



MGSC-662 DECISION ANALYTICS

Optimizing Emissions in Canada's Electricity Sector

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1 Introduction

Developing climate resilience is one of the most pressing mandates for the global community in the face of the climate crisis. Canada, as a signatory of the Paris Agreement, has committed to achieving net-zero greenhouse gas emissions by 2050, and to reducing its emissions by 40-45% from 2005 levels by 2030. These ambitious targets require significant transformations in various sectors of the economy, one of which is the electricity sector – the focus of this project.

Building on the work of the Canada Energy Regulator (CER), we sought to develop our own models to examine the implications of Canada’s commitments for its electricity sector. This is done firstly using a base model with a multi-objective mixed integer programming (MIP) approach, then through an additional model centred on a goal programming (GP) approach. The base model allows us to find an optimal solution satisfying our specified objectives and constraints, while the GP model enables us to explore the trade-offs and compromises among the objectives when they are conflicting or infeasible. Through the MIP formulation, we sketch out a roadmap of electricity generation and technology investment decisions to get as near as possible to Canada’s net-zero emissions targets for the sector – given exclusion of carbon sequestration from the model. This is done while considering mandates such as minimizing costs and ensuring reliable energy supply. Through the GP formulation, we assess the broader feasibility of emissions, energy generation, energy capacity, and capital cost goals over the same time period and subject to the same reliability mandates.

Our team chose to centre our project on this problem due to its inherent complexity and the critical role that untangling such problems plays in contemporary environmental and energy debates. Getting Canada’s electricity sector to zero emissions by 2035 presents a multifaceted dilemma balancing environmental, economic, and social factors. Problems like this elude straightforward understanding and greatly benefit from methods like data modeling for conceptualization. The resulting artifacts can be powerful tools for building shared understanding, and ideally, collective action.

The following report details the formulation and implementation of these models, their results and their implications, potential extensions, and lessons learned regarding both the potential and the practical limitations of linear optimization as a prescriptive analytics tool in complex and uncertain environments.

2 Problem Description and Formulation

2.1 Formulation Strategy

We begin with the MIP formulation. Here, we take a hierarchical approach to our objectives. Firstly, the model seeks the minimum deviation from Canada’s emissions targets for 2025, 2030, and 2035. This invokes the assumption that the urgency of the climate crisis is given priority at the expense of other objectives. Minimizing total cost to hit the targets, which includes both the per GWh cost of generation and the cost of investment in additional generation capacity, was chosen as the second objective. Given that investment decisions would transmit to public budgets, and general affordability of electricity would impact cost of living and of doing business in Canada, it lends itself as a very useful metric for examining the economic and political feasibility of the model’s proposed transition plan.

2.2 Parameters

Canada’s electricity sector has an emissions target of 34.98 MTCO₂e in 2025, 27.55 MTCO₂e in 2030 and -6.18 MTCO₂e in 2035 – which our model simplifies to zero. These are based on what the CER targeted for emissions from electricity in order to meet Canada’s overarching goal of having net-zero emissions by 2050 in a “Global Net-Zero” scenario. In such a scenario, Canada works towards its target while the rest

of the world also reduces emissions enough to limit global warming to 1.5 degrees Celsius. The broader impacts of this on Canada as a trading nation, for example on the cost of renewable technologies, are not explicitly modeled mathematically but embedded through data sources based on this scenario. This is the scenario the model assumes to be operating under overall. Refer to Appendix 1 for itemized model assumptions.

Let T denote the set of time periods under consideration.

$$T = \{2025, 2030, 2035\}$$

Let X_t denote the emissions target for time period $t \in T$.

$$X_{2025} = 35.19MTCO_2e, X_{2030} = 28.89MTCO_2e, X_{2035} = 0MTCO_2e$$

From CER analysis, we also derive the projected end-use electricity demand for each time period. Projected electricity demand would increase more rapidly than it has historically and more than projected under the current green transition measures. This is partly attributed to the enhanced role of electricity as an energy source in a net-zero energy system, which requires the electrification of devices that currently operate on fossil fuels. We incorporate this demand information into our model as follows:

Let D_t denote the electricity demand for time period $t \in T$. The demands for the respective years are given as follows:

$$D_{2025} = 611,806.94GWh, D_{2030} = 694,406.68GWh, D_{2035} = 787,841.11GWh$$

The electricity sources considered in the model are those currently in Canada's electricity portfolio: wind, solar, oil, nuclear, hydro, natural gas, coal, and geothermal. All source-specific data in the model are based on these.

Let G denote the set of energy sources considered in the model:

$$G = \{\text{Wind, Solar, Oil, Nuclear, Hydro, Natural Gas, Coal \& Coke, Biomass \& Geothermal}\}$$

Let $E_{g,t}$ denote the emission factor for energy source $g \in G$ in time period $t \in T$, measured in $MTCO_2e/GWh$. Refer to Appendix 2 for emission factors.

Let $C_{g,t}$ denote the cost for energy source $g \in G$ in time period $t \in T$, measured in CAD per GWh. Refer to Appendix 2 for the costs.

Increase_Cost_{g,t} : Cost associated with increasing the capacity for power generation technology g in time period t . Refer to Appendix 3 for the capital investment costs

The model begins with parameters for the maximum electricity in GWh that can be generated from each source in 2025. Following 2025, this generation cap changes based on investment decisions for additional capacity. These decisions are considered for the lowest emitting energy sources in step increments of one or two plants.

Let F_{2025} denote the fixed generation capacity for energy source $g \in G$ measured in GWh in 2025. Refer to Appendix 4 for the fixed generation capacity for each source

Let $\text{Capacity_Added}_{g,t}$ denote the capacity of an additional plant for source $g \in G$ in time period $t \in T$.

2.3 Decision Variables

The model decides on the optimal generation mix across available source capacity in each time period. For simplicity of modelling, the decisions are reflected as snapshots of the electricity portfolio at each checkpoint until the 2035 goal. The auxiliary emissions variable is introduced to capture the CO2 emissions from each source as a result of the generation decisions.

Let $\text{Emissions}_{g,t}$ denote the total emission per source in each time period $\forall g \in G, \forall t \in T$.

