Capital Regional District

625 Fisgard St.,
Victoria, BC V8W 1R7

Notice of Meeting and Meeting Agenda
Environmental Services Committee

Wednesday, January 19, 2022 | **1:30 PM** | **6th Floor Boardroom, 625 Fisgard St., Victoria, BC V8W 1R7**

B. Desjardins (Chair), N. Taylor (Vice Chair), D. Blackwell, L. Helps, M. Hicks, G. Holman, G. Orr, J. Ranns, K. Williams, R. Windsor, C. Plant (Board Chair, ex-officio)

The Capital Regional District strives to be a place where inclusion is paramount and all people are treated with dignity. We pledge to make our meetings a place where all feel welcome and respected.

1. Territorial Acknowledgement

2. Approval of Agenda

3. Adoption of Minutes

3.1. 22-051 Minutes of the October 20, 2021 Environmental Services Committee Meeting

Recommendation: That the minutes of the October 20, 2021 Environmental Services Committee be adopted as circulated.

Attachments: Minutes - October 20, 2021

4. Chair's Remarks

5. Presentations/Delegations

In keeping with directives from the Province of BC, there is limited space for the public to attend CRD Board meetings in-person at this time. However, the public may continue to view meeting materials and Live Webcasts online. If you wish to attend a meeting in-person, please email legserv@crd.bc.ca.

CRD encourages delegations to participate electronically. Please complete the online application for "Addressing the Board" on our website and staff will respond with details.

Alternatively, you may email your comments on an agenda item to the CRD Board at crdboard@crd.bc.ca.

6. Committee Business

6.1. 22-035 2022 Environmental Services Committee Terms of Reference

Recommendation: That the Environmental Services Committee receive the 2022 Terms of Reference, attached as Appendix A.

Attachments: Staff Report: 2022 Environmental Services Committee TOR

Appendix A: Terms of Reference

6.2. 22-039 2020 Regional Greenhouse Gas Inventory

Recommendation: The Environmental Services Committee recommends to the Capital Regional District Board:
That the 2020 Regional Greenhouse Gas Inventory report be received for information.

Attachments: Staff Report: 2020 Regional Greenhouse Gas Inventory

Appendix A: 2020 GPC BASIC & Community GHG Inventory - Stantec

Appendix B: 2007 Base Year & 2020 Reporting Year - Stantec

Appendix C: Capital Region CO2E Emissions Per Capita

6.3. 22-034 Zero-Emissions Fleet Initiative - Final Study Report

Recommendation: The Environmental Services Committee recommends to the Capital Regional District Board:
That the Zero-Emissions Fleet Initiative Final Study Report be received for information.

Attachments: Staff Report: Zero-Emissions Fleet Initiative - Final Study Report

Appendix A: Zero-Emissions Fleet Initiative - Final Study Report

7. Notice(s) of Motion

8. New Business

9. Adjournment

Next Meeting: February 16, 2022

Meeting Minutes

Environmental Services Committee

Wednesday, October 20, 2021	1:30 PM	6th Floor Boardroom 625 Fisgard St. Victoria, BC V8W 1R7

PRESENT
Directors: B. Desjardins (Chair), N. Taylor (Vice Chair), M. Alto (for L. Helps) (EP), M. Hicks (EP), G. Holman (EP), K. Kahakauwila (for J. Ranns) (EP), G. Orr (EP), L. Szpak (for D. Blackwell), K. Williams (EP), R. Windsor (EP)

Staff: L. Hutcheson, General Manager, Parks and Environmental Services; R. Smith, Senior Manager Environmental Resource Management; M. Lagoa, Deputy Corporate Officer; S. Orr, Senior Committee Clerk (Recorder)

EP - Electronic Participation

Regrets: D. Blackwell, L. Helps, J. Olsen, J. Ranns, C. Plant

The meeting was called to order at 1:33 pm.

1. Territorial Acknowledgement

Vice Chair Taylor provided the Territorial Acknowledgement.

2. Approval of Agenda

MOVED by Director Taylor, SECONDED by Director Blackwell,
That the agenda for the October 20, 2021 Environmental Services Committee meeting be approved.
CARRIED

3. Adoption of Minutes

3.1. 21-711 Minutes of the July 21, 2021 Environmental Services Committee Meeting

MOVED by Alternate Director Szpak, SECONDED by Director Taylor,
That the minutes of the Environmental Services Committee meeting of July 21, 2021 be adopted as circulated.
CARRIED

3.2. 21-803 Minutes of the September 29, 2021 Environmental Services Committee Meeting

MOVED by Alternate Director Szpak, SECONDED by Director Taylor,
That the minutes of the Environmental Services Committee meeting of September 29, 2021 be adopted as circulated.
CARRIED

4. Chair's Remarks

The Chair stated we are celebrating waste reduction week from October 18-24, 2021 and the Capital Regional District (CRD) is putting on a number of programs to help residents reduce their waste, and encouraged committee members to reach out to their communities in an effort to reduce waste. She stated that the CRD is hosting public tours of the landfill on November 5 and 6, 2021.

5. Presentations/Delegations

There were no presentations or delegations.

6. Committee Business

6.1. 21-721 Recycling in British Columbia - Extended Producer Responsibility Five-Year Action Plan

R. Smith spoke to Item 6.1.

Discussion ensued regarding:
- Mattress recycling
- Electric vehicle batteries
- Multi-family, industrial and commercial recycling
- Short term action plan

MOVED by Director Taylor, SECONDED by Alternate Director Szpak,
The Environmental Services Committee recommends to the Capital Regional District Board:
That this report be received for information
CARRIED

6.2. 21-771 Waste Stream Management Licensing

R. Smith spoke to Item 6.2.

Discussion ensued regarding:
- Licensing benefits
- Impact of investigation on short-term priorities
- Implications for Electoral Areas
- Hauling contractors

MOVED by Alternate Director Alto, SECONDED by Alternate Director Szpak,
The Environmental Services Committee recommends to the Capital Regional District Board:
That staff include the investigation of waste stream management licensing as part of the Solid Waste Management Plan Short-Term Implementation Framework.
CARRIED

7. Notice(s) of Motion

There were no notice(s) of motion.

8. New Business

There was no new business.

9. Adjournment

MOVED by Director Blackwell, SECONDED by Director Taylor,
That the October 21, 2021 Environmental Services Committee meeting be adjourned at 2:11 pm.
CARRIED

____
CHAIR

____
RECORDER

REPORT TO ENVIRONMENTAL SERVICES COMMITTEE
MEETING OF WEDNESDAY, JANUARY 19, 2022

SUBJECT **2022 Environmental Services Committee Terms of Reference**

ISSUE SUMMARY

This report is to provide the 2022 Environmental Services Committee Terms of Reference for the Committee's review.

BACKGROUND

Under the *Local Government Act* and the CRD Board Procedures Bylaw, the CRD Board Chair has the authority to establish standing committees and appoint members to provide advice and recommendations to the Board.

On December 8, 2021, the Regional Board approved the 2022 Terms of Reference for standing committees. Terms of Reference (TOR) serve to clarify the mandate, responsibilities and procedures of standing committees and provide a point of reference and guidance for the Committees and members.

This year, there were no changes to the defined purpose of the Committee's TOR.

The TOR are being provided for review by the Committee. Any proposed revisions to the TOR will require ratification by the Board.

CONCLUSION

Terms of Reference serve to clarify the mandate, responsibilities and procedures of committees and provide a point of reference and guidance for the committees and their members.

RECOMMENDATION

That the Environmental Services Committee receive the 2022 Terms of Reference, attached as Appendix A.

Submitted by:	Kristen Morley, JD, General Manager and Corporate Officer, Corporate Services
Concurrence:	Larisa Hutcheson, P.Eng., General Manager, Parks & Environmental Services
Concurrence:	Robert Lapham, MCIP, RPP, Chief Administrative Officer

ATTACHMENT

Appendix A: 2022 Environmental Services Committee Terms of Reference

Terms of Reference

ENVIRONMENTAL SERVICES COMMITTEE

PREAMBLE

The Capital Regional District (CRD) Environmental Services Committee is a standing committee established by the CRD Board and will oversee and make recommendations to the Board regarding waste management, resource recovery, climate change and other environmental matters.

The Committee's official name is to be:

Environmental Services Committee

1.0 PURPOSE

a) The mandate of the Committee includes overseeing and making recommendations to the Board regarding the following functions:

   i. Regional solid waste function
   ii. Environmental protection, monitoring and compliance
   iii. Community climate action
   iv. Resource recovery opportunities

b) The Committee will also:

   i. Serve as the Plan Monitoring Advisory Committee for the current Solid Waste Management Plan (SWMP)
   ii. Stand as the steering committee for the revised SWMP

c) The following committees will report through the Environmental Services Committee:

   i. Climate Action Inter-Municipal Task Force
   ii. Solid Waste Advisory Committee (SWAC)

2.0 ESTABLISHMENT AND AUTHORITY

a) The Committee will make recommendations to the Board for consideration; and

b) The Board Chair will appoint the Committee Chair, Vice Chair and Committee members annually.

3.0 COMPOSITION

a) Committee members will be appointed CRD Board Members;

b) All Board members are permitted to participate in standing committee meetings, but not vote, in accordance with the CRD Board Procedures Bylaw; and

c) First Nation members are permitted to participate in standing committee meetings at their pleasure, in accordance with the CRD Procedures Bylaw, where the Nation has an interest in matters being considered by the committee.

4.0 PROCEDURES

a) The Committee shall meet on a monthly basis, except August and December, and have special meetings, as required

b) The agenda will be finalized in consultation between staff and the Committee Chair and any Committee member may make a request to the Chair to place a matter on the agenda through the Notice of Motion process;

c) With the approval of the Committee Chair and the Board Chair, Committee matters of an urgent or time sensitive nature may be forwarded directly to the Board for consideration; and

d) A quorum is a majority of the Committee membership and is required to conduct Committee business.

5.0 RESOURCES AND SUPPORT

a) The General Manager of Parks & Environmental Services will act as liaison to the Committee; and

b) Minutes and agendas are prepared and distributed by the Corporate Services Department.

Approved by CRD Board December 8, 2021

Making a difference...together

EEP 22-03

REPORT TO ENVIRONMENTAL SERVICES COMMITTEE
MEETING OF WEDNESDAY, JANUARY 19, 2022

SUBJECT **2020 Regional Greenhouse Gas Inventory**

ISSUE SUMMARY

To provide the results of the 2020 Capital Regional District (CRD) and regional local government community greenhouse gas (GHG) emissions inventory.

BACKGROUND

The CRD's 2018 Regional Growth Strategy (RGS) targets a reduction in community GHG emissions of 33% (from 2007 levels) by 2020, and 61% by 2038. In February 2019, the CRD Board declared a climate emergency and committed to regional carbon neutrality. At its March 13, 2019 meeting, the CRD Board directed staff to complete a regional GHG inventory and, in July 2020, staff delivered a 2018 regional GHG Global Protocol for Cities (GPC) BASIC + GHG emission inventory.

Utilizing the internationally recognized GPC framework, the CRD retained Stantec Consulting Ltd. to update the CRD regional GPC BASIC + GHG emission inventory for the 2020 calendar year (Appendix A).

The 2020 CRD inventory indicates the capital region emits approximately 1.8 million tonnes of C02e annually. This represents a 9.8% reduction from 2007 levels and a 5% reduction from 2018. This precipitous drop is largely the result of a reduction in transportation-related emissions associated with the early 2020 COVID-19 pandemic response. Emissions associated with buildings increased 8.1% in 2020 relative to 2018. The Municipalities and Electoral Areas inventories (Appendix B) show increases in natural gas emissions in residential buildings relative to 2007 for most municipalities, as measured by Fortis BC. That result is partially indicative of the 2020 trend, as well as the proliferation of gas appliances in the capital region over the past 10 years. An increase in emissions from buildings electricity use can also be observed, which is largely due to a change in the electricity emission factor used. Trends for propane, wood and fuel GHG emissions were estimated using linear regression methods, with the exception of the City of Victoria and District of Saanich where fuel oil consumption was estimated based on the number of known tanks, average heated floor areas and fuel volume intensity.

Together building and transportation-related emissions continue to be the largest sources of emissions (approximately 79% in 2020), and waste-related emissions were observed to be approximately 34% below 2007 levels. Per capita emissions (Appendix C) were observed to be approximately 24% below 2007, which speaks to the efforts by the CRD and regional local governments to reduce energy consumption and GHG emissions despite significant regional growth. However, as established in the new 2021 Climate Action Strategy, the region will not meet the 2038 target unless greater effort is taken.

This inventory represents the best available information and includes several notable updates, including the best available emission factor for electricity for each inventory year, Insurance

Corporation of BC vehicle counts, and the separation of sequestration and land use change values. Due to limitations in how to quantify GHG emissions from sequestration and land use change, these values have been excluded from the calculation of total emissions. Values for these items are disclosed for information only in the CRD and regional local government community GHG emissions inventory reports. Understanding the sequestration potential of the region's natural assets will become increasingly important as emissions drop toward the RGS goal of a 61% reduction by 2038. Staff continue to pursue better data for estimating the sequestration rates of the region's natural assets and land use changes occurring in the region. See Figure 1 for the emission trend since 2007 and the approximate trajectory of emissions reductions to 2038 established in the 2021 Climate Action Strategy.

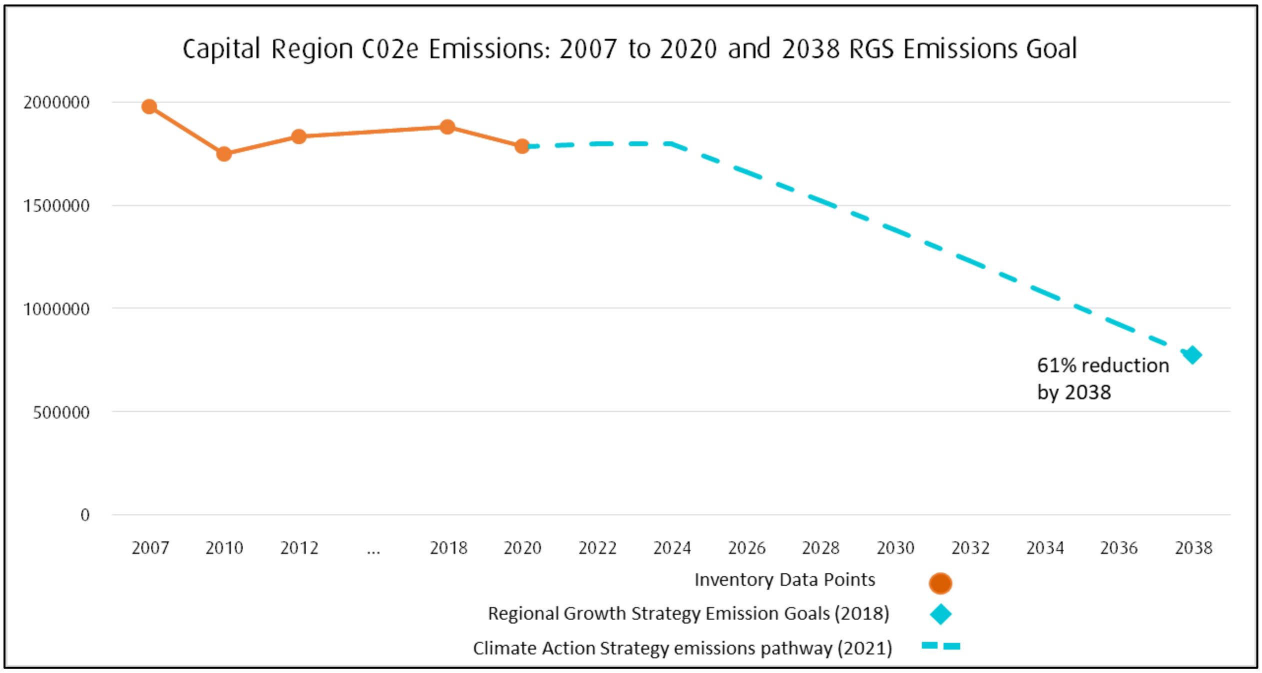

Figure 1: Capital Region Greenhouse Gas Global Protocol for Cities Basic + Emissions and 2038 Regional Growth Strategy Goal

CONCLUSION

The CRD completed a greenhouse gas emission inventory and report for the 2020 calendar year. Results indicate an approximate 9.8% decrease in regional emissions from 2007 to 2020, and a 5% reduction from 2018, largely associated with the early 2020 COVID-19 pandemic response. The analyses also indicated that on-road transportation and the built environment are the main sources of regional emissions, together accounting for approximately 79% of all emissions in 2020.

RECOMMENDATION

The Environmental Services Committee recommends to the Capital Regional District Board:
That the 2020 Regional Greenhouse Gas Inventory report be received for information.

Submitted by:	Glenn Harris, Ph.D., R.P.Bio., Senior Manager, Environmental Protection
Concurrence:	Larisa Hutcheson, P. Eng., General Manager, Parks & Environmental Services
Concurrence:	Robert Lapham, MCIP, RPP, Chief Administrative Officer

ATTACHMENTS

Appendix A: Capital Regional District 2020 GPC BASIC and Community Greenhouse Gas Emissions Inventory Report – Stantec Consulting Ltd. – October 2021
Appendix B: Capital Region District – Municipalities and Electoral Areas – 2007 Base Year and 2020 Reporting Year Energy & Greenhouse Gas Emissions Inventory – Stantec Consulting Ltd. – October 2021
Appendix C: Capital Region $C0_{2e}$ Emissions Per Capita

APPENDIX A

Capital Regional District 2020 GPC BASIC+ Community Greenhouse Gas (GHG) Emissions Inventory Report

Prepared for:
Capital Regional District
625 Fisgard Street, PO Box 1000
Victoria, BC V8W 2S6

Prepared by:
Stantec Consulting Ltd.
200-325 25 Street SE
Calgary, AB T2A 7H8

October 29, 2021

Limitation of Liability

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Executive Summary

There is increasing evidence that global climate change resulting from emissions of carbon dioxide (CO_2) and other greenhouse gases (GHGs) is having a significant impact on the ecology of the planet. Delayed actions to respond to the effects of climate change are expected to have serious negative impacts on global economic growth and development.

Beyond the costs associated with delayed climate action, there are cost savings to be realized through efforts to improve energy efficiency, conserve energy, and reduce GHG emissions intensity. To make informed decisions on reducing energy use and GHG emissions at the community scale, community managers must have a good understanding of these sources, the activities that drive them, and their relative contribution to the total. This requires the completion of an energy and GHG emissions inventory. To allow for credible and meaningful reporting locally and internationally, the Global Protocol for Community-Scale Greenhouse Gas Emission Inventories (the GPC Protocol) was developed. The GPC Protocol has been adopted by the Global Covenant of Mayors—an agreement led by community networks to undertake a transparent and supportive approach to measure GHG emissions community-wide. The Global Covenant of Mayors and the Federation of Canadian Municipalities promotes the use of the GPC Protocol as a standardized way for municipalities to collect and report their actions on climate change.

This project set out to compile a detailed GHG inventory for the Capital Regional District (CRD) for the 2020 reporting year using the GPC Protocol. The CRD has historically relied on the Provincial 2007, 2010 and 2012 Community Energy and Emissions Inventories (CEEI) to baseline and track community GHG emissions. However, there have been some limitations to the CEEI which has resulted in the CRD preparing a GPC BASIC+ inventory. Following the requirements of the GPC Protocol, the GHG inventories considered emissions from all reporting Sectors, including Stationary Energy, Transportation, Waste, Industrial Process and Product Use (IPPU), and Agriculture, Forestry and Other Land Use (AFOLU). The purpose of this document is to describe the quantification methodologies used to calculate GHG emissions for the 2020 reporting year, and to present the CRD's 2020 community GHG emissions.

In 2020, the CRD's BASIC+ GHG emissions totaled 1,785,814 tonnes of carbon dioxide equivalent (tCO_2e). On an absolute basis, this is a 10% decline from the 2007 base year GHG emissions and a decline of 24% on a per capita basis. The 2020 energy and GHG emissions year was not typical in terms of energy and GHG emissions largely due to COVID-19 restrictions and associated closures. Transportation emissions were decreased and building emissions increased, which aligns with expectations associated with residents spending more time at home. However, building emissions were partially derived via estimates. Trends for propane, wood and fuel GHG emissions were estimated using linear regression methods, with the exception of the City of Victoria and District of Saanich, which were estimated based on the number of known tanks, average heated floor areas and fuel volume intensity. Due to limitations in how to quantify GHG emissions resulting from land use change (e.g., residential development), these GHG emissions have been excluded from the CRD's GHG emissions inventory, but have been disclosed, until a more robust measurement methodology can be developed. The GHG emissions inventory does, however, include GHG emissions sequestered as a result of biological ecosystems (e.g., forests).

A summary of the 2020 GHG emissions is presented in Table E-1.

Table E-1 BASIC+ 2007 Base Year And 2020 Reporting Year GHG Emissions

Sector	Sub-Sector	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)
Stationary Energy	Residential Buildings	425,806	406,896
	Commercial & Institutional Buildings	262,171	303,112
	Manufacturing Industries & Construction	-	0
	Energy Industries	418	9,563
	Agriculture, Forestry & Fishing activities	62,060	56,418
	Fugitive Emissions	1,003	1,408
Transportation	In-Boundary On-road Transportation	869,591	692,329
	Trans-Boundary On-road Transportation	13,333	6,019
	Waterborne Navigation	48,246	22,341
	Aviation	26,120	12,564
	Off-road Transportation	56,291	51,623
Waste	Solid Waste	111,234	66,237
	Biological Treatment of Waste	72	5,307
	Wastewater Treatment & Discharge	18,998	15,035
IPPU	IPPU	77,348	130,139
AFOLU	Land-Use: Emissions Sequestered **(Disclosure Only - Not Included In Total)**	-396,487	-399,707
	Land-Use: Emissions Released **(Disclosure Only - Not Included In Total)**	151,516	89,610
	Livestock	2,665	3,545
	Non-CO_2 Land Emission Sources	743	715
Change in GHG Emissions from Base Year		**1,976,100**	**1,783,251**
Total Per Capita GHG Emissions (tCO_2e / Capita)		**5.6**	**4.2**
Change GHG Emissions per Capita from Base Year			**-25.6%**
Change in GHG Emissions from Base Year			**-9.8%**

Data in the table above is depicted in Figure E-1.

Figure E-1 CRD's 2020 BASIC+ GHG Emissions Profile

Abbreviations

ACERT	Airport Carbon Emissions Reporting Tool
ACI	Annual Crop Inventory
AFOLU	Agriculture, Forestry, and Other Land Use
BC	British Columbia
C40	C40 Cities Climate Leadership Group
CH_4	Methane
CO_2	carbon dioxide
CO_2e	carbon dioxide equivalents
CEEI	Community Energy and Emissions Inventories
CRD	Capital Regional District
VIA	Victoria International Airport
eMWh	megawatt hours equivalents
FCM	Federation of Canadian Municipalities
GDP	gross domestic product
GHG	greenhouse gas
GJ	Gigajoules
GPC	Global Protocol for Community-Scale Greenhouse Gas Emission Inventories
GVHA	Greater Victoria Harbour Authority
GWP	global warming potentials
HFC	Hydrofluorocarbons
ICAO	International Civil Aviation Organization
ICBC	Insurance Corporation of BC

ICLEI	International Council for Local Environmental Initiatives
IE	included elsewhere
IPCC	Intergovernmental Panel on Climate Change
IPPU	Industrial Process and Product Use
ISO	International Organization for Standardization
kg	Kilograms
kW	Kilowatt
kWh	kilowatt hours
L	Litres
MWh	megawatt hours
N_2O	nitrous oxides
NE	not estimated
NIR	National Inventory Report
NPRI	National Pollutant Release Inventory
NO	not occurring
PCP	Partnership for Climate Protection
PFC	Perfluorocarbons
SC	Other Scope 3
SF_6	sulfur hexafluoride
VIA	Victoria International Airport
WIP	waste-in-place
WRI	World Resources Institute

Glossary

Air pollution	The presence of toxic chemicals or materials in the air, at levels that pose a human health risk.
Base Year	This is the reference or starting year to which targets and GHG emissions projections are based.
BASIC	An inventory reporting level that includes all Scope 1 sources except from energy generation, imported waste, IPPU, and AFOLU, as well as all Scope 2 sources (GPC, 2014).
BASIC+	An inventory reporting level that covers all GPC BASIC sources, plus Scope 1 AFOLU and IPPU, and Scope 3 in the Stationary Energy and Transportation Sectors (GPC, 2014).
Biogenic emissions	Emissions produced by living organisms or biological processes, but not fossilized or from fossil sources (GPC, 2014).
Carbon dioxide equivalent (CO_2e)	The amount of carbon dioxide (CO_2) emissions that would cause the same integrated radiative forcing, over a given time horizon, as an emitted amount of a greenhouse gas (GHG) or a mixture of GHGs. The CO_2e emission is obtained by multiplying the emission of a GHG by its Global Warming Potential (GWP) for the given time horizon. For a mix of GHGs, it is obtained by summing the CO_2e emissions of each gas (IPCC 2014).
Climate change	Climate change refers to a change in the state of the climate that can be identified by changes in the mean and/or the variability of its properties and that persists for an extended period, typically decades or longer. Climate change may be due to natural internal processes or external forces such as modulations of the solar cycles, volcanic eruptions, and persistent anthropogenic changes in the composition of the atmosphere or in land use (IPCC, 2014).
Emission	The release of GHGs into the atmosphere (GPC, 2014).
Emission factor(s)	A factor that converts activity data into GHG emissions data (GPC, 2014).
Flaring	The burning of natural gas that cannot be used.
Fossil fuels	A hydrocarbon deposit derived from the accumulated remains of ancient plants and animals which is used as an energy source.
Fugitive emission	Emissions that are released during extraction, transformation, and transportation of primary fossil fuels. These GHG emissions are not combusted for energy.
Geographic boundary	A geographic boundary that identifies the spatial dimensions of the inventory's assessment boundary. This geographic boundary defines the physical perimeter separating in-boundary emissions from out-of-boundary and transboundary emissions (GPC, 2014).
Gigajoule (GJ)	A gigajoule (GJ), one billion joules, is a measure of energy. One GJ is about the same energy as: • Natural gas for 3-4 days of household use • The electricity used by a typical house in 10 days

Global warming	A gradual increase in the Earth's temperature which is attributed to the greenhouse effect caused by the release of greenhouse gas (GHG) emissions into the atmosphere.
Global warming potential (GWP)	An index measuring the radiative forcing following an emission of a unit mass of a given substance, accumulated over a chosen time horizon, relative to that of the reference substance, carbon dioxide (CO_2). The GWP thus represents the combined effect of the differing times these substances remain in the atmosphere and their effectiveness in causing radiative forcing. The Kyoto Protocol is based on global warming potentials over a 100-year period (IPCC 2014).
Greenhouse gas (GHG)	GHGs are the seven gases covered by the UNFCCC: carbon dioxide (CO_2); methane (CH_4); nitrous oxide (N_2O); hydrofluorocarbons (HFCs); perfluorocarbons (PFCs); sulphur hexafluoride (SF_6); and nitrogen trifluoride (NF_3) (GPC, 2014).
GHG intensity	The annual rate to which GHG emissions are released in the atmosphere, relative to a specific intensity.
Gross domestic product (GDP)	An economic measure of all goods and services produced in an economy.
In-boundary	Occurring within the established geographic boundary (GPC, 2014).
Reporting year	The year for which emissions are reported (GPC, 2014).
Scope 1	Emissions that physically occur within a community.
Scope 2	Emissions that occur from the use of electricity, steam, and/or heating/cooling supplied by grids which may or may not cross Community boundaries.
Scope 3	Emissions that occur outside a community but are driven by activities taking place within a community's boundaries.
Tonne of CO_2e	A tonne of greenhouse gases (GHGs) is the amount created when we consume: • 385 litres of gasoline (about 10 fill-ups) • Enough electricity for three homes for a year (38,000 kWh)
Transboundary GHG emissions	Emissions from sources that cross the geographic boundary (GPC, 2014).

1.0 INTRODUCTION

1.1 CLIMATE CHANGE AND GREENHOUSE GAS EMISSIONS

There is increasing evidence that global climate change resulting from emissions of carbon dioxide and other greenhouse gases (GHGs) is having an impact on the global climate system. The Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), states the following consensus of scientific opinion about climate change and its causes and effects (IPCC, 2014):

- Warming of the climate system is unequivocal, as is now evident from observations of increases in global average air and ocean temperatures, widespread melting of snow and ice and rising global average sea level.
- Anthropogenic GHG emissions have increased since the pre-industrial era, driven largely by economic and population growth, and are now higher than ever. Most of the observed increase in global average temperatures since the mid-20th century is very likely due to the observed increase in human-caused GHG concentrations.
- Continued emission of GHG will cause further warming and long-lasting changes in all components of the climate system, increasing the likelihood of severe, pervasive, and irreversible impacts for people and ecosystems.
- There is high agreement and much evidence that with current climate change mitigation policies and practices, global GHG emissions will increase over the next few decades.

1.2 COMMUNITIES AND GREENHOUSE GAS EMISSIONS

Communities are centers of communication, commerce, and culture. They are, however, also a significant and growing source of energy consumption and GHG emissions. On a global scale, communities are major players in GHG emissions. They are responsible for more than 70% of global energy-related carbon dioxide emissions and thus represent the single greatest opportunity for tackling climate change.

For a community to act on mitigating climate change and monitor its progress, it is crucial to have good quality GHG emissions data to build a GHG inventory. Such an inventory enables cities to understand the breakdown of their emissions and plan for effective climate action. The Global Protocol for Community-Scale Greenhouse Gas Emission Inventories (GPC Protocol) seeks to support exactly that, by giving cities the standards and tools that are needed to measure the emissions, build more effective emissions reduction strategies, set measurable and more ambitious emission reduction goals, and to track their progress more accurately and comprehensively.

Until recently there has been no internationally recognized way to measure community-level emissions. Inventory methods that community managers have used to date around the globe vary significantly. This inconsistency has made comparisons between cities and over the years difficult. The GPC Protocol offers an internationally accepted, credible emissions accounting and reporting practice that will help communities to develop comparable GHG inventories.

1.3 VARIANCE FROM COMMUNITY ENERGY AND EMISSIONS INVENTORIES (CEEI)

The CRD has historically relied on the Provincial 2007, 2010 and 2012 Community Energy and Emissions Inventories (CEEI) to baseline and track community GHG emissions. However, there have been some limitations to the CEEI in that it is an in-boundary inventory, the most recent version published is for 2012, and the CEEI Protocol does not fully meet the requirements of the GPC Protocol BASIC or BASIC+ reporting requirements which is the required reporting standard for local governments that have committed to the Global Covenant of Mayors—an agreement led by community networks to undertake a transparent and supportive approach to measure GHG emissions community-wide. A high-level summary of the differences between the CEEI and GPC Protocol inventories are presented in Table 1.

Table 1. Summary of GHG Inventory Scope Differences

Reporting Sector	CEEI	GPC BASIC	GPC BASIC+
Residential Buildings	✓	✓	✓
Commercial And Institutional Buildings And Facilities	✓	✓	✓
Manufacturing Industries And Construction	✓	✓	✓
Energy Industries		✓	✓
Energy Generation Supplied To The Grid		✓	✓
Agriculture, Forestry And Fishing Activities		✓	✓
Non-Specified Sources		✓	✓
Fugitive Emissions From Mining, Processing, Storage, And Transportation Of Coal		✓	✓
Fugitive Emissions From Oil And Natural Gas Systems		✓	✓
On-Road Transportation	✓	✓	✓
Railways		✓	✓
Waterborne Navigation		✓	✓
Aviation		✓	✓
Off-Road Transportation		✓	✓
Solid Waste	✓	✓	✓
Biological Waste	✓	✓	✓
Incinerated And Burned Waste		✓	✓
Wastewater		✓	✓
Emissions From Industrial Processes			✓

Reporting Sector	CEEI	GPC BASIC	GPC BASIC+
Emissions From Product Use			✓
Emissions From Livestock	✓		✓
Emissions From Land			✓
Emissions From Aggregate Sources And Non-CO_2 Emission Sources On Land	✓		✓

1.4 PURPOSE OF THIS REPORT

The purpose of this document is to describe the quantification methodologies used by the CRD to calculate its BASIC+ GHG emissions for the 2020 reporting year.

2.0 GLOBAL PROTOCOL FOR COMMUNITY (GPC) SCALE EMISSION INVENTORIES PROTOCOL

2.1 OVERVIEW

The GPC Protocol is the result of a collaborative effort between the GHG Protocol at the World Resources Institute (WRI), C40 Cities Climate Leadership Group (C40), and ICLEI—Local Governments for Sustainability (ICLEI). The GPC Protocol is recognized as one of the first set of standardized global rules for cities to measure and publicly report community-wide GHG emissions. It sets out requirements and provides guidance for calculating and reporting community-wide GHG emissions, consistent with the 2006 IPCC guidelines on how to estimate GHG emissions (IPCC, 2006). Specifically, the GPC Protocol seeks to:

- Help cities develop a comprehensive and robust GHG inventory to support climate action planning.
- Help cities establish a base year GHG emissions inventory, set GHG reduction targets, and track performance.
- Ensure consistent and transparent measurement and reporting of GHG emissions between cities, following internationally recognized GHG accounting and reporting principles.
- Enable community-wide GHG inventories to be aggregated at subnational and national levels.
- Demonstrate the important role that cities play in tackling climate change and facilitate insight through benchmarking—and aggregation—of comparable GHG data.

2.2 GPC PROTOCOL STRUCTURE

The GPC Protocol sets several assessment boundaries which identify the restrictions for gases, emission sources, geographic area, and time span covered by a GHG inventory:

- The GHG inventory is required to include all seven Kyoto Protocol GHGs occurring within the geographic boundary of a community. These include:
  - Carbon dioxide (CO_2)
  - Methane (CH_4)
  - Nitrous oxide (N_2O)
  - Hydrofluorocarbons (HFCs)
  - Perfluorocarbons (PFCs)
  - Sulfur hexafluoride (SF_6)
  - Nitrogen trifluoride (NF_3)
- The GHG emissions from community-wide activities must be organized and reporting under the following five Sectors, based on the selected reporting level:
  - Stationary Energy
  - Transportation
  - Waste
  - Industrial Processes and Product Use (IPPU)

– Agriculture, Forestry, and Other Land Use (AFOLU)

The GPC Protocol also requires that a community define an inventory boundary, identifying the geographic area, time span, gases, and emission sources.

Under the GPC Protocol, a community has the option of reporting GHG emissions under three different levels:

- **GPC BASIC—**This level covers emissions Scopes 1 and 2, from stationary energy and transportation, as well as emissions Scopes 1 and 3 from waste. The BASIC level aligns with the Community Energy and Emissions Inventories (CEEI) that have been released in the past for local governments by the Province of BC.
- **GPC BASIC+—**This level covers the same scopes as BASIC and includes more in-depth and data dependent methodologies. Specifically, it expands the reporting scope to include emissions from Industrial Process and Product Use (IPPU), Agriculture, Forestry, and Other Land-Use (AFOLU), and transboundary transportation. The sources covered in BASIC+ also align with sources required for national reporting in IPCC guidelines.
- **GPC BASIC+ Scope 3 (SC)—** This inventory extends beyond the BASIC+ GHG inventory to include Other Scope 3 (SC) emissions such as GHG emissions from goods and services production and transportation.

Activities taking place within a community can generate GHG emissions that occur inside a Community boundary as well as outside a Community boundary. To distinguish between these, the GPC Protocol groups emissions into three categories based on where they occur: Scope 1, Scope 2, or Scope 3 emissions. The GPC Protocol distinguishes between emissions that physically occur within a Community (Scope 1), from those that occur outside a Community but are driven by activities taking place within a Community's boundaries (Scope 3), from those that occur from the use of electricity, steam, and/or heating/cooling supplied by grids which may or may not cross community boundaries (Scope 2). Scope 1 emissions may also be termed "territorial" emissions, because they are produced solely within the territory defined by the geographic boundary (see Figure 1).

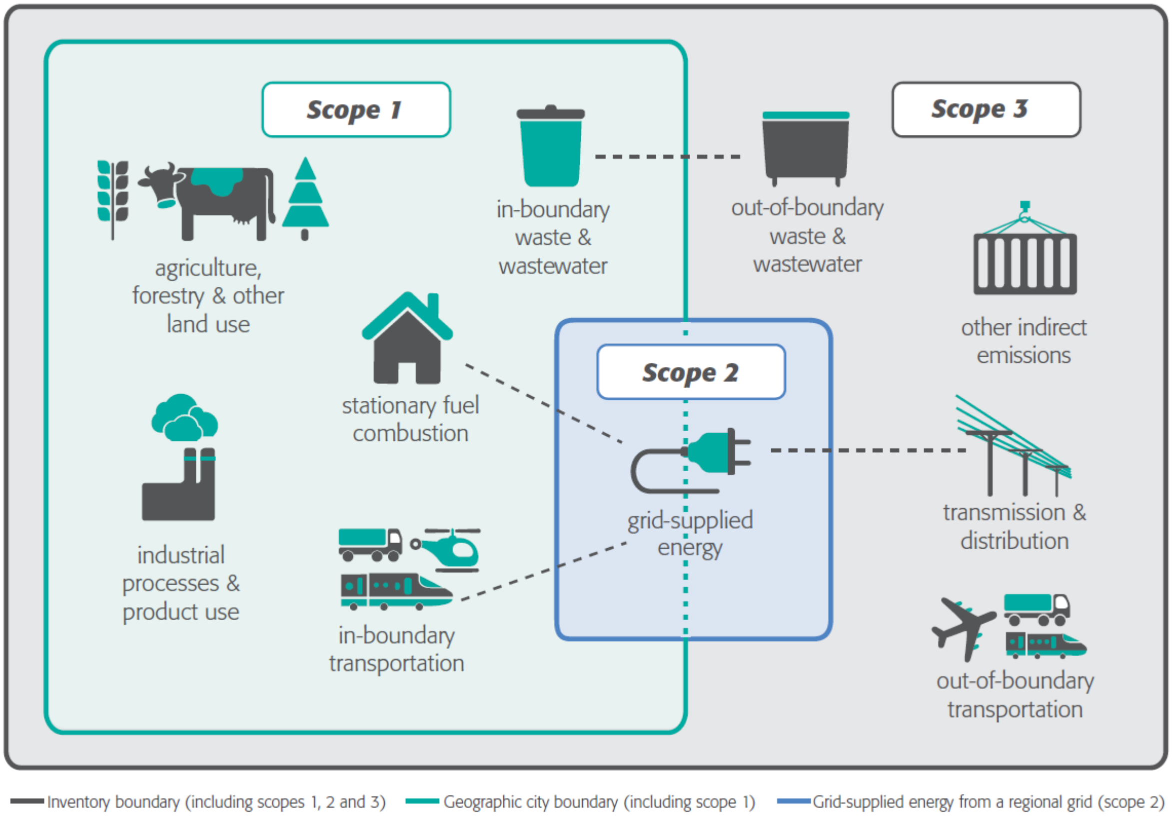

Figure 1 Sources and Boundaries of a Community's GHG Emissions (GPC 2014)

2.3 GHG EMISSION CATEGORIES

As noted previously, the GPC Protocol requires that different emission sources to be categorized into six main reporting Sectors. These high-level categories are described in more detail in Section 2.3.1 to Section 2.3.6. More information on how GHG emissions are captured within the GPC Protocol is available on the Greenhouse Gas Protocol website.

2.3.1 Stationary Energy

Stationery energy sources are typically one of the largest contributors to a community's GHG emissions. In general, these emissions come from fuel combustion and fugitive emissions. They include the emissions from energy to heat and cool residential, commercial, and industrial buildings, as well as the activities that occur within these residences and facilities, such as off-road transportation emissions from construction equipment. Emissions associated with distribution losses from grid-supplied electricity/steam/heating/cooling are also included, as are some fugitive emissions from sources such as coal piles, and natural gas distribution systems.

The Stationary Energy Sector includes the following Sub-Sectors:

- Residential buildings
- Commercial and institutional buildings and facilities
- Manufacturing industries and construction
- Energy industries
- Energy generation supplied to the grid*
- Agriculture, forestry, and fishing activities
- Non-specific sources
- Fugitive emissions from mining, processing, storage, and transportation of coal
- Fugitive emissions from oil and natural gas systems

*Emissions related with electricity generation activities occurring within a community's boundaries are to be reported; however, the GHG emissions from these sources are not included in the total GHG inventory to prevent double counting (GPC 2014).

Under the GPC Protocol, cities are to report off-road GHG emissions under the Off-road Transportation Sub-Sector if and only if the GHG emissions are occurring at transportation facilities (e.g., airports, harbors, bus terminals, train stations, etc.). Other off-road transportation GHG emissions that occur on industrial premises, construction sites, agriculture farms, forests, aquaculture farms, and military premises, etc., are to be reported under the most relevant Stationary Energy Sub-Sector (GPC, 2014). For example, GHG emissions from commercial building off-road construction equipment would be included in the Commercial And Institutional Buildings And Facilities Sub-Sector, whereas GHG emissions from residential lawn mowers would be reported under the Residential Buildings Sub-Sector.

2.3.2 Transportation

The GHGs released to the atmosphere to be reported in the Transportation Sector are those from combustion of fuels in journeys by on-road, railway, waterborne navigation, aviation, and off-road. GHG emissions are produced directly by the combustion of fuel, and indirectly using grid-supplied electricity. Unlike the Stationary Energy Sector, transit is mobile and can pose challenges in both accurately calculating GHG emissions and allocating them to a specific Sub-Sector. This is particularly true when it comes to transboundary transportation, which includes GHG emissions from trips that either start or finish within a community's boundaries (e.g., departing flight emissions from an airport outside a Community boundaries) (GPC, 2014). Transboundary GHG emissions are only required for GPC BASIC+ GHG reporting.

The Transportation Sector includes the following Sub-Sectors:

- On-road
- Railways

- Waterborne
- Aviation
- Off-road

As noted previously, cities are to report off-road GHG emissions under the Off-road Transportation Sub-Sector if and only if the GHG emissions are occurring at transportation facilities (e.g., airports, harbors, bus terminals, train stations, etc.). For example, off-road railway maintenance support equipment GHG emissions are reported under the Off-Road Transportation Sub-Sector.

2.3.3 Waste

Cities produce GHG emissions that arise from activities related to the disposal and management of solid waste. Waste does not directly consume energy, but releases GHG emissions because of decomposition, burning, incineration, and other management methods.

The Waste Sector includes the following Sub-Sectors:

- Solid waste disposal
- Incineration and open burning
- Biological treatment of waste
- Wastewater treatment and discharge

Under the GPC Protocol, the Waste Sector includes all GHG emissions that result from the treatment or decomposition of waste regardless of the source of the waste (e.g., another community's waste in a Community's landfill). However, the GHG emissions that are associated with waste from outside a Community's boundary that is treated or decomposes within a Community boundary are deemed to be "reporting only" emissions and do not contribute to the GHG inventory (GPC 2014).

Any GHG emissions that result from the combustion of waste or waste related gases to generate energy, such as a methane capture and energy generation system at a landfill, are reported under Stationary Energy Generation Supplied To The Grid Sub-Sector (GPC, 2014). Any waste related GHG emissions that are combusted but not related to energy generation are reported in the appropriate Waste Sub-Sector. Lastly, any waste GHG emissions that are released to the atmosphere are also captured in the appropriate Waste Sub-Sector.

2.3.4 Industrial Processes and Product Use (IPPU)

Emissions from this Sector are only required for BASIC+ GHG reporting under the GPC Protocol. This Sector encompasses GHG emissions produced from industrial processes that chemically or physically transform materials and using products by industry and end-consumers (e.g., refrigerants, foams, aerosol cans) (GPC, 2014).

The IPPU Sector includes the following Sub-Sectors:

- Industrial processes
- Product use

Any GHG emissions associated with energy use for industrial processes are not reported in the IPPU Sector; rather, they are reported under the appropriate Stationary Energy Sub-Sector.

2.3.5 Agriculture, Forestry, and Other Land Use (AFOLU)

Emissions from the AFOLU Sector are only required for BASIC+ GHG reporting. AFOLU GHG emissions are those that are captured or released because of land-management activities. These activities can range from the preservation of forested lands to the development of crop land. Specifically, this Sector includes GHG emissions from land-use change, manure management, livestock, and the direct and indirect release of nitrous oxides (N_2O) from soil management, rice cultivation, biomass burning, urea application, fertilizer, and manure application (GPC, 2014).

The AFOLU Sector is organized into the following Sub-Sectors:

- Livestock
- Land
- Aggregate sources and non-CO_2 emission sources on land

2.3.6 Other Scope 3 Emissions

Cities, by their size and connectivity, inevitably give rise to GHG emissions beyond their boundaries. The GPC Protocol already includes the following Scope 3 emissions in other Sectors:

- On-road, waterborne, and aviation transboundary transportation
- Transmission and distribution losses associated with grid-supplied energy
- Solid waste disposal
- Biological treatment of solid waste
- Wastewater treatment and discharge

Cities may voluntarily report on other Scope 3 emissions as they are estimated. In the case of the CRD, no other Scope 3 GHG emissions, other than those listed above, have been estimated.

2.4 ACCOUNTING AND REPORTING PRINCIPLES

All GHG inventories following the GPC Protocol are required to meet GHG accounting principles. Specifically, these inventories should be relevant, consistent from year to year, accurate and transparent about methodologies, assumptions, and data sources. The transparency of inventories is fundamental to the success of replication and assessment of the inventory by interested parties.

The GHG inventories must also properly account for key energy and GHG emission sinks, sources, and reservoirs (SSR) that are occurring within municipal boundaries. The SSRs are a convenient way to identify and categorize all the GHG emissions to determine if they should be included or excluded from a GHG inventory. A "Source" is something that releases GHG emissions to the atmosphere, such as a diesel generator. A "Sink" is a process or item that removes GHG from the atmosphere, such as photosynthesis and tree growth. Finally, a "Reservoir" is a process or item with the capability to store or accumulate a GHG removed from the atmosphere by a GHG sink, such as a wetland or a peat bog. By assessing and reporting on the applicable SSRs, users of the GHG inventory can have confidence that the inventory is complete and representative of the types and quantities of the GHGs being released within community limits.

2.5 BASE AND REPORTING YEAR RECALCULATIONS

As communities grow and expand, significant changes to the GHG emissions profile can alter materially thus making it difficult to meaningfully assess GHG emission trends and changes over time. The GPC Protocol has requirements on how to treat changes in a community's GHG profile—this is presented in Table 2.

Table 2 GPC Protocol Recalculation Thresholds

Threshold	Example Change	Recalculation Needed	No Recalculation Needed
Changes in the assessment boundary	A local government is annexed in or removed from the administrative boundary	✓	
	Change in protocol reporting method (e.g., from BASIC to BASIC+, addition of GHGs reported, etc.)	✓	
	Shut down of a power plant		✓
	Building a new cement factory		✓
Changes in calculation methodology or improvements in data accuracy	Change in calculation methodology for landfilled municipal solid waste (MSW) that results in a material change in GHG emissions to that sector (i.e., +/-10%).	✓	
	Adoption of more accurate local emission factors, instead of a national average emission factors that results in a material change in GHG emissions (i.e., +/-10%).	✓	
	Change in electricity emission factor due to energy efficiency improvement and growth of renewable energy utilization.		✓
Discovery of significant errors	Discovery of mistake in unit conversion in formula used.	✓	

2.6 DATA QUALITY

Data collection and the assessment of its quality is an integral component of compiling any GHG inventory. Like the IPCC, the GPC Protocol requires users to establish first whether a source exists, and then assess the data availability and quality. To support GHG reporting, the following notation keys are used.

- If the GHG sink, source or reservoir does not exist, a "NO" is used to indicate it is "not occurring".
- If the GHG sink, source or reservoir does occur, and data is available, then the emissions are estimated. However, if the data is also included in another emissions source category or cannot be disaggregated, the notation key "IE" would be used to indicate "included elsewhere" to avoid double counting.
- When GHG emissions are occurring in the CRD, but data is not available, then the notation key "NE" would be used to indicate "not estimated".

For GHG data that does exist, in accordance with the GPC Protocol, an assessment of quality is also made on emission factors and GHG estimation methodologies deployed. The GPC Protocol data quality assessment notation keys are summarized in Table 3.

Table 3 GPC Protocol Data Quality Assessment Notation Keys

Data Quality	Activity Data	Emission Factor
High (H)	Detailed activity data	Site-specific emission factors
Medium (M)	Modeled activity data using robust assumptions	More general emission factors
Low (L)	Highly modeled or uncertain activity data	Default emission factors

3.0 GHG ASSESSMENT BOUNDARIES

This section sets out the reporting boundaries of the CRD's GHG inventory.

3.1 SPATIAL BOUNDARIES

This GHG inventory is defined geographically by the CRD's jurisdictional boundaries. As shown in Figure 2, the CRD consists of 13 municipalities and 3 electoral areas. For the purposes of this report, only the CRD GHG emissions are presented. A breakdown of GHG emissions by each CRD municipality and electoral area has been presented in a separate report.

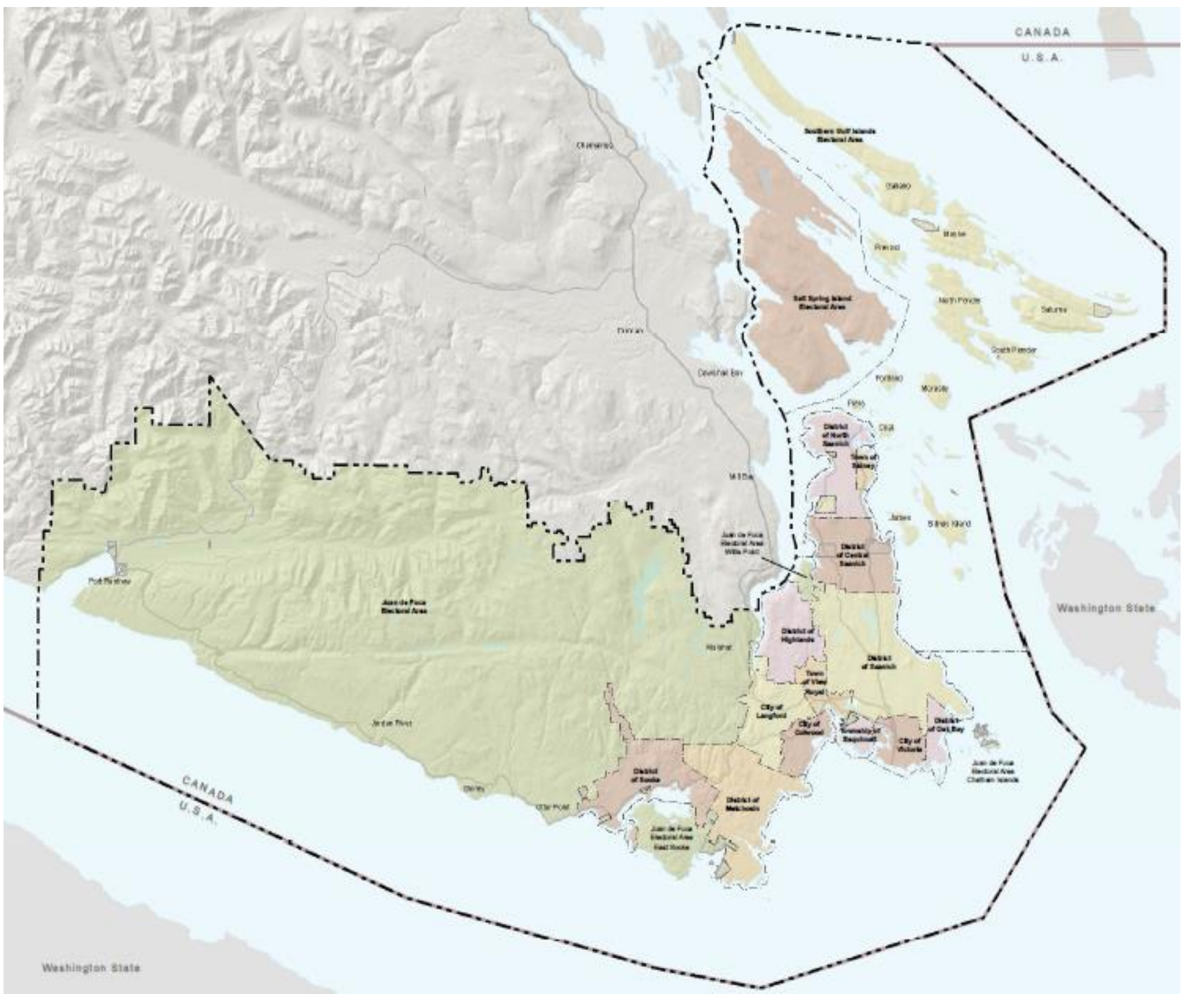

Figure 2 GHG Boundary

Table 4 Inventory Information

Inventory Boundary	Community / District Information
Name of Community / District	Capital Regional District
Municipality / Electoral Area	• District of Central Saanich • City of Colwood • Township of Esquimalt • District of Highlands • Juan de Fuca Electoral Area • City of Langford • District of Metchosin • District of North Saanich • District of Oak Bay • District of Saanich • Salt Spring Island Electoral Area • Town of Sidney • District of Sooke • City of Victoria • Town of View Royal • Southern Gulf Islands Electoral Area
Country	Canada
Inventory Year	2020
Geographic Boundary	See Figure 2
Land Area (km^2)	2,310.18
Resident population	419,697
GDP (US$)	Unknown at time of reporting
Composition of Economy	Government
Climate	Temperate, warm summer

3.2 TEMPORAL BOUNDARIES

3.2.1 2007 Base Year

Federal and provincial initiatives and legislation have been implemented to support local governments in acting to advance energy efficiency, promote energy conservation, and reduce GHG emissions. The CRD and its local governments have already been working to address sustainability and climate change through several initiatives over the past decade. The CRD's Regional Growth Strategy set a regional GHG reduction target) of 61% by 2038 (below 2007 levels).

To maintain consistency with the current reporting year, and as required by the GPC Protocol, the CRD has updated its 2007 GHG base year GHG emissions profile to be consistent with the GPC Protocol BASIC+ reporting level. Between the current reporting year and the 2007 base year, there were no boundary changes (e.g., annexes) and thus no additional modifications were made. All methods and assumptions, adjusted for the 2007 reporting year, are the same.

Due to limitations in how to quantify GHG emissions resulting from land use change (e.g., residential development), these GHG emissions have been excluded from the CRD's 2007 and 2020 GHG emissions inventories, but have been disclosed, until a more robust measurement methodology can be developed. The GHG emissions inventory does, however, include GHG emissions sequestered as a result of biological ecosystems (e.g., forests).

Table 5 summaries the original 2007 and the updated 2007 base year GHG emissions reported as tonnes of carbon dioxide equivalent (tCO_2e).

Table 5 Original And Updated BASIC+ Base Year

Aspect	Quantification Protocol	2007 GHG Base Year (tCO_2e)
Original Base Year	CEEI Protocol	1,563,000
Updated Base Year	GPC Protocol BASIC+	1,976,100

3.2.2 GHG Reduction Target

Recognizing the role that the CRD plays in achieving a significant and immediate reduction in global GHG emissions, the CRD has set a regional GHG reduction target of 61% (from 2007 levels) by 2038. With the CRD's 2007 base year GHG emissions being 1,976,100 tCO_2e, a 39% reduction would require a reduction of approximately 770,679 tCO_2e. On a per capita basis, this amounts to reducing emissions from approximately 4.3 tCO_2e per person in 2020 to 2.4 tCO_2e per person by 2038.

In February 2019, the CRD declared a climate emergency and committed to regional carbon neutrality.

3.2.3 2020 GHG Boundary

This inventory covers all GHG emissions for the 2020 reporting year. Where 2020 data was not available, the most recent year's data have been used, and the timescale noted accordingly. These are as follows:

- **Global Warming Potentials (GWP)**. The BC government is currently applying GWPs from the fourth IPCC report despite the fact that there are updated GWPs in available in the fifth IPCC report. On this basis, the CRD is applying GWPs from the fourth IPCC report.
- **Stationary Energy: Emission Factors.** The BC Government updated 2010-2020 electricity emission factors to include emissions from imported electricity resulting in a 5-10% increase in GHG emissions intensities. Since there was no update to the 2007, the BC Government has suggested utilizing the 2010 emission factor for 2007.

- **Stationary Energy: Electricity Data.** In 2019, the Province of BC received updated electricity data for 2007-2018 as a systematic error was uncovered across all years of BC Hydro data. The 2007 inventory was updated with the corrected information.
- **Stationary Energy: Residential, Commercial and Institutional Buildings**. Propane, and wood GHG emissions were estimated using linear regression methods. The data used in the estimates included historical propane and wood energy data published in the 2007, 2010 and 2012 CEEIs, and heating degree days (HDD) published by Environment and Climate Change Canada. This approach was also applied to the estimate of heating oil for all local governments, except the City of Victoria and District of Saanich. For the District of Saanich and the City of Victoria, heating oil GHG emissions were estimated based on the number of known tanks, average heated floor areas and fuel volume intensity.
- **Stationary Energy: Fugitives**. Fortis BC provided total fugitive emissions for the 2020 reporting year at the CRD level. Since no historical numbers were provided, the 2020 value was applied to the 2007 base year as well.
- **Transportation: On-Road**. The on-road transportation emissions are based on the total estimated fuel sales in the CRD, and the number of registered vehicles. Insurance Corporation of BC (ICBC) compiles data on an April 1 to March 31 basis, and thus the current on-road GHG emission estimate is based on the number of registrations from April 1, 2020 – March 31, 2021.
- **Transportation: Aviation.** 2020 aviation GHG emissions were estimated using 2015 aircraft flight profiles (the last available data), and the total number of aircraft movements reported in 2020.
- **Transportation: Waterborne Recreational Watercraft.** GHG emissions from recreational watercraft and US/Canada ferries were estimated based on a publicly available year 2000 study for the Victoria, Vancouver, and Washington harbors.
- **Transportation: Ferries.** BC Ferries did not disclose its total reported fuel use for 2020 but did publish that fuel consumption volumes fell by approximately 40% as compared to the 2019 reporting year. As such, the 2019 fuel volumes and the 40% factor were applied to estimate 2020 fuel volumes.
- **Transportation: Cruise Ships.** The Greater Victoria Harbour Authority (GVHA) reported on cruise ship emissions for the 2010 and 2018 reporting years but did not provide an estimate for 2007. As a result, the 2010 GHG emissions estimate and number of cruise ship visits to Ogden Point was used to create a proxy to estimate 2007 cruise ship emissions. The GVHA reported 163 visits in 2007. As a result of COVID-19 restrictions, there were no cruise ships in 2020.
- **Waste: Solid Waste.** To quantify GHG emissions from the Hartland Landfill, the CRD utilized the waste-in-place (WIP) method which is accepted under the GPC Protocol. The WIP assigns landfill emissions based on total waste deposited during that year. It counts GHGs emitted that year, regardless of when the waste was disposed. Except for the City of Victoria, who claims 31% of the CRD's landfill GHG emission, the remaining landfill GHG emissions were allocated to each local government on a per capita basis. Using this allocation method, the CRD members may over, or underestimate associated solid waste GHG emissions as the current year landfill GHG emissions are based upon cumulative waste over time, and each member may have contributed more waste in past years than the current year (and vice versa).
- **AFOLU: Aggregate Sources And Non-CO_2 Emission Sources On Land.** These emissions are based on the 2021 NIR as prepared by ECCC and the total area of farmland BC in 2016 as reported

by Statistics Canada. These GHG emissions were assigned to each local government on a per hectare (ha) of cropland basis.

- **AFOLU: Land-Use.** The land cover change analysis requires a consistent land-use category attribution and spatial data. For parts of the CRD, spatial data was available for the 2007, 2011 and 2019 reporting years. Differences between these data sets in terms of resolution and their timing of collection increase the uncertainty as to the accuracy of the land-use classifications. For example, the 2007 and 2011 land use data was collected at different times of the year and may not accurately reflect tree cover. Furthermore, no land use spatial data was collected the Juan de Fuca, Salt Spring Island and Gulf Islands and thus Annual Crop Inventory (ACI) settlement data collected by Agriculture Canada was used to inform the analysis. The challenge in utilizing this data is that it is provided in a 30m resolution. Furthermore, since annual data is not available, the change between land cover data years (2007-2011, 2011-2019) for all areas was averaged and may not represent actual changes in each year. Since no data was available for 2020, the 2019 estimates were applied.
  Due to limitations in how to quantify GHG emissions resulting from land use change (e.g., residential development), these GHG emissions have been excluded from the CRD's GHG emissions inventory, but have been disclosed, until a more robust measurement methodology can be developed.

3.3 GHG EMISSION SOURCES AND SCOPES

The following table summarizes the CRD's GHG emissions by source and GHG emission scope.

Table 6 Summary of Emissions Scope and GPC Protocol Reporting Sector

GHG Emissions Scope	GPC Protocol Reporting Sector
Scope 1	The GHG emissions occurring from sources located within the CRD's limits: • Stationary fuel combustion: – Residential buildings – Agriculture, forestry, and fishing activities – Commercial and institutional buildings, and facilities – Energy industries – Fugitive emissions from oil and natural gas systems • Transportation: – On-road: In Boundary – Waterborne Navigation – Off-road • Waste: – Solid waste disposal – Biological treatment of solid waste – Wastewater treatment and discharge • Industrial processes and product use (IPPU): – Product use • Agriculture, Forestry, and Other Land Use (AFOLU): – Land-use: emissions sequestered – Livestock

GHG Emissions Scope	GPC Protocol Reporting Sector
	– Aggregate sources and non-CO_2 emission sources on land
Scope 2	The GHG emissions occurring from using grid-supplied electricity, heating and/or cooling within the CRD's boundary: • Stationary fuel combustion: – Residential buildings – Commercial and institutional buildings and facilities • Transportation: – On-road
Scope 3	Other GHG emissions occurring outside of the CRD's limits as a result of the CRD's activities: • Stationary Energy: – Transmission, Distribution, and Line Losses • Transportation: – Aviation – On-Road: Transboundary – Waterborne Navigation

3.4 GHG REPORTING

Where relevant, the GPC Protocol recommends using methodologies that align with the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. The GHG inventory is required to include all seven Kyoto Protocol GHGs occurring within the geographic boundary of a community. These include:

- Carbon Dioxide (CO_2)
- Methane (CH_4)
- Nitrous oxide (N_2O)
- Hydrofluorocarbons (HFCs)
- Perfluorocarbons (PFCs)
- Sulfur hexafluoride (SF_6)
- Nitrogen trifluoride (NF_3)

Each GHG listed above has a different global warming potential (GWP) due to its ability to absorb and re-emit infrared radiation. This chemical property is recognized by the GWP set out by the IPCC Fourth Assessment Report. A larger GWP value means the substance has a greater affinity to absorb and re-emit infrared radiation. The GWP of these GHGs are CO_2 = 1.0, CH_4 = 25, N_2O = 298 (IPCC, 2006).

Total GHG emissions are normally reported as CO_2e, whereby emissions of each of the GHGs are multiplied by their GWP and are reported as tonnes of CO_2e.

The GHG inventory results following the GPC Protocol reporting table format is presented in Section 5.0. The GPC Protocol reporting format is presented in Table 7 below which also indicates the reporting level (BASIC / BASIC+) for each source.

Table 7 GPC Protocol Summary Table

GPC Protocol Reference Number	Reporting Level	Emissions Scope	GHG Emissions Source
I	**Stationary Energy Sources**		
I.1	**Residential Buildings**		
I.1.1	BASIC	1	Emissions from in-boundary fuel combustion
I.1.2	BASIC	2	Emissions from consumption of grid-supplied energy
I.1.3	BASIC+	3	Transmission and distribution losses from grid-supplied energy
I.2	**Commercial and Institutional Buildings/Facilities**		
I.2.1	BASIC	1	Emissions from in-boundary fuel combustion
I.2.2	BASIC	2	Emissions from consumption of grid-supplied energy
I.2.3	BASIC+	3	Transmission and distribution losses from grid-supplied energy
I.3	**Manufacturing Industry and Construction**		
I.3.1	BASIC	1	Emissions from in-boundary fuel combustion
I.3.2	BASIC	2	Emissions from consumption of grid-supplied energy
I.3.3	BASIC+	3	Transmission and distribution losses from grid-supplied energy
I.4	**Energy Industries**		
I.4.1	BASIC	1	Emissions from in-boundary production of energy used in auxiliary operations
I.4.3	BASIC+	3	Transmission and distribution losses from grid-supplied energy
I.5	**Agriculture, Forestry, and Fishing Activities**		
I.5.1	BASIC	1	Emissions from in-boundary fuel combustion
I.5.2	BASIC	2	Emissions from consumption of grid-supplied energy
I.5.3	BASIC+	3	Transmission and distribution losses from grid-supplied energy
I.7	**Fugitive Emissions from Mining, Processing, Storage, And Transportation of Coal**		
I.7.1	BASIC	1	In-boundary fugitive emissions
I.8	**Fugitive Emissions from Oil and Natural Gas Systems**		
I.8.1	BASIC	1	In-boundary fugitive emissions
II	**Transportation**		
II.1	**On-road Transportation**		
II.1.1	BASIC	1	Emissions from in-boundary transport
II.1.2	BASIC	2	Emissions from consumption of grid-supplied energy
II.1.3	BASIC+	3	Emissions from transboundary journeys

Table 7 GPC Protocol Summary Table

GPC Protocol Reference Number	Reporting Level	Emissions Scope	GHG Emissions Source
II.2	**Railways**		
II.2.1	BASIC	1	Emissions from in-boundary transport
II.2.2	BASIC	2	Emissions from consumption of grid-supplied energy
II.2.3	BASIC+	3	Emissions from transboundary journeys
II.3	**Waterborne Navigation**		
II.3.1	BASIC	1	Emissions from in-boundary transport
II.3.2	BASIC	2	Emissions from consumption of grid-supplied energy
II.3.3	BASIC	3	Emissions from transboundary journeys
II.4	**Aviation**		
II.4.1	BASIC	1	Emissions from in-boundary transport
II.4.2	BASIC	2	Emissions from consumption of grid-supplied energy
II.4.3	BASIC+	3	Emissions from transboundary journeys
II.5	**Off-road**		
II.5.1	BASIC	1	Emissions from in-boundary transport
II.5.2	BASIC	2	Emissions from consumption of grid-supplied energy
III	**Waste**		
III.1	**Solid Waste Disposal**		
III.1.1	BASIC	1	Emissions from waste generated and treated within the Community
III.1.2	BASIC	3	Emissions from waste generated within but treated outside of the Community
III.2	**Biological Treatment of Waste**		
III.2.1	BASIC	1	Emissions from waste generated and treated within the Community
III.2.2	BASIC	3	Emissions from waste generated within but treated outside of the Community
III.3	**Incineration and Open Burning**		
III.3.1	BASIC	1	Emissions from waste generated and treated within the Community
III.3.2	BASIC	3	Emissions from waste generated within but treated outside of the Community
III.4	**Wastewater Treatment and Discharge**		
III.4.1	BASIC	1	Emissions from wastewater generated and treated within the Community

Table 7 GPC Protocol Summary Table

GPC Protocol Reference Number	Reporting Level	Emissions Scope	GHG Emissions Source
III.4.2	BASIC	3	Emissions from wastewater generated within but treated outside of the Community
IV	**Industrial Processes and Product Use (IPPU)**		
IV.1	BASIC+	1	In-boundary emissions from industrial processes
IV.2	BASIC+	1	In-boundary emissions from product use
V	**Agriculture, Forestry, and Other Land Use (AFOLU)**		
V.1	BASIC+	1	In-boundary emissions from livestock
V.1	BASIC+	1	In-boundary emissions from land
V.1	BASIC+	1	In-boundary emissions from other agriculture
VI	**Other Scope 3 Emissions**		
VI.1	BASIC / BASIC+	3	Other indirect emissions

4.0 GHG METHODOLOGIES BY SOURCE CATEGORY

The following sections describe the reporting source category, assumptions, activity data applied, and quantification methodology. The results of the analysis are presented in Section 5.0.

4.1 STATIONARY ENERGY

4.1.1 Overview

Stationery energy sources are one of the largest contributors to the CRD's GHG emissions. For the District, the Stationary Energy Sector encompasses the following GHG emissions scopes and Sub-Sectors:

- Scope 1 Emissions:
  - Residential buildings
  - Agriculture, forestry, and fishing activities
  - Commercial and institutional buildings, and facilities
  - Energy industries
  - Fugitive emissions from oil and natural gas systems
- Scope 2 Emissions:
  - Emissions from the consumption of grid-supplied electricity, steam, heating, and cooling.
- Scope 3 Emissions:
  - Transmission and distribution losses of electricity, steam, heating, and cooling.

There are GHG emissions from construction of buildings and infrastructure as the CRD region grows and changes. However, these GHG emissions have not been quantified due to a lack of available data. Environment and Climate Change Canada does estimate BC GHG emissions for manufacturing industries, mining and construction, but these GHG emission sources are not disaggregated and cannot reasonably be applied to the CRD (there is no mining and limited manufacturing activities). As a result, the notation "Not Estimated (NE)" is reported.

4.1.2 Scope 2: Market Based Method

As per the GPC Protocol, cities can report on Scope 2 GHG emissions using either the market-based, or the location-based method. A market-based method utilizes utility-specific grid emission intensity factor, whereas a location-based method uses a regional or Provincial average grid emission intensity factor. At present, the fuel mix and GHG emissions data relative to the CRD's energy consumption is not available. As such, the CRD is defaulting to the BC Provincial electricity grid consumption intensity factor of 0.04010 tCO_2e/MWh reported by the BC Government.[1]

[1] https://www2.gov.bc.ca/gov/content/environment/climate-change/industry/reporting/quantify/electricity

4.1.3 Activity Data

BC Hydro and Fortis BC provided the Province of BC electricity and natural gas consumption data in MWh and GJ, respectively. Based on the utility provider descriptions of the data, each is categorized as follows:

- Residential Buildings based on the BC Hydro and Fortis BC descriptor: “Residential”
- Commercial and Institutional Buildings/Facilities based on BC Hydro and Fortis BC descriptors: “Commercial”, and “CSMI”

The Province developed 2007, 2010 and 2012 residential fuel oil, propane and wood GHG energy use estimates from the number and type of dwellings and the average dwelling consumption by authority and region from the BC Hydro Conservation Potential Review. This data was used to estimate the reporting year GHG emissions for all CRD members except for the District of Saanich and the City of Victoria who provided fuel oil estimates for residential and commercial buildings.

Fortis BC provided the fugitive emission estimate.

The CRD provided landfill gas energy generation data from the Hartland landfill.

Applicable, off-road GHG emissions included in the Stationary Energy Sector are based on the 2021 NIR as prepared by Environment and Climate Change Canada. These emissions are pro-rated to the CRD on a per capita basis.

4.1.4 Assumptions and Disclosures

The following assumptions were made in the calculation of the 2020 GHG emissions:

- The Province of BC received updated electricity data for 2007-2018 as a systematic error was uncovered across all years of BC Hydro data. The 2007 base year inventory was updated with the corrected information.
- The BC Government updated 2010-2020 electricity emission factors to include emissions from imported electricity resulting in a 5-10% increase in GHG emissions intensities. Since there was no update to the 2007 value, the BC Government has suggested utilizing the 2010 emission factor for 2007.
- BC Hydro estimates that the combined energy losses- transmission and distribution- to be approximately 6.28%. This value was used to calculate the Scope 3 emissions for each Stationary Energy Sub-Sector. It is assumed that this is accurate.
- Fortis BC provided total fugitive emissions for the 2020 reporting year at the CRD level. Since no historical numbers were provided, the 2020 value was applied to the 2007 base year as well.
- Propane and wood GHG emissions were estimated using linear regression methods. The data used in the estimate included historical propane and wood energy data published in the 2007, 2010 and 2012 CEEIs, and heating degree days (HDD) published by Environment and Climate Change Canada.

- Fuel oil consumption values for the District of Saanich and the City of Victoria were derived by each local government and provided to the CRD. For the remaining local governments, fuel oil values were estimated using linear regression methods. The data used in the estimate included historical fuel oil data published in the 2007, 2010 and 2012 CEEIs, and heating degree days (HDD) published by Environment and Climate Change Canada.

4.1.5 Calculation Methodology

The Province of BC developed residential fuel oil, propane and wood GHG energy use estimates for the 2007, 2010 and 2012 reporting years, using the number and type of dwellings and the average dwelling consumption by authority and region contained in the BC Hydro Conservation Potential Review. Actual electricity and natural gas consumption values were subtracted from the total energy use, with the remainder assumed to be heating oil, propane, or wood. To estimate the 2020 propane, fuel oil and wood energy use, historical 2007, 2010 and 2012 values and the number of heating degree days (HDD) were linearly regressed to estimate future propane and wood energy use using reporting year HDD values. these values were prorated to each local government based on the 2012 consumption estimates. This resulted in the development of the following equations:

- Propane (L) = 163,133 + 87.38 * HDD
- Wood (GJ) = 557,864 + 191.39 * HDD
- Fuel Oil (GJ) = 1,728,690 + 127.49 * HDD

To calculate GHG emissions from electricity, natural gas, heating oil, propane, and wood, the total net annual energy values (where applicable, less transmission, distribution, and line losses of 6.28%) were multiplied by applicable emissions factors. These values were then multiplied by the pollutant's GWP to give total CO_2e emissions in tonnes.

These quantification methods are captured as follows:

$$Energy_{\text{Stationary Energy – Electricity}} = Electricity * (1 – Line\ Loss\ (\%))$$

$$Energy_{\text{Stationary Energy – Transmission, Distribution, and line Losses}} = Electricity * Line\ Loss\ (\%)$$

$$Emissions_{\text{Stationary Energy – Electricity}} = Fuel\ (MWh) * EF_{tCO2e}$$

$$Emissions_{\text{Stationary Energy – Natural Gas}} = (Fuel\ (GJ) * EF_{CO2}) + (Fuel\ (GJ) * EF_{CH4} * GWP_{CH4}) + (Fuel\ (GJ) * EF_{N2O} * GWP_{N2O})$$

$$Emissions_{\text{Stationary Energy – Propane}} = (Fuel\ (GJ) * EF_{CO2}) + (Fuel\ (GJ) * EF_{CH4} * GWP_{CH4}) + (Fuel\ (GJ) * EF_{N2O} * GWP_{N2O})$$

$$Emissions_{\text{Stationary Energy – Wood}} = (Fuel\ (GJ) * EF_{CO2}) + (Fuel\ (GJ) * EF_{CH4} * GWP_{CH4}) + (Fuel\ (GJ) * EF_{N2O} * GWP_{N2O})$$

$$Emissions_{\text{Stationary Energy – Heating Oil}} = (Fuel\ (GJ) * EF_{CO2}) + (Fuel\ (GJ) * EF_{CH4} * GWP_{CH4}) + (Fuel\ (GJ) * EF_{N2O} * GWP_{N2O})$$

The emission factors used in the 2020 reporting year are from the 2021 NIR. These are summarized in Table 8.

Table 8 Stationary Energy GHG Emission Factors

Emission Factor	Units	CO_2	CH_4	N_2O	tCO_2e
Electricity (BC Hydro)	tCO_2e / MWh				0.0401000
Natural Gas	tonne CO_2e / m^3	0.0019260	0.0000000	0.0000000	0.0019374
Propane	tonne CO_2e / L	0.0015150	0.0000000	0.0000001	0.0015478
Heating Oil	tonne CO_2e / GJ	0.0681200	0.0000007	0.0000008	0.0683759
Wood	tonne CO2e / kg	-	0.0000150	0.0000002	0.0004227

4.2 TRANSPORTATION

4.2.1 Overview

Transportation covers all GHG emissions from combustion of fuels in journeys by on-road, railways, waterborne navigation, aviation, and off-road. GHG emissions are produced directly by the combustion of fuel, and indirectly using grid-supplied electricity. For the CRD, the Transportation Sector encompasses the following GHG emissions scopes and Sub-Sectors:

- Scope 1 Emissions:
  - On-road: In Boundary
  - Waterborne
  - Aviation
  - Off-road
- Scope 2 Emissions:
  - Emissions from the consumption of grid-supplied electricity.
- Scope 3 Emissions:
  - On-road: Transboundary
  - Waterborne
  - Aviation
  - Off-road

4.2.2 Activity Data

The Province of BC provided 2007, 2010 and 2020 ICBC vehicle registration data.

BC Transit provided total diesel and gasoline fuel use. This data was used to estimate GHG emissions from busses serving the CRD.

The 2017 CRD Origin Destination Travel Survey was used to estimate on-road in-boundary and transboundary split for registered vehicles and busses. The CRD Origin Destination Travel Survey is based on travel patterns observed in the Capital Regional District (CRD) level.

Aviation GHG emissions from the Victoria International Airport were estimated using 2015 aircraft flight profiles, and the total number of aircraft movements reported in 2020. These data sets were provided by the Victoria International Airport.

Victoria harbour aviation GHG emissions were estimated using Victoria harbor aircraft movement statistics, estimated taxi times, and estimated fuel use for the DHC-6 Twin Otter type of plane. This data was taken from Statistics Canada.

Marine watercraft GHG emissions were estimated using published BC Ferries fuel statistics. GHG emissions from the Coho Ferry, the Victoria Clipper Ferry, personal and commercial watercraft, were estimated based on a Study entitled “Marine Vessel Air Emissions in BC and Washington State Outside of the GVRD and FVRD for the Year 2000”. The Transport Canada Vessel Registration System provided the total number of registered waterborne vehicles for the reporting year.

Other off-road transportation emissions are based on the 2021 NIR as prepared by Environment and Climate Change Canada.

4.2.3 Assumptions and Disclosures

The following assumptions were made in the calculation of the Transportation Sector GHG emissions:

- The on-road transportation emissions are based on the total estimated fuel sales in the CRD, and the number of registered vehicles. Insurance Corporation of BC (ICBC) compiles data on an April 1 to March 31 basis, and thus the current on-road GHG emission estimate is based on the number of registrations from April 1, 2020 – March 31, 2021.
- Vehicle fuel consumption rates and Vehicle Kilometer Travelled (VKT) were taken from the activity data summary for British Columbia on-road transportation from the 2021 National Inventory Report (1990-2019) as prepared by Environment and Climate Change Canada. Based on the clear diesel and clear gasoline consumption values reported by the Province of BC for the Victoria region, the VKT and fuel efficiency values are reasonable and result in a similar estimate of fuel consumption for the Region.
- Gasoline and diesel GHG emissions from BC Transit busses are pro-rated to the CRD based on the proportion of population in each municipality within the CRD. A more accurate estimation method would be to prorate fuel use based on total bus service kilometers in the CRD. However, this data is not available, and thus the method applied provides the best estimate at the time of reporting.
- It is assumed that the 2015 aircraft flight profiles at the Victoria International Airport are representative of the 2020 reporting year.
- Statistics Canada stopped collecting Victoria Harbor aircraft movement data in 2016. To estimate 2020 marine aviation GHG emissions, the 2016 Victoria data was applied and adjusted using the

change in aircraft traffic between the 2016 and 2020 reporting years at the Victoria International Airport. It is assumed that the activity at both airports would be corelated, but not causational.

