Government of Canada Gouvernement du Canada

Open and Common Approaches for Evaluating Marginal Emission Factors: A Case Study of the Alberta Electric Grid

Prepared by:

Vahid Raissi Dehkordi, Indrajit Das, Véronique Delisle, Sophie Pelland

CanmetENERGY – Varennes

Matthew Hansen, Mantaj Hundal

Canadian Energy Regulator

Farid Bensebaa

National Research Council

Present to:

Energy Modelling Initiative

March 19, 2021

Canada

Abstract

Future energy scenarios for the electricity sector must include reliable emission factors at the very time the energy is consumed to account for changes in load and generation. This report compares the hourly marginal emission factors (MEFs) estimated for the province of Alberta for the year 2018 using two different approaches: a multiple linear regression model (MLR) and the Canadian Energy Regulator (CER) Energy Futures model. The models are evaluated by comparing their results for the fraction of the time that different generator types are marginal on an annual basis to data provided by the Alberta Electric System Operator (AESO). Results from the CER model are much closer to those of the AESO than those of the simpler MLR model, which significantly underestimates the fraction of time that coal generators are marginal, and significantly overestimates the fraction of time that gas and hydroelectric generators are marginal. In line with this, the MEF predictions from the two models are quite different: the annual average MEF predicted by the MLR model is 693 kg of CO_2/MWh whereas the CER model estimates this value at 842 kg of CO_2/MWh. Average MEFs are computed for each model by month and hour of the day to examine systematic patterns that could be used for instance to schedule loads such as electric vehicle charging. Again, the two models give significantly different results: there is much less variability across months and hours with the MLR model as the standard deviation is of only 4 kg of CO_2/MWh compared to 126 kg of CO_2/MWh for the CER model.

Résumé

Les scénarios énergétiques futurs pour le secteur de l'électricité doivent inclure des facteurs d'émission fiables au moment même où l'énergie est consommée pour tenir compte des changements dans la demande et la production. Ce rapport compare les facteurs d'émission marginaux (FEM) horaires estimés pour la province de l'Alberta pour l'année 2018 à l'aide de deux approches différentes : un modèle de régression linéaire multiple (MLR) et le modèle Energy Futures de la Régie de l'énergie du Canada (REC). Les modèles sont évalués en comparant leurs résultats pour la fraction du temps où les différents types de générateurs sont marginaux sur une base annuelle aux données fournies par l'Alberta Electric System Operator (AESO). Les résultats du modèle REC sont beaucoup plus proches de ceux de l'AESO que ceux du modèle plus simple MLR, qui sous-estime considérablement la fraction de temps pendant laquelle les générateurs au charbon sont marginaux, et surestime considérablement la fraction de temps pendant laquelle les générateurs au gaz et hydroélectriques sont marginaux. Dans le même ordre d'idées, les prévisions de FEM des deux modèles sont très différentes : le FEM moyen sur une base annuelle prévu par le modèle MLR est de 693 kg de CO_2/MWh alors que le modèle REC estime cette valeur à 842 kg de CO_2/MWh. Les FEMs moyens sont calculés pour chaque modèle par mois et par heure de la journée afin d'examiner les tendances systématiques qui pourraient être utilisées, par exemple, pour programmer des charges telles que la recharge des véhicules électriques. Encore une fois, les deux modèles donnent des résultats très différents : il y a beaucoup moins de variabilité parmi les données par mois et par heure de la journée avec le modèle MLR, puisque l'écart type n'est que de 4 kg de CO_2/MWh, contre 126 kg de CO_2/MWh pour le modèle REC.

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1. Introduction

Developing sound policies for energy planning requires a clear science-based demonstration of the environmental impact that may ensue. Electricity represents 10% of Canada's greenhouse gas (GHG) emissions even if more than 80% of electricity in Canada comes from non-GHG emitting sources [1]. Whereas baseload production is relatively clean overall, the imbedded carbon intensity still varies depending on location, time of day and day of year. Thus, future energy scenarios for the electricity sector must include reliable emission factors at the very time the energy is consumed to account for changes in load (e.g. from electric vehicle (EV) charging) and generation. Most of the models that can carry these studies are either proprietary or incomplete and the data to run the simulation or train the models are often unavailable to the research community.

