Electric Mobility Emission Reduction Policies: A Multi-Objective Optimization Assessment Approach

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Abstract: The passenger transportation sector is notoriously sticky to decarbonize because it is interlinked with urban form, individual choice, and economic growth. As the urgency to respond to climate change increases and the transport sector disproportionately increases its contributions to global GHG emissions, there is a need for a more meaningful and transparent application of tools to cost GHG emission reduction. This study presents a multi-objective integer optimization (MIO) model to support the costing and GHG reduction estimation of electric mobility road passenger transportation policies. The model considers both cost and GHG emission minimization under resource constraints and background changes in policy interventions within interval ranges for the province of Ontario’s (Canada) in year 2030. All Pareto optimal solutions are included but results that indicate the optimal policy allocation for two discrete targets are discussed in detail; one scenario where $3 billion spending over ten years is the target and another scenario where the target is 40% GHG reduction in year 2030 (relative to 2005 levels). The MIO approach offers an out-of-the-box solution to support the GHG-reducing decision-making process at all levels of government by implementing optimal policy combinations to achieve GHG emission reductions under a target GHG emission reduction target and/or budget.

Keywords: life cycle GHG emission; transport policy; multi-objective optimization

1. Introduction

The urgency to respond to climate change is stronger than ever. As imperatively stated in the most recent Intergovernmental Panel on Climate Change (IPCC) report, current global plans to address climate change are not ambitious enough to limit warming to 1.5 °C above pre-industrial levels; remaining below this warming threshold is a necessity to limit some of the most catastrophic global impacts [1]. Many studies have identified a uni- or bi-directional causality between economic growth and GHG emissions [2–4]. These two objectives are traditionally regarded as conflicting in absence of mitigation mechanisms [5,6] and which are both increasing with rates of globalization [7,8].

A particularly difficult sector to decarbonize—in part due to the high proportion of individual behaviour and systematic complexity—is the transportation sector [9–13]. In absolute terms, the transportation sector accounted for approximately 15% of total greenhouse gas (GHG) in 2019 (only accounting for fuel combustion) [12] and is tied with the industrial sector as the largest total end-use energy consumer [13] (accounting for all components of energy use from production to use). Furthermore, the transportation sector’s emissions have increased faster than any other end-use sector since 2010, averaging +1.8% annual growth [12]. Due to the complex nature transportation-related GHG emission reduction, many nations’ GHG reduction timelines are falling short of 2030 targets; this is in part due to ambiguous targets with insufficient or non-existent national plans [14] that do not engage with all stakeholders [15]. As the urgency to respond to climate
change increases and the transport sector disproportionately increases its contributions to global GHG emissions, there is a dire need to introduce more meaningful and transparent application of tools to cost GHG emission reduction. Most notably, the current literature falls short in utilizing advanced optimization techniques to inform transportation GHG emission reduction policies.

To this end, this study demonstrates a novel application of deterministic multi-objective integer optimization (MIO) problem to the realm of GHG emission reduction. The developed MIO model is formulated for the passenger transportation sub-sector in Ontario, Canada and maximizes the GHG reduction and minimizes the policy costs associated with current and hypothetical passenger vehicle electrification policies. We are not aware of any other studies that utilize MIO in the context of electric mobility GHG emission reduction policies.

The MIO model can be formatted to correspond to any jurisdiction but in this study, Ontario is selected as the case study. It is the most populous province in Canada and has a provincial-level climate action plan that is less ambitious than the federal plan while also lacking details corresponding to the GHG reduction policy outcomes and associated costs [16]. We thus analyze four hypothetical, though realistic (as discussed later), provincial policy solutions in the MIO model:

- Monetary incentives for Battery electric vehicle (BEV);
- Monetary incentives for plug-in hybrid electric vehicle (PHEV);
- Governmental fleet battery electric vehicle (BEV\textsubscript{GOV}) replacement;
- Urban transit battery electric bus (BEB) replacement.

Parameters that are incorporated in the model include estimated life cycle (LC) GHG emissions for vehicles in existing transit and light-duty fleets (private and public) and interval ranges to account for some of the variation in the total-cost-of-ownership (TCO) for EV and BEB as well as private EV sales.

In the Canadian context, provinces are an administrative division of Canada with their own powers to enact climate change mitigation plans; however, provincial policies exist alongside policies which are offered at the federal level. As such, four federal policies that are currently implemented or planned are considered as background emissions reductions in this study [17]. It is assumed that federal policies come at no cost to the province, and thus only their emissions reduction impact is considered in the model.

To address these research needs, the research questions investigated in this study are:

- What is the optimal allocation of different GHG reduction policies in the passenger road transportation sub-sector under varying budgets?
- What is the associated cost to achieve the 2030 GHG reduction targets?

Through the analysis of the developed Pareto front (i.e., GHG emission reduction vs. cost efficient solutions as part of the MIO model), the optimal allocation of policies for a few scenarios assuming a few fixed ten-year budgets as well as for scenarios assuming a ten-year (2030) emission target are showcased. These Pareto front solutions demonstrate the extent at which GHG emission reduction and cost objectives conflict and show how MIO can be used by decision-makers to plan budgets needed to achieve targets in a transparent way. This is missing from current climate change plans across a variety of sectors in Ontario [16,18,19].

2. Background on Optimization Approaches in GHG Reduction Policy Planning

Optimization approaches, which are a subset of mathematical approaches [20], have been used in the literature to support decision-making processes and quantify uncertainties associated with GHG mitigation, energy system planning, and policy costs at different scales. These methods take the form of deterministic and inexact approaches, and some consider a LC assessment (LCA) approach.

Before discussing optimization approaches, it is advantageous to briefly highlight some LCA approaches. LCA approaches have been increasingly used in the literature to assess the LC environmental impacts of passenger transportation vehicles and inform policy
decisions [21,22]. From a bottom-down perspective, Milovanoff et al. (2020) demonstrated that the United States mitigation gap to prevent more than 2 °C global warming by 2050 for the light-duty transport sector would require 90% of the fleet to be electrified [23]. This transition would account for half of the national electricity demand and excessive amounts of materials required to produce EVs to be deployed in 2050. A highlight from their findings includes a need for a mix of policy solutions, which include reducing vehicle ownership, usage, and improving conventional vehicle efficiency.

