Optimizing Transportation GHG Reduction Policy Cost under GHG Emission Constraints: A Canadian Provincial Perspective

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Abstract

The passenger transportation sector is a notoriously difficult sector to decarbonize as it is so closely linked with individual choice and economic growth. There is a need in literature to evaluate the uncertainty associated with a set of GHG mitigation policy decisions while simultaneously optimizing the policy costs under a GHG emission constraint. Using policies which target travel behaviour change and emerging technology uptake, an interval pure integer quadratic optimization model is developed to minimize the associated policy action cost under the constraints of the 30% GHG reduction target for the Canadian province of Ontario. To achieve the short-term target GHG reduction, between 3% to 6% of the province's annual budget must be spent every year from 2020 to 2030 in electric vehicle incentives, government fleet replacement, bus network expansion and bus fare subsidies. This optimization approach can be used to support passenger road transportation GHG reduction policy cost and target decision-making at all levels of government.

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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 outlines the continued implementation of the national plan (the *Pan-Canadian Framework on Clean Growth and Climate Change* also referred to as the Pan-Canadian Framework) and the estimated progress towards the 2030 target (30% below 2005 levels). The Pan-Canadian Framework includes policy actions which focus on the reduction 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, based on the impact of federal and individual provincial/territory climate change policies for each sub-sector and forecasted GDP and energy prices indicate that under the reference and best-case scenario, the emissions will decrease between 8% to 17% below 2005 levels respectively (ECCC, 2019).

Canada has one of the cleanest energy systems in the world due to a high proportion of renewable electricity production and is also one of the largest consumers of energy per capita globally (Kennedy, 2015). Reducing energy demand by switching to more energy efficient technology without significantly changing travel behaviour may be sufficient to meet short-term GHG reduction targets (J. D. Hughes, 2018). However, transparency in the cost associated with the short-term policy implementation and a consistent target is a necessary first step to achieving GHG reduction targets.

The aim of this model is to present a generalized and interpretable passenger road transportation sub-sector model which minimizes the policy cost associated with a change from 2020 to 2030 vehicle fleet emissions under a GHG reduction target. Through a case study of Ontario, the most populous province in Canada, an interval pure-integer linear model is developed to minimize policy costs under a quadratic 30% GHG reduction constraint and linear vehicle sales and replacement constraints. Four federal policies are considered in the reference case as they have or will be implemented in the ten-year period at no cost to the province, and four hypothetical provincial policies are considered. All provincial policies encourage a reduction in the GHG emissions produced by the vehicle fleet; namely through electric vehicle (EV) point-of-purchase incentives which result in the purchase of an EV in lieu of a conventional new gasoline vehicle, the purchase of EVs to replace aging government fleet vehicles (light-duty vehicles (LDV) and transit buses (Bus)), and the addition of new buses and reduction in bus-fare which reduces the number of LDV by improving the public transportation network.

The passenger road transportation sector in Ontario is a well suited case study, as to the author's knowledge, the provincial and federal GHG reduction forecasts do not capture all the opportunity for GHG reduction potential (ECCC, 2019). The GHG reduction forecast in the most recent Biennial Report falls short in accounting: 1) the full life-cycle (LC) emissions (which capture the full extent of emissions), 2) modal shift as a result of transit investment is neglected (the removal of 1 new passenger vehicle sale and shifting those trips to transit can have a significant impact on emission reductions (Boisjoly et al., 2018)), and 3) the uncertainty associated with policy expenses. This study aims to address these shortfalls by including the associated costs and deterministic LC GHG emissions in the model and incorporating interval programming techniques to address some of the uncertainties directly associated with policy cost. Through best-worst case scenario analysis, three solutions are generated, one representing the do-nothing provincial policy (just federal action), the two representing an optimistic and pessimistic 2030 EV scenarios. The scenarios are based on different new EV sales targets and varying total-cost-of ownership (TCO). To the author's knowledge, this is the first study which 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.

The paper is organized in the following sections. Section 2 summarizes relevant literature pertaining to optimization methods applied to GHG reduction in energy systems and policy decision making, Section 3 outlines the data used, the associated assumptions, and the developed scenarios. Section 4 presents the results of each scenario as well as the sensitivity analysis of the EV sales constraint. Discussion of the results is presented in Section 5, along with comparisons to recent literature, and implications on policy making. Section 6 concludes and summarizes the key contributions for policy-makers as well as outlines room for future considerations.

