

McGill University Department of Bioresource Engineering BREE 495 - Engineering Design 3 Fall 2024



Optimization Software for Developing a Sustainable Hydrogen Refueling Network in Quebec's Freight Sector

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List of Abbreviations

Abbreviation Full Form

GHG Greenhouse Gas

FCEV Fuel Cell Electric Vehicle

BEV Battery Electric Vehicle

MHDV Medium and Heavy-Duty Vehicle

NSGA-II Non-dominated Sorting Genetic Algorithm II

LCA Life Cycle Assessment

LCC Life Cycle Cost

CAPEX Capital Expenditures

OPEX Operational Expenditures

LCOH Levelized Cost of Hydrogen

CF Capacity Factor

T Annual Operational Hours

PCORT Plan for Clean On-Road Transportation

SDATTC Summer Daily Average Truck Traffic Count

UHS Unit Hydrogen Station

GWP Global Warming Potential

DJME Daily Traffic for Summer Average

EIA Environmental Impact Assessment

Preference Ranking Organization Method for Enrichment

PROMETHEE Evaluation

MWH Megawatt Hour

CO2 Carbon Dioxide

IEC Institute of Civil Construction

MAMH Ministry of Municipal Affairs and Housing

MELCCFP Ministry of Environment, Climate Change, Wildlife, and Parks

CPTAQ Agricultural Land Protection Commission of Quebec

Abstract

Quebec's freight industry, a vital economic sector with over \$150 billion in annual trade, accounts for approximately 10% of Canada's greenhouse gas (GHG) emissions. To meet climate commitments under the Paris Agreement and Canada's Net-Zero Emissions Accountability Act, transitioning from diesel-powered trucks to Fuel Cell Electric Vehicles (FCEVs) is essential. Leveraging Quebec's abundant hydroelectric energy, this project focuses on developing a software solution to optimize hydrogen refueling infrastructure for the freight sector. The software uses Non-dominated Sorting Genetic Algorithm II (NSGA-II) and PROMETHEE to balance objectives such as cost minimization, environmental impact reduction, and equitable hydrogen distribution. It incorporates critical constraints, including land-use restrictions and regulations on Indigenous territories, to ensure social and environmental responsible planning. The tool features a user-friendly interface with geospatial visualizations and actionable recommendations, enabling stakeholders to design efficient hydrogen networks. The software outputs reliable networks with average total cost of CAD 3 billion, a levelized cost of Hydrogen of 4 CAD/kg which is competitive with today's diesel cost before governmental subsidies, no encroachment on natural parks, and minimal environmental impact.

1. Introduction

1.1. Background

The freight industry in Quebec plays an essential role in the province's economy, facilitating over \$150 billion in trade annually and enabling the exchange of goods with Canada's primary economic partner, the United States (Mordor, Intelligence, 2024). However, this sector is also responsible for approximately 10% of Canada's national greenhouse gas (GHG) emissions, making it a significant contributor to climate change (Fan et al., 2022). Quebec, as part of Canada, is a signatory to the Paris Agreement, adopted in 2015, committing to limit global temperature rise below 2°C. Building on this commitment, Canada enacted its own Net-Zero Emissions Accountability Act, legally binding the country to achieve carbon neutrality by 2050. Despite these motivations, the continued expansion of the freight industry threatens to reach these goals. Transitioning from diesel-powered trucks to sustainable alternatives is therefore essential, but this shift requires the lengthy development of an entire transportation ecosystem. This ecosystem includes not only new vehicles but also the supporting infrastructure, manufacturing, maintenance systems, and energy supply chains needed to sustain them. To meet its climate commitments, Quebec must act decisively and without delay.

To decarbonize diesel vehicles, the primary technologies available today are Battery Electric Vehicles (BEV) and Fuel Cell Electric Vehicles (FCEV). FCEVs are powered by hydrogen gas. While BEVs are well-suited for smaller vehicles such as cars, MHDV often favor FCEV technology due to operational demands and the significant weight of batteries required for such vehicles. FCEVs are particularly advantageous for replacing heavy-duty internal combustion vehicles because of their high specific energy density and the energy efficiency of fuel cells (Çabukoglu, 2019). This allows FCEVs to offer faster charging times and greater autonomy compared to BEVs due to the compressed state of the hydrogen.

In addition, local case-studies have shown that the production capacity of electrolyser does not vary greatly during cold winters. Similarly, the efficiency of FCEV does decrease with cold temperatures but in reduced proportion compared to lithium batteries (Ministry of Economy, Innovation and Energy, 2024). The cost of hydrogen, though currently high, is expected to decrease in the coming years with technological advancements and the increased scale of the hydrogen ecosystem, making FCEVs more competitive (Nieves Camacho et al., 2022).

Interestingly, Quebec is exceptionally well positioned to become a renowned global leader in hydrogen production. The province has abundant water and clean electricity from hydroelectric sources, key components required to produce green hydrogen via electrolysis. While the technology itself is not novel, it remains largely unexplored for application in the freight sector in Quebec. While Quebec has acknowledged the importance of developing a hydrogen ecosystem, it has yet to provide the necessary roadmap or strategy to achieve this vision. Our solution addresses this problem by exploring how to optimally locate refueling stations and determine the production capacity each should support. This innovative approach could help Quebec deploy hydrogen infrastructure effectively, forecast future demand, and minimize impacts on the environment and natural resources. Additionally, our software would serve as a platform for stakeholders to collaboratively envision and develop the hydrogen ecosystem in a systemic and integrated manner.

1.2. Project Scope

This project addresses a core optimization problem: the strategic implementation of a hydrogen ecosystem in Quebec. Optimization, as defined in the literature, is a mathematical approach to identifying the best solution from a set of feasible alternatives to achieve specific objectives while satisfying constraints (Skormin, 2016). It is widely applied in infrastructure planning to maximize resource use, reduce costs, and align with sustainability goals (Li et al., 2011).

An optimization problem is particularly relevant to our project as it involves balancing competing objectives—minimizing costs, reducing environmental impacts, and ensuring reliable hydrogen availability—within a framework of logistical, regulatory, and spatial constraints. The optimization process is crucial because it allows decision-makers to evaluate and prioritize trade-offs, ultimately identifying the most effective and sustainable solution.

The purpose of optimization in this project is to provide actionable recommendations for hydrogen infrastructure development that maximize economic and environmental benefits. By systematically analyzing feasible configurations, the tool ensures efficient resource allocation, enabling stakeholders to make informed decisions aligned with strategic goals.

Key features of the project include:

- 1. **Optimization Goals**: The primary focus is solving the multi-objective optimization problem of hydrogen infrastructure planning. This involves maximizing resource efficiency, reducing carbon emissions from freight transportation, and ensuring economic feasibility. By leveraging genetic algorithms, the tool identifies configurations that achieve these goals while adhering to practical constraints (Zavadskas et al., 2019).
- Stakeholder Support: The tool is designed to assist policymakers, engineers, and planners in making data-driven decisions. By offering precise recommendations for station locations and configurations, it ensures that infrastructure development aligns with regional objectives and stakeholder priorities.
- 3. **Flexibility and Customization**: The tool accommodates diverse input variables, including time horizons, zoning regulations, hydrogen demand forecasts, and truck autonomy. This flexibility allows users to explore multiple scenarios and customize outputs to specific needs, enhancing its relevance for varied applications.
- 4. **Innovative Techniques**: The use of genetic algorithm is a cornerstone of this project. These algorithms efficiently navigate large solution spaces to identify optimal configurations, ensuring robust performance in solving complex, multi-objective optimization problems. Their ability to incorporate diverse constraints, such as zoning regulations (agriculture and Indigenous lands) and environmental impact, ensures practical and scalable solutions (Morcous & Lounis, 2005).

The final output of this project is a user-friendly interface that integrates a visual map, economic metrics, and actionable insights. By combining advanced optimization methods with an intuitive design, the

platform empowers stakeholders to make informed, impactful decisions that drive the sustainable development of Quebec's hydrogen infrastructure.

1.3. Prior Work Summary

The first part of our capstone provided a critical foundation for optimizing hydrogen infrastructure in Quebec's freight transportation sector. It focused on the feasibility of hydrogen as a sustainable fuel alternative and identified key factors influencing the successful deployment of hydrogen refueling stations. This initial research laid the groundwork for Design 3, transitioning the focus from theoretical analysis to practical implementation and advanced optimization.