From a different top-up perspective, Soukhov and Mohamed (2022) demonstrate how the per passenger-trip LC GHG emissions vary depending on the passenger occupancy, operating characteristics, and service mode (ride-share, private passenger car, or fixed route transit but) for a variety of conventional and emerging LDV and bus technologies [24]. From the findings, decision-makers can draw GHG competitive thresholds depending on energy and operating characteristics. For instance, under an average Canadian electricity grid, BEB technologies have the potential to reduce up to 2.3 times more GHG per passenger-trip than comparable technologies operating in a ride-share service mode.

For medium- to long-term policy planning, optimization approaches are often employed in the literature to support the optimum allocation of energy resources under an administrative objective. Deterministic models are less computationally intensive and simpler to interpret relative to other approaches. A few notable works in the realm of deterministic transportation-related GHG emission policy modelling are discussed as follows.

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 [25]. They 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. Meanwhile, Sen et al. (2019) developed a multi-objective 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 [26]. 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 deterministic models developed in these two studies have high interpretability, they do not reflect the range of potential reductions associated with LC GHG emissions, energy system planning, and associated policy cost. Some of these considerations can be considered inexact approaches; these 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. For example, the work of Kang et al. (2021) employs both deterministic and inexact approaches [21]. They first develop a deterministic (linear programming) model to determine optimal options of LDV technologies for the reduction in operation- and capital-related LC CO₂ emissions in China. They then extend this model through an inexact approach (stochastic linear programming) to address the uncertainties associated with technology cost and emission reduction intensity.

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 additional examples of stochastic applications, 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 [27,28].

From a different perspective, interval approaches can be applied when upper and lower bound solutions are appropriate to derive optimistic and pessimistic solutions [29]. For instance, Chen et al. (2018) formulated a dynamic interval chance-constrained programming model for the Yukon Territory, Canada, to estimate the optimal energy system under different policy scenarios with different system costs, GHG emission controls, and renewable energy [30], while Li et al. (2011) combined interval-parameter programming and
minimax regret analysis techniques to support optimal long-term planning of GHG abatement in energy systems under uncertainty [31]. Both studies used interval programming approaches to present upper and lower bound solutions that demonstrate the uncertainty in the decision variables.

In addition, lastly, fuzzy-based approaches are often applied to model the uncertainty when precise data are not available or are varied within a range [32]. An application is within life-cycle (LC) assessment, where Tan et al. (2008, 2009) integrated 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 [33,34]. Another application is in the extension of calibrated energy systems models; the work of Martinsen and Krey (2008) forecasted the energy system based on outputs of the IKARUS energy systems model (computable general equilibrium (CGE) model) using a time-step dynamic linear optimization model calibrated to Germany’s primary energy supply and demand [35]. The study implemented fuzzy constraints which represent the contradictory political targets (e.g., the CO$_2$ reduction target, the proportion of energy imports, the share of renewable electricity, the quantity of domestic coal) and determines the fuzzy optimal total primary energy supply, CO$_2$ emissions, and final energy for each time step.

Optimization models that incorporate inexact optimization techniques can also be coupled with other modelling approaches to provide additional flexibility in incorporating historic trends, technological demand trends, and/or macro-economic considerations when considering complex systems [36]. The work of Vaillancourt et al. (2014) [37] developed the TIMES-Canada model, a dynamic linear programming model, and a detailed database to analyze long-term future energy systems under different oil price and socio-economic growth trend scenarios and implemented policies. Similarly, Jaccard et al. (2003) [36] developed the LEAP model to generate Canada’s energy system outlook in the long-term but incorporates multiple approaches (optimization, simulation, accounting-based, and technology-specific trends). Accurately forecasting energy supply and demand is a critical step in GHG emission mitigation policy abatement [38].

As an extension of previous efforts on the topic of energy planning, GHG mitigation, and policy cost minimization, this study develops and presents the results of an optimization model that uses both deterministic (multi-objective interval programming) and inexact (interval) to estimate policy costs associated with meeting a GHG reduction target. The input data and the constraints of the model are calibrated for the province of Ontario, Canada and for a target year of 2030. The GHG data employed consider manufacturing, life-time operation, and maintenance of LDV and buses for conventional and electric technologies.

To the author’s knowledge, there is a gap in the literature that applies optimization methods to the cost estimation and policy allocation of electric mobility-related policies within Ontario’s passenger road transportation sub-sector. As such, this study offers the following two novel scientific and practical contributions:

- Firstly, a relatively straight-forward mathematical approach to transportation climate change policy decision-making. It is presented and applied to the province of Ontario, Canada but can be reformulated and applied to different jurisdictions to transparently outline the estimated costs and estimated GHG emissions reduced.
- Secondly, since a MIO approach is selected, a set of optimal solutions are generated. Hence, depending on the budget or depending on the GHG emission reduction target, the most optimal policy package can be selected with a certain range based on TCO and EV sales.

3. Methodology
3.1. Background on Canada and Ontario GHG Reduction Policies

We consider four provincial policies (and their associated costs and GHG emission reductions) as well as four federal policies that occur at no cost to the province (i.e., background policies). Ontario has responsibility for energy systems within its borders,
however, policies which are financed at the federal level impact resulting GHG emissions within Ontario. As such, considering these background policies, that are cost-free from Ontario’s perspective, is critical to more accurately evaluating the overall GHG reductions and costs associated transport-related policies.

At the federal level, 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 and the estimated progress towards the 2030 target. The 2030 target was a 30% reduction in emissions below 2005 levels—Canada’s nationally determined contribution (NDC) [39]. In advance of COP26, Canada introduced a more ambitious NDC for 2030, that is a 40% to 45% reduction in GHG emissions in 2030 [17]. The national 2030 emissions reduction plan includes policy actions that focus on the reduction in GHG emissions across all sectors; namely carbon pollution pricing strategy, complementary actions to reduce emissions, adaptive and resilience measures, and support for clean technology [17]. Aspects of these federal policies pertaining to passenger transportation GHG emission reduction are considered as background policies in this study.

Canada consists of 10 provinces and 2 territories, all of which should conform to the national reduction goals. In Canada’s most populous province of Ontario, the climate action plan is less ambitious and clear [16]. The Made-in-Ontario report specifies that by 2030, a 30% reduction in GHG emissions (relative to 2005 levels) will be realized. Approximately 50% of these reductions are estimated to be a result of transport sector interventions such as the increase in the uptake of electrified vehicles, clean fuel standard, and vehicle emission performance standards (assumed half of the reductions from the ‘innovation’ category are transport-related). Since a breakdown on the split between passenger and freight emissions or other additional details are not provided [18,19], it can be assumed that if half of these transport measures are related to passenger transportation, the provincial passenger transportation sub-sector CO₂ eq in 2030 will be 4.5 MT lower than in 2020 (i.e., before the COVID-19 pandemic). This value is reflected as the 2030 GHG emissions under ‘no additional provincial action’ (and can be later seen in Figure 1 in the Result section).