Emission factors for electricity generation in Canadian provinces are generally provided as annual averages. Average emission factors is one type of metric that can be used for strategic assessments such as climate change policy comparisons. However, when for example assessing the impact of specific technologies, alternative metrics may be considered to quantify GHG emissions. One of these metrics is marginal emission factors (MEFs) that provide the emissions impact resulting from an incremental unit of electricity demand, such as an electric vehicle. In the last few years, different approaches have been developed to quantify hourly MEFs. Unfortunately, there have been few attempts at comparing these different approaches particularly in the Canadian context where the electricity market is segmented across provincial utilities. This project conducts a review of models to calculate hourly MEFs and a comparison of two approaches using a specific province as a case study. This report focuses on the Alberta electric grid as a case study.

Alberta's electric system represents an interesting case study for a variety of reasons. First, data is available on the hourly electric generation of each generator from the Alberta Electric System Operator (AESO). Second, Alberta has an increasingly diverse grid containing renewables, coal, and natural gas generation which is flexible to various degrees (Figure 1). This creates the possibility that the MEFs and average emission factors (AEFs) could be significantly different. Finally, while Alberta does have interties with neighbouring regions, these represent a fairly small share of electricity generation in the province. Therefore, the comparisons across estimation techniques should not be especially biased by how detailed they are with respect to coverage of neighbouring regions.

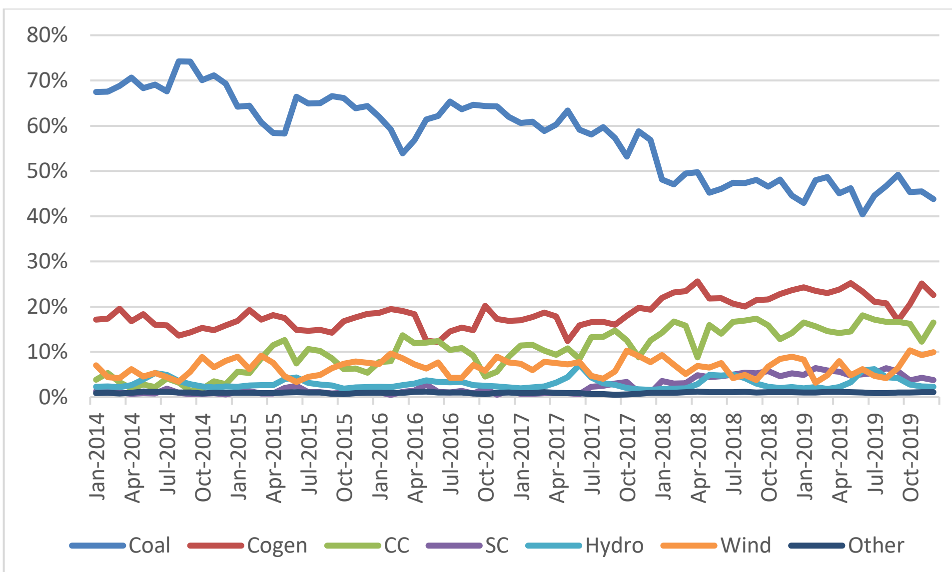

Figure 1: Share of Energy Production by Generation Technology, Alberta, 2014-2019 [2]

The objectives of this study are to:

- Build a "fair" approach (including common inputs/outputs and comparison metrics) to compare the different MEF calculation models

- Identify data required to estimate reliable hourly MEFs
- Investigate methods to fill data gaps and model gaps
- Compare approaches (specific to the requirements – e.g. small vs big incremental load) for calculating hourly MEFs

At first, a literature review of MEF calculation methods was performed to identify the approaches to pursue. This was followed by defining the modelling framework required for selected approaches, e.g. inputs and comparison metrics. Once the framework was defined, the data required for selected modelling approaches was collected. The hourly MEFs were then modelled, evaluated and compared using different approaches for the Alberta electric grid.

2. Literature Review

Electricity greenhouse gas emission factors indicate how much carbon would be emitted or saved by changing electricity usage in terms of kg of carbon dioxide emissions per MWh of power usage (kg of CO_2/MWh). Emissions taken into account are associated with power generators and transmission/distribution losses. Two types of greenhouse gas emission factors are commonly used for such assessment:

- Average Emission Factor (AEF) which is defined as the ratio of CO_2 emitted to electricity generated. It represents the average kg of CO_2/MWh of electricity consumed at the point of final consumption.
- Marginal Emission Factor (MEF) which is defined as the incremental change in carbon dioxide emissions as a result of an increase in demand.