Let $\text{Gen}_{g,t}$ denote the total generation from source g in time period t , $\forall g \in G, \forall t \in T$.

The model similarly decides how much more CO2 than the target is deemed acceptable– given the problem parameters and constraints. This is captured by the deviation decision variables.

Let Dev_t denote the deviation from the emission goal in time period $t \quad \forall t \in T$.

We introduce binary variables for investment decisions in renewable technologies for 2030 and 2035. The auxiliary variable Capacity Increase links this decision to the resulting costs and capacity benefits. Note that in this formulation, “capacity increase” refers directly to an increase in possible generation output in GWh, rather than the industry definition of capacity as the maximum output of a generator at one time in MW.

Let $B_{g,t}^{(1)} \in 0, 1$ denote adding or not adding a plant $\forall g \in \text{Wind, Solar, Nuclear}, \forall t \in 2030, 2035$

Let $B_{g,t}^{(2)} \in 0, 1$ denote adding or not adding a second plant $\forall g \in \text{Wind, Solar, Nuclear}, \forall t \in 2030, 2035$

Let $I_{g,t}$ denote additional capacity in GWh $\forall g \in \{\text{Wind, Solar, Nuclear}\}, \forall t \in \{2030, 2035\}$

2.4 Objective Functions

The primary objective function minimizes deviations from emissions targets, while the secondary objective function minimizes the total cost associated.

The primary objective function is given by:

$$\min \sum_{t \in T} \text{Dev}_t$$

The secondary objective function is given by:

$$\min \text{Total_Cost} = \sum_{g \in G} \sum_{t \in T} C_{g,t} \cdot \text{Gen}_{g,t} + \sum_{g \in \{\text{Wind, Solar, Nuclear}\}} \sum_{t \in \{2030, 2035\}} (\text{Increase_Cost}_{g,t} \cdot B_{g,t}^{(1)} + \text{Increase_Cost}_{g,t} \cdot B_{g,t}^{(2)})$$

2.5 Constraints

2.5.1 Maximum Emissions and Energy Reliability Constraints

The model constrains generated emissions to the target plus the deviation, which is being minimized. This constraint is aided by the integrity constraint linking emissions to generation.

$$\sum_{g \in G} Emissions_{g,t} \leq Goal_t + Dev_t \quad \forall t \in T, \forall g \in G$$

$$Emissions_{g,t} = E_{g,t} \cdot Gen_{g,t} \quad \forall t \in T, \forall g \in G$$

We also assume that demand for electricity must be met in each time period. This is noted as a simplification of our base model, variations of which are explored in the discussion of results. While modeled as an inequality, the minimizing nature of the problem forces this to an equality.

$$\sum_{g \in G} Gen_{g,t} \geq D_t \quad \forall t \in T$$

The maximum electricity that can be generated from each source is modelled as a fixed constraint in 2025 which can be increased at a cost in later years. Another set of constraints ensures capacity is only added if needed.

2.5.2 Maximum Generation and Capacity Increase Constraints

To reflect the technological and policy constraints on the electricity generation capacities, the following constraints are formulated:

$$Gen_{g,2025} \leq F_{g,2025} \quad \forall g \in G$$

$$Gen_{g,2030} \leq F_{g,2025} + I_{g,2030} \quad \forall g \in \{Wind, Solar, Nuclear\}$$

$$Gen_{g,2030} \leq F_{g,2025} \quad \forall g \in G \setminus \{Wind, Solar, Nuclear\}$$

$$Gen_{g,2035} \leq F_{g,2025} + I_{g,2030} + I_{g,2035} \quad \forall g \in \{Wind, Solar, Nuclear\}$$

$$Gen_{g,2035} \leq F_{g,2025} \quad \forall g \in G \setminus \{Wind, Solar, Nuclear\}$$

$$I_{g,t} \leq B_{g,t}^{(1)} \cdot Capacity_Added_{g,t} + B_{g,t}^{(2)} \cdot Capacity_Added_{g,t} \quad \forall g \in \{Wind, Solar, Nuclear\}, t \in \{2030, 2035\}$$

$$I_{g,t} \leq B_{g,t}^{(1)} \cdot Capacity_Added_{g,t} + B_{g,t}^{(2)} \cdot Capacity_Added_{g,t} \quad \forall g \in \{Wind, Solar, Nuclear\}, \forall t \in \{2030, 2035\} \quad (1)$$

$$Gen_{g,t} - Utilization_Threshold \cdot \left(F_{g,2025} + \sum_{\tau < t} I_{g,\tau} \right) \leq M \cdot (1 - y_{g,t}) \quad \forall g \in \{Wind, Solar, Nuclear\}, \forall t \in T$$

Where y is a binary variable and M is a large number

(2)

$$B_{g,t}^{(1)} + M \cdot y_{g,t} \geq 1 \quad \forall g \in \{\text{Wind, Solar, Nuclear}\}, \forall t \in T \quad (3)$$

$$\begin{aligned} Gen_{g,t} - \text{Utilization_Threshold} \cdot \left(F_{g,2025} + \sum_{\tau < t} I_{g,\tau} + \text{Capacity_Added}_{g,t} \right) \\ \leq M \cdot (1 - y_{g,t}^{(2)}) \quad \forall g \in \{\text{Wind, Solar, Nuclear}\}, \forall t \in T \end{aligned} \quad (4)$$

$$B_{g,t}^{(2)} + M \cdot y_{g,t}^{(2)} \geq 1 \quad \forall g \in \{\text{Wind, Solar, Nuclear}\}, t \in T$$

Where Utilization_threshold=1 and M is a large number

Finally, the model incorporates constraints reflecting Canada’s policy commitments to phase out non-renewable energy sources by certain deadlines.

$$Gen_{\text{Coal \& Coke},2030} = 0, \quad Gen_{\text{Oil},2035} = 0$$

2.6 Final Model

These parameters, decision variables, objective functions, and constraints come together to form a model which makes decisions to achieve the least deviation from net-zero goals in the most cost-effective manner possible. Refer to Appendix 5 for full formulation).

3 Numerical Implementation and Results

3.1 Data Sources

The CER’s “Projections to 2050” Report and accompanying datasets offered a comprehensive outlook of Canada’s energy trajectory in the coming decades and provided key data for developing both optimization models.

