Uncertainty in Derivation of Transportation Sector Inputs and Parameters for a Canadian Energy System Optimization Model

by

Felipe Rashid Zetter Salcedo

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Department of Civil and Mineral Engineering
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Abstract

Energy system models (ESMs) provide an evidence base for climate policy analysis. However, model prognoses vary dramatically across different ESMs, undermining credibility and hindering knowledge transfer. This is compounded by limited access to disaggregated energy data in Canada, leading to reliance on foreign sources and heuristic assumptions, while underrepresenting key sectors, including transportation and chemical fuels supply.

Rather than comparing the systematic differences between ESMs, this thesis steps back to demonstrate the influence that input data derivation and parameterization have on model results, with emphasis on road transportation in Ontario. Using Tools for Energy Model Optimization and Analysis (Temoa), this thesis evaluates system responses to different modeling choices and parameterization methods. It addresses uncertainties related to: (i) using ad hoc constraints to capture market and political dependencies, (ii) technological change in efficiency and projections, (iii) electric vehicle charging demand representation, and (iv) global sensitivities of decision variables to transportation parameters.

Preface

This thesis outlines the modeling work I conducted during my Master of Applied Science program. It offers a detailed explanation of how the transportation sector was represented in the Canadian open-source energy system optimization model, CANOE, as described in **Section 2.2**, while characterizing some of the main parameter uncertainties that arose throughout the modeling process.

The development of the transportation sector database relied on an aggregation framework that I developed to compile data sources, harmonize parameters, and formulate the uncertainty analysis. You can access the repository for this framework at: https://github.com/rashidzetter/CANOE-transportation.git

Due to time constraints, the contents of this thesis were not reviewed by my program supervisors prior to its submission. If you have any questions about this thesis project, please feel free to contact me at: rashidzetter@gmail.com

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The research environment created by these exceptional individuals embodies what every research group should aspire to – a community of brilliant yet humble minds who are always willing to offer their time and support to whomever needs it.

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Chapter 1: Introduction

Energy system models (ESMs) are instrumental in shaping Canadian climate policy. From economic signals to sector-specific performance standards, policies are evaluated by assessing the structure of the economy and emissions using a variety of ESM frameworks that combine bottom-up and top-down approaches. However, greenhouse gas (GHG) emissions and economic projections differ dramatically across these frameworks, undermining the credibility of their outcomes and hindering knowledge transfer between model developers and the target audience, in most cases, policymakers.

This chapter introduces the background of the thesis, outlining the foundations of the study and the objectives it aims to achieve.

1.1 Background and Problem Statement

The IPCC Sixth Assessment Report (WG1) highlights our generation's most pressing challenge: as of January 2024, we have a remaining carbon budget (RCB) of around 340 $GtCO_2$ to limit global warming above preindustrial levels below 1.5°C with a 50% chance (Friedlingstein et al., 2023; Masson-Delmotte et al., 2021). Crossing this threshold could trigger multiple climate tipping points (e.g., Amazon rainforest dieback), meaning that large parts of the Earth's climate system would change to irreversible, self-perpetuating positive feedback states that increase the likelihood of crossing other tipping points (Armstrong M. et al., 2022). Yet, our current global emissions are around 40 $GtCO_2$/year; considering the IPCC and other updated RCB estimates (Forster et al., 2024), this corresponds to about 5 to 8 years before this threshold is crossed at the current pace.

Canada is among the ten countries with the highest greenhouse gas (GHG) emissions (670 $MtCO_2eq$) and has the second-highest emissions per capita (18 tCO_2eq) among those, over three times the global rate. Moreover, half of Canadian emissions in 2021 solely came from the oil & gas (O&G) and transportation sectors, with 189 $MtCO_2eq$ (28%) and 150 $MtCO_2eq$ (22%) of national emissions, respectively (ECCC, 2023b). The provinces that most contributed to each sector –by far– were Alberta with more than 70% of O&G emissions and Ontario with 33% of transportation emissions (NRCan, 2024b). Therefore, Canada plays a significant role in maintaining the RCB above zero to avoid the collapse of Earth's climate balancing mechanisms. However, this requires long-term transformational measures that range from the economy-wide to the provincial subsector levels.

Energy accounts for more than 75% of GHG emissions both nationally and internationally (ECCC, 2023b; IEA, 2024), putting it at the center of climate policymaking. With ever-changing regulatory and market landscapes, and the *net-zero emissions imperative* accelerating state leadership on climate and energy issues, there is an increasing demand for decision-support tools that inform long-term decarbonization strategies (CESA, 2023). For instance, the Government of Canada's 2030 Emissions Reduction Plan, uses energy models to chart net-zero pathways, which set more stringent interim GHG reduction targets of 20% below 2005 levels by 2026 and 40-45% by 2030. Additionally, Ontario's climate plan targets 30% reduction below 2005 levels by 2030 (ECCC, 2023a). These strategies have been aided by gTech-IESD, E3MC, EC-Pro, and other proprietary simulation models that combine bottom-up (e.g., technology detailed) and top-down (e.g., partial equilibrium) modelling frameworks (ECCC, 2022), also called energy-economy models.

However, recent in-house government projections indicate that, while Canada has been able to reverse its historical upward trend in overall emissions and is on track to exceed its 2026 target, additional measures are needed at both federal and provincial levels to meet its 2030 enhanced target (ECCC, 2023a). Moreover, economic and GHG projections vary dramatically across models from other research organizations (Rhodes et al., 2022), yet, there is a consensus – decarbonization requires substantial electrification in every sector of Canada's economy (Kanduth, 2023).

As electric vehicle (EV) adoption accelerates, energy system planners must address critical design questions like "when" and "where" EV charging occurs, "how much" generation capacity is needed, and "which" synergies chemical fuels may have in some applications (Yip et al., 2023). In Canada, limited access to spatially and technologically disaggregated energy data about costs, performance, energy use, and consumer behavior often leads to reliance on U.S. sources or heuristic assumptions, thus complicating accurate energy system representation and introducing model uncertainties (Whitmore & Pineau, 2022).

Until recently, energy system models (ESMs) have traditionally been designed with a primary focus on power generation and transmission, partly due to its centralized nature and availability of data (Huckebrink & Bertsch, 2021). Nonetheless, crafting successful policy strategies requires a representation of multiple energy carriers and their interdependencies across sectors (Fodstad et al., 2022) as there is no one-size-fits-all approach for achieving net-zero emissions and the optimal roles between electrification and chemical fuels are not well understood. Meeting the climate targets calls for rapid and far-reaching efforts aimed at meeting economy-wide carbon neutrality by 2050 (J. F. DeCarolis et al., 2020).

These issues underscore the need for (i) unprecedented, deep decarbonization incorporating multi-sectoral deployment of available and prospective technologies that require novel policy and finance innovation; (ii) a nuanced understanding of differences in frameworks and data used to capture interdependencies between technology, decision-making, and real-world system dynamics; and (iii) overcoming institutional barriers that hinder model reproducibility and auditability. In response to these needs within the Canadian context, the Canadian Open Energy Model (CANOE) is being developed through a collaboration among Canadian universities, government agencies, and consulting firms, while contributing to the discussion about energy data access and availability in Canada. My role in this project involved developing the representation framework for the transportation sector, beginning with Ontario. This development process forms the foundation of the discussion in this thesis.

1.2 Research Objectives

The scope of this research involves the following objectives:

- Develop an open-source, technology-detailed transportation demand module for a large, multi-sector energy system optimization model in Ontario.
- Assess uncertainties associated with system-level responses to different parameterization methods and modeling choices, with emphasis on road transportation.
- Evaluate global sensitivities of system costs and greenhouse gas emissions to model parameters from the transportation sector to identify which parameters influence decision variables the most.

1.3 Relevance

As any modeler would know, modeling choices matter. The problem is that understanding which choices influence model results the most remains unclear. This study focuses on providing evidence to broaden our understanding of the implications from these choices and their influence in model outcomes, particularly in the context of transportation system representation within large bottom-up optimization models developed for Canadian energy systems.

This thesis offers a comprehensive exploration of transportation systems modeling within technology-detailed linear optimization models. It covers a diverse range of topics crucial to the quantitative representation of the transportation sector, addressing everything from theoretical foundations to practical modeling applications. Main topics include the challenges encountered, recognized solutions, and the evaluation of sources of uncertainty in the model parameterization, while emphasizing which transportation parameters have the most significant impact on system-level outcomes.

Furthermore, the thesis contributes to a broader conversation about access and availability to disaggregated Canadian energy data, from technical, spatial, temporal and societal standpoints. It examines the challenges these present and discusses how access to higher resolution, or more detailed, data could improve representation based on model result sensitivities; ultimately strengthening the evidence base for climate policy analysis.

1.4 Thesis Outline

This thesis investigates the impact of input data derivation and parameterization on energy system model results, focusing specifically on the transportation sector in Ontario. It begins with an introduction to the role of energy system models (ESMs) in supporting Canadian climate policy and the challenges associated with modeling greenhouse gas emissions and economic projections. The thesis uses the Canadian Open Energy Model (CANOE), which runs on the Temoa optimization framework, to assess system-level responses to various parameterization methods, particularly those related to road transportation. Key areas of focus include explicit constraints, technological change in cost and performance, electric vehicle charging demand representation, and the global sensitivity of model decision variables to transportation parameters.

Chapter 2 details the construction of a comprehensive transportation demand module, which aggregates data from various sources to represent Ontario's transportation sector within the CANOE model. This chapter includes a scenario-based analysis that measures the influence of different modeling choices on decision variables, including a global sensitivity analysis to explore the parameter space and evaluate parameter influence. The thesis concludes by discussing the limitations of the current modeling approach, highlighting the need for improved data access and suggesting future research directions to better capture the complexities of the transportation sector in energy system models. Overall, the thesis provides a detailed exploration of how data gaps and methodological decisions affect model outcomes during development process.

Chapter 2: Transportation Sector Uncertainty Analysis

This chapter provides an overview of the Canadian Open Energy Model (CANOE), introduces the underlying motivations for its development, describes the inputs and parameters used to represent the transportation sector in Ontario, and discusses underlying challenges, assumptions and implications from modeling choices and methods used for the transportation sector – the main contribution of this thesis project. This chapter also assesses the uncertainties associated with modeling choices and parameterization of road transportation technologies.

The chapter is organised as follows: **Section 2.1** provides background on the motivation behind the development of CANOE, **Section 2.2** covers some of the main aspects about CANOE and its scope within Canadian energy systems. While **Section 2.3** addresses important details about each main technoeconomic parameter used in the transportation sector and the scenario assumptions used in the uncertainty analysis, **Section 2.4** summarizes some of the key challenges that I faced during model development and the assumptions that I chose to address these. Lastly, **Section 2.5** assesses system responses to distinct parameterization options, to evaluate the underlying uncertainty in these modelling choices.

In this chapter, the term *period* is mostly used to refer to both a model period (i.e., consecutive block of years) and a representative period (i.e., a time-slice at the sub-period scale) consisting of 24 hours to represent a typical day of system operating conditions. To avoid confusion, the former use is always accompanied by an adjective such as *model period* or *multi-year period*.

2.1 Introduction

The average fuel consumption of ICEVs has been improving due to more stringent GHG emissions regulations such as the announced light- and heavy-duty vehicle emission regulations (ECCC, 2023a). However, these improvements have slowed down in more recent years and they are not sufficient for the deep decarbonization that is required in the transportation sector (IPCC, 2023). As plug-in EV sales are gaining momentum, above 10% of the LDV market share in Canada and above 7% in Ontario in 2023 (StatCan, 2024a), and the light-duty zero-emissions vehicle (ZEV) sales mandate is proceeding through regulatory approval (ECCC, 2023a), it is clear that a substantial electrification of road transportation (RT) will occur within the next few decades.

However, an internal combustion engine vehicles (ICEV) phase-out is in the order of decades (IEA, 2023; Morfeldt et al., 2021) and the demand for chemical fuels will likely hold for several decades even at high electrification rates (Millinger et al., 2022). Abatement alternatives to decarbonize the hard-to-electrify subsectors –such as heavy-duty long-haul trucking, maritime transport, aviation, and high-temperature industrial processes– are needed to meet the interim and net-zero emissions targets. Abatement options range from short-term biofuel adoption and improvements in oil & gas to synthetic hydrocarbons and electrolytic hydrogen supply in the long-term (Millinger et al., 2021, 2022). Thus, chemical fuels have a transitional role in achieving a carbon-neutral energy system, particularly in high energy density and high temperature applications (Dreizler et al., 2021).

As policy makers have to address the unprecedented challenge of crafting effective climate policy within the confines of future uncertainty that grows over time (J. DeCarolis et al., 2017), the following section describes a Canadian energy system optimization framework that is being developed to (i) envision the optimal mix of chemical fuels across the economy; (ii) address capacity planning problems such as meeting additional demand from plug-in electric vehicle (PEV) charging while considering spatiotemporal variability to a limited extent; (iii) identify cross-sectoral co-benefits and trade-offs between technologies and fuel supply pathways; (iv) expand emissions accounting to include capacity-related emissions and (v) provide a framework capable of assessing major sources of uncertainty and quantify their effects on policy scenarios.

2.2 Canadian Open Energy Model (CANOE)

While numerous types of energy-economy models exist, bottom-up architectures are better suited to address research questions that originate from the need for multi-energy system-wide transformations facilitated by the deployment of novel technologies at unprecedented rates to cost-optimally neutralize GHG emissions at the subsector level (Ringkjøb et al., 2018). To model these net-zero transitions, both the evolution of long-lived energy infrastructure and the short-term variability in supply and demand of energy vectors (e.g., electricity and heat) need to be captured across sectors. Prina et al. (2020) found that the simultaneous achievement of high resolution in time, space, sector-coupling and technoeconomic detail has not been achieved by any of the long-term bottom-up models they reviewed, including TIMES, OSeMOSYS and Temoa. Thus, even with dramatic advancements in computing resources in the last two decades, balancing computational tractability with spatiotemporal resolution has remained a main challenge for large bottom-up models (Fodstad et al., 2022; Pfenninger et al., 2014).

CANOE is a long-term technology-detailed energy system model building framework that runs on the open-source linear optimization framework, Temoa, also used to develop the US Open Energy Outlook (OEO) (J. F. DeCarolis et al., 2020). Currently, CANOE can be used to determine least-cost system configurations of energy carriers and energy technologies, from supply of primary energy to consumption of final energy to satisfy exogenous energy service demands across sectors while tracking GHG emissions. These demands are projected through 2050 by indexing end-use demands from 2019 (latest year is 2021, still in pandemic levels) by province and technology class (NRCan, 2024b) to population or GDP growth projections relative to 2019 levels by province (CER, 2021). CANOE is envisioned as a transparent, accessible multi-energy investment decision support tool that captures cross-sectoral trade-offs between climate policies and energy technologies while under uncertainty, with the aid from integrated uncertainty assessment features.

Models using the Temoa framework have a limited temporal resolution, usually a few time-slices that represent a full year of data, whereas its time horizon spans multiple decades in multi-year periods, usually five years. This framework assumes that every year within a multi-year period has the same system conditions, except for technologies whose lifetimes expire during an inter-period, therein, their capacity is weighted based on the remaining years of lifetime and equally distributed throughout every inter-period year. Thus, for each model period, Temoa optimizes capacity and activity for the first year, and assumes the results for the remaining years within that model period are identical, while accounting for the total discounted cost across all years in all model periods (J. F. DeCarolis et al., 2015). CANOE's spatial resolution is at the provincial level, with the design in mind to cover all of Canada, though this study focuses only on Ontario. Its energy carrier supply sectors include chemical fuels (e.g., gasoline, ethanol, diesel, biodiesel, natural gas, etc.), electricity generation and storage, and hydrogen production, whereas its demand sectors initially are transportation, buildings (residential and commercial) and industry (in aggregated form).

Given that CANOE is a large bottom-up model designed for modelling scenarios with high electrification rates and VRE penetration to meet net-zero targets, representative periods that describe diurnal operational variability across the system were characterized, such as electricity load at end-use sectors and generation capacity factors. To achieve this, the CANOE team used a hierarchical feature-based-merging approach for annual time series aggregation (TSA), with the direct addition of periods with peak values and means, from Hoffmann et al. (2020); focusing only on the aggregation of time series based on their auto-correlation (i.e., aggregation of redundant information within each time series). The annual time series used in this approach are: the capacity factors of existing and new hydro, solar and wind generators from (Sutubra, 2024); solar irradiance, temperature and wind speed from population-weighted profiles from *renewables.ninja* (Pfenninger & Staffell, 2016); market demand for electricity (Hendriks, R.M. et al., 2023); historical load (IESO, 2018); net load from internal derivation; and the LDV charging profiles, which I characterized using stochastic aggregation with RAMP-mobility, described in more detail on **Section 2.3.1.11**.

I was responsible for developing the transportation sector representation within CANOE, currently the most technology-detailed sector, it encompasses around 159 technologies (both intermediate and end-use) with more than 5,000 parameters to represent all the major existing and emerging technology options. **Figure 1** is a graphical network representation of the CANOE model. Each sector starts with the direct import of fuels from the *ethos* (i.e., unlimited supply) depicted in green, wherein intermediary process flows reach end-use demands depicted in orange. Electricity supplied by generators connects every sector. There is also the connection between industry and transportation, as hydrogen gas is supplied by industry technologies (parameterized for this study).

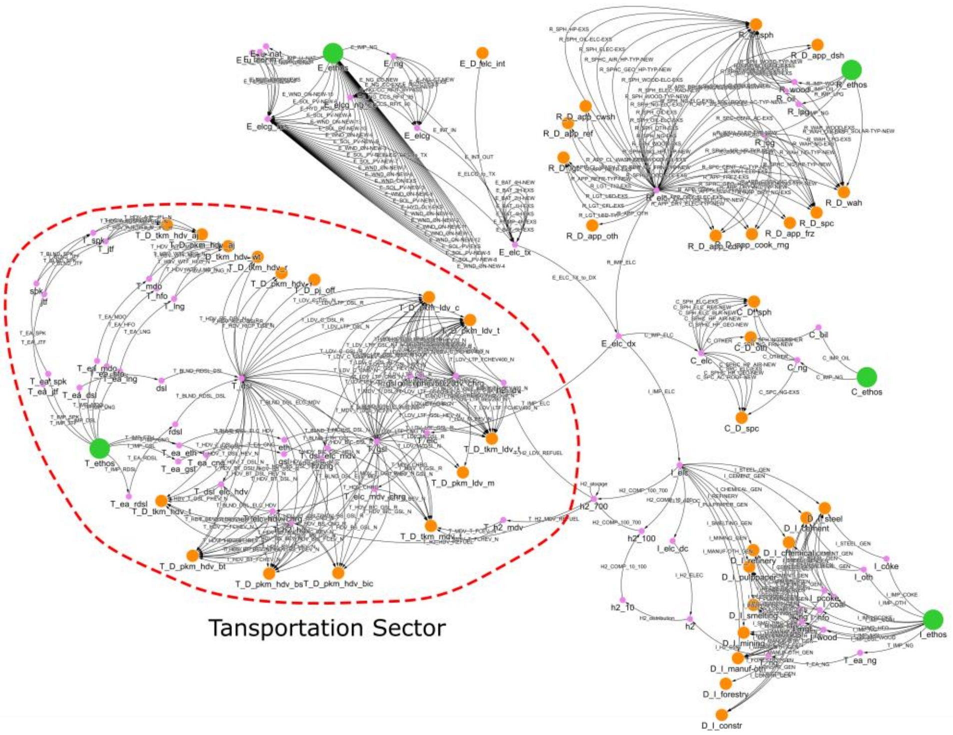


Figure 1: Network diagram of the CANOE model. Pink circles represent commodities (i.e., energy carriers) that are imported from green circles representing unlimited supply (i.e., no infrastructure constraints). Every line represents a

technology with technoeconomic parameters, demand technologies consume energy carriers to meet end-use demands represented by orange circles.

2.3 Data and Methods

This section provides an overview of my work in representing the transportation with as much technology detail as possible given the availability and access to open-source databases, technology assessment models, transportation and mobility studies and other energy system models. Each of the main model parameters are described with a few paragraphs, while briefly discussing some challenges, assumptions, and implications from modeling choices.

Temoa's objective is to cost-minimize technology deployment based using the initial state of the system as reference to meet the end-use demands, in the transportation sector that is cost-optimal vehicle deployment (mostly) to satisfy travel and freight needs measured in billion passenger-km and billion tonne-km, respectively. Each transportation technology is parameterized following the Temoa nomenclature and indexing. Parameters can be indexed by *region*, *model period*, *day*, *hour*, *input commodity*, *emission commodity*, *technology*, *vintage,* and *output commodity*, though not all parameters need every index. For instance, efficiency is only indexed by region, input commodity, technology, vintage, and output commodity. Each of these parameters may also vary depending on the scenario in question.

