POLITECNICO DI TORINO

Master’s Degree course in

Management Engineering

Master's Degree Final Thesis

Retailer Fleet Mix Optimization: Economic and Environmental Impacts Across Different Scenarios

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A.A. 2024/2025

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Nomenclature

- $x\ (i)$: $Truck\ quantity\ of\ type\ i\ [units]$
- $y\ (j)$: $Cooler\ quantity\ of\ type\ j\ [units]$
- Et_i: $Emissions\ of\ the\ fuel\ i\ for\ truck\ type\ i\ [\frac{€}{km}]$
- km_i: $Annual\ kilometers\ to\ be\ covered\ by\ a\ truck\ type\ i\ [km]$.
- km_j: $Annual\ kilometers\ to\ be\ covered\ by\ a\ cooler\ type\ j\ [km]$.
- Ct_i: $Operational\ cost\ per\ km\ for\ truck\ type\ i\ \left[\frac{€}{km}\right]$.
- Cc_j: $Operational\ cost\ per\ km\ for\ truck\ type\ j\ [\frac{€}{km}]$.
- $\mathrm{BioLNG_t}$: $Truck - Cooler\ Coefficient\ of\ BioLNG\ Trucks\ for\ Cooler\ type\ t$.
- $TOTKM$: $Total\ annual\ kilometers\ covered\ by\ all\ trucks\ [km]$.

El pasado es arcilla que el presente labra a su antojo.

El futuro no es lo que va a suceder sino aquello que vas a hacer.

Jorge Luis Borges

Acknowledgements

By submitting this document, I mark the conclusion of one of the most challenging and rewarding chapters of my life. This journey has been demanding yet deeply fulfilling, bringing me invaluable friendships, experiences, and knowledge.

As a student, I have faced numerous challenges, from mastering complex Engineering topics to adapting to new languages and academic environments. Studying in French in UC Louvain during my time in Belgium and now completing my degree in Italian at one of Italy's most prestigious universities has been both a test of resilience and a source of immense growth.

I will be forever grateful to the Instituto Tecnológico de Buenos Aires, for selecting me for this opportunity of the Double Degree at Politecnico di Torino and that provided me with a great engineering knowledge. The university's high standards have equipped me to tackle today and tomorrow's complex challenges. I also thank Politecnico di Torino for introducing me to the fascinating world of engineering management, strategy, and logistics.

First and foremost, I want to express my heartfelt gratitude to my family for making this achievement possible. To my parents, who supported me every step of the way with phone calls and smiles, and to my sister, Mia, whose laughter always brightened my days. A special thanks goes to my grandparents, who, since I was a child, have always insisted: "Agustín, vos tenés que tener una profesión." Today, I am proud to say that I am fulfilling that vision, turning into an engineer and I hope it makes my grandparents, José and Nilda, proud as well.

A special thanks to Dr. Andrea Tuni for his invaluable guidance as an expert in logistics and sustainability throughout the development of this thesis. Professor, without your help, availability, and continuous support, none of this work would have been possible. I am also deeply grateful for the opportunity you gave me to explore and study the challenges addressed in this thesis, a journey through which I learned immensely and truly enjoyed.

I also want to thank to my friends of Politecnico di Torino, specially to Juan and Fran, that are not only the people that live with me at Torino, but are great friends and brothers, and they are my new family here in Italy.

I don't want to forget as well from my great friend Mancho, who with we supported each other along the way through our five years of study at ITBA. Endless days and nights of study, ordering Chinese food and discussing complex topics now turn into gold. I want to thank as well to the "AVALANCHA", for making all of this possible and for motivating me each day to continue improving myself.

Abstract

The increasing pressure on companies to balance economic efficiency with environmental sustainability has made fleet management a critical challenge. In the context of a leading of a leading supermarket company, optimizing truck and cooler configurations under different fuel types and operational constraints is essential to meeting both cost and carbon reduction goals.

This thesis develops a multi-objective optimization model for sustainable fleet management, aimed at minimizing operational costs and carbon emissions for a leading supermarket company. The research focuses on optimizing truck and cooler configurations under various operational constraints and fuel types. By employing the epsilon-constraint method and exploring diverse scenarios, including regulatory, risk management, and operational events, the study evaluates trade-offs between economic and environmental objectives. The analysis offers actionable insights and recommendations tailored to the company's current business environment, supporting its sustainability and budget goals for 2030.

Key findings highlight that the trade-off between environmental and economic performance is unbalanced, with cost reductions often conflicting with sustainability improvements. Pareto frontiers generated for both baseline scenarios, those incorporating potential technological innovations and those showing the effects of potential exogenous events. These scenarios consider the company's existing fleet and requirements, future EU regulations, and strategies to address compliance challenges. Additionally, alternative scenarios account for external effects, acknowledging their potential to significantly influence decision-making. Time-series models were also developed to predict fuel prices, enhancing the strategic value of the recommendations.

From a theoretical perspective, this research contributes to the academic discourse on sustainable fleet optimization by integrating multi-objective optimization with real world operational constraints and regulatory frameworks into decision-making models, offering a methodology that can be adapted to face similar challenges.

The results from the study provide practical solutions for fleet mix allocation, equipping the supermarket company with strategies to achieve its sustainability objectives while aligning with regulatory mandates and mitigating operational risks.

1 Introduction

The transportation sector is vital for the global economic activity, as it facilitates trade, supply chain and the movement of people and goods. Nearly every aspect of modern life depends on transportation. On the same way it is related to activities that run the daily life of a society, it has a substantial impact on the environment. Transportation is the only sector where greenhouse gas emissions have increased over the past three decades, rising by 33.5% between 1990 and 2019, and in this last year, it was responsible for approximately 25% of the European Union's total CO2 emissions, with 71.7% attributed to road transportation (European Environment Agency, 2023). With this information it is possible to depict that the reliance on internal combustion engine vehicles (ICEVs), fuelled by diesel and gasoline, is addressing immediate needs but compromising future priorities. As 68% of the world population projects to live in urban areas by 2050 (UN, 2018), it is possible to say that towards the future, there will be an increase in the road transportation services demand to the cities (Krause et al., 2024). To ensure long-term sustainability, businesses must adapt their supply chain and operations to align to the demands of the modern world and turn their operations greener. This transition could represent a strategic economic advantage on top of mitigating environmental harm, ultimately benefitting the society. Environmental pressure was put on this topic due to the severity and urgency of the climate issue; the United Nations has emphasized the urgency of achieving carbon neutrality by 2050 to address the climate crisis (Guterres, 2020). Taking action today positions the firms to remain competitive in a future where sustainability is a key driver of success.

1.1 Context and Societal Importance

Society is gradually shifting towards prioritizing environmental sustainability. After the Paris Agreement, a turning point was marked, which made many firms have set objectives for 2030 and 2050 to reduce greenhouse gas emissions (GHG) and limit global warming (European Environment Agency, 2024). As consumers are shifting their spending their spending towards products with ESG-related claims (McKinsey & Company, 2023), this has become essential in a strategic point for businesses. Notably, consumer's willingness to pay for sustainably sources product has risen 9.7% on average, despite the cost-of-living concerns and weigh (PwC, 2024).

Beyond environmental consequences, GHG emissions have severe implications for public health. The air that allows substances and chemicals to be transported around the world, and evidence suggests that air pollution and GHG emissions almost always go hand in hand (European Environment Agency, 2020). The emission of gases like CO_2, CH_4, N_2O, HFC and SF_6 is strongly correlated the Disability adjusted life years (DALY) metric, that represents the loss of the equivalent of one year of full health (Gavurova, 2021). As a result of this, the increasing number of diseases linked to poor air quality remarks the urgent need for integrated solutions not to address only climate change but also to protect public health on a global scale.

Many businesses have aligned with the global environmental agreements made by committing to net-zero targets and undercoming the barriers that are needed to take to make this happen. Overtaking these barriers will not be that easy. While the transition would create opportunities, sectors with high-emissions products or operations, that generate around the 20 % of the global GDP, would face substantial effects on demand, production costs and employment (McKinsey & Company, 2022). The logistics sector is clearly involved and must be one of the first movers of the carbon neutrality global transition as from the 71.7% percent of the emissions attributed to road transportations, 11% are related to light duty trucks and 27.1% to heavy duty trucks as seen on Figure 1.1. Carbon neutrality requires fundamental modifications in firms' internal and supply chain operations and the wider business environment (Zhang et al., 2022).

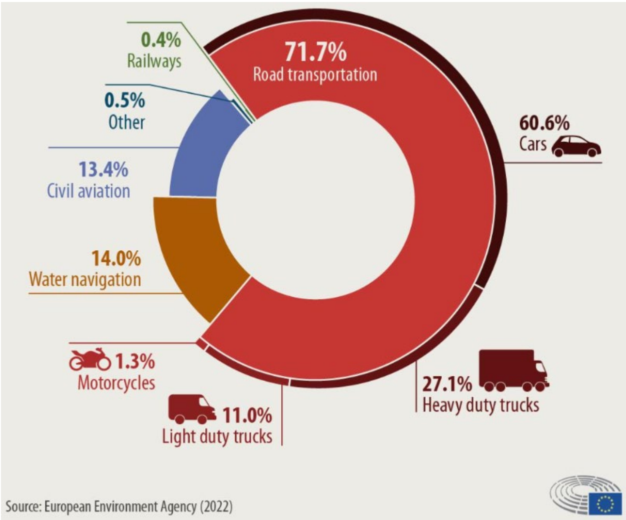

Figure 1: CO_2 emissions from cars in the EU.
Source: European Environment Agency, "CO2 Emissions from Cars: Facts and Figures (Infographics)," March 22, 2019, updated February 14, 2023, https://www.eea.europa.eu/highlights/co2-emissions-from-cars-facts

Innovation could play a critical role in addressing these challenges and advancing sustainable practices. The industry 4.0 has introduced technologies that enable firms to enhance their operations in relation to sustainability objectives. In the logistics sector, solutions such as route optimization, smart freight management and real-time emissions tracking using blockchain are transforming traditional transportation and distribution processes. Blockchain-enabled systems, for example, provide transparency in carbon emissions across multi-tier supply chains, while AI-driven predictive analytics optimize fleet utilization, reducing fuel consumption and costs (Lee et al., 2023). These advancements can not only be the correct track to mitigate environmental impact but to drive competitiveness and long-term resilience for businesses strategically.

1.2 Environmental Sustainability Challenges in Logistics

The transportations sector's push towards sustainability brings significant operational challenges, especially for the companies that rely on ICEVs. Firms are facing a primary issue that lies in transitioning types of freight to drive their daily operations. Green logistics (GL) is becoming a way of doing business, but it also represents the next stage in the development of the concept of logistics (Larina et al., 2021). The aim of GL is to supply goods and services sustainably without hindering the long-run economic performance of the industry (Ibrahim,2 024). This future phase of transitions involves various substantial changes to the fleet mix, introducing electric vehicles (EVs), hybrid vehicles or alternative fuel-powered trucks. The process of fleet mix optimization is crucial as firms must balance their operational needs such as cost-effectiveness, capacity and efficiency with the adoption of the newer and cleaner technologies. From an economical point of view this represents an interesting path as well to follow as approximately the 30% of shippers are willing to pay from 10% to 20% more for carbon-neutral shipments in the logistics sector, represented on Figure 1.2 (McKinsey & Company, 2024).

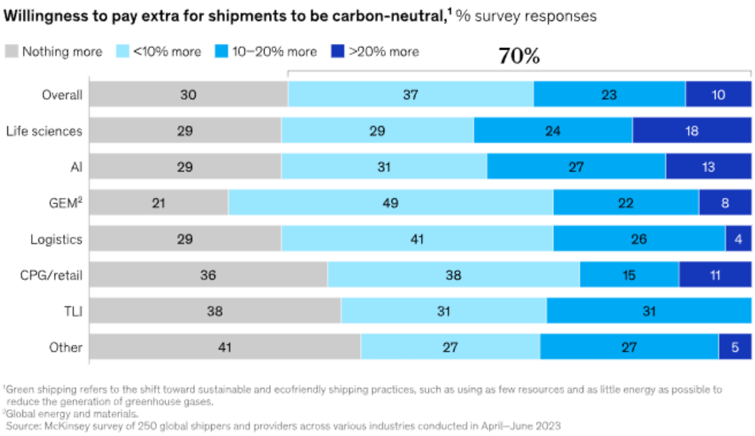

Figure 2: Willingness to pay for carbon-neutral shipments.
Source: McKinsey & Company "Decarbonizing Logistics: Charting the Path Ahead," June 19, 2024,
https://www.mckinsey.com/capabilities/operations/our-insights/decarbonizing-logistics-charting-the-path-ahead

To account some practical examples of successful green logistics, several companies have implemented sustainable strategies with notable outcomes:

- UPS has incorporated hybrid vehicles to its fleet. The company has made a $130 million investment adding more than 700 vehicles to their natural gas fuelled fleet as well as on-site natural gas fuelling stations throughout the US. These vehicles consume 35% less fuel compared to conventional ones, leading to a 42% reduction in CO2 emissions annually (UPS, 2024).

- Maersk has partnered with Danone, one of the world's leading food and beverages companies to reduce GHG emissions by using Maersk ECO Delivery Ocean. This is a product based on reduced emissions fuels such as bio-diesel and bio-methanol, produced solely from waste feedstocks. With the application of this program, emissions could be reduced by more than 40% compared to conventional fossil fuels (Maersk, 2024).
- DHL Group, part of the Deutsche post and leader in the door-to-door delivery industry has introduced the GoGreen program, which tracks and calculates the CO2 emissions from each shipment. It offers customers the option to offset emissions by paying 3% more. In 2022, they offset over 2 million tons of CO2 emissions through GoGreen Offsetting and added more than 28,000 electric vehicles to their fleet (DHL, 2024).

For the logistics companies, one of the major complications is the financial burden of acquiring and maintaining greener vehicles (Mohammed & Villegas, 2023). The initial investment to be made as well as the alignment with the strategic fit of the companies are a point to take in account despite the long-term environmental and economic benefits. In the actual scenario, the limits in the availability of specific charging infrastructure, particularly for electric vehicles and the supply for alternative fuels introduces another key point to consider when depicting business transition to sustainable logistics (Singh, Wen, Palu, & Sachan, 2022). This is why vertical and horizontal cooperations between stakeholders from the different stages of the supply chain are so important to reach the goal of more efficient operations and higher responsiveness to consumer demands (Plazier et al., 2024).

Fleet mix optimization emerges as a strategy within the logistics sector to deal with both operational demands and sustainability goals. A multi-objective framework adoption uprises from the need to handle the demand in a cost-efficient way while contributing to long-term societal and environmental goals. The strategy takes in account critical decisions, such as transitioning to alternative fuels and evaluating investment scenarios while meeting with regulatory standards. By using computational methods to determine an optimal fleet mix, companies can quantitatively and qualitatively assess truck requirements, building the way to the transition toward sustainable logistics.

1.3 Thesis Scope and Structure

This thesis focuses on determining the optimal fleet mix for a major supermarket company operating in Italy (for practical purposes we will name it Ginobili), using operations and environmental data provided by the firm and the work previously being done on this topic by Poropat (2024). The study examines the introduction of various truck types and fuel alternatives to assess which is the best option to align with the company's environmental and economic goals for 2030. With the development of an optimization mathematical model, the aim is to provide a recommendation, studying the space of feasible solutions, that minimizes operational costs as well as $CO2$ emissions, taking in account constraints such as truck maintenance, budget limits and emissions caps.

In parallel, diverse scenarios are going to be analysed, including future EU regulations, possible exogenous events and the company's requirements. A fuel price forecasting model will be constructed to simulate and anticipate to future cost trends of the considered fuel types. This model will be used to support the strategic decision-making process accounting for possible market volatility and the assessing long-term planning that is required for Ginobili's operations.

The research begins with an exploration of the available literature (Section 2) on fleet mix optimization and feasibility, possible exogenous scenarios that could affect the project, fuel price modelling techniques and the economic and environmental context within the logistics sector. From there, the mathematical optimization model is proceeded to be developed while detailing the key decision variables, objectives and constraints (Section 3). After this, the study applies results and the framework to Ginobili's data, generating recommendations to their reality and objectives for 2030 (Section 4). With this we get an approach that involves realistic data for the decision-making process, the mathematical modelling of the problem and a level of stochasticity related to the prediction of future economic scenarios.

2 Literature Review

The literature review process provides a foundation for understanding the scenario in which the problem is going to be modelled. In this way, the exploration of existing research on fleet optimization, sustainability and methods for forecasting fuel prices and emissions can be combined with the theoretical and practical advancements already made. Insights are going to be studied to guide the development of the models and methodologies applied in this thesis. The keywords searched in the main research platforms were fleet management, fleet mix, green logistics, sustainable logistics, green vehicle routing problem, multi objective optimization, time series forecasting and decarbonization strategies. The searches were done by combining keywords with AND, OR and NOT Boolean operators.

2.1 Sustainability Barriers and Opportunities

The literature on sustainability barriers and opportunities addresses the substantial challenges of green logistics, its impact in modern society and the implemented strategies to drive change. This field is broad, as the definition of logistics varies vastly depending on the area of focus. A common factor of this field of study is the efficient and effective implementation of complex operations for either forward or reverse flow of goods and services to conform customer requirements (Ibrahim, 2024).

However, in the context of supply chain decarbonization, many barriers are identified as: major upfront investment cost, lack of awareness, lack of expertise and a resistant mindset (Zhang, 2022). Despite these challenges, studies indicate that while the initial cost for Carbon Efficient Practices (CEP) may be significant, the practices are financially successful on the long-term, having a direct impact on firm's economic performance and product redesign capability (Subramanian & Abdulrahman, 2017).

A growing body of work from management consulting firms highlights how more companies are now managing sustainability to improve processes, pursuing growth and adding value not just focusing on their reputation alone (McKinsey & Company, 2011). Strategies are being developed on how to overcome with the barriers that a green project can pose such as securing commercial advantages, achieving execution excellence, establishing ecosystem partnerships and solidifying financial strengths (BCG, 2024). In the actual economic scenario, an investment of this kind could reflect a high initial cost for a company but as 72% of Europeans are willing to pay more for products that are considered environmentally friendly, the barriers could mean also a potential business opportunity (Morone et al., 2021).

There is a shift happening as companies work to meet the sustainability targets as these set to comply with global agreements and enhance their value chain. Many companies have their own environmental objectives, but sometimes the alignment with their strategy complicates. According to Lichtenau et al. (2023), 60% of businesses that have set a target to reduce upstream Scope 3 emissions do not have a dedicated strategy to deliver. However, more than 6,000 companies, representing close to 50 different sectors, had set Science-Based Targets for emissions reduction.

Among the key sustainability challenges in logistics, transportation accounts for a significant share of the global carbon output. The companies that seek to decarbonize their supply chains must explore the complex trade offs between operational efficiency, cost management and environmental responsibility. The choice of fleet composition, vehicle types, fuel sources and route optimization become crucial in mitigating emissions while maintaining service levels. Emerging technologies such as electric and hydrogen powered vehicles present viable pathways for firms to align their fleet strategies with sustainability goals, in spite that some considerations have to be made as the investment planning of the new infrastructures such as the charging one (Alp, Tan, & Udenio, 2022).

2.2 Fleet Mix Optimization

The fleet mix optimization field has been an area of research focused on optimizing routes, loading strategies (homogeneous and heterogeneous) and more recently, its adaptation to new technologies such as fleet electrification. It aims to determine the minimum cost for a fleet of vehicles or vessels of a certain type required to cover a set of routes in a given period of time (Silva et al., 2024). These optimization problems and models have been applied across many transportation methods that account from sea freight (ships) to land freight (trucks and trains) and even buses.

The optimization of fleet composition in trucking has developed progressively. Early research by Powell (1986) introduced a stochastic dynamic programming approach to truckload carrier operations, addressing real-time demand fluctuations and uncertainty in freight allocation. This work established the need for decision models that account for both operational constraints and long-term strategic planning. On the same track, Crainic and Laporte (1997) conducted a review of freight transportation models, emphasizing the necessity of integrating fleet sizing, routing, and load management to optimize overall efficiency.

In subsequent years, Wu et al. (2005) developed an integrated approach that linked operational decisions, such as demand allocation and empty truck repositioning, with tactical choices, including asset procurement and resale. Their linear programming model proved highly effective in optimizing fleet utilization across different logistical phases, reinforcing the role of structured mathematical techniques in solving complex transportation problems.

More recent advancements have expanded the scope of fleet mix optimization to incorporate managerial priorities and environmental considerations. Sarangi et al. (2023) addressed this shift by formulating a multi-objective fleet composition model that balances profitability, cost, and service efficiency within distribution networks. Their research introduced two distinct decision-making frameworks: the Competing method, treating all objectives as equally important, and the Compensatory method, which prioritizes synergies between them.

In the same way, Islam and Gajpal (2021) integrated sustainability concerns into optimization models using ant colony algorithms. Their findings indicated that incorporating green vehicles alongside traditional fleets led to a 6.9% reduction in carbon emissions, demonstrating the feasibility of environmentally conscious fleet management. Meanwhile, Malladi et al. (2022) explored electromobility in urban logistics, focusing on the impact of planned versus realized driving ranges of electric vehicles (EVs) on fleet composition. Expanding on these perspectives, Zhao et al. (2021) introduced a bi-objective programming model for vehicle routing, incorporating carbon emissions and charging constraints for both electric and conventional vehicles.

2.3 Operational Optimization Problems

The literature mostly focuses on the operational advances on fleet planning, particularly through the vehicle routing problem (VRP), which optimizes routes for a given set of vehicles. As an operational problem, VRP deals with determining the most efficient way to use the available fleet. In contrast, fleet mix optimization is a tactical decision-making process that focuses on selecting the most suitable combination of vehicles to meet operational needs. Over time, the green vehicle routing problem (G-VRP) has emerged as an important area of research. It aims to design cost efficient delivery routes while considering the limited driving range of vehicles, its loading capacity and fuel constraints. The objective is to minimize overall costs or total travel distance while integrating sustainability considerations. To achieve this, vehicles must navigate their routes with access to a limited number of refuelling stations (Koç & Karaoglan, 2016). The G-VRP becomes particularly relevant when the fleet includes alternative fuel vehicles, aligning with the objective of this thesis.

Most studies in G-VRP considered a single objective, being his distance, cost, emissions or fuel consumption. However, to evaluate the possible trade-offs between multiple objectives, some other works have incorporated these objectives as constraints controlled by an epsilon such as emissions limits, customer requirements or fuel consumption thresholds. This procedure requires the use of multi-objective optimization programming to allow an evaluation of possible trade-offs between different objectives in the Pareto efficient frontier (Mohammadbagher & Torabi, 2022).

Studies have also focused on optimizing fleets for various types of vehicles, including ships and land ones by solving the problem of route optimization, fleet composition and the number designated for each vehicle type to provide the input data necessary for the decision-making process of the logistics management sector.

In the context of electric vehicles, that were taken in consideration in innovative scenarios, the electric vehicle routing problem (EVRP) has been developed to address the challenges of serving customers with a fleet of EVs. These vehicles require trips to charging stations (CS), as well as studies on urban infrastructure, such as the availability of CS and the impact of non-linear charging times on route planning (Wang et al., 2024, Pelletier et al., 2019).

In sea logistics, dynamic programming routing algorithms have been used to address these challenges (Fagerholt, 2006) as well as optimization techniques such as Two-phase Tabu Search (Zeng & Yang, 2005) and mixed integer linear programming (Wu et al., 2021) to model real life sea freight fleet mix scenarios. Anyways, the studies highlighted the need for more accurate decision support models to integrate the fluctuations in the shipping market and the frequent mismatches between fleet capacities and demands (Silva et al., 2024).

In land logistics, available studies on emission models show the significant impact that the vehicle type has on fuel consumption (Koç et al., 2014). Demir et al. (2011), has made significant contributions in this matter, categorizing the factors influencing fuel consumptions into four groups: vehicle, driver and environmental and traffic conditions. Their work also introduced various models for fuel consumption and GHG in road transportation, addressing the pollution-routing problem (PRP) with an extended adaptive large neighbourhood search heuristic (ALNS). This methodology involves two stages: vehicle route planning and a speed optimization algorithm that determines the optimal speed for each route segment.

Further advancements in the literature have focused on multi objective approaches to the PRP. Some studies developed a bi-objective PRP that minimized both fuel consumption and driving time. Others incorporated the concept of heterogeneous fleets categorizing vehicles into light duty, medium duty and heavy duty as each vehicle has its own costs and emission parameters to solve the PRP (Koç et al., 2014).

The literature also explores several *a posteriori* optimization methods, that most of these match with those used in sea logistics. These optimization methods include epsilon-constraint methods, weighted-sum approaches and hybrid techniques combined with adaptive large neighbourhood search (ALNS). These methods enable researchers to analyse the trade-offs along the Pareto frontier effectively. Amiri et al. (2022) reported in their study, integrating the epsilon constraint method, that doubling the number of refuelling stations within an area could reduce transportations costs by 2% and emissions by 18%. These findings remark the potential of integrating operational strategies with environmental objectives in the land logistics field.

The principal optimization method to study accordingly the Pareto frontier and the trade-offs in the decision-making process is the one with the epsilon-constraint-based algorithm (Mavrotas, 2009). The computational experiments conducted have proved the effectiveness in providing valuable insights into sensitivity analyses, particularly regarding the impacts of various disruption types and fluctuating unit fuel costs (Elmi et al., 2023). Complementing this, Ghasemi et al. (2023) extended the application to the location routing problem (LRP) incorporating both cost minimization and reliability maximization, addressing customer time windows and probabilistic travel times. In this work they combined epsilon-constraint methods with metaheuristic algorithms, such as NSGA-II, used for large dimensionality data, to tackle complex supply chain challenges.