A variety of public and commercial assessment tools have been used to calculate emissions from electricity usage. They range in complexity from simple emission factors to multifaceted grid models with market-based dispatch of generation assets. Some articles provide a comprehensive comparison of various methods to give a general overview of the techniques available and the impact of model selection. Thirty-two methods and models are identified and reviewed in [3]. The methods and models are then classified into two distinct categories: i) empirical data and relationship models, including eGRID and AVERT which use historical data and are not necessarily adapted to predict future emissions, and ii) power system optimization models to address economic dispatch, unit commitment and capacity planning for long-term changes.

Relationship models: Development of empirical data and relationship models has been showcased and discussed in numerous publications. In [4], the output of each generator, system load and picture of the future generation mix are used to calculate hourly and monthly MEFs using a linear regression model. Regression techniques are used in [5] to compute MEFs and to determine the marginal generator type using changes in emission and generation. A statistical method is introduced in [6] to determine capacity factors for each generator type depending on the load, decide on the dispatch and compute the emissions, having a large penetration of EVs in mind. In [7], a relationship model is developed between emissions and consumption using a least square technique. Also, regression coefficients are calculated for individual regions in a state in order to compute MEFs by location in the same market zone. The AVERT tool [8] implements a statistical approach using emission, generation and load data to calculate MEFs. The methodology is based on Monte Carlo analysis and includes computation of the frequency of operations for fossil-fuel generators. The focus of the analysis in [9] is the greater Toronto and Hamilton area in Ontario where hourly MEFs are calculated using multiple linear regression models. Also, GHG emissions associated with EV charging are estimated at two penetration rates (5% and 30%) using five charging scenarios: home, work and shopping, night, downtown versus suburbs and an optimal low-emission charging scenario, matching charging time with the lowest available MEFs. A machine learning approach is used in [10] which employs support vector machine regression to estimate marginal emissions with load and wind data among inputs. Marginal emissions are also calculated by linking local marginal prices to the generation type on the margin and associating an emission factor to each generator type [11][12].

Power system optimization models: the use of power system optimization models is attested in [13] with the simulation of the entire electricity system using PROMIX, with different demand possibilities to evaluate the impact of demand changes. PLEXOS market model software is used in [14] to model the grid and to do a case study on the impacts of EV charging (with charging scenarios). The TIMES modelling environment is employed in [15] to report the account of structural and operational effects in electricity systems on the calculation of MEFs in the long-run. The above works are followed by a unit commitment model for New York State with scenarios of change in electricity grid up to 2025 [16] and a model of the California electricity grid capable of differentiating hourly and seasonal GHG emissions by generation source incorporating the potential use of different types of plug-in hybrid electric vehicles [17]. The Electricity Dispatch model for Greenhouse gas Emissions in California (EDGE-CA) is introduced in [18] where it simulates near-term electricity supply on an hourly basis in order to estimate emissions from marginal generation for vehicle and fuel demands. As a spreadsheet-based accounting tool, it determines the capacity and allocates generation among available power plants to meet demand in three regions of California, including imported power from out of state. Simulation of the operation of national energy systems in Denmark is showcased in [19] on an hourly basis using a user-friendly interface and including the electricity, heating, cooling, industry, and transport sectors. Finally, Integrated Planning Model (IPM) of the electric power sector is presented in [20] which is designed to help government and industry analyze a wide range of issues such as economic activities in key components of energy markets. The applications of IPM include capacity planning, environmental policy analysis and compliance planning, wholesale price forecasting and asset valuation. It also captures the linkages in electricity markets which leads to integrated analysis of the impacts of alternative regulatory policies on the power sector.

Electric vehicles: As the usage of EVs increases, calculation of emissions related to these vehicles – both conception and operation – becomes a topic of interest for case studies. The emissions of EVs across their whole life cycle are addressed in [21] while the computation of the EV footprint with marginal emission factors for the USA electricity system is discussed in [22]. The computation and comparison take into account marginal grid mix, ambient temperature, patterns of vehicle miles travelled and driving conditions. The method described in [23] uses short run marginal cost curves and a dispatch merit order strategy to compute the emissions factor and apply it to the EVs. Finally, studies covering the longer-term planning of EV incorporation include [24] where long-term effects of large penetration rate of EVs are modelled using MEFs determined by a dispatch algorithm.

The above literature review briefly shows the vast scope of work already done or in progress regarding the evaluation of GHG emissions. Different models focus on certain elements which are often region-specific such as current energy policies, generation mix and power systems, EV market penetration and so on. It is important to have the right values regarding the emissions as understanding and quantifying the impact of GHG emissions is a key element for electrification studies. To do this, the present study provides a comparison of different models developed and used in Canadian institutes, as the first step in building a consensus for generating this type of information required for decarbonisation and electrification studies within the Canadian context.