One of the primary accomplishments of Design 2 was the detailed exploration of hydrogen as a clean energy source, emphasizing its advantages for medium and heavy-duty vehicles. The project highlighted hydrogen's potential to decarbonize freight transportation, leveraging Quebec's abundant renewable energy resources for green hydrogen production. Early feasibility studies examined essential factors for hydrogen infrastructure planning, including truck autonomy, grid connectivity, zoning laws, water availability, and production capacities. These parameters informed the design of an optimization framework tailored to real-world challenges.

The preliminary work evaluated various optimization methodologies using a Pugh chart to address the complexity of hydrogen station placement. This tool compared Reinforcement Learning, Mixed Integer Linear Programming (MILP), and Genetic Algorithms (GA) against criteria such as multi-objective optimization, adaptability, constraint handling, and convergence rates. The analysis revealed that genetic algorithms were the ideal solution to the problem. GAs excelled in balancing economic, environmental, and logistical objectives while efficiently handling complex constraints like restricted areas and resource availability. Their ability to converge quickly and avoid suboptimal solutions further reinforced their suitability.

NSGA-II (Non-dominated Sorting Genetic Algorithm II) is a popular multi-objective optimization algorithm widely used for solving problems involving conflicting objectives. It employs a fast non-dominated sorting approach to classify solutions into different Pareto fronts and uses a crowding distance mechanism to maintain solution diversity. By balancing convergence towards the optimal Pareto front and diversity among solutions, NSGA-II is highly effective in identifying a set of trade-off solutions, enabling decision-makers to choose the best compromise. This algorithm is computationally efficient and robust, making it a preferred choice for applications in engineering, economics, and environmental management (Deb et al., 2002).

Pugh Chart Evaluation:

The evaluation highlighted key differences among the methodologies:

- **Reinforcement Learning** demonstrated low effectiveness in handling constraints and multiobjective problems, making it less suitable for the task (Pardalos & Resende, 2002).
- MILP showed moderate performance but lacked the capability of handling the linear aspect of the complex relationships between the chosen parameters.

• **NSGA-II** outperformed both alternatives by delivering high performance across all evaluation criteria, making them the optimal choice for solving the multicriteria problem (Deb et al., 2002).

Table 1: Pugh Chart

Criteria / Objectives	Reinforcement Learning	Mixed Integer Linear programming (MILP)	NSGA-II
Multi-Objective Optimization	Limited ability to handle multiple objectives effectively.	Moderately capable but struggles with complex interdependencies.	Highly effective in managing trade-offs between multiple objectives.
Handling Constraints	Poor constraint management, leading to infeasible solutions in complex scenarios.	Moderate at handling linear constraints but limited in addressing non-linear aspects.	Excellent at incorporating complex constraints, including non-linear relationships.
Adaptability	Rigid; requires significant reconfiguration for new problem setups.	Limited flexibility; primarily suited for specific types of optimization problems.	Highly adaptable; can address diverse problems with minimal modifications.
Convergence rate	Slow, requires extensive training to achieve reasonable results.	Moderate; performs well on smaller problems but slows with increased complexity.	Fast; consistently converges to solutions efficiently even in large solution spaces.
Avoiding suboptimal solutions	Frequently trapped in local optima, failing to explore broader solution spaces.	Susceptible to suboptimal solutions due to its deterministic nature.	Effective in avoiding local optima through its stochastic and exploratory mechanisms.

The insights and methodologies developed in Design 2 have been instrumental in shaping the objectives of our implementation in Design 3. By identifying the strengths of Genetic Algorithms in solving our multicriteria problem, and understanding the constraints of real-world implementation, this presented approach focuses on refining the optimization framework and transitioning from a theoretical model to a practical decision-support tool.

2. Analysis and Methods

Our design project required extensive data collection, specifically geospatial quantitative and temporal. In this section, we discuss the different types of data we have collected, their sources and our preprocessing methods to simplify the subsequent steps.

Truck data collection: The first step of the data collection process was to acquire data for truck traffic throughout Quebec. This data was crucial for forecasting the hydrogen truck population using a model we developed and for modeling hydrogen demand from trucks, which is essential for our optimization problem. We downloaded traffic data obtained from Données Québec - in the form of shapefiles which we processed using ArcGIS Pro. This polyline layer comprises a myriad of segments representing the Quebec road network. These files provide a detailed map of Quebec's road network, segmented into numerous polylines. Each segment, varying in length, is identified by its "ide_sectn_" field and includes comprehensive traffic information from 2012-2022. From this large quantity of data, we focused on three attributes: "annee_1," representing data from 2022, "val_djme_1," the summer average daily traffic count for all vehicles in 2022, and "val_cam_1," the percentage of truck traffic per segment. We created a new attribute, "DJME2022_T," by calculating the product of the latter two fields to derive the Summer Daily Average Truck Traffic Count (SDATTC) for each road segment.

We opted to use the summer average rather than winter or yearly averages because it reflects the peak traffic period. This choice, while leading to an overestimation of traffic for nine months of the year, ensures our network is equipped for the highest demand season. We acknowledge this approach results in excess hydrogen production during off-peak months. However, we prefer this scenario as surplus hydrogen can be sold to neighboring industries, whereas a shortage would be more problematic.

		-				,—	(C-2)
	FID	Shape *	ide_sectn_	val_djme_1	val_cam1	*	DJME2022_T
1	1347	Polyline	28888	1250	9.9		124
2	3643	Polyline	25646	4600	9.9		455
3	4614	Polyline	22266	4200	9.84		413
4	281	Polyline	4169	11600	9.83		1140
5	301	Polyline	16005	37000	9.8		3626

Figure 1: ArcGIS table, truck data

Using the "Select by Attribute" function, we strictly kept the segments with truck traffic and deleted those who didn't. Since some road segments do not have any trucks passing on them, this operation resulted in gaps in the road network as illustrated below:



Figure 2: ArcGIS, road network

To overcome this issue, we manually interpolated the DATTC data to fill geospatial quantitative gaps in the dataset excluding secondary roads while favoring the main truck transportation axis described by Gouvernement du Quebec. Our approach ensured that the truck density (SDATTC per meter of road) remained consistent across segments of varying lengths. This method was designed to preserve a realistic representation of truck flux throughout the network, ensuring that the interpolation accurately reflected the spatial distribution and flow dynamics of trucks on the road system. Discontinued segments were connected manually using the "trace" function in ArcGIS Pro following the roads while the interpolated SDATTC field was mentally estimated. We recognize this method presents its own set of limitations, but without available data and under time constraints we chose to proceed this way. The following map illustrates the "Adjusted Truck Passes 2022" layer obtained from "Quebec Traffic Data 2022" after undergoing the above mentioned operations:



Figure 3: ArcGIS complete road network

Agricultural Land: This polygon layer was obtained from the CPTAQ's website. We used the "Select by Attribute" function to filter, isolate and conserve agricultural zones. It's worth noting that agricultural land only represents 5% of the province's territory by area. It is crucial to preserve these parcels of land that

contribute an important service: feeding the population. This underlines how crucial this consideration is for the optimized and integrated placement of hydrogen stations.

Indigenous Land: This polygon layer was obtained from Donnees Quebec's open dataset - b. It describes the repartition of indigenous reserves across the province giving us valuable information for the optimization.

Natural Parks: This polygon layer was obtained from Donnees Quebec's open dataset - c. Both indigenous and agricultural land layers were left as is since they had all the necessary information from the bat and thus didn't require any preprocessing.

Plotting all of the above mentioned data in ArcGIS yields the following map:



Figure 4: ArcGIS, land types (Agricultural, Protected Natural Land, Indigenous Land)

Now that we were able to compile all the required geospatial data, we needed to ensure it was efficiently readable by the optimization code, which we chose to write in Python using Visual Code Studio. Therefore, we've pre-processed it as follows: we chose to discretize our truck data into uniform 20 km segments for several key reasons. First, this reorganization standardizes segments of varying lengths into consistent units, simplifying the dataset and ensuring uniformity for analysis. Second, it facilitates the optimization process by providing evenly spaced midpoints for each segment, allowing the software to create nodes upon which the optimization process is based upon and subsequently the recommendations for station placement. This uniform segmentation enhances the software's capacity to handle data and perform calculations with greater precision. Lastly, discretization enables the integration of geospatial data into our analysis. By adjusting the SDATTC for each new segment, we could implement an intersection code to evaluate overlaps with indigenous territories, agricultural lands, and natural parks. For each category, the code assigns a binary value (1 for overlap, 0 for no overlap), creating an intersection field for every segment and facilitating optimization by incorporating environmental and social constraints directly into the process.