It is worth noting that the provincial and federal targets are cross-sectoral goals, and a specific transportation reduction target has not been set at either government level. Additionally, the GHG emissions reduction forecasts for the transportation sector only considers tailpipe emissions (i.e., tank-to-wheel emissions) as not to double-count emissions within the transportation sector and industry sector (see the national GHG emission inventory [40]. However, from the perspective of this study, we evaluate vehicle LC emissions which include not only tail-pipe operating emissions but also vehicle production, energy production (for the vehicle), and maintenance of the vehicle. Evaluating the full LC of vehicles is critical to equivalent comparing and selecting between passenger transportation related policies.

Since sector-specific targets nor targets which incorporate LC emissions exist in Ontario, we create a hypothetical yet reasonable GHG emission target range for transportation emission reductions which Ontario can implement from year 2020 to 2030. These hypothetical policy scenarios are constructed to demonstrate the trade-offs between achieving GHG reductions and the costs associated with technology-related passenger transportation policies.

The study considers four provincial policies, four federal policies, and their respective ten-year costs as listed in Table 1. Though the provincial policies modelled in this study are hypothetical, they represent actions that have been in place or are currently in place in jurisdictions within the province. For instance, Ontario cancelled EV incentives in 2018 [41,42] and municipalities have pledged and are beginning to electrify their municipal light-duty vehicles (LDV) fleets and bus fleets [43–46].
Table 1. Provincial policies, costs, and GHG reduction outcomes and background ongoing federal policies.

| Policy | Cost * | Outcome | Source | Policy | Outcome | Source |
|--------|--------|---------|--------|--------|---------|--------|
| BEV incentive ($x_1$) | $3000 point-of-purchase incentive per BEV. | An increase in one BEV and a reduction in one conventional gasoline LDV. | [47] | Carbon price | An increase in the proportion of EV sold and reduction in conventional vehicles use due to increased fossil fuel price. | [39] |
| PHEV incentive ($x_2$) | $1500 point-of-purchase incentive per PHEV. | An increase in one PHEV and a reduction in one conventional gasoline LDV. | [47] | iZEV Program | Additional point-of-purchase incentives will further increase the proportion of EV sold and reduction in gasoline LDV ($5000 BEV, $2500 PHEV). | [39] |
| BEV Gov Replacement ($x_3$) | Between $9000 to $3000 saved per BEV (compared to conventional gasoline LDV) depending on TCO A | Retire conventional gasoline LDV and replace with BEV. | [48,49] | Passenger Automobile and Light Truck Greenhouse Gas Emission Regulations | Incremental reduction in operational emission intensity of gasoline LDV (Model year 2011 to 2025). | [39] |
| BEB Replacement ($x_4$) | Between $50,000 to $100,000 per BEB (compared to conventional diesel bus) depending on TCO B | Retire conventional bus and replace with BEB. | [50,51] | Clean Fuel Standard | Incremental reduction in emission intensity of fossil fuel combustion. | [39] |

A includes the price one charging station. B includes the price of overnight charging stations (1:2 buses) and on-route charging stations (3:10 buses). * All prices in 2020 CAD.

3.2. Model Data Sources

The proposed model is formulated as a MIO problem with the following two conflicting objectives: the total cost of policies and total GHG emissions in year 2030. The decision variables ($x_1 \ldots x_4$) represent integer units of transportation policy: Policy $x_1$ and $x_2$ correspond with the units of BEV and PHEV vehicle incentive rebate, respectively, and policy $x_3$ and $x_4$ correspond to the units of BEV Gov and BEB, respectively. Interval values (i.e., upper and lower boundary values) for the cost the TCO of BEV Gov and BEB and the range in private EV sales are incorporated as parameters in the model to demonstrate how a range in values can be evaluated using MIO.

All parameters used in the MIO model with associated detailed descriptions are presented in Table 2 including the provincial policies in Table 1, and justifications are briefly summarized in this sub-section. Readers should bear in mind that assumptions made in this case study are simplistic due to data availability. However, the aim of this study is to illustrate the use of the MIO approach to evaluate policy options and important potential trends across policy options within a range of uncertainty.

LC GHG emissions associated with the average vehicle in 2020 and 2030 are retained from Canada’s vehicle LC emissions software GHGenius (v 5.01 g) [52]. The MIO model considers LDV and transit buses, as they represent the majority of passenger vehicles on the road [53]. Three vehicle powertrains that reflect dominant and emerging powertrain technologies and energy sources are considered: (1) a conventional option (gasoline for LDV and diesel for bus), (2) a reduced emission option (PHEV for LDV), and (3) an emerging power sources option (BEV for LDV and BEB).

The GHG emissions in year 2020 are estimated using the GHGenius outputs (g CO$_2$ eq/km), utilizing an average annual VKT for each vehicle type (retrieved from the U.S. Department of Energy and assumed constant for the ten year period [54]), and the estimated proportion of vehicle types. In this respect, the estimated proportion of vehicle types are: 95% of the LDV fleet being gasoline while only 0.4%, 0.3%, and 1.2% are BEV, PHEV, and hybrid, respectively. The remaining 3.1% are diesel fuel-type. These proportions are estimated based on the sum of EV, PHEV, and hybrid LDV sold between 2011 (latest year available) to 2020 (all are assumed to exist in the 2020 fleet) relative to the number of total LDV registered in Ontario in 2020 (7,789,714 LDV) [55,56].
The Ontario bus fleet in 2020 is estimated to be 7,813 buses based on the population of Ontario, the population of Canada, and the federal bus stock [57]. It is reasoned that the bus fleet in 2020 is 87% diesel, 1.4% BEB, with the remaining amount accounting for alternative low-carbon technologies, namely 1.9% compressed natural gas (CNG) and 9.7% hybrid and bio-fuel buses. The proportion of bus technology types is retrieved from a variety of news articles and transit agency websites as the information is not centrally available (i.e., BEB, CNG, hybrid and bio-fuels [58–62]).