Currently, fuel-cycle emission factors (EFs) are modelled directly in the fuel supply pathway, meaning that every end-use technology is assumed to have the same direct combustion emissions of a given fuel and every GHG is released per unit of energy of fuel utilized. For example, on a fuel-cycle basis, both light trucks and a heavy trucks are assumed to release approximately 88 g CO_2, 34 mg CH_4 and 5 mg N_2O per MJ of diesel used by either vehicle class, whereas LCA models differentiate the amount of GHG emissions that are emitted during fuel combustion for every vehicle class and transportation mode (Kelly et al., 2023).

As illustrated in the simplified system diagram of the transportation sector in **Figure *1***, there are currently 13 energy carriers, two of which are produced endogenously through intermediate technology pathways (electricity and gaseous hydrogen) and the rest is imported directly using fuel prices while assuming unlimited supply (no infrastructure constraints). Moreover, there are 44 intermediate technologies including PEV chargers, H_2 refuelling stations and dummy technologies that represent blending ratios, EFs, and intermediate conversions such as H_2 compression. The end-use technologies are classified into four categories, two-wheelers, light-, medium- and heavy-duty vehicles, the latter including other modes such as rail, jet aircrafts and marine vessels.

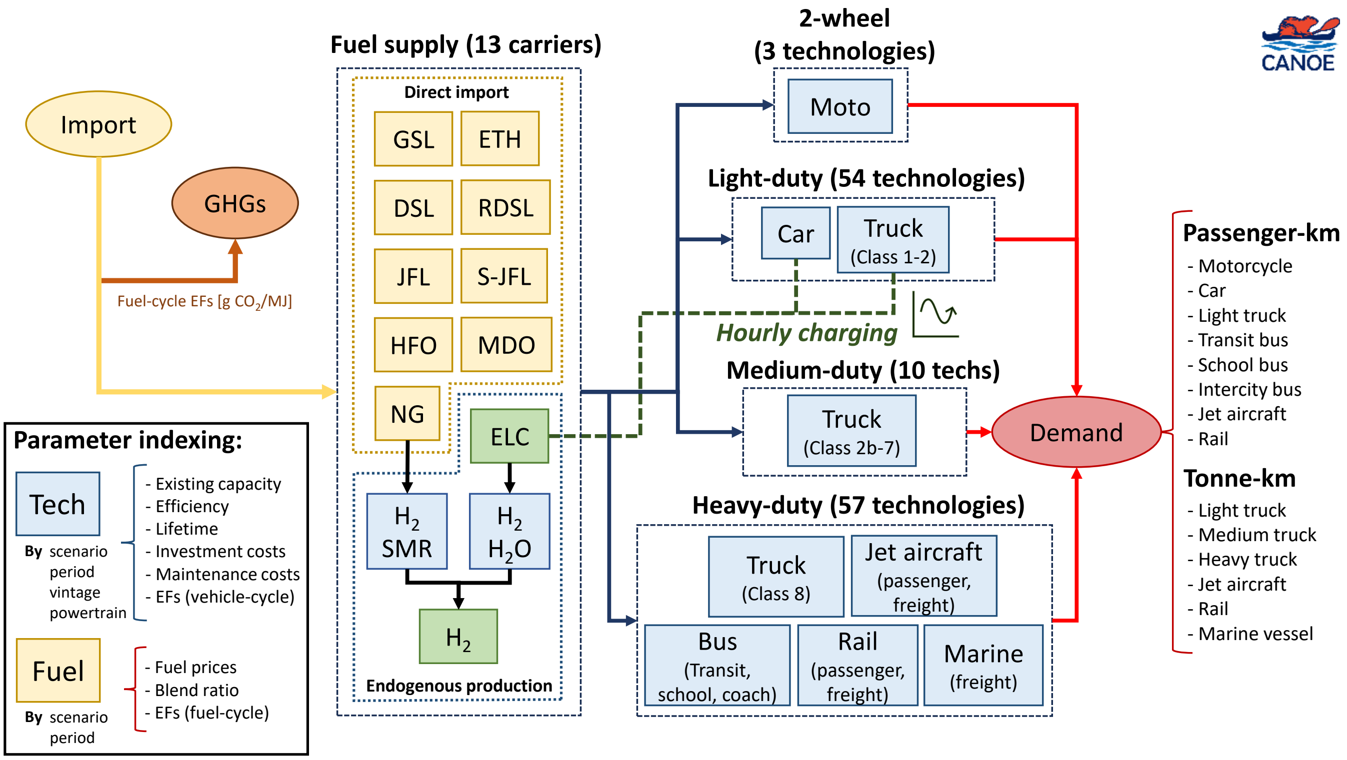


Figure 2: Transportation sector simplified system diagram. Parameter indexing shows some of the main parameters that represent technologies and energy carriers by model indices. Green-colored carriers are produced endogenously, whereas yellow-colored are directly imported by assuming unlimited supply. Abbreviations mean - GSL: gasoline; ETH: ethanol; DSL: diesel; RDSL: renewable diesel; JFL: jet fuel; S-JFL: synthetic jet fuel; HFO: heavy fuel oil; MDO: marine diesel oil; H_2: gaseous hydrogen

Every transportation subcategory (e.g., cars and light trucks within light-duty vehicles) is linked to one of two end-use demands, billion passenger-km (bn pkm) and billion tonne-km (bn tkm) for each subcategory (transportation class). Meaning that only heavy trucks can satisfy demand for tonne-km within that technology class. Therefore, this study did not model modal shifting (i.e., switching from a transport mode or class to another by means of affordability or convenience), which is an important feature of transportation models, specially in a disruptive context such as the net-zero transition (Pedinotti-Castelle et al., 2022).

For this study, alternative versions of the *reference* (base case) system were also compiled to assess the variable and epistemic uncertainty within CANOE model parameters. These versions of the model are detailed in **Section 2.3.3**. For every model run conducted in this study, the model had complete knowledge of future system conditions in every model period, starting with 2021 (as a calibration period), followed by 2025, through 2050 in 5-year periods. This approach is referred to as *perfect foresight*, meaning that all decision variables in all model periods are solved simultaneously. It is also possible to solve the model *myopically*, meaning that only a subset of model periods is solved at a time, in sequence. Some studies have found that perfect foresight might over- or underestimate energy system costs when compared to myopic, as the latter better resembles reality given that decisionmakers do not have absolute knowledge of the future (Payet-Burin et al., 2021).

Nonetheless, the aim of this study is not to find quantitative predictions, but rather to evaluate underlying uncertainties in ideal system conditions, to identify which transportation sector parameters (and their representation methods) influence model results the most.

2.3.1 Vanilla Model

The *vanilla* model simply refers to the CANOE *reference case* model without explicit constraints, meaning that the Temoa framework will find the cost-optimal system configuration that is feasible from a technoeconomic standpoint to satisfy input end-use demands, bounded by implicit boundary conditions from model inputs and parameters. However, these cost-optimal solutions neglect socio-technical aspects of technology transitions. Each of the main model inputs and parameters compiled for the transportation sector are briefly explained in this subsection.

2.3.1.1 Existing Capacity

The model's first optimization period starts in 2021, as we already have historical data on energy use, emissions and system capacities, the first year can serve as calibration year for the subsequent model periods, ensuring that the model projections will be better grounded to current trends. To decide how much new capacity to install on the first periods, the existing capacity of a given technology class needs to be defined, otherwise the model assumes there is no pre-existing capacity. The capacity of every RT class was represented as thousands of vehicles (k units), based on vehicle class sales by vintage (i.e., year when a technology is introduced), calibrated to match the fleet stock in 2020, as the fleet stock composition by class is known (NRCan, 2024b).

Whereas for off-road modes such as rail, air jets and marine vessels, their capacity is represented in demand units (bn pkm or bn tkm), which are estimated with provincial secondary energy use divided by national avg. fleet energy intensity (NRCan, 2024b), as their provincial stocks are not reported. Other similar models have represented off-road mode capacity with demand units, such as NATEM, ACES, OEO, Temoa-Italy and Temoa-Europe (J. F. DeCarolis et al., 2020; Lerede et al., 2024; Nicoli et al., 2022; Vaillancourt et al., 2017). This approach is not ideal as it does not discretize the appropriate amount of investment required to build new fleet capacity, but rather assumes it is continuous, which is not appropriate in capacity-planning models (Dodds & McDowall, 2014). However, due to limited access to disaggregated energy data, demand units had to be used directly. Existing capacities for every technology and year between 2000-2020 are compiled and then aggregated into 5-year vintages using summation, while ensuring that the total sum of existing capacity of each vehicle class and transportation mode is around the 2020 fleet stock (or 2019 demand, for off-road modes).

Several technologies across transportation modes were either aggregated into a single class or neglected, mainly due to the limited resolution in transportation demand (activity) provided by the NRCan National Energy Use Database (NEUD) (NRCan, 2024b). For instance, LDV technologies by size class were aggregated into cars and light trucks; trucks by weight class were aggregated into medium and heavy trucks; different types of two-wheelers (e.g., mopeds, e-scooters, etc.) were excluded while only motorcycles (engines of 50cc or more) are included due to missing classification detail in the NRCan NEUD.

A similar case occurs with passenger rails, there is no clear indication of which types of rail modes are included in the demand class, thus, it is assumed that only intercity rail and urban commuter rail are accounted for (excluding streetcars and subways). Finally, air transportation is assumed to be only from jet aircrafts as the use of aviation gasoline is less than 0.5% of the provincial energy use in aviation. Demand quantification in the NRCan NEUD excludes non-commercial aviation, whereas marine transportation excludes passenger vessels and recreative boating, with no differentiation of freight demand by type of vessel.

2.3.1.2 Utilization Factor

To properly assign capacity units (in thousand units) to vehicle fleets, the model needs to know to which extent can the built capacity deliver the units of demand that need to be met on each year. This is particularly important for consumer-end technologies such as passenger vehicles, given that it has been demonstrated that private cars are parked 95% of the time (Kondor et al., 2020). As expressed in **Equation 1**, the parameters that relate real annual utilization with vehicle capacity are estimated from the ratio between the total annual activity (demand) delivered by a vehicle fleet class and the annual activity that it could potentially deliver if used all the time.

$$UF[-] = \frac{Activity\,[\text{bn pkm/year}]}{Stock\ [\text{k units}]\ \cdot\ Cap2Act\ [\text{bn pkm/k units-year}]}$$

Equation 1: Utilization factors (UF) of road vehicle fleets. Where Stock is the fleet size on a given year and Cap2Act is an arbitrary factor that converts capacity units into activity (demand) units. Cap2Act assumes the maximum deliverable activity of a given vehicle class – while being driven at an avg. speed of 100 km/h for 8,760 hours a year.

For every RT technology, utilization factors corresponding to activity and stock in 2019 are used for the 2021 calibration period. Another option was to use those of 2021; however, pandemic-level utilization was lower than pre-pandemic levels, which could be adequate for 2021, but not for subsequent years as the model would assume the same parameter for inter-period years. For subsequent model periods, from 2025 to 2050, utilization factors correspond to maximum historical ratios between activity and stock, as it is assumed that utilization will at least improve to record-high levels due to more wide-spread use of emerging technologies such as ride-sharing applications and connected autonomous vehicles.

Nonetheless, this approach locks in the assumption that in future years, RT vehicles will be utilised as per recent usage trends, which might not be the case when considering changing consumer preferences or modal shifting from cars and trucks to other modes in both passenger travel (e.g., walking, biking, public transport) and commercial freight (e.g., rail). This could lead to erroneous conclusions about required investments in energy, vehicle and road infrastructure to support projected demand of RT vehicles.

2.3.1.3 Demand

Exogenous input demands are what drive the optimization objective function of the model, by mobilizing end-use technology options that utilize different forms of final energy. As previously explained, demands in CANOE are indexed to population and GDP growth projections from the Canada's Energy Futures (CEF) 2021 provincial macroeconomic indicators of the Evolving Policies Scenario; this scenario assumes that the reduction of GHG intensity in the energy system will follow the same trend from recent years (as per 2021).

For each of the 15 different modes of transportation, demand was indexed solely to GDP growth, as in a study about improving future travel demand projections by Yeh et al. (2022), it was found that passenger distance per capita and GDP per capita exhibit a strong linear correlation in log-transformed historical data between 1980-2018 from the International Transport Energy Modeling (iTEM) open data project, suggesting that a 1% increase in GDP is associated with a 1.07% increase in road passenger distance travelled for the subset of countries studied, including Canada. It was also found that Canada has the second-highest passenger distance travelled per capita in 2021, only after the US and followed by Australia. For freight and other off-road transportation classes, demand projections were also indexed to GDP growth, as the ENERGY 2020 demand model from the CEF 2023 study use GDP projections from the PROVMODS macroeconomic model to index future freight and off-road transportation demand (CER, 2024).

Nonetheless, because bottom-up models fail to capture feedbacks from macroeconomic effects of technical changes (Fattahi et al., 2020), their projections are entirely dependent on how end-use demands are projected. This could lead to biased model results that neglect important drivers such as structural changes in the economy (e.g., telecommuting) and other socio-political factors (Filippov et al., 2021). It is recommended to accompany model projections with multiple scenarios to better explore the decision space and avoid narrow conclusions (J. DeCarolis et al., 2017). However, this study does not focus on developing decarbonization strategies nor quantitative predictions, thus, demand projections were not varied.

2.3.1.4 Technology Lifetime

In the Temoa framework, a technology's lifetime is represented only as a fixed integer, usually the median lifetime in years, which assumes that all its capacity ever installed will have the same lifetime. However, this approach is far from ideal, especially for consumer-side technologies like vehicles, whose retirement is distributed over a longer time period, up to 35-40 years for passenger vehicles (NHTSA, 2022; Tattini & Gargiulo, 2018) depending on several behavioral and technical factors. These distributions are referred as scrappage, retirement or survival profiles, representing the probability of a vehicle surviving a given year of lifetime.

For most RT technologies, except buses and heavy-duty trucks, their lifetime in years was obtained from the US National Highway Traffic Safety Administration Corporate Average Fuel Economy (CAFE) Final Rule modelling for 2024-2026 passenger car and light trucks performance standards (NHTSA, 2022). Wherein the median lifetime of each class was obtained from the input survival profiles of the CAFE model, including medium-duty trucks (Class 2b-3). Sources for other transport technology classes include (EPA, 2023; Lenox, 2019; StatCan, 2022a; Venkatesh et al., 2022).

2.3.1.5 Efficiency and Road Transportation Aggregation

Efficiencies of the existing LDV fleet, representing more than 55% of secondary energy use in Ontario (NRCan, 2024b), were obtained from the NRCan Fuel Economy Guide fuel efficiency ratings by vehicle size class from 2005-2020 (NRCan, 2023). Wherein the mapped size classes (e.g., compact, full-size, small SUV, etc.) were aggregated into the end-use classes provided by the NRCan NEUD (e.g., cars and passenger light trucks) using average national size-class vehicle sales market shares from (Wards Intelligence, 2022). Given that energy use across the model runs on PJ to ensure consistency, conversion from volume-based to energy-based fuel efficiencies (and other parameters) used higher heating values (HHV), e.g., 34.66 MJ/$L_{gasoline}$. This also ensured consistency with parameters from other Canadian models used in CANOE (ECCC, 2024; S&T Squared Consultants Inc., 2022) and good practice recommendations (Navius Research, 2018).

For the remaining technology classes (i.e., medium and heavy trucks, motorcycles, buses, air jets, rails and marine vessels) a more simplified approach was used. The fuel efficiency at a given year was obtained from the average provincial fleet fuel consumption (all in L_{ge}/100 km), except for off-road modes, where the national fleet energy intensity (e.g., MJ/p-km) was used instead (NRCan, 2024b). All efficiencies from RT were harmonized by converting from distance units into activity units (e.g., vehicle-km to passenger-km) using average provincial load factors and occupancy rates between 2015-2019 by class, locking in the assumption that load factors will remain constant in future model periods. These load factors and occupancy rates were calculated by dividing reported activity over the product of average distance travelled and fleet stock, for each vehicle class.

The efficiencies of future technology options were indexed to efficiency projections of RT technologies from Islam et al. (2023), using the low technology progress uncertainty scenario (aligned with original equipment manufacturers' improvements based on business as usual regulatory and market environments in the US) projections through 2050. Only base performance projections were used, ignoring high performance from high-end vehicle options. These projections include those for LDVs by size class and MHDVs by vocation and gross-weight vehicle rating class (GVWR), buses included. LDV classes are also aggregated using vehicle sales market shares (Wards Intelligence, 2022), whereas MDVs are aggregated based on commercial vehicle GVWR registration shares from the Ontario Ministry of Transportation (2023) vehicle population database, following the definition of medium trucks – vehicles with GVWR between 8,501 and 33,000 lb as per NRCan (2015). Finally, heavy trucks (GVWR of more than 33,000 lb) are aggregated based on national shipment type (local vs long distance) based on shipment distance (StatCan, 2020). These aggregation approaches lock in the assumption that the current subclass share distributions will remain constant in future periods; ideally, they should be projected to at least extrapolate recent trends in size class, GVRW class and shipment distance distribution changes.

On the other hand, off-road transportation modes have varied approaches. Given that off-road transport capacity is assumed to be in demand units (e.g., bn pkm), their parameters are better represented from a fleet level rather than from the vehicle level. In that regard, efficiency improvements are projected starting from historical energy intensities in 2019 by mode of transport, as subsequent years were affected by the COVID-19 pandemic. Energy intensity improvement in rail transportation technologies are indexed to the Greenhouse gases, Regulated Emissions, and Energy use in Technologies (GREET) projections used in the Fuel-Cycle Model (Wang et al., 2023); marine technologies are indexed to the improvements from the OEO, which are based on conservative estimates of an efficiency improvement scenario from the Third IMO Greenhouse Gas Study (IMO, 2015); and air transportation also uses GREET 2023 energy intensity estimates with no efficiency improvements. New technology options for off-road modes are obtained from the OEO, while excluding biodiesel technologies such as B20 or B100 (i.e., engines using diesel with 20% renewable content or more), due to seasonal limitations of biodiesel blending in Canada's weather conditions and limited warranty coverage of engines using B20 and higher (NRCan, 2024a). However, these limitations do not suggest that it is unfeasible to use B20 technologies in Canada during a fraction of the year.

2.3.1.6 Investment Cost

The Temoa objective function calculates the costs incurred from energy supply over the model time horizon (e.g., through 2050), discounted to the first year in the horizon (e.g., 2021), using process flows (e.g., supplied energy or activity), installed capacity and emissions released. This approach sums up capital, fixed, variable and emission costs, under the assumption that capital costs are paid through loans, whereas emission costs account for the social cost of carbon. The capital (or investment) cost of installing new technology capacity is amortized using technology-specific discount rates (hurdle-rates) over a technology lifetime (could also be over a shorter loan period), then the lump sum of the stream of payments is calculated and discounted back to the first period using a social discount rate of 3% as per the cost-benefit guide for regulatory proposals (TBS, 2022).

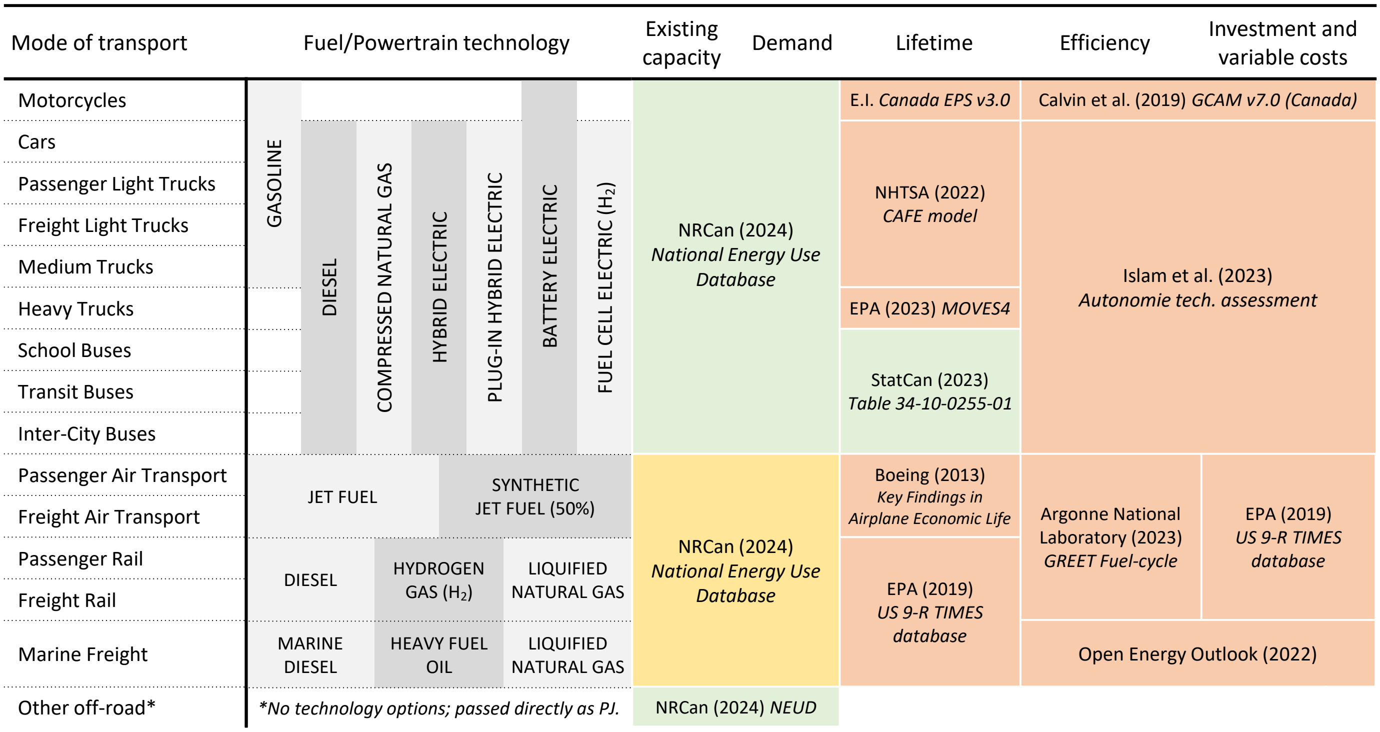
If there are loan payments beyond the time horizon, Temoa removes them, and recalculates the lump sum.