H2 Truck Forecast: To design an optimized hydrogen ecosystem, it was crucial to forecast the population of H2-compatible trucks on Quebec roads and in turn predict H2 demand along the network. To do this, we referred to regulatory strategies surrounding low-carbon trucks taking place at both provincial and federal level. Namely, the Plan for Clean On-Road Transportation (PCORT) schedules the removal of diesel trucks from the new vehicle market from 2040 onwards. We modeled the H2 truck population as a percentage of

total 2022 truck population – which we've used as a baseline year throughout the project – assuming 3 distinct phases as follows:

- *From 2022 to 2040:* To reflect the approaching new regulation, we assume that the H2 truck population follows an exponential growth with a yearly increase of 1.6% x year/2040 as suggested by McKinsey (2024).
- *From 2040 to 2047:* H2 truck population follows a steep 12% yearly increase to reflect the adoption of the PCORT. This increase of H2 vehicle sale is due to the progressive decommissioning of diesel trucks.
- From 2047 to 2100: H2 truck population follows a steady 2% yearly increase indefinitely. At this stage, all diesel trucks have been decommissioned.

It's important to note we did not model the progressive decommissioning of H2 trucks which would describe a stabilization of the H2 truck population eventually. We chose to omit this detail for the sake of simplicity.

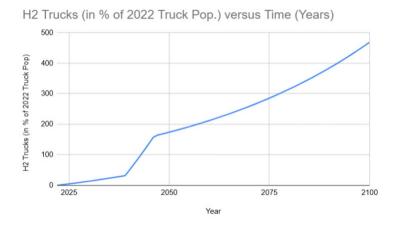


Figure 5: H2-compatible truck population versus time as modeled by our team

From this forecast, we're able to express the H2 truck population as a multiple of the 2022 truck population – which serves as the basis for all traffic calculations. We've stored these multiplying factors and their corresponding year in an array. This enabled us to simulate the H2 truck traffic, and in turn the H2 demand, for each year from 2022-2100 in the entire province.

2.1. Life Cycle Assessment (LCA) Framework

Goal and Scope

A critical component of our platform was to illustrate to our users that the hydrogen network proposed by our algorithm can drastically reduce GHG emissions associated to the freight industry. To do so, we conducted a Life Cycle Assessment (LCA) of both the diesel and hydrogen ecosystems. The goal of our LCA is to compare the impact of hydrogen and diesel station as well as hydrogen and diesel

vehicles. The scope of our analysis is a well-to-wheel assessment which includes both the fuel cycle and the use phase. Steps within these categories include extracting the fuel source, production/refinement, distribution, storage in car tank, and finally the use phase. The following figure highlights the different steps included within our LCA analysis.

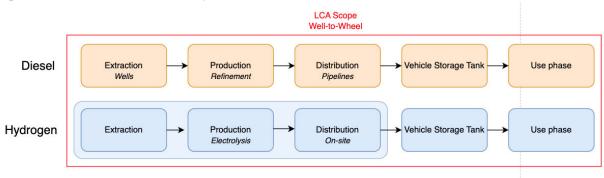


Figure 6: LCA System Boundaries

The functionnal unit chosen for comparison between the two fuel sources is kWh. Assuming both vehicles have similar motor efficiency, a fixed amount of kWh will propel both vehicles the same distance.

Our analysis focuses on two key impact categories that are highly relevant to both fuel cycles. The first is Greenhouse Gas (GHG) emissions, which is critical for stakeholders striving to achieve net-zero emissions goals. The second, often less emphasized in North America, is Land Use. We assessed the land area occupied by each fuel cycle, measured in square kilometers (km²). By calculating land use intensity—the amount km²2 required to produce one MWh—we provide a basis for comparing the two fuel cycles. This metric is essential for optimizing land use, enabling us to produce more energy with a smaller environmental footprint.

Life Cycle Inventory

Once the goal, scope, and functional unit were defined, we began the data-gathering process. Most of the information related to hydrogen was readily available in scientific literature. However, for specific data points that were challenging to locate, we received valuable input from Sebastien Comazzi, an engineer at the Ministry of Economy, Innovation, and Energy. For instance, while information on hydrogen electrolyzers was scarce, he provided critical guidance on the spatial requirements for on-site hydrogen production facilities. According to his recommendations, a plant producing 1,000 kg of hydrogen per day would require approximately 1,000 m², while a plant with a capacity of 4,000 kg/day would need up to 10,000 m². In addition, the Ministry of the Environment and the Fight Against Climate Change in Quebec previously conducted a life cycle assessment of the hydrogen cycle. According to their report, the production of 1 kg of hydrogen is associated with 0.075 kg of CO₂ emissions (Cassanaz, S., et al., 2022). We then found that 1kg of hydrogen contained 33.33 kWh. Therefore:

$$\frac{0.075 kgCo2eq}{33.33 kWh} = 0.00225 kgCO2eq/kWh$$

On the other hand, information regarding the diesel fuel cycle within Quebec was less readily available. To accurately assess land use, we traced the origin of the diesel fuel consumed in Quebec. Approximately 95% of this fuel is sourced from Alberta, specifically the Athabasca oil sands. The oil sands are initially processed into crude oil before being transported via pipelines to the Island of Montreal for further refinement. Once refined into diesel, the fuel is distributed to refueling stations.

To ensure precision in our analysis, we focused on oil provided by Suncor, as detailed data about their operations was the most accessible. Using ArcGIS, we identified that approximately 1,823.354 km² of land is utilized for oil recovery, as illustrated in the following screenshot.



Figure 7: Area covered for oil sands recovery by Suncor Energy

The next logical step was to trace the pipelines transporting crude oil from the Athabasca oil sands to the Montreal refinery located in Côte-Saint-Léonard. Using Canada's open data on pipelines and mapping the routes in ArcGIS, we calculated that the total area covered by these pipelines amounted to 490 km². Lastly, we delineated the boundaries of Suncor's installations in Montreal, as well as the nearest truck refueling stations. The combined land area for these two sections was determined to be 1.33 km². In total the total area covered for all diesel related infrastructure was 2,314.46 km² (Government of Alberta, (2018), Suncor Energy, (2024), Canada Energy Regulator, (2023)).

The carbon intensity of diesel is widely documented in various scientific databases. Based on our analysis and online sources, the Well-to-Tank phase (fuel cycle) emits 0.072 kg CO₂ eq per kWh, while the Tank-to-Wheel phase accounts for 0.256 kg CO₂ eq per kWh (Bieker, G. 2021). Combining these, the total life cycle emissions of diesel amount to 0.328 kg CO₂ eq per kWh.

Life Cycle Inventory Analysis

With the data collected, the next step was to adapt it for both systems to enable a meaningful comparison. The land use intensity of both types of refueling stations was then calculated. For hydrogen stations, the analysis focused on a facility with a maximum land use of 10,000 m², capable of producing 4,000 kg of hydrogen per day. In line with standard practices in energy-related fields, a lifetime value of 25 years was assumed for the calculations:

Land Use Intensity =
$$\frac{\frac{10\ 000\ m^2}{10^6}}{4000(kgH2/day) \times 365.25(days/year) \times 25(years) \times 0.03333(MWh/kgH2)}$$
$$= 8.21 \times 10^{-9} km^2/MWh$$

Similarly, for diesel, it was necessary to determine the daily production at each stage of the production cycle, extend these figures to an annual basis, and calculate the land use over a 25-year lifetime. The total lifecycle land intensity, encompassing the four stages—recovery, pipeline transport, refinery, and refueling station—was calculated to be 0.0000415 km²/MWh.

<u>Interpretation</u>

The results obtained in this LCA can be illustrated in the following table:

 Hydrogen
 Diesel

 kgCO2eq/kWh
 0.00225
 0.328

 Land Use Intensity (km^2/MWh)
 8.21 x 10⁻⁹
 41,500.00 x 10⁻⁹

Table 2: LCA results

This LCA demonstrates that hydrogen-powered freight trucks offer substantial environmental benefits compared to diesel. With lifecycle emissions of 0.00225 kg CO_2 eq/kWh, hydrogen reduces emissions by over 99% compared to diesel's 0.328 kg CO_2 eq/kWh. Additionally, hydrogen infrastructure uses significantly less land, with a land use intensity of $8.21 \times 10^{-9} \text{ km}^2/\text{MWh}$ versus $41,500 \times 10^{-9} \text{ km}^2/\text{MWh}$ for diesel.

To further emphasize hydrogen's potential in creating a more sustainable freight industry, the total emissions avoided by transitioning to zero-emissions vehicles was calculated. Assuming a 2% annual growth rate, this transition could potentially prevent up to 24.8 trillion metric tons of CO₂ equivalent emissions by 2050.