2. Literature Review

GHG emission mitigation is paired with energy system planning, as both energy-intensive end-use sectors must increase their energy efficiency (as simply a reduction in energy-use signifies a decrease in industrial economic activity) and the region's energy systems must become less carbon-intensive (L. Hughes et al., 2020). A less carbon-intensive energy grid has the additional benefit of supporting energy-efficient indirect economic activity as seen in the electrification of passenger transportation. Optimization approaches have been used in literature to address uncertainties and incurred as a result of economic, technical, environmental, and political factors at different scales to help inform decision-making processes. The following four subsections discuss deterministic, inexact (interval, stochastic, fuzzy-set, and dynamic), and model-based decision support tools in the optimization of GHG mitigation, energy system planning, and associated policy costs.

2.1. Deterministic optimization approaches

Deterministic models have been widely used to support optimum allocation of energy resources under administrative objectives. (Mustapa & Bekhet, 2016) developed a short-term linear programming optimization model for the Malaysian transportation sector which estimated the composition of the vehicle fleet to minimize the 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 mixed-integer linear programming model which optimized the extent of fuel balancing and fuel switching which would 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 modeling approach to determine the optimal fleet mix of heavy-duty-trucks (electric, hybrid, and/or fossil-fuel/bio fuel) in five U.S. economic sectors based on their life-cycle 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.

2.2. Inexact optimization approaches

While deterministic models have higher interpretability, they do not reflect the uncertainties in associated with GHG mitigation, energy system planning, and associated policy cost. Inexact optimization approaches model the parameters and/or coefficients in objective functions and constraints as non-deterministic, namely through a combination of stochastic, fuzzy, and/or interval-based approaches.

The stochastic approaches are appropriate when decisions parameters can be expressed as 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) implements a stochastic optimization model to generate the optimal EV specification and power generation capacity of a solar system such that GHG emissions are minimized under a budget constraint. Probability distributions based on historic and forecasted EV specifications and power generation capacity of a solar system inform the model. (Cristóbal et al., 2013) proposed a two-stage stochastic mixed-integer linear programming approach to generate the optimal investment timing and operation of CO_2 capture system under the uncertainty of the CO_2 allowance price in the EU cap-and-trade framework. Both studies use stochastic optimization to address uncertainty in their decision variable and/or constraint parameters.

When precise data is not available and can vary, fuzziness of the uncertainty is modelled and integrated into the parameters of the objective and/or constraints of the optimization model (Rommelfanger, 1996). An application is within life-cycle (LC) assessment, where (Tan et al., 2008, 2009) integrates a fuzzy approach in an input-output based LC model to estimate the optimal bioenergy system configuration under the Philippine's national flexible targets on land use, water, and GHG emissions. Another application is in the extension of calibrated energy systems models, as (Martinsen & Krey, 2008) forecasts the energy system based on the IKARUS energy systems model, a time-step dynamic linear optimization model calibrated to Germany's primary energy supply to energy services. The study then implements fuzzy constraints which represent the contradictory political targets (e.g. % CO2 reduction target, % energy imports, share of renewable electricity, amount of domestic coal, etc) and determine the fuzzy optimal total primary energy supply, CO2 emissions, and final energy for each time step.

When upper and lower bound solutions are appropriate, the interval approach is applied to derive optimistic and pessimistic solutions (Zeng et al., 2011). (Chen et al., 2018) formulates a dynamic interval chance-constrained programming model for the Yukon Territory to estimate the optimal energy system under different policy scenarios with different system costs, GHG emission controls, and renewable energy.

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 pure-integer quadratic optimization model to estimate the policy cost associated with meeting a GHG reduction target. The model is applied to Ontario's passenger transportation sub-sector and assesses various policy alternatives which take into account emerging technology policies as well as policies which target modal shift from passenger vehicles to transit. To the author's knowledge, optimization approaches have not need been applied within this context and this study offers a novel contribution to the literature.

3. Methodology

3.1. Data Sources

The scope of this model is limited to road passenger transportation technology and four policy actions which Ontario can feasibly implement between 2020 to 2030 to meet the 2030 GHG emissions reduction target at a minimized cost. The four provincial policies target converting the number and proportion of privately owned and publicly owned vehicles to more GHG-efficient options. The vehicles types considered are light-duty passenger vehicles (LDV) and transit buses (Bus), as they represent the majority of passenger vehicles on the road (ECCC, 2017). The three considered vehicle powertrains reflect dominant and emerging powertrain technologies and energy sources, namely the conventional option (gasoline for LDV (G.LDV) and diesel for Bus (D.Bus)), reduced emission option (plug-in hybrid electric vehicle (PHEV) for LD), and emerging power sources (battery electric for LDV (BEV) and Bus (BEB)). Four federal policies are also considered as they are planned or ongoing during the ten-year time period (ECCC, 2019) but are of no cost to the province. Both provincial and federal policies are listed in Table 1.