The investment costs are specified in 2020 CAD per unit of capacity. These costs for new RT technologies are obtained directly from the same reference case projections as the efficiencies (Islam et al., 2023), while also using the same size class and GVWR aggregation approach. These projections represent the manufacturing costs of each vehicle by size class and powertrain based on the sum of all vehicle component costs (i.e., component-based analysis), which are determined through a bottom-up iterative sizing algorithm that varies component characteristics until all vehicle technical specifications (VTS) are met. These VTS requirements are representative of the American automotive market (Moawad et al., 2016). All efficiencies and costs of every technology option represented for each RT class, were obtained from Islam et al (2023) – ensuring that (i) competing technologies share the same parameter simulation framework and (ii) efficiency and cost assumptions of the underlying vehicle components remain consistent.

Manufacturing costs were chosen over minimum suggested retail prices (MSRPs) as, from of a central planner perspective, MSRPs are market-driven and do not reflect true economic resource costs. Important vehicle technology assessment studies from US national laboratories usually convert manufacturing costs to MSRP using a scaling factor of 1.5 (Burnham et al., 2021; Hunter et al., 2021). Moreover, vehicle taxes were excluded as these represent intra-society transfers from consumers to government. Investment costs from off-road transportation modes and intermediate technologies (e.g., PEV chargers and H_2 refuelling infrastructure) were primarily obtained from the OEO 2022 cost assumptions. All costs were converted to 2020 CAD using exchange rates from the Bank of Canada and GDP deflator indices (Bank of Canada, 2024; StatCan, 2024b).

Table 1 summarizes powertrain options and main sources of new technology parameters for each transportation mode, while depicting the underlying geographical scope of the data with colors. Every source has been mentioned except US sources for motorcycles (Calvin et al., 2019; Energy Innovation & Pembina Institute, 2023).

Vanilla Model – Powertrain options and parameter sources of **new** transportation technologies (2021 to 2050)



Mode of transport	Fuel/Powertrain technology	Existing capacity	Demand	Lifetime	Efficiency	Investment and variable costs
Motorcycles	GASOLINE BATTERY ELECTRIC	NRCan (2024) *National Energy Use Database*	NRCan (2024) *National Energy Use Database*	E.I. Canada *EPS v3.0*	Calvin et al. (2019) *GCAM v7.0 (Canada)*	Calvin et al. (2019) *GCAM v7.0 (Canada)*
Cars	GASOLINE DIESEL COMPRESSED NATURAL GAS HYBRID ELECTRIC PLUG-IN HYBRID ELECTRIC BATTERY ELECTRIC FUEL CELL ELECTRIC (H_2)			NHTSA (2022) *CAFE model*	Islam et al. (2023) *Autonomie tech. assessment*	Islam et al. (2023) *Autonomie tech. assessment*
Passenger Light Trucks	GASOLINE DIESEL COMPRESSED NATURAL GAS HYBRID ELECTRIC PLUG-IN HYBRID ELECTRIC BATTERY ELECTRIC FUEL CELL ELECTRIC (H_2)					
Freight Light Trucks	GASOLINE DIESEL COMPRESSED NATURAL GAS HYBRID ELECTRIC PLUG-IN HYBRID ELECTRIC BATTERY ELECTRIC FUEL CELL ELECTRIC (H_2)					
Medium Trucks	GASOLINE DIESEL COMPRESSED NATURAL GAS HYBRID ELECTRIC PLUG-IN HYBRID ELECTRIC BATTERY ELECTRIC FUEL CELL ELECTRIC (H_2)					
Heavy Trucks	DIESEL COMPRESSED NATURAL GAS HYBRID ELECTRIC PLUG-IN HYBRID ELECTRIC BATTERY ELECTRIC FUEL CELL ELECTRIC (H_2)			EPA (2023) *MOVES4*		
School Buses	DIESEL COMPRESSED NATURAL GAS HYBRID ELECTRIC PLUG-IN HYBRID ELECTRIC BATTERY ELECTRIC FUEL CELL ELECTRIC (H_2)			StatCan (2023) *Table 34-10-0255-01*		
Transit Buses	DIESEL COMPRESSED NATURAL GAS HYBRID ELECTRIC PLUG-IN HYBRID ELECTRIC BATTERY ELECTRIC FUEL CELL ELECTRIC (H_2)					
Inter-City Buses	DIESEL COMPRESSED NATURAL GAS HYBRID ELECTRIC PLUG-IN HYBRID ELECTRIC BATTERY ELECTRIC FUEL CELL ELECTRIC (H_2)					
Passenger Air Transport	JET FUEL SYNTHETIC JET FUEL (50%)	NRCan (2024) *National Energy Use Database*	NRCan (2024) *National Energy Use Database*	Boeing (2013) *Key Findings in Airplane Economic Life*	Argonne National Laboratory (2023) *GREET Fuel-cycle*	EPA (2019) *US 9-R TIMES database*
Freight Air Transport	JET FUEL SYNTHETIC JET FUEL (50%)					
Passenger Rail	DIESEL HYDROGEN GAS (H_2) LIQUIFIED NATURAL GAS			EPA (2019) *US 9-R TIMES database*		
Freight Rail	DIESEL HYDROGEN GAS (H_2) LIQUIFIED NATURAL GAS					
Marine Freight	MARINE DIESEL HEAVY FUEL OIL LIQUIFIED NATURAL GAS				Open Energy Outlook (2022)	Open Energy Outlook (2022)
Other off-road*	**No technology options; passed directly as PJ.*	NRCan (2024) *NEUD*	NRCan (2024) *NEUD*			

Table 1: Summary of representation of new transportation technology parameters, colored by geographical scope. Efficiency of existing LDVs is obtained from the NRCan 2023 Fuel Consumption Guide. Provincial data (e.g., Ontario) is colored green, national data is yellow and data from the US is red.

2.3.1.7 Variable and Fixed Costs

Variable costs represent the cost of a process-specific activity, specified as 2020 CAD per unit of activity, meaning that when a given technology is not utilized, its associated variable cost is not incurred. For RT technologies, only maintenance & repair costs that vary by vehicle class, powertrain and distance travelled, were accounted for. These were obtained from Burnham et al. (2021), one of the most comprehensive total cost of ownership quantification studies evaluating conventional and alternative technologies of both LDVs and MHDVs, whose results utilize key vehicle parameters from Autonomie technology assessments, such as Islam et al. (2023). Vehicle distance travelled varies by vehicle class and age, based on travel schedules from the US for LDVs and MHDVs (NHTSA & EPA, 2020; U.S. Census Bureau, 2004).

Variable cost elements other than maintenance & repair, such as insurance and labor (i.e., driver wages) costs, were excluded as they reflect market and regulatory dependencies, whereas maintenance & repair costs simply account for vehicle-specific scheduled and unscheduled replacements, repairs and services that are out-of-warranty – limiting the transfer of US market and regulatory conditions into the Canadian context. Ideally, these cost elements should be included as they capture important trade-offs between technology options, especially for commercial vehicles, such as:

- additional labor costs from extended refueling time, e.g., for 500-mile all-electric range (AER) heavy trucks, battery recharging can take more than an hour using 1 MW fast chargers
- payload capacity loss from additional weight of battery storage, e.g., around 8,000 lb of cargo capacity could be lost if traveling at 80,000 lb GVWR limit
- higher insurance premiums from more expensive technology options

The previous examples are based on vehicle parameters from Islam et al. (2023). For off-road transportation, constant operation and maintenance (O&M) costs were obtained directly from the OEO 2022 cost assumptions. Meaning that variable costs remain constant throughout model periods, whereas variable costs for RT technologies vary with model periods, following maintenance and travel schedules.

Currently, conventional fuel supply is represented as direct import with no infrastructure constraints (i.e., unlimited availability) using exogenous fuel price projections. This includes fossil and renewable hydrocarbons, whereas gaseous H_2 is produced endogenously using direct import of natural gas for steam methane reforming (SMR) at industry market price and endogenous production of electricity for electrolysis. Fuel prices of conventional fuels like gasoline, diesel and natural gas (for H_2 production via steam methane reforming) use CEF 2023 provincial historical prices in 2021 (CER, 2024), which are later indexed to the reference case wholesale price projections from the Annual Energy Outlook (AEO) 2023 at the East North Central Region, including distribution costs (EIA, 2023b). Gasoline prices represent gasoline blendstock before oxygenate blending (BOB).

Conventional fuels used in off-road modes were obtained directly from AEO projections (EIA, 2023a). Moreover, renewable hydrocarbons like ethanol and renewable diesel are aggregated from Wolinetz & Harrison (2023), accounting for biofuel transportation costs in Ontario, wherein constant average annual prices between 2012-2022 were used with no projected change. Renewable diesel supply is assumed to contain 50% soy-based biodiesel and 50% hydrogenated renewable diesel, based on observed renewable fuel sales in Ontario (Wolinetz & Harrison, 2023).

On the other hand, fixed costs are specified as 2020 CAD per unit of capacity. In addition to investment costs, once the capital is paid off (assuming different loan period than a process lifetime), fixed costs are still incurred for every year the technology exists. For the transportation sector, only intermediate technologies incur fixed costs, namely LDV, MDV and HDV chargers, H_2 refuelling infrastructure and H_2 endogenous production technologies. These were obtained from the OEO 2022 cost assumptions.

2.3.1.8 Emission Factors

Process emissions are modeled as a secondary output to any technology activity. For hydrocarbon fuel-supply in transportation, GHG emissions are solely modeled in supply-side direct fuel import, specified as k tonne of CO_2eq per PJ of fuel imported and utilized in the transportation sector. Fuel pricing and emissions accounting is currently applied the same way for every sector in CANOE. Therefore, GHG emission variations from direct combustion of different vehicle classes are not represented. Emission factors (EFs) of gasoline, diesel, natural gas, jet fuel and marine fuels represent fuel-cycle (well-to-wheel) emissions released from land-use change and crude oil extraction to the distribution and combustion of the refined product; excluding the construction and end of life of infrastructure systems that support these pathways. These EFs were obtained from the Canadian Fuel LCA Model, based on 2016 Canadian average data, developed to represent the Canadian context while containing some international feedstock and electricity processes (ECCC, 2024).

EFs of renewable liquid hydrocarbons also represent fuel-cycle emissions, with the distinction that biogenic CO_2 is treated as carbon neutral, meaning that CO_2 emissions from combustion are offset by CO_2 uptake by plants. These EFs are obtained from the GREET 2023 Fuel-cycle Model, using the following fuel pathways – corn ethanol (combined dry and wet milling), a combination of 50% soy oil-based biodiesel and 50% tallow-based renewable diesel, and hydrogenated renewable jet fuel, based on observed renewable fuel sales by volume in Ontario (except for renewable jet fuel). GHG emissions, namely CO_2, CH_4 and N_2O, were represented separately, while also CO_2eq using 100-year global warming potentials from the IPCC AR6 (Masson-Delmotte et al., 2021).

Vanilla Model – Parameter sources and delivery method of secondary energy supply to transportation sector

Energy carrier	Delivery method	Energy cost (2020 CAD/PJ)	Emission factor (g/HHV MJ)	Blending ratio (use %)
Gasoline blendstock (BOB)	Direct supply (no infrastructure constraints)	EIA (2023) *Fuel price projections from AEO East North Central Region*	ECCC (2023) *Fuel LCA Model*	10% ethanol to 15% by 2030 (Cleaner Transportation Fuels)
Ethanol (corn-based)		Navius Research (2023) *Biofuels in Canada*	Argonne National Laboratory (2023) *GREET Fuel-cycle*	
Diesel		EIA (2023) *Fuel price projections from AEO East North Central Region*	ECCC (2023) *Fuel LCA Model*	4% renewable content in diesel
Biodiesel & Ren. Diesel		Navius Research (2023) *Biofuels in Canada*	Argonne National Laboratory (2023) *GREET Fuel-cycle*	Assuming 50/50 biodiesel and HDRD based on sales data in ON
Jet fuel		EIA (2023) *Fuel price projections from AEO East North Central Region*	ECCC (2023) *Fuel LCA Model*	Available up to 50% SPK (ASTM standards)
Synthetic jet fuel (SPK)		NREL (2023) *2022 Transportation ATB*	Argonne National Laboratory (2023) *GREET Fuel-cycle*	
Natural gas (CNG & LNG)		EIA (2023) *Fuel price projections from AEO East North Central Region, reference case*	ECCC (2023) *Fuel LCA Model*	
Marine diesel oil				
Heavy fuel oil				
Electricity	Endogenous; through LDV and MHDV chargers	Electricity is imported from the electricity sector (prices and emissions are endogenous)		
H_2 gas (@700 bar)	Endogenous; through LDV and MHDV refuelling stations	Simplified H_2 production pathways; SMR w/o CCS & electrolysis (technology parameters from the Open Energy Outlook 2022)		

Region
🟩 Ontario
🟨 Canada
🟥 US

Table 2: Summary of fuel supply representation sources and delivery method, colored by geographical scope of the data. Gasoline, diesel and natural gas prices use CEF 2023 historical prices in 2021, subsequent prices are indexed to AEO 2023 projections. Provincial data (e.g., Ontario) is colored green, national data is yellow and data from the US is red.

Table 2 summarizes main sources of fuel supply parameters and delivery method for each energy carrier used in the transportation sector, also depicting the underlying geographical scope of the data with colors as **Table 1**. Despite making efforts to use as much Canadian data as possible, most of the parameter data originates from US sources in both tables, evidencing the lack of availability of Canadian data for energy system models.

2.3.1.9 Process Input Split

Technologies that require more than a single input fuel (i.e., commodity) to operate are parameterized using fixed shares of commodity inputs to a specific technology each model period. Such processes include light-, medium- and heavy-duty plug-in hybrids (PHEVs) and fuel blending with renewable content, as laid out in **Table 2**. Light-duty PHEVs have two technology options, 35- and 50-mile AER, for each, different gasoline-to-electricity consumption ratios were estimated using utility-factor weighted averages of adjusted fuel and electricity consumption over combined urban and highway driving cycles in both charge depletion (CD) and charge sustaining (CS) modes (Islam et al., 2023). Medium- and heavy-duty PHEVs are not differentiated by range classes, though the gasoline and electricity consumption estimates use a combination of three different drive cycles depending on vocation and size class as prescribed by an EPA's final rule for MHDV GHG emissions (EPA, 2016).

Following the same approach as with efficiencies and costs, these ratios were aggregated by vehicle and GVWR classes. To meet travel demands, 35- and 50-mile AER light-duty PHEVs utilize around 62.8% and 49.9% of gasoline on average, respectively, whereas medium- and heavy-duty PHEVs utilize 63.3% and 39.7% diesel on average, respectively; the rest of secondary energy use comes from electricity. All input split parameters are assumed to be constant across model periods since Temoa does not index technology input and output splits by vintage, only by model period.

2.3.1.10 Representative Day Aggregation

As mentioned in **Section 2.2,** short-term variability in electricity load at end-use sectors is accounted for, specifically the diurnal electricity demand from end-use technologies such as LDVs in transportation, space heating and cooling technologies and other appliances in commercial and residential buildings. To achieve this in a large bottom-up model, while balancing computational tractability and the representation of highly variable supply and demand of electricity – full-year hourly time series (i.e., 8,760 hours) representing internal (e.g., plant capacity factors and electricity demand profiles) and external (e.g., weather variables) system operating conditions were merged into 12 typical time-slices (representative days) that partially capture peak and seasonal variations of every time series parameterized in the model, at once. Hence, this merging approach is applied to all time series, simultaneously at each time step, under the premise that energy systems behave similarly under similar internal and external conditions. The ideal case of this premise assumes perfect periodicity, where a time series can be represented by a subset of time-slices (periods) and their cardinality without the loss of information (Hoffmann et al., 2020).

The TSA algorithm used for this model was feature-based agglomerative clustering (i.e., Ward's hierarchical clustering), from the *tsam* python library (Hoffmann et al., 2020). This aggregation method is based on the autocorrelation of time-series, merging redundant information within each time series. TSA was applied to the following annual time series to identify representative days: the capacity factors of existing and new hydro, solar and wind generators from (Sutubra, 2024); solar irradiance, temperature and wind speed from population-weighted profiles from *renewables.ninja* (Pfenninger & Staffell, 2016); market demand for electricity (Hendriks, R.M. et al., 2023); historical load (IESO, 2018); net load from internal derivation; and the LDV charging profiles. Thus, 24-hour representative periods were identified to reduce the time steps which the model optimizes over, effectively reducing computational complexity. This algorithm essentially consists of four steps:

1. **Preprocessing –** time series min-max normalization to avoid overweighting of attributes; resampling of each time series (attributes) into 365 row vectors (days) so that each vector represents a period in which all attributes with 24 time steps (hours) are concatenated.
2. **Hierarchical clustering –** using the Euclidean distance of the hyperdimensional space, period vectors are iteratively merged into 12 distinct groups (clusters) by minimizing the increase in intra-cluster variance, wherein cluster centers are determined by their medoids.
3. **Extreme period forcing –** periods containing min and max peak temperature, max peak load and max mean (daily max) net load are used as cluster medoid; it is checked if clusters fit better this new medoid or the original medoid.
4. **Rescaling –** as medoids are real datapoints, rather than the mean of the cluster, they do not meet the overall average value when weighted by the number of periods within a given cluster that they represent, thus, attributes are rescaled to the respective cluster mean.

The outputs include the indices of the medoids (calendar days), and the number of cluster members (periods) associated with each medoid, which are used to weight the representative days. A disadvantage of this and other conventional methods (e.g., k-means and k-medoids) that use normalized Euclidean distances, is that all attributes are weighted equally during clustering. This means that when finding the representative days, wind speed profiles are given the same influence on system operating conditions as total electricity load. However, hierarchical clustering has an advantage over other methods because it is deterministic; it does not require random initialization points, allowing the resulting set of representative days to be consistently replicated.

2.3.1.11 Light-duty Electric Vehicle Charging Profiles

Short-term temporal resolution is crucial for the implementation of storage, capturing the different behaviors of VRE technologies and specific patterns in the distribution of end-use demands. In Temoa, only the capacity factors for each VRE technology that correspond to the representative days from clustering are included. Similarly, load profiles for each end-use technology from the same representative days are included, with the distinction that these profiles are weighted by the number of days that belong to each representative day's cluster. Also, both weights and load profiles are L1-normalized as the model distributes the annual energy demand throughout the normalized weighted profiles, referred as *demand specific distributions* (DSDs). These represent the fraction of annual demand occurring during each time-slice.

Light-duty battery-electric vehicle (BEV) charging profiles were simulated using RAMP-mobility. As described in , it is a generally-applicable stochastic BEV fleet aggregation tool that implements occasional use time frames (referred as functioning windows) in which mobility and charging events can randomly occur given a probability that varies by driver occupation, time of day and day type (weekday, Saturday or Sunday). Its adaptability to different contexts using limited behavioral data makes it suitable to simulate long-term mobility patterns and extreme sensitivity scenarios, which may deviate from today's conditions. It relies mostly on driver and trip characteristics, subject to stochastic variability from a uniform distribution; these characteristics are derived from activity-travel surveys such as household travel surveys (HTSs).

The driver and trip data were collected from the Tomorrow Transportation Survey 2016 (TTS), the largest HTS in Ontario, covering most of the Greater Golden Horseshoe (GGH) area and representing more than 7.4 million habitants, compared to the 13.4 million habitants in Ontario (2016), it surveyed more than half the province population during a typical workweek in the Fall season (Data Management Group, 2018; StatCan, 2022b). However, the rest of Ontario, consisting mostly of rural and non-metropolitan areas, has not been surveyed with sufficient detail to represent mobility patterns. The 2021 Census covers the entire province, but only has single home-to-work trip data of the labour force (StatCan, 2022c).