The Greenhouse Gas Emissions Dataset contained projected GHG emissions across different scenarios. Those in the Global Net-Zero scenario were used to set the emissions targets across time periods which drove our models. The Electricity Generation Technology Dataset was used to determine the projected generation output of different electricity technologies over time. Incorporating this data provided our models an informed view of Canada’s potential electricity landscape by 2035 and enabled the accurate reflection of the potential for new technologies to increase in dominance. The Primary Demand dataset provided projections of future electricity demand and enabled the creation of informed electricity reliability constraints.

For estimating emissions factors, the models utilized the median lifecycle emissions from Table A.III.2 from Annex III of the Fifth Assessment Report by the Intergovernmental Panel on Climate Change (IPCC) Working Group 3. This data enabled the models to derive emissions per GWh as determined by electricity generation decisions. For energy sources which the IPCC divided into subtypes while the CER did not, such as solar, averages were used. Finally, several sources were consulted to determine reasonable cost estimates. From Synapse Energy, a research and consulting firm focused on the intersection of energy, economics, and the environment, we obtained data on the cost of additional nuclear power plants. Similar estimates for obtained for solar power via ProEst, a construction estimation business, and for wind power through the environmental non-profit Windustry. From the IPCC, levelized electricity costs are obtained.

3.2 Formulation in Gurobi Python

Gurobi’s hierarchical optimization functionality enabled sequential and prioritized decision-making across multiple layers of decision-making and constraints. This approach permitted the modelling of a context in which the urgency of the climate crisis permitted the requisite changes to be fully prioritized. A weighted sum approach, which in this model would entail considering both emissions reductions and cost at once, would also be possible through Gurobi’s functionality. This method of was explored in a base model extension.

3.3 Results of Base Model

Upon optimization, the model proposes a strategy aimed at approaching net-zero emissions, given the established context. The results include different total expenditures and energy mixes across the three time periods. While 2025 and 2035 present notable deviations from the emission goals, the model is able to achieve the goal in 2035. Over the three years, the model indicates a total emission of 63.18 MTCO_{2e} and total expenditures of \$175.3 billion.

In 2025, the model allowed for the selection of less clean energy sources due to their relatively low cost. Even though establishing new plants for cleaner energy sources was not yet an option and fossil fuels had not begun to phase out, the total emissions for the year were 35.19 MTCO_{2e} deviating from the goal by a mere 0.001 MTCO_{2e}, with a total cost of \$31.8 billion. These results contravened our understanding of the problem and suggested that some element of the real-world difficulty in achieving emissions targets, potentially in our data or in our constraints, was insufficiently captured. Nevertheless, the resulting energy mix still provides insight into an optimized pathway for Canada’s net-zero transition.

Hydroelectricity was the most utilized energy source, generating 402.5k GWh, followed by nuclear with 78.6k GWh, and wind at 64k GWh. Oil saw the least usage, with a generation of 1,379 GWh. A significant portion of emissions came from natural gas, followed by hydro and coal (Appendix 6). This year’s energy snapshot was dependent on available resources, their emission factors, and relative costs. This set the stage for a dramatic shift over subsequent time periods in which clean energy capacity can be added, leading to reduced emissions.

2030 was the most successful of the time periods. With the model free to add clean energy capacity, coal’s high-emitting generation phased out according to policy decisions, and a non-zero emissions target, it not only met its goal but surpassed it - achieving emissions of 14.49 MTCO_{2e}. This transition was achieved through substantial investment, including decisions to construct two nuclear plants and two additional wind plants, incurring \$27 billion in capital costs (Appendix 7). Hydro retained its position as the leading energy source, generating 402.5k GWh, followed by wind at 151.9k GWh, and nuclear at 130k GWh. Oil usage remained constant as in 2025. The total cost for the year was \$64.2 billion, reflecting the substantial investments in new clean energy infrastructure (Appendix 6).

Fortunes change, however, in 2035. In the year slated for net-zero, the model deviated from the goal by 13.5 MTCO_{2e}, with a total cost of \$79.2 billion. Notably, the rate of emissions reduction from 2030 was not much – going from 14.49MTCO_{2e} to 13.50 MTCO_{2e} – even while incurring an additional \$15 billion in cost. As in 2030, the model added two wind plants and two nuclear plants, along with increased capacity from the previous year. The disproportionate costs for relatively modest returns in 2035 were attributed to higher demand. The model endeavored to meet this demand, even if it necessitated commissioning additional energy plants that may not be fully utilized.

Hydro continued as the primary energy source in 2035, with a generation of 277k GWh, closely followed by nuclear at 271k GWh and wind at 239k GWh. Wind, due to its lifecycle emission factor, contributed the most to total emissions, second only to hydro. The energy mix for this year comprised solely these three sources, as oil was phased out. Surprisingly, the model did not opt for adding a

solar plant, possibly due to its elevated cost of generation and higher emission factor when compared to nuclear and wind generation (Appendix 6). It is worth noting that the model does not account for the regional variations in the feasibility and desirability of different technologies. This may have influenced the optimal allocation of capacity investments.

Though comprehensive sensitivity analysis is not straightforward with MIP, information could still be obtained concerning which constraints were binding. Demand satisfaction constraints across time periods were binding. As discussed in the problem formulation, this is expected as the minimizing nature of the problem push the model to resist as much as possible the forces driving it to emit. It also speaks to electricity demand as a potential lever for reducing emissions. This lever could be addressed through innovative low-energy technology designs or innovative policy incentives to change consumption habits. In more extreme scenarios where the time horizon for gradual changes has been depleted, this element could also push policy makers towards rationing measures.

We also discovered that in 2025, the fixed generation capacities for wind, oil, hydro and biomass are binding – indicating full utilization of their generation capacities. In 2030, these same sources were fully utilized. By contrast, in 2035, it is the capacities of Wind and Nuclear that are binding. In the model, Wind and Nuclear are prioritized in 2030 and 2035 due to their lower emissions, despite higher costs, aligning with stringent emission goals. Biomass and Oil, cheaper but higher in emissions, are preferred when emission targets are less strict. Hydro, balancing low emissions and costs, is favored for 2025 and 2030. By 2035, Wind and Nuclear are increasingly favored over Hydro, reflecting a strategic emphasis on further reducing emissions, as these sources offer even lower emission rates which help in reaching the environmental targets.