The provincial policies are as follows; First, *EV incentive*, which is an indirect financial action encouraging the up-take of clean technology by financially encouraging a shift in consumer purchase behaviour. Second, *retire conventional vehicles and replace with BEV and BEB*, a direct financial action which also encourages the up-take of clean technology but through a different path – through directly replacing less emission efficient vehicles with more emission-efficient vehicles. Third, *adding additional BEB to bus networks*, and fourth, *subsidization of user-end bus fare*, both policies are direct financial action which encourage a change in travel behaviour and a reduction of light-duty vehicles on road, namely through improving bus service, coverage, and reducing cost-to-ride.

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

Provincial Policies				Background Federal Policies (no associated provincial cost)		
Policy	Cost	Outcome	Sources	Policy	Outcome	Sources
1. EV incentive	$1,500 to $3,000 point-of-purchase incentive per EV depending on powertrain	Increase in BEV and PHEV purchased, reduction in G.LDV	(British Columbia, 2019)	1. EV incentive	Top-up point-of-purchase incentives which will further increase proportion of EVs sold and reduction in G.LDV	(ECCC, 2019)
2. Replace provincially owned light-duty fleet with EV and bus fleet with BEB	-$9,000 to -$3,000 per BEV depending on the difference in TOC[1]	Increase in BEV purchased, reduction in G.LDV	(Lutsey & Nicholas, 2019; Plug'n Drive, 2020)	2. Carbon price	Increase in fuel price will further increase proportion of EV sold and reduction in G.LDV.	(ECCC, 2019)
	$0 to $76,000 per bus depending on the difference in TOC[2]	Increase in BEB on road, reduction in D.Bus	(Mohamed et al., 2018; Quarles et al., 2020)	3.Passenger Automobile and Light Truck Greenhouse Gas Emission Regulations	Incremental reduction in operational emission intensity of G.LDV (Model year 2011 to 2025)	(ECCC, 2019)
3. Adding additional BEB to network	$3,560,000 to $3,640,000 per bus depending on the difference TOC[3]	Decrease in G.LDV on road as a result of increased service and coverage	(Mohamed et al., 2018; Quarles et al., 2020)			
4. Subsidize user bus fare	$4,300,000 per cent fare reduction to supplement transit agencies for every cent of fare reduced	Decrease in G.LDV on road as a result of decreased fare	(CUTA,2014; Kain and Liu, 1999)	4. Clean Fuel Standard	Incremental reduction in emission intensity of fossil fuels	(ECCC, 2019)

[1] includes the price 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 life-time operation costs ($356k annual salary for operational staff) of an additional bus in addition to the life-time cost difference between BEB and D.Bus
* all prices in 2020 CAD

3.2. 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 ($x_1 \dots x_6$) represent integer units of transportation policy: Policy x_1 and x_2 correspond with the units of EV vehicle incentive rebate, policy x_3 and x_4 correspond to the units of EV and BEB the government purchases, and policy x_5 and x_6 corresponds to the number of additional BEBs added to the network and the cent reduction in bus fare, respectively. The decision variables x_i, their optimistic and pessimistic cost C_i, and the corresponding justification is summarized in Table 2. The interval linear objective function is shown in Equation 1. It should be noted that the model only considers one ten-year time period, from 2020 to 2030.

Table 2: Provincial policy actions (decision variables) and associated optimistic and pessimistic costs per unit policy

	$[C_i^-, C_i^+]$	**Justification**	**Data source**
x_1**= BEV incentive**	$3,000	Clean BC incentive offering	(British Columbia, 2019)
x_2**= PHEV incentive**	$1,500		
x_3 **= Government BEV Replacement**	[-$9,000, -$3,000] [1]	The difference in TOC between conventional ICEV and BEV.	(Lutsey & Nicholas, 2019; Plug'n Drive, 2020)
x_4 **= BEB Replacement**	[$0, $76,000] [1]	The difference in TOC between D.Bus and BEB. Range associated with fuel price, maintenance, and market price uncertainty.	(Mohamed et al., 2018; Quarles et al., 2020)
x_5 **= BEB Additional**	[$3,560,000, $3,640,000] [1]	Cost of additional bus and bus-operator added to network ($356k annual salary).	(Mohamed et al., 2018; Quarles et al., 2020)
x_6 **= Cents Bus Fare Reduced**	$66,425,000 [2]	Estimated cost to supplement transit agencies for every cent of fare reduced for ten years.	(CUTA, 2014; Kain & Liu, 1999)

[1] Range associated with life-cycle fuel price, maintenance, and market price uncertainty.
[2] See Table A- 1 for calculation details.

$$Min\ f^{\pm} = \sum_{i=1}^{6} C_i^{\pm} x_i^{\pm} \qquad (1)$$

Where:

$x_i^{\pm} = \{x_i | x_i^- \leq x_i \leq x_i^+\}$ for a real set of numbers

i = 1,2,…,6 is policy index

C_i = cost per unit of policy with respect to policy index (i)