This method displays an interesting approach for the objective pursued in this thesis to determine the optimal fleet mix for the major supermarket company, optimizing considering both operational and environmental objectives.

2.4 Forecasting Fuel Prices

Reliable gasoline demand forecasting is essential for petroleum supply chain planning (Mardiana et al., 2020). To forecast fuel prices, the literature uses time series statistical models. These are classified into univariate time series models and multivariate time series models.

Univariate time models use historical price data as its only input, indicating that only past trends are indicative of the future price behaviour (He, 2023). The simplest techniques like moving averages (MA) and simple exponential smoothing (SES) are the most commonly used by their simplicity, but they may struggle to provide reliable predictions in complex scenarios (Lusk, 2019). Introducing time series work approach, more advanced methods, such as Autoregressive Integrated Moving Average (ARIMA) are used due to its accuracy, mathematical soundness and flexibility by including the autoregressive (AR) and moving average terms (MA). Additionally, the errors in the ARIMA models are smaller than in Simple Exponential Smoothing (SES), Double Exponential Smoothing (DES) and Triple Exponential Smoothing (TES) (Zulu et al., 2022). ARIMA was compared to other methods such as Holt Winters to forecast electricity demand (Taylor, 2003) and the conclusion was that ARIMA had a superior performance. Oliveira and Oliveira (2018) as well conducted a study of electricity consumption in developed countries of 24 months in advance. They made the analysis comparing ARIMA and exponential smoothing, where ARIMA provided the most accurate results.

Multivariate time series models can include trend and seasonality in addition to predictor variables while training the model. Several works have compared the performance of ARIMA, Holt-Winters, and multivariate regression models, with this generally obtaining better results. In the study done by He (2023), a multivariate time series model captured better the variability of the historical data to perform future predictions due to its ability to take in account external variables such as GDP, CPI and Oil Prices. Gosasang et al. (2011) compared traditional techniques with neural networks for a container throughput at a Bangkok Port using GDP, exchange rate, inflation and fuel price as explanatory variables. Similarly, Moscoso-Lopez et al. (2021) proposed a machine learning based forecasting system to predict cargo flow at the port of Algeciras. These models not only improve forecasting accuracy but are as well useful to interpret managerial and policy implications, as they introduce connections between petroleum prices, natural gas, heating oil and gasoline and other independent macroeconomic variables (Chinn et al., 2005).

As technology is evolving, so are the prediction methods. In some cases, innovative approaches were proposed such as the one in Qin et al. (2023) in which crude oil price was forecast with machine learning and Google Search data. In this case, the trends provided by Google were introduced as exogenous variables and it was concluded that multiple-model methods outperform several popular single-model methods in terms of prediction accuracy. The comparison between machine learning models was made in Sofianos et al. (2024), evaluating the performance of fuel price forecasting models with the introduction of non-linear exogenous variables, with models like XGBoost and Random Forest (RF) with RF having a lower Mean Absolute Percentage Error (MAPE) of them all. Shaik S. et al. (2019) provided a similar exploration process and emphasized the challenge that forecasting crude oil prices and fuels in general means due to the high volatility of oil prices.

Hybrid models have also shown remarkable potential. These models were proposed in the following way: one of the selected models forecasts the trend part of the curve while another model is trained to forecast the residuals. In Wang (2024), US Gasoline prices were forecasting with this method, firstly doing comparisons between the single-models approach actually available and then showing the effectiveness of a hybrid Linear-ARIMA model.

Given that the objective of this thesis requires a stochastic level of input data for the alternative Fuel Price Forecast Scenario based on market data for the optimization model, the analysis on the literature of the most performing methods is crucial. This review of current methodologies provides a foundation for the forecasting of alternative fuel prices in base to historical data and exogenous variables.

2.5 Research Gap

In spite of the significant advancements that have been made in fleet optimization, sustainability and fuel price forecasting, several key gaps remained unaddressed and these form the basis for this thesis. While most of the methods take in account the Green Vehicle Routing Problem (G-VRP), the majority of the studies on fleet mix optimization focus on singular objectives such as cost, emissions or distance. There is a lack of exploration into simultaneous objective optimization, especially of environmental and operational factors. By adding another level of research in the fleet mix optimization topic, there is not much literature available on multi-objective optimization for truck fleets. Most of the studies have been made for other types of freight such as sea or even buses. Moreover, epsilon-constraint method and metaheuristic algorithms have not been extensively applied to practical fleet planning scenarios.

Another challenge is shown in the difficulty to forecast fuel prices due to their high volatility. Although models like ARIMA and machine learning approaches have shown robust capabilities, they often fail to capture the stochastic nature of the fluctuations involved in this type of time series variable. When this analysis is down to alternative fuels, as most of this technologies are relatively new, the forecasting process and price trend evaluation on these is not much addressed by the literature, that concentrates in the most conventional type of fuels. Hybrid models, such as the Linear-ARIMA approach, offer a new potential opportunity but remains underutilized in decision-support systems for logistics. Additionally, most of the research is done by comparing and evaluating models fitting on historical data and not by doing long-term forecasting processes. Many models, such as ARIMA, have great short-term results but have to be refined when predicting longer periods of study.

The literature also highlights an insufficient focus on sustainability in fleet optimization studies. While the economic and long-term benefit of Carbon Efficient Practices (CEPs) have been documented, there is a lack of support by reliable decision models combining sustainability targets and fleet operations. Many companies and papers have set objectives based on CEP but not in forecasting and planning models with algorithms or optimization approaches. The potential trade-offs between fleet costs and achieving emission-reduction targets has been poorly addressed, especially under dynamic and uncertain market conditions, which remarks the novelty of the current work to the actual literature.

While recent and innovative forecasting methods such as the one that incorporate new machine learning techniques or Google Search trends demonstrate potential, their integration to fleet optimization problems remains minimal. The possibilities on the combination of forecasting techniques and optimization algorithms have not been fully explored, like it could be using fuel price predictions as inputs to optimize fleet compositions.

It is useful to say that most of the literature is applied to theoretical or historical scenarios, which introduces some limitations in its applicability to real-world contexts. The complexities that real-world problems incur such as fuel availability, maintenance structures, country's infrastructure, vehicle requirements are often overlooked leaving a gap that is needed to be handled.

This thesis seeks to address the existing gaps by developing a multi-objective optimization (MOO) framework that integrates economic and environmental goals for fleet mix decisions. By incorporating forecasts of fuel prices with statistical techniques, it aims to bridge that exists between forecasting and the theory on MOO and decision-making processes by companies. This research explores the trade-offs as well between environmental and economic efficiency through scenario analysis and Pareto optimization, evaluating the best set of feasible solutions for a major supermarket company. Through this approach, the thesis contributes a real practical world application to a sustainable logistics challenge.

3 Methodology

3.1 Problem description

The problem focuses on optimizing a major supermarket's fleet of trucks and cooling systems to enhance efficiency while aligning with sustainability objectives. The goal is to determine the optimal fleet composition required to meet the company's annual distribution mileage in Italy while transitioning toward greener logistics. This optimization must strike a balance between operational costs, CO_2 emissions, and energy efficiency, considering both the power generation system and the refrigeration requirements necessary for perishable goods. The solution must account as well for long-term fleet adaptability, infrastructure readiness for alternative fuels, and regulatory compliance to support a sustainable supply chain.

3.2 Assumptions and hypotheses

This problem, along with the deterministic data from the supermarket company was provided by Poropat (2024) and this thesis is an extension of the analysis conducted in that study.

The total distance expected to be covered in a year of operations is 70,000,000 km, assuring daily delivery of goods from distribution centres to the stores. Another critical aspect for the company is the budget, that must be lower than €131,000,000 for its entire fleet.

In line with the environmental sustainability goals for the business, there is the need to cap transportation-related CO_2 emissions at a maximum of 22,400,000 kg and providing a diesel-free truck fleet for the year 2030. Meeting environmental objectives highlights the need of considering alternative fuels to shift the company into a greener structure.

Striking a balance between cost efficiency with emissions reduction represents a critical step for the major supermarket company's future in turn to their objectives for the year 2030.

To develop the fleet optimization model, the following assumptions and hypotheses were made:

- All the trucks have the same load capacity, creating a homogeneous fleet.
- Transportations costs include variable costs based on fuel prices and fixed costs according to vehicle depreciation, insurance, registration, overhead and financial charges.
- Each truck covers a certain quantity of kilometres per year:
    - Diesel: 140,000 km.
    - LNG: 130,000 km.
    - BioLNG: 130,000 km.
    - HVO100: 140,000 km.
    - Electric: 70,000 km.

    - Hydrogen: 100,000 km.
- CO_2 emissions are directly proportional to the fuel consumed per kilometre per type of truck.
- Cold chain requirements must be maintained throughout the transportation process, with daily operations lasting six hours for each cooler.
- Based on the assumptions of Poropat (2024), the number of annual operating hours for the truck refrigeration units is determined based on an average daily usage of 6 hours over 316 working days per year, resulting in a total of 1,896 hours per year.
- It is assumed that there is an adequate infrastructure in Italy for the daily use of the vehicles in the fleet.

3.3 Research Overview

The research follows a step-by-step approach looking forward to addressing the optimization of a sustainable fleet mix under operational, budget and environmental constraints.
The methodology used includes deterministic components based on data to achieve results that model real world uncertainties. The research design is shown in Figure 3.3.

Problem Definition and Scope

The research begins taking in account the problems of the actual situation in the supermarket logistics field: Minimizing fleet costs and reducing CO2 emissions, while addressing specific constraints such as emission caps and truck-cooler compatibility. An optimization procedure was essential to advance towards the definition of an optimal sustainable fleet mix for a major supermarket company based in Italy to meet its 2030 sustainability goals.

Literature review

Existing works in fleet optimization, optimization models, stochastic statistical modelling for fuel prices in the actual economic and social environment and sustainability reports in the transportation sector in relation to emissions were reviewed to contextualize the study and adapt the literature to the model to be developed.

Data Collection and Analysis

Relevant data on fuel costs, including conventional and alternative ones that were collected from industry sources and historical records that would serve as inputs for the model to cover both the truck and the cooler fuel. An analysis was conducted in base of the data provided by the major supermarket company regarding the deterministic fuel prices, costs and the truck-cooler combinations used.

Optimization Mathematical Model Formulation

Based on the data available in the literature, an optimization mathematical model utilizing the epsilon constraint method was constructed in Python to capture the relationships between decision variables, such as truck types and cooling systems, the objectives like minimizing costs and emissions and the constraints in the truck-cooler combinations, budget and emissions. The model was designed in a two-step approach, first to be trained and validated with historical data of actual fuel prices, actual fuel prices provided by the company and a posteriori evaluation incorporating data through different quantitative and qualitative scenarios that could be involved in the decision-making prices.

Optimization Model Implementation

The epsilon-constraint method was applied in Python to generate a Pareto-efficient frontier, that would balance costs and emissions by means of the epsilon values used in each iteration. In this way, it would be possible to take in account the environmental and economic variables to determine, in each case and for those cost-emission values, the optimal fleet mix. The parameters used were deterministic fuel costs initially provided by a major supermarket company for each one of the fuels in 2024. The type of fuels used, to be introduced in the trucks and coolers, were both of conventional and alternative sources. After running the model, each solution on the Pareto Frontier was evaluated and after an iterative process in analysis if the model met the requirements, the configurations that were best aligned for the sustainability goals and the budget cap were identified.

Future Scenarios Analysis

With the model already being tested with base data, the base case scenarios were developed and introduced to the model with criteria based on EU Regulations, company data and recommendations and Risk Management perspectives.

As well, when these were validated, alternative scenarios were developed as an additional analysis of potential future cases, in a quantitative and qualitative approach.

For the quantitative approach, fuel price prediction models were developed to introduce to the model an alternative scenario based on market data and statistics. A review of statistical time series models from the literature was conducted to identify the solutions being used for this purpose and assess the adaptability to the fleet mix optimization problem. These models, trained and tested by the historical fuel price data available, were evaluated with performance metrics to determine in this way the most accurate method to forecast fuel prices up to the date required to be used in the model as an alternative quantitative (Fuel Price Forecasting) scenario.

For the qualitative approach, exogenous scenarios were constructed around potential supply chain challenges, macroeconomic events, and market or technological innovations. These scenarios provided new data inputs to the model, enabling an analysis of the optimal fleet mix for the major supermarket company under varying economic and operational conditions. This approach ensured a comprehensive understanding of how external factors could influence decision-making and fleet optimization outcomes.

Optimization Model Solution Using Epsilon-Constraint Method

The epsilon-constraint model was employed to solve the problem and provide a solution to the fleet mix optimization problem evaluating the possible solutions set. This ensured a systematic exploration of the trade-offs required to minimize costs and emissions with fluctuating fuel costs. Each solution represented a potential fleet configuration that satisfied all constraints, such as the truck-cooler combinations, budget cap and emission limitations.

Results Analysis and Conclusions

Demonstration of the viability of the epsilon-constraint method to meet cost and emission objectives under constraints. The Pareto-efficient frontier developed by the Python model enables actionable insights to provide recommendations in the selection of fleet mix configurations that would align with the 2030 sustainability goals of the supermarket company, including the transition to a diesel-free fleet. The analysis reported the importance of balancing conventional and alternative fuel sources to achieve long term-cost effectiveness and environmental compliance. The base case scenario analysis as well as the possible alternative scenarios in changing atmospheres are used to provide data for the company to make a decision.

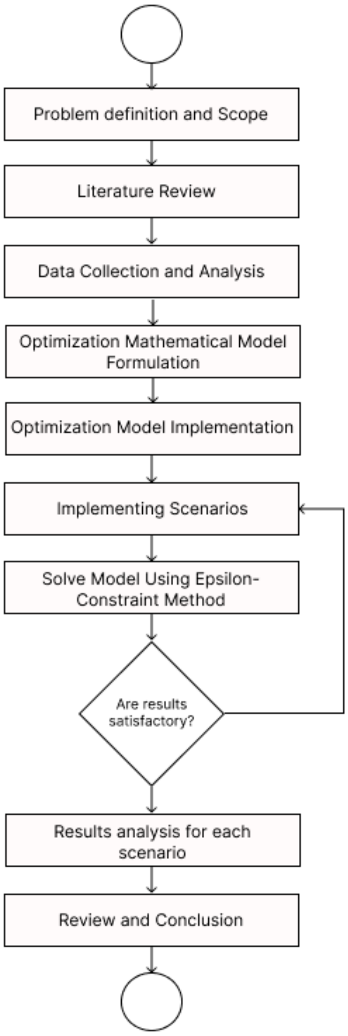

Figure 4: Methodology workflow

3.4 Conceptual Framework

Objective of the Conceptual Framework

The conceptual framework provides a qualitative representation of the sustainable fleet mix optimization problem. It defines the elements involved in the study of problem's objective, constraints and relationships between variables. The model is structured around core processes and decisions of the approach used in order to optimize fleet and cooling configuration around economic, operational and environmental constraints.

Objectives

The model has dual objectives defined for this problem regarding determining the optimal fleet mix that are:

- Minimize total operational costs from fuel and cooling sources.
- Minimize CO_2 emissions from transportation activities.

Decision variables

- x_i**:** Number of trucks of type i in the fleet.
- y_j**:** Number of coolers of type j in the fleet.

Inputs

- Truck and cooler data:
  - Maximum yearly kilometres allowed per truck.
  - Truck and cooler types available, including their compatibility.
- Fuel cost data.
  - Historical and forecasted costs for conventional and alternative fuels, being these:
    - Trucks: Diesel, LNG, BioLNG, HVO100, Electric and Hydrogen.
    - Cooler: Diesel, HVO100, Nitrogen and Electric.
- Budget cap.
- Emission cap.

Constraints

- Distance: The fleet must collectively cover the required mileage to fulfil the distribution activities of the company. This corresponds to 70 million kilometres annually in the case study.
- Truck-cooler compatibility:

Coolers	**Trucks**
Diesel	LNG
HVO100	HVO100, BioLNG
Nitrogen	BioLNG
Electric	Hydrogen, BioLNG

Table 1: Truck-cooler compatibility

3.5 Epsilon-Constraint Method and Model Bases

The Epsilon-Constraint Method is a technique used for solving multi-objective optimization problem (Ji et al., 2018). It optimizes one of the functions up, maximizing or minimizing it while treating the other objectives as constraints, bounded by an epsilon. This method generates a representative Pareto-frontier set of solutions as different ranges of epsilon values are selected in each iteration to build the curve.

In this type of problem, the decision makers have to seek a solution that is the most preferred by them, as it is impossible to satisfy and optimize all of the objectives simultaneously. When changing the epsilon values, the whole possible set of solutions is explored, providing a comprehensive approach of the trade-offs when there are conflicting objectives (Chircop & Zammit-Mangion, 2013). This is why this method is especially useful in situations where the decision-makers need to take in account a complete set of alternatives before selecting their solution (Mavrotas, 2009).

Theoretical model

Mathematically, the method focuses on optimizing one primary objective function $f_1(x)$ while treating the remaining objectives $f_2(x), f_3(x), \ldots, f_n(x)$ bounded by an epsilon value.

As shown in Mavrotas (2009):

$$\min f_1(x)\,, x \in S, f_2(x) \leq \varepsilon_{2\,,}\ {}_{\ldots,}\, f_n(x) \leq \varepsilon_p \tag{1}$$

Model application

To apply this technique to the fleet mix optimization problem, a code in Python was made using Pyomo. In this way it was possible to explore the trade-offs between cost minimization and emissions reduction in the transport operations of the major supermarket company. The economic function, representing the cost of the trucks and coolers is treated as the main objective and the environmental function is treated as a constraint bounded with an epsilon. This approach involves generating a Pareto frontier by solving the optimization problem, with its respective constraints, by bounding its level of emissions per iteration with an epsilon. The model integrates data on truck and cooler types, operational distances, costs, emissions and uses predicted fuel prices to provide the decision maker a range of solutions to be taken in account.

Objective function

$$\min \left(\sum_{i \epsilon Trucks} Ct_i * x_i * km_i + \sum_{j \epsilon Coolers} Cc_j * y * km_j \right) \tag{2}$$

being:

- $Ct_i: Operational\ cost\ per\ km\ for\ truck\ type\ i\ [\frac{€}{km}]$
- $km_i: Annual\ kilometers\ to\ be\ covered\ by\ a\ truck\ type\ i$
- $Cc_j: Operational\ cost\ per\ km\ for\ for\ cooler\ type\ i\ [\frac{€}{km}]$
- $km_j: Annual\ kilometers\ to\ be\ covered\ by\ a\ cooler\ type\ i$
- $x_i: Quantity\ of\ trucks\ type\ i$
- $y_j: Quantity\ of\ coolers\ type\ j$

Constraints

Emissions constraint:

$$\sum_{i \epsilon Trucks} Et_i * x_i * km_i + \sum_{j \epsilon Coolers} Ec_j * x_j * km_j \leq \varepsilon \tag{3}$$

being:

- $Et_i: Emissions\ for\ truck\ type\ i\ due\ to\ operations\ [\frac{€}{km}]$
- $Et_j: Emissions\ for\ truck\ type\ j\ due\ to\ operations\ [\frac{€}{km}]$

Total annual distance constraint:

$$\sum_{i \epsilon Trucks} x_i * km_i \geq TOTKM \tag{4}$$

Truck-cooler balance:

$$\sum_{i \epsilon Trucks} x_i = \sum_{j \epsilon Coolers} y_j \tag{5}$$

With all this being introduced to the model, a range of epsilon is selected to impose emission level restrictions.

To account the range of epsilon possible to provide feasible solutions for the model, an environmental single objective optimization was done, to know the epsilon minimum emissions and additionally, to know the maximum epsilon value, an economical single objective optimization was done (where the emissions constraint was taken).

$$\varepsilon \epsilon \, (E_{environmental};\ E_{economic}) \tag{6}$$

Single Environmental Objective Function

$$\min \Big(\sum_{i \epsilon Trucks} Et_i * x_i * km_i + \sum_{j \epsilon Coolers} Ec_j * x_j * km_j \Big) \tag{7}$$

Single Economic Objective Function

$$\min \Big(\sum_{i \epsilon Trucks} Ct_i * x_i * km_i + \sum_{j \epsilon Coolers} Cc_j * y * km_j \Big) \tag{2}$$

Note: In this iteration the emission constraint was deactivated so the model could explore the most economically efficient solution.

With this minimum and maximum epsilon constraint in the iterations, it is possible to explore the feasible solution set of the fleet mix. As well, between this minimum and maximum emission values, a number of intermediate points was chosen between the emissions' minimum and maximum to construct the optimal Pareto frontier, capturing the trade-off between cost and emissions.

For the actual needs of the problem, for an accurate resolution of the curve and definition of the results 50 points were selected between the environmental objective emissions solution and the economic objective emissions solution.

Outputs

- Optimal fleet mix for each iteration: this determines the number of trucks and the number of coolers.
- Total costs and emissions for each iteration.

3.6 Scenarios

For all scenarios, the baseline prices used to account for truck and cooler investments were derived from data provided by a major supermarket company. These figures were previously utilized in Poropat (2024), which this work continues to build upon and expand.

The pricing structure was designed to detail the costs per kilometre for each truck type. It encompasses purchase costs, fuel expenses, maintenance, tire costs, road taxes, insurance, depreciation, salaries, tolls, structural costs, and specific fees as provided by the supermarket company due to the studies done on their current operations. The base costs can be seen in the Appendix 7.1 section. It is important to highlight that, building on Poropat's 2024 work on this topic, incentives for hydrogen trucks have now been incorporated into the cost structure, similar to how they were previously considered for electric trucks.

The scenarios are divided into base case and alternative scenarios to examine the factors that Ginobili will address under current trends, as well as potential hypothetical situations the company may encounter by 2030.

The study explores three base case scenarios (A, B, and C), each built on a different approach to truck-cooler allocation. One method (.1 Scenarios) uses on predetermined truck-cooler pairings as stated in section 3.5. The alternative (.2 Scenarios) introduces truck-cooler coefficients as decision variables, giving the model the flexibility to determine the most suitable cooler for each truck type based on fleet capabilities and technological constraints. While all scenarios maintain the core model constraints from Section 3.5, additional constraints are introduced in each case to reflect specific operational conditions.

For the initial scenarios, with a fixed coefficient for the truck-cooler combination a linear optimization model is used (Cplex Direct) while a nonlinear one is used (Ipopt) in the cases with BioLNG truck-cooler coefficients as decision variables.

The base case scenarios that were analysed are presented in the table below:

<table>
<tr><th>Scenario</th><th>Identification</th><th>Characteristics</th><th>Truck-Cooler Allocation</th></tr>
<tr><td rowspan="2">A</td><td>A.1</td><td rowspan="2">EU Guidelines
Risk Management</td><td>Base
(Linear)</td></tr>
<tr><td>A.2</td><td>Optimized
(Non-Linear)</td></tr>
<tr><td rowspan="2">B</td><td>B.1</td><td rowspan="2">Current fleet composition
Risk Management</td><td>Base
(Linear)</td></tr>
<tr><td>B.2</td><td>Optimized
(Non-Linear)</td></tr>
<tr><td rowspan="2">C</td><td>C.1</td><td rowspan="2">Current fleet composition
Company constraints</td><td>Base
(Linear)</td></tr>
<tr><td>C.2</td><td>Optimized
(Non-Linear)</td></tr>
</table>

Table 2: Base case scenarios

For the hypothetical situations that were sighted as possible alternatives, reflected operationally by changing the constraints of the model. All alternatives were based on the A.1 scenario, as the EU Regulations are a current problem that Ginobili will have to face according to the European Comission, 2018.

The different alternatives are reported in the next table:

<table>
<tr><th>Scenario</th><th>Group</th><th>Identification</th><th>Characteristics</th><th>Truck Cooler Allocation</th></tr>
<tr><td colspan="3">Fuel Pricing Forecast Scenario</td><td>Fuel price prediction model</td><td>Base
(Linear)</td></tr>
<tr><td rowspan="4">Qualitative</td><td rowspan="2">Supply chain and Resource Scarcity Scenarios</td><td>Scarcity of Raw Materials for HVO100</td><td>30% HVO100 fuel price increase</td><td>Base
(Linear)</td></tr>
<tr><td>Gas Crisis in Europe</td><td>200% Diesel, LNG and Electricity price increase</td><td>Base
(Linear)</td></tr>
<tr><td rowspan="2">Macroeconomic and Policy Scenarios</td><td>LNG Ban</td><td>LNG trucks excluded</td><td>Base
(Linear)</td></tr>
<tr><td>Renewable Content Mandates Increase</td><td>25% fleet minimum renewable energy content and 7.5% minimum biofuel share</td><td>Base
(Linear)</td></tr>
</table>

Table 3: Alternative scenarios

3.6.1 Base case scenarios

The base case scenarios serve as the foundation for the fleet mix optimization model analysis, integrating EU regulatory guidelines, operational constraints and risk management strategic considerations explained in the next sections. These scenarios are designed to reflect a set of realistic operational conditions, adapting the constraints stated in section 3.4 according to the actual structure and recommendations of the major supermarket company. Different minimum and maximum truck numbers for each type are going to be reviewed for each scenario to consider diverse approaches. As these conditions to be analysed are the most feasible considering the company's actual situation, they are going to be the basis of the investigation to provide information for the decision-making process to attain 2030 sustainability goals.