All the number of LDV sales (\(F_{\text{NS}_{\text{LDV}}}\)), LDV and bus registrations (\(F_{\text{NV}_{\text{LDV}}}, F_{\text{NV}_{\text{gov}_{\text{LDV}}}}, F_{\text{NV}_{\text{Bus}}}\)), and the proportions of EV sales, EV and BEB registered used to calculate the emission factors for the estimated fleet (\(E_{F_{\text{LDV}}}, E_{F_{\text{Bus}}}\)) and for the 2030 gasoline LDV, EV, PHEV, diesel bus, and BEB (\(E_{F_{G_{\text{LDV}}}}, E_{F_{E_{\text{LDV}}}}, E_{F_{PHEV}, E_{F_{D_{\text{Bus}}}}, E_{F_{BEB}}}\)) are forecasted using the ‘forecast’ package in R and the best fit ARIMA model for univariate time series [63,64].

The composition of the \(F_{\text{NS}_{\text{LDV}}}\) is forecasted from the historic growth in registered LDV in Ontario and annual EV sales in the province of British Columbia, Canada 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 [39,47]. As such, the level of EV adoption under federal incentives in Ontario (‘no additional provincial action’) is estimated to result in 15.4% of the LDV fleet being electric by 2030 estimated based on historic sales proportions [55]. We assume that the number of BEV in the fleet will be two times the proportion of PHEVs such that 15.9% of sales are BEV and 8% of sales is PHEV in year 2030; it should be noted that the proportion of BEV to PHEV was larger than two in the case of British Columbia in 2019, but we assume since range of PHEV has and will continue increasing, they will be a more preferred option for the early majority. The \(F_{\text{NV}_{\text{Bus}}}\) is estimated assuming 15% of the conventional bus fleet is replaced with BEB by 2030.

The total number of vehicles in 2030 (\(F_{\text{NV}_{\text{LDV}}}\)) and the number of vehicles sold between 2020 and 2030 (\(F_{\text{NS}_{\text{LDV}}}\)) is forecasted assuming historic growth of registered LDV and LDV sales, respectively [55,56]. The number of government LDV (\(F_{\text{NV}_{\text{gov}_{\text{LDV}}}}\)) in 2030 is extrapolated from the number of municipal LDV owned in Toronto relative to Ontario’s population [65]. Similarly, the number of forecasted buses in 2030 (\(F_{\text{NV}_{\text{Bus}}}\)) 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 [57]. 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 [54].

The maximum and minimum proportions of vehicles (\(\eta_{\text{LDV}}, \eta_{\text{gov}}, \eta_{\text{max}}, \eta_{\text{min}}\)) correspond to the limits for the effectiveness of provincial policy at reducing GHG emissions. \(\eta_{\text{LDV}}\) signifies the upper and lower proportion of EV that will make up the LDV fleet in 2030, where at the lower bound policy action will result in 40% EV sales in 2030 (i.e., 25% of the fleet) and the upper bound policy action will result in 60% EV sales in 2030 (i.e., 38% of the fleet); the lower limit is an estimate and the upper limit reflects the federal government’s year 2030 EV sales target [17]. \(\eta_{\text{gov}}\) signifies the maximum proportion of government vehicles which can get converted to EV or BEB in 2030; this is hypothetically assumed as a full conversion to electric by 2030 is unlikely as associated infrastructure planning to support this electric conversion is beginning. \(\eta_{\text{max}}\) and \(\eta_{\text{min}}\) represent the minimum and maximum GHG emissions reductions, relative to 2005 levels (31 MT CO\(_2\) g eq), to be seen in 2030; they range between 40% to 80% as these limits yield a variety of feasible solutions for the selected provincial policy action.

A forecasted LDV and bus emission factors (\(E_{F_{\text{LDV}}}, E_{F_{\text{Bus}}}\)) is estimated for the vehicle fleet in 2020 and 2030 based on the assumed proportion of vehicle types (i.e., percentage of conventional vehicles and EV (\(E_{F_{G_{\text{LDV}}}, E_{F_{E_{\text{LDV}}}}, E_{F_{PHEV}, E_{F_{D_{\text{Bus}}}}, E_{F_{BEB}}}\})).
Table 2. Parameters and associated justification for MIO model.