The optimization model is subject to a non-negative integer decision variables and the following four groups of constraints:

3.2.1. GHG Emissions Target Constraint

The model is optimized under the 30% GHG reduction target (Equation 2) which describes 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 spending (GHG_2,GHG_3). The constraint was simplified under a few assumptions. GHG_1 represents the forecasted vehicle fleet number and emissions in 2030 as a result of no-provincial action (only federal action). GHG_2 represents the reduction of GHG emissions in 2030 as a result of the EV incentives; one EV incentive equals one new EV purchased in lieu of a new ICEV. GHG_3 represents the reduction of GHG emissions as a result of increased additional bus service and reduced fare reduction; as ridership is assumed to increase, fewer new vehicles are purchased thus their emissions are subtracted from the total vehicle fleet. It is assumed that all policy spending decisions (provincial and federal action) is consistently applied for the full 10-year time period. All coefficients in GHG_1 and GHG_2 are listed in Table A- 2 and the calculation of the modal shift coefficient variables in GHG_3 is presented in Table A- 3.

$$GHG_1 - GHG_2 - GHG_3 \leq (1 - 30\%) * 31\ MT\ CO2\ eq \qquad (2)$$

$$GHG_1 = EF_{F.LDV} FNV_{LDV} KM_{LDV} + EF_{F.BUS} FNV_{BUS} KM_{BUS} \quad (2a)$$

$$GHG_2 = \left(\sum_{i=1}^{3} EF_{G.LDV} x_i KM_{LDV}\right) + EF_{D.BUS} x_4 KM_{BUS} - \left(\sum_{i=1}^{5} EF_i x_i KM_i\right) \quad (2b)$$

$$GHG_3 = EF_{F.LDV} KM_{LDV} \left(\frac{AVOCC_{Bus} + ADOCC_{fare} x_6 + ADOCC_{addBus} x_5}{AVOCC_{LDV}} x_5 + CR x_6\right) \quad (2c)$$

Where:

$EF =$ average life-cycle emission factor (CO2 eq kg/km) for forecasted LDV (F.LDV), forecasted transit bus (F.Bus), gasoline light-duty vehicle (G.LDV), diesel bus (D.Bus), and vehicle as a result of policy spending (i)

$FNV =$ forecasted number of vehicles on road in 2030 for light-duty vehicle (LDV) and transit bus (Bus)

$KM =$ average kilometers travelled in year for light-duty vehicle (LDV) and transit bus (Bus)

$x_i =$ unit of policy purchased where i is from 1…6

$AVOCC =$ average occupancy for light-duty vehicle (LDV) and transit bus (Bus)

$ADOCC =$ increase in occupants per bus for each cent fare reduction (fare) and for each additional bus (addBus)

$CR =$ car removed for every 1 cent of bus fare reduction

3.2.2. Vehicle sales constraint

The number of EV purchased over ten years (equivalent to the number of incentives distributed) cannot realistically exceed a target proportion of total new vehicle sales. This constraint is simplified assuming the provincial incentives will further encourage an increase in annual EV sales in addition to the federal policies such that the 2030 annual sales will be between 20% (pessimistic case) and 30% (optimistic case assumption is derived from the BC 2030 EV sales target (British Columbia, 2019)). Additionally, it is assumed that the number of BEVs sold in the ten year period should be double the PHEVs sold based on historic consumer vehicle performance (Statistics Canada, 2019a).

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

$$x_1 + x_3 - 2 * x_2 = 0 \quad (3a)$$

Where:

FNS_{LDV} is the forecasted number of LDV sold in the ten-year period (see Table A- 1 for values).

3.2.3. Government vehicles

The electrification of the government LDV and Bus fleet and expansion of the Bus fleet is realistically constrained. The LDV and Bus electrification is assumed not to exceed 80% and bus network expansion is assumed not to exceed three times the existing fleet.

$$x_3 \leq 80\% * FNV_{LDV} \quad (4a)$$

$$x_4 \leq 80\% * FNV_{Bus} \quad (4b)$$

$$x_5 \leq 3 * FNV_{Bus} \quad (4c)$$

3.2.4. Fares

The maximum fare reduction is constrained to 299 cents which reflects the upper bound of historic fare levels (CUTA, 2014).

$$x_8 \leq 299\ cents \tag{5}$$

4. Results and Discussion

The estimated GHG reduction in Ontario's passenger road transportation subsector without provincial action (just federal action), provincial action with optimistic EV sales and TOC projections, and provincial action with pessimistic EV sales and TOC projections are shown in Figure 1. If no provincial policies are implemented, it is estimated that the federal action alone will result in a 17% reduction of GHG emissions below 2005 levels in 2030, missing the 30% target by 4 MT of CO_2 eq. To achieve the 30% target, between **$50 billion** (optimistic) to **$98 billion** (pessimistic) will need to be spent in EV incentives, government fleet replacement, bus network expansion and bus fare subsidies.