3.6.1.1 A Scenarios

This scenario is designed to target compliance requirements with the EU RED II Targets (European Commission, 2018), published in November 2016 and revised in December 2018, entering into force in 2023 in a trial period. As an overall target, in RED II, member states must require fuel suppliers to supply a minimum of 14% of the energy consumed in road and rail transport by 2030 as renewable energy. Additionally, it states that the contribution of advanced biofuels and biogas produced from the feedstocks listed in the regulation as a share of final consumption of energy in the transport sector shall be at least 0.2 % in 2022, at least 1 % in 2025 and at least 3.5 % in 2030. This regulation, for what concerns the fleet optimization model, introduces a constraint on the minimum truck quantity for certain truck types.

From a risk management perspective, a maximum share of trucks constraint is introduced, as it is excessively risky to have all the trucks of the same type in an environment with varying operating conditions. As different trucks have different kilometric range, the constraint is written for each truck type not to cover more than the 50% of the total kilometric range specified by Ginobili.

This scenario is proposed in two ways, one with fixed cooler-truck combinations, as specified by the company and another version with this coefficients as decision variables to let the model choose which would be the optimal cooler to be used for the BioLNG according to emission and economic targets in each iteration. As the objective and the emission and budget targets remain the same to what explained in section 3.5, the only point that changes are the constraints.

Scenario A.1

Truck-cooler combination constraints

- Total Truck-Cooler Balance:

$$\sum_{i \in TruckVector}^{n} x_i = \sum_{j \in CoolerVector}^{m} y_j \qquad (5)$$

- Diesel cooler constraint:

$$y_{Diesel} = x_{Diesel} + x_{LNG} \qquad (8)$$

- HVO100 cooler constraint:

$$y_{HVO100} = x_{HVO100} + 0.25 * x_{BioLNG} \qquad (9)$$

- Nitrogen cooler constraint:

$$y_{Nitrogen} = 0.5 * x_{BioLNG} \qquad (10)$$

- Electric cooler constraint:

$$y_{Electric} = x_{Electric} + x_{Hydrogen} + 0.25 * x_{BioLNG} \qquad (11)$$

- Diesel free fleet truck constraint:

$$x_{Diesel} \leq 0 \qquad (12)$$

Environmental regulation minimum truck constraints

- EU RED II Target: At Least 3.5% Advanced Biofuels by 2030

$$x_{BioLNG} * km_{BioLNG} + x_{HVO100} * km_{HVO100} \geq 0.035 * \sum_{i \in TruckVector}^{n} (x_i * km_i) \qquad (13)$$

- EU RED II Target: At Least 14% Renewables by 2030

$$x_{BioLNG} * km_{BioLNG} + x_{HVO100} * km_{HVO100} + x_{Electric} * km_{Electric} + x_{Hydrogen} * km_{Hydrogen} \geq 0.14 * \sum_{i \in TruckVector}^{n} (x_i * km_i) \qquad (14)$$

Risk Management maximum truck limit constraints: Limit Each Truck Type to Less Than 50% of Total Kilometres

- Total truck kilometre variable definition:

$$Total\ Km = \sum_{i \in TruckVector}^{n} (x_i * km_i) \qquad (15)$$

- Constraints for each truck type:

$$x_{Diesel} * km_{Diesel} \leq 0.5 * Total\ Km \quad (16)$$

$$x_{LNG} * km_{LNG} \leq 0.5 * Total\ Km \quad (17)$$

$$x_{BioLNG} * km_{BioLNG} \leq 0.5 * Total\ Km \quad (18)$$

$$x_{HVO100} * km_{HVO100} \leq 0.5 * Total\ Km \quad (19)$$

$$x_{Electric} * km_{Electric} \leq 0.5 * Total\ Km \quad (20)$$

$$x_{Hydrogen} * km_{Hydrogen} \leq 0.5 * Total\ Km \quad (21)$$

Scenario A.2

In this scenario three additional decision variables are added. These represent the coefficients as a percentage of the coolers of Nitrogen, HVO100 and Electric that would be used for BioLNG trucks in each case. As each iteration has a different epsilon value, thus, a different environmental target, this coefficients will vary, telling the analyst which the optimal cooler type is to be used in each case.

Coefficient variables definition

$$\mathrm{BioLNG}_{\mathrm{HVO100}_{\mathrm{coef}}} \in [0,1] \quad (22)$$

$$\mathrm{BioLNG}_{\mathrm{Nitrogen}_{\mathrm{coef}}} \in [0,1] \quad (23)$$

$$\mathrm{BioLNG}_{\mathrm{Electric}_{\mathrm{coef}}} \in [0,1] \quad (24)$$

Coefficient initial percentage constraint

$$\mathrm{BioLNG}_{\mathrm{HVO100}_{\mathrm{coef}}} + \mathrm{BioLNG}_{\mathrm{Nitrogen}_{\mathrm{coef}}} + \mathrm{BioLNG}_{\mathrm{Electric}_{\mathrm{coef}}} = 1 \quad (25)$$

The only constraints that change in respect to scenario A.1 are the ones that state truck-cooler combinations for BioLNG trucks.

- HVO100 cooler constraint:

$$y_{HVO100} = x_{HVO100} + \mathrm{BioLNG}_{\mathrm{HVO100}_{\mathrm{coef}}} * x_{BioLNG} \quad (26)$$

- Nitrogen cooler constraint:

$$y_{Nitrogen} = \mathrm{BioLNG}_{\mathrm{Nitrogen}_{\mathrm{coef}}} * x_{BioLNG} \quad (27)$$

- Electric cooler constraint:

$$y_{Electric} = x_{Electric} + x_{Hydrogen} + \mathrm{BioLNG}_{\mathrm{Electric}_{\mathrm{coef}}} * x_{BioLNG} \quad (28)$$

B Scenarios

The current fleet composition of the major supermarket company also represents an important information to be accounted for. Ginobili's existing fleet, categorized by truck type, was provided as key information to use in the model. By incorporating the existing truck types in the fleet as a constraint on the minimum number of trucks to be selected for specific power generation systems, these could be used in the company's supply chain model and involved in the feasible solution set for the fleet mix optimization process. Current owned cooler quantity information was not provided by Ginobili, so the number of coolers to be introduced was considered by the optimization model.

In regard to the maximum number of trucks constraint, the perspective was similar to the one used in A Scenarios for the company's risk management. The truck maximum per type was limited to less than 50% of the total kilometres ran in the company's supply chain operations.

This scenario is as well proposed in two ways, one with fixed cooler-truck combinations, as specified by the company (B.1) and another version with this coefficients as decision variables to let the model choose which would be the optimal cooler to be used for the BioLNG according to emission and economic targets in each iteration (B.2). As the objective function and the emission and budget targets remain the same as in Scenarios A, only additional constraints will be displayed.

Scenario B.1

Truck-cooler combination constraints

- Total Truck-Cooler Balance:

$$\sum_{i \in TruckVector}^{n} x_i = \sum_{j \in CoolerVector}^{m} y_j \tag{5}$$

- Diesel cooler constraint:

$$y_{Diesel} = x_{Diesel} + x_{LNG} \tag{6}$$

- HVO100 cooler constraint:

$$y_{HVO100} = x_{HVO100} + 0.25 * x_{BioLNG} \tag{7}$$

- Nitrogen cooler constraint:

$$y_{Nitrogen} = 0.5 * x_{BioLNG} \tag{8}$$

- Electric cooler constraint:

$$y_{Electric} = x_{Electric} + x_{Hydrogen} + 0.25 * x_{BioLNG} \tag{9}$$

- Diesel free fleet truck constraint:

$$x_{Diesel} \leq 0 \tag{10}$$

Current fleet composition minimum truck constraints

$$x_{BioLNG} \geq 52 \tag{29}$$

$$x_{HVO100} \geq 5 \tag{30}$$

$$x_{Electric} \geq 3 \tag{31}$$

Risk Management maximum truck limit constraints: Limit Each Truck Type to Less Than 50% of Total Kilometres

- Total truck kilometre variable definition:

$$Total\ Km = \sum_{i \in TruckVector}^{n} (x_i * km_i) \tag{15}$$

- Constraints for each truck type:

$$x_{Diesel} * km_{Diesel} \leq 0.5 * Total\ Km \tag{16}$$

$$x_{LNG} * km_{LNG} \leq 0.5 * Total\ Km \tag{17}$$

$$x_{BioLNG} * km_{BioLNG} \leq 0.5 * Total\ Km \tag{18}$$

$$x_{HVO100} * km_{HVO100} \leq 0.5 * Total\ Km \tag{19}$$

$$x_{Electric} * km_{Electric} \leq 0.5 * Total\ Km \tag{20}$$

$$x_{Hydrogen} * km_{Hydrogen} \leq 0.5 * Total\ Km \tag{21}$$

Scenario B.2

This scenario mirrors Scenario A.2 as three decision variables are added. These represent the coefficients as a percentage of the coolers of Nitrogen, HVO100 and Electric that would be used for BioLNG trucks in each case. As each iteration has a different epsilon value, thus, a different environmental target, this coefficients will vary, telling the analyst which the optimal cooler type is to be used in each case.

Coefficient variables definition

$$\mathrm{BioLNG}_{\mathrm{HVO100}_{\mathrm{coef}}} \in [0,1] \tag{22}$$

$$\mathrm{BioLNG}_{\mathrm{Nitrogen}_{\mathrm{coef}}} \in [0,1] \tag{23}$$

$$\mathrm{BioLNG}_{\mathrm{Electric}_{\mathrm{coef}}} \in [0,1] \tag{24}$$

Coefficient initial percentage constraint

$$\mathrm{BioLNG}_{\mathrm{HVO100}_{\mathrm{coef}}} + \mathrm{BioLNG}_{\mathrm{Nitrogen}_{\mathrm{coef}}} + \mathrm{BioLNG}_{\mathrm{Electric}_{\mathrm{coef}}} = 1 \tag{25}$$

The only constraints that change in respect to scenario A.1 are the ones that state truck-cooler combinations for BioLNG trucks.

- HVO100 cooler constraint:

$$y_{HVO100} = x_{HVO100} + \mathrm{BioLNG}_{\mathrm{HVO100}_{\mathrm{coef}}} * x_{BioLNG} \tag{26}$$

- Nitrogen cooler constraint:

$$y_{Nitrogen} = \mathrm{BioLNG}_{\mathrm{Nitrogen}_{\mathrm{coef}}} * x_{BioLNG} \tag{27}$$

- Electric cooler constraint:

$$y_{Electric} = x_{Electric} + x_{Hydrogen} + \mathrm{BioLNG}_{\mathrm{Electric}_{\mathrm{coef}}} * x_{BioLNG} \tag{28}$$

C Scenarios

These scenarios represent an even more realistic approach than the previous ones. This is because it incorporates constraints defined directly by the company's management. These constraints include a minimum number of trucks based on Ginobili's existing fleet composition, ensuring that the current operational capacity is maintained. Additionally, a maximum cap is introduced for LNG, BioLNG, HVO100, Electric and Hydrogen trucks, reflecting the company's strategic preferences for these vehicle types, accounting for the maturity of technologies and expected infrastructural development for alternative fuels in Italy.

Similarly to previous scenarios, this scenario is as well proposed in two ways, one with fixed cooler-truck combinations (C.1), as specified by the company and another version with this coefficients as decision variables to let the model choose which would be the optimal cooler to be used for the BioLNG according to emission and economic targets in each iteration (C.2). As the objective and the emission and budget targets remain the same, the only point that changes are the constraints.

Scenario C.1

Truck-cooler combination constraints

- Total Truck-Cooler Balance:

$$\sum_{i \in TruckVector}^{n} x_i = \sum_{j \in CoolerVector}^{m} y_j \tag{5}$$

- Diesel cooler constraint:

$$y_{Diesel} = x_{Diesel} + x_{LNG} \tag{6}$$

- HVO100 cooler constraint:

$$y_{HVO100} = x_{HVO100} + 0.25 * x_{BioLNG} \tag{7}$$

- Nitrogen cooler constraint:

$$y_{Nitrogen} = 0.5 * x_{BioLNG} \tag{8}$$

- Electric cooler constraint:

$$y_{Electric} = x_{Electric} + x_{Hydrogen} + 0.25 * x_{BioLNG} \tag{9}$$

- Diesel free fleet truck constraint:

$$x_{Diesel} \leq 0 \tag{10}$$

Current fleet composition minimum truck constraints

$$x_{BioLNG} \geq 52 \tag{29}$$

$$x_{HVO100} \geq 5 \quad (30)$$
$$x_{Electric} \geq 3 \quad (31)$$

Company management defined maximum truck constraints

$$x_{LNG} \leq 101 \quad (32)$$
$$x_{BioLNG} \leq 350 \quad (33)$$
$$x_{HVO100} \leq 350 \quad (34)$$
$$x_{Hydrogen} \leq 5 \quad (35)$$
$$x_{Electric} \leq 26 \quad (36)$$

Scenario C.2

In this scenario three decision variables are added. These represent the coefficients as a percentage of the coolers of Nitrogen, HVO100 and Electric that would be used for BioLNG trucks in each case. As each iteration has a different epsilon value, thus, a different environmental target, this coefficients will vary, telling the analyst which the optimal cooler type is to be used in each case.

Coefficient variables definition

$$\mathrm{BioLNG}_{\mathrm{HVO100}_{\mathrm{coef}}} \in [0,1] \quad (22)$$
$$\mathrm{BioLNG}_{\mathrm{Nitrogen}_{\mathrm{coef}}} \in [0,1] \quad (23)$$
$$\mathrm{BioLNG}_{\mathrm{Electric}_{\mathrm{coef}}} \in [0,1] \quad (24)$$

Coefficient initial percentage constraint

$$\mathrm{BioLNG}_{\mathrm{HVO100}_{\mathrm{coef}}} + \mathrm{BioLNG}_{\mathrm{Nitrogen}_{\mathrm{coef}}} + \mathrm{BioLNG}_{\mathrm{Electric}_{\mathrm{coef}}} = 1 \quad (25)$$

The only constraints that change in respect to scenario A.1 are the ones that state truck-cooler combinations for BioLNG trucks.

- HVO100 cooler constraint:

$$y_{HVO100} = x_{HVO100} + \mathrm{BioLNG}_{\mathrm{HVO100}_{\mathrm{coef}}} * x_{BioLNG} \quad (26)$$

- Nitrogen cooler constraint:

$$y_{Nitrogen} = \mathrm{BioLNG}_{\mathrm{Nitrogen}_{\mathrm{coef}}} * x_{BioLNG} \quad (27)$$

- Electric cooler constraint:

$$y_{Electric} = x_{Electric} + x_{Hydrogen} + \mathrm{BioLNG}_{\mathrm{Electric}_{\mathrm{coef}}} * x_{BioLNG} \quad (28)$$

3.6.2 Alternative scenarios

3.6.2.1 Fuel Price Forecast Scenario

In this scenario, an alternative approach based on market data is introduced. Using statistical econometric models on time series, fuel prices for 2030 were forecasted to be integrated into the optimization model as inputs. This allows analysis on how market-based data could influence the decision-making process of the major supermarket company, serving as a sensitivity analysis within the optimisation method. To achieve this, an analysis of fuel price forecasting was done, along with a detailed examination of the specific characteristics and trends of the different fuel types.

Fuel price forecasting model

To align with the company's the sustainability goals for 2030, a fuel price forecasting model became essential to be developed in order to provide input data for the optimization model to be used. This forecasting model ensures the meeting of the defined constraints and objectives.

Based on the literature analysed, several potential approaches were considered. This includes multivariate linear regression models, seasonal ARIMA models, machine learning models and hybrid methods that combine trend modelling with a separate time series model for residuals (Wang, 2024). These methodologies were evaluated, being trained and tested with the historical fuel price data available from 2020 onwards.

The variable to be explained by the model is:

$$z_i: Fuel\ price\ in\ the\ date\ i\ (EUR).$$

It has to be taken in account that the historical fuel prices in the past years have been influenced not just by the COVID-19 pandemic (2020-2022) but also because of the war between Russia-Ukraine (2022-), the OPEC+ decisions (2020-) and the macroeconomic policies of the countries.

Theorical models analysed

To develop the fuel price forecasting model, various time series statistical models were analysed from the theoretical information available and previous investigation being done on the topic.

Multivariate linear regression model

The multivariate linear regression model analysed to capture the fluctuations in the fuel prices by using exogenous variables. This type of models is used to study extremely volatile gasoline price and to improve the forecasting accuracy. Given that macroeconomic factors such as inflation, USD/EUR exchange rates, global crude oil priced and the consumer price index are linked to transportation costs (He, 2023), this model was proposed initially to capture these dynamics. Since petroleum products are traded around the world in dollars, the exchange rate became part of the analysis as this is done particularly in the context of Italy. Integrating external factors to model fuel price in a specific date is a contextually relevant approach for the subsequent optimization model.

To evaluate whether these contextual macroeconomic variables were representative of the fuel price historical data available, a correlation analysis was developed (Data: ISTAT, European Central Bank, Trading Economics). The analysis was done comparing initially the Diesel price, which is the most used type of fuel used in logistics operations.

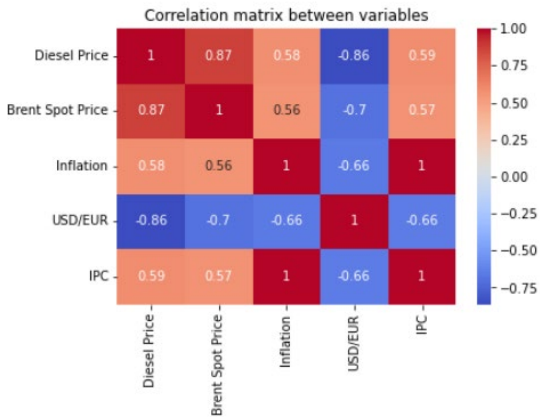

Figure 5: Correlation analysis

After conducting the correlation matrix analysis, it is possible to state that there is a very strong positive correlation with the Brent Oil spot price and a very strong negative correlation with the USD/EUR exchange rate.

When assessing multivariate linear regression models, there is the need to execute the Variance Inflation Factor (VIF) to measure the severity of multicollinearity in the analysis.

VIF ≥ 10 states for severe multicollinearity, indicating that the variable might be redundant or problematic in the model.

Variable	VIF
Brent Spot Price	2.11
Inflation	309.6
USD/EUR	2.53
IPC	308.13

Table 4: First iteration's variance inflation factor

From the results presented in Table 4, it could be seen that Inflation and IPC are strongly correlated with one or more variables in the model. One of these variables might be redundant or problematic, so the decision was to proceed taking out the IPC from the analysis. As IPC is a direct indicator of inflation and run another VIF.

Variable	VIF
Brent Spot Price	2.02
Inflation	1.84
USD/EUR	2.45

Table 5: Second iteration's variance inflation factor

After taking out IPC from the analysis, there is no sign of severe multicollinearity, and the multivariate linear regression model is constructed.

As highlighted in the literature, fuel price time series often exhibit seasonal patterns. To capture this seasonality in the analysis, it was incorporated into the model by introducing monthly dummy variables, adding them alongside the previously seen contextual variables (He., 2023). The seasonality, trend and residual analysis of the Diesel Price historical data from 2020 onwards can be seen on Figure 6.

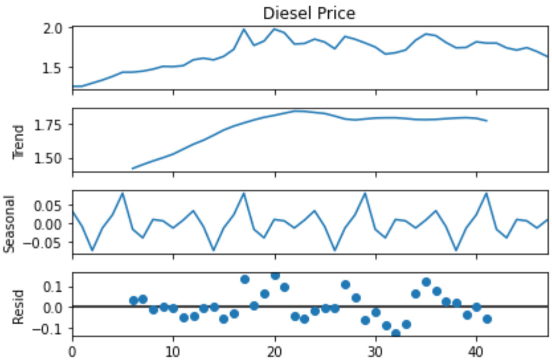

Figure 6: Trend, seasonality and residuals of the Diesel Price historical data

The resulting multivariate linear regression curve is the following:

$$Z = \beta_0 + \beta_1 * t + \Sigma S_j + OILPRICE + INF + USDEUR + \varepsilon$$

Explanation of terms:

- $Z_i: Fuel\ price\ in\ the\ date\ i\ (EUR)$
- $\beta_0: Intercept\ where\ all\ explanatory\ variables\ are\ zero.$
- $\beta_1 * t: Time\ trend.$
- $\Sigma S_j: Seasonality\ monthly\ dummies\ corresponding\ to\ the\ months\ of\ the\ year.$

- $OILPRICE, INF, USDEUR$: $Exogenous\ variables.$

SARIMAX

To improve the prediction accuracy of fuel prices introducing seasonality terms, due to the time-dependent nature of fuel prices, the SARIMAX (Seasonal Autoregressive Integrated Moving Average), an extension of the ARIMA model, was considered. This model, differently from the previous described one, focuses on the temporal structure of the data, capturing trend and seasonality patterns (Ntare, 2023).

The general ARIMA model is defined by three primary components: autoregressive (AR), differencing (I), and moving average (MA) as shown in the formula ARIMA (p,d,q):

$$z_t = \delta + \phi_1 z_{t-1} + \phi_2 z_{t-2} + \cdots + \phi_p z_{t-p} + \alpha_t - \theta_1 \alpha_{t-1} - \cdots - \theta_q \alpha_{t-q} \quad (36)$$

where z_t is level of differencing of the time series, the constant is notated by δ, while φ is an autoregressive operator, a is a random shock corresponding to time period t, and θ is a moving average operator (Permanasari et al., 2013).

The Seasonal ARIMA (SARIMAX) $(p, d, q) * (P, D, Q)_s$ is then composed of six primary terms:

p: Captures the relationship between the observation and a number of lagged observations in the dataset, explaining how the lagged values of fuel prices can predict future values.

d: Introduces the technique of differencing the data, subtracting the previous value from the current one, to transform it into a stationary series.

q: This is the moving average term, that models the relationship between the observation and the residual errors from lagged observations.

P, D, Q: Seasonal components that represent the same concepts as p, d, and q, but specifically for seasonal patterns in the data.

XGBoost

As seen in the literature, XGBoost was used as one of the possible machine learning approaches to model time series. It is an advanced supervised technique in which there are *n* decision trees and iteratively, each new tree is iteratively refined using a gradient-based algorithm. As this process continues, each tree considers the residual errors of the previous one until the most accurate result is produced. The objective function of XGBoost consists of training loss and a regularization term (Yang et al., 2023).

$$L^{(t)} = \sum_{i=1}^{m} l(b_{i,}\ b_i^*) + \sum_{t=1}^{T} \omega(f_t) \tag{37}$$

- $\sum_{i=1}^{m} l(b_{i,}\ b_i^*)\ represents\ the\ training\ loss.$
- $\sum_{t=1}^{T} \omega(f_t)\ represents\ the\ regularization\ term.$

This leads to the result of the model in the equation below, that is the sum of all the output values of the trees produced:

$$b = \sum_{t=1}^{T} f_t(v_i) \tag{38}$$

Hybrid Models

To combine the strength of different predictive time series techniques, hybrid modelling is proposed. This type of models show often more accuracy than the standard ones (Wang, 2024).

The first model is applied over the base case and the model added is applied to model the residuals between the predicted value from the first model and the historical data.

Two hybrid models are explored in this analysis:

- Multivariate linear regression + SARIMAX.
  - This model addresses global trends with the linear regression by means of macroeconomic factors and temporal patterns due to SARIMAX.
- Multivariate linear regression + XGBoost.
  - This combination brings together statistical and machine learning techniques to lead with predictive accuracy.
    Linear regression identifies global trends with the macroeconomic factors and XGBoost uses gradient-boosting algorithms to model residual errors.

Model selection and application

Each of the models proposed was structured and developed in Python. These were trained and tested for each fuel to evaluate their performance with the historical data available. Train data was selected as prior to 2024 while the test data is defined as from 2024 onwards.

In the models, the parameters for the SARIMAX model were determined using the auto_arima Python library. This library uses the Akaike Information Criterion (AIC) as well in each of the iterations evaluating model performance and selecting the parameters that show the lowest AIC value as a result.

Consistent with the literature (He, 2023), each one of the models is ranked based on their Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE).

Diesel

Diesel fuel remains one of the most used energy sources in the logistics industry due to its efficiency and availability. The historical prices for diesel fuel from 2017 onward are shown in Figure 7 below, obtained from Ministero dello Sviluppo Economico (n.d.).

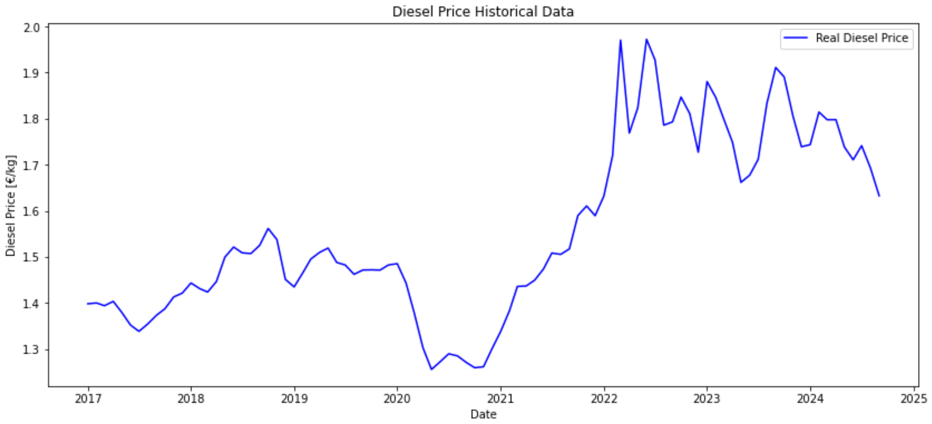

Figure 7: Diesel price historical data

From 2021 onward, diesel prices presented an upward trend. This was because the global economy was recovering from the COVID-19 pandemic and as well geopolitical tensions between Russia and Ukraine were emerging.