- The aviation GHG emissions are prorated based on the total Victoria population relative to the CRD population.
- As there is currently no publicly available energy or GHG related information on the operation of the Coho and the Victoria Clipper Ferries, it was assumed that the GHG emissions for these ferries calculated in the Study entitled "Marine Vessel Air Emissions in BC and Washington State Outside of the Greater Victoria Regional District (GVRD) and FVRD for the Year 2000".
- There were no cruise ships in 2020.
- BC Ferries did not disclose its total reported fuel use for 2020 but did publish that fuel consumption volumes fell by approximately 40% as compared to the 2019 reporting year. As such, the 2019 fuel volumes and the 40% factor were applied to estimate 2020 fuel volumes.
- The Transport Canada Vessel Registration System provided the total number of registered waterborne vehicles for the reporting year; however, it does not provide any detail on the type, size, use, and owner of the watercraft. It was therefore assumed that the watercraft would have been similar to those in the referenced study.
- No railway GHG emissions are occurring in the CRD.
- The off-road transportation emissions are based on the 2021 NIR as prepared by Environment and Climate Change Canada. This is deemed to be the best available data.

4.2.4 Calculation Methodology

4.2.4.1 On-Road

The GPC Protocol identifies several methods for determining on-road emissions. The vehicle kilometers travelled (VKT) methodology and fuel sales methods were utilized to estimate the GHG emissions from on-road transportation (Scope 1) and transboundary transportation (Scope 3). The VKT uses the number and type of vehicles registered in a geopolitical boundary, the estimated fuel consumption rate of individual vehicles, and an estimate of the annual vehicle kilometres traveled (VKT) by various vehicle classes. ICBC provided the number of registered vehicles in the CRD by style and by fuel type for 2020. To estimate the split between on-road in-boundary and transboundary traffic, data from the 2017 CRD Origin Destination Survey was applied. The results of the survey as it applies to the CRD is presented in Table 9.

Table 9 CRD On-Road In-Boundary/Transboundary Split

Aspect	By Vehicle
Estimated proportion of on-road in-boundary travel	99.1%
Estimated proportion of on-road transboundary travel	0.9%

To quantify the 2020 reporting year on-road and transboundary GHG emissions, the following steps were taken:

1. Sort the ICBC vehicle registration data by postal code.

2. Review each vehicle model and fuel type and assign it to one of 4 classes (for each fuel type): LDV, LDT, HDV, ORVE
3. Assign estimated NRCan vehicle fuel consumption rates and estimated VKT to each vehicle class (Table 10).
4. Estimate total fuel use by vehicle classification.
5. Summate and allocate estimated fuel use, by vehicle class using the applicable in-boundary and transboundary split.
6. Pro-rate the gasoline and diesel fuel use from busses.
7. Summate and allocate estimated bus fuel use using the applicable in-boundary and transboundary split.
8. Compare fuel estimated fuel volumes to the regional fuel sales volumes reported by the CRD. Adjust the VKTs as needed to make sure that the fuel estimate is at least above the fuel sales volumes reported in the region.

Table 10 Estimated VKT And Fuel Efficiencies by Vehicle Class For Reporting Year

Vehicle Classification	Estimated VKT / Year	Estimated Fuel Efficiency (L/100 km)
Diesel-HDV	25,730	45.6
Diesel-LDT	12,916	11.8
Diesel-LDV	14,746	9.2
Diesel-ORVE	Not Estimated	45.6
Electric-HDV	9,651	30.0
Electric-LDT	10,290	20.0
Electric-LDV	11,328	20.0
Electric-ORVE	Not Estimated	30.0
Gasoline-HDV	9,180	54.1
Gasoline-Hybrid-HDV	8,214	37.9
Gasoline-Hybrid-LDT	8,901	10.0
Gasoline-Hybrid-LDV	9,799	7.0
Gasoline-Hybrid-ORVE	Not Estimated	37.9
Gasoline-LDT	8,901	12.2
Gasoline-LDV	9,799	9.0
Gasoline-ORVE	Not Estimated	54.1
Hydrogen-Hybrid-LDV	10,883	Not Estimated
Hydrogen-LDV	11,717	Not Estimated
Hydrogen-LDT	12,840	Not Estimated
Motorcycle - Electric	1,973	17.0
Motorcycle - Non catalyst	1,973	9.9
Natural Gas-HDV	25,730	22.9
Natural Gas-LDT	12,916	8.3

Vehicle Classification	Estimated VKT / Year	Estimated Fuel Efficiency (L/100 km)
Natural Gas-LDV	14,746	5.4
Natural Gas-ORVE	Not Estimated	22.9
Propane-HDV	25,730	22.9
Propane-Hybrid-LDV	16,384	13.1
Propane-LDT	12,916	12.6
Propane-LDV	14,746	8.2
Propane-ORVE	Not Estimated	22.9

Table 11 Total Registered Vehicles & Estimated Fuel Use For Reporting Year

Vehicle Classification	Total Estimated Registered Vehicles	Total Estimated Fuel Use	Units
Diesel-HDV	2,335	35,372,719	Liters (L)
Diesel-LDT	9,380	14,320,821	Liters (L)
Diesel-LDV	1,541	2,083,052	Liters (L)
Diesel-ORVE	2,309	-	Liters (L)
Electric-HDV	17	49,218	kWh
Electric-LDT	4,039	8,312,213	kWh
Electric-LDV	3,951	8,951,252	kWh
Electric-ORVE	44	-	kWh
Gasoline-HDV	3,451	17,329,273	Liters (L)
Gasoline-Hybrid-HDV	1	3,111	Liters (L)
Gasoline-Hybrid-LDT	609	542,059	Liters (L)
Gasoline-Hybrid-LDV	3,848	2,639,344	Liters (L)
Gasoline-Hybrid-ORVE	2	-	Liters (L)
Gasoline-LDT	140,562	152,118,048	Liters (L)
Gasoline-LDV	96,400	85,200,133	Liters (L)
Gasoline-ORVE	2,673	-	Liters (L)
Hydrogen-Hybrid-LDV	-	-	Liters (L)
Hydrogen-LDV	3	-	Liters (L)
Hydrogen-LDT	3	-	Liters (L)
Motorcycle - Electric	2	671	kWh
Motorcycle - Non catalyst	5,491	1,074,790	Liters (L)
Natural Gas-HDV	16	738,879	Kilogram (kg)
Natural Gas-LDT	41	43,953	Kilogram (kg)

Vehicle Classification	Total Estimated Registered Vehicles	Total Estimated Fuel Use	Units
Natural Gas-LDV	3	2,389	Kilogram (kg)
Natural Gas-ORVE	7	-	Kilogram (kg)
Propane-HDV	54	318,585	Liters (L)
Propane-Hybrid-LDV	2	4,284	Liters (L)
Propane-LDT	179	291,303	Liters (L)
Propane-LDV	12	14,510	Liters (L)
Propane-ORVE	75	-	Liters (L)
Total	**277,050**	**N/A**	**N/A**

Once the fuels were allocated amongst the vehicle classes and sectors, the GHG emissions were calculated accordingly. The GHG quantification method is captured, for all fuel types, is as follows:

$$Emissions_{On\text{-}road} = In\text{-}Boundary\ Split\ \% * ((Vol.\ Fuel * EF_{CO2}) + (Vol.\ Fuel * EF_{CH4} * GWP_{CH4}) + (Vol.\ Fuel * EF_{N2O} * GWP_{N2O}))$$

$$Emissions_{Transboundary} = Transboundary\ Split\ \% * ((Vol.\ Fuel * EF_{CO2}) + (Vol.\ Fuel * EF_{CH4} * GWP_{CH4}) + (Vol.\ Fuel * EF_{N2O} * GWP_{N2O}))$$

The emission factors used in the reporting year GHG inventory are from the 2021 NIR. These are summarized in Table 12.

Table 12 Vehicle GHG Emission Factors

Vehicle Class	Units	CO_2	CH_4	N_2O	tCO_2e
Gasoline-LDV	tonne CO_2e / L	0.00220000	0.00000023	0.00000047	0.00234581
Gasoline-LDT	tonne CO_2e / L	0.00220000	0.00000024	0.00000058	0.00237884
Gasoline-HDV	tonne CO_2e / L	0.00220000	0.00000068	0.00000020	0.00227660
Gasoline-ORVE	tonne CO_2e / L	0.00220000	0.00000270	0.00000050	0.00241650
Gasoline-Hybrid-LDV	tonne CO_2e / L	0.00220000	0.00000023	0.00000047	0.00234581
Gasoline-Hybrid-LDT	tonne CO_2e / L	0.00220000	0.00000024	0.00000058	0.00237884
Gasoline-Hybrid-HDV	tonne CO_2e / L	0.00220000	0.00000068	0.00000020	0.00227660
Gasoline-Hybrid-ORVE	tonne CO_2e / L	0.00220000	0.00000270	0.00000050	0.00241650
Electric-LDV	tonne CO_2e / kWh	-	-	-	0.00004010
Electric-LDT	tonne CO_2e / kWh	-	-	-	0.00004010
Electric-HDV	tonne CO_2e / L	-	-	-	0.00004010
Electric-ORVE	tonne CO_2e / L	-	-	-	0.00004010
Diesel-LDV	tonne CO_2e / L	0.00258200	0.00000005	0.00000022	0.00264884

Vehicle Class	Units	CO_2	CH_4	N_2O	tCO_2e
Diesel-LDT	tonne CO_2e / L	0.00258200	0.00000007	0.00000022	0.00264926
Diesel-HDV	tonne CO_2e / L	0.00258200	0.00000011	0.00000015	0.00262975
Diesel-ORVE	tonne CO_2e / L	0.00258200	0.00000015	0.00000100	0.00288375
Hydrogen-Hybrid-LDV	tonne CO_2e / L	-	-	-	-
Hydrogen-LDV	tonne CO_2e / L	-	-	-	-
Hydrogen-LDT	tonne CO_2e / L	-	-	-	-
Natural Gas-LDV	tonne CO_2e / kg	0.00273800	0.00001300	0.00000009	0.00308863
Natural Gas-LDT	tonne CO_2e / kg	0.00273800	0.00001300	0.00000009	0.00308863
Natural Gas-HDV	tonne CO_2e / kg	0.00273800	0.00001300	0.00000009	0.00308863
Natural Gas-ORVE	tonne CO_2e / kg	0.00273800	0.00001300	0.00000009	0.00308863
Propane-LDV	tonne CO_2e / L	0.00151500	0.00000064	0.00000003	0.00153934
Propane-LDT	tonne CO_2e / L	0.00151500	0.00000064	0.00000003	0.00153934
Propane-HDV	tonne CO_2e / L	0.00151500	0.00000064	0.00000003	0.00153934
Propane-ORVE	tonne CO_2e / L	0.00151500	0.00000064	0.00000003	0.00153934
Propane-Hybrid-LDV	tonne CO_2e / L	0.00151500	0.00000064	0.00000003	0.00153934
Motorcycle - Non catalyst	tonne CO_2e / L	0.00231600	0.00000230	0.00000005	0.00238780
Motorcycle - Electric	tonne CO_2e / L	-	-	-	0.00004010

4.2.4.2 Aviation: Victoria International Airport

The Victoria International Airport (VIA) estimated its 2015 airplane GHG emissions following the ACI ACERT standard. This includes GHG emissions from aircraft and GHG emissions from auxiliary power units (APU). APUs provides electricity to the aircraft prior to the engine start up. Within the ACERT model, it is assumed all aircraft have APUs and the duration of the APU operation (of five minutes per aircraft) was generically applied to every landing take-off (LTO) cycles. It should also be noted that the EIA has quantified aircraft GHG emissions from planes up to 3,000 ft. to avoid double counting with other airports and cities. This is consistent with the ACERT standard.

The CRD's 2020 aviation emissions estimate is based on the 2015 aircraft flight profiles, which included the estimated landing and takeoff (LTO) and auxiliary power unit (APU) fuel use, and an estimated percentage allocation of total flights to the following aviation class groupings (Table 13). The total reported flight movements for the reporting year (79,099) provided by the VIA and the aircraft flight profile data was used to estimate aviation GHG emissions for the reporting year at the VIA.

Table 13 Aircraft Type, Estimated Percentage of Total Reported Movements, And Estimated Fuel Use

Aviation Class	Aircraft Type	Estimated Percentage of Annual Movements	Estimated LTO Fuel Use by Aircraft Type (kg)	Estimated APU Fuel Use by Aircraft Type (kg/min)
Jet	Large: 2-aisle, long-haul	0.01%	1,853	4.00
	Medium: 2-aisle, medium-haul	0.01%	1,321	4.00
	Small: 1-aisle, small/medium haul	7.95%	565	1.78
	Regional: 1-aisle, short-haul	0.01%	315	1.78
	Business: 2-eng business jets	0.01%	41	1.78
Turboprop	Turboprop (all engines)	22.29%	46	1.78
Piston	Piston (all engines)	66.30%	41	0.00
Helicopter	Helicopter small (1 engine/turbine)	1.72%	13	0.00
	Helicopter large (2 engine/turbine)	1.72%	8	0.00

Calculating fuel use for each aviation class applied the following equation:

Fuel Use ***Per Aviation Class*** = *Number of Aircraft Movements * (LTO Fuel Use + (APU Fuel Use * 15 minutes))*

The GHG quantification method, that was applied to each aviation class, is as follows:

$$Emissions_{Per\ Aviation\ Class} = (Vol.\ Fuel * Aviation\ Class\ EF_{CO2}) + (Vol.\ Fuel * Aviation\ Class\ EF_{CH4} * GWP_{CH4}) + (Vol.\ Fuel * Aviation\ Class\ EF_{N2O} * GWP_{N2O}))$$

The ACERT GHG calculator used by the VIA utilized emission factors from the 2021 NIR. Actual airplane emission factors are from the International Civil Aviation Organization (ICAO) GHG database. These are summarized in Table 14.

These GHG emissions were reported in the Scope 3 category as directed by the GPC Protocol.

Table 14 Aviation GHG Emission Factors

Airplane Type	Units	CO_2	CH_4	N_2O	tCO_2e
Jet	tCO_2e/kg fuel	0.0031380	0.0000001	0.0000003	0.0032254
Turbo Propeller	tCO_2e/kg fuel	0.0031380	0.0000001	0.0000003	0.0032254
Piston	tCO_2e/kg fuel	0.0032530	0.0000031	0.0000003	0.0034154
Helicopter	tCO_2e/kg fuel	0.0031380	0.0000001	0.0000003	0.0032254

4.2.4.3 Aviation: Victoria Harbour

Victoria harbor aviation emissions were estimated using 2016 NAV Canada airplane movement statistics, estimated taxi times, and estimated fuel use for the DHC-6 Twin Otter type of plane (Table 15).

Table 15 Aircraft Type, Estimated Percentage of Total Reported Movements, And Estimated Fuel Use

Aviation Class	Aircraft Type	Estimated Percentage of Annual Movements	Estimated LTO Fuel Use by Aircraft Type (kg)	Estimated APU Fuel Use by Aircraft Type (kg/min)
Turboprop	DHC-6 Twin Otter	100%	56	0.00

Statistics Canada stopped collecting Victoria Harbor aircraft movement data in 2016. To estimate 2020 Victoria harbor aviation GHG emissions, the 2016 data was applied and adjusted using the change in aircraft traffic between the 2016 and 2020 reporting years at the Victoria International Airport. This resulted in an estimated 19,573 movements.

Calculating aviation fuel use in the Victoria harbor for applied the following equation:

$$\textbf{Fuel Use}_{\textbf{Per Aviation Class}} = \textit{Number of Aircraft Movements} * (\textit{LTO Fuel Use} + (\textit{APU Fuel Use} * 15 \textit{ minutes}))$$

The GHG quantification method is as follows:

$$\textbf{Emissions}_{\textbf{Per Aviation Class}} = \textit{CRD Population} * ((\textit{Vol. Fuel} * \textit{Aviation Class } EF_{CO2}) + (\textit{Vol. Fuel} * \textit{Aviation Class } EF_{CH4} * GWP_{CH4}) + (\textit{Vol. Fuel} * \textit{Aviation Class } EF_{N2O} * GWP_{N2O}))$$

The airplane emission factors are from the International Civil Aviation Organization (ICAO) GHG database. These are summarized in Table 16.

Table 16 Marine Aviation GHG Emission Factors

Airplane Type	Units	CO_2	CH_4	N_2O	tCO_2e
Turbo Propeller	tCO_2e/kg fuel	0.0031380	0.0000001	0.0000003	0.0032254

These GHG emissions were reported in the Scope 3 category as directed by the GPC Protocol.

4.2.4.4 Waterborne Transportation

4.2.4.4.1 BC Ferries

Marine waterborne transportation emissions encompass GHG emissions from the use of the BC Ferries. GHG emissions from BC Ferries are estimated using an estimated fuel use 64,650,000 liters of diesel and

8,100,000 liters of CNG for the 2020 reporting year, and a provincially derived GHG emissions factor (Table 17).

Table 17 BC Ferries GHG Emission Factors

Aspect	Units	CO_2	CH_4	N_2O	tCO_2e
Ferry (Diesel)	tonne CO_2e / L	0.0025820	0.0000002	0.0000011	0.0029136
Ferry (CNG)	tonne CO2e / L	0.0011782	0.0000046	0.0000004	0.0014137

As BC Ferries operate outside of the CRD's boundary, the GHG emissions were allocated to Scope 3 based on the proportion of the CRD population relative to the total Vancouver Island and Mainland / Southwest populations.

4.2.4.4.2 Other Watercraft

The GHG emissions from the Coho Ferry, the Victoria Clipper Ferry, and personal and commercial watercraft were estimated based on a publicly available year 2000 study for the Victoria, Vancouver, and Washington harbors and the Transport Canada Vessel Registration System. As there is currently no publicly available energy or GHG related information on the operation of the Coho and the Victoria Clipper Ferries, it was assumed that the GHG emissions for these ferries were 25% of the value calculated in the Study entitled "Marine Vessel Air Emissions in BC and Washington State Outside of the GVRD and FVRD for the Year 2000" for 2020 to account for the change in transportation patterns associated with COVID-19. The GHG emissions for these ferries are summarized in Table 18.

Table 18 Coho and the Victoria Clipper Ferries Estimated GHG Emissions

Aspect	Units	CO_2	CH_4	N_2O	tCO_2e
Coho Ferries	tonnes	290.00	0.03	0.10	320.43
Victoria Clipper	tonnes	473.75	0.03	0.20	533.98

Cruise ship GHG emissions were estimated by the Greater Victoria Harbour Authority.[2] The Greater Victoria Harbour Authority (GVHA) reported on cruise ship emissions for the 2010 and 2020 reporting years but did not derive an estimate for 2007. As a result, the 2010 GHG emissions estimate and number of cruise ship visits to Ogden Point was used to create a proxy to estimate 2007 cruise ship emissions. The GVHA reported 163 visits in 2007. There were no cruise ships in 2020.

The GHG quantification method to estimate 2007 GHG emissions from the Odgen Point cruise ship terminal was as follows:

$$Emissions_{Waterborne} = (GVHA\ Reported\ Emissions_{2010} / Cruise\ Ship\ Visits_{2010}) * Cruise\ Ship\ Visits_{2007}$$

[2] https://gvha.ca/wp-content/uploads/2019/10/EmissionsInventory-2019.pdf

The Transport Canada Vessel Registration System provided the total number of registered waterborne vehicles which was 2,215 vessels all registered boats in Victoria; however, the registration system does not provide any detail on the type, size, use, and owner of the watercraft. It was therefore assumed that the watercraft would have been similar to those in the referenced study. To estimate the personal / watercraft GHG emissions, the breakdown of vessels and total fuel use by category were used to estimate what the current population and fuel use might be in the reporting year. To do this, the following steps were taken.

1. Calculate the percentage of the population and per unit fuel use of the year 2000 population (Table 19).
1. Take the total number of registered vessels, and the percentage breakdown of the year 2000 population, and apply the per unit fuel use factor to determine the total gasoline and diesel fuel use (Table 20).
2. Using 2021 NIR emission factors estimate the GHG emissions from other watercraft.

Table 19 Year 2000 Other Watercraft Population Breakdown And Estimated Fuel Use

Type of Watercraft from Year 2000 Study	Year 2000 Study Vancouver Island Population	Percentage of Population	Fuel Use (m^3/Year)	Fuel Use Per Unit (m^3/Year)
Inboard: 4 stroke - gasoline	1,689	0.19%	175	0.10
Inboard: Diesel	199	0.02%	62	0.31
Outboard: 2 stroke - gasoline	23,494	2.66%	1,632	0.07
Outboard: 4 stroke - gasoline	622	0.07%	7	0.01
Stemdrive: 2 stroke - gasoline	68	0.01%	8	0.12
Stemdrive: 4 stroke - gasoline	6,576	0.74%	535	0.08
Stemdrive: Diesel	784	0.09%	216	0.28
Personal Watercraft: 2 stroke - gasoline	848,492	96.00%	342	0.00
Sailboat Auxiliary Inboard: 4 stroke - gasoline	428	0.05%	1	0.00
Sailboat Auxiliary Inboard: Diesel	1,088	0.12%	6	0.01
Sailboat Auxiliary Outboard: 2 stroke - gasoline	396	0.04%	1	0.00
Sailboat Auxiliary Outboard: Diesel	1	0.00%	0	0.01

Table 20 Reporting Year Other Watercraft Population Breakdown and Estimated Fuel Use

Type of Watercraft	Estimated Breakdown of Currently Registered Vessels	Estimated Fuel Use (L/year)
Inboard: 4 stroke - gasoline	4	438.6

Type of Watercraft	Estimated Breakdown of Currently Registered Vessels	Estimated Fuel Use (L/year)
Inboard: Diesel	0	155.4
Outboard: 2 stroke - gasoline	59	4,090.0
Outboard: 4 stroke - gasoline	2	17.5
Stemdrive: 2 stroke - gasoline	0	20.0
Stemdrive: 4 stroke - gasoline	16	1,340.8
Stemdrive: Diesel	2	541.3
Personal Watercraft: 2 stroke - gasoline	2,126	857.1
Sailboat Auxiliary Inboard: 4 stroke - gasoline	1	1.3
Sailboat Auxiliary Inboard: Diesel	3	15.0
Sailboat Auxiliary Outboard: 2 stroke - gasoline	1	1.3
Sailboat Auxiliary Outboard: Diesel	0	0.0

To calculate the GHG emissions, for the other watercraft, provincially derived GHG emissions factors were used (Table 21).

Table 21 Watercraft GHG Emission Factors

Aspect	Units	CO_2	CH_4	N_2O	tCO_2e
Marine Gasoline	tonne CO_2e / L	0.0022000	0.0000013	0.0000001	0.0022522
Marine Diesel	tonne CO_2e / L	0.0025820	0.0000002	0.0000011	0.0029136

The GHG quantification method, that was applied to the BC Ferries and other watercraft was as follows:

$$\textbf{Emissions}_{Waterborne} = (CRD\ Population / Vancouver\ Island; Mainland; Southwest\ Population) * ((Vol.\ Fuel * EF_{CO2}) + (Vol.\ Fuel * EF_{CH4} * GWP_{CH4}) + (Vol.\ Fuel * EF_{N2O} * GWP_{N2O}))$$

4.2.4.5 Off-Road

Currently, there is limited data available to estimate off-road GHG emissions. As such, a GHG emissions per capita estimate for each off-road category was developed using Provincial emissions data from the 2021 NIR, and BC's population from Statistics Canada. To develop each off-road factor, the total BC GHG emissions for each reporting category was divided by the BC population for the NIR reporting year (2021). Each derived per-capita value was applied to the current reporting year CRD population (2020) to estimate off-road GHG emissions.

The NIR currently reports the following off-road emissions:

- Total BC off-road agriculture and forestry GHG emissions
- Total BC off-road commercial and institutional GHG emissions
- Total BC off-road residential GHG emissions
- Total BC other off-road GHG emissions

Total BC off-road manufacturing, mining, and construction GHG emissions were not included on the basis that manufacturing and mining GHG emission could not be split out.

Other than other off-road GHG emissions, which is reported in the Off-Road Transportation Sub-Sector, the remaining off-road GHG emissions are reported in the Stationary Energy Sector as required by the GPC Protocol.

The GHG quantification method is presented below:

Emissions *$_{Off\text{-}Road}$ = (NIR Off-Road GHG Emissions $_{BC}$ / BC Population $_{BC}$) * Current Reporting Year Population $_{CRD}$*

4.3 WASTE

Cities produce GHG emissions because of the disposal and management of solid waste, incineration and open burning of waste, the biological treatment of waste, and through wastewater treatment and discharge. Waste does not directly consume energy, but releases GHG emissions because of decomposition, burning, incineration, and other management methods.

For the CRD, the Waste Sector encompasses the following GHG emissions scopes and Sub-Sectors:

- Scope 3: Emissions:
  - Solid waste disposal
  - Biological treatment of waste
  - Wastewater treatment and discharge

4.3.1 Activity Data

The CRD provided landfill gas volumes, energy and GHG related data for the Hartland landfill (fugitives and flaring), total CRD wastewater volumes, average biological oxygen demand (BOD) and Total Kjeldal Nitrogen (TKN) annual average values (mg/L) from the wastewater for all relevant outfalls. The wastewater volumes are based on total budgeted sewer costs.

Some GHG emissions from incineration and open burning are likely to be occurring in the CRD but cannot readily be estimated. This the notation key for “Not Estimated” has been used to indicate this.

4.3.2 Assumptions and Disclosures

The following assumptions were made in the calculation of the 2020 GHG emissions:

- To quantify GHG emissions from the Hartland Landfill, the CRD utilized the waste-in-place method which is accepted under the GPC Protocol. The Waste-in-place (WIP) assigns landfill emissions based on total waste deposited during that year. It counts GHGs emitted that year, regardless of when the waste was disposed. GHG emissions from the Hartland Landfill for the reporting year are allocated based upon the percentage of Community waste, relative to total waste received at to the Hartland Landfill. It is assumed that the GHG emissions data provided is reasonably accurate and the method deployed correct.

- It is assumed that the landfill gas has a constant higher heating value (HHV) of 0.01865 (GJ/m^3).
- Composting GHG emissions are estimated based on the total tonnage estimated by the CRD. It is assumed that all compost is treated aerobically.
- Wastewater is not currently treated. As such, IPCC wastewater methane (CH_4) producing capacity and CH_4 correction default factors were used. These factors used are for untreated wastewater being deposited into deep or moving waters. It is likely that ocean sequesters more CH_4 than is estimated.
- It is likely that GHG emissions from incineration and open burning are occurring on an infrequent and controlled (property by property) basis, but without available data the GHG emissions cannot be reasonably quantified.

4.3.3 Calculation Methodology

4.3.3.1 Solid Waste

The Hartland Landfill has a landfill gas (LFG) collection and destruction system at the Hartland Landfill to which the LFG is either combusted in a flare, or in an engine to generate electricity which is exported to the grid. The GHG emissions associated with energy generation are reported as a reporting only GHG emission under Stationary Energy: Energy Industries Reporting Only and are not included in the total GHG emissions estimate. The GHG emissions associated with flaring of the landfill gas are reported under Stationary Energy: Energy Industries Scope 1.

The GHG quantification method for Stationary Energy: Energy Industries is as follows:

$$\textbf{Emissions}_{\text{Stationary Energy: Energy Industries}} = (LFG\ Consumed_{m3} * HHV_{LFG} * EF_{RNG\ CH4} * GWP_{CH4}) + (LFG\ Consumed_{m3} * HHV_{LFG} * EF_{RNG\ N2O} * GWP_{N2O})$$

The fugitive landfill GHG emissions estimates were generated by the CRD using the waste-in-place (WIP) method which is accepted under the GPC Protocol. The WIP assigns landfill emissions based on emissions during that year. It counts GHGs emitted that year, regardless of when the waste was disposed.

4.3.3.2 Biological Treatment of Solid Waste

The CRD provided 2020 composting data which is assumed to be treated aerobically at the Hartland Landfill. The composting emission factor used in the estimation of GHG emissions was derived from the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (Volume 5, Chapter 4: Biological Treatment of Solid Waste) (Table 22).

Table 22 Composting Emission Factor

Emission Factor	Units	CO_2	CH_4	N_2O	tCO_2e
Composting	tCO_2e / kg waste	-	0.0000010	-	0.0000250

To quantify GHG emissions from the biological treatment of solid waste, the following GHG quantification methods was deployed:

$$Emissions_{Anaerobic\ Waste} = Compost\ Waste_{Total} * EF_{CH4} * GWP_{CH4}$$

4.3.3.3 Wastewater Treatment And Discharge

Wastewater is currently treated on Vancouver Island prior to being sent to ocean-based outfalls. The CRD provided the 2020 wastewater volumes (m^3), the average biological oxygen demand (BOD) and the average Total Kjeldal Nitrogen (TKN) in wastewater. IPCC default wastewater methane (CH_4) producing capacity (0.6 kg CH_4/kg BOD) and methane correction factor (MCF) (0.1 – unit less) were used to estimate CH_4 from the wastewater. To estimate N_2O from the wastewater, the Total Kjeldal Nitrogen (TKN) annual average in conjunction with the total wastewater volumes to calculate the total TKN in the wastewater. The IPCC default conversion value of 0.01 kg N_2O-N/kg sewage-N was used to estimate N_2O from the wastewater. These factors used are for treated wastewater being deposited into deep or moving waters. It is likely that ocean sequesters more CH_4 than what has been estimated.

To quantify GHG emissions from the wastewater treatment, the following GHG quantification method is deployed:

$$Emissions_{Wastewater\ CH4} = ((Wastewater_{m3} * (BOD_{ml/L} / 1000) * (0.06_{kg\ CH4/kg\ BOD} * 0.01)) / 1000) * GWP_{CH4}$$

$$Emissions_{Wastewater\ N2O} = ((Wastewater_{m3} * (TKN_{ml/L} / 1000) * 0.01_{kg\ N2O\text{-}N/kg\ sewage\text{-}N}) / 1000) * GWP_{N2O}$$

4.4 INDUSTRIAL PROCESSES AND PRODUCT USE (IPPU)

4.4.1 Overview

Emissions from the IPPU Sector are only required for BASIC+ GHG reporting under the GPC Protocol. This Sector encompasses GHG emissions produced from industrial processes that chemically or physically transform materials and using products by industry and end-consumers (e.g., refrigerants, foams, and aerosol cans) (GPC, 2014).

For the CRD, the IPPU encompasses the following GHG emissions scopes and Sub-Sectors:

- Scope 1 Emissions:

- Product use

No GHG emissions from Industrial Processes are known to be occurring and thus the notation key for "Not Occurring" has been used to indicate this.

4.4.2 Activity Data

As there is limited data available on Product Use GHG emissions, the GHG Emissions estimate was derived on a per capita basis using the 2021 NIR GHG data for the Province of BC and BC population data for the reporting year.

4.4.3 Assumptions and Disclosures

The following assumptions were made in the calculation of the 2020 GHG emissions:

- The product use emissions are based on the 2021 NIR product use GHG emissions as prepared by Environment and Climate Change Canada.
- The NIR uses the Tier 1 methodology to estimate these emissions and thus uncertainty around their accuracy remains quite high.

4.4.4 Calculation Methodology

4.4.4.1 Product Use Emissions

For the 2020 reporting year, only the emissions estimated were production and consumption of halocarbons, SF_6 and NF_3 were estimated for the Province. To estimate product use GHG emissions for the CRD, a per capita estimate was developed using the Provincial emissions data from the 2021 NIR, and BC's NIR reporting year population from Statistics Canada. This value was applied to the 2020 reporting year CRD population to estimate the total product use emissions.

The GHG quantification method is presented below:

***Emissions** **Product Use** = (NIR Product Use GHG Emissions BC / NIR Population BC) * Current Reporting Year Population*

4.5 AGRICULTURE, FORESTRY, AND OTHER LAND USE (AFOLU)

4.5.1 Overview

The AFOLU Sector includes emissions from livestock, land-use, and all other agricultural activities occurring within a community's boundaries. For the CRD, the AFOLU encompasses the following GHG emissions scopes and Sub-Sectors:

- Scope 1 Emissions:
  - Land
  - Livestock
  - Aggregate Sources And Non-CO_2 Emissions Sources On Land

4.5.2 Activity Data

The CRD provided remotely sensed imagery to estimate land-cover change. This data included:

- Habitat Acquisition Trust (HAT) Land Cover Mapping (2007 and 2011)
- Annual Crop Inventory (ACI), Agriculture Canada
- Satellite Imagery interpretation (2011 and 2019), CRD
- Vegetation Resources Inventory (VRI), British Columbia Government.
- Earth Observation for Sustainable Development of Forests (EOSD) Land Cover Classification, Service Natural Resources Canada

Livestock and aggregate sources and non-CO_2 emissions sources on land were estimated using GHG emissions data from the 2021 NIR, and land-use data from the 2016 Statistics Canada Census of Agriculture, to create a GHG emissions per hectare value.

4.5.3 Assumptions and Disclosures

The following assumptions were made in the calculation of the 2020 GHG emissions:

- It is conservatively assumed that all cropland is used for livestock and agricultural purposes.
- Infrequent and small source open burning may be occurring, but there is no data to estimate this emissions source.
- The land cover change analysis requires a consistent land-use category attribution and spatial data. For parts of the CRD, spatial data was available for the 2007, 2011 and 2019 reporting years. Differences between these data sets in terms of resolution and their timing of collection increase the uncertainty as to the accuracy of the land-use classifications. For example, the 2007 and 2011 land use data was collected at different times of the year and may not accurately reflect tree cover. Furthermore, no land use spatial data was collected for the Juan de Fuca, Salt Spring Island or Gulf Islands and thus Annual Crop Inventory (ACI) settlement data collected by Agriculture Canada was used to inform the analysis. The challenge in utilizing this data is that it is provided in a 30m resolution. Furthermore, since annual data is not available, the change between land cover data years (2007-2011, 2011-2019) for all areas was averaged and may not represent actual changes in each year. Lastly, due to limitations in how to quantify GHG emissions resulting from land use change (e.g., residential development), these GHG emissions have been excluded from the CRD's GHG emissions inventory, but have been disclosed, until a more robust measurement methodology can be developed. Since no data was available for 2020, the 2019 estimates were applied.

4.5.4 Calculation Methodology

4.5.4.1 Land Use

Remotely sensed imagery was used to estimate land-cover changes during the 2007-2020 reporting periods. Using the remotely sensed imagery an annual average land-use change between land classes (e.g. cropland forestland, etc.) was determined and applied to BC-based emission factors to estimate GHG emissions resulting from changes between land-uses for the reporting year.

The following table identifies the data sources used for the reporting years for each of the study area's geographies.

Table 23 Spatial Data Sources Representing Land Cover For The CRD Study Area

		CRD Study Area Geography		
		CRD Core	**Gulf Islands**	**Juan de Fuca Region**
Reporting Year	**2007**	2005 HAT Land Cover Mapping	2001 EOSD Land Cover Classification	2011 HAT Land Cover Mapping[2]
	2011	2011 HAT Land Cover Mapping	2001 EOSD Land Cover Classification + 2011 ACI 'Settlement'	2011 HAT Land Cover Mapping[2] + 2011 ACI 'Settlement'
	2020	2019 HAT Land Cover Mapping + 'Settlement' satellite image interpretation[1]	2001 EOSD Land Cover Classification + 2019 ACI 'Settlement'	2011 HAT Land Cover Mapping[2] + 2019 ACI 'Settlement'

Notes:

[1] Settlements land cover category is a combination of i) municipality provided building footprint as acquired mostly from digitizing roofline from satellite and orthoimagery, ii) new roads (ParcelMap BC parcel with parcel start dates > 2011 and parcel class = 'road') and iii) and theoretical building footprints (average building footprint areas as buffered centroids of new ParcelMap BC parcel with start dates > 2011 with a residential parcel class)

[2] The 2011 land cover classification was interpreted mostly from 2005 imagery in the Juan de Fuca region making it more suitable for the 2007 reporting year.

The spatial data sources representing land cover in this analysis include more categories than the 6 IPCC land-use categories. To align with the IPCC land classification definitions (as required by the GPC Protocol), the following data categories were re-assigned to the most appropriate IPCC land class.

Table 24 IPCC Land Use Classification Cross-References

IPCC Land Cover	EOSD Land Cover	HAT Land Cover	Annual Crop Inventory
Cropland	Annual Cropland, Perennial Cropland And Pasture	Agricultural Fields	-

IPCC Land Cover	EOSD Land Cover	HAT Land Cover	Annual Crop Inventory
Forest	Broadleaf Dense, Broadleaf Open, Coniferous Dense, Coniferous Open, Coniferous Sparse	Tree	-
Grassland	Grassland, Herb, Shrub Low	Grass, Herb	-
Settlement	Developed	Pavement/Building	Developed
Wetland	Wetland - Herb, Wetland - Shrub, Wetland - Treed	Riparian Tree, Riparian Herb, Pond	-
Other	Water, Exposed Land	Shadow, Ocean, Lake, River, Sand/Gravel Shoreline, Bedrock Shoreline, Exposed Soil, Exposed Bedrock	-

The analysis resulted an estimate of an annual average change in hectares' value for each land class. Once the land use change values were determined for the reporting year, BC-based and IPCC emission factors were applied to estimate reported and disclosed (not-reported) GHG emissions from land use (Table 25).

Table 25 Land-Use Change Emission Factors

Sector	Emission Factor	Units
Forestland	224.1	tCO_2e / ha
Grasslands	205.7	tCO_2e / ha
Wetlands	471.5	tCO_2e / ha
Cropland	239.8	tCO_2e / ha
Settlements	0	tCO_2e / ha
Other	0	tCO_2e / ha
Forestland	1.8	tCO_2e / ha / year
Grasslands	2.6	tCO_2e / ha / year
Wetlands	3.3	tCO_2e / ha / year
Croplands	0.4	tCO_2e / ha / year
Settlements	0	tCO_2e / ha / year
Other	0	tCO_2e / ha / year

The GHG quantification methods for land use change is presented below:

$$\textbf{Emissions}_{\textbf{Lands Not Converted}} = \textit{Land Type}_{ha} * EF_{Sequester}$$

$$\textbf{Emissions}_{\textbf{Lands Converted}} = \textit{Land Type}_{ha} * (EF_{Release} / (\textit{Current Land Reporting}_{Year} - \textit{Last Land Reporting}_{Year} + 1))$$

4.5.4.2 Emissions from Aggregate Sources and Non-CO_2 Emission Sources on Land

Emissions from Aggregate Sources and Non-CO_2 Emission Sources on Land includes direct N_2O emissions from agricultural soil management and indirect N_2O emissions from applied nitrogen. To estimate these GHG emissions, the total area of farmland for BC was used in conjunction with 2021 NIR data to develop a tCO_2e / ha value estimate for:

- Livestock
- Aggregate Sources And Non-CO_2 Emissions Sources On Land

To calculate GHG emissions from urea application, the calculated total crop land in hectares for the reporting year was applied against an IPCC GHG emissions factor of 0.20 tCO_2e / ha. This emission factor is also applied in the 2021 NIR.

The GHG quantification method is presented below:

$$\textbf{Emissions}_{\textbf{Direct \& Indirect N2O}} = ((BC_{\text{Direct N2O Emissions}} + BC_{\text{Indirect N2O Emissions}} + BC_{\text{Indirect N2O Manure Management Emissions}}) / BC_{\text{Land In Crops ha}})) * \textit{CRD Cropland}_{ha}$$

$$\textbf{Emissions}_{\textbf{Urea Application}} = \textit{CRD Cropland}_{ha} * 0.66\ tCO_2e / ha$$

5.0 2020 GHG REPORTING YEAR RESULTS

5.1 OVERVIEW

This section presents the 2020 reporting year GHG emissions for the CRD. The following table classifies each of the GPC Protocol GHG emission categories by scope and reporting level. Note that these are cumulative.

Table 26 GHG Emissions Reporting Breakdown by GPC Reporting Method

GHG Emissions Scope	BASIC Reporting Level	BASIC+ Reporting Level
Scope 1	• Emissions from in boundary fuel combustion • In boundary fugitive emissions • Emissions from in boundary transport	Everything in the box at left, plus in-boundary emissions from: • Industrial process and product use • Livestock • Land use • Emissions from Aggregate Sources and Non-CO_2 Emission Sources on Land
Scope 2	• Emissions from consumption of grid-supplied energy	• Emissions from consumption of grid-supplied energy
Scope 3	• Emissions from solid waste, and composting generated within but treated outside of the GHG boundaries	Everything in the box at left, plus: • Transmission, distribution, and line losses from grid-supplied energy • Emissions from transboundary journeys
Outside of Reporting Scopes & GPC Protocol	• Upstream fuel emission extraction, processing, and transport • Food and drink imports • Construction materials (imports) • Other supply chain emissions • Vehicle fuel exports	

5.2 SUMMARY

Total BASIC, and BASIC+ emissions for the CRD for the 2020 reporting year are presented in the Figure 3 below.

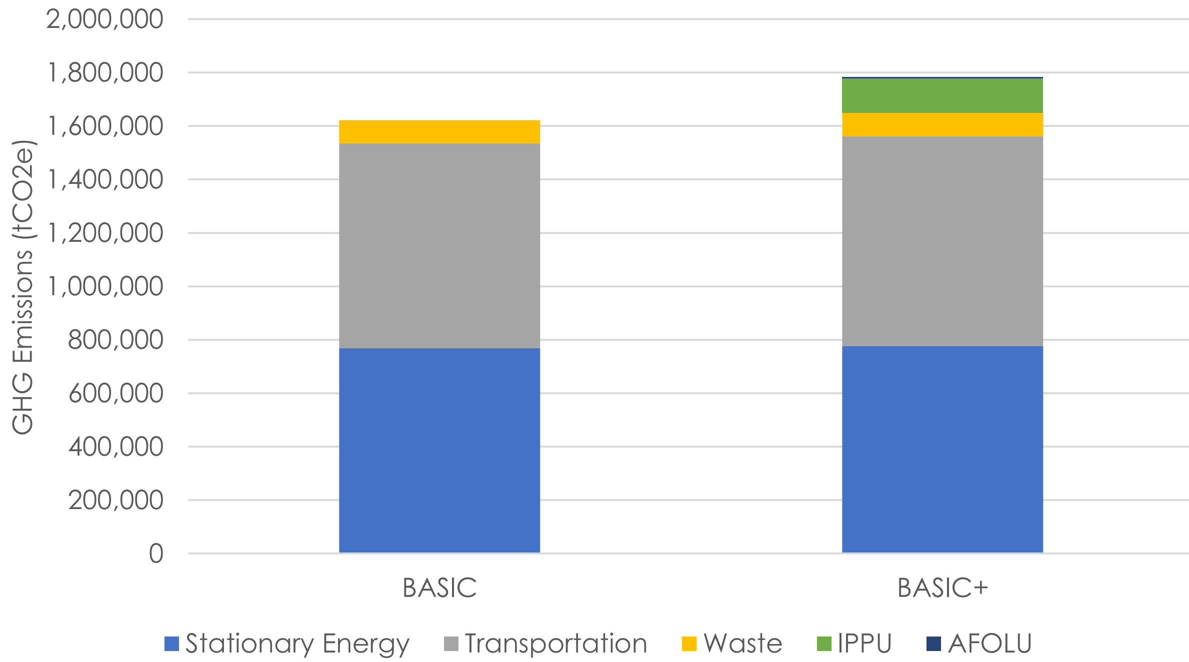

Figure 3 2020 GHG Emissions Summary by GPC Reporting Level

Emission by reporting level are presented in the Table 27 below which shows a difference in emissions under the GPC Protocol's BASIC, and BASIC+ reporting levels. This is due to the inclusion of additional sources in BASIC+ which are very significant for almost any growing community. These additional emissions include transboundary emissions, industrial and product use emissions, and emissions from land-use change. Under the GPC Protocol, emissions included within each higher reporting level are cumulative from lower levels.

Table 27 Breakdown of the CRD's 2020 GHG Emissions in GPC Reporting Format

GHG Emissions Source (by Sector)		Total GHGs (metric tonnes CO_2e)					
		Scope 1	Scope 2	Scope 3	BASIC	BASIC+	BASIC+ S3
Stationary Energy	Energy use (all emissions except I.4.4)	643,162	125,805	8,430	768,967	777,397	777,397
	Energy generation supplied to the grid (I.4.4)	8,209					
Transportation	(all II emissions)	765,604	694	18,577	766,298	784,875	784,875
Waste	Waste generated in the Community (III.X.1 and III.X.2)	86,580		0	86,580	86,580	86,580
	Waste generated outside community (III.X.3)	NO					
IPPU	(all IV emissions)	130,139				130,139	130,139
AFOLU	(all V emissions)	4,261				4,261	4,261
Other Scope 3 (S3)	(all VI emissions)	86,580		0	86,580	86,580	86,580
TOTAL		**1,629,745**	**126,499**	**27,007**	**1,621,845**	**1,783,251**	**1,783,251**

NOTES:
Notation Keys: IE = Included Elsewhere; NE = Not Estimated; NO = Not Occurring.
Cells in green are required for BASIC reporting
Cells in green and blue are required for BASIC+ reporting
Cells in purple are for disclosure purposes only but are not included in the summary totals as required by the GPC Protocol.
Cells in orange are not required for BASIC or BASIC+ reporting

Table 28 presents the breakdown of the CRD's BASIC+ GHG emissions by Sector and Sub-Sector.

Table 28 Breakdown of the CRD's 2020 BASIC+ GHG Emissions in the GPC Protocol Reporting Format

GPC ref No.	GHG Emissions Source (by Sector and Sub-Sector)	Total GHGs (metric tonnes CO_2e)			
		Scope 1	Scope 2	Scope 3	Total
I	**Stationary Energy**				
I.1	Residential buildings	323,268	78,377	5,252	406,896
I.2	Commercial and institutional buildings and facilities	252,506	47,428	3,178	303,112
I.3	Manufacturing industries and construction	NE	NE	NE	NE
I.4.1/2/3	Energy industries	9,563	NO	NO	9,563
I.4.4	Energy generation supplied to the grid	8,209			
I.5	Agriculture, forestry, and fishing activities	56,418	IE	IE	56,418
I.6	Non-specified sources	IE	IE	IE	IE
I.7	Fugitive emissions from mining, processing, storage, and transportation of coal	1,408			1,408
I.8	Fugitive emissions from oil and natural gas systems	NO			0
Sub-Total	(community induced framework only)	**643,162**	**125,805**	**8,430**	**777,397**
II	**Transportation**				
II.1	On-road transportation	691,640	694	6,013	698,348
II.2	Railways	NO	NO	NO	NO
II.3	Waterborne navigation	22,341	IE	IE	22,341
II.4	Aviation	NO	IE	12,564	12,564
II.5	Off-road transportation	51,623	IE	IE	51,623
Sub-total	(community induced framework only)	**765,604**	**694**	**18,577**	**784,875**
III	**Waste**				
III.1.1/2	Solid waste generated in the Community	66,237		NO	66,237
III.2.1/2	Biological waste generated in the Community	5,307		NO	5,307
III.3.1/2	Incinerated and burned waste generated in the Community	NE		NE	NE
III.4.1/2	Wastewater generated in the Community	15,035		IE	15,035
III.1.3	Solid waste generated outside the Community	NO			
III.2.3	Biological waste generated outside the Community	NO			
III.3.3	Incinerated and burned waste generated outside community	NE			

Table 28 Breakdown of the CRD's 2020 BASIC+ GHG Emissions in the GPC Protocol Reporting Format

GPC ref No.	GHG Emissions Source (by Sector and Sub-Sector)	Total GHGs (metric tonnes CO_2e)			
		Scope 1	Scope 2	Scope 3	Total
III.4.3	Wastewater generated outside the Community	NO			
Sub-total	(community induced framework only)	**86,580**		**0**	**86,580**
IV	**Industrial Processes and Product Uses**				
IV.1	Emissions from industrial processes occurring in the Community boundary	NE			NE
IV.2	Emissions from product use occurring within the Community boundary	130,139			130,139
Sub-Total	(community induced framework only)	**130,139**			**130,139**
V	**Agriculture, Forestry, and Other Land Use**				
V.1	Emissions from livestock	3,545			3,545
V.2	Emissions from land	NE			NE
V.3	Emissions from aggregate sources and non-CO_2 emission sources on land	715			715
Sub-Total	(community induced framework only)	**4,261**			**4,261**
VI	**Other Scope 3**				
VI.1	Other Scope 3			NE	NE
Total	(community induced framework only)	**1,629,745**	**126,499**	**27,007**	**1,783,251**

NOTES:
Cells in green are required for BASIC reporting
Cells in green and blue are required for BASIC+ reporting
Cells in purple are for disclosure purposes only but are not included in the summary totals as required by the GPC Protocol.
Cells in orange are not required for BASIC or BASIC+ reporting

5.3 TOTAL GHG EMISSIONS

Under the BASIC+ method, the CRD's GHG emissions totaled 1,783,251 tCO_2e. On a per capita basis, this works out to 4.2 tCO_2e per person.

Table 29 Total Energy and GHG Emissions Per Person by Sector

Sector	Sub-Sector	Energy (GJ)	GHG Emissions (tCO_2e)	GJ Per Capita	tCO_2e Per Capita
Stationary Energy	Residential Buildings	13,592,223	406,896	32	1.0
	Commercial & Institutional Buildings	9,361,348	303,112	22	0.7
	Manufacturing Industries & Construction	-	-	-	-
	Energy Industries	-	9,563	-	0.0
	Agriculture, Forestry & Fishing Activities	804,183	56,418	2	0.1
	Fugitive Emissions	-	1,408	-	0.0
Transportation	In-Boundary On-road Transportation	11,001,396	692,329	26	1.6
	Trans-Boundary On-road Transportation	95,649	6,019	0	0.0
	Waterborne Navigation	304,172	22,341	1	0.1
	Aviation	168,854	12,564	0	0.0
	Off-road Transportation	735,833	51,623	2	0.1
Waste	Solid Waste		66,237		0.2
	Biological Treatment of Waste		5,307		0.0
	Wastewater Treatment & Discharge		15,035		0.0
IPPU	Product Use		130,139		0.3
AFOLU	Land-Use: Emissions Sequestered **(Disclosure Only - Not Included In Total)**		(399,707)		(1.0)
	Land-Use: Emissions Released **(Disclosure Only - Not Included In Total)**		89,610		0.2
	Livestock		3,545		0.0
	Non-CO2 Land Emission Sources		715		0.0
Total		**36,063,658**	**1,783,251**	**85.9**	**4.2**

Total GHG emissions for 2020 are 1,783,251 tCO_2e and have decreased 10% from the 2007 base year. Scope 1 and 2 Emissions are 91% and 7% of the total GHG inventory. Scope 1 emissions are the GHG emissions that result from the combustion of fuel in sources within the CRD's boundaries, primarily from Stationary Energy and Transportation. Scope 1 GHG emissions also include IPPU and some AFOLU GHG emissions. Scope 2 emissions result from the use of electricity supplied to the CRD which includes emissions associated with the generation of electricity and other forms of energy (e.g., heat and steam). Scope 2 emissions are low compared to other geographies, due to the predominance of hydroelectric generation technologies in the BC. Scope 3 emissions are emissions from electricity line losses, transboundary traffic, and emissions associated with the CRD that are occurring outside of the CRD's boundaries. For 2020, Scope 3 GHG emissions make up 2% of the GHG inventory. This breakdown by emission scope is depicted in Figure 4.

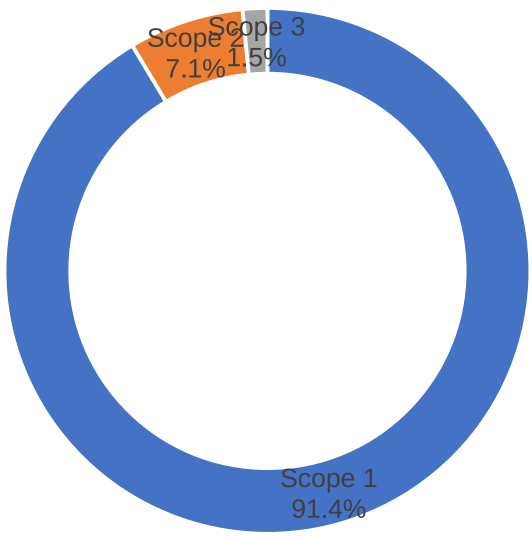

Figure 4 CRD BASIC+ GHG Emissions by Emissions Scope

A breakdown of GHG emissions by reporting scope for the 2007 base and reporting year are presented in Table 30 below.

Table 30 Change in GHG Emissions from Base Year

Emissions Scope	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change
Scope 1	1,812,737	1,629,745	-10.1%
Scope 2	116,129	126,499	8.9%
Scope 3	47,234	27,007	-42.8%
Total	**1,976,100**	**1,783,251**	**-9.8%**

5.4 SECTORAL GHG EMISSIONS ANALYSIS

5.4.1 Stationary Energy

Stationary energy sources are one of the largest contributors to the CRD's GHG emissions. In 2020, it contributed 44% of the community's GHG emissions. In general, stationary energy emissions include the energy to heat and cool residential, commercial, and industrial buildings, as well as the activities that occur within these residences and facilities. Fugitive methane emissions from natural gas pipelines and other distribution facilities, and related off-road GHG emissions, are also reported in this Sector. The table below shows the breakdown of energy use in the stationary energy reporting category.

Table 31 summarizes the energy and GHG emissions for the 2020 reporting year.

Table 31 2020 Energy and GHG Emissions by Stationary Energy Sector

Sector	Electricity (tCO_2e)	Natural Gas (tCO_2e)	Heating Oil (tCO_2e)	Propane (tCO_2e)	Wood (tCO_2e)	Other Sources (tCO_2e)	**Total GHG Emissions (tCO_2e)**	**Total Energy (GJ)**
Residential Buildings	83,628	128,018	136,540	21,219	22,556	14,934	**406,896**	**13,592,223**
Commercial & Institutional Buildings	50,606	209,576	9,778			33,152	**303,112**	**9,361,348**
Energy Industries						9,563	**9,563**	
Agriculture, Forestry & Fishing activities						56,418	**56,418**	**804,183**
Fugitive Emissions						1,408	**1,408**	
Total GHG Emissions (tCO_2e)	**134,235**	**337,594**	**146,318**	**21,219**	**22,556**	**115,475**	**777,397**	
Total Energy (GJ)	**12,050,882**	**6,769,810**	**2,139,902**	**346,989**	**960,568**	**1,489,604**		**23,757,755**

It can be seen in Figure 5 that heating oil and natural gas use contributed to 62% of the CRD's total Stationary Energy GHG emissions.

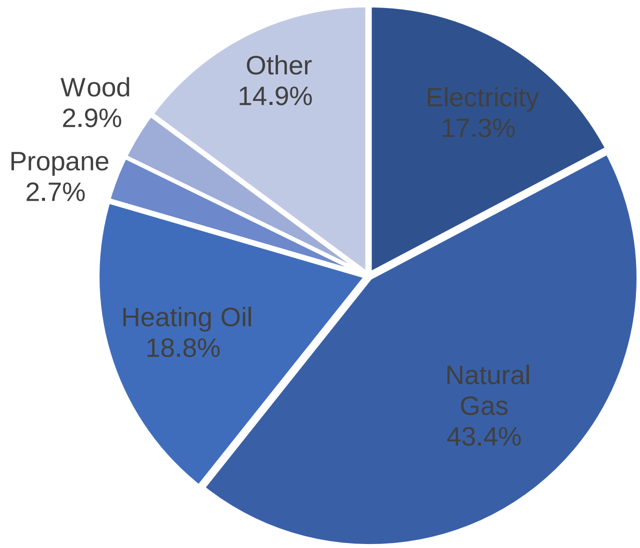

Figure 5 Stationary Energy GHG Emissions Contribution to the GHG Inventory

Figure 6 shows that more than 90% of the stationary GHG emissions arise from the operation of buildings.

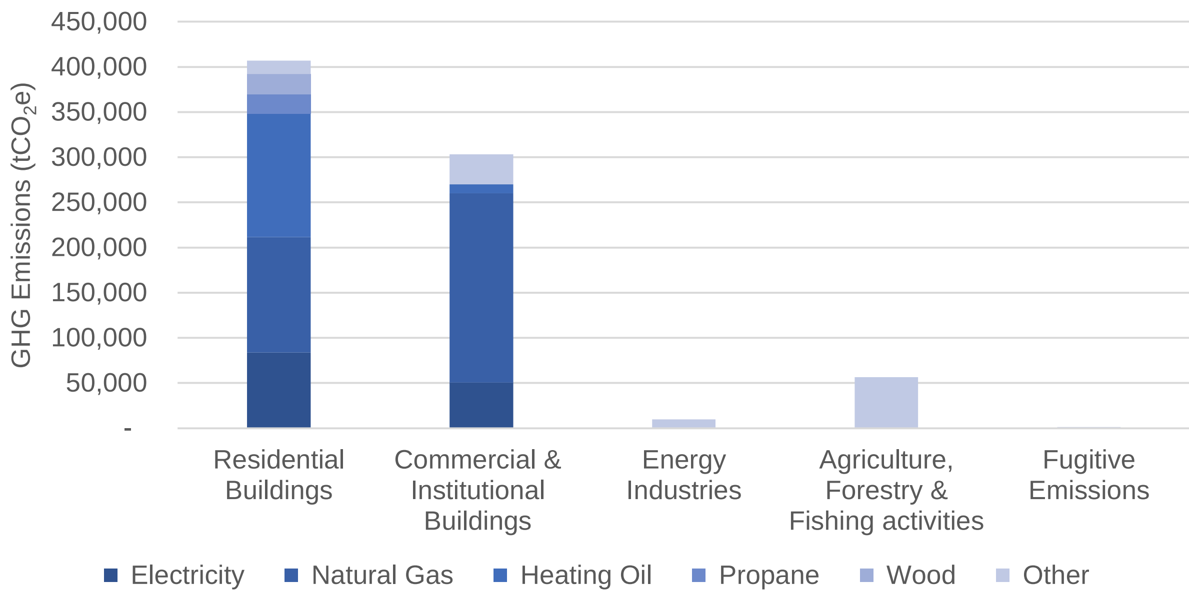

Figure 6 Total Stationary Energy Use By Sub-Sector

Stationary energy GHG emissions have increased by nearly 4% since the base year (Table 32). This is mainly the result of the changing electricity emission factor which increased by 12% in 2020 (as compared to 2007).

Table 32 Stationary Energy—Energy and GHG Emissions Trends

Sector	Change in GJ: 2007 & 2020	Change in tCO_2e: 2007 & 2020
Residential Buildings	-4.2%	-4.4%
Commercial & Institutional Buildings	5.1%	15.6%
Energy Industries	N/A	2,186.5%
Agriculture, Forestry & Fishing activities	-3.4%	-9.1%
Fugitives	N/A	40.4%
Total	**-0.7%**	**3.5%**

5.4.2 Transportation

Transportation covers all emissions from combustion of fuels in journeys by road, rail, water, and air, including inter-community and international travel. For the 2020 reporting year, transportation GHG emissions accounted for 44% of the CRD GHG inventory with the bulk of transportation GHG emissions resulting from the on-road transportation sub-sector (89%). The transportation GHG emissions are produced directly by the combustion of fuel or indirectly because of the use of grid-supplied electricity. Unlike stationary emission sectors, transit is mobile and can pose challenges in both accurately calculating emissions and allocating them to the cities linked to the transit activity. The following sections summarize energy and GHG emissions by on-road transportation, which is then followed by off-road transportation (marine, aviation, and other).

Table 33 summarizes the on-road energy and GHG emissions for the 2020 reporting year.

Table 33 2020 On-Road Transportation Energy And GHG Emissions by Fuel Type

Fuel Type	Number of Registered Vehicles	Total Fuel Use	Fuel Use Units	Energy (GJ)	GHG Emissions (tCO_2e)
Electricity	8,053	17,313,354	kWh	62,328	694
Gasoline	253,037	258,906,758	Liters (L)	8,973,708	566,035
Diesel	15,565	51,776,592	Liters (L)	2,002,719	128,426
Propane	322	628,682	Liters (L)	16,050	911
Hydrogen	6	-	Liters (L)	-	-
Natural Gas	67	785,220	Kilograms (kg)	42,240	2,282
Total	**277,050**	**N/A**	**N/A**	**11,097,044**	**698,348**

Overall, GHG emissions from on-road transportation have decreased by 21% compared to the 2007 base year. The majority of these GHG emissions (82%) are from passenger vehicles, light trucks, and SUVs (Figure 7).

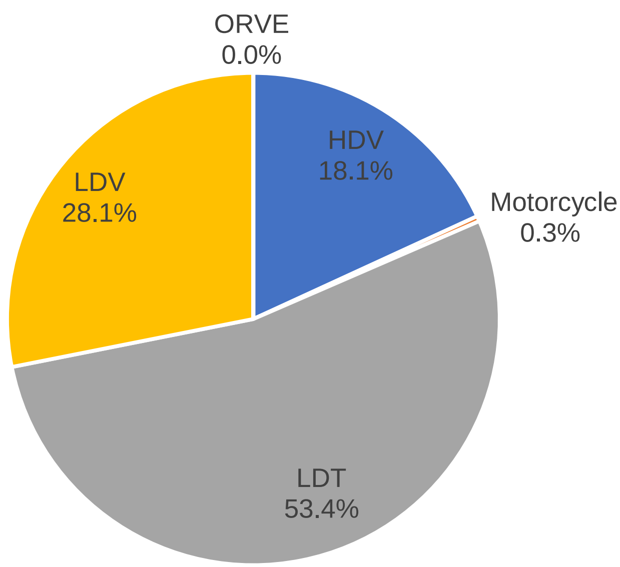

Figure 7 Breakdown of On-Road GHG Emissions by Vehicle Type

Table 34 summarizes the aviation, waterborne, and off-road transportation energy and emissions by fuel type. These GHG emissions contribute to 11% of the total transportation GHG emissions and 5% to the total inventory (Figure 8).

Table 34 2020 Aviation, Waterborne, and Off-Road Transportation Energy and Emissions by Fuel Type

Fuel Type	Total	Units	Energy (GJ)	GHG Emissions (tCO_2e)
Marine Gasoline	7,478	Liters (L)	259	17
Marine Diesel	7,010,603	Liters (L)	271,170	20,426
Marine Natural Gas	842,791	Liters (L)	32,742	1,898
Aviation Jet Fuel	4,866,104	Liters (L)	168,854	12,564
Other Off-Road Transportation Diesel	19,023,601	Liters (L)	735,833	51,623
Total	**N/A**	**N/A**	**1,208,859**	**86,527**

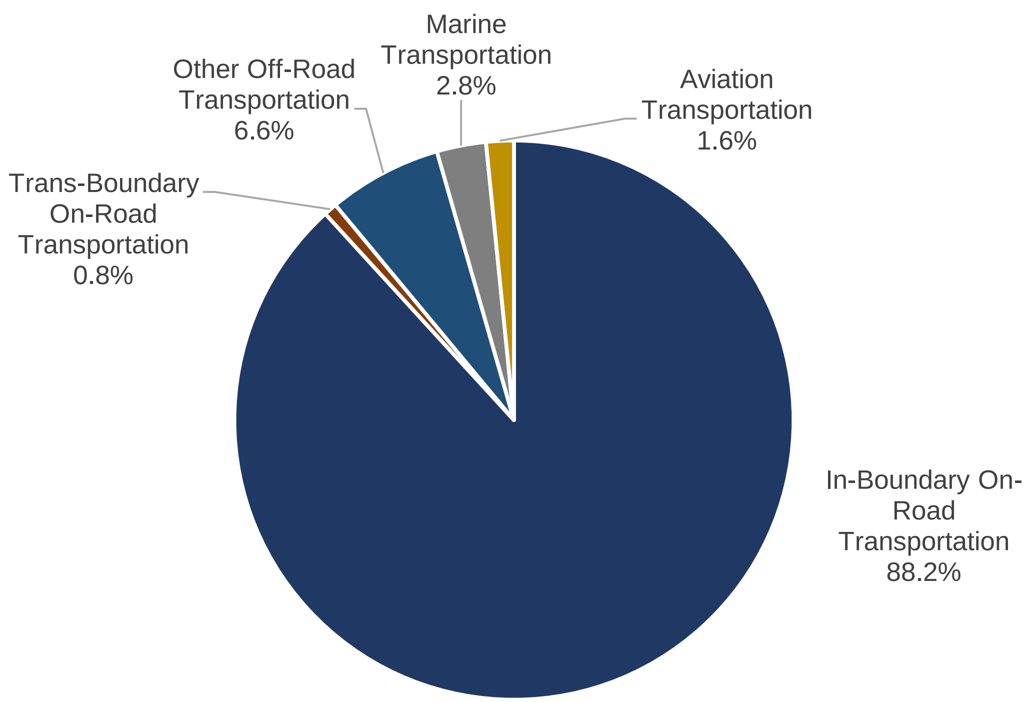

Figure 8 Summary of Transportation GHG Emissions by Sub-Sector

5.4.3 Waste

Communities produce solid waste, compost, and wastewater. Waste does not directly consume energy, but when deposited into landfills, or left exposed to the atmosphere, it decomposes and releases methane (CH_4) gas which is a potent GHG. The GHG emissions from the solid waste, composting, and wastewater facilities for the reporting year is summarized in the following table. For the 2020 reporting year, waste emissions contributed 5% to the GHG inventory. A breakdown of the Waste Sub-Sector GHG emissions is presented in Table 35.

Table 35 Summary of Waste Sub-Sector GHG Emissions

Sector	2020 GHG Emissions (tCO_2e)	GHG Emissions Per Capita (tCO_2e / Capita)	Change from Base Year (2007)
Wastewater Treatment And Discharge	15,035	0.04	-20.9%
Biological Treatment of Solid Waste	5,307	0.01	7236%
Solid Waste	66,237	0.16	-40.5%
Total	**86,580**	**0.21**	**-33.6%**

For the 2020 reporting year, in scope GHG emissions from waste have decreased by 34% compared to the 2007 base year. Fluctuations in waste will occur over the reporting periods as waste is driven by both the population, as well as economic prosperity in the region. The Solid Waste Sub-Sector contributes more than 77% of total waste GHG emissions (Figure 9). To reduce the amount of waste landfilled, and thus GHG emissions, the CRD and its members are making a significant effort to reduce waste going to landfills through organics diversion and recycling.

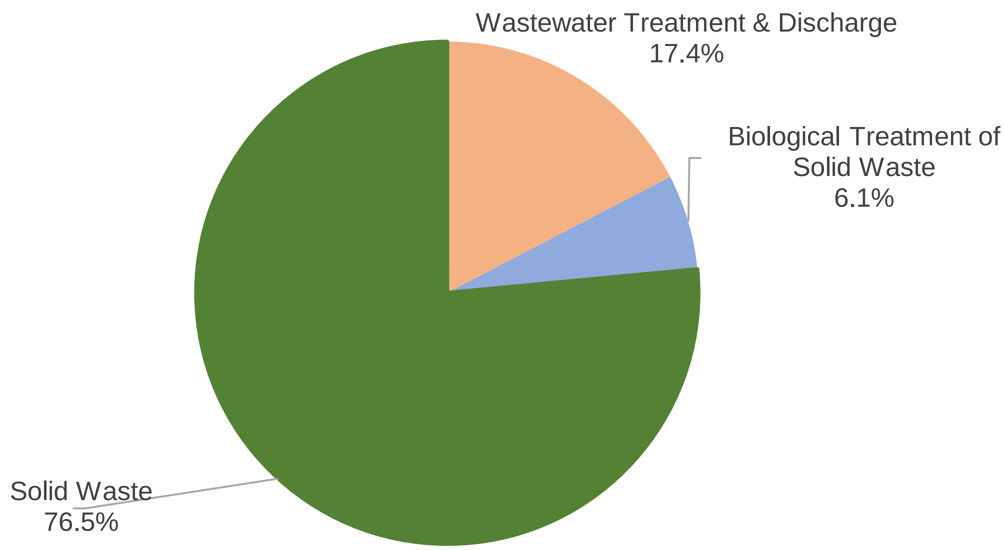

Figure 9 2020 GHG Emissions from Waste (tCO_2e)

5.4.4 Industrial Processes and Product Use (IPPU)

Reporting on IPPU GHG emissions are required for BASIC+ reporting only. Industrial GHG emissions are produced from a wide variety of non-energy related industrial activities which are typically releases from industrial processes that chemically or physically transform materials. During these processes, many different GHGs can be produced. It is not clear if there are industrial GHG emissions occurring within the CRD's boundaries and thus a "Not Estimated" notation is used in the GPC tables.

Also included in the IPPU Sector is Product Use GHG emissions. Certain products used by industry and end-consumers, such as refrigerants, foams or aerosol cans, also contain GHGs which can be released during use and disposal and thus, as with best-practice, must be accounted for. For the reporting year, only the emissions estimated were production and consumption of halocarbons, SF_6 and NF_3 were estimated for the CRD on the basis that other GHG emissions sources identified in the NIR are not likely to be occurring in the CRD. The sources of these GHG emissions are typically fridges, heat pumps, and air conditioners. To estimate Product Use GHG emissions for the CRD, a per capita estimate was developed using the Provincial emissions data from the 2021 NIR, and BC's NIR reporting year population from Statistics Canada. This value was applied to the 2020 reporting year population to estimate the total Product Use emissions for the CRD.

Between the 2007 and 2020 reporting years, IPPU GHG emissions have increased 68%. The reason for the increase is attributed to Environment and Climate Change Canada having better data available to make the estimate, than the actual GHG emissions increasing such an amount.

Table 36 Product Use GHG Emissions for the 2007 and 2020 Reporting Years

Sub-Sector	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change
Product Use Emissions	77,348	130,139	68.3%

5.4.5 Agriculture, Forestry, and Other Land Use

The AFOLU Sector includes GHG emissions from livestock, land use, and all other agricultural activities occurring within the CRD's boundaries.

The following information is provided for disclosure purposes only. Using remotely sensed imagery, land cover data was used to estimate land use changes between the reporting years. In 2020, the CRD's greenspace is estimated to have sequestered and stored 339,707 tCO_2e (Table 37), released 89,610 tCO_2e for a net effect of 244,972 tCO_2e. Upon review, the result was deemed to contradict expectations relative known trends of development in the region. Therefore it was excluded from the total inventory calculations.

Table 37 Summary of Land-Use Change in 2020

Land Type	Total Hectares (Ha)	GHG Emissions Sequestered (tCO_2e)	GHG Emissions Released (tCO_2e)
Forest Land	170,611.2	(311,402.2)	-
Cropland	6,044.8	(2,592.9)	-
Grassland	16,052.4	(43,783.8)	-
Wetlands	11,972.8	(41,928.1)	-
Settlements	12,938.0	-	46,066.8
Other Land	13,373.4	-	43,542.9
Total	**230,992.6**	**(399,707.0)**	**89,609.7**

5.4.5.1 Livestock and Other Agriculture

In addition to land use change, GHG emissions from the AFOLU Sector are produced through a variety of non-land use pathways, including livestock (enteric fermentation and manure management), and aggregate sources and non-CO_2 emission sources on land (e.g., fertilizer application). Under this Sector, the CRD is reporting on GHG emissions from the following sources, and Sub-Sectors:

- Scope 1 GHG Emissions:
  - Livestock:
    - Methane (CH_4) Emissions from Enteric Fermentation
    - Methane (CH_4) Emissions from Manure Management
    - Direct Nitrous Oxide (N_2O) GHG Emissions
  - Aggregate Sources and Non-CO_2 Emissions Sources on Land
    - Direct Nitrous Oxide (N_2O) Emissions from Agricultural Soil Management
    - Indirect Nitrous Oxide (N_2O) Emissions from Applied Nitrogen

Table 38 summarizes these other land-use GHG emissions for the 2020 reporting year. Compared to the 2007 base year, these GHG emissions have increased 25%.

Table 38 Total AFOLU GHG Emissions for 2020

AFOLU Sub-Sector	GHG Emissions (tCO_2e)
Livestock	3,545
Aggregate Sources And Non-CO_2 Emissions Sources On Land	715
Total	**4,261**

6.0 QUALITY ASSURANCE AND QUALITY CONTROL

Quality Assurance and Quality Control (QA/QC) procedures are applied to add confidence that all measurements and calculations have been made correctly and to reduce uncertainty in data. Examples include:

- Checking the validity of all data before it is processed, including emission factors
- Performing recalculations to reduce the possibility of mathematical errors
- Recording and explaining any adjustments made to the raw data
- Documenting quantification methods, assumptions, emission factors and data quality

With respect to the GHG inventory, the data was subject to various quality assurance and quality control checks throughout the collection, analysis, and reporting phases. Specifically, the following procedures were followed:

- Upon receipt of data from the CRD, the data was checked for completeness (e.g., all months of data are present), relevancy (e.g., the correct calendar year is presented), and reasonableness (e.g., comparing similar transportation data sets). Incorrect or incomplete datasets were queried directly with the data provider.
- Where estimates were used (e.g., fuel oil consumption), all possible data sources were considered for their accuracy and relevance to the community before a final method and data source was selected.
- All manual data transfers were double-checked for data transfer accuracy.
- The inventory was compared to other third party inventories (e.g. CEEI) to assess for reasonableness of the estimates.
- The inventory underwent internal CRD reviews to confirm assumptions, data and reasonableness of the estimates.

7.0 RECOMMENDATIONS

To remain accurate and reflective of the current community conditions, the CRD should revise and improve its GHG emissions inventory either annually or in line with capital planning cycles (i.e., every 3-4 years), to which there are the following aspects should be focused on:

- Improving activity data collection and management, including Sector and Sub-Sector allocations.
- Performing recalculations, where applicable, and tracking GHG emissions over time.
- Reviewing methodologies and data to assess for opportunities to improve the estimates.
- Assessing changes to boundaries, methodologies, assumptions or data that may be material and require a base year restatement.

The next section provides a summary of specific GHG inventory improvement recommendations.

7.1 INVENTORY ASSUMPTIONS, ASSESSMENT, AND RECOMMENDATIONS

In the preparation of the 2020 GHG emissions inventory, there are several assumptions were made in the analysis that will have some influence on accuracy of the CRD's estimate of GHG emissions. Most emission sources have been calculated with a high level of confidence, due to the presence of utility records, and direct energy and emissions data being provided by stakeholders. Data sources and assumptions with medium to high uncertainty are presented in Table 39 which summarizes the main assumptions, possible impacts on the data, and recommended improvement. It is recommended that the CRD prioritize improvements for that are likely to have a material (>5%) influence on the GHG inventory estimate.

Table 39 Summary of GHG Inventory Assumptions, Estimated Impacts, and Recommended Improvements

Sector	Assumption	Possible Impact on The GHG Inventory	Recommended Improvements
Stationary Energy	The energy utility providers provide energy in lump sum amounts for: residential, commercial, and industrial. As such, other sectors, like agricultural buildings, could not be split out. A related accuracy issue is the assignment of mixed use buildings without separate metering.	No impact on the GHG inventory. The change would only happen between emission sub-sectors.	Work with the utility provider to get a more detailed breakdown of energy use by sub-sector.

Table 39 Summary of GHG Inventory Assumptions, Estimated Impacts, and Recommended Improvements

Sector	Assumption	Possible Impact on The GHG Inventory	Recommended Improvements
Stationary Energy	Propane, fuel oil and wood GHG emissions were estimated based on 2007, 2010, and 2012 CEEI GHG emissions. for the District of Saanich and the City of Victoria, heating oil emissions were estimated based on the number of known tanks and the estimated square footage based on BC Assessment data, and the estimated average annual energy usage.	Immaterial impact on the GHG inventory (<5%)	Consider completing a residential energy labelling program. With such a program, an energy and fuel profile for buildings could be developed so that a reasonable estimate of other fuel use be determined. Work with the Province on developing a methodology to estimate wood fuel use.
Stationary Energy	FortisBC provided a total estimate of fugitive emissions for the CRD region for 2020; however, this did not include upstream fugitive emissions as suggested as best practice by the GPC Protocol.	Immaterial impact on the GHG inventory (<5%)	Work with FortisBC to refine this estimate.
Transportation	Taxable fuel volumes only represent about 67% of taxable fuel sales (a value that fluctuates yearly). Without more detailed information, a fuel allocation amount could not be allocated to the CRD. As such, the CRD had to rely on vehicle registration data from ICBC and estimated vehicle kilometers travelled (VKT). The CRD's 2016 Origin and Destination Study estimates total VKT data was considered but was deemed to likely result in significant underestimate of GHG emissions as the study estimates that light duty vehicles in the CRD travel less than 5,000 km per year. This is less than 1/3 of the national average. On this	Possibly material (>10%) impact to the GHG inventory. Using the estimated VKT data, it is likely that the CRD is over-estimating the GHG emissions from transportation. This is the most conservative approach available to the CRD at this point.	If the CRD can get complete fuel sales data for the Region, a more robust estimate of fuel use and GHG emissions, using vehicle registration data, can be determined. If the CRD can incorporate estimated travel data, in VKT through its next Origin Destination Survey, this data could be used to replace the 2009 study and be more specific to CRD and its members.

Table 39 Summary of GHG Inventory Assumptions, Estimated Impacts, and Recommended Improvements

Sector	Assumption	Possible Impact on The GHG Inventory	Recommended Improvements
	basis, the VKTs from a 2009 National vehicle travel study for Canada were applied.		
Transportation	The Victoria International Airport does not report on GHG emissions from tenants or aircraft. Keeping in line with the GPC Protocol, only the aircraft GHG emissions were estimated using NAV Canada airplane movement statistics, estimated taxi times, and estimated fuel use. The fuel use only accounts for departing and arriving planes up to 3,000ft to avoid double counting with other cities.	Immaterial impact on the GHG inventory (<5%)	The Victoria International Airport will not be collecting or reporting on GHG emissions from tenants or aircraft. This is the best available data at this point.
Transportation	The GHG emissions from recreational watercraft and US/Can ferries were estimated based on a publicly available year 2000 study for the Victoria, Vancouver, and Washington harbors.	Immaterial impact on the GHG inventory (<5%)	Work with the Victoria Harbor Master as they begin to deploy a database tracking the types and number of boats entering the Victoria harbor.
Transportation	The GHG emissions from marine aviation are estimated based on Victoria Harbor NAV Canada air traffic movements for 2016. Statistics Canada stopped collecting Victoria Harbor aircraft movement data in 2016. To estimate 2020 marine aviation GHG emissions, the 2016 data was applied and adjusted using the change in aircraft traffic between the 2016 and 2020 reporting years at the Victoria International Airport. It is assumed that the activity at both airports would be corelated, but not causational.	Immaterial impact on the GHG inventory (<5%)	No recommended improvement currently.