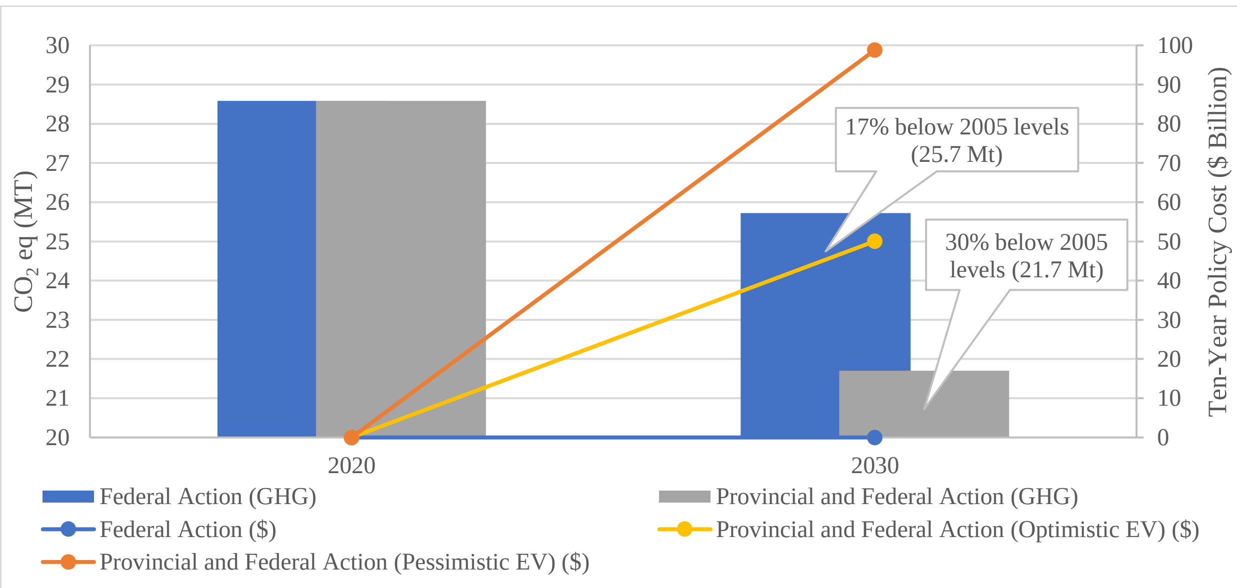

Figure 1: Estimated GHG emission reduction and cost in 2030 with and without provincial action

The optimistic scenario depicts the policy costs associated with meeting the 2030 30% annual EV sales target and an optimistic EV TOC savings compared to G.LDVs of the same model year. The breakdown of costs and associated number of units for each policy is presented in Figure 2 for both EV scenarios. In both EV scenarios, once the EV sales constraint and the replacement of D.Bus for BEB is met, the subsidization of bus fare is favoured and then the addition of new BEBs to the network is selected. Both scenarios are constrained by the GHG emission target and the conventional provincial fleet which can be replaced by EVs and BEBs. As the pessimistic scenario has a lower EV sales target (20% of 2030 vehicle sales are EV), the GHG reduction target is met through the more expensive option of adding additional BEBs to the transit network (13,351 additional BEBs).