| Parameters | Description | Justification | Value |
|------------|-------------|---------------|-------|
| $c_1$ | Cost of BEV incentive ($/unit) | British Columbia EV incentive offering [47]. | $3000 |
| $c_2$ | Cost of PHEV incentive ($/unit) | The difference in TCO between conventional GLDV and BEV [48,49]. | $1500 |
| $c_3$ | TCO upon replacing a provincially owned gasoline LDV to BEV ($/unit) | The difference in TCO between D. Bus and BEV. Range associated with fuel price, maintenance, and market price uncertainty [50,51]. | [$50,000, $100,000] |
| $c_4$ | TCO upon replacing a diesel bus to BEB ($/unit) | Forecasted value assuming historical growth in new LDV registered vehicles through years 2011–2019 [55]. The final number is reduced by 20% to account for the removal of medium-duty and heavy-light duty vehicles in the resulting value in addition to a decreasing trend in LDV sales. The ARIMA time-series method is used for forecasting [63,64]. | 7,521,535 |
| $FNS_{LDV}$ | The forecasted number of LDV sales from 2020 to 2030 (#) | Extrapolated from the number of municipal light-duty vehicles owned in Toronto (3800) and its proportional population (20%) compared to Ontario’s population. | 19,000 |
| $FNV_{LDV}^{ago}$ | The forecasted number of the government owned LDV in 2030 (#) | Forecasted value assuming historical growth in registered LDV vehicles through years 1999–2019 [56]. The final number is reduced by 10% to account for the removal of medium-duty and heavy-light duty vehicles in the resulting value. The ARIMA time-series method is used for forecasting [63,64]. | 8,902,593 |
| $FNV_{bus}$ | The forecasted number of buses in 2030 (#) | Forecasted from Canada-wide historic urban transit bus stock growth from 2005–2019 assuming number of buses is proportion to the population in Ontario (i.e., 40% of Canada’s population) [57]. The ARIMA time-series method is used for forecasting [63,64]. | 8569 |
| $p_{LDV}$ | Maximum proportion of EV from the FNS of LDV (%) under a no additional provincial action scenario | The lower bound corresponds to an assumed linear growth of EV sales proportion beginning at 0.7% of the 2020 sales being EV and 40% of new vehicles being EV in 2030. For the upper bound, 2030 EV sales are assumed to be 60% of new vehicles. The upper bound represents the federal target of annual EV sales proportion [17]. It is assumed that 2 times more BEV are sold than PHEVs from 2020 to 2030. | 70% |
| $p_{bus}$ | Maximum proportion of electrified government-owned vehicle (%) | The conversion of the government LDV and bus fleets are assumed not to exceed 70%. | 70% |
| $GHG_{2005}$ | GHG emissions in 2005 from the passenger road transportation sub-sector (g CO\(_2\) eq) | Retrieved from historic reported year 2005 GHG emissions [16,40]. Used as a baseline to compare LC GHG emission reductions in year 2020 and 2030. | 31 MT CO\(_2\) eq |
| $p_{AVG}$ | Maximum proportion of 2030 GHGs to 2005 GHGs (%) | A hypothetical lower bound of GHG emission reduction. Indicates a 20% reduction in 2005 levels. | 80% |
| $p_{MIN}$ | Minimum proportion of 2030 GHG to 2005 GHGs (%) | A hypothetical higher bound of GHG emission reduction. Indicates a 60% reduction in 2005 levels. | 40% |
| $VKT_{LDV}$ | Annual VKT driven by average LDV (km) | Average VKT driven by average LDV and bus [54]. | 14,500 |
| $VKT_{bus}$ | Annual VKT by bus (km) | | 43,647 |
| $EF_{LDV}$ | Forecasted LC emission factor of LDV in 2030 per km (g CO\(_2\) eq /km) | Assumes 15.4% of fleet is EV in 2030 (i.e., 23.9% of all new LDV sales are EV in 2030). For the EV, 10.2% are BEV (39.4 g/km) and 5.2% are PHEV (78.9 g/km). The remaining proportion is assumed to be 81.5% Gasoline (176.7 g/km) and 3.1% are hybrid electric (117.8 g/km). GHG values are retrieved from GHGenius for Ontario, target year 2030, Gasoline low-sulfur LDV, Battery Electric LDV, PHEV—EV50/Gasoline50 km LDV, and HEV low-sulfur LDV [66]. | 155.83 g CO\(_2\) eq/km |
| $EF_{bus}$ | Forecasted LC emission factor of bus in 2030 per km (g CO\(_2\) eq /km) | Assumes 15% of bus fleet is BEB in 2030. GHG values are retrieved from GHGenius for Ontario, target year 2030, 75% Gasoline Diesel Bus (1766.3 g/km), 15% Battery Electric Bus (149.2 g/km), 7% hybrid diesel bus (1070.0 g/km), and 1% Hydrogen fuel cell (1239.1 g/km), renewable natural gas bus (546.9 g/km), and compressed natural gas bus (1474.0 g/km) [66]. | 1454.6 g CO\(_2\) eq / km |
| $EF_{LDV}$ | Emission factor of gasoline LDV in 2030 per km (g CO\(_2\) eq /km) | | 176.7 g CO\(_2\) eq/km |
| $EF_{bus}$ | Emission factor of EV in 2030 per km (g CO\(_2\) eq /km) | GHG values are retrieved from GHGenius for Ontario, target year 2030 [66]. | 39.4 g CO\(_2\) eq/km |
| $EF_{PHEV}$ | Emission factor of PHEV in 2030 per km (g CO\(_2\) eq /km) | | 78.9 g CO\(_2\) eq/km |
| $EF_{DiBus}$ | Emission factor of diesel bus in 2030 per km (g CO\(_2\) eq /km) | | 1766.3 g CO\(_2\) eq/km |
| $EF_{BEV}$ | Emission factor of BEB in 2030 per km (g CO\(_2\) eq /km) | | 149.2 g CO\(_2\) eq/km |
3.3. Model Configuration

The objective functions for the MIO model are shown in Equations (1) and (2). Solving the MIO model for all the associated policy costs policies (upper and lower bound) and the GHG emission reduction targets (upper and lower bound) provides four Pareto fronts as the model is only solved for the year 2030 assuming spending and policy implantation throughout 2020 to 2030. A Pareto front is a set of Pareto efficient solutions that illustrate the optimal solutions of each policy cost and GHG emission reduction target for the entire range of solutions (i.e., 40% to 80% GHG reduction and policy costs between -$109 mil (cost savings) to a maximum $7.66 bil). The MIO problem is then scalarized to convert it into a single-objective optimization problem [67]. These scalarized Pareto optimal solutions demonstrate the conflicting objectives (i.e., cost versus GHG emission reduction) at each data point to help the decision-maker select the appropriate solution.

\[
\min f_{\text{cost}} = \sum_{i=1}^{4} c_i^+ x_i \tag{1}
\]

\[
\min f_{\text{GHG}} = GHG_{2030} \tag{2}
\]

To bind the decision variables such that the cost of policy measures and GHG reduction targets are within a realistic range, the model is subject to the following four 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 (3a) 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 $1500 to $3000 through the provincial incentive) will result in all registered LDV consisting of 25% (lower bound) to 38% (upper bound) EV in year 2030 as justified in Table 2. 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 preference [55] as summarized in Equation (3b).

\[
\sum_{i=1}^{3} x_i \leq \eta_{\text{LDV}} FNS_{\text{LDV}} \tag{3a}
\]

\[
x_1 + x_3 = 2x_2 \tag{3b}
\]

Second, the conversion of the government LDV and bus fleets are assumed not to exceed 70% as represented in Equations (4a) and (4b).

\[
x_3 \leq \eta_{\text{gov}} FNV_{\text{LDV}}^{\text{gov}} \tag{4a}
\]

\[
x_4 \leq \eta_{\text{gov}} FNV_{\text{Bus}}^{\text{gov}} \tag{4b}
\]

Third, the model is optimized under GHG emission constraints. Firstly, the constraint of 80% and 40% GHG reduction relative to the GHG value in 2005 (i.e., a 20% and 60% of 2005 levels, respectively) shown in Equation (5a). This range in reduction allows decision makers to see the cost associated, based on the input parameters, on achieving a certain GHG reduction. Next, the GHG emissions for year 2030 is calculated based on the difference between the annual GHG emissions of the total forecasted vehicle fleet in 2030 (\(GHG_1\)) (i.e., no additional provincial action) and the lower emission vehicle fleet in 2030 as a result of policy action (\(GHG_2\)). This constraint is presented in Equation (5b) where \(GHG_1\) and \(GHG_2\) are defined in Equations (5c) and (5d), respectively. It is assumed that all policy spending decisions (provincial and federal action) are consistently applied for the ten-year time period.