3. Model and Methodology

Two models were selected for the comparison and are described in the following sub-sections:

- A multiple linear regression model
- The Canadian Energy Regulator (CER) Energy Futures model

These models were run for the year 2018 for the Alberta grid and compared based on their predicted average hourly marginal emission factors for each month of the year and hour of the day. No actual data on hourly marginal and/or average emission factors for the Alberta grid are available making the validation of the models challenging. The AESO does provide, however, the fraction of time different generator types are on the margin on an annual basis as well as the fraction of total generation provided by different generator types. These two metrics were therefore used as the primary means of evaluating the different models when possible, i.e. when the model provided outputs that allowed calculating these metrics.

3.1. Multiple Linear Regression (MLR) Model

The multiple linear regression model of marginal greenhouse gas emission factors is based on the work of [9] at the University of Toronto. In this model, MEFs depend both on the total generation level G and on the change in total generation from one hour to the next (*ΔG*), as follows:

$$\Delta E = \overbrace{(\beta_1 + \beta_2 G + \beta_3 \Delta G)}^{MEF} \Delta G + \beta_0 \tag{1}$$

where *ΔE* is the change in total GHG emissions from one hour to the next and the expression in parentheses (red font) is the marginal emission factor for a given hour.

(This expression corresponds to MLR2 in the terminology of [9], but with the addition of the constant term β_0.)

In the same vein, this model was extended in [25] to provide the fraction of time (γ_k) that each generator type is marginal, via the following equations:

$$\Delta G_k = \overbrace{\left(\in_{1,k} + \in_{2,k} G + \in_{3,k} \Delta G\right)}^{\gamma_k} \Delta G + \in_{0,k} \quad (2)$$

where k corresponds to the generator type (e.g. coal, gas, hydro, wind) and ΔG_k is the change in generation levels for generators of type k from one hour to the next.

Prior to fitting this model, the hourly generator output data were filtered to remove generators that could not be marginal for each hour. Only coal, gas and hydro generators were considered as potentially marginal based on AESO annual market statistics data [2]. In addition, generators were excluded from the marginal generation pool for a given hour when their change in generation was of opposite sign to the change in the total generation. After data filtering, the coefficients of the model ($\beta_0, \beta_1, \beta_2, \beta_3, \in_{0,k}, \in_{1,k}, \in_{2,k}, \in_{3,k}$) were obtained by fitting the model to hourly AESO data for all of 2018.

[25] evaluated different versions of simple linear regression, multiple linear regression and artificial neural network models using data from Ontario (IESO) and Alberta (AESO), and found that the multiple linear regression model in equation (1) performed well overall in terms of predicting changes in emissions from one hour to the next [25]. However, one limitation of this model is that it is trained on historical data. As such, it remains valid only to the extent that the generation fleet remains sufficiently similar to what it was during the period used for model training.

3.2. CER Model

The Canada Energy Regulator (CER) approach uses components of its Energy Futures Modeling System (EFMS) to analyze marginal generation sources. The EFMS is a collection of models and modules that are soft and/or hard linked in order to produce CER Energy Futures scenarios. For this analysis, we focus on the electricity sector, where the EFMS utilizes Python for Power System Analysis (PyPSA), an open-source power flow optimization model, to complement the electricity analysis in the EFMS's core energy system model, ENERGY2020. An overview of the EFMS and integration with PyPSA is found in [26].

PyPSA is included in the EFMS to add additional granularity, particularly greater temporal resolution, for electricity modelling. This section provides a brief overview of PyPSA. Full documentation of PyPSA is available from its website. The objective function for the optimization is comprised of total capital and generating costs for each network component and generator. Several constraints are added to generators. Minimum and maximum generation constraints for each hour along with hour-to-hour ramping constraints are added for certain technology groups. For example, the maximum hourly generation for wind and solar is determined by the site level historical wind speed and solar irradiance data. Similarly, minimum and maximum generating constraints on hydroelectricity are incorporated, based on seasonal availability. Ramping constraints are also imposed based on technology operating characteristics. For example, coal plants and nuclear reactors cannot rapidly ramp their generation up or down, while technologies like simple cycle gas turbines can quickly change generation. These differences are reflected in the ramping constraints. On the demand side, future hourly demand is simulated using a combination of historical hourly load factors and ENERGY2020's forecasted peak demand. The historical load factors are scaled up using the projected peak loads, which gives an hourly demand profile for the given year. All of the above discussed constraints and data are then fed into PyPSA to create the optimal generation profile for each province and forecast year.