3.3.1 Results Extensions – Sensitivity of the Model to Demand

The demand satisfaction constraint in the model is binding, meaning that any minor increase in demand will significantly alter the optimal solution and affect the deviation from emission targets. In this extension, we tested the limits of these demand increases – all else being equal. It was discovered that after an 11% increase in demand, the model becomes infeasible. In such a scenario, demand outpaces the supply combinations available to the model and the constraint is violated.

3.3.2 Results Extensions – Leeway in Demand Satisfaction

In 2035, the model opts to incur penalties for not meeting demand, irrespective of the penalty’s magnitude. This approach likely stems from prioritizing the minimization of emission deviations in 2035 as much as possible, taking precedence over cost considerations. To properly balance the trade-off between these two factors, employing a weighted sum method for the multi-objective problem is necessary. This method would offer a quantifiable means to navigate the compromise between emission targets and demand satisfaction. After implementing this with equal weights assigned to the two objectives, the results indicate that the maximum penalty the government can afford for not satisfying demand is \$182,000 per GWh. Beyond this threshold, the model prefers to satisfy demand across the years.

$$\begin{aligned}
\min Z = & \sum_{t \in T} (Dev_t) + \\
& \left(\sum_{g \in G, t \in T} C_{g,t} \cdot Gen_{g,t} + \right. \\
& \text{pen} \cdot \sum_{t \in T} \left(D_t - \sum_{g \in G} Gen_{g,t} \right) + \\
& \left. \sum_{g \in \{\text{Wind}, \text{Solar}, \text{Nuclear}\}, t \in T} \left(IncCost_{g,t} \cdot B_{g,t}^{(1)} + IncCost_{g,t} \cdot B_{g,t}^{(2)} \right) \right)
\end{aligned} \tag{5}$$

Where pen is the cost of not satisfying demand

The demand constraint is expressed as:

$$\sum_{g \in G} Gen_{g,t} \leq D_t \quad \forall t \in T \quad (6)$$

3.3.3 Results Extension - Weighted Sum Approach

Continuing our exploration of the weighted sum approach, we solved the original form of the model – requiring demand to be met – with the equal weights across objectives. Results showed significant deviations from the emission goals for the three time periods, which might more accurately reflect real-world outcomes. The emission deviations for 2035 were 64.11 MTCO₂e, 10.25 MTCO₂e for 2030, and 7.78 MTCO₂e for 2025. Moreover, the total costs were lower, with \$50 billion for 2035, \$45 billion for 2030, and \$30 billion for 2025, reflecting the dual focus on minimizing costs. To make the application of this method more robust, a literature review of Canada’s economic and environmental policy commitments could be used to inform the relative weights in a more realistic manner.

$$\begin{aligned} \min Z = & \sum_{t \in T} (Dev_t) + \\ & \left(\sum_{g \in G, t \in T} C_{g,t} \cdot Gen_{g,t} + \right. \\ & \left. \sum_{g \in \{\text{Wind, Solar, Nuclear}\}, t \in T} \left(IncCost_{g,t} \cdot B_{g,t}^{(1)} + IncCost_{g,t} \cdot B_{g,t}^{(2)} \right) \right) \end{aligned} \quad (7)$$

Subject to the original constraints

4 Problem Extension- Goal Programming Approach

4.1 Model Comparisons – The Case for Considering the Goal Programming Approach

The base Mixed-Integer Programming (MIP) model is adept at optimizing singular objectives like cost and emissions but lacks dexterity in handling balanced approaches for conflicting goals in complex scenarios like that presented by electricity planning. This limitation prompted the adoption of goal programming, which excels in multi-objective scenarios by introducing deviation variables to accommodate real-world variability and uncertainties in energy systems. GP prioritizes feasible and satisfactory solutions, aligning with the need for trade-offs in dynamic energy markets and policies. Both MIP and GP models cover diverse energy sources, with MIP emphasizing simultaneous minimization of emissions and costs, while GP aims for balance by minimizing deviations in emissions, cost, generation, and generation capacity. MIP suits discrete decisions like capacity expansion, while GP shines in scenarios requiring trade-offs and a comprehensive approach to energy planning. The choice between MIP and GP depends on specific electricity planning requirements, with MIP offering focus and GP providing flexibility and balance.

4.2 Overview of Lexicographic Goal Programming

The work of Ignizio (1983), Ignizio (1985), Jones & Tamiz (2010), Schniederjans (1995), Lozano & Contreras (2022), and Azmi & Tamiz (2010) inform the understanding of goal programming applied in our model. Goal programming aims for specific target levels for multiple criteria and minimizes the deviations from these targets. It offers flexibility by softening constraints into goals with deviation and

priority factors, making the model adaptable and balanced. This is useful in complex planning scenarios like energy management. The lexicographic, otherwise termed as hierarchical, aspect sequences the goals by importance and optimizes them sequentially, ensuring higher-ranked goals are not compromised. Trade-offs are managed through a sacrifice system, where lower-priority goals may be sacrificed to maintain higher-priority ones. This approach helps determine the optimal power generation mix over time, considering various plant types to meet electricity demand efficiently.

4.3 Goal Programming Model Formulation

The lexicographic goal-programming model for Canadian energy planning, spanning 2025, 2030, and 2035, prioritizes four main objectives with distinct targets: minimizing emissions deviations (highest priority), followed by deviations in generation output, generation capacity, and associated costs (Appendix 8). It incorporates decision variables and unique deviation variables for emissions, generation, capacity, and costs, measuring performance against predetermined targets. Constraints ensure meeting forecasted demands, avoiding technology capacity exceedance, and staying within defined limits for emissions and costs. The model aligns with specific generation output and capacity targets, offering a comprehensive framework for sustainable and efficient energy planning.