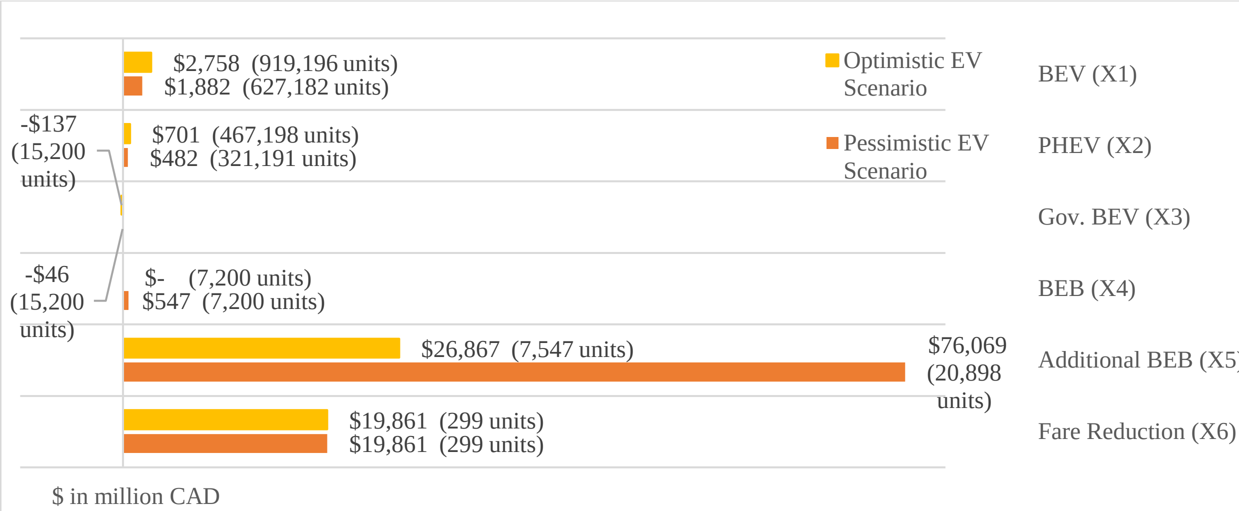

Figure 2: Optimized ten-year cost of associated GHG reduction policies under optimistic and pessimistic EV sales scenarios

Once the maximum number of buses are converted to BEBs, both optimistic and pessimistic scenarios suggest that incentivizing the purchase of EVs through point-of-purchase incentives is the most cost-effective way of achieving the GHG emission reduction target from the short-term policies evaluated. Feasibly seeing an increase in EV sales which exceeds a proportion of 16% EVs of all new vehicle sales (16% of vehicles purchased from 2020 to 2030) is unrealistic based on historical trends and the incentive offerings. However, if the proportion of EV sales was constrained, 23% of all new vehicles sold in the ten-year period would need to be EVs to reach the 2030 GHG reduction target. Assuming linear growth in EV sales from 3% in 2020, this would represent 43% of annual EV sales in 2030. If the same incentives remained in place, the ten-year cost would only be between **$4.9** and **$5.6** billion. The cost breakdown assuming optimistic and pessimistic TOC estimations for government BEV and BEB assuming unconstrained EV sales is provided in Figure 3.

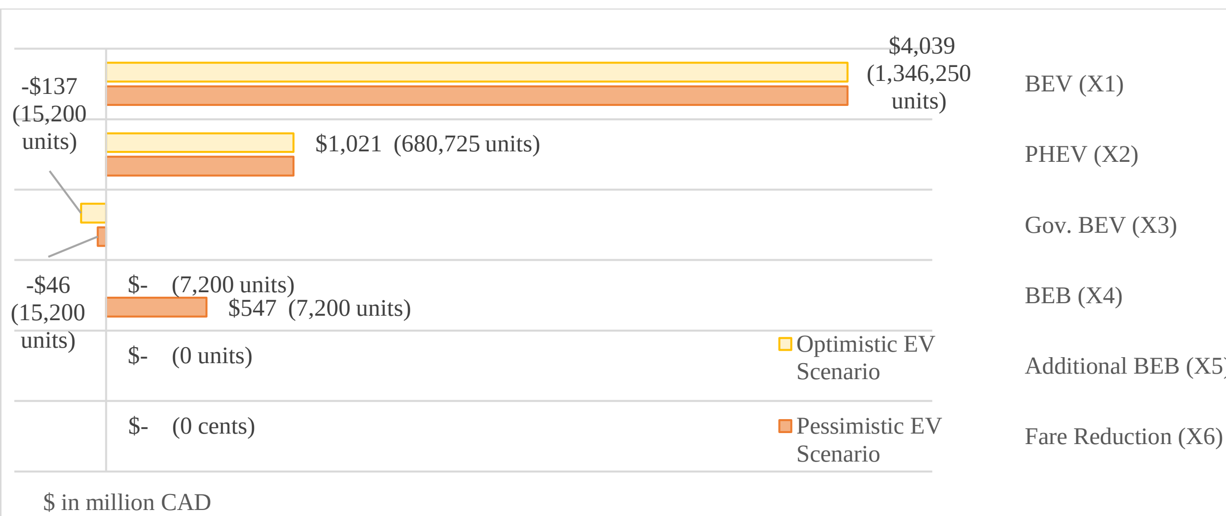

Figure 3: Optimized ten year policy cost with no EV sales constraint

Achieving the GHG reduction target by 2030 under the short-term policies considered and the associated 20 to 30% EV sales assumptions is costly but not infeasible as it is equal to **3%- 6%** of the annual budget ($150 billion in 2018-2019 (Ontario, 2019a)) every year for the ten-year period. It should also be noted that the most cost-effective GHG reduction policies are firstly the conversion of D.Bus to BEB and secondly the EV incentives; while these two policies alone are not sufficient to reach the 2030 target, they should be priority when considering short-term GHG reduction within the transportation sector.

Furthermore, while 30% EV sales target in 2030 is realistically feasible through EV incentives it can also be achieved (or exceeded) through the combination of other more cost-effective financial policies included in the model which would reduce the required spending. 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 EVs 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 (reduced TOC, 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).