\[
\eta_{\text{min}} GHG_{2005} \leq GHG_{2030} \leq \eta_{\text{max}} GHG_{2005} \tag{5a}
\]

\[
GHG_{2030} = GHG_1 - GHG_2 \tag{5b}
\]
\[ GHG_1 = EF_{F,LDV}FNV_{LDV}VKT_{LDV} + EF_{F,Bus}FNV_{Bus}VKT_{Bus} \]  
\[ GHG_2 = (EF_{G,LDV} - EF_{BEV})VKT_{LDV}x_1 + (EF_{G,LDV} - EF_{PHEV})VKT_{LDV}x_2 + (EF_{G,LDV} - EF_{BEV})VKT_{LDV}x_3 + (EF_{D,BUS} - EF_{BEB})VKT_{BUS}x_4 \]  

Fourth, the non-negativity constraint.

\[ x_i \in Z_{\geq 0} \quad \forall \; i = 1, 2, 3, 4 \]  

The technique utilized to solve the proposed model is the Relaxed-Interactive Sequential Hybrid Optimization Technique (RI-SHOT) developed in the work of El-sobky et al. (2018) [68]. This technique is an interactive classical method hybrid between the weighted, \( \epsilon \)-constrained, and step methods. The advantages of using the RI-SHOT in solving the proposed MIO model are the following: Firstly, it provides interaction between the analyst and the decision-maker in selecting an appropriate Pareto optimal solution. Secondly, RI-SHOT provides the ability to classify the objectives in every iteration and improve the unacceptable objective values by relaxing the other one. Thirdly, it generates several Pareto-optimal solutions by varying the weights and/or the thresholds values, and it detects the non-convex regions of the Pareto set.

The proposed model and RI-SHOT technique are coded in MATLAB R2021a. The MIO model which is then scalarized into a single objective problem is solved using the integer programming function in the GurobiTM solver with a 0.001\% relative optimality gap on a 2.40 Lenovo Laptop with 16 GB RAM.

4. Results

Before presenting Pareto-optimal solutions associated with ten years of policy intervention (2020 to 2030), the boundary solutions are first presented in Figure 1. The GHG emissions in 2005 (used as a comparative baseline value), 2020, and the 2030 estimated GHG emissions in Ontario’s passenger road transportation subsector under no additional provincial actions are shown in blue. In year 2030 under no additional provincial action (i.e., no BEB or EV incentives are distributed), it can also be observed that the background federal policies are estimated to induce a GHG emission reduction of 34.8\% (relative to 2005 levels) in Ontario at no additional cost.

Shown in green bars are the boundary solutions assuming the MIO model optimizes only for a minimum cost and between a lower- and upper-bound EV sales scenario will see a GHG emission reduction of 35.0\% (relative to 2005 levels) at a cost savings of between $29.9 to $109.7 million. These cost savings are generated through the maximum electrification of the provincially owned LDV fleet and some BEB electrification, the former of which is cost saving. This is the minimum among of cost which results in only a marginal increase in GHG emission reductions compared to the background policies (i.e., 35.0\% reduction compared to 34.8\%).

The yellow bars represent the boundary solutions for the MIO model only minimizing GHG emissions. GHG can be reduced between 45.6\% to 51.3\% (relative to 2005 levels) but at a cost of between $4.84 to $7.28 billion depending on if it is a lower- and upper-bound EV sales scenario and TCO. The cost associated with only minimizing GHG emissions, and not assuming cost in the multi-objective target, results in the maximum number of EVs being sold depending on the EV scenario in addition to the maximum number of BEBs and provincially owned LDVs being purchased. This is the maximum amount of GHG emission reductions which also results in the maximum amount of cost.
Figure 1. The provincial GHG emission reduction and cost boundaries of the MIO model. Green and yellow bars present results with provincial action in 2030. Blue bars represent no additional provincial action in 2030, the baseline conditions in 2020, and the 2005 values for comparison. These MIO model boundaries (yellow and green bars) demonstrate the realistic nature of conflicting objectives as well as contextualize the range of feasible solutions that exist within sets of the four Ontario policy solutions considered.

With the boundaries of the results in mind, Figure 2 demonstrates two discrete results between these boundaries along the four Pareto fronts.

The first is the policy choice (green bars, orange points) if the decision maker is aiming for a 40% road passenger transportation GHG emission reduction target. This is in line with the total (all sectors) national GHG reduction target of 40 to 45%. The second demonstrates the policy choice if the decision maker aims to only spend $3.0 billion (grey bars, yellow point), which is less than a third of the estimated ten year cost of building the proposed highway 413, a disputed highway expansion project [69,70].
Figure 2. The optimized ten-year costs, savings, and allocation of GHG reduction policies ($x_1$, $x_2$, $x_3$, and $x_4$) for two discrete scenarios. The scenarios demonstrate upper- and lower-bound costs as a result of total cost of ownership (TCO) and EV sales associated. The first scenario S1 (green) represents a target of $3$ billion in spending over ten years and the resulting policy allocation and GHG reduction. The second scenario S2 (grey) represents a target of $40\%$ GHG reduction in year 2030 and the resulting ten-year policy allocation and costs. The points on the graph correspond to the secondary y-axis in which the first scenario is represented by orange points and the second scenario is represented by yellow points.

Readers should keep in mind that these are two discrete results among a variety of Pareto-optimal sets. In other words, if there is a budget or GHG emission target which is more suitable, decision-makers can refer to the four Pareto-front graphs available in Appendix A associated with the MIO model. A graph is provided for each of the scenarios (low or high EV sales and low or high TCO for BEV$_{gov}$ and BEB) to express the full range of solutions.

In the no additional provincial action scenario (blue bar, black triangular point), GHG emissions are estimated to be $20.2$ MT at no cost (same as displayed in Figure 1). In the first policy choice (green bars, orange points), we can observe that GHG emitted in year 2030 range between $18.14$ to $18.44$ MT ($40.5\%$ to $41.5\%$ GHG reductions relative to 2005 levels) and the costs are all approximately $3$ billion in spending over the ten-year period.

