PHEV sales are related to BEV sales, the cost-effectiveness of EV incentives are considered together (average $1,329 per tonne of CO_2e reduced).

Conversely, the most cost-effective policies in terms of GHG abatement are the government replacement of LDV and buses. Retiring government LDV and replacing them with BEV instead of conventional gasoline LDV offers GHG abatement savings due to lower TCO and g CO_2e per km emitted compared to conventional gasoline LDV. Retiring conventional buses and replacing them with BEB instead of conventional diesel buses costs between $0 to $72,000 (comparative TCO) and reduces g CO_2e per km emitted by 89%.

Furthermore, it should be noted that the magnitude of GHG reduced by converting government LDV to BEV is relatively low as the number of provincially owned LDV replacements is small compared to purchased personal LDV. However, replacing conventional buses with BEB can reduce GHG emissions by 0.50 MT CO_2e; these savings are approximately a quarter of the GHG reductions, which all scenarios of personal EV sales BEB offset (i.e. 1.6 to 2.3 MT CO_2e).

Table 2-4: GHG abatement costs per policy based on optimized scenarios

Scenarios	Units	GHG Emission Reductions (MT CO2e)	Cost for Policy Units ($ billion)	GHG Abatement ($ / T CO2e Reduced)
BEV incentive (x_1)				
Lower Bound EV Sales (Low TCO)	629,510	1.20	1.89	1,570
Lower Bound EV Sales (High TCO)			1.89	1,570
Upper Bound EV Sales (Low TCO)	863,890	1.65	2.59	1,570
Upper Bound EV Sales (High TCO)			2.59	1,570
PHEV incentive (x_2)				
Lower Bound EV Sales (Low TCO)	314,755	0.43	0.47	1,088
Lower Bound EV Sales (High TCO)			0.47	1,088
Upper Bound EV Sales (Low TCO)	439,535	0.61	0.66	1,088
Upper Bound EV Sales (High TCO)			0.66	1,088
Government BEV Replacement (x_3)				
Lower Bound EV Sales (Low TCO)	15,200	0.03	-0.14	-4,709
Lower Bound EV Sales (High TCO)			-0.05	-1,570
Upper Bound EV Sales (Low TCO)	15,200	0.03	-0.14	-4,709
Upper Bound EV Sales (High TCO)			-0.05	-1,570
BEB Replacement (x_4)				
Lower Bound EV Sales (Low TCO)	7,200	0.50	0.00	0
Lower Bound EV Sales (High TCO)			0.55	1,100
Upper Bound EV Sales (Low TCO)	7,200	0.50	0.00	0
Upper Bound EV Sales (High TCO)			0.55	1,100

2.5. Discussion and Conclusion

Achieving the 30% GHG reduction level compared to 2005 levels by 2030 in the passenger road transportation sector is not feasible under the four short-term provincial policies considered. The largest feasible reduction is between 24% to 26%, with the range depending on if EV annual sales target total of 20% or 30% of all new vehicles in 2030. To achieve the 24% to 26% reduction, the provincial government must spend between **$2.86 to $3.11 billion** over ten years, representing **0.19% - 0.21%** of the annual budget, assuming a $150 billion annual spending on programs (Ontario, 2019) every year for the ten-year period. It should also be noted that the most short-term cost-effective GHG reduction policies are firstly the conversion of provincial LDV and buses to EV and secondly the EV incentives. While these two policies alone are not sufficient to reach the 2030 target, they should be a priority when considering short-term GHG reduction within the transportation sector.

Furthermore, to achieve the 30% GHG emissions target additional policies, which may even be more cost-effective, must be considered. For instance, an *EV sales mandate* is in effect in Quebec in addition to point-of-purchase incentives (Quebec, 2020). The *EV sales mandate* legislates auto dealerships to sell a certain percentage of EV annually, which has been shown to secure consistent supply, a significant deterrent to EV adoption (Melton et al., 2017). Other non-financial methods can also be considered such as increased awareness of EV benefits (i.e. reduced TCO, green plate benefits, access to high-occupancy vehicle lanes, etc.) and continued spending on public charging infrastructure to combat range anxiety (Ferguson et al., 2018; Lin & Greene, 2011; Melton et al., 2017).

Limitations on the estimation of LC GHG emissions also present a degree of uncertainty due to data availability. Manufacturing and fuel production emissions are sourced from GHGenius, a LC emissions tool used by Natural Resources Canada (NRC) (S&T Squared Consultants Inc, 2018). The software forecasts the emissions for the input target year and province, but a detailed methodology is lacking, and a range in estimates is not provided. Emissions produced by E are especially variable as the composition of energy sources differences temporally and across provinces and jurisdictions (CER, 2018).

2.6. Acknowledgment

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Chapter 3. e-Bus, e-Ride-Share or Other Alternative? Passenger-Trip Emission Thresholds for Alternative Technologies

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Abstract

This paper estimates the environmental impact of alternative and conventional transportation technologies across the dimensions of service mode and power source pathway. We simulate the Well-to-Wheel energy consumption and GHG emissions of eight transit buses and passenger car powertrains. Vehicles are simulated under three generalized North American operating contexts (450 operating scenarios) using *Autonomie* and the GREET Well-to-Wheel emission database. All technologies are normalized by passenger-service-mode-trip-km-travelled GHG emissions to facilitate equivalent comparison. The results indicate that all simulated mobility solutions carry a wide variability; however, the most beneficial solution are fuel cell electric car-share, battery electric car-share, and battery-electric bus all powered by low-carbon intensity power sources at average occupancy (7.9-19.7 gCO2e passenger-service-mode-trip-km-travelled^{-1}). Furthermore, transit bus technologies have the potential to reduce up to 2.3 times more GHG per passenger-trip than comparable ride-share technologies. Overall, the occupancy thresholds for environmentally competitive service modes are defined to inform the decision-making process.

Keywords: Well-to-Wheel GHG Emissions; dynamic vehicle simulation; transit bus; ride-share; electric bus; occupancy thresholds.

3.1. Introduction

Passenger transportation decision-makers are challenged with the environmental consequences of motorization. The transportation sector accounts for a significant proportion of globally emitted greenhouse gases (GHG) and criteria air pollutants (CAP) (Anenberg et al., 2019; Solaymani, 2019). Globally, all levels of governments are responding by targeting passenger transportation through the introduction of decarbonization plans. A variety of approaches have been reviewed in the literature, including demoting the reliance on low occupancy vehicles (Amatuni et al., 2020; McQueen et al., 2020; Smargiassi et al., 2020), incentivizing electric powertrain (Kamiya et al., 2019; Xylia et al., 2019), low-carbon power sources (i.e., electric, hybrid, hydrogen, alternative fuels) (Lajunen & Lipman, 2016; Logan et al., 2020; Mahmoud et al., 2016), and the promotion of emerging technologies and service modes (i.e., mobility-as-a-service such as car-share, ride-share, and connected and autonomous vehicles) (T. D. Chen & Kockelman, 2016; Kopelias et al., 2020; T. Liu et al., 2016). These approaches are shown to have a significant bearing on reducing the life-cycle passenger transportation GHG emissions.

However, as transportation power sources and service modes continue to rapidly develop, determining the extent of the environmental benefits associated with the adoption of an electric powertrain, alternative fuel, or alternative service mode (e.g., car-share and ride-share compared to conventional private and public transit) is becoming increasingly complicated, yet fundamental to achieving significant GHG emission reductions.

Literature that assesses the environmental impact of different technologies and service modes has rapidly responded to the increasing interest and complexity of the topic in recent years. From the perspective of passenger road transportation, studies often focus on different technologies within the same service mode; such as comparisons of life-cycle energy consumption and GHG emissions between low-carbon power sources for transit buses (Dreier et al., 2018; Harris et al., 2018; Lajunen & Lipman, 2016; X. Li et al., 2018; Nordelöf et al., 2019; Rupp et al., 2019; Tong et al., 2017), passenger cars operating under private service mode (Ahmadi & Kjeang, 2015; Ambrose et al., 2020; de Souza et al., 2018; Z. Yang et al., 2020), and car- and ride-share service modes (Amatuni et al., 2020; T. D. Chen & Kockelman, 2016; Cramer & Krueger, 2016; Ding et al., 2019; Henao & Marshall, 2019). There have also been efforts to compare transit buses and passenger cars on a passenger kilometer travelled basis (Bouter et al., 2020; Chester & Cano, 2016; Chester & Horvath, 2009; Kolbe, 2019; Logan et al., 2020; Schäfer & Yeh, 2020; Silva, 2013). However, these previous efforts fall short in including operational impacts (e.g., grade, route characteristics, and increased mass due to passenger occupancy), which have been shown to have an impact on energy consumption and GHG emissions (Abdelaty et al., 2021; Abdelaty & Mohamed, 2021; Alam & Hatzopoulou, 2014; Pourahmadiyan et al., 2021; Rosero et al., 2021; Vepsäläinen et al., 2018). Similarly, previous efforts that explore the impact of passenger cars service modes (T. D. Chen & Kockelman, 2016; Henao & Marshall, 2019) have not identified the variation in GHG emissions under different operational conditions, different vehicle power sources, and contrasted findings with conventional transit buses.

This paper aims to bridge the outlined gaps in passenger transportation life-cycle literature by quantifying the emissions of low-carbon technologies across different service modes while accommodating the impact of operating conditions and differences in the trip distance for passengers. We highlight the variability in energy consumption and GHG emissions as a result of operating context (i.e., under a generalized Urban-Low Speed, Urban-Intermediate Speed, and Suburban Speed classifications), power source pathways (i.e., life-cycle gasoline, diesel, alternative fuel, and above and below average carbon-intense electricity generation), and trip length as a result of service mode. We demonstrate that the *most* environmentally beneficial option must be locally determined, and some technologies and service modes are worse than conventional options on a GHG per passenger adjusted kilometre travelled basis.

A dynamic (second-by-second) vehicle simulator is operationalized to produce the energy consumption and average GHG emissions for a variety of passenger cars and transit buses under various: operating contexts (i.e., occupancy, grade, initial battery state of charge (SoC), vehicle power source, and travel routes), powertrains and power source pathways (i.e., gasoline, liquified natural gas, diesel, electricity and hydrogen), and average trip distances of vehicles under different service modes (i.e., private-car, car-share, ride-share, and transit bus). Further, we integrate the concept of passenger-kilometres travelled (PKT), which has been well established in literature to normalize the emission produced by transit buses and passenger cars under different service modes (Schäfer & Yeh, 2020). We go a step further and adjust the trip-level PKT travelled relative to a private passenger car trip-distance through a term named *passenger private car-adjusted kilometre travelled*

(PPCKT) for equivalent comparison across service modes. To the authors' knowledge, no previous efforts have synthesized results across all three categories using a dynamic vehicle simulator to answer the following questions:

1) What are the per passenger GHG emissions associated with private passenger cars, car-sharing, ride-sharing, and transit bus service modes? and;
2) What is the range of break-even passenger occupancies for each technology and service mode relative to a conventional gasoline passenger car that achieves the same emissions levels?

The paper is organized in the following sections. Section 3.2 discusses the relevant literature, emphasizing life-cycle assessment (LCA) models and GHG emissions of different transportation service modes and powertrain technologies. Section 3.3 outlines the data used, the vehicle and emission simulation tools, scenario development and the associated assumptions. Section 3.4 presents the results in terms of energy consumption and well-to-wheel (WTW) GHG emissions per kilometre for each powertrain, initial battery SoC, road grade, and occupancy across three speed classifications. Lastly, in Section 3.5, a discussion of the results is presented across speed classifications and associated break-even values (i.e., occupancies at which one power source and service mode is *more* environmentally detrimental than another). Concluding remarks and avenues for future research are highlighted in Section 3.6.

3.2. A Review of Transportation LCA Models Methods

Life-cycle assessments (LCA) methodologies have received significant attention and have been used to comparatively assess the environmental impact of passenger transportation. LCAs boundaries are often drawn at the fuel-cycle (referred to as Wheel-to-Well (WTW) stage) and report the direct operational emissions (i.e., Pump-to-Wheel (PTW)) and indirect emissions from fuel or electricity generation production and distribution (i.e., Well-to-Pump (WTP)) over the vehicles' lifetime. The WTW assessment, from the perspective of GHG emissions, have been conducted in literature (Dreier et al., 2018; Kamiya et al., 2019; Logan et al., 2020; Pourahmadiyan et al., 2021) and are used by a number of regulatory directives (EU, 2009; U.S. EPA, 2007). Vehicle-cycle boundaries have also been included in studies that consider the environmental impacts of a vehicle's manufacturing, maintenance and/or end-of-life disposal (Ahmadi & Kjeang, 2015; de Souza et al., 2018; Nordelöf et al., 2019; Z. Yang et al., 2020). LCAs with even broader boundaries have been conducted; for example, Chester and Cano (2016) and Chester and Horvath (2009) have considered associated vehicle infrastructure construction and lifetime maintenance in addition to the vehicle- and fuel-cycles.

LCA methodologies have also largely varied with respect to their resolution of input data. A variety of studies utilize average energy consumption and emission factors developed from average power source pathways (Chester & Horvath, 2009; Nordelöf et al., 2019). As noted in the literature, results from studies with average operational or route inputs are more intuitive to interpret but fall short in representing the context-specific emissions (Bigazzi, 2019; Chester & Cano, 2016). These context-specific emissions are especially significant when considering the impact of transportation electrification (Graff Zivin et al., 2014; Kamiya et al., 2019; Logan et al., 2020; Rupp et al., 2019; Wang et al., 2020) and emerging transportation service modes and trends (Ambrose et al., 2020; T. D. Chen & Kockelman, 2016; Wang et al., 2018).