2.2. LCC Framework

The Life Cycle Cost (LCC) analysis evaluates the total costs associated with establishing and operating hydrogen refueling stations over their entire lifespan. This includes initial investments, recurring operational expenses, and maintenance costs, all projected using realistic economic assumptions. The analysis provides a comprehensive financial framework for assessing the long-term feasibility of hydrogen infrastructure in Quebec.

The Capital Expenditures (CAPEX) represent the upfront costs required to construct a hydrogen refueling station. These expenses include essential components like electrolyzers, compressors, hydrogen storage systems, dispensing units, and site preparation. The CAPEX is determined using the formula:

$$CAPEX (in million CAD) = 2.453333 + 0.003011111.x$$

Here, *x* refers to the station's daily hydrogen production capacity in kilograms. This linear formula ensures that larger stations with higher capacities incur proportionally greater costs. For example, a station capable of producing 1,000 kilograms of hydrogen daily would have a CAPEX of approximately 5.46 million CAD (ASME, 2021). This approach ensures scalability and precise budgeting for projects of varying sizes.

To make CAPEX manageable, it is annualized using a capital recovery factor. This factor spreads the initial investment over the station's 20-year operational lifespan, using a discount rate of 7% to account for the time value of money. The formula for annualized CAPEX is:

Annualized CAPEX =
$$CAPEX \cdot \frac{i \cdot (1+i)^n}{(1+i)^n - 1}$$

where i is the discount rate and n is the project lifespan (Hydrogen Strategy for Canada, 2021).

The Operational Expenditures (OPEX) are categorized into fixed and variable costs. Fixed OPEX accounts for recurring expenses like system monitoring, routine inspections, and administrative overhead. These costs are modeled as 5% of CAPEX annually. For instance, a station with a CAPEX of 5.46 million CAD would incur a fixed OPEX of approximately 273,000 CAD per year (Hydrogen Council, 2020).

Variable OPEX depends on the station's hydrogen production volume and includes energy consumption, water usage, and consumables. Energy is the most significant expense, with hydrogen production requiring 50 kWh per kilogram at a cost of 0.07 CAD/kWh, amounting to 3.5 CAD per kilogram. Water consumption costs an additional 0.0135 CAD per kilogram, while labor and other consumables contribute 0.05 CAD per kilogram. The total variable OPEX is calculated as:

$$OPEX(var) = x.365.(3.5 + 0.0135 + 0.05)$$

For a station producing 1,000 kilograms of hydrogen daily, the variable OPEX would total approximately 1.3 million CAD annually (Eberle et al., 2022).

The effective production capacity is critical for determining the cost per kilogram of hydrogen. It accounts for operational parameters, including the maximum power demand of the electrolyzer, its efficiency, and the station's utilization rate. The power required for production is estimated at 50 kWh per kilogram of hydrogen, adjusted by an electrolyzer efficiency (K) typically between 80% and 95% (IEA, 2021). The capacity factor (CF), typically 85% to 95%, reflects the station's actual operational time, and the annual operational hours (T) are set at 8,760, assuming continuous operation.

The Levelized Cost of Hydrogen (LCOH) integrates CAPEX, OPEX, and production capacity into a single metric representing the cost of producing one kilogram of hydrogen over the station's lifecycle. The LCOH is calculated as:

$$LCOH = \frac{CAPEX \cdot \frac{i (1+i)^n}{(1+i)^n - 1} + OPEX (fixed) + OPEX (var)}{\frac{p (elec. max)}{K} \times CF \times T}$$

$$LCOH = \frac{CAPEX \cdot \frac{i \ (1+i)^n}{(1+i)^n - 1} + OPEX \ (fixed) + OPEX \ (var)}{\frac{p \ (elec. max)}{K} \times CF \times T}$$

$$LCOH = \frac{2.453333 + 0.003011111.x \cdot \frac{i \ (1+i)^n}{(1+i)^n - 1} + 0.05 \ (CAPEX) + x \cdot 365 \cdot (3.5 + 0.0135 + 0.05)}{\frac{x \cdot 50}{K} \times CF \times 8760}$$

This formula ensures that both fixed and variable costs are appropriately distributed across the station's total hydrogen output. For example, a station operating at high capacity and efficiency would achieve a lower LCOH, demonstrating improved cost efficiency.

The LCC analysis provides a detailed understanding of the economic trade-offs involved in hydrogen refueling station operations. By integrating realistic economic assumptions, such as the discount rate, operational lifespan, and capacity factors, the model enables stakeholders to optimize station design and operations.

2.3. **Objective Functions and Constraints**

Multi-objective optimization seeks to optimize multiple conflicting objectives while satisfying certain constraints. Unlike single-objective optimization, which minimizes or maximizes a single objective, multi-objective optimization produces a set of solutions, each representing a trade-off among the objectives. These solutions, collectively known as the Pareto front, balance different priorities without one solution dominating another. This approach is indispensable in engineering and complex industrial design, where conflicting goals and real-world restrictions must be carefully balanced (Rao & Waghmare, 2014).

2.3.1. The Unit Hydrogen Station (UHS)

At the core of our optimization framework is the Unit Hydrogen Station (UHS), a modular functional unit designed to quantify hydrogen refueling station capacity. Each UHS is defined with a production capacity of 1,000 kg/day, providing a standardized measure for station output. This modularity allows the optimization algorithm to assign an appropriate number of UHS units to each segment, reflecting local demand requirements. Additionally, each UHS is associated with an area footprint, environmental impact, and capital and operational costs, as detailed in Sections 2.2 and 2.3.

Objective Functions 2.3.2.

Objective functions are critical in guiding the optimization process, defining the goals that the algorithm strives to achieve. Unlike single-objective approaches, multi-objective optimization produces a set of Pareto-optimal solutions, where no solution is strictly superior in all objectives (Coello, 2006). For this study, the algorithm minimizes three primary objectives:

Environmental Cost

This objective evaluates the environmental impact of hydrogen station placements. It is calculated as the sum of the carbon dioxide equivalent (CO2e) emissions for each UHS installed, using the methodology

outlined in Section 2.2. This ensures that the optimization promotes environmentally sustainable network designs.

Economic Cost

Economic cost encompasses both capital expenditure (CAPEX) and operational expenditure (OPEX), evaluated as discounted annuities over the project's 25-year lifecycle. CAPEX includes the installation costs of UHS units, while OPEX accounts for recurring expenses such as maintenance and hydrogen production. Detailed cost formulas are provided in Section 2.3.

Demand Mismatch

This objective quantifies the discrepancy between hydrogen supply and demand across the network. Each road segment has a defined hydrogen demand, adjusted based on projected growth rates. The supply is distributed from stations, decreasing with distance as governed by a supply distribution function. The mismatch is computed as the sum of absolute differences between supply and demand for all segments, emphasizing the importance of an equitable supply network.

2.3.3. Constraints

Constraints ensure that the algorithm generates practical and implementable solutions, aligning with the geospatial and regulatory context of Quebec. These constraints are divided into hard and soft constraints:

Hard Constraints

Maximum Distance Between Stations: To ensure refueling availability, the distance between consecutive stations is limited by the autonomy of trucks operating in the network. This autonomy is divided by a safety factor of three and further adjusted to account for the length of discretized segments. Any violation adds to a penalty count, discouraging solutions that fail to meet this requirement.

Area Restrictions: Stations are prohibited on protected lands such as natural parks or indigenous territories. The algorithm imposes a penalty for placing stations on such lands, ensuring compliance with legal and environmental restrictions. This logic is implemented in the optimization code.

```
restricted_land_penalty = np.sum(genome *
segment_gdf['land_type'].isin(['Natural Park']))
```

Soft Constraints

Water Resources: Hydrogen production via electrolysis requires significant water resources, which vary geographically. The availability of water along highways is incorporated as a constraint to prioritize feasible station placements.

Agricultural Land: Protecting agricultural land is vital for Quebec's economic sustainability. A penalty function quantifies the economic loss of placing stations on agricultural land, calculated as \$30/m² of land utilized.

This value is derived from several key components:

- 1. **Land Acquisition Costs**: Based on Statistics Canada data, the average cost of agricultural land in Quebec is \$1/m², reflecting its base market value (Statistics Canada).
- 2. **Zoning and Legal Fees**: Converting agricultural land for industrial use incurs zoning and legal costs, which average \$0.5/m² according to Quebec's Ministry of Municipal Affairs and Housing (MAMH).
- 3. **Environmental Impact Assessments (EIA)**: Mandatory for hydrogen projects, EIA costs average \$4/m², as reported by the Quebec Ministry of Environment and WSP Global.
- 4. **Infrastructure Development Costs**: Basic infrastructure, including utilities and site preparation, incurs a cost of \$18/m², based on estimates from the Institute of Civil Construction (ICC).
- 5. **Hydrogen-Specific Infrastructure Costs**: Specialized requirements for hydrogen stations, such as storage tanks and safety systems, add an average of \$7.5/m², according to the Hydrogen Council and Clean Energy Canada.