Table 39 Summary of GHG Inventory Assumptions, Estimated Impacts, and Recommended Improvements

Sector	Assumption	Possible Impact on The GHG Inventory	Recommended Improvements
Waste	There is tracking to the origin of solid waste but is based on reported origin which may or may not be accurate. For example, some haulers will identify that they are hauling waste from Victoria when in fact the waste is originating from Saanich.	There is no impact to the GHG Inventory for the CRD but will have impacts to the CRD member inventories.	Work with waste haulers to devise a better system to track waste origination.
IPPU	Product use emissions were estimated on a per capita basis using the 2021 NIR estimates. The product use emissions were estimated by the NIR using an IPCC Tier 1 approach and thus will have high uncertainty.	Immaterial impact on the GHG inventory (<5%)	No recommendations currently.
AFOLU	GHG estimates for land use change are based on a period of years (2011-2019) and thus were averaged for each period. As there was no current data, land use change for the reporting year was estimated using the average value between the data years.	Immaterial impact on the GHG inventory (<5%)	Work with the planning department to track land-use change annually so that a more refined estimate can be made.
AFOLU	The land-use sequestration and storage GHG emission factors are taken from the literature, for BC ecozones, and may not reflect the productivity, or lack thereof, of land uses in the CRD. The land-change emission factors for changes between land types were derived by the Province. These are average values by ecozone and are based on a 20-year horizon. Since land-use change in the CRD is typically related to development, it was assumed that the loss of emissions is immediate which may overestimate GHG emission	Possibly a material impact on the GHG inventory (>10%)	Work with the Province and the post-secondary institutions to derive refined sequestration emission factors.

Table 39 Summary of GHG Inventory Assumptions, Estimated Impacts, and Recommended Improvements

Sector	Assumption	Possible Impact on The GHG Inventory	Recommended Improvements
	losses. In both emission factor applications, the use of non-site emission factors may result in an over or underestimate of GHG emissions.		

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CAPITAL REGIONAL DISTRICT 2020 GPC BASIC+ COMMUNITY GREENHOUSE GAS (GHG) EMISSIONS INVENTORY REPORT

October 29, 2021

Stantec

APPENDIX B

Capital Region District – Municipalities and Electoral Areas
2007 Base Year and 2020 Reporting Year Energy & GHG Emissions Inventory

Prepared for:

Capital Regional District
625 Fisgard Street, PO Box 1000
Victoria, BC V8W 2S6

Prepared by:

Stantec Consulting Ltd.
200-325 25 Street SE
Calgary, AB T2A 7H8

Date: October 29, 2021

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SUMMARY

Climate change has emerged as the next unprecedented social, economic, and environmental challenge facing society today. It poses a serious threat to quality of life, jobs, and physical and natural assets. Scientists believe that the human-production of greenhouse gas (GHG) emissions since pre-industrial times have already surpassed the Earth's "carrying capacity" of natural systems and pose significant future risks to human well-being.

Recognizing the role that Capital Regional District (CRD) plays in achieving a significant and immediate reduction in global GHG emissions, the CRD set a regional GHG reduction target of 61% (from 2007 levels) by 2038. In February 2019, the CRD declared a climate emergency and committed to regional carbon neutrality. Local governments across the region have also set similar ambitious GHG reduction targets and commitments.

To meet these climate commitments, the CRD seeks a better understanding of the energy and GHG emissions at the regional level, as well as at the local government level which includes 13 municipalities and 3 electoral areas. The following document presents a summary of energy and GHG emissions at both the CRD and local government level for the 2007 and 2020 reporting years. This document compliments a 2020 inventory report which describes the methodologies and data sources applied to derive the estimate of GHG emissions for the CRD and local governments. A summary of the 2007 and 2020 energy and GHG emissions by local government is presented in **Table 1** and **Table 2**.

Table 1. Summary of GHG Emissions By CRD Local Government

Local Government	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
District of Central Saanich	97,077	96,437	-0.7%
City of Colwood	82,439	76,591	-7.1%
Township of Esquimalt	96,314	80,712	-16.2%
District of Highlands	11,358	14,614	28.7%
Juan de Fuca Electoral Area	62,493	69,270	10.8%
City of Langford	134,791	165,160	22.5%
District of Metchosin	27,015	20,624	-23.7%
District of North Saanich	63,747	54,424	-14.6%
District of Oak Bay	90,483	76,427	-15.5%
District of Saanich	582,422	486,037	-16.5%
Salt Spring Island Electoral Area	48,689	42,920	-11.8%
Town of Sidney	62,744	53,276	-15.1%
District of Sooke	51,194	55,790	9.0%
City of Victoria	484,582	408,761	-15.6%
Town of View Royal	49,949	54,477	9.1%
Southern Gulf Islands Electoral Area	30,803	27,730	-10.0%

Table 2. Summary of Energy Use By CRD Local Government

Local Government	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)
District of Central Saanich	1,867,417	1,903,819	1.9%
City of Colwood	1,533,734	1,487,893	-3.0%
Township of Esquimalt	1,784,465	1,565,499	-12.3%
District of Highlands	217,328	291,021	33.9%
Juan de Fuca Electoral Area	1,282,178	1,399,797	9.2%
City of Langford	2,594,734	3,335,434	28.5%
District of Metchosin	513,449	436,613	-15.0%
District of North Saanich	1,323,026	1,234,114	-6.7%
District of Oak Bay	1,664,925	1,484,989	-10.8%
District of Saanich	11,054,201	9,457,076	-14.4%
Salt Spring Island Electoral Area	1,058,268	1,002,959	-5.2%
Town of Sidney	1,234,379	1,096,986	-11.1%
District of Sooke	961,620	1,114,759	15.9%
City of Victoria	9,852,916	8,467,486	-14.0%
Town of View Royal	962,988	1,080,921	12.2%
Southern Gulf Islands Electoral Area	754,738	704,290	-6.7%

1 INTRODUCTION

1.1 GHG Emissions & Climate Change

There is overwhelming evidence that global climate change resulting from emissions of carbon dioxide and other greenhouse gases (GHGs) is having a significant impact on the ecology of the planet. In addition, climate change is expected to have serious negative impacts on global economic growth and development. In 2005, the UK government commissioned an independent economic review called the Stern Review, which states that the *"costs of stabilizing the climate are significant but manageable; delay would be dangerous and much more costly"*.

Beyond the costs associated with delayed action, there are cost savings to be realized through efforts to conserve energy and to use it more efficiently, and economic opportunities available to communities that develop local energy supply and infrastructure. Actions to encourage energy efficiency and conservation and to promote implementation of renewable energy will assist local governments in developing energy resilient communities, in addition to mitigating climate change. Local governments are at the forefront of global action on climate change, setting both ambitious commitments and targets while going about the difficult task of reducing emissions. Per the latest report from the C40 Cities Climate Leadership Group, ICLEI Local Governments for Sustainability, UN Habitat, and others, most GHG reduction commitments are set for 2020 or 2050 and range from a 10% to 100% reduction (**Figure 1**).

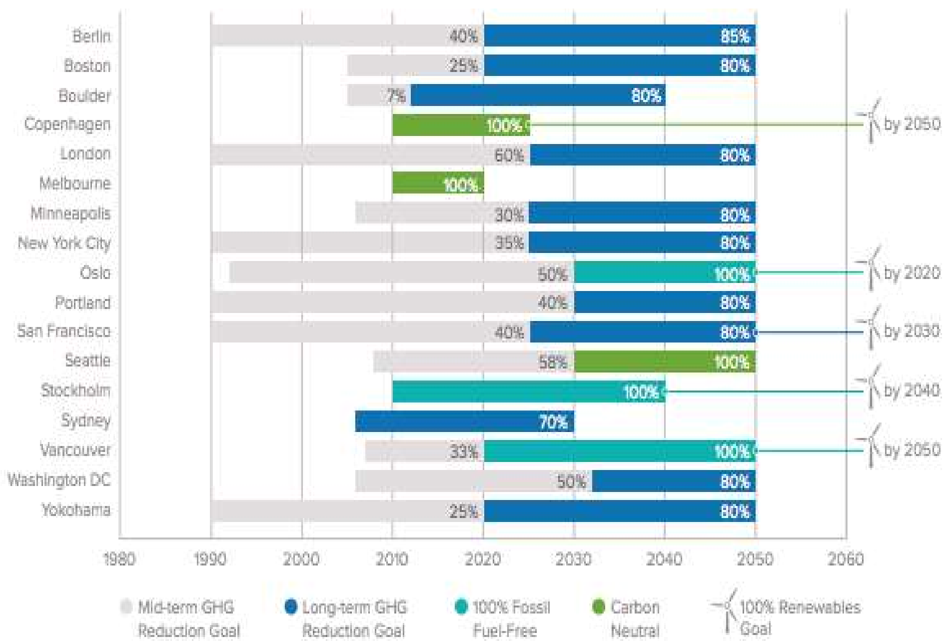


Figure 1. Summary of Long-Term Global GHG Emission Reduction Targets[1]

[1] http://www.c40.org/

1.2 GPC Protocol

To make informed decisions on reducing energy use and GHG emissions at the regional and local government scale, community managers must have a good understanding of these sources, the activities that drive them, and their relative contribution to the total. This requires the completion of an energy and GHG emissions inventory. To allow for credible and meaningful reporting locally and internationally, the Global Protocol for Community-Scale Greenhouse Gas Emission Inventories (the GPC Protocol) was developed as a partnership between ICLEI-Local Governments for Sustainability, The World Resources Institute (WRI) and C40 Cities Climate Leadership Group (C40), with additional collaboration by the World Bank, United Nations Environment Program (UNEP) and UN-Habitat. The GPC Protocol has now become recognized as the standardized way for local governments to collect and report their actions on climate change. Over 9,000 cities have committed to using the GPC Protocol.

The Protocol has two established levels of reporting: BASIC and BASIC+ which are defined as the following:

- The BASIC level covers scope 1 and scope 2 emissions from stationary energy and in-boundary transportation, as well as scope 1 and scope 3 emissions from waste.
- The BASIC+ level covers the same scopes as BASIC and includes more in-depth and data dependent methodologies. Specifically, it expands the reporting scope to include emissions from industrial process and product use (IPPU), agriculture, forestry and other land-use (AFOLU), and transboundary transportation.

1.3 Variance from Community Energy and Emissions Inventories (CEEI)

The CRD has historically relied on the Provincial 2007, 2010 and 2012 Community Energy and Emissions Inventories (CEEI) to baseline and track community GHG emissions. However, there have been some limitations to the CEEI in that it is an in-boundary inventory, the most recent version published is for 2012, and the CEEI Protocol does not fully meet the requirements of the GPC Protocol BASIC or BASIC+ reporting requirements which is the required reporting standard for local governments that have committed to the Global Covenant of Mayors—an agreement led by city networks to undertake a transparent and supportive approach to measure GHG emissions community-wide. A high-level summary of the differences between the CEEI and GPC Protocol inventories are presented in **Table 3**.

Table 3. Summary of GHG Inventory Scope Differences

Reporting Sector	CEEI	GPC BASIC	GPC BASIC+
Residential Buildings	✓	✓	✓
Commercial And Institutional Buildings And Facilities	✓	✓	✓
Manufacturing Industries And Construction	✓	✓	✓
Energy Industries		✓	✓
Energy Generation Supplied To The Grid		✓	✓
Agriculture, Forestry And Fishing Activities		✓	✓
Non-Specified Sources		✓	✓

Reporting Sector	CEEI	GPC BASIC	GPC BASIC+
Fugitive Emissions From Mining, Processing, Storage, And Transportation Of Coal		✓	✓
Fugitive Emissions From Oil And Natural Gas Systems		✓	✓
On-Road Transportation	✓	✓	✓
Railways		✓	✓
Waterborne Navigation		✓	✓
Aviation		✓	✓
Off-Road Transportation		✓	✓
Solid Waste	✓	✓	✓
Biological Waste	✓	✓	✓
Incinerated And Burned Waste		✓	✓
Wastewater		✓	✓
Emissions From Industrial Processes			✓
Emissions From Product Use			✓
Emissions From Livestock	✓		✓
Emissions From Land			✓
Emissions From Aggregate Sources And Non-CO_2 Emission Sources On Land	✓		✓

1.4 Purpose of Document

The purpose of this document is to provide the 2007 and 2020 GPC BASIC+ energy and GHG emissions inventories at the regional and local government level. This document compliments a 2020 inventory report which describes the methodologies and data sources applied to derive the estimate of GHG emissions for the CRD region and local governments.

2 INVENTORY SCOPE

2.1 GPC BASIC+ Inventory Scope

In accordance with the GPC Protocol, the 2007 and 2020 BASIC+ GHG inventories presented herein accounts for GHG emissions from the following Reporting Sectors:

- **Stationary Energy** – These are GHG emissions from fuel combustion, fugitive emissions, and some off-road transportation sources (e.g. construction equipment, residential mowers, etc.). They include the emissions from energy to heat and cool residential, commercial, institutional, and light/heavy industrial buildings, as well as the activities that occur within these residences and facilities.
- **Transportation** – These are GHG emissions from the combustion of fuels as a result of vehicular on-road, off-road, including marine, aviation, and other off-road, and trans-boundary journeys.
- **Waste** – These are GHG emissions from the disposal and management of solid waste, the biological treatment of waste, and wastewater treatment and discharge. Waste does not directly consume energy, but releases GHG emissions because of decomposition, burning, and other management methods.
- **Industrial Process and Product Use (IPPU)** – These are GHG emissions from products such as refrigerants, foams or aerosol cans can release potent GHG emissions, known as product use GHG emissions. There are no known industrial process emissions in the CRD.
- **Agriculture, Forestry and Other Land-Use (AFOLU)** – These are GHG emissions that are captured or released as a result of land-management activities. These activities can range from the preservation of forested lands to the development of crop land. This Sector includes GHG emissions from land-use change, manure management, livestock, and the direct and indirect release of nitrous oxides (N_2O) from soil management, urea application, fertilizer and manure application.

  Due to limitations in how to quantify GHG emissions resulting from land use change (e.g., residential development), these GHG emissions have been excluded from the GHG emissions inventories presented herein but have been disclosed.

2.2 GHG Emissions Boundary

The GHG inventories are defined geographically by the CRD, which includes 13 municipalities and 3 electoral areas, as shown in Figure 2.

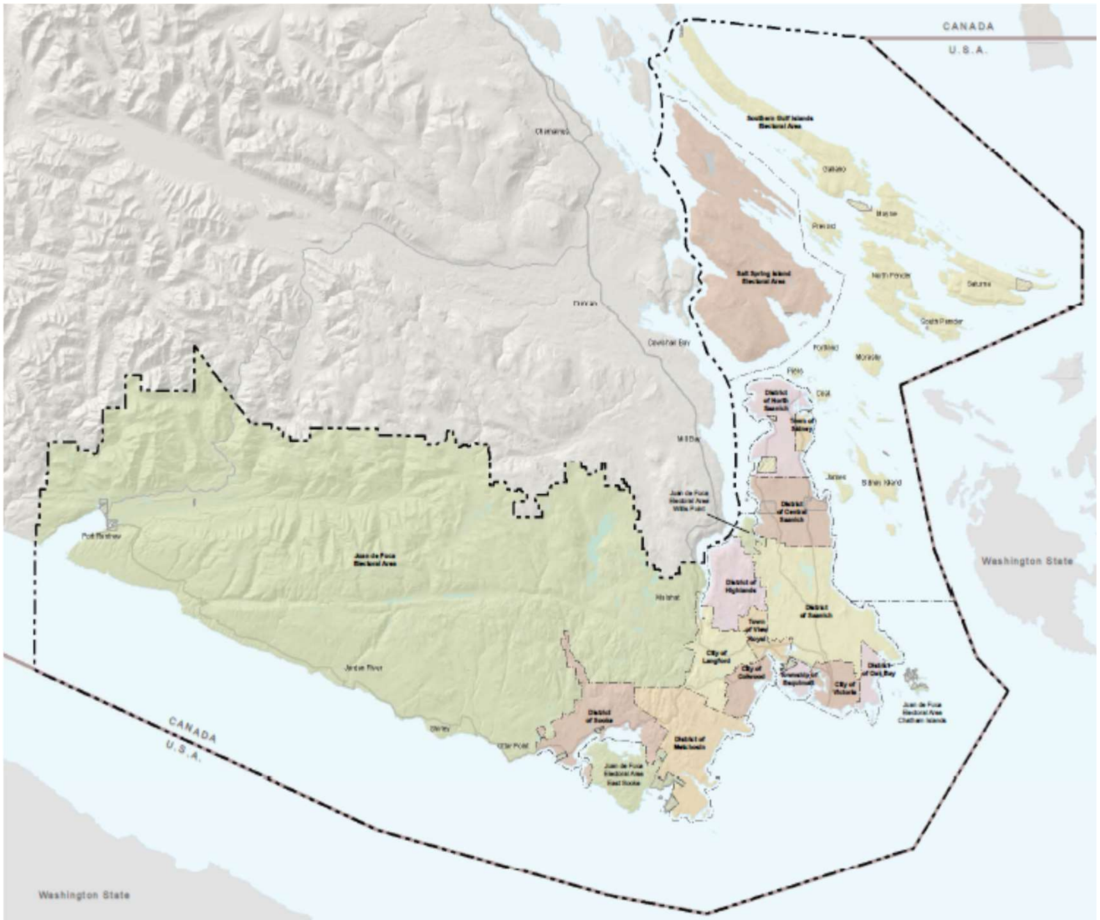


Figure 2 CRD GHG Boundary

2.3 Assumptions & Disclosures

The following inventories covers all GHG emissions for the 2007 and 2020 reporting years. Where data was not available, the most recent year's data have been used, and the timescale noted accordingly. These disclosures are as follows:

- **Global Warming Potentials (GWP)**. The BC government is currently applying GWPs from the fourth IPCC report despite the fact that there are updated GWPs in available in the fifth IPCC report. On this basis, the CRD is applying GWPs from the fourth IPCC report.
- **Stationary Energy: Emission Factors.** The BC Government updated 2010-2020 electricity emission factors to include emissions from imported electricity resulting in a 5-10% increase in GHG emissions intensities. Since there was no update to the 2007, the BC Government has suggested utilizing the 2010 emission factor for 2007.

- **Stationary Energy: Electricity Data.** In 2019, the Province of BC received updated electricity data for 2007-2018 as a systematic error was uncovered across all years of BC Hydro data. The 2007 inventory was updated with the corrected information.
- **Stationary Energy: Residential, Commercial and Institutional Buildings**. Propane, and wood GHG emissions were estimated using linear regression methods. The data used in the estimates included historical propane and wood energy data published in the 2007, 2010 and 2012 CEEIs, and heating degree days (HDD) published by Environment and Climate Change Canada. This approach was also applied to the estimate of heating oil for all local governments, except the City of Victoria and District of Saanich. For the District of Saanich and the City of Victoria, heating oil GHG emissions were estimated based on the number of known tanks, average heated floor areas and fuel volume intensity.
- **Stationary Energy: Fugitives**. Fortis BC provided total fugitive emissions for the 2020 reporting year at the CRD level. Since no historical numbers were provided, the 2020 value was applied to the 2007 base year as well.
- **Transportation: On-Road**. The on-road transportation emissions are based on the total estimated fuel sales in the CRD, and the number of registered vehicles. Insurance Corporation of BC (ICBC) compiles data on an April 1 to March 31 basis, and thus the current on-road GHG emission estimate is based on the number of registrations from April 1, 2020 – March 31, 2021.
- **Transportation: Aviation.** 2020 aviation GHG emissions were estimated using 2015 aircraft flight profiles (the last available data), and the total number of aircraft movements reported in 2020.
- **Transportation: Waterborne Recreational Watercraft.** GHG emissions from recreational watercraft and US/Canada ferries were estimated based on a publicly available year 2000 study for the Victoria, Vancouver, and Washington harbors.
- **Transportation: Ferries.** BC Ferries did not disclose its total reported fuel use for 2020 but did publish that fuel consumption volumes fell by approximately 40% as compared to the 2019 reporting year. As such, the 2019 fuel volumes and the 40% factor were applied to estimate 2020 fuel volumes.
- **Transportation: Cruise Ships.** The Greater Victoria Harbour Authority (GVHA) reported on cruise ship emissions for the 2010 and 2018 reporting years but did not provide an estimate for 2007. As a result, the 2010 GHG emissions estimate and number of cruise ship visits to Ogden Point was used to create a proxy to estimate 2007 cruise ship emissions. The GVHA reported 163 visits in 2007. As a result of COVID-19 restrictions, there were no cruise ships in 2020.
- **Waste: Solid Waste.** To quantify GHG emissions from the Hartland Landfill, the CRD utilized the waste-in-place (WIP) method which is accepted under the GPC Protocol. The WIP assigns landfill emissions based on total waste deposited during that year. It counts GHGs emitted that year, regardless of when the waste was disposed. Except for the City of Victoria, who claims 31% of the CRD's landfill GHG emission, the remaining landfill GHG emissions were allocated to each local government on a per capita basis. Using this allocation method, the CRD members may over, or underestimate associated solid waste GHG emissions as the current year landfill GHG emissions are based upon cumulative waste over time, and each member may have contributed more waste in past years than the current year (and vice versa).
- **AFOLU: Aggregate Sources And Non-CO_2 Emission Sources On Land.** These emissions are based on the 2021 NIR as prepared by ECCC and the total area of

farmland BC in 2016 as reported by Statistics Canada. These GHG emissions were assigned to each local government on a per hectare (ha) of cropland basis.

- **AFOLU: Land-Use.** The land cover change analysis requires a consistent land-use category attribution and spatial data. For parts of the CRD, spatial data was available for the 2007, 2011 and 2019 reporting years. Differences between these data sets in terms of resolution and their timing of collection increase the uncertainty as to the accuracy of the land-use classifications. For example, the 2007 and 2011 land use data was collected at different times of the year and may not accurately reflect tree cover. Furthermore, no land use spatial data was collected the Juan de Fuca, Salt Spring Island and Gulf Islands and thus Annual Crop Inventory (ACI) settlement data collected by Agriculture Canada was used to inform the analysis. The challenge in utilizing this data is that it is provided in a 30m resolution. Furthermore, since annual data is not available, the change between land cover data years (2007-2011, 2011-2019) for all areas was averaged and may not represent actual changes in each year. Since no data was available for 2020, the 2019 estimates were applied.

Details surrounding all GHG emissions sources quantification methods, assumptions, and assessment of uncertainties are contained in a complimentary GHG emissions methodology document and are not presented herein.

3 CAPITAL REGIONAL DISTRICT ENERGY & GHG EMISSIONS

3.1 Base Year (2007) Energy & GHG Emissions

In 2007, the CRD's GHG BASIC+ emissions totaled 1,976,100 tCO_2e. Buildings are the CRD's second largest GHG emissions source at 35%, with 40% of those GHG emissions coming from natural gas for heating and cooling, 21% from heating oil for heating, 17% from electricity use, 7% from wood and propane use for heating and the remainder from other-related off-road activities like residential lawn mowing. On-road transportation GHG emission sources contributed 45% to the GHG inventory, almost all of which came from passenger vehicles, light trucks, and SUVs (83%). Off-road transportation, which includes marine, aviation, and other off-road emission sources contributed 7% to the overall GHG inventory. Solid waste, organic waste treatment methods, and wastewater treatment and discharge accounted for 7% of the total community GHG emissions. IPPU emissions accounted for 4% of total GHG emissions while AFOLU GHG emissions resulted for less than 1% of community GHG emissions.

A summary of the GHG emissions by sector and energy use by source is presented in the following table and figures.

Table 4. Base Year (2007) CRD Regional GHG Energy & GHG Emissions by Source

Source	Type	Consumption	Units	Energy (GJ)	GHG Emissions (tCO_2e)
Stationary Energy					
Residential Buildings	Electricity	2,102,967	MWh	7,570,620	75,076
	Natural Gas	2,639,980	GJ	2,639,980	131,649
	Fuel Oil	83,335	L	2,147,821	146,859
	Propane	10,747	L	424,600	25,882
	Wood	1,144,369	GJ	1,144,369	26,872
	Diesel	6,750,851	L	261,123	19,468
Commercial & Industrial Buildings	Electricity	1,367,919	MWh	4,924,469	48,835
	Natural Gas	3,352,456	GJ	3,352,456	167,179
	Fuel Oil	6,272	L	161,638	11,052
	Diesel	12,173,666	L	470,877	35,106
Energy Industries	LFG Combustion				6,956
Agriculture, Forestry And Fishing Activities	Diesel	21,520,635	L	832,418	62,060
Natural Gas Fugitive Emissions					1,003
Total				**23,930,370**	**751,459**
On-Road Transportation					
Electric Vehicles	Electricity	51,201	MWh	0	0

Source	Type	Consumption	Units	Energy (GJ)	GHG Emissions (tCO_2e)
Hydrogen Vehicles	Hydrogen	0	L	0	0
Passenger Vehicles	Gasoline + Diesel	163,062,222	L	5,673,042	384,119
Light Trucks, Vans, SUVs	Gasoline + Diesel	142,617,615	L	5,003,722	343,341
Heavy Duty Vehicles	Gasoline + Diesel	59,156,416	L	2,230,995	150,544
Propane Vehicles	Propane	1,322,222	L	33,756	2,035
Natural Gas Vehicles	Natural Gas	0	kg	0	0
Motorcycles	Gasoline	1,208,124	L	41,874	2,885
Total On-Road Transportation				**12,983,390**	**882,924**
Off-Road Transportation					
Marine, Aviation and Other Off-Road Vehicles	Marine Gasoline + Marine Diesel + Jet Fuel	46,196,808	L	1,746,608	130,656
Total Off-Road Transportation				**1,746,608**	**130,656**
Waste					
Wastewater					18,998
Composting					72
Solid Waste					111,234
Total Waste					**130,304**
Agriculture Forestry & Other Land Use (AFOLU)					
Land-Use: Emissions Sequestered **(Disclosure Only - Not Included In Total)**					-396,487
Land-Use: Emissions Released **(Disclosure Only - Not Included In Total)**					151,516
Livestock, Aggregate Sources and Non-CO_2 Emission Sources on Land					3,408
Total AFOLU					**3,408**
Industrial Process & Product Use (IPPU)					
Process Use Emissions					77,348
Total IPPU					**77,348**
TOTAL				**38,660,368**	**1,976,100**
TOTAL Per Capita				**110.0**	**5.6**

Energy consumption and GHG emissions by source are shown in **Figure 3**, **Figure 4** and **Figure 5**. On-road and transboundary transportation (82%) account for most of the energy consumption in the region.

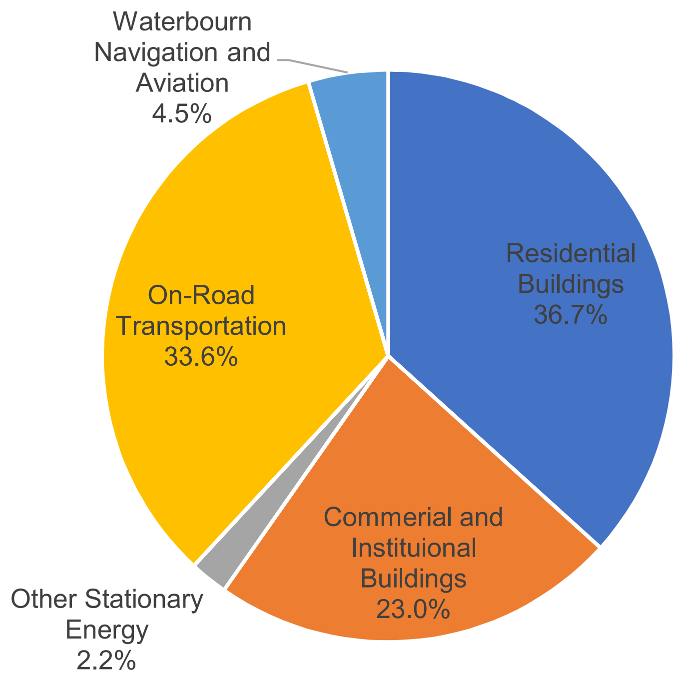


Figure 3. 2007 Regional Energy Consumption By Sector

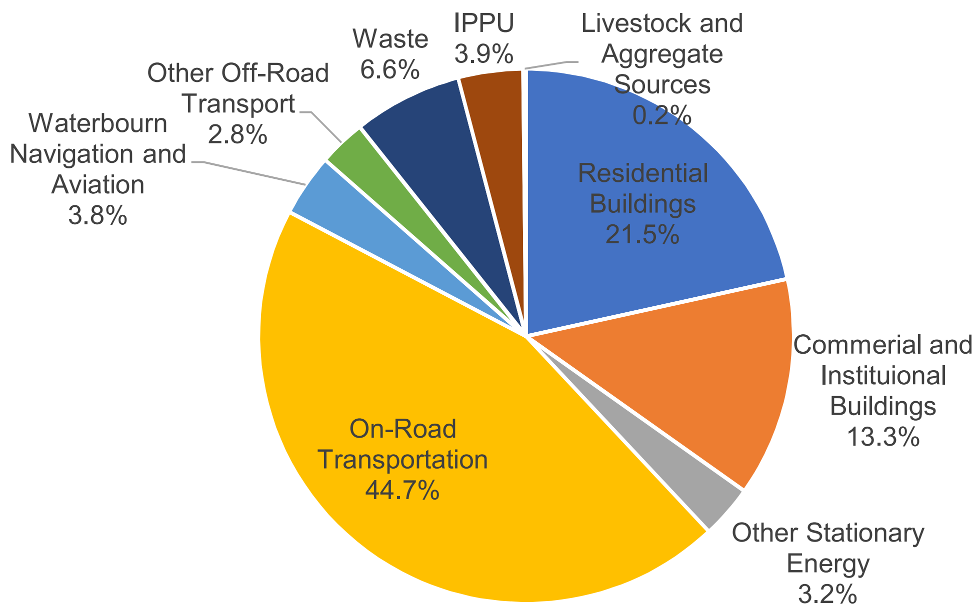


Figure 4. 2007 Regional GHG Emissions By Sector

GHG emissions by fuel type is presented in **Figure 5**.

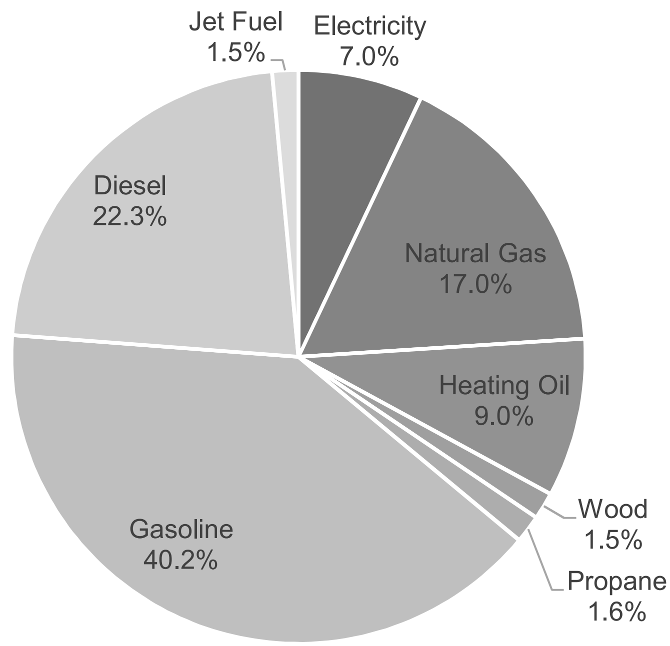


Figure 5. 2007 Regional GHG Emissions By Fuel Type

3.2 CRD GHG Reduction Target

Recognizing the role that the CRD plays in achieving a significant and immediate reduction in global GHG emissions, the CRD has set a regional GHG reduction target of 61% (from 2007 levels) by 2038. With the CRD's 2007 base year GHG emissions being 1,976,100 tCO_2e, a 39% reduction would require a reduction of approximately 770,679 tCO_2e. On a per capita basis, this amounts to reducing emissions from approximately 4.3 tCO_2e per person in 2020 to 2.4 tCO_2e per person by 2038.

In February 2019, the CRD declared a climate emergency and committed to regional carbon neutrality.

3.3 Reporting Year (2020) Energy & GHG Emissions

In 2020, the CRD's BASIC+ GHG emissions totaled 1,785,814 $tCO_{2.}$ On an absolute basis, this is a 10% decline from the 2007 base year GHG emissions and a decline of 24% on a per capita basis. The 2020 energy and GHG emissions year was not typical in terms of energy and GHG emissions largely due to COVID-19 restrictions and associated closures.

Similar to the 2007 base year, buildings are the second largest GHG emissions source at 40%, with 44% of those GHG emissions coming from natural gas for heating and cooling, 19% from heating oil for heating, 17% from electricity use, 6% from wood and propane use for heating and the remainder from other-related off-road activities like residential lawn mowing. On-road transportation GHG emission sources contributed 44%, almost all of which came from passenger vehicles, light trucks, and SUVs (82%). Off-road transportation, which includes marine, aviation, and other off-road emission sources contributed 5% to the overall GHG inventory. Solid waste, organic waste treatment methods, and wastewater treatment and discharge accounted for 5% of the total community GHG emissions. IPPU emissions accounted for 7% of total GHG emissions while AFOLU GHG emissions contributed to less than 1% of community GHG emissions.

A summary of the 2020 GHG emissions by sector and energy use by source is presented in the following table and figures.

Table 5. Reporting Year (2020) CRD Regional GHG Energy & GHG Emissions by Sector

Source	Type	Consumption	Units	Energy (GJ)	GHG Emissions (tCO_2e)
Stationary Energy					
Residential Buildings	Electricity	2,085,498	MWh	7,507,733	83,628
	Natural Gas	2,567,162	GJ	2,567,162	128,018
	Fuel Oil	77,480	L	1,996,899	136,540
	Propane	8,782	L	346,989	21,219
	Wood	960,568	GJ	960,568	22,556
	Diesel	5,503,439	L	212,873	14,934
Commercial & Industrial Buildings	Electricity	1,261,996	MWh	4,543,149	50,606
	Natural Gas	4,202,648	GJ	4,202,648	209,576
	Fuel Oil	5,549	L	143,003	9,778
	Diesel	12,216,854	L	472,548	33,152
Energy Industries	LFG Combustion				9,563
Agriculture, Forestry And Fishing Activities	Diesel	20,790,676	L	804,183	56,418
Natural Gas Fugitive Emissions					1,408
Total				**23,757,755**	**777,397**
On-Road Transportation					
Electric Vehicles	Electricity	124,712	MWh	62,328	694
Hydrogen Vehicles	Hydrogen	0	L	0	0
Passenger Vehicles	Gasoline + Diesel	89,922,529	L	3,125,089	195,999
Light Trucks, Vans, SUVs	Gasoline + Diesel	166,980,928	L	5,845,129	371,982
Heavy Duty Vehicles	Gasoline + Diesel	52,705,103	L	1,968,957	124,065
Propane Vehicles	Propane	628,682	L	16,050	911
Natural Gas Vehicles	Natural Gas	785,220	kg	42,240	2,282
Motorcycles	Gasoline	1,074,790	L	37,252	2,415
Total On-Road Transportation				**11,097,044**	**698,348**
Off-Road Transportation					
Marine, Aviation and Other Off-Road Vehicles	Marine Gasoline + Marine Diesel + Jet Fuel	31,750,577	L	1,208,859	86,527
Total Off-Road Transportation				**1,208,859**	**86,527**

Source	Type	Consumption	Units	Energy (GJ)	GHG Emissions (tCO_2e)
Waste					
Wastewater					15,035
Composting					5,307
Solid Waste					66,237
Total Waste					**86,580**
Agriculture Forestry & Other Land Use (AFOLU)					
Land-Use: Emissions Sequestered **(Disclosure Only - Not Included In Total)**					-399,707
Land-Use: Emissions Released **(Disclosure Only - Not Included In Total)**					89,610
Livestock, Aggregate Sources and Non-CO_2 Emission Sources on Land					4,261
Total AFOLU					**4,261**
Industrial Process & Product Use (IPPU)					
Process Use Emissions					130,139
Total IPPU					**130,139**
TOTAL				**36,063,658**	**1,783,251**
TOTAL Per Capita				**85.9**	**4.2**

Energy consumption and GHG emissions by source are shown in **Figure 6**, **Figure 7** and **Figure 8**.

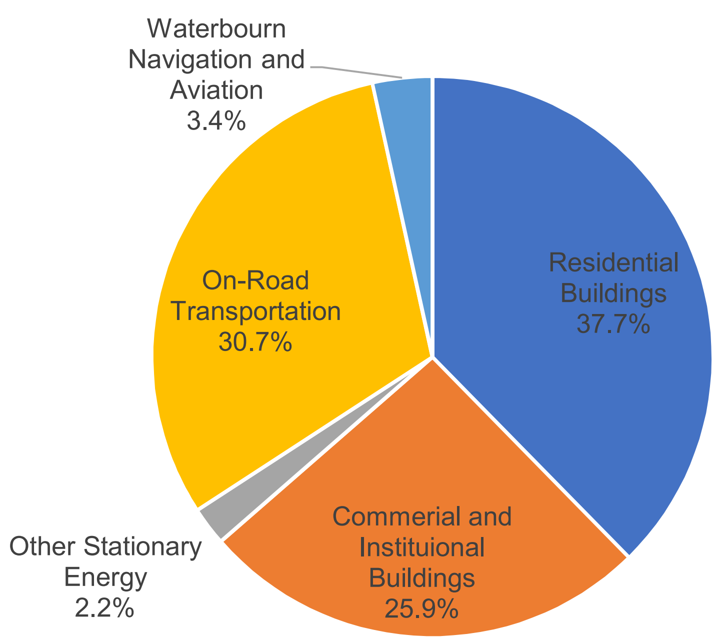


Figure 6. 2020 Regional Energy Consumption By Sector

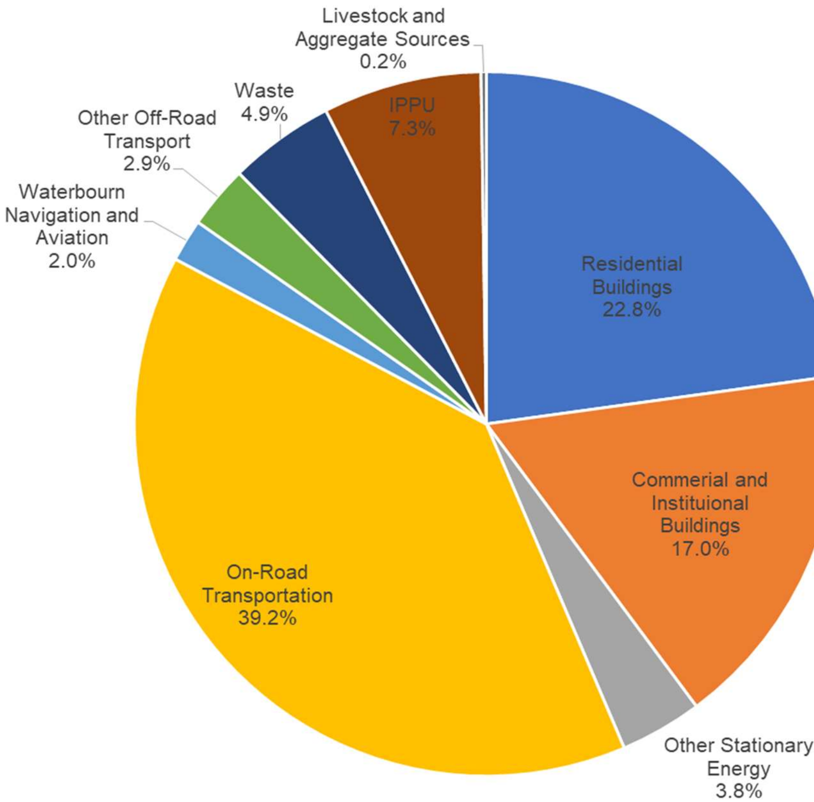


Figure 7. 2020 Regioanal GHG Emissions By Sector

GHG emissions by fuel type is presented in **Figure 8**.

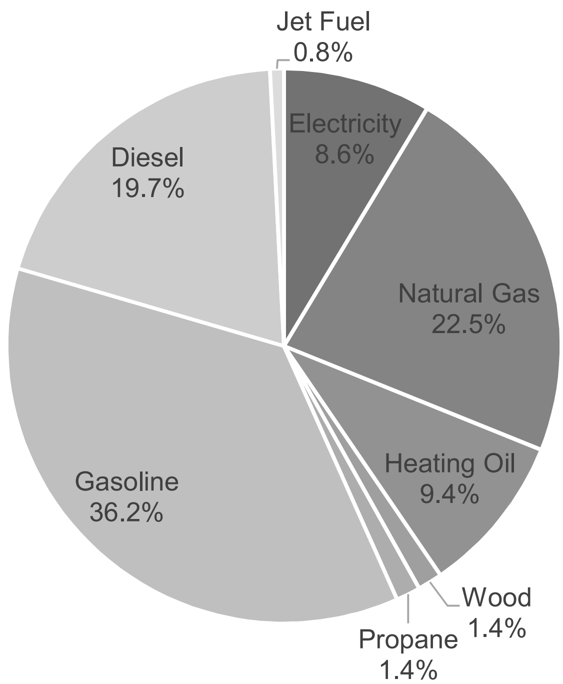


Figure 8. 2020 Regional GHG Emissions By Fuel Type

3.4 Energy & GHG Emissions Trends

Table 6 presents the changes between the 2007 and 2020 reporting years, showing that GHG emissions decreased in most reporting sectors. There were decreases in energy consumption in the stationary energy and transportation sectors as a result of COVID-19 restrictions. While there was a corresponding decrease in transportation GHG emissions, there was a slight increase in GHG emissions in the stationary energy sector simply due to the electricity grid emissions factor increasing by approximately 13% from 2007.

There was an increase in composting emissions which is the direct result of waste diversion programs which result in some direct GHG emissions, but overall have a net reduction impact as the process avoids releasing more fugitive methane emissions from the landfill. Total waste emissions declined 34% from the base year as a result.

IPPU GHG emissions increased as these GHG emissions are driven by population and increased by 68%. AFOLU GHG emissions, which accounted for livestock, aggregate sources and non-CO_2 emission sources on land, increased 25%.

Table 6. Change in CRD GHG Energy & GHG Emissions

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Stationary Energy							
Residential Buildings	Electricity	7,570,620	7,507,733	-0.8%	75,076	83,628	11.4%
	Natural Gas	2,639,980	2,567,162	-2.8%	131,649	128,018	-2.8%
	Fuel Oil	2,147,821	1,996,899	-7.0%	146,859	136,540	-7.0%
	Propane	424,600	346,989	-18.3%	25,882	21,219	-18.0%
	Wood	1,144,369	960,568	-16.1%	26,872	22,556	-16.1%
	Diesel	261,123	212,873	-18.5%	19,468	14,934	-23.3%
Commercial & Industrial Buildings	Electricity	4,924,469	4,543,149	-7.7%	48,835	50,606	3.6%
	Natural Gas	3,352,456	4,202,648	25.4%	167,179	209,576	25.4%
	Fuel Oil	161,638	143,003	-11.5%	11,052	9,778	-11.5%
	Diesel	470,877	472,548	0.4%	35,106	33,152	-5.6%
Energy Industries	LFG Combustion			-	418	9,563	2186.5%
Agriculture, Forestry And Fishing Activities	Diesel	832,418	804,183	-3.4%	62,060	56,418	-9.1%
Natural Gas Fugitive Emissions				-	1,003	1,408	40.4%
Total		**23,930,370**	**23,757,755**	**-0.7%**	**751,459**	**777,397**	**3.5%**
On-Road Transportation							
Electric Vehicles	Electricity	-	62,328	-	-	694	-
Hydrogen Vehicles	Hydrogen	-	-	-	-	-	-
Passenger Vehicles	Gasoline + Diesel	5,673,042	3,125,089	-44.9%	384,119	195,999	-49.0%
Light Trucks, Vans, SUVs	Gasoline + Diesel	5,003,722	5,845,129	16.8%	343,341	371,982	8.3%
Heavy Duty Vehicles	Gasoline + Diesel	2,230,995	1,968,957	-11.7%	150,544	124,065	-17.6%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Propane Vehicles	Propane	33,756	16,050	-52.5%	2,035	911	-55.3%
Natural Gas Vehicles	Natural Gas	-	42,240	-	-	2,282	-
Motorcycles	Gasoline	41,874	37,252	-11.0%	2,885	2,415	-16.3%
Total On-Road Transportation		**12,983,390**	**11,097,044**	**-14.5%**	**882,924**	**698,348**	**-20.9%**
Off-Road Transportation							
Marine, Aviation and Other Off-Road Vehicles	Gasoline + Diesel + Jet Fuel	1,746,608	1,242,888	-28.8%	130,656	89,090	-31.8%
Total Off-Road Transportation		**1,746,608**	**1,208,859**	**-31.8%**	**130,656**	**86,527**	**-33.8%**
Waste							
Wastewater					18,998	15,035	-20.9%
Composting					72	5,307	7235.5%
Solid Waste					111,234	66,237	-40.5%
Total Waste					**130,304**	**86,580**	**-33.6%**
Agriculture Forestry & Other Land Use (AFOLU)							
Land-Use: Emissions Sequestered **(Disclosure Only - Not Included In Total)**					-396,487	-399,707	0.8%
Land-Use: Emissions Released **(Disclosure Only - Not Included In Total)**					151,516	89,610	-40.9%
Livestock, Aggregate Sources and Non-CO_2 Emission Sources on Land					3,408	4,261	25.0%
Total AFOLU					**3,408**	**4,261**	**25.0%**
Industrial Process & Product Use (IPPU)							
Process Use Emissions					77,348	130,139	68.3%
Total IPPU					**77,348**	**130,139**	**68.3%**
TOTAL		**38,660,368**	**36,097,687**	**-6.6%**	**1,976,100**	**1,785,814**	**-9.6%**

Table 7 presents the changes between the 2007 and 2020 years for each CRD local government.

Table 7. Change in Member GHG Energy & GHG Emissions

Member	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
District of Central Saanich	1,867,417	1,903,819	1.9%	97,077	96,437	-0.7%
City of Colwood	1,533,734	1,487,893	-3.0%	82,439	76,591	-7.1%
Township of Esquimalt	1,784,465	1,565,499	-12.3%	96,314	80,712	-16.2%
District of Highlands	217,328	291,021	33.9%	11,358	14,614	28.7%
Juan de Fuca Electoral Area	1,282,178	1,399,797	9.2%	62,493	69,270	10.8%
City of Langford	2,594,734	3,335,434	28.5%	134,791	165,160	22.5%
District of Metchosin	513,449	436,613	-15.0%	27,015	20,624	-23.7%
District of North Saanich	1,323,026	1,234,114	-6.7%	63,747	54,424	-14.6%
District of Oak Bay	1,664,925	1,484,989	-10.8%	90,483	76,427	-15.5%
District of Saanich	11,054,201	9,457,076	-14.4%	582,422	486,037	-16.5%
Salt Spring Island Electoral Area	1,058,268	1,002,959	-5.2%	48,689	42,920	-11.8%
Town of Sidney	1,234,379	1,096,986	-11.1%	62,744	53,276	-15.1%
District of Sooke	961,620	1,114,759	15.9%	51,194	55,790	9.0%
City of Victoria	9,852,916	8,467,486	-14.0%	484,582	408,761	-15.6%
Town of View Royal	962,988	1,080,921	12.2%	49,949	54,477	9.1%
Southern Gulf Islands Electoral Area	754,738	704,290	-6.7%	30,803	27,730	-10.0%

4 DISTRICT OF CENTRAL SAANICH

4.1 2020 Profile

Profile	
Population	18,353
Dwellings	7,672
Registered Vehicles	17,330
Energy (Thousands of GJ)	1,904
GHG Emissions (tCO_2e)	96,437

4.2 Energy & GHG Emissions

Table 8 presents a summary comparison of the District of Central Saanich's 2007 and 2020 energy and GHG emissions.

Table 8. Estimated Energy and GHG Emissions By Reporting Source

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Stationary Energy							
Residential Buildings	Electricity	400,574	372,185	-7.1%	3,972	4,146	4.4%
	Natural Gas	101,999	137,929	35.2%	5,086	6,878	35.2%
	Fuel Oil	18,644	25,623	37.4%	1,275	1,752	37.4%
	Propane	3,220	2,625	-18.5%	196	161	-18.2%
	Wood	7,150	5,957	-16.7%	168	140	-16.7%
	Diesel	11,997	9,309	-22.4%	894	653	-27.0%
Commercial & Industrial Buildings	Electricity	231,056	224,451	-2.9%	2,291	2,500	9.1%
	Natural Gas	152,986	147,828	-3.4%	7,629	7,372	-3.4%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
	Fuel Oil	-	-	-	-	-	-
	Diesel	21,633	20,664	-4.5%	1,613	1,450	-10.1%
Energy Industries	LFG Combustion			-	-	-	-
Agriculture, Forestry And Fishing Activities	Diesel	57,230	51,363	-10.3%	4,267	3,603	-15.5%
Natural Gas Fugitive Emissions				-	57	77	36.0%
Total		**1,006,488**	**997,933**	**-0.8%**	**27,449**	**28,731**	**4.7%**
On-Road Transportation							
Electric Vehicles	Electricity	-	3,573	-	-	40	-
Hydrogen Vehicles	Hydrogen	-	-	-	-	-	-
Passenger Vehicles	Gasoline + Diesel	278,538	158,354	-43.1%	18,862	9,933	-47.3%
Light Trucks, Vans, SUVs	Gasoline + Diesel	324,185	381,136	17.6%	22,243	24,262	9.1%
Heavy Duty Vehicles	Gasoline + Diesel	179,749	307,951	71.3%	12,153	19,279	58.6%
Propane Vehicles	Propane	2,375	664	-72.0%	143	38	-73.7%
Natural Gas Vehicles	Natural Gas	-	43	-	-	2	-
Motorcycles	Gasoline	2,245	1,798	-19.9%	155	117	-24.7%
Total On-Road Transportation		**787,093**	**853,520**	**8.4%**	**53,556**	**53,670**	**0.2%**
Off-Road Transportation							
Marine, Aviation and Other Off-Road Vehicles	Gasoline + Diesel + Jet Fuel	73,836	52,366	-29.1%	5,520	3,746	-32.1%
Total Off-Road Transportation		**73,836**	**52,366**	**-29.1%**	**5,520**	**3,746**	**-32.1%**
Waste							
Wastewater					668	592	-11.4%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Composting					0	0	-
Solid Waste					5,110	2,579	-49.5%
Total Waste					**5,778**	**3,170**	**-45.1%**
Agriculture Forestry & Other Land Use (AFOLU)							
Land-Use: Emissions Sequestered **(Disclosure Only - Not Included In Total)**					-5,014	-4,845	-3.4%
Land-Use: Emissions Released **(Disclosure Only - Not Included In Total)**					5,925	154	-97.4%
Livestock, Aggregate Sources and Non-CO_2 Emission Sources on Land					1,221	1,408	15.3%
Total AFOLU					**1,221**	**1,408**	**15.3%**
Industrial Process & Product Use (IPPU)							
Process Use Emissions					3,554	5,711	60.7%
Total IPPU					**3,554**	**5,711**	**60.7%**
TOTAL		**1,867,417**	**1,903,819**	**1.9%**	**97,077**	**96,437**	**-0.7%**

5 CITY OF COLWOOD

5.1 2020 Profile

Profile	
Population	19,373
Dwellings	7,345
Registered Vehicles	12,247
Energy (Thousands of GJ)	1,488
GHG Emissions (tCO_2e)	76,591

5.2 Energy & GHG Emissions

Table 9 presents a summary comparison of the City of Colwood's 2007 and 2020 energy and GHG emissions.

Table 9. Estimated Energy and GHG Emissions By Reporting Source

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Stationary Energy							
Residential Buildings	Electricity	304,680	320,194	5.1%	3,021	3,567	18.0%
	Natural Gas	100,740	159,872	58.7%	5,024	7,972	58.7%
	Fuel Oil	65,936	90,620	37.4%	4,508	6,196	37.4%
	Propane	11,388	9,284	-18.5%	694	568	-18.2%
	Wood	25,284	21,063	-16.7%	594	495	-16.7%
	Diesel	11,473	9,826	-14.4%	855	689	-19.4%
Commercial & Industrial Buildings	Electricity	159,630	134,739	-15.6%	1,583	1,501	-5.2%
	Natural Gas	94,097	90,451	-3.9%	4,692	4,511	-3.9%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
	Fuel Oil	-	-	-	-	-	-
	Diesel	20,689	21,813	5.4%	1,542	1,530	-0.8%
Energy Industries	LFG Combustion			-	-	-	-
Agriculture, Forestry And Fishing Activities	Diesel	54,732	54,218	-0.9%	4,081	3,804	-6.8%
Natural Gas Fugitive Emissions				-	61	98	61.1%
Total		**848,651**	**912,079**	**7.5%**	**26,656**	**30,930**	**16.0%**
On-Road Transportation							
Electric Vehicles	Electricity	-	2,215	-	-	25	-
Hydrogen Vehicles	Hydrogen	-	-	-	-	-	-
Passenger Vehicles	Gasoline + Diesel	233,329	125,517	-46.2%	15,797	7,871	-50.2%
Light Trucks, Vans, SUVs	Gasoline + Diesel	265,308	274,955	3.6%	18,205	17,500	-3.9%
Heavy Duty Vehicles	Gasoline + Diesel	112,247	80,606	-28.2%	7,581	5,095	-32.8%
Propane Vehicles	Propane	1,441	566	-60.7%	87	32	-63.0%
Natural Gas Vehicles	Natural Gas	-	34,784	-	-	1,879	-
Motorcycles	Gasoline	2,145	1,893	-11.8%	148	123	-17.0%
Total On-Road Transportation		**614,470**	**520,536**	**-15.3%**	**41,818**	**32,525**	**-22.2%**
Off-Road Transportation							
Marine, Aviation and Other Off-Road Vehicles	Gasoline + Diesel + Jet Fuel	70,613	55,277	-21.7%	5,279	3,955	-25.1%
Total Off-Road Transportation		**70,613**	**55,277**	**-21.7%**	**5,279**	**3,955**	**-25.1%**
Waste							
Wastewater					397	516	30.0%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Composting					0	0	-
Solid Waste					4,887	2,722	-44.3%
Total Waste					**5,285**	**3,238**	**-38.7%**
Agriculture Forestry & Other Land Use (AFOLU)							
Land-Use: Emissions Sequestered **(Disclosure Only - Not Included In Total)**					-2,536	-3,208	26.5%
Land-Use: Emissions Released **(Disclosure Only - Not Included In Total)**					2,482	2,755	11.0%
Livestock, Aggregate Sources and Non-CO_2 Emission Sources on Land					2	0	-83.9%
Total AFOLU					**2**	**0**	**-83.9%**
Industrial Process & Product Use (IPPU)							
Process Use Emissions					3,399	5,942	74.9%
Total IPPU					**3,399**	**5,942**	**74.9%**
TOTAL		**1,533,734**	**1,487,893**	**-3.0%**	**82,439**	**76,591**	**-7.1%**

6 TOWNSHIP OF ESQUIMALT

6.1 2020 Profile

Profile	
Population	19,015
Dwellings	9,268
Registered Vehicles	11,322
Energy (Thousands of GJ)	1,565
GHG Emissions (tCO_2e)	80,712

6.2 Energy & GHG Emissions

Table 10 presents a summary comparison of the Township of Esquimalt's 2007 and 2020 energy and GHG emissions.

Table 10. Estimated Energy and GHG Emissions By Reporting Source

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Stationary Energy							
Residential Buildings	Electricity	282,544	258,816	-8.4%	2,802	2,883	2.9%
	Natural Gas	133,315	87,824	-34.1%	6,648	4,380	-34.1%
	Fuel Oil	116,338	159,889	37.4%	7,955	10,933	37.4%
	Propane	20,190	16,460	-18.5%	1,231	1,007	-18.2%
	Wood	44,358	36,952	-16.7%	1,042	868	-16.7%
	Diesel	12,894	9,645	-25.2%	961	677	-29.6%
Commercial & Industrial Buildings	Electricity	167,991	172,756	2.8%	1,666	1,924	15.5%
	Natural Gas	323,843	321,319	-0.8%	16,149	16,023	-0.8%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
	Fuel Oil	-	-	-	-	-	-
	Diesel	23,251	21,409	-7.9%	1,733	1,502	-13.4%
Energy Industries	LFG Combustion			-	-	-	-
Agriculture, Forestry And Fishing Activities	Diesel	-	-	-	-	-	-
Natural Gas Fugitive Emissions				-	44	52	17.5%
Total		**1,124,723**	**1,085,069**	**-3.5%**	**40,231**	**40,248**	**0.0%**
On-Road Transportation							
Electric Vehicles	Electricity	-	1,968	-	-	22	-
Hydrogen Vehicles	Hydrogen	-	-	-	-	-	-
Passenger Vehicles	Gasoline + Diesel	263,197	139,858	-46.9%	17,819	8,771	-50.8%
Light Trucks, Vans, SUVs	Gasoline + Diesel	215,762	225,218	4.4%	14,805	14,325	-3.2%
Heavy Duty Vehicles	Gasoline + Diesel	97,205	55,964	-42.4%	6,551	3,507	-46.5%
Propane Vehicles	Propane	1,908	467	-75.5%	115	27	-76.9%
Natural Gas Vehicles	Natural Gas	-	548	-	-	30	-
Motorcycles	Gasoline	2,312	2,151	-7.0%	159	139	-12.5%
Total On-Road Transportation		**580,384**	**426,175**	**-26.6%**	**39,450**	**26,820**	**-32.0%**
Off-Road Transportation							
Marine, Aviation and Other Off-Road Vehicles	Gasoline + Diesel + Jet Fuel	79,358	54,255	-31.6%	5,933	3,882	-34.6%
Total Off-Road Transportation		**79,358**	**54,255**	**-31.6%**	**5,933**	**3,882**	**-34.6%**
Waste							
Wastewater					1,388	1,037	-25.3%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Composting					0	95	-
Solid Waste					5,493	2,672	-51.4%
Total Waste					**6,880**	**3,804**	**-44.7%**
Agriculture Forestry & Other Land Use (AFOLU)							
Land-Use: Emissions Sequestered **(Disclosure Only - Not Included In Total)**					-828	-1,152	39.2%
Land-Use: Emissions Released **(Disclosure Only - Not Included In Total)**					1,155	1,284	11.2%
Livestock, Aggregate Sources and Non-CO_2 Emission Sources on Land					0	0	-
Total AFOLU					**0**	**0**	**-**
Industrial Process & Product Use (IPPU)							
Process Use Emissions					3,819	5,959	56.0%
Total IPPU					**3,819**	**5,959**	**56.0%**
TOTAL		**1,784,465**	**1,565,499**	**-12.3%**	**96,314**	**80,712**	**-16.2%**

7 DISTRICT OF HIGHLANDS

7.1 2020 Profile

Profile	
Population	2,451
Dwellings	920
Registered Vehicles	2,657
Energy (Thousands of GJ)	291
GHG Emissions (tCO_2e)	14,614

7.2 Energy & GHG Emissions

Table 11 presents a summary comparison of the District of Highland's 2007 and 2020 energy and GHG emissions.

Table 11. Estimated Energy and GHG Emissions By Reporting Source

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Stationary Energy							
Residential Buildings	Electricity	63,637	73,144	14.9%	631	815	29.1%
	Natural Gas	69	5,126	7281.1%	3	256	7281.1%
	Fuel Oil	9,468	13,012	37.4%	647	890	37.4%
	Propane	1,633	1,331	-18.5%	100	81	-18.2%
	Wood	3,637	3,030	-16.7%	85	71	-16.7%
	Diesel	1,459	1,243	-14.8%	109	87	-19.8%
Commercial & Industrial Buildings	Electricity	6,447	15,511	140.6%	64	173	170.3%
	Natural Gas	20,440	24,233	18.6%	1,019	1,208	18.6%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
	Fuel Oil	-	-	-	-	-	-
	Diesel	2,630	2,760	4.9%	196	194	-1.3%
Energy Industries	LFG Combustion			-	-	-	-
Agriculture, Forestry And Fishing Activities	Diesel	6,958	6,859	-1.4%	519	481	-7.2%
Natural Gas Fugitive Emissions				-	0	3	1527.9%
Total		**116,378**	**146,249**	**25.7%**	**3,374**	**4,259**	**26.2%**
On-Road Transportation							
Electric Vehicles	Electricity	-	523	-	-	6	-
Hydrogen Vehicles	Hydrogen	-	-	-	-	-	-
Passenger Vehicles	Gasoline + Diesel	25,510	19,587	-23.2%	1,728	1,229	-28.9%
Light Trucks, Vans, SUVs	Gasoline + Diesel	43,712	63,436	45.1%	2,999	4,044	34.9%
Heavy Duty Vehicles	Gasoline + Diesel	21,645	53,613	147.7%	1,461	3,411	133.5%
Propane Vehicles	Propane	779	192	-75.3%	47	11	-76.8%
Natural Gas Vehicles	Natural Gas	-	-	-	-	-	-
Motorcycles	Gasoline	327	427	30.5%	23	28	22.8%
Total On-Road Transportation		**91,972**	**137,778**	**49.8%**	**6,258**	**8,729**	**39.5%**
Off-Road Transportation							
Marine, Aviation and Other Off-Road Vehicles	Gasoline + Diesel + Jet Fuel	8,978	6,993	-22.1%	671	500	-25.5%
Total Off-Road Transportation		**8,978**	**6,993**	**-22.1%**	**671**	**500**	**-25.5%**
Waste							
Wastewater					0	0	-

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Composting					0	0	-
Solid Waste					621	344	-44.6%
Total Waste					**621**	**344**	**-44.6%**
Agriculture Forestry & Other Land Use (AFOLU)							
Land-Use: Emissions Sequestered **(Disclosure Only - Not Included In Total)**					-7,090	-7,504	5.8%
Land-Use: Emissions Released **(Disclosure Only - Not Included In Total)**					1,957	3,157	61.4%
Livestock, Aggregate Sources and Non-CO_2 Emission Sources on Land					2	4	102.2%
Total AFOLU					**2**	**4**	**102.2%**
Industrial Process & Product Use (IPPU)							
Process Use Emissions					432	777	79.9%
Total IPPU					**432**	**777**	**79.9%**
TOTAL		**217,328**	**291,021**	**33.9%**	**11,358**	**14,614**	**28.7%**

8 JUAN DE FUCA ELECTORAL AREA

8.1 2020 Profile

Profile	
Population	5,098
Dwellings	2,234
Registered Vehicles	4,212
Energy (Thousands of GJ)	1,400
GHG Emissions (tCO_2e)	69,270

8.2 Energy & GHG Emissions

Table 12 presents a summary comparison of Juan de Fuca Electoral Area's 2007 and 2020 energy and GHG emissions.

Table 12. Estimated Energy and GHG Emissions By Reporting Source

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Stationary Energy							
Residential Buildings	Electricity	275,784	296,557	7.5%	2,735	3,303	20.8%
	Natural Gas	-	-	-	-	-	-
	Fuel Oil	442,152	606,090	37.1%	30,233	41,442	37.1%
	Propane	82,743	67,453	-18.5%	5,044	4,125	-18.2%
	Wood	184,018	153,297	-16.7%	4,321	3,600	-16.7%
	Diesel	3,223	2,586	-19.8%	240	181	-24.5%
Commercial & Industrial Buildings	Electricity	47,620	62,548	31.3%	472	697	47.5%
	Natural Gas	-	-	-	-	-	-

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
	Fuel Oil	-	-	-	-	-	-
	Diesel	5,812	5,740	-1.2%	433	403	-7.1%
Energy Industries	LFG Combustion			-	-	-	-
Agriculture, Forestry And Fishing Activities	Diesel	15,377	14,269	-7.2%	1,146	1,001	-12.7%
Natural Gas Fugitive Emissions				-	-	-	-
Total		**1,056,729**	**1,208,540**	**14.4%**	**44,624**	**54,752**	**22.7%**
On-Road Transportation							
Electric Vehicles	Electricity	-	823	-	-	9	-
Hydrogen Vehicles	Hydrogen	-	-	-	-	-	-
Passenger Vehicles	Gasoline + Diesel	7,521	36,872	390.2%	513	2,315	351.2%
Light Trucks, Vans, SUVs	Gasoline + Diesel	119,903	104,053	-13.2%	8,225	6,631	-19.4%
Heavy Duty Vehicles	Gasoline + Diesel	76,109	33,664	-55.8%	5,174	2,129	-58.9%
Propane Vehicles	Propane	1,830	815	-55.5%	110	46	-58.1%
Natural Gas Vehicles	Natural Gas	-	-	-	-	-	-
Motorcycles	Gasoline	247	482	94.8%	17	31	83.3%
Total On-Road Transportation		**205,611**	**176,709**	**-14.1%**	**14,040**	**11,161**	**-20.5%**
Off-Road Transportation							
Marine, Aviation and Other Off-Road Vehicles	Gasoline + Diesel + Jet Fuel	19,838	14,547	-26.7%	1,483	1,041	-29.8%
Total Off-Road Transportation		**19,838**	**14,547**	**-26.7%**	**1,483**	**1,041**	**-29.8%**
Waste							
Wastewater					0	0	77.5%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Composting					0	0	-
Solid Waste					1,373	716	-47.8%
Total Waste					**1,373**	**717**	**-47.8%**
Agriculture Forestry & Other Land Use (AFOLU)							
Land-Use: Emissions Sequestered **(Disclosure Only - Not Included In Total)**					-259,223	-255,625	-1.4%
Land-Use: Emissions Released **(Disclosure Only - Not Included In Total)**					31,481	706	-97.8%
Livestock, Aggregate Sources and Non-CO_2 Emission Sources on Land					18	6	-68.5%
Total AFOLU					**18**	**6**	**-68.5%**
Industrial Process & Product Use (IPPU)							
Process Use Emissions					955	1,594	67.0%
Total IPPU					**955**	**1,594**	**67.0%**
TOTAL		**1,282,178**	**1,399,797**	**9.2%**	**62,493**	**69,270**	**10.8%**

9 CITY OF LANGFORD

9.1 2020 Profile

Profile	
Population	44,069
Dwellings	16,654
Registered Vehicles	26,768
Energy (Thousands of GJ)	3,335
GHG Emissions (tCO_2e)	165,160

9.2 Energy & GHG Emissions

Table 13 presents a summary comparison of the City of Langford's 2007 and 2020 energy and GHG emissions.

Table 13. Estimated Energy and GHG Emissions By Reporting Source

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Stationary Energy							
Residential Buildings	Electricity	514,977	724,587	40.7%	5,107	8,071	58.0%
	Natural Gas	122,432	248,420	102.9%	6,105	12,388	102.9%
	Fuel Oil	103,002	141,561	37.4%	7,043	9,679	37.4%
	Propane	17,793	14,505	-18.5%	1,085	887	-18.2%
	Wood	39,489	32,896	-16.7%	927	772	-16.7%
	Diesel	18,289	22,352	22.2%	1,364	1,568	15.0%
Commercial & Industrial Buildings	Electricity	343,772	429,804	25.0%	3,409	4,788	40.4%
	Natural Gas	186,387	344,294	84.7%	9,295	17,169	84.7%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
	Fuel Oil	-	-	-	-	-	-
	Diesel	32,980	49,618	50.5%	2,459	3,481	41.6%
Energy Industries	LFG Combustion			-	-	-	-
Agriculture, Forestry And Fishing Activities	Diesel	87,246	123,333	41.4%	6,505	8,652	33.0%
Natural Gas Fugitive Emissions				-	81	167	106.9%
Total		**1,466,368**	**2,131,371**	**45.4%**	**43,378**	**67,623**	**55.9%**
On-Road Transportation							
Electric Vehicles	Electricity	-	4,542	-	-	51	-
Hydrogen Vehicles	Hydrogen	-	-	-	-	-	-
Passenger Vehicles	Gasoline + Diesel	364,717	284,365	-22.0%	24,694	17,833	-27.8%
Light Trucks, Vans, SUVs	Gasoline + Diesel	432,627	591,061	36.6%	29,684	37,619	26.7%
Heavy Duty Vehicles	Gasoline + Diesel	211,623	187,913	-11.2%	14,314	11,886	-17.0%
Propane Vehicles	Propane	3,348	1,547	-53.8%	202	88	-56.5%
Natural Gas Vehicles	Natural Gas	-	5,250	-	-	284	-
Motorcycles	Gasoline	3,488	3,643	4.4%	240	236	-1.7%
Total On-Road Transportation		**1,015,805**	**1,078,322**	**6.2%**	**69,134**	**67,997**	**-1.6%**
Off-Road Transportation							
Marine, Aviation and Other Off-Road Vehicles	Gasoline + Diesel + Jet Fuel	112,562	125,741	11.7%	8,415	8,996	6.9%
Total Off-Road Transportation		**112,562**	**125,741**	**11.7%**	**8,415**	**8,996**	**6.9%**
Waste							
Wastewater					621	1,093	76.0%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Composting					0	0	-
Solid Waste					7,791	6,192	-20.5%
Total Waste					**8,412**	**7,285**	**-13.4%**
Agriculture Forestry & Other Land Use (AFOLU)							
Land-Use: Emissions Sequestered **(Disclosure Only - Not Included In Total)**					-6,609	-7,108	7.6%
Land-Use: Emissions Released **(Disclosure Only - Not Included In Total)**					6,886	8,316	20.8%
Livestock, Aggregate Sources and Non-CO_2 Emission Sources on Land					35	52	47.7%
Total AFOLU					**35**	**52**	**47.7%**
Industrial Process & Product Use (IPPU)							
Process Use Emissions					5,417	13,207	143.8%
Total IPPU					**5,417**	**13,207**	**143.8%**
TOTAL		**2,594,734**	**3,335,434**	**28.5%**	**134,791**	**165,160**	**22.5%**

10 DISTRICT OF METCHOSIN

10.1 2020 Profile

Profile	
Population	5,049
Dwellings	2,018
Registered Vehicles	3,794
Energy (Thousands of GJ)	437
GHG Emissions (tCO_2e)	20,624

10.2 Energy & GHG Emissions

Table 14 presents a summary comparison of the District of Metchosin's 2007 and 2020 energy and GHG emissions.

Table 14. Estimated Energy and GHG Emissions By Reporting Source

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Stationary Energy							
Residential Buildings	Electricity	136,893	138,768	1.4%	1,358	1,546	13.9%
	Natural Gas	8,173	10,441	27.8%	408	521	27.8%
	Fuel Oil	9,003	12,373	37.4%	616	846	37.4%
	Propane	1,553	1,266	-18.5%	95	77	-18.2%
	Wood	3,457	2,880	-16.7%	81	68	-16.7%
	Diesel	3,601	2,561	-28.9%	268	180	-33.1%
Commercial & Industrial Buildings	Electricity	38,037	39,630	4.2%	377	441	17.0%
	Natural Gas	33,858	27,808	-17.9%	1,688	1,387	-17.9%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
	Fuel Oil	-	-	-	-	-	-
	Diesel	6,494	5,685	-12.5%	484	399	-17.6%
Energy Industries	LFG Combustion			-	-	-	-
Agriculture, Forestry And Fishing Activities	Diesel	17,180	14,130	-17.8%	1,281	991	-22.6%
Natural Gas Fugitive Emissions				-	4	4	9.7%
Total		**258,249**	**255,542**	**-1.0%**	**6,660**	**6,460**	**-3.0%**
On-Road Transportation							
Electric Vehicles	Electricity	-	970	-	-	11	-
Hydrogen Vehicles	Hydrogen	-	-	-	-	-	-
Passenger Vehicles	Gasoline + Diesel	80,035	32,755	-59.1%	5,421	2,057	-62.1%
Light Trucks, Vans, SUVs	Gasoline + Diesel	110,966	92,513	-16.6%	7,613	5,897	-22.5%
Heavy Duty Vehicles	Gasoline + Diesel	40,316	39,888	-1.1%	2,721	2,521	-7.3%
Propane Vehicles	Propane	1,051	125	-88.1%	63	7	-88.8%
Natural Gas Vehicles	Natural Gas	-	-	-	-	-	-
Motorcycles	Gasoline	668	414	-38.1%	46	27	-41.7%
Total On-Road Transportation		**233,036**	**166,665**	**-28.5%**	**15,865**	**10,520**	**-33.7%**
Off-Road Transportation							
Marine, Aviation and Other Off-Road Vehicles	Gasoline + Diesel + Jet Fuel	22,165	14,406	-35.0%	1,657	1,031	-37.8%
Total Off-Road Transportation		**22,165**	**14,406**	**-35.0%**	**1,657**	**1,031**	**-37.8%**
Waste							
Wastewater					0	0	-

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Composting					0	0	-
Solid Waste					1,534	709	-53.8%
Total Waste					**1,534**	**709**	**-53.8%**
Agriculture Forestry & Other Land Use (AFOLU)							
Land-Use: Emissions Sequestered **(Disclosure Only - Not Included In Total)**					-12,139	-12,971	6.9%
Land-Use: Emissions Released **(Disclosure Only - Not Included In Total)**					4,011	4,030	0.5%
Livestock, Aggregate Sources and Non-CO_2 Emission Sources on Land					232	294	26.3%
Total AFOLU					**232**	**294**	**26.3%**
Industrial Process & Product Use (IPPU)							
Process Use Emissions					1,067	1,611	51.0%
Total IPPU					**1,067**	**1,611**	**51.0%**
TOTAL		**513,449**	**436,613**	**-15.0%**	**27,015**	**20,624**	**-23.7%**

11 DISTRICT OF NORTH SAANICH

11.1 2020 Profile

Profile	
Population	11,965
Dwellings	5,096
Registered Vehicles	10,318
Energy (Thousands of GJ)	1,234
GHG Emissions (tCO_2e)	54,424

11.2 Energy & GHG Emissions

Table 15 presents a summary comparison of the District of North Saanich's 2007 and 2020 energy and GHG emissions.

Table 15. Estimated Energy and GHG Emissions By Reporting Source

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Stationary Energy							
Residential Buildings	Electricity	375,413	355,429	-5.3%	3,723	3,959	6.3%
	Natural Gas	41,591	79,120	90.2%	2,074	3,946	90.2%
	Fuel Oil	5,953	8,182	37.4%	407	559	37.4%
	Propane	1,027	837	-18.5%	63	51	-18.2%
	Wood	2,286	1,905	-16.7%	54	45	-16.7%
	Diesel	8,138	6,069	-25.4%	607	426	-29.8%
Commercial & Industrial Buildings	Electricity	156,437	182,752	16.8%	1,551	2,036	31.2%
	Natural Gas	99,927	101,626	1.7%	4,983	5,068	1.7%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
	Fuel Oil	-	-	-	-	-	-
	Diesel	14,674	13,472	-8.2%	1,094	945	-13.6%
Energy Industries	LFG Combustion			-	-	-	-
Agriculture, Forestry And Fishing Activities	Diesel	38,821	33,486	-13.7%	2,894	2,349	-18.8%
Natural Gas Fugitive Emissions				-	21	38	80.1%
Total		**744,266**	**782,876**	**5.2%**	**17,471**	**19,421**	**11.2%**
On-Road Transportation							
Electric Vehicles	Electricity	-	3,078	-	-	34	-
Hydrogen Vehicles	Hydrogen	-	-	-	-	-	-
Passenger Vehicles	Gasoline + Diesel	208,096	105,673	-49.2%	14,094	6,633	-52.9%
Light Trucks, Vans, SUVs	Gasoline + Diesel	227,960	231,300	1.5%	15,641	14,730	-5.8%
Heavy Duty Vehicles	Gasoline + Diesel	89,923	74,597	-17.0%	6,043	4,691	-22.4%
Propane Vehicles	Propane	1,012	680	-32.8%	61	39	-36.8%
Natural Gas Vehicles	Natural Gas	-	231	-	-	12	-
Motorcycles	Gasoline	1,684	1,540	-8.6%	116	100	-13.9%
Total On-Road Transportation		**528,675**	**417,098**	**-21.1%**	**35,956**	**26,238**	**-27.0%**
Off-Road Transportation							
Marine, Aviation and Other Off-Road Vehicles	Gasoline + Diesel + Jet Fuel	50,085	34,140	-31.8%	3,744	2,442	-34.8%
Total Off-Road Transportation		**50,085**	**34,140**	**-31.8%**	**3,744**	**2,442**	**-34.8%**
Waste							
Wastewater					196	235	19.8%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Composting					0	0	-
Solid Waste					3,467	1,681	-51.5%
Total Waste					**3,663**	**1,916**	**-47.7%**
Agriculture Forestry & Other Land Use (AFOLU)							
Land-Use: Emissions Sequestered **(Disclosure Only - Not Included In Total)**					-5,055	-5,135	1.6%
Land-Use: Emissions Released **(Disclosure Only - Not Included In Total)**					4,758	5,160	8.5%
Livestock, Aggregate Sources and Non-CO_2 Emission Sources on Land					502	665	32.4%
Total AFOLU					**502**	**665**	**32.4%**
Industrial Process & Product Use (IPPU)							
Process Use Emissions					2,410	3,741	55.2%
Total IPPU					**2,410**	**3,741**	**55.2%**
TOTAL		**1,323,026**	**1,234,114**	**-6.7%**	**63,747**	**54,424**	**-14.6%**

12 DISTRICT OF OAK BAY

12.1 2020 Profile

Profile	
Population	18,918
Dwellings	8,132
Registered Vehicles	11,966
Energy (Thousands of GJ)	1,485
GHG Emissions (tCO_2e)	76,427

12.2 Energy & GHG Emissions

Table 16 presents a summary comparison of the District of Oak Bay's 2007 and 2020 energy and GHG emissions.