The use of PyPSA is guided by the overall goal of the EFMS, which is to produce long-term scenarios. In the EFMS, PyPSA provides important insights on how the electricity system could operate at an hourly level, which is important for assessing factors such as variable renewable generation and battery storage. While PyPSA can be utilized to include more granular data (such as generators by unit or facility, or sub-hour time intervals), the focus is on broad technology groupings (wind, solar, combined cycle natural gas, simple cycle natural gas, etc.) and an hourly time interval. Because PyPSA integrates with broader energy system modelling, this level of detail provides a trade-off between realism and tractability for long-term scenario analysis.

For each time slice, the model outputs generation and a location-specific marginal price. The marginal fuel type is inferred based on the marginal price for each time slice. Emissions for each hour are computed by multiplying each fuel type's generation by the corresponding emission factor assumption for that fuel and level of output. The average emissions factor is computed by dividing the sum of emissions for each hour by the sum of generation. The marginal emissions factor is equal to the emissions output of the marginal fuel type divided by its generation.

4. Data Sources

The models discussed in Section 3 use different sets of input data which include both common and model-specific items. Sometimes, the input data are processed before being used in a model. Also, it is possible that some input data are used to further process the output of a certain model in order to evaluate a common metric. Table 1 summarizes the input data and associated sources.

This analysis focuses on the year 2018, meaning that most of the input data used by the models are recorded in 2018 except some technical information which may not need to be updated every year such as heat rate curves or operational information of different types of generators.

Note that both models consider Alberta as one zone so information such as transmission constraints and costs (intra-provincial congestion) as well as the generation and transmission network architecture are not required.

Table 1: Sources for the inputs of the different models

<table>
<tr><th rowspan="2">Input</th><th colspan="2">Data Source</th></tr>
<tr><th>MLR Model</th><th>CER Model</th></tr>
<tr><td>Hourly marginal electricity prices</td><td colspan="2">AESO[29]</td></tr>
<tr><td>Hourly imports from all interties</td><td>AESO[30]</td><td></td></tr>
<tr><td>Type of generator</td><td colspan="2">AESO[30]</td></tr>
<tr><td>Heat rate curves by type of coal/gas generator (all generators)</td><td>Literature[27][28]*</td><td>AESO[30]+ Literature[27][28]*</td></tr>
<tr><td>CO_2 emissions per unit fuel consumption</td><td colspan="2">U.S. Energy Information Administration (EIA)[31]</td></tr>
<tr><td>British Columbia average annual emission factor</td><td rowspan="2">National Inventory Report (NIR)[32]</td><td rowspan="2"></td></tr>
<tr><td>Saskatchewan average annual emission factor</td></tr>
<tr><td>Montana intertie average annual emission factor</td><td>EIA[33]</td><td></td></tr>
</table>

Input	Data Source	
	MLR Model	**CER Model**
Hourly output of all generators in Alberta	*AESO*[30]	
Hourly load*		*AESO*[30]
Operational information of each type of generator (e.g. ramp, start-up cost)**		*Literature*[34]
Renewable energy availability forecast		*AESO*[30]

* The heat rate curves for coal, natural gas combined cycle, and natural gas steam generators were first estimated by taking their respective curves in [27] and scaling such that their full-load heat rate values matched those provided by the EIA [28]. They were then modelled by fitting a quadratic to the resulting curves (the quadratic providing a best fit). The search for a heat-rate curve for natural gas simple-cycle generators was inconclusive; thus, a flat (constant) heat rate was used, corresponding to its full-load heat rate in [28].

** Hourly constraints for ramp limits and minimum/maximum output are expressed as percentages of the total capacity for the entire generation fleet, based on AESO's unit generation data. There are no constraints for shut down and start-up costs or ramps.

5. Results and Analysis

In this section, the results of the two models are discussed and compared with the data from AESO. The AESO provides the fraction of time that each generator type is marginal on an annual basis [2]. This information can be used to validate how well both models capture marginal generation. As shown in Table 2, the results of the CER model are much closer to the data from AESO than those of the MLR model, which significantly underestimates the fraction of time that coal is on the margin and overestimates the fraction of time that hydroelectric and gas generators are on the margin.