This penalty is added to the economic cost objective, discouraging solutions that compromise agricultural areas.

Penalty_agri= 30×Total Agricultural Area (m2)

3. Stakeholders Framework for Collaboration

As the main goal of our capstone project is to provide the base ground for collaboration at the government/industry level, we wanted to ensure our software was relevant to these stakeholders. During the first weeks of this semester, we reached out to key players in three different fields of the hydrogen ecosystem.

We first contacted Sebastien Comazzi, an engineer working in the "Bureau du développement de l'hydrogène vert et des bioénergies" within the Ministry of Economy, Innovation and Energy. This partnership with the ministry allowed us to gather critical feedback to improve our project and implement features that were most relevant to the government. A really interesting comment we had from discussions with Sebastien is his recommendations to implement additional demand location, on top of the truck energy demand, to allow for additional industry to use hydrogen as there primary energy source of for various chemical transformations. This is particularly interesting because Quebec highlights the benefits hydrogen could have in the multiple sectors and by implementing this feature we greatly enhance the scope of our project. Additionally we wanted to understand Quebec's plan to implement hydrogen and we were told that our approach was unique and could have significant impact on how decision-makings processes occur at the ministry level.

Our second stakeholders interviewed is Pierre Deprez. He is a former employee of the city of Montreal and worked in the urban planning department. His expertise was particularly important when we took into account zoning laws and understanding the current vision of Montreal and Quebec when managing its territory's development. He told us that agricultural lands were extremely important to the eyes of the province and that we should establish a heavy penalty function if the algorithm wanted to implement a station on these lands.

In our correspondances, he also mentions that addressing the placement of hydrogen stations on constrained lands, such as agricultural, rural, or protected natural areas, involves complex processes. Government-led initiatives require collaboration with the *Ministère de l'Énergie et des Ressources Naturelles*, the *Ministère des Affaires Municipales et de l'Habitation*, the *Ministère de l'Environnement, de la Lutte Contre les Changements Climatiques, de la Faune et des Parcs, MELCCFP*, and the *Commission de Protection du Territoire Agricole du Québec, CPTAQ*, for zoning changes. Alongside local consultations that may extend timelines. For private enterprises, challenges include navigating municipal regulations, securing zoning approvals, consulting landowners, and addressing water infrastructure needs, such as servitudes for connecting water sources and evaluating agricultural impacts. While this topic extends beyond the scope of our project, it provides a valuable starting point for stakeholders to reflect on future policy and planning discussions.

Finally, we wanted to gain insight from a hydrogen promoter who plans the implementation of hydrogen on site electrolyser. Friedrich Dehem-Lemelin, from Hydrolux was the right person to talk to. We believe our software would be of the most use to this stakeholder due to the fact that it allows for rapid profitability calculations for each station while minizing environmental impact which can improve the credibility and reputation of the company. Friedrich's main point of interest was to highlight the points were electricity was available and readily accessible. He finds that his main challenge was to place stations where sufficient electric power was available. As explained previously in section 2.1, we had trouble finding data for the electric grid in Quebec. We made sure our lines on ArcGIS matched as precisely as possible the actual distribution of powerlines to have the most realistic electricity distribution.

In conclusion, our collaboration with key stakeholders ensured our project was practical, relevant, and tailored to the needs of Quebec's hydrogen ecosystem. Feedback from government, urban planning, and industry experts helped refine our software, enhancing its ability to account for industrial hydrogen demand, respect zoning laws, and address electricity accessibility. These insights strengthened the functionality and usability of our tool, making it a valuable resource for decision-making at the government and industry levels. By incorporating these considerations, we believe our project lays a solid foundation for advancing hydrogen infrastructure in Quebec.

4. Prototyping

4.1. NSGAII Algorithm Process

The optimization process begins with the implementation of the NSGA-II, a widely used multiobjective optimization algorithm. NSGA-II evolves a population of candidate solutions through selection, crossover, and mutation. It introduces key mechanisms, such as non-dominated sorting and crowding distance, to ensure diversity and convergence toward optimal solutions. The algorithm produces a Paretooptimal set of solutions, where each solution represents a trade-off between conflicting objectives, ensuring no solution in the set is strictly better than another in all objectives. The Pareto front, a graphical representation of these trade-offs, depicts the boundary of optimal solutions in the objective space (Deb et al., 2002). The implementation begins with defining the problem-specific parameters and input data, including the road network represented as a geospatial DataFrame (segment_gdf) represented in Figure 5, the year of implementation, and the hydrogen production capacity per UHS. The road network data includes attributes such as truck traffic, land type along the segment, and hydrogen demand. The demand is adjusted using coefficients derived from projected growth rates for the specified year.

	start_longitude	start_latitude	end_longitude	end_latitude	length	truck_passes	land_type	geometry	water_source_type	demand
0	-72.953803	46.217718	-72.955781	46.221683	674.835588	395.010010	Agricultural Land	LINESTRING (-72.9538 46.21772, -72.95578 46.22	Ground	21.325345
1	-72.953913	46.217687	-72.955781	46.221683	675.668272	395.010010	Agricultural Land	LINESTRING (-72.95391 46.21769, -72.95578 46.2	Ground	21.351658
2	-71.213218	48.400408	-71.176161	48.400473	4125.083040	2016.000000	Agricultural Land	LINESTRING (-71.21322 48.40041, -71.17616 48.4	Ground	665.293393
3	-71.213190	48.400697	-71.176123	48.400747	4126.251936	2016.000000	Agricultural Land	LINESTRING (-71.21319 48.4007, -71.17612 48.40	Ground	665.481912
4	-71.865794	45.345004	-71.863002	45.352883	1286.218567	840.559998	Agricultural Land	LINESTRING (-71.86579 45.345, -71.863 45.35288)	Municipal	86.491510
1533	-71.473795	46.740894	-71.427395	46.755143	5660.343466	1000.000000	Agricultural Land	LINESTRING (-71.4738 46.74089, -71.42739 46.75	Ground	452.827477
1534	-71.718208	46.622332	-71.873505	46.659699	18318.560759	160.000000	Natural Park	LINESTRING (-71.71821 46.62233, -71.87351 46.6	Ground	234.477578
1535	-71.873505	46.659699	-71.991106	46.576390	18806.433160	160.000000	Natural Park	LINESTRING (-71.87351 46.6597, -71.99111 46.57	Surface	240.722344
1536	-71.991106	46.576390	-71.991710	46.574229	356.332083	160.000000	Agricultural Land	LINESTRING (-71.99111 46.57639, -71.99171 46.5	Surface	4.561051
1537	-72.274885	46.402711	-72.200867	46.499580	17687.853834	250.000000	Natural Park	LINESTRING (-72.27489 46.40271, -72.20087 46.4	Surface	353.757077

Figure 8: Dataframe of discretized road segments with attributes

The algorithm generates an initial population of candidate solutions using a combination of Latin Hypercube Sampling (LHS) and heuristic-based initialization strategies. Latin Hypercube Sampling ensures a diverse initial population by dividing the parameter space into equal intervals and sampling within these intervals to cover the entire range of possible values uniformly. In this implementation, LHS is applied to the number of segments, scaled to the maximum allowable number of hydrogen station units (UHS) per segment, and cast to integer values. Approximately 70% of the initial population is derived from this method to ensure broad exploration of the solution space.

The heuristic-based initialization complements this diversity by seeding specific configurations based on predefined rules. While not explicitly used in this setup, potential strategies could include prioritizing high-traffic segments (e.g., using sorted indices of truck traffic data) or maintaining uniform station spacing (e.g., placing stations at regular intervals across segments). A random sampling of UHS values is also employed for additional diversity in about 30% of the population, ensuring a mix of structured and exploratory solutions. This tailored approach balances systematic coverage of the search space with targeted exploration of promising configurations.

Each candidate solution is evaluated using a fitness function that calculates the values of the three objectives. The demand mismatch is calculated as the absolute difference between adjusted demand and a computed supply vector. The supply vector is derived from the genome (candidate solution) using a weighted distribution model, where hydrogen supply diminishes with distance from the station as described earlier.