4.4 Model Results and Implications

The model's results indicate a significant shift towards renewable energy sources, particularly wind, solar and hydro. By 2025, wind energy contributes 60,666.67 GWh with a substantial cost of CAD 5.204 billion. Solar energy generates 11,685.39 GWh, costing CAD 2.5 billion. Hydroelectric power dominates with 401,666.67 GWh, the highest among all technologies, reflecting its key role in energy production but also the highest cost at CAD 24.77 billion. Nuclear and natural gas technologies contribute 94,391.94 GWh and 87,081.63 GWh, respectively, with significant costs. Geothermal, oil, and coal make smaller contributions with corresponding lower costs.

By 2030, the model shows increased generation from wind (92,666.67 GWh) and solar (15,280.90 GWh), with corresponding rises in costs. Hydroelectric power slightly increases its output, maintaining its lead, but with a steep rise in cost to CAD 27.31 billion. Nuclear generation sees a significant increase to 133,450.89 GWh. Natural gas generation drops, while geothermal slightly increases. Coal shows no generation or costs, indicating its phase-out.

In 2035, the model predicts peak generation from renewable sources. Wind energy reaches 184,000 GWh, and solar reaches 42,247.19 GWh, with the cost for wind escalating to CAD 26 billion. This is apparent by its positive cost deviation, highlighting significantly higher financial expenditures than expected. This could be due to higher installation, maintenance costs, or investment in new technology. Hydroelectric and nuclear technologies maintain high generation levels, with hydro leading in terms of generation and cost (CAD 28.72 billion). There is a notable reduction in natural gas generation, while geothermal sees a substantial increase in capacity with its positive capacity deviation, suggesting better-than-expected performance and potential for further development in this technology. Oil maintains a minor presence, and coal is completely phased out. Overall, the results indicate a steady transition towards renewable and clean energy sources and a clear reduction in fossil fuel reliance although not reaching net zero due to lifecycle emission factors' limitation of no true zero and no carbon capture technology considered in the model. Hydroelectric power remains a significant contributor, alongside substantial inputs from wind and solar energies. This shift towards greener energy, while environmentally advantageous, is accompanied by high financial costs and operational complexities, as revealed by deviations in energy production and costs. These deviations highlight the necessity for adaptive management, substantial investments, and strategic planning in sustainable energy infrastructure.

5 Recommendations and Conclusions

Our optimization analyses underscore how ambitious of a challenge achieving net-zero emissions is, even for a sector that has already reduced its emissions 56% from 2000 levels. Renewable energy sources, despite having zero direct carbon emissions, still emit over their lifecycles. Accordingly, the models we have developed can only strive towards coming as close as possible to the emissions targets. This highlighted the extent to which achieving and maintaining net-zero goals depend on carbon sequestration technology. Without scaling such offset methods, meeting the nation’s electricity demands while reducing emissions becomes impossible.

Findings from the base MIP model reveal that the model’s optimal path involves significant deviation from the 2035 emission goals. The year 2030 presents an optimistic picture, with a substantial shift towards clean energy, making the goals more attainable. However, the transition is costly. In order to achieve the goal, the construction of two wind energy plants and two nuclear plants were required in both 2030 and 2035. This produced a total investment cost of \$54.8 billion over these periods.

Comparing the results from the MIP and GP models, the strategic value of wind and nuclear energy investments becomes increasingly clear. The GP model indicates cost overruns for both energy sources in 2030 and 2035, suggesting a potential need for reframing the prioritization of investments to meet future energy requirements. Both the MIP and GP models concur that hydroelectricity will continue to play a central role in Canada’s electricity supply, remaining the leading energy source throughout the three time periods. Wind and nuclear energy are positioned as future leading sources, with the MIP model recommending an escalation in investments in both energy sources for the years 2030 and 2035. The GP model corroborates this, identifying these sources as the most economically viable renewable options. However, other energy sources such as solar and geothermal do not meet these performance benchmarks in either model, indicating their relatively lower economic viability.

Given these insights, it would be prudent for the Canadian government to anchor their net-zero transition strategy in wind and nuclear energy investments by effectively planning to add capacities for these two clean energy sources, supported by a complementary mix of other clean sources such as solar and geothermal. Such a strategy would not only be economically wise but also pave the way toward a sustainable and achievable energy future.

Regarding changes required to scale this project’s methods to larger instances, one key recommendation is adopting a regionally tailored data collection approach. Our research uncovered a high degree of regional variability in lifecycle emissions factors. This requires resolution for the model to produce the reliability required to drive decisions with economic and environmental implications as consequential as those presently under consideration.

5.1

Appendices

A Appendix 1: Model Assumptions

- Modeling performed under assumptions of Canada Energy Regulator’s ”Global Net Zero” scenario
- Carbon offset methods (abatement, sequestration, etc.) are excluded
- Costs include levelized costs and capacity expansion costs
- Battery storage and hydrogen are excluded from the generation technologies
- Lifecycle emissions, based on international records, are used for emissions factors

B Appendix 2: Emission Factors and Cost Data of Technologies

Energy Source	MTCO ₂ e/GWh	\$CAD/GWh
Wind	0.000015	80,830
Solar	0.0000445	205,500
Oil	0.00049	61,650
Nuclear	0.000012	89,050
Hydro	0.000024	30,140
Natural Gas	0.00049	97,270
Coal	0.00082	83,570
Geothermal	0.000038	82,200

Lifecycle emission factors and generation costs used for optimization models.

C Appendix 3: Capacity Increase Investment Cost Data

Power Plant Type	Cost (\$B)
Nuclear	9.59
Solar	12.878
Wind	4.11

Cost estimates used in base model for capacity increases.

D Appendix 4: Fixed Generation Capacity Data

Energy Source	Fixed Generation Capacity (GWh)
Wind	64389.48
Solar	12184.92
Oil	1379.91
Nuclear	78631.37
Hydro	402575.9
Natural Gas	106529.07
Coal & Coke	8184.54
Biomass & Geothermal	8281.2

Fixed generation capacity estimates used in base model.