Table 16. Estimated Energy and GHG Emissions By Reporting Source

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Stationary Energy							
Residential Buildings	Electricity	370,574	323,663	-12.7%	3,675	3,605	-1.9%
	Natural Gas	276,642	299,206	8.2%	13,795	14,921	8.2%
	Fuel Oil	66,466	91,348	37.4%	4,545	6,246	37.4%
	Propane	11,487	9,364	-18.5%	700	573	-18.2%
	Wood	25,469	21,217	-16.7%	598	498	-16.7%
	Diesel	13,651	9,595	-29.7%	1,018	673	-33.9%
Commercial & Industrial Buildings	Electricity	106,747	95,438	-10.6%	1,059	1,063	0.4%
	Natural Gas	83,140	122,251	47.0%	4,146	6,096	47.0%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
	Fuel Oil	-	-	-	-	-	-
	Diesel	24,616	21,300	-13.5%	1,835	1,494	-18.6%
Energy Industries	LFG Combustion			-	-	-	-
Agriculture, Forestry And Fishing Activities	Diesel	-	-	-	-	-	-
Natural Gas Fugitive Emissions				-	83	110	32.6%
Total		**978,790**	**993,382**	**1.5%**	**31,454**	**35,280**	**12.2%**
On-Road Transportation							
Electric Vehicles	Electricity	-	4,154	-	-	46	-
Hydrogen Vehicles	Hydrogen	-	-	-	-	-	-
Passenger Vehicles	Gasoline + Diesel	322,115	148,012	-54.1%	21,812	9,282	-57.4%
Light Trucks, Vans, SUVs	Gasoline + Diesel	199,128	235,082	18.1%	13,665	14,953	9.4%
Heavy Duty Vehicles	Gasoline + Diesel	78,248	48,579	-37.9%	5,271	3,048	-42.2%
Propane Vehicles	Propane	857	239	-72.1%	52	14	-73.8%
Natural Gas Vehicles	Natural Gas	-	58	-	-	3	-
Motorcycles	Gasoline	1,771	1,506	-15.0%	122	98	-20.0%
Total On-Road Transportation		**602,119**	**437,628**	**-27.3%**	**40,922**	**27,444**	**-32.9%**
Off-Road Transportation							
Marine, Aviation and Other Off-Road Vehicles	Gasoline + Diesel + Jet Fuel	84,016	53,978	-35.8%	6,281	3,862	-38.5%
Total Off-Road Transportation		**84,016**	**53,978**	**-35.8%**	**6,281**	**3,862**	**-38.5%**
Waste							
Wastewater					1,968	1,229	-37.5%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Composting					0	95	-
Solid Waste					5,815	2,658	-54.3%
Total Waste					**7,783**	**3,982**	**-48.8%**
Agriculture Forestry & Other Land Use (AFOLU)							
Land-Use: Emissions Sequestered **(Disclosure Only - Not Included In Total)**					-1,461	-1,846	26.3%
Land-Use: Emissions Released **(Disclosure Only - Not Included In Total)**					1,731	1,898	9.6%
Livestock, Aggregate Sources and Non-CO_2 Emission Sources on Land					0	0	68.7%
Total AFOLU					**0**	**0**	**68.7%**
Industrial Process & Product Use (IPPU)							
Process Use Emissions					4,044	5,860	44.9%
Total IPPU					**4,044**	**5,860**	**44.9%**
TOTAL		**1,664,925**	**1,484,989**	**-10.8%**	**90,483**	**76,427**	**-15.5%**

13 THE DISTRICT OF SAANICH

13.1 2020 Profile

Profile	
Population	125,107
Dwellings	50,365
Registered Vehicles	81,162
Energy (Thousands of GJ)	9,457
GHG Emissions (tCO_2e)	486,037

13.2 Energy & GHG Emissions

Table 17 presents a summary comparison of the District of Saanich's 2007 and 2020 energy and GHG emissions.

Table 17. Estimated Energy and GHG Emissions By Reporting Source

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Stationary Energy							
Residential Buildings	Electricity	2,358,702	2,161,003	-8.4%	23,391	24,071	2.9%
	Natural Gas	743,960	847,026	13.9%	37,099	42,239	13.9%
	Fuel Oil	518,953	318,823	-38.6%	35,484	21,800	-38.6%
	Propane	97,519	79,499	-18.5%	5,944	4,862	-18.2%
	Wood	216,161	180,074	-16.7%	5,076	4,229	-16.7%
	Diesel	82,502	63,455	-23.1%	6,151	4,452	-27.6%
Commercial & Industrial Buildings	Electricity	1,176,089	1,004,564	-14.6%	11,663	11,190	-4.1%
	Natural Gas	759,454	817,053	7.6%	37,872	40,744	7.6%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
	Fuel Oil	38,936	20,302	-47.9%	2,662	1,388	-47.9%
	Diesel	148,774	140,861	-5.3%	11,092	9,882	-10.9%
Energy Industries	LFG Combustion			-	418	9,563	2186.5%
Agriculture, Forestry And Fishing Activities	Diesel	393,575	350,128	-11.0%	29,343	24,563	-16.3%
Natural Gas Fugitive Emissions				-	314	438	39.4%
Total		**6,534,625**	**5,982,788**	**-8.4%**	**206,509**	**199,421**	**-3.4%**
On-Road Transportation							
Electric Vehicles	Electricity	-	19,566	-	-	218	-
Hydrogen Vehicles	Hydrogen	-	-	-	-	-	-
Passenger Vehicles	Gasoline + Diesel	1,877,530	959,118	-48.9%	127,117	60,145	-52.7%
Light Trucks, Vans, SUVs	Gasoline + Diesel	1,549,388	1,681,901	8.6%	106,319	107,018	0.7%
Heavy Duty Vehicles	Gasoline + Diesel	564,907	442,895	-21.6%	38,090	27,964	-26.6%
Propane Vehicles	Propane	8,605	3,749	-56.4%	519	213	-59.0%
Natural Gas Vehicles	Natural Gas	-	807	-	-	44	-
Motorcycles	Gasoline	11,374	9,288	-18.3%	784	602	-23.2%
Total On-Road Transportation		**4,011,803**	**3,117,323**	**-22.3%**	**272,828**	**196,203**	**-28.1%**
Off-Road Transportation							
Marine, Aviation and Other Off-Road Vehicles	Gasoline + Diesel + Jet Fuel	507,773	356,966	-29.7%	37,961	25,538	-32.7%
Total Off-Road Transportation		**507,773**	**356,966**	**-29.7%**	**37,961**	**25,538**	**-32.7%**
Waste							
Wastewater					4,989	3,995	-19.9%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Composting					0	3,923	-
Solid Waste					35,144	17,578	-50.0%
Total Waste					**40,134**	**25,496**	**-36.5%**
Agriculture Forestry & Other Land Use (AFOLU)							
Land-Use: Emissions Sequestered **(Disclosure Only - Not Included In Total)**					-15,421	-16,969	10.0%
Land-Use: Emissions Released **(Disclosure Only - Not Included In Total)**					22,453	13,619	-39.3%
Livestock, Aggregate Sources and Non-CO_2 Emission Sources on Land					551	649	17.9%
Total AFOLU					**551**	**649**	**17.9%**
Industrial Process & Product Use (IPPU)							
Process Use Emissions					24,438	38,730	58.5%
Total IPPU					**24,438**	**38,730**	**58.5%**
TOTAL		**11,054,201**	**9,457,076**	**-14.4%**	**582,422**	**486,037**	**-16.5%**

14 SALT SPRING ELECTORAL AREA

14.1 2020 Profile

Profile	
Population	11,697
Dwellings	5,158
Registered Vehicles	8,996
Energy (Thousands of GJ)	1,003
GHG Emissions (tCO_2e)	42,920

14.2 Energy & GHG Emissions

Table 18 presents a summary comparison of Salt Spring Island Electoral Area's 2007 and 2020 energy and GHG emissions.

Table 18. Estimated Energy and GHG Emissions By Reporting Source

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Stationary Energy							
Residential Buildings	Electricity	360,697	362,362	0.5%	3,577	4,036	12.8%
	Natural Gas	-	-	-	-	-	-
	Fuel Oil	9,967	14,122	41.7%	682	966	41.7%
	Propane	9,006	7,569	-16.0%	549	463	-15.7%
	Wood	75,133	64,526	-14.1%	1,764	1,515	-14.1%
	Diesel	7,344	5,933	-19.2%	548	416	-24.0%
Commercial & Industrial Buildings	Electricity	91,954	105,860	15.1%	912	1,179	29.3%
	Natural Gas	-	-	-	-	-	-

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
	Fuel Oil	-	-	-	-	-	-
	Diesel	13,243	13,170	-0.5%	987	924	-6.4%
Energy Industries	LFG Combustion			-	-	-	-
Agriculture, Forestry And Fishing Activities	Diesel	35,033	32,736	-6.6%	2,612	2,297	-12.1%
Natural Gas Fugitive Emissions				-	-	-	-
Total		**602,377**	**606,278**	**0.6%**	**11,630**	**11,796**	**1.4%**
On-Road Transportation							
Electric Vehicles	Electricity	-	3,002	-	-	33	-
Hydrogen Vehicles	Hydrogen	-	-	-	-	-	-
Passenger Vehicles	Gasoline + Diesel	166,502	74,130	-55.5%	11,276	4,651	-58.8%
Light Trucks, Vans, SUVs	Gasoline + Diesel	191,257	217,638	13.8%	13,124	13,852	5.5%
Heavy Duty Vehicles	Gasoline + Diesel	50,339	66,371	31.8%	3,348	4,157	24.2%
Propane Vehicles	Propane	857	950	10.9%	52	54	4.4%
Natural Gas Vehicles	Natural Gas	-	-	-	-	-	-
Motorcycles	Gasoline	1,737	1,214	-30.1%	120	79	-34.2%
Total On-Road Transportation		**410,693**	**363,306**	**-11.5%**	**27,920**	**22,827**	**-18.2%**
Off-Road Transportation							
Marine, Aviation and Other Off-Road Vehicles	Gasoline + Diesel + Jet Fuel	45,198	33,375	-26.2%	3,379	2,388	-29.3%
Total Off-Road Transportation		**45,198**	**33,375**	**-26.2%**	**3,379**	**2,388**	**-29.3%**
Waste							
Wastewater					49	10	-79.6%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Composting					0	0	-
Solid Waste					3,128	1,643	-47.5%
Total Waste					**3,177**	**1,653**	**-48.0%**
Agriculture Forestry & Other Land Use (AFOLU)							
Land-Use: Emissions Sequestered **(Disclosure Only - Not Included In Total)**					-33,060	-33,443	1.2%
Land-Use: Emissions Released **(Disclosure Only - Not Included In Total)**					32,083	12,143	-62.2%
Livestock, Aggregate Sources and Non-CO_2 Emission Sources on Land					407	604	48.4%
Total AFOLU					**407**	**604**	**48.4%**
Industrial Process & Product Use (IPPU)							
Process Use Emissions					2,175	3,652	67.9%
Total IPPU					**2,175**	**3,652**	**67.9%**
TOTAL		**1,058,268**	**1,002,959**	**-5.2%**	**48,689**	**42,920**	**-11.8%**

15 TOWN OF SIDNEY

15.1 2020 Profile

Profile	
Population	12,312
Dwellings	6,182
Registered Vehicles	8,066
Energy (Thousands of GJ)	1,097
GHG Emissions (tCO_2e)	53,276

15.2 Energy & GHG Emissions

Table 19 presents a summary comparison of the Town Sidney's 2007 and 2020 energy and GHG emissions.

Table 19. Estimated Energy and GHG Emissions By Reporting Source

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Stationary Energy							
Residential Buildings	Electricity	242,453	222,028	-8.4%	2,404	2,473	2.9%
	Natural Gas	70,155	91,578	30.5%	3,498	4,567	30.5%
	Fuel Oil	58,189	79,973	37.4%	3,979	5,468	37.4%
	Propane	10,069	8,209	-18.5%	614	502	-18.2%
	Wood	22,263	18,547	-16.7%	523	436	-16.7%
	Diesel	8,473	6,245	-26.3%	632	438	-30.6%
Commercial & Industrial Buildings	Electricity	187,401	168,687	-10.0%	1,858	1,879	1.1%
	Natural Gas	80,240	85,014	5.9%	4,001	4,239	5.9%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
	Fuel Oil	-	-	-	-	-	-
	Diesel	15,280	13,862	-9.3%	1,139	973	-14.6%
Energy Industries	LFG Combustion			-	-	-	-
Agriculture, Forestry And Fishing Activities	Diesel	40,422	34,457	-14.8%	3,014	2,417	-19.8%
Natural Gas Fugitive Emissions				-	47	67	40.7%
Total		**734,947**	**728,600**	**-0.9%**	**21,710**	**23,459**	**8.1%**
On-Road Transportation							
Electric Vehicles	Electricity	-	1,393	-	-	16	-
Hydrogen Vehicles	Hydrogen	-	-	-	-	-	-
Passenger Vehicles	Gasoline + Diesel	199,863	94,379	-52.8%	13,532	5,919	-56.3%
Light Trucks, Vans, SUVs	Gasoline + Diesel	162,604	167,907	3.3%	11,158	10,685	-4.2%
Heavy Duty Vehicles	Gasoline + Diesel	82,565	68,182	-17.4%	5,565	4,293	-22.9%
Propane Vehicles	Propane	973	384	-60.5%	59	22	-62.8%
Natural Gas Vehicles	Natural Gas	-	-	-	-	-	-
Motorcycles	Gasoline	1,276	1,011	-20.8%	88	66	-25.5%
Total On-Road Transportation		**447,282**	**333,256**	**-25.5%**	**30,401**	**20,999**	**-30.9%**
Off-Road Transportation							
Marine, Aviation and Other Off-Road Vehicles	Gasoline + Diesel + Jet Fuel	52,151	35,130	-32.6%	3,899	2,513	-35.5%
Total Off-Road Transportation		**52,151**	**35,130**	**-32.6%**	**3,899**	**2,513**	**-35.5%**
Waste							
Wastewater					612	563	-8.1%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Composting					0	170	-
Solid Waste					3,610	1,730	-52.1%
Total Waste					**4,222**	**2,463**	**-41.7%**
Agriculture Forestry & Other Land Use (AFOLU)							
Land-Use: Emissions Sequestered **(Disclosure Only - Not Included In Total)**					-543	-514	-5.3%
Land-Use: Emissions Released **(Disclosure Only - Not Included In Total)**					823	1,251	52.1%
Livestock, Aggregate Sources and Non-CO_2 Emission Sources on Land					2	24	1373.0%
Total AFOLU					**2**	**24**	**1373.0%**
Industrial Process & Product Use (IPPU)							
Process Use Emissions					2,510	3,818	52.1%
Total IPPU					**2,510**	**3,818**	**52.1%**
TOTAL		**1,234,379**	**1,096,986**	**-11.1%**	**62,744**	**53,276**	**-15.1%**

16 DISTRICT OF SOOKE

16.1 2020 Profile

Profile	
Population	15,083
Dwellings	5,936
Registered Vehicles	10,132
Energy (Thousands of GJ)	1,115
GHG Emissions (tCO_2e)	55,790

16.2 Energy & GHG Emissions

Table 20 presents a summary comparison of the District of Sooke's 2007 and 2020 energy and GHG emissions.

Table 20. Estimated Energy and GHG Emissions By Reporting Source

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Stationary Energy							
Residential Buildings	Electricity	257,364	316,621	23.0%	2,552	3,527	38.2%
	Natural Gas	13,108	58,248	344.4%	654	2,905	344.4%
	Fuel Oil	56,455	77,589	37.4%	3,860	5,305	37.4%
	Propane	9,744	7,943	-18.5%	594	486	-18.2%
	Wood	21,667	18,049	-16.7%	509	424	-16.7%
	Diesel	7,633	7,650	0.2%	569	537	-5.7%
Commercial & Industrial Buildings	Electricity	68,790	82,223	19.5%	682	916	34.3%
	Natural Gas	16,506	33,412	102.4%	823	1,666	102.4%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
	Fuel Oil	-	-	-	-	-	-
	Diesel	13,765	16,982	23.4%	1,026	1,191	16.1%
Energy Industries	LFG Combustion			-	-	-	-
Agriculture, Forestry And Fishing Activities	Diesel	36,415	42,212	15.9%	2,715	2,961	9.1%
Natural Gas Fugitive Emissions				-	13	44	243.7%
Total		**501,448**	**660,930**	**31.8%**	**13,997**	**19,962**	**42.6%**
On-Road Transportation							
Electric Vehicles	Electricity	-	1,944	-	-	22	-
Hydrogen Vehicles	Hydrogen	-	-	-	-	-	-
Passenger Vehicles	Gasoline + Diesel	141,887	103,480	-27.1%	9,610	6,493	-32.4%
Light Trucks, Vans, SUVs	Gasoline + Diesel	187,290	231,487	23.6%	12,850	14,742	14.7%
Heavy Duty Vehicles	Gasoline + Diesel	80,537	71,487	-11.2%	5,442	4,497	-17.4%
Propane Vehicles	Propane	1,986	839	-57.8%	120	48	-60.2%
Natural Gas Vehicles	Natural Gas	-	58	-	-	3	-
Motorcycles	Gasoline	1,490	1,499	0.6%	103	97	-5.3%
Total On-Road Transportation		**413,191**	**410,793**	**-0.6%**	**28,125**	**25,901**	**-7.9%**
Off-Road Transportation							
Marine, Aviation and Other Off-Road Vehicles	Gasoline + Diesel + Jet Fuel	46,981	43,036	-8.4%	3,512	3,079	-12.3%
Total Off-Road Transportation		**46,981**	**43,036**	**-8.4%**	**3,512**	**3,079**	**-12.3%**
Waste							
Wastewater					0	0	-

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Composting					0	0	-
Solid Waste					3,252	2,119	-34.8%
Total Waste					**3,252**	**2,119**	**-34.8%**
Agriculture Forestry & Other Land Use (AFOLU)							
Land-Use: Emissions Sequestered **(Disclosure Only - Not Included In Total)**					-9,952	-11,192	12.5%
Land-Use: Emissions Released **(Disclosure Only - Not Included In Total)**					6,213	5,442	-12.4%
Livestock, Aggregate Sources and Non-CO_2 Emission Sources on Land					47	149	212.9%
Total AFOLU					**47**	**149**	**212.9%**
Industrial Process & Product Use (IPPU)							
Process Use Emissions					2,261	4,580	102.6%
Total IPPU					**2,261**	**4,580**	**102.6%**
TOTAL		**961,620**	**1,114,759**	**15.9%**	**51,194**	**55,790**	**9.0%**

17 CITY OF VICTORIA

17.1 2020 Profile

Profile	
Population	94,415
Dwellings	49,635
Registered Vehicles	53,483
Energy (Thousands of GJ)	8,467
GHG Emissions (tCO_2e)	408,761

17.2 Energy & GHG Emissions

Table 21 presents a summary comparison of the City of Victoria's 2007 and 2020 energy and GHG emissions.

Table 21. Estimated Energy and GHG Emissions By Reporting Source

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Stationary Energy							
Residential Buildings	Electricity	1,235,156	1,186,142	-4.0%	12,249	13,212	7.9%
	Natural Gas	952,641	453,369	-52.4%	47,506	22,608	-52.4%
	Fuel Oil	617,245	287,746	-53.4%	42,205	19,675	-53.4%
	Propane	118,617	96,698	-18.5%	7,230	5,913	-18.2%
	Wood	259,255	215,974	-16.7%	6,088	5,072	-16.7%
	Diesel	60,085	47,888	-20.3%	4,480	3,360	-25.0%
Commercial & Industrial Buildings	Electricity	1,983,621	1,648,080	-16.9%	19,671	18,358	-6.7%
	Natural Gas	1,377,709	1,937,984	40.7%	68,703	96,643	40.7%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
	Fuel Oil	122,702	122,702	0.0%	8,390	8,390	0.0%
	Diesel	108,350	106,304	-1.9%	8,078	7,458	-7.7%
Energy Industries	LFG Combustion			-	-	-	-
Agriculture, Forestry And Fishing Activities	Diesel	-	-	-	-	-	-
Natural Gas Fugitive Emissions				-	240	260	8.3%
Total		**6,835,381**	**6,102,886**	**-10.7%**	**224,839**	**200,949**	**-10.6%**
On-Road Transportation							
Electric Vehicles	Electricity	-	11,335	-	-	126	-
Hydrogen Vehicles	Hydrogen	-	-	-	-	-	-
Passenger Vehicles	Gasoline + Diesel	1,250,314	692,954	-44.6%	84,656	43,457	-48.7%
Light Trucks, Vans, SUVs	Gasoline + Diesel	774,818	1,017,832	31.4%	53,168	64,746	21.8%
Heavy Duty Vehicles	Gasoline + Diesel	468,309	348,840	-25.5%	31,632	22,032	-30.3%
Propane Vehicles	Propane	5,840	3,944	-32.5%	352	224	-36.5%
Natural Gas Vehicles	Natural Gas	-	404	-	-	22	-
Motorcycles	Gasoline	8,968	8,555	-4.6%	618	555	-10.2%
Total On-Road Transportation		**2,508,250**	**2,083,864**	**-16.9%**	**170,425**	**131,161**	**-23.0%**
Off-Road Transportation							
Marine, Aviation and Other Off-Road Vehicles	Gasoline + Diesel + Jet Fuel	509,285	280,736	-38.2%	38,153	20,127	-40.5%
Total Off-Road Transportation		**509,285**	**280,736**	**-44.9%**	**38,153**	**20,127**	**-47.3%**
Waste							
Wastewater					7,699	5,400	-29.9%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Composting					72	854	1080.1%
Solid Waste					25,595	20,533	-19.8%
Total Waste					**33,367**	**26,787**	**-19.7%**
Agriculture Forestry & Other Land Use (AFOLU)							
Land-Use: Emissions Sequestered **(Disclosure Only - Not Included In Total)**					-1,798	-1,932	7.4%
Land-Use: Emissions Released **(Disclosure Only - Not Included In Total)**					3,725	3,744	0.5%
Livestock, Aggregate Sources and Non-CO_2 Emission Sources on Land					0	0	-
Total AFOLU					**0**	**0**	**-**
Industrial Process & Product Use (IPPU)							
Process Use Emissions					17,798	29,736	67.1%
Total IPPU					**17,798**	**29,736**	**67.1%**
TOTAL		**9,852,916**	**8,467,486**	**-14.0%**	**484,582**	**408,761**	**-15.8%**

18 TOWN OF VIEW ROYAL

18.1 2020 Profile

Profile	
Population	11,829
Dwellings	4,796
Registered Vehicles	10,297
Energy (Thousands of GJ)	1,081
GHG Emissions (tCO_2e)	54,477

18.2 Energy & GHG Emissions

Table 22 presents a summary comparison of the Town of View Royal's 2007 and 2020 energy and GHG emissions.

Table 22. Estimated Energy and GHG Emissions By Reporting Source

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Stationary Energy							
Residential Buildings	Electricity	185,833	195,051	5.0%	1,843	2,173	17.9%
	Natural Gas	75,155	89,003	18.4%	3,748	4,438	18.4%
	Fuel Oil	22,724	31,231	37.4%	1,554	2,135	37.4%
	Propane	3,926	3,201	-18.5%	239	196	-18.2%
	Wood	8,710	7,256	-16.7%	205	170	-16.7%
	Diesel	6,704	6,000	-10.5%	500	421	-15.8%
Commercial & Industrial Buildings	Electricity	113,772	130,614	14.8%	1,128	1,455	29.0%
	Natural Gas	123,868	149,375	20.6%	6,177	7,449	20.6%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
	Fuel Oil	-	-	-	-	-	-
	Diesel	12,088	13,319	10.2%	901	934	3.7%
Energy Industries	LFG Combustion			-	-	-	-
Agriculture, Forestry And Fishing Activities	Diesel	31,979	33,105	3.5%	2,384	2,322	-2.6%
Natural Gas Fugitive Emissions				-	38	50	31.8%
Total		**584,760**	**658,154**	**12.6%**	**18,717**	**21,744**	**16.2%**
On-Road Transportation							
Electric Vehicles	Electricity	-	2,319	-	-	26	-
Hydrogen Vehicles	Hydrogen	-	-	-	-	-	-
Passenger Vehicles	Gasoline + Diesel	138,335	116,597	-15.7%	9,366	7,313	-21.9%
Light Trucks, Vans, SUVs	Gasoline + Diesel	135,581	221,254	63.2%	9,303	14,081	51.3%
Heavy Duty Vehicles	Gasoline + Diesel	60,935	47,063	-22.8%	4,111	2,950	-28.2%
Propane Vehicles	Propane	895	446	-50.2%	54	25	-53.1%
Natural Gas Vehicles	Natural Gas	-	-	-	-	-	-
Motorcycles	Gasoline	1,223	1,336	9.3%	84	87	2.8%
Total On-Road Transportation		**336,970**	**389,016**	**15.4%**	**22,919**	**24,481**	**6.8%**
Off-Road Transportation							
Marine, Aviation and Other Off-Road Vehicles	Gasoline + Diesel + Jet Fuel	41,258	33,752	-18.2%	3,084	2,415	-21.7%
Total Off-Road Transportation		**41,258**	**33,752**	**-18.2%**	**3,084**	**2,415**	**-21.7%**
Waste							
Wastewater					386	361	-6.7%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Composting					0	170	-
Solid Waste					2,856	1,662	-41.8%
Total Waste					**3,242**	**2,193**	**-32.4%**
Agriculture Forestry & Other Land Use (AFOLU)							
Land-Use: Emissions Sequestered **(Disclosure Only - Not Included In Total)**					-2,585	-2,738	5.9%
Land-Use: Emissions Released **(Disclosure Only - Not Included In Total)**					1,738	1,807	4.0%
Livestock, Aggregate Sources and Non-CO_2 Emission Sources on Land					1	6	355.1%
Total AFOLU					**1**	**6**	**355.1%**
Industrial Process & Product Use (IPPU)							
Process Use Emissions					1,986	3,638	83.2%
Total IPPU					**1,986**	**3,638**	**83.2%**
TOTAL		**962,988**	**1,080,921**	**12.2%**	**49,949**	**54,477**	**9.1%**

19 SOUTHERN GULF ISLANDS ELECTORAL AREA

19.1 2020 Profile

The Southern Gulf Islands Electoral Area consists of: Galiano, Mayne, North Pender, Saturna and South Pender.

Profile	
Population	4,963
Dwellings	2,432
Registered Vehicles	4,300
Energy (Thousands of GJ)	704
GHG Emissions (tCO_2e)	27,730

19.2 Energy & GHG Emissions

Table 23 presents a summary comparison of the Southern Gulf Islands Electoral Area 2007 and 2020 energy and GHG emissions.

Table 23. Estimated Energy and GHG Emissions By Reporting Source

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Stationary Energy							
Residential Buildings	Electricity	205,339	201,183	-2.0%	2,036	2,241	10.1%
	Natural Gas	-	-	-	-	-	-
	Fuel Oil	27,326	38,718	41.7%	1,868	2,647	41.7%
	Propane	24,684	20,746	-16.0%	1,505	1,269	-15.7%
	Wood	206,032	176,945	-14.1%	4,838	4,155	-14.1%
	Diesel	3,658	2,517	-31.2%	273	177	-35.2%

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Commercial & Industrial Buildings	Electricity	45,106	45,491	0.9%	447	507	13.3%
	Natural Gas	-	-	-	-	-	-
	Fuel Oil	-	-	-	-	-	-
	Diesel	6,596	5,588	-15.3%	492	392	-20.3%
Energy Industries	LFG Combustion			-	-	-	-
Agriculture, Forestry And Fishing Activities	Diesel	17,449	13,889	-20.4%	1,301	974	-25.1%
Natural Gas Fugitive Emissions				-	-	-	-
Total		**536,190**	**505,076**	**-5.8%**	**12,760**	**12,362**	**-3.1%**
On-Road Transportation							
Electric Vehicles	Electricity	-	922	-	-	10	-
Hydrogen Vehicles	Hydrogen	-	-	-	-	-	-
Passenger Vehicles	Gasoline + Diesel	115,551	33,438	-71.1%	7,821	2,098	-73.2%
Light Trucks, Vans, SUVs	Gasoline + Diesel	63,232	108,354	71.4%	4,339	6,898	59.0%
Heavy Duty Vehicles	Gasoline + Diesel	16,337	41,345	153.1%	1,084	2,605	140.3%
Propane Vehicles	Propane	-	441	-	-	25	-
Natural Gas Vehicles	Natural Gas	-	58	-	-	3	-
Motorcycles	Gasoline	916	495	-45.9%	63	32	-49.1%
Total On-Road Transportation		**196,036**	**185,054**	**-5.6%**	**13,307**	**11,672**	**-12.3%**
Off-Road Transportation							
Marine, Aviation and Other Off-Road Vehicles	Gasoline + Diesel + Jet Fuel	22,512	14,160	-37.1%	1,683	1,013	-39.8%
Total Off-Road Transportation		**22,512**	**14,160**	**-37.1%**	**1,683**	**1,013**	**-39.8%**
Waste							

Source	Type	2007 Energy (GJ)	2020 Energy (GJ)	Change (%)	2007 GHG Emissions (tCO_2e)	2020 GHG Emissions (tCO_2e)	Change (%)
Wastewater					24	5	-78.7%
Composting					0	0	-
Solid Waste					1,558	697	-55.2%
Total Waste					**1,582**	**702**	**-55.6%**
Agriculture Forestry & Other Land Use (AFOLU)							
Land-Use: Emissions Sequestered **(Disclosure Only - Not Included In Total)**					-33,172	-33,526	1.1%
Land-Use: Emissions Released **(Disclosure Only - Not Included In Total)**					24,093	24,143	0.2%
Livestock, Aggregate Sources and Non-CO_2 Emission Sources on Land					387	400	3.5%
Total AFOLU					**387**	**400**	**3.5%**
Industrial Process & Product Use (IPPU)							
Process Use Emissions					1,083	1,581	45.9%
Total IPPU					**1,083**	**1,581**	**45.9%**
TOTAL		**754,738**	**704,290**	**-6.7%**	**30,803**	**27,730**	**-10.0%**

Capital Region $C0_{2e}$ Emissions Per Capita

January 2022

Capital Region $C0_{2e}$ (tonnes) Emissions Per Capita	2007	2020
Capital Region	5.6	4.2
Central Saanich	6.0	5.3
Colwood	5.3	3.9
Esquimalt	5.5	4.2
Highlands	5.8	6.0
Juan De Fuca Electoral Area	14.4	13.6
Langford	5.5	3.7
Metchosin	5.6	4.1
North Saanich	5.8	4.5
Oak Bay	4.9	4.0
Saanich	5.2	3.9
Salt Spring Island Electoral Area	4.9	3.7
Sidney	5.5	4.3
Sooke	5.0	3.7
Victoria	6.0	4.3
View Royal	5.5	4.6
Southern Gulf Islands Electoral Area	6.3	5.6

REPORT TO ENVIRONMENTAL SERVICES COMMITTEE
MEETING OF WEDNESDAY, JANUARY 19, 2022

SUBJECT **Zero-Emissions Fleet Initiative – Final Study Report**

ISSUE SUMMARY

To present the Final Study Report to the Capital Regional District (CRD) Board as the final commitment of the Zero-Emissions Fleet Initiative (ZEFI).

BACKGROUND

In September 2017, the Federation of Canadian Municipalities' Green Municipal Fund approved a $350,000 pilot project grant to fund the CRD's Zero-Emissions Fleet Initiative. The project was a multi-year, federally-funded partnership between the CRD, the University of Victoria's Institute for Integrated Energy Systems, and the BC Ministry of Energy, Mines and Petroleum Resources.

The project had three primary areas of focus:

- a zero-emission vehicle (ZEV) pilot in the CRD's corporate fleet
- research and analysis; and
- public outreach

The ZEV pilot included two electric vehicles, two plug-in hybrid electric vehicles, two hydrogen fuel cell electric vehicles and several e-bikes. Vehicle driving distances were recorded and driver feedback was gathered to better understand how ZEVs could be effectively integrated into the CRD fleet. The fuel cell electric vehicles were some of the first users of the newly-built hydrogen refuelling station in Saanich, a provincial government-supported project. Operation of the ZEVs resulted in a reduction of 41.8 tonnes of greenhouse gas emissions during their operation.

The research and analysis conducted as part of this project produced several reports that are appended to the Final Study Report (Appendix A):

- A *Fleet Telematics and EV Suitability Study* to enable the CRD to identify improvements to fleet use.
- An *E-bike Fleet Deployment Analysis* to understand the environmental, economic, and logistical performance of the operation of E-bikes in corporate fleets.
- A *Fleet Vehicle Energy Consumption Software Prediction Thesis Project* that proposes a data-driven model for prediction of the energy consumption of fleet vehicles in various missions.
- A report on *Earthquake Resiliency Implications of CRD EV Adoption* to examine possible post-earthquake use scenarios for Electric Vehicles.

Results of the project were shared with the public through two outreach sessions:

- A *ZEV Symposium*, an in-person event that enabled practitioners in government, non-profits, and industry to connect, share best practices and identify potential collaborations

- An *E-bikes in Fleets presentation*, as part of a West Coast Electric Fleets online webinar focused on E-bike adoption in the Pacific Northwest.

With completion of the final steps of the initiative, staff finalized a project report summarizing the activities, results and conclusions of the project.

ENVIRONMENTAL & CLIMATE IMPLICATIONS

The project was integral in developing new information and experience for the CRD around ZEVs. With strong future goals for EV adoption and greenhouse gas emission reduction, the project was a key step on the CRD's path to its climate goals.

From 2017 to 2021, the grant funding provided a zero-emission vehicle jump-start for the capital region. It provided the opportunity for the CRD to purchase and test its first ZEVs and install charging infrastructure, leading to continued corporate EV purchases and charging infrastructure installations. The program supported the development of the first hydrogen fuelling station for vehicles on Vancouver Island. The project also supported and funded localized academic research regarding ZEVs.

The project was essential in CRD policy development, informing the development of the CRD's corporate Green Fleet Strategy and recently-updated Climate Action Strategy.

CONCLUSION

The CRD has completed the Zero-Emissions Fleet Initiative that kick-started the organization's adoption and promotion of zero-emission transportation, both corporately and in the community. The project was funded through federal grant money aligned to promote a pathway to net zero by 2050. The information has been used for several initiatives under the CRD's Climate Action Strategy. The results motivate the continuing effort to transition the corporate fleet to Electric Vehicles through the corporate Green Fleet Policy and fleet procurement procedures. This rate of adoption is expected to accelerate as EV prices continue to decrease and more all-wheel drive and medium- and heavy-duty vehicle options become available. The summary report needs to be received by the Board as a final commitment to the grant funding.

RECOMMENDATION

The Environmental Services Committee recommends to the Capital Regional District Board:
That the Zero-Emissions Fleet Initiative Final Study Report be received for information.

Submitted by:	Glenn Harris, Ph.D., R.P.Bio., Senior Manager, Environmental Protection
Concurrence:	Larisa Hutcheson, P. Eng., General Manager, Parks & Environmental Services
Concurrence:	Robert Lapham, MCIP, RPP, Chief Administrative Officer

ATTACHMENT

Appendix A: Zero-Emissions Fleet Initiative – Final Study Report

APPENDIX A

ZERO-EMISSIONS FLEET INITIATIVE

Final Study Report

Making a difference...together

Capital Regional District | January 2022

The preparation of this pilot project was carried out with assistance from the Green Municipal Fund, a fund financed by the Government of Canada and administered by the Federation of Canadian Municipalities. Notwithstanding this support, the views expressed are the personal views of the authors, and the Federation of Canadian Municipalities and the Government of Canada accept no responsibility for them.

Introduction

The Capital Regional District's (CRD) Zero-Emissions Fleet Initiative (the Initiative) launched in February 2018 and completed in October 2021. The 'technology neutral' initiative focused on testing and comparing the use of zero-emissions vehicles, including battery electric vehicles (BEV), hydrogen fuel cell electric vehicles (FCEV), plug-in hybrid gas/electric vehicles (PHEV), and electric bicycles (e-bikes).

Project Objectives

The aim of the initiative was to embark on a process to eventually reduce greenhouse gas (GHG) emissions from the CRD fleet to almost zero. The Initiative supports the gradual replacement of internal combustion engine (ICE) vehicles with zero-emission models using hydrogen or electricity for fuel, as well as sizing vehicles for the appropriate use, reducing kms travelled, improving driver efficiency and, in some cases, using a modal shift with e-bikes replacing vehicles. The CRD has the potential to replace up to 100 existing ICE vehicles in the coming years as part of its ongoing fleet replacement process.

This project aimed to meet multiple objectives:

- Reduce GHG emissions in the CRD fleet by:
    - Conducting a field trial of FCEVs as part of the CRD fleet, with a view to broad adoption of this technology within the fleet
    - Testing and analyzing the use of additional zero-emission alternatives, including BEV and e-bikes where operationally appropriate
    - Conducting an in-depth "smart fleet" study to learn from and optimize these applications in terms of operating costs and GHG reduction
    - Investigating opportunities to use electric vehicles as an emergency power source
- Reduce GHG emissions from other vehicles on southern Vancouver Island by:
    - Sharing the results of the CRD pilot with local governments, businesses and interested individuals within the region and across British Columbia
    - Supporting fuel cell electric vehicle infrastructure deployment in coordination with the provincial government, the private sector and the host municipality
    - Supporting the uptake of FCEVs by other fleets and individuals on southern Vancouver Island
- Support economic development opportunities associated with hydrogen fuelling infrastructure

Project Partners

The CRD was the lead partner for this initiative, supported by the Institute for Integrated Energy Solutions at the University of Victoria (IESVic) and the Province of British Columbia (through the Ministry of Energy and Mines).

Capital Regional District

The CRD is the regional government for 13 municipalities and three electoral areas on southern Vancouver Island and the nearby Gulf Islands, serving more than 377,000 citizens. As a local government and shared services provider, the CRD develops partnerships to facilitate and deliver projects and services that benefit municipalities, electoral areas, First Nations and the region as a whole. The CRD has more than 200 service, infrastructure and financing agreements with municipalities and electoral areas to deliver services in the following categories:

- regional, where all municipalities and electoral areas are served;
- sub-regional, where two or more jurisdictions are served; and
- local, in the electoral areas where the CRD is the local government.

The CRD has clearly acknowledged and committed to taking action to address climate change within our operations, as well as at the regional level, to reduce emissions and to prepare for the uncertainty a changing climate brings. This was highlighted in the CRD Board's declaration of a climate emergency in early 2019 and commitment to taking a leadership role to pursue regional carbon neutrality.

In response to the climate emergency, the CRD developed an updated five-year Climate Action Strategy in 2021, replacing two former strategies and integrating with existing local, provincial and federal climate action initiatives.

Developing and supporting low-carbon mobility within the capital region is a key pillar of the CRD's Climate Action Strategy. The CRD is technology neutral and is committed to exploring and using zero-emissions technology that can meet operational and duty-cycle needs in a cost-effective manner.

The Institute for Integrated Energy Systems at the University of Victoria

The mission of the IESVic is "To chart feasible paths to sustainable energy." IESVic conducts sustainable energy research, using a collaborative approach between mechanical engineers, economists and environmental scientists. It has become a 'go-to' source of expertise for industry leaders.

Study of fuel cell technologies is part of IESVic's current research. Researchers are working to address most steps in a hydrogen energy system, including generation, storage, distribution, economics, and fuel cell electricity generation. Because the transportation sector poses particularly strong challenges to eliminating carbon emissions, fuel cell stack and system development is a key initiative at IESVic. The institute receives support from a number of government and industrial partners for its research into stack modelling and design for vehicle scale polymer electrolyte membrane (PEM) systems. More recently, research on regenerative hydrogen systems driven by renewable energy sources have been investigated with a focus on the dynamic response and efficiency. As well, IESVic researchers are pursuing the development of novel methods for storing hydrogen with a focus on new liquefaction processes.

IESVic is working on a Transportation Futures project focusing on electrification of transportation. This includes a wide range of vehicle classes, from e-bikes through to personal vehicles, busses, fleet (e.g., delivery) vehicles and heavy-duty transport. The emphasis on the project is optimizing the introduction of these vehicles, understanding battery degradation effects, and quantifying overall CO_2 reductions resulting from plugging into the interconnected BC/AB to California grid with and without control over charging behaviour. An aspect of the work also involves comparing battery-electric drivetrains to fuel cell options, in terms of performance, cost and overall round-trip energy efficiency.

IESVic undertook various aspects of research in this project, both during the developmental stages and analyzing the project implementation.

British Columbia Ministry of Energy and Mines

The Province of British Columbia has set legislated targets for reducing GHG emissions that contribute to global climate change. Under the *Greenhouse Gas Reduction Targets Act*, the Province must achieve a 33% reduction in GHG emissions below 2007 levels by 2020, and an 80% reduction by 2050. Personal and commercial vehicle transportation account for 13% and 24% of BC's GHG emissions, respectively, making a transition to clean energy vehicles an important part of the Province's climate strategy.

Through the BC Ministry of Energy and Mines and the Clean Energy Vehicle Program, the Province supports the adoption of clean energy vehicles, including FCEVs. Currently, the purchase or lease of a hydrogen fuel cell vehicle can qualify for an incentive of up to $6,000, while purchasers of BEV can qualify for up to $5,000 off of the purchase price. The Province also supports the Fleet Champions Program, which assists fleets in British Columbia in their efforts toward deploying clean energy vehicles by offering technical and financial support for an electric vehicle business case, as well as providing incentives for the installation of charging infrastructure.

The Province provided funding toward the installation of a hydrogen fuelling station for southern Vancouver Island. In addition, BC Ministry of Energy and Mines staff provided technical support to this project.

Part 1: Zero-Emission Vehicle Pilot Project

A key objective of the Initiative project was to test multiple types of zero-emissions vehicles, including hydrogen fuel cell vehicles, BEV, plug-in hybrid electric/gas vehicles, and e-bikes. This pilot project investigated matching zero-emission vehicles with operational requirements and the challenges and benefits they would provide.

Program Design

The complete pilot project was designed as three separate vehicle tests:

Fuel Cell Electric Vehicles

The FCEV pilot was designed as the follows:

- Lease six FCEVs (ultimately reduced to two FCEVs due to supply issues from vehicle manufacturer).
- Provide training for staff on the use and fuelling of these vehicles.
- Work with CRD staff and IESVic to monitor the benefits and challenges of using FCEVs in the CRD fleet.
- Work with the Province and Canadian Hydrogen and Fuel Cell Association to provide publicly available hydrogen fuelling facilities in the CRD region.

E-bikes

The initial testing of e-bikes will be done by source control inspectors who inspect businesses within a 5-km or less radius of CRD headquarters. The City of Victoria is continuously upgrading its system of cycling lanes, making cycling an even more desirable choice. The e-bikes were equipped with data loggers, and the benefits and challenges of this trial were monitored by IESVic, which provided an analysis of the program and recommendations for expanding this trial.

The pilot project included the following actions:

- Purchase two e-bikes and associated gear (helmets, lights, high-vis vests, locks, etc.);
- Coordinate safety training for inspectors using the bikes;
- Map the inspection territories to be visited by e-bike;
- Create standard operating procedures (and ensuring adherence to) to guide e-bike use and care (safety, parking, anti-theft, recharging, etc.);
- Define minimums for use (e.g., minimum twice per week, dependent on safety/weather factors);
- Track the mileage and electric energy use and estimate GHG savings; and
- Provide final reporting out of number of trips, distances travelled, cost benefits, successes/challenges, observations and recommendations.

Battery Electric Vehicles

The BEV pilot project included the following:

- Purchasing two 'tester' BEVs
- Adding at least two more BEVs to the fleet, replacing ICE vehicles
- Adding telematics to 40 fleet vehicles
- Studying the opportunities for using EVs as an emergency or off-grid power source

The CRD purchased two BEVs that are additional to normal fleet requirements and made them available to staff to test their applicability. These BEVs did not replace existing vehicles, but were used in a series of different locations for a test period of two-six weeks so that staff could test them and provide feedback on the results. At the end of the two-year testing period, the "tester" BEVs were incorporated fully into the fleet as replacements for ICE vehicles.

Two additional PHEVs were added to the pilot instead of additional electric vehicles. The earlier fleet analysis indicated that all-wheel drive (AWD) and long driving distances were a requirement for some vehicle operation scenarios, and available EVs at the time could not meet these requirements.

Implementation

The procurement and testing of ZEVs stretched across a five-year period, and some changes in scope occurred. Details are described, as follows.

Timeline

The ZEV pilot project began with the installation of an electric vehicle charger in September 2016, and ended with the return of the FCEVs in April 2021. A brief outline of the timeline is presented below:

2016	September	First Level 2 electric vehicle charger installed at CRD HQ
2017	January	Two Kia Soul electric vehicles purchased
	March	Twin Level 2 electric vehicle charger installed at Integrated Water Services building
2018	February	E-bikes were purchased and the four-month trial was completed
	November	First Mitsubishi Outlander AWD PHEV purchased
2019	February	Second Mitsubishi Outlander AWD PHEV purchased
2020	September	Two FCEVs leased
2021	January	Hydrogen fuelling station completed; FCEV pilot beings
	April	FCEV pilot ends and vehicles returned

Changes in Scope

Over the three-year project timeline, some changes from the initial project plan occurred, as described below. While implementation details varied, the goals of the project remained the same.

Replacement of Two Electric Vehicles with Plug-in Hybrid Electric Vehicles

The project plan called for the CRD to procure four EVs. Results of the telematics analysis found that PHEVs were better suited for the CRD's uses (offering AWD), and would be used in electric mode for over 97% of trips taken, while providing greater range for the 3% of trips that were beyond the plug-in electric vehicle range. Consequently, the CRD shifted procurement of two of the EVs to PHEVs. This change was confirmed with the Green Municipal Fund advisor. The change in environmental benefits is expected to be negligible.

Procurement of Additional E-bikes

The project plan anticipated piloting two e-bikes. However, bicycles come in various sizes and to accommodate all of the staff participating in the pilot, three bicycles (sized small, medium and large) were required. This change has no impact on the environmental benefits. Additional costs were covered by the CRD.

Delay in Procurement of Hydrogen Fuel Cell Electric Vehicles

The project plan anticipated piloting six FCEVs in the CRD fleet beginning in 2017, subject to the availability of hydrogen fuelling in the capital region. Synergistically, but separate to the Initiative, a hydrogen fuelling station is opening in the capital region, as part of the Province of BC's Hydrogen Fuelling Infrastructure Program. The opening of the hydrogen fuelling station was delayed until 2021. Consequently, the CRD delayed procuring and piloting the FCEVs until January 2021. Due to the limits of the vehicle leases, the vehicles were returned in April 2021, resulting in a four-month trial period rather than the initial goal of three years.

Results

The pilot program looked for insight and feedback in the following categories. Summary of results are described in each.

Vehicle Performance

ZEVs were generally found to be acceptable for the use cases expected of them. Full BEVs with AWD were not available, so PHEV with AWD were substituted, resulting in higher emissions. The driving range of the Kia Soul EVs (approx. 150 km) was seen as sufficient for most intended trips, but too short for some, leading staff to select ICE or PHEV vehicles for these trips instead.

It should be noted that range and AWD availability is improving with time. The average electric vehicle driving range on a single charge is now double that of the Kia Souls from 2017, thanks to technological improvements.

Driver Response

After the FCEV pilot, a qualitative survey was sent to staff who had operated the vehicle asking about what they enjoyed, disliked, their refuelling experience, and overall opinion of the vehicles.

Driver feedback was generally positive, with some mixed feedback, particularly regarding refuelling. Operators appreciated the smooth driving experience and knowing that the vehicle was greener to drive. Users mentioned the vehicle was a little different to drive compared to what they were used to, for example, the acceleration was "quiet".

There were concerns and hesitancy about refuelling. Some had no issues, but some mentioned learning the new procedure was slow and one user called it frustrating. The single available location for refuelling was seen as inconvenient by several users and it was not necessarily in a location that they were normally driving in.

One user was concerned about the safety of driving with compressed hydrogen on board.

Benefits and Challenges

Fuelling of the FCEVs provided the benefit of the CRD not having to own and operate fuelling infrastructure, as this was handled by the private company.

However, the lack of widespread fuelling locations was seen as an inconvenience by FCEV operators and likely results in more distance being driven by the vehicles to reach the fuelling station.

The new fuelling method is more complicated than an electric vehicle charger, and required additional training for staff.

Public Response

The testing of FCEVs received some negative reaction from the public. On January 21, 2019, the Residents for Responsible Renewables lobby group sent a letter to the CRD Board Chair and Members, cc-ing municipal staff across the region. The group presented economic and environmental concerns related to the development of hydrogen fuelling infrastructure in the capital region, and the CRD's pilot of FCEVs within the CRD fleet.

Hydrogen Fuelling Infrastructure

The external partners experienced some challenges in establishing a hydrogen fuelling station in the region, resulting in a significant time delay to open the station. Other than the initial station, no other growth in hydrogen fuelling for passenger vehicles has been seen in the capital region so far.

Part 2: Research and Analysis

The second objective of the Initiative was supporting vehicle trials with research into ways to substantially reduce energy use in the fleet through use of telematics and modelling; additional zero-emission transportation through BEVs and e-bikes replacing traditional vehicles; and exploring the potential for innovative ways to use electric vehicles as a power source in an emergency situation. These are described in detail below.

Fleet Telematics and Electric Vehicle Suitability Study

Partnering with Fleet Carma, a fleet management consultant, and student researchers at IESVic, the goal of this portion of the project was to conduct a smart fleet analysis and tools for fleet optimization.

Initial Program Design

The smart fleet analysis was designed to focus on the existing fleet and its usage. Analysis would be aided by the addition of telematics on about 30 ICE vehicles, to gather detailed information on vehicle usage. IESVic would analyze this data to answer the question of the adequacy of each alternative fuel technology or any combination of them that will lead to the lowest GHG emissions per year. The analysis would then look at the question of the optimal scheduling of functions/operations associated to each unit in the fleet over a time span, having the fundamental targets of minimizing the operational cost and associated GHG emissions. Both evaluations would be bounded by the operational and corporate constraints.

Operational constraints include vehicle status/performance, weather conditions, fuelling/charging locations, etc. Corporate structural constraints are those imposed by the corporate body of the CRD, which is characterized by a fleet distributed throughout a wide region in sub-fleets, each one of them serving the specific needs and under the particular conditions of each CRD service. Corporate constraints may include topology and/or geography, spectrum of ranges served, services provided, number and classes of vehicles assigned, etc. Comparing the scenarios with and without the corporate constraints, would be essential for future policy decision making regarding GHG emissions.

The outcomes of this research were planned to include:

- A mathematical tool for planning replacement of fleet units, considering alternative fuel drive train technologies.
- A mathematical tool for optimal scheduling of a mixed fleet of vehicles.
- Data-based recommendations for fleet renewal decisions and policy developments to promote reduction of corporate GHG emissions in the public sector in BC.

This information was planned to enable CRD to identify improvements to fleet use with existing vehicles, as well as vehicles that could practically be replaced by BEV or FCEV options.

Implementation

Between February 2018 and February 2019, 43 telematics devices were installed within 62 fleet vehicles. Information was gathered on vehicle usage, with a focus on reducing GHG emissions, enhancing utilization and reducing operating costs. Before installing the devices, CRD undertook a privacy impact assessment, and rolled out an extensive internal communications campaign in conjunction with the device installment.

Results of the telematics study were presented in an Electric Vehicle Suitability Assessment (Appendix A) based on the telematics data, which recommended replacing 13 ICE vehicles with plug-in hybrid electric vehicles. An IESVic post-graduate student is currently conducting a more comprehensive analysis of the data, and trying to verify fuel consumption predictions through a micro-trip approach and assumed stoichiometric fuel rates from mass airflow sensors against data-logger fuel consumption predictions.

Summary of Results

From the Electric Vehicle Suitability Assessment, it was found that if 13 of the baseline vehicles were replaced with the plug-in hybrid vehicles, the fleet would see the following total savings over the service lives of the baseline vehicles:

- the fleet could save $147,446 in total savings over the service life. This represents 13% of the fleet budget.
- the fleet could realize an emission reduction of 49.2 tonnes per year over the service life, representing a 43% reduction in CO_2 emissions.
- the fleet could reduce gasoline and diesel consumption by a total of 16,067 L annually over the service life, representing a 43% reduction in fuel.

The study found that few vehicles are being used heavily, and a few were under-utilized. The threshold for an under-utilized vehicle is less than 25 kms per day, and less than one hour of engine on-time. Vehicles that meet this criteria could be replaced by a mileage reimbursement vehicle or a pool vehicle.

Evaluation of anonymized, averaged driver behaviour indicated possible opportunities within the fleet to review safe driving practices. Smooth braking and smooth acceleration can help reduce maintenance costs over the life of the vehicle. For an electric vehicle, smooth braking allows for more energy to be captured via the regenerative braking process.

Looking at the comparative data in the reports, two key areas were identified to consider in order to begin plug-in vehicle adoption:

1. Implementing PHEVs will ensure the vehicles are range capable and able to support the level of utilization observed in the fleet. To facilitate the implementation of an electric fleet, charging stations must be available and drivers must be encouraged to plug in the vehicles to maintain a high electric vehicle fraction. This will allow the fleet to realize the maximum level of savings.

2. There is a large opportunity to transition light duty trucks and/or SUVs to PHEV SUVs. At the time of the study, there were not many SUV EVs available. However, additional significant fuel and emission savings can be realized if the conventional light duty trucks and SUVs can be replaced with suitable PHEVs or newly available BEV.

E-bike Fleet Deployment Analysis

The CRD E-bike pilot was a joint project between IESVic and the CRD. The proposed research goals for the e-bike project were:

1. To make recommendations regarding the optimal use of e-bikes in urban commercial fleets
2. To compare the environmental, economic, and logistical performance of the operation of e-bikes in urban fleets to other vehicle modes
3. To make recommendations regarding the regulatory constraints placed on e-bike use with respect to motor power limits

Methodology

The research goals were answered through the deployment of three e-bikes outfitted with multiple sensors to capture a variety of data. The purpose of this work is to provide quantifiable, evidence-based results to inform the CRD as to the efficacy of the use of e-bikes in their corporate fleet. Additionally, this project was meant to inform other fleet operators as to the operational costs and benefits of e-bikes in commercial fleets. The project abstract is presented below and the complete project report is available in Appendix B.

Abstract of Final Report

The deployment of three e-bikes into the CRD fleet resulted in over 600 km of recorded trip data. This data was used to inform several academic research projects, as well as to determine typical operational capabilities of e-bikes for the CRD fleet. The collected data showed a reduction of emissions by 99% when compared to a typical car found in the CRD fleet. Even compared to battery electric cars, the e-bikes represent a 95% reduction in emissions. Compared to both of these modes, the e-bikes also represent an over 80% reduction in capital and operating costs.

Overall, the deployment of the e-bikes saved approximately 250 kg of CO_2, if they are considered to have replaced ICE car trips. The operating capabilities of e-bikes show them as having half the pace of cars in urban environments. Where a car can cover 5 km in 8.5 minutes, an e-bike typically covered the same distance in 20 minutes.

Fleet Vehicle Energy Consumption Software Prediction Project

In partnership with IESVic, CRD fleet logger data was used as a basis for development and verification of a data-driven, software-based tool for improved-accuracy predictions of fleet fuel and energy consumption. The resulting deliverable was a Master's thesis by student Autumn Umanetz. The thesis abstract is presented below and the complete thesis document is available in Appendix C.

Abstract of Final Thesis Project

This study proposes a data-driven model for prediction of the energy consumption of fleet vehicles in various missions, by characterization as the linear combination of a small set of exemplar travel segments. The model was

constructed with reference to a heterogeneous study group of 29 light municipal fleet vehicles, each performing a single mission, and each equipped with a commercial global positioning system logger. The logger data was cleaned and segmented into three-minute periods, each with 10 derived kinetic features and a power feature. These segments were used to define three essential model components, as follows:

The segments were clustered into six exemplar travel types (called "eigentrips" for brevity). Each vehicle was defined by a vector of its average power in each eigentrip. Each mission was defined by a vector of annual seconds spent in each eigentrip. Ten percent of the eigentrip-labelled segments were selected into a training corpus (representing historical observations), with the remainder held back for testing (representing future operations to be predicted). A Light Gradient Boost Machine classifier was trained to predict the eigentrip labels with sole reference to the kinetic features, i.e., excluding the power observation. The classifier was applied to the held-back test data, and the vehicle's characteristic power values applied, resulting in an energy consumption prediction for each test segment. The predictions were then summed for each whole-study mission profile, and compared to the logger-derived estimate of actual energy consumption, exhibiting a mean absolute error of 9.4%. To show the technique's predictive value, this was compared to prediction with published L/100 km figures, which had an error of 22%. To show the level of avoidable error, it was compared with a Light Gradient Boost Machine direct regression model (distinct from the Light Gradient Boost Machine classifier), which reduced prediction error to 3.7%.

Earthquake Resiliency Implications of CRD Electric Vehicle Adoption

This sub-project of the Initiative was aimed at assessing the ramifications and potential roles of electric vehicles in a post-disaster scenario. A Cascadia earthquake has been chosen as the disaster framework to analyze as many of its disaster effects (e.g., damaged roads, landslides, disruption of power) are also experienced during other disaster concerns for Victoria, such as landslides and wildfires. The project summary is presented below and the complete report is available in Appendix D.

Background

The goal of the project was to provide a research paper for use cases tailored specifically to the CRD based on two key research question covered below:

1. What is the risk inherent in the adoption of an increasing share of electric vehicles in a local government fleet?
    a. To answer this question, research is being conducted into the resiliency of the liquid fuel vs. electrical supply infrastructure in a post-earthquake context. Initial research in this area has been conducted into what information is available for the Cascadia subduction zone of North America (extending from northern Vancouver Island to northern California), but the paper itself will focus Lower Mainland and the entirety of Vancouver Island, with more detail given to Vancouver Island.

    b. Research will also be conducted into the post-earthquake resiliency of electric vehicle charging infrastructure (electric vehicle charging stations for multiple vehicles, individual workplace charging ports, connectors).

2. What are the possible post-earthquake use scenarios for electric vehicles?
    a. How could electric vehicles act as individual nodes in an ad-hoc communication network in the case that the main 5G communication network has failed?

    b. Could electric vehicles provide power to emergency response shelters for people displaced in the earthquake?

Executive Summary

The following is the executive summary from the final research report, which can be found in its entirety in the appendices.

The adoption of electric vehicles has many benefits, such as reduced emissions, better performance, and economic savings on maintenance and fuelling. The Greater Victoria area has one of the largest concentrations of electric vehicles in BC, and this concentration is only expected to grow with time. Greater Victoria is also located in a portion of BC with a high seismic hazard and would be profoundly affected by a Cascadia subduction zone earthquake. Until recently, maintaining vehicle use after an earthquake has depended on the resilience of the fuel infrastructure, but the increasing use of electric vehicles will transfer some of that dependence to the resilience of the electrical system.

Analyzing past earthquakes in Chile, Japan and New Zealand provides some insight into how to increase earthquake resilience. The 2010 Chile earthquake showed the importance of available excess generation capacity, private forms of communication, and utilizing small generators for recovery in isolated areas. The 2011 Japan earthquake illustrated the value of not locating too much generation capacity in tsunami zones, utilizing rolling blackouts for recovery, and the exceptional performance of microgrids. The 2011 New Zealand earthquake taught the danger of buried cables in liquefaction zones and how impactful spending money on resilience upgrades can be.

BC Hydro can improve the resilience of the electrical grid by adding generation capacity, relocating grid elements from tsunami and liquefaction zones, planning to have resources for repairs available, and establishing aid agreements with surrounding areas. Vancouver Island can improve its fuel resilience by retrofitting ports, increasing fuel storage, and planning for how fuel will be prioritized after an earthquake.

The CRD can improve its organizational earthquake resilience by establishing a local microgrid and utilizing the battery capacity of its electric vehicle fleet to provide mobile storage following an earthquake. The CRD can also plan for what its expected vehicle and generator fuel needs would be after an earthquake and establish sufficient storage.

Electric vehicles can be used after an earthquake to establish a communication network by acting as individual nodes in the network. Over 24 hours, an electric vehicle would use 0.533 kWh to provide this function, and a Nissan Leaf Plus could act in this capacity for about 116 days before battery depletion. In a 24-hour period, a Nissan Leaf Plus was found to able to donate 400 kWh of energy to a local shelter, assuming the vehicle had access to a fast charger and a microgrid with a 100 kW solar array. Given the Leaf's 363-km single-charge range, the same microgrid was able to provide power for eight Leafs to deliver supplies and people for a 24-hour period, assuming that each vehicle charged once per 24 hours.

Part 3: Project Outreach

A key focus of the Initiative project was community benefit through outreach and knowledge sharing. Final results and reports will be available on the CRD's public-facing website. Additionally, the project included the following direct outreach activities.

Zero-Emission Vehicle Symposium

The CRD hosted the Zero-Emission Vehicle Transportation Showcase on October 28, 2021 at the University of Victoria. This event enabled practitioners in government, non-profits and industry to connect, share best practices and identify potential collaborations.

Event Overview

The Showcase included:

- three themed sessions focused on local government best practices, academic research trends, and long-term community vision; and
- an evening networking event with local practitioner presentations.

Participation and Feedback

The event brought together 22 in-person participants, including 12 presenters and 11 online participants.

The CRD received positive feedback overall on the content, with guests noting that the event was a balance of detail and big-picture presentations, underscoring the value of knowledge sharing. Participants enjoyed the hybrid format, though the in-person attendees were particularly pleased to be able to discuss the topic in person, often for the first time since the COVID-19 pandemic began.

This event could be a useful model for regional knowledge sharing as more municipalities and organizations move forward on their paths to decarbonized transportation. It also highlighted the importance of regional coordination and the role the CRD can play in helping to connect key players and support the delivery of important initiatives.

Key Themes

Several key themes emerged from participant questions and comments, as well as from the various presentations:

Table 1: Key Themes of ZEV Symposium

Theme	Description
Beyond the commute	Many governments and organizations have made key steps toward supporting or requiring zero-emission passenger vehicles for commuting and other household travel. Showcase discussions highlighted interest in looking beyond the commute to broader ZEV opportunities, such as recreation, tourism, and emergency planning, and emphasized other co-benefits like health metrics and economic development.
Beyond the car	Efforts to shift passenger vehicle kms to zero-emission are important. However, organizations are investigating how to reduce the total number of vehicle kms by shifting and electrifying other modes. Participants identified e-bikes, electric buses, and mode connectivity as increasingly important parts of the transportation system.
Knowledge sharing is vital	Municipalities across the region have different approaches and are at various stages of ZEV transportation implementation. It can be difficult to balance local interests in electric vehicle infrastructure and requirements. Integrating best practices and learnings from other organizations is highly valuable when tailored to the local municipal context. The CRD's efforts to connect and support municipalities play a key role in this exchange.
Measuring what matters	Data from zero-emission vehicle and infrastructure adoption is critical for tracking climate, transportation, and implementation metrics. Strong data can inform future designs, capture benefits, and mitigate negative impacts. Further, data availability can also foster research collaborations, as data availability can be a limiting factor in analysis.
A transition for everyone	Ensuring equitable access to zero-emission transportation is top of mind. Organizations are aiming to bring everyone along in the transition, but the 'how' continues to be explored and iterated. Pilot projects and dedicated funding for target groups are being explored to evaluate potential solutions.

E-Bike Fleet Webinar

On February 26, 2019, CRD staff shared results of the e-bike pilot as part of an 'E-Bikes in Fleets' webinar presented by West Coast Electric Fleets, an initiative of the Pacific Coast Collaborative, a joint initiative of California, Oregon, Washington, and BC to accelerate a vibrant, low-carbon economy on the West Coast. The presentation covered the following topics:

- Introduction to the CRD and the Initiative project as a whole
- E-Bike pilot project description
- Safe staff operating procedures
- Cost and procurement
- Storage and Security
- Results and GHG reductions
- Lessons learned and next steps

The complete presentation can be found Appendix E.

Final Project Results

The Initiative project aimed to take essential first steps toward reducing GHG emissions from the CRD fleet to almost zero. The project piloted zero-emission models using hydrogen or electricity for fuel, including FCEVs, EVs, PHEVs and e-bikes.

This project aimed to directly reduce GHG emissions in the CRD fleet, support the reduction of GHG emissions from other vehicles on southern Vancouver Island, and support economic development opportunities associated with hydrogen fuelling infrastructure.

A summary of the project results is as follows.

Benefits and Drawbacks of ZEV Technologies

The Initiative examined a number of ZEV technologies and use cases. A brief summary of the benefits and drawbacks of these technologies identified by the project are outlined in the table below.

Table 2: Benefits and Drawbacks of ZEV Technologies

New Technology	Benefits	Drawbacks
Smart fleet analysis	Rigorous evidence-based comparative data on zero-emissions vehicles; new applied research findings for optimizing Smart Fleets. Microtrip modelling of vehicle duty cycles appears to be quite promising in terms of applying method to other fleets with varied duty cycles, as an alternative to trying to build bottom-up drivetrain models.	Data loggers do not capture data from heavy-duty fleet vehicles (however, a suitable electric vehicle or FCEV replacement does not exist at this time).
FCEVs	Reduced GHGs; support for emerging industry	Difficulty in providing fuelling for new technology type; difficulty procuring vehicles; lack of models suitable for CRD needs capital cost of vehicles (without factoring in subsidies).
BEV	Reduced GHGs; reduced operational costs	Vehicle range; range anxiety; limited electric vehicle charging infrastructure; length of charge time; lack of models suitable for CRD needs (e.g., pickups, heavy duty, AWD SUV with range). *Continued on next page*

New Technology	Benefits	Drawbacks
Plug-in Hybrid Electric Vehicles	Longer ranges; more model types available (e.g., AWD); can refuel at gas stations; reduced GHGs compared to ICE vehicles	Can operate without being charged using fuel only and limiting their GHG reduction and operating cost savings; dual drive-train requires more maintenance than either EVs or ICEs
E-bikes	Reduced GHGs; reduced operational costs; employee health and fitness. E-bike modelling has been useful in showing implications of regulatory limitations and rider behaviour on GHG emissions impacts.	Mode of transport not suitable for all staff, or for all weather/climates; lack of cargo capacity; slower mode of transport, when compared to conventional vehicle.
Electric vehicles for emergency power	Potential to enhance emergency preparedness and resiliency.	Many external factors in post-disaster recovery are beyond the CRD's direct control (e.g., delivery of fuel or electricity).

Quantitative Results

From its initiation, the Initiative project defined several quantitative project parameters to track the effect of the program. These are outlined in the table below with commentary, as follows.

Table 3: Quantitative results summary of complete project

Project Parameter	Units	Baseline Performance (before project)	Final Performance (in 2020)
Greenhouse gas emissions (target portion of fleet)	t CO_2e	158.4	116.6 (reduction of 41.8)
Vehicles in fleet	number	304	296 (in 2020)
Vehicle km travelled (total fleet)	km	1,443,828	1,791,500
Electric vehicles in fleet	number	1	9 permanently (11 during lease period of FCEV; 9 on order for 2022
E-bikes in fleet	number	0	9
Hydrogen fuelling stations in region	number	0	1

t CO_2e = tonnes of carbon dioxide equivalent emissions

Greenhouse Gas Emissions

The vehicles purchased and tested as part of the Initiative project directly avoided 16.8 t of GHG emissions and indirectly avoided an additional 25 t thanks to additional electric vehicles purchased by the CRD after the success of the Initiative pilot. In total, 41.8 t of GHG emissions were avoided (see Table 4). For the FCEVs, this considers only the tank-to-wheel emissions and it assumes that hydrogen can be produced in a zero-emission method (e.g., hydro-power).

Table 4: Estimated GHG reductions from ZEV operations

ZEV	GHG reduction ($t\ CO_2e$)	Notes
2 FCEVs	0.4	44 total trips totaling 1,969 km of driving distance over four months; tank-to-wheel
2 BEV	11	Purchased as part of Initiative pilot project; 41,000 km driven
2 PHEV	3.9	Purchased as part of Initiative pilot project; 25,000 km driven
E-bikes	1.5	Extrapolated data from four-month trial: eight months per year for three years
Additional EVs	25	The CRD has purchased five additional electric vehicles since the Initiative pilot project; 94,000 km driven
TOTAL	41.8	

While the avoided GHG emissions were significant, the initial program goals were higher than what was achieved. Several project setbacks reduced the final number. Due to lack of manufacturer availability, the FCEV pilot was reduced from six vehicles to only two. Additionally, due to the delay by external parties in opening the hydrogen fuelling site on Vancouver Island, the FCEV pilot was reduced in scope from three years to four months. Furthermore, lacking available AWD electric vehicle models, two of the four vehicles in the electric vehicle pilot were swapped for PHEVs, which have improved fuel efficiency, but significantly more GHG emissions than an electric vehicle.

Advantageously for the future, most of these setbacks were solved by the end of the project. Because the electric vehicle pilot project was seen as successful, the CRD has purchased an additional five electric vehicles for its corporate fleet, resulting in further GHG reductions as a result of the Initiative. The CRD has nine electric vehicles on order for 2022 and further plans to purchase an additional 12.

Vehicles in Fleet

Over the course of the pilot project, the CRD corporate fleet reduced from 304 vehicles in 2017 to 296 vehicles in 2020. While not directly related to the Initiative, the project has significantly increased awareness of fleet usage and vehicle alternatives and undoubtedly informed fleet purchasing decision-making that has resulted in an approximate 3% reduction in fleet size.

Vehicle kms Travelled

The aim of the Initiative project was to analyze fleet usage and hopefully identify possibilities to reduce vehicle use. Unfortunately, vehicle use based on distance travelled has increased over the course of the project. Accurate data gathering was put in place in 2020; however, due to the COVID-19 pandemic, it is likely that fleet behaviour changed in 2020 compared to the baseline year. For example, drivers were less likely to share vehicles and more likely to drive to sites individually, which would have resulted in increased kms driven.

Beneficially, the Initiative project was a contributing factor in the CRD developing accurate distance data monitoring that will support future efforts in fleet analysis.

Electric Vehicles in Fleet

One of the triumphs of the Initiative was the success in breaking electric vehicles into the CRD fleet. Over the course of the project, the CRD went from zero electric vehicles in operation to nine electric vehicles in 2021, with nine more already on order for 2022. This exceeded the expectations of the project. By overcoming the initial challenges of installing charging infrastructure, and giving staff experience with electric vehicles to ensure that they would fit existing work requirements, the Initiative program opened the door for widespread electric vehicle adoption at the CRD.

E-bikes in Fleet

E-bike adoption was another success for the project and the CRD. Due to popularity, additional e-bikes were purchased after the pilot program, bringing the total number of e-bikes to nine. They continue to be used regularly by CRD staff, as shown in the figure below.

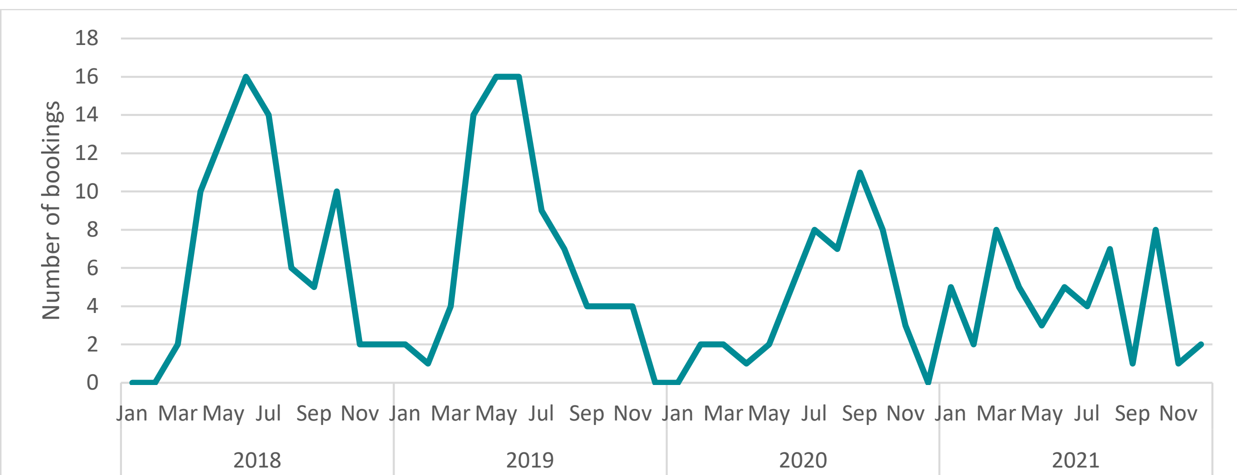


Figure 1: CRD E-bike usage by month

Hydrogen Fuelling Stations in Region

While there were some delays in timeline, the support of the Initiative program helped bring about the development of a hydrogen fuelling station in the Greater Victoria area. The hydrogen infrastructure safety study (Appendix F) completed in support of this project provided valuable information about the feasibility of the fuelling station and addressed common concerns. This project provides new opportunity for future use and development of hydrogen fuel cell technologies in the region.

Socio-Economic Impacts

In addition to the environmental benefits of reducing GHG emissions, the Initiative project also had a variety of social and economic benefits.

Social

Some of the social benefits of the program included the following:

- Improved air quality in CRD service areas, including neighbourhoods and parks.
- Reduced noise pollution in CRD service areas, including neighbourhoods and parks.
- Increased visibility of ZEVs throughout the capital region to draw public attention, instill curiosity, and generate impromptu opportunities for engaging with the public.
- Significant organizational experience with ZEVs will provide significant knowledge to be shared as part of outreach programs.
- Hydrogen fuelling infrastructure made available to Vancouver Island residents.
- Notable opportunity for civic pride about being early adopters and significant adopters of ZEV technology.
- Significant increase in electric vehicles, and resulting increased opportunity for electric vehicles to be used as a power source in emergency events.

Economic

Economic benefits of the program included the following:

- Reduction in fleet operational costs in fuel purchases and maintenance.
- Multiple hydrogen fuelling stations in the region would result in business growth and local employment opportunities, and accelerate the development of a clean hydrogen industry in BC and Canada.
- Widespread availability of hydrogen fuelling infrastructure would support new supporting business, such as hydrogen vehicle and infrastructure maintenance. Businesses that benefit from the availability of hydrogen would be attracted.

Conclusion

From 2017 to 2021, the Initiative provided a zero-emission vehicle jump-start for the capital region. It supported and funded academic research regarding ZEVs. It gave the opportunity for the CRD to purchase and test its first ZEVs and install the required infrastructure. The opportunity to understand ZEV applicability led to a further five electric vehicle purchases for the CRD corporate fleet and a growing rate of adoption (nine more purchases on order for 2022, with potential for 12 more), as well as efforts to expand the corporate charging infrastructure. The program supported the development of the first hydrogen fuelling station for vehicles on Vancouver Island, opening up business and economic opportunities that may use this infrastructure. Overall, the program contributed to increasing rate of ZEV adoption both at the CRD and regionally.

The Initiative project was essential in CRD policy development around transportation emissions. It supported and informed the development of the CRD's corporate Green Fleet Strategy, ensuring ZEVs are considered in all fleet purchases. Furthermore, the findings and experience gained from the Initiative were key in the development of the CRD's Climate Action Strategy, with goals for reducing emissions from vehicle use in the capital region and the CRD corporate fleet, as well.

The project encountered some challenges; however, the hydrogen fuelling station was delayed and FCEVs were not available from the manufacturer in the quantity expected. The project overall timeline increased, while the FCEV pilot duration was significantly shortened. Finding AWD electric vehicles was challenging, requiring PHEVs to be selected as alternatives, which are lower-emission but not zero-emission vehicles. Encountering and overcoming these challenges was valuable organizational learning and provided a basis for future ZEV decisions.

In summary, the Initiative was integral in developing new information and experience for the CRD around ZEVs. With strong future goals for electric vehicle adoption and GHG emission reduction, the Initiative project was a key stepping-stone on the CRD's path to its climate goals.

List of Abbreviations

AWD	All-wheel drive
BEV	Battery electric vehicle
CO_2	Carbon dioxide
FCEV	(hydrogen) fuel cell electric vehicle
GHG	Greenhouse gas
HQ	Headquarters
ICE	Internal combustion engine
IESVic	Institute for Integrated Energy Systems at the University of Victoria
PHEV	Plug-in hybrid gas/electric vehicles
SUV	Sport utility vehicle
t CO_2e	Tonnes of carbon dioxide equivalent

List of Appendices

Appendix A: Electric Vehicle Suitability Assessment Report
Appendix B: CRD-UVic E-Bike Fleet Deployment Report
Appendix C: Predicting Fleet-Vehicle Energy Consumption With Trip Segmentation Thesis Paper
Appendix D: Earthquake Resiliency Implications of CRD EV Adoption Report
Appendix E: Incorporating Electric Bikes into a Regional Government Fleet CRD Webinar Presentation
Appendix F: CRD Feasibility Study-Zero Emissions Fleet Initiative-Infrastructure Safety Study

Attachment 1

ELECTRIC VEHICLE SUITABILITY ASSESSMENT

Capital Regional District

DECEMBER 2018

Making a difference...together

STRATEGICALLY ADOPT PLUG-IN ELECTRIC VEHICLES SO THAT THEY WORK BEST FOR YOU.

Table of Contents

INTRODUCTION

FleetCarma's efficiency assessments inform organizational decision-making by using data from your current vehicles to evaluate the potential pathways to a cleaner and more cost-effective vehicle fleet.

The primary purpose of this fleet assessment report is to demonstrate the potential strategies that can be employed to achieve efficiency savings through the use of plug-in electric vehicles and enhanced management of existing vehicle assets. Efficiency savings include the financial benefits gained through Total Cost of Ownership (TCO) reductions as well as the corresponding reductions in fuel usage and greenhouse gas (GHG) emissions.

This process started with collecting second-by-second vehicle diagnostics data from your existing vehicles to formulate your fleet baseline, and in turn, drive FleetCarma's EV analysis. This approach ensures you are comparing vehicle options in your own real-world drive cycles.

The powertrain analysis developed by FleetCarma provides an independent third party methodology for your organization to evaluate your options. This predictive analytics system also simplifies the complexity of adopting plug-in vehicles that offer a range of performance and suitability capabilities across any fleet's portfolio of applications. The algorithms used deliver a reliable determination of the amount of

fuel and electricity that would be used by your plug-in vehicles and the anticipated savings potential of the more efficient vehicles you are considering. The data provided in this summary report serves as a review of the results from the study and a guide for making decisions regarding the electrification of your vehicle fleet. We start this report with highlights from the fleet baseline data that serve as a benchmark on how your vehicle fleet is currently performing. We follow with a summary of results from the powertrain model outputs and translate those into actionable recommendations. Our primary objective is to evaluate the extent to which plug-in electric vehicles would be suitable for your organization. This includes an examination of when and how they may charge, the anticipated reductions in operating costs and emissions, and the electric driving range capabilities as they relate to each of your duty cycles. In the final section of the report, we examine other types of efficiency opportunities to take advantage of, even in areas where plug-in electric vehicles may not work for you. For example, you will find specific saving opportunities as they relate to idle reduction, eco-driving, and fleet right-sizing. We welcome any and all questions and appreciate being partners with you in this process.

This process begins with data collected from your current vehicles to drive FleetCarma's EV powertrain algorithms in your real-world drive cycles.

FLEET BENCHMARK

Data logging your current duty cycles with FleetCarma devices provides two benefits. (1) The granularity of the data collected enables us to drive EV powertrain models with statistical confidence and (2) the data from your current vehicles provides a comparative benchmark to evaluate a series of potential EV adoption scenarios. Below are some baseline metrics collected from your vehicles.

All Fleet

39
duty cycles
(were monitored)

11 light duty trucks, 17 SUVs, 5 passenger vans, 3 full-sized vans and 3 sedans monitored.

45
kilometres
(average daily utilization)

This translates to an average calendar year utilization of 7,115 kilometres per vehicle.

13
L/100 km
(average fleet fuel economy)

Baseline vehicle fuel economy ranged from 4-27 L/100 km.

1.5
hours / day
(average engine-on hours)

Engine-on hours can help you evaluate the potential maintenance benefits of vehicles that run on electricity.