Once the fitness values are assigned to the initial population, the NSGA-II algorithm progresses with the non-dominated sorting step. This process categorizes candidate solutions into hierarchical Pareto fronts. Each solution is compared with every other solution to determine whether it dominates or is dominated based on two criteria: (1) objective comparisons, where a solution is considered better if it performs equally well or better in all objectives and strictly better in at least one, and (2) constraint satisfaction, where

solutions with fewer total constraint violations (e.g., penalties for restricted land use or station density) are favored. Solutions with no dominators are assigned to the first Pareto front, while subsequent fronts are iteratively determined by removing dominated solutions.

The algorithm then calculates the crowding distance for each solution within the Pareto fronts to maintain population diversity. Crowding distance measures how "crowded" a solution is by computing the distance between neighbouring solutions in the objective space. Solutions at the boundaries of the front are assigned an infinite distance to ensure their preservation. For solutions within the same front, those with higher crowding distances are prioritized during selection.

In the selection phase, a new population is formed by combining solutions from the current generation's Pareto fronts, starting with the first front and proceeding sequentially until the population size limit is reached. When a front's inclusion exceeds the limit, solutions within the front are ranked by their crowding distance, and the top solutions are selected to complete the population.

The next step involves generating offspring through crossover and mutation operations:

Crossover: Two parent solutions are randomly selected from the current population. With a probability of 0.8, a crossover point is chosen, and the genome segments from the two parents are exchanged to produce two offspring. This promotes recombination of high-performing traits.

Mutation: Each offspring genome undergoes mutation with a probability of 0.15. A random position in the genome is selected, and its value is replaced with a random integer within the allowable range of hydrogen station units (UHS). This introduces genetic diversity and enables the exploration of new solutions.

The newly generated offspring are evaluated using the same fitness function as the initial population, and their fitness values are used to perform non-dominated sorting and crowding distance calculation in the subsequent generation. The algorithm iterates through multiple generations, refining the population to approach the Pareto-optimal set of solutions.

Throughout the optimization, the algorithm enforces constraints, such as penalties for placing stations on restricted lands or exceeding acceptable station density thresholds, by incorporating these penalties into the fitness evaluation. This ensures that infeasible solutions are deprioritized in the selection process.

The process continues for a predefined number of generations or until convergence criteria are met, yielding a final population that represents a diverse set of Pareto-optimal solutions.

4.2. PROMETHEE-Based Decision Analysis

Choosing the optimal network from the last population is a task that requires taking all the fitness functions and constraints into consideration. This is why using a Multicriteria Decision Analysis method is suitable for our problem. After the NSGA-II process, the final population is evaluated using the Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE). PROMETHEE integrates decision-makers' preferences by assigning weights to each objective and calculating net preference flows for each solution. The preference function evaluates the relative performance of solutions based on the objectives and the specified criterion type (minimization or maximization). The best solution is selected as

the one with the highest net preference flow. The combination of NSGA-II and PROMETHEE enables the generation of a Pareto-optimal set of solutions for hydrogen station placement. NSGA-II ensures efficient exploration of trade-offs between objectives, while PROMETHEE incorporates decision-makers' preferences to select the most suitable solution for real-world implementation. This framework provides a robust tool for designing optimized hydrogen refuelling networks that balance economic, environmental, and operational objectives.

4.3. Graphical User Interface (GUI) and Interactive Map

Since our tool was destined to be used by a variety of stakeholders, we had to tailor it to their needs, make it simple to use and make sure all key metrics were effectively displayed. Assuming that most stakeholders might not be proficient in Python programming, we aimed to make the optimization parameters adjustable without requiring them to modify the code directly. To achieve this, we opted to develop a Graphical User Interface (GUI). This approach allows users to interact with the tool seamlessly and adjust settings through a user-friendly visual platform, enhancing accessibility and usability for all users, regardless of their technical background.

4.3.1. Graphical User Interface Design

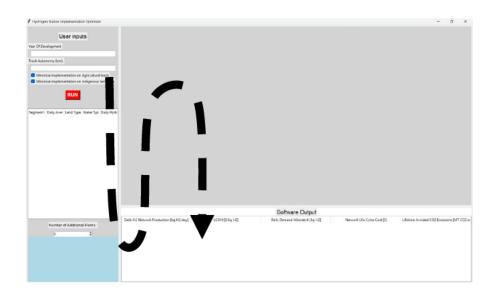


Figure 9: Empty GUI layout and user interaction flow

The design of our GUI was driven by two key goals: ease of use, compatibility with the backend. First, we designed the GUI to be intuitive, allowing users to navigate and interact without confusion or the need for extensive instructions. This started with the layout which we've built in a strategic manner aligning with the English reading pattern from left to right and top to bottom as depicted by the arrow in figure 9. The left panel organizes inputs hierarchically: optimization parameters are placed at the top to ensure they are the first elements the user interacts with, followed by a table of road segments in the middle for easy

reference, and additional inputs at the bottom. The central, largest section of the GUI was allocated to a graphical visual representation. Initially, we intended to populate it with an interactive map but due to limitations, we opted for a graph of supply versus demand along the road network (see figure 10). Finally, the bottom section hosts a table of outputs where key metrics are displayed. Second, regarding backend compatibility, we wanted to ensure the GUI would be able to read and display the results of the optimization algorithm in a quick and computationally efficient manner. For this reason, we picked Tkinter, a Python library intended to design GUI for Python backends. This enabled us to write the GUI code in the same file as the optimization code, ensuring computational efficiency. Further, by having both front-end and backend code in the same file and language, we significantly eased the development process and ensured that adjustments could be made swiftly and effectively.

4.3.2. User Input Identification

In developing our optimization tool, we meticulously selected parameters that give users control over crucial aspects of network optimization. The "Year of Development" parameter allows users to project truck population dynamics into the future (as discussed in section 2.1), choosing a specific year for which the hydrogen fueling network will be optimal. This is vital as it reflects the anticipated growth in hydrogen truck usage over time. For "Truck Autonomy" (Range in km), we considered the evolving technology of hydrogen trucks, which are expected to have increasing ranges as development progresses. To ensure safety and practicality, we set the maximum distance between stations at one-third of a truck's range, providing a safety net in case a truck misses up to two stations. This parameter can be adjusted by users, allowing flexibility in network planning. The "Minimize Implementation on Agricultural Land" parameter addresses the limited availability of arable land in Quebec, approximately 5%, giving policymakers the option to minimize station implementation on such lands. Lastly, the "Minimize Implementation on Indigenous Land" parameter offers stakeholders the discretion to factor in or exclude these lands from development plans, ensuring sensitive handling of cultural and environmental concerns. Each parameter is designed to adapt to different user needs and evolving scenarios, making the tool robust and flexible.

4.3.3. Output Metric Identification

Further, we needed to provide our users with some key metrics to evaluate the feasibility of such infrastructure at a quick glance. These metrics needed to be easy to read, interpret and widely used in multiple industries. For this reason, we identified the following five key metrics to output to our users: "Daily H2 Production (in kg/day)", "LCOH (in \$/kg H2)", "Daily Demand Mismatch (in kg H2)", "Network Life Cycle Cost (in \$)" and "Lifetime Avoided CO2 Emissions (in Mt CO2 e)". Daily H2 Production was calculated by summing up the production of all UHS in the network, informing users of the total hydrogen supply they can expect from the network. LCOH indicates the life cycle cost of each kilogram of H2 in dollars, enabling stakeholders to evaluate the cost-effectiveness of an optimized H2 network and the price competitiveness compared to diesel. This was calculated using the formula in Appendix E. Daily Demand Mismatch highlights gaps between supply and demand in kilograms, guiding necessary network adjustments and informing users of where they occur on the network. This was calculated by subtracting the demand by the supply for each segment along the network. Network Life Cycle Cost offers a comprehensive view of the financial implications of such a project over its entire useful lifetime and was calculated using the formulas in Appendix E. Lastly, Lifetime Avoided CO2 Emissions

quantifies the environmental benefits of switching from diesel-powered trucks to H2-powered trucks. This was estimated by calculating the global warming potential difference between H2 and diesel for all the trucks in the network assuming all diesel trucks have been replaced by H2 trucks. All of these metrics are crucial for stakeholders assessing the feasibility of a hydrogen ecosystem for freight trucks. Details on how they were calculated can be found in Appendix E.