E Appendix 5: Full Base Model Formulation

Primary Objective Function:

$$\min \sum_{t \in T} Dev_t$$

Secondary Objective Function:

$$\min \text{Total_Cost} = \sum_{g \in G} \sum_{t \in T} C_{g,t} \cdot \text{Gen}_{g,t} + \sum_{g \in \{\text{Wind, Solar, Nuclear}\}} \sum_{t \in \{2030, 2035\}} (\text{Increase_Cost}_{g,t} \cdot B_{g,t}^{(1)} + \text{Increase_Cost}_{g,t} \cdot B_{g,t}^{(2)})$$

Subject to:

Emissions Constraints:

$$\sum_{g \in G} \text{Emissions}_{g,t} \leq \text{Goal}_t + Dev_t \quad \forall t \in T, \forall g \in G$$

$$\text{Emissions}_{g,t} = E_{g,t} \cdot \text{Gen}_{g,t} \quad \forall t \in T, \forall g \in G$$

Demand Satisfaction Constraint:

$$\sum_{g \in G} \text{Gen}_{g,t} \geq D_t \quad \forall t \in T$$

Maximum Generation Constraints:

$$\text{In 2025:} \quad \text{Gen}_{g,2025} \leq F_{g,2025} \quad \forall g \in G$$

$$\text{In 2030:} \quad \text{Gen}_{g,2030} \leq F_{g,2025} + I_{g,2030} \quad \forall g \in \{\text{Wind, Solar, Nuclear}\}$$

$$\text{Gen}_{g,2030} \leq F_{g,2025} \quad \forall g \in G \setminus \{\text{Wind, Solar, Nuclear}\}$$

$$\text{In 2035:} \quad \text{Gen}_{g,2035} \leq F_{g,2025} + I_{g,2030} + I_{g,2035} \quad \forall g \in \{\text{Wind, Solar, Nuclear}\}$$

$$\text{Gen}_{g,2035} \leq F_{g,2025} \quad \forall g \in G \setminus \{\text{Wind, Solar, Nuclear}\}$$

Capacity Increase Constraints:

$$I_{g,t} \leq B_{g,t}^{(1)} \cdot \text{Capacity_Added}_{g,t} + B_{g,t}^{(2)} \cdot \text{Capacity_Added}_{g,t} \quad \forall g \in \{\text{Wind, Solar, Nuclear}\}, \forall t \in \{2030, 2035\}$$

Utilization Threshold Constraint:

For $g \in \{Wind, Solar, Nuclear\}, \forall t \in T$

$$Gen_{g,t} - Utilization_Threshold \cdot \left(F_{g,2025} + \sum_{\tau < t} I_{g,\tau} \right) \leq M \cdot (1 - y_{g,t})$$

Binary Decision Variable Constraint:

$$B_{g,t}^{(1)} + M \cdot y_{g,t} \geq 1 \quad \forall g \in \{Wind, Solar, Nuclear\}, \forall t \in T$$

Additional Capacity Increase Constraint:

For $g \in \{Wind, Solar, Nuclear\}, \forall t \in T$

$$Gen_{g,t} - Utilization_Threshold \cdot \left(F_{g,2025} + \sum_{\tau < t} I_{g,\tau} + Capacity_Added_{g,t} \right) \leq M \cdot (1 - y_{g,t}^{(2)})$$

Additional Binary Decision Variable Constraint:

$$B_{g,t}^{(2)} + M \cdot y_{g,t}^{(2)} \geq 1 \quad \forall g \in \{Wind, Solar, Nuclear\}, \forall t \in T$$

Phasing Out Non-Renewable Energy Sources:

$$Gen_{Coal \& Coke, 2030} = 0, \quad Gen_{Oil, 2035} = 0$$

All decision variables are non-negative.

F Appendix 6: Base Model Projections - Energy Mix, Cost, Generation, and Emission Factors

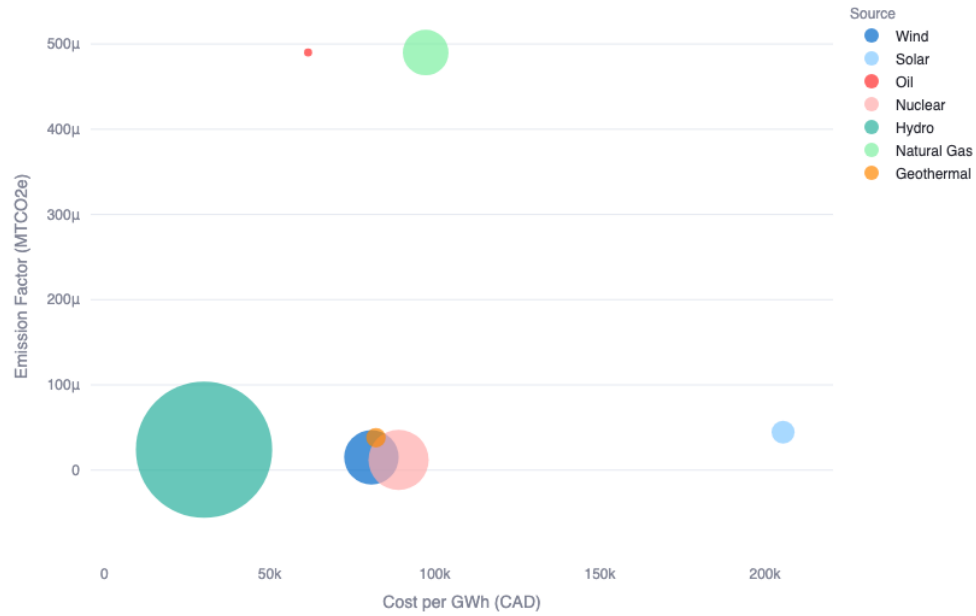


Figure 1: 2025 projections. The sizes of the components reflect their respective total generation.