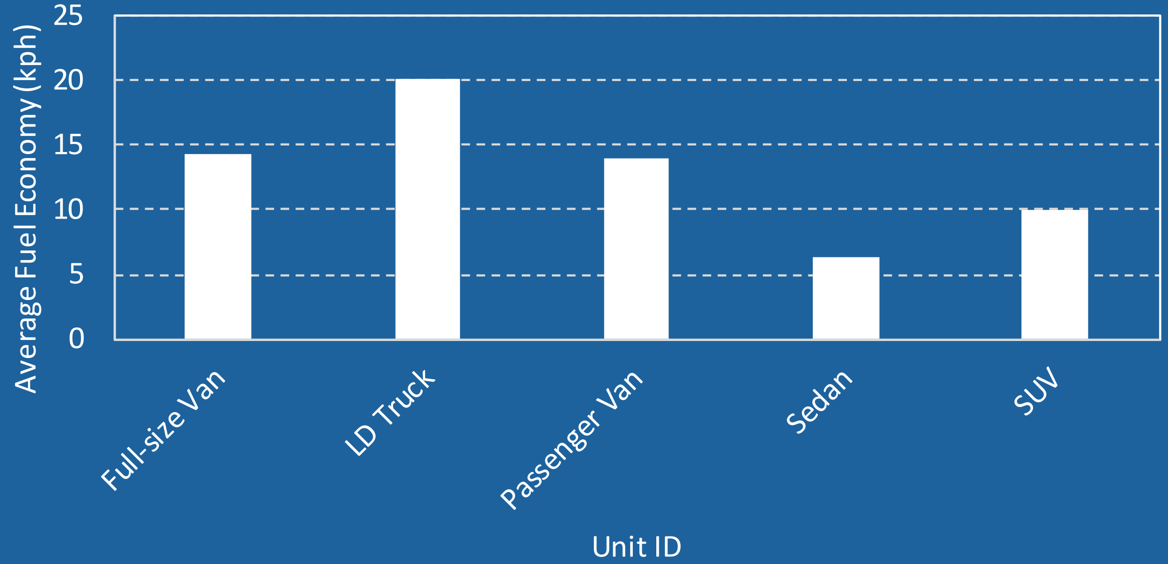
29
kph
(average duty cycle speed)

Average speeds are a high level indicator of the type of driving that your drivers do (highway or city).

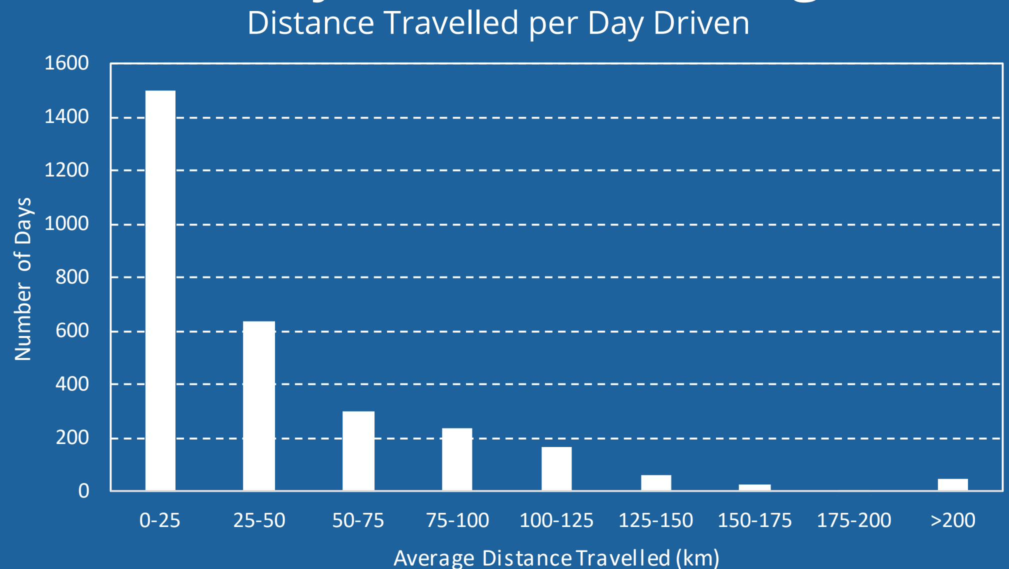
27
%
(average time idling)

The amount of idling will impact fuel spend, tailpipe emissions, and even maintenance requirements.

Fuel Economy by Vehicle Type



Your Daily Utilization Histogram



Your average fuel economy is shown in the graph above with the current mix of vehicle types in your fleet. We provide the full fuel economy picture for every vehicle and every trip in the FleetCarma web portal as well. Clearly, since the fuel economy of your baseline vehicles varies from one duty cycle to the next, the potential fuel cost savings from plug-in vehicles should be highest on a per kilometer basis with the duty cycles that have the lowest fuel economy. However, daily utilization will have a substantial impact on the overall electric vehicle miles travelled (eVMT). In your daily utilization histogram above, we can see that of the days on which your vehicles were driven, 72% drove less than 50 kilometres, and 90% drove less than 100 kilometres. When considering EVs in ideal operating conditions, these thresholds are useful to evaluate the suitability of a hybrid or fully electric vehicle for your fleet.

FLEETCARMA RECOMMENDED EV DEPLOYMENT

This section shows your FleetCarma recommended EV deployment. Given this deployment, our simulation models show that in order to maximize ROI, the purchase price of your EVs should be no larger than the target.

The table below shows the recommended EV deployment purchase price, based upon the MSRP. By purchasing all recommended vehicles at this price and spreading savings across the fleet, you can expect to achieve the returns indicated on page 12. This analysis assumes that all of the recommended vehicles are purchased and deployed as indicated below. Please see page 9 to match the duty cycle with the recommended electric vehicle.

EV Model	Number of Vehicles	Bid Price	Duty Cycles
Mitsubishi Outlander PHEV	13	$43,000	See Page 9

BEST FIT DUTY CYCLES FOR EVs

In the table below, all of the baseline vehicles are listed in order of highest to lowest TCO Savings over the service life.

Department	Make & Model	Recommended EV	TCO Savings
Integrated Water Services	2017 Ford F-150	Mitsubishi Outlander PHEV	$35,339.06
Integrated Water Services	2017 Ford F-150	Mitsubishi Outlander PHEV	$32,645.42
Integrated Water Services	2017 Ford F-150	Mitsubishi Outlander PHEV	$18,335.52
Parks & Environmental Services	2018 Toyota RAV4	Mitsubishi Outlander PHEV	$16,164.51
Executive Services	2017 Ford F-150	Mitsubishi Outlander PHEV	$11,685.18
Planning & Protective Services	2017 Chevrolet Equinox	Mitsubishi Outlander PHEV	$8,857.45
Executive Services	2017 Ford F-150	Mitsubishi Outlander PHEV	$5,343.46
Integrated Water Services	2011 Ford Ranger	Mitsubishi Outlander PHEV	$4,723.49
Integrated Water Services	2017 Toyota RAV4 Hybrid	Mitsubishi Outlander PHEV	$3,835.21
Executive Services	2017 Ford F-150	Mitsubishi Outlander PHEV	$3,214.73
Integrated Water Services	2007 Ford Ranger	Mitsubishi Outlander PHEV	$3,131.00
Parks & Environmental Services	2010 Ford Ranger	Mitsubishi Outlander PHEV	$2,480.89
Integrated Water Services	2009 GMC Canyon	Mitsubishi Outlander PHEV	$1,690.23

The vehicles above were chosen based upon information provided by the Captial Regional District (CRD). By downsizing duty cycles that do not need the passenger or cargo capacity provided by a LD truck, van or SUV, there is an additional opportunity to reduce CO_2 emissions, and fuel expenditure.

BEST FIT DUTY CYCLES FOR EVs

13 Mitsubishi Outlander PHEV

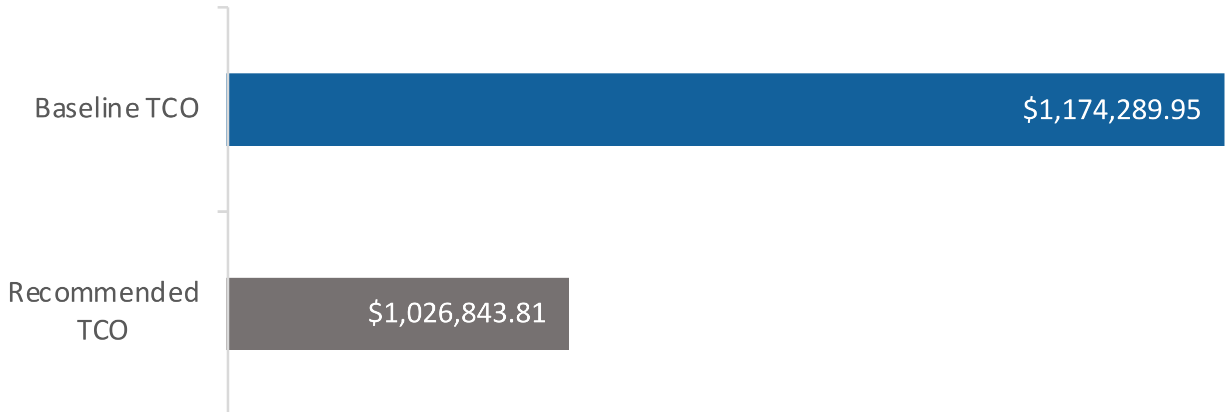
$43,000 Bid Price

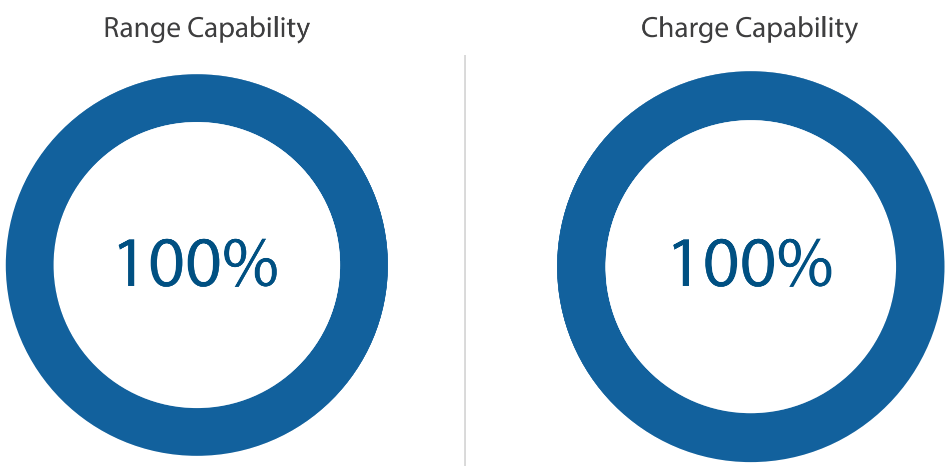
SUMMARY RESULTS

Providing quantified, independent third party, financial, and environmental results of plug-in electric vehicles in your duty cycles is what we do best.

Imagine logging all the speeds and all the energy demands from your vehicles for every second of every trip that your fleet drivers make. Now, imagine being able to use all that data to determine how alternative, more efficient technology would perform for any given trip, day, week, or year. These are the results that we are able to capture here. Using these data and our powertrain modelling tools we accurately compare the total cost of ownership of your baseline vehicles to the vehicles you are considering. Total costs include the vehicle acquisition costs and operating costs. In all cases presented, we assess EV suitability with one chance to charge per day, at the time that the vehicle finishes its final trip. For plug-in hybrids, the powertrain models determine the electric distance travelled and the corresponding overall fuel economy to drive the TCO calculations. In addition to the total cost perspective, these results help provide the framework to discuss further EV benefits such as GHG reductions, green marketing opportunities, and grid services that could enhance the total EV value equation.

When comparing your baseline vehicles to the optimal EV deployment scenario, it is clear that there is the potential for significant cost savings across the fleet.





Using the results of the recommended deployment shown on page 9, we can determine the potential savings that can be achieved from the most optimal EV deployment. We anticipate this potential to be about $147,446.16 in Total Cost of Ownership savings over the individual vehicle service lives. To do this analysis, we chose electric vehicles which we thought would be the most suitable to carry out each individual duty cycle in this fleet study and save your fleet the most on cost. We also take into account the capabilities of any potential EV deployments by running powertrain models of each EV on the data that we obtained from your baseline vehicles to determine whether the EV would be able to do the job of the baseline. We never recommend an EV which is not range capable. In your fleet, we found that the best-fit vehicles were 100% charge capable. This is the percentage of overnight times on average the vehicles will be able to fully charge.

If 13 of the baseline vehicles are replaced with the FleetCarma Recommended plug-in vehicles, the fleet will see the following total savings over the service lives of the baseline vehicles.

Total Fleet Savings (13%)

$147,446

If 13 vehicles are replaced with the best fit vehicle, the fleet could save $147,446 in total savings over the service life. This represents 13% of the fleet budget.

Annual Emission Reductions (43%)

↓49 tons

If 13 vehicles are replaced with the best fit vehicle, the fleet could realize an emission reduction of 49.2 tons per year over the service life, representing a 43% reduction in CO_2 emissions.

Annual Fuel Reduction (43%)

↓16,067 L

If 13 vehicles are replaced with the best fit vehicle, the fleet could reduce gasoline and diesel consumption by a total of 16,067 L annually over the service life, representing a 43% reduction in fuel.

MORE THOUGHTS ON FLEET EFFICIENCY

We understand that not every duty cycle in the fleet will be suitable for a plug-in electric vehicle right away. In the meantime, we present in this section of the report other opportunities for your fleet to capture further efficiency savings which relate to idling, eco-driving, and fleet right-sizing.

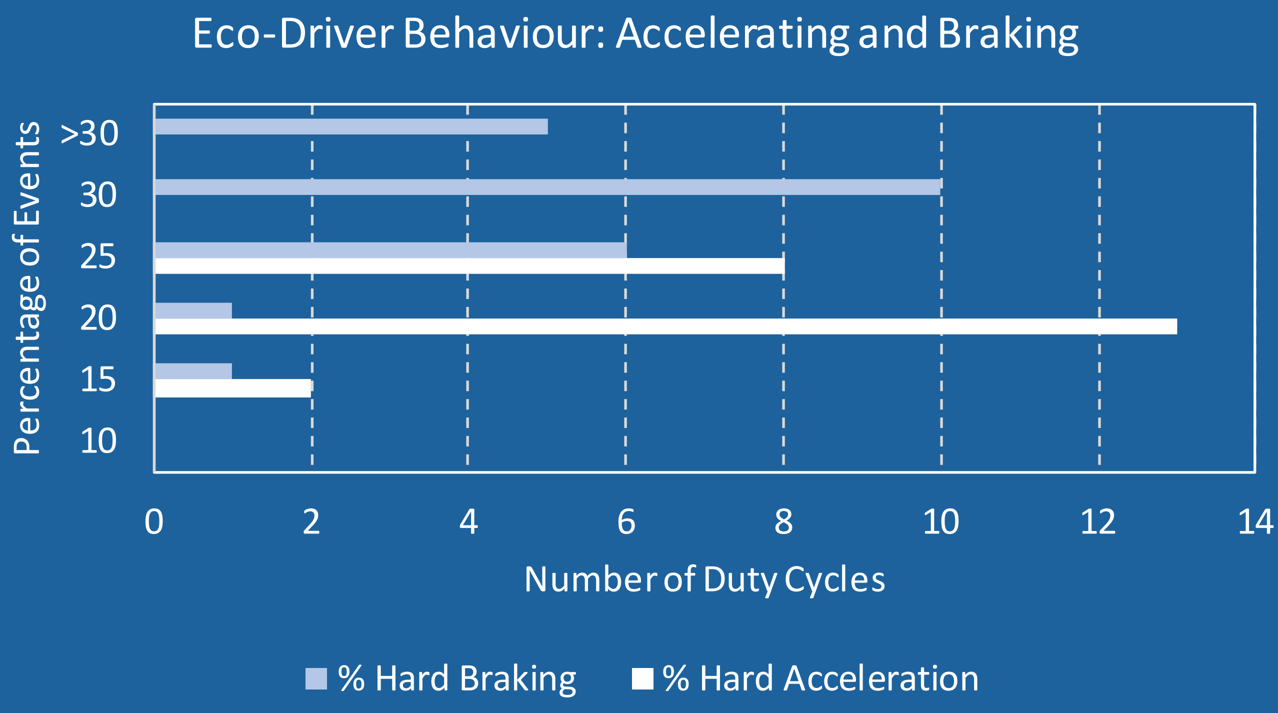
IDLING

Based on the data collected from your vehicles, 27% of engine-on time is spent idling. Using a telematics system to manage idle-reduction programs could save 187 L of gasoline per month, resulting in a savings of $7 per vehicle.

27%	187 L	$7
engine-on time spent idling	total monthly fuel used for idling	average potential savings each month per vehicle

DRIVER SAFETY

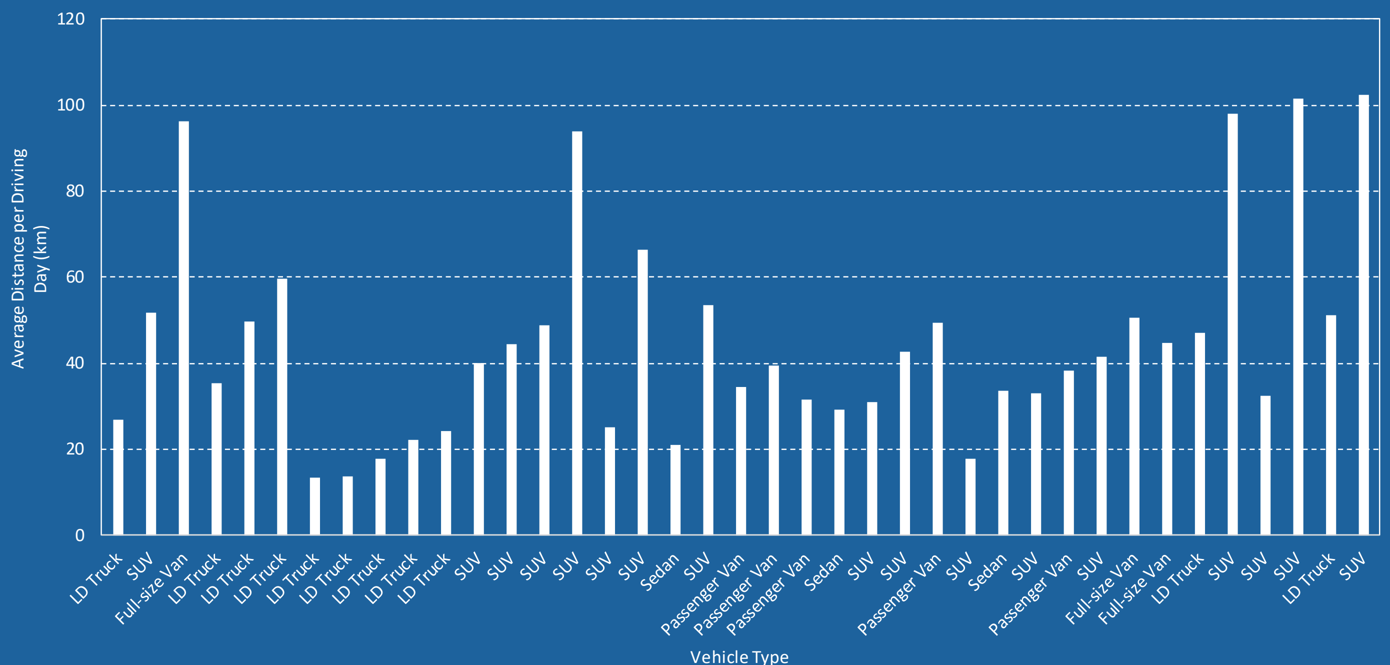
The graph below shows a histogram of the acceleration and braking scores for each driver. In this case, the lower the score the better they are performing. For your fleet, 95% of drivers are below the hard braking threshold of 20% and 100% of drivers are below the hard acceleration threshold of 20%.

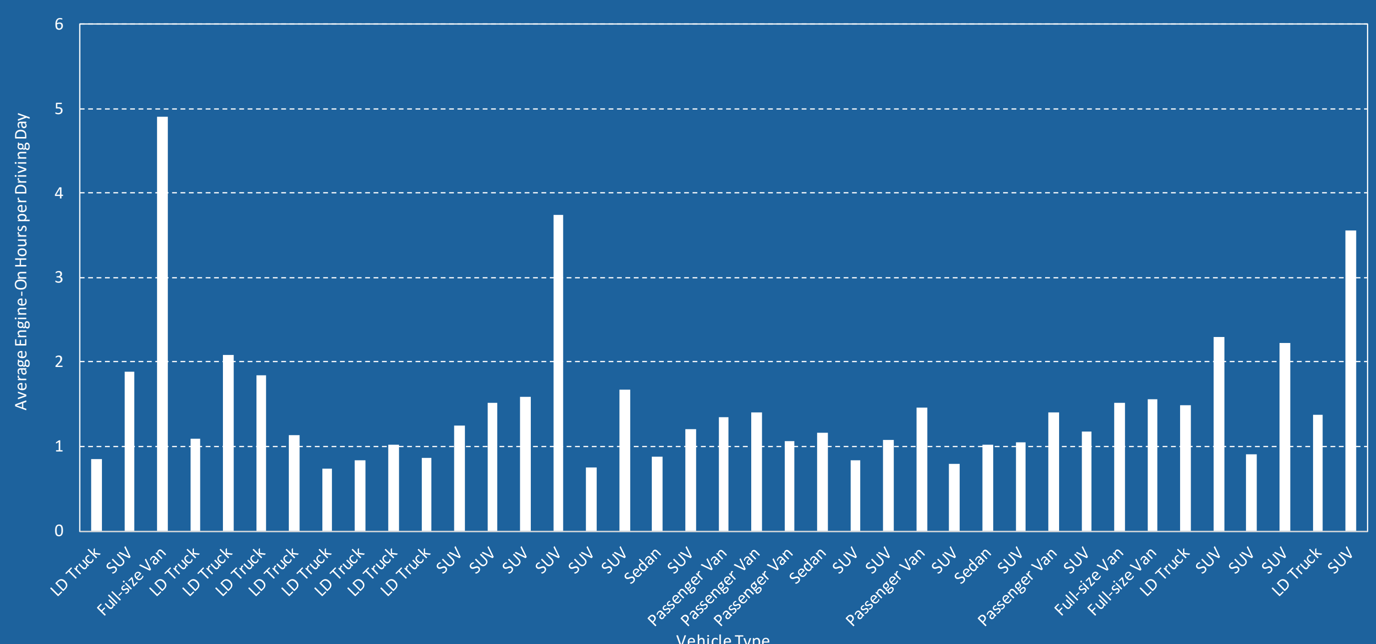


These Eco-Driver Behaviour scores may indicate opportunities within your fleet to review safe driving practices. Smooth braking and smooth acceleration can help reduce maintenance costs over the life of the vehicle. For an electric vehicle, smooth braking allows for more energy to be captured via the regenerative braking process.

UTILIZATION

Based on your daily utilization, we found that few of your vehicles are being used heavily, and a few were under utilized. The threshold for an under utilized vehicle is less than 25 kilometres per day, and less than 1 hour of engine on-time. Vehicles that meet this criteria could be replaced by a mileage reimbursement vehicle or a pool vehicle.





VEHICLE CHARGING INFRASTRUCTURE

To find out what to expect in terms of the charging needs of your new EVs, we looked at the amount of time your current vehicles spend parked overnight - their "dwell time".

Current Dwell Time[1]	Number of Vehicles
Short	4
Medium	1
Long	8

Based on the recommended EV deployment on page 8, we estimated the amount of time each vehicle would need to charge at a Level 1 station versus a Level 2 station to determine the potential charging needs of your EV fleet. These requirements from the EV can then be combined with the nightly dwell times[2] for each of your current vehicles to determine the number and types of charging stations your fleet may require with this deployment. There are multiple strategies that can be employed when purchasing charging infrastructure to make sure you meet the needs of your fleet drivers, budget, and organization. We offer four of these potential strategies below so that your organization can determine what will work best in your particular case. The options we consider here include Level 1 (wall outlet), Level 2 (charging station) Single Port, and Level 2 Dual Port. Dual port stations are generally more expensive, but do not require someone to move the plug from one vehicle to another when the first vehicle has completed charging.

Infrastructure Scenario	Total Cost[3]	Charging Power Level	Number of Stations
1 - Dedicated	$15,000	1	8
		2	5
2 - Plug Sharing	$15,000	1	8
		2	5
3 - Power Sharing	$15,000	1	8
		2	5 Single Port / 0 Dual Port
4 - Complete	$39,000	1	0
		2	13

1 Short, medium, and long dwell times for the suggested PHEVs are < 4 hrs, 4-8 hrs, and > 8 hrs, respectively. Short, medium, and long dwell times for the suggested BEVs are < 12 hrs, 12-16 hrs, and > 16 hrs, respectively.

2 Please see the Appendix for more information on the nightly dwell times for each vehicle and strategies to optimize charging.

3 We assumed Level 1 stations cost $0 and Level 2 stations cost $3,000 for single port and $4,500 for dual port.

WHERE TO BEGIN

As you start purchasing plug-in vehicles for your fleet, you want to begin with the vehicles that will have the lowest total cost of ownership when compared to the vehicles you are currently operating with.

Looking at the comparative data in the reports, we can identify two key areas to begin to consider plug-in vehicle adoption.

1. Implementing PHEVs will ensure the vehicles are range capable and able to support the level of utilization observed in this fleet. To facilitate the implementation of an electric fleet, charging stations must be available and drivers must be encouraged to plug in the vehicles to maintain a high EV fraction. This will allow you to realize the maximum level of savings.
2. There is a large opportunity to transition light duty trucks and/or SUVs to PHEV SUVs. At this time, there are not many SUV EVs available. However, additional significant fuel and emission savings can be realized if the conventional light duty trucks and SUVs can be replaced replaced with suitable PHEVs.

STUDY DETAILS

The results and recommendations in this report have been analyzed using the following information while accounting for vehicle resale value, range capability, and charge capability:

Service Life and Energy Costs		Emissions Factors	
Service life per vehicle	7 years	Tailpipe (Gas)	2,325g $C0_2$/L
Current cost of fuel	$1.45/L (Gasoline)	Upstream (Gas)	740g $C0_2$/L
Current cost of electricity	$0.12/kWh	Upstream (Electricity)	259g $C0_2$/kWh

ELECTRIC FLEET MANAGEMENT GOALS

Once you have begun to deploy electric vehicles in your fleet, the following goals will help you to realize the savings potentials described in this report. FleetCarma Telematics Technology can be used to track performance on the KPIs listed below.

Along with opportunities for savings on costs, fuel, and emissions, electric vehicles also offer new opportunities to better manage the vehicles you own. Active management of fleet vehicles to ensure that EVs get used first can drive up your EV ROI and ensure that your fleet is never paying for high-cost, high-emissions fuel when it is not necessary.

Adding EVs to your fleet also opens up opportunities to show sustainability leadership as an organization through implementing new and more efficient technologies. Electric vehicles are just one part of a holistic sustainability plan which aims to reduce the overall greenhouse gas emissions of the organization as well as promoting and educating others about sustainability best-practices.

Employing systems to manage charging and day-to-day usage can help fleet drivers feel comfortable driving the new electric vehicles that have been added to the fleet, avoiding hesitation and range anxiety. With the remaining gasoline vehicles that you have in the fleet, there are also opportunities to improve fuel efficiency and driver safety mentioned earlier in this report. This section allows us to attach goals to these metrics like Hard Acceleration and Braking.

QUALITATIVE GOALS

1. Demonstrate EV leadership through outreach and technology demonstration.

2. Practice environmental stewardship through reductions in carbon intensity (CO_{2eq}) per mile

QUANTITATIVE GOALS

>80%
Electric Driving Fraction

The electric driving fraction refers to the percentage of trips driven using electricity rather than gasoline. This applies to Plug-in Hybrid Electric Vehicles. A higher electric driving fraction results in a lower TCO.

100%
Plug-in Compliance

Plug-in compliance refers to the percentage of nights that drivers plug in their vehicles after the last trip of the day so that it can have time to charge overnight. It ensures that Starting SOC is as high as possible.

100%
Starting SOC

SOC stands for State of Charge and refers to the degree to which the high-voltage battery of a plug-in vehicle has been charged or depleted. Starting SOC refers to the SOC at the beginning of the first trip of the day. A more fully charged battery allows for a higher electric driving fraction, and limits range anxiety.

<15%
Hard Acceleration Events

Hard Acceleration Events is another metric used by FleetCarma clients to measure driving efficiency and driver safety. This is calculated as a percentage of total acceleration events.

<15%
Hard Braking Events

Braking style does impact plug-in vehicle efficiency since smooth braking helps the vehicle regenerate energy while driving and also improves driver safety. This is calculated as a percentage of total braking events.

NEXT STEPS

The core objective of an EV suitability assessment is to help you determine your best strategy for EV adoption, to formulate customized EV utilization goals, and to have the information your need to move forward with confidence.

Understanding your fleet utilization to the level presented here should give you all that you need to make informed decisions about your fleet composition. If fleet efficiency is a priority for your organization then we have got your back. As vehicle technology evolves, the complexity of managing these vehicles changes. This is why at FleetCarma we have worked hard to provide our customers with a vehicle monitoring and fleet management system flexible enough to work on all vehicle types. As you continue to strive to deploy a diverse set of vehicles, we would be happy to help you along the way. For more information see some of the features we offer through our telematics system on the next page or contact us again any time.

EV Utilization Metrics

Track all the your EV KPIs with FleetCarma EV monitoring system. No need to pay for sub-metering - with this system you can track all your driving and charging data in one common system.

Charge Management

Want to improve the TCO of your electric vehicles? Consider using them as energy assets for your local grid. With real-time EV monitoring, we can automate your managed charging strategy.

Vehicle Location Tracking

FleetCarma's vehicle monitoring technology can help you keep track of real-time vehicle location with live mapping tools. Also track historic locations of trips and charge events for your vehicles.

Odometer Readings & DTCs

Can you benefit from a more automated preventive maintenance program? With FleetCarma's system you can instantly know your vehicles' odometers and when diagnostic trouble codes are present.

Full Fleet Support

Monitor plug-in vehicles, conventional vehicles, and heavy-duty vehicles with one common system. FleetCarma's system is the most flexible fleet monitoring technology on the market today.

EV ROI Scorecard

FleetCarma's customer support team will work with you along the way to a positive EV experience. We'll provide periodic EV ROI Scorecards for you and your team to ensure goals are met.

APPENDIX 1

This appendix was included to show the individual dwell times of the vehicles.

Department	Make & Model	Recommended EV	Dwell Time
Integrated Water Services	2017 Ford F-150	Mitsubishi Outlander PHEV	Short
Integrated Water Services	2017 Ford F-150	Mitsubishi Outlander PHEV	Short
Integrated Water Services	2017 Ford F-150	Mitsubishi Outlander PHEV	Long
Parks & Environmental Services	2018 Toyota RAV4	Mitsubishi Outlander PHEV	Long
Executive Services	2017 Ford F-150	Mitsubishi Outlander PHEV	Long
Planning & Protective Services	2017 Chevrolet Equinox	Mitsubishi Outlander PHEV	Long
Executive Services	2017 Ford F-150	Mitsubishi Outlander PHEV	Long
Integrated Water Services	2011 Ford Ranger	Mitsubishi Outlander PHEV	Short
Integrated Water Services	2017 Toyota RAV4 Hybrid	Mitsubishi Outlander PHEV	Short
Executive Services	2017 Ford F-150	Mitsubishi Outlander PHEV	Long
Integrated Water Services	2007 Ford Ranger	Mitsubishi Outlander PHEV	Medium
Parks & Environmental Services	2010 Ford Ranger	Mitsubishi Outlander PHEV	Long
Integrated Water Services	2009 GMC Canyon	Mitsubishi Outlander PHEV	Long

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2-60 Northland Road,
Waterloo Ontario, N2V2B8
1-800-975-2434

www.fleetcarma.com

CRD-UVic E-bike fleet deployment

Daniel Clancy, B.Eng

February 4, 2019

Abstract

The deployment of three E-bikes into the CRD fleet resulted in over 600km of recorded trip data. This data was used to inform several academic research projects as well as determine typical operational capabilities of E-bikes for the CRD fleet. The collected data showed a reduction of emissions by 99% when compared to a typical car found in the CRD fleet. Even compared to battery electric cars, the E-bikes represent a 95% reduction in emissions. Compared to both of these modes, the E-bikes also represent an over 80% reduction in capital and operating costs.

Overall, the deployment of the E-bikes saved approximately 250kg of CO2 if they replaced internal combustion engine car trips. The operating capabilities of E-bikes shows them as having half the pace of cars in urban environments. Where a car can cover 5km in 8.5 minutes, an E-bike typically covered the same distance in only 20 minutes.

Contents

List of Figures

1 Introduction

The CRD E-bike pilot is a joint project between IESVic and the Capital Regional District (CRD) that is funded by a grant from the Federation of Canadian Municipalities (FCM). The E-bike project forms one part of a larger FCM funded transportation program, the Zero Emissions Fleet Initiative (ZEFI) that focuses on reducing the transportation based emissions of the CRD through fleet equipment upgrades, and academic research to support this goal.

The proposed research goals for the E-bike project are:

1. To make recommendations regarding the optimal use of E-bikes in urban commercial fleets

2. To compare the environmental, economic, and logistical performance of the operation of E-bikes in urban fleets to other vehicle modes;

3. to make recommendations regarding the regulatory constraints placed on E-bike use with respect to motor power limits

The research goals are answered through the deployment of three E-bikes outfitted with multiple sensors to capture a variety of data. The purpose of this work is to provide quantifiable, evidence-based results to inform the CRD as to the efficacy of the use of E-bikes in their corporate fleet. Additionally, this project is meant to inform other fleet operators as to the operational costs and benefits of E-bikes in commercial fleets. The final purpose of the project that is of less relevance of the CRD is to provide insight into regulatory constraints and future E-bike design guidelines to manufacturers.

The remainder of this report details the methodology and results that were used to answer the first two research goals, with some of the results that are of less relevance to the CRD detailed in the appendix.

Section 2 provides further details regarding the deployment of equipment and data collection.

Section 3 shows the relevant parts of the raw data before further analysis.

Section 4 presents the results of the analysis and subsequent discussion

2 Project Details

The data collection side of the project was achieved through the deployment of three E-bikes outfitted with sensors that logged performance metrics during each trip: a speed sensor, a GPS sensor, and a power meter. The sensor package installed on each E-bike consisted of a Garmin Edge 520 cycle computer, a Garmin ANT+ protocol speed sensor mounted on the front wheel hub, and an PowerTap ANT+ protocol hub based power meter built into the rear wheel.

Each of these sensors was connected to a Norco VLT R1 E-bike, synced to the Garmin Edge 520, with the data collected from the Garmin Edge on a weekly

Table 1: Data collection equipment for CRD E-bike Trial.

Sensor	Accuracy	Metric	OEM
Edge 520 Cycle Computer	Not listed	GPS	Garmin
Bike Speed Sensor	Not listed	m/s	Garmin
G3 Power Meter	$\pm$ 1.5 %	Watts	PowerTap

basis. The CRD staff involved in the project could reserve an E-bike through the CRD's internal online vehicle booking system. Each time staff rode the E-bike they would simply press a button to initiate data logging, and press the same button to end the ride and save the data. Seventeen users were recruited into the project, with each rider's trip data anonymized to meet CRD privacy concerns.

By the end of data collection, the CRD project resulted in a large number of trips representing over 4 months of data. There was a significant amount of non-compliance when it came to data recording with the E-bike odometers showing a total of nearly 1200km and the actively recorded data only totalling just over 600km. While the data logging was optional for CRD staff, this did likely impact the fidelity of the results as a large number of trips were missed. A summary of the recorded data used in the final analysis is presented in table 2.

Table 2: Summary statistics of E-bike use in urban commercial fleet. Values show mean of results along with one standard deviation

Metric	Value
Total kilometres travelled	607 km
Number of trips	92
Average speed	20.3 $\pm$ 5.9 kph
Average trip length	6.6 $\pm$ 5.8 km
Average trip time	25.9 $\pm$ 25.2 min

3 Energy Results

The recorded energy use while riding the E-bikes comes from the PowerTap G3 power-meter. The power data, along with the other ride characteristics (speed, location, grade) are used to understand how and when energy was expended during the trip. The energy use also allows for determination of the GHG emissions that occur from using the E-bike, as well as the electricity costs.

Table 3 shows the total energy use and power as recorded by the power meter over the course of the experimental campaign. In addition to the summary table, the recorded power data can be categorized into total energy use in response to distance travelled, grade, and speed to provide further insight as to how E-bikes are used in an urban setting.

Table 3: Total energy use and power as recorded by the rear-hub power meter.

Metric	Value
Average per-trip power	234 ± 73 W
Average per-trip energy use	40.3 ± 48.0 Wh
Average per-kilometre energy use	7.8 ± 2.5 Wh/km

Figure 1 shows on the top the per-trip values for total energy use, in the middle the average instantaneous power, and on the bottom the distance per-trip. This is done to provide further insight into how the trips vary. Some of the trips don't have a recorded power value due to issues with the sensors pairing improperly during use by CRD staff. This was remedied early on but the speed and distance values are still useful to include in the overall results.

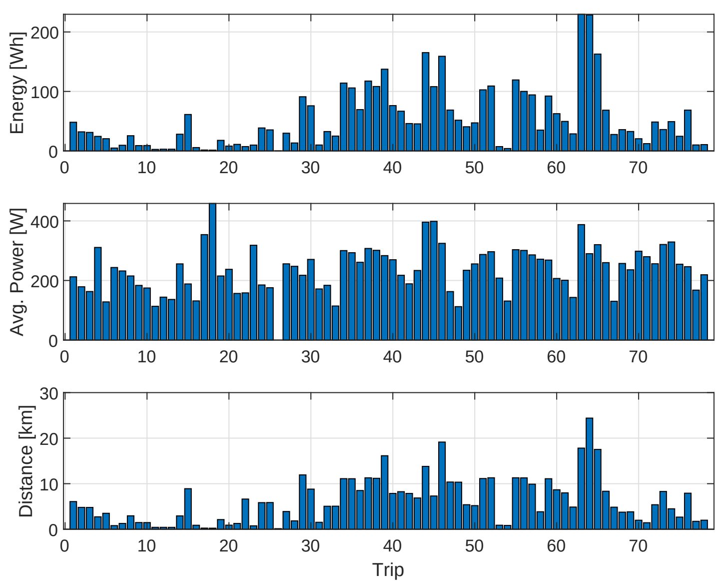

Figure 1: Per-trip energy use, average per-trip power, and trip distance for all recorded CRD project trips.

Figure 2 shows on top the time spent moving on a given grade during all trips, and on the bottom the time spent moving at a given speed during all trips. This figure is shown so that weight can be given to further findings and claims relating to energy use at these different speed, grade, and distance states. The more time spent in one of these states, the more reliable the findings can be

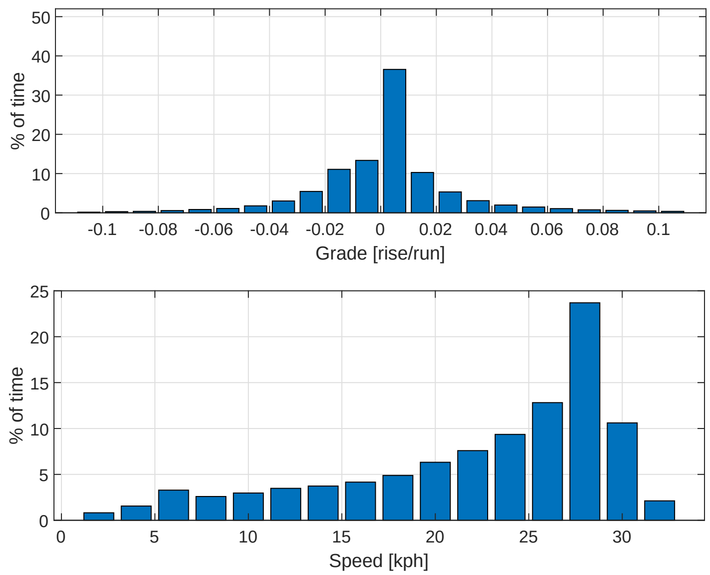

Figure 2: The percentage of total time of occurrence of energy, power, and distance for each trip that had a recorded power value

labelled. The grade portion of the figure can also be thought of as a topological characterization of the riding environment in downtown Victoria for comparisons to any other urban environments with the caveat that it is dependent upon the routes chosen by the CRD participants.

In the bottom half of figure 2 it can be seen that a clear majority of the time (50%) is spent at near the speed limit of the E-bike, meaning that participants are able to reach and maintain optimal speeds during the majority of trips.

Figure 3 shows three different figures. The top shows the energy use per distance travelled as determined by calculating the cumulative energy for each trip, divided by the cumulative distance covered. The middle shows the average instantaneous power within each distance segment. Both the top and middle sub-figure indicate that the participants did not appear to significantly reduce energy expenditure the longer they rode. This would imply that for longer trips, riders did not tire noticeably in total system output, either through maintaining personal exertion or by increasing the assist factor. The energy use remains relatively constant regardless of the distance, which shows that at least for the distances covered, the riders didn't show any major signs of fatigue. The bottom sub-figure shows some consistency in that at positive grades the rider had to output on average more power.

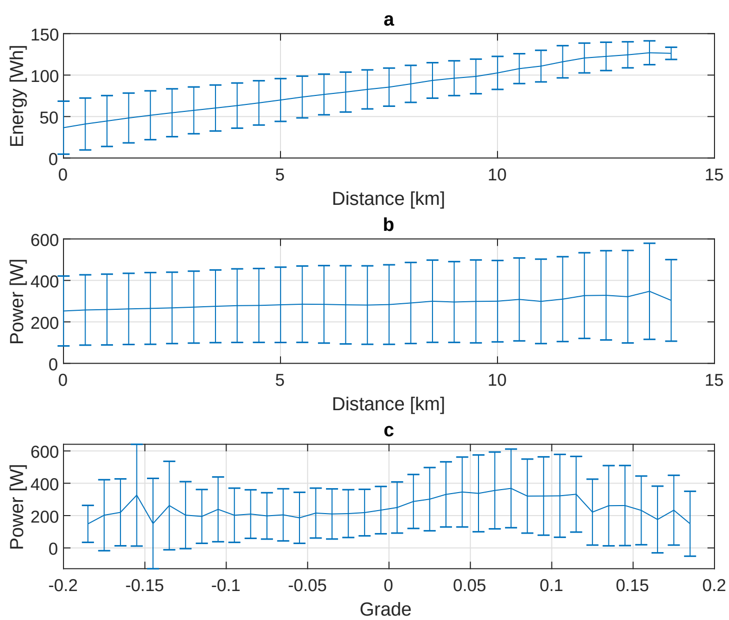

Figure 3: Energy and power related to distance and grade. Mean and standard deviation are shown in each subfigure.

4 Environmental and Economic Assessment

This section covers the quantification of the impacts of the CRD E-bike pilot project as relevant to the CRD or any other commercial fleet operator. Using the energy data detailed in the previous section, the use-phase emissions are reported, along with the operational and capital expenditures. The results are then compared to some standard fleet vehicle values to give further context as to the benefit of E-bikes in commercial fleets.

The emission accounting is straight forward. The electric energy use per kilometre as required to charge the battery at a wall outlet includes the efficiency losses due to the E-bike charger, the battery, the motor, and the losses through the mechanical drive train which are detailed in table 4.

Table 4: E-bike system efficiency estimates that links the recorded power at Powertap power meter to electricity at a wall outlet.

Charger efficiency	0.95
Charging efficiency	0.85
Motor efficiency	0.90
Drive train efficiency η_{DT}	0.96
Total electrical system efficiency η_{Elec}	0.70

The CRD E-bike emission intensity is the product of the efficiencies, times the recorded power, times the BC Hydro electrical emission intensity. The per-kilometre emission intensity is listed in table 5 along with comparative estimates for a typical sedan used in the CRD fleet. The sedan data was obtained from CRD fleet data involved in another ZEFI project. The average pace includes time stopped in traffic so at to best represent typical urban driving conditions.

Table 5: Use-phase emission intensity along with typical urban pace for E-bikes, fossil fuel and electric cars, and walking [1, 2].

Mode	Emission Intensity [kg CO2e/km]	Typical Pace [min/km]
E-bike	0.00009	4
Standard sedan	0.21580	1.7
Electric Car	0.00210	1.7
Walking	0	20

These results show a very favourable comparison for E-bikes. The E-bike offers a relative reduction in emissions of 99% compared to standard fossil fuel power cars, and a relative reduction of 95% compared to electric cars when comparing 'tail-pipe' emissions only. This near complete reduction in use-phase emissions only comes at the cost of being just over two times slower, which can shift a 5 minute trip to nearly 12 minutes.

Walking reduces emissions over E-bikes but E-bikes already represent a bare-fraction of emissions relative to fossil fuel and electric cars such that the trade-offs between emissions and pace aren't as worth-while. Since the E-bike project with the CRD logged approximately 1160 km (the riders only actively logged 623 km), an estimate of the total use-phase emissions from the E-bikes is accounted for and presented in table 6 along with an estimate of the same distance covered by a standard car.

Table 6: CRD Project tail-pipe emissions for E-bikes and comparison to other transportation modes for the same distance.

Mode	Total Emissions [kg CO2e]
E-bike	0.104
Standard Sedan	250
Electric Car	2.44

The other metric of importance is the financial costs for each of these modes. While electric cars reduce emissions versus the traditional fossil fuel car by nearly 99%, they cost significantly more than E-bikes. The financial costs of the E-bikes were detailed by the CRD and are summarized in table 7. E-bike values is sourced from the CRD project and includes safety equipment for users, added security features, and added storage such as panniers and baskets on the E-bike. Also includes regularly scheduled maintenance and an estimate of annual parts replacement costs (tires, drivetrain, etc). It does not include training costs for users or parking requirements for the E-bikes (such as secured storage, charging infrastructure, etc) as these can vary quite widely from one organization to the next and are not included in the car ownership costs.

The vehicle values assume annual travel of 10,000 km which is a low value for a commercial fleet but is meant to make it more comparable to the E-bike with respect to short urban trips. It includes maintenance, license and registration feeds, insurance costs, and upfront vehicle cost. Vehicle capital costs are sourced from respective brand websites, and the operating costs are sourced from the CAA online car costs calculator.

Table 7: E-bike, fossil fuel and electric car capital and operational costs per vehicle representing ownership over 5 years. [3, 4, 5].

mode	Capital costs [$ CAD]	Operational Costs [$ CAD]
E-bike	4,400	1,730
Chevrolet Malibu	22,295	14,000
Kia Soul EV	35,895	8,300

The type of trips the E-bikes are typically used for definitely do not cover the entire range of trip types presented by traditional cars. Cars provide a much wider range of possible trip lengths and cargo capacities. For a smart fleet planner, E-bikes open up a new category in the fleet that is optimal for short urban single occupancy trips. Larger vehicles will still be needed but when appropriate, E-bikes offer a virtual elimination of use-phase emissions as accounted for by the fleet manager, as well as an 83% and 86% cost reduction over 5 years when compared to a typical CRD fleet car and electric car respectively.

5 Conclusion

The deployment of the E-bikes resulted in a substantial amount of data to be collected detailing the costs and capabilities of these vehicles as used in an urban commercial fleet. From this data, it was shown that E-bikes emissions and operating costs are dramatically lower than both internal combustion engine and battery electric cars. E-bikes also have a highly competitive pace in urban environments with travel time only double that of cars on average.

The research also showed that the power output of the rider and E-bike didn't decrease over time even on trips longer than 10 kilometres. The energy in relation to distance in the top sub-figure of figure 2 is linear which means that average energy expenditure remained constant across most trips regardless of distance. This would imply that according to the data collected so far, fatigue is not a major issue for E-bike trips.

The data also incorporated a significant amount of travel along varying road grade. The power and speed measurements on inclines did not show any significant impacts that would indicate riders having to exert themselves or slow down dramatically.

The data collected shows E-bikes as a cost effective, environmentally friendly, and effective urban transportation solution that would fit well in most any fleet that has the appropriate trip types: 10km or less, urban environments with stop and go traffic, and limited cargo requirements.

Appendix

This section of the appendix covers a small portion of the additional analysis that was performed on the collected data. This section is included as an overview of what some of the other research was aiming to achieve.

Human Energy Contributions The typical human energy contributions that occur while riding an E-bike are important because they allow for later analysis to model larger motors while still replicating expected human behaviour. This section estimates the human power contributions that occurred during the CRD project by using a differential equation that is detailed in the author's thesis, along with equation 1 which shows the relationship between human power ($\dot{E}_h$) and motor power ($\dot{E}_m$) as a function of assist level (A).

$$\dot{E}_m = A\dot{E}_h \tag{1}$$

This analysis follows a similar format to that of section 4 but without any human or electrical energy conversion efficiencies. The results of this analysis will show the range of human power contributions as a function of speed of the E-bike as delivered directly to the shaft of the pedals from the motor and the human. Figure 4 was created by discretizing all of the power data from the CRD project into speed bins. Within each speed bin, the power was averaged (not including zero values), and the grade data was also averaged within each bin. The assist varies from a factor of 0.5 up to 2.75, matching the capabilities of the Norco E-bike used in the CRD project.

Figure 4 shows the definitive impacts of the max assisted speed (approximately 30-32 kph) after which the electric motor stops assisting the rider. As the limited speed is approached, the human power contributions diminish rapidly due to the increased power requirements. It also shows that riders don't typically exceed the maximum assisted speed unless they are on a decline (or negative grade) and in doing so have dramatically decreased power requirements.

The discretization process was repeated but now with the filter that only uses data that has a recorded grade less than 0.02 (2%) and greater than -0.02, in an attempt to remove the impact of grade on human power. The results of this process are shown in figure 5 and are used to compare with the results of an external study. Langford et al recorded an average human power contribution of 62 watts at approximately 20 kph while on level ground while using a maximum level of assist on an E-bike. Langford et al's results are very similar to the results of figure 5 which show a power of approximately 60 W at maximum assist and relatively level ground.

Finally, human power as a function of speed and grade is modelled using MATLAB's surface fit function. This fit will act as a look-up table to determine an averaged human power contribution at any particular speed and grade, such that later research can dynamically subtract this amount to determine motor contributions as loads are increased. Figure 6 shows human power as a function of grade and speed.

The surface fit plot in figure 6 has negative power values removed as displayed

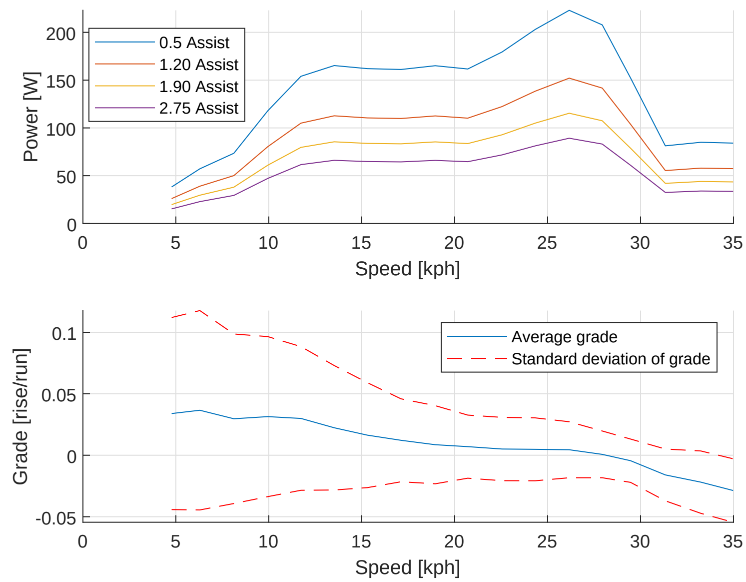

Figure 4: Estimated upper and lower average typical human power contributions for full range of Bosch Assist levels. Corresponding average grade for each speed and power.

by the white space in the figure. A clear trend can be seen that for positive grade values, speed doesn't typically exceed about 30 kph (at which point the electric assist cuts off due to B.C. regulations on pedal assisted E-bikes). In addition, almost all human power input, assuming maximum levels of assist, is less than 150 watts except in a few cases of large grade and high speed when it gets up to approximately 250 to 300 watts.

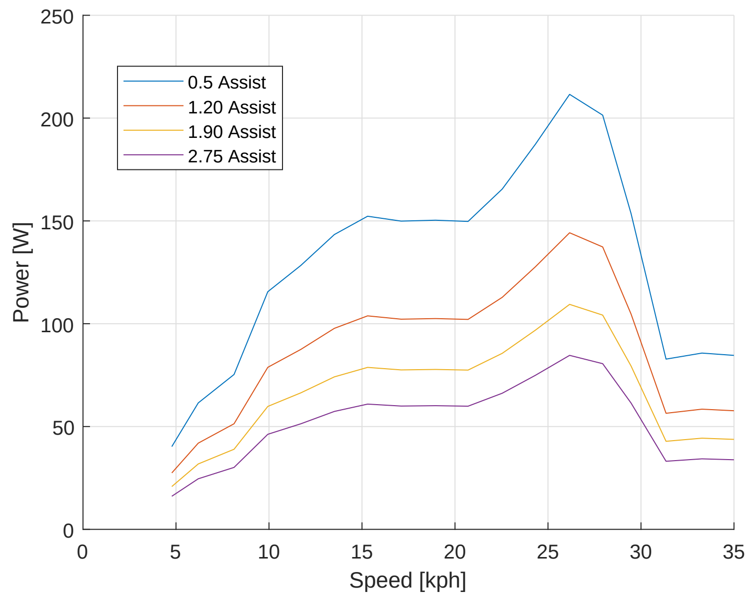

Figure 5: Human power contributions for various assist levels with impacts of grade removed. Filtered to only include power corresponding to grades less than 2%.

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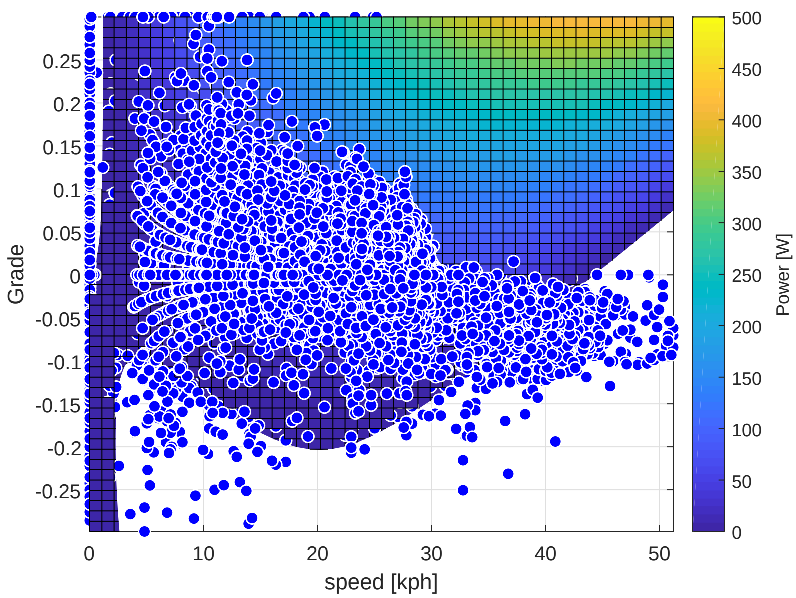

Figure 6: Human power contributions with speed and grade data points at maximum assist factor A = 2.75

Predicting fleet-vehicle energy consumption with trip segmentation

by

Autumn Umanetz

B.A.Sc, University of Waterloo, 1995

A Thesis Submitted in Partial Fulfillment

of the Requirements for the Degree of

Master of Applied Science

in the Department of Mechanical Engineering

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Supervisory Committee

Dr. Curran Crawford, Co-Supervisor

Department of Mechanical Engineering

Dr. Nedjib Djilali, Co-Supervisor

Department of Mechanical Engineering

Abstract

This study proposes a data-driven model for prediction of the energy consumption of fleet vehicles in various missions, by characterization as the linear combination of a small set of exemplar travel segments.

The model was constructed with reference to a heterogenous study group of 29 light municipal fleet vehicles, each performing a single mission, and each equipped with a commercial OBD2/GPS logger. The logger data was cleaned and segmented into 3-minute periods, each with 10 derived kinetic features and a power feature. These segments were used to define three essential model components as follows:

- The segments were clustered into six exemplar travel types (called "eigentrips" for brevity)
- Each vehicle was defined by a vector of its average power in each eigentrip
- Each mission was defined by a vector of annual seconds spent in each eigentrip

10% of the eigentrip-labelled segments were selected into a training corpus (representing historical observations), with the remainder held back for testing (representing future operations to be predicted). A Light Gradient Boost Machine (LGBM) classifier was trained to predict the eigentrip labels with sole reference to the kinetic features, i.e., excluding the power observation. The classifier was applied to the held-back test data, and the vehicle's characteristic power values applied, resulting in an energy consumption prediction for each test segment.

The predictions were then summed for each whole-study mission profile, and compared to the logger-derived estimate of actual energy consumption, exhibiting a mean absolute error of 9.4%. To show the technique's predictive value, this was compared to prediction with published L/100km figures, which had an error of 22%. To show the level of avoidable error, it was compared with an LGBM direct regression model (distinct from the LGBM classifier) which reduced prediction error to 3.7%.

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Glossary

BAU business-as-usual

BEV battery electric vehicle

CAN controller area network

CRD Victoria Capital Regional District

CSV comma-separated-value

ECU engine control unit

EM expectation maximization

EV electric vehicle

FCEV hydrogen fuel-cell electric vehicle

GHG greenhouse gas

GMM Gaussian mixture model

GPS global positioning system

GWP global warming potential

HEV hybrid electric vehicle

HV high-voltage

HWFET highway fuel economy test

ICEV internal combustion engine vehicle

ICE internal combustion engine

IQR inter-quartile range

K number of clusters in K-means clustering

L_e equivalent to litres of gasoline

LCA life-cycle analysis

LGBM light gradient boosting machine

LVQ learning vector quantization

MAF mass-airflow

MAPE mean absolute percentage error

MMAPE modified mean absolute percentage error

mission typical whole-study travel pattern observations for a specific vehicle

ML machine learning

MOE Canadian Ministry of Environment & Climate Change Strategy

MSE mean-square error

OBD2 on-board diagnostic system v2

PCA principle component analysis

PID parameter identifier

PAE percent absolute error

PHEV plug-in hybrid electric vehicle

PS power-scaling factor

Q95 95th percentile

Q98 98th percentile

RPM revolutions per minute

SAE Society of Automotive Engineers

SHAP Shapley additive explanations

SOC state of charge

SSE sum of squared errors

UDDS urban dynamometer driving schedule

US EPA United States Environmental Protection Agency

ZEFI Zero Emissions Fleet Initiative

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The deepest thanks of all go to my thesis-widow and partner in everything, Sarah, whose turn it is now.

1 Introduction

1.1 Overview

1.1.1 Problem statement

In the effort to reduce operational fleet greenhouse gas (GHG) emissions, one important tool is the selective replacement of individual vehicles with low-emission alternatives. Given limited capital, it is important to ensure that the correct vehicles are targeted for replacement in the course of rightsizing, ongoing fleet turnover, or policy-driven phased replacement of individual high-emission vehicles.

No clear path is seen to directly modelling the GHG emissions of existing and replacement vehicles. However, a change in operational CO2 emissions can be inferred with reasonable accuracy from the change in the quantity and type of fuel consumed. It should be possible to predict the change in GHG footprint by modelling the change in operational energy consumption caused by vehicle replacement, and applying an appropriate fuel-specific emission intensity factor.

1.1.2 Goals and motivations

Fleet vehicles are typically assigned to perform an ongoing specific set of duties, commonly referred to as a "mission." In order to more easily predict GHG emission changes resulting from mission-vehicle replacement, this thesis proposes a data-driven model for estimating the change in input energy consumption associated with assigning new vehicles to existing, well-known roles.

In other words, the model will be suitable for estimating the GHG emissions reduction associated with performing a known mission profile with a different vehicle. As discussed below in §1.2.2, this approach is specific to operational emissions, a decision which is limiting, but appropriate for use with many current policy initiatives, such as the municipal GHG action plan [1] that inspired this work.

Since one important application is in a decision support tool for non-technical fleet managers, it should be accessible to the end-user without installing custom software. Even a cloud-hosted service may violate privacy requirements – the movements of individual vehicles are considered protected private information by many organizations.

The traditional method of predicting vehicle operational energy consumption – applying distance-based L/100km fuel economy ratings such as those provided by Natural Resources Canada [2] or the US EPA [3] – is held to be too inaccurate for travel which does not precisely match the conditions under which the ratings were measured [4, 5].

Conversely, a fully accurate fuel consumption model that infers nonlinear relationships from a much larger list of operational properties would have impractical data collection requirements, and would require the distribution and management of specialized software. The source data may provide information regarding the movements of fleet users, and there would be significant privacy and security concerns if a model were to be cloud-deployed [6]. These criteria would make such a model impractical for use as a fleet procurement decision support tool. Such a model would potentially be so computationally expensive that the model itself would have a significant GHG footprint.

In short, in order to promote emissions reduction, it is desirable to develop a new method for predicting operational vehicle energy consumption in fleets, which is:

- simple enough to perform in a spreadsheet
- does not require massive cloud computing overhead
- requires a minimum amount of data collection

- is more accurate than distance-based economy ratings

This thesis explores the development of a data-driven model that will meet all of these criteria, in the context of vehicles with logger data, and mission profiles which have been previously logged.

1.1.3 Document outline

This document begins with an extensive Introduction, which (a) lays out the above overview of the problem, motivation and goals, (b) describes the research context in terms of municipal partnership that provided the data and informed the motivations, and (c) explains the structure of the research problem.

The remainder of the document roughly follows the chronology of the research effort, as follows:

§2. The Background section provides a literature review, and a summary of background material fundamental to understanding the topic and approach.

§3. Data Cleaning and Preparation was a key and challenging element of the work undertaken, and was sufficiently involved to merit its own section.

§4. The actual machine learning techniques used to build the predictive model are described in Methodology.

§5. The model's predictive error is evaluated, its value is demonstrated by comparison with L_e/100km, and avoidable error quantified by comparison to an ML regression model in Results.

§6. Finally, the findings are wrapped up and summarized in the form of a short section of Conclusions.

§7. Lays out a number of potential topics for further refinement, exploration and other Recommendations and Future Work.

1.2 Project Context

1.2.1 CRD ZEFI project

As a part of the Victoria Capital Regional District (CRD)'s Zero Emissions Fleet Initiative (ZEFI) project, a number of vehicles in the CRD fleet were equipped with FleetCarma on-board diagnostic system v2 (OBD2) telematic logging devices at various periods for approximately a year starting in early 2018 [7].

A motivating goal in this project was to determine actions needed to meet the organization's GHG reduction targets, given that 47% of the CRD's baseline 2007 GHG emissions resulted from fleet fuel consumption [1]. An early finding was that, at least on the restricted basis of range requirements, nearly all of the studied vehicle missions could be executed by current battery electric vehicles (BEVs) [8].

Further detail on the nature of the data collection and the logged data is presented in §2.3.1.

1.2.2 Operational and embodied emissions

The intent of this research is to address a core accessibility problem for modelling fleet operational emissions, as needed to address reduction goals similar to those of the CRD's ZEFI program.

For internal combustion engine vehicles (ICEVs), this reduces to tailpipe emissions, calculated by estimating the fuel directly consumed by the vehicle – traditionally called "tank-to-wheel" energy. For gasoline, the GHG emissions of this energy are estimated at an intensity of 88.1 $g\ CO2_e/MJ$ [9]. For electric vehicles (EVs), this is a reflection of the emissions associated with the grid electricity consumed by the drive motor, at the utility's published carbon intensity. For BC Hydro, this is 10.67 t $CO2_e/GWh$ [10] (2.96 $g\ CO2_e/MJ$).

The BC GHG Reduction Act [11] references the 2007 baseline GHG inventory report [12] as a baseline. Emissions in the inventory report are attributed to the jurisdiction where emission is *generated*, rather than the jurisdiction where the *benefit* of the emission accrues. E.g. if H2 gas or lithium-ion batteries are used in BC, the associated manufacturing emissions are attributed to the foreign H2 steam reformation plant or battery factory, rather than to the BC point of beneficial use. This may be seen as constituting a perverse incentive, insulating end-users from any financial costs associated the embodied emissions of manufactured goods, and driving manufacturing to under-regulated jurisdictions.

In the late 2010s there were claims in the US popular press such as [13, 14] that BEVs have a higher lifetime GHG impact than equivalent ICEVs. Anecdotally, the claims are sometimes echoed by concerned Canadian citizens. The core argument appears to be that BEV proponents ignore or under-represent emissions associated with manufacturing the battery pack, and the high carbon intensity of some sources of grid electricity. Although this probably constitutes an example of the "balance-as-bias" fallacy [15], a short discussion is warranted regarding the full cradle-to-grave lifecycle analysis for different light vehicle technologies and their fuel sources.

A 2018 comprehensive comparison by Elgowainy et al [16] summarized full cradle-to-grave GHG emissions (including fuel cycle and manufacturing cycle), for several different types of light vehicles. The study included ICEVs, hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), hydrogen fuel-cell electric vehicles (FCEVs) and BEVs, as well as other vehicle types excluded from this discussion. Retaining that study's figures for manufacturing and fuel efficiency, but applying current and forecasted 2030 intensities for the appropriate fuel pathways for BC as follows, it is clear that alternative fuel vehicles have a significant and improving advantage, shown in table 1. Some discussion of the assumptions and calculations for this comparison appears in appendix B.

Ultimately, the scope of this research is constrained to local tailpipe emissions as required for the planning requirements of organizations like the CRD. It explicitly excludes a full carbon lifecycle analysis, including all carbon emissions embodied in the vehicle's manufacture and eventual recycling, as well as all carbon emitted or embodied

Table 1: Current and 2030 vehicle combined operational and embodied LCA GHG footprint, at BC fuel carbon intensities

Vehicle	2018 Fuel Intensity (g CO2e/MJ)	Emissions (g CO2e/km)	2030 Fuel Intensity (g CO2e/MJ)	Emissions (g CO2e/km)
ICEV	88.1	295	70.5	187
HEV	88.1	221	70.5	130
PHEV35	64.9	129	51.1	83.1
FCEV	5.	48.2	1.18	34.5
BEV90	2.5	29.6	1.11	23.1

by associated infrastructure for manufacture, repair, fuelling, and eventual recycling.

1.2.3 Simple distance-based fuel consumption

In Canada, light passenger vehicles are labelled with EnerGuide fuel consumption ratings, reflecting their expected performance in typical conditions [17]. This program is similar to the US EPA's fuel economy database, fueleconomy.gov [18]. The EPA's fuel economy ratings have been found to be quite inaccurate, with recent studies finding that they predict consumption ranging from 15.5% too low [4] to 17% too high [5] relative to real-world consumption.

EnerGuide numbers result from manufacturer tests of vehicles against defined drive cycles [19], in order to provide an apples-to-apples comparison between vehicles. Prior to 2015, the test platform was a 2-cycle city/highway test (essentially a modified UDDS/HWFET [20]). In 2015, three additional cycles were added, resulting in a 5-cycle test (adding tests to reflect the impacts of cold-weather conditions, aggressive driving, and air conditioning [21]), with incremental updates in 2016 and 2017 [22]. For accessibility, this rating is expressed in units of litres of fuel consumed per 100km driven: L/100km. Non-internal combustion engine (ICE) vehicles are rated in litres-equivalent (L_e), at a standard conversion rate of 8.9 kWh per litre of gasoline [23]. Notwithstanding the 2015 change from two to five cycles, three separate fuel consumption numbers are published to reflect city, highway, and combined performance.

This method of predicting consumption is an important baseline, since the fundamental metric for evaluating an individual vehicle replacement will be "avoided emissions”, which quantifies the change in operational emissions associated with replacing a current (incumbent) vehicle, with a lower-emission alternative (replacement) vehicle.

The traditional method of computing avoided emissions is to apply the difference in fuel consumption ratings and fuel carbon intensities between the incumbent (1) vs replacement (2) vehicles, thus:

$$\Delta Emissions = CO_2e^{(2)} - CO_2e^{(1)} \tag{1}$$

$$\text{where} \begin{cases} CO_2e \approx D \times [\eta \times e \times I]^{(vehicle)} \\ D = \text{Distance } (km) \\ \eta_{c/h} = \text{Vehicle's static tested city/hwy fuel economy } (L_e/100km) \\ e = \text{Fuel energy density } (kWh/L) \\ I = \text{CO2 intensity of vehicle's fuel } (kg/kWh) \end{cases} \tag{2}$$

In other words, each vehicle has a pair of characteristic CO2 emission values per km of operation, directly related to its standardized rates of fuel consumption.

This approach is an oversimplification, assuming constant values for η, and neglecting the facts that drivetrains are optimized for specific drive cycles, and that efficiency is impacted significantly by the nature of the driving undertaken. For example: electric-drivetrain vehicles have technologies such as regenerative braking and automatic shutoff, allowing them to perform efficiently in conditions where conventional internal combustion engine (ICE) vehicles are wasteful, such as stop-and-go traffic, or conditions requiring extensive idling. Conversely, a conventional diesel ICE drivetrain is designed specifically to optimize efficiency at constant highway speed, while a series-hybrid in the same conditions would suffer from avoidable energy conversion losses.

1.3 Research Structure

1.3.1 Research hypothesis

This study proposes and tests the hypothesis that energy consumption for arbitrary periods of vehicle travel can be accurately predicted by decomposing the proposed travel period into a linear combination of characteristic trip segments, each with a known constant characteristic power consumption for each vehicle type. The prediction will be the sum of vehicle-specific energy consumption totals for that combination of segments. The prediction should hold for travel periods ranging in duration from a single trip to a multi-month mission profile.

To simplify further discussion, the following terms are defined:

"*Mission profile*" refers to the operations typically undertaken by a specific vehicle. Municipal examples include "bylaw supervisor", "meter reader", and pool vehicle".

"*Kinetic travel data*" refers to a specific portion of a vehicle's speed history, or summary statistics derived from it.

"*Eigentrips*" are a basis set of vehicle-agnostic travel segments with the following characteristics:

- Each eigentrip is defined by characteristic kinetic travel data
- Every vehicle has characteristic energy consumption for each eigentrip
- All historical and predicted travel data can be decomposed into a linear combination of eigentrips

The primary technical problems addressed in this thesis are:

- Selecting an appropriate basis set of eigentrips using kinetic travel data.
- Evaluating the predictive power of a linear combination of eigentrips, relative to the observed energy consumption of vehicles on specific missions.

1.3.2 Model validity and predictive power

The new method's validity will be evaluated by comparing its prediction error to the real-world energy consumption, as inferred from the full raw dataset. This prediction error will be contrasted with the prediction error of the traditional distance-based fuel economy statistic described above in §1.2.3.

It is worth noting that the "observed energy consumption" baseline is an estimate of unknown accuracy derived from the available proxy values (MAF and SOC) as discussed in §3.3. This assumption is addressed in §7.5.2.

1.3.3 Preliminary validation

The author conducted a preliminary experiment [24] as a coursework project, studying 300 hours of kinetic travel data and fuel flow rates inferred from MAF (mass-airflow) values, for ten similar vehicles.

In that study, the data was partitioned into 10-minute segments by clock time (segment boundaries were placed at even 10-minute intervals starting at the top of each hour). A fingerprint of representative statistics was then calculated for each segment. K-means clustering [25, §10.4.3] was performed on the resultant dataset to find three clusters. Based on the clustering results, held back test data was classified with a softmax [25, §6.6.2] logistic classifier [26], and engine load was predicted. The average engine load prediction error using this method was approximately 2%.

Although not proven to generalize, the result was sufficient to suggest that the method warranted further study.

1.3.4 Research contributions

This research explores and validates a new method for predicting the energy consumption of different vehicle types when used to execute a well-known mission profile.

The method requires logger data attainable with nearly any commodity OBD2 logger – although some care must be taken to assure the quality of fuel / energy consumption

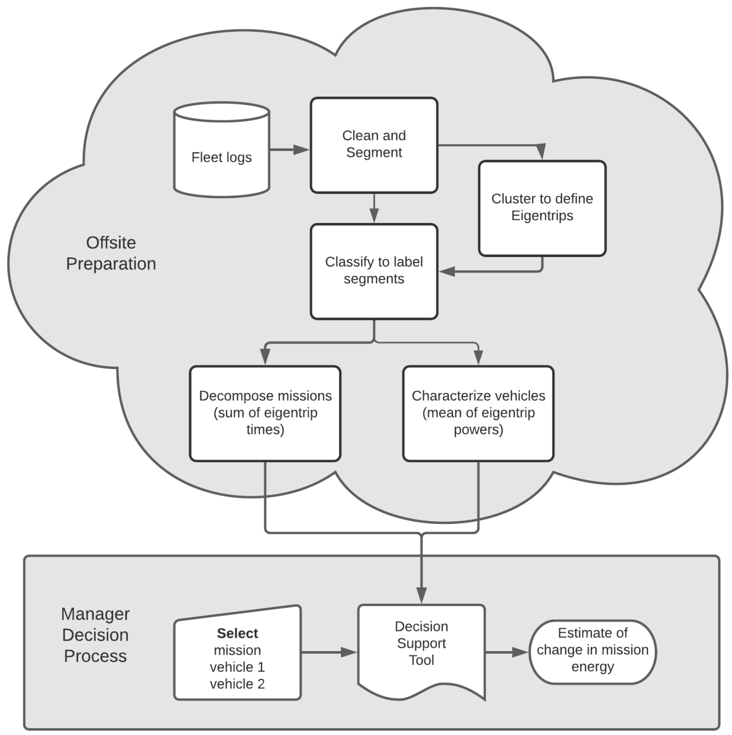


Figure 1: Decision support data-flow and work-flow

data. The data will be used to calculate characteristic parameters describing the study vehicles and mission profiles. The characteristic parameters can then be used to predict energy consumption according to a simple linear calculation that can be implemented in a spreadsheet-based decision support tool. A potential data-flow is shown in figure 1, illustrating the path that the data takes from initial capture, through the generation of the decision-support spreadsheet. This figure also illustrates the fleet manager's workflow, where a known mission is selected from those listed in the tool, along with a pair of vehicles (presumably the incumbent and a potential replacement), resulting in a predicted change in energy footprint.

This will allow fleet managers to accurately predict the energy requirements (and hence GHG emission footprint) of any logger-equipped vehicle, applied to any mission profile which has been previously performed by any other logger-equipped vehicle. In other words, the characterization of the fleet's various *missions* can be collected by any ICEV or BEV. The collection of logger data to compute characteristic energy consumption for the same or other vehicles of the same type can be collected on entirely different routes/missions, and even by entirely different organizations. Sharing real-world vehicle performance data between organizations would improve estimation of energy consumption based on different procurement scenarios, including new vehicle models of which a given organization has no direct experience – in much the same manner as $L_e/100km$ figures are currently used.

Other research contributions include:

- Shapley additive explanations (SHAP) showing the relative importance of various input features to the prediction of input power.
- a technique for reconstructing serial OBD2 values that have been tabularized
- evaluation of error inherent in traditional L/100km technique
- comparison to direct regression, to gauge efficacy & accuracy of both proposed method and L/100km method

2 Background

This section addresses background material fundamental to the topic. Quantitative analysis of travel patterns is typically performed on data comprising *drive cycles* and *microtrips*, so a brief background on these concepts is presented.

The proposed method involves *feature selection, clustering, and classification* of multi-dimensional timeseries data, so various tools for these tasks are discussed.

Finally, this section contains a short background of the technology used for *data collection*, and limitations around the collection of *fuel flow rates*.

2.1 Travel Data

2.1.1 Drive cycles

A drive cycle (or driving cycle) is the speed-time data that describe a portion of a vehicle's travel history [27], either measured, generated, or synthesized. A large number of standardized drive cycles have been published by various government agencies and private organizations, to facilitate optimization and testing to standardized benchmarks [28].

Two of the most heavily-referenced examples are the urban dynamometer driving schedule (UDDS) and highway fuel economy test (HWFET) cycles [29], defined by the United States Environmental Protection Agency (US EPA), and shown in figure 2. Elevation and grade are not a fundamental part of the generally accepted drive cycle definition and no mention is made of these in UDDS, HWFET, nor the other drive cycles referenced in the EPA's federal test procedure [1]. However, vehicle performance is strongly impacted by road grade, so an elevation profile is often used in parallel for simulations [30]. As discussed in §7.5.3, the road grade information used in this study was not of particularly high quality, and the topic merits additional work.

In machine learning, "classification" is the process of labelling an observation with a discrete nominal label (e.g., a category name) which best corresponds, on the basis of a set of "training" observations with known labels [25]. Drive cycle classification has been the subject of a substantial body of work. A frequent topic is the optimization of HEV battery energy management, such as the work of Wu et al on fuzzy energy management [31], with the goal of determining whether a vehicle was being operated in urban, suburban, or highway conditions. This paper used fixed-length partitions of 3 minutes, to match the typical urban stop-go-stop cycle length.

Other papers had goals such as BEV range estimation by Yu et al [32], or optimization for battery size (Redelbach et al) [33] and battery lifespan (Smith et al) [34].

However, most treatments of the subject do not restrict themselves to easily-logged kinetic parameters, but include classification features such as engine power, road gradient, and road-type. Indeed, in many papers, the data was collected by shadowing each subject vehicle with a chase-car, a method that is prohibitive for any kind of fleet data collection at scale.

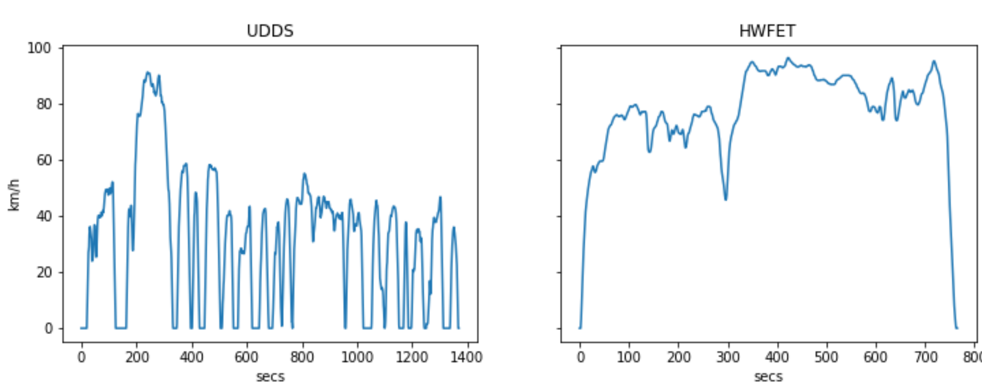


Figure 2: UDDS and HWFET drive cycles

2.1.2 Microtrips

Microtrips are "the sections of travel between consecutive stops", first used for travel analysis by General Motors Research in 1976 [35], where it was used to demonstrate that fuel rate varied linearly with average trip speed (true of the automotive technology of the time). They are used frequently as an aid to the development of new drive cycles, as per Kamble et al [36], where synthetic geography-specific drive cycles were created from a number of real microtrips.