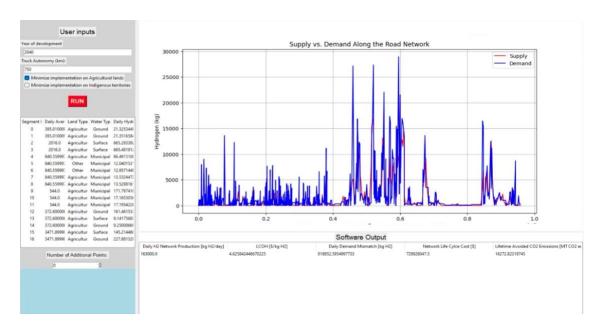


Figure 10: User interface and associated graphs

4.3.4. Interactive Map

To offer adequate visual representation of the network, we opted for Folium, a Python library which enabled us to generate an interactive map. The resulting map can be seen in Figure 10, we've represented the truck network as blue segments, the recommended hydrogen refuelling stations as red dots, as well as all of the spatial constraints (indigenous land in purple, natural parks in green and agricultural land in yellow). The interactive map is intuitive — as it follows the same format as widespread cartographic tools available on most devices — which allows users to navigate the province and identify the location of stations as well as their production which is proportional to the size of the dot.

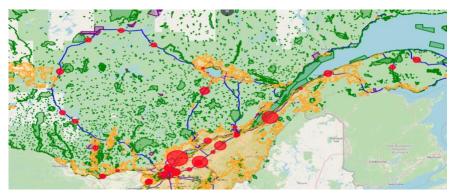


Figure 11: Output map with ideal station location and size

Furthermore, we've programmed pop-ups to appear as the user hovers over a specific station, giving key information to the user such as daily H2 production in kg and life cycle cost of each station as well as the daily emissions reductions at each station (see Figure 11). The latter was calculated by comparing the global warming potential (GWP) differences between hydrogen and diesel, relative to the station's daily hydrogen production. We've intentionally limited the displayed indicators to these three key metrics to maintain clarity and prevent information overload for the user. This design choice ensures that users receive the most relevant data without compromising the interface's usability.



Figure 12: Map focus on UHS

5. Testing and Optimization

5.1. Testing and Optimization

Once the initial implementation of the NSGA-II algorithm was developed, several key challenges needed to be addressed to enhance its performance and effectiveness. These challenges included improving runtime, increasing the convergence rate, refining the selection process for the last population, and avoiding entrapment in local optima. Systematic modifications were introduced to tackle these issues.

5.2. Reducing Runtime

One significant bottleneck in the algorithm's runtime was the repetitive computation of hydrogen supply distributions for each genome across generations. To address this, a supply matrix was developed. This matrix precomputes the impact of each segment on every other segment, allowing the supply vector (the hydrogen availability on each segment) to be calculated efficiently by multiplying the matrix with the genome vector. This innovation significantly reduced runtime, as it eliminated the need to recalculate segment relationships for every network configuration in each generation. By leveraging this matrix, the algorithm achieved a substantial reduction in computational overhead, making the genetic operations more efficient.

5.3. Improving Convergence Rate

The initial version of the algorithm used purely random initialization for the first population. While this approach ensured diversity, it often led to slow convergence. The randomly generated networks frequently placed hydrogen stations on nearly all segments, requiring repeated mutations and crossovers over many generations to evolve networks with a reasonable number of stations. To address this, diverse initialization methods were introduced:

Latin Hypercube Sampling (LHS): 50%Randomized Heuristic Initialization: 20%

Mixed Randomization: 30%

Additionally, tuning the mutation and crossover probabilities played a crucial role in improving convergence. After experimenting with various configurations, an optimal mutation probability of 10% and a crossover probability of 80% were identified. These values struck a balance between exploration (introducing new solutions) and exploitation (refining existing solutions), accelerating convergence without compromising solution quality.

5.4. Avoiding Local Optima

During testing, it was observed that networks initialized with a high percentage of stations on high-density segments often resulted in local optima. For instance, these networks consistently converged to solutions with stations concentrated in regions like Montreal and Quebec, neglecting other potential placements. To counter this, the initialization strategy was modified to include a mix of 70% LHS-based solutions and 30% random solutions. This approach retained the benefits of systematic sampling while introducing sufficient randomness to escape local optima. As a result, the algorithm achieved both improved convergence rates and better exploration of the solution space.

5.5. Performance Analysis and Sensitivity Testing

To determine the optimal parameters for population size and the number of generations, a sensitivity analysis was conducted. Various configurations were tested, revealing that the algorithm performed best with a population size of 200 individuals and 1,000 generations. This configuration provided a good balance between computational cost and the ability to explore the solution space thoroughly. The sensitivity analysis underscored the importance of these parameters in shaping the efficiency and effectiveness of the algorithm. After finetuning with general settings, the software outputs networks with total cost around CAD 3 billion, a levelized cost of Hydrogen of 4\$/kg which is competitive with today's diesel cost before governmental subsidies.

6. Discussion

6.1. Algorithm Effectiveness

The hydrogen optimization tool has proven to be a robust and effective solution for tackling the complexities of hydrogen infrastructure planning. By utilizing Genetic Algorithms (GA), the tool identifies optimal station locations and sizes while ensuring system-wide reliability in meeting hydrogen demand.

The network layouts produced by the tool showcase how hydrogen availability is strategically maintained across key transportation corridors, ensuring robust supply chain support.

Critical outputs, including the Levelized Cost of Hydrogen (LCOH), daily hydrogen production, and demand fulfillment metrics, allow stakeholders to assess the economic feasibility and operational efficiency of the proposed network. The interactive drag-and-drop feature empowers users to modify station placements, with real-time recalculations providing immediate feedback. This flexibility enables stakeholders to test various configurations and ensure the network meets both their strategic objectives and specific regional requirements.

Environmental metrics, such as avoided emissions measured in metric tonnes of CO2 equivalent, highlight the tool's contribution to sustainability. By offering a clear comparison between hydrogen-based transportation and traditional diesel systems, the tool supports informed decision-making aligned with environmental goals.

Additionally, the tool integrates user preferences in addressing sensitive areas such as agricultural lands or indigenous communities. This approach promotes a collaborative decision-making process that involves stakeholders early in the planning stages, fostering engagement and ensuring alignment with local priorities.

6.2. Limitations

The limitations of the hydrogen optimization framework are not unique to this tool but reflect broader challenges in the field of infrastructure planning. One such challenge is the dependency on high-quality, comprehensive datasets, such as detailed traffic patterns, hydrogen demand projections, and grid energy availability. Ensuring data accuracy and accessibility is a general concern across similar optimization models and infrastructure projects.

Another general limitation lies in the computational demands of Genetic Algorithms. While GA is highly effective for multi-objective optimization, its processing times can increase significantly with larger datasets or more complex constraints. However, advancements in computational power and algorithmic efficiency are continually addressing this issue across the industry.

The dynamic nature of stakeholder needs and localized challenges presents another area for refinement. For example, while the tool effectively integrates user choices regarding station placement on agricultural lands or near Indigenous communities, further stakeholder engagement could enhance the planning process. Involving local authorities and communities early in the decision-making cycle ensures that the network respects social and cultural sensitivities while fostering trust and cooperation. This inclusion represents an opportunity for deeper collaboration rather than a limitation of the tool itself.

6.3. Future Considerations

Future enhancements to the hydrogen optimization tool hold great potential to address these general challenges and further increase its utility. Integrating real-time data streams, such as live traffic flows and seasonal demand variations, will improve accuracy and adaptability, ensuring the tool remains responsive to changing conditions.

The seamless inclusion of existing and newly operational hydrogen production sites into the optimization process will continue to enhance efficiency. This will ensure that production resources are fully utilized while avoiding overproduction and unnecessary infrastructure costs.

Expanding the tool's features to include flexible modeling of station capacities, the addition of renewable energy sources, and broader environmental metrics would support more comprehensive planning. Exploring the conversion of existing gas stations into hydrogen refueling stations offers another promising avenue for faster network deployment and reduced costs.

Dynamic economic modeling that incorporates fluctuating energy prices, advancements in hydrogen production technology, and evolving carbon credit policies will ensure the tool stays relevant in a rapidly changing market. These refinements will make the platform even more robust and aligned with long-term goals, such as achieving net-zero emissions targets.

By addressing these opportunities, the hydrogen optimization tool can remain a cutting-edge solution, driving sustainable and efficient transportation networks that align with regional and global energy transitions. It empowers stakeholders with actionable insights and flexible solutions, paving the way for the widespread adoption of hydrogen infrastructure.