The alignment of the time series statistical model in the training step to the test data from 2024 is shown in Figure 8. Among the models evaluated, it is possible to see that the hybrid Linear + SARIMAX model is the one that best follows the historical data of Diesel Prices shown in blue.

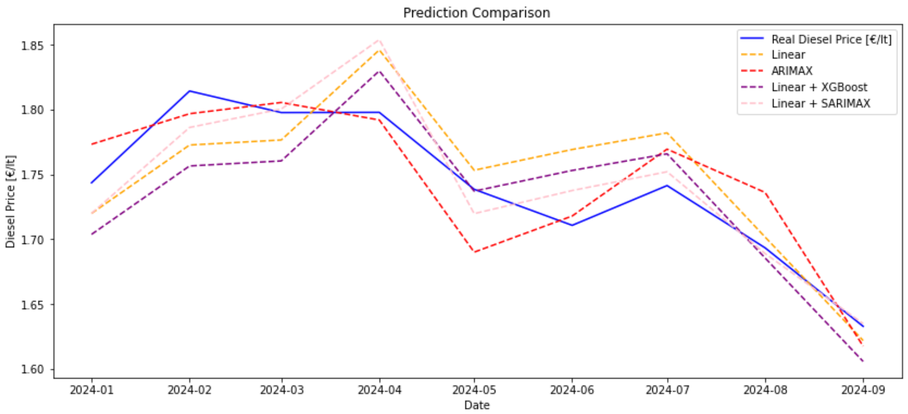

Figure 8: Diesel Price model prediction comparison versus Diesel test data

After analysing visually, the calibration of the model to the historical data, a quantitative evaluation was conducted to assess the different model's predictive accuracy. The MLR + SARIMAX achieves the best performance of the four, with the lowest MAPE and RMSE, confirming it ability to cover both macroeconomic and seasonal factors.

Model	MAPE (%)	RMSE	Ranking
SARIMAX	1.302	0.027	2
MLR	1.697	0.034	3
MLR + XGBoost	1.713	0.034	4
MLR + SARIMAX	1.092	0.025	1

Table 6: Diesel model accuracy and validation

When selecting the top-ranked model, the forecast is made up to 2030 generate results to input into the optimization model. The projected Diesel price values up to 2030 are be shown in the figure below. To account for potential errors in the predictions, one standard deviation of the residuals was added to the forecasted Diesel price that is shown represented by the orange-shaded area above and below the predicted points.

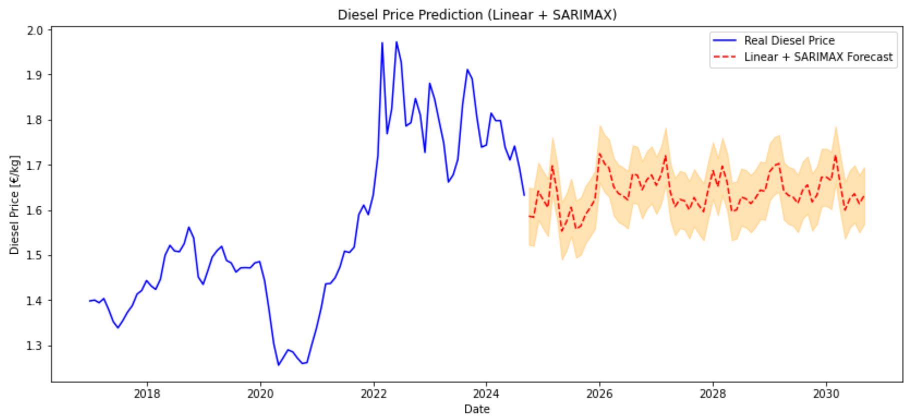

Figure 9: Diesel price prediction up to 2030

LNG

Liquified Natural Gas (LNG) has become a key source in the logistics industry. It offers a cleaner alternative to the most traditional fossil fuels like diesel. The war and the recent geopolitical changes in the European region had a substantial impact in LNG prices, that is why for convenience the range of the selected historical data is bigger to evaluate trends and seasonality with a better accuracy.

The historical prices for LNG from 2017 onwards are shown below, obtained from Mercato Elettrico (n.d.).

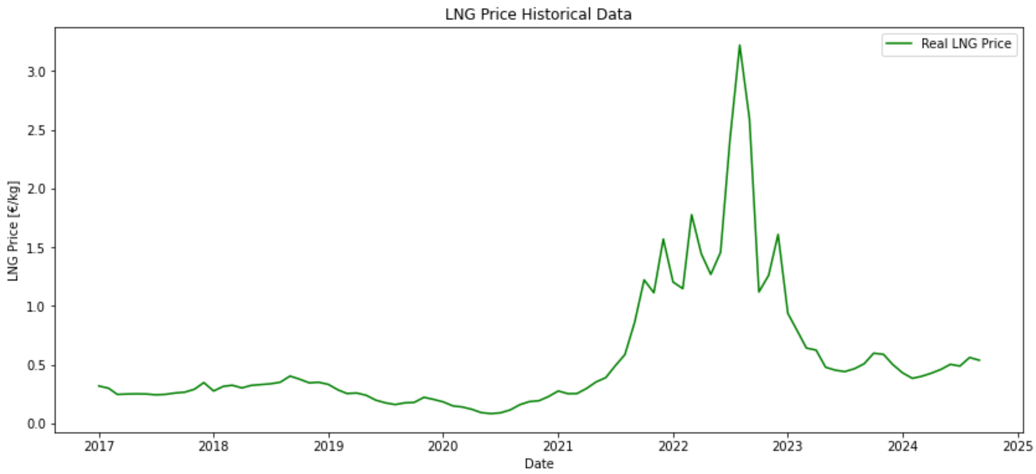

Figure 10: LNG price historical data

The figure highlights an all-time high in LNG prices during August 2022. This spike could be attributed to the geopolitical tensions and sanctions imposed to Russia because of the Russia-Ukraine war, that disrupted global energy markets.

After analysing the historical data, the statistical models were trained and fitted with data from 2017 onward due to the significant price spikes in 2022 because of the war. The availability of an extensive data source fulfilled model requirements, as having more data makes the peak price less impactful for future price predictions. These were subsequently tested on data from 2024 to evaluate their performance.

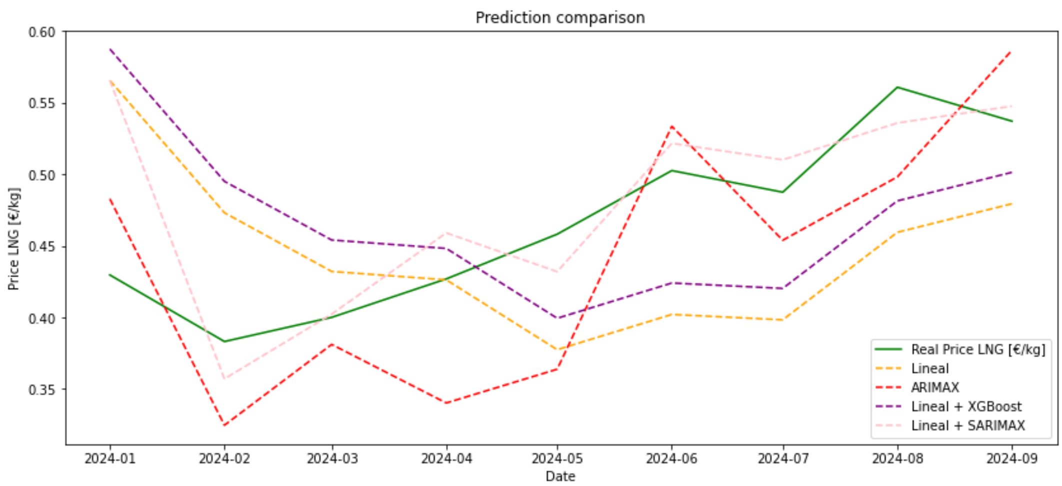

Figure 11: LNG Price model prediction comparison versus LNG test data

After analysing visually, the calibration of the model to the historical data, a quantitative evaluation was conducted to assess the different model's predictive accuracy. The MLR + SARIMAX achieves the best performance of the four, with the lowest MAPE and RMSE, confirming its ability to cover both macroeconomic and seasonal factors.

Model	MAPE (%)	RMSE	Ranking
SARIMAX	12.901	0.069	2
MLR	16.076	0.081	4
MLR + XGBoost	14.914	0.079	3
MLR + SARIMAX	12.357	0.069	1

Table 7: LNG model accuracy and validation

When selecting the top-ranked model, the forecast is made up to 2030 generate results to input into the optimization model. The projected LNG price values up to 2030 are be shown in the figure below. To account for potential errors in the predictions, one standard deviation of the residuals was added to the forecasted LNG price that is shown represented by the orange-shaded area above and below the predicted points.

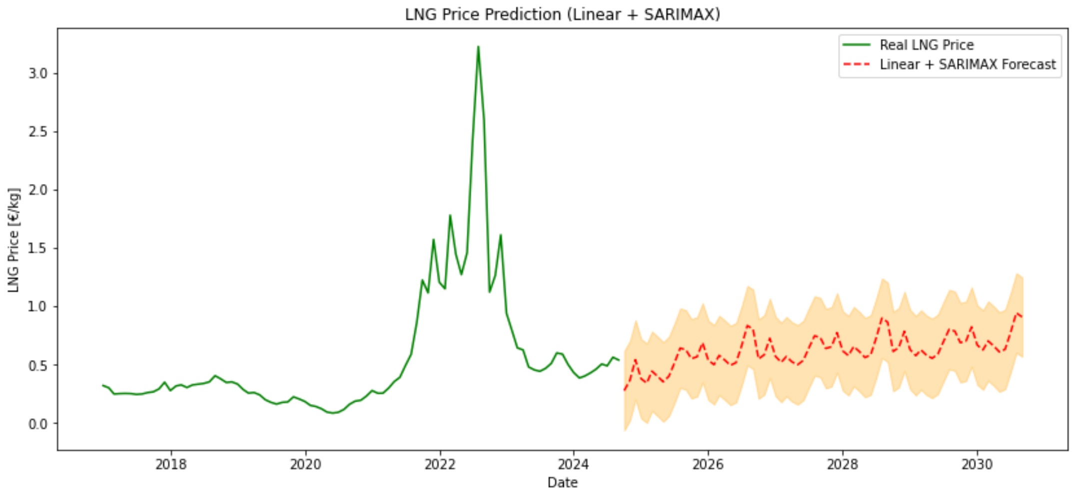

Figure 12: LNG price prediction up to 2030

BioLNG

BioLNG is an innovative fuel derived from renewable sources. It is LNG but from a non-fossil origin. It is a fuel produces from biogas, developed from the treatment of organic waste flows such as agricultural waste, sewage sludge or landfills. This renewable energy source offers a carbon-neutral alternative as its production and use can reduce GHG emissions in comparison to fossil fuels.

In the last years, BioLNG has gained attention in the logistics and transportation industries because of its high potential to decarbonize supply chain operations. As regulations on the environment increase, this fuel type provides an environmentally friendly alternative without compromising operational efficiency, as it is even used in heavy-duty trucking and shipping operations. Historical development and market adoption of this type of fuel is tied to advancements and investments in technology, joined to policy shifts and promotion of renewable energy sources. The challenge of increasing the availability of the infrastructure for the availability of this fuel remains, but advances are made as years pass by.

Historical prices for BioLNG from the data available from 2022 onward are presented below, retrieved from Agriportance (n.d.) representing its recent market evolution.

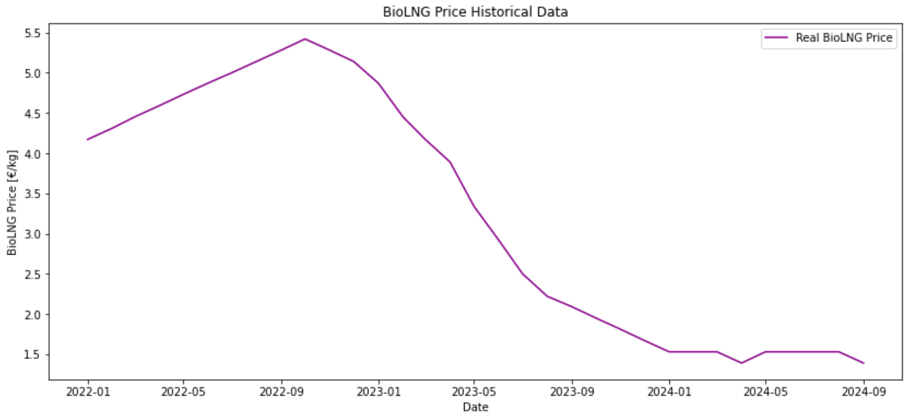

Figure 13: BioLNG price historical data

Figure 13 highlights a price peak during the year 2022, likely driven by the war in Ukraine and the world's geopolitical context. In the next years, as technological advances in production and infrastructure improved and market conditions stabilized, prices steadily lowered.

After analysing the historical data, statistical models were trained and fitted with data from 2022 onwards to capture trends and seasonality. Model performance was tested using data from 2024 to look for their predictive accuracy on recent trends.

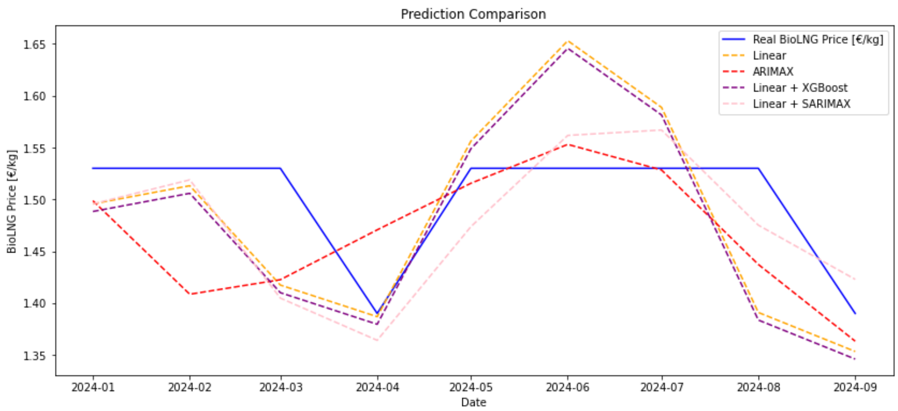

Figure 14: BioLNG Price model comparison versus BioLNG test data

After analysing visually, the calibration of the model to the historical data, a quantitative evaluation was conducted to assess the different model's predictive accuracy. The MLR + SARIMA achieves the best performance of the four, with the lowest MAPE and RMSE, confirming its ability to cover both macroeconomic and seasonal factors.

Model	MAPE (%)	RMSE	Ranking
SARIMAX	3.705	0.069	2
MLR	4.028	0.077	4
MLR + XGBoost	4.2	0.079	3
MLR + SARIMAX	3.014	0.055	1

Table 8: BioLNG model accuracy and validation

When selecting the top-ranked model, the forecast is made up to 2030 generate results to input into the optimization model. The projected BioLNG price values up to 2030 are be shown in the figure below. To account for potential errors in the predictions, one standard deviation of the residuals was added to the forecasted BioLNG price that is shown represented by the orange-shaded area above and below the predicted points.

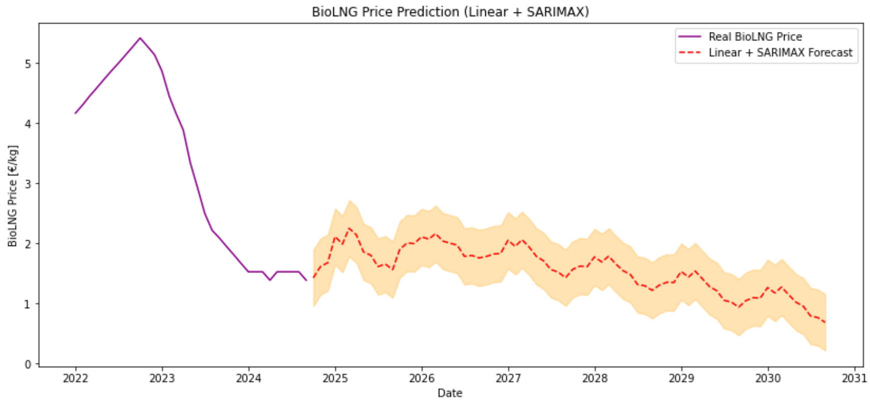

Figure 15: BioLNG price prediction up to 2030

HVO100

HVO100 is a renewable diesel fuel derived from various vegetable oils or animal fats using a hydro-treating process. The process indicated removes oxygen from the raw materials, creating compatibility with modern diesel engines and offering GHG reduction (Suarez-Bertoa et al. 2019).

In the recent year, this fuel type has gained popularity due to its high performance and strict environmental regulations. It provides an efficient alternative for decarbonizing read transportation. Currently, the production of HVO100 is largely based on feedstocks such as palm oil and other vegetable oils, raising concerns about its sustainability due to the environmental and social impacts associated with palm oil cultivation.

Historical prices for HVO100 are presented in the figure below, retrieved from Vespertool (n.d.) showcasing its price evolution from 2021 onwards.

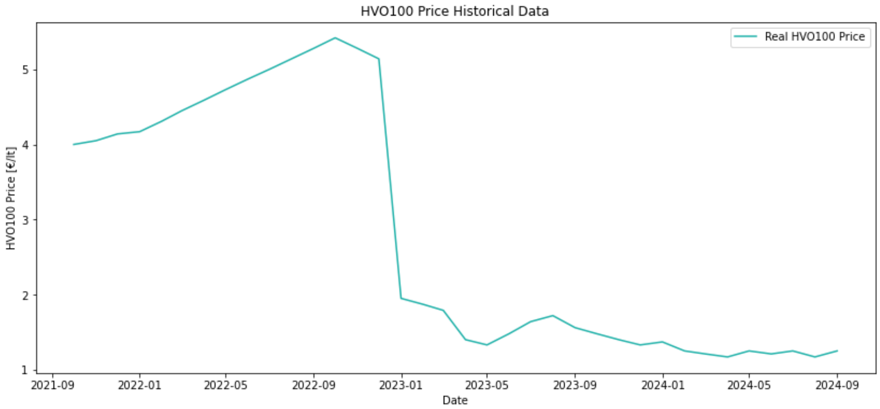

Figure 16: HVO100 price historical data

The graph highlights the impacts of geopolitical and market events on HVO100 pricing such as price peaks during the energy crisis in 2022, where the demand for this type of fuel was growing. Within the years, this fuel is improving its production capacity and supply chain resilience, while stabilizing in prices.

To better understand market behaviour and predict future trends, statistical models were trained using historical data from Vespertool (n.d.). The models included SARIMA, MLR, MLR combined with XGBoost and MLR combined with SARIMA, with their performance evaluated on data from 2024.

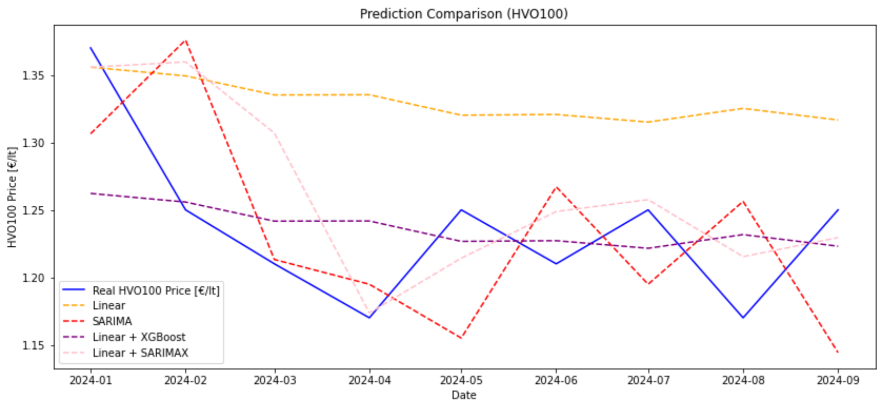

Figure 17: Model prediction comparison versus HVO100 test data

Model	MAPE (%)	RMSE	Ranking
SARIMA	6.231	0.087	4
MLR	6.373	0.085	3
MLR + XGBoost	4.987	0.077	2
MLR + SARIMA	4.695	0.066	1

Table 9: HVO100 model accuracy and validation

As seen on table 9, the best performing model is MLR + ARIMA and therefore it was selected for long-term forecasting. The forecast of HVO100 prices up to 2030, represented in the figure below, includes an uncertainty band to account for potential errors by incorporating one standard deviation of residuals.

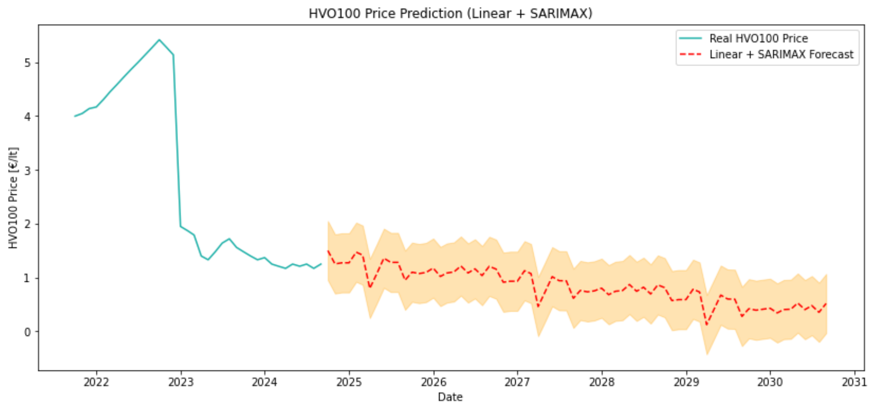

Figure 18: HVO100 price prediction up to 2030

Green Electricity

As the world moves towards a sustainable future, electricity generation is shifting away from fossil fuels and towards renewable sources such as wind, solar and hydropower. This transition to green electricity is critical for reducing GHG and achieving energy security. However, as demand for electricity demanding products increases, so does its renewable and non-renewable sourcing. The variability of its price remains a challenge, as it depends on production capacity, city electrification, geopolitical factors and weather conditions.

In this model, it is important to distinguish between grid electricity (which may still rely on non-renewable sources) and green electricity, which directly supports sustainability goals for 2030. To align with the goals for the major supermarket company, the model incorporates GO (Guarantees of Origin) prices into the electricity cost. This approach emphasizes the promotion of renewable energy sources like wind, solar, and hydropower in Italy.

Over a third of the electricity produced in Italy comes from green sources: hydroelectric power has always dominated, followed by solar photovoltaic, bioenergy, wind power, and geothermal (Enel, 2023). In this country, mountainous regions, particularly in the Alps and the Apennines, provide excellent opportunities for hydroelectric plants. The panorama in this aspect is evolving as of 2021, 40.91% of the country's electricity comes from renewables, compared to 27.68% in 2011 (HivePower, 2021).

For Ginobili, this would represent a new initiative, and the most practical solution lies in purchasing both GO certificates and electricity from the grid, thus reinforcing their commitment to green energy objectives.

Historical data on grid electricity prices and GO prices were analysed, as illustrated in Figures 19 and 20 below. The GO price data was sourced from Gestore Mercati Elettrici (n.d.). This data included details such as the type of energy source (wind, solar, hydroelectric), the volume available per source, and the corresponding price. To account for the availability and variability of different sources, a weighted monthly average price was calculated based on the data available from GME and the energy sources available per date. The weighting was based on the total volume of electricity produced and the contribution of each energy source on a given date, ensuring a comprehensive and accurate representation of GO prices in the model.