To address this variability, studies have used temporally and/or spatially sensitive input data such as varying scenarios of vehicle technology penetration (Gai et al., 2019), impacts on the change of demand on electricity grids (Kamiya et al., 2019; Logan et al., 2020), and the impact of operational or route characteristics as a result of the introduction of a new technology or service mode (Alam & Hatzopoulou, 2014; Ambrose et al., 2020; Pourahmadiyan et al., 2021; Rosero et al., 2021; Vepsäläinen et al., 2018). Moving away from using single point average data, LCAs which use marginal input data can better capture the variation of estimates associated with the decentralized identity of the passenger road transportation sector. Leveraging data to better inform environmentally sustainable decision-making is fundamental as transformative technologies carry unprecedented uncertainties (Miller & Keoleian, 2015).

3.2.1. The Impacts of Spatial and Temporal LCA Resolution

With respect to the scope of analysis, tools used in LCA literature vary based on spatial resolution. Studies with a national or regional scope often use average fuel-based emission models (e.g., EPA’s GREET, Environment Canada’s GHGenius) to generate WTW based on representative fuel and electricity pathways (Ambrose et al., 2020; Archsmith et al., 2015; Milovanoff, Posen, Saville, et al., 2020). Full LCAs also often consult established databases (e.g., Ecoinvent) on the extraction and production of materials and end-of-life treatment based on average global or multi-regional values as data on a more local spatial scope may be unavailable (Nordelöf et al., 2019; Rupp et al., 2019; Xylia et al., 2019). LCA studies with a regional or city-wide scope source WTP and/or end-of-life and manufacturing data from national or global databases but have taken a network-level approach to more precisely measure PTW emissions. In this respect, they couple vehicle activity data and traffic simulators (e.g., EMME, AIMSUN, VISSIM) with average speed emission factors from established emission models (e.g., EPA's MOVES model, European Environment Agency's COPERT model) (Wang et al., 2018; Xu et al., 2016). Network-level PTW emissions have also been estimated using traffic simulators combined with more computationally intensive second-by-second engine operation emission models (e.g., AVL CRUISE, Passenger Car and Heavy-Duty Emission Model 'PHEM') (Lejri et al., 2018; Samaras et al., 2018).

Furthermore, studies have approached PTW emission estimation from the vehicle-level through energy consumption estimation and emission factors or directly through emission estimation. Studies that estimate emissions through energy consumption models use dynamic vehicle simulators (e.g., Autonomie, ADVISOR, ALPHA Tool, FASTSim, Simcenter Amesim) (Ambrose et al., 2020; Bouter et al., 2020; Dreier et al., 2018; Lajunen & Lipman, 2016; Pourahmadiyan et al., 2021) or empirical data collected through on-board diagnostic (OBD) (He et al., 2018; L. Yang et al., 2016). Energy consumption results are then coupled with the corresponding power source average emission factors (Ambrose et al., 2020; Bouter et al., 2020; Dreier et al., 2018; Lajunen & Lipman, 2016; Pourahmadiyan et al., 2021) or the average-speed emission factors (D. Y. Lee et al., 2019) to generate PTW emissions. Other studies estimate PTW emissions, without energy consumption models, through the utilization of GPS devices to collect empirical driving routes and coupled results with second-by-second emission factors (Alam et al., 2014; He et al., 2018). Studies have also empirically measured PTW emissions using Portable Emission Measurement Systems (PEMS) (He et al., 2018; Hooftman et al., 2016; Rosero et al., 2020; Zhou et al., 2016). Vehicle-level studies which focus on PTW emission estimation capture the variability in emissions and/or energy consumption across different operational conditions (e.g., grade, route characteristic, passenger occupancy, ambient conditions, and charging scenarios). Ultimately, the availability of data and the spatial scope of the LCA, whether national, regional, or vehicle-level, dictate the consulted databases and the operationalized methodology.

3.2.2. GHG Emission Impacts of Passenger Car and Public Transit Service Modes

In addition to the operational conditions of passenger transportation vehicles, the service mode (e.g., passenger car driven as a private vehicle, car-share, or ride-share, and conventional bus transit) have significant impacts on life-cycle emissions. In particular, these different transportation service modes influence trip-level GHG emissions on a per passenger-kilometre travelled (PKT) and vehicle-kilometre travelled (VKT) basis (Amatuni et al., 2020; T. D. Chen & Kockelman, 2016; Cramer & Krueger, 2016; Ding et al., 2019; Henao & Marshall, 2019; Jung & Koo, 2018).

For instance, car-share is emerging as a more flexible and affordable alternative to transit and traditional car ownership. In North America, as of 2018, 40 car-share organizations are operating with over two million members sharing 23,376 vehicles

(Shaheen & Cohen, 2020). These organizations operate one-way programs (i.e., members can pick up a vehicle at one location and drop it off at another) such as Communauto, BlueIndy, and Eco Car Share, and rental cars programs such as Enterprise Holdings, UHaul, and Avis Budget Group's Zipcar brand (Shaheen & Cohen, 2020). As such, research on the topic of car-share from the perspective of GHG emission reduction is a growing topic of research. Chen and Kockelman (2016) conducted a meta-analysis of cradle-to-grave LCA GHG emission savings and found that when a US private vehicle owner shifted to a car-share model, they reduced GHG emissions by 51% relative to a private vehicle PKT. These savings result from a decreased VKT among other variables (i.e., modal shift to transit and/or active transportation, increase fleet fuel economy, lower car ownership, and parking infrastructure needs). However, this work did not include rebound effects such as car manufacturing from a decreased number of owned vehicles (Amatuni et al., 2020) nor did it investigate the implications of electrified powertrains, as more recent studies have included (Ding et al., 2019; Jung & Koo, 2018). It also has been assumed that the occupancy of car-share trips is the same as private car trips (Ding et al., 2019) and, as such, the reduced trip-GHG emissions per PKT is a result of reduced VKT travelled.

In regards to passenger cars used as ride-share services (e.g., Lyft, UberX, LyftLine, and UberPool) instead of private cars, Henao and Marshall (2019) found that ride-share trips in the Denver, Colorado region increased VKT by passenger cars and decreased the occupancy. They concluded that 40.8% of the VKT were deadhead, 46.2% of the miles driven had only one passenger (2 occupants), and 19.0% of travellers would have driven their private vehicle if ride-share was not available (Henao & Marshall, 2019). Similarly, Cramer and Krueger (2016) found that ride-hailing VKT and taxi VKT were 40.3% and 60.1% deadhead on average in Los Angeles and Seattle, respectively. These studies suggest that from an operating perspective, ride-share trips both decrease occupancy and increase VKT (as a result of deadhead distance), thus can contribute to increasing the relative average trip-GHG per PKT.

On the same note, low occupancy buses experience a similar issue as ride-share trips from the perspective of GHG emissions per PKT. For instance, a conventional ICE diesel transit bus with four passengers emits approximately the same fuel-cycle GHG emissions per PKT as a single occupied conventional gasoline SUV as reported by the comprehensive LCA of US passenger transportation modes by Chester (2008). In a recent study, battery-electric buses (BEB), hydrogen fuel cell electric buses (FCEB), and conventional ICE diesel buses with approximately four, nine, and ten passengers respectively emit approximately the same fuel-cycle GHG emissions per PKT as a single occupied conventional ICE gasoline vehicle in the UK in 2017 (Logan et al., 2020). They found that in 2017, a conventional gasoline single-occupied car produces 120 g CO_2e per PKT and buses at 25% occupancy (i.e., 20 passengers) produce 65.2 g CO_2 per PKT, 51.6 g CO_2 per PKT, and 21.2 g CO_2 per PKT, for diesel, FCEB and BEB buses respectively. They anticipate that in 2050, the carbon intensity of electricity and hydrogen production will decline significantly more than the WTW gasoline CO_2 emissions. As such, a conventionally fuelled gasoline vehicle will produce 1.5 times, 13 times, and 55 times less g CO_2 per PKT at 25% occupancy for diesel, FCEB, and BEB. While this study put a renewed focus on the need for the modal shift to public transit and the long-term potential of FCEB and BEB, it does not include the impacts of varied operational conditions nor comparisons across multiple service modes within its scope.

Furthermore, emissions as a result of low bus transit occupancy can be amplified through excess passenger VKT relative to private passenger car VKT. This concept has been measured as *circuity*, a ratio of the mode network and Euclidean distance (i.e., “as the crow flies”) between origin-destination (OD) (Huang & Levinson, 2015; Levinson & El-Geneidy, 2009; Nikel et al., 2020; Zhao & Ubaka, 2004). *Circuity* has been used to assess the performance of a network; for instance, Huang and Levinson (2015) measured the circuity of real and random passenger car and transit OD trips for 35 metropolitan areas in the US. They found that on average, transit trips were more circuitous than if those trips were made by car (i.e., transit and car circuity is 2.19 and 1.15, respectively) (Huang & Levinson, 2015). This comparative transit circuity can infer that, on average, 1.04 more VKT are needed to complete a trip on transit than a car. It can also be inferred that an increase in VKT and low-occupancy within transit buses have the potential to increase GHG emissions on a PKT basis.

Our paper aims to address the following gaps outlined in transportation LCA literature:

- The impact of operational conditions on energy consumption and WTW emissions of different passenger transportation technologies,

- Quantify PPCKT (passenger *private car-adjusted* kilometres travelled) emissions across passenger transportation technologies and service modes to facilitate holistic break-even comparison.

This aim is achieved through energy-consumption-based GHG emission estimation. First, a well-established dynamic (second-by-second) vehicle simulator is used to estimate the PTW energy consumption on a vehicle-level for various ICE, hybrid electric, battery-electric, and fuel cell electric passenger car and transit bus power trains under generalized operating scenarios. The generalized operating scenarios are constructed from significant parameters identified in the literature to reflect representative operating conditions (i.e., drive cycles, road grade, passenger occupancies, and the initial state of battery charge) and service modes (i.e., single occupancy driver, ride-sharing, transit bus) in generalized Urban-Low Speed, Urban-Intermediate Speed, and Suburban-Speed classification operating contexts. Second, the trip and emission factors are then applied to determine the GHG emissions per PPCKT for each service mode and technology. Third, PPCKT results are compared across operating contexts, and the optimal thresholds for environmentally beneficial operation with respect to each transportation mode, service mode, and technology are identified.

Our paper significantly contributes to transportation LCA research in several ways; 1) it utilizes a common unit of measurement to compare several service modes that directly and indirectly compete with one another: private passenger cars, transit buses, car-share passenger cars, and ride-share passenger cars. 2) It combines a dynamic vehicle simulation model with established GHG emission models for the purpose of WTW LCA. 3) It quantifies the variability and uncertainties of associated GHG emissions estimations across various modes and powertrain technologies.

Literature has shown that the PTW emissions from vehicles are variable and context-dependent; this paper demonstrates to what extent this variability influences *which* combination of service modes and technologies and under *what* operating context these service modes and technologies are environmentally beneficial. For policy-makers, this paper provides a clear insight into the environmental benefits associated with different modes of mobility across different technology choices. It also offers a practical framework for a context-specific estimation of life-cycle emissions, which is used to establish environmentally competitive thresholds for different mobility options.

To the authors' knowledge, LCA literature has not previously incorporated operating parameters and a dynamic vehicle simulator to communicate the differences in GHG emissions per PKT (or PPCKT) of private and public service modes and technologies.

3.3. Methodology

Following the objectives of this paper, the methodology is carried out in three sequential steps, as highlighted in Figure 3-1. The LCA boundary is drawn at the fuel-cycle (i.e., WTW GHG emissions). The functional unit is taken as the gram of GHG per one passenger private car adjusted-kilometre travelled (1 g GHG $PPCKT^{-1}$). This functional unit has been derived by LCA literature which used passenger-kilometre-travelled (PKT) to compare passenger car service modes and transit (Chester & Cano, 2016; Hoehne & Chester, 2017). The $PPCKT^{-1}$ unit is discussed in detail in the following subsection.

In this paper, the WTW GHG emissions considered are carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), carbon monoxide (CO), and volatile organic compounds (VOC). CO_2, CH_4, and N_2O most significantly contribute to global warming potential (GWP) (IPCC, 2014), while CO and VOC have indirect contributions and are considered within some GHG emission inventories such as EPA's GREET (Argonne National Laboratory, 2019b). CO_2 equivalent (CO_2e) is also reported as it is a weighted composite of all GHG based on their respective 100-year GWP (IPCC, 2014). The GWP is a standard measure developed to allow comparison across GHG by accounting for their relative impact on climate change under the same time horizon.