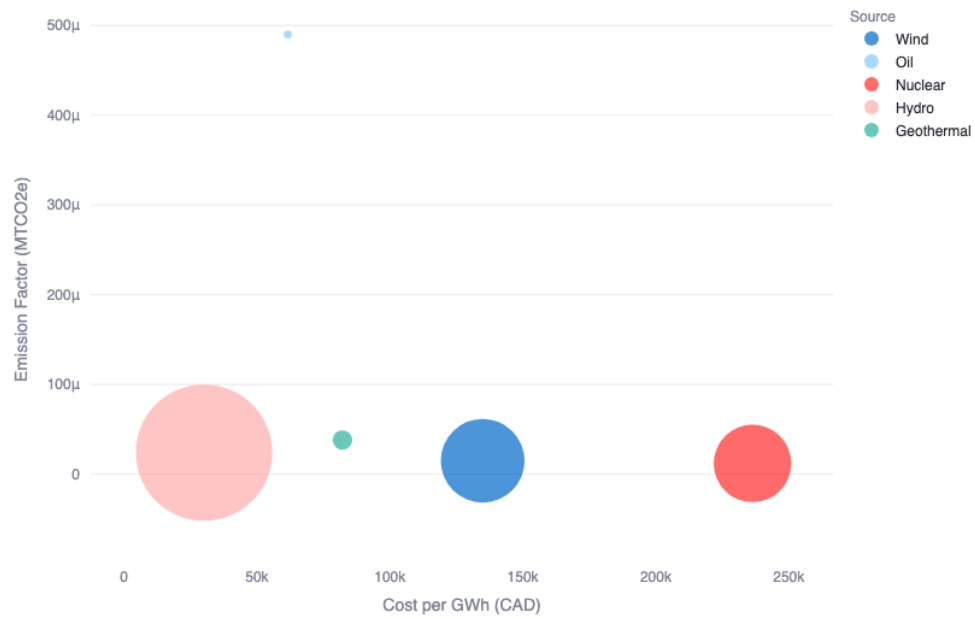


Figure 2: 2030 projections. The sizes of the components reflect their respective total generation.

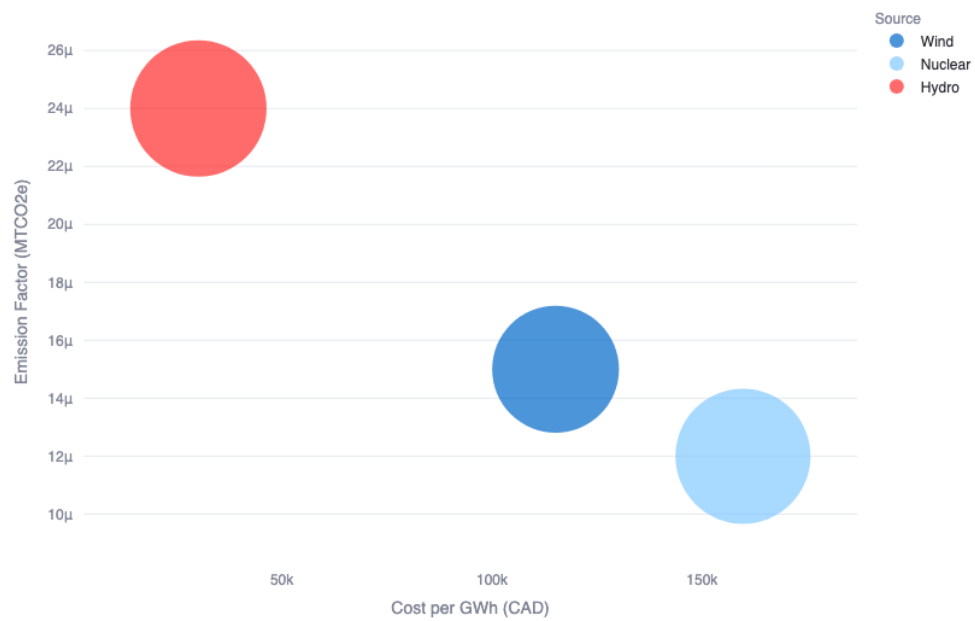


Figure 3: 2035 projections. The sizes of the components reflect their respective total generation.

G Appendix 7: Total Cost Projections of Base Model

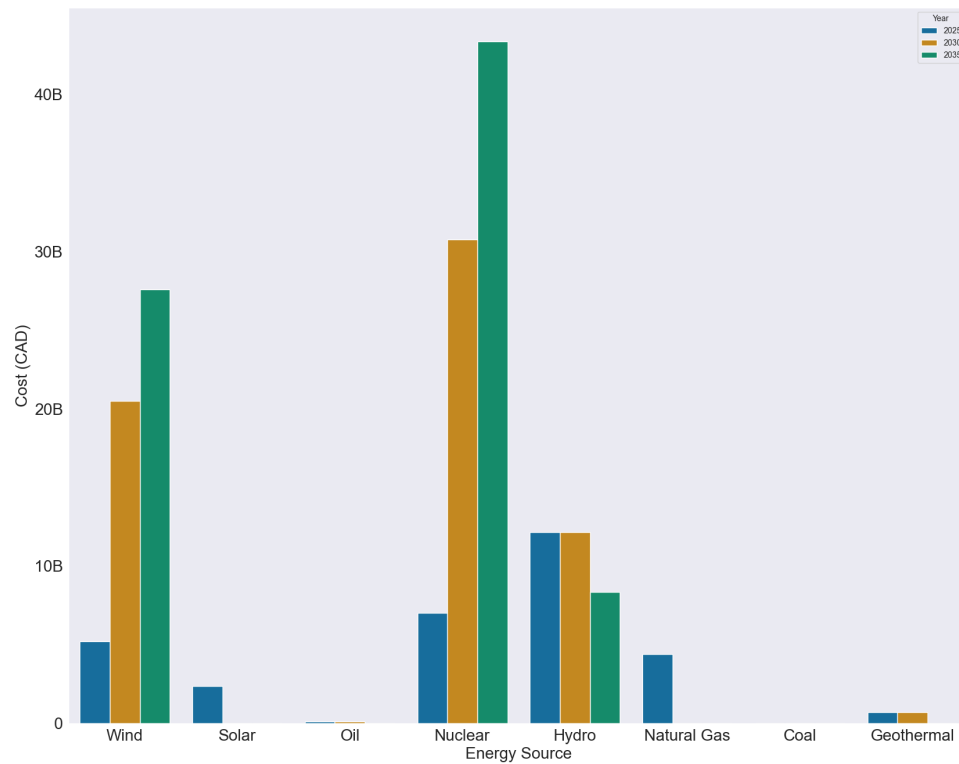


Figure 4: Base model projection of total cost for each source.