The microtrip concept has seen very little use in the problem of drive cycle classification, with only a couple of examples seen in the literature. One example is described by Shankar and Marco in [37], which applies neural network classification to determine the road-type (e.g., highway, arterial, or local), as well as a congestion index, for use in predicting an input power appropriate to the driving conditions. However, the method was addressed specifically to battery vehicles, and presumes that the only factors influencing energy consumption are derived from road congestion and type. The method does not consider the possibility that different travel types in the same context might have different energy requirements, for example because the mission requires regular stops or extensive idling.

Shankar and Marco's paper does point out an inherent limitation of microtrips: that they are defined from stop to stop. This means that a single microtrip is likely to encompass more than one type of travel, and/or to unnecessarily segment a single type of travel that includes stops.

Another relevant example [38] by He et al extracted microtrips from the definitions of several predefined drive cycles, calculated the first seven of the aggregated velocity-derived features shown in table 2, and applied principle component analysis (PCA) to retain four principal components. These principal components were calculated on segments of actual travel data, in order to classify the segments in an learning vector quantization (LVQ) neural net, with very good classification results. The first seven features gave excellent classification results and may be expected to provide an excellent

Table 2: Studied kinetic features, as derived from logger data

Description	Units
Mean speed	(km/h)
Max speed	(km/h)
Mean acceleration	$(m/2^2)$
Max acceleration	(m/s^2)
Mean deceleration	$(-m/s^2)$
Max deceleration	$(-m/s^2)$
Idle time fraction	$(\%)$
Mean climb	(m/s)
Mean descent	(m/s)
Acceleration reversals	$(\#/s)$
Power	(kW)

starting point for fuel consumption prediction. However, features were excluded from that work, which will contribute to fuel consumption in a heterogeneous fleet; road grade and a count of acceleration reversals were added, and other non-studied examples include payload, accessory load, and others discussed in §7.5.

He's technique is not directly applicable to fleet fuel prediction, for a number of reasons:

- The technique was only demonstrated on artificial drive-cycles, and may not perform well on the complexity of real local driving conditions
- The exemplar microtrips are not shown to be predictive of fuel consumption between vehicle types
- PCA uses the largest eigenvectors to project data onto the lower-dimensional space that best represents the data's variation [25]. By design, PCA is an unsupervised technique with no relationship to regression; it captures the variance of the individual input features by weighting them accordingly, but without explicit regard to their relationship to the target variable. Hence, the weight of a feature in the principal components is not indicative of whether it has predictive power.

In general, the body of work on microtrips is informative with regards to feature selection and supports the notion of predictive analysis by decomposition. However, the fundamental definition of a micro-trip as a "stop-go-stop" cycle means that it is likely to mix some types of travel that should be separated, and to artificially partion others

Table 3: Derived ICE features with relative impact on fuel consumption [39]

Relative impact	Factor description
5	stop
4	acceleration with strong power demand
2	speed oscillation
2	acceleration with moderate power demand
2	extreme acceleration
-2	speed 50+/-70
-2	moderate engine speeds at gears 2 and 3
1	late gear changing from gear 2 and 3
-1	deceleration
-1	speed 70+/-90
-1	low engine speed at gear 4
-1	low engine speed at gear 5
0	speed 15+/-30
0	speed 90+/-110
0	engine speed $>$ 3500
0	speed $>$ 110

that would more effectively be considered as a unit.

2.2 Machine Learning

2.2.1 Feature selection

In machine learning, a "feature" is a measured property of the system under study, and usually implies a dimension in the system's state-space, either direct or a projection. It is not always obvious which features are salient for a given problem, so careful consideration of the problem is required with respect to the available data, plus experimentation, pre-processing, and investigation. There are a number of important problems that can arise from an improper choice of features for use in a machine-learning model.

When aspects of a feature's behaviour can be probabilistically predicted from knowledge of another feature (such as when the features are correlated, or otherwise functionally related), the two features are said to share "mutual information" [25, §A.7.3]. For most cost or distance functions, error related to given information is redundantly counted for every additional feature axis on which the information is represented. In many machine learning algorithms, this has potential to create a problem wherein the learning system over-values the importance of the duplicated information.

The curse of dimensionality [40] refers to the counter-intuitive fact that adding additional features will degrade accuracy for many forms of machine learning. This property devolves out of two geometric properties of high dimensional spaces.

First, the state-space volume expands exponentially with the addition of dimensions, quickly leading to a sample density too low for generalizable classification. A second property, called the "concentration of norms," refers to the surface area of a hypersphere expanding faster than its volume with the addition of dimensions – meaning that in a set of data normally distributed in multiple dimensions, most points will lie in the tail of at least one dimension. In this situation, it is easy to inadvertently construct an arbitrary classifier which works extremely well on the existing data, but which does not generalize – a situation referred to as over-fitting [41]. Together, these issues mean that intuition is not informative as to the behaviour of high-dimensional models, and the feature set should be minimized as much as practical.

The question of which loggable features are most clearly related to fuel consumption and/or emissions was addressed comprehensively for conventional ICE vehicles in [39]. In this study, 62 logged and derived features were investigated, and reduced to the most important compound features using PCA and factor analysis (which is similar to PCA in that it attempts to find a lower-dimensional representation, but dissimilar in that it accounts for correlations among the features [25]). These techniques are problematic in that PCA selects for high variance but not prediction, and factor analysis corrects for correlation, but not for any other forms of mutual information. Nevertheless, the resultant set of factors seems to be an excellent starting point for selecting features that will describe the fuel consumption rate of ICE vehicles. The relative impact on fuel consumption (in units of 1/10ths of a standard deviation) of several of the compound factors found in Ericsson's study are shown in table 3.

2.2.2 Time-series analysis

Time-series data consists of sequential measurements of the same feature over time, with the characteristic property that the data are generated by a process, and are not statistically independent of earlier samples in the process [42]. A drive-cycle is an excellent example, describing a trip in terms of measurements of the vehicle's speed over time.

Time-series data is commonly analyzed by the direct application of time-domain analysis techniques – finding patterns and behaviours with respect to temporal ordering. In the context of trip-segment similarity, it seems intuitively obvious that order does *not* much matter, relative to many other aspects of the driving patterns. For example: the segments of the urban drive cycle, driven in reverse order, could be expected to have energy consumption very similar to that of the forward-ordered version (stipulating a similar net elevation profile), but it is hard to imagine a meaningful time-domain measure that would expose the similarity. This intuition suggests that time-domain analysis techniques will miss important commonalities between trips.

Transforming into the frequency domain can address this problem and give insight into the relative importance of various cyclical behaviours. Applied to segments of kinetic driving data, it might give insight into the rate of start-stop or speed-slow cycles, where they exist. However, since acyclic behaviours might be critical differentiators, and would be lost in the transformation out of the time domain, we certainly cannot rely on frequency analysis alone.

Apart from the inter-sample interval necessary to calculate acceleration, the key features used in this research draw no useful information from their time sequencing. Thus, for the insights to be derived from the data, time series techniques do not provide a great deal of analytical power, and are left as a topic for future investigation (§7.3).

2.2.3 Binning and segmentation

Data binning is the process of grouping data points with similar values together, such that they can be referenced by a common value. This is useful to reduce the volume of data for faster processing, or to improve its comprehensibility, as with histograms. Segmentation is conceptually similar; it consists of partitioning time series data into time intervals, allowing each segment to be characterized as a group [43].

A key technique used in this research combines both techniques: partitioning the data into fixed-length segments, which are thereafter treated as non-time series bins. A selection of representative summary statistics (a fingerprint) for each segment are calculated, after which the time information can be discarded or ignored. Similar segments can then be binned, allowing the application of simple and intuitive non-time series analytical techniques.

This has the advantage that the similarity measure between segments can be as simple as Euclidean distance, or as complex as necessary to capture prior understanding of "similarity" for the system in question.

The primary disadvantages of using bin fingerprints are difficulties in (a) determining appropriate statistics such that if two trips are subjectively similar, then their statistics will have objectively similar values, and (b) finding segment boundaries, such that segments do not encompass multiple types.

2.2.4 Regression analysis

Regression analysis is a branch of mathematical statistics concerned with quantifying the relationships between some number of variables using statistical data [44]. In the most general sense, this involves finding the appropriate parameters for a mathematical model, which will allow it to calculate predicted values for the dependent variable(s) based on the input values for the independent variables.

The most commonly used example is *linear* regression, which consists of finding the coefficients $\boldsymbol{b}$ for the independent variables $\boldsymbol{x}$ that will best predict target variable y, typically by minimizing the mean-square error (MSE) for all training values $\hat{y}$.

$$y = b_0 + b_1 x_1 + ... + b_n x_n + \epsilon \tag{3}$$

$$MSE = \frac{1}{n} \sum (y - \hat{y})^2 \tag{4}$$

If the relationship between the independent and dependent variables is more complex, nonlinear techniques are used – either by fitting coefficients to a more complex formula that better describes the relationship, or by using some other model entirely, such as a decision tree or artificial neural net [41]. These nonlinear techniques result in a better fit to the observed data, but at the cost of a more complex formula and the risk of overfitting.

Traditional regression techniques are not a good fit for the primary stated goals of this research, as it would not be possible to develop a spreadsheet-deployable model that could clean and process the millions of rows of logger data. Setting aside the unique requirements of a deployable decision support tool, tree or neural net regression would be the simplest path to predicting vehicle energy consumption, and will be used in §5 to provide a basis for comparison of the accuracy of the proposed spreadsheet-capable model.

2.2.5 Clustering

Clustering is the general name for unsupervised techniques that have the goal of grouping similar data samples according to an appropriate definition of similarity.

For the problem at hand, it is impractical to manually define a basis set of eigentrips that will (a) adequately represent all travel in the dataset, and (b) be sufficiently discriminatory with regards to fuel consumption between the studied vehicle types. In this study, the entire corpus of segmented travel data will be clustered, and the characteristics of each group will be considered to represent one eigentrip. This section will address appropriate methods for clustering.

The simplest and arguably most intuitive clustering technique is K-means clustering, most easily understood with an interactive visualization, such as the one linked at [45]. The technique consists of selecting a number *(k)* of randomly distributed cluster centroids, assigning every data point to the cluster defined by the nearest centroid, and then iteratively redefining each cluster centroid as the mean of its constituent points. The technique's simplicity is balanced by two significant limitations. First, it must be provided with a predefined cluster count [25], which is a key tuning parameter. Second, it presumes clusters in normal, spherical distributions; its cost function is most appropriate for points which have a Gaussian distribution of equal variance in every dimension.

The technique can be generalized to data in non-spherical distributions by maximizing the probabilistic membership in each cluster – this is called expectation maximization (EM) clustering – or more specifically, Gaussian mixture models (GMMs) if the clusters are normally distributed.

Any clustering technique relies on an appropriate definition of distance between points in the feature space. A common and intuitive choice is the L2 norm – Euclidean distance – applied to appropriately normalized features. This works well, because non-discriminatory features are likely to balance themselves by virtue of being equally distributed between the clusters. However, the measure is sensitive to outliers, and cannot account for desired similarities that can only be described by nonlinear combinations of features.

K-means also requires a number of clusters (k) as an input. Typically, this number is found by inspection (the "elbow" method [46]) or by minimizing a loss function such as silhouette score [47]) against different values for k.

In addition to the advantage of simplicity, K-means has a well-known implementation in the Scikit-learn library. Although it presumes spherical, normalized clusters [48], this requirement is also an advantage, since it allows features to be given relative weights by the simple expedient of linear scaling.

There is an obvious argument against the use of K-means: that the best clusters (for a domain-specific definition of similarity) may not be normal and spherical. However, the travel data at hand is continuous, and does not *have* distinct clusters. For the immediate goal – selecting "similar" data to train the eigentrip classifier, we can allow the clustering algorithm to define the shape of its clusters. Reviewing the impact of alternate clustering techniques on classifier accuracy will be an excellent topic for future refinement of the model.

2.2.6 Classification

Classification is similar to regression analysis, but with a goal of predicting a discrete value, rather than a scalar, commonly used for determining which of a fixed number of categories is the best fit for a particular datum [41].

Classification is a key element of the proposed method: each trip segment will be classified and labelled with its most similar eigentrip. If the thesis is correct, the characteristic power of that eigentrip will be similar to the actual power of the trip segment.

Classification algorithm selection is more art than science, with the "No Free Lunch" theorem demonstrating that there is no model that is best across domains [41]. In general, the researcher must evaluate the characteristics of their data and the requirements of their model, and attempt to find an algorithm that suits both.

In this case, since several of the features have unknown multi-modal distributions, Bayesian algorithms will not be a good fit. Neural nets require computationally intensive training, have non-explainable results, and do not extrapolate outside their training volume. The remaining family of classifiers which seem appropriate are ensemble decision trees. The light gradient boosting machine (LGBM) algorithm is selected for initial review as demonstrating a good balance between training speed and prediction accuracy.

2.2.7 Gradient boost and LGBM

Model selection is arguably the most difficult aspect of practical, applied ML. The proposed model has aspects that make it particularly challenging:

- features are multi-modal and do not follow a common distribution
- features may have unknown mutual information
- target feature has no obvious structure
- explanation of feature impact on prediction may be important for future work
- millions of data points

The unknown distribution renders Bayesian methods impractical. The possible shared information duplicated between features and potential requirement for explainability comprise good arguments against artificial neural nets. Finally, due to the need for iterative evaluation over the relatively large dataset discussed below in §4.6, slow-training methods would not be practical. Given these exclusions, an ensemble decision tree method warranted consideration.

Although at risk of running afoul of Maslow's Hammer [49], the common-sense admonition that practitioners are prone to over-application of familiar tools, the popular LightGBM model meets all of the above criteria, described in more detail in §4.3.

2.3 Data Collection

2.3.1 OBD2 logger implementation

In order to understand a significant primary data collection issue, the reader will require some background on the technology used for data collection.

The dataset used in this study was collected by FleetCarma Inc., a commercial company based in Waterloo, Ontario. FleetCarma uses telematics loggers connected to the vehicles' OBD2 interface. OBD2 is a protocol defined by Society of Automotive Engineers (SAE) standard J1962 for vehicle data access, and specifies a female 16-pin electrical connector for access, commonly known as the OBD2 port. It accesses the vehicle's controller area network (CAN) bus, a serial hardware layer commonly used to transport vehicle sensor data between various engine control unit (ECU)s. Information in this subsection is summarized primarily from an instructional website [50] and the original Texas Instruments application document [51].

Devices on a CAN bus communicate exclusively by broadcast. Some devices may report their status at a regular interval, while others only report in response to a request broadcast, and others may communicate by both methods. In essence, the CAN bus data stream consists of a sequence of (key, value) pairs.

Fleet Carma's logger has a list of parameter identifier (PID) values that are to be collected from the OBD2 system. Whenever any of those PIDs appear on the CAN bus, the logger records and timestamps it. To ensure a data log meeting the specified resolution requirements (1 second while moving), the logger periodically sends update requests for over the CAN bus for appropriate PIDs, requesting that a new value be returned.

The problem derives from the logger's conversion of the sequential stream of PID-value pairs, into an analyst-friendly timeseries table format, with one row per timestamp and one column per PID. In this conversion, a row is generated shortly after an updated value is received over the CAN bus. Unfortunately, any PIDs which have *not* reported updated values appear to have been assigned *their last known value* for a given row. Table 4 presents an exaggerated illustration of the problem, showing how a reasonable acceleration to $5\,m/s$ over 10s could generate an apparent acceleration of $50\,m/s^2$:

Table 4: OBD2 Log Problem Example

Seconds	ΔT	**CAN message**	**MAF** (g/s)	**Speed** (m/s)	**Acceleration** (m/s^{2})
30.0	-	speed=0	4.3	0	-
30.1	0.1	MAF=11.3	11.3	0	0
39.9	9.8	MAF=10.9	10.9	0	0
40.0	0.1	speed=5	10.9	5	50

2.3.2 Fuel vs airflow

Unfortunately, a parameter for fuel-flow rate is not part of the OBD2 specification [52]. Most vehicle manufacturers supply a proprietary PID for this value, but our FleetCarma loggers were not configured to retrieve it from the individual vehicles. A valuable proxy for fuel flow is the standard PID mass-airflow (MAF), which estimates the mass of air entering the engine from measurements of airstream temperature and velocity at the intake. The well-known stoichiometric mass ratio of 14.7 for gasoline combustion is inferred from the oxidation reaction [53]:

$$25\,O_2 + 2\,C_8H_{18} \rightarrow 16\,CO_2 + 18\,H_2O + E \tag{5}$$

Since tailpipe emissions are an important design consideration, modern vehicles attempt to minimize emissions by ensuring good operation of the catalytic converter. One outcome of this intent is that the vehicle continually modifies its fuel flow (a process referred to as *trimming*) relative to MAF, in order to maintain clean combustion as indicated by the oxygen content of the exhaust stream. There *do* exist standard PIDs for both the commanded and measured ratios of fuel to air [52], but these values were unavailable to this study, having not been logged in the CRD's Smart Fleet project.

In any case, a properly operating vehicle should generally have a fuel flow within 10% of the stoichiometric ratio relative to the MAF [54]. It is noteworthy that there are certain events (notably engine-braking) that will be expected to cause significant transient departures from the stoichiometric ratio. The author's personal experience, having reviewed trim data logs from five personal vehicles, is that short and long-term fuel trim levels generally remain consistent within 3% for normal driving, outside of a few minutes for engine warm-up.

The conclusion from this background material is that calculating fuel flow by applying the stoichiometric ratio of 14.7 to the measured MAF can be reasonably expected to have a *per-vehicle precision* of ±3%, and an *absolute accuracy* within ±10%.

Ultimately, the MAF estimate must stand alone as a ground truth for this work, as no means of validating the MAF estimate was found. The CRD does track fleet fuel consumption under BC's Climate Action Revenue Incentive Program (CARIP) program, but not in a manner that could be isolated to specific vehicles, or even to the subset of vehicles under observation. A project was underway to implement a card system that will ultimate track the fuel consumption of individual vehicles, but no data was available for the study period.

3 Data Cleaning and Preparation

This section describes the process required to make the timeseries logger data ready for segmentation and fingerprinting. This was a key and challenging element of the research, requiring approximately 4000 lines of python code.

3.1 Raw Data

3.1.1 Collection

As discussed above, the CRD's ZEFI project [7] included telematic loggers installed in fleet vehicles for approximately a year starting in early 2018. Summary statistics of the data collection effort are shown in table 5, with the distribution of samples between vehicle-missions shown in figure 3.

The loggers were capable of logging and transmitting global positioning system (GPS) locations and a collection of engine data parameters that differed from vehicle to vehicle, but which always included speedometer (wheel) speed. FleetCarma was asked to collect fuel flow rates, but as this is not part of the OBD2 standard, FleetCarma instead collected various proxies for fuel flow, primarily MAF and AbsLoad.

3.1.2 Parsing and selection

The raw logger data was received in one text file per trip, where trips comprised periods of time where the logger was supplied with accessory power from the host vehicle. The

Table 5: Data Collection Statistics

Feature	Value
Total vehicles	55
Total samples	18356982
Study vehicles	29
Study samples	10617365
First datum	2018-01-29
Last datum	2019-02-20

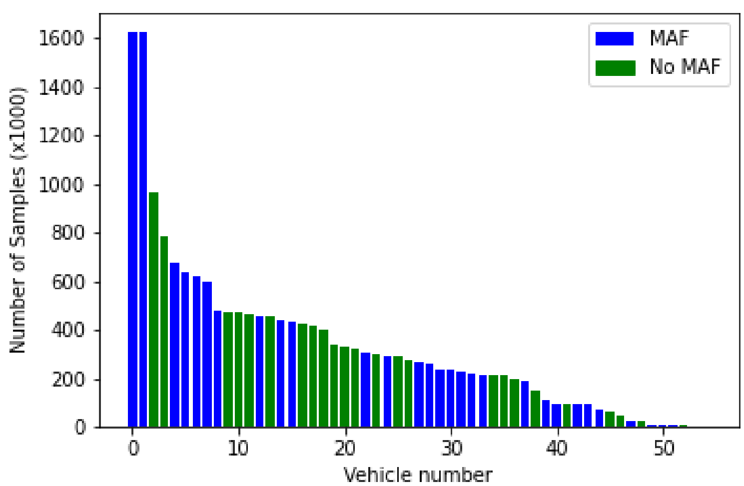


Figure 3: Sample counts by vehicle, studied and non-studied

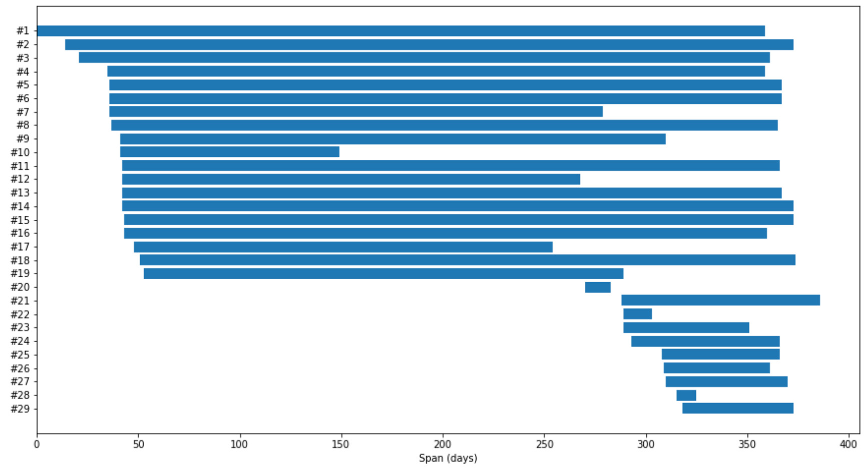


Figure 4: Data collection timespans for individual vehicles

files were in comma-separated-value (CSV) format, indexed by time or time-offset (one row per timestamp, one column per sensor), but did not use consistent file-formats, units, column selections, nor column naming conventions, so ingestion of the data into a standard format was a challenging and time-consuming task.

Only about half of the ICE study vehicles were configured to log MAF. The OBD2 PID AbsLoad was provided for the remainder, but this is not a proxy for fuel consumption without reference to engine revolutions per minute (RPM), which was not collected. ICE vehicles without MAF were therefore eliminated from the study group. This was a significant and disappointing setback, and a stern reminder to attempt a limited model proof of concept early in the data collection process. However, the remaining data is sufficient in breadth and depth to demonstrate the core thesis, albeit not so clearly shown to generalize across many different vehicle and mission types.

The various vehicles were monitored for different time periods, with the length of their study period shown in figure 4.

3.1.3 Feature selection

The complete list of attribute names collected by the various loggers is listed in appendix A, table 14. Several of these features are duplicated with alternate names – e.g., Speed and Signal #131 are synonymous. For this work, only various aspects of vehicle speed (including vertical speed, from GPS altitude) and derived variables were selected as features, with a target feature of vehicle energy consumption – derived from MAF on ICE vehicles, and primarily state of charge (SOC) for BEVs.

3.2 Speed Data Cleaning

3.2.1 Speed data problems

Various statistics related to vehicle acceleration were of primary interest to this study. Accelerations were trivially computed from the measured timeseries speed logs for each trip, but examination showed a large fraction of impossibly high accelerations.

It seems well-accepted that consumer-grade tires on dry pavement offer a peak static friction coefficient of around 0.7 [55], so all acceleration values in excess of $0.7 \times 9.8 = 6.9\frac{m}{s^2}$ are suspect. About 132k (or 1.25%) of the 10.6M speed samples implied accelerations above this threshold. Examination of the log data showed 56.2% of log speed values were unchanged from the previous value, suggesting "sticky" sensor readings at the OBD2 logger, as described in section §2.3.1.

Since statistics derived from vehicle acceleration comprise the primary features to be investigated for fingerprinting travel segments, it was of critical importance to remediate the speed data collection/integration errors and restore a true reflection of the vehicles' speed and acceleration profiles prior to attempting analysis. This section explains how the speed data was cleaned.

3.2.2 Recurrent speeds

Since the speed of a moving vehicle is inherently variable, nonzero speed values should only recur very infrequently. It seems obvious that a large fraction of the recurring values are invalid data integration artifacts. In the absence of any information about *which* recurrent speed values happened to be valid, the author elected to eliminate all of

Table 6: *Impact of data cleaning methods on rate of "impossible acceleration" errors*

Rows removed	Samples	Errors	Error Rate (%)	Error reduction (%)
Nil	10,617,365	132,291	1.25	NaN
Moving recurrent	7,874,102	12,727	0.162	90.4
Impossible starts	7,861,375	69	0.000878	99.5

them. This substantially improved the quality of the data – that is to say, the deletions removed most of the invalid acceleration values. The number of valid data points also deleted is believed to be very small, and in aggregate likely to do little harm for the purpose of this study. The obvious exception is made for periods of zero speed, where it was to be expected that the vehicle's zero speed was indeed constant for some period of time.

Accordingly, all recurrent speed samples were deleted, except for zero-speed samples. This deletion reduced the number of samples by almost 1/3, but reduced the number of impossible acceleration events from 132k to 12k – a reduction of 91.4%.

A summary of the reduction in error rates from data cleaning is shown in table 6

3.2.3 Stop-start errors

Of these remaining impossible acceleration events, nearly all occur during vehicle starts – samples where the previous speed was zero.

This comprises an error rate of 5.01% during starts from zero speed. Examination of the offending high-acceleration samples reveals an extraordinarily high number of short (sub-second) intervals after the final zero-speed sample. This strongly implies that these accelerations are another artifact of the "sticky" value problem discussed in section 2.3.1.

In the interest of simplicity, these roughly 12,000 impossible-start samples were dropped. Since the way a vehicle is started may have useful predictive power (e.g., jackrabbit starts), future work should be applied to recovering the information in start samples, as discussed in section 7.2.1.

3.2.4 Other errors

With the above cleaning methods applied, the corpus contained only 69 remaining samples with impossibly high acceleration values. Inspection showed these to generally correspond to high rates of change over short sample periods, but with no obvious cause. These samples could very well be true values, perhaps due to wheels spinning under high power or wheel-lockup due to hard braking. These samples have been left intact.

3.3 Power Data Cleaning

Again, the core problem of this thesis is to predict each vehicle's characteristic input power for each eigentrip. The model's ground truth will be the input power consumed during each trip segment, so a new power feature was calculated from the available features.

3.3.1 ICE power

For ICE vehicles, the energy input is fuel consumed. Fuel consumption was approximated from logged MAF at the stoichiometric fuel:air ratio, an assumption discussed in §2.3.2 and §7.1. The energy value was then calculated using the LHV of 46.4 $\frac{MJ}{kg}$ [56].

The MAF PID suffered from the same "stickiness" problem as the other PIDs discussed above, and had an effective sample period of about 2 s. This was addressed by the same means as for speed: removing all recurrent values, except zero-value periods.

3.3.2 BEV power

For the BEVs, input power is from the high-voltage (HV) main drive battery.

Although FleetCarma attempted to provide 1-second resolution power data, the data suffered from the same stickiness problem as elsewhere; the real sampling rate was much lower than expected. SOC was sampled at a median period of 87 s, HV battery current at 29 s, and HV battery voltage at 30 s. This low sampling frequency complicated the power calculation; multiplying spot-sampled voltage and current with the elapsed time would miss transient events, and be unlikely to provide an accurate reflection of total consumption. Reported SOC is not perfectly suitable, being unlikely to have been sampled near a given segment boundary.

A rejected course of investigation was to interpolate SOC along the better-sampled HV voltage reading, on the assumption that battery voltage would drop linearly with expended energy. Plots of SOC vs voltage for multiple trips (figure 5) suggested that there is a good relationship between these features. However, inspection of a number of actual time-domain plots of battery voltage and SOC similar to figure 6 suggest that the correlation only exists reliably at a scale too broad to be of practical use.

As shown in figure 6, the HV system's voltage readings are highly variable while the vehicle is in motion; this reading shows system voltage rather than open-circuit battery voltage. Furthermore, the system's logging resolution is far too low to estimate energy consumption (E) from voltage (V) and amperage (I) in the typical manner, as:

$$\Delta E = \int V(t) \times I(t) \, dt \tag{6}$$

Fortunately the vehicle's on-board computer has high-resolution access to the electrical sensors, and can make use of a combination of several methods for establishing the remaining useful charge in the battery [57]. SOC is therefore a reasonably trustworthy absolute measurement relative to the vehicle's known battery pack capacity, and a reasonable estimate of energy consumption over time can be obtained from it.

Ultimately, no better method was found than applying vehicle-reported SOC to manufacturer-published battery capacity of 27 kWh for the Kia Souls [58, 59], and 12 kWh for the Outlander PHEV [60]. This required linear interpolation of SOC to the

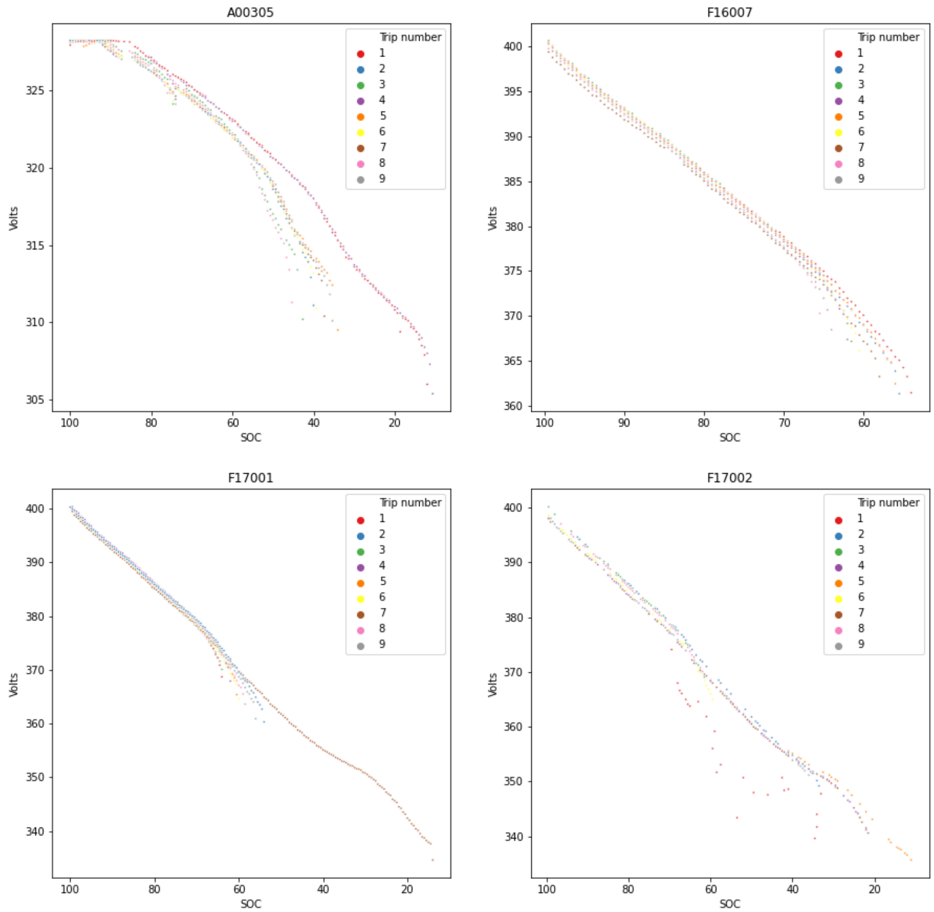


Figure 5: EV example trips showing the broad relationship of SOC vs the main battery's voltage

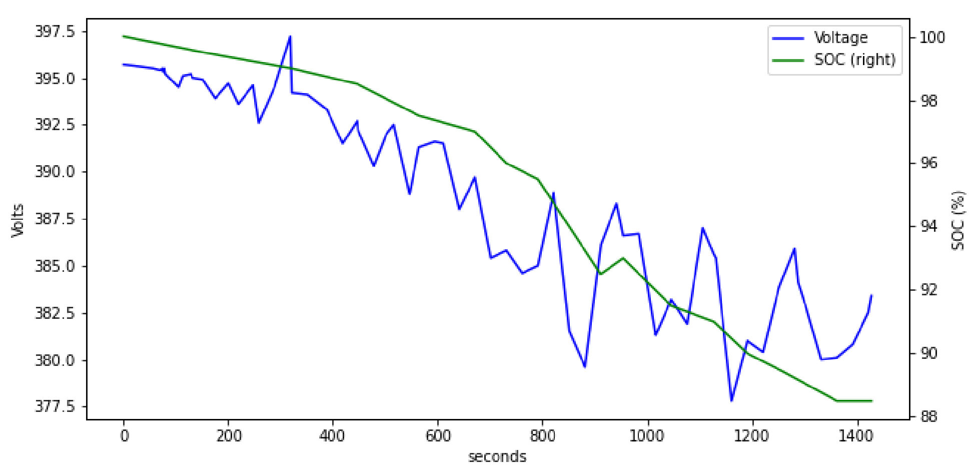


Figure 6: One EV example trip showing the rapid changes of voltage readings over time

Table 7: Number of samples and trips removed by EV data cleaning procedures

	EV Samples	Removed	EV Trips
Nil	817,820	0	2,308
Zero power	817,641	179	2,181
Charging	796,022	21,619	1,762
Zero-time	796,022	0	1,762

segment boundaries as described below in §3.4, a significant assumption that merits the future work discussed in §7.2.3. Given these assumptions, energy used in a period is then simply:

$$\Delta E = \Delta SOC \times Capacity \tag{7}$$

Inspection of the power thus calculated showed a large number of null SOC and V-I measurements. Nearly all of these were addressed by deleting a small number of unusable data-logs, presumed to represent data collection artifacts generated by loggers not well-configured for their host BEVs, described in table 7.

3.4 Regularization

In order to reduce the amount of data uploaded over the cellular devices, the supplier configured their loggers to use a sample period of about 1 second while moving, and 30 seconds while stopped. After collection was complete, the "sticky" problem discussed in §2.3.1 was discovered, and with it the realization that various sensor values were recorded at different frequencies, and at fractional-second offsets from each other. The above process of removing recurrent values adequately eliminated the spurious readings, but introduced two distinct problems:

1. The longer-than-expected sampling period introduces complexity in handling segment boundaries – the final sample in each segment must be extrapolated across the boundary in order to be included in the second segment.

2. the sample following a 'stopped' sample may have a non-zero speed; barring the

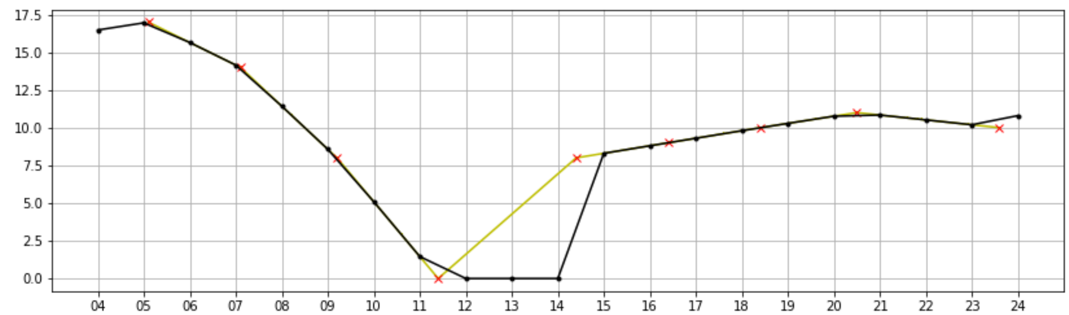


Figure 7: Problems caused by linear sample interpolation with and without regularization

introduction of synthetic 0-speed samples to terminate each stop, point-wise interpolation would result in apparent movement during the stop period. This is illustrated in figure 7, with sample points in red, direct interpolation in yellow, and the regularized interpolation shown in black.

To address these problems, the entire dataset was regularized to uniform 1s intervals, zeroed to clock time. I.e., regularized timestamps are at even multiples of 1 second from the top of the hour, rather than from the beginning of the trip, which would likely have been offset by a fractional second. Zero-speed periods were forward-filled to 1s intervals, and all in-motion data was linearly interpolated onto the regularized 1s interval.

4 Methodology

This section describes the process chosen to build a spreadsheet-compatible energy prediction model from the cleaned timeseries logger data. In broad terms, the steps were as follows:

- Divide travel data into segments
- Compute kinetic fingerprint features and average power
- Select reasonable starting clustering parameters
- Cluster into groups representing eigentrips
- Characterize missions by classifying travel data
- Iteratively refine clustering parameters and model hyperparameters

4.1 Feature Preparation

4.1.1 Segmentation

As in Wu's drive cycle classifier [31], the data was consolidated into 3-minute segments to match the resolution of a typical urban stop-go-stop cycle. The resampling is relative

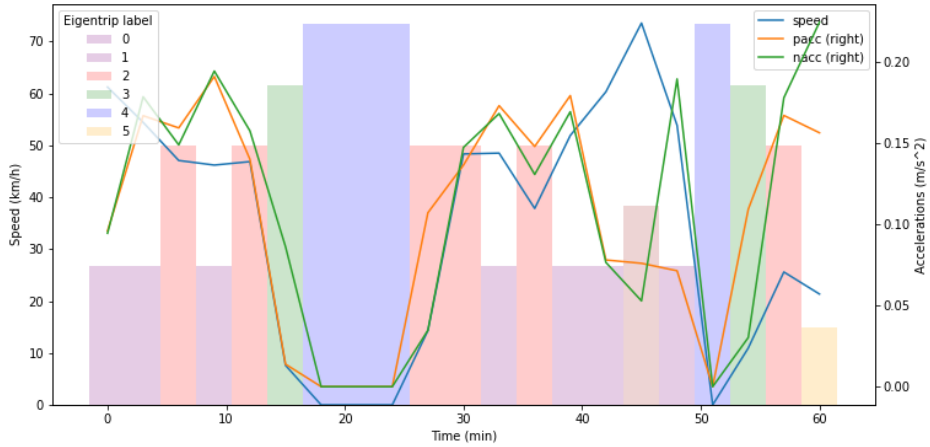


Figure 8: Timeseries trace of speed and accelerations, overlaid with eigentrip labels

to the top of the hour (IE, segments begin and end at even multiples of 3 minutes past the hour). This has the advantages of consistency and simplicity with the tools at hand, but it also results in the first and last segment of each trip having shorter durations. E.g., if a trip began at 15:02:15, its first segment will end at 15:02:59 for a duration of only 45 seconds.

The fixed segment duration, the choice of 3-minute segments, and the clock-time interval boundaries are all assumptions meriting further investigation as discussed in §7.3.4 and §7.3.5.

An example period of travel is shown in in figure 8, with a timeseries plot of the average speed, acceleration, and deceleration values in each 3-minute segment. The plot segments are superimposed on blocks representing their eigentrip labels, to give a sense of the decomposition process.

4.1.2 Feature values

For each 3-minute segment, Wu's vehicle-independent trip features [31] were computed, including averages and maximums for speed, acceleration, and deceleration, as well as the fraction of time spent idling (see table 2).

One oversight in Wu's choice of features is road grade – a significant factor in short-term power requirements. Fully 42% of the data collected in this study lacked GPS altitude, and of the non-null data, 61% were repeat values. Where possible however, positive and negative vertical speed features were calculated. To give some insight into regenerative braking, an additional feature was computed from the count of acceleration reversals – the number of times the vehicle changed from acceleration to deceleration, or vice versa.

Each travel segment was additionally labelled with its mean input power in kW. The derivation of power from the available log data is described in detail above in §3.3. In brief, ICEV power is derived from MAF at the stoichiometric ratio, and BEV power from the time-interpolated SOC.

4.1.3 Assumptions

Refining and simplifying assumptions were applied to the feature calculations as follows:

- Null samples indicate that either the logger or CANbus is inactive, which should typically only happen when the vehicle is at rest and/or the engine is stopped. Null values were therefore presumed to indicate zero speed and/or energy consumption.
- For maximum values, the 98th percentile (Q98) value was selected to minimize the effect of outliers and incorrectly captured values.
- In spite of using a quantile for maximums, the mean was used to represent average, since the other measures of central tendency minimize the informational effect of skewness, which is valuable here.
- Information doubly-represented in other statistics (eg, zero-speed samples, also captured in the idle-fraction statistic) was not excluded.

4.1.4 Data review

Histograms of the feature values plus power consumption rate are visualized stripped of outliers (beyond 2.5 IQR) in figure 9, and further stripped of the minimal value and maximal value in 10.

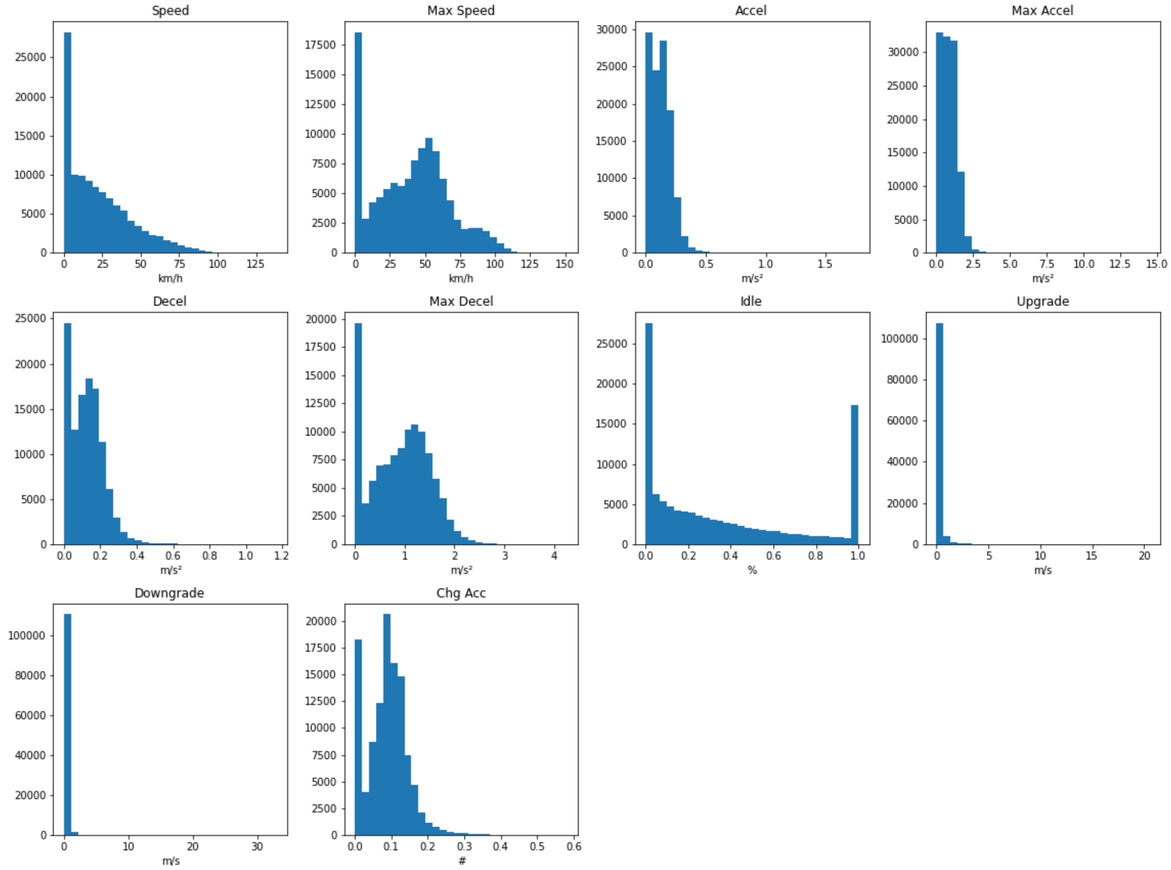


Figure 9: Feature value distributions, including end-of-range values

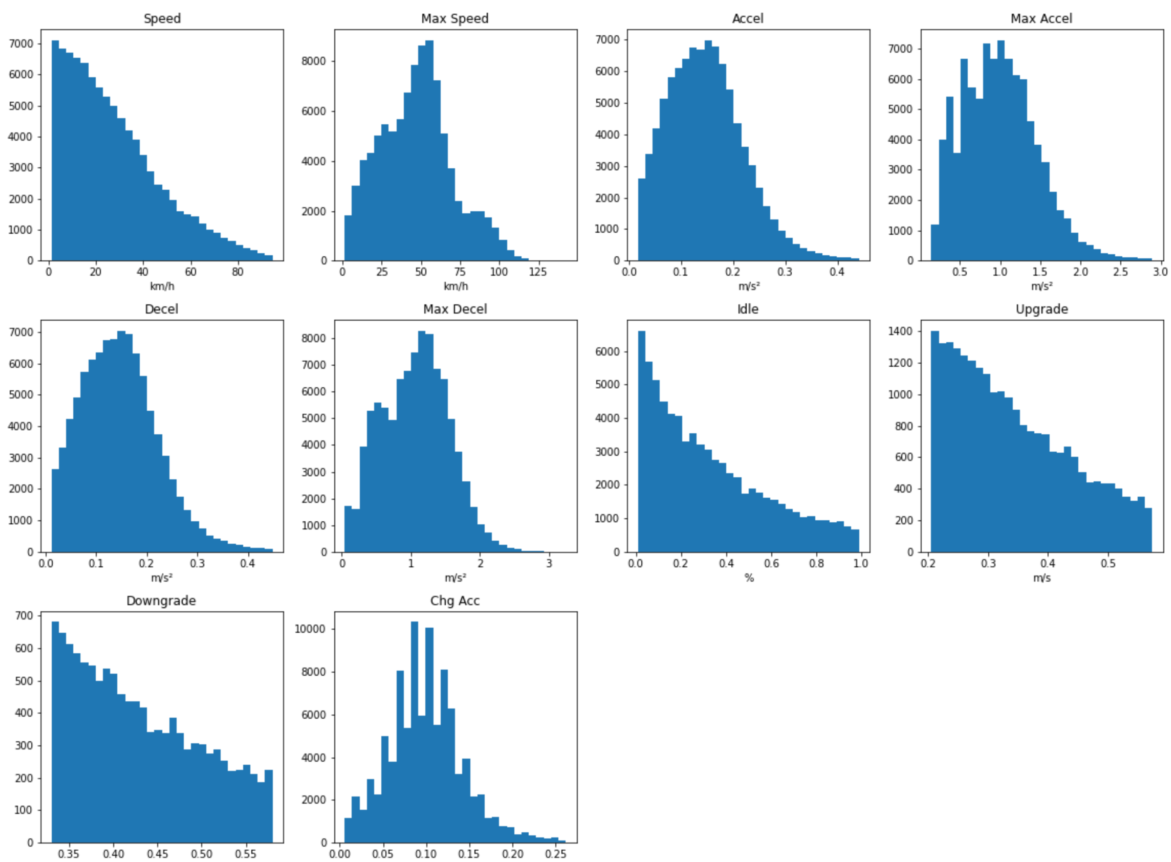


Figure 10: Feature value distributions after removing common end-of-range values

4.2 Clustering

Having established a clean corpus of fingerprinted travel segments, the next step was to perform a preliminary clustering of the segments into similar groups.

The individual features did not exhibit significant modalities other than those obviously caused by segments where the vehicle was idle; there is no reason to expect that the data is inherently clustered. Since the clusters will be selected arbitrarily to improve the model's performance, a simple clusterer using Euclidean distance suffices for initial validation. K-means clustering was chosen due to its simplicity and the fact that the Scikit-learn implementation does not scale its inputs, permitting feature weighting by scaling. Since K-means greedily minimizes within-cluster sum-of-squares [48],

$$\sum_{i=0}^{n} \min_{\mu_j \in C}(||x_i - \mu_j||^2) \quad (8)$$

it tends to result in clusters which are roughly spherical, rather than elongated or convex. This is a limiting factor deserving additional work (§7.4.1), but it does not prevent the technique from establishing reasonable cluster centroids, nor from providing labelled groups which will train a functional classifier.

4.2.1 Intent

The centroids of these groups define the characteristic travel-type exemplars that we are calling "eigentrips". The eigentrips are used to estimate a vehicle's input power according to the vehicle's type, and the kinetic characteristics of the travel it is undertaking. The goal is therefore to find a set of eigentrips, each of which represent a travel regime with both (a) consistent kinetic characteristics, and (b) similar input power within each vehicle type.

4.2.2 Key insight

It was desired that the eigentrips represent regimes of travel with similar power *within each vehicle-type*, but not necessarily *across* vehicle-types, so power was added as a feature for the purpose of clustering, and weighted to emphasize its importance relative to the individual kinetic features.

The inter-vehicle difference in power for a given travel-type would be a confounding factor, so the power feature is standardized to Mahalanobis distance (shifted to have a zero mean, and scaled to number of standard deviations) *separately for each vehicle.*

4.2.3 Cluster visualization

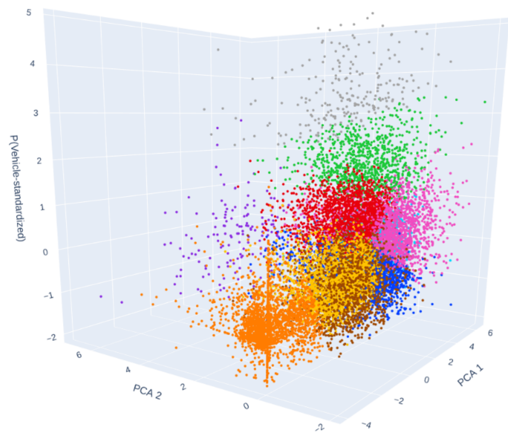
A preliminary K-means clustering operation was performed with K=10 clusters, and the power feature weighting increased by applying a power-scaling factor (PS) of 2.0. The kinetic features were reduced to 2 dimensions with PCA as shown in table 8. The PCA-reduced kinetic features were visualized on a 3D scatter plot, with the Z axis showing power, and the cluster labels differentiated by colour. Clustering for the complete training datasest is visualized in figure 11(a), with power standardized within each vehicle. The similar subfigure (b) shows the subset of data for a single vehicle, with non-standardized power.

4.3 Classification Algorithm

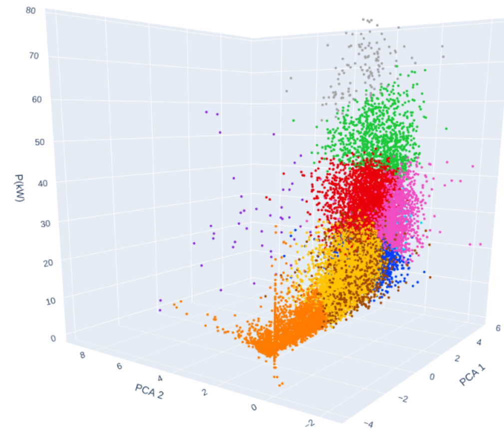
4.3.1 Algorithm selection

The core of the proposed model is the classification of travel segments by their kinetic features, and labelling them with the most-similar eigentrip. This label permits predicting a likely vehicle-specific characteristic power for the segment. In other words, the clustering process above has *defined* the eigentrips, and now they can be *applied.*

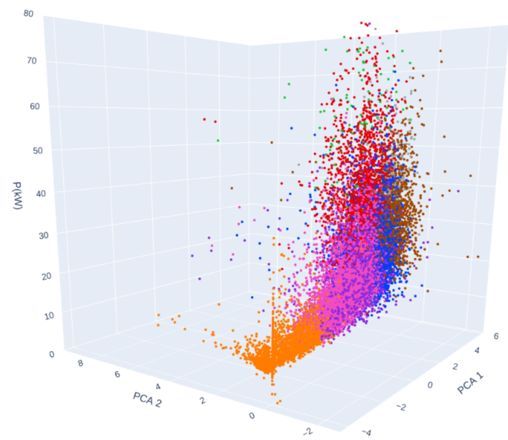
The feature histograms (figure 10) showed the bulk of feature data in well-ordered distributions, but many with a large additional peak at zero (as well as unity, in the case



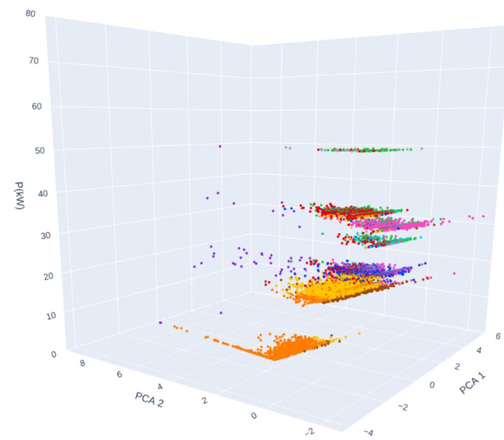
(a) Standardized power (all training data)



(b) Actual power



(c) Actual power, predicted labels



(d) Predicted characteristic power

Figure 11: Visualization of preliminary clustering (K=10, PS=2) and classification, as applied to one example vehicle

Table 8: PCA components for 2D visualization of kinetic features(K=10, PS=2)

	PCA 1	PCA 2
Speed	0.302	0.0828
Max speed	0.355	0.0551
Acceleration	0.372	-0.100
Max acceleration	0.342	-0.110
Deceleration	0.365	-0.0745
Max deceleration	0.368	-0.0778
Idle	-0.39	0.0139
Climb	0.0884	0.684
Descent	0.0878	0.692
Acceleration reversals	0.303	-0.0976

of the idle fraction feature). This modality means that parametric classifiers assuming a single distribution will be ill-suited. Since selecting cluster parameters required an iterative search of K (number of clusters) and PS (power-scaling) combinations, a fast classifier was desired.

The LightGBM classifier [61] meets these requirements. LightGBM is a gradient boosting framework, with several interesting optimizations. The remainder of §4.3 is a short introduction to some core concepts underlying the LightGBM model: decision trees, boosting, gradient boosting, and a short description of LightGBM's optimizations.

4.3.2 Decision Trees

The simplest possible decision tree is a single inequality criterion that branches a dataset into two leaves. Figure 12 illustrates an example, letting records where feature #2 <= 4.85 go into the *left* leaf, the remainder into the right.

Selecting the best choice for the split criterion requires a method of quantifying the "purity" of potential splits – the degree to which information is added by by creating the split. Shannon entropy, mis-classification error rate, and Gini impurity are common metrics for classification, and sum of squared error for regression [62, §9.2]. In the simplest illustration, every unique datum is examined as a split point, selecting the one which results in the lowest total impurity in its leaves.

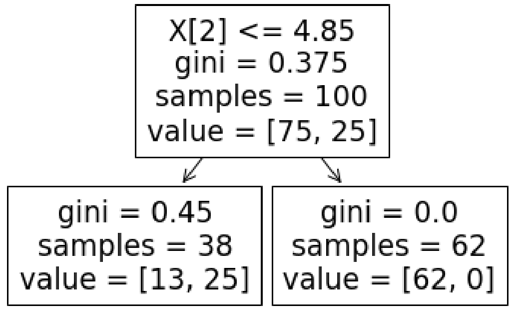


Figure 12: Example of a single-node decision tree, or "stump"

4.3.3 Boosting and AdaBoost

Gradient Boosting is the name for a group of methods for building an ensemble of "weak" learning machines (often small decision trees), each building on the weaknesses of its predecessors.

It is best illustrated with AdaBoost, the first adaptive boosting machine, and arguably the simplest and best-known [62]. The following pseudocode, derived from [63], uses the simplest possible real classifier (a decision tree stump) applied to an input dataset X with labels y.

1. Start by defining the first weak learner F_1 (a decision tree stump, as discussed in §4.3.2), trained from the initial input dataset $X_1 = X, y_1 = y$

2. Use the F_1 to generate predictions $\hat{y}_1$ against labels y_1.

3. Compute loss L_1. For classification, this might be the fractional error rate

$$L_1 = \frac{1}{N} \sum |\hat{y} \neq y| \tag{9}$$

4. Compute *performance value* α_1, a number that is larger if the classifier performs well.

$$\alpha_1 = 0.5 log(\frac{1 - L_1}{L_1}) \tag{10}$$

5. Halt iteration if stop conditions met (e.g. a predetermined number of iterations).

6. Create a new input dataset X_2, y_2, with a larger proportion of records incorrectly classified by L_1. Selection is pseudo-random, using a weight vector

$$w_2 = e^{-\alpha_1 s_1} \tag{11}$$

$$\text{where } s_1 = \begin{cases} 1, \hat{y_1} = y_1 \\ -1, \hat{y_1} \neq y_1 \end{cases} \tag{12}$$

7. Train a new tree F_2 from the new dataset X_2, y_2, and iterate from step 2.

The final classification decision takes the form of a weighted vote between the weak learners, weighted by each learner's performance metric α_i.

4.3.4 Gradient Boosting Machines

Gradient Boosting Machines are a generalization of the AdaBoost concept, allowing different loss functions, and applying a kind of gradient descent in order to reduce error in a smaller number of iterations. A gradient boost model is superficially similar to AdaBoost, in that it consists of an ensemble of weighted weak learners:

$$F(X) = F_0(X) + F_1(X) + ... + F_m(X) \tag{13}$$

$$where \begin{cases} F_i = & \gamma_i r_i \\ r_i = & -g(L)|_{i-1} \text{ (negative gradient of loss function)} \\ \gamma_i = & \underset{\gamma}{argmin} L(F_{i-1} - \gamma r_i) \end{cases} \tag{14}$$

Where γ_i are weights and r_i are the pseudo-residuals of the preceding weak learners. In essence, each element F_m is the output of a decision tree trained to predict the pseudo-residual r_m. In the special case where the loss function is sum of squared errors (SSE), this is the (true) residual of the prior elements. The output is then scaled by a weighting factor γ_m, selected to minimize the overall loss.

In other words, gradient boosting is conceptually different from AdaBoost in that each element F_i is a weak learner tuned to directly address a pseudo-residual – an incremental step in the direction of steepest improvement in the loss function. In other words, the gradient of loss L with respect to the prediction F: $\frac{\delta L}{\delta F}$ [62, §10.10].

Unsurprisingly, nearly every teaching example (e.g. [64]) of gradient boosting tends to use the same, extremely convenient loss function; the one which produces the simplest gradient:

$$L_i = \frac{1}{2}(y - \hat{y}_i)^2 \tag{15}$$

$$\text{so...}\ r_i = -\frac{\delta L_i(X)}{\delta F_i(X)} = \hat{y}_i - y \tag{16}$$

Additional weak learners are added until a stop condition is met, typically either (a) a specified number of estimators have been added, or (b) the loss has been reduced to an acceptable threshold.

4.3.5 LightGBM

The Light Gradient Boosting Machine (LGBM) is a framework for applying gradient-boosted decision trees (a specialization of GBM where the weak learners are always small decision trees), with a number of optimizations to improve training speed and improve accuracy [65]. In particular, it provides the following [66]:

- gradient-based one-side sampling (GOSS) histogram split finding: an alternative method of tree construction which finds high-performance splits very quickly by keeping high-gradient rows, as well as samples from rows with small gradients
- exclusive feature bundling (EFB), allowing sparse, mutually exclusive features (IE, those with few overlapping nonzero values) to be grouped into a single feature for split evaluation
- best-first tree training; for a given maximum number of leaves, this method often improves overall accuracy by splitting the leaf which most reduces loss
- bagging, helpful to reduce variance [62], and implicitly to reduce the likelihood of over-fitting

4.4 Classification Method

An LGBM classifier was constructed by training with the kinetic features using 10% of the labelled data for each vehicle, with the remaining 90% held back for testing. This method is at odds with the apparent industry standard method of 80% training / 20% hold-back, but given a reasonable quantity of data, a small, well-distributed training set in conjunction with extensive testing serves to ensure that the model is generalizable and not over-fitted.

Figure 11 shows the results of classification on the sample vehicle. Subfigure (c) shows the eigentrip label (colour) of each segment predicted by the classifier solely with reference to the kinetic parameters, and subfigure (d) shows the as-clustered original labels, but with the predicted power.

4.4.1 Wrong-class error

In general, a multi-class classifier returns the set of probabilities that a given element (in this case, a travel segment) belongs to each possible class (in this case, the various eigentrips). Typically, the class with the highest probability (the *maximum likelihood* class) is selected. Applying this technique, the trained classifier had a label selection accuracy of 77.9%. The misclassification rate is not as concerning as it might seem: since the dataset is not in distinct clusters, segments of indeterminate class can be expected to have an actual power somewhere between the characteristic powers of its most probable classes.

It seems possible that the correct power may often fall between the highest and second-highest probability classifications. A refinement for future work (discussed in §7.4.2) is for cases where membership is unclear, to attempt selecting the two most probable classes, and pro-rating the segment's eigentrip membership by probability.

4.5 Energy Prediction

For the purpose of energy prediction, each travel segment is represented as a time-weighted vector, where each element represents a time-weighted (and potentially probability-weighted) count of eigentrips. E.g., if the segment is 180s long, and is best represented by eigentrip e_2, the segment is now represented by $\boldsymbol{S} = [0, 180, 0, 0, ...]$, where the elements of $\boldsymbol{S}$ represent the number of seconds spent in each of the eigentrip types. Any period of travel ($\boldsymbol{T}$) can now be represented as the sum of its segment vectors:

$$\boldsymbol{T} = \sum \boldsymbol{S_i} \tag{17}$$

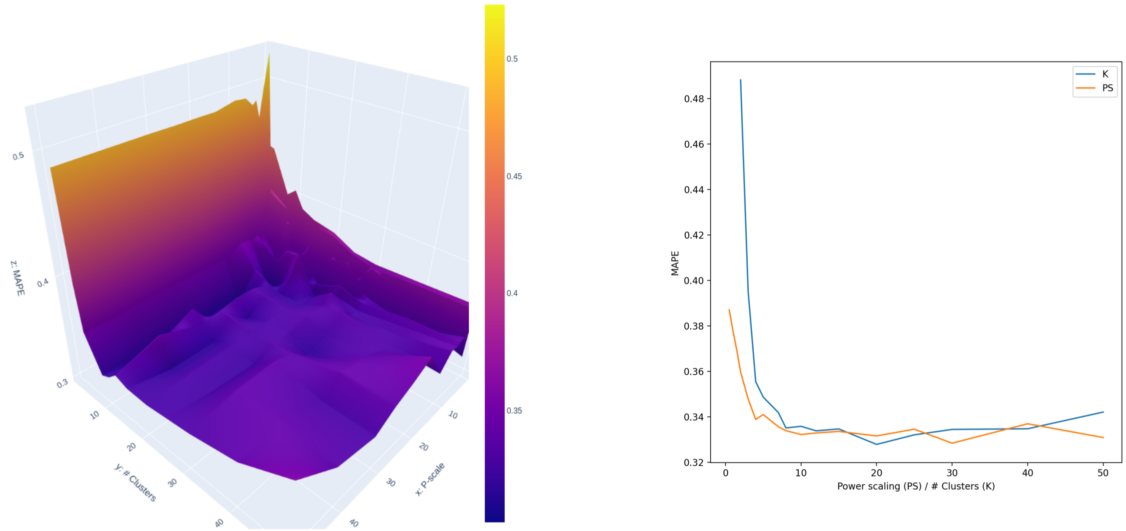
Given a vehicle's list of characteristic power values for each eigentrip $\boldsymbol{C_v} = [P_{v,e1}, P_{v,e2}, ...]$, the predicted energy consumption for that travel is:

$$E = \boldsymbol{T} \cdot \boldsymbol{C_v} \tag{18}$$

Accuracy is assessed relative to the logger estimate of observed power for any given period of travel, in terms of modified mean absolute percentage error (MMAPE):

$$MMAPE = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{y_t - \hat{y}_t}{1 + y_t} \right| \tag{19}$$

This initial model configuration (K=10, PS=2) exhibited a per-segment MMAPE of 37.4%, somewhat better than the baseline prediction error of 50.9%, calculated below in §5.



(a) MMAPE surface

(b) Median MMAPE cross-sections

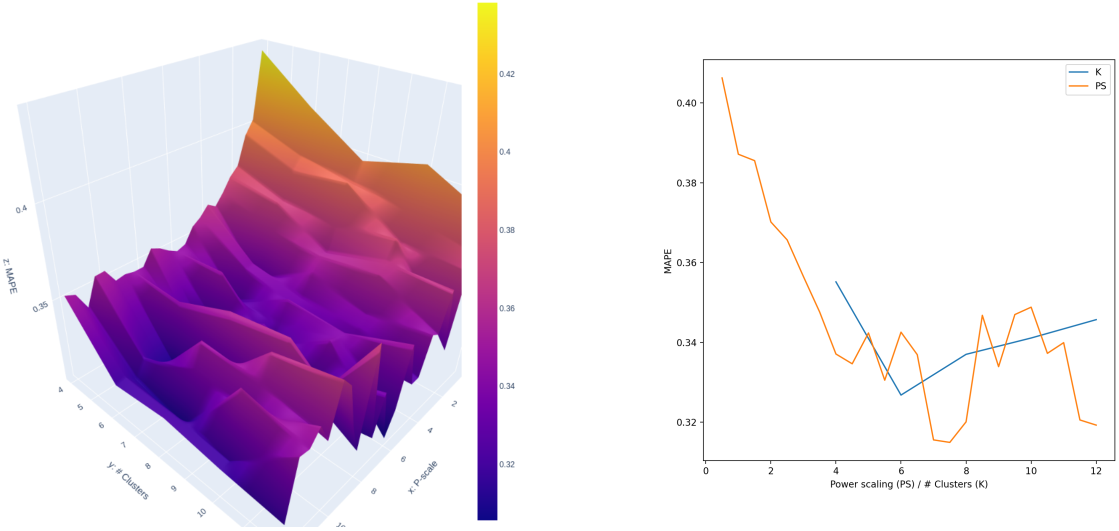
Figure 13: Two visualizations of prediction error (MMAPE) versus a broad selection of number of clusters (K) and power-scaling factor (PS)

4.6 Parameter Refinement

4.6.1 First pass iteration

Having elected to cluster by K-means with a weighted power feature and demonstrated a process, the next step was to select (a) an appropriate number of clusters (K), and (b) appropriate weighting with power-scale (PS).

A number of values for K and PS were evaluated by clustering at each combination, and generating a prediction of average segment power to each configuration as described in §4.4 and §4.5. The MMAPE was calculated for each configuration, shown in figure 13(a). For clarity, the median of MMAPE values at various levels of PS is plotted for each value of K and vice-versa in (b). The figures show substantial random-appearing variation in error as PS is increased, presumably the result of classification error as the importance of the kinetic features in the clusters is reduced by over-weighting the power feature.



(a) MMAPE (b) Median MMAPE

Figure 14: Local visualizations of prediction error (MMAPE) versus a narrowed selection of number of clusters (K) and power-scaling factor (PS)

Table 9: LGBM hyperparameters selected for optimization

Hyperparameter	Value
bagging fraction	0.800
feature fraction	0.900
learning rate	0.0100
max bin	60.0
max depth	27.0
min data in leaf	39.0
min sum hessian in leaf	59.0
num leaves	80.0
subsample	0.0100

4.6.2 Second pass iteration

Noise notwithstanding, the figures show a significant drop in MMAPE in the vicinity of K=8 and PS=5, so a smaller-scale, higher-resolution iteration was performed in those regions (figure 14).

4.6.3 Hyperparameter tuning

As with most ML algorithms, LGBM uses data-nonspecific settings called hyperparameters, which must be adjusted for best performance with the specific application.

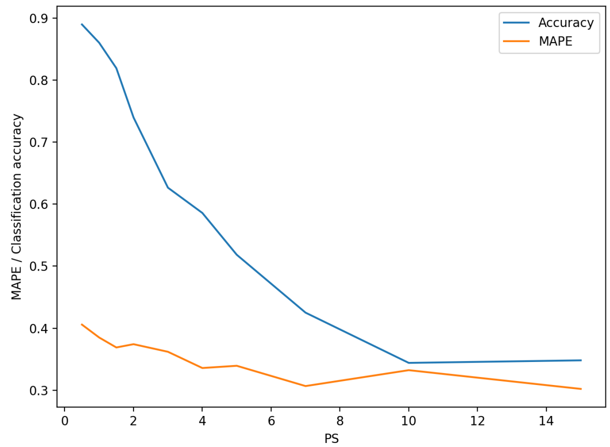


Figure 15: Prediction error and Classification Accuracy for various values of power-scaling factor (PS) with 10 clusters (K=10)

It is common to select these by iteratively testing the cross-validated performance of various values, and selecting the set which reliably perform best. A popular method is implemented in Fernando Nogueira's optimization toolkit [67], which employs an evolving Bayesian process to home in on a likely minimum value for the loss function in a shorter number of steps than required by an exhaustive grid search. The technique is not central to this research; a simple grid search would return similar results at the cost of time. However, the implementation details are interesting and well illustrated in the author's github page [68], with an application to LGBM published to Kaggle by Somang Han [69]. The application of this technique resulted in the hyperparameters shown in table 9.

4.6.4 Interpretation and parameter selection

A deterministic optimization could be employed to find an absolute minimum MMAPE, but since the results would vary with every new random draw of training data, the improvement would not be persistent. Instead, parameters were selected from the region of the plot which appeared to best balance low MMAPE with low randomness. 10 clusters was chosen as a starting point due to the visible trough on the 3D surface plot.

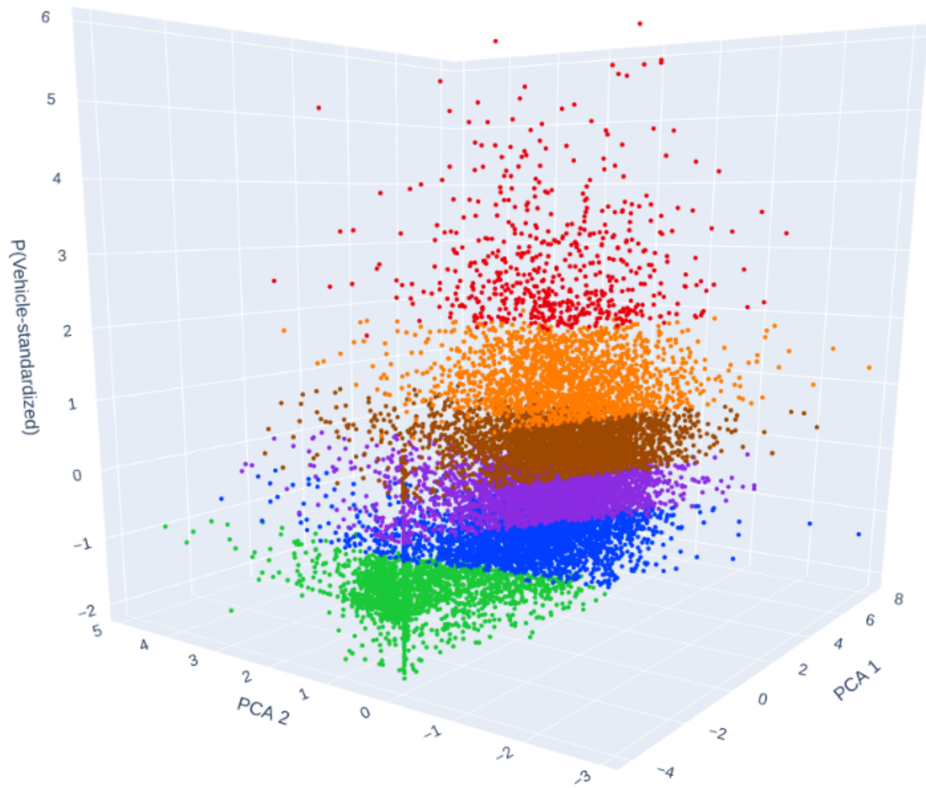


Figure 16: Final clustering (K=6 PS=7), PCA kinetic features, and power

Classification accuracy and MMAPE were plotted at various values of PS that number of clusters, with results shown in figure 15. As desired, the increase in PS initially improves MMAPE, as clusters are defined with less internal scatter with respect to power. Classification accuracy drops rapidly with increasing PS, as clusters are defined which cannot be recalled without reference to the power feature, quickly overriding the improved prediction accuracy.

The final clustering with K=6 and PS=7 is visualized in figure 16. The noteworthy visual difference relative to the original clustering is that at the same visual Z-axis scale, the clusters appear "pancaked" – this reflects the desired stratification according to power levels. It is important to remember that this is a visual artifact; in the 11-dimensional hyperspace where the clustering operation was performed, the cluster boundaries still approximate hyperspheres, much as a cluster of soap bubbles approximate spheres.

This final clustering also permits the calculation of characteristic power values for each vehicle. Figure 17 shows the spread of actual power observations sorted by their cluster (eigentrip) labels, and divided into the various vehicle categories.

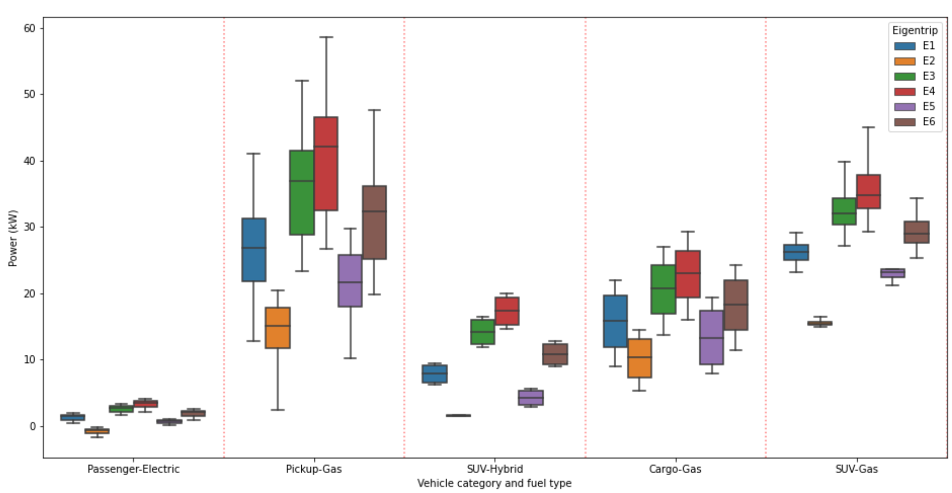


Figure 17: Power distribution of each vehicle category, as divided between the eigentrip labels

The average per-segment MMAPE of the eigentrips model was 32.3%.

4.7 Comparison Predictions

4.7.1 Published fuel economy

Business-as-usual (BAU) energy consumption prediction was established by applying published city/highway $L_e/100km$ figures to the logged travel distances for each segment. The consumption test protocol [17] drive cycles had a mean speed of 34 km/h for city driving and 78 km/h for highway, so a dividing speed of 56 km/h was established midway between those means. Travel segments with an average speed at or below that dividing speed were predicted at the city figure, and those above predicted at the highway figure.

Fuel economy figures were selected for each vehicle with reference to NRCan's fuel consumption rating search tool [70]. In each case, the base model was selected unless the CRD's vehicle database indicated a specific sub-model or trim level.

The average per-segment MMAPE of this method was 50.9%.

4.7.2 LGBM regression

Finally, to establish the level of avoidable error with the information available to the model, a LightGBM regression model [66] was trained on the 10 kinetic features, as well as three additional features capturing specific information about each vehicle: its fiel type (ICE, HEV, BEV), vehicle category (passenger, pickup, SUV, etc), and an identifier for each specific vehicle.

The decision to include all three of these additional features was not obvious; the vehicle ID is over-specific, and in a wider application would instead use a detailed model and trim-level specification. Furthermore, much of the predictive information in the vehicle's fuel and category is shared with the vehicle ID, and as discussed in §2.2 mutual information and unnecessary features are to be avoided.

The core conflict is that on one side, some vehicle categories spanned a wide range of power levels (e.g., a modern F-150 base-model vs an older F-150 4x4 super-duty), best addressed by permitting the model to modify power based on the observations of specific vehicles. On the other hand, some specific vehicles were only observed for a short period of time, and would not generalize well without reference to the information of other similar vehicles. On the balance, it was decided to include all three, since boosted tree models split on a single feature at a time, and therefore do not tend to overemphasize based on mutual information.

Once the feature-set was selected, the regression model's hyperparameters were tuned as described in §4.6.3, and power predictions made for each segment. The average per-segment MMAPE of this method matched that of the eigentrips model, at 32.3%.

5 Results

This section presents the predictive error of the proposed "eigentrips" model relative to the logger-data estimate of actual power. The eigentrips model is compared with two alternative means of prediction: first, business-as-usual prediction based on standard L/100km fuel economy figures, and second, an LGBM regression model trained to directly predict segment fuel consumption. The eigentrips model is piecewise-constant, so the regression model is presented to give a sense of the eigentrip model's avoidable quantization error.

Much of the discussion in this section is with regards to the MMAPE for individual 3-minute segments, since that is the most intuitive initial indicator of the model's accuracy. For the end user's purpose, trip-level or mission-level (ie, for the duration of the vehicle's participation in the study) aggregate error is likely to be of more interest, and that is addressed at greater length in the discussion section, §5.3.

5.1 Presentation of Error

5.1.1 Error measures

The most appropriate intuitive measure for prediction error was not immediately obvious, for the following reasons:

- Absolute (non-relative) error over-represents error in high-power vehicles.
- Relative (to actual-error) over-represents error when actual power is very low.
- Relative (to vehicle) requires a fixed per-vehicle denominator, resulting in unexpected error values for segments unrelated to the selected denominator.

Several measures of prediction error were considered, described below with their shortcomings. For the formulae below, a=actual, p=predicted, q=vehicle max power, μ=vehicle mean power.

1. **MSE (mean squared error)**

$$\epsilon = (a - p)^2 \tag{20}$$

   Problem: Although $Min(\Sigma MSE)$ is the model's actual objective function, it does not give a good intuitive grasp of the magnitude of the prediction error when actually applied to a real-world prediction problem. A lay user would expect that a model described as having 25% error will generate predictions incorrect by approximately 25%, not by 50%.

2. η **(absolute/non-relative error)**

$$\eta = |a - p| \tag{21}$$

   Problem: Error will be exaggerated in high-power vehicles, and they will dominate summary results.

3. ϵ_μ **(relative to vehicle-mean)**

$$\epsilon_\mu = \left|\frac{a-p}{\mu_v}\right| \tag{22}$$

Problem: The mean can be different in similar vehicles, depending on operation. Some mission profiles are dominated by idle!

4. ϵ_q **(relative to vehicle-max)**

$$\epsilon_q = \left|\frac{a-p}{q_v}\right| \tag{23}$$

Problem: Unintuitive at low power. EG: consider a 100kW vehicle, on a segment where actual power is 1kW and prediction was 2kW. This measure would return an error of $\epsilon_q = (2-1)/100 = 1\%$, even though the prediction was double the observed value.

5. **TMAPE (true mean absolute-value percent error)**

$$TMAPE = \left|\frac{a-p}{a}\right| \tag{24}$$

Problem: Segments with zero or near-zero actual power will have excessively high error. This is of particular concern with EVs and HEVs, which frequently "idle" at fractional kW power. Almost 1% of EV samples were observed at under 1kW, causing unreasonably high segment prediction errors.