This results and methodology of this study presents some limitations due to the assumptions made. For instance, the largest cost for both EV scenarios attributed to the expansion of the bus network (the lifetime cost of bus operation, maintenance) and the impact of bus fare subsidization. The relationship assumed between the increase in additional buses, decrease in bus fare, and the resulting increase in bus occupants and decrease in vehicles on the road is a highly simplified deterministic quadratic relationship (Table A- 3). The parameters were tailored to represent the population areas of Ontario but a more sophisticated modeling technique and local data which is not accessible to the author is needed to represent the complex relationships. Further, fare subsidisation can take many forms, such as a direct decrease in bus-fare for all riders (as modelled), a decrease in bus fare for targeted groups, a decrease in monthly ridership cards, a frequent-rider reward, among others (Liu et al., 2019). The cost-effectiveness of a fare reform should be considered in conjunction with the built-environment, land-use, and socio-economic demographics as all these factors contribute to how responsive people are in shifting their travel behaviours (Liu et al., 2019). Efforts to quantify externalities which offset the cost of transit expansion and integrate other modes of public transportation such as rail and ridesharing will lead to more accurate (and cost-effective) estimates.

Limitations on the estimation of life-cycle GHG emissions also present a degree of uncertainty due to the lack of data available. Manufacturing and operating emissions were sourced from GHGenius, a life-cycle emissions tool used by Natural Resources Canada (NRC) ((S&T)2 Consultants Inc, 2018). The tool forecasts the emissions for the input target year and province, but a detailed methodology is lacking and a range in estimates is not provided. Estimating the emissions reduction through the simulation of vehicle operating characteristics (e.g. grade, passenger occupancy, vehicle-kilometre travelled, route and charging characteristics, carbon intensity of fuel and electricity pathways, and ambient conditions), which have been concluded to significantly impact emissions produced and energy consumed (Bishop et al., 2019; Kivekäs et al., 2018; Rupp et al., 2019). Including the variability of these characteristics would improve estimates by defining the range of GHG reduction uncertainty.

5. Conclusion and Future Work

In combination with the ongoing federal Pan-Canadian climate change policies, Ontario can achieve a 30% reduction in 2005 levels within the road passenger transportation sector by 2030 through point-on-purchase EV incentives, bus electrification, expansion of the bus network, and through bus fare subsidies. While the policy measures are costly ($50 to $100 billion over ten years), the integer quadratic programming model presents the most cost-effective allocation of funding to each policy. The creation of a pessimistic and optimistic scenarios through interval programming techniques addresses some of the uncertainties associated with policy costs such as forecasting EV sales and total cost of ownership. The model also provides a novel approach to optimizing the cost of GHG mitigation from the perspective of policy outcomes and with the integration of differing types of policy action (policies which encourage emerging technology uptake and policies which target a shift in travel behaviour). The development of simplified models which demonstrate the relationship between policy funding and GHG outcomes can help support transparent decision-making towards reduction targets.

There is plenty of room for future work. The model does not consider the current or future short-term electricity capacity requirements. As increased electrification will result in higher energy demand, a low-carbon intensity electricity grid capacity is vital to support GHG mitigation efforts. Temporal considerations for EV charging should also be considered as the source of electricity will influence the mitigation potential of EVs (Gai et al., 2019; Karan et al., 2016). The model results suggest that in the short-term Ontario can witness a reduction in GHG emissions through electrification (i.e. reduction in energy demand), however, to achieve long-term decarbonization (targets for 2050 and onwards) continued efforts are needed to decarbonizing the province's energy systems (L. Hughes et al., 2020) and through the reduction of total kilometres travelled per vehicle.

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Appendix

Table A- 1: Calculation of the ten-year cost of one cent of bus fare reduction

The cost of one cent bus fare reduction over ten years is based on the following relationship

$$bus\ fare\ revenue = fare * riders$$

If a proportional decrease in fare is equal to the proportional increase in ridership then revenue is unaffected. (Kain & Liu, 1999) found that in San Diego over the course of 10 years of transit expansion and fare subsidies, ridership increased at a rate of 5% due to a corresponding 14% fare reduction. This relationship is applied to Ontario and it is assumed that provincial funding is proportionally distributed based on population and suburban and rural areas are less likely to increase their ridership than urban areas. The following is assumed:

- Bus fare can only be reduced a maximum of 300 cents.
- An annual provincial bus fare revenue of \$2.5 billion (CUTA, 2014) is assumed over 10 years.
- Based off the (Kain & Liu, 1999), it is assumed that for a 14% fare decrease, ridership will increase 5% in urban, 3.5% in suburban (1/2 of urban) and 1% (1/5 of urban) in rural areas.
- 70% of the population lives in suburban, 20% live in urban, and 10% live in rural areas.