Regarding the fraction of total generation provided by each generator type, as shown in Table 3, CER model calculations are again very close to those reported by AESO. Note that the CER model was run without taking interties into account, so it naturally neglects their contribution. There are no results reported for the MLR model since it considers the generation information as a model input.

Figure 2 shows a heat map of average MEFs by hour and month for the two models (in kg of CO2/MWh) and Table 4 summarizes key statistics of these data. The average MEF heat map may serve as a guide to decide when the best time is to add a marginal load, e.g. EV charging load, to the system so that the emissions are the least. As can be seen from Figure 2, the MEFs from the MLR model have very low variability compared to those of the CER model, with MEFs from the MLR model being relatively insensitive to month and time of day. The CER model shows roughly the same hourly pattern across all months, with the lowest MEFs occurring in the morning (roughly 5:00-8:00) and afternoon (roughly 12:00-15:00). Meanwhile, the MLR model predicts lower emissions in the late evening to early morning, but the pattern is much less pronounced than for the CER model so not as apparent in the heat map. Given the better agreement between the CER model and the available AESO data, it seems plausible that its hourly MEF pattern is closer to the reality, but this cannot be directly validated at this stage.

Table 2: Fraction of time different generator types are on the margin

Generator Type	MLR Model	CER Model	AESO[2]
Coal	*57%*	*73%*	*79%*
Gas	*35%*	*27%*	*18%*
Hydroelectric	*9%*	*0%*	*1%*
Wind	*0%*	*0%*	*0%*
Other	*0%*	*0%*	*1%*

Table 3: Fraction of total generation provided by different generator types

Generator Type	MLR Model	CER Model	AESO[2]
Coal		*47%*	*45%*
Gas		*43%*	*40%*
Hydroelectric		*3%*	*3%*
Wind		*7%*	*6%*
Imports			*5%*
Other		*0%*	*1%*

Table 4: Statistical properties of the distribution of MEFs (kg of CO_2/MWh) in Figure 2

Parameter	MLR Model	CER Model
Minimum	*681*	*482*
Maximum	*701*	*999*
Average	*693*	*842*
Median	*693*	*886*
Standard Deviation	*4*	*126*

MLR Model

Hour \ Month	1	2	3	4	5	6	7	8	9	10	11	12	Average
1	690	688	688	684	681	683	686	687	687	689	690	692	687
2	690	689	688	685	683	684	688	688	687	690	691	692	688
3	690	689	689	685	683	684	688	688	688	690	691	693	688
4	691	690	689	686	683	684	687	689	688	690	692	694	689
5	692	692	691	687	684	685	689	689	689	691	693	695	690
6	694	694	693	689	685	686	689	692	691	693	695	696	691
7	698	697	696	692	688	689	691	693	695	695	697	698	694
8	699	700	697	693	692	692	694	694	695	698	698	700	696
9	699	696	695	692	692	693	696	696	695	695	697	700	696
10	696	696	695	691	692	693	696	697	695	695	697	699	695
11	696	696	694	692	692	693	696	696	695	696	696	699	695
12	696	695	694	691	692	693	695	696	694	695	696	698	695
13	695	695	693	691	692	692	696	696	693	694	694	698	694
14	695	694	692	691	692	692	695	696	694	694	696	697	694
15	695	694	692	690	691	692	695	696	694	693	696	698	694
16	696	695	693	690	691	692	695	696	694	694	697	698	694
17	699	697	694	691	692	693	696	696	694	695	697	701	695
18	701	698	694	691	691	692	694	695	695	695	698	701	695
19	697	699	694	688	689	689	693	694	693	695	696	698	694
20	695	696	695	689	689	690	693	694	694	695	697	698	694
21	695	694	695	691	688	689	691	694	695	693	696	698	693
22	694	693	692	691	688	688	692	694	691	692	693	697	692
23	691	690	689	686	686	688	692	691	688	690	692	695	690
24	690	689	688	684	682	685	689	688	687	690	691	694	688
Average	695	694	693	689	688	689	692	693	692	693	695	697	693 (Annual average)