After allocating typical daily travel needs and trip characteristics using HTS data, battery consumption during travel is mapped to annual population-weighted temperature profiles from Ontario (Pfenninger & Staffell, 2016). This mapping uses 15-minute temperature datapoints and average trip speeds by occupation class and type of day subject to stochastic variation from a uniform distribution. Three vehicle classes are represented based on registered vehicle shares by size class in Ontario (StatCan, 2023a), each with distinct battery capacities using aggregated data from Islam et al. (2023). Moreover, there are three driver occupations with different travel schedules and trip characteristics from the TTS: workers (in the labour force), students (attending school) and inactive (everyone else). Their shares are determined from the 2021 Census (StatCan, 2023b). RAMP-mobility assumes workers and students behave similarly to inactive drivers in weekends and holidays by sharing the same occasional use probabilities, since workers and students also engage in other activities during those days.

This framework accommodates various charging strategies, such as night or day charging or when there is excess VRE generation. Currently, no charging logic is implemented; instead, drivers charge during parking events (i.e., after a trip ends) if two conditions are met: a charging port is available, and the driver chooses to charge. The former is modelled with a piece-wise probability function, simulating higher access outside of peak mobility hours (i.e., outside 7:00 to 19:00), based on home and public charging access estimates from Quebec (ICCT, 2022). Whereas the latter is modelled with a logistic curve that represents the probability of charging during a parking event as a function of the vehicle’s state of charge (SOC), with the exception that BEVs will always charge after ending a trip if the SOC is at 20% or less. All BEV charging events will always charge to 80% SOC.

Charging infrastructure is primarily represented as public (including workplace) and private charging ports, classified into L1 (1.6 kW), L2 (7.2 kW) and direct-current fast chargers (50 kW), assuming 90% charging efficiency. The probability of using each type is based on (i) a national charging network inventory, where it was found that 70% of LDV charging occurs at home (Mogile Technologies Inc., 2022); and (ii) a charging experience survey (40% of respondents are from Ontario) that evaluates home and public charging access, finding that 15% and 85% of PEV owners have L1 and L2 chargers at home, respectively, with 43% of them having access to workplace charging (Pollution Probe & Mobility Futures Lab, 2024). Finally, as per Mangipinto et al. (2022), a fleet size of 2500 EVs was simulated to estimate the annual CPs since larger fleets did not produce substantially different aggregate results, but increased simulation run time.

Vanilla model – main parameters for simulation of annual EV charging profiles, including descriptions and sources

Parameter	Descriptions and values			Source
Temperature annual profile	Ontario, weighted by population density (2018 weather year)			*renewables.ninja*
Trip characteristics (workweek only)	**Total avg. daily driven distance** 38.65 km	**Avg. trip distance** Commuting 19.0 km Personal 8.8 km	**Avg. trip duration** Commuting 23.1 min Personal 10.0 min	TTS 2016
BEV classes (relative share)	**Small (39.0%)** Passenger cars	**Medium (39.5%)** SUVs and crossovers	**Large (21.5%)** Pickups and vans	StatCan (2023)
Driver occupation classes (relative share)	**In the labor force (62.8%)** Inc. employed and unemployed	**Student (13.7%)** Attended school	**Inactive (23.5%)** Rest of population aged 15+	Census 2021
Main travel time windows (time frames where most trips occur)	**In the labor force** Main 1 6:00 to 9:30 Main 2 15:00 to 18:30	**Student** Main 1 7:00 to 9:30 Main 2 14:00 to 18:30	**Inactive** Main 1 7:30 to 20:30	TTS 2016
Charging infrastructure availability (probability of home vs. public)	**Piecewise function** – time frames based on TTS 2016; infrastructure access probability from ICCT Home: p(19:00 to 7:00) = 0.85 Work & public: p(7:00 to 19:00) = 0.34			TTS 2016 & ICCT (2022)
Charging port classes (probability of usage by class)	**Level 1 (10.5%)** 1.6 kW	**Level 2 (83.5%)** 7.2 kW	**DCFC (6.0%)** 50 kW	NRCan & Pollution Probe (2023)
Stochastic variability of parameters	**Uniform distributions** – total daily distance (±30%), avg. speed (±30%), power consumption (±10%)			Default parameters from Mangipinto et al. (2022)
Prob. of charging during parking (if SOC=20%, vehicle is always charged)	**Logistic function:** $p(SOC) = 1 - \frac{1}{1+ e^{-k(SOC-SOC_0)}}$, SOC is always charged to 80%			
Occasional use by time window (probability that mobility event occurs)	**Time window in workweeks** During main travel hours p = 1 Outside main travel hours p = 1/7	**Time window in weekends & holidays** During main travel hours p(Sat) = 0.6 | p(Sun) = 0.5 Outside main travel hours p = 0.3		
BEV battery capacity by vehicle class (aggregated with sales market shares)	**Small (41.0 kWh)** 200- and 300-mile AER	**Medium (58.1 kWh)** 300-mile AER	**Large (100.8 kWh)** 300- and 400-mile AER	Islam et al. (2023) & Wards (2022)

Table 3: Summary of simulation parameters used in RAMP-mobility to generate light-duty BEV annual charging profile from a representative fleet of 2,500 vehicles. Occasional use probabilities are assigned to every driver occupation class, with the distinction that workers and students have two time windows during workweeks (Monday to Friday) representing the round-trip from daily commuting to their main activity. Whereas inactive occupation drivers only have one time window during workweeks, their main activity involves any other activity from the HTS. Every occupation class behaves similarly during weekends and holidays. Parameters from provincial data (Ontario) is colored green, data from national or other province sources is yellow and data from the US is red.

Table 3 summarizes the main simulation parameters used for RAMP-mobility, including brief descriptions and sources that are colored by geographical scope.

Figure *3* and **Figure *4***show the 8760-hour charging demand of light-duty EVs simulated using RAMP-mobility and the recreated annual time series generated from 12 representative calendar days identified by the clustering algorithm, respectively. In the recreated time series, the representative days (medoids) are repeated according to the days that correspond to each medoid's cluster. Since the time series aggregation (TSA) process includes additional time series not directly relevant to transportation system conditions and only about 3% of the original annual profile is used in the recreation, it is evident why **Figure *4*** lacks some distinctive behavioral features of the original data. The most noticeable difference is the absence of the periodically lower aggregate demand seen every weekend and holiday, represented by blue strips that typically appear each week.

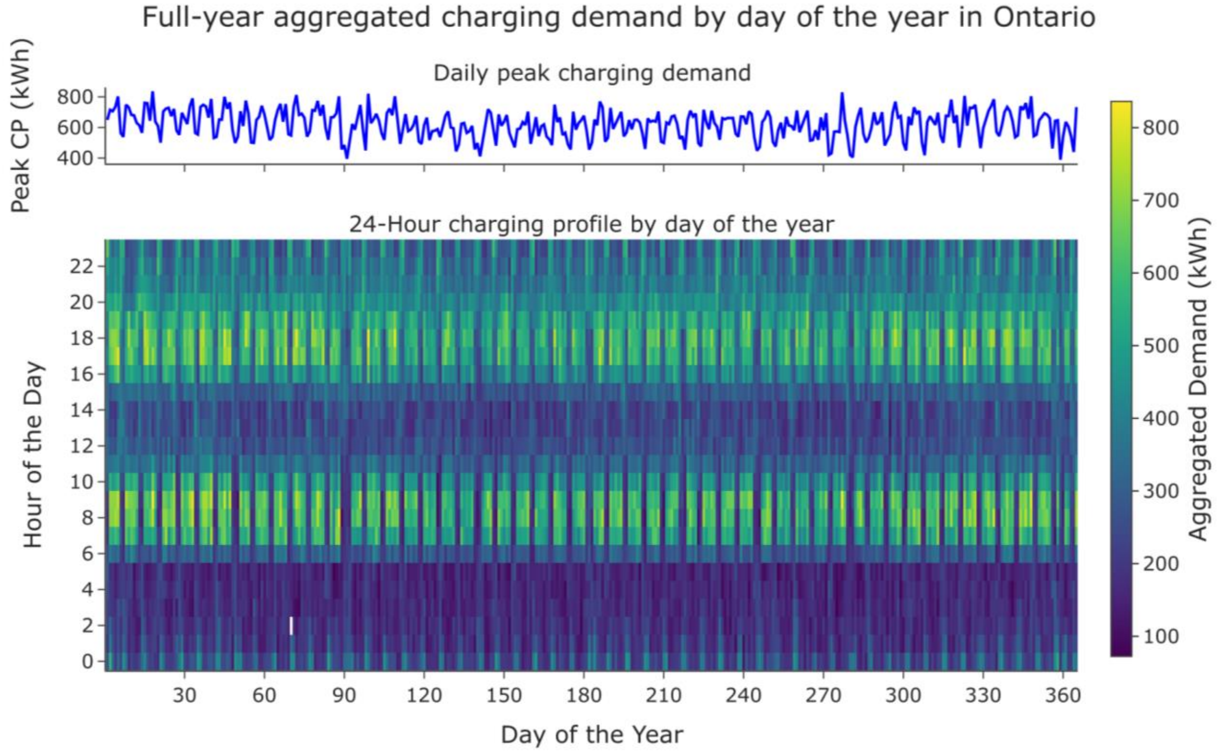


Figure 3: The upper graph represents the peak charging demand for each day of the year, wherein the average peak charging demands during summer and winter are around 600 kWh and 665 kWh, respectively; reflecting the impact of temperature variation on battery consumption throughout the year. The lower graph represents the daily 24-hour charging profiles aligned on the y-axis, with the magnitude of the charging demand represented with color.

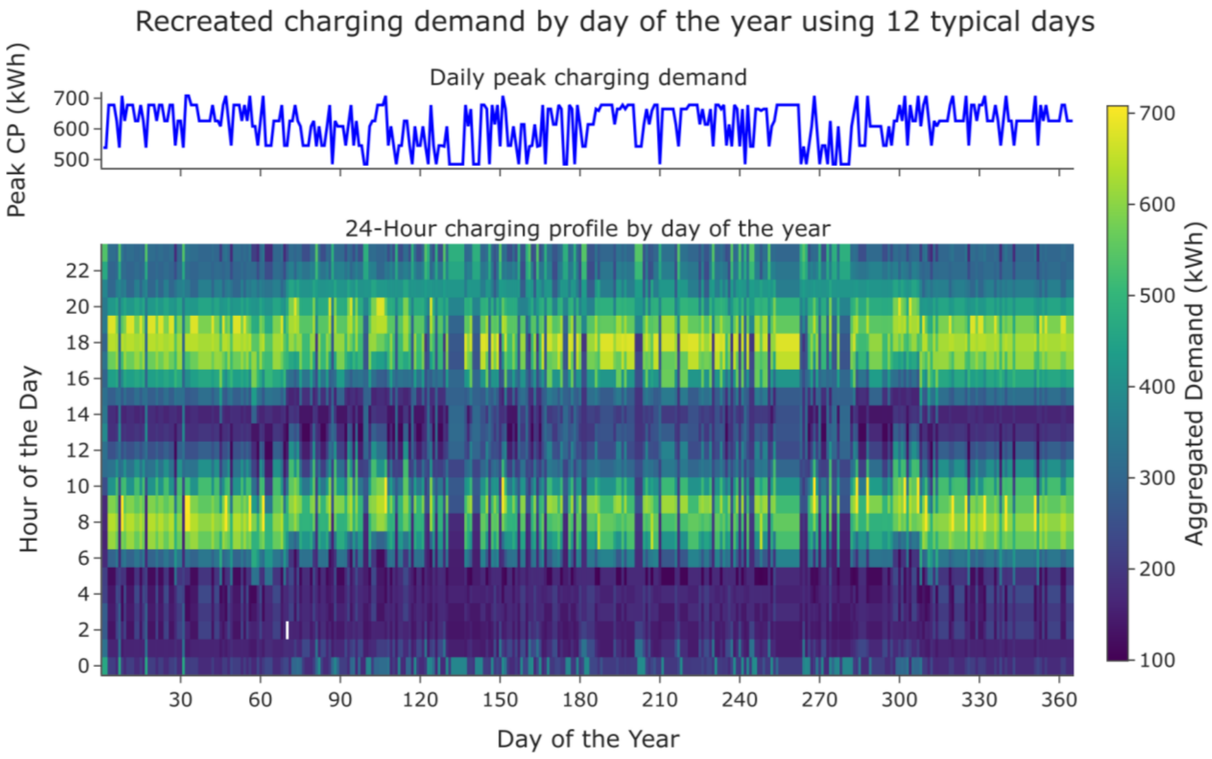


Figure 4: Same layout as the previous Figure. Both upper and lower graphs represent the recreated annual time-series by only using the representative days of the medoid indices (e.g., D007, D185, etc.) from agglomerative clustering between the time-series described in the fourth paragraph of **Section 3.2**. The average peak charging demands during summer and winter are around 612 kWh and 640 kWh, respectively.

2.3.2 Reference Scenario Model

Large bottom-up optimization models focus on finding least-cost solutions. However, empirical evidence suggests that while these solutions are techno-economically feasible, they fail to provide insights that are socially and politically feasible (Dioha et al., 2023). The *reference* scenario model in this section, is the *vanilla* model with the addition of explicit (user-defined) constraints designed to introduce complex interactions between the energy system and society to a very limited degree. These constraints add boundary conditions to the linear optimization problem. As explained in the **Appendix**: Literature Review, simulation models like the Canada Energy Regulator (CER) Canada's Energy Futures Modeling System can also use economic optimization. However, instead of solely the least-cost solution, they prioritize specific decisions or have a priori system responses to a given set of signals.

In contrast, CANOE is an optimization model, not a simulation one. Rather than setting predetermined future expectations, the explicit constraints used in CANOE are designed to ground its findings to present-day socio-political conditions. This allows for a reasonable comparison of scenario results with those from other national simulation models (with provincial-level results) that incorporate similar socio-political assumptions. While CANOE operates under a different modeling paradigm than national simulation models, its use of explicit constraints highlights how such additions can bring bottom-up models closer to real-world conditions, as seen in other validated national models. This provides an indirect measure of socio-political feasibility. The following subsection details each explicit constraint used in the *reference* scenario, representing the most relevant political and market conditions affecting the Canadian transportation sector in recent years.

2.3.2.1 Policy Constraints

The *reference* scenario incorporates a set of legislated policies aimed at decarbonizing the economy, aligned with the 2030 Emissions Reduction Plan. The Greenhouse Gas Pollution Pricing Act (GGPA), or simply federal carbon pricing, is the main economy-wide GHG reduction strategy of the Canadian government, first introduced by the Pan-Canadian Framework on Clean Growth and Climate Change. It sets minimum national standards of GHG price stringency with flexible provincial implementation, a backstop pricing system consisting of two parts – a regulatory charge on fossil fuels based on the CO_2e intensity of fossil fuels (i.e., carbon levy) and a performance-based emissions trading system for industries that are large-emitters and trade exposed. Both elements use the Canadian average combustion EFs of each fossil fuel and the technology that is most commonly used with (ECCC, 2017).

In the *reference* model, emission costs were applied directly to all the equivalent carbon content of fuels used throughout the system, following the price schedule laid through 2030 and onwards (see **Section 2.3.1.8** for more details on emissions accounting). In CANOE, since hydrocarbon fuels are directly imported into each sector –with no representation of energy used by upstream fuel infrastructure except for electricity and hydrogen produced endogenously– fuel-cycle EFs are used to account for economy-wide GHG emissions pricing. The model does not account for the output-based pricing system, including special accommodations for industries deemed trade exposed to protect competitiveness; instead, it applies charges to all emissions, regardless of the emitter. Additionally, land use emissions are exempted from the regulatory charge, though the EFs used in the transportation sector do account for land-use change emissions (ECCC, 2021).

The provincial Cleaner Transportation Fuels (CTF) is Ontario's implementation of the Clean Fuel Regulations, requiring a reduction in the life-cycle (or fuel-cycle) GHG intensity (GI) of gasoline and diesel fuels. This is achieved through a credit-based compliance market where blending fuels with low-carbon renewable content generates tradeable credits by reducing the fuel's GI below the set limit. The CTF enforces minimum volumetric blending rates of renewable content in gasoline and diesel, with a minimum GI reduction benchmark. If the Gi is lower than the benchmark, the required blend rate may also be lower.

In CANOE, these blending mandates strictly follow the schedule set through 2030 and onwards, regardless of whether the GHG intensities are well below the reduction benchmark. The EF used for renewable diesel (21 g CO_2e/MJ) is compliant with the CTF, while the EF for ethanol (51 g CO_2e/MJ) was slightly adjusted to meet the GI reduction benchmark, based on GI levels from the Fuel LCA Model (truncated to 46 g CO_2e/MJ). As noted earlier, all energy units are based on HHVs. **Table 4** summarizes the legislated policies modeled as constraints in the reference scenario.

Table 4: Reference scenario constraints – modeled legislated policies that affect the transportation sector in Ontario

Policy	Model assumption
Backstop Carbon Pricing	Emission costs are incurred for every tonne of CO_2e emitted by hydrocarbon fuels, starting at $40 per tonne in 2021 and annually to $170 per tonne by 2030 (nominal dollars). From 2030 to 2050, the cost remains constant in nominal terms.
Cleaner Transportation Fuels	Gasoline supply is blended with ethanol, starting at 10% and increasing to 15% by 2030; ethanol has a GHG intensity 50% lower than gasoline in all model periods. Diesel supply is blended with renewable diesel at a rate of 4%; renewable diesel has a GHG intensity 77% lower than diesel in all model periods.

2.3.2.2 Market Constraints

The first model period (2021) is used to calibrate the model's decision variables, such as energy use, installed capacity, and GHG emissions, against historical data. Model calibration is an iterative process that usually involves model refinement of initial system responses to better represent real-world conditions at a specific period, validated with empirical data. For the transportation sector, RT vehicle market heterogeneity in 2021 was reproduced using capacity constraints based on vehicle sales in 2023 and registrations data in 2021 (StatCan, 2023a, 2024a).

These constraints force the model to invest in a mix of conventional and emerging technologies in addition to BEVs, such as ICEVs, hybrids and plug-in hybrids, given that light-duty BEVs' levelized cost of driving (LCOD) is the lowest among powertrain options. This observation is derived from *vanilla* model results, showing that BEVs outperform all other powertrains in the light-duty sector in terms of overall cost, leading the model to only invest in BEVs. This phenomenon in linear optimization models, where a single technology dominates the market, has been coined *winner-takes-all* (Tash et al., 2019) and *all or nothing* (Ramea et al., 2018) behavior.

In linear optimization models, a centralized, cost-minimizing decision-maker guides the investment portfolio, resulting in corner solutions where a single technology is exclusively chosen. For example, the model might decide to invest entirely in one technology in one model period and then switch completely to another technology the following period. This abrupt shift, driven by minor cost changes, is another particular phenomenon in linear models, referred to as *penny switching* (Lopion et al., 2019). This study touches on agent behavior due to the recognized importance of behavioral realism in modeling demand sectors, particularly transportation (Luh et al., 2022). However, its appropriate representation requires extensive consumer preference data and detailed modeling beyond the scope of this study and CANOE's current technoeconomic capabilities. Instead, ad-hoc constraints were imposed for conventional and emerging technologies to avoid unrealistic technology adoption, to a limited degree.

Adoption of emerging RT technologies was constrained by estimates of the market's capacity to supply (i.e., sell) new vehicles, limiting new vehicle capacity each model period based on the highest recorded annual sales by vehicle class; so that by 2035, the vehicle market is able to supply around 50-70% of the projected sales limit of each class (NRCan, 2024b). For reference, BloombergNEF forecasts that EVs will comprise 70% of new LDV sales in Canada by 2035, even with the zero-emission vehicle (ZEV) sales mandate in place (Bloomberg News, 2024). Accordingly, the growth rates (GR) of new vehicle capacity were estimated with results from the vanilla model and compounded annual growth rates (CAGR) from NRCan NEUD fleet sales data. These GRs assume exponential growth, considering that emerging RT technologies may be far from market saturation (i.e., the inflection point in a logistic s-curve) as described in Nemet et al. (2023).

Hurdle rates (HRs) were also assigned to emerging RT technologies to account for consumer perception of less mature technologies, such as higher investment risk and imperfect knowledge. Conservative HRs not larger than double the global discount rate (3%) were chosen, similar to how the OEO model applied HRs to RT technologies. Ultimately, HRs uplift the annual payments spread over a loan period (e.g., technology's lifetime), increasing total system costs. Moreover, Laera et al. (2024) found, in a study using Temoa, that HRs do not significantly affect the optimal system configuration. In addition to the LDV technology classifications described in **Section 2.3.1.5**, plug-in electric vehicles (PEVs) were represented with Islam et al. (2023) BEV and PHEV AER classes: 150, 200, 300 and 400 miles, and 35 and 50 miles, respectively. The inclusion of range classes rather than a single PEV option was proactively designed to facilitate seamless formulation of studies involving behavioral features and socio-technical modeling aspects into future work.