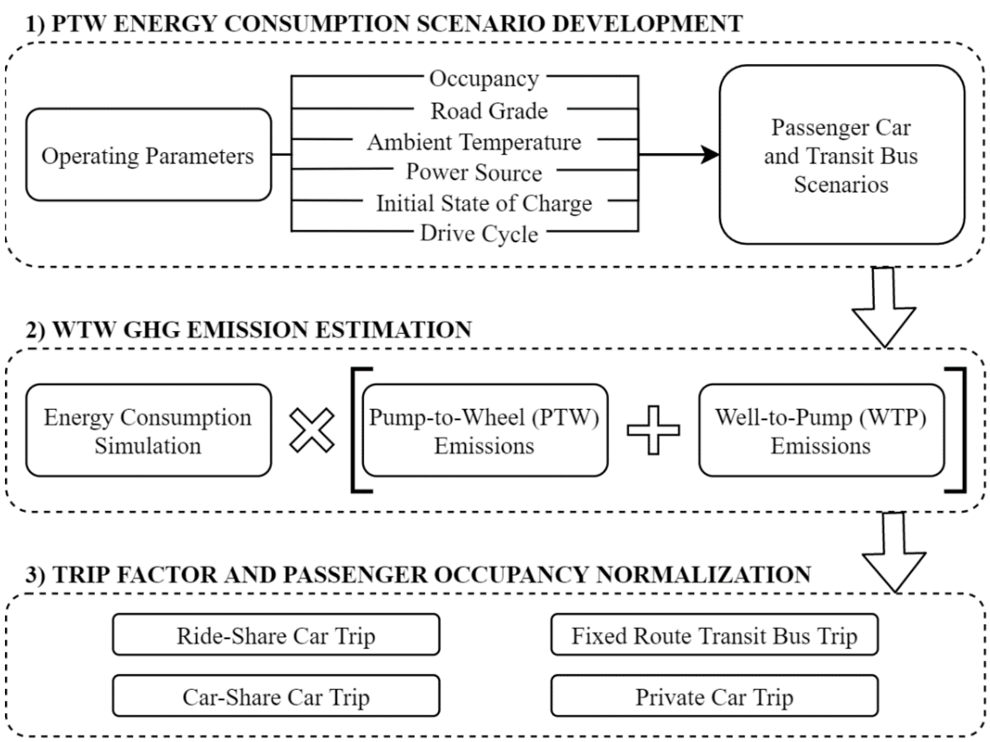


Figure 3-1: Methodological flow chart

3.3.1. PTW Energy Consumption Scenario Development

A full-factorial experimental design of 450 unique operating scenarios is implemented to capture the variation in passenger car and transit bus energy consumption, resulting from varying operating contexts and associated trip-level WTW GHG emissions. The experimental design is generated for three speed classifications across a set of six parameters for the passenger car and transit buses, as detailed in Table 3-1. Each scenario is carried out for three speed classifications to represent different operational contexts, namely: Urban-Low Speed operation, Urban-Intermediate Speed operation, and Suburban Speed operation. The parameters include drive cycles, occupancy, road grade, ambient temperature, propulsion system, and the initial state of charge (SoC).

To generalize the model outcomes, the parameters' values are retrieved from various sources: namely, case-specific and experimental studies (Abdelaty et al., 2021; Abdelaty & Mohamed, 2021; Duarte et al., 2014; Giakoumis & Zachiotis, 2018; Guo et al., 2019; Hoehne & Chester, 2017; Kivekäs et al., 2018; Lajunen & Lipman, 2016; Zhang & Yao, 2015), the U.S. EPA (EPA, 2014, 2018), UNECE test procedures (UNECE, 2014), and the SEA J2711 recommended practice (Huertas et al., 2018).

Together, the operating scenarios reflect the range of typical passenger car operating conditions in a generalized North American context. They do not represent specific operating contexts but instead lay the foundation for quantifying the variation in energy consumption and WTW CO_2e $PPCKT^{-1}$ across different technologies and service modes within these generalized contexts. To generate results at a local level, scenarios that represent local parameters should be used.

Table 3-1: Summary of the operating scenario parameters for passenger car and transit bus by operational context

	Urban – Low Speed Operation		**Urban – Intermediate Speed Operation**		**Suburban Speed Operation**	
Parameters	Passenger Car	Transit Bus	Passenger Car	Transit Bus	Passenger Car	Transit Bus
Drive Cycles	NYC_City	MAN	WTLC CITY	OCTA	HWFET & FTP-72	BEELINE
Occupancy (# of passengers)	1 2 3 4 5	5 15 30 45	1 2 3 4 5	5 15 30 45	1 2 3 4 5	5 15 30 45
Constant Road Grade	-2% 0% 2%	-2% 0% 2%	-2% 0% 2%	-2% 0% 2%	-2% 0% 2%	-2% 0% 2%
Ambient Temperature	20 C	20 C	20 C	20 C	20 C	20 C
Powertrain and Power Source	ICE – Gasoline PHE – Gasoline and Electricity BE – Electricity FCE – C.H2	ICE – Diesel ICE – LNG HE – Diesel BE – Electricity	ICE – Gasoline PHE – Gasoline and Electricity BE – Electricity FCE – C.H2	ICE – Diesel ICE – LNG HE – Diesel BE - Electricity	ICE – Gasoline PHE – Gasoline and Electricity BE – Electricity FCE – C.H2	ICE – Diesel ICE – LNG HE – Diesel BE - Electricity
Initial State of Charge (SoC)[1]	90% 50%	90% 50%	90% 50%	90% 50%	90% 50%	90% 50%
No. of Unique Combinations	90	60	90	60	90	60
Total Scenarios	**450**					

ICE – Internal Combustion Engine
HE – Hybrid Electric Power Split Engine
PHE – Plug-in Hybrid Electric Power Split Engine
BE – Battery Electric
FCE – Fuel Cell Electric
LNG – Liquid Natural Gas
C.H2 – Compressed Natural Gas
[1] Only applicable for BE and PHE

3.3.1.1. Drive Cycles

Energy consumption varies depending on operating conditions (i.e., speed, acceleration, idle time, and stop-frequency) as identified by previous studies (Giakoumis & Zachiotis, 2018; Kivekäs et al., 2018; D. Y. Lee et al., 2019). As such, well-established drive cycles (i.e., second-by-second vehicle speeds on a route) are selected to represent the Urban-Low Speed, Intermediate-Low Speed, and Suburban Speed operations for the passenger car and transit bus scenarios independently (Figure 3-2). To ensure approximately equivalent trip distances for each scenario, all cycles are repeated, in full, to equal or surpass 100 km. It is also assumed that car-share, ride-share, and private passenger car drive cycles operate on the same drive cycles as well-established drive cycles for these service modes are not available in the literature.

The Urban-Low Speed operation is characterized by the New York City Cycle (NYCC) and the Manhattan Bus Cycle (MAN) for the passenger cars and transit buses, respectively. The NYCC simulates extreme urban driving conditions for passenger cars (Giakoumis & Zachiotis, 2018). The MAN cycle is frequently used in Urban-Low Speed transit bus simulation studies (Hoehne & Chester, 2017; Kivekäs et al., 2018; Lajunen & Lipman, 2016) and recommended by SAE J2711 for Urban-Low Speed fuel economy and emissions testing (Huertas et al., 2018). Both cycles exhibit low speeds and high acceleration, higher stop-frequency, and idling times; these parameters reflect stop-and-go urban driving conditions as detailed in Figure 3-2-a (Giakoumis & Zachiotis, 2018; Kivekäs et al., 2018).

The Urban-Intermediate Speed operation features the low and medium phases of the World Harmonized Light Vehicle Test Cycles (WLTC City) for the passenger cars and the US Orange Country Transit Agency Cycle (OCTA) for the transit buses. The WLTC City cycle is reflective of higher-speed real-world urban passenger car driving patterns (Giakoumis & Zachiotis, 2018; Tutuianu et al., 2015). The OCTA is commonly used in transit bus simulation studies (Hoehne & Chester, 2017; Kivekäs et al., 2018; Lajunen & Lipman, 2016) and is recommended by SAE J2711 for Urban-Intermediate Speed testing (Huertas et al., 2018). Both cycles reflect less extreme urban driving conditions in terms of higher speeds and lower acceleration, stop-frequency, and idle percentage (Figure 3-2-b) compared to the Urban-Low Speed cycles.

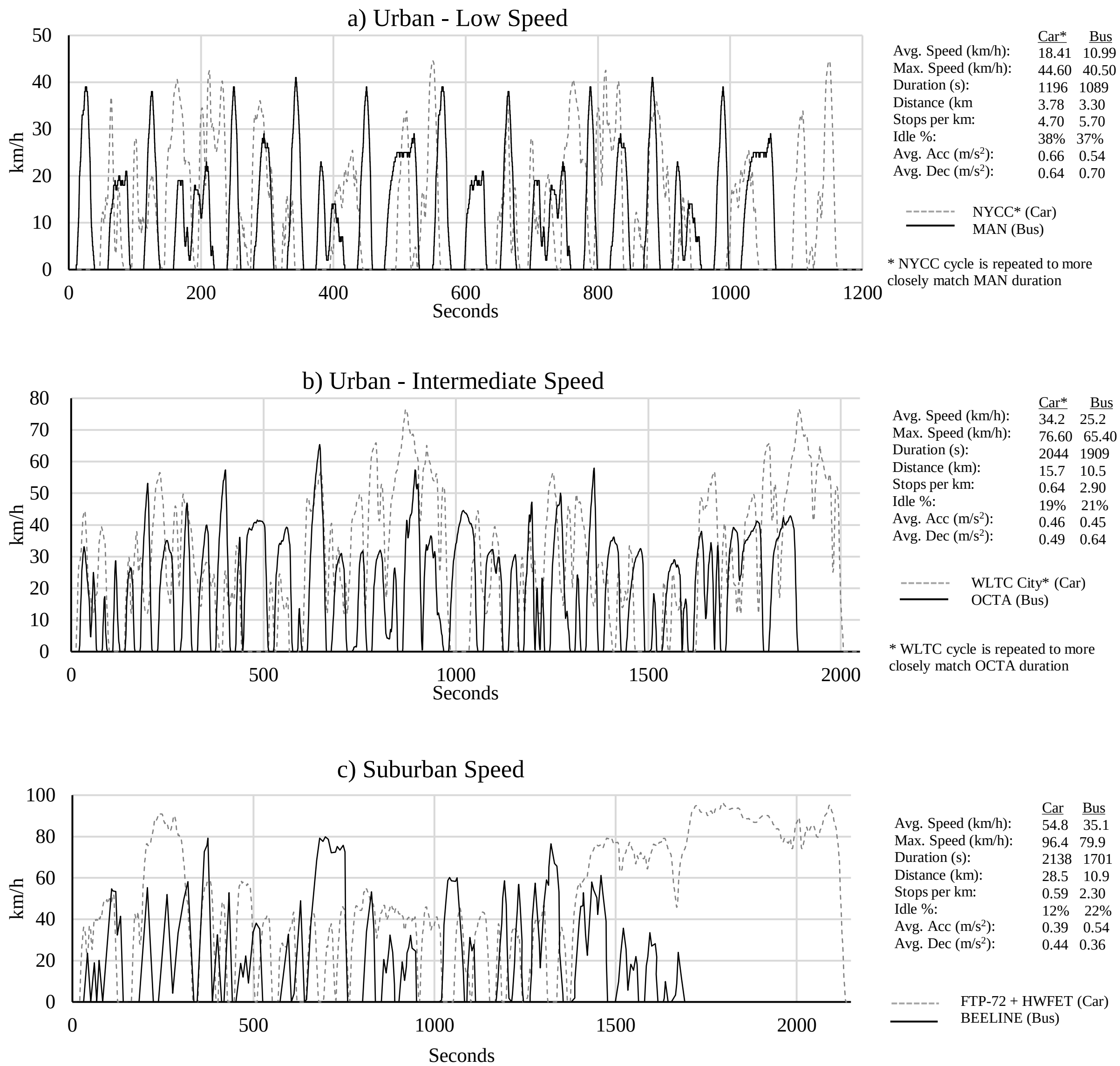


Figure 3-2: Drive cycles for each speed operation classification and vehicle type

The Suburban Speed operation is classified by the U.S. EPA legislated FTP-72 and HWFET for passenger cars (Giakoumis & Zachiotis, 2018) and by New York State's Westchester County's (WC) bus cycle (BEELINE) for transit buses (Sandoval et al., 2012). To more closely reflect suburban passenger car operation, the FTP-72 cycle, which reflects urban driving, is added to the HWFET highway driving segment (Giakoumis & Zachiotis, 2018). The use of both urban and highway drive cycles is not uncommon as LCA literature often assumes a proportion of both operating speeds to represent lifetime light-duty vehicle (LDV) operation (Lombardi et al., 2017). Further, the BEELINE cycle was selected for the transit bus operation as it is based on a real-world higher-speed drive cycle, which is faster than OCTA (Sandoval et al., 2012). The selected Suburban Speed cycles have the highest speeds and lowest acceleration, stop-frequency, and idle percentage among all speed classifications in this paper, as detailed in Figure 3-2-c.

3.3.1.2. Vehicle Power Sources and Initial State of Charge (SoC)

With respect to powertrain technology, the most dominant, transitional, and emerging vehicle power sources were simulated for all scenarios. The simulated passenger car powertrains include gasoline internal combustion engines (ICE), battery-electric (BEV) propulsion, plugin hybrid electric (PHEV) propulsion, and hydrogen fuel cell electric (FCEV). Jaensch & Bantle and (2020) estimates that ICE vehicle sales in the US, the largest vehicle market in North America, will dominate the market beyond 2050. While electrified vehicles, namely BEV and PHEV, will continue to rise in popularity. Hydrogen is also included as a power source in this paper, as literature has pointed to its potential viability as an environmentally sustainable power source (Álvarez & Sergio, 2018; Manoharan et al., 2019) and growing sales in regions within North America (IEA, 2020).

The simulated transit bus power sources include diesel ICE, liquid natural gas (LNG) ICE, full battery electric (BEB), and hybrid electric (HEB). Diesel transit buses are the most dominant power source in North America, but as the pressure to meet sustainability targets increase, lower-emission alternatives such as LNG, BEB and HEB are being considered and rolled out (Ferguson et al., 2019; IEA, 2020; Mahmoud et al., 2016; Song et al., 2017; Sun & Ertz, 2020).

For all battery or battery plug-in electric passenger car and transit bus propulsion scenarios (BEV, PHEV, BEB), two initial battery SoC are simulated. Initial SoC is a significant influential parameter on energy consumption (Abdelaty et al., 2021; Abdelaty & Mohamed, 2021; Duarte et al., 2014; Guo et al., 2019; Zhang & Yao, 2015) and as such, an optimistic 90% and a 50% initial battery SoC are simulated for each propulsion scenario.

3.3.1.3. Occupancy Level, Grade, and Ambient Temperature

Generalized vehicle occupancy, grade, and ambient temperature parameter values supplement the driving cycles and vehicle power source selections to better estimate the energy consumption and emission production variation under the three Speed classifications.

Occupancy values are between 1-5 passengers for passenger car scenarios and 5-45 passengers for transit bus scenarios with passenger weight equaling 68 kg as specified in the Federal Transit Administration (FTA) bus testing procedure (FTA, 2012) for both vehicle scenarios. The range in passengers reflects a variety of vehicle occupancies, which contextualize the Speed Classification and the service mode.