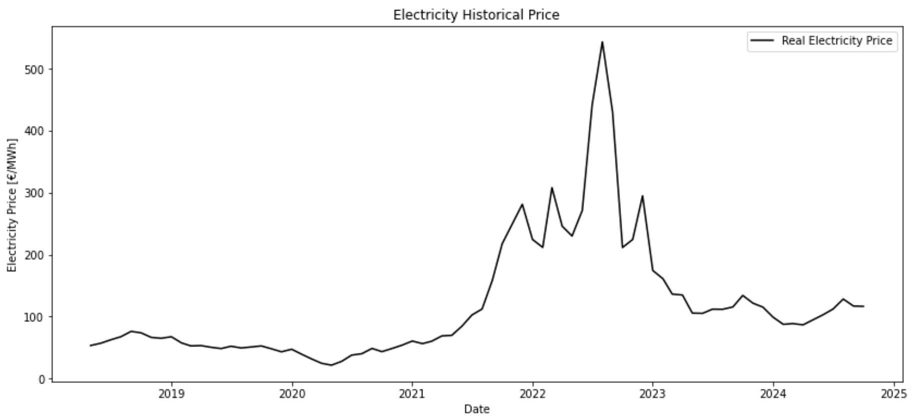

Figure 19: Electricity historical price

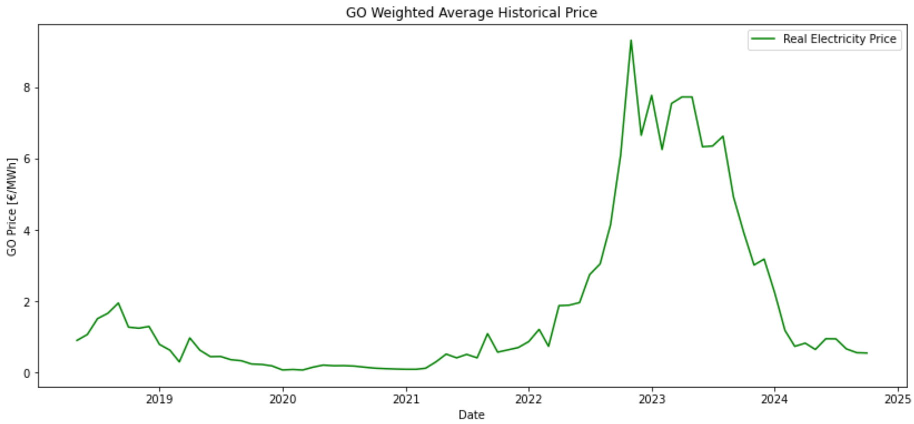

Figure 20: GO historical price

The figure illustrates price volatility, with peaks resembling those of LNG during the 2022 energy crisis when electricity costs surged due to gas supply disruptions and rising demand. Stability followed as infrastructure improvements, supply chain adaptability, and market adjustments helped reshape the landscape. A similar trend is visible in GO prices, which saw significant spikes during the energy shortages caused by the Russia-Ukraine war.

To forecast electricity prices, statistical models were developed and tested using Gestore Mercati Elettrici (n.d.) historical data to capture trends and seasonality. These models include SARIMAX, MLR and hybrid models as MLR + XGBoost and MLR + SARIMAX.

Their performance was evaluated using 2024 data and can be seen in the figure below.

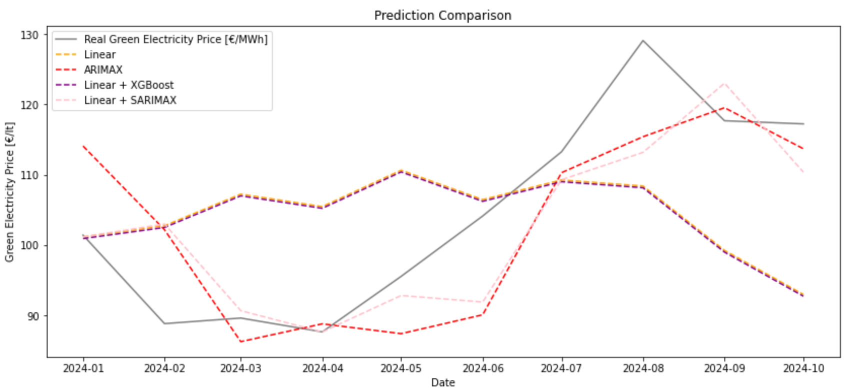

Figure 21: Model prediction comparison versus green electricity test data

The table below summarized the quantitative evaluation of these models with the MAPE and RMSE metrics, with MLR + SARIMAX achieving the best performance.

Model	MAPE (%)	RMSE	Ranking
SARIMAX	7.193	9.079	2
MLR	12.915	15.445	4
MLR + XGBoost	12.801	15.443	3
MLR + SARIMAX	5.826	8.286	1

Table 10: Green electricity model accuracy and validation

The prediction made with the model can be seen in the figure below, that captures linear trends as well as seasonality patterns.

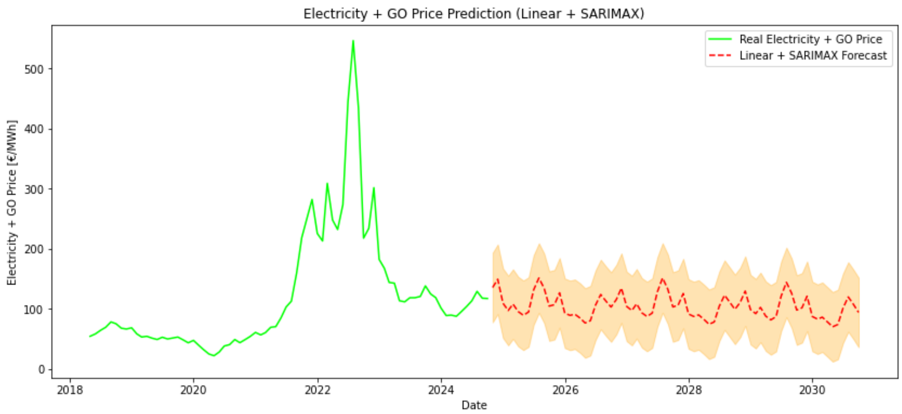

Figure 22: Electricity + GO historical price

Hydrogen

Green hydrogen faces major challenges, especially in transportation due to high costs and safety risks. Its low energy density requires intensive compression or liquefaction, making distribution inefficient as well as introducing safety concerns (GenHydro, 2023).

Deciding between in-house production or external sourcing remains uncertain. Hybrid models may also develop. As a result, green hydrogen is excluded from quantitative analysis for now, given the lack of reliable data needed for a complete evaluation. Studies show that current production, transport and storage costs are higher than fossil fuels with carbon capture (The Wall Street Journal, 2024).

To offset costs, financial support is crucial. The European Union funds hydrogen projects through the Connecting Europe Facility for Energy, the Innovation Fund, and Horizon Europe (EU Hydrogen Observatory, 2023). Research, policy support and subsidies are essential for green hydrogen to compete with traditional energy sources.

3.6.2.2 Qualitative Scenarios

In a dynamic context, multiple exogenous scenarios could emerge, significantly influencing the outcomes of the fleet mix optimization model. These scenarios encompass a wide rage of uncertainties, including shifts in resources supply chain, technological advancements, economic conditions and regulatory frameworks representing different macroeconomic and policy scenarios.

The inclusion of qualitative scenarios allows for a comprehensive exploration of the potential challenges and opportunities that could surge in the world. Exogenous events such as the war between Ukraine and Russia and the COVID-19 pandemic showed that external factors significantly affect the way of doing business in certain contexts and involve a different process of decision-making for the companies. The major supermarket company should also take into consideration its ability to adapt to external factors that could happen on the way to 2030 and how would these affect their decision to be taken to comply with their sustainability goals. In this way, a sensitivity analysis is provided to the model, based on possible real and accountable situations in the future.

Through this analysis, the model not only offers optimized solutions but also equips decision-makers with a deeper understanding of the contextual drivers that may affect the project implementation. These insights are critical for ensuring that the proposed fleet configurations remain resilient and aligned with long-term economic, environmental, and operational objectives.

3.6.2.2.1 Supply chain and Resource Scarcity Scenarios

Global supply chains are highly susceptible to disruptions, with resource scarcity and geopolitical instability being critical factors that could significantly impact fuel availability and pricing (Rasshyvalov et al., 2024). These scenarios explore how constraints in the supply key of raw materials and energy resources could influence the supermarket company's fleet mix optimization set of solutions.

The scarcity of raw materials, such as those required for the HVO100 production with the palm oil export restrictions, exemplify how domestic policies can ripple though global markets (Lin, 2025). For instance, Indonesia's brief palm oil export ban in 2022 caused a sharp increase in prices, illustrating the potential for such disruption to inflate production costs and create reliance on fossil fuels like diesel (Medina, 2022), what would differ from Ginobili's sustainability goals in the fleet mix for 2030.

In a similar way, the gas crisis in Europe during 2022-2023 showed the volatility of energy markets in the face of geopolitical conflicts. Russian gas supply disruptions, compounded by

EU’s sanctions let to an unprecedented LNG price volatility and cascading effects on electricity and diesel prices (Chen et al., 2023).

Scarcity of Raw Materials for HVO100

Global production capacity for biogenic fuels is expanding rapidly. By 2025, global HVO production is expected to surpass 30 million tonnes, offering a potential reduction in carbon emissions of up to 90% compared to fossil diesel (CLAAS, 2023). In the current market trends, about 70% of biodiesel is based on vegetable oils (14% rapeseed oil, 23% soybean oil, and 29% palm oil) and used cooking oils (25%) (OECD &FAO, 2023). This contextual information shows that palm oil is and was the dominant feedstock for HVO production, but this trend could shift following the 2023 ban on palm oil in Germany and other EU countries due to concerns over deforestation linked to Indonesia and Malaysia. Together, Indonesia and Malaysia account for 85% of global palm oil production, making them leaders in biodiesel production (Mai, 2024). The EU's Renewable Energy Directive, which seeks to reduce the use of palm oil-based biofuels, has sparked significant criticism from both Indonesia and Malaysia, with their leaders stating the EUDR as “regulatory imperialism” (Mai, 2024). In relation to this, it is possible to say that the actual environment around this regulation is tense and could make changes towards the future following the complaints from the Asian countries’ leaders.

It is useful to add as well that a potential rise in the HVO price can be accounted for due to the anticipated increase in palm oil prices, driven by Indonesia’s plan to implement a 40% biodiesel blending mandate (B40) by 2025. This mandate requires a certain share of diesel fuel, particularly in the transportation sector, to be blended with 40% palm oil, replacing the current B35 blend (Biofuels International, 2024). This policy is expected to support palm oil prices, possibly pushing them 10 to 15 percent higher in early 2025 (Sun & Palma, 2024).

The tighter supply of palm oil in the EU, combined with Indonesia’s subsidy structure and plans to increase blending mandates could result in higher costs for palm oil, which is currently a key feedstock for HVO production.

As a sensitivity analysis to account for this palm-oil resource scarcity as a mean of HVO100 production, a 30% price increase was introduced in the model for this fuel type, to simulate an extreme situation, following the magnitude of the maximum limit amount of the rise of palm-oil prices. In this way, the model offers an insight for the major supermarket’s company decision making process in order to account with a possible HVO100 price rise in the future years.

Gas Crisis in Europe

The gas crisis scenario is a perfect example of how a geopolitical situation as a war can affect the fuel prices and therefore the results of the fleet mix optimization process. The European gas crisis of 2022-2023 revealed the fragility of energy markets when reliant on unstable supply chains. Following significant Russian gas supply disruptions, LNG prices exhibited unprecedented volatility, increasing approximately 14-fold from 2019 to 2022, peaking at $70/MMBtu in August 2022 (IMF, 2022).

This price increase was driven by European sanctions on Russia, increased dependence on U.S. and Qatari LNG (which accounted for nearly 50% of EU imports in 2023), and insufficient gas storage infrastructure (IMF, 2022). Simultaneously, electricity prices in key EU markets rose by 200-300% due to the region's heavy reliance on natural gas, which represented 20-25% of its energy mix (IEA, 2022).

This volatile context underscores the importance of resilience in energy market decision-making. For instance, to consider possible geopolitical events as crisis in the model developed, a sensitivity adjustment was applied to simulate a 200% increase in LNG and electricity prices as price spikes, based in the historical data of what happened in the case of the gas crisis because of the Russia-Ukraine war (Chen et al., 2023). This is introduced a posteriori for the epsilon constraint model, performed as a sensitivity analysis to provide an attainable solution set in this context.

3.6.2.2.2 Macroeconomic and Policy Scenarios

Understanding macroeconomic shifts and policy developments is crucial for evaluating fleet mix optimization strategies. By analysing historical trends and as well projecting the impact of possible future events, key scenarios can be simulated that could affect energy markets and thus fuel prices, having an impact in the major supermarket company's decision-making process. These insights provide valuable information for the sensitivity study to assess potential risks and opportunities for Ginobili under changing economic and policy scenarios.

LNG Ban

The potential for an LNG truck ban in urban areas across certain EU countries in the coming years is examined as a possible scenario for the European continent, particularly in light of the 2030 sustainability goals. Following the removal of diesel vehicles from cities like Paris, Madrid, and Athens by 2025 (UNFCCC, 2020) to improve air quality, similar regulations could be implemented for LNG trucks as part of a broader transition to more sustainable fuel alternatives in the future. This scenario is incorporated as a sensitivity test to assess the model's response in the event that LNG trucks are excluded from the optimal fleet mix within the feasible solution set.

Renewable Content Mandates Increase

In the A Scenarios, the minimum number of trucks is determined based on the EU RED II regulation, which mandates that by 2030, at least 14% of the transport fleet must be powered by renewable fuels, with a minimum of 3.5% derived from biofuels. As part of the sensitivity evaluation, analysing variations in the optimal fleet mix by adjusting these percentages offers valuable insights. Considering that European mandates may be updated or revised in the future, this analysis provides a realistic perspective for assessing the viability of the project within the context of evolving regulations.

For this scenario, two new inputs will be used for the model to show an extreme situation of a possible revision made in the RED II mandate: the fleet's minimum renewable energy content is set at 25% and its minimum biofuel share is set to 7.5%.

4 Results and Discussion

The results section illustrates the optimal fleet mix for the major supermarket company, depicting the trade-off between costs and emissions that emerges in the decision-making process of making an investment of this kind. The company has to fit their sustainability 2030 goals while covering its operations costs generating a surplus profit margin to justify the investment.

The solution of each scenario (Base and Alternative case scenarios) is visualised through a Pareto frontier to visualize the decision process trade-off, a cost and emission graph to show the impact across iterations because of the truck and cooler choices and by depicting the truck and cooler quantities selected by the model in each case.

Initial and advanced subcases are detailed in each case, with the initial having fixed truck-cooler combinations and, in the advanced subcase, the possible combinations are introduced as decision variables, to let the model decide which cooler to select for the truck types that are not reliant in one specific fuel technology for their operation.

The Pareto frontier represents the range of feasible cost and emission values, enabling Ginobili to visualize their operational trade-offs. This visualization identifies fleet mix solutions that align with both budgetary and emissions constraints.

4.1 Base Case Results

The results of the evaluation of these scenarios are presented in the Section 7.2 of this thesis.

4.1.1 A Scenarios

As mentioned in section 3.5.2, the A scenarios align with the EU RED II directive, which was revised in October 2023. This directive requires at least 14% of the fleet to be powered by renewable energy and at least 3.5% by biofuels (European Commission, 2018). Additionally, these scenarios introduce a risk management approach by setting a maximum truck usage limit, ensuring that no single truck accounts for more than 50% of the annual distance.

Scenario A.1

The pathway to analysing the initial approach for the regulation-compliant, risk-managed scenario revealed the Pareto frontier shown in Figure 23.

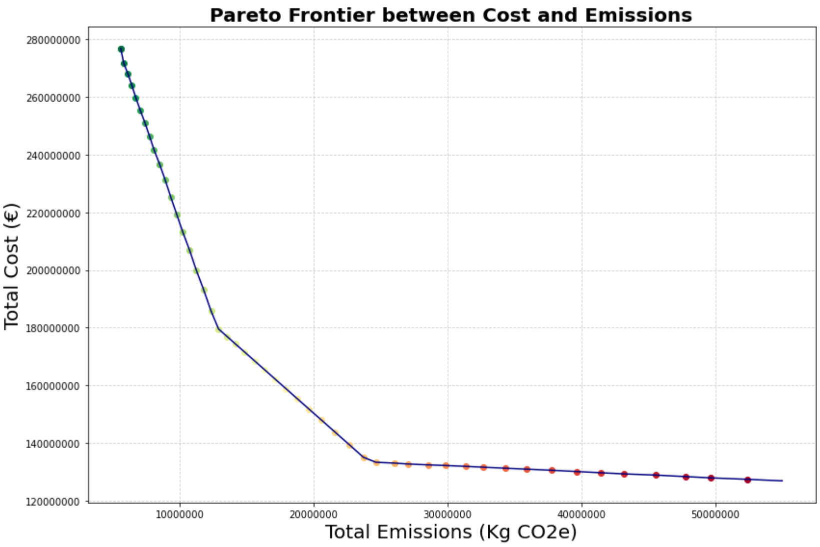

Figure 23: Scenario A.1: Eco-efficient Pareto Frontier

The pareto frontier graph highlighted the trade-off between total emissions in Kg CO2e and the total costs in euro for Ginobili's fleet mix decisions. The curve is developed in the range of 5,568,548 Kg CO2e as single environmental objective and of 55,025,819 Kg CO2e as the single economic objective. The steep decline in the leftmost portion of the curve (with a gradient of -13 €/kgCO2) indicated that achieving low emissions incurred significantly higher costs, reflecting the adoption of expensive low-emission technologies or fuels. As the curve flattened in the middle, the cost reduction slowed, suggesting a more balanced trade-off where moderate emissions reductions can be achieved without disproportionate increases in cost. Towards the right, the curve showed a plainer structure, showing that beyond the 24,640,000 kg CO2e emission level (where the gradient passes from -4.13 €/kgCO2 to -0.215€/kgCO2 according to the calculations seen in the Appendix 7.2) further increases in emissions yield minimal cost savings, likely due to reliance on more cost-efficient but higher-emission options like LNG could be.

A truck-cooler cost and emissions comparison provided valuable insights by visualizing the distribution of total costs across each solution set, highlighting the individual contributions of both trucks and coolers to the overall expenses.

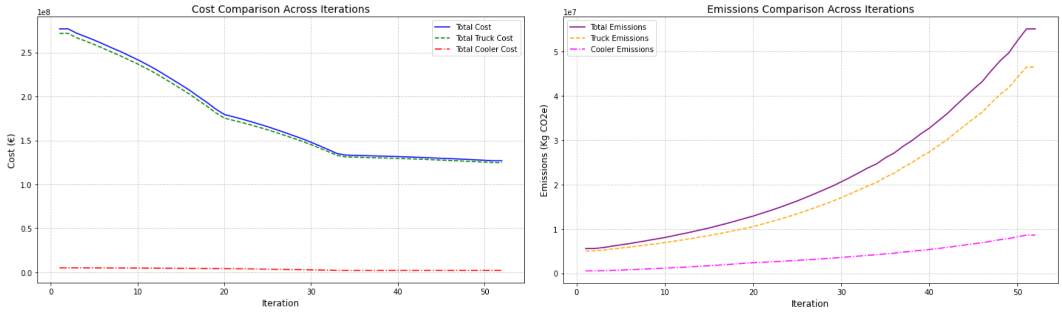

Figure 24: Scenario A.1: Cost and emissions comparison

It becomes evident in figure 24 that trucks dominated the cost curve, contributing the majority of the expenses. However, when analysing emissions, coolers exhibited a slightly higher relative impact compared to their cost contribution, though their overall emissions impact remained much lower than that of trucks.

To evaluate the solution set provided by the epsilon constraint optimization process it is useful to examine the figure 25 below, separating the truck quantities between two different bounds: Under and over budget.

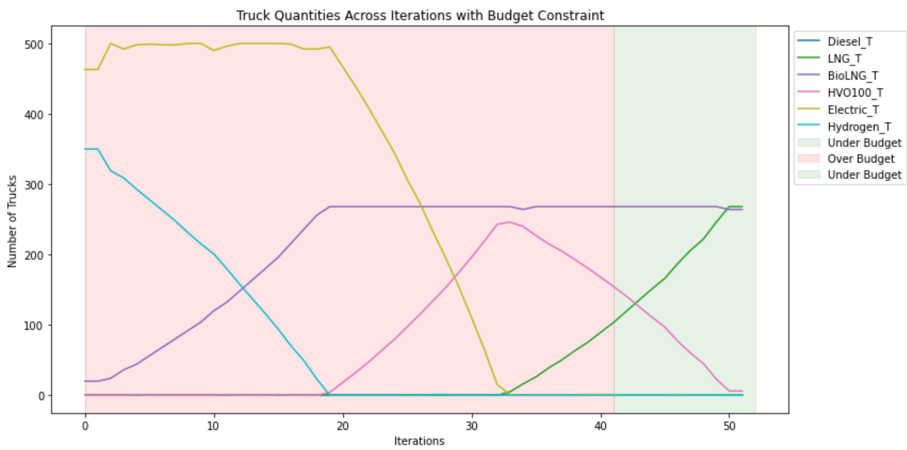

Figure 25: Scenario A.1: Truck quantities

In Figure 4.1.3, the initial iterations (up to iteration 30, focused on environmental priorities) show a clear emphasis on selecting environmentally friendly alternatives, particularly Hydrogen and Electric trucks. During the early iterations, where the emissions cap was set very low, these trucks dominated the fleet composition. However, as the emissions cap gradually increased, the number of Hydrogen trucks decreased, while the model began to incorporate more BioLNG trucks.

Electric trucks, on the other hand, were consistently chosen by the model up to the 20th iteration, corresponding to an emissions cap of 14,000,000. Beyond this point, the model shifted its focus, prioritizing BioLNG and HVO100 trucks due to their favourable balance of cost and emissions.

By the 33rd iteration, when the emissions cap exceeded 25,000,000, the model began to favour the most cost-efficient option, LNG trucks, while maintaining a steady number of BioLNG trucks. At the same time, it progressively reduced the number of HVO100 trucks, eventually phasing them out completely.

In the under-budget part of the curve, Ginobili has the possibility to evaluate the truck quantities to be chosen for their project to be established into their economically constrained structure. The trade-off relied in a constant quantity of 268 BioLNG trucks and, according to the emissions cap desired, a choice between adding a specific number of LNG or HVO100 trucks.

The graph in figure 26 illustrates the evolution of cooler quantities across iterations, driven by the model's constraints, linking cooler choices to truck types.

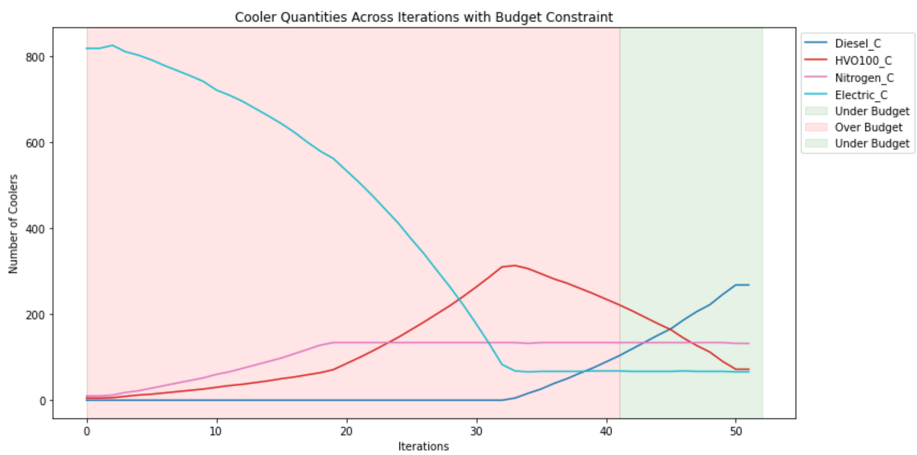

Figure 26: Scenario A.1: Cooler quantities

Electric coolers dominated early iterations (they start in 818 coolers) due to their association with Electric and Hydrogen trucks. However, as the model transitioned toward iterations with a higher emissions cap and a stronger focus on cost-efficiency, the quantity of Electric coolers steadily decreased up to the constant number of 67 coolers.

HVO100 coolers, represented in the red line, gradually rise, peaking around iteration 30, with 313 coolers, as they are tied to HVO100 trucks and partially tied to BioLNG trucks, but their number declined as the model's focus shifts to LNG trucks and cost-effective solutions.

Diesel coolers started to rise around the same iteration number that the HVO100 coolers peaked and started to fall. In the model's greatest economic approach, the number of Diesel coolers had its peak in 268 coolers. Nitrogen coolers, remain relatively constant (132 coolers) but limited in quantity, reflecting their connection to the BioLNG trucks' number shown in the previous analysis.

In the budget efficient portion of the graph, the major supermarket company's choice would be selecting a constant number of 132 nitrogen coolers and 67 electric coolers and a decision between a number of Diesel and HVO100 coolers.

Scenario A.2

This scenario advanced Scenario A.1 by considering the coefficients that represent the combinations of different cooler types and BioLNG trucks as decision variables. This introduced an additional degree of freedom to the model, allowing for a more advanced approach that enabled the model to select the best possible solution in each case using a non-linear optimization method.

The pareto frontier of this advanced configuration is shown in the figure 27 below.

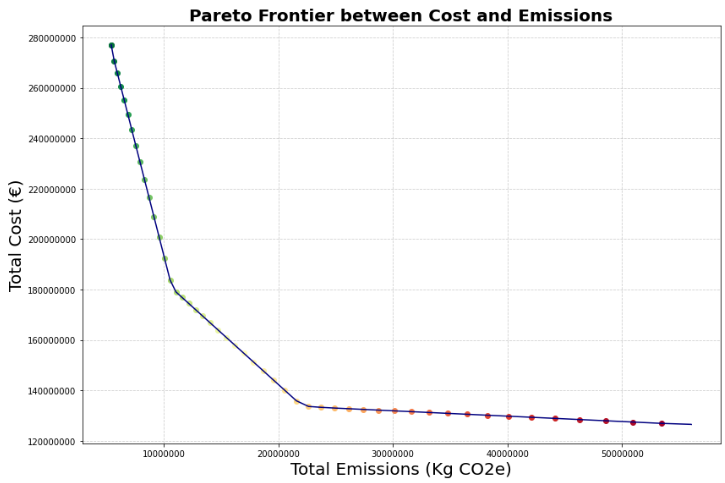

Figure 27: Scenario A.2: Pareto Frontier

The pareto frontier for scenario A.2 demonstrated a different cost-emissions relationship compared to the one of scenario A.1. The curve started from an environmental single objective on 5,403,631 kgCO2 ended on the economic single objective of 56,049,844 kgCO2. In figure 4.1.5, the initial steep decline (average gradient -17.43€/kgCO2) is heavier than the one of scenario A.1, indicating a stronger focus on minimizing emissions at the expense of higher costs for the actual situation. The degree of freedom that having the BioLNG coefficients as decision variables involves is that the curve started in both slightly lower cost and emission points. With respect to scenario A.1, the steep is similar in the midsection part of the curve.