In the second policy choice (grey bars, yellow points), that the GHG reductions are approximately at $18.6$ MT in year 2030 ($40\%$ GHG reduction relative to 2005 levels) and the ten-year costs range between $2.4$ to $2.8$ billion.
What is notable, is that both policy options have the same number of Gov. BEV units. This is because their GHG reducing efficiency ($ per T GHG reduced) is higher than all other policy units. Additionally, PHEV cost efficiency is similar to BEB but only for the lower-bound TCO for BEB. BEB has the lowest cost efficiency at the upper bound, even higher than the BEV as such it is never selected by the MIO since the target for the first policy scenario (S1) is too high and the target of the second policy scenario (S2) is too low to necessitate the selection of the most expensive option. The summary of the allocation and GHG reduction efficiency of the policies over the ten-year period follow in Table 3.

Table 3. The range of policy unit allocation, proportion of GHG emission reductions, proportion of cost, and GHG reduction efficiency of provincial policies for policy scenario 1 (S1) and 2 (S2). The range of values is a result considering the upper and lower bounds of TCO and EV sales.

| Policy Intervention | Policy Units (Over Ten Years) | Proportion of GHG Emission Reductions (in Year 2030 Relative to Each Policy Scenario) | Proportion of Cost | GHG Reduction Efficiency ($/T CO$_2$eq Reduced) |
|---------------------|-------------------------------|----------------------------------|-------------------|----------------------------------|
| BEV incentive        | 762,620 to 807,980            | 60% to 73%                       | 75% to 81%        | 1,507                           |
| PHEV incentive       | 387,960 to 410,640            | 22% to 26%                       | 19% to 21%        | 1,058                           |
| BEV$_{Gov}$ Replacement | 13,300                       | 1%                               | −1% to −4%        | −4521 to −1507                   |
| BEV$_{Gov}$ Replacement | 0 to 5998                     | 0% to 17%                        | 0% to 10%         | 780 to 1417                     |

S1 = Policy scenario 1 (green): Target ~ $3 billion in spending. S2 = Policy scenario 2 (grey): Target ~ 40% GHG Reduction. A GHG reduction efficiency is calculated by dividing the cost of the policy unit by the estimated GHG emission reduction for that scenario.

5. Discussion on Policy Implementation

Given that this is the first study to optimize policy unit allocation using MIO in Ontario’s transportation sub-sector, it is not possible to directly discuss our findings with the literature. Hence, the results are discussed independently and related to the relevant literature.

The GHG reduction efficiency of the four policies considered (i.e., cost per GHG reduction per unit—provided in Table 3) are quite different. The MIO model selects the most optimal, or in other words, most cost-to-GHG emission reduction-efficient configuration of policy units for the selected scenario target.

For scenario two (S2), to achieve a 40% reduction relative to 2005 levels in year 2030, BEV$_{Gov}$ is most preferred policy since the TCO in both the upper and lower bound conditions are cost saving (relative to a conventional gasoline LDV TCO). However, only 13,300 vehicles can feasibly be replaced which only corresponds to 1% of the GHG reductions needed to achieve the 40% GHG reduction target. The GHG reduction efficiency of this policy suggests that the provincial government should lead by example and switch over as many government vehicles as possible. In addition to being cost saving, this action can provide confidence in the technology for private consumer in which range anxiety is still a prominent barrier for slowing adoption [71].

If only the upper bound TCO is considered, the PHEV and BEV incentive is the second and third most preferred policy options, respectively. These two policy interventions are tied together since each PHEV correspond to two BEV purchased. As such, PHEV only account for 21% to 26% of the GHG reduction target while BEV accounts for approximately four times the proportional amount of cost to achieve the target. These findings additionally highlight that the largest contributor to GHG emissions in the road passenger transportation sub-sector is the private LDV fleet, so to achieve the 40% GHG reduction target, electrification of the LDV composes most policy costs. Recognizing the importance of the electrification of the private LDV fleet and the TCO saving potential for EV, there has been federal and some provincial promises to impose an EV sales mandate in the near future [17,72].
If the lower bound TCO is considered, BEB is more cost efficient than the PHEV and BEV incentives. This is notable since only 5997 buses can be electrified within the ten-year period. However, BEB represent 26% of the GHG emissions and only 19% of the cost to achieve the GHG reduction target. Per bus, GHG emission savings are over 35 times greater than compared to one conventional gasoline vehicle to BEV (i.e., 1.99 T CO$_2$ eq compared to 70.58 T CO$_2$ eq LC GHG emissions saved, in year 2030, from one BEV converted compared to one BEB converted).

Since the GHG reduction magnitude per bus is so much higher than LDV replacement, we believe that even under the inefficient upper bound TCO bus electrification should not be discounted by decision-makers. The promotion of buses can provide electric mobility for more people since they are a public good which can be accessed by most (though unevenly [73]), while BEV and PHEV incentives policies promote the ownership of privately-owned personal vehicles. As such, decision-makers should consider working with transit agencies to realize a switch to electric buses in addition to supporting efficient and improved service that will have a long-term impact on reducing single-passenger vehicle dependence and increasing transit ridership [74,75]. A focus on uptake in transit with a sufficient-occupancy is the most effective way to reduce motorized passenger-related GHG emissions in the long term [24,76,77]. To realize an uptake in transit, urban planning that supports active transportation modes, micro-mobility, shared mobility, and mixed-use residential development all play a vital role [78,79]. Furthermore, social norm and barriers are also integral [80–83].

Since Ontario, like many other North American regions, is majority suburban development primarily supporting passenger vehicle transportation, focusing on electrification can realize immediate GHG emissions (assuming the EV infrastructure is in place). However, retrofitting communities to support all that encourages transit uptake can also be carried out in the medium- and long-term.

6. Conclusions

In this study, we formulate and apply a deterministic MIO model to cost-effectively plan GHG emission reduction policies for the year 2030 in Ontario’s passenger road transportation sub-sector. The MIO model’s objective is to maximize the GHG reduction and minimize the policy costs associated with four realistic, but currently not in place, provincial policy solutions: BEV incentives, PHEV incentives, BEV$_{GOV}$ replacements, and BEB replacements. Parameters which are incorporated in the model include estimated LC GHG emissions for vehicles in estimated existing transit and light-duty fleets (private and public). Parameters also include estimated interval ranges to account for some of the variation in the TCO for EV and BEB as well as private upper and lower bound EV sales.

We first present the boundaries of the model, in which when the model is minimized for the cost objective, it realizes a GHG emission reduction of 34.9% (relative to 2005 levels) at a cost savings of between $29.9 to $109.7 million (depending on upper or lower bound EV sales). When the MIO model only minimizes GHG emissions a reduction of 47.1% to 52.8% (relative to 2005 levels) is realized for a cost of between $4.86 to $7.66 billion (depending on upper or lower bound EV sales and TCO).