Further, three constant road grade values (-2%, 0%, 2%) and an air temperature of 20°C are utilized to reflect moderate road topology and moderate ambient conditions. These parameters were held constant, as impacts of grade and temperature on fuel economy are outside the paper’s scope.

3.3.2. WTW GHG Emission Estimation

In this paper, the trip-level WTW GHG emission estimation is the product of emission factors, passenger energy consumption, and relative trip distance for the scenario's service mode; these three values, for each scenario, are summarized below and detailed in the following subsections.

With regards to emission factors, the Wheel-To-Pump (WTP) emissions ($EF_{WTP,GHG,S}$) and Pump-to-wheel (PTW) emissions ($EF_{PTW,GHG,S}$) are considered for multiple GHG emissions (CO_2, CH_4, N_2O, CO, VOC, and CO_2e) for each scenario. The WTP emission factors account for the emissions pathway through feedstock production to the transport to vehicle refilling stations, in units of g MJ^{-1} consumed. The PTW emission factors approximate the emissions during average vehicle operation in units of g MJ^{-1} of fuel consumed. It is worth noting that the PTW emissions are only produced by vehicles with an ICE.

Next, the dynamic vehicle simulation is conducted to report the energy consumption (EC_S) during vehicle operation for the 450 scenarios (described in Section 3.3.1.) in MJ km^{-1} consumed. EC_S is then divided by the number of simulated passengers onboard the vehicle (i.e., increased vehicle mass) ($No.pass$) to derive the energy consumed per passenger for the scenario. The average trip distance factor corresponding to the service mode (private, car-share, ride-share, or transit bus) is then selected for each scenario ($TF_{SM,S}$); this factor adjusts the energy consumed per passenger relative to a passenger private car trip distance, and this unit is referred to as passenger private car-adjusted kilometre travelled (PPCKT) throughout the paper.

Ultimately, the product of the emission factors, passenger energy consumption, and trip factors results in the emissions for each GHG and scenario ($\mathrm{E}_{GHG,S}$) in units of grams of GHG PPCKT^{-1} as estimated by Equation 3-1.

$$\mathrm{E}_{GHG,S} = \left(EF_{WTP,GHG,S} + EF_{PTW,GHG,S}\right) * \frac{\mathrm{EC}_S}{No.pass} * TF_{SM,S}$$

Equation 3-1

Where:

- EF is the PTW and WTP GHG emission factors for each scenario (S) in units of grams of GHG MJ^{-1};
- EC is the energy consumed during vehicle operation for each scenario (s) in units of MJ km^{-1};
- $No.pass$ represents the number of simulated passengers onboard the vehicle for each scenario (s); and
- TF is the trip factor for the service mode (SM) for each scenario (S). TF adjusts the trip distance of a private passenger car detailed in Section 3.3.2.3.

3.3.2.1. WTP and PTW Emission Factors (EF)

The power source WTP and PTW emission factors are retrieved from Argonne's Greenhouse gas, Regulated Emissions, and Energy use in Transportation (GREET) model v. 1.3.0. 13656 and a 2020 target year for simulation (Argonne National Laboratory, 2019b). Additionally, the default GWP are used, namely 1, 30, 265, 1.571, and 3.117 for carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O), carbon monoxide (CO), and volatile organic compounds (VOC). Additionally, the reported CO_2 includes biogenic (natural source emission reductions) and land use changes emissions.

Further, EF for each GHG are reported in the unit of mass over energy (g MJ^{-1}) available at the pump and consumed by the vehicle (Table 3-2). The default values from GREET are used for all emission factors (e.g., average U.S. fossil fuel pathway mixes, average regional electricity mixes, and absolute quantities are assumed for EF_{WTP}). The average GREET emission combustion of the default type-2 light-duty vehicle conventional weight and heavy-duty transit bus are assumed for EF_{PTW}.

With respect to electricity and compressed gases hydrogen (G.H_2) power sources, multiple sets of emissions are reported. Emissions from electricity production for a region are dependent on their mix of power generation. For instance, WTP intensities range from 290 g CO_2 e MJ^{-1} for coal-fired plants to almost negligible emissions from hydroelectric power generation (Argonne National Laboratory, 2019b). To capture the variability in electricity mixes between nations, the threshold defined by Kennedy (2015) is used to select national average mixes with emission factors below and above 167g CO_2 e MJ^{-1}. This threshold reflects the carbon intensity at which electrifying transportation may become competitive compared to conventional fossil fuel alternatives (Kennedy, 2015). Consequently, Canada (significantly below), U.S. (moderately below), and China's (above) mixes are selected.

Two pathways for G.H_2 production are considered for light-duty vehicles; one produced from natural gas steam methane reforming (SMR) plants and another through water electrolysis via renewable energy (D. Y. Lee et al., 2018). While natural gas SMR production is the most prominent G.H_2 production method currently, future advancements in carbon capture technology (Ewing et al., 2020) and renewable energy (D. Y. Lee et al., 2018) may increase the viability of electrolysis methods.

Table 3-2: Well-to-Pump (WTP) and Pump-to-Wheel (PTW) emission factors of vehicle power sources in (g MJ^{-1})

Power Sources		CO_2[1]		CH_4		N_2O		CO		VOC		CO_2e	
		WTP	PTW	WTP	PTW	WTP	PTW	WTP	PTW	WTP	PTW	WTP	PTW
Fossil Fuels	Gasoline	17.536	66.962	0.107	0.002	0.002	0.001	0.014	0.587	0.028	0.027	21.446	68.392
	Diesel	12.082	74.910	0.103	0.002	0.000	0.000	0.011	0.017	0.007	0.002	15.255	75.016
	LNG	10.577	55.251	0.290	0.110	0.000	0.000	0.018	0.630	0.007	0.001	19.368	59.543
Electricity	China Mix	190.488	0.000	0.283	0.000	0.003	0.000	0.023	0.000	0.015	0.000	199.864	0.000
	U.S. Mix	111.445	0.000	0.225	0.000	0.002	0.000	0.038	0.000	0.012	0.000	118.752	0.000
	Canada Mix	42.064	0.000	0.079	0.000	0.001	0.000	0.028	0.000	0.005	0.000	47.640	0.000
Compressed Gaseous Hydrogen (H_2)	SMR via Natural Gas	88.464	0.000	0.222	0.000	0.001	0.000	0.020	0.000	0.011	0.000	95.387	0.000
	Via Electrolysis	16.941	0.000	0.035	0.000	0.000	0.000	0.009	0.000	0.003	0.000	18.096	0.000

[1](including land use change and biogenic carbon)

3.3.2.2. Vehicle Energy Consumption (EC)

Autonomie vehicle simulation software is used to simulate the EC_S for each scenario as outlined in Section 3.3.1. Autonomie is a dynamic vehicle simulator developed by the Argonne National Laboratory and the US Department of Energy (Argonne National Laboratory, 2019a) and their default powertrains have been extensively benchmarked in various studies (Namdoo Kim et al., 2013, 2014, 2016; Namwook Kim et al., 2012; D. Lee et al., 2014; Vijayagopal et al., 2018). The default vehicles are developed and sized to represent average powertrain technology in the U.S and are used as-is in this paper aside from changes in vehicle mass and the initial SoC as specified in Table 3-3.

Table 3-3: Specifications of light-duty vehicles and transit bus components

		Passenger Cars				Transit Buses			
		Power Source							
Vehicle Parameters		Gasoline	PHEV	FCEV	BEV	Diesel	LNG	HEB	BEB
Autonomie Name		Small SUV Gasoline Automatic Transmission	PHEV Power Split Midsize Gasoline	Phev20_fuel_cell_midsize_auto_manual_trans	Electric Midsize 200 Mile Range fixed gear Transmission	Conv class 8 Transit bus	Conv class_8 Transit_bus w/ LNG Engine	HEV Parallel Pre-Transmission class8_transitbus	BEV class 8 transit bus
Curb Weight (kg)		1609	1681	1784	1956	10806	11269	13600	15717
Drag Coefficient		0.356	0.311	0.311	0.311	0.65	0.65	0.65	0.65
Frontal Area (m^2)		2.841	2.372	2.372	2.372	7.33	7.33	7.33	7.33
Wheel Radius (m)		0.3413	0.3014	0.3014	0.3014	0.4655	0.4655	0.4655	0.4655
Rolling Resistance		0.0084	0.008	0.008	0.008	0.008	0.008	0.008	0.008
Max Power (kW)	Engine	140 kW (Spark Ignition)	98 kW (Spark Ignition)	-	-	209 kW (6 Compression Ignition)	224 kW (Compression Ignition)	172 kW (Compression Ignition)	-
	Electric Motor 1	-	68 kW	115 kW	155 kW	-	-	114 kW	374 kW
	Electric Motor 2	-	57 kW	-	-	-	-	-	-
	Fuel Cell	-	-	96 kW (21 L Tank)	-	-	-	-	-
Battery	Configuration	-	Li 41 Ah cells, 60 cells in series in a pack, 1 pack in parallel	Li 41 Ah cells, 60 cells in series in a pack, 1 pack in parallel	Li 41 Ah cells, 165 cells in series in a pack, 2 packs in parallel	-	-	Li 4 Ah cells, 79 cells in series in a pack, 8 packs in parallel	Li 66 Ah cells, 144 cells in series in a pack (2 cells in ultracapacitor pack connected in parallel), 25 packs in parallel
	Total Voltage (V)	-	216 V	216 V	594 V	-	-	285 V	540 V
	Total Capacity (kWh)	-	8.8 kWh	8.8 kWh	48.7 kWh	-	-	9.1 kWh	446 kWh
	SoC Window (%)	-	90%-20%	90%-20%	99%-4%	-	-	70-50%	90-20%
Constant Electrical Accessory Load (kW)		0.2 kW	0.2 kW	0.2 kW	0.5 kW	5 kW	5 kW	6 kW	10 kW
Transmission		6 speed, Automatic	Power Split, Automatic	2 Gear Automated Manual	1-Speed Fixed Drive, Automatic	6 speed, Automatic	6 speed, Automatic	Parallel Pre-Transmission, Automatic	1-Speed Fixed Drive, Automatic
Final Drive		3.51	4.059	4.44	3.02	5.13	5.13	5.4341	4.704

With respect to default passenger car selection, the small SUV and a midsize vehicle size class are chosen for the gasoline and electric power sources, respectively. Global passenger car sales data indicates that small sport utility vehicles (SUVs) represent the largest vehicle market share category (IEA, 2019). As such, the small SUV spark ignition gasoline vehicle model in Autonomie is selected to represent the conventional power source. For emerging and transitional power source vehicles, the midsize vehicle model is selected to represent the BEV, FCEV, and PHEV as the category represents the highest proportion of electrified market share sales (IEA, 2020), with the Tesla Model 3, Honda Clarity, and the Toyota Plug-in Prius being the most sold vehicle in their power source category in 2019 respectively (Gohlke & Zhou, 2020; IEA, 2020).

The Gasoline, BEV, and PHEV powertrains used in this paper have been validated against OEM data to ensure accurate energy consumption (Namdoo Kim et al., 2014, 2016; D. Lee et al., 2014), while the algorithm and case studies for the FCEV is not derived from test data due to lack of availability as detailed in past publications (Moawad et al., 2012; Pagerit et al., 2005). The default vehicles do not represent specific vehicles, rather, they represent the average vehicles with the highest U.S. market share within that vehicle size category and powertrain configuration.

For transit buses, the default transit bus vehicles from Autonomie, which are based on the chassis of a Nova Bus LFS 40 ft (Vijayagopal et al., 2018), were selected for the Diesel, BEB, LNGB, and HEB. Transit buses are predominately fuelled by diesel, emerging propulsion is BEB, and a portion of transitional vehicles are fueled by LNG or are HEB (APTA, 2020; CUTA, 2014). The diesel and BEB vehicles are simulated as-is. The LNG vehicle is based on the diesel model with two modifications: the default diesel engine was swapped for the LNG engine (available in the initialization file library), and the curb weight was adjusted to reflect the increased mass. The HEB vehicle weight was adjusted to reflect the curb weight of the Hybrid-Electric Nova Bus LA94 (PTI, 2019). While these powertrain algorithms have not been validated against OEM data, they have been detailed and reported in previous publications (D. Y. Lee et al., 2019; Vijayagopal et al., 2018).

The output of the simulations reports the energy consumption in terms of fuel or electricity per distance. To represent all power sources on a common unit, all power sources are converted to the unit of a litre of gasoline-equivalent (L_e 100 km^{-1}) by their heat content (Table 3-4).

Table 3-4: Heating values and litre of gasoline-equivalent (Le/100km) conversion for all power sources

Power Source	**Heat Content**[1]	**Conversion**	**Source**
Gasoline	34.8 MJ/L	1 L = 1 L_e	(Davis & Boundy, 2021)
Electricity	3.60 kWh/L	9.68 kWh[2] = 1 L_e	
Compressed Hydrogen	10.0 MJ/L (142 MJ/kg)	3.48 kg = 1 L_e	
Diesel	38.6 MJ/L	0.901 L = 1 L_e	
LNG	23.6 MJ/L	1.47 L = 1 L_e	

[1]Higher heating value (HHV), also known as gross energy intensities, are used, as done by the Energy Information Administration (EIA) (Davis & Boundy, 2021)
[2]value reflects energy content of gasoline in units of kWh, it does not account for electricity generation and distributional efficiency

3.3.2.3. *Service Mode Trip Factors (TF)*

The defined trip factors (TF) aim to normalize the VKT for each vehicle under the corresponding service mode to ensure an equivalent comparison of the vehicle's WTW grams of GHG $PPCKT^{-1}$ from a trip perspective. Table 3-5 displays the TF for each service mode relative to the shortest path of a private passenger car trip and source. Specifically, the private passenger car trip is 1.0, and all other modes are above or below 1.0 if their average and equivalent VKT for the trip is more or less than the private passenger car trip.