For conventional RT technologies, a *market floor* was implemented to limit their market decline, reflecting the inertia of vehicle fleets (Rosenberg et al., 2023). Minimum capacity share constraints were estimated based on conventional vehicle sales in the last five years by vehicle class (StatCan, 2024a), assuming current market trends will hold. Similar constraints were applied to hybrid powertrains, following current adoption trends, to prevent the model from maxing out BEV growth constraints of each range class. For instance, gasoline cars experienced a 13% decline in market share between 2019 and 2023, with the market floor constraint, decline will persist at a similar rate, reaching a 20% market share by 2050. Market adoption was also benchmarked against reference scenario projections from gTech-IESD, Navius Research national simulation model (Navius Research, 2023). A comparison between reference CANOE and gTech-IESD models from are shown in **Figure 5**. Their reference scenario did not enforce ZEV sales mandate as well. The market share retraction of LD BEVs in 2050 can be explained by increased adoption of hybrids and plug-in hybrids, which are considered ICEVs in this market share comparison.

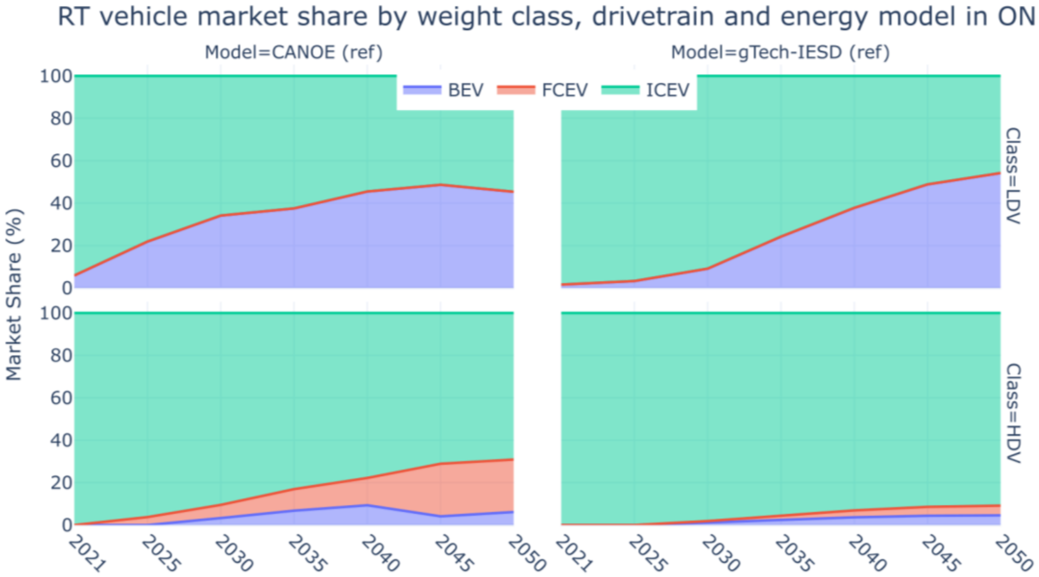


Figure 5: Road transportation vehicle technology mix projections for LDVs and HDVs by energy system model, compared with the available provincial data from Navius Research national model. Market shares from 2021 in the CANOE model are based on empirical data, whereas projected shares are based on ad hoc growth constraints for emerging technologies and minimum market shares for conventional ones. ICEVs include hybrids and plug-in hybrids in this classification, as per gTech-IESD data.

Although ad hoc constraints lack strong theoretical underpinning, such as the ones used in the *reference* scenario of this model, they were applied to bound the results from the scenario analysis with reference conditions from other recognized national models that provide provincial-level results. However, it is crucial to acknowledge these limitations, as the somewhat arbitrary nature of such constraints has been criticized for undermining the validity of optimization models (Ramea et al., 2018).

Table 5: Reference scenario constraints – market-related constraints that affect road transportation in Ontario. Conventional powertrains refer to internal combustion engine vehicles (ICEV), whereas emerging powertrains refer to hybrids (HEV), plug-in hybrids (PHEV), battery electric (BEV) and fuel cell electric vehicles (FCEV).

Market constraint	Model assumption
2021 fleet technology mix	Min and max capacity constraints to reflect vehicle powertrain shares from sales and registrations data by vehicle class in 2023 and 2021, respectively (StatCan, 2023a, 2024a).
Maximum growth rate (GR)	Maximum GRs on new vehicle capacity are applied to emerging powertrains based on fleet expansion results from vanilla model and CAGRs of fleet sales by vehicle class from NRCan NEUD (NRCan, 2024b).
ICEV market floor	Minimum vehicle capacity share constraints are applied to conventional and hybrid powertrains based on market trends from vehicle sales in the last five years (StatCan, 2024a).
Hurdle rate (HR)	HRs not larger than double the global discount rate (3%) were assigned to emerging powertrains. LD and MD hybrids, BEV and FCEV had 4%, 4-5% and 6% HRs, respectively; whereas HD hybrids had 5%, and HD BEV and FCEVs had 6% HRs.

2.3.3 Other Scenarios

EV charging profiles representation in capacity planning models have become an indispensable variable to capture the increasing variable demand from passenger fleet electrification (Yip et al., 2023). Thus, to better understand the system responses to different parameterization alternatives for simulating charging profiles with RAMP-mobility and merging annual time-series into representative days, two additional scenarios were developed to capture extreme sensitivities in the energy system in terms of electric vehicle adoption. Namely a scenario that incorporates the announced zero-emission vehicles (ZEV) mandate (ECCC, 2023a), assuming it is widely implemented in Ontario for LDVs and MHDVs, and a *no-EVs* scenario that assumes no new EV deployment apart from the ones already deployed through 2023, accounted for in initial model period from the *reference* scenario. **Table 6** describes each alternative scenario and the assumptions implemented for the scenario analysis of LDV charging profiles in **Section 2.5.3**.

Table 6: Alternative scenarios and their additional constraints, based on the reference scenario with some distinctions.

Scenario	Description
Road transportation ZEV sales regulations	*Reference* scenario constraints, excluding the ICEV market floor, with the addition of: LD ZEV sales mandate – enforcing a 15% ZEV sales market share in 2025, followed by 60% in 2030, reaching a 100% in 2035 and onwards. MD ZEV sales mandate – enforcing a 10% ZEV sales market share in 2025, followed by 35% in 2030, 60% in 2035 and 100% in 2040 and onwards. HD ZEV sales mandate – enforcing a 7% ZEV sales market share in 2025, followed by 30% in 2030, 50% in 2035, 75% in 2040 and 100% in 2045 and onwards; excluding buses.
No-EV sales after 2021	*Reference* scenario constraints, excluding max growth rates, with the addition of: No new capacity allowed for plug-in electric vehicles after 2021.

2.4 Data Challenges and Assumptions

This section outlines the main challenges encountered during the development of the transportation sector and details the assumptions made to address these issues partially or fully.

Due to the large size of the optimization problem, existing capacity is aggregated into 5-year model periods to reduce computational burden. It is a common practice in long-term bottom-up models to aggregate technoeconomic parameters into multi-annual periods, including those that represent multiple demand sectors such as transportation (Aryanpur et al., 2022; Lerede et al., 2024; Nicoli et al., 2022; Pedinotti-Castelle et al., 2022; Saeid Atabaki et al., 2023; Venkatesh et al., 2022). However, this approach introduces unrealistic technology retirement rates in terms of how many units of capacity retire on a given year. This is particularly detrimental for discrete units of capacity (e.g., thousand vehicles) from consumer-end technologies given that real-world retirement is distributed over a longer time period than the lifetime parameter used for a given technology, represented as integer numbers in Temoa.

Moreover, consumer-end technologies usually retire at a faster rate than energy and infrastructure technologies (e.g., power plants). For instance, it is estimated that 90% of existing car fleet stock can be replaced within 13 to 26 years under European replacement rates (IEA, 2023). Thus, models like CANOE are forced to retire 5-years worth of fleet stock in just a single year, several times throughout the time horizon through 2050. These dramatic large retirements lead to unrealistic lump investment behavior in each model period that is unusually high, more than five times the compounded quinquennial growth rate (every 5 years) of 20% seen in sales for light trucks (NRCan, 2024b). ***Figure 6*** demonstrates this behavior, between 2021 and 2035 there is a dramatic increase in the deployment of light trucks per period, followed by a decrease in 2040 as most of the existing fleet in 2020 has been replaced by new vehicle capacity. This behavior repeats again after 2035, as most of the fleet from that model period begins to retire as large batches in subsequent periods.

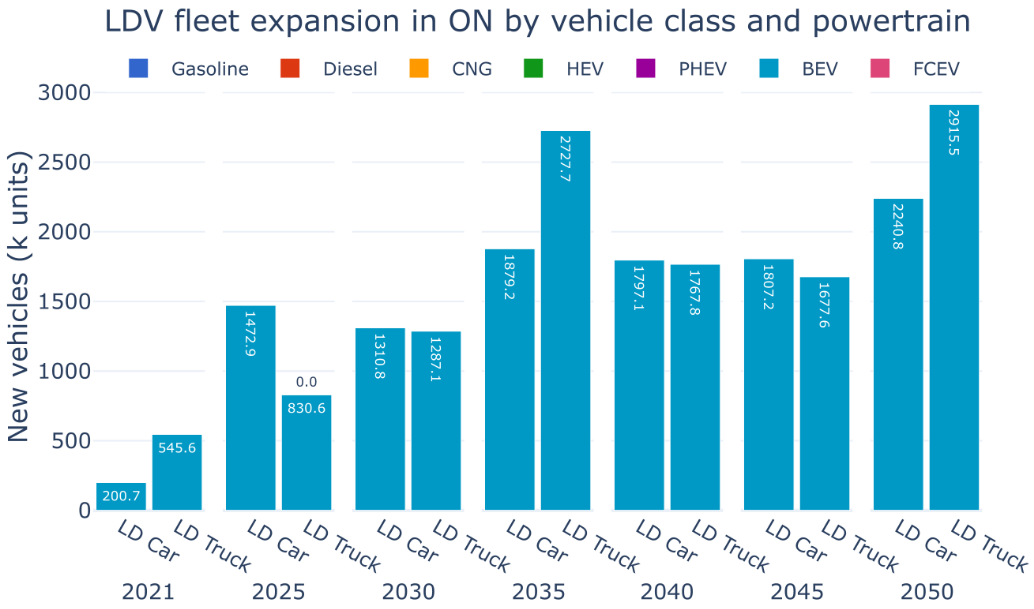


Figure 6: Vanilla model LDV fleet expansion results, showcasing the problem with using capacity aggregation of vehicle fleets that have an integer lifetime of 14 years for cars and 16 years for light trucks.

Since aggregation of parameters into multi-annual periods is necessary, particularly for national large bottom-up models with regional spatial resolution, this behavior could likely be resolved with retirement profiles of different vehicle classes, as demonstrated by Aryanpur et al. (2022). In around half the occasions, vehicles will remain operational even after they have reached their median lifetimes. Whereas in models that use integer-based lifetimes these vehicles are assumed to be retired usually after they reach their median lifetime (Jaroudi et al., 2023; Keller et al., 2019; Lerede et al., 2024; Nicoli et al., 2022; Pedinotti-Castelle et al., 2022; Venkatesh et al., 2022). Ultimately, lump deployment in consumer-end technologies due to aggregated capacities with integer-based lifetimes may lead to unrealistic stock turnover rates and, therefore, conclusions about transitions into less energy and GHG intensive technologies that are socio-technically unfeasible at the rates given by unrealistic large retirements.

Figure 6 also showcases a main problem with linear optimization models, which lead to corner solutions as described in **Section 2.3.2.2**, wherein investment decisions are solely based on cost-optimization while neglecting socioeconomic feasibility. It is a type of structural uncertainty from linear frameworks. However, introducing ad hoc market constraints introduce their own parametric uncertainty due to reliance on assumptions about future market uptake.

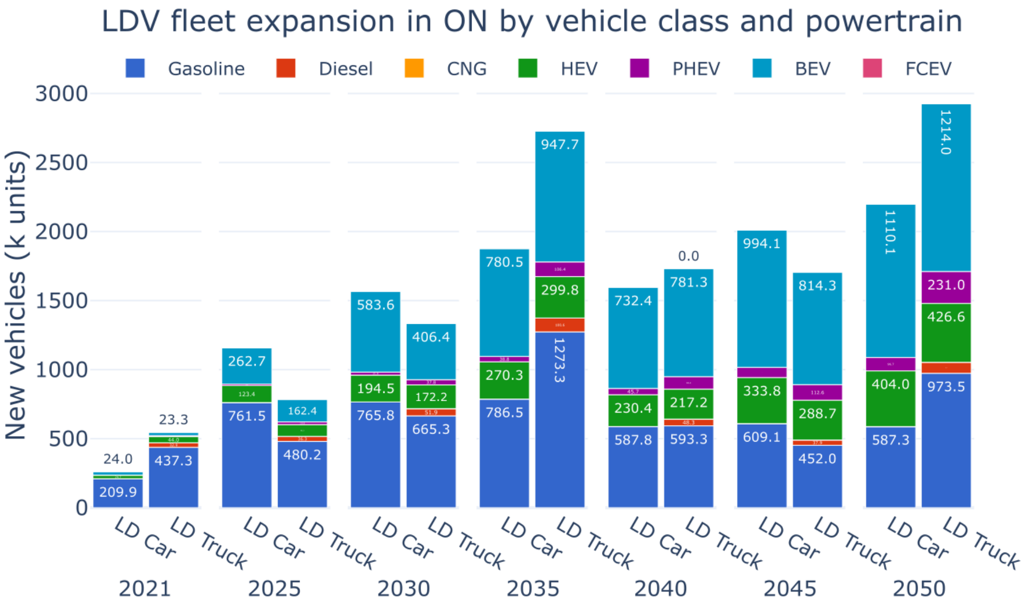


Figure 7: Reference model LDV fleet expansion results, from the addition of explicit constraints to the vanilla model. Lump deployment of new vehicle capacity becomes clearer than in **Figure 5**, due to the required market floor of conventional vehicles. Technology mix and new capacity was calibrated for the initial 2021 model period.

On the other hand, **Figure *7*** illustrates how the *reference* scenario constraints from **Table 4** and **Table 5** influence the deployed technology mix on the LDV sector when compared with **Figure 6**. The introduction of such constraints increased the net present value (NPV) of total energy system costs (model objective) from 1.82 trillion CAD (in 2020) without explicit constraints to 2.24 trillion CAD, a 23% increase in costs. Without considering the incurred model costs on GHG emissions from the federal carbon pricing, this would only amount to 1.94 trillion CAD, 7% increase. However, carbon pricing signals are designed to account for the negative externalities that originate from GHG emissions. Thus, a fairer comparison would be to also account for emission costs in the *vanilla* model. By doing so, the *vanilla* model plus the federal carbon pricing scheme results in an NPV of system costs of 2.09 trillion CAD, 8% below the *reference* scenario system costs.

Section 2.5.1 provides a more detailed analysis of how the system responds to explicit constraints, expanding on the earlier results that briefly highlight the influence of user-defined constraints on fleet expansion and total system costs. However, drawing significant conclusions from these findings requires a deeper evaluation of the broader system-level impacts. These results illustrate a common approach used by modelers to incorporate socio-political factors into the model. This approach can introduce significant arbitrariness and uncertainty, as these ad hoc constraints often depend heavily on the modeler's judgment.

The remaining identified challenges of this project and other important assumptions discussed throughout **Section 2.3** are included in **Table 7**, covering main challenges encountered during the development of the transportation sector and the assumptions that were used to partially or fully address them.

Table 7: Summary of transportation sector modeling challenges in the Canadian context not discussed yet and the assumptions that were used to address these. ESOMs refer to energy system optimization models; the remaining acronyms have been previously defined.

Challenge	Description	Model assumption
Limited vehicle size and GVWR class resolution	Detailed size and weight class resolution from vehicle technology assessments cannot be leveraged due to limited end-use demand classification from NRCan NEUD (NRCan, 2024b).	Vehicle cost and efficiency parameters are aggregated to match NRCan EUD end-use demand resolution using LDV sales market shares in 2021 by vehicle model (Wards Intelligence, 2022) and MHDV registrations (Ontario Ministry of Transportation, 2023). **Wards** **Autonomie** **NRCan** Nissan Sentra → Midsize → Car Nissan Versa → Compact → Car
Aggregation of size and GVWR classes using constant vehicle market shares through 2050	Constant vehicle size and weight class market shares were used to aggregate technoeconomic parameters from vehicle technology assessment projections through 2050 (Islam et al., 2023), neglecting future changes in consumer ownership.	
Activity-based travel surveys limited to metropolitan areas	Household travel surveys (HTS) with detailed trip characteristics and activity schedules by demographic class are limited to metropolitan areas; with no characterization of travel variability in weekends and different seasons.	A regional HTS from the GGH area that covered more than half the population in ON was used to represent provincial mobility patterns and trip characteristics from vehicle usage in a typical workweek during the Fall season (Data Management Group, 2018).
Unavailability of disaggregated end use demands by economic sector	The use of disaggregated end use demand projections by economic sector allows for more nuanced results that better account for structural and technological changes, referred as disturbances (Filippov et al., 2021).	Using macroeconomic indicators from top-down models for demand projections is a customary practice in ESOMs. Passenger and freight transportation are indexed to provincial GDP growth through 2050 (CER, 2021).
Unavailability of Canadian fuel price projections other than diesel and gasoline	There is limited access to fuel price projections for demand sectors. For transport, only gasoline and diesel projections are available through 2050 (CER, 2023b).	Given that other transportation fuel price projections are needed, and each of them have their own market drivers, the AEO 2023 reference case projections at the East North Central Region (EIA, 2023b, 2023a).
Simulation of light-duty PHEV charging profiles	Due to the flexible utilization of charge sustaining and charge depleting modes in PHEVs, it becomes less trivial to derive variable charging demand profiles from these vehicle technologies.	Given that this study relied on the RAMP-mobility simulation framework, and it does not represent PHEVs, but their load demand matters, it was assumed that PHEVs follow the same charging demand distribution as BEVs.
Inaccessible or outdated energy, cost and activity	Access to underlying data and assumptions from the NRCan NEUD are key to understand allocation of energy use and activity to different transport	Data gaps from inaccessible sources were addressed with information from alternative government sources wherever possible. Off-

Challenge	Description	Model assumption
data from official sources	modes. However, assumptions from the End-Use Model are restricted and underlying statistical reports (e.g., Canadian Vehicle Survey, Rail in Canada) are outdated (NRCan, 2022); including official cost studies (Transport Canada, 2008).	road modes were affected the most by these gaps, since the technoeconomic assumptions relied heavily on those from the OEO 2022 (Venkatesh et al., 2022). Other sources more than a decade old include (Research and Traffic Group, 2013; Transport Canada, 2008).
Limited off-road transportation data by province	Activity data and energy intensity for off-road transportation modes from NRCan EUD is only provided at the national level.	Existing capacity (in demand units) was downscaled to provincial estimates using provincial energy use divided by the national fleet's energy intensity. These intensities were also used as technology efficiencies, therefore, neglecting individual efficiencies by vintage.
Locked in occupancy and load rates through 2050	The NRCan NEUD uses occupancy and load rates from multiple surveys and End-Use Model assumptions (NRCan, 2022). However, using historical values locks in the assumption that vehicles will be operated as per recent trends.	Load factors and occupancy rates were calculated from reported activity over the product between avg. distance travelled and fleet stock, for each vehicle class. Using historical values between 2015-2019.
Locked in utilization factors through 2050	Temoa converts installed capacity of a given technology into process activity with their annual utilization factors. However, vehicle annual utilization could significantly differ in the future with changing consumer preferences.	Utilization factors from RT technologies were estimated with the maximum historical ratio between activity and stock, multiplied by a harmonization constant.
Aggregated passenger rail modes	NRCan NEUD aggregated intercity rail and urban rail transit as passenger rail. Having disaggregated rail modes and their service activities is important for studies incorporating modal choice, specially in urban areas.	Technoeconomic parameters from intercity rail were assigned to passenger rail mode, obtained from the OEO (Venkatesh et al., 2022).
Deep reliance on US technoeconomic data and projections	Having a sizable portion of model data come from a foreign country can transfer underlying socio-technical and economical conditions. This might not have significant implications for industrial technologies that often maximize utilization and performance, but for consumer-end technologies, the effects on overall fleet efficiency and costs might be significant.	The Autonomie assessments are tailored for US industries and users, utilizing technical specifications of the US automotive market. Its energy use estimates rely on drive cycle combinations from US protocols, and utility factors of PHEV efficiencies are based on US driving statistics. Moreover, O&M costs from off-road modes are based on US sources.