CER Model

Hour \ Month	1	2	3	4	5	6	7	8	9	10	11	12	Average
1	812	784	875	938	980	908	887	871	915	972	856	790	882
2	902	760	869	959	971	941	880	923	962	970	912	836	907
3	913	772	917	947	952	945	865	926	961	914	915	939	914
4	896	796	806	857	911	902	960	862	765	720	887	908	856
5	706	699	710	734	806	886	856	694	616	638	744	762	738
6	560	637	623	701	754	812	739	621	655	658	638	662	672
7	579	667	771	796	824	778	742	667	797	876	640	737	740
8	716	800	939	875	866	887	841	784	918	957	816	826	852
9	886	932	930	915	867	862	999	883	981	939	909	922	919
10	888	947	809	897	874	885	980	941	942	848	930	980	910
11	758	948	734	779	827	825	941	822	641	669	831	867	803
12	611	783	623	659	652	564	649	726	621	593	693	734	659
13	557	641	574	655	580	508	572	727	646	601	616	679	613
14	530	643	691	790	646	495	482	633	782	754	554	646	637
15	637	730	885	903	799	651	610	652	959	944	677	683	761
16	819	847	918	951	919	889	794	780	964	954	932	871	887
17	925	834	917	973	931	944	915	929	974	960	967	937	934
18	937	822	917	973	954	961	954	957	953	972	954	930	940
19	947	821	907	972	978	974	964	968	961	960	965	949	947
20	930	809	918	973	978	974	942	967	954	953	954	949	942
21	920	813	929	973	978	955	928	949	962	954	965	949	940
22	920	838	903	974	977	954	966	955	973	974	965	942	945
23	883	801	940	961	978	942	965	967	972	971	851	814	920
24	761	782	889	941	978	928	921	921	948	971	802	772	884
Average	791	788	833	879	874	849	848	839	868	863	832	837	842 (Annual average)

Figure 2: Average MEFs by hour and month for the two models (kg of CO_2/MWh)

Figure 3 shows heat maps of AEFs by hour and month from the CER model, and derived directly from AESO generator output data using the heat rate curves and CO2 content assumptions from Table 1. In both cases, the main variations occur across months rather than across hours, with lowest AEFs during the early summer (May and June) and highest AEFs during shoulder months (March and September). The variability of the AEF values in both cases is comparable and much lower than for the CER MEFs, as shown in Table 5.

Month

Hour	1	2	3	4	5	6	7	8	9	10	11	12	Average
1	649	633	676	632	591	609	663	671	695	681	679	671	654
2	646	627	672	629	588	604	667	670	698	684	678	669	653
3	645	624	671	628	589	600	670	672	703	684	675	671	653
4	643	624	671	627	591	597	671	673	706	685	676	672	653
5	647	624	673	627	590	597	671	672	705	685	679	672	654
6	650	624	673	628	588	601	669	673	705	681	675	672	654
7	660	626	681	635	587	608	670	676	704	675	672	665	655
8	659	629	682	631	588	607	660	665	692	660	658	655	649
9	668	636	683	640	600	619	667	670	688	658	662	656	654
10	669	640	683	638	604	624	672	678	689	656	663	658	656
11	663	647	682	644	602	628	668	676	689	662	665	658	657
12	661	646	679	648	608	631	664	673	686	663	666	659	657
13	661	650	681	652	615	629	665	673	683	659	665	659	658
14	657	649	678	653	618	627	661	670	679	658	666	659	656
15	654	651	675	650	618	623	660	666	679	653	667	659	655
16	652	649	674	649	617	621	655	663	679	651	668	656	653
17	650	648	671	647	618	620	656	664	677	651	660	651	651
18	652	647	670	646	618	615	652	661	680	652	656	652	650
19	654	651	669	643	618	608	653	663	682	652	659	650	650
20	652	650	669	640	615	607	648	663	684	652	664	649	650
21	654	647	673	640	611	609	644	665	684	649	666	650	649
22	656	647	677	643	603	610	646	666	691	660	669	653	652
23	650	639	674	637	596	606	652	664	691	664	672	654	650
24	650	636	676	636	600	614	665	668	699	674	681	661	655
Average	654	639	675	639	603	613	661	669	690	665	668	660	653