Table 3-5: Trip factors for each service mode

Service Mode	Trip Factor (Relative to Private Passenger Car Trip)	Source
Private Passenger Car	1.0	Base model
Car-Share Passenger Car	0.6	(T. D. Chen & Kockelman, 2016)
Ride-Share Passenger Car	1.5	(Cramer & Krueger, 2016; Henao & Marshall, 2019)
Conventional Fixed Route Transit Bus	1.2	(Huang & Levinson, 2015)

Comparative TF based on VKT for car-share, ride-share, and bus transit trips are derived from reviewed literature. More specifically, the reduction in VKT as a result of passenger car-sharing (relative to private passenger car ownership) was retrieved from the meta-analysis of cradle-to-grave LCA GHG emissions conducted by Chen and Kockelman (2016). The passenger ride-sharing trip factor was inferred and averaged from two studies, one which reported that 40.8% of the distance driven by ride-share were deadhead (i.e., only one driver, no occupant) and another reported 40.3% and 60.1% deadhead distance travelled (Cramer & Krueger, 2016; Henao & Marshall, 2019). The bus transit trip factor was selected from Huang and Levinson (2015) study of the circuity of urban transit and passenger car trips. They found that, on average, real transit trips were more circuitous (less similar to the Euclidean distance) compared to the same trips made by car. It should be noted that transit trips in the Huang and Levinson (2015) study includes bus, light rail, and commuter rail. Therefore, in the present paper, an average circuity of real transit trips for six metropolitan areas with bus-only systems (three multi-destination and three radial service orientation), as specified by Brown & Thompson (2008), are selected.

3.4. Results

3.4.1. PTW Energy Consumption

The PTW energy consumption for all operating contexts, power sources, and constant grades (-2%, 0%, and 2%) across all passenger car and transit bus powertrains is reported in litre gasoline-equivalent (L_e) per 100 km in Figure 3-3. Energy consumption is converted to L_e by the corresponding heat content of the power source as described in Section 3.3.2.2. Results for constant grades of -2% (orange), 0% (grey), and +2% (yellow) are depicted with error bars reflecting the standard deviation for all vehicle simulation weights.

In addition to this, the results indicate that the drive cycle significantly influences energy consumption, with Urban-Intermediate Speed and Suburban Speed operating contexts resulting in 40% lower energy consumption on average than Urban-Low Speed operating context across all powertrains and grades. For all scenarios, the grade has the most severe impact on the energy consumption: with 51%-78% absolute difference in energy consumption for passenger cars and 32%-48% difference for buses relative to 0% constant grade across all operating contexts. Electric powertrains (BEB, PHEV, BEV) are most impacted by grade, with a 53%-78% absolute difference compared to a 16%-28% absolute difference in ICE powertrains relative to 0% constant grade across all operating contexts. The results for all scenarios in L_e 100 km^{-1} and in MJ 100 km^{-1} are available in the supplemental data.

Overall, L_e $100km^{-1}$ significantly varies across operating conditions and varies at different magnitudes for different powertrains as echoed by the literature: Dreier et al. (2018) found that PTW simulated energy use for conventional, biofuel, HEB, and plug-in hybrid bus in the BRT system in Curitiba, Brazil by up to 77% depending on drive cycle, powertrain, vehicle type and occupancy. Further, Lajunen & Lipman (2016) highlighted the energy consumption and WTW GHG emission variation on six routes for ICE, hybrid, and electric bus powertrains. While Abdelaty & Mohamed (2021) indicated that grade and stops per km have the greatest influence on the energy consumption of BEBs. Along the same lines, Yang et al. (2020) found that driving speed (i.e., highway driving, urban, or mixed) has a differing impact on electric and ICE passenger cars.

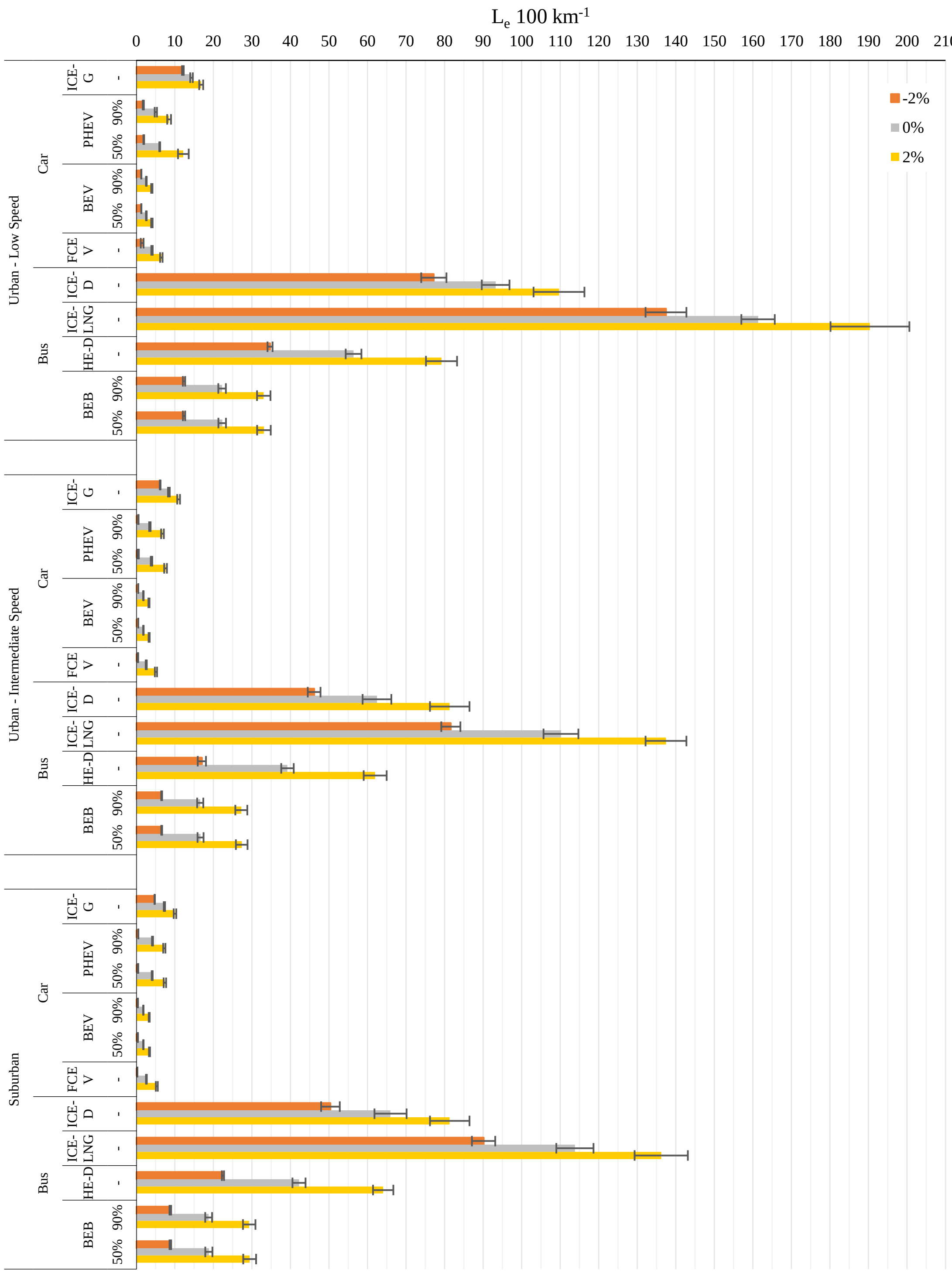


Figure 3-3: Litre of gasoline-equivalent (L_e) per 100km for simulated passenger car and transit bus technologies under grade and Urban, Urban-Intermediate, and Suburban Speed operating contexts.

3.4.2. WTW GHG Emissions

Based on the PTW energy consumption for each scenario summarized in Figure and the WTW GWP-weighted GHG emissions per km for each passenger car and transit bus powertrain and the power source is summarized across operating contexts in Figure 3-4.

The average CO_2e emissions (i.e., sum of all five GWP-weighted GHG emissions) for all grade, initial SoC (if applicable), and weight scenarios are averaged, and corresponding error bars represent the standard deviation. Three electricity grid mixes, two hydrogen fuel pathways, and one fossil-fuel pathway for each fuel are shown.

The results clearly demonstrate that CO_2 (Red) is the dominant GWP-weighted GHG emissions among technologies and power source pathways (93%), CH_4 (Green) is the second most dominant (6%), and N_2O (Purple), CO (Blue), and VOC (Orange) are all less than 1%.

From the perspective of WTW GHG emissions, PTW energy consumption varies across operating contexts, as seen in Figure 3-3. However, WTW GHG emissions also vary across the additional dimension of the power source pathway. This variation especially impacts electric powertrains where the CO_2e km^{-1} produced by BEV and PHEV under a US mix (moderately below the threshold identified by Kennedy (2015)) is 166% greater than Canada mix (significantly below the threshold), while China's mix (above the threshold) is 347% greater than Canada's mix across all operating contexts.

On a similar note, the difference in the hydrogen production SMR natural gas pathway for the FCEV is 427% greater on average across all operating contexts than the hydrogen production electrolysis-renewable electricity production pathway. This difference is not trivial as it determines if FCEV is more or less competitive, on a CO_2e km^{-1} basis, than a BEV powered by US electricity mix (when considering SMR natural gas production) or BEV powered by the Canadian electricity mix (when considering electrolysis) under average grade and occupancies. For instance, the FCEV powered by hydrogen SMR natural gas pathway is more CO_2e km^{-1} intense than the BEV powered by US electricity mix. This trend is contrary to what is observed if only considering the g CO_2e MJ^{-1} produced by the associated WTP hydrogen production pathway, which is less carbon intense than the US electricity mix (Table 3-2). However, as BEV has a sufficiently lower L_e $100km^{-1}$ compared to FCEV (Figure 3-3) the resulting WTW g CO_2e km^{-1} is more environmentally competitive despite the higher carbon intensity power source pathway. This is not the case with BEV powered by Canada's electricity mix, where the carbon intensity of the electricity pathway is significantly *more* carbon intense than a FCEV powered by renewable energy electrolysis; as such, the higher relative energy consumption (L_e 100 km^{-1}) of the FCEV is overcome by the relatively low carbon intensity of its pathway making it the most environmentally competitive passenger car in WTW g CO_2e km^{-1}

Furthermore, normalizing energy consumption through GWP-weighted GHG emissions reveals insights on the choice of fuel for ICE powertrains and on the differences in Suburban and Urban-Intermediate operation between passenger cars and buses. For instance, despite LNG bus producing less CO_2e overall compared to conventionally used diesel bus, LNG produces more CH_4 per km^{-1}. This is a result of a 181% more CH_4 intense WTP pathway and a 39% lower heat content compared to diesel, and this finding is recently echoed in a WTW analysis of diesel, LNG, and CNG buses (Pourahmadiyan et al., 2021).

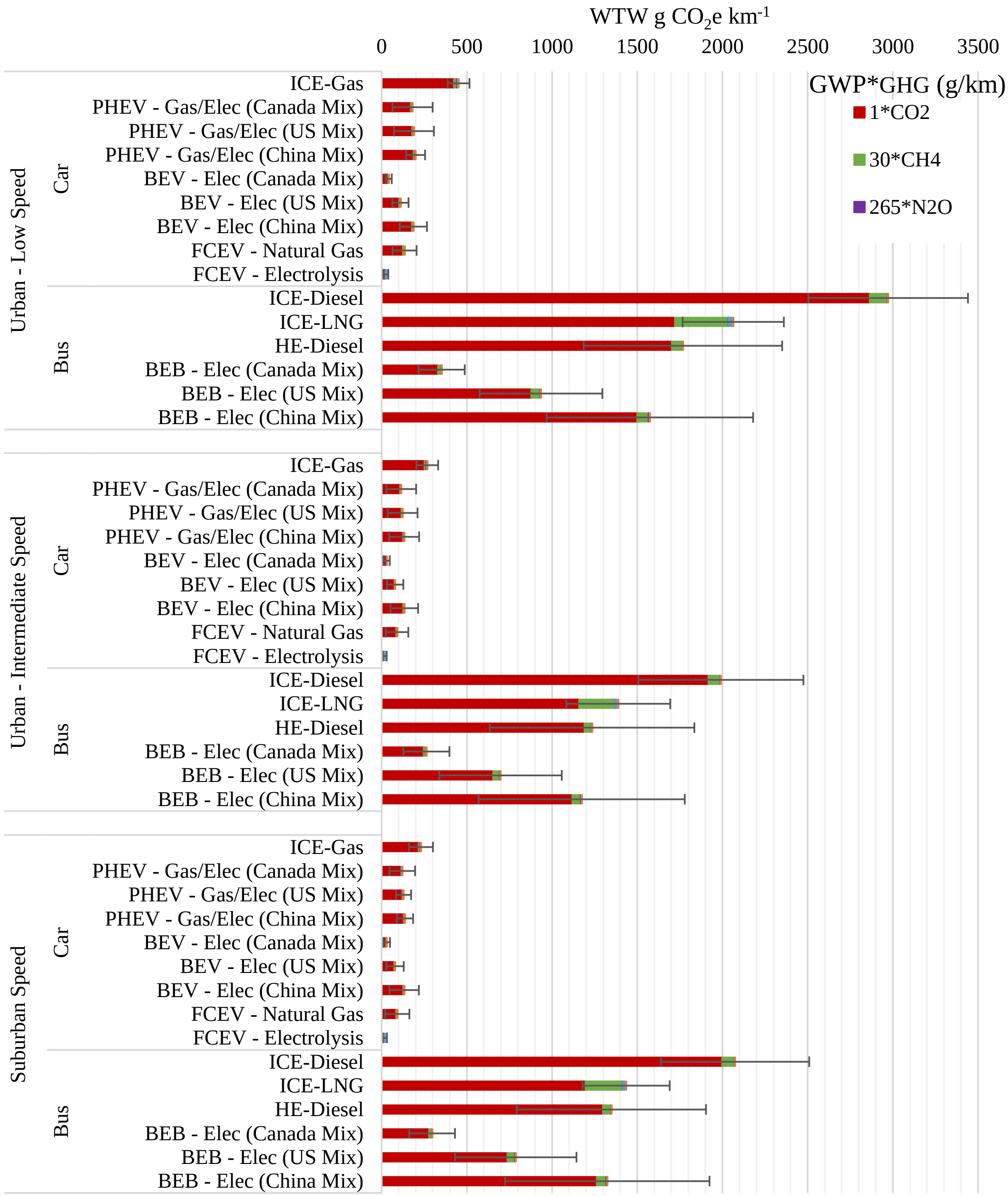


Figure 3-4: Average WTW CO_{2e} g per km for each powertrain technology under Urban-Low Speed, Urban-Intermediate Speed, and Suburban Speed operating context.