With the aim to demonstrate how MIO can be used as a tool to aid decision-makers, we present two discrete results, one scenario where $3 billion spending over ten years is the target and another scenario where the target is 40% GHG reduction in year 2030 (relative to 2005 levels). These two scenarios represent realistic targets which may be selected and the associated number of policy units, their GHG reducing cost efficiency, and proportional GHG reduction and cost are discussed. These two scenarios demonstrate only two sets of results out of an uncountable set of pareto-optimal solutions contained within the boundaries of the MIO model (see select points on the four Pareto fronts in Appendix A).

Key take-aways from the Ontario case study, are that the range in TCO for BEV$_{GOV}$ and BEB and the number of EV sold (and thus BEV and PHEV incentives distributed)
both significantly impact how much GHG emissions are reduced and the cost of those reductions. If considering the lower TCO for BEB and either of the TCO for BEV_{GOV}, these two policies are more GHG reduction efficient ($ spent per T CO_2 eq reduced) than the BEV and PHEV incentives (at a provincially paid price of $3000 and $1500 each, respectively). Even when the higher TCO for BEB is considered, we argue that since the GHG reduction magnitude per bus is still so much higher than LDV replacement (with EV), this option should still be strongly considered by decision-makers. Ultimately, a focus on increasing the uptake in sufficiently-occupied transit is the most effective way to reduce GHG emissions in the long term [24,76,77]. To realize such an uptake, urban planning that supports active transportation modes, micro-mobility, shared mobility, and mixed-use residential development all play a vital role [78,79].

It is important to mind the limitations of the application of this model. Firstly, since LC GHG emissions are considered for all road passenger transportation within this study, its application can be considered cross-sectoral. As such, all results reported in this study are end-user specific and thus cannot be directly compared to traditional transportation sector GHG emissions which typically only account for tailpipe emissions (i.e., fuel combustion and not full LC). Within traditional GHG emission accounting, non-tailpipe emissions associated with manufacturing of vehicles, end-of-life, maintenance, etc., are sometimes accounted for in other sectors within the boundaries and/or outside the boundaries as not to double-count emissions across sectors. However, from a transportation climate policy decision-making perspective, accounting for the LC emissions and costs associated with offsetting those emissions, as carried out in this study, is critical to equivalently compare policies. In this way, isolating elements of a sector which a decision-maker has jurisdiction to influence is an alternative approach to establishing and costing element-specific GHG emission targets. This is precisely what the application of MIO in this study accomplishes; it can help decision-makers select the most efficient combination of hypothetical policies, within the sub-sector, under competing objectives.

As such, this study provides novel contribution to the decision-making process in quantifying the effectiveness of transportation-related GHG emission-reduction policies. What is produced is a mathematical modeling framework—the input data, though empirical, are simplified and forecasted for the purpose of demonstration. In this way, the results lack some accuracy in capturing some social, economic, and political factors [84].

It is important to remind the readers that since the developed model captures GHG emission reduction policies in Ontario, Canada, the results cannot be used to draw conclusions for areas outside of Ontario. However, the MIO model formulation is generalizable and could be altered to fit any jurisdiction and policy scenarios can be augmented. Future research could focus on national-level GHG policies that are cross-sectorial, and integrates all sectors (e.g., industrial, commercial, energy, and transportation). It can also include policy estimates to support non-motorized modes (e.g., walking and cycling) and lower-carbon motorized modes (e.g., e-scooters, e-bikes, shared-mobility).

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Abbreviations

BEB Battery electric bus
BEV Battery electric vehicle
BEV\textsubscript{GOV} Governmental fleet battery electric vehicle
EV Electric vehicle (includes BEV, PHEV)
FNS Forecasted number of vehicle sales
FNV Forecasted number of vehicles
GHG Greenhouse gases
LC Life-cycle
LDV Light-duty vehicles
MIO Multi-objective interval optimization
PHEV Plug-in hybrid electric vehicle
TCO Total cost of ownership
VKT Vehicle kilometers travelled

Appendix A

Included within this appendix are four Pareto fronts from the MIO model presented in this study (Figures A1–A4). Each Pareto front represents a scenario combination of high or low LDV EV fleet percentage in 2030 (high-EV, low-EV) and high or low provincially-owned passenger vehicle TCO (high-TCO, low-TCO).

Each Pareto front is a set of optimal solution of each policy cost and the associated GHG emission reduction target. Combined, the four Pareto fronts cover the entire range of solutions, i.e., 40% to 80% GHG reduction in 2030 relative to 2005 levels (31 MT) and policy costs between $−109$ mil (cost savings) to a maximum $7.66$ bil.

The Pareto fronts are presented to demonstrate the cost versus GHG emission reduction conflicting objectives to better inform the decision-making process. In other words, if there is a budget or GHG emission target which is more suitable than the two scenarios discussed in Section 4, readers can refer to blue points in Figure A1 through A4, associated with the four MIO modelled scenarios, respectively.

Figure A1. Pareto front 1 calculated from the MIO model. Assumes LDV fleet is 38% EV in 2030 (high-EV) and upper-bound TCO (high-TCO). Green and grey points represent the two policy scenarios (~$3$ billion ten-year policy costs in 2030 and 40% GHG reduction relative to 2005 levels in year 2030) presented in Section 4.
Figure A2. Pareto front 2 calculated from the MIO model. Assumes LDV fleet is 38% EV in 2030 (high-EV) and lower-bound TCO (low-TCO). Green and grey points represent the two policy scenarios (~$3 billion ten-year policy costs in 2030 and 40% GHG reduction relative to 2005 levels in year 2030) presented in Section 4.

Figure A3. Pareto front 3 calculated from the MIO model. Assumes LDV fleet is 25% EV in 2030 (low-EV) and upper-bound TCO (high-TCO). Green and grey points represent the two policy scenarios (~$3 billion ten-year policy costs in 2030 and 40% GHG reduction relative to 2005 levels in year 2030) presented in Section 4.
Figure A4. Pareto front 4 calculated from the MIO model. Assumes LDV fleet is 25% EV in 2030 (low-EV) and lower-bound TCO (low-TCO). Green and grey points represent the two policy scenarios (~3$ billion ten-year policy costs in 2030 and 40% GHG reduction relative to 2005 levels in year 2030) presented in Section 4.

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