Other important assumptions while not necessarily posing modeling challenges, are noteworthy. Islam et al. (2023) assume that short-range battery capacities are oversized to maintain consistent performance until the end-of-life, affecting present-day vehicle costs and weight the most; however, these oversize factors are reduced for future vehicles. Additionally, for commercial MHDVs, cargo weights are assumed to be uniform across all powertrain classes to facilitate a fair comparison of technologies. In real world operations, this assumption does not hold as vehicle owners are expected to maximize cargo load, thus, payload losses will incur in powertrains with lower energy density storage, such as BEVs. Furthermore, as outlined in **Section 2.3.1.9**, fuel and electricity consumption ratios are assumed to remain constant through 2050, given that Temoa does not currently assign these by vintage. Moreover, important variable cost elements beyond maintenance and repair, such as costs associated with reduced payload capacity (due to battery weight) and labor costs (which could be impacted by longer BEV recharging times), were not considered.

2.5 Scenario-based Analysis

This section presents the results of an uncertainty analysis that examines how the system responds to various modeling choices and parameter settings across three aspects that are relevant to transportation sector representation – the use of explicit constraints to introduce behavioral realism, technological change and variability in LDV charging demand. Additionally, it evaluates the global sensitivities of total system costs and total GHG emissions to six main parameter groups relevant to transportation system planning.

Section 2.5.1 starts with the modeling choices of introducing socio-political realism in the *vanilla* model through ad hoc constraints, some of which are commonly used by modelers (Ramea et al., 2018), to bring optimal pathways from model results closer to socio-technically feasible scenarios from national simulation models. **Section 2.5.2** evaluates the importance of choosing technology assessments to source RT cost and efficiency projections by comparing system responses to different parameters from two recognized simulation models, Autonomie and the National Energy Modeling System (NEMS) from the EIA. **Section 2.5.3** follows a similar approach to the previous section, but instead of varying frameworks to source parameters, it varies activity-based surveys to characterize travel behavior for simulating LDV charging profiles with RAMP-mobility, namely the Tomorrow Transportation Survey (TTS) and the US National Household Transportation Survey (NHTS). Finally, **Section 2.5.4** discusses results from a global sensitivity analysis via Method of Morris to identify which parameter groups relevant to transportation system optimization have the highest impact on main decision variables.

2.5.1 Explicit Constraints

User-defined explicit constraints in linear optimization models add boundary conditions to the solution space. These constraints might help the model indirectly capture other factors that govern energy system transformations beyond technoeconomic feasibility, such as market and political drivers. However, their formulation usually lacks strong theoretical formulation (Ramea et al., 2018), like the market constraints used for this scenario analysis, as described in **Section 2.3.2.2**. Though their application is deemed necessary to highlight the challenges and uncertainties associated with their use and to understand to a better degree how socio-technically feasible the optimal solutions from the model might be relative to reference scenarios from national models. The national models' reference scenarios that serve as benchmarks for decision variables such as projected secondary energy demand from the transportation sector in Ontario are Canada's Energy Futures Modeling System (CEF) from CER and the gTech-IESD simulation model from Navius Research. Both reference scenarios only account for legislated policies as of March 2023 and January 2023, respectively (CER, 2023a; Navius Research, 2023). This coincides with the legislated policies in the *reference* scenario that are relevant to the transportation sector alone, as discussed in **Section 2.3.2.1**.

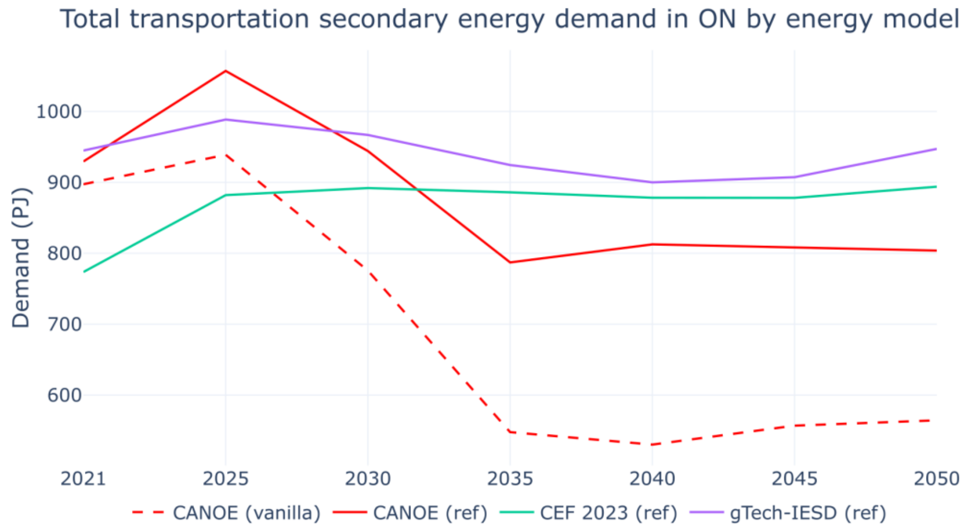


Figure 8: Total transportation secondary energy demand in Ontario by model scenario. This graph compares the CANOE vanilla model with the CANOE reference (ref), including those from CER and Navius Research national models.

Figure 8 shows the projected total energy demand from the transportation sector in Ontario by model (and scenario). A drastic surge in demand between 2021-2025, followed by a steeped decrease through 2035 in both CANOE scenarios are explained by how the vehicle fleet is expanding, which relates to the lump vehicle investment behavior explained in **Section 2.4**. Energy demand reaches a minimum point after most of the LDV and MHDV fleets are replaced by more efficient technologies, mainly BEVs. While it is not strictly necessary to compare CANOE results with those from other models to identify this anomaly and derive conclusions, doing so helps provide a reference point for the model's initial conditions, which fall within range, at least in the first model period. Without the lump vehicle investment behavior, the *reference* model would likely fall within range in subsequent periods, until reaching its projected minimum demand of around 800 PJ by 2035. The fact that the *reference* model maintains a lower demand than the other models after replacing a significant portion of the fleet could be explained by their choice of techno-economic parameter projections. Reference efficiency projections from Islam et al. (2023) – used for the *reference* scenario – are comparably more optimistic than other recognized sources such as the Annual Energy Outlook (NEMS model). Nonetheless, the CEF model uses cost and efficiency projections from the Electric Power Research Institute US-REGEN model (EPRI, 2023) for RT technologies, which projects even more optimistic improvements in efficiency than Islam et al. (2023). **Section 2.5.2** discusses these implications in more depth.

On the other hand, without the use of explicit constraints, the projected secondary energy use from the *vanilla* model reaches significantly lower levels than provincial reference projections from CER and Navius Research. This scenario comparison also helps support the argument that, considering inertia of vehicle fleets (Rosenberg et al., 2023) and the time it takes to replace entire fleets (IEA, 2023), results from the *vanilla* model can be deemed socio-technically unfeasible, even though they are techno-economically feasible. It projects a purely cost-optimal pathway that neglects supply chain constraints and other socio-political factors by investing in LD BEVs alone and a combination of BEVs and FCEVs for medium- and heavy-duty vehicles, exhibiting the *winner-takes-all* behavior from linear optimization models that often leads to corner solutions (Tash et al., 2019).

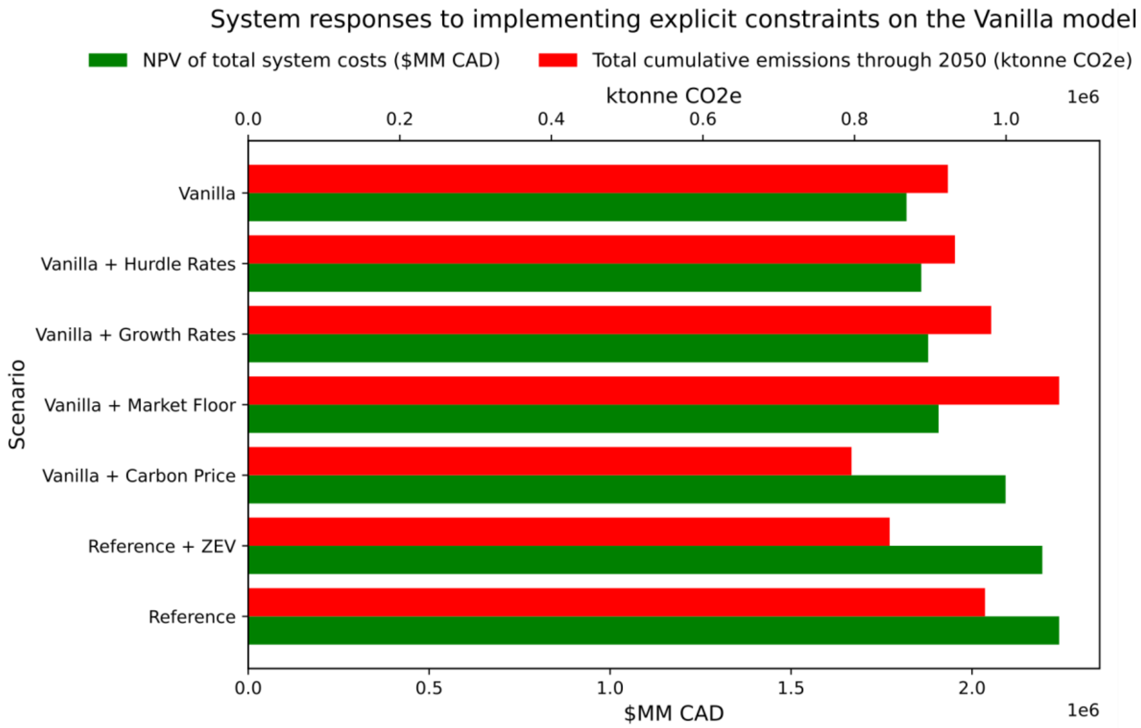


Figure 9: System responses in terms of model objective total system costs and cumulative energy system emissions through 2050 to explicit constraints. Ranging from the *vanilla* model (without explicit constraints), and each constraint in isolation, to a combination of all constraints in the *reference* scenario and the addition of ZEV sales mandate.

To assess the isolated impact of explicit constraints on total system costs and cumulative GHG emissions through 2050, as briefly discussed in **Section 2.4**, **Figure 9** compares system responses to explicit market and policy constraints relevant to the transportation sector in Ontario. Each constraint is tested in isolation, except for the ZEV sales mandate, as described in **Table 6**, it is added to the *reference* scenario, given that the *vanilla* model by itself already floods the market with BEVs.

While they are not a sector-specific metrics, the total system costs and cumulative GHG emissions provide a measure of influence that these constraints have, when compared to the unconstrained *vanilla* model. This shows that carbon pricing is by far the most influential constraint as, in isolation, it reduces emissions and increases system costs the most. However, its impacts also extend beyond the transportation sector to every other sector. Furthermore, the *market floor* constraint is the sector-specific constraint with the largest impact, increasing both system costs and cumulative emissions by around 5% and 16%, respectively. This occurs mainly due to the ICEV market share retraction that maintains recent trends. Whereas enforcing the ZEV sales mandate to the *reference* scenario significantly reduces emissions, and costs. Providing evidence that, a strict enforcement of the ZEV sales mandate could effectively reduce cumulative emissions through 2050 by up to 13% with virtually no additional system costs, from a central planner's perspective.

It is also noteworthy that the impact of individual constraints is not entirely additive, meaning that their combination in the *reference* scenario leads to a lower marginal response (relative to the *vanilla* model) than the sum of their marginal responses in isolation. Recognized metrics such as marginal abatement costs were not utilized in this analysis given that there were no direct GHG constraints enforced in the model and most scenarios beyond the *vanilla* model actually increased overall cumulative GHG emissions, except for the federal carbon pricing and the ZEV mandate.

2.5.2 Road Transportation Technological Change

The choice of simulation frameworks projecting vehicle efficiencies and costs has significant implications for model results, as suggested in the previous section. This section provides more evidence for that argument.

To achieve this, an additional scenario is formulated, based on the CANOE *reference* scenario, with the distinction that LDV cost and efficiencies and MHDV efficiencies are replaced by reference case projections from the National Energy Modeling System (NEMS), a partial-equilibrium energy-economy model developed by the US Energy Information Administration (EIA). Whereas Islam et al. (2023) projections used in the *reference* model are based on the Autonomie model, a dedicated physics-based simulation model that projects vehicle cost and performance based on vehicle component sizing to match technical specifications, where the technology improvements of newer components is calibrated with expert consultation and industry input. Conversely, NEMS follows a different simulation paradigm that is not dedicated to the technology assessment of vehicles. Of its numerous outputs, efficiency and cost projections are based on manufacturers' choice to adopt incremental technology improvements that reflect Corporate Average Fuel Economy (CAFE) regulatory standards until 2026. After 2027 no standards are enforced, though improvements are still possible as long as they are perceived as cost-effective by consumers, (EIA, 2023c).

Figure 10 showcases the differences in improvements of vehicle efficiency by simulation framework, namely Autonomie and NEMS (referred as AEO since the projections are reported on the Annual Energy Outlook 2023), relative to the initial simulation year (2023).

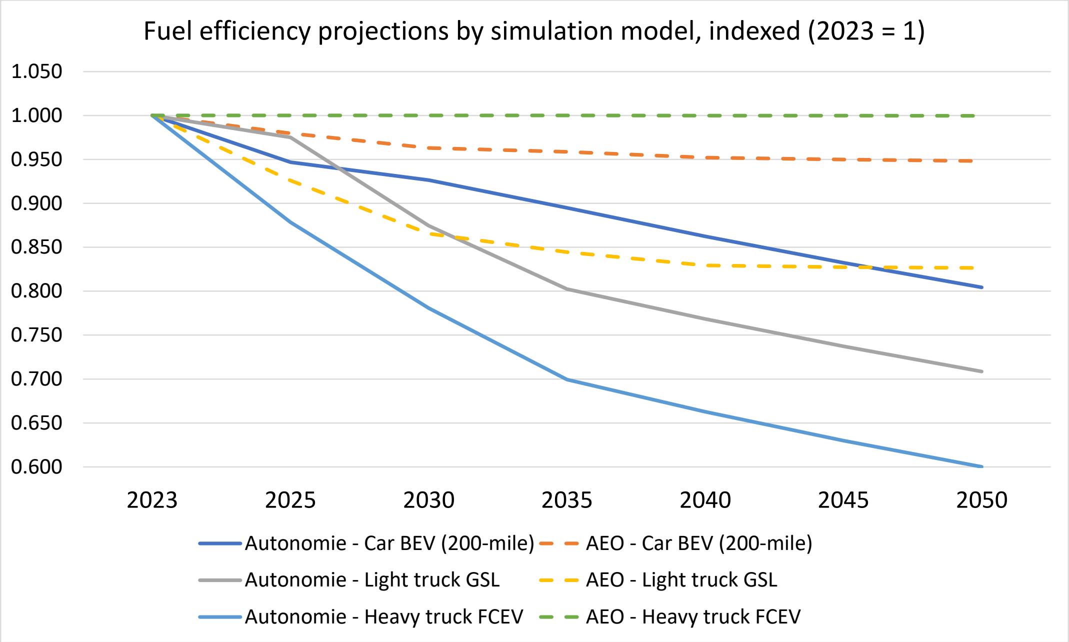


Figure 10: Index graph of fuel efficiency projections from comparable RT vehicle technologies, namely a 200-mile BEV car, a gasoline (GSL) light truck and a FCEV heavy truck. These projections are based on aggregated efficiencies used directly in the CANOE model, using size class and GVWR market shares as described in **Section 2.3.1.5**.

With such a comparison it becomes clear that overall energy consumption in the *reference* scenario will be significantly lower than the scenario utilizing AEO efficiency projections. It can also be observed that after 2030, efficiency improvements in the AEO plateau, particularly for emerging technologies. This could be explained by CAFE standards not being enforced after 2026. Nonetheless, gasoline light trucks maintain slight improvements even after 2035, likely due to the consumer demand for more cost-effective ICEV technologies as manufacturers need to improve energy efficiency continuously to maintain cost competitiveness against emerging technologies. In the Autonomie model, an annual efficiency improvement in BEVs of around 0.9% can be observed, whereas the AEO only exhibit around 0.2% annual improvement, between 2023 to 2050.

Figure 11 presents the comparison between energy demand by carrier from the transportation sector in Ontario. The lump vehicle investment behavior remains present as depicted in **Figure 8**, however, energy demand projections between the *reference* scenario and the scenario with AEO projections differ significantly, despite requiring the same fleet size to satisfy end-use demands. By 2050, secondary energy consumption can differ by up to 170 PJ, almost an 18% increase from the *reference* scenario to the AEO scenario. This can also be further explained by the differences in LDV and MHDV technology mixes. In the AEO scenario, CANOE has less preference for emerging technologies in the MHDV sector due to the less competitive efficiencies and the same costs that are maintained from the Autonomie projections. Whereas, in the LDV sector, investment in PHEVs is significantly higher given that the costs for longer range BEVs are greater than in the *reference* scenario. Thus, the max growth rate constraints intervene and prevent lower range BEVs from flooding the market, forcing the model to invest in the next best alternative, PHEVs.

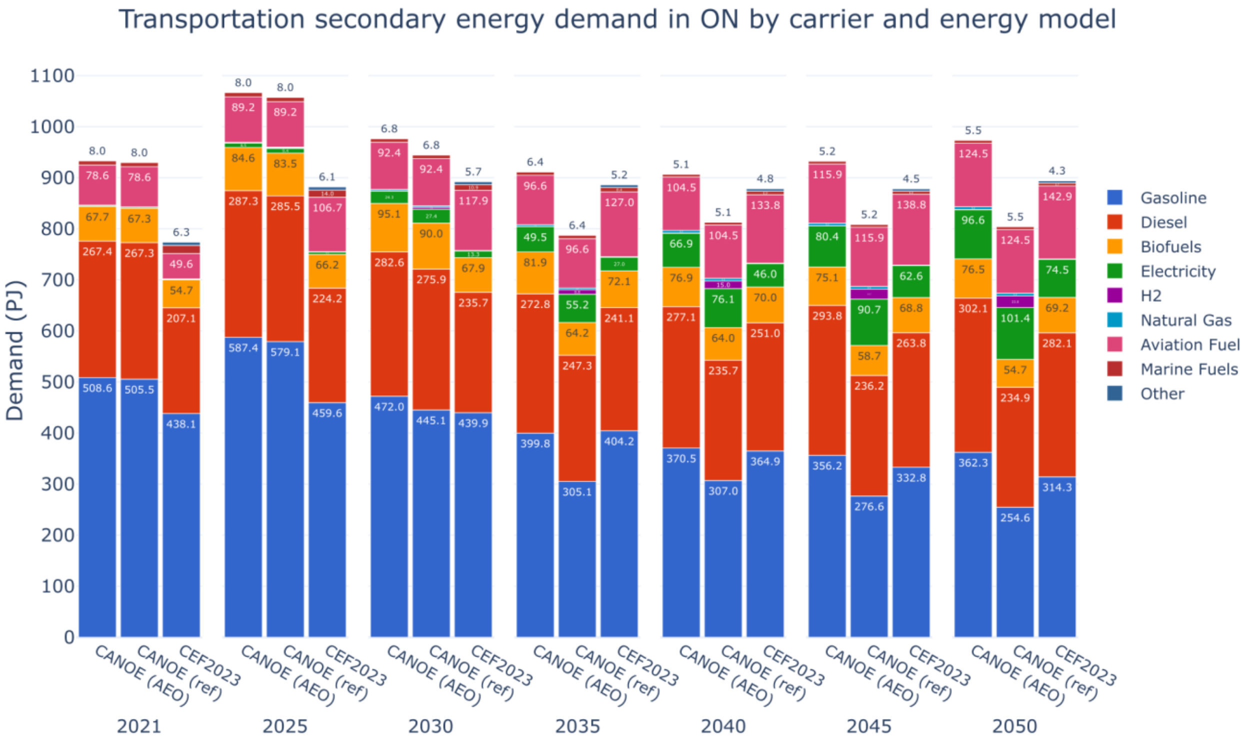


Figure 11: A side-by-side comparison of transportation secondary energy demand in Ontario by energy carrier, from two scenarios in the CANOE model, the *reference* scenario and the *AEO* scenario utilizing vehicle efficiency and cost projections from the Annual Energy Outlook 2023 reference case. Additionally, the CER national model projections are included.

It is also important to acknowledge that Islam et al. (2023) projections also include a high uncertainty scenario, wherein technology improvements of vehicle components are based on targets set by the Vehicle Technologies Office of the US Department of Energy. Hence, this scenario includes more optimistic projections which, if incorporated into the *reference* scenario, would further increase the disparity between these projections and those of the AEO scenario.