The GWP-weighted GHG emission results also reveal that suburban buses produce slightly more emissions than buses operating under the Urban-Intermediate context. However, almost all suburban passenger car powertrain types produce slightly less emission than under Urban-Intermediate operating contexts. This variation is a result of drive cycle selection, in which the Suburban operating context contains a portion of highway driving for passenger cars which is more efficient on a km basis (Z. Yang et al., 2020), while suburban buses have slightly higher speeds and fewer stops per km relative to the Urban-Intermediate Speed context which does not have a significant impact on relative energy consumption. Refer to the WTP and PTW GHG emission data available in the supplemental data for results for all vehicle technologies.

3.4.3. Passenger Private Car-Adjusted Kilometres Travelled WTW GHG Emission Thresholds

From the average CO_2e km^{-1} results visualized in Figure 3-4, Figure 3-5 depicts the WTW g CO_2e $PPCKT^{-1}$ for each operating context, at different occupancy percentages, for select powertrains, power sources, and bus and passenger car service modes. The passenger occupancy percentages reflect the g CO_2e $PPCKT^{-1}$ at the corresponding vehicle occupancy. Private and car-share passenger car service modes have an occupancy range between 1 to 5 passengers, ride-share passenger car service mode has a range between 1 to 4 passengers, and bus service mode has a value of 5, 15, 30 or 45 passengers. As described in Section 3.3.2.3, a trip factor corresponding to trip-level VKT is assigned to each service mode and three transit buses (Diesel bus (dark green), BEB powered by Canada's electricity mix (light green), and BEB powered by China's electricity mix (medium green)) under conventional transit service mode, ICE gasoline passenger car (orange), and BEV passenger car powered by Canada's electricity mix (red) under car-share, ride-share, and private service mode are depicted.

It is worth reiterating that the trip factors serve to reflect the difference in g CO_2e $PPCKT^{-1}$ as a result of average increased or decreased VKT associated with a trip of a specific service mode, relative to a private passenger car. Overall, to contextualize the g CO_2e $PPCKT^{-1}$ at different occupancies, an average occupancy reported in the literature for each service mode is also visualized (square point). For ride-share (which takes into account deadhead VKT and increased VKT due to mode replacement), car-share, and private car this is 1.3 passengers (Ding et al., 2019; Henao & Marshall, 2019), and for transit is 15 passengers is assumed based on the average ridership ranges in North America.

Figure 3-5 visually depicts at which occupancy levels diesel bus, BEB (Canada electricity mix), BEB (China electricity mix), gasoline ICE private car, gasoline ICE ride-share, and gasoline ICE car-share are environmentally competitive from a trip-level perspective. Different competitive thresholds exist for all three operating contexts.

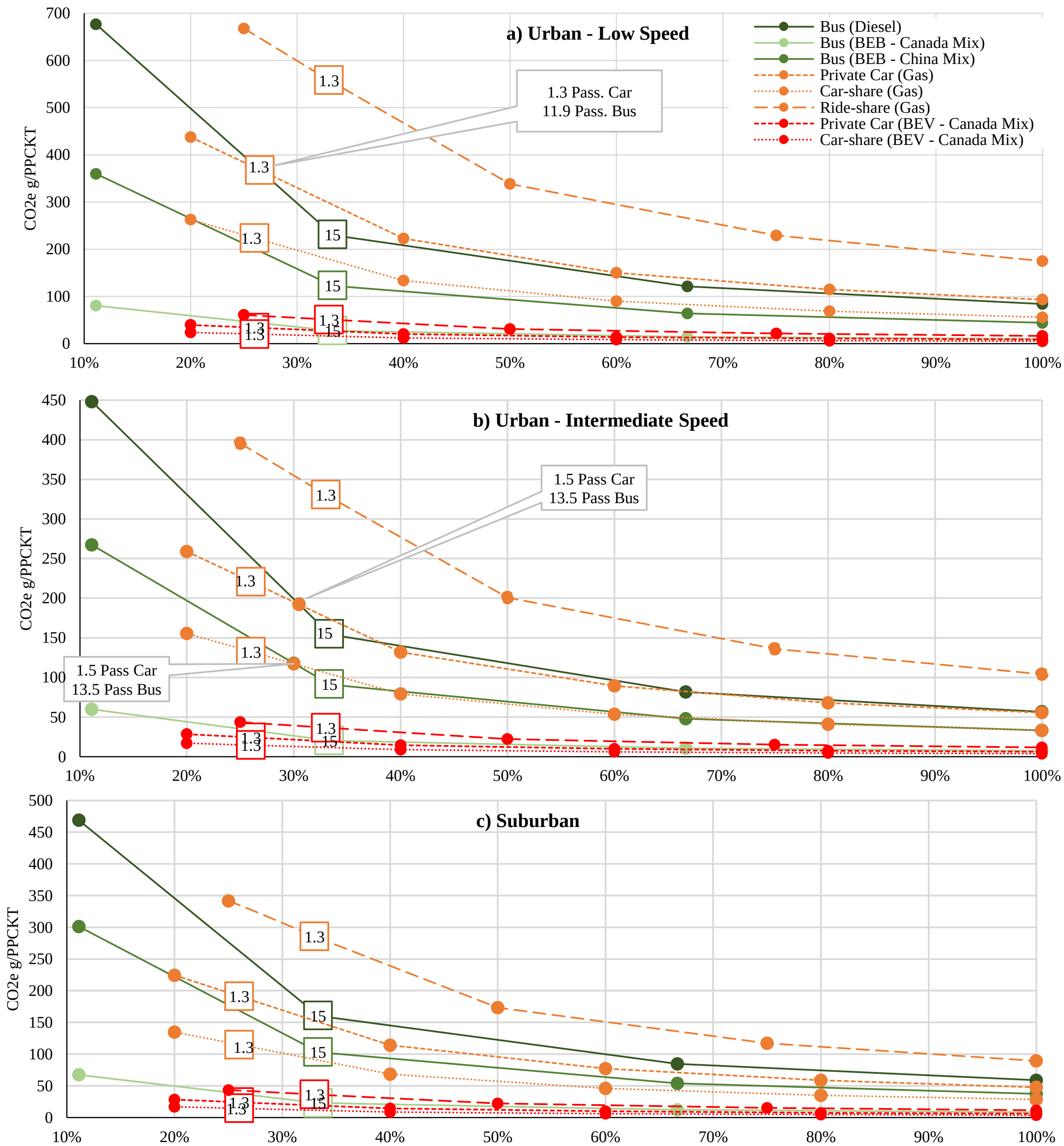
With respect to the Urban-Low Speed scenarios (Figure 3-5-a), the following findings are notable: 1) Gasoline ICE ride-share is always more carbon-intense, at the same relative occupancy percentages than all other vehicles technologies; this is a result of the higher energy consumption urban drive cycles and the increased VKT and decreased passenger occupancy associated with ride-share service mode; 2) At 27% occupancy, a gasoline-ICE private car (1.3 passengers) produces the same amount of g CO_2e $PPCKT^{-1}$

as a diesel bus (11.9 passengers). At greater occupancies, gasoline-ICE private car surpasses the g CO_2e $PPCKT^{-1}$ produced at the same occupancy percentage, relative to a diesel bus; 3) Gasoline ICE car-share and BEB (China electricity mix) have similar CO_2e $PPCKT^{-1}$ intensity though Gasoline car-share is more carbon intense at all relative occupancies; 4) Lastly, all BEV (Canada electricity mix) service modes and BEB are the least CO_2e $PPCKT^{-1}$ intense. BEB is always more carbon intense than private and car-share BEV at the same occupancy percentage and is always *less* carbon intense than ride-share BEV. The Urban-Intermediate Speed scenarios (Figure 3-5-b) depict similar trends as the Urban-Low Speed scenarios at different magnitudes.

Under the Suburban Speed scenarios (Figure 3-5-c), the following differences between the Urban-Intermediate speed operating scenarios are noted: 1) relative to the transit buses, gasoline-ICE passenger cars are less carbon-intense in Suburban scenarios than in Urban scenarios. This difference can be attributed to more energy consumption efficient (L_e 100 km^{-1}) highway driving seen in suburban drive cycle for the passenger car, while the energy consumption efficiency is transit bus (L_e 100 km^{-1}) are relatively similar between Urban-Intermediate and Suburban. Despite this, Gasoline ICE ride-share is still the most CO_2e $PPCKT^{-1}$ intense option at all relative occupancy percentages, but BEB (China electricity mix) has a higher CO_2e $PPCKT^{-1}$ intensity than gasoline-ICE car-share (instead of being similar or lower intensity in Urban scenarios) at relative occupancy percentages; 2) the electric powertrains are relatively comparable to Urban-Intermediate Speed scenarios.

In addition to the analysis of CO_2e $PPCKT^{-1}$ at comparative occupancies, Figure can also be evaluated based on fixed passenger occupancies by drawing a horizontal line from the average occupancy g CO_2e $PPCKT^{-1}$ of the service mode and powertrain of interest until it intersects with the comparative service mode and powertrain of interest. One can then compare the resulting g CO_2e $PPCKT^{-1}$ of that comparative service mode and powertrain technology and determine if it is higher or lower. From this perspective, considering the Urban-Low Speed operating context (Figure 3-5-a), the following can be noted: 1) a diesel bus with 15 passengers produces 231g CO_2e $PPCKT^{-1}$ and a gasoline ride-share passenger car requires an average of at least three passengers to produce a similar or more competitive g CO_2e $PPCKT^{-1}$. As ride-share has an average occupancy of 1.3 passengers, gasoline ICE ride-share trips are on average 2.4 times more g CO_2e $PPCKT^{-1}$ intense (558 g CO_2e $PPCKT^{-1}$) than average occupancy diesel buses and are thus *not* environmentally competitive under the assumed occupancies; 2) When comparing another set of vehicle power sources, namely BEB (Canada electricity mix) and BEV (Canada electricity mix) ride-share, the ride-share service mode is still not environmentally competitive at the assumed average occupancies. The average 15 passenger BEB produces a similar g CO_2e $PPCKT^{-1}$ (27 g CO_2e $PPCKT^{-1}$) only when the occupancy of the BEV ride-share is at 2.4 passengers (60% occupancy), which is above the average ride-share occupancy of 1.3 passengers. Thus, a BEV ride-share produces 1.8 times more CO_2e $PPCKT^{-1}$ than an average occupancy BEB. This indicates that both ride-share as a BEV or gasoline ICE car are *not* environmentally competitive compared to a BEB and a diesel bus, respectively, within the Urban-Low Speed operating context. These trends hold true for the same average occupancies across Urban-Intermediate (Figure 3-5-b) and Suburban (Figure 3-5Figure -c) Speed contexts.

Furthermore, it should be noted that all values depicted in Figure 3-5 are based on average g CO_2e $PPCKT^{-1}$ and do not reflect the variability represented by the error bars (i.e., grade, weight, and SoC). Under different electrification and energy pathways, these emission thresholds at different occupancies will change. That said, the methodology developed herein could be replicated to any operating context and under any context-sensitive energy pathway. Other power sources and powertrains can be compared to conduct a similar emission threshold analysis (see supplemental data).



Service Mode	Occupancy Percentage (Passenger Number)										
	11%	20%	25%	33%	40%	50%	60%	67%	75%	80%	100%
Private Car		(1)			(2)		(3)			(4)	(5)
Car-share		(1)			(2)		(3)			(4)	(5)
Ride-share			(1)			(2)			(3)		(4)
Bus	(5)			(15)				(30)			(45)

* Values within boxes at 33% and 26% occupancy represent average passenger occupancies for the corresponding service mode

Figure 3-5: average WTW g CO_2e $PPCKT^{-1}$ for gasoline ICE, BEV, diesel bus, and BEB operating under all service modes by occupancy percentages across (a) Urban-Low Speed, (b) Urban-Intermediate Speed, (c) Suburban Speed

3.5. Discussion

The aim of this paper is to answer, firstly, what is the most environmentally competitive mobility solution from a trip perspective, and secondly, what are their occupancy corresponding thresholds. To address these questions, we have developed 450 generalized operating scenarios for a variety of passenger car and transit bus powertrain and power sources. We simulated PTW energy consumption using a dynamic vehicle simulator and consulted an established WTW database to retrieve the corresponding GHG emissions per km. We then converted GHG emissions per km to a passenger private car-adjusted kilometres travelled (PPCKT) basis considering the service mode trip factor (i.e., the relative increase or decrease in VKT associated with service mode as a result of either fewer km travelled, deadhead distance, or route circuity) and the simulated occupancies.

3.5.1. The Most Competitive Operating Context and Power Source Pathway

To address the first question, the results highlight that the most environmentally competitive mobility solution from a WTW trip-level perspective depends on the power source pathway and the operating context (i.e., drive cycle and grade). The variability of results and the magnitude of their variability are amplified when normalized by the associated PPCKT.