At the tail end of both scenarios, the behaviour converged, as both frontiers flattened and reached similar low-cost solutions for higher emissions caps. However, A.2 (average gradient -0.218 €/kgCO2) higher flexibility allowed the curve to reach lower cost values than the previous scenario. While A.1 adopted a more balanced approach with lower gradients in the curve, A.2 had higher gradients due to the model's higher adaptability to the objectives to be searched.

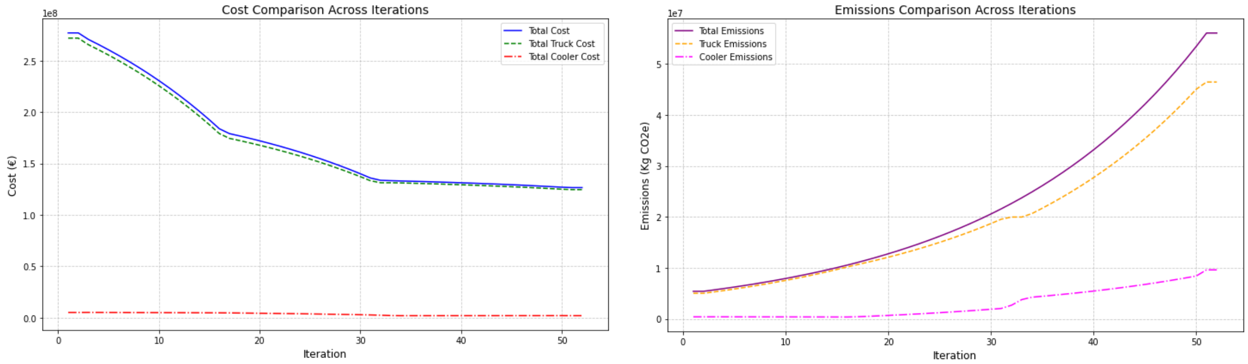

Figure 28: Scenario A.2: Cost and emissions comparison

In figure 28, a cost and emissions breakdown were developed. The results from these graphs were very similar to the ones from A.1, with the trucks incurring most of the costs for the different fleet solution sets. It can be seen in the emissions graph, that due to the coolers' coefficient adaptability, the coolers represented a relatively lower cost than in A.1 in respect to the trucks.

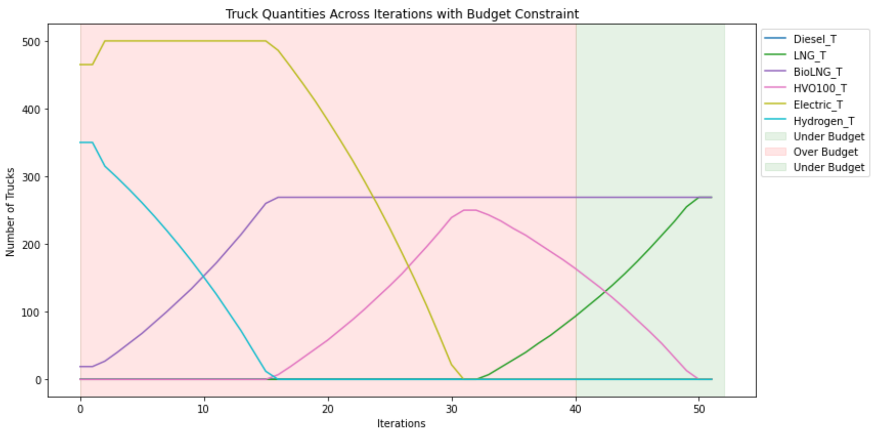

Figure 29: Scenario A.2: Truck quantities

While evaluating figure 29, the review is very similar to the one of scenario A.1, with almost no impact in truck choices with the insertion of the cooler coefficients as decision variables in the model. However, the importance of this coefficient-varying alternatives, relied in the cooler quantities that the model chooses, that can be seen in the figure 30.

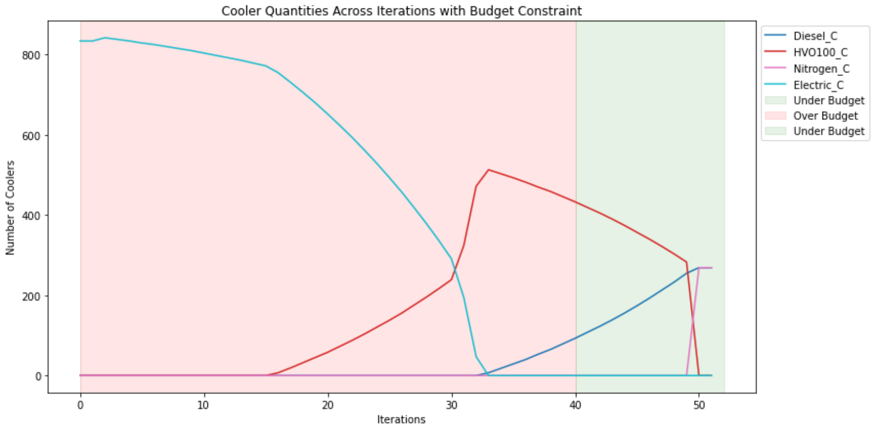

Figure 30: Scenario A.2: Cooler quantities

As seen in figure 30, in this scenario, the cooler selection under non-linear optimization showed a more abrupt progression compared to the linear approach in Scenario A.1. Electric coolers started at 834 units and declined steeply to just 47 by iteration 32, while in A.1, they began at 818 and decreased more gradually to 83.

HVO100 coolers remained unused until iteration 16 in A.2, then rapidly increased to 513 by iteration 33, contrasting with A.1, where they started at 5 units and grew steadily to 310 by the same point. Nitrogen coolers were only selected in the final iterations of A.2, reflecting a clear preference for HVO100 over Nitrogen, unlike A.1, which consistently integrated 134 Nitrogen coolers from iteration 10 onward. Diesel coolers in A.2 were introduced later but peak at the same 269 units as A.1, illustrating the non-linear model's flexibility and efficiency focus. The breakdown of coolers for BioLNG trucks is depicted in figure 4.1.9. It is observable that the model chose optimally Electric coolers for its BioLNG trucks in the environmentally efficient segment of the graph while then selected HVO100 and Nitrogen coolers in economically efficient solution sets. The freedom of choice of different coolers to connect with BioLNG trucks makes Nitrogen coolers appear in the end of the curve of Figure 4.1.8 what shows the impact of having a non-linear model in the optimization process.

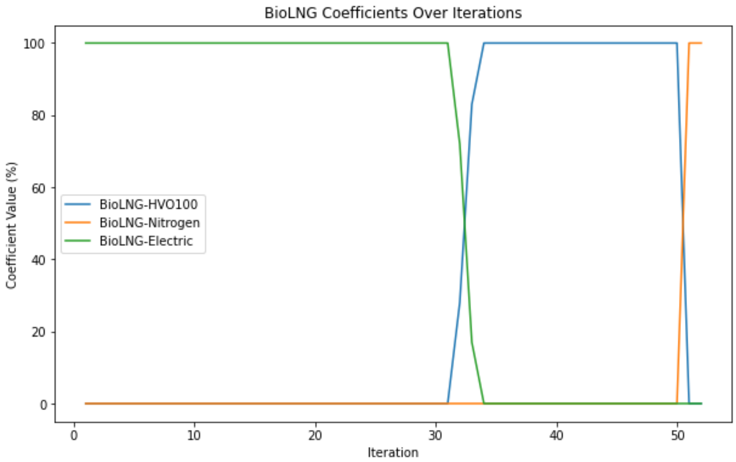

Figure 31: Scenario A.2: BioLNG coefficients

4.1.2 B Scenarios

B Scenarios, following the approach depicted in section 3.5.1, have a constraint in the minimum number of trucks based on the existing fleet available at the supermarket company. The maximum number of trucks constraint is defined as in scenario A based on the mileage of the trucks following a risk-based approach, not allowing any of the truck types to cover more than the 50% of the total yearly distance travelled.

The trucks available in the major supermarket's company fleet at the time the information was provided are:

- BioLNG Trucks: 52.
- HVO100 Trucks: 5.
- Electric Trucks: 3.

So, in each of the solution sets provided, the model will consider these trucks as part of the final composition.

Scenario B.1

The pathway to analysing the initial approach for the current fleet, risk-managed scenario reveals the Pareto frontier shown in Figure 32, as done in scenario A.

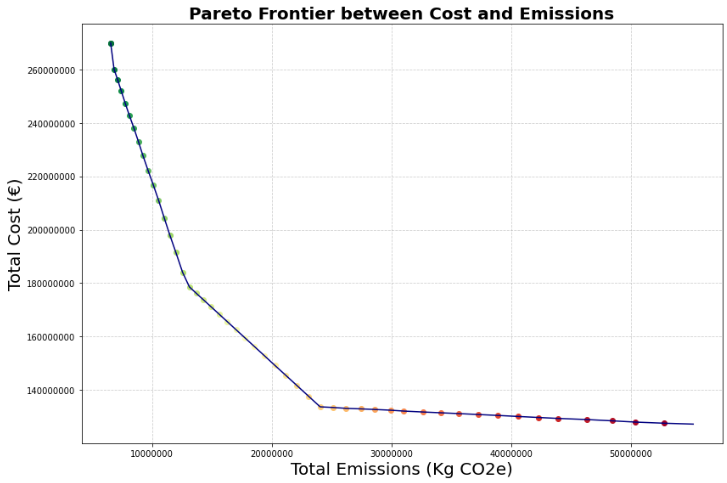

Figure 32: Scenario B.1: Pareto Frontier

In this case, the initial value of emission starts in 6,527,783 kgCO2 and it ends in 55,227,486 kgCO2 for the single economic objective. As part of the curve interpretation, the initial steep decline zone (with an average gradient of -13.29€/kgCO2), which prioritizes environmental objectives, had a slightly lower duration than the one from scenario A.1, indicating that the significant cost reductions were achievable over a shorter emission range. This could show this case offered a lower selection of cost-saving transitions, likely through a different mix of trucks.

The single objective environmental optimization (the first point in the pareto frontier) reported an emissions value 17.22% higher than the one in scenario A.1, that is seen on Appendix 7.2 results and that showed the effect on the degree of freedom taken from the A models as using the trucks existing in the actual fleet and not having the possibility to select the max quantity of eco-efficient trucks. Comparatively, the Scenario A.1 offered consistently lower emissions throughout iterations.

In the mid part of the curve (with an average gradient of -4.1 €/kgCO2) the model did a transition between the environmental and the economical approach, particularly doing a trade-off between the quantity of BioLNG and Electric trucks, that can be seen as well in figure X. With respect to A.1 scenario, the model needed one less iteration to arrive to the tail of the curve, this means the adjustment is made a faster in term of cost and emissions.

In the tail of the curve, it is useful to consider, that with an average gradient of -0.212€/kgCO2, the model arrived to a higher cost economic single objective solution in respect to A.1 (127,245,918€ vs. 126,841,320€). This outcome is understandable from the perspective that this model had an initial fixed truck number. This reflects an initial cost increase as the model can't use the most efficient solution in each case because of the lower degree of freedom.

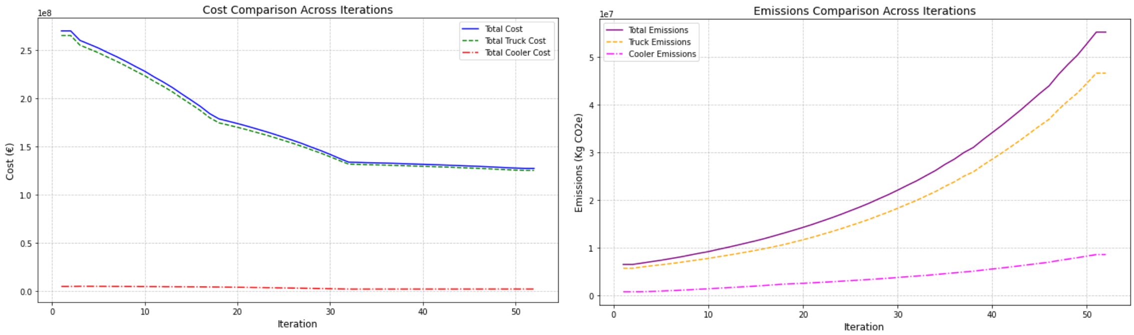

Figure 33: Scenario B.1: Cost and emissions comparison

As examined in previous scenarios, the trucks take most of the cost and emissions structure, shown in figure 33.

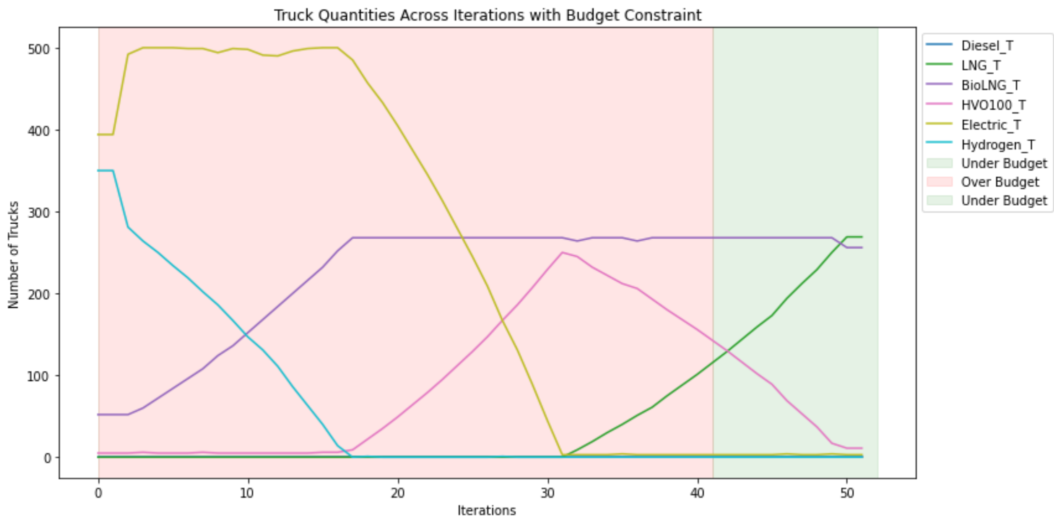

Figure 34: Scenario B.1: Truck quantities

In Scenario B.1, as shown in figure 34, the transition towards alternative fuels is evident, with a complete absence of diesel trucks across all iterations. LNG trucks emerged only after iteration 31, steadily increasing to 269 units by the end, while BioLNG trucks started with 52 and rapidly grew to dominate the fleet with 268 units by iteration 19, maintaining this count throughout. Electric trucks, initially prominent at 394 units, were gradually phased out, reaching just three units by iteration 31. Similarly, hydrogen trucks started strong with 350 units but declined steadily, disappearing completely after iteration 20. HVO100 trucks showed a sharp rise, peaking at 250 units by iteration 31, but this was followed by a significant drop, leaving only 11 units by the last iteration.

The methodology in Scenario B.1 suggests a strategic focus on BioLNG as a primary fuel source, with the initial 52 trucks present in the actual fleet, with LNG as a late addition to the mix. Electric and hydrogen trucks, despite their early dominance, are deprioritized as iterations progress, reflecting a shift away from these technologies. HVO100 trucks also experience a temporary surge but were ultimately phased out, indicating their limited role in the long-term fleet composition.

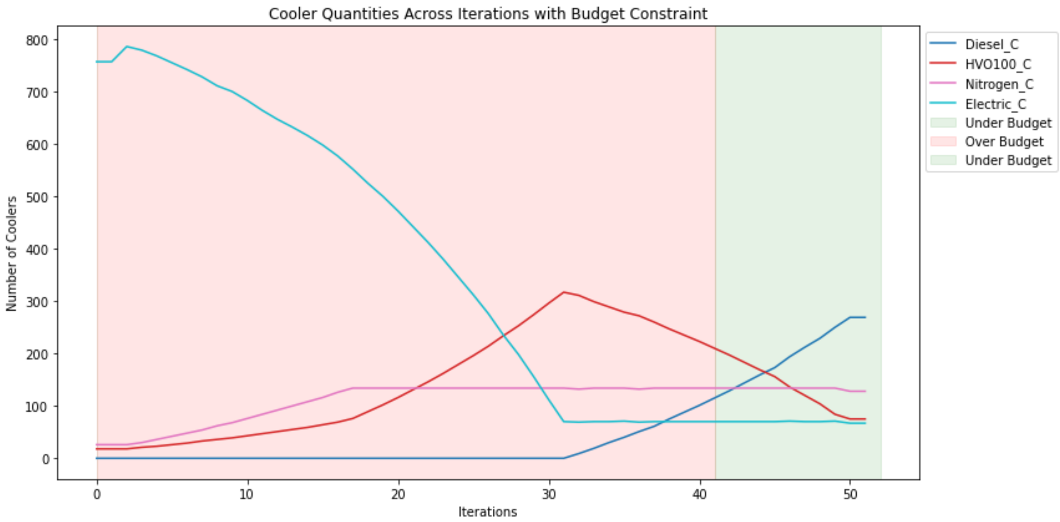

Figure 35: Scenario B.1: Cooler quantities

In figure 35 it is possible to see, as in scenario A.1, the cooler selection began with Electric coolers as the dominant choice, starting at 757 units in the Environmental Single Objective (A.1 started with 818) and steadily decreasing to just 70 units by the later multi-objective stages. HVO100 exhibited a sharp upward trend, growing from 18 units in the initial stages to a peak of 317 units in the final multi-objective stage. Nitrogen coolers usage also increased gradually, peaking at 134 units, while Diesel coolers were introduced late in the process, beginning at 9 units and reaching 269 units under the Economic Single Objective strategy.

Comparing to Scenario A.1, the trends aligned in general, but there were differences in magnitude and pace. For instance, Electric coolers started higher in A.1 at 818 units and decreased more gradually to 67 units in the final stages. The transition in HVO100 coolers was more abrupt in B.1, where its peak of 317 units was higher than A.1's peak of 310. This indicated a stronger emphasis on biofuels in Scenario B.1. Additionally, Diesel coolers appear slightly later in B.1 and grew more aggressively, reaching the same final value of 269 units as in A.1 but over a shorter range of optimization steps. The truck-cooler connections previously depicted are maintained in the models and this is why the cooler selection only differed in magnitude between scenarios, but the trends were similar.

Scenario B.2

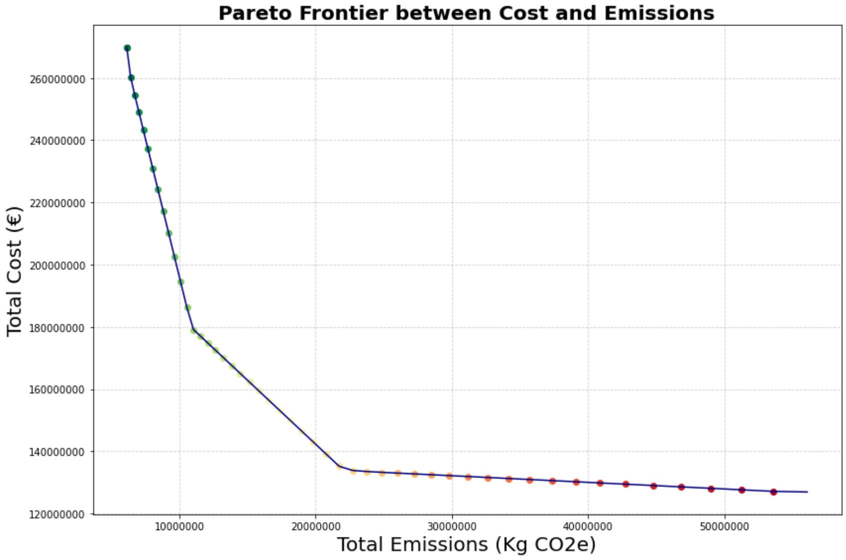

Figure 36: Scenario B.2: Pareto Frontier

In the analysis of scenario B.2 Pareto frontier, visualized in figure 36, the curve began with a steep initial decline phase characterized by an average gradient of approximately -17.83€/kgCO2. This segment is much steeper than the one provided in figure X, for scenario B.1 (average gradient -13.29€/kgCO2). This indicates that B.2 offered more significant opportunities for cost-effective emission reductions.

The single-objective environmental optimization points in B.2 achieved an emissions value of 6,139,589.96 kgCO2, which represented a 5.95% reduction compared to the B.1 equivalent value of 6,527,782.91 kgCO2. However, this improvement came at nearly the same cost (269,836,470€ in B.2 vs. 269,871,155€ in B.1), demonstrating the efficiency of the additional decision variables in achieving environmental objectives without significant cost penalties.

In the middle section of the curve, B.2 spanned a smaller range of emissions reductions compared to B.1, with the same gradient, suggesting a faster adaptation to cost-effective solutions as more degrees of freedom are introduced.

In the tail of the curve, the slope resembled that of B.1. However, the final economic solution in B.2 achieved a cost of 126,947,212€ with emissions of 56,091,471.88 kgCO2, compared to 127,245,918.9€ and 55,227,486.48 kgCO2 in B.1. The difference is primarily attributed to the steeper slopes observed in B.2 during the earlier iterations.

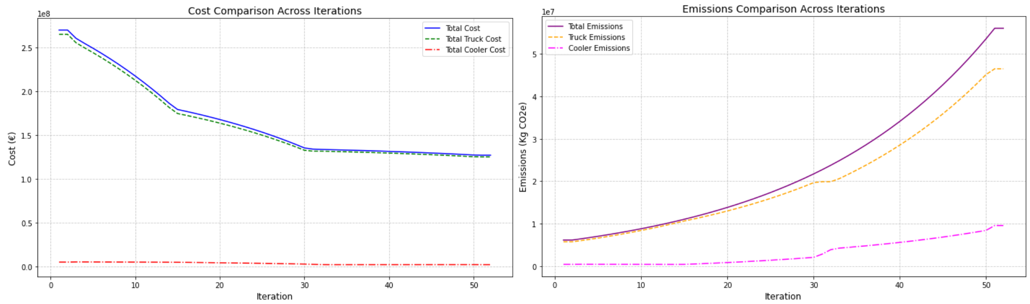

Figure 37: Scenario B.2: Cost and emissions comparison

In figure 37, a cost and emissions breakdown were developed. The results from these graphs were very similar to the ones from B.1, with the trucks incurring most of the costs for the different fleet solution sets, whereas cooler impact more on the emissions profile.

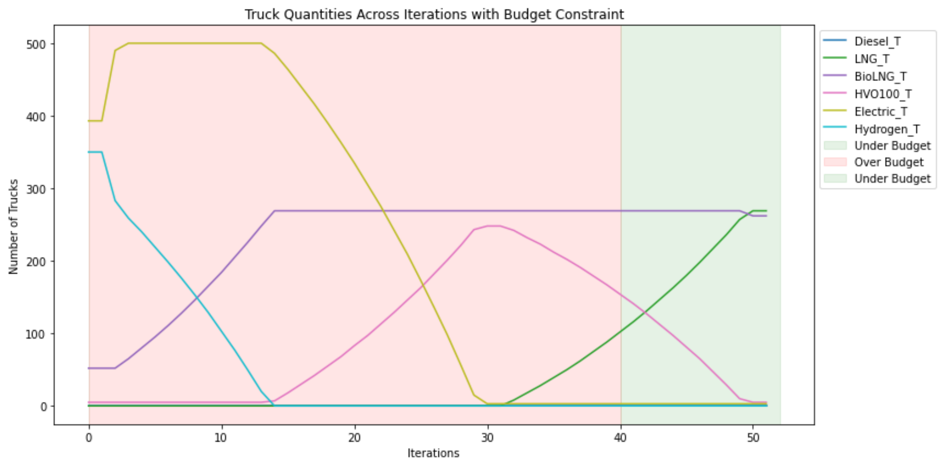

Figure 38: Truck quantities Scenario B.2

To perform the truck quantities analysis in this scenario, comparisons were developed between the fixed coefficient scenario to give an overview to the effect of adding truck-cooler coefficients as decision variables.

To start, LNG trucks, absent in the initial iterations of both scenarios, emerged earlier in Scenario B.2, appearing at iteration 32 compared to iteration 33 in Scenario B.1. They reached the same peak of 269 units by the end. BioLNG trucks showed similar initial behaviour in both scenarios, starting at 52 units.

In Scenario B.2, they reach stability at 269 units by iteration 14, two iterations earlier than in Scenario B.1, where they stabilized at iteration 16. This earlier stabilization underlines the efficiency of Scenario B.2 in allocating resources to the most promising technology sooner. Electric trucks displayed a more gradual decline in Scenario B.2, beginning at 393 units and phasing out completely by iteration 30. In Scenario B.1, the phase-out occurred at iteration 31. Hydrogen trucks disappear entirely by iteration 14 in Scenario B.2, compared to iteration 17 in

Scenario B.1. For example, at iteration 12, hydrogen trucks counted 49 units in Scenario B.2, while in Scenario B.1, they count 111, showing a sharper reduction in Scenario B.2. This earlier phase-out further highlights the non-linear optimization's capacity to streamline the adoption of alternative fuels by deprioritizing less favourable options in anticipation.