6. **MMAPE (mean absolute-value percent error, modified)**

$$MMAPE = \left|\frac{a-p}{1+|a|}\right| \tag{25}$$

This metric retains much of the intuitive power of TMAPE, while avoiding excessive error at for very small values of actual power.

Problem: The added 1 in the denominator is arbitrary. In the previous example,

Table 10: Error for various timescales, contrasting eigentrips model vs business-as-usual vs LightGBM regression

	L/100km (%)	Eigentrips (%)	Regression (%)
Segment	50.9	32.0	32.4
Trip	38.5	23.7	20.3
Mission	21.8	9.59	2.90
Study	19.3	7.45	0.120

Table 11: Per-trip error for various vehicle fuels/categories, contrasting eigentrips model vs business-as-usual vs LightGBM regression

Fuel	Category	L/100km (%)	Eigentrips (%)	Regression (%)
Electric	Passenger	47.8	64.8	127.
Gas	Cargo	43.9	56.0	34.1
	Pickup	51.6	35.1	21.0
	SUV	17.0	21.9	10.4
PHEV	SUV	34.6	38.9	33.5

MMAPE $= (2-1)/(1+1) = 50\%$, which bears no contextual intuitive relationship to the error.

5.1.2 Chosen error measure

In the remainder of this chapter, modified MMAPE is used to compare and contrast relative error. The arbitrary 1 added to the denominator is a common means of addressing the near-zero error problem, while retaining a sensible range of relative error across the range of actual values.

5.2 Discussion

5.2.1 Error interpretation

Table 10 shows MMAPE at various levels of aggregation, split out for business-as-usual L/100km prediction, for the proposed eigentrips model, and for direct regression with the LightGBM comparison model. In general, the prediction performance is as

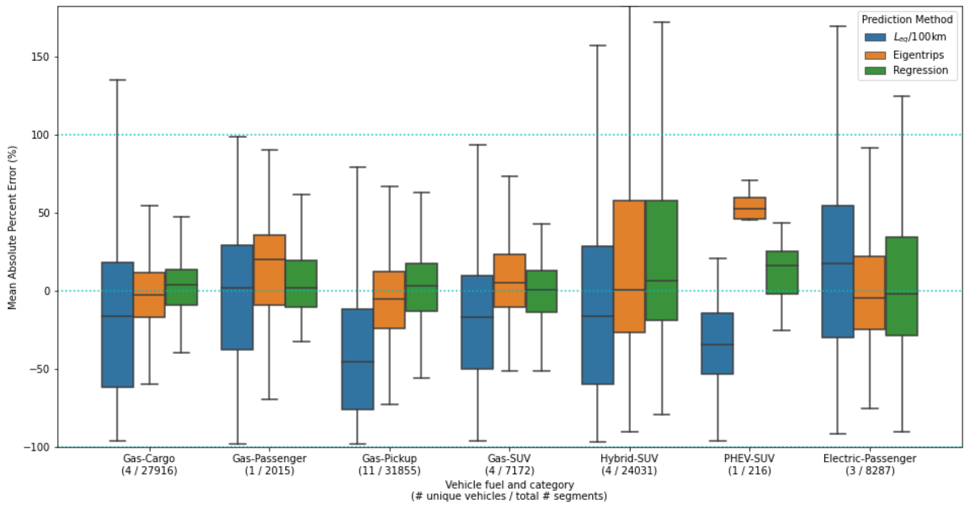


Figure 18: Prediction error distribution of segment-level predictions, contrasting eigentrips model vs business-as-usual vs LightGBM regression

expected: the eigentrips model outperforms traditional L/100km prediction, and is in turn outperformed by direct regression.

The segment level error for both the Eigentrips and Direct regression models is very high, and remarkably similar. Since the eigentrips model is expected to have significantly more error due to quantization inherent in the technique, the behaviour is anomalous, and suggests that the predictions are missing information relative to the ground truth. This may reflect an erratic ground truth (due to error in the MAF approximation of true fuel flow), or changes in power requirement disguised by missing features such as missing or inaccurate road grade, or other features discussed in §7.5.5.

Table 11 shows the per-trip aggregate error, broken down by "fuel" (actually drivetrain type) and vehicle category. It is noteworthy that the LightGBM regression model and eigentrips model did not perform particularly well for the various hybrid and battery-electric vehicles, although they did still tend to outperform traditional fuel economy.

Figure 18 shows the per-segment MMAPE for each fuel and vehicle type. The boxes show the quartile range of error values (25% and 75%, with a horizontal line to indicate median), with whiskers to show the extent of the 10th and 90th percentile. The plot does an excellent job of showing that in general, the LightGBM regression model and the eigentrips model have lower bias and lower variance than the L/100km technique.

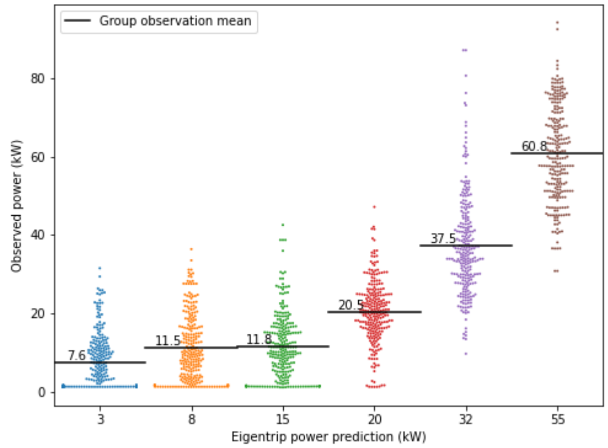


Figure 19: Example power versus prediction within eigentrips

However, this plot also shows unexpectedly wide variance for HEVs and BEVs, and high bias *and* variance for the PHEV, all discussed in detail below. It is also noteworthy that the $L_e/100km$ prediction shows an error of -100% in many cases, since it has no means to appropriately predict idle power.

Figure 19 uses a single example vehicle to illustrate the variance in actual powers within each labelled eigentrip, presented in the form of a swarm plot against the power prediction, taken as the vehicle's characteristic power. The horizontal bar on each swarm shows the mean *actual* power, which is seen to be quite close to the quantized *predicted* power – which is the vehicle's characteristic power for that eigentrip.

5.2.2 BEV prediction

For the BEVs, this excessive variability is attributed largely to the 90-second low-resolution power sampling discussed in §3.3. Although the BEVs' onboard SOC computation is presumed to be reliable, it is impossible to know how much power consumption is measured in one segment when it is better attributed to the next. This lack of accuracy is a key outcome of this research: high-resolution data-driven energy prediction requires high-resolution input data.

It is noteworthy that since the reported error is relative to actual consumption, the apparent error of the BEVs is amplified relative to the ICEVs; the 25-75 IQR in figure

18 shows that the eigentrip model has about double the relative error for BEVs as for ICE pickup trucks – but since the BEV's power is so much lower, this in fact represents a prediction of 35.7 ± 7.0 kW for the pickup truck, and 3.0 ± 0.88 kW for the BEV; the BEV's absolute error range is in fact much smaller.

5.2.3 PHEV prediction

The single PHEV suffered from the same low-resolution sampling problem as the BEVs, and additionally had a very short data-collection period, with only 216 travel segments recorded, totalling about 10 hours of travel.

Furthermore, the PHEV had no mechanism for capturing the likelihood that a given segment is in ICE-mode. Future work with PHEVs should attempt to create additional kinetic features to capture that information, such as total distance travelled this trip, or total distance today.

5.2.4 HEV prediction

The study included 4 Toyota RAV4 mild HEVs, which were predicted with a reasonable MMAPE, but a wide spread in the segment level predictions. The loggers in the HEVs were not configured to capture HV battery status, so it can be presumed that the short-term error included a significant amount of energy consumption being shifted between adjacent segments, EG, by regenerative braking.

Improving HEV energy prediction would be an interesting extension to this work, and would require additional feature engineering to capture HEV-specific behaviour, such as regenerative braking and any periods of sub-optimal engine operation.

5.2.5 Physical interpretation

Figure 20 shows a box plot for each kinetic feature, showing the distribution of values broken down by eigentrip label. Examination of these plots may help with understand-

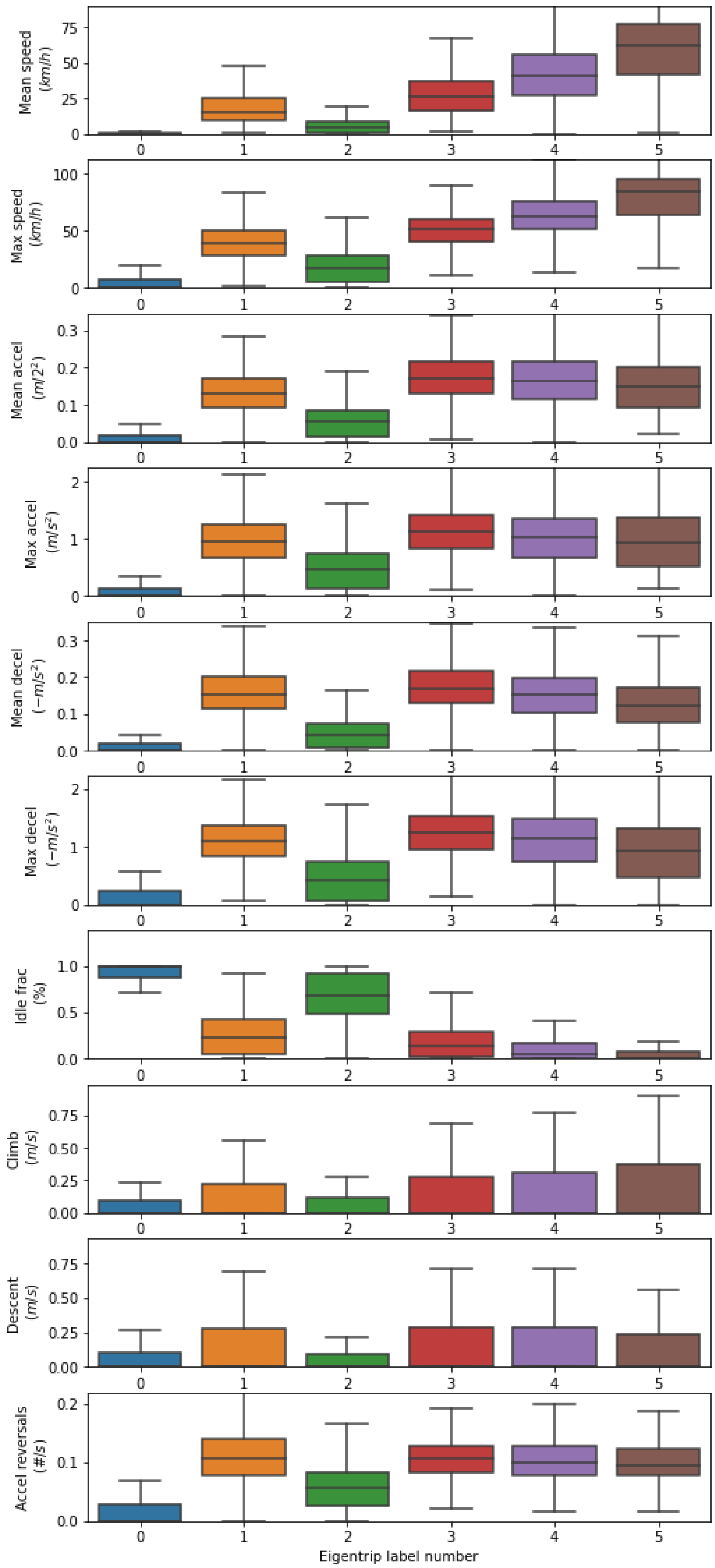


Figure 20: Per-eigentrip distribution of feature values across all missions

ing of the physical nature of travel likely to be labelled as most similar to a particular eigentrip.

5.3 Application

To illustrate the application of the eigentrip model, imagine that a fleet manager has been allocated budget for three new vehicles, with the explicit goal of minimizing annual carbon-based fuel consumption. The manager is faced with the decision of which vehicles to replace. Without logger information (and, for this purpose, in the absence of mission constraints) the decision will be informed by whatever information is at hand.

This section explores the information that the manager might have, the vehicle replacement decisions they might make with various information, and the likely impact of those decisions in light of the logger data. The impact is given in terms of saved energy in MJ, and the volume of consumed gasoline for ICEVs. Additionally, to highlight the impact of high-efficiency BEVs consuming low-intensity BC grid electricity, the related GHG emissions are also listed, given global warming potentials (GWPs) of 88.1 $g\ CO2_e/MJ$ for gasoline [9] and 2.96 $gCO2_e/MJ$ for BC Hydro's grid electricity [10].

Fuel consumption in this section is given relative to a power baseline derived from the logger MAF and SOC data, as described in §3.3. As discussed in §7.5.2, the validity of this baseline estimate is one of the study's core assumptions – there is no validated fuelling data from which to calculate error bars.

The prediction estimates are given as maximum likelihood values – given the vehicle's single characteristic power value for each eigentrip, and a count of the most-probable eigentrips for the mission, the prediction estimate becomes a simple dot product. As discussed in §7.3.6, it would be valuable to have a generalized measure of uncertainty for each mission-vehicle prediction, but this would require characterizing each mission and vehicle as a probability distribution rather than a singular value, defeating the model's core goal of simplicity. To give *some* sense of the prediction reliability and impact on decision-making, the replacement vehicle's whole-study MMAPE is applied

Table 12: Whole-mission error averaged for various vehicle fuels/categories, contrasting eigentrips model vs business-as-usual vs LightGBM regression

FuelType	L/100km (%)	Eigentrips (%)	Regression (%)
Electric-Passenger	20.7	15.3	19.2
Gas-Cargo	20.1	13.8	9.43
Gas-Pickup	40.2	9.55	11.2
Gas-SUV	9.44	7.15	0.685
PHEV-SUV	40.2	0.0965	2.85

to the resulting prediction. The replacement vehicle in all cases happens to be the Kia Soul BEV, so an expected error of 10.7% is selected from the Electric-Passenger row of table 12 and calculated for each prediction.

5.3.1 Replacement by predicted distance

If the fleet manager has accurate mileage records and can predict the mission distances, then they might choose to predict per-mission energy consumption by multiplying predicted mission distance by the published fuel economy of the vehicle currently assigned. The top three energy consumers by this prediction would be two pickup trucks and a van, predicted to annually drive 58,700 km, and to consume 246 GJ of fuel.

The actual logged consumption of these three vehicles extrapolated to a full year was in fact 350 GJ (equating to 10300 L of gasoline, and GHG emissions of 30900 $kg\ CO2_e$) – an error of 24%, illustrating that this method is not particularly accurate. Applying the eigentrips model, we find that replacing these three vehicles with a BEV similar to one of the tested passenger vehicles (not actually an appropriate replacement for a cargo vehicle) would result in a predicted consumption of 26.9 GJ, and cause GHG emissions equating to about 79.7 $kg\ CO2_e$. This replacement, if it were possible, would save 321 GJ of energy and avoid 30800 $kg\ CO2_e$ of GHG emissions. The expected prediction error of 10.7% for this vehicle category equates to an error estimate of ± 2.88 GJ and ± 8.5 $kg\ CO2_e$.

5.3.2 Replacement by published fuel economy

Lacking mileage or fuelling records, the fleet manager might select the three vehicles in the fleet with the worst fuel economy ratings – two pickup trucks and an SUV, in this example. In the absence of distance or fuelling records, there will be no predicted consumption better than the manager's educated guess, perhaps by pro-rating the fuel budget for the entire studied fleet (1167 GJ) by fuel economy numbers, resulting in a predicted consumption of 203 GJ.

The extrapolated logger data suggests that these vehicles would have a total annual consumption of 200 GJ (5900 L gasoline, emitting 17600 $kg\ CO2_e$ of GHGs). Their BEV replacements would result in a new predicted consumption of 14.9 GJ (44.2 $kg\ CO2_e$) – a savings of 185 GJ, and avoiding 17600 $kg\ CO2_e$ of GHG emissions. The expected error of 10.7% equates to an error estimate of ± 1.60 GJ and ± 4.73 $kg\ CO2_e$.

5.3.3 Replacement by logged energy

In the absence of actual pump-to-tank records, the loggers themselves have the best record of the energy consumed by each vehicle. Extrapolating each vehicle's actual logged consumption to a year, the top three consumers will total 388 GJ (11500 litres gasoline, emitting 34200 $kg\ CO2_e$). Their BEV replacements would consume 25.7 GJ (76.3 $kg\ CO2_e$), saving 362 GJ and avoiding 34100 $kg\ CO2_e$ of GHG emissions. The BEV's expected error of 10.7% equates to an error estimate of ± 2.75 GJ and ± 8.16 $kg\ CO2_e$.

5.3.4 Replacement by best savings

The theoretical best solution is to consider all missions, and select the replacements offering the highest predicted savings over the incumbent vehicles. In this case, the result happens to be the same as the case above: replacing the highest energy consumers with the most efficient available alternative. However, this would not be the case if the highest energy consumers were already relatively efficient.

Table 13: Illustration of SHAP for a single prediction

	Feature Values	SHAP Values
Speed	52.8	18.8
Max speed	64.7	1.01
Acceleration	0.125	-0.382
Max acceleration	1.03	0.0332
Deceleration	0.104	0.797
Max deceleration	1.06	0.195
Idle	0	-0.769
Climb	0.324	0.0151
Descent	0.273	-3.32
Acceleration reversals	0.15	1.85
vid	Vehicle 10	23.1
Type	Pickup	4.8
Fuel	Gas	2.16

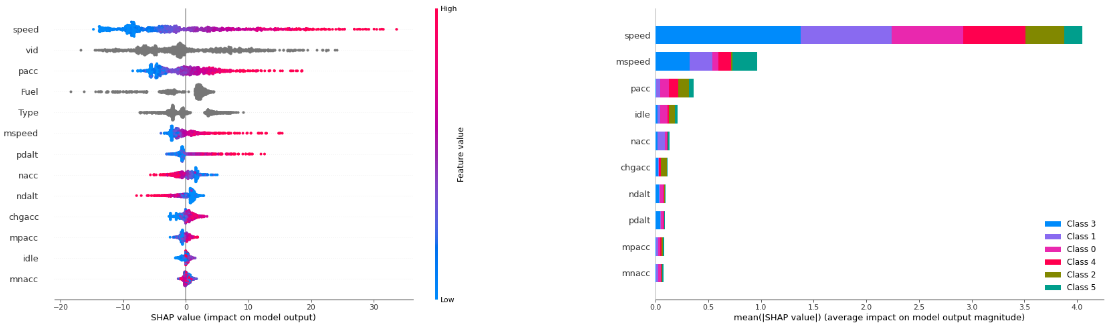
5.4 Shapley Additive Explanation

5.4.1 SHAP overview

Shapley additive explanation (SHAP) [71] is a method for understanding the contribution of each individual feature to a specific final prediction. The explanation is *additive*, because the individual contributions sum to the actual prediction.

To illustrate, consider the lightGBM regression comparison model described above in §5.2, applied to predict the power of a single segment vector. An example is shown in the "Feature Values" column of table 13. The SHAP explainer constructs a general null prediction (an estimate in the absence of any feature information, typically the training mean), and then computes the individual additive contributions of each feature to increase or decrease the specific prediction under consideration from the general null prediction. In this case, the sum of the 28.4 kW null prediction and the individual SHAP values (again, shown in table 13) is equal to the regression model's final prediction of 89.0 kW.

The method of computing the individual feature contributions is somewhat involved. Mazzantzi has written an excellent simplified explanation in [72]. Further summarized, the method involves creating a directed graph of models for every possible combination



(a) Regression SHAP, showing feature relationship to prediction impact

(b) Multiclass SHAP, showing absolute feature impact on individual class membership probabilities

Figure 21: SHAP explanation summaries, showing each feature's contributions to the model's prediction, across the entire dataset

of available features, arranged such that the edges in the graph imply the addition of an individual feature relative to the source node. The contribution of a feature is a weighted average of the change in predicted values along all the edges where that feature is added.

5.4.2 SHAP summary visualization

A second application of SHAP is to explain the relative importances of the features, across all samples in a dataset [73]. It is easy to imagine, for example, that the climb rate feature would have a much larger impact on the visible power requirement of a heavily loaded ICE cargo vehicle, as opposed to a mild hybrid using its traction battery to invisibly average its engine power output between climbs and descents.

Figure 21(a) addresses this requirement by showing the distribution of absolute contributions of each feature to the predictions. For numeric values, red implies a high value, and the right side of the chart indicates a positive impact on the power prediction. EG, higher mean speed (red) tends to increase the power prediction (i.e., rightward), and a low mean speed (blue) tends to decrease the power prediction (i.e., leftward). The categorical features have no scalar values (grey), and this SHAP visualization has no intuitive way to show *which* categories shift the prediction in a particular direction; the only information presented is the range of impact magnitudes caused by various values in the feature.

The eigentrip technique centrally uses a multiclass classifier, not a regression model; the classifier's output for each prediction is in fact a vector of class probabilities, rather than a single predicted value. Plot (a) could at best be used to show the absolute impact of each feature on the probability of predicting one of six eigentrips. Instead, figure 21(b) illustrates the *mean absolute* impact of each feature on each class probability – in other words the absolute change on the prediction probability if the feature is known, vs not known. For example, the figure shows that knowing the Speed value tends to change the probability of class 3 by an absolute magnitude of about 1.4; it has a large impact, although the plot gives no information about whether the impact tends to be positive, negative, or even mixed.

5.4.3 SHAP implications

On the summary figure(21a), the features for acceleration reversals (chgacc), maximum positive acceleration (mpacc), idle fraction (idle), and maximum deceleration (mnacc) are seen to have relatively small contributions to the prediction.

To illustrate that this is valid, the regression and eigentrip models were re-applied with reference to only the *other* features. The impact of deleting these less-important features from the direct regression model was indeed quite modest, increasing the average segment MMAPE by only 0.21% – from 32.7% to 32.9%.

The impact on the Eigentrips model was somewhat more significant, increasing from 32.1% to 39.4% – perhaps highlighting the impact of an increased number of marginal samples no longer being nudged into the correct classification by the additional features.

6 Conclusions

The eigentrip approach developed in this research has reasonably good accuracy, and produces whole-year mission predictions averaging a MAPE of 9.4%. The concept can be expected in the field to give significantly better predictive results than the baseline (L/100km) method's MAPE of 22%, although there is clearly room for improvement, as shown by the direct-regression model's average MAPE of 3.7%.

The reduced error of either machine-learning model is balanced against added complexity; adding a new vehicle to the model would require computing the new vehicle's per-eigentrip characteristic power values. Similarly, adding a new mission profile (or updating a modified one) would require logging some weeks worth of representative travel data, sanitizing it, and deconstructing it into a combination of eigentrips.

The criterion of spreadsheet-compatibility no longer seems as important as it originally was, due to the advent of low-barrier options for deploying ML models in the cloud, such as managed notebook hosting services. Such a model would have better predictive accuracy, and could be designed to facilitate the direct upload of new data – either representing new vehicles, or in order to better represent the evolution of the fleet's mission profiles. That said, a spreadsheet-deployed model would still be helpful to address potential concerns around the public exposure of individual travel information. This issue was deeply significant for the CRD, whose requirements informed this research.

The research performed here has been severely limited on several fronts, hampered by data collection problems and limited by inadequate temporal resolution. One of the initial goals, choosing the best of several alternative high-efficiency replacements, has been rendered impossible by the elimination of alternatives in the source data – the initial study was intended to include several HFCEVs, PHEVs, and other types of BEV beyond the Kia Soul EV. None of the desired alternatives were ultimately included in the logged data, and the single PHEV logged only about 10 hours of travel time before the data collection phase was terminated.

An important outcome of this research is reinforcement of the idea that any data-driven model for predicting per-trip or per-mission vehicle energy consumption will be limited in accuracy by the quality of the data that informs it. A good model would require higher-resolution input data, and an exploratory data campaign facilitating iterations of the experiment with various sampling frequencies and methods would be yet another excellent subject for further study.

Ultimately, a data-driven model will be an effective recommendation tool for selecting replacement vehicles to minimize energy consumption and carbon footprint. Careful design of a data collection strategy will be the foundation of any trustworthy model.

7 Recommendations and Future Work

This section discusses a number of limitations, assumptions, and other potential improvements to the studied process and model.

7.1 Assumptions

Several simplifying assumptions were made that could benefit from more rigorous treatment, either to quantify the resultant error, or to find a more precise method.

7.1.1 Stationarity and ergodicity

This entire study is predicated on two key assumptions: that the power and kinetic features are stationary (i.e., that the statistics do not change over time) and that they are ergodic (the statistics do not change erratically and inconsistently with respect to uncontrolled parameters).

All of this is to say that the work assumes that the kinetic features are dictated by the mission, and not unduly influenced by changing factors such as the physical characteristics of the vehicle, the habits of the driver, and changing traffic patterns. Future work should validate and quantify these assumptions by observing the same mission operated with different vehicles, and confirming that e.g., a difference in power or handling characteristics doesn't result in a confounding change in the observable kinetic features.

Most power-impacting differences in driver habits would likely be captured and accounted for in the speed and acceleration features. However, an exploration of driver-mission and driver-vehicle stability might be warranted since (a) drivers might affect non-engine power consumption, such as climate control, changing the power characterization of a vehicle, and (b) a difference in driving technique might be so extreme as to alter the kinetic profile of a measured mission, depending on who is driving it.

The same assumptions apply to the per-vehicle characteristic power values. Future work should compare data collected from similar or identical vehicles, while driven by different drivers, in different missions, in different geography, and in different organizations.

7.1.2 Baseline energy consumption

This thesis evaluates the validity of the new method for predicting energy consumption, as compared to the traditional model-specific fuel economy statistic measured in $L_e/100km$. The validity of the two predictions is compared by measuring error relative to the best available estimate of "actual" energy consumption, as derived from MAF and SOC.

It is a significant assumption that the inferred estimate of input energy from logger values is valid and correct. As discussed in §7.5.2, it would be a significant improvement to this research to collect actual per-vehicle fuelling records for ICEVs and electrical metering for grid-powered BEVs in order to establish the accuracy of the logged energy consumption estimates.

7.1.3 Standardized GHG intensity

A primary intended use of this work – the prediction of GHG emissions – presumes that it is possible to easily convert a known quantity of input energy into a specific GHG footprint in kg CO2e, by applying standard GHG intensities such as those published by the BC Canadian Ministry of Environment & Climate Change Strategy (MOE) or BC Hydro [74, 10].

Events such as Volkswagen's "Dieselgate" [75] have made it clear that this is a weak assumption for ICE vehicles, and that there may be a need for model-specific intensity factors. Further investigation will be necessary to quantify the associated error.

Other factors may impact the emissions calculation for grid-powered BEVs, depending on how grid emissions intensity is to calculated. BC Hydro reports an overall carbon intensity of 11 $gCO2_e/kWh$, with specific renewable and fossil sources rated at 4g and 593g respectively, and conducts a significant bidirectional trade with Alberta, which is attributed an intensity of 820g [76]. A 2017 paper found that carbon intensity in New Zealand should be considered as varying between 32g and 188g depending strictly on time-of-day [77]. It is easy to imagine a dynamic fleet model with reallocates vehicles according to changing requirements for calculating emissions, or even from the the time-dependent change in the carbon intensity attributed to their power sources.

7.1.4 Fixed MAF ratio

Fuel consumption rates were inferred from the OBD2 log values for MAF. This is only accurate if the fuel:air mixture is known. The stoichiometric ratio of 14.7 is commonly accepted [54], and as described above in §2.3.2, the author's undocumented personal experience supports it. No peer-reviewed literature nor authoritative texts were found supporting or refuting this assumption.

Since fuel flow is not a standard OBD2 PID, it would be an excellent contribution to the literature to publish a model or a dataset helping to more accurately infer actual fuel flow from MAF and other standard OBD2 parameters.

7.1.5 Clustered eigentrip definitions

An early assumption was that the eigentrip definitions should be inferred from the data, rather than synthesized from expert knowledge of how different driving patterns are likely to influence fuel consumption. The basis set was therefore constructed using unsupervised clustering.

It would be possible to instead construct a set of exemplar trips that are representative of trip-types which a domain expert intuitively believes are likely to be predictive of energy consumption variability between vehicle types. Examples might include situations such as

- point-to-point highway travel, off-peak hours
- highway travel, rush-hour
- point-to-point city travel
- patrolling and parking enforcement
- idling to supply vehicle-mounted equipment

If the eigentrips were modelled on intuitively understandable travel-type exemplars, users would be better able to infer the nature of new or blended missions, and be better able to apply sanity checking to unexpected model results.

It would be interesting to repeat the experiment with such a set of intuitive eigentrips, and contrast the level of error with that found from the inferred ones.

7.2 Cleaning Decisions

The extensive data cleaning and preparation process required a number of judgement calls and simplifications. The most important of those are listed here.

7.2.1 Smoothing starts

As discussed above in §3.2.3, a large number of in-motion samples immediately following an at-rest sample were dropped due to impossibly high accelerations, presumably due to sampling errors.

Simple rejection of these potentially informative samples was to be avoided. An aborted attempt was made to impute reasonable speed profiles to these samples using the following process:

1. Compute a "typical low-speed acceleration" for each vehicle, consisting of the median of in-motion positive acceleration values at speeds below an arbitrary threshold of 15 km/h.

2. For vehicle starts with impossibly high logged accelerations, the zero-speed sample is time-shifted to an earlier time that would reflect that vehicle's typical acceleration – but never such that it would precede the prior speed sample.

3. If the time-shifting would cause the zero-speed sample to precede a legitimate logged non-speed sample, then "required acceleration" is computed from that legitimate sample. If that required acceleration is found to have a reasonable magnitude, then the earlier sample time is retained and deemed to be the new start time.

Unfortunately, many of the error periods were found to bracket other sensor readings, particularly MAF readings. Inserting an imputed speed value would call into question the validity of the the subsequent MAF observation, causing irreconcilable discrepancies between inferred acceleration and inferred fuel flow. The method has potential, but requires detailed review of the original datastream to be sure that it was not introducing more error than it is removing.

7.2.2 Regularization

As discussed in §3.4, the entire corpus was regularized to 1s intervals to simplify segmentation. This implies linear interpolation and extrapolation – both of which unavoidably introduce error relative to the actually-measured real samples.

Given the potential to process variable-length segments as discussed in §7.3.5, it would instead be possible to divide segments precisely at sample times, minimizing the amount of interpolation required.

7.2.3 BEV power interpolation

Since sampling of the BEV's power was done at a relatively low resolution, a simple time-interpolation on SOC was performed to help estimate power consumption within each trip segment.

Hopefully future work will have direct access to higher resolution BEV power data.

With only the data at hand, a number of techniques might do better at predicting SOC at the segment boundaries, perhaps using a timeseries regression model inferring from additional other features such as distance travelled and acceleration profile.

7.3 Data Structure

7.3.1 Time-domain features

As discussed in §2.2.2, there are good reasons for this model to be structured as a non-timeseries problem. However, there are likely to be some time-domain or frequency-domain features with predictive power. Examples for possible exploration include the effects of stop-and-go traffic and time-of-day. Possibilities to extract predictive features from these characteristics include spectral power density [42] as a fingerprint feature, and the use of time-domain techniques like Kalman filters, [78] might help to generate predictions of otherwise unknowable state features such as the vehicle's kinetic energy or a mild hybrid's drive battery SOC. Another possibility is the employment of dynamic time warping, [79] or wavelet convolutions [80] in order to find recurrences of observed patterns that might characterize driving segments as being similar.

7.3.2 Feature evaluation

The initial short set of features in §4.1 is based on the work of others [38]. It would be a valuable contribution to compile an exhaustive list of features directly available from OBD2 or computed from them, and apply a rigorous evaluation for relative predictive power. A simple example is the selection of the 98th percentile to illustrate the feature "maximum acceleration". It is possible that some other quantile (or even the unfiltered maximum observed value) would be more predictive.

One method for this would be to derive an expanded feature set (such as those listed in §2.1.2), and apply SHAP [73] analysis to determine which features are most predictive of energy consumption.

7.3.3 Microtrip boundaries

An early assumption was the rejection of stop-go-stop microtrips as the fundamental trip segment, due to concern about excessive mixing of trip types. The requirement for fixed-length segments added significant complexity to the data preparation phase.

It is possible that the presumptive concern is unfounded. It would be interesting to perform the entire experiment again with microtrips to see the impact on prediction accuracy.

7.3.4 Clock time segment boundaries

For simplicity, the segments were regularized to clock time, beginning at even multiples of three minutes from 00:00:00 each day. This assumption results in final and initial segment in each trip being shorter by an average of 50%. Since each segment is given equal weight in the model, this difference over-weights the importance of measurements in those segments. However, since the first and last segments might legitimately have more predictive power than mid-trip segments, it is possible that over-weighting them is doing more good than harm.

It would be reasonable to validate this assumption by using only segments of precisely 3 minutes' length, discarding a contiguous period of "leftover" modulus samples between a random segment-pair.

7.3.5 Iterative segment refinement

Another simplifying assumption was the use of segments of specified (3-minute) constant duration. This naturally has the following effects at the arbitrary boundaries:

- combines disparate travel types into single segments
- arbitrarily splits similar travel types, creating unneeded additional segments

A refinement to this approach would be to use the boundaries defined by the initial classifier in order to re-partition the travel data. Given an initial set of characteristic travel types, it would instead be possible to segment the trip at "type boundaries", where travel transitions from one type to another. This would result in segments of variable length, but of more consistent travel types. It is to be expected that this would result in more accurate energy consumption prediction within each travel type.

7.3.6 Characterize as distributions

The eigentrips model characterizes each vehicle as a vector of characteristic power values for each eigentrip, and each mission as a vector containing the sum of time spent in each eigentrip. The prediction of energy for applying a vehicle to a new mission is the dot product of the two vectors. This value does not give any reflection of the prediction's level of uncertainty, and it would be preferable to have some sense of the variance of the prediction.

Many regression models (including LightGBM) support so-called "quantile regression", allowing the model to output a prediction interval – eg, the 90th percentile model will return a prediction indicating a value higher than 90% of actual expected values. This allows the user to intuitively understand the broadness of the prediction, as well as its central value.

This intuitive simplicity does not transfer to the eigentrips model. Extracting the 90th percentile energy prediction from a combination of vehicles and missions is *not* the dot product of the 90th percentile characteristic powers with the vector of singular mission times. It would instead require the computing the product of the nonparametric random variable representing the distribution of characteristic powers, with the eigentrip class probabilities, and determining the desired interval limits of the resulting product distribution.

Given that a primary goal of the eigentrips model is simplicity, this is *not* a recommended topic for future research. If a prediction interval is required, direct quantile regression would be a simpler and more reliable path.

7.4 Modeling

7.4.1 Improved clustering

The clustering step was performed by means of the well-known K-means algorithm, which returned a set of cluster centroids that were effective and useful, and which provided an excellent basis to prove the concept. The number of clusters was selected by inspection (the "elbow method"), and it would be informative to investigate more refined methods.

Other clustering mechanisms which do not presume spherical, normally distributed data would be likely to provide more representative centroids, and/or would lead more directly to an optimal number of clusters. For example, density clustering is a well-regarded process when the appropriate number of clusters is not known, however it was deemed unsuitable since the dataset is continuous without sparse regions between clusters.

Finally, the simple method used to select centroids predictive of energy consumption (adding weight to the energy consumption feature) does not necessarily select the optimal centroids for the following criteria:

1. minimize error from the selected fuel consumption model, but
2. are maximally discriminatory on fuel consumption for at least some vehicle features
3. provide adequate representation for all vehicle-eigentrip pairs

Finding centroids that meet all of these criteria may require developing a clustering strategy from first principles. A good first step would be to implement a GMM clusterer from first principles, in such a way as to allow feature-weighting.

7.4.2 Probabilistic class membership

Multiclass classifiers initially provide a probability of membership in *every* class, and only provide a singular prediction by application of maximum likelihood. A preliminary experiment with pro-rating segment time to *all* eigentrips by class probability was found to increase segment MAPE by nearly 50%.

However, for segments which fall close to the boundary between two (or more) segments, it seems reasonable that the segment's power contribution is likely to fall somewhere between the characteristic powers of the nearest segments. It might therefore be reasonable to assign the segment a blended contribution to energy consumption, weighted by the fractional probability of its nearest eigentrips. Since there is no requirement that a travel segment be characterized by whole numbers of eigentrips, it would be entirely acceptable to use multiple fractional membership, if it were found to reduce error.

7.4.3 Prediction error and missing features

Evaluating the actual operation associated with clusters that have the highest predictive error will be an excellent starting point for determining whether additional features are needed to improve accuracy.

7.4.4 Characteristic power by vehicle model

Predictions are executed by multiplying the number of eigentrips by the characteristic eigentrip power as calculated for each individual vehicle. It would be valuable to have an understanding of the model's accuracy when energy consumption is predicted by vehicle *model or category*, rather than by specific vehicle. Figure 17 shows the spread of characteristic power values within each vehicle category in the study. It appears that each category's power is relatively consistent, in spite of each category containing several models with different performance characteristics.

7.5 Data and Features

7.5.1 Data requirements

This model has been demonstrated to generalize quite well, even when trained on only 10% of the available data. An interesting exploration would be to evaluate how much log data is required to accurately characterize each mission profile.

Additionally, when a new vehicle type is added to the fleet, it would be valuable to know how much logging (and of what sorts of travel) should be conducted before its power consumption characteristics are sufficiently well known for use with this model.

7.5.2 High-quality energy input data

As described in sections 2.3.2 and 3.3, the fuel and electrical consumption data logged for this project was not of ideal quality. It would be an excellent extension to this work to evaluate its accuracy against target energy data of known accuracy. To that end, future work would be well-served by a logger-data corpus that includes:

- time-integrated fuel-flow (IE, total fuel since last sample) OR
- fuel-flow sampled at 1s resolution or better, OR

- all PIDs necessary to accurately calculate fuel flow, such as MAF and commanded air-fuel equivalence ratio

Additionally, in fleets where vehicle fuelling is controlled and monitored through a per-vehicle card system, it would be instructive to cross-check logger consumed-fuel totals against actual pumped-fuel totals.

For EVs, charging totals could be compared to consumption totals to evaluate accuracy and charge-discharge efficiency.

7.5.3 Road grade

Road grade has an obvious impact on power requirements, and can be expected to illustrate a significant difference in energy consumption between conventional vs hybrid or electric vehicles. A reliable road-grade feature would be an excellent addition to this study.

Positive and negative vertical speed features were calculated from the available GPS data. Unfortunately, the altitude feature was completely missing from a significant fraction of travel data. The feature was informative, improving predictive error from 45% to 35% in spite of large gaps in coverage, and the inherently low precision of the GPS altitude signal.

Since the horizontal accuracy of GPS is better than vertical, consideration was given to the idea of extracting elevation data from an open elevation dataset, such as NRCan's High Resolution Digital Elevation Model [81], based on the vehicle's reported coordinates. A preliminary investigation of this technique showed improvement, but still yielded an unfortunately high fraction of impossible grades, perhaps due to a failure of the terrain dataset to account for the significant amount of grade smoothing involved in road building in the Victoria area. This method showed some potential, but was felt to be a large source of complexity for an unknown amount of predictive power; it may merit future study, but is neglected in this work.

The best realistic source for road grade would be a barometric altimeter. For example, The Freematics open-hardware logger provides for the direct integration of external sensors [82]. It would also be an interesting side project to determine whether the OBD2 PID 0x133 (barometric pressure) [83] has sufficient precision to be used for a road grade calculation.

7.5.4 Features to support other vehicle types

Prediction was less precise than anticipated for the high-tech, high-efficiency vehicles. In particular:

- Prediction was poor for the mild HEVs. Investigation will be required to determine what additional features are required to capture hybrid performance, such as HV battery state, or additional kinetic features related to stop-and-go behaviour that could be impacted by regenerative braking.
- The BEV had a very wide range of error. Higher-resolution power data will be required, but they might also benefit from additional features indicating stop-and-go performance.
- If multi-fuel vehicles become common, a kinetic feature will be needed that can differentiate the circumstances under which they will switch from one energy source to the other. EG, total travel distance this day, or since last charge would probably work well for PHEVs.

7.5.5 Other features

There are other known/predictable factors that might be suspected to have a significant impact on fuel consumption, although most of them would present substantial data-collection challenges. Examples include:

- payload, particularly in heavy vehicles. It could be estimated given road grade and high-resolution torque and acceleration.
- different drivers, subject to privacy concerns
- accessory load

- environmental load
- vehicle maintenance status
- road type, perhaps inferred from GIS data
- traffic density by location and time-of-day, perhaps from a data source such as Google Maps
- rigorous collection of vehicle sub-model and trim level

7.6 Applications

The originally envisioned application was evaluating re-allocation of existing vehicles, and evaluating procurement decisions for additional copies of existing known fleet vehicles. This subsection addresses additional potential applications.

7.6.1 Real-time allocation

It would be reasonable for a booking system to respond to a request for a pool-vehicle by preferentially assigning the vehicle which is most energy-efficient (or most GHG-efficient) for the specific task at hand. The proposed system is simple enough to be implemented in a browser-based booking application, allowing the back-end to be simplified to a simple database lookup for availability, potentially requiring no additional custom back-end software development.

7.6.2 Information sharing

If multiple municipalities (or other organizations) established a shared set of eigentrip definitions, it would allow them to share information about their vehicles and their missions.

Vehicle information sharing would allow organization A to evaluate the local performance of a vehicle model owned by organization B.

On the other hand, sharing mission information sharing might highlight opportunities to improve operational efficiency. For example, organization A's parking enforcement mission might have a much more efficient eigentrip profile, as its new optical license plate reading equipment allows it to spend a much higher portion of its time cruising rather than idling. The improved energy performance might be sufficiently impressive to encourage organization B to acquire the same equipment, solely to save the associated vehicle emissions.

7.6.3 Connected Vehicles

The advent of fully-connected vehicles (e.g., Tesla and other new EV manufacturers) has potential to provide a ready source of detailed, high-resolution vehicle performance data. It would be quite simple for a manufacturer to publish real-world samples of operations logs, allowing potential buyers to evaluate mission-vehicle energy and GHG performance without any need to purchase an evaluation copy.

It would also be reasonable to establish a universal set of eigentrips, allowing manufacturers to publish statistically verifiable real-world performance statistics for their vehicles.

Having new vehicles providing logger information by default would provide other opportunities when connected to a power-vs-mission analysis. For example, departure from manufacturer-published vehicle performance statistics could trigger owner alerts, as a potential indication of required maintenance.

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A Logger features

Table 14: CRD FleetCarma logger features

Feature	Unit	Comment
Absolute Load	[%]	
Air Conditioning Power	[W]	
Altitude	[m]	GPS
C2 Input Voltage	[V]	
Charge Latitude	[deg]	
Charge Longitude	[deg]	
Engine RPM	[RPM]	
GpsAlt	(m)	
GpsLat	(deg)	
GpsLon	(deg)	
HDOP		
HV Battery Current	[A]	
HV Battery SOC	[%]	
HV Battery Voltage	[V]	
Heater Power	[W]	
Is Charging	[bool]	
Is Driving	[bool]	
Latitude	[deg]	GPS
LoggerName		
Longitude	[deg]	GPS
MAF	[g/sec]	
NumberOfSatellites	GPS	
OAT	[degC]	
Pck		
Signal #131		Speed
Start Time	(UTC)	
Time	(UTC)	
Timestamp	(ms)	
Vehicle Speed	[km/h]	
Vin		

B Embodied energy and Fuel Intensity

This is a discussion of assumptions and sources needed to convert life-cycle analysis (LCA) figures by Elgowainy et al [16] to apply study-contemporaneous and forecasted fuel intensities for BC. Detailed column calculations are shown for 2018 in table 15 and for 2030 in table 16.

B.0.1 Vehicle assumptions

Elgowainy's (reasonable) PHEV efficiency figure was not supported; to properly apportion emissions to gasoline and BC grid electricity, Elgowainy's figure was decomposed and found to imply an operational regime of 27.1% in BEV mode for 2018, and at 28.0% BEV mode in 2030.

In order to give a fair apples-to-apples comparison, the BEV90 was given the full lifetime travel distance of 286,000 km, differing from Elgowainy's treatment, which amortized the vehicle' manufacturing emissions over a much shorter lifetime travel distance.

B.0.2 Legend for LCA tables

Legend for tables 15 and 16:

- MPGGE: miles per gallon, gasoline equivalent, taken directly from Elgowainy
- Le/100km: MPGGE directly converted to metric Gasoline-equivalent litres per 100km
- Fuel Intensity: assumptions and sources are discussed in the remainder of this section
- Tailpipe: total lifetime tailpipe emissions, at Elgowainy's assumption of a 15-year vehicle life of 286,000 km (178,000 miles)
- Vehicle: total vehicle manufacturing and decommissioning emissions
- Lifetime: sum of Tailpipe and Vehicle fields
- Amortized: Lifetime emissions, divided by lifetime travel distance.

Table 15: Calculations to apply BC intensities to 2018 vehicle LCA

		ICEV	HEV	PHEV35	FCEV	BEV90
Efficiency	(MPGGE)	26.2	36.5	53.7	54.1	100
	(Le/100km)	8.98	6.44	4.38	4.35	2.34
	(MJ/km)	3.04	2.18	1.48	1.47	0.793
Fuel Intensity	(gCO2e/MJ)	88.1	88.1	64.9	5.	2.5
Emission	(gCO2e/km)	268	192	96.3	7.37	1.98
Tailpipe	(tCO2e)	76.8	55.1	27.6	2.11	0.568
Vehicle	(tCO2e)	7.78	8.2	9.4	11.7	7.9
Lifetime	(tCO2e)	84.6	63.3	37	13.8	8.47
Amortized	(gCo2e/km)	295	221	129	48.2	29.6
Battery-mode	(fraction)	0	0	0.271	0	1

Table 16: Calculations to apply BC intensities to 2030 vehicle LCA

		ICEV	HEV	PHEV35	FCEV	BEV90
Efficiency	(MPGge)	34.5	53.5	72	72	120
	(Le/100km)	6.82	4.4	3.27	3.27	1.97
	(MJ/km)	2.31	1.49	1.11	1.11	0.667
Fuel Intensity	(gCO2e/MJ)	70.5	70.5	51.1	1.18	1.11
Emission	(gCO2e/km)	163	105	56.5	1.31	0.74
Tailpipe	(tCO2e)	46.6	30.1	16.2	0.375	0.212
Vehicle	(tCO2e)	6.9	7.1	7.6	9.5	6.4
Lifetime	(tCO2e)	53.5	37.2	23.8	9.88	6.61
Amortized	(gCo2e/km)	187	130	83.1	34.5	23.1
Battery-mode	(fraction)	0	0	0.28	0	1

- Battery-mode: Fraction of time that PHEV is assumed to be operating from grid power

B.0.3 Intensity assumptions - 2018

Gasoline: The MOE published a 2018 intensity of 88.1 g CO2e/MJ [84].

BC grid power: BC Hydro's published intensity of 2.50 g CO2e/MJ for grid power is the average of internal generation, and that purchased from independent power producers [85].

Hydrogen fuel: For the small volumes required by the current low adoption rates for FCEVs, it is reasonable to assume a carbon intensity for H2 gas of 5.0 g CO2e/MJ. This figure is based on the energy requirements for small-scale electrolysis [86] at BC Hydro's grid power intensity, and short-range transportation in high-pressure tube trailers [87].

At higher volumes, it would in the short term likely be necessary to import hydrogen produced by steam-methane reformation, at a probable intensity of 85.3 g CO2e/MJ [88].

B.0.4 Intensity assumptions - 2030

The following forecasts were were used for 2030 fuel carbon intensities.

Gasoline: 70.51 g CO2e/MJ as required under the BC Renewable & Low Carbon Fuel Requirements Regulation [9].

BC Hydro grid electricity: 1.11 g CO2e/MJ. In the absence of any public goal or regulatory target, it seems reasonable to expect to use the intensity of BC Hydro's directly owned facilities; on the assumption that there will be pressure on external independent power producers to find low-carbon power sources, or require them to purchase offsets [85]. This will vary depending on the level of import/export trade, any changes in the associated carbon accounting practices, and the amortized emission associated with the Site C hydroelectric project.

Hydrogen fuel: Schmidt et al [89] suggest that H2 electrolysis efficiency will not improve significantly. However, the same work states that a solid-oxide electrolyser can take much of its input energy in the form of heat, and can deliver electrical efficiencies in excess of 100%. The assumed 2030 intensity of 1.18 g CO2e/MJ for H2 gas [87] is a best-case assumption, predicated on the existence of an SOEC plant with a source of zero-impact industrial heat, and fully powered by electricity at BC Hydro's internal grid power intensity.

University of Victoria

CRD Report

Earthquake Resiliency Implications of CRD EV Adoption

Mike Churchill – MASc Candidate

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Executive Summary

The adoption of electric vehicles (EVs) has many benefits, such as reduced emissions, better performance, and economic savings on maintenance and fueling. The Capital Regional District (CRD) of Victoria has one of the largest concentrations of EVs in British Columbia (BC), and this concentration is only expected to grow with time. The CRD is also located in a portion of BC with a high seismic hazard and would be profoundly affected by a Cascadia Subduction Zone (CSZ) earthquake. Until recently, maintaining vehicle use after an earthquake has depended on the resilience of the fuel infrastructure, but the increasing use of EVs will transfer some of that dependence to the resilience of the electrical system.

Analyzing past earthquakes in Chile, Japan, and New Zealand provides some insight into how to increase earthquake resilience. The 2010 Chile earthquake showed the importance of available excess generation capacity, private forms of communications, and utilizing small generators for recovery in isolated areas. The 2011 Japan earthquake illustrated the value of not locating too much generation capacity in tsunami zones, utilizing rolling blackouts for recovery, and the exceptional performance of microgrids. The 2011 New Zealand earthquake taught the danger of buried cables in liquefaction zones and how impactful spending money on resilience upgrades can be.

BC Hydro can improve the resilience of the electrical grid by adding generation capacity, relocating grid elements from tsunami and liquefaction zones, planning to have resources for repairs available, and establishing aid agreements with surrounding areas. VI can improve its fuel resilience by retrofitting ports, increasing fuel storage, and planning for how fuel will be prioritized after an earthquake.

The CRD can improve their organizational earthquake resilience by establishing a local microgrid and utilizing the battery capacity of their EV fleet to provide mobile storage following an earthquake. The CRD can also plan for what their expected vehicle and generator fuel needs would be after an earthquake and establish sufficient storage.

EVs can be used after an earthquake to establish a communication network by acting as nodes in a mobile network, and a 180 s simulation showed that a Nissan Leaf Plus would only use 0.018% of its battery capacity to provide this function for that time. In a 24 hour period, a Nissan Leaf Plus was found to able to donate 400 kWh of energy to a local shelter, assuming the vehicle had access to a fast charger and a microgrid with a 100 kW solar array. Given the Leaf's 363 km single charge range, the same microgrid was able to provide power for 8 Leafs to deliver supplies and people for a 24 hour period.

Introduction

Motivation

The adoption of electric vehicles (EVs) offers a host of benefits compared to internal combustion engine (ICE) vehicles, such as reduced greenhouse gas (GHG) emissions, better performance, and economic savings over the vehicle lifetime [1]. EVs also offer the emergent ability to transfer power from EV batteries to the grid or a building which allows better integration of renewable energy, controlled charging, and the ability to use EVs as mobile energy storage [1] [2].

EVs have seen rapid growth during the last decade, and, even during the pandemic, worldwide EV registrations increased by 41% in 2020 [3]. The resilience of EV sales to the pandemic can be attributed to many countries strengthening emissions standards and ZEV sales mandates, along with the expanding number of available EVs and falling battery costs [3]. By 2040, EVs could represent 12 – 28% of the global fleet, depending on factors such as battery cost reduction and the amount of government subsidies [4].

EV Adoption in the Capital Regional District (CRD)

The British Columbia Hydro and Power Authority (BC Hydro) is the main electricity distributor in the province of BC and generates 43,000 GWh of electricity annually to supply more than 1.9 million residential, commercial, and industrial customers [5]. Close to 95% of BC's electricity comes from renewable sources (hydro, wind, biomass), and about 90% of the province's installed generating capacity is renewable energy [6]. This means that operating and charging an EV in BC has very little associated GHG emissions, and EV fleet adoption has huge potential to reduce GHG emissions for organizations such as the CRD.

Compared to other provinces, BC has been ahead of the curve for EV adoption, and 2020 saw BC with the highest uptake of zero emissions vehicles (ZEVs) in North America, with ZEV sales averaging 9.4% of new vehicle sales for the year [7]. The greatest adoption of EVs in BC continues to be in major urban centers where public charging is more readily available. In particular, the largest concentrations of EVs in BC can be found in the Metro Vancouver area and the Capital Regional District (CRD) on Vancouver Island [8]. With the passing of the Zero Emissions Vehicles Act, mandating 100% of light-duty vehicle sales to be ZEVs by 2040, adoption of ZEVs is almost certain to continue increasing in these regions.

Vehicle Disaster Relief Functions and Propulsion System Resiliency

Vehicles play crucial roles during the early stages of disaster recovery. In the hours or days following a disaster, vehicles are needed for search and rescue efforts and provide assistance by transporting people in medical need, along with critical supplies, such as food, water, and medicine. In medium to long term recovery, vehicles resume their pre-disaster functions as permanent physical and social structures begin to be restored [9].

Until recently, maintaining vehicle propulsion after a disaster relied on the resilience of the fuel infrastructure, and vehicles would only be able to provide disaster relief for as long as fuel supplies lasted.

Natural disasters can impact the fuel infrastructure in a multitude of ways. Loss of power can lead to refineries being unable to operate and pumping stations not able to move oil and gas through pipelines. Pipelines themselves can be damaged by high winds, flooding, and earthquake induced stresses. Additionally, natural disasters can impact fuel supply by blocking or destroying transportation networks such as roadways, bridges, and ports [10].

While the fuel infrastructure will remain critical for the foreseeable future, increased adoption of EVs will mean that maintaining vehicle propulsion after a disaster will start to depend more heavily on the resilience of the electrical system.

Focus of the Report

As shown in figure 1, the CRD coincides with the portion of BC that has a high level of seismic hazard and would be most affected by a great Cascadia Subduction Zone (CSZ) earthquake. As this type of earthquake is considered a worst-case natural disaster for the region, it will be the focus of this report. To study the impacts of this scale of earthquake on the power system, past earthquakes in Chile, Japan, and New Zealand will be examined. Lessons from these earthquakes will be compiled and applied to how the CRD can increase earthquake resiliency and maintain the use of EVs in the disaster aftermath. These suggestions will be compared with how fuel resiliency might be improved in the region.

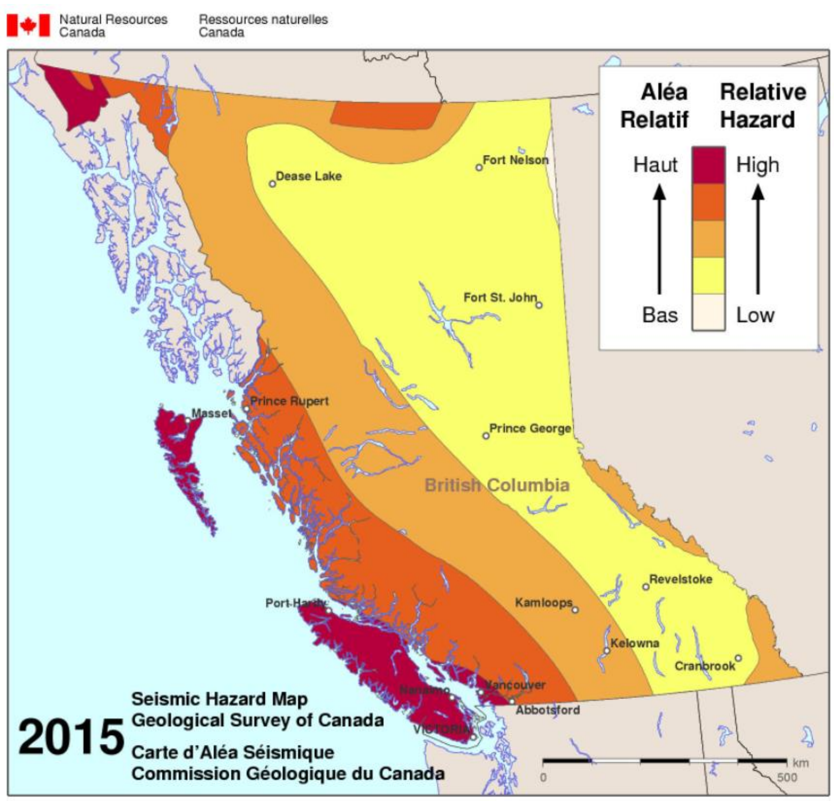

Figure 1 - British Columbia Seismic Hazard Map [11]

Cascadia Earthquake Background

The CSZ is a region extending from northern California to central Vancouver Island (VI), where the Juan De Fuca, Explorer, and Gorda plates are driven beneath the North American plate in a subduction process [12]. Shown in figure 2, VI is located where the eastward moving Juan De Fuca plate is sliding beneath the western portion of the North American plate. The subduction zone is locked and slowly accumulating strain. When the strain is released, a massive “megathrust” earthquake is produced. This type of great subduction zone earthquake is the largest in the world and the only type capable of earthquake magnitudes in excess of 8.5 M [13]. Geologic evidence from buried soils, tsunami deposits, and liquefaction features have provided the understanding that many great earthquakes have occurred in this region over the last several thousand years, with the most recent being a 9.5 M earthquake in 1700 AD [14]. Estimates of the probability of another earthquake of this magnitude occurring over the next 50 years range from 7-15% for an earthquake that affects the entire Pacific Northwest to about 37% for an earthquake that affects southern Oregon and northern California [12] [13].

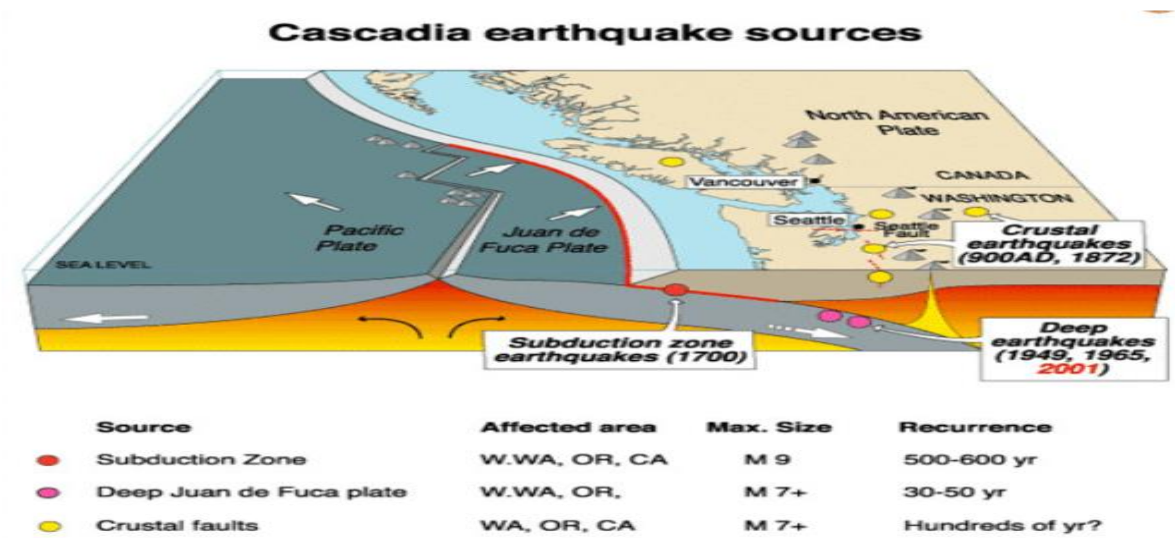

Figure 2 - Cascadia Subduction Zone and Earthquake Sources [15]

Earthquakes mainly cause damage through ground shaking and secondary effects, such as liquefaction, landslides, and tsunamis. Liquefaction is a phenomenon where an earthquake increases pore-water pressure in sediment and reduces grain-to-grain contact forces. The sediment then loses strength and behaves as a fluid [14]. Large earthquakes can also cause damage through aftershocks which can bring down already weakened structures. Following the 2010 earthquake in Chile, 19 aftershocks larger than 6.0 M were experienced in the first month [12].

The economic impacts of a Cascadia earthquake would be staggering, with losses estimated at upwards of $70 billion USD for Washington, Oregon, and California [12]. Much of the infrastructure in the region was constructed before it was understood that this area could experience subduction zone earthquakes. Roads and bridges are likely to see damage from shaking and landslides. Coastal ports could see damage from tsunami, severe currents, and liquefaction. Underwater landslides and debris could lead to the closure of shipping channels. Water systems could take from weeks to months to restore functionality and could take several years for complete restoration. Power outages could only be a matter of days in inland areas but could range from weeks to months in coastal regions. Communication networks may see damage or be overwhelmed in the immediate aftermath [12]. Many critical infrastructure systems are also interdependent. Damaged transport routes may impair crews from repairing downed power lines, and extended blackouts can lead to the failure of communication systems, water treatment plants, and hospitals [16]. Figure 3 shows an example of the possible connections between critical infrastructures.

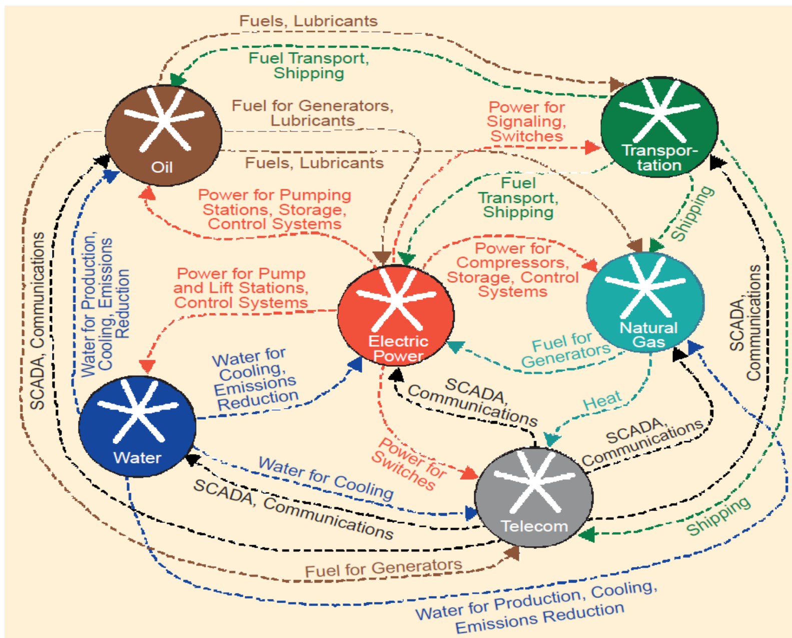

Figure 3 - Network of Dependencies between Critical Infrastructures [16]

Past Earthquake Impacts on the Power System

Chile 2010 Earthquake

On Saturday, February 27th, 2010, an 8.8 M earthquake struck the central region of Chile, affecting over 8 million people [17]. 521 people were killed, and the economic impact was valued at $30 billion US dollars [18]. The epicenter of the quake was located where the Nazca plate subducts beneath the South American plate. It resulted in a rupture 500 km long by 100 km wide and produced a tsunami that damaged 500 km of coastline. Highways, railroads, ports, and airports all saw damage due to ground shaking and liquefaction [17]. The earthquake caused a blackout that affected 4.5 million people and took days in some areas, and weeks in others, to recover the full supply [18].

The Chilean Central Interconnected System (SIC) provides power to over 93% of the population. Following the earthquake, a blackout took place for a load of 4522 MW. 693 MW of the existing generation plants were affected and removed from service for repairs, while 950 MW of plants that were still being built were put on hold to conduct assessment [19]. In previous years, Chile had seen growing investment in power plants, so the missing plants did risk the general supply of energy [18].

Generation equipment is generally built to high standards which contributed to its good performance during the quake. Figure 4 illustrates the impact the earthquake had on the various sources of energy generation.

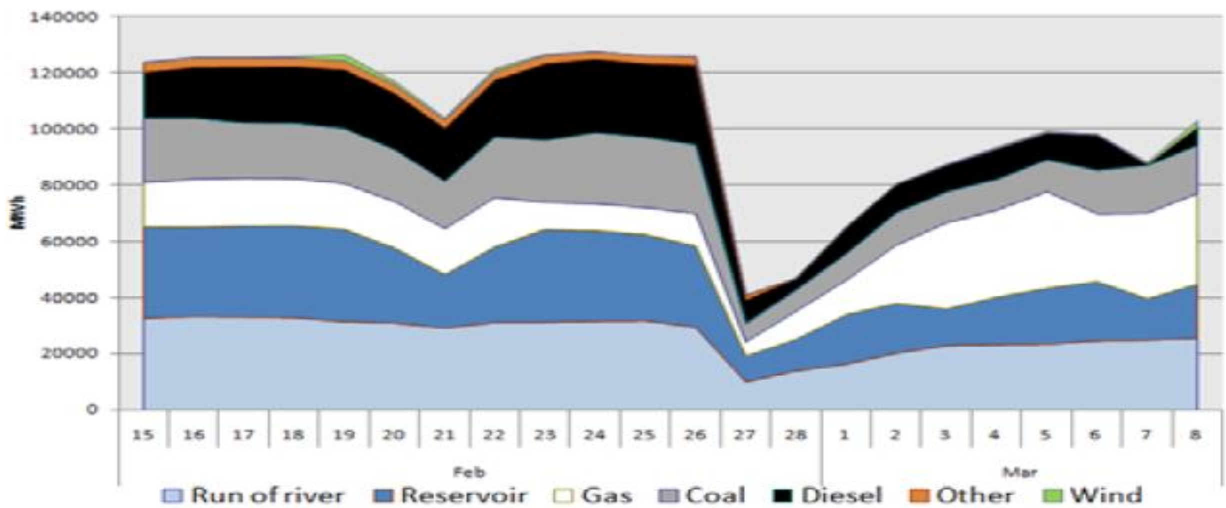

Figure 4 - Chilean Energy Generation Mix Before and After Earthquake [19]

Chile's transmission network has limited route dispersion and redundancy since it follows the long and narrow layout of the country [17]. The electrical grid in Chile is designed using the N-1 security criteria which allows system operation to continue normally in front of any line circuit or generation outage, without cascading failure. After the earthquake, the central part of the country was separated from the south and a two-island scheme was used for operation [19]. The transmission network was able to provide power within 24 hours and the islands were connected within two days. The fast recovery of the transmission service was attributed to quality infrastructure construction and the fast and competent response of the repair staff.

While restoring supply at the generation and transmission levels was quick, restoring the supply to the end consumer was a longer process. Several parts of the distribution network were severely damaged, and there were coastal regions where the distribution network was completely destroyed by falling houses or washed away by the tsunami [19]. The 220 kV system had been designed to appropriate seismic standards and performed well. In coastal regions, the lower voltage subtransmission system suffered sporadic damage from high levels of shaking. After two weeks, distribution system service was brought back online [17].

Commercial power outages and loss of reserve power in distributed network facilities lead to telecommunication being overwhelmed [17]. Problems with the communication network lead to difficulty assessing the damage and safety of the distribution network and reporting points of failure between low level voltages lines and buildings [17] [19]. Private communication systems remained functional as they used repeaters that fed through still operational low voltages lines, batteries, and photovoltaic (PV) panels. While these networks collapsed when the batteries had lost their capacity, they still offered enough use to facilitate the initial energy restoration activities [18].

The distribution companies did not have the resources available for the huge number of repairs and relied heavily on imported human and technical resources from other parts of the country and subsidiaries in neighbouring countries [18]. Since distribution equipment generally failed due to collapsing walls, landslides, and tsunamis, and not due to design, it didn't seem necessary for Chile to increase future design specifications. Rather, investigators in the incident have encouraged Chile to use a decentralized, local focus on distribution dispatch, during system recovery, to improve operation reaction speed and adapt to local realities [18]. Mobile generators in the 100 to 250 kW range were found to be most effective in supporting recovery in isolated areas and tsunami affected towns. Units in the 1 to 10 kW range were helpful in supplying electricity to critical loads such as hospitals, firehalls, gas stations, and communication antennas. Unfortunately, fuel supplies were extremely limited due to the behaviour of the population, damaged roads, and fallen bridges. Emergency trucks were still able to be refueled by using the army's strategic fuel reserves [18].

Japan 2011 Earthquake

On March 11th, 2011, a large earthquake occurred off the coast of Tohoku, Japan. The earthquake was 9.0 M, caused intense shaking for 120 – 190 s, and triggered a tsunami that reached heights of 9.3 m along the coastline of the Fukushima prefecture [20]. The earthquake resulted 15,984 confirmed deaths, with more than 2,000 people unaccounted for, and caused an estimated $15 billion (US) worth of damage [21]. Most of the earthquake damage was in the Tohuku region, served by the Tohuko Electric Power Company (ToPo), and the northern part of the Kanto region, served by the Tokyo Electric Power Company (TEPCO). The earthquake interrupted electricity for 8.7 million customers [20]. After two days, 1.5 million were still without power, and after three days, 300,000 remained without electricity [21].

14,000 MW of generation plants were impacted, mainly by the tsunami and some shaking damage [22]. Significant damage was caused to thermal power stations. Three thermal stations (generation capacity of 3.4 GW) were flooded by the tsunami and required one to two years to fully recover [20]. Renewable energy generation capacity generally performed well. No major damaged was reported on wind farms, and PV capacity outside of the affected region was undamaged but was unavailable due to grid-tied inverters that disconnected during the outage. There was some landslide damage to penstocks and headraces at small hydroelectric power facilities [22].

In February 2011, nuclear power supplied roughly 31% of Japan's electricity. It was considered to be the country's baseload energy and represented 40% of TEPCO's output [23]. The greatest damage inflicted by the earthquake took place at the Fukushima Daiichi Nuclear Power Station. The plant had a total generation capacity of 4.7 GW and consisted of six reactors, three of which were in operation when the earthquake struck [20]. The earthquake caused the loss of the plant's external power supply, and, while the emergency generators started successfully, they were located underground and were flooded by the tsunami [24]. The loss of power lead to core melt in reactors 1, 2, and 3, releasing a massive amount of radioactive material. Within a few days, hydrogen had leaked from the reactor pressure vessels into the building and caused the explosion of reactors 1, 3, and 4 [24].

High voltage transmission lines saw damage from shaking and floating debris and high voltage substations were damaged by shaking [22]. For more than two decades before the disaster, Japanese power utilities had been installing high voltage substations that met seismic qualification guidelines. Quite a number of components at these substations still failed which was likely caused by older, non-qualified equipment encountering higher than assumed ground motions [22].

The tsunami caused some damage to medium voltage substations (66 kV) and extreme damage to the low voltage distribution system [22]. It was noted that an important substation in Hachinohe City stayed intact due to being elevated above tsunami height [20]. Some inland substations suffered short circuits and ground faults from seismic damage. Substations also saw damage to circuit breakers and disconnectors, as well as oil leaking from transformer bushings [20].

Following the earthquake, TEPCO's electrical capacity decreased from 52 million kW to 31 million kW [23]. To combat the power shortage, each electric power company took measures to restore their older fossil fuel-based generation facilities. This lead to thermal power accounting for 90% of ToPo and TEPCO's generating capacity [25]. The disaster also caused the operation of many nuclear power plants to be postponed, dropping nuclear plant operation to 15% by the end of 2011 [25]. To continue meeting customer demand after the earthquake, TEPCO implemented rolling blackouts, allowing groups of two to three million customers to receive power for a three-hour window every 24 hours. TEPCO and ToPo both targeted reductions in customer power use by 15% and achieved this by having large factories shift operation to off-peak hours and installing onsite generation, the commercial sector reducing the use of lighting and air conditioning, and households reducing consumption through any means possible [20].

Japan uses mainly above ground low voltage lines and relatively few buried high voltage or distribution power lines. This design style helped to minimize liquefaction damage to buried power lines [22]. Mobile transformers were an effective measure to quickly restore power to small substations that were damaged [22]. A study by the American Society of Civil Engineers (ASCE) noted that distributed generation resources could reduce the risk associated with extensive power outages after a disaster [21]. The earthquake also showcased the role electric vehicles could play in disasters when 65 Nissan Leafs were made available to local authorities in Sendai to deliver goods and medical supplies while the fuel infrastructure continued to be unavailable [26].

Analysis of the earthquake brought attention to the exceptional performance of microgrids in the aftermath. The Sendai microgrid at the Tohoku Fukushi University in Sendai, shown in figure 5, was developed by NTT Facilities and consists of several distributed energy resources (DERs). Under normal conditions, the microgrid is connected to the ToPo grid and can be disconnected in times of power outage. While the gas engines initially stopped function due to abnormal voltage detection, the PV and battery storage systems remained able to supply critical loads during the outage. The following day, the gas engines were able to be restarted and provided power to important loads until full service was returned [20].

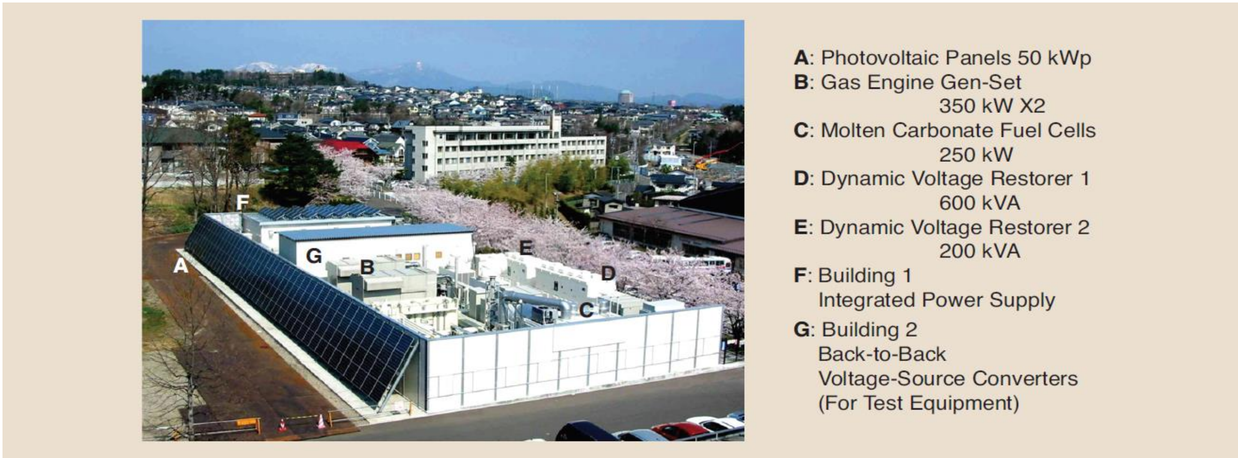

Figure 5 – The Sendai Microgrid at Tohuku Fukushi University [27]

New Zealand 2011 Earthquake

On September 4th, 2010, a 7.1 M earthquake occurred near the Canterbury region of New Zealand. Due to its distance from urban areas, the earthquake only injured approximately 100 people and caused no fatalities. This earthquake initiated an aftershock sequence which lead to a 6.3 M earthquake beneath Christchurch, New Zealand on February 22nd, 2011 [28]. This earthquake was substantially more damaging due to extreme ground shaking, with recorded accelerations of up to 2.2 g, and resulted in 185 fatalities and 7,171 people injured [28]. Although, it was relatively small in magnitude, the position of the epicentre, depth, acceleration experienced, and ground conditions combined to create an extremely devastating event [29]. The repair cost of the earthquake sequence was estimated at around $28 billion US dollars [28].

The earthquake caused significant changes to the environment through liquefaction, lateral spreading near waterways, land level changes, and landslides. Liquefaction caused large amounts of damage to the built environment of Christchurch, with much of the damage experienced by unreinforced masonry buildings [28]. The initial effects on the power grid were primarily due to liquefaction, even though strong ground shaking was observed. Although landslides and rockfalls occurred, they were primarily in regions without dense power infrastructure deployment [30]. It took 10 days to get 90% of the power back on [29]. As electric power is generated south of Christchurch, and was not in the area affected by the Canterbury earthquake sequence, the earthquakes had no impact on power generation [30].

The electric power system in Christchurch is served by Transpower and Orion which operate the country-wide transmission system and local distribution system, respectively [31]. The impacts of both Canterbury earthquakes on the transmission grid were negligible. The Christchurch earthquake caused power to the Christchurch City feeders and substations to be unavailable for 4.5 hours to facilitate safety checks and minor repairs. Following the safety checks, the supply at the grid exit points was restored to full capacity and n-1 security, excluding the Bromley substation which had supply restored to an n security level [31]. The minimal damage to the transmission grid can be credited to the implementation of lessons learned after the 1987 Edgecrumbe earthquake which demonstrated the need to seismically restrain heavier equipment on substations [31]. Transpower's equipment for 220 kV lines were also well installed to IEEE 693 (high zone) standards and were well anchored [30]. Figure 6 illustrates damage from the Christchurch earthquake at various levels of the electrical grid.

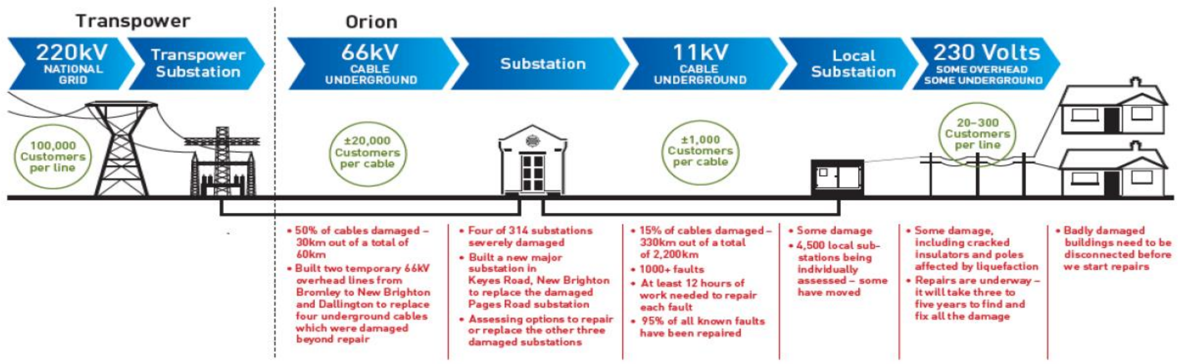

Figure 6 - Christchurch, New Zealand 2011 Earthquake Electrical Grid Damage [29]

While most of Transpower's power lines are overhead, Orion's lines are mostly buried underground. The difference in performance between the transmission and distribution networks can be attributed to buried infrastructure being more vulnerable to the effects of liquefaction [30]. 4 of 314 substations were severely damaged: one due to liquefaction, one from shaking, one from a boulder, and one from its infill wall failing [29]. The lack of damage to the above ground distribution network was credited to work Orion had performed in the previous decade, such as the reinforcement of unreinforced masonry substation buildings [30]. Orion was able to restore power to 50% of households on the day of the event, 75% after two days, 90% within ten days, and 98% after two weeks [31].