This finding echoes the results of Yang et al. (2020) and Logan et al. (2020), which highlight the significant impact of power source pathways on GHG emissions for passenger cars and/or transit buses, respectively. Along the same lines, our paper showcases the impact of operational context on PPCKT, affirming the work of Abdelaty & Mohamed (2021), Pourahmadiyan et al., (2021), Vepsäläinen et al., (2018) that demonstrated the significant impact of operating context (i.e., grade and drive cycle) on energy consumption. Considering the variability between service modes, it is implicit that assigned trip factors will impact PPCKT. For instance, the work of Amatuni et al. (2020) demonstrates the reduction in GHG emissions seen in car-sharing previously reported in the literature (and used within this paper) may overestimate the reduction in emissions as a result of the modal shift.

Acknowledging such a variation at the scenario level, we are addressing the first question by using the average values for all scenarios. The rationale is that any vehicle can combine trips within different operating contexts (i.e., urban-low, urban-intermediate, and suburban), and service mode trip factors and average occupancies are subject to change. Under these average assumptions, the FCEV car-share coupled with hydrogen production from renewable-electricity electrolysis is the most environmentally competitive service mode, followed by a BEV car-share and BEB powered by a Canadian electricity mix. For more details, Table 3-6 presents the top 15 and bottom 15 environmentally competitive options while considering the operating context for each combination of service mode, power source pathway, and powertrain technology. The values in Table 3-6 are based on all the assumptions described in Section 3.3 and reflect the average of all grade, vehicle test weights, and initial battery state of charge (SoC) when appliable.

Overall, this paper demonstrates that attention to local and context-specific power source pathways is crucial in informing environmentally competitive mobility solution selection. One is encouraged to integrate additional data to improve the accuracy of trip-level GHG emission estimations. For example, using marginal emission factors (i.e., emissions produced as a result of a marginal change in electricity demand) at varying temporal resolutions instead of average emission factors have shown to lead to varying WTP emissions, which is discussed in the work of Gai et al. (2019), Kamiya et al. (2019), and Bigazzi (2019). That said, this paper offers a replicable framework that could be implemented for any given power source pathway, powertrain technology, and service mode under operating contexts that are similar to the drive cycles selected to represent Urban-Low, Urban-Intermediate, and Suburban Speed classifications.

Table 3-6: The top 15 most environmentally competitive and bottom 15 least environmentally competitive mobility solutions based on an average passenger occupancy

Rank	**Operating Context**	**Service Mode**	**Powertrain**	**Power Source**	**CO_2e PPCKT^{-1}**
1	Urban-Int. Speed	Car-Share	FCEV	Electrolysis – Renewable	7.9
2	Suburban Speed	Car-Share	FCEV	Electrolysis – Renewable	8.0
3	Urban-Low Speed	Car-Share	FCEV	Electrolysis – Renewable	11.8
4	Urban-Int. Speed	Private	FCEV	Electrolysis – Renewable	13.2
5	Suburban Speed	Private	FCEV	Electrolysis – Renewable	13.4
6	Suburban Speed	Car-Share	BEV	Electricity – Canada Mix	13.7
7	Urban-Int. Speed	Car-Share	BEV	Electricity – Canada Mix	13.7
8	Urban-Int. Speed	Bus	BEB	Electricity – Canada Mix	17.5
9	Urban-Low Speed	Car-Share	BEV	Electricity – Canada Mix	19.2
10	Urban-Low Speed	Private	FCEV	Electrolysis – Renewable	19.6
11	Suburban Speed	Bus	BEB	Electricity – Canada Mix	19.7
12	Urban-Int. Speed	Ride-Share	FCEV	Electrolysis – Renewable	19.9
13	Suburban Speed	Ride-Share	FCEV	Electrolysis – Renewable	20.1
14	Suburban Speed	Private	BEV	Electricity – Canada Mix	22.8
15	Urban-Int. Speed	Private	BEV	Electricity – Canada Mix	22.9
…					
85	Urban-Int. Speed	Ride-Share	BEV	Electricity – China Mix	153.6
86	Urban-Low Speed	Ride-Share	FCEV	Electrolysis – Nature Gas SMR	155.4
87	Suburban Speed	Ride-Share	PHEV	Gasoline & Electricity – China Mix	158.1
88	Suburban Speed	Private	ICE	Gasoline	177.7
89	Urban-Low Speed	Bus	ICE	Diesel	198.2

90	Urban-Int. Speed	Private	ICE	Gasoline	206.0
91	Urban-Low Speed	Car-Share	ICE	Gasoline	208.4
92	Urban-Low Speed	Ride-Share	PHEV	Gasoline & Electricity – Canada Mix	209.1
93	Urban-Low Speed	Ride-Share	BEV	Electricity – China Mix	214.6
94	Urban-Low Speed	Ride-Share	PHEV	Gasoline & Electricity – US Mix	219.0
95	Urban-Low Speed	Ride-Share	PHEV	Gasoline & Electricity – China Mix	229.9
96	Suburban Speed	Ride-Share	ICE	Gasoline	266.6
97	Urban-Int. Speed	Ride-Share	ICE	Gasoline	309.0
98	Urban-Low Speed	Private	ICE	Gasoline	347.3
99	Urban-Low Speed	Ride-Share	ICE	Gasoline	521.0

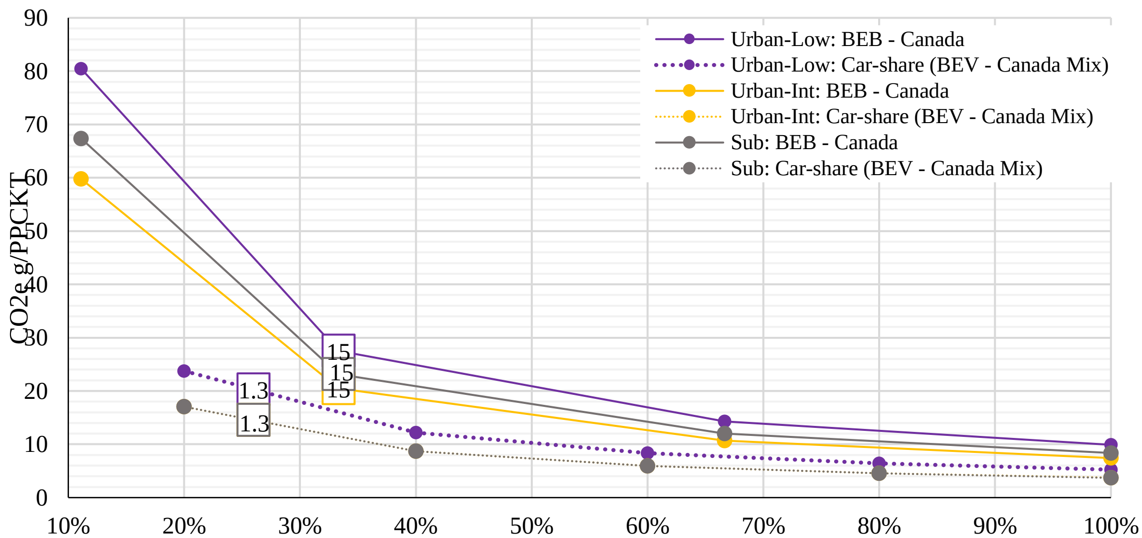
[1] assumes average passenger occupancy of 1.3 for passenger car and 15 passengers for bus
[1] assumes 1 km of private passenger car travel equals 1.5 km ride-share, 0.6km car-share, and 1.2 km transit bus

3.5.2. The Most Competitive Occupancy Thresholds

What is not reflected in the answer to the first question is the potential to maximize GHG emission savings at the trip-level through the identification of passenger occupancy thresholds. This question has never been fully addressed through dynamic vehicle simulators at the trip-level for transit bus and car-share, ride-share, and private passenger car modes.

Considering the growing popularity of ride-share and car-share service modes and electric powertrain technologies, we present the g CO_2e PPCKT^{-1}car-share (Figure 3-6) and ride-share (Figure 3-7) in comparison to BEB under the same operating contexts. With these figures, we demonstrate a way in which the generated results could be used to inform the trip-level decision-making process, with the aim to highlight the g CO_2e PPCKT^{-1} across various service modes from their occupancy rates. A fixed electricity mix, that of the Canadian average, is visualized. The figures are visualized in three subcategories: firstly, long-dashed lines are ride-share, short-dashed lines are car-share, and solid lines are transit service mode. Secondly, Urban-Low Speed context are purple lines, Urban-Intermediate Speed context are yellow lines, Suburban Speed context are grey lines.

Figure 3-6 demonstrates that under the same occupancy percentages, car-share BEV is more environmentally competitive than BEB from a g CO_2e PPCKT^{-1} perspective. This finding is true for all operating contexts indicating that at linearly increasing occupancy percentages, BEV car-share will out compete BEB. Furthermore, when considering the assigned average occupancy for car-share (1.3 passengers) and bus transit (15 passengers), the BEV car-share option dominates. Assuming an average of 1.3 passengers for BEV car-share, BEB only becomes more competitive with an occupancy greater than 60% (26 passengers) for Suburban and 53% occupancy (23 passengers) for Urban-Intermediate and Urban-Low Speed operating contexts, respectively.

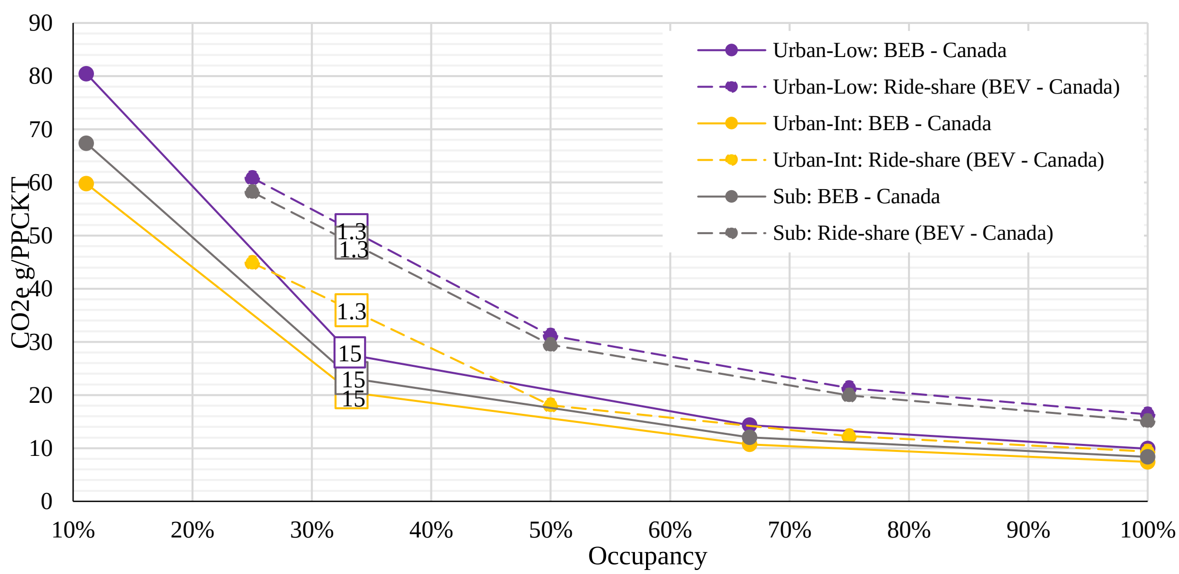


	Occupancy Percentage (Passenger Number)							
Service Mode	**11%**	**20%**	**33%**	**40%**	**60%**	**67%**	**80%**	**100%**
Car-Share		(1)		(2)	(3)		(4)	(5)
Bus	(5)		(15)			(30)		(45)

* Values within boxes at 33% and 26% occupancy represent average passenger occupancies for the corresponding service mode

Figure 3-6: BEV car-share and BEB g CO_2e PPCKT^{-1} for all passenger occupancy percentages across all operating contexts

Figure 3-7 demonstrates the opposite relationship between BEB and BEV ride-share. BEB is always *more* competitive relative to BEV ride-share under the same occupancy percentages and under the average service mode occupancies (i.e., 1.3 passengers for ride-share and 15 passengers for transit bus). More specifically, under the BEV ride-share occupancy of 1.3, BEB is always *more* environmentally competitive when occupancy is greater than 26% occupancy (12 passengers) for Suburban, 25% occupancy (11 passengers) for Urban-Intermediate, and 23% occupancy (10 passengers) for Urban-Low Speed operating contexts respectively. It should be reiterated that ride-share service mode is more impacted by a higher trip factor (i.e., more VKT) and lower 100% occupancy (i.e., up to 4 passengers) relative to car-share.



	Occupancy Percentage (Passenger Number)						
Service Mode	**11%**	**25%**	**33%**	**50%**	**67%**	**75%**	**100%**
Ride-share		(1)		(2)		(3)	(4)
Bus	(5)		(15)		(30)		(45)

* Values within boxes at 33% occupancy represent average passenger occupancies for the corresponding service mode

Figure 3-7: BEV ride-share and BEB g CO_2e $PPCKT^{-1}$ for all passenger occupancy percentages across all operating contexts

Our paper can also be scaled and compared on an annual (or even life-cycle perspective if additional assumptions are integrated) to inform potential GHG emissions offset by different technologies and service modes from the passenger-trip perspective. For instance, assuming an average annual kilometre travel of 7000 km using an ICE-Gasoline private passenger car for 1.3 passengers, a range between 1244 to 2431 kg CO2e PPCKT-1 would be produced depending on the operating context. Our paper suggests that if the ICE-Gasoline private passenger car is replaced with BEV (Canada Electricity mix) ride-share, private passenger car, and car-share, between 1005 to 2095, 1085 to 2207, and 1149 to 2297 g CO2e PPCKT-1 annually would be offset, respectively. From a different perspective, if the same year's worth of average occupancy gasoline ICE private-car kilometres travelled on a BEB (in this paper this is equivalent to 8400 km) with an average occupancy of 15 passengers (i.e., 11.5 gasoline ICE private passenger cars are replaced with 1 BEB) would result in significantly higher savings of between 14189 to 27856 kg CO_2e $PPCKT^{-1}$ offset annually.