HVO100 trucks exhibited a distinctive trend in Scenario B.2. Starting with 5 units, they incrementally rise to a peak of 248 units at iteration 30, before tapering off. By contrast, Scenario B.1 showed a sharp rise to 250 units at iteration 31, followed by a rapid decline. For instance, at iteration 25, Scenario B.2 has 163 HVO100 trucks compared to 129 in Scenario B.1, suggesting that Scenario B.2 allowed for a more sustained use of this technology, aligning operational choices with long-term fleet objectives. This can be attributed to the introduction of real-time decision variables as the cooler selection, which enable the model to make cleaner and more sustainable fleet transition decisions by dynamically adjusting allocation based on evolving constraints.

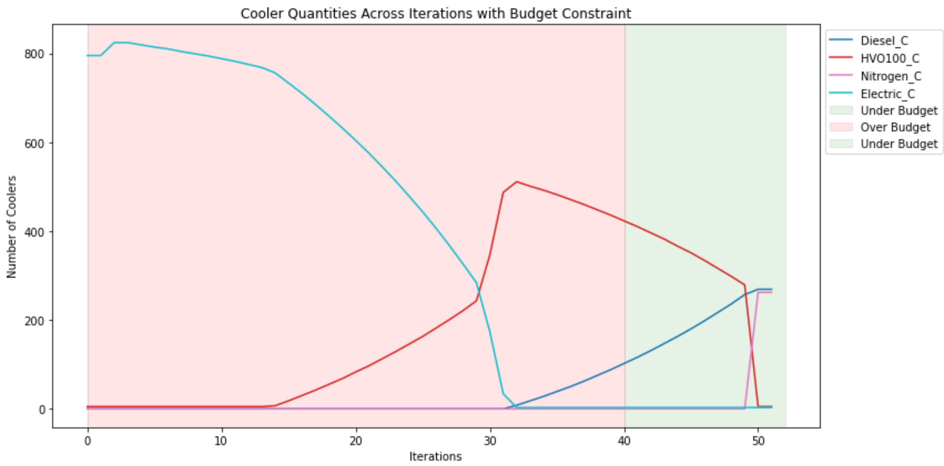

Figure 39: Cooler quantities Scenario B.2

Cooler quantities were the most affected by means of this non-linear optimization process. As seen in figure 39, HVO100 coolers exhibited distinct trends in both scenarios. In Scenario B.2, they gradually increased to a peak of 511 units at iteration 33 before tapering off to just 5 units by iteration 52.

In Scenario B.1, the allocation was more abrupt, stabilizing at 134 units by iteration 18 and maintaining this level until a sharp decline after iteration 30. In contrast, Scenario B.2 introduced nitrogen coolers, which are the most economical option, at higher levels. Starting from 0 units, they reached a steady count of 262 units from iteration 50 onward. This outcome, driven by the non-linear optimization model, highlighted a cost advantage by selecting nitrogen coolers over HVO100, which was previously chosen as the economic alternative. The slight cost difference between diesel and nitrogen played a key role in this selection. Meanwhile, Scenario

B.1 stabilized nitrogen coolers at a lower level of 134 units by iteration 17. At iteration 20, Scenario B.2 allocated 604 electric coolers compared to 442 in Scenario B.1, with these coolers being prioritized in scenarios that favoured more environmentally sustainable approaches for building the BioLNG truck fleet.

The number of electric coolers gradually declined in both scenarios, though at different rates. Scenario B.2 saw a reduction from 795 units at the beginning to only 3 units by iteration 32, indicating a more controlled transition. In contrast, Scenario B.1 retained 67 coolers through the latest iterations, with this count still present by iteration 31. The decrease in electric coolers occurred when the model did not consider them a cost-efficient option under the epsilon constraint approach, despite their lower environmental impact. This trend is illustrated in Figure 40.

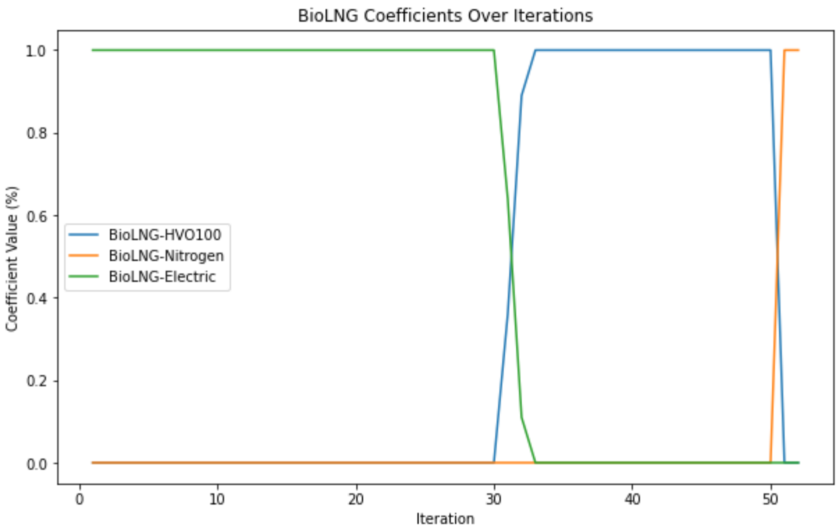

Figure 40: Scenario B.2: BioLNG coefficients.

4.1.3 C Scenarios

These scenarios were designed to incorporate constraints defined directly by the company's management. These constraints included a minimum number of trucks based on Ginobili's existing fleet composition, ensuring that the current operational capacity is maintained. Additionally, a maximum cap was introduced for LNG, BioLNG, HVO100 and Electric trucks, reflecting the company's strategic limitations and preferences for these vehicle types.

The trucks available in the major supermarket's company fleet at the time the information was provided are, involved as minimum truck constraints:

- BioLNG Trucks: 52.
- HVO100 Trucks: 5.
- Electric Trucks: 3.

The maximum number of trucks per type disposed for some trucks by the company manager are:

- LNG Trucks: 101.
- BioLNG Trucks: 350.
- HVO100 Trucks: 350.
- Electric Trucks: 26.
- Hydrogen Trucks: 5.

Scenario C.1

The Pareto frontier analysis for Scenario C.1 provided valuable insights into the trade-off between cost and emissions.

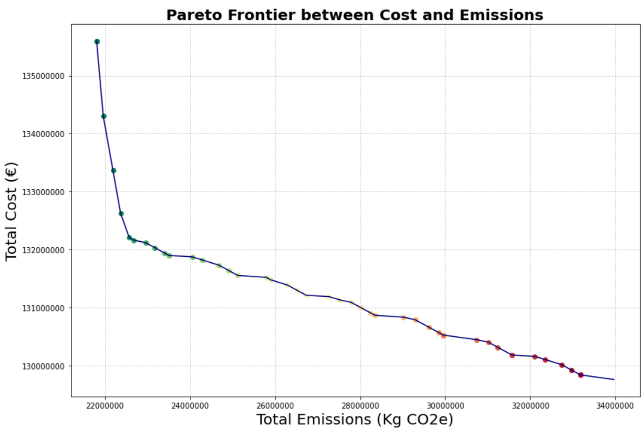

Figure 41: Scenario C.1: Pareto Frontier

The emission range in this Pareto curve is significantly narrower than in Scenarios A and B. This constraint is primarily due to the strict limitations on the maximum number of LNG, BioLNG, HVO100, and Electric Trucks that can be selected in Scenario C. Emissions span from 21,804,410 kgCO_2 in the most environmentally focused solution to a peak of 33,966,526 kgCO_2. The rigid constraints imposed on the model result in a more compressed emission range, making the data more restricted in comparison.

Initially, the curve exhibited an average gradient of -4.1 €/kgCO_2, which is considerably lower than the starting gradients observed in Scenarios A and B. This suggests that the model is operating within a more restrictive emission space. As the curve progresses through its middle and final sections, it flattens, reflecting a gradual trade-off between cost and emissions. Over time, costs decline from €131,898,112 to €129,760,699, while emissions increase from 23,510,255 kgCO_2 to 33,966,526 kgCO_2. In this phase, incremental cost savings become less pronounced, with an average gradient of -0.4 €/kgCO_2.

While Scenarios A and B reach emission levels close to 50,000,000 kgCO_2, the constraints applied in this case enforce a much tighter solution space. By introducing upper limits on truck selections, Ginobili's constraints significantly restrict the model’s ability to explore alternative configurations. As a result, the potential for identifying optimal pathways to meet 2030 environmental targets is considerably reduced.

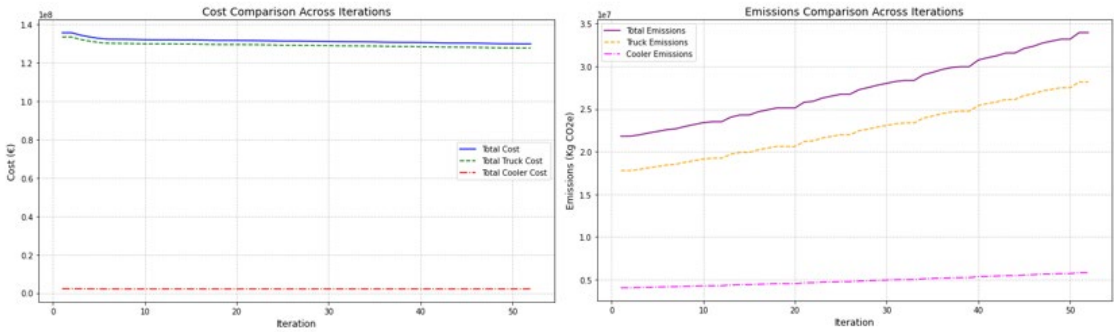

Figure 42: Scenario C.1: Cost and emissions comparison

In figure 42, a cost and emissions breakdown were developed. The results from these graphs were very similar to the ones from the previous scenarios, with the trucks incurring most of the costs for the different fleet solution sets.

Continuing the analysis, as seen in figure 43, it is possible to evaluate the model’s optimal fleet mix decision with the constraints provided by Ginobili.

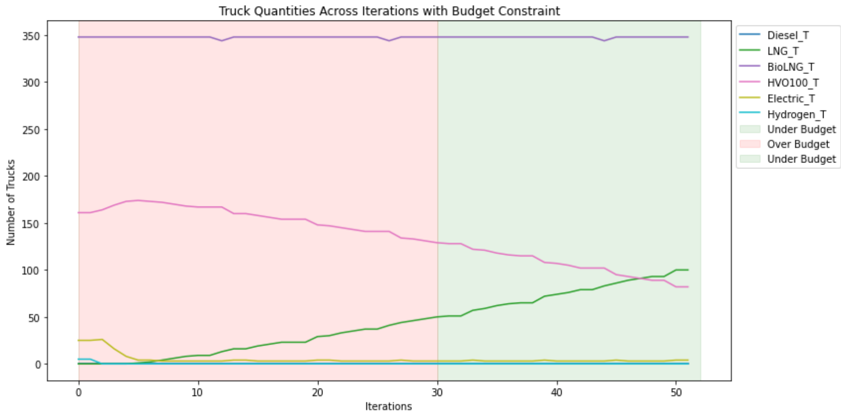

Figure 43: Scenario C.1: Truck quantities

In the early iterations, the model prioritized environmental goals, leading to a fleet composed mainly of BioLNG and HVO100 trucks, along with a few electric and hydrogen trucks. As the optimization continued, adjustments reflected a shift toward balancing emissions and cost while maintaining BioLNG Trucks. Hydrogen trucks were quickly phased out, likely due to their high costs despite their low emissions. At the same time, HVO100 trucks increased, peaking at 174 units, indicating the model saw them as a viable middle ground between sustainability and affordability.

A turning point came around iteration 23, when LNG trucks started to appear. This marked a move toward more cost-efficient solutions, as LNG offers a compromise between operational feasibility and emissions reduction. By the final iterations, the model had completely eliminated hydrogen trucks, while LNG trucks grew steadily, reaching 100 units in the most cost-driven solution. HVO100 trucks declined, dropping to 82 units, signalling the increasing preference for more economical options.

The results suggest that initial environmental selections prioritized technologies with lower carbon footprints, but high costs or infrastructure constraints led to their reduction as cost efficiency became a bigger factor. Hydrogen trucks, despite their emissions benefits, were likely too expensive or impractical, while BioLNG remained stable throughout, likely due to its balance of sustainability and cost.

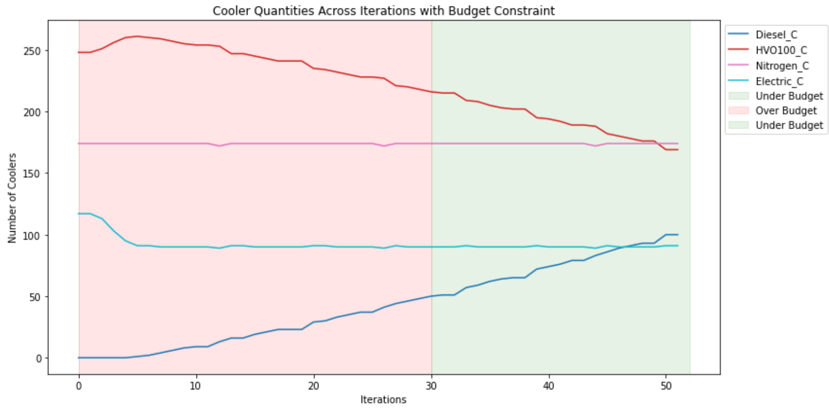

Figure 44: Scenario C.1: Cooler quantities

The evolution of cooler allocation in Scenario C.1 reflects a gradual shift from environmentally driven choices to cost-effective solutions. When emissions were the main concern, Electric coolers dominated, starting strong at 117 units. HVO100 coolers followed closely with 248 units, while Nitrogen coolers held steady at 174 units. It is useful to say that as the BioLNG truck quantity stayed still, the cooler selection for the technologically available types for the BioLNG truck remained stable as well through the iterations. Initially, Diesel coolers were completely absent, reinforcing the initial preference for lower-emission technologies.

As the iterations progressed and economic factors began to carry more weight, Electric coolers saw a steady decline. By iteration 3, their numbers had dropped to 103 units, and within a few more steps, they settled at 90 units, where they remained largely unchanged. Meanwhile, HVO100 coolers briefly increased, reaching a peak of 261 units, before gradually losing ground. Nitrogen coolers, in contrast, remained a constant presence at 174 units, with only minor fluctuations.

Around iteration 12, a clear shift took place and Diesel coolers entered the mix. By iteration 30, their presence had grown to 50 units, signalling a move toward more cost-effective alternatives. Electric coolers continued their downward trend, while HVO100 units also started to decline, slipping from 256 to 215 units.

In the later stages, when economic efficiency became the priority, the fleet composition changed significantly. Diesel coolers surged, reaching 100 units in the final economic single-objective solution. At the same time, HVO100 coolers dropped to 169 units, and Electric coolers, once the clear favourite in early iterations, dwindled to just 91 units. Throughout the entire process, Nitrogen coolers remained strikingly stable, holding at 174 units, reinforcing their role as a reliable, balanced option, selected because of being part of BioLNG truck composition.

Scenario C.2

As part of the advanced scenario, that relied on setting the BioLNG cooler-truck coefficients as decision variables, the analysis of the pareto frontier was performed.

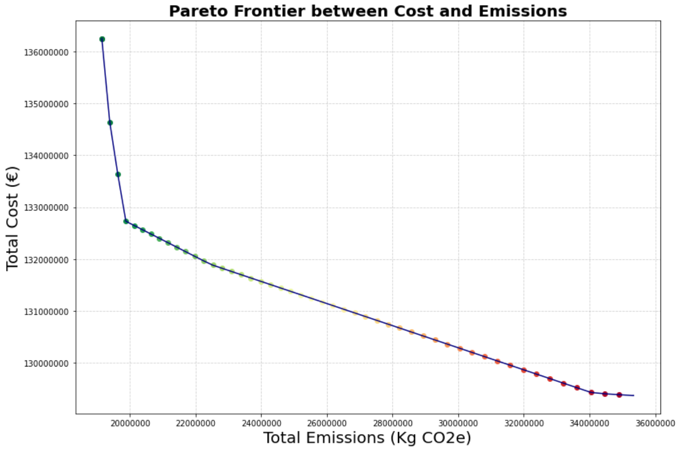

Figure 45: Scenario C.2: Pareto Frontier

As shown in Scenario C.1, the emissions range for Scenario C.2 is also significantly more constrained than those of Scenarios A and B. In this case, emissions vary between 19,143,040 kgCO2 and 33,966,526 kgCO2. This confirms that the non-linear model, once again, provides better solutions at both extremes compared to Scenario C.1, making it more optimized.

The initial section of the Pareto frontier had an average gradient of -4.1 €/kgCO2, similar to Scenario C.1. The limited number of points in this region highlights the model's difficulty in finding environmentally optimized solutions, as the cost difference between iterations 1 and 5 is nearly €3 million. Given the minimal changes between iterations, this is a substantial amount in the context of this problem as the normal change amount between iterations remains under €50,000.

As the curve transitions through its middle and final sections, cost reductions slow down, with the gradient softening to -0.212 €/kgCO2. Costs decreased from €131,966,704 to €130,283,815, while emissions rose from 22,244,808 kgCO2 to 30,037,524 kgCO2. Toward the end, the curve stabilized, showing a steady decline toward the economically optimized solutions. Observing the curve's behaviour, it is evident that the model struggles more to optimize for the environmentally preferred solution than for the economic optimum. This is expected due to the constraints imposed in this scenario.

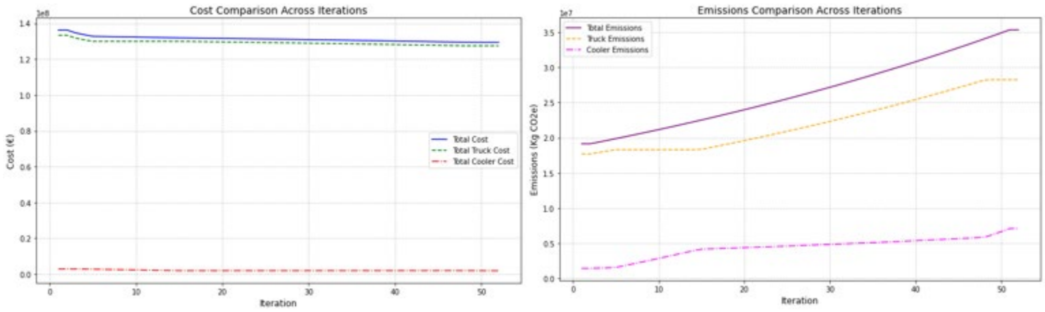

Figure 46: Scenario C.2: Cost and emissions comparison

As seen on previous scenarios, the trend kept the same, with the cooler costs and emissions being very low compared to the ones of trucks.

To continue the analysis in this non-linear optimization scenario, the truck quantities study is performed in the figure 47 below.

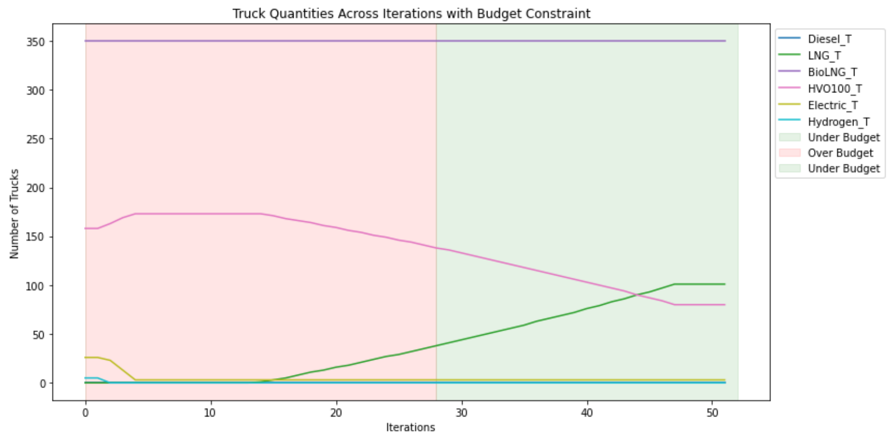

Figure 47: Scenario C.2: Truck quantities

As this is a non-linear optimized scenario with respect to C.1, it is notable to spot the key distinctions in the model truck selection. At first, the distinction is in the rate of LNG truck adoption. In C.1, LNG trucks appeared earlier at iteration 5 and steadily grew to 100 units by the final iteration. In C.2, LNG trucks only appeared at iteration 14 and then increased at a much faster rate, reaching 101 units by the last iteration. This suggests that C.2 delayed the introduction of LNG but ultimately committed to it more strongly in the cost-driven phase.

Another notable difference is how HVO100 trucks declined. In C.1, they peaked slightly higher at 174 units and started decreasing earlier, reaching 82 units by the final iteration. In contrast, in C.2, HVO100 trucks peaked at 173 but held that level for longer, only declining to 80 units at the end. This indicates that C.2 sustained its reliance on HVO100 for a longer period before a sharper reduction in favour of LNG.

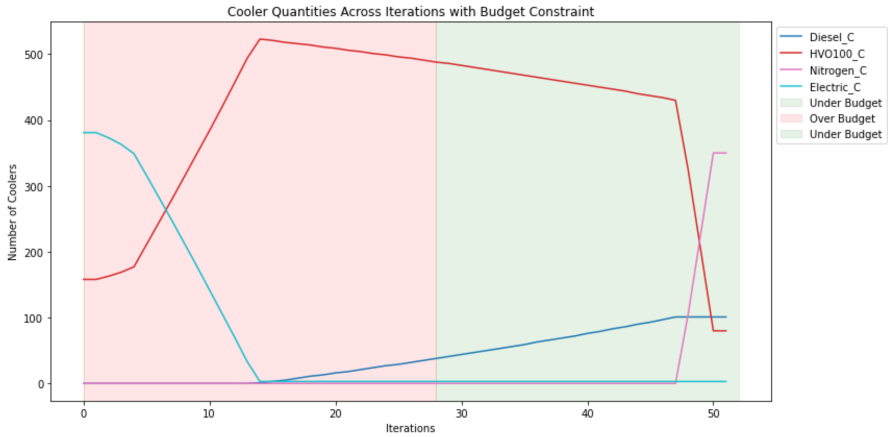

Figure 48: Scenario C.2: Cooler quantities

Scenario C.2 demonstrates a clear shift in cooler optimization, particularly in its approach to BioLNG truck refrigeration. Unlike C.1, where nitrogen-cooled systems were consistently used alongside electric and HVO100 coolers, C.2 initially relied mostly on HVO100 coolers and an initial quantity of electric coolers, phasing out nitrogen until iteration 48. This suggests a strategic delay in integrating nitrogen-cooled units, likely to maximize efficiency. HVO100 cooler use increased significantly in C.2, peaking at 523 units before gradually decreasing, while electric coolers saw a sharp decline from 381 to just 3 units. This indicates a more aggressive transition toward HVO100-cooled trucks before reintroducing nitrogen coolers at the later stages of optimization.

In contrast, C.1 maintained a more balanced distribution of nitrogen, electric, and HVO100 coolers throughout, with nitrogen units consistently present in all iterations. The nitrogen-cooled units remained stable at 174 for most of the iterations, whereas in C.2, nitrogen cooling only appeared in iteration 48, growing rapidly to 350 units by the final stage. This suggests that C.2 optimized the use of nitrogen-based cooling specifically for BioLNG trucks at the final stage, whereas C.1 relied on a constant nitrogen presence throughout. Additionally, C.2 showed a sharper increase in HVO100 cooler utilization, surpassing C.1's more gradual shifts.

The choices performed by the non-linear model in regard to the coefficient used as decision variables are reported below in figure 49.

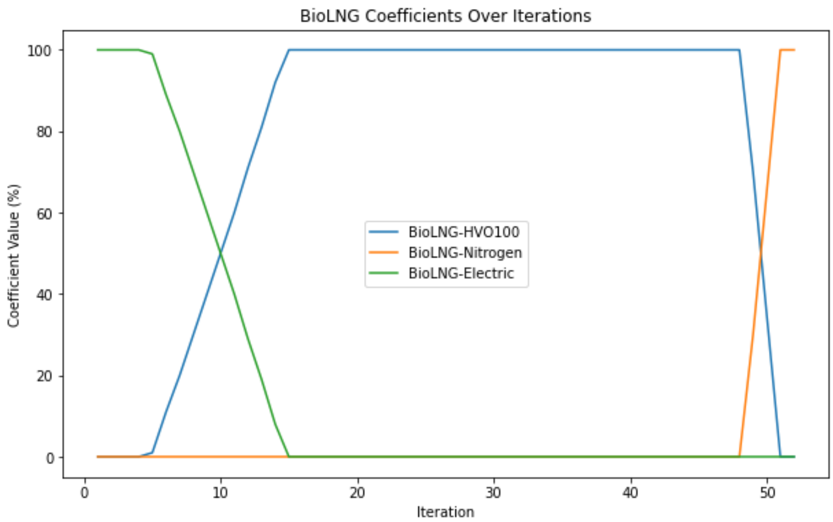

Figure 49: Scenario C.2: BioLNG coefficients

4.2 Combined Results

To compare the different scenarios from both cost and emissions perspectives, the curves were overlaid on various graphs. Initially, it was useful to examine their Pareto frontiers, highlighting the solution sets selected by the model in each case. This approach revealed the trade-offs, slopes, and most efficient truck-cooler configurations. Subsequently, a detailed breakdown of costs and emissions was provided for each scenario and the graph with the Pareto Frontiers of the base scenarios for their comparison.