H Appendix 8: Goal Programming Formulation

The lexicographic goal programming (GP) formulation presented here addresses the multi-objective decision-making problem associated with electricity generation planning over the years 2025, 2030, and 2035. The GP model is designed hierarchically and encompasses a comprehensive set of sets, parameters, decision variables, and deviation variables. The goal is to minimize deviations in emissions, generation, capacity, and cost successively across the defined time periods.

H.1 Sets and Parameters

Sets:

$$T = \{2025, 2030, 2035\}$$

$$\text{Gen Tech} = \{ "wind", "solar", "hydro", "nuclear", "naturalgas", "geothermal", "oil", "coal" \}$$

Parameters:

$$D_t \quad : \text{Electricity demand in year } t$$

$$I_t \quad : \text{Budget in time } t$$

$$M_t \quad : \text{Emissions goal in time } t$$

$$E_{gt}(g, t) \quad : \text{Emission factors for } g \text{ in } t$$

$$L_{gt}(g, t) \quad : \text{Generation targets for } g \text{ in } t$$

$$U_{gt}(g, t) \quad : \text{Capacity targets for } g \text{ in } t$$

$$K_{gt}(g, t) \quad : \text{Cost targets for } g \text{ in } t$$

$$B_{gt}(g, t) \quad : \text{Emission targets for } g \text{ in } t$$

$$C_{gt}(g, t) \quad : \text{Singular cost figures for } g \text{ in } t$$

$$L_{gt_UB}(g, t) \quad : \text{Generation upper bounds for } g \text{ in } t$$

$$U_{gt_UB}(g, t) \quad : \text{Capacity upper bounds for } g \text{ in } t$$

$$K_{gt_UB}(g, t) \quad : \text{Cost upper bounds for } g \text{ in } t$$

$$B_{gt_UB}(g, t) \quad : \text{Emission upper bounds for } g \text{ in } t$$

H.2 Decision Variables

Decision Variables:

$$X_{gt} \quad : \text{Generation capacity for } g \text{ in } t$$

$$Y_{gt} \quad : \text{Generation for } g \text{ in } t$$

$$Z_{gt} \quad : \text{Emissions for } g \text{ in } t$$

$$C_{gt} \quad : \text{Cost for } g \text{ in } t$$

H.3 Deviation Variables

Deviation Variables:

$e_{t+}(g, t), e_{t-}(g, t)$: Positive and negative emission deviation for g in t
$c_{t+}(g, t), c_{t-}(g, t)$: Positive and negative cost deviation for g in t
$g_{t+}(g, t), g_{t-}(g, t)$: Positive and negative generation deviation for g in t
$q_{t+}(g, t), q_{t-}(g, t)$: Positive and negative capacity deviation for g in t

H.4 Objective Functions

Objective Functions (in order of priority):

Minimize emission deviations:

$$\min \sum_{g \in G, t \in T} (e_{t+}(g, t) + e_{t-}(g, t))$$

Minimize generation deviations:

$$\min \sum_{g \in G, t \in T} (g_{t+}(g, t) + g_{t-}(g, t))$$

Minimize capacity deviations:

$$\min \sum_{g \in G, t \in T} (q_{t+}(g, t) + q_{t-}(g, t))$$

Minimize cost deviations:

$$\min \sum_{g \in G, t \in T} (c_{t+}(g, t) + c_{t-}(g, t))$$

H.5 Constraints

Upper bound constraints:

For all $g \in G, t \in T$:

UB Constraints on Cost Deviations:

$$c_{t+}(g, t) \leq K_{gt.UB}(g, t)$$

$$c_{t-}(g, t) \leq K_{gt.UB}(g, t)$$

UB Constraints on Emission Deviations:

$$e_{t+}(g, t) \leq B_{gt.UB}(g, t)$$

$$e_{t-}(g, t) \leq B_{gt.UB}(g, t)$$

UB Constraints on Generation Deviations:

$$g_{t+}(g, t) \leq L_{gt.UB}(g, t)$$

$$g_{t-}(g, t) \leq L_{gt.UB}(g, t)$$

UB Constraints on Capacity Deviations:

$$q_{t+}(g, t) \leq U_{gt.UB}(g, t)$$

$$q_{t-}(g, t) \leq U_{gt.UB}(g, t)$$

Generation cannot exceed Capacity:

$$Y(g, t) \leq X(g, t) \text{ for all } g \in G, t \in T$$

Defining emissions calculation:

$$Z(g, t) = E_{gt}(g, t) \cdot Y(g, t) \text{ for all } g \in G, t \in T$$

Defining cost calculation:

$$C(g, t) = C_{gt}(g, t) \cdot X(g, t) \text{ for all } g \in G, t \in T$$

Goal Constraints:

$$L_{gt}(g, t) = Y(g, t) - g_{t+}(g, t) + g_{t-}(g, t) \text{ for all } g \in G, t \in T$$

$$U_{gt}(g, t) = X(g, t) - q_{t+}(g, t) + q_{t-}(g, t) \text{ for all } g \in G, t \in T$$

$$B_{gt}(g, t) = Z(g, t) - e_{t+}(g, t) + e_{t-}(g, t) \text{ for all } g \in G, t \in T$$

$$K_{gt}(g, t) = C(g, t) - c_{t+}(g, t) + c_{t-}(g, t) \text{ for all } g \in G, t \in T$$

H.6 Non-negativity and Continuity Constraints

Non-negativity:

$$\begin{aligned} &X_{gt}, Y_{gt}, C_{gt}, Z_{gt}, e_{t+}(g, t), e_{t-}(g, t), c_{t+}(g, t), c_{t-}(g, t), \\ &g_{t+}(g, t), g_{t-}(g, t), q_{t+}(g, t), q_{t-}(g, t) \geq 0 \text{ for all } g \in G, t \in T \end{aligned}$$

Continuous variables:

$$\begin{aligned} &X_{gt}, Y_{gt}, C_{gt}, Z_{gt}, e_{t+}(g, t), e_{t-}(g, t), c_{t+}(g, t), c_{t-}(g, t), \\ &g_{t+}(g, t), g_{t-}(g, t), q_{t+}(g, t), q_{t-}(g, t) \text{ are continuous for all } g \in G, t \in T \end{aligned}$$

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