2.5.3 Light-duty Vehicle Charging Profiles

Since there is no ideal source to characterize travel behavior from the LDV sector in Ontario, other available alternatives with sufficient detail in terms of trip characteristics and activity-travel schedules need to be leveraged. The only activity-based travel survey with enough behavioral detail and population coverage to represent mobility patterns in Ontario, to a limited degree, is the

Transportation Tomorrow Survey (TTS) (Data Management Group, 2018). However, this household travel survey (HTS) does not cover the remaining 45% of the population in Ontario living outside the largest metropolitan region in Southern Ontario, the Greater Golden Horseshoe area. Mobility events occurring outside metropolitan areas will likely have different trip distances, durations, travel schedules and, therefore, charging events. Moreover, there are certain limitations to the TTS, such as no direct representation of travel behavior during weekends. Nonetheless, RAMP-mobility assumes workers and students behave as inactive users during weekends and holidays, assigning the same probability of occasional use, for more details, see **Section 2.3.1.11.**

To evaluate the system response to this limitation (i.e., representation of travel behavior from urban areas alone), the LDV charging profiles are simulated from a regional to a national geographical level. To test the national level, the US National Household Transportation Survey (NHTS), covering both rural and urban areas, is used to simulate an alternative version of the LDV charging profiles, wherein charging infrastructure, driver demographics and vehicle characteristics are maintained as in the original *reference* scenario, only trip characteristics and travel schedules are changed with data from this survey. Thus, it is used to evaluate system responses by varying simulated charging profiles from a regional HTS representing urban populations in Southern Ontario and a national HTS representing urban and rural populations of the entire US.

To isolate the effects from varying travel surveys to simulate alternative LDV charging profiles, incremental GHG emission factors (IEF) were used, following Belman M. et al. (2024), to evaluate the GHG emissions tied to electricity generation for new light-duty PEVs. This is derived by computing the ratio of the difference between electricity sector emissions and electricity sector activity from a scenario that envisions a future with abundant PEVs – achieved by enforcing the zero-emission vehicles (ZEV) sales regulation – and a scenario that restricts the deployment of new plug-in electric vehicles (PEV) after 2022, namely the no-EVs scenario, as described in **Table 6**. The ratio is calculated as:

$$IEF\ [\mathrm{g\ CO_2e/kWh}] = \frac{ESE - ESE_{no\ EVs}}{ESA - ESA_{no\ EVs}}$$

Equation 2: Incremental emission factors (IEF), representing the ratio between the difference in electricity sector emissions (ESE) and the difference in electricity sector activity (ESA) from a scenario with abundant EVs (ZEV) and a scenario without EVs (no EVs) to isolate emissions tied to a to electricity generation for a particular technology.

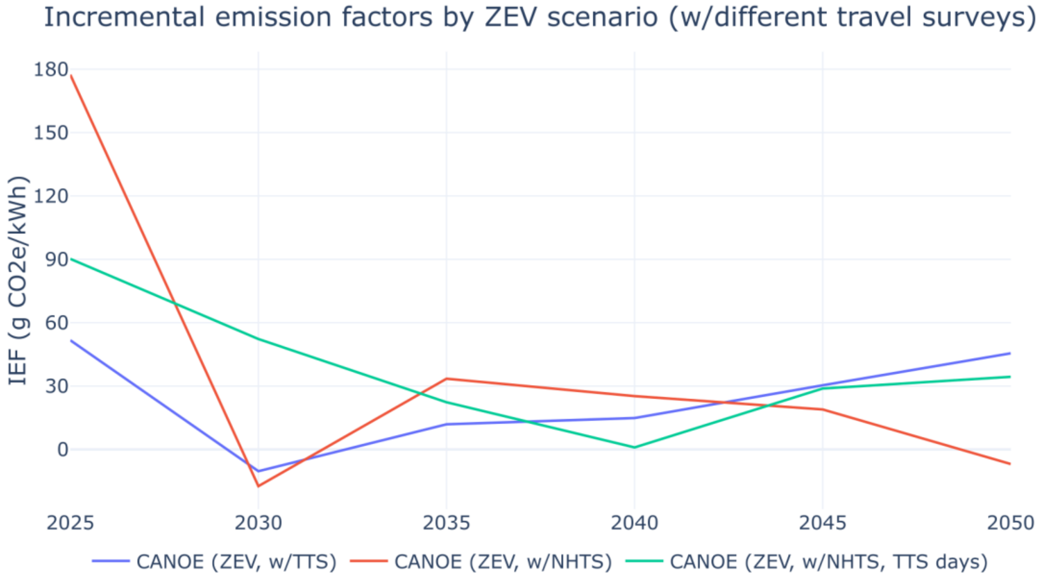


Figure 12: Incremental emission factors (IEF) between the no-EVs scenario and three alternative ZEV scenarios that incorporate different HTS to characterize travel behavior. Note that time-series aggregation was applied independently to two scenarios (ZEV w/TTS and ZEV w/NHTS), therefore, the selected representative days have changed between these scenarios, which could also influence the differences in IEFs. For that reason, a third scenario that uses NHTS data was created, where the representative days from the TTS scenario were forced in (ZEV w/NHTS, TTS days).

Figure 12 shows the system responses in the electricity sector to varying the underlying HTS that is used to characterize vehicle travel behavior and, consequently, charging behavior from LDVs through RAMP-mobility simulations. Note that a third ZEV scenario was modeled, given that representative day aggregation was applied independently to two ZEV scenarios with charging profiles simulated with either TTS or NHTS data. Therefore, the selection of representative days differs between these two scenarios, for every parameter with short-term variability, further exacerbating the differences in system responses. The third scenario uses charging profiles simulated with NHTS data, with the distinction that representative days from the scenario using TTS data were forced into this third scenario and re-normalized, to match the calendar days chosen from time-series aggregation. Thus, this third scenario with has the exact same time-slices, except for LDV charging profiles from NHTS data, which belong to the same calendar days as those from the ZEV scenario with charging profiles from TTS data. This isolates the variation of HTS data, to avoid accounting system responses due to a selection of different representative days.

The largest difference in all three scenarios can be appreciated in the model period 2025, between ZEV w/TTS and ZEV w/NHTS, leading to a 240% difference (around 126 gCO_2e/kWh). However, it remains unclear whether these differences come mainly from the characterization of travel behavior, since the aggregation of representative days has proven to have far-reaching implications in energy system performance and investment decisions (Poncelet et al., 2016). Therefore, a more isolated estimate of IEF variation due to the selection of different HTS to simulate charging profiles is obtained from the difference between ZEV w/TTS and ZEV w/NHTS-TTS days (both with the exact same representative days), leading to a smaller 75% difference (around 38 gCO_2e/kWh) for the same model period. The latter results reinforce the argument that the differences in travel behavior characterization for the simulation of LDV charging profiles can be substantial, at least in the context of stochastic aggregation methods like RAMP-mobility. To conclude that the choice of HTS will influence model results significantly, would require a deeper analysis, such as using a different simulation framework to test these variations.

The relatively high incremental emission factors data can be explained by the concentration of peak demand on a given day that is met by natural gas generation as a peak generator. This is inferred by the fact that, without direct GHG emissions constraints, the model has demonstrated to prefer natural gas power plants to satisfy the reserve margins, which have significant impact in terms of carbon intensity for earlier model years where the share of VRE sources remains much smaller than future model periods.

2.5.4 Global Sensitivity Analysis

This section leverages a built-in framework in Temoa for conducting a global sensitivity analysis using the Method of Morris; this method estimates sensitivities accurately and efficiently (Usher W et al., 2023). The current setup in Temoa is only capable of exploring input parameters from variable costs, investment costs and efficiencies. Therefore, this analysis will be restricted to those parameters. The aim of this approach is to conduct factor prioritization, by identifying the main parameters that influence decision variables the most, namely NPV of total system costs and total cumulative emissions. A distinction is made regarding previous scenario analyses – the *vanilla* model is the basis for this analysis, with the intention to isolate parameter influence apart from uncertainties that are introduced with explicit constraints. To reduce computational complexity, the parameters of interest will be grouped. This approach will provide insights on parameter influence, but not on the interaction between parameters within a group. Thus, parameter groups must be carefully chosen. For this case, six parameter groups were considered for all model periods:

- RT fuel costs: grouping of fuel costs, focusing on fossil fuels supplied to road transportation technologies, namely gasoline, diesel and natural gas.

- LD BEV efficiencies: grouping of vehicle efficiencies from the LDV sector, focusing on battery-electric technologies alone, as they have proven to be the dominant choice.
- LD BEV investment costs: grouping of vehicle investment costs from the LDV sector, focusing on battery-electric technologies alone.
- MHD FCEV efficiencies: grouping of vehicle efficiencies from the medium- and heavy-duty sectors, focusing on FCEVs alone, as they also have proven to be the dominant choice, relying entirely on natural gas SMR production.
- MHD FCEV investment costs: grouping of vehicle investment costs from the medium- and heavy-duty sectors, focusing on FCEVs alone.
- H_2 production investment costs: grouping of gaseous hydrogen supply technologies, from production to distribution, including refuelling stations.

Given that the CANOE model is a large bottom-up model, its parameter space is considerably large. The results from a global sensitivity analysis cover the entire parameter space of a model, clearly only for those parameters that are varied. It measures the isolated influence of the parameter group and the combined effect from every group. Grouped parameters move together at different levels in the grid. Given the six parameter groups, the framework chooses random start values within a six-dimensional space spanned by parameter groups. Following a step-by-step approach, the value of a single group is changed in each iteration, leading to a trajectory of (6+1) points in the parameter space (Tröndle et al., 2024). To comprehensively explore such space, 12 different trajectories were generated – creating 84 grouped parameter combinations, with a variation of ±15%. This resulted in 84 consecutive model runs to explore the parameter space and obtain relatively robust parameter sensitivities given the model's size.

Figure 13 present the results from the Method of Morris. The main indicator from this sensitivity analysis is the absolute average elementary effect by parameter group (i.e., the absolute average expected change in the decision variable, or simply). The absolute value is used to provide a better measure of influence on decision variables, as variations can change these variables on the positive and negative sides, the absolute value captures both without canceling them out due to averaging. Whereas the error bar represents the 95% bootstrapped confidence interval of the absolute values, meaning that when the resulting absolute values are randomly resampled with replacement, 95 out of 100 times these would fall within the confidence intervals (error bars).

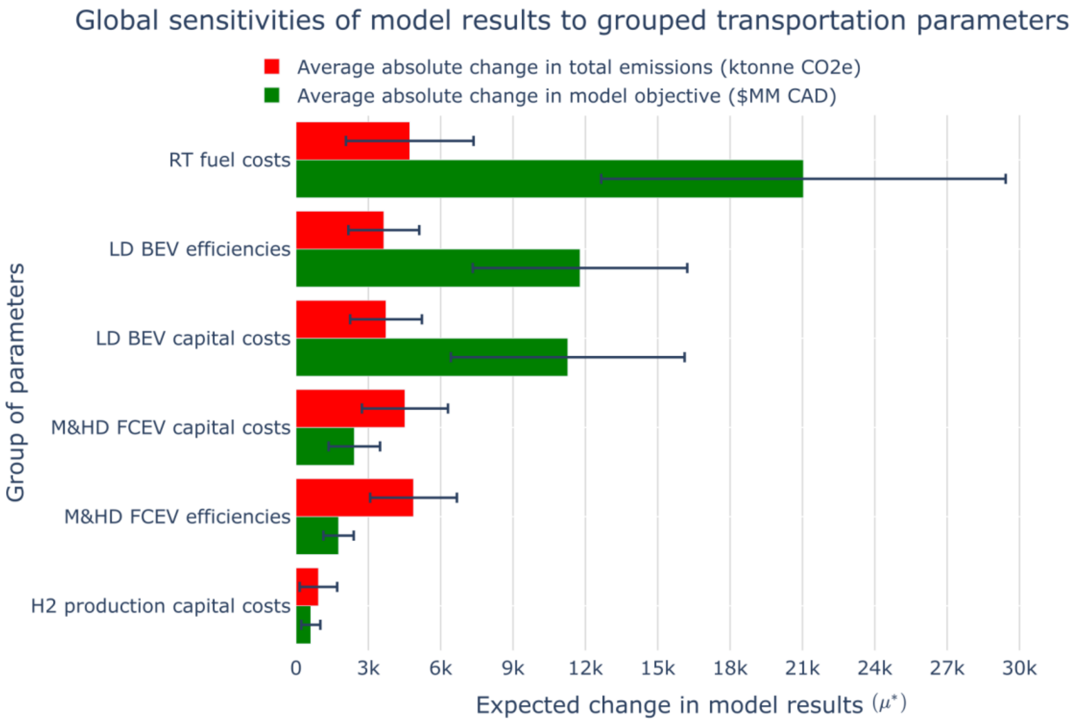


Figure 13: Results from global sensitivity analysis using the Method of Morris approach with six different parameter groups that cover main transportation-related technologies. This analysis involved 84 consecutive model runs that varied parameter groups by ± 15% across 12 different trajectories.

These results indicate that fuel costs from road transportation activity are by far the most influential parameters in the sector, in terms of total system costs. This suggests that fuel price uncertainties introduced by the NEMS model assumptions have profound implications in model results, a reason of concern given that results from a Canadian model are highly dependent on predictions from an US model. BEV technologies have the second highest perceived influence, as their cost and performance projections are also very influential, previously demonstrated in **Section 2.5.2**, where energy use significantly increased due to reduced deployment of BEVs. Moreover, an outcome falls into FCEVs from the medium- and heavy-duty sectors, proving that cost-optimal futures rely on hydrogen production, and its source of production matters for the system's GHG intensity. As fuel cell technologies have demonstrated to have the largest influence on cumulative GHG emissions, since the model opts for hydrogen synthesis through natural gas SMR (without carbon capture). These latter findings could be enhanced with the introduction of less GHG intensive H_2 production pathways apart from electrolysis, such as SMR with carbon capture and storage, and biomass gasification.

It should be noted that the range of confidence intervals from the grouped parameters with the highest average absolute change in total system costs is considerably large.

2.6 Discussion

Comparing reference scenarios from CANOE, Canada's Energy Futures, and gTech-IESD models, even when CANOE belongs to a different paradigm (e.g., bottom-up optimization against hybrid partial equilibrium), offers valuable insights for model development and refining. Primarily, because CANOE's *reference* scenario – intended to match present day conditions and follow a similar trend into the future – can be better represented with insights provided by other integrated models that account for system interactions or drivers of system transformations beyond those described in CANOE. Secondly, sourcing technology parameters can be a delicate task when considering the differences between technology assessment frameworks, which can differ by scope, technical resolution, methodology and assumptions. The fact that most integrated hybrid models leverage economic optimization, within the context of this study, makes the comparison of scenario projections more justifiable.

Therefore, a scenario comparison can also reflect the implications of using projections from a particular framework, as it was demonstrated in **Section 2.5.2** that, even from a reference case standpoint, the level of optimism in terms of cost or efficiency improvement can vary significantly. Recognizing the parametric uncertainty behind technoeconomic projections is crucial for understanding our own model's projections, as they rely on exogenous assumptions that are indirectly transferred into our results. Lastly, expectations of scenario projections, whether it is from a pure optimization or constrained optimization (i.e., with explicit constraints), can be better grounded to real conditions with the aid from projections of recognized models, as a measure of socio-technical feasibility; something the current version of the CANOE cannot directly account for. For example, if a techno-economically feasible pathway dramatically deviates from projections of other models, it gives a reason to suspect that something might be odd about that pathway, with the condition that scenarios share reasonably similar assumptions.

The choice for simulation frameworks that represent technological change has significant implications for modeling results. Since these frameworks can belong to very distinct modeling paradigms, technology improvements are implemented through different mechanisms and, therefore, can be expressed differently in their projections, as depicted in **Figure *10***. For instance, while both Autonomie and the NEMS model implement technology improvements at the vehicle component level, the mechanisms that drive these changes are completely different. The Autonomie model seeks to adjust the size (i.e., power and capacity) of the vehicle components based on their physical performance, which is subject to gradual improvements of their technical parameters, to match vehicle market specifications.

Whereas the NEMS model has predefined component improvements in the form of efficiency, weight and power changes that have predefined cost of implementation for manufacturers, this implementation is subject to performance standards (that expire in 2026) and cost-effectiveness metrics that govern consumer decisions. Even though more comprehensive comparison is needed, based on the observed results, it can be inferred that technology improvements governed by implementation during design phase (i.e., hard implementation) accumulate to a larger extent than implementations that implementations governed by market responses (i.e., soft implementation). This argument, however, neglects the intended use of each technology assessment framework; Autonomie simulates projections at the individual vehicle level, whereas NEMS simulates projections to provide a measure of a fleet's aggregate energy use and economic implications. Moreover, despite efficiency improvements from Autonomie being far more optimistic than those form NEMS, the real efficiency values are comparably lower, even from 2023. For instance, 200-mile battery electric cars in the AEO have an (aggregated) efficiency of 21 kWh/100km, compared to 14 kWh/100km from Autonomie, both in 2023, a more than 30% difference. Hence, the consideration of these differences is crucial for a deeper understanding of scenario results from optimization models.

The use of simulation models like RAMP-mobility, which have flexible application to different contexts using limited activity-travel data that can be sourced from different geographical regions, presents great advantages in countries with limited availability of household travel surveys (HTS). In the Canadian context, more specifically Ontario, the fact that there is a comprehensive HTS representing around half the population in the province, available to researchers, solves many problems for the development of LDV charging demand representation. However, for the remaining provinces where there is not as much comprehensive activity-travel data available, generally-applicable simulation models such as RAMP-mobility could be leveraged to characterize travel behavior of each province with as much regional data as possible to then simulate the corresponding charging profiles of each. While the Canadian 2021 Census touches on trip characteristics with high spatial resolution, it is limited to single home-to-work trips. Furthermore, system responses isolated to the exclusive variation of HTS data showed significant differences in earlier model periods, thus, it cannot yet be concluded that these variations originate entirely from the choice of HTS to simulate charging profiles. The different system responses to the modeled scenarios could also be driven by stochasticity in the LDV charging profiles per se, even though Mangipinto et al. (2022) claimed that simulating a fleet of 2500 EVs would be sufficient to represent the aggregate distribution of even larger fleets, it could be the case that under the circumstances of this study, larger fleet size could reduce the abrupt variations coming from stochasticity, which could affect the selection of representative days or investment choice of power plants for electricity generation.

Based on results from the global sensitivity analysis (GSA), fuel price projections are perceived as the most influential set of parameters used by road transportation technologies. This poses an important challenge for the formulation of reliable Canadian net-zero strategies, given that energy system models (Keller et al., 2019; Net Zero Atlantic, 2023) including CANOE rely on fuel price projections from the Annual Energy Outlook 2023, which reflects market and regulatory dependencies from the US, not from Canada. This reliance occurs since fuel price projections from the Canada Energy Future's (CEF) scenarios do not include all the necessary transportation fuels to properly represent secondary energy demand from every mode of transportation of the NRCan NEUD. This challenge also extends to other demand sectors, where only the price projections from main fuels are included (CER, 2023b).

In an attempt to mitigate differences in price assumptions between the US and Ontario, fuel prices from the East North Central Region were chosen due to their proximity to Southern Ontario, where most of the economic activities within the province occur. Light-duty BEV efficiencies and costs are the second most influential set of parameters identified by GSA results in terms of discounted total system costs; since these technologies dominate the market as they have the lowest levelized cost of driving, based on model parameters. FCEV technologies in the medium- and heavy-duty sectors appear to have the highest influence in cumulative GHG emissions, given the model's preference for hydrogen production through SMR (without CCS). This behavior is mainly driven by the significantly cheaper costs of natural gas in the industry sector, when compared to other fossil fuels, both in the CEF historical prices and AEO projections. Hence, a broader representation of H_2

production pathways would provide more insights on the real influence that FCEV technologies have on decision variables.

Chapter 3: Conclusions and Future Work

This section summarizes the main findings from this study, particularly from results of the scenario-based uncertainty analysis.

3.1 Summary of Findings

While explicit constraints can introduce uncertainties due to their soft theoretical formulation and arbitrary nature (i.e., nobody knows how the system will behave), they also provide a heuristic measure to gain insights into model responses before developing or applying more rigorous approaches. In the context of market constraints, these can be interpreted as the indirect accounting of socio-technical feasibility when benchmarked with other model paradigms that have a more robust representation of those same drivers. When market constraints are introduced to the *vanilla* model while accounting for the federal carbon pricing scheme, it was found that total discounted system costs and cumulative GHG emissions through 2050 are increased by around 7% and 22%, respectively. Moreover, when enforcing the zero-emission vehicle (ZEV) sales mandate on the reference scenario, cumulative GHG emissions are reduced by up to 13% with no additional discounted system costs.

The selection of technology assessment frameworks that simulate vehicle cost and performance projections significantly impacts model outcomes. In Canada and the US, energy system models draw on diverse sources of technoeconomic parameters, with two of the most recognized being Autonomie and the NEMS (AEO) model. These frameworks are widely used due to their rigorous formulations and high technology detail (i.e., vehicle and powertrain classification). However, they differ greatly in terms of their reference case vehicle cost and efficiency projections. Both from an absolute value and improvement rate standpoints. For instance, comparing reference scenarios that vary only in the cost (absolute values) and efficiency (improvement rates) projections from Autonomie or AEO reveals that the total secondary energy use from the transportation sector can differ by up to 170 PJ in 2050, increasing by almost 18% in the AEO-based scenario. Consequently, the choice of cost and performance projections not only significantly affects model decision variables but should also align with the underlying mechanisms of technology improvements most relevant to the specific research question the energy system model aims to address.