$$\$66{,}425{,}000 \ = \ \$25{,}000{,}000{,}000 \ *(1 - \left(1 - \frac{1}{300}\right) * \left(1 + \frac{1}{300} * \frac{70\% * 2.5\% + 20\% * 5\% + 10\% * 1\%\ ridership\ increase}{14\%\ fare\ reduction}\right))$$

Table A- 2: Vehicle coefficients for GHG emissions target constraint

Index						Life-cycle Emission Factor (EF) *(CO2 eq kg/km)*		Forecasted number of vehicles in 2030 (FNV)	Forecasted number of vehicles sold from 2020 to 2030 (FNS)	Kilometres travelled a year (KMT)
	2020	*2030*				*2020*	*2030*			
	Total life-cycle emissions	*Manufacturing*	*WTT (fuel production)*	*TTW (operating emissions)*	*Total life-cycle emissions*					
Gasoline LDV (G.LDV)	-	22.7	34.3	120.5	177.5 [1]	233.96		10,300,000 or which 19,000 are government owned [2]	8,760,000	14,500[1]
EV (i=1, i=3)	-	26.3	19.4	0	45.7 [1]	59.66				
PHEV (i=2)	-	25.4	21	36	82.4 [1]	71.11				
F.LDV	223.7 [1]	-	-	-	0.92(G.LDV) + 0.05(EV) + 0.03(PHEV)	220.36 [3]				
Diesel Bus (*D.Bus)*	-	30.9	399.4	1338.4	1768.8 [4]			9,000[5]	-	43,647 [6]
BEB (i=4, i=5)	-	36.6 [5]	149.3	0	185.9 [4]					
F.BUS	1794.0 [4]	-	-	-	0.9(D.Bus) + 0.1(EB)					

[1] Ontario, target year 2020 and 2030, Gasoline low sulfur LDV, Battery Electric LDV, and PHEV - EV50/Gasoline50km LDV ((S&T)2 Consultants Inc, 2018)

		[2] Forecasted assuming historic 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 it is 20% Ontario's population (City of Toronto, 2020). [3] 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 representing. In 2030, assuming a linear growth in proportional EV sales, this will result in 8% of the vehicle fleet will be electric assuming a lifecycle of ten years (5% will be EV and 3% will be PHEV based on historic sales proportion). [4] Canada, target year 2020 and 2030, Gasoline Diesel Bus, and Battery Electric Bus ((S&T)2 Consultants Inc, 2018) [5] Forecasted from Canada-wide historic urban transit bus stock growth from 2008-2018 assuming number of buses is proportion to the population in Ontario (40%) (Statistics Canada, 2018) [6] Average KMT driven by bus (USDOE, 2020)

Table A- 3: Modal shift coefficients for GHG emissions target constraint

It is assumed that an increase in buses added to the network (x_5) and a decrease in bus fare (x_6) will result in a reduction of LDV on the road as estimated in the following quadratic relationship: the average LDV (1.5) and bus occupancies (10.5), the maximum average bus occupancy (30), the maximum bus fare reduction (300 cents), the maximum number of buses that can be added to the network (18,000), and the estimated number of bus riders (2,100,000) assuming 70% of their trips are on bus, is used to establish the quadratic relationship described below:

$$AVOCC_{Bus} = 10.5\ occupants\ per\ bus$$

$$ADOCC_{fare} = \left(\frac{1\ cent}{300\ cents} * \frac{5\%\ ridership\ increase}{14\%\ fare\ decrease}\right) * 10.5\ occupants = 0.0125\ \frac{occupants\ per\ bus}{one\ cent\ fare\ reduction}$$

$$ADOCC_{addBus} = \left(\frac{30\ max\ bus\ occ - (10.5+0.012*299\ cents)}{18{,}000\ buses}\right) = 0.00083\ \frac{occupants\ per\ bus}{additonal\ bus\ in\ network}$$

$AVOCC_{Bus} = 1.5$ occupants per LDV

$$CR = 1176\ \frac{cars\ removed}{one\ cent\ fare\ reduction} = \frac{2{,}100{,}000\ \ bus\ riders * \%70\ of\ trips\ on\ bus * 0.0012\ \frac{\%\ ridership\ increase}{cent\ bus\ fare\ reduction}}{1.5\ \frac{occ}{car}}$$

* The 14% fare decrease resulting in a 5% ridership increase is sourced from (Liu et al., 2019)
* maximum average bus occupancy is assumed to be 30
*maximum number of buses that can be added to the network is 18,000 (2 times the forecasted no-provincial policy action 2030 bus fleet).
*forecasted provincial population of 16.6 million in 2030 (Ontario, 2019b), assuming 13% are commuting transit riders, this is 2.1 million riders. Assumed that 70% of the trips are commuting trips