Both Figure 3-6 and Figure 3-7 contextualize literature that suggests that the electrification of car-share or ride-share has a significant potential to reduce GHG emissions. For instance, one of the findings of Jenn (2020) suggests that the electrification of the private passenger car in California will result in a *lower* total GHG emission offset than the electrification of a ride-share vehicle as a result of higher VKT by ride-share (and thus higher amount of km electrified). Our paper alternatively demonstrates the importance of g CO_2e associated with a passenger-trip; from this perspective, fundamentally, the g CO_2e associated with each trip is still higher for ride-share than a private car. Furthermore, under the majority of occupancy and operating contexts, the BEB has the potential to offset *more* g CO_2e PPCKT^{-1} than BEV ride-share. Literature that echoes the importance of reducing low-occupancy VKT and the g CO_2e associated with each passenger-trip is present in the work of Schäfer & Yeh (2020), Logan et al. (2020), and (Chester & Cano, 2016)). However, unlike our paper, these works did not identify the optimal occupancy thresholds associated with emerging service modes and technologies to overcome the impact of low occupancy on GHG emissions.

It should be noted that we have presented thresholds for mature powertrain technologies and emerging service modes. However, all thresholds could be extracted for the considered powertrain technologies and service modes from the detailed supplementary data.

3.6. Conclusion

Overall, our paper is one of the first to compare the energy consumption and WTW GHG emissions by distance travelled and passenger kilometre travelled of various transit bus technologies (diesel-ICE, LNG-ICE, HEB, BEB) and passenger car (Gas-ICE, PHEV, BEV, FCEV) operating under three service modes and operating scenarios. In a nutshell, this paper addressed the following questions:

1) What are the per passenger GHG emissions associated with private passenger cars, car-share, ride-share, and transit bus service modes? and;

2) What is the range of break-even passenger occupancies for each technology and service mode relative to a conventional gasoline passenger car that achieves the same emissions levels?

Answers to these questions depend on the comparison between combinations of technology, power source, occupancy, and service mode. However, we found that: firstly, power source pathways matter, especially those concerning electric powertrains as a result of the range in carbon intensity associated with electricity production. Secondly, reflecting local operating parameters in simulation is important, especially parameters concerning road grade, and to varying extents (for some technologies) initial SoC and vehicle test weight; Thirdly, the percentage occupancy of a vehicle critically impacts GHG emissions from the passenger trip-level perspective (PPCKT) and can increase or decrease the environmental competitiveness of any technology and service mode. It is imperative for policy-makers to consult our data-driven occupancy thresholds associated with each power train technology and service mode to determine which mobility solutions will achieve their GHG emission targets according to the vehicle's operating context, typical passenger occupancies, locally available power source pathways, and available technologies.

To arrive to these conclusions, the WTP energy consumption per km was first modelled using a dynamic vehicle simulator. These results yielded that the most energy consumption efficient passenger car technology averaged across all operating scenarios is BEV (0.4 to 4.0 L_e100 km^{-1}) followed by FCEV (0.2 - 6.5 L_e100 km^{-1}), PHEV (0.5 - 12 L_e100 km^{-1}), and Gas-ICE (4.8 - 17 L_e100 km^{-1}) based on averages for all operating scenarios. The most energy consumption efficient transit bus was BEB (6.6 - 33 L_e100 km^-

^{1}), then HEB (17 - 79 L_e100 km^{-1}), Diesel-ICE (46 - 109 L_e100 km^{-1}), and LNG-ICE (82 - 190 L_e100 km^{-1}) based on averages for all operating scenarios (Figure 3-3). Next, after factoring in additional dimensions of WTP and PTW GHG emissions and multiple power source pathways (when applicable), BEV and FCEV are the least carbon-intense depending on the power source pathway and operating scenarios, followed by PHEV and Gas-ICE in units of g CO_2e km^{-1}; refer to Figure 3-4 for averaged results for simulated operation scenarios.

As an additional step, this paper then normalized the WTW GHG per km findings through trip factors informed by the VKT travelled by each service mode for a passenger to reach an origin and destination relative to a private passenger car trip (a unit reported as g CO_2e $PPCKT^{-1}$). This normalization suggests that primarily, FCEV (powered by renewable electricity electrolysis produced hydrogen) and BEV (Canada electricity mix) serving as *car-share* and BEB (Canada electricity mix) are the most environmentally competitive options in terms of WTW g CO_2e $PPCKT^{-1}$ based on average operating scenarios and average occupancies of all the technology combinations simulated.

Although there is literature which indicates the environmental benefit of strategic technology-switching for different service modes, such as the work of Jenn (2020) which highlights the benefit of electrification of ride-share; our paper demonstrates that the impact of the g CO_2e associated with each passenger-trip is important. A low-carbon vehicle technology can be more or less environmentally competitive if operating under a different service mode.

In this respect, a BEV (powered by Canada's electricity mix) operating as ride-share would require approximately 1.9 passengers or greater to achieve a g CO_2e PPCKT^{-1} which is equal to or lower than 1.3 passenger private passenger car trip (i.e., 24 - 34 g CO_2e PPCKT^{-1} depending on the operating context). Furthermore, the same BEV ride-share is only more environmentally competitive at an occupancy of at least between 2 to 2.4 passengers or more compared to a BEB (Canada's electricity mix) with 15 passengers (21 - 27 g CO_2e PPCKT^{-1}). Looking into the future, we highlight that the increased occupancy of vehicles especially transit buses, the continued promotion of FCEV and BEV car-share in addition to BEB, and decarbonizing electricity production (and associated hydrogen production), will yield the most optimal WTW GHG emission reductions.

It worth mentioning the limitations of this paper. Due to the nature of simulation scenario variability, the generalized scenarios developed only operate during a specific scenario at a time, i.e., it is assumed that over the 100 km simulated, a vehicle only travels on multiple runs of the same cycle, the same road grade, test vehicle weight, and ambient temperature. Caution should be taken if applying the simulated results to local case studies as real-world energy consumption will differ. Additionally, the following topics such as impact of PTW emissions due to vehicle age, environmental conditions (cold temperature, pressure, AC), and isolating impacts of aggressive driving have not been included this paper's scope but are considerations for future work. These topics, while not exhaustive, have been identified to have an impact on energy consumption and/or PTW emissions (Abdelaty & Mohamed, 2021; H. Liu et al., 2020; Zhou et al., 2016). Furthermore, it should be noted that this paper's analysis does not replace a GHG inventory or fleet- level approaches in measuring GHG emissions, it instead is another dimension that reports GHG emissions from the passenger kilometer trip perspective which decision-makers should investigate when encouraging and implementing mobility options.

Overall, we present a replicable framework for the decision-making process that could be implemented in any context to guide the future implementation of mobility solutions and powertrain technology choice.

3.7. Acknowledgment

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Chapter 4. Conclusions

At the fast pace of technology development and the urgent pressure to mitigate GHG emissions, policy which targets transportation emission mitigation must get it right. This thesis broadly addresses this theme in all chapters.

4.1. Key Remarks

In Chapter 2, a linear programing approach is operationalized to estimate the cost and GHG reduction potential of selected technology-adoption policies in an Ontario context under a GHG reduction target. The results of this effort demonstrate that: 1) The GHG reduction target (30% reduction of emissions within the passenger subsector by 2030) cannot be reached with just vehicle electrification policies; 2) The largest feasible reduction is between 24% to 26%, with the range depending on two different EV annual sales target in year 2030. To achieve the 24% to 26% reduction, the model estimates that the optimal provincial government spending is between $2.86 to $3.11 billion over ten years; 3) The most short-term cost-effective GHG reduction policies is firstly the conversion of provincial LDV and buses to EV and secondly the EV incentives.; 4) Additional policies should be considered to realize a short-term (2030) and long-term reduction (2050) targets.

Literature has previously echoed the findings of Chapter 2 in different ways. For instance, Milovanoff, Posen, & MacLean (2020) demonstrated that if the LDV electrification was the sole policy considered to meet the 2 degree global warming target within the sector for the US, the national light-duty fleet would have to be 90% electric by 2050. This immense vehicle electrification would require half of the current US national electricity demand and infeasibly excessive amounts of lithium, cobalt, and manganese for the lithium-ion batteries within PHEV and BEV (Milovanoff, Posen, & MacLean, 2020).

The conclusion of Chapter 2 begs the question: if electrification of LDV and BEB is not sufficient to meet the GHG reduction target than what technology, operating conditions, and passenger threshold *will* contribute to further reducing emissions? Due to the various dimensions under which emission reduction potential of vehicle technology is impacted, the work in Chapter 3 focuses on vehicle passenger-trip-level thresholds to determine: 1) What is the environmental benefit of emerging passenger vehicle technologies?; and 2) Under what operational conditions, passenger occupancies, and power source pathways, are these technologies no longer beneficial?

The results in Chapter 3 demonstrate that the *most* environmentally beneficial option must be locally determined and depends on how benefit is measured. From the perspective of PTW energy consumption, the most efficient passenger car technology averaged across all operating scenarios is BEV (0.4 to 4.0 L_e100 km^{-1}) followed by FCEV (0.2 to 6.5 L_e100 km^{-1}), PHEV (0.5 to 12 L_e100 km^{-1}), and Gas-ICE (4.8 to 17 L_e100 km^{-1}). The most energy consumption efficient transit bus is BEB (6.6 to 33 L_e100 km^{-1}), then HEB (17 to 79 L_e100 km^{-1}), Diesel-ICE (46 - 109 L_e100 km^{-1}), and LNG-ICE (82 - 190 L_e100 km^{-1}). Next, after factoring in additional dimensions of WTP and PTW GHG emissions and multiple power source pathways (when applicable), BEV and FCEV are the least carbon-intense depending on the power source pathway and operating scenarios, followed by PHEV and Gas-ICE in units of g CO_2e km^{-1} averaged across all simulated operation scenarios. Lastly, when WTW GHG per km findings are normalized through trip factors informed by the passenger VKT travelled by each service mode (a unit reported as g CO_2e $PPCKT^{-1}$), FCEV (powered by renewable electricity electrolysis produced hydrogen) and BEV (Canada electricity mix) serving as *car-share* and BEB (Canada electricity mix) are the most environmentally competitive options in terms of WTW g CO_2e $PPCKT^{-1}$ based on average operating scenarios and average occupancies of all the technology combinations simulated.

These results demonstrate that the impact of the g CO_2e associated with each passenger-trip is important. A low-carbon vehicle technology can be more or less environmentally competitive if operating under a different service mode. In this respect, a BEV (powered by Canada's electricity mix) operating as *ride-share* would require approximately 1.9 passengers or greater to achieve a g CO_2e $PPCKT^{-1}$ which is equal to or lower than 1.3 passenger *private* passenger car trip (i.e., 24 to 34 g CO_2e $PPCKT^{-1}$ depending on the operating context). Furthermore, the same BEV *ride-share* is only more environmentally competitive at an occupancy of at least between 2 to 2.4 passengers or more compared to a BEB (Canada's electricity mix) with 15 passengers (21 to 27 g CO_2e $PPCKT^{-1}$). Looking into the future, the increased occupancy of vehicles (especially transit buses), the continued promotion of FCEV and BEV car-share in addition to BEB, and decarbonizing electricity production (and associated hydrogen production), will yield the most optimal WTW GHG emission reductions.

The conclusions of Chapter 3 are also echoed in literature from a different perspective. Smargiassi et al. (2020) simulated the environmental and health impacts of transportation and land use scenarios in the Great Montreal area for year 2030 and year 2061. One of their findings demonstrate that a significant penetration of EVs (50% of fleet) will have a greater impact on reducing daily GHG emissions (relative to year 2031 business-as-usual (BAU) scenario) than optimal land use and a vehicle fleet predominately of type ICE. The optimal land use scenario assumes a significant car-share reduction (i.e. decreases to 34% and 62% in urban and suburban areas respectively) and all new year 2061 population is located in the urban area. However, even with BAU land-use and a 50% EV fleet, optimal land-use is linked with significant positive health impacts as a result of increased active transportation and air pollution. These findings suggest that a change in passenger car technologies (i.e. electrification) is one action in the broader mix required to sustainably transform our communities. The broader mix should include land-use policies and political action which reduces car-share, encourages densification, and reduces motorized VKT.

4.2. Future Work

Overall, the novel contributions contained in this thesis showcase that policy needs to not only consider conventional technologies but also adjust to reflect the environmental competitiveness of technologies through a passenger-trip perspective. To achieve deep decarbonization, simply reducing the carbon intensity of a vehicle while *not* addressing the potential to reduce VKT with use of car-share, the potential to offset trip-level emissions by increasing bus occupancies, and technologies depending on specific power source pathways are sorely missed opportunities. A focus on estimating the occupancy and the GHG emissions associated with each trip, while proven variable across operating context, and changing travel behavior is fundamental to realizing deep decarbonization of the passenger transportation sector as there will always be limitations to alternative GHG reduction technologies.

Low-carbon technologies and service modes have the potential to reduce WTW emissions significantly in many scenarios, but they are not the ‘silver bullet’ to meeting GHG emission targets. Future work needs to examine the impact of technology-driven policy on potential social implications and how it is benefiting some while negatively impacting others; this includes associated environmental impact measurements which are not captured by CO_2e, the social burden associated with adopting new technologies, and the equity of these negative impacts. While a complex undertaking, Canada, like many other OECD countries, is responsible for the highest proportions of GHG emissions per capita than non-OECD countries, and as such has a global obligation to proportionally address their environmental impact.

Chapter 5. References

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