In Canada there is not an equivalent activity-based travel survey such as the US NHTS survey, the only household travel survey with sufficient behavioral detail and population coverage that can represent mobility patterns in Ontario to simulate LDV charging profiles from different demographic groups is the TTS survey, though it only represented 55% of the population in Ontario in 2016. To evaluate if the lack of coverage of the remaining population, which include travel patterns outside metropolitan areas, has significant influence in decision variables relevant to electricity systems planning, the travel surveys used to characterize travel behavior and simulate LDV charging profiles were varied in three scenarios: one using the regional TTS survey; another using the national NHTS survey (which covers mobility in rural areas), but the same representative days as the first one; and the last one also using NHTS data, but with its own set of representative days (since the annual time series is different). It was found that, in the isolated comparison with equal representative days, the incremental emission factors tied to electricity generation for new light-duty PEVs can reach up to a 75% difference (38 gCO_2e/kWh) between isolated scenarios in 2025. However, before any definitive conclusion can be made, a deeper understanding on the cause of these variations is needed.

Conducting a global sensitivity analysis in a large bottom-up model to account for direct and combined effects of parameters can be a hard task due to the huge size of the parameter space. With Method of Morris, the grouping of parameters allows for a more manageable analysis of parameter influence. Through 84 model runs, relatively consistent results were achieved, for parameter prioritization between six groups that belong to or are used by the transportation sector. It was found that modeling choices involving fuel prices and their projections through 2050 are by far the most influential in terms of discounted energy system costs. Presenting an important source of uncertainty, particularly of price projections that cannot be obtained from Canadian sources, given that US sources introduce market and regulatory dependencies that may not fit the Canadian context.

For technology choices, only the parameters from the most prevalent technologies observed in the scenario analyses were varied. As expected, light-duty BEVs dominate the picture due to their relatively high impact on total system costs, followed by medium- and heavy-duty FCEVs, which showed the largest influence in cumulative GHG emissions. This high-level of influence is explained by the model's preference for producing H_2 gas through steam methane reforming, due to the comparatively cheaper natural gas prices. Therefore, the results from the global sensitivity analysis that uses the latest vehicle cost and performance projections from Islam et al. (2023) suggest that

FCEV technologies remain an important facilitator of road freight decarbonization due to their high influence on cumulative emissions with relatively lower system cost influence. However, a more thorough analysis with specific variations of fuel cell technologies and better representation of hydrogen production pathways is necessary to reinforce this claim.

The presented findings in this section are a non-exhaustive narration that does not encompass every finding and insight provided throughout Chapter 2:.

3.2 Model Limitations

This section summarizes the main model limitations of the transportation sector in Ontario, described throughout Chapter 2:.

General limitations about missing model features and technologies include:

- Missing hourly charging demand profiles from medium- and heavy-duty freight trucks, Temoa assumes a flat annual demand.
- No direct representation of consumer heterogeneity and preference (e.g., consumer segments, disutility costs, range anxiety, etc.)
- No representation of modal shift (e.g., exogenous modal shift, constant elasticities of substitution, discrete choice models, etc.)
    - In that regard, no representation of active transportation (e.g., walking and biking)
- No representation of e-fuel pathways (e.g., e-gasoline, e-diesel, e-methane, etc.)
- Missing alternative renewable fuel powertrains – end-use technologies using B20, B100, RD100 and DME were not represented.
- No representation of micromobility – the smallest vehicles represented are motorcycles, which have internal combustion engines larger than 50cc.

Limitations regarding limited representation of technologies or commodities:

- Limited representation of gaseous hydrogen production pathways – current pathways are limited to steam methane reforming without carbon capture and storage, and electrolysis.
- Air freight technology costs – these were roughly represented using loose price assumptions based on a cost of transportation study from (Transport Canada, 2008); none of the sources used for the rest of technoeconomic parameters included air freight.

- Limited plug-in electric vehicle charging and H_2 refuelling infrastructure representation, most parameters were obtained from the Open Energy Outlook.
- Emission factors are not vehicle-specific, which is particularly important for air quality studies. Emissions are only released per energy unit utilized by the entire sector.
- Occupancy rates and utilization factors from road transportation technologies are based on historical data without the use of projections, which locks in current occupancy and utilization in future years.
- Limited road transportation vehicle size and weight class resolution, due to limited demand resolution from NRCan NEUD.
- Limited off-road technology resolution of passenger rails and marine freight, again due to limited demand resolution from NRCan NEUD.

Limitations regarding the simulation of LDV charging profiles with RAMP-mobility:

- No representation of:
    - drivers' subsequent trips after first one (no chain logic) – as these are modelled to occur randomly depending on time frame, which is characterized by occupation class, time of day and day type,
    - seasonal changes in travel patterns, as travel survey data is reduced to averages with stochastic variability,
    - drivers' modal shifts throughout daily schedules, also influenced by seasonal changes,
    - Plug-in hybrids, only battery-electric vehicles are modelled.
- Limited representation of:
    - battery capacity, reduced to the relative shares of three classes,
    - BEV size classes, also reduced to the shares of three classes,
    - charging stations, reduced to the probability of using one of three classes,
    - charging infrastructure availability, reduced to a piecewise function of time of day.
- Limited representation of the following parameters since the input data is reduced to averages subject to stochastic variability from a uniform distribution:
    - trip distance and duration by occupation class,
    - drivetrain power demand driven by trip speed,
    - drivers' daily distance quota.

Limitations regarding Canadian representativeness from cost and efficiency projections of road transportation technologies, from Islam et al. (2023) Autonomie technology assessment:

- Vehicle components are sized to meet technical specifications of the US market.
- LDV energy use estimates are based on a combination of dynamometer tests from the US, the Urban Dynamometer Driving Schedule (UDDS) and the Highway Federal Emissions Test (HWFET)
- MHDV energy use estimates are also based on a combination of dynamometer tests from the US, EPA 55 mph, EPA 65 mph and the (California) Air Resource Board (ARB) transient cycle
- Cargo weights in commercial vehicles were assumed to be uniform across all powertrain classes, this assumption would not hold in real world operations.

3.3 Future Work

To improve the identified gaps and address modeling challenges neglected in this study, the following list includes refinements that will be applied to the model in the near future:

- Addressing the lump vehicle investment behavior originating from aggregated capacities in the transportation sector and the use of integer-based lifetimes.
- Expansion of emissions accounting to incorporate vehicle-cycle emissions; including a new constraint that allows for a restriction in embodied emissions from vehicle manufacturing.
- Representation of more provinces, by expanding data aggregation framework and automatizing data collection.
- Improvements to RAMP-mobility simulations by using parameter distributions other than uniform ones. Implementation of charging strategies, including the use of residual load from VRE curtailment. Potentially, including the representation of PHEVs.
- Incorporate MHDV charging profiles based on simulation results from the CANOE team.
- Improve representation of H_2 production pathways, by characterizing technologies and technoeconomic parameters with more detailed assessments.

3.4 Conclusions

Modeling choices matter, yet determining which choices to prioritize remains unclear, especially in demand sectors like transportation. By focusing on the transportation sector in Ontario through a rigorous examination of available Canadian data, this study addresses its underrepresentation in some existing models and contributes to the broader conversation about improving access to technologically and spatiotemporally disaggregated energy data in Canada.

This thesis advances our understanding of how input derivation and parameterization influence modeling outcomes, advocating for a development process of large bottom-up models with greater consideration of underlying implications of parameter choices, as such choices often transfer predefined expectations and exogenous uncertainties into our models. The scenario analysis from this study evidenced the implications of using heuristic constraints, varying technological change assumptions and characterizing travel behavior through different sources. The global sensitivity analysis provided a measure of influence from parameters that embody uncertainties from these modeling choices. However, further investigation is needed before these findings can be generalized to other modeling frameworks.

The findings in this study are far from ideal in terms of what a fully validated modeling effort should deliver. This model touches on several recognized modeling gaps without fully addressing them, leaving room for improvement in the assumptions used and the parameterization methods applied. The goal of this work is not to present a state-of-the-art large bottom-up model but rather to discuss the main modeling challenges and uncertainties in deriving inputs and parameters for the transportation sector, identify gaps in representation, and explore techniques to address these gaps. It also evaluates the extent to which identified uncertainties may influence decision variables.

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Appendix: Literature Review

This appendix provides reference points for the application of concepts and theory behind the modeling rationale and interpretation of results throughout this thesis.

Energy System Models and Their Role in Climate Policy

In their essence, energy system models (ESMs) simulate the function and growth of energy systems (CESA, 2023) by leveraging economic optimization to balance the provision of primary and secondary energy to meet demand services across economic sectors (Nasta & Wissmiller, 2023). They offer an evidence base for climate policy analysis (Rhodes, E. et al., 2021). Until recently, the scope of such models was limited to the electricity sector, used by utility companies for operation and investment decision support.

Pfenninger et al. (2014) conceptualized four ESM paradigms that encapsulate the overall formulation logic of most models, including optimization, simulation and power system analysis frameworks. Optimization frameworks, which are normative (i.e., prognose what should happen), are predominantly bottom-up (i.e., represented from the individual process to the aggregate level) Whereas simulation frameworks, which are predictive (i.e., prognose what might happen), are usually integrated hybrid frameworks (i.e., combine bottom-up and top-down approaches) (Lund et al., 2017). Thus, optimization frameworks are used to identify potential policy pathways or decarbonization strategies from prescribed outcomes, whereas simulation frameworks evaluate the outcomes from the implementation of climate policies and other strategies (Usher W et al., 2023). This thesis focuses on the former, a pure bottom-up optimization framework was used.

ESMs play a critical role in shaping climate policy by providing projections of emissions reductions, technology adoption, and investment needs. However, discrepancies across models due to varying assumptions and structures can lead to significantly different policy insights. For instance, energy-economy models often show differing outcomes in response to carbon pricing and technology uptake, affecting the reliability of policy recommendations (Pfenninger et al., 2014; Rhodes, E. et al., 2021). As a result, the assumptions and design choices in these models must be carefully considered to avoid misleading conclusions.

Evaluating ESMs involves assessing their technological detail, temporal and spatial resolution, and treatment of uncertainty. High-resolution models can offer detailed insights into energy demand

and renewable integration but are more resource-intensive. Another critical factor is how well models represent policy impacts and behavioral factors, such as consumer preferences and market dynamics. These aspects are essential for capturing the real-world effects of energy transitions and are increasingly integrated into modern models (Fattahi et al., 2020; Fodstad et al., 2022).

To improve ESMs, future efforts should focus on enhancing transparency, addressing uncertainty through global sensitivity analysis, and incorporating emerging technologies and social behavior. DeCarolis et al. (2017) recommendations can help standardize model development and ensure that results are robust and useful for policymakers. Additionally, open-source models and improved data availability are key to advancing the field and making ESMs more relevant for long-term climate planning.

Uncertainty in Energy System Models

Uncertainty in energy system models (ESMs) arises from a mix of parametric, structural, and scenario-based factors. Addressing this uncertainty is crucial for improving the credibility and utility of these models in policy decision-making (Walker et al., 2003; Yue et al., 2018). Parametric uncertainty refers to the unknown or variable nature of input values, such as fuel prices, demand forecasts, or technology costs (Feng et al., 2023; Yue et al., 2018). Structural uncertainty comes from the assumptions within model formulation, particularly regarding how it represents the technology interactions within energy systems, which may not fully capture real-world dynamics (J. DeCarolis et al., 2017).

Several methods exist to assess and manage uncertainty in ESMs. Monte Carlo analysis is one of the most widely used, generating random samples from input distributions to produce a range of model outcomes. This approach helps quantify parametric uncertainty by showing how variability in input data affects model results (Yue et al., 2018). Another common method is Stochastic programming, which incorporates uncertainty into the optimization process by considering multiple possible future scenarios and finding robust solutions that perform well across different conditions (Feng et al., 2023).

Robust optimization aims to identify solutions that remain effective under worst-case uncertainty realizations. This approach is particularly useful when uncertainties are large and difficult to quantify, as it helps policymakers minimize downside risks (Fodstad et al., 2022; Patankar et al., 2022). A more recent approach, modeling to generate alternatives (MGA), creates a set of near-optimal solutions that are maximally different from each other to give decision-makers a range of policy options under uncertainty (J. F. DeCarolis et al., 2016), effectively escaping corner solutions that are so common in energy system optimization models (Ramea et al., 2018). Nonetheless, this study relies on global sensitivity analysis via the Method of Morris, which instead of varying only one parameter in the multi-dimensional space, multiple parameters are varied simultaneously to capture both direct and interaction effects from parameters altogether (Usher W et al., 2023).

Uncertainty has major implications for decision-making. Failing to account for it can lead to misleading or overconfident results. Incorporating formal uncertainty analysis makes model insights more robust, reliable, and valuable for policymakers. Effective uncertainty management also supports long-term planning by identifying critical factors that could affect the feasibility of decarbonization pathways and infrastructure investments (J. F. DeCarolis et al., 2020)

Transportation Sector Representation in Energy System Models

This subsection describes the main topics that were investigated to better understand what representation methods were more appropriate for the availability and access to Canadian energy and economic data related to its energy system.

Methodologies for Representing Transportation Systems

The choice of technoeconomic data sources across ESOMs in Canada is varied across studies, suggesting that there is no standardization of transportation sources to represent technologies more homogeneously across frameworks (Bahn et al., 2013; Doluweera et al., 2020; Keller et al., 2019; McPherson et al., 2023; Pedinotti-Castelle et al., 2022; Saeid Atabaki et al., 2023; Vaillancourt et al., 2017; Xu et al., 2023) allowing a more comparable evaluation of system-level implications. Fortunately, this data gap is being addressed by initiatives like (McPherson et al., 2022), which aims at providing a standardized database for Canadian energy system models. However, this has primary focus on the electricity sector, wherein demand sectors like transportation have not been standardized yet.

The representation of transportation sectors in energy system models (ESMs) typically involves methodologies that balance technological detail with system-wide consistency. A common approach is to segment the transport market, especially for private vehicles, based on factors such as vehicle type, fuel type, and trip distance. This disaggregation allows for a more detailed analysis of different vehicle technologies and their adoption rates, particularly when comparing electric and hydrogen powertrains with conventional internal combustion engine vehicles (ICEVs) (Aryanpur et al., 2022; Dodds & McDowall, 2014)

For example, Aryanpur et al. (2022) describe how the TIMES-Ireland Model incorporates spatial resolution and consumer heterogeneity to represent region-specific transportation dynamics. This involves characterizing vehicle fleets, public transport availability, and fuel consumption across sub-regions to capture regional differences in electric vehicle (EV) adoption and its associated electricity demand. Similarly, Dodds & McDowall (2014) emphasize the importance of including non-cost factors like consumer behavior and fuel infrastructure development, which are critical for the market adoption of new technologies like hydrogen vehicles.

The integration of modal shifts within ESMs is also essential for capturing transportation dynamics. Saeid Atabaki et al. (2023) highlight the need to account for shifts from private vehicles to public transport or active modes like cycling. These models assess travel costs, time, and infrastructure constraints to evaluate the impact of policy measures promoting more sustainable transportation modes, offering insights into how enhanced public transport infrastructure can reduce emissions.

Modeling behavioral realism has become increasingly important in studying technology transitions due to its dependence on social perceptions and market constraints (Dioha et al., 2023). However, due to the framework used by the model for this study and the objective of developing a technology-detailed model, a comprehensive accounting of behavioral factors was beyond the scope of this research.

Light-duty Electric Vehicle Charging Demand

EV adoption is accelerating as governments aim to decarbonize transportation. This has resulted in challenges for society’s stakeholders, particularly in the interface between mobility and electricity sectors. To meet the electricity demand from the increasingly electrified vehicle fleets, utility planners need to estimate the current and future hourly electricity loads from charging stations – i.e., charging profiles (CPs), the natural result of the interplay between EV drivers’ routines and the available charging network.

As Pareschi et al. (2020) suggest, researchers have devised two ways to predict CPs:

- public trials – investigating real EV usage patterns from study participants or data sensing of deployed charging stations.
- simulation models – a digital transportation system designed to emulate real drivers.

Some studies employ a mixture of both, by grounding a model with information extracted from EV trials. However, the representativity of public trials risks being limited, as the participants or stations in place can belong to specific demographics or geographies. A recent study that estimates CP distributions from public and private stations with data from almost 7,880 charging stations across British Columbia and Quebec was conducted by Jonas et al. (2023). Even though the authors did not address the representativeness of their findings, the typical hourly CPs were used in the City of Toronto's capacity and operation planning model LENZ, to estimate the temporal disaggregation of the EV charging demand calculated by the optimization module Temoa-TO (Jaroudi et al., 2023).

On the other hand, simulation models can be designed around drivers' characteristics that highly influence CPs, such as mobility needs, vehicle characteristics and charging infrastructure access, as described by Powell et al. (2022). In that study, to better capture behavioural differences, driver groups were identified by clustering drivers from a large dataset of real charging sessions. Driver groups can be used to represent revealed preferences or distinctive trip patterns. Overall, typical EV charging demand is driven by driver behaviour and vehicle type – when, where, how, how often and how much each driver charges by session.

Electric Vehicle Usage Simulation Models

In the interest of power infrastructure capacity planning, the model categories better suited to address the short-term (hourly) interaction with the charging infrastructure are the activity-based models (ABM) and the direct use of observed activity-travel schedules (DUOATS), as conceptualized by Daina et al. (2017), in their review, the advantages and disadvantages of different categories are discussed. The main difference between ABM and DUOATS is the flexibility in building the activity-travel schedule – ABMs can generate and optimize the schedule endogenously, whereas DUOATS use an exogenous schedule, typically derived from household travel surveys. Even though these surveys are usually composed of conventional ICEVs as they are performed on the general population, studies like Pareschi et al. (2020) employed empirical validation to prove that household travel surveys can still be an appropriate instrument for generating EV insights, while also laying out the best practices to avoid biases. The latter study also found that CPs mostly depend on charging power, vehicle efficiency, and battery size; and that drivers' decision to charge is similar across different empirical contexts.

DUOATS models work on the underlying assumption that the introduction of EVs does not significantly alter travel patterns, even in large deployment scenarios. These models encapsulate the complexity of human mobility behavior because they are grounded in the observed travel choices found on HTSs. While ABMs can enjoy more degrees of freedom and integrate features like mode shift or activity adjustments, they can only be derived through rich detail and multiple parameters that emulate the behaviour and the decision process behind activity and trip allocation. Thus, ABMs are not compatible with both the current data availability and the province-level spatial resolution aimed for in the development of the CANOE model, see **Section 2.2**.

Due to the limited availability of household travel surveys in Canada, especially outside metropolitan areas, it is hard to characterize trip patterns from larger regions. Moreover, limited access to survey data presents more challenges to researchers, as in some places there are no clear and uniform confidentiality rules to allow access to disaggregated data sets (Whitmore & Pineau, 2022). Thus, provincial-level studies like Doluweera et al. (2020), had to rely on the US National Household Transportation Survey (NHTS) to obtain probability density functions that characterize fleet behavior, by assuming that the driving behaviour between a province like Alberta and an entire nation like the US do not differ much. The NHTS data was used in a stochastic vehicle aggregation module integrated into their power system simulation model to estimate EV CPs, making a precedent for the use of stochastic aggregation approaches in Canadian charging energy demand studies.

Stochastic EV Fleet Aggregation

Pareschi et al. (2020), Powell et al. (2022) and Doluweera et al. (2020) all use a probabilistic method to capture driver charging preferences based on patterns derived from empirical data. The latter study stated that the most used approach for modelling EV fleet charging curves at that point is the stochastic approach. Although different modelling approaches have been used to aggregate fleet charging behaviour (e.g., historical, deterministic, stochastic, cloud model and diffusion theory approaches), researchers predominantly choose to describe the variable nature of private mobility through a stochastic formulation – as charging behavior per se is stochastic, also dependent on EVs' state of charge (Pareschi et al., 2020).

Mangipinto et al. (2022) developed a generally-applicable DUOATS model that uses stochastic aggregation to simulate EV fleets' CPs, called RAMP-mobility. Driven by the premise that most stochastic approaches fail to decouple from context-specific empirical data rather than developing a flexibly adaptable approach that can capitalize on time-of-use surveys available from different contexts. RAMP-mobility implements occasional use time frames in which mobility and charging events can randomly occur given a probability that varies by driver occupation, time of day and day type. One of the main advantages over other common stochastic approaches, like Markov chains models, is that RAMP-mobility's algorithm is not heavily intertwined with present-day travel behavior, since drivers' chain of activities over a day do not need to be explicitly characterized. This fact makes it a suitable approach to model extreme sensitivity scenarios and long-term mobility patterns that deviate from present conditions.

Hence, as driver behaviour is highly heterogeneous, the literature suggests that a stochastic formulation is the most studied approach. Additionally, RAMP-mobility's adaptability to different contexts with limited behavioural data seems to be an appropriate method to estimate the current and future EV fleet CPs from the different Canadian provinces, while accounting for battery power consumption as a function of average trip velocity and ambient air temperature.