7. Conclusion

The transition from diesel-powered freight transportation to a hydrogen-powered ecosystem is an essential step for Quebec to meet its ambitious climate commitments under the Paris Agreement and the Net-Zero Emissions Accountability Act. By leveraging Quebec's abundant hydroelectric resources and applying advanced computational methods, this project developed a robust software tool for optimizing the hydrogen refueling infrastructure for the province's freight sector. This software integrates cutting-edge techniques, such as the Non-dominated Sorting Genetic Algorithm II (NSGA-II), to balance economic costs, environmental impact, and hydrogen supply-demand distribution. With its user-friendly interface and interactive geospatial mapping features, the tool empowers policymakers, engineers, and industry stakeholders to make informed decisions. Key considerations, such as land-use restrictions, Indigenous territories, and agricultural preservation, have been integrated into the optimization process to ensure socially and environmentally responsible planning. The tool's ability to forecast hydrogen demand, recommend optimal station placements, and provide actionable insights demonstrates its value as a decision-making platform. By addressing critical challenges in freight decarbonization, such as infrastructure placement, lifecycle cost analysis, and stakeholder collaboration, this project lays the foundation for the widespread adoption of hydrogen in Quebec's freight industry. While limitations, such as data dependency and computational demands, highlight areas for refinement, future enhancements can address these challenges. Integrating real-time data, expanding environmental metrics, and adapting to dynamic economic scenarios will ensure the tool's continued relevance and effectiveness. This project not only advances Quebec's hydrogen ecosystem but also establishes a replicable framework for sustainable transportation planning worldwide. By aligning innovation with environmental and social priorities, the optimization tool contributes to building a cleaner, more sustainable future for the freight industry and beyond.

8. Acknowledgements

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Thank you for inspiring us to push boundaries, think critically, and deliver a project we are truly proud of. It has been an incredible learning experience, and we are deeply appreciative of the opportunity to work on such a meaningful endeavor.

The authors employed AI tools, specifically Grammarly for feedback on writing and Quillbot for plagiarism checks, to enhance the structure and clarity of the document. All research, analysis, and conclusions contained in this paper are the authors' original work (Design 3 Lecture, Dr. Clark).

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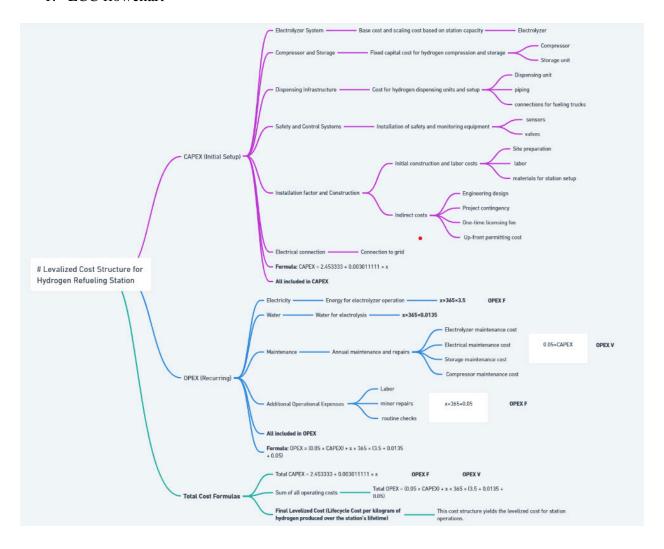
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10. Appendix 1: Life Cycle Costing Analysis

1. LCC flowchart



2. CAPEX Breakdown

CAPEX Formula Breakdown

The Total CAPEX formula represents the initial setup cost required for infrastructure, based on the capacity of the station in kilograms of hydrogen: 2.453333 + 0.003011111 x x

where:

- 2.453333: Fixed base cost of setting up a hydrogen refueling station in millions of CAD. This represents initial setup costs, regardless of capacity, covering foundational infrastructure.
- 0.003011111: Variable cost factor per unit of capacity (million CAD per kg), representing the incremental costs for larger capacity stations due to additional
 equipment and storage requirements.
- x: Station capacity in kilograms (kg) of hydrogen per day. This is the total daily hydrogen dispensing capacity, influencing the size of electrolyzers, compressors, storage, and dispensing systems needed.

3. OPEX Breakdown

OPEX Formula Breakdown

The Total OPEX formula represents the recurring operational expenses for the station, covering annual electricity, water, maintenance, and operational costs.

where each term is defined as follows:

1. Maintenance Cost: 0.05×CAPEX

- Units: CAD per year
- · Context: Represents annual maintenance and repairs, estimated at 5% of the initial CAPEX.

1. Electricity Cost: x×365×3.5

- Units: CAD per year
- Context: The cost of electricity for hydrogen production, assuming 50 kWh per kg of hydrogen at \$0.07 CAD per kWh.
 - · x: capacity per unit station in kg of hydrogen.
 - · 365: Days per year.
 - 3.5: Cost per kg of hydrogen in CAD/kg (derived from 50 kWh/kg × \$0.07 CAD/kWh).

2. Water Cost: x×365×0.0135

- · Units: CAD per year
- · Context: Cost of water required for electrolysis, assuming 9 liters of water per kg of hydrogen at \$0.0015 CAD per liter.
 - · x: capacity per unit station in kg of hydrogen.
 - · 365: Days per year.
 - 0.0135: Cost per kg of hydrogen in CAD/kg (derived from 9 L/kg x \$0.0015 CAD/L).

3. Additional Operational Expenses: x×365×0.05

- · Units: CAD per year
- · Context: General operating costs for labor, minor repairs, and routine operational checks.
 - x: capacity per unit station in kg of hydrogen.
 - · 365: Days per year.
 - . 0.05: Estimated additional cost per kg of hydrogen in CAD/kg.

4. Detailed explanation of each component in the LCOH2

tailed Explanation of Each Component in the LCoHZ. $LCoHE_1 = \frac{CAPEX \times \frac{(x+3+1)^2}{16-F^2} + OPEX_{cot} + OPEX_{cot}}{\frac{d^2}{26} \times CF \times T}$ $re's a treation of each component with all known parameters:$ $umorator: Total Costs (CAPEX and OPEX)$	CAPEX	$2.453333 + 0.003011111 \times x$	Capital Expenditure, initial investment cost based on daily capacity x in kg of
al Expenditure (CAPE). al Expenditure (CAPE). formula: context. This represents the initial investment cost in millions of CAD to set up the hydrogen refueling station, where x is the daily capacity of the station in kg of hydrogen. alliand CAPE: formula:	š	Discount Rate	Represents the time value of money, typically between 5% and 10%.
 I Discount rain, representing the time value of movey. This reflects the cost of capital or expected return, typically in the range of 8.05 to 9.10 (5-10%). Project Rétime in years. This represents the lifespan of the station's infrastructure, other assumed to be 20 to 30 years. Context: The term converts CAPEX into an equivalent annual cost, spreading it over the entire project's lifetime. 	*	Project Lifetime	The lifespan of the hydrogen station, often 20 to 30 years.
Formats DPCKinsd-0.05.CAPEX Contest. Ever costs for maintenance, and other recurring annual expenses, assumed to be 5% of the initial CAPEX each year. Variable Operating Expenses: Formats. xx35x15.xx00.155x10.051 Section 1.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05x10.05	OPEX _{fixed}	0.05 × CAPEX	Fixed operating expenses, estimated as 5% of initial CAPEX each year.
Components - SSCMD per lag of hydrogen, based on 55 MMb, per lag at 86 EC 4 GADANS. Leaching Ceat SSCMD per lag of hydrogen, accounter lag of the SSCMD per lag at 86 EC 4 GADANS. - Additional Variable Ceats: 1000 CED per lag for labor and miner operational costs. - Ceatest: These are variable ceats till officery to hydrogen production levels, scaling with x, the daily hydrogen capacity. Initiator: Effective Production Capacity variant Section 8 Production 8 Product Section 8 Product	OPEX _{vie}	$x \times 365 \times (3.5 + 0.0135 - 0.05)$	Variable operating expenses based on daily capacity as including electricity, water, and labor costs.
	$P_{\rm obs, trace}$	x × 50	Maximum electrical power demand (XVV), based on 50 kWh perkg of hydrogen.
Contact The percentage of time the station operates at full capacity, representing utilization. Typical values range from 0.85 to 0.95 (05-95%) for a well-utilized station. Units: Dimensionless Operational Hours per Year (T): Value: [197407] = 179431 = 17945 hours for continuous 24/7 operation. Context: The footh hours per year that the station could operate, assuming it's fully operational year-round. distilling a, the only unknown — optimize the daily indroven capacity to achieve the lowest cost park kilogram, taking into account all relevant CAPDX and OPEX components.	K	Conversion Efficiency	Efficiency factor for converting electricity into hydrogen, typically between 0.8 and 1.
equating a, are viring unknown — operative one daily frydrogen capacity to achieve the lowest cost per xalogram, taking into account as relevant CAPLA and OPEX components.	CF	Capacity Factor	Utilization rate of the station, typically between 85% and 95%
	T	8,760	Total operational hours per year for continuous operation (24/7).