Earthquake liquefaction lead to damage of 50% of the 66 kV and 10% of the 11 kV buried cables which lead to widespread power outage [32]. In the 66 kV lines, the cables that were damaged beyond repair were oil-filled. Oil-filled cables in the run from Bromley GXP to the New Brighton and Dallington substations were deemed unrepairable and replaced by temporary 66 kV overhead lines [29]. A total of more than 1,000 faults were identified in the 11 kV cables and occurred in either aluminum or copper core cables [31]. 66 and 11 kV cable failures generally occurred in places that experienced substantial permanent ground displacement (5 cm to 50 cm) [30]. A large amount of the damage occurred in the PILCA (paper-insulated, lead-covered, armoured) 11 kV cables due to existing joints pulling apart.

The successful performance of the New Zealand electrical infrastructure came from a combination of risk planning for likely earthquake events, seismic strengthening of the substations, improvement to key bridge approaches, and improvements in design standards [29]. After the mid-1990s, Orion contributed over $6 million to seismic protection work and a further $35 million to build resilience into their network. It is likely that Orion's $70 million earthquake repair costs would have more than doubled without this work [31]. Following the earthquake, a long-term recommendation was made for Orion and other power utilities to re-assess the seismic weakness of buried power cables. Use of these cables could be mitigated by using overhead transmission and distribution lines through liquefaction zones [30].

Discussion

Lessons Learned from Past Earthquakes

- Available excess generation capacity enables quick recovery
- Electrical grid design with n-1 criteria prevents cascading failure
- The ability to island different portions of the electrical grid increases resilience
- Have available resources to perform grid repairs and plan for aid agreements with surrounding areas
- Where possible, move distribution equipment away from seismically vulnerable buildings, landslide areas, and coastal regions in tsunami zones
- Reinforce unreinforced masonry buildings that contain, or could collapse on, grid components
- If transformers cannot be moved out of tsunami inundation areas, they can be elevated to above flooding height
- Mobile generators and transformers are effective for restoring power
- Telecommunication systems are crucial after an earthquake but can be overwhelmed or unavailable due to lack of power, better to use private forms of communication
- Fuel supply is often scarce following an earthquake
- All three countries had improved grid seismic resilience before the event and were able to restore power to the vast majority of consumers within a week or two
- Utilizing above ground components can prevent liquefaction damage, if buried components must be used, locate them out of liquefaction zones where possible
- There is risk involved in locating generation capacity in tsunami zones or locating too much generation capacity in a single location that could sustain damage – opt instead for a distributed layout
- Rolling blackouts paired with customers reducing demand can be an effective recovery tool if available generation capacity will not meet demand
- Microgrids can remain functional during grid outages and allow power to still be supplied to critical loads
- Electric vehicles can provide mobile energy storage in the aftermath of an earthquake
- Seismic strengthening of existing substations is effective at improving resilience
- Building resilience is less costly than repairing or replacing damaged components after an earthquake

Vancouver Island Electrical Grid

Vancouver Island (VI) is located in the northeastern Pacific Ocean and is part of the Canadian province of British Columbia (BC). The island trends northwest-southeast and is located about 50 km off the southwest coast of mainland BC. VI is separated from the Lower Mainland by the Salish Sea, extends 460 km from northwest to southeast, and is up to 80 km in width [33]. In 2016, VI was home to a population of close to 800,000, with about half of that number living in the metropolitan area of Greater Victoria [34]. Located where the Juan De Fuca plate is subducting beneath the western portion of the North American plate, VI's tectonic environment predisposes the region to earthquakes of the shallow crustal, deeper sub-crustal, and great inter-plate (subduction zone) variety [33].

On VI, BC Hydro runs four hydroelectric systems, with six generating stations and a total capacity of 471 MW. These facilities are supported by transmission infrastructure and additional facilities on the mainland and represent 4% of BC Hydro's total capacity [35]. Figure 7 shows the different hydroelectric systems on VI.

Figure 7 - BC Hydro Vancouver Island Hydroelectric Systems [35]

BC Hydro's generating facilities are only able to meet about 20% of VI's total demand, with about 80% the electricity coming from the mainland through underwater cables [36]. The bulk of VI's power is provided by BC Hydro from the Peace River hydroelectric system through the Kelly Lake substation and from the Columbia River system through the Nicola substation [37]. VI is also home to several independent power producers (IPPs). These include biogas facilities, a wind farm in Cape Scott, run of river hydro projects, a natural gas generation station, and the T'Souke First Nation solar energy project [37].

VI's power grid is connected to the mainland by AC and DC submarine and overhead cables. Two parallel HVAC 525 kV circuits connect the south of Powell River to VI in two submarine and three overhead sections, with a reactor station on Texada Island. There is one 138 kV and one 230 kV AC line that connect Delta to North Cowichan in two submarine and three overhead sections. There are also two HVDC links from Delta to North Cowichan that are considered obsolete and unreliable [38].

Conversations between UVIC and BC Hydro have provided some insight into what damage a Cascadia earthquake event could cause to the VI electrical grid.

BC Hydro expects that damage from a CSZ event could be severe for both the power and natural gas infrastructure (BC Hydro uses a 275 MW natural gas plant in Campbell River which may not renew its electricity production contract in 2022 [39]). Damage to the northern or southern lines connecting with the mainland would lead to outages on the island, and the extent of damage would determine the outage length. The length of the outage could extend anywhere from days to months, depending on the severity of the earthquake. BC Hydro's modelling of CSZ events generally lead to estimates of weeks to months without power and partial restoration following that. After the event, the timeline could extend to years to get back to full functionality. All of the generation plants on the island can run disconnected from the mainland but would not be able to serve the full load. A partial load would be created by temporarily cutting service to industrial customers and by utilizing rolling blackouts (blackout could range from 1 hour on/off to 12 hours or more). It is also likely that load will be reduced due to damage in the distribution system that would lower demand. It was noted that seismic design is not used on system elements past the substations since those portions are commodity designed.

The Peace River and Columbia River hydroelectric systems are located far enough away from the CSZ that they would sustain no damage from the earthquake. It is also likely that the 500 kV transmission system connecting those dams to the Lower Mainland would remain unscathed. BC Hydro is in the process of upgrading dams and water passage systems on VI to align with the necessary seismic standards. If there were to be a major earthquake (over 1 in 1000-year event) before the upgrades are completed, the dams would be at risk of failure. The John Hart dam provides 50% of power generation on the island and has received seismic upgrading. Two upstream upgrades for the John Hart are to be completed by the 2030s, along with a power tunnel replacing the aging penstocks. As it stands, power generation from BC Hydro's VI facilities would not be dependable following a CSZ event.

While the CRD is the most population dense region of VI, it has relatively little nearby generation capacity. The Jordan River Dam is close to Victoria but has the highest seismic hazard of any of VI's dams and is likely to fail in a CSZ event. BC Hydro has also acknowledged that seismically upgrading the dam is not feasible [40]. The Hartland Landfill Project is located within the CRD and generates energy from methane from decomposing waste but would only be capable of producing a fraction of the energy required by the area. Of the nearby AC line connections to Delta, the 138 kV line has the highest risk of failure, and, as of 2021, is not BC Hydro's ten-year plan for replacement. The 230 kV line (installed in 2010/2011) is engineered for a 1 in 2475 earthquake event and would likely weather a CSZ event quite well. There is concern for how much of a power bottleneck would form if the 138 kV line went down and only the 230 kV line was available to bring power to the area. The oil-filled northern crossing lines (found to be bulging and leaking oil in a June 2021 heatwave which resulted in it being temporarily removed from service [41]) from Powell River are only engineered for a 1 in 475 event and are at risk from earthquake damage to their pumping stations. If these lines went down, it is possible that power would have to be directed from the Victoria area to the central and northern reaches of VI. That said, the central and northern regions of VI are closer to the upgraded dam systems and may be able to rely on power from there. There are also elements of the CRD area electrical grid that are located in regions of intermediate tsunami run-up potential of 1-5 m and strong to very strong peak ground accelerations of 0.1 to 0.3 g, shown in figure 8, which could result in substantial damage.

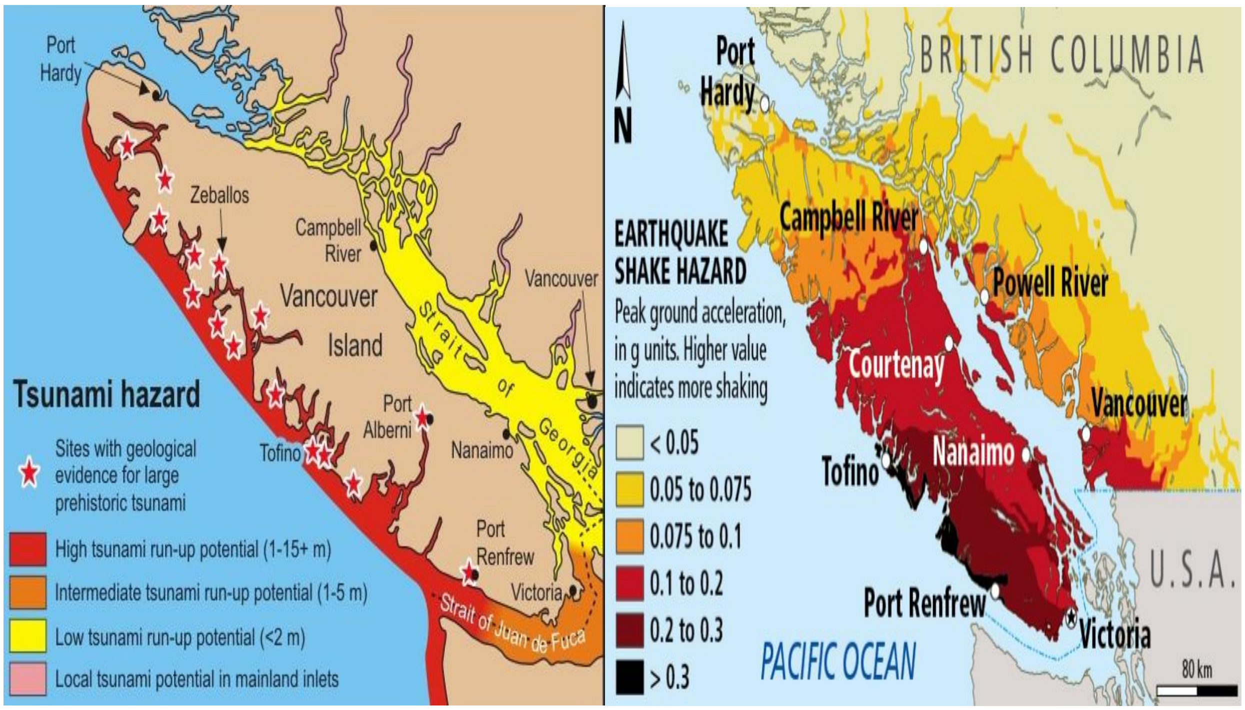

Figure 8 - Tsunami Hazard [42] and PGA for Vancouver Island [43]

Increasing the Resilience of the Electrical Grid

This section will cover actions that can be taken by BC Hydro and the CRD to increase grid resilience and maintain the use of EVs following an earthquake. As it stands, a CSZ event could cause a power outage lasting multiple months on VI. The past earthquakes in Chile, Japan, and New Zealand all had power returned to greater than 90% of customers within two weeks. The actions suggested to BC Hydro are made with the intent of hopefully reducing the outage time from months to weeks. The suggested actions for the CRD are intended to keep their organization able to power their vehicle fleet during an outage and provide power for critical loads.

Suggestions for BC Hydro

More generation capacity should be added to VI which would allow faster recovery in the aftermath of an earthquake. This new generation capacity should be added in a distributed layout, ideally close to the end user, and located outside of tsunami zones. As mentioned above, the CRD contains close to half the population of VI but has little nearby power generation. Adding new generation capacity to the region will mean that it is constructed to modern seismic standards and will able to help meet the increasing electrical load expected from the growing uptake of EVs. If BC Hydro does not want to add more generation to the region, the Province could look at ways to encourage IPPs to create power generation projects in the area.

BC Hydro should ensure that the grid on VI is designed with n-1 criteria and has the ability to island different portions. Where possible, vulnerable system elements should be moved away from seismically unfit buildings (unreinforced masonry buildings, common in Victoria, are a particular concern) and landslide areas. As much of VI has areas of tsunami run up potential ranging from 1 to 15+ meters, grid elements in these areas should be relocated, if possible, or raised to above flooding height. Liquefactions maps can be used to determine where buried system elements cross liquefaction zones and whether they can be relocated above ground. BC Hydro could also focus on seismically reinforcing substations and unreinforced masonry buildings that could damage electrical equipment.

BC Hydro can increase earthquake resiliency by planning for the event. They can plan to have resources available to perform grid repairs and establish agreements with surrounding areas to provide aid following an earthquake. VI should have an available supply of mobile generators and transformers on hand to aid recovery in more remote areas. BC Hydro could also plan for how rolling blackouts can be utilized as power is slowly brought back online and how customers can be compelled to reduce power use if available generation cannot meet demand.

Suggestions for the CRD

Since public communication networks can be brought down due to power outages or from being overwhelmed following an earthquake, the CRD could consider establishing private forms of communication to be able to coordinate their organization in the aftermath of a disaster. Further in this report, an example is provided of a private communication network that could be established with the use of EVs.

The CRD could establish a microgrid to assure that power can still be supplied to charge EVs and power critical loads after an earthquake. The purpose of a microgrid is to generate energy close to the end user. This is different from a more centralized grid, such as operated by BC Hydro, where power is transported long distances from where it is generated to arrive at the end user. Microgrids can be connected to the central grid or operate independently which allows them to continue to provide for customers during a power outage. Microgrids are generally constructed with battery storage and some arrangement of distributed energy resources (solar, wind, combined heat and power, natural gas, fuel cells etc). Currently, BCIT operates a campus microgrid that utilizes wind, solar, and thermal co-gen, along with battery storage, smart grid control systems, and EV charging stations, among other features [44]. In the “EV Use Cases” portion of this report, we’ll look at a Victoria based microgrid that uses a solar array to provide energy for EVs in a post-earthquake scenario.

In net metering programs, a customer who generates electricity is billed for the difference between their electricity use and the electricity that they have provided to the grid. BC Hydro's current policy is to temporarily disconnect net metering customers after a disaster, since they are considered a danger until BC Hydro can conduct site visits. This means that a microgrid that has been established as a net metering customer would not be able to be used after a disaster. To work around this, microgrids can be established "behind the meter", meaning that the power that is generated can be used on site but does not pass through a meter to the larger grid. An organization like the CRD could build a behind-the-meter microgrid that would help to reduce their need for power from BC Hydro under normal circumstances and would allow for EV charging during a disaster. Ideally, a microgrid would allow the CRD to continue charging EVs for an outage lasting a couple of weeks. In the case of an outage lasting multiple months, a microgrid would need substantial attached generation capacity (diesel generators, natural gas turbines etc) to remain a viable source of energy for that entire time period.

Finally, the CRD could utilize the EVs in their fleet as a form of mobile energy storage. Through Vehicle-to-Building (V2B) technology, the CRD can use the battery capacity of their EVs to provide power for important loads. This will be looked at further in the subsequent "EV Use Cases" section.

Vancouver Island Fuel Infrastructure

The information in this section comes from a 2016 University of British Columbia thesis by Allanah Brown that illustrated the fuel transportation system in coastal British Columbia [45].

BC receives crude and refined oil from Alberta, eastern Canada, and Washington State. Fuel arrives in the Lower Mainland by the Trans-Mountain Pipeline (TMPL), marine tankers, rail, and truck. These modes of transport bring fuel to several large storage and distribution facilities in the region. Almost all fuel imports arrive refined, but some crude oil is refined locally at Chevron's Burnaby refinery. A third of BC's transportation fuel is produced at Chevron Burnaby which receives the majority of its crude oil by pipeline, with supplemental deliveries by rail and truck. More than 50% of Vancouver's fuel demand comes via the TMPL and almost 30% of the TMPL's daily oil arrivals are transported from the Westridge Terminal to California, the Gulf Coast, and China. Supplementary fuel supply for the region is imported from Washington State refineries. Marine fuel transport arrives in the Port Metro Vancouver or one of the four petroleum terminals within it. Transportation from distribution centers to end-users is done through trucks, pipelines, storage tanks, and barges. The airport receives its fuel via a 41 km jet fuel pipeline that connects the airport to Chevron Burnaby and the Westridge Marine Terminal.

The majority of fuel that arrives on VI is delivered via the TMPL to the Lower Mainland and then by marine transport to VI. Fuel is transported from the Lower Mainland by barge or marine vessel across the Strait of Georgia to various ports along the East coast of VI. Some ports receive fuel every other week, while others see deliveries as frequently as 2 to 3 times per week. VI has tank farms near Nanaimo, Cobble Hill, and Chemainus which receive fuel through pipelines from nearby marine terminals. After arriving at a port, fuel can be pumped directly into storage where trucks collect and deliver fuel to depots and end-users. Fuel can also be transported in the "roll-on roll-off" fashion, where trucks drop their load on to a departing marine vessel and the load is picked up by another truck after the vessel docks. Additionally, some of the fuel transport on VI is done via rail. The region also receives supplementary fuel from Washington State.

Increasing the Resilience of the Fuel Infrastructure

It bears mention that, as VI gets much of its fuel from the Lower Mainland, VI is directly dependent on how resilient the Lower Mainland fuel infrastructure is.

The Lower Mainland should ensure that the sections of the TMPL that run through potential earthquake damaged areas are built to current seismic standards or are retrofit. TMPL pumping stations should have back up power available to deal with the likely power outage that will follow an earthquake. A study should be conducted to look at locations that receive fuel in the Lower Mainland and how seismically vulnerable they are. Ports in liquefaction areas can improve resiliency through retrofitting or by hardening liquefaction prone soils. The region could also develop an alternate location for a fuel delivery hub that is outside of liquefaction zones [46]. As it is a crucial facility for the region, it should be ensured that the Chevron Burnaby location is seismically robust. Planning should be done with respect to how fuel will be prioritized following an earthquake. There may be temporary measures after an earthquake to stop fuel deliveries to other parts of the world and possibly Vancouver Airport, assuming flights are grounded.

Since VI depends so heavily on ports to receive fuel, it should be a top priority for the region to study how the current port structures are likely to weather an earthquake event. Other than retrofitting existing ports, VI could add additional port locations or capacity, emergency berth structures, alternate landings with roll-on-roll-off capabilities, floating tank farms, and ships equipped with cranes to transfer cargo to land [45]. As VI receives fuel using a "just in time model" that allows 3 days-worth of fuel at any given time, resiliency can be increased by adding additional fuel storage to the region. Planning should be done for how much fuel is expected to be required after an earthquake for vehicle operation and generators. VI should also coordinate planning with the Lower Mainland for how fuel will be prioritized after an earthquake and how much of a decrease in supply from the Lower Mainland could be expected. It may be that regions of the US are less affected by the earthquake and are able to supplement fuel deliveries from the Lower Mainland.

Suggestions for the CRD

The CRD can determine how much liquid fuel the organization would need per day in the aftermath of an earthquake. This would include an assessment of how many gas or diesel vehicles are expected to be operating in that scenario and how much liquid fuel various backup generators would require. Since it is highly likely that ports and road transport networks will be damaged after an earthquake, the Victoria area may be cut off from fuel shipments for some time. As VI only has about a three day supply of fuel at any given time, the CRD could establish a private storage of fuel for the organization.

It is worth noting that hydrogen vehicle fuel would have the same resilience issues as gas and diesel with respect to how it would be transported to VI after an earthquake. The CRD would be need to stockpile enough hydrogen fuel locally to continue the use of hydrogen vehicles after a disaster. An idea to increase hydrogen resilience would be to add local production of it to VI. There is potential to reform hydrogen through thermal, electrolytic, solar-driven, and biological processes [47]. Production of hydrogen via electrolysis using BC's clean energy would also have very low carbon intensity [48].

The CRD can also consider what the resilience implications are of their fleet composition. Adoption of EVs will allow the organization to reduce GHG emissions, lower costs for fuel and maintenance, and potentially donate energy in a disaster. That said, if there is a prolonged power outage, and there is no local energy generation, the EV fleet would become effectively useless after their batteries had been drained. There is also the question of charging availability. If fast charging is unavailable, it could take up to 8 hours to charge an EV at a conventional charger which would be 8 hours that the vehicle would be unable to provide disaster relief for. ICE vehicles would still contribute to the organization's GHG emissions but would have beneficial features in a disaster, such as further travel distance on a full tank and very short times to refuel. ICE vehicles are also dependent on fuel that could be unable to make it to VI following an earthquake. Hydrogen vehicles don't create GHG emissions (assuming hydrogen fuel has been refined from clean energy) and offer quick refueling times but rely on hydrogen that may be unavailable after an earthquake. An idea for optimal fleet resilience would be for the CRD to maintain a fleet of several different vehicle types, along with trying to mitigate vehicle risk by methods such as using microgrids and creating storage of conventional fuel and hydrogen.

EV Use Cases after an Earthquake

EV Communication Network

As mentioned previously, public forms of communication are frequently overwhelmed in the aftermath of an earthquake. Communication networks are important for disaster recovery as they allow the delivery of crucial information to help the preservation of life. Mobile ad hoc networks (MANETs) offer the ability to connect a group of wireless mobile nodes without the use of existing network infrastructure or centralized administration. These wireless nodes can form a temporary network dynamically which makes them well suited for disaster recovery and search and rescue efforts [49].

A vehicular ad-hoc network (VANET) is a variety of MANET where vehicles act as mobile nodes. In the past, VANETs have often been constructed with gasoline powered vehicles. A benefit of using an EV in a VANET is that an EV can operate as a communication node for a long period of time whether it is moving or stationary, due to the large capacity battery of an EV [50]. It has also been proposed that unmanned aerial vehicles (UAVs) could be used in conjunction with EVs to help guide rescue efforts, due to their ability to monitor terrain from an elevated perspective [51].

Researchers at the University of Malaga studied the energy consumption of a VANET composed of 40 vehicles and covering an area of 120,000 m^2. In a 180 s scenario, each vehicle consumed roughly 4,000 J of energy [52]. This would only represent 0.0018% of a Nissan Leaf Plus's 62 kWh battery capacity.

EV Donating Power with V2B

Another application of EVs is the use of them as mobile energy storage. With its onboard battery, an EV can charge at a station, drive to another location, and donate its power via V2B (vehicle-to-building) technology. Until recently, EVs had only been capable of one-way charging. Bidirectional charging allows vehicles to discharge battery power into a building or the electrical grid. Currently, the Nissan Leaf and the Mitsubishi Outlander are the only vehicles capable of this on the Canadian market [53]. For the purpose of this example, we'll assume that the CRD is using the Nissan Leaf Plus, shown in figure 9, with a 62 kWh battery capacity.

Figure 9 - 2022 Nissan Leaf Plus [54]

The example for this use case takes place after an earthquake in July. There is a complete power outage, and the CRD is providing a Nissan Leaf Plus to donate its power to a shelter for people displaced in the earthquake. The Nissan Leaf Plus will have access to a 50 kW fast charger that can charge the battery to full in about 60 minutes [55]. The fast charger is located on a community microgrid that is still able to provide power during the outage. The shelter that the EV will donate power to is located 10 km away from the charging station, and the Nissan Leaf Plus uses roughly 2 kWh/10 km [56]. We will assume that the Nissan Leaf Plus will discharge a power of 50 kW to the shelter for about one hour, an energy donation of 50 kWh. For reference, the average Canadian household uses about 19 kWh per day [57]. In this example, the total energy use for the EV to provide this function is 54 kWh (50 kWh for energy donation, 4 kWh for travel). We will also assume that the time required to drive the round trip distance of 20 km in a post-earthquake damaged transport network, along with the time to hook the EV up at either the shelter or the charging station, will take a total of one hour. The process would look as follows:

1. EV starts at fully charged state
2. EV drives 10 km to shelter and hooks up V2B discharging (about 30 mins)
3. EV donates 50 kW of power for one hour
4. EV drives 10 km to fast charging station and hooks up to charger (about 30 mins)
5. EV is charged fully at fast charging station in one hour

All told, the process would take around 3 hours, and each 3 hour cycle would donate another 50 kWh to the shelter while using 54 kWh of energy at the fast charging station. It is worth noting that discharging this deeply, fast charging, and charging the battery to 100% capacity would increase battery degradation, but it is assumed that post-disaster circumstances have necessitated using the EV in this fashion. If the vehicle provides disaster relief for a full 24 hours (assuming employees working in shifts), the EV could repeat this cycle 8 separate times, donating 400 kWh to the shelter and using 432 kWh at the fast charging station.

The microgrid that the vehicle returns to is assumed to have a 100 kW (standard size for a commercial rooftop) solar array available. Using the System Advisor Model (SAM) software provided by the National Renewable Energy Lab (NREL), a simulation was performed for a 100 kW roof-mounted solar array in Victoria, BC with a fixed tilt angle. Figure 10 shows what the monthly energy production would look like for the proposed array.

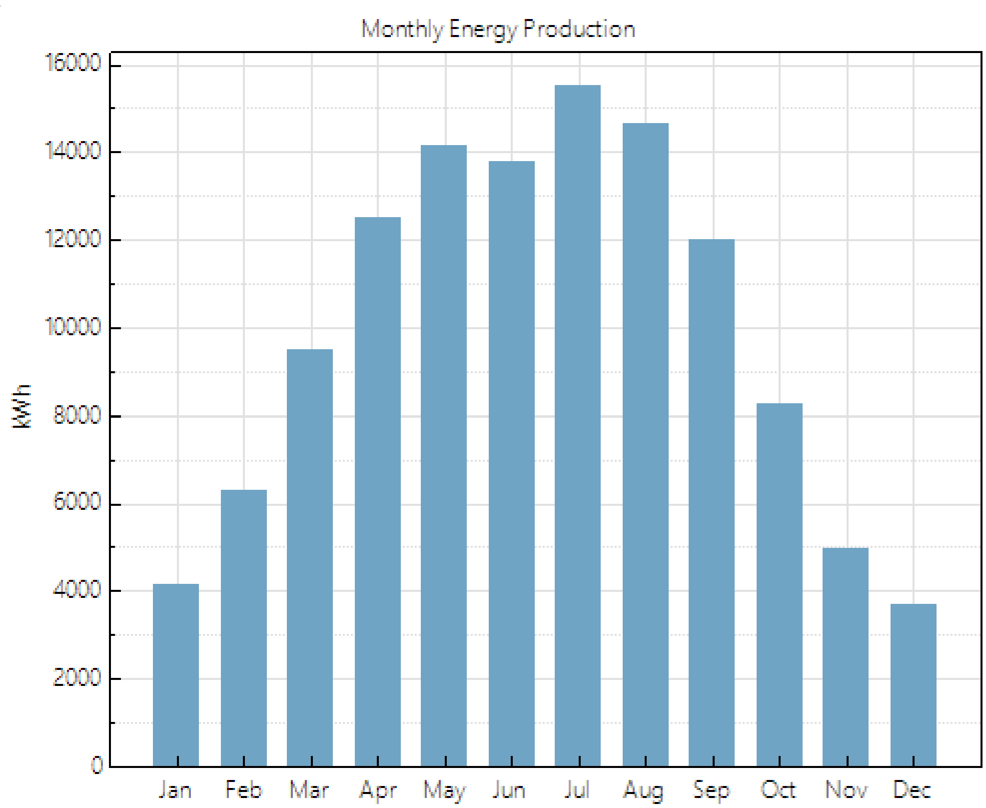

Figure 10 - Monthly Energy Production of a 100 kW Fixed Tilt Solar Array in Victoria, BC

Looking at the energy generation for the month of July, the array would produce about 15,500 kWh. Averaging this number over the 31 days of the month leads to an average daily energy production of 500 kWh. This means that the 24 hour EV use case of 432 kWh, described above, would use almost the total daily energy production of the array. It bears mention that this is also for an earthquake occurring in a month with the most available solar energy. The solar array would only produce about 122 kWh of energy in an average December day which would only accommodate 2 of the energy donation cycles described previously. If multiple EVs were wanted to provide this same functionality, the microgrid would have to have substantial battery storage, along with alternative forms of attached energy generation, such as diesel generators or natural gas turbines. A green solution to this problem could be to use renewable natural gas synthesized from the Hartland Landfill.

EV Providing Transport for Goods and People

A final application of EVs in a post-earthquake setting is the transport of important goods, such as food and medical supplies, along with people. In this context, people could be skilled employees to perform a certain task or those in medical need. It may be the case that certain CRD duties, such as ones relating to water and waste, continue to be crucial in the aftermath of a disaster.

For this case, we will once again consider the 62 kWh Nissan Leaf Plus. Nissan lists the Leaf Plus's maximum single charge range as 363 km [55]. While it's hard to predict what sort of driving distances would occur when providing earthquake relief, it is likely that an EV that is providing 24 hour disaster relief would only need to charge once or twice a day with that amount of vehicle range.

Assuming that the vehicle is close to completely discharged after use, it would take about 60 kWh to charge the vehicle completely. If a vehicle providing disaster relief is only charged once a day, the 500 kWh solar energy production, described in the previous July earthquake scenario, would be able to provide for 8 separate vehicles acting in this fashion. In comparison with the previous EV use case, you would be looking at a single vehicle that performs 8 power donation cycles over a 24 hour period vs 8 separate vehicles that are transporting supplies or people over the same period of time.

Conclusions

EVs offer many benefits when compared to ICE vehicles, such as reduced GHG emissions, better performance, and economic savings. EVs sales have continued to grow, even during the pandemic, and could represent 12-28% of the global fleet by 2040. The CRD has one of the largest concentrations of EVs in the province, and this will only continue to grow as the Zero Emissions Vehicles Act takes effect in 2040. The CRD also coincides with the region of BC that would be hugely impact by a CSZ earthquake event. To maintain the use of EVs in an earthquake, it is integral that the power system infrastructure is resilient.

To understand how to improve earthquake resilience, this report examined past earthquakes in Chile, Japan, and New Zealand. The 2010 Chile showed the importance of having available excess generation capacity, designing the grid with n-1 security criteria, establishing private forms of communication, and utilizing smaller sized generators for recovery in isolated areas. The 2011 Japan earthquake illustrated the risks of locating generation capacity in a tsunami zone and taught lessons on the importance of elevating transformers in flood zones, utilizing rolling blackouts for recovery, and the resilience of microgrids after an earthquake. The 2011 New Zealand earthquake taught lessons on the potential damage that can be caused to electrical equipment running through liquefaction zones, along with how impactful spending money on resilience upgrades can be. All three earthquakes had power returned to most customers within two weeks, and this success can be at least somewhat attributed to the robust seismic standards that had been put into place in all three countries.

The electrical grid on VI was examined and ideas for increasing resilience were applied to the region. The grid on VI depends heavily on imported power from the mainland of BC. BC Hydro's earthquake modelling suggest that the region could experience power outages in the range of months after a CSZ event. BC Hydro could increase resilience by adding more generation to the area, specifically near to the CRD, where there is little nearby generation capacity. BC Hydro could also relocated grid elements from tsunami zones, reinforce substations and masonry buildings, move buried system elements from liquefaction zones, and plan for the event by having resources available and arranging for aid agreements with surrounding areas. The CRD could increase organizational resilience by establishing private forms of communication, building a local microgrid to be able to charge EVs in a disaster, and utilizing their EV fleet battery capacity to provide mobile storage and provide power to important loads.

The fuel infrastructure on VI was also examined, including its connections to the Lower Mainland. VI depends heavily on fuel that arrives in the Lower Mainland from the TMPL and is then brought to VI by marine transport. Improvement to the Lower Mainland fuel resilience, such as hardening liquefaction prone soils in ports, providing backup power for pumping stations, and deciding fuel prioritization will all help to ensure there is a supply of Lower Mainland fuel available for VI. VI can also improve its resilience by adding additional ports or emergency berth structures, increasing fuel storage, and planning for how fuel will be prioritized and where it can be sourced from. As an organization, the CRD can plan for what their expected fuel needs will be after an earthquake for vehicles and generators and establish how much storage that would require.

Post earthquakes use cases were examined for EVs. EVs have the potential to act as nodes in a mobile communication networks. In a 180 s simulation, the power need for this application was found to only represent 0.018% of a Nissan Leaf Plus's 62 kWh battery. In a scenario with an EV donating power to a shelter and charging at a 50 kW fast charger, it was found that an EV could donate about 400 kWh to a shelter in a given 24 hour period. It was assumed that the EV was recharging at a microgrid with a 100 kW solar array which was able to provide power for a single vehicle acting in this fashion. Finally, the case of an EV delivering supplies and personnel was observed, and it was found that, given the Leaf's single charge range of 363 km, 8 vehicles could charge once a day at the 100 kW solar microgrid and provide this function for 24 hours.

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Incorporating Electric Bikes into a Regional Government Fleet

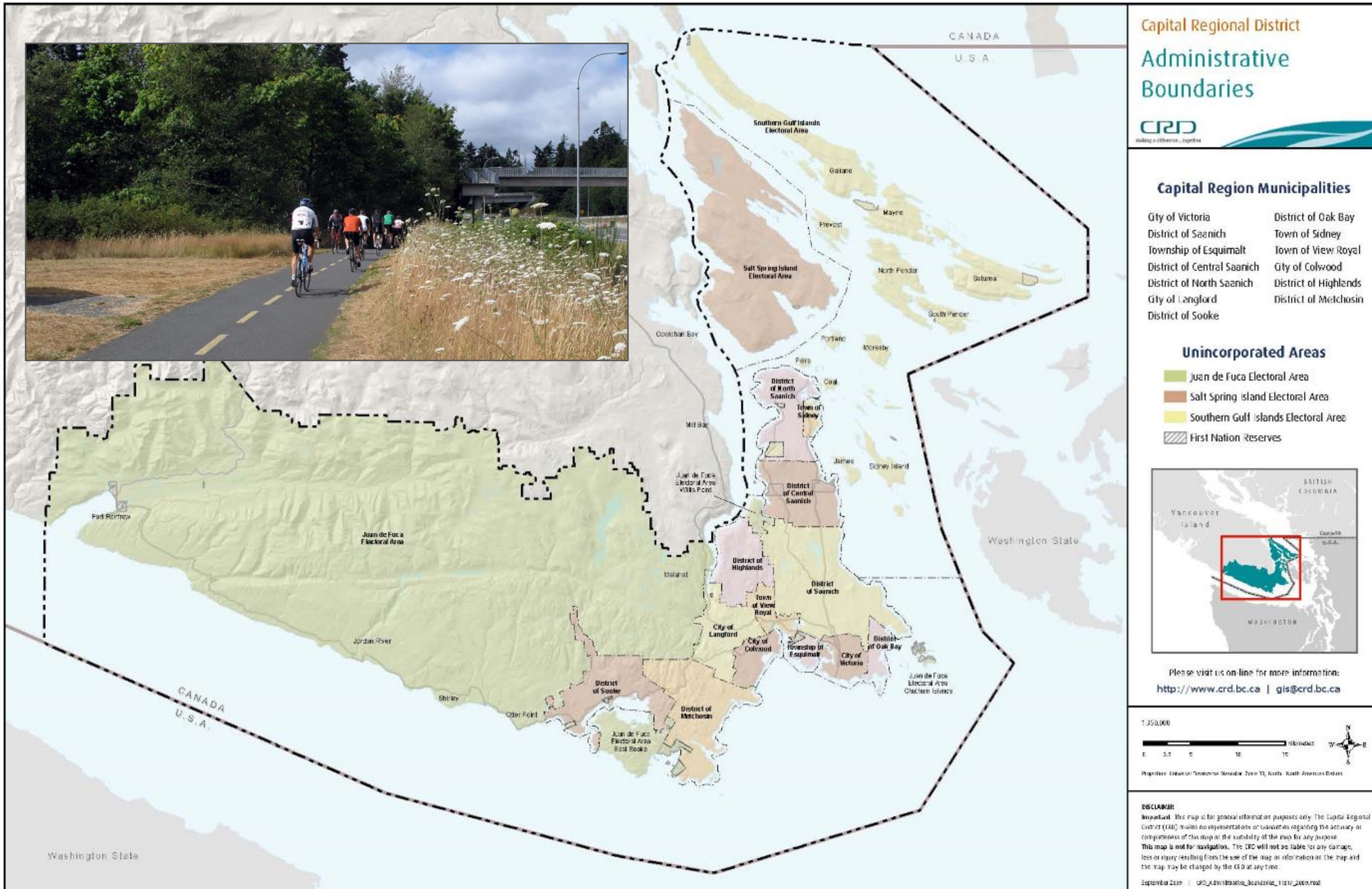
Lessons Learned from the CRD

Attachment 5

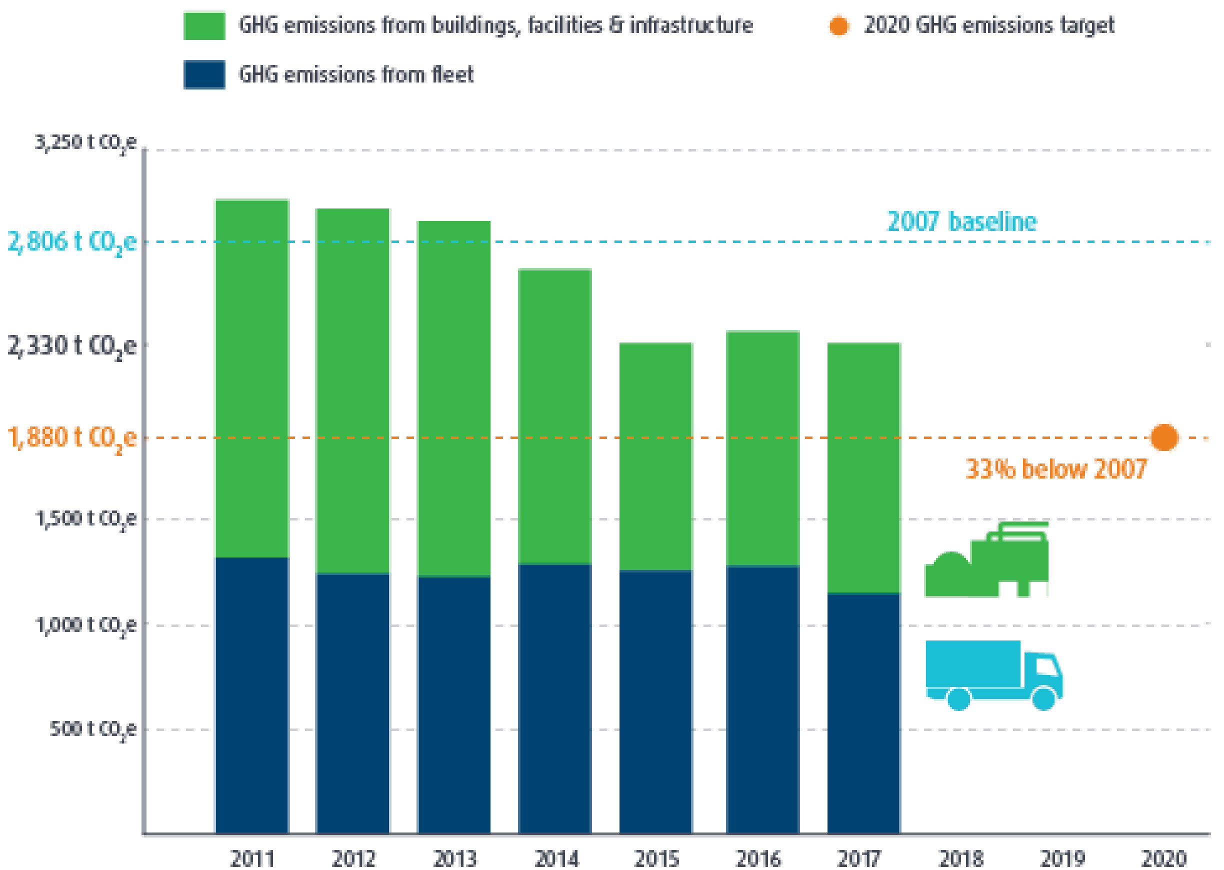
Liz Ferris, Corporate Climate Action Coordinator

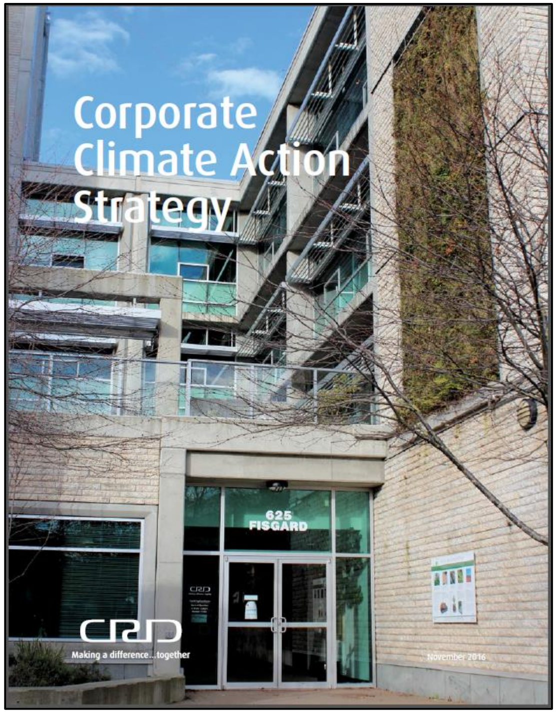
CRD
Making a difference...together

The Capital Region



Climate Action at CRD

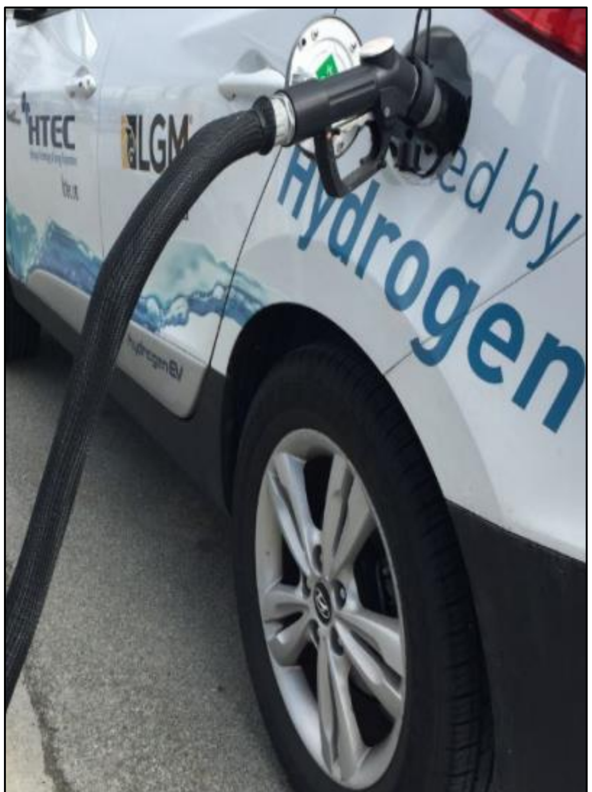




- ✓ Signatory of the BC Climate Action Charter
- ✓ Signatory of the West Coast Electric Fleet Initiative
- ✓ Carbon neutral in operations since 2012

Zero Emissions Fleet Initiative

The CRD ZEFI is technology neutral *and* committed to investigating any cost effective technology that can reduce GHG emissions and meet operational needs.



Pilot Summary

Timeline

February 2018 - September 2020: trial within corporate fleet

February 2018 - February 2019: 1 year intensive focus with IESVic

Participants

17 staff from 4 Departments

3 E-bikes

Purpose

Transport to:

✓ Site inspections

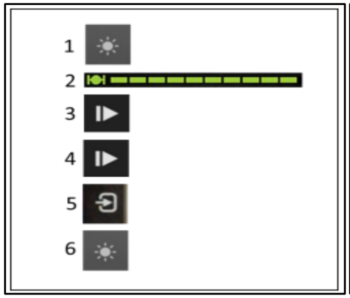
✓ Meetings

E-bike Pilot Research Goals

1. Recommend the optimal use of e-bikes in urban commercial fleets.

2. Compare the environmental, economic, and logistical performance of the operation of e-bikes in urban fleets to other vehicle modes.

3. Recommend regulatory constraints placed on E-bike use with respect to motor power limits.



At the start of the trip:
1. Turn the Garmin on
2. Wait for GPS bar to turn green
3. Press the start button

At you destination:
4. Press the stop button
5. Save the trip
6. Turn the Garmin off

Note: Please take the Garmin with you when locking up the bike

E-bike data collection instructions

Standard Operating Procedures

- ✓ PPE & safety training
  - ✓ Safe routes & cycling infrastructure
  - ✓ Communication/ navigation device
  - ✓ Weather restrictions
- ✓ Booking procedure
- ✓ Pre/post trip checklists
- ✓ Research requirements
- ✓ Bike security

STANDARD OPERATING PROCEDURES
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Procurement

Norco VLT S1 – Bosch Performance CX motor

Photo credit: Norco Bicycles, https://www.norco.com/bikes/2018/pavement/e-urban/vlt-aluminum/vlt-s1/

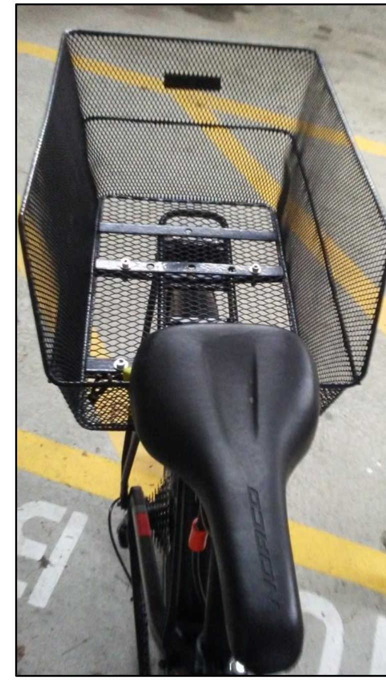
Outfitting the Bikes

zero emissions fleet initiative

Branding

First Aid Kit

Water bottle holder



Lockable trunk vs. Basket with rain cover

Capital Cost

Category	Item	Cost (taxes excluded)
E-bikes	3 E-bikes	~$11,200
PPE	21 helmets, 6 visi vests, 3 first aid kits, bells	~$1,100
Security	Wheel pinheads, cables, locks	~$700
Storage on the Bike	3 bicycle baskets & covers, 3 water bottle holders, 1 bungie net, 1 locked truck	~$300
Storage of Bikes	Electrical installation, labour, lockers, painting	~$5,500
Branding	40 bike stickers, 6 bike stickers	~$100
	Capital Cost of E-bike Pilot	~$18,900

Operating Cost

Category	Item	Cost (taxes excluded)
Maintenance	6 bi-annual tune-ups ($85 ea)	~$500
	Ongoing maintenance (drivetrain replacement, & other parts; $300 -$1,300 per bicycle over its lifecycle)	Variable
	Tire pump, chain lube, tube replacement	~$100
Training	Safety training (17 staff)	~$1000
	Operating Cost of E-Bike Pilot	~$1,600

Storage & Security

Secure storage includes:

- ✓ Racks
- ✓ Electrical outlets
- ✓ Storage lockers

Bike security includes:

- ✓ Abus Bordo 6000 folding lock
- ✓ Cable for quick release bike seat
- ✓ Pinheads through rear & front axle

Summary Statistics

Summary Statistics of CRD E-bike Use April 2018 – August 2018 (mean value +/- one standard deviation)	
Total km travelled	607 km
Total trips taken	92
Average speed	20.3 +/- 5.9 km/h
Average trip length	6.6 +/- 5.8 km
Average trip time	25.9 +/- 25.2 min

Source: Clancy, Dan. (2019). CRD-UVic E-bike Fleet Deployment.

GHG Emissions Reductions

Emission Intensity for Four Transportation Modes April 2018 – August 2018 (mean value +/- one standard deviation)	
Mode	Emissions (kg CO_2e/km)
E-bike	0.00009
Standard sedan	0.216
Electric car	0.002
Walking	0

Source: Clancy, Dan. (2019). CRD-UVic E-bike Fleet Deployment.

- ✓ 99% reduction in GHGs compared to typical CRD fleet vehicle
- ✓ 95% reduction in GHGs compared to battery electric cars
- ✓ ~250kg of CO_2 was saved by the deployment of the e-bikes

Cost Savings

Capital & Operational Costs per Vehicle over 5 years		
Mode	Capital costs ($)	Operational Costs ($)
E-bike	4,400	1,700
Chevrolet Malibu	22,300	1,400
Electric car	35,900	8,300

Source: Clancy, Dan. (2019). CRD-UVic E-bike Fleet Deployment.

- ✓ E-bike use results in an 80% reduction in capital and operating costs.

Utilization

Comparison between E-bikes & Pool Vehicles April 1, 2018 - August 31, 2018	
Vehicle	**Total % use**
Large e-bike	15%
Medium e-bike	19%
Small e-bike	8%
Prius	28%
Smart	13%
Kia Soul (Electric)	35%
Chevy Malibu (Hybrid)	25%

✓ E-bikes may save up to 2 hours daily in downtown area.

Staff Taking Climate Action

"Arriving to businesses on an e-bike sparks discussions around ***CRD climate action*** *initiatives, work efficiencies, and health benefits of cycling."*

-e-bike pilot participant

2019 - 2022 Board Priorities

Community Wellbeing – Transportation & Housing

The CRD Board will advocate, collaborate and form partnerships to address the affordable housing and transportation needs of the region's diverse and growing population.

Climate Action & Environmental Stewardship

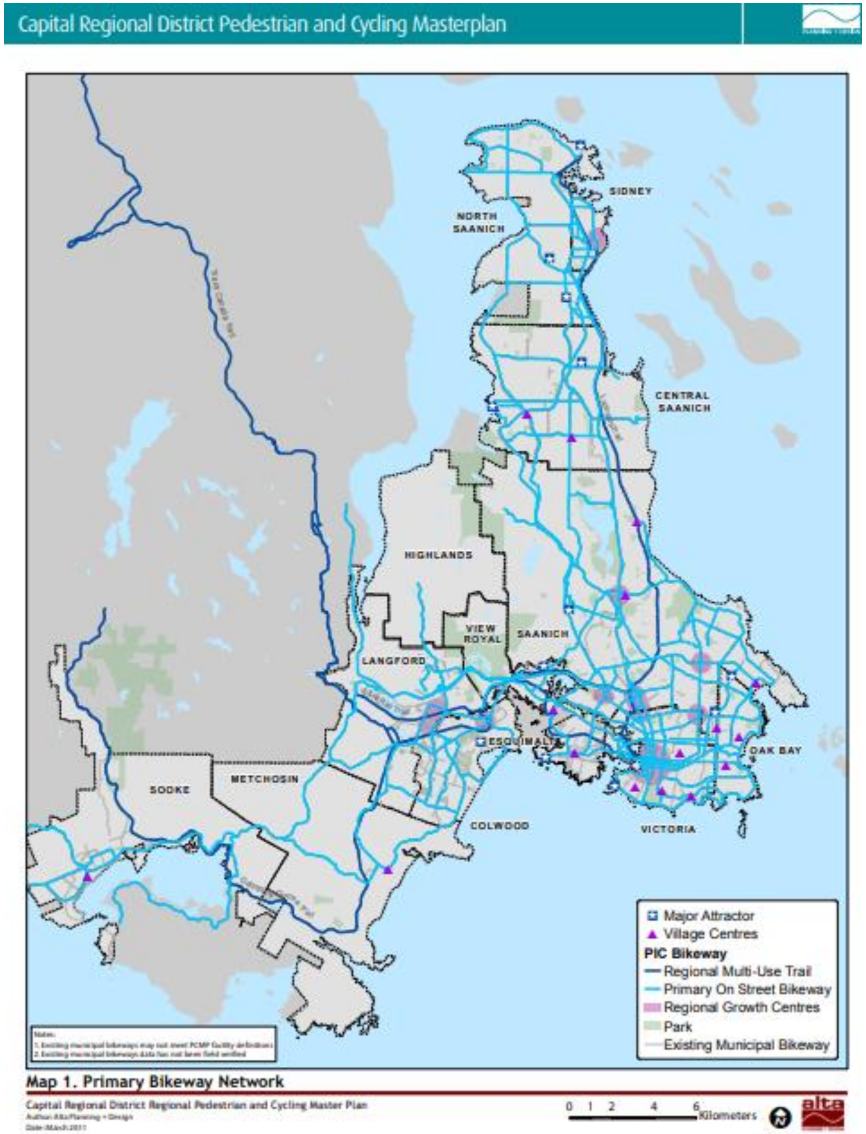
The CRD Board will encourage and implement bold action on climate change by enhancing its natural and built assets to achieve environmental resilience, food security and continued wellbeing of our current and future residents.

Lessons Learned

- Fit testing
- Data collection compliance (for IESVic)
- Completion of pre/post trip inspection forms
- Training time required
- Style of bike
- Battery life for extended trips
- Storage constraints on bike
- Secure storage of bikes
- Staff uptake

Next Steps

- ✓ Continue pilot until September 2020, unless new direction is given
- ✓ Maintain waitlist of interested staff
- ✓ Integrate e-bikes into fleet upon pilot's completion
- ✓ Provide lunch n learn for CRD Board members
- ✓ Continue to support and promote regional cycling infrastructure



Thank-you!

Questions?

Contact:

Liz Ferris, Corporate Climate Action Coordinator
lferris@crd.bc.ca
250-360-3643

Attachment 6

Feasibility Study

Zero Emissions Fleet Initiative- Infrastructure Safety Study

Capital Regional District | 6-Nov-2017

Feasibility Study

Zero Emissions Fleet Initiative- Infrastructure Safety Study

Developed by:

The Capital Regional District, Zero Emissions Fleet Initiative Team

Supported by:

Ministry of Energy and Mines, Province of British Columbia
Institute for Integrated Energy Solutions at the University of Victoria

Prepared by:

HTEC Hyrogen Technology & Energy Corp
North Vancouver, BC

Table of Contents

1. Introduction

This document summarizes the overall requirements for the safe and successful construction of a permanent hydrogen fuelling station to fill Fuel Cell Electric Vehicles (FCEVs) within the Capital Regional District (CRD). These requirements relate to the vehicle Original Equipment Manufacturers' (OEM) key expectations for station performance, overall technical specifications, station components, common safety concerns, and applicable codes and regulations for safe operation. Permitting and the importance of early public engagement, as well as the practicality of mobile refuelling will also be discussed.

2. Hydrogen - a safe fuel

Hydrogen is a carbon-free, non-toxic fuel that can be domestically produced from local resources. Most hydrogen is made from natural gas, but increasingly it is made from water, biogas and biomass. For more than 75 years, hydrogen has been safely handled, distributed and dispensed.

a. Properties and why it is safe

Hydrogen is the lightest molecule in the universe and diffuses rapidly in its gaseous state, elevating at approximately 20 meters per second. This property is known as high buoyancy. High buoyancy makes it unlikely to accidentally form a flammable mixture with hydrogen. Codes and standards take into account the buoyancy and diffusivity of hydrogen when designing structures to store, transport, and use hydrogen safely. Generally, a hydrogen release dissipates very quickly.

Hydrogen is odorless, colorless and tasteless: Hydrogen sensors are used to detect leaks and have been used to meet safety standards for decades.

Hydrogen falls under special electrical classification as it is deemed flammable, and as such, explosive atmospheres exist when this gas is present above the lower explosive limits (LEL). The LEL of hydrogen gas is 4.0% by volume. Section 18 of the Canadian Electrical Code, CSA22.1, requires the use of specific classified electrical equipment in locations defined as Hazardous.

A typical fueling station will have from 76 000 to 284 000 liters of gasoline on site at a time, while the current hydrogen station configurations will have 50kg to 1 000 kg on site. Typical gasoline tankers will carry 34 000 liters of gasoline, while hydrogen delivery vehicles will carry 100 to 300 kg of the gas.

A hydrogen fueling station has several safety features that include emergency stop button to de-energize the system if problems occur, fire and flame detection equipment in both open and enclosed spaces, hydrogen detection equipment, pressure relieving devices throughout, safety signage, and equipment interlock to ensure only trained personnel have access.

b. Hydrogen as a regulated fuel

Hydrogen is a recognized fuel for transportation and has been classified as such. In addition to transportation, hydrogen is commonly used in large quantities in the petroleum refinery process, in several industrial applications, and as fuel for space exploration. These uses resulted in reliable standards used to safely produce, store, and transport hydrogen. For example the National Fire Protection Association standard - NFPA 55 – Compressed Gases and Cryogenic Fluids Code, which is still in use, was established as early as 1975 and covered the installation and safe handling of hydrogen equipment. With the continued development of hydrogen as a fuel for transportation, a dedicated standard, NFPA 2 - Hydrogen Technologies Code was first issued in 2011, to better issues associated with dispensing and laboratory applications.

The Canadian Hydrogen Installation Code, Standard CAN/BNQ 1784-000, sets the installation requirements for hydrogen generating equipment, hydrogen-powered equipment, hydrogen dispensing equipment, hydrogen storage containers, hydrogen piping systems and their related accessories. The code applies to all gaseous and liquid hydrogen applications with some exceptions that don't relate to fuelling stations. This code is approved by the Standards Council of Canada, however NFPA-2 is the most widely adopted standard and also the standard that the British Columbia Safety Authority (BCSA, now known as Technical Safety BC) is most familiar with. It can be argued that a precedent has been set in BC to follow NFPA-2 for the time being.

The application of appropriate codes and standards make hydrogen fuel just as safe as—or safer than—gasoline or other commonly used fuels, such as compressed natural gas (CNG). Hydrogen systems are engineered systems that follow prescriptive hydrogen standards. They have proven to be very safe in numerous stations and vehicles, and they are approved by a wide variety of groups for operation in public settings in British Columbia, California, Germany, UK, Korea, and Japan. Many other countries are also beginning to install hydrogen station networks.

A series of typical questions and answers as they related to community concerns around hydrogen can be found in Appendix A. These questions can be reasonably anticipated at a public meeting.

3. Permitting

Permitting requirements will differ from station to station depending on the site characteristics, station type, and the local jurisdiction's unique processes. In BC, local governments have the ultimate authority to approve or deny any project. A design approved in one community does not guarantee approval of the same design in another community. However HTEC has successfully applied for permits in Vancouver, North Vancouver, Surrey, Burnaby, Whistler, and Woodside California, which should lend itself to valuable guidance for the permitting process within the CRD.

A major piece of the station permitting process is dedicated to ensuring stations are built to current codes and standards. The following text provides references to BC codes and guidance, which can be amended by local jurisdictions in certain circumstances. In BC, cities typically grant building permits as they relate to site usage, parking, setbacks, building code and electrical code compliance. Technical Safety BC is responsible for pressurized systems to ensure they comply with code and are operated safely. Both the Jurisdiction having authority (JHA) and Technical Safety BC will grant the operating permits.

a. Applicable Codes and Regulations

The following is a list of the most applicable codes to hydrogen fuelling infrastructure in BC.

- NFPA-2 National Fire Protection Association Hydrogen Technologies Code (2016). The purpose of this code shall be to provide fundamental safeguards for the generation, installation, storage piping, use, and handling of hydrogen in compressed gas (GH2) form or cryogenic liquid (LH2) form.
- CAN/BNQ 1784-000/2007 – Canadian Hydrogen Installation Code. The purpose of this code is to establish the installation requirements for hydrogen generating equipment, hydrogen utilization equipment, hydrogen dispensing equipment, hydrogen storage containers, hydrogen piping systems and their related accessories.
- ASME – B31.12 – Hydrogen Piping and Pipelines. This code is applicable to piping in gaseous and liquid hydrogen service and to pipelines in gaseous hydrogen service.
- CSA - C22.1-12 Canadian Electrical Code (2012) the object of this Code is to establish safety standards for the installation and maintenance of electrical equipment. In its preparation, consideration has been given to the prevention of fire and shock hazards, as well as proper maintenance and operation.
- CSA - B51-14 Boiler, Pressure Vessel, and Pressure Piping Code (2014) It is intended mainly to fulfill two objectives: first, to promote safe design, construction, installation, operation, inspection, testing, and repair practices, and second, to facilitate adoption of uniform requirements by Canadian jurisdictions.

b. Temporary Installations

The subject of temporary installations, moving stored hydrogen, and mobile refuellers as an option to permanent installations reveals that the overall permitting and safety requirements are similar at best, and in the case of mobile refuellers much more complex (see Appendix B for a discussion of mobile refuelling in California).

Moving stored hydrogen in Canada requires special Transport Canada permits, while moving a temporary fuelling station simply requires the station to be completely purged of any hydrogen, essentially making it an inert assembly of equipment.

Installing a temporary fuelling station has few precedents and by all indications would need to meet all of the codes and regulations set out for a permanent station. A temporary installation might fall under the category of a short term event, and each municipality may have less stringent requirements for foundations and structures, however it is unlikely the requirements around siting, setbacks, and related safety equipment will be any different from a permanent station.

c. Regulatory Approval and Safety

Fuelling stations must meet the requirements of the local authorities having jurisdiction which include:

- Approval of the Municipality and Fire Department in which the Hydrogen refuelling station will be installed.
- Registration of pressure vessels pressure piping and fittings Boiler and Pressure Vessel Safety Program of the BCSA. The pressure retaining components for which the Boiler and Pressure Vessel Program has jurisdiction and for which design registration is required are defined in Part 1, section5.1
- Approval in principle from the BCSA, Engineering and Standards, for the proposed installation design.
- Satisfactory site inspection of the installed pressure vessels by a BCSA Boiler Safety officer as well as the complete fuelling station by a BCSA Gas Safety officer.

d. Site layout, setbacks and hazardous zone considerations.

Choosing the correct site is critical for hydrogen fuelling stations because installation of pressurised gas systems in British Columbia requires the review and approval by the BCSA. For public fuelling facilities a definitive set of Canadian codes and standards is not available when it comes to setback requirements. As such a Professional Engineering firm like HTEC must work with the BCSA and apply a combination of best practice and applicable codes from similar installations. From this, a design basis would be generated that ensures a safe design that would be accepted by the BCSA and fit on the selected site.

What makes this process complex is the need to balance regular building code requirements, hazardous zone needs, hydrogen specific setbacks, and general aesthetics. The biggest driver of setback requirements is the amount of stored hydrogen on site, and how far the storage is from exposures, which is defined as, among other things, existing building HVAC, property lines, public roads, sidewalks, parking, adjacent buildings, and overhead power lines.

A hydrogen fuelling facility integrated into an existing gas station needs to consider several codes including gasoline, cryogenic fluids, and hydrogen installation codes. Setbacks, or clearances to exposures, are prescribed by the codes in the case where there is a real risk to people or property (exposures) due to the amount of energy contained in the system. These are distinctly different from the hazardous zones required for electrical equipment. Hazardous zones for electrical equipment add further complexity to the siting requirements and have a direct bearing on the overall footprint of the hydrogen fuelling infrastructure and therefor the site itself. Hazardous zones are defined in Table 3.2 below.

The National Fire Protection Association's NFPA -2 and the National Standard of Canada's BNQ-1784-000 Canadian Hydrogen Installation Code set out a number of requirements regarding the installation of hydrogen systems. The NFPA-2 code is set to provide fundamental safeguards for the generation, installation, storage, piping, use, of hydrogen in compressed gas form. NFPA-2 provides a more comprehensive set of guidelines and as such HTEC recommends following NFPA-2 for hydrogen installations.

Table 3.1 is an excerpt from NFPA-2 and outlines the required clearance distances from bulk storage to exposures based on typical maximum pipe size. The hydrogen system will need to be examined for specific pressures and line size to determine exact setback requirements. The bulk storage system is defined as the storage vessel and associated pipework to the automatic shut-off valve, which the system can close in the event of a shut-down (emergency or otherwise). Bulk storage is any amount of compressed hydrogen storage above 141.6 Nm^3 (5,000 scf).

Table 3.1 : Excerpt from NFPA 2 – Minimum Distance from Outdoor GH2 Systems to Exposures (NFPA -2 Table 7.3.2.3.1.1(a))

Pressure	**>15 to ≤ 250 psig**	**>250 to ≤3000 psig**	**>3000 to ≤7500 psig**	**>7500 to ≤15000 psig**
Group 1 Exposures	m	m	m	m
• Lot line • Air intakes (HVAC, compressors, other) • Operable openings in buildings and structures • Ignition sources such as open flames and welding	12	14	9	10
Group 2 Exposures	m	m	m	m
• Exposed persons other than those servicing the system • Parked cars	6	7	4	5
Group 3 Exposures	m	m	m	m
• Buildings of non-combustible non-fire-rated construction • Buildings of combustible construction • Flammable gas storage systems above or below ground *Cont'd…*	5	6	4	4

• Hazardous materials storage systems above or below ground • Heavy timber, coal, or other slow-burning combustible solids • Ordinary combustibles, including fast-burning solids such as ordinary lumber, excelsior, paper, or combustible waste and vegetation other that found in maintained landscaped areas • Inoperable openings in buildings and structures • Encroachment by overhead utilities (horizontal distance from the vertical plane below nearest overhead electrical wire of building service) • Piping containing other hazardous materials • Flammable gas metering and regulating stations such as natural gas or propane				

In addition to setbacks based on stored energy, hazardous zone classification is required to meet section 18 of the Canadian Electrical Code. Section 18 of the Canadian Electrical Code, CSA22.1, requires the use of specific classified electrical equipment in locations defined as Hazardous. Hydrogen falls under this classification as it is deemed flammable, and as such, Class I atmospheres exist when this gas is present above the lower explosive limits (LEL). The LEL of hydrogen gas is 4.0% by volume.

Class I locations are further divided in to three zones depending on the frequency and duration of the explosive atmosphere. These zones are defined as follows:

Table 3.2 Hazardous Zone Definition

Zone	Definition
Zone 0	Explosive gas atmosphere present continuously or are present for long periods of time
Zone 1	Explosive gas atmosphere are likely to occur in normal operation, or, the location is adjacent to a Class I, Zone 0 from which explosive gas atmosphere could be communicated
Zone 2	Explosive gas atmospheres are not likely to occur in normal operation and, if they do occur, they will exist for a short time only; or, the location is adjacent to a Class I, Zone 1 location, from which explosive gas atmospheres could be communicated, unless such communication is prevented by means of positive ventilation (with safety system)

Depending on the rating of the classified zone, different requirements exist for the installation of electrical equipment. The specifics of these installation requirements are beyond the scope of this report, but can be ascertained from Section 18 of CSA22.1. Rigorous engineering calculations are required to ensure each hydrogen installation meets the electrical code in order to be considered safe. HTEC has gone through this exercise on numerous projects and is well equipped to provide guidance on hazardous zone classifications and related design and installation requirements. Pre-application outreach, public engagement, stakeholder buy in.

HTEC successfully designed and built a H2 station in Woodside, California and has successfully garnered building permits and BCSA approval for the first public hydrogen fuelling station to be built in BC, sited in the city of Vancouver. HTEC has installed, or participated in installing private stations in BC, which went through the same approval process as the public station, with the AHJ being the BCSA.

Key elements of success were finding the right site. For the public station in California HTEC analysed over 50 different site locations around San Francisco and engaged with specific station owners at good potential sites.

A good site is one that is situated close to early adopter neighbourhoods and close to major routes. The site has to have enough space to put an H2 station and separated H2 dispenser without complicated underground piping and without significantly affecting current traffic flows in area. Typically, it would require between 85-135 m^2 depending on the H2 production and onsite storage. The site has to have enough space for the manoeuvrability of a class 8 truck and trailer, which is similar to current gasoline delivery trucks. Since the compressors can generate noise a station should not be located in a very quiet neighbourhood. Compressor noises from a station located next to a relatively busy street would hardly be noticeable. The site should ideally already have high voltage supply onsite (600VAC).

In order to facilitate a successful approval early engagement and education of the property owner, particularly around the technology, the opportunities and the risks is important. The property owner will be called on throughout the application and construction process, so it is critical that they are fully educated to avoid costly changes or retraction of their commitment to the project.

Engagement with the fire department to provide first responder training, and local neighbours, educating them on the technology, the applicable codes, and how a proposed station will meet those codes will impart confidence and stave off any uninformed resistance during any public hearings.

Early engagement with the local municipality to understand concerns and local public hearings on site with vehicles, responding to public queries face to face meetings are all effective tools to facilitate a smooth permitting process.

HTEC are the only experts in BC in designing and building high pressure hydrogen systems, especially filling stations. HTEC is well positioned to would work with the local municipality, fire department, and the BCSA to get the approval of the building permit, and HTEC can work with the contractors to facilitate trade specific permits and ensure problem free construction and commissioning.

4. Infrastructure – OEM requirements and station components

In order to ensure complete compatibility between hydrogen vehicles and fuelling stations a set of protocols and equipment standards have been developed. These protocols and standards ensure problem free fuelling at any station build in North America. Stations that conform to these standards and protocols can reliably sell hydrogen fuel to for any hydrogen vehicle built by North American OEMs.

a. OEM Requirements

Published standard protocols and standards that relate to hydrogen fueling have been adopted by OEMs and most jurisdictions in order to ensure safety. The OEMs require rigorous validation testing of new hydrogen stations against the standards before they will allow their vehicles to be filled by customers. These protocols and standards are discussed here.

The Society of Automotive Engineers (SAE) International J2601:2014 – Fueling Protocols for Light Duty Gaseous Hydrogen Surface Vehicles sets out the filling rate and target pressure of the vehicle based on a number of input conditions such as vehicle temperature, ambient temperature, pressure and tank size. The protocol specifies a maximum hydrogen temperature of the hydrogen gas leaving the station. This standard also establishes under what conditions a fill must fall back to a more conservative fill case, and ultimately when a fill must be aborted. The outcome of the standard is to limit the maximum temperature of the hydrogen in the vehicle at the end of the fill. The act of filling a vehicle causes the hydrogen to warm up, and the Type 4 tanks used on FCEV have a maximum working temperature of 85C. This standard was developed to ensure that this temperature would never be exceeded under all conditions.

SAEs J2799:2014 - Communication Protocol establishes how the vehicle communicates critical information to the station, and is an integral part of J2601. There is provision within J2601 to fill a vehicle without this communication, but it is at a substantially reduced rate as a conservative alternative.

SAE J2600:2012 - Nozzle Geometry or ISO 14687 establishes the physical hydrogen interface between the vehicle and station to ensure a proper fit of the nozzle and the vehicle receptacle.

Hydrogen dispensed at the station shall meet the requirements in the SAE J2719: 2011, “Hydrogen Fuel Quality for Fuel Cell Vehicles”. This standard establishes the purity requirements for fuel cell grade hydrogen for use in FCEVs. The OEM’s will require a Quality

Control Plan to be implemented as part of the ongoing verification of compliance to J2719. Stations must undergo and pass the hydrogen purity test to become considered to be operational, and must undergo testing every 6 months. Station must also be tested if hydrogen lines are potentially exposed to contamination due to maintenance or other activity.

Under NFPA 2, hydrogen stations are required to conduct an initial leak check with the vehicle and 1-2 mid-fill checks depending on the starting pressure of the vehicle. While NFPA 2 is not legislated in BC, it is generally accepted as the best practice.

Under NFPA 2, hydrogen stations are required include a pressure reliving valve which conforms to ASME B31.3 and CGA S-1.3 located as close to the vehicle as possible. This is typically positioned inside the dispenser housing. While NFPA 2 is not legislated in BC, it is generally accepted as the best practice.

Hydrogen Vent Systems - CGA 5.5 and API 521 outline requirements for the design and installation of hydrogen vent systems. These are the requirements under both NFPA 2 and BNQ CHIC.

b. Station components

Hydrogen stations will have different designs depending on how the hydrogen is produced, delivered, and where the station is located. Hydrogen stations may be integrated into an existing fueling station, such as a gasoline or compressed natural gas station, or constructed as a stand-alone project. Every hydrogen station includes, at minimum:

i. Hydrogen storage tank(s)

At a fuelling station, hydrogen is stored on site in a storage tank. Different tanks exist to accommodate cryogenic liquid hydrogen, and low- and high-pressure compressed gaseous hydrogen. Storage tanks are constructed from hydrogen-safe materials and contain several pressure relief and safe-venting mechanisms. While all stations will have medium and high-pressure storage tanks, the hydrogen supply method will dictate the bulk storage tank design (cryogenic, low or medium pressure gaseous). Most stations in North America utilise gaseous delivery due to the proximity of liquid hydrogen facilities.

ii. Compressor

Hydrogen flows from the storage tank to the compressor, which reduces the volume and increases the pressure, preparing the hydrogen for fuelling. Compressors also contain real-time monitoring controls and pressure relief systems.

iii. Chiller

After leaving the compressor, hydrogen typically enters a closed-loop cooling system to chill the molecules prior to dispensing. The chiller enables high-pressure, fast fills. The SAE J2601 standard requires the hydrogen to be delivered (when possible, for maximum transfer rate) at -

37C. This results in a fairly large cooling load to be handled by the station. Alternatively, the station may choose to cool a warmer temperature (with a slower filling rate). The old J2601 standard allowed for very slow fills at ambient conditions, but this now requires special approval from the OEM's as it is not currently part of the current version of J2601.

iv. Dispenser

Modern hydrogen dispensers are very similar to typical gasoline, diesel or CNG dispensers. Dispensing equipment can sometimes be placed under the canopy at an existing fueling station, but some station agreements do not allow alternative fuels to be co-located under the branded canopy. Some stations have hydrogen dispensers on the same island as other dispensers; other stations have hydrogen dispensers on their own island under the fueling canopy, just outside of canopy or on a separate section of property. This typically comes down to the site owner's preference.

- The station shall meet the requirements of SAE J2601:2014 "Fuelling Protocols for Light Duty Gaseous Hydrogen Surface Vehicles.
- Applicant should describe how they will demonstrate to the OEMs that they meet all performance and safety requirements.
- Station communications available for H70 fuelling according to SAE J2799

c. Hydrogen fuelling station maintenance considerations

General principles of routine preventative maintenance shall be applied, each component will require specific maintenance considerations and those need to be included in a comprehensive maintenance program. Information should be obtained from the equipment supplier to establish recommended practice for each item of the plant. The station developer should establish the overall maintenance program to be implemented once the station is operational.

Specific considerations for hydrogen fuelling station will include:

- Weekly on-site visual inspections
- Daily remote inspections via system monitoring and onsite security cameras
- Routine leak detection (monthly), such as bubble tests, at connections along the hydrogen supply infrastructure
- Routine calibration of hydrogen sensing equipment (every 3 months)
- Routine calibration of heat sensing equipment (every 3 months)
- Routine calibration of process sensors (annually) (pressure, flow, temperature, etc.)
- Periodic pressure tests of the pressurized systems
- Typical station control systems will run daily diagnostic pressure integrity test.
- Hydrogen compressor maintenance (annually).
- Coolant system inspection of level, temperature, and circulation loop integrity (monthly).
- Periodic third-party hydrogen quality sampling to ensure SAE standard compliance.
- Maintenance of hazardous zone compliance in terms of site cleanliness and proper storage of combustible materials

- Periodic manual safety system tests, including triggering hydrogen and flame sensors and e-stop push buttons (every 6 months)
- Safety relief device inspection and recertification (every 3 years)

Prior to station start-up a comprehensive maintenance program and supporting documentation should be in place.

Appendix A

Typical Safety Questions and Answers:

How safe is venting hydrogen? Venting hydrogen is safe. Vented hydrogen does not directly pose a threat to humans as it is neither toxic nor carcinogenic. However, it can lead to a fire, explosion or excessive noise so it is vented through vent stacks high above people and equipment. Once in the atmosphere, the vented hydrogen disperses and rises very rapidly thus further reducing any potential issues.

Is hydrogen safe to breathe in? Hydrogen should not be inhaled due to its fuel properties. In the event of inhalation or contact, hydrogen is neither toxic nor carcinogenic.

Does hydrogen have an odour like Natural Gas? Hydrogen does not have an odour. It is noted that pure natural gas does not have an odour. A sulphur smelling additive causes the odour of natural gas smelt by the public.

Is hydrogen flammable and could there be an explosion? Hydrogen is flammable and can lead to an explosion in a similar way as gasoline and diesel. All fuels need to be used and handled properly to ensure safety. Hydrogen stations have numerous safety systems including fire sensors, hydrogen sensors, non-sparking electrical systems, and specifically designed vent systems to ensure safety.

Is hydrogen more or less flammable than typical fuels? The flammability of hydrogen is very similar to gasoline and natural gas however ignition and burning characteristics are slightly different. Both gasoline and diesel will ignite if a flame or spark is applied to a mixture of less than 1.5% in air, hydrogen needs to be in a mixture of at least 4% in air to ignite. Due to the lightness of hydrogen compared to air, hydrogen will disperse rapidly in an open area which means hydrogen will not pool like the fumes of other fuel sources. . Although hydrogen has a lower energy density, it can be ignited with a smaller amount of energy, therefore the potential dangers of hydrogen are similar to incumbent fuels. All need to be treated as flammable.

Can my kids still play outside during venting/deliveries? Yes, no problems at all, the process and systems are designed to be safe with multiple fail-safe features.

What are the risks for neighbors (especially those that live nearby) and customers visiting the site? The addition of hydrogen fuel to an existing fueling station does not increase the risk to neighbors or drivers, or general public. The quantity of hydrogen fuel at the site is far less than what is contained in gasoline, diesel or propane tanks at a typical station. Hydrogen is delivered in fully contained systems such that any venting is directed away safely. Customers will not be exposed to hydrogen fuel in the way they are to gasoline or diesel while using filling nozzles.

What are we doing to ensure the safety of the community and customers/site staff?
Emergency response programs will be created that integrate with existing site procedures as well as coordinating with first responders and fire fighters to make sure they are aware that hydrogen is on site and how to handle it in the event of emergency. Special site signage is also added to help improve safety.

Appendix B

As more FCEVs take the road and the hydrogen station network expands, mobile refuelers will be able to provide additional capacity in the case of station repair, or other unforeseen needs. With a hydrogen compressor, storage and dispenser on-board, mobile refuelers have capability to travel to designated locations and fill vehicles.

Mobile refuelers require specific approvals. Tanks on the mobile refueler will need to meet U.S. Department of Transportation (DOT) standards for moving flammable gases, either as pre-approved DOT tanks or special permit tanks. (The primary relevant regulation is 49 CFR 173.301.)67,68

The Compressed Gas Association TB25 “Design Considerations for Tube Trailers,” which has been incorporated by reference into 49 CFR 173.01, offers a solid starting point for planning to comply with DOT regulations. It should be used for performing analysis or performance testing. For composite tanks commonly used to store hydrogen, DOT standards require a full range of testing to verify integrity. Prior to testing, it is recommended that manufacturers of mobile refuelers contact the Pipeline and Hazardous Materials Safety Administration (PHMSA) at DOT to ensure tests and methods meet all requirements.

The California Fire Code and International Fire Code do not contain guidance on mobile fueling, but, depending on the site, there is information on mobile refueling in NFPA 2. Manufacturers of mobile refuelers should review NFPA 2 to ensure project compliance.