	Best Environmental		**Best Economic**	
Scenario	Cost (€)	Emissions (kgCO2)	Cost (€)	Emissions (kgCO2)
A.1	276,838,224	5,568,548	126,841,321	55,025,819
A.2	277,041,285	5,403,631	126,532,096	56,049,844
B.1	269,871,155	6,527,783	127,245,919	55,227,486
B.2	269,836,470	6,139,590	126,947,212	56,091,472
C.1	135,594,775	21,804,410	129,760,699	33,966,526
C.2	136,248,191	19,143,040	129,370,041	35,344,079

Table 11: Comparison of Base Scenarios Tail Solutions

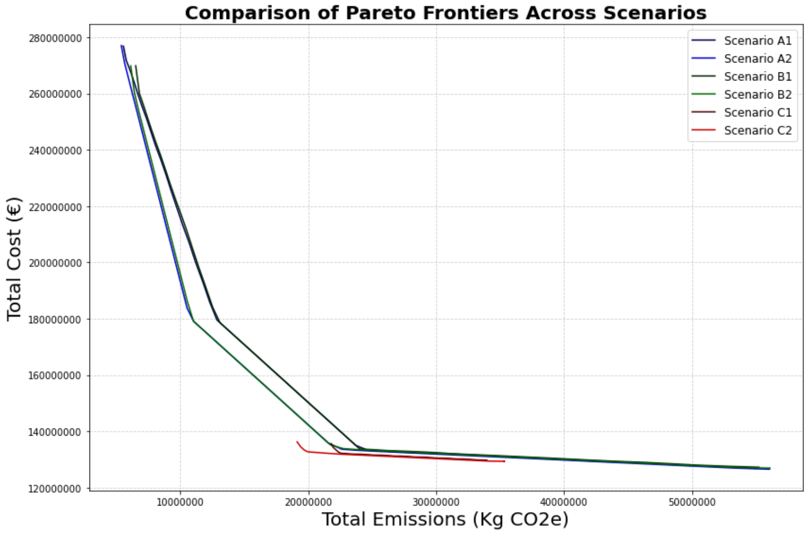

Figure 50: Comparison of Pareto Frontiers across Scenarios

The Pareto analysis in Figure 4.2.1 illustrates the cost-emission trade-offs for different fleet scenarios, highlighting key insights for adapting Ginobili's operations to 2030 sustainability goals. Each scenario follows a distinct pattern, showing how emissions increase as costs decrease, but the degree of this trade-off varies across the A, B, and C series. Understanding these differences is essential for logistics managers aiming to balance economic and environmental priorities.

The A-series offers the most stable and efficient solutions. Scenario A.1 shows emissions ranging from 5,568,548 kg CO2e to 55,025,819 kg CO2e, with costs decreasing from €276.8 million to €126.8 million. A.2 follows a similar trend, starting at 5,403,631 kg CO2e and reaching 56,049,844 kg CO2e while costs drop from €277.0 million to €126.5 million. The results suggest that A-series scenarios allow for an optimal cost-emission balance while complying with RED II regulations. A.2, in particular, emerges as the most effective configuration, delivering the lowest costs and emissions due to its lack of operational constraints.

The B-series follows a similar trajectory but under additional constraints, requiring a minimum number of trucks from the existing fleet. While cost and emission values remain close to those in the A-series, these limitations reduce optimization flexibility. The presence of pre-existing fleet requirements makes B-series solutions slightly less efficient, yet still viable for companies needing to integrate current assets into their transition plans. From the evidence shown in the table, in the case of emissions in the most environmental solution, the A-Scenarios outperform B-Scenarios on 17.2% while only a 0.3% on cost. This shows that the operational constraint that B-Scenarios face affects more to the most environmental solutions, as the fleet mix is set to have a set of base trucks even before the optimization process started. In the case of A-

Scenarios, the degree of freedom the model has on operational causes, enhances better environmental results.

C-series scenarios present a different challenge, as the model operates within a much smaller set of feasible solutions. The initial emissions range is significantly higher, spanning from nearly 20,000,000 kg CO_2e to 35,000,000 kg CO_2e. Unlike the A and B scenarios, the C-series struggles to offer a broad range of cost-effective solutions. Budget constraints limit investment in cleaner technologies, and operational restrictions, such as the cap on 26 electric and 5 hydrogen trucks, prevent further environmental optimization. While some cost advantages appear in certain ranges, the trade-off is a smaller fleet, constrained by strategic company decisions rather than pure optimization potential.

At the extreme points of the Pareto front, logistics managers must consider the implications of these trade-offs. Lower-cost solutions tend to come with high emissions, posing challenges for sustainability commitments, while the most environmentally friendly setups require substantial financial investment. The slopes of the Pareto curves quantify how much cost must be sacrificed for each unit of emissions reduction. The A-series represents a much steeper decline in the initial part of the curve, which evidences the facility of this model to search for environmentally optimized solutions.

Examining the limits of each scenario helps define realistic strategies. The A-series presents an optimal benchmark, offering maximum efficiency under regulatory guidelines and a higher degree of freedom. The B-series provides a practical middle ground, maintaining a balance between compliance and real-world operational constraints. It is known that the company would clearly want to use the actual fleet of truck it has in its operations, so for the development of a 2030 environmental transition, in most of the cases, to be into budget, they would make use of the trucks that are already part of the fleet. The C-series, despite some cost advantages, remains limited by structural restrictions, making it less flexible for long-term planning. Logistics managers must weigh these findings carefully, ensuring that strategic decisions align with both budget constraints and sustainability goals.

4.3 Alternative Scenario Results

The results of the analysis performed in each of the scenarios is shown in section 7.4 of this work.

4.3.1 Fuel Pricing Forecast Scenario

Based on the time-series analysis presented in Section 3.5.2.1, various fuel price prediction models were developed to forecast prices for 2030. These predictions were then integrated into the truck cost structure provided by the supermarket company to calculate the marginal costs per truck. The resulting values, detailed in Section 7.3 of the Appendix, served as inputs for price adjustments in Scenario A. This is part of a sensitivity analysis, for Ginobili to have the possibility to see the feasible solution sets considering potential prices for 2030, following a quantitative approach.

Comparisons will focus on the A.1 scenario as it is the base scenario, aligned with future EU RED II regulations and adopting a risk management perspective. The comparison maintains the same model structure and constraints but substitutes the base pricing structure outlined in Appendix 7.1 with the updated prices from the tables in Section 7.3. This approach ensures an evaluation of the impact of the predicted fuel prices on the scenario.

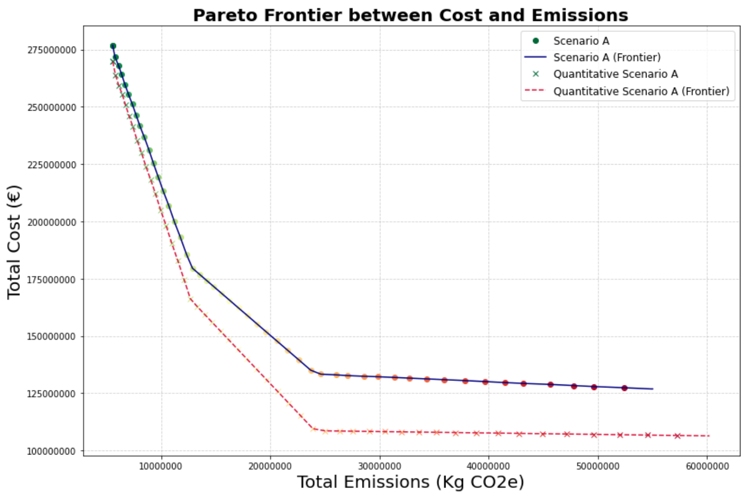

Figure 51: Fuel Pricing Forecast Scenario: Comparison of Pareto Frontiers

The cost reductions predicted by the fuel price models, based on historical trends and time-series analysis, result in a decrease in costs along the Pareto Frontier. The Scenario A.1 curve, shown in blue, followed a similar slope to the red dotted line of the Fuel Price Forecast Scenario up to 13,000,000 kg CO2e. Beyond this point, the red curve became significantly steeper. This indicated that the new costs provide greater reductions per kg of CO2e emitted, presenting a positive outlook for achieving the company's 2030 goals. At the far end of the curve, cost differences reached up to €2.5 million, reinforcing this optimistic perspective. If costs continue to follow historical trends, the project could prove viable for the supermarket company, supporting fleet mix decisions that comply with EU RED II regulations while maintaining a risk management approach. As well, the tail of the blue curve showed a steeper gradient compared to the red one, suggesting that, at these points, the cost reductions for the base alternative were much higher. Despite this, the overall costs in the Fuel Price Forecast Scenario remained significantly lower, as previously mentioned.

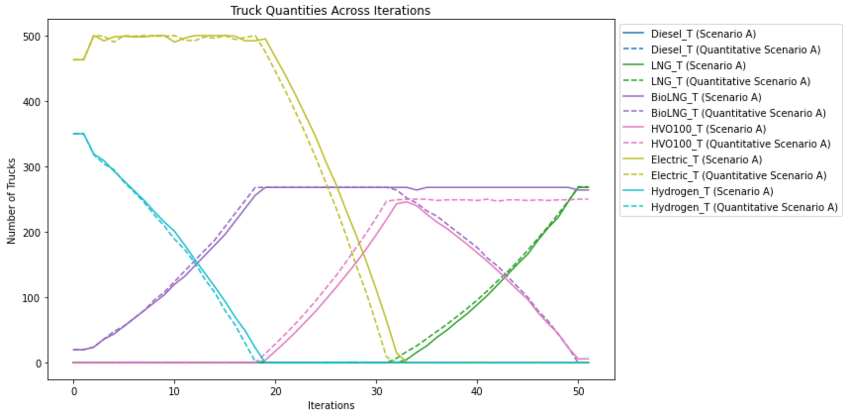

Figure 52: Fuel Pricing Forecast Scenario: Comparison of Truck Quantities

As part of the sensitivity analysis, the truck quantities selected by the different models are shown in Figure 4.3.1.2. It is perceptible that the Fuel Price Forecast Scenario model shifted the truck quantity curves to the left compared to the original Scenario A. In spite of this, the trend changed in the final iterations, where the model, using the updated price structure, opted to replace BioLNG trucks with HVO100 and LNG trucks in the fleet for the most economical approach. This decision highlighted an important consideration for the major supermarket company: based on historical prices, HVO100 trucks appeared to be more cost-efficient than BioLNG trucks for 2030.

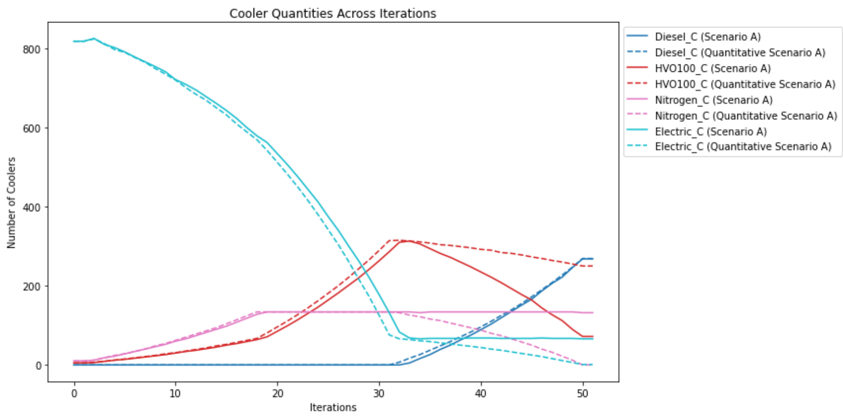

Figure 53: Fuel Pricing Forecast Scenario: Comparison of Cooler Quantities

For cooler quantities, the relationship between scenarios mirrored the trend observed in Figure 52 for trucks. In Figure 53, the cooler quantity curves were shifted to the left across all iterations, except those that reflected an economical objective approach. In these iterations, the model prioritized HVO100 coolers as more efficient than those using Nitrogen or Electricity, reducing their quantities from 134 and 67 to zero, respectively, in the final stages. This aspect of the sensitivity analysis further supported the conclusion that HVO100 fuel is more efficient than Nitrogen and Electricity for cooler operations under the projected fuel price changes for 2030.

4.3.2 Qualitative Scenarios

4.3.2.1 Supply chain and Resource Scarcity Scenarios: Scarcity of Raw Materials for HVO100

An analysis was conducted to evaluate the potential impact of a 30% increase in HVO100 fuel prices, driven by supply chain limitations stemming from palm oil regulations and scarcity. This study was included as part of the sensitivity analysis for the scenario-based modelling and was compared to Scenario A in terms of emissions and costs. The analysis provided useful points of view for the model and the company, highlighting the possible effects that such regulatory measures, rooted in environmental policies, such as the ones mentioned in Indonesia and Malaysia (Mai, 2024) could have on the supply chain structure for materials required to produce HVO100 biodiesel.

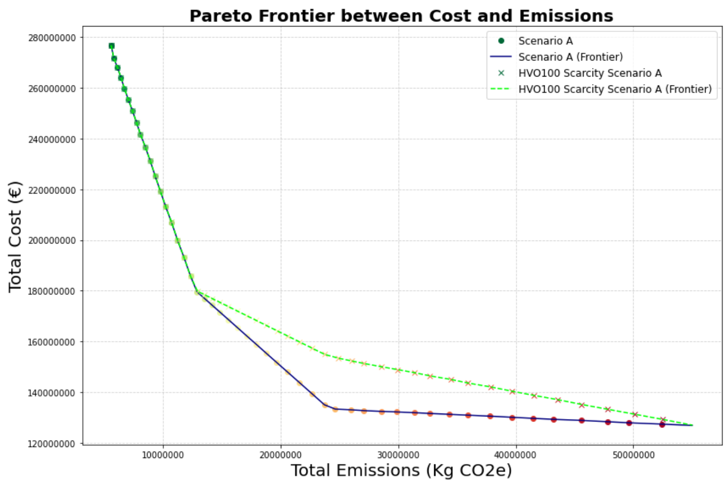

Figure 54: Scarcity of Raw Materials for HVO100: Comparison of Pareto Frontiers

In Figure 54, which compared the Pareto Frontier between the HVO100 Resource Scarcity Scenario and the base case Scenario A.1, most points on the curve showed higher costs for equivalent emission levels. This was expected due to the increased costs of HVO100 fuel but also highlighted that the model could not identify cost-effective solutions for these points, reinforcing the critical role of HVO100 trucks. The A-Scenario curve dominated in most of the points to the HVO100 curve. In the environmental-focused approach, the price difference had minimal impact initially. However, around 12,000,000 kg CO2, there was a detectable shift, with the gradient decreasing (average gradient: -2.3 €/kgCO2) and costs rising under the

HVO100 Resource Scarcity Scenario. The green line's slope is shallower than the blue line, reflecting the model's challenges in reducing costs for the same level of emissions. Interestingly, at the tail of the graph, the gradient of the green curve (-0.95 €/kgCO2) became steeper than in the blue curve, while the environmental single-objective solution remained the same for both scenarios. From a sensitivity analysis perspective, it is significant that the model continued to select, from iteration 20 to 35, HVO100 trucks despite their price increase, underscoring the importance of taking in account this potential event. The optimization model reflects then than this price increase and effect on the HVO100 truck selection has been balanced with the selection BioLNG, LNG and electric trucks from the pool of choices available.

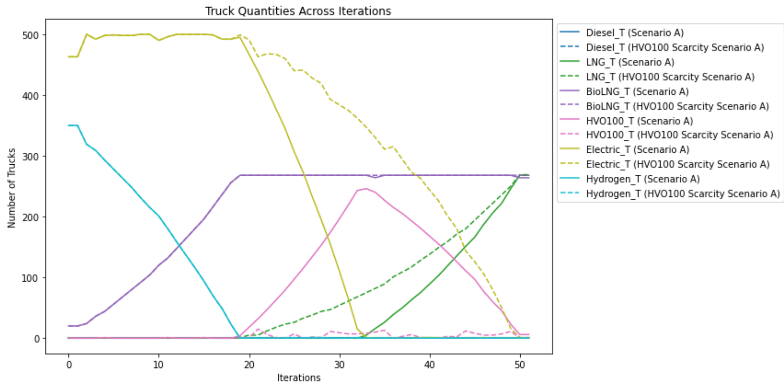

Figure 55: Scarcity of Raw Materials for HVO100: Comparison of Truck Quantities

When comparing the truck quantities selected by the model, it could be seen that an increase in HVO100 fuel prices significantly reduced the number of these trucks selected for the optimal solution set. In response, the model substituted them with electric, BioLNG and LNG trucks, creating a trade-off depending on the objectives pursued. Electric trucks saw a sharp rise in quantity compared to Scenario A.1. While Scenario A.1 phased out electric trucks entirely by iteration 33, the HVO100 Scarcity case, shown in the dotted lines, resulted in the model selecting 347 electric trucks to meet its goals. BioLNG truck quantities remained constant, highlighting that the trade-off primarily occurred between other types of trucks.

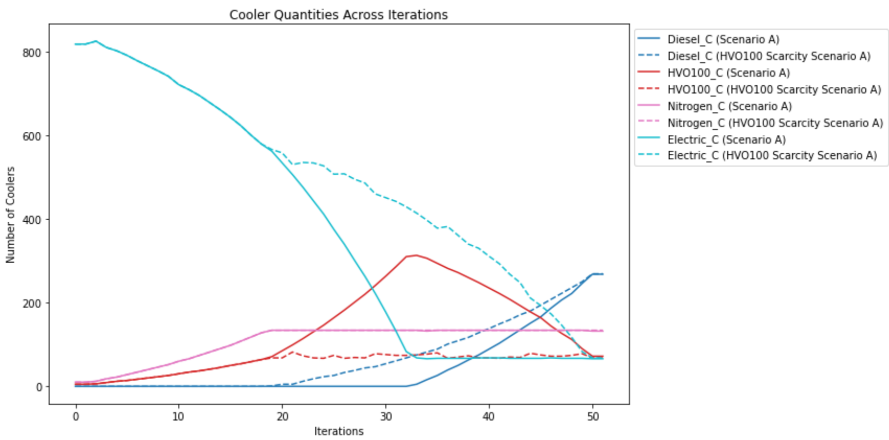

Figure 56: Scarcity of Raw Materials for HVO100: Comparison of Cooler Quantities

In regard to the cooler quantities chosen in this scenario, it could be seen that HVO100 powered coolers stabilize at 68 coolers while they peaked 313 in base case scenario A.1. The exchange of the HVO100 coolers was done with electric coolers, following similar trends to the ones seen in the truck quantities. Also, here there was a trade-off between these cooler types and the diesel ones. By iteration 33, in scenario A.1, electric coolers were 68 while by iteration 33, in this HVO100 resource scarcity scenario, the model selected 414 of this kind. The efficient solution set for the budget of the company deals with a trade-off between more or less the same quantity of Nitrogen, Electric, HVO100 and Diesel coolers, already shown in Scenario A.1 but with a slight change in the Resource Scarcity Scenario, where nearly 100 of the HVO100 coolers were traded from this type to Diesel and Electric coolers.

4.3.2.2 Supply chain and Resource Scarcity Scenarios: Gas Crisis in Europe

The supply chain and resource scarcity scenario drew from the recent geopolitical events, which caused significant spikes in LNG and electricity prices. These fluctuations created a volatile market environment, highlighting how geopolitical crises could directly impact the model. To reflect this, a 200% price increase for Diesel (effect only on coolers), LNG and electricity was introduced into the model as part of the sensitivity analysis, simulating the extreme price surges seen in the past (IEA, 2022). This allows the major supermarket company to understand how such events could influence future operations. By considering a scenario that mirrors past disruptions, the company gains valuable insights for making more resilient investment decisions moving forward.

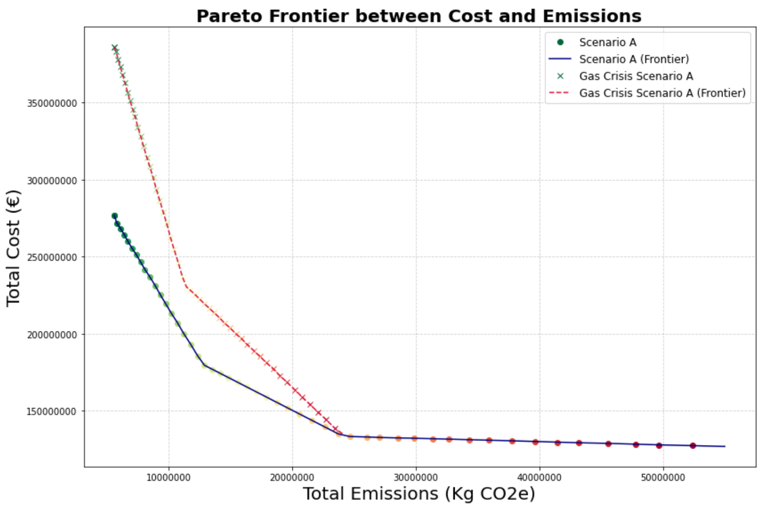

Figure 57: Gas Crisis in Europe: Comparison of Pareto Frontiers

The impact of this price increase was evident in the differences between the Pareto Frontiers shown in Figure 57. The effect was most pronounced in the environmentally feasible solution set, particularly in the iterations up to 24,000,000 kg CO2. The red curve, with an average gradient of -13.29 €/kg CO2, was significantly steeper than the blue curve in the early iterations, illustrating how the price surge affects the environmental portion of the graph. This outcome, further analysed in the truck quantity breakdown, stemmed from the reduced selection of electric trucks due to their higher costs under this scenario. Towards the tail of the curve, the model consistently identified BioLNG and HVO100 trucks as the most cost-efficient option under the given constraints. This suggested that, in the most cost-focused iterations, the EU RED II regulations had a relatively limited impact on the optimal solutions.

The impact of this alternative can be highlighted in figure 58 below analysing the truck quantities chosen for each feasible solution set in the optimization model.

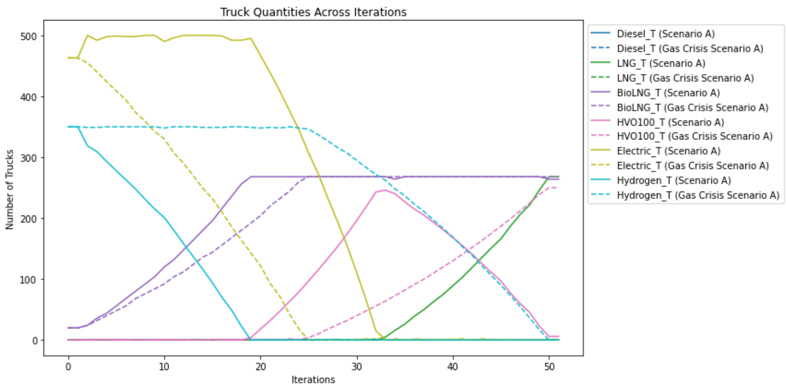

Figure 58: Gas Crisis in Europe: Comparison of Truck Quantities

The truck quantities shown in Figure 58 provided many elements to be studied into the model's sensitivity during a simulated gas crisis. With rising electricity prices, the model began favouring hydrogen trucks over electric ones in the environmental section of the curve, reflecting the shifting cost dynamics. BioLNG trucks maintained a similar trend to Scenario A.1, though their adoption progressed more slowly. A similar pattern was observed with HVO100 trucks, which remained part of the feasible solution set but at a reduced rate. It is reliable to state that BioLNG trucks and HVO100 trucks replaced LNG trucks in the economically driven set of iterations. The model, in spite of the assumptions made on Hydrogen prices by the information provided by Ginobili, selected this technology as possible cost-efficient choice in some of the last iterations.

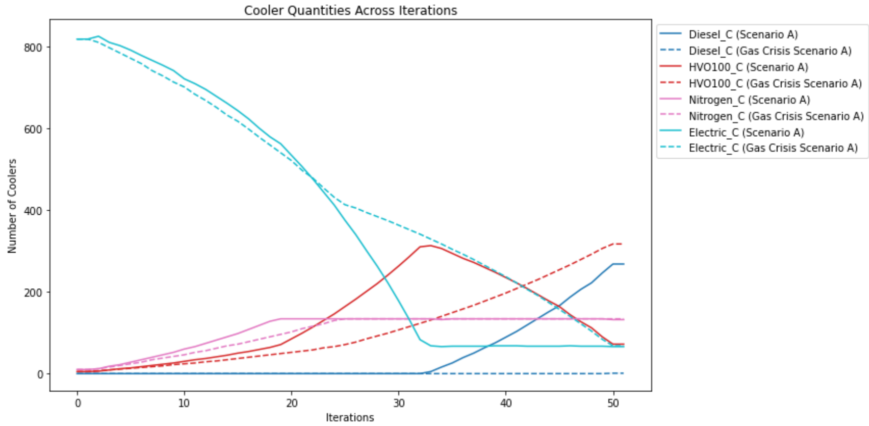

Figure 59: Comparison of Cooler Quantities

The gas crisis also affected cooler selection, as shown in Figure 59. Up to the transition between the most environmental and most economical approaches, the trends resembled those of the base case scenario. In spite of this, with rising diesel prices, the model shifted away from diesel-powered coolers, as LNG trucks are not being selected (results of the model shown in section 7.4), favouring HVO100 and electric coolers instead, even though with the lastly named type of cooler experiences a 2x price increase. Nitrogen coolers maintained the same constant quantity as in Scenario A.1. It is useful to say that HVO100 coolers took on a larger share in the cost-optimal solutions, surpassing the role