Derived from AESO — Annual average

Month

Hour	1	2	3	4	5	6	7	8	9	10	11	12	Average
1	638	664	651	620	604	597	621	625	627	620	634	638	628
2	637	664	650	617	601	590	612	621	628	620	632	634	626
3	634	665	654	618	597	587	605	618	628	617	629	629	623
4	631	663	656	619	590	585	602	614	629	617	624	625	621
5	626	661	652	610	580	576	601	609	622	610	616	621	615
6	617	655	646	601	576	574	600	603	615	602	607	613	609
7	606	647	636	590	565	566	594	593	605	592	601	610	600
8	597	642	630	582	561	558	585	582	597	587	593	606	593
9	592	636	626	578	559	556	583	575	595	584	583	599	589
10	590	632	626	580	561	556	582	576	598	587	579	597	589
11	593	629	632	585	563	562	585	579	607	596	582	599	593
12	605	631	639	593	569	571	592	586	619	606	590	605	601
13	617	636	646	600	577	581	603	597	625	612	599	614	609
14	624	638	652	604	581	587	608	599	624	611	604	618	612
15	627	642	658	614	597	601	622	613	629	619	608	618	621
16	639	651	660	618	599	606	631	627	634	623	617	625	627
17	642	654	661	622	597	612	637	632	637	628	620	628	631
18	641	659	662	626	601	612	639	636	636	629	624	626	633
19	642	662	663	627	605	612	641	634	632	626	625	628	633
20	641	667	662	628	606	609	638	633	630	623	626	628	633
21	640	667	660	625	607	604	636	631	630	618	627	627	631
22	636	667	657	625	607	603	633	630	631	616	629	627	630
23	635	668	656	626	608	602	632	630	630	619	630	628	630
24	636	667	654	624	608	600	630	626	632	620	633	631	630
Average	624	653	649	610	588	588	613	611	623	612	613	620	617

CER Model — Annual average

Figure 3: AEFs by hour and month estimated from AESO data and the CER model (kg of CO_2/MWh)

Table 5: Statistical properties of the distribution of AEFs (kg of CO_2/MWh) in Figure 3

Parameter	MLR Model	CER Model
Minimum	*587*	*556*
Maximum	*706*	*668*
Average	*653*	*617*
Median	*658*	*620*
Standard Deviation	*26*	*25*

6. Discussion

In this analysis, two approaches have been used to estimate marginal emission factors for Alberta in 2018. Each can provide useful policy-applicable insights on the dynamics of marginal emission factors in a given province for its grid at a given point in time. For example, if marginal emissions factors are typically lower during certain hours of the day, policies to encourage load shifting to those hours could realize some emission reductions.

With respect to future decarbonisation pathways, the MLR model differs from the CER model in that it is solely focusing on current/historical analysis. The CER model has the ability to provide outlooks for future years, and in fact, this is their most common use case. When similar MEF analysis is done for a future year for these models, it will be done by analyzing the marginal generator in that future electricity system, which could have significantly different characteristics compared to today in areas such as load, load shape, generation technology mix, or trade. In the context of deep decarbonisation pathway analysis, much of the attention and interest are on non-marginal changes, such as electrifying personal transportation or space heating, or decarbonising the electricity generation mix. Therefore, the estimated MEF in a future year represents a marginal change in that future energy system, not the change from current conditions to that future system, which could be large.

Both modelling techniques rely on detailed historical data for parameters such as load, generation, trade, and prices. Data availability is one of the key reasons we have focused on Alberta in this analysis. Availability of data is a critical component for similar analysis to be done for other regions. In some cases, simplifying assumptions could be made where data is not available (such as applying load shapes from a neighbouring or similar region), but could possibly undermine the accuracy and policy relevance of the analysis. Other regions may have unique characteristics that should be considered. For example, analysis such as [35] and [36] focus on jurisdictions with large hydro resources. In these studies, the operational characteristics of hydro facilities are particularly important.

There would definitely be benefits in integrating the different models presented in this report in a national modelling platform as these could be used for future projects of Canadian electricity systems. Their assumptions and limitations would have to be clearly stated, however, so these are not used beyond their capabilities. The main challenge would be in providing publicly available input data for all Canadian provinces and territories. Such data would be very valuable especially if sources are identifiable and estimations and assumptions are vetted by experts in the field.

7. Future Work

As an immediate next step, the comparison proposed in this report will be expanded to cover more provinces starting with Ontario as most of the input data required will be readily available from the Independent Electricity System Operator (IESO). Other models providing outputs that can be used to compute metrics such as average and marginal emission factors will also be investigated. This includes various open-source unit commitment and dispatch (UC&D) models such as the SILVER model developed by the University of Victoria in British Columbia and the E3 RESOLVE model. Unit Commitment and Dispatch approaches have several applications beyond marginal emission factors calculation. In addition, these models are critical to consider in the planning stage to ensure that solutions are feasible – especially given changes in load characteristics from electrification and increased adoption of variable renewables. In the context of larger planning exercises, it will feed into other power system models as well as other applications models, taking their output as input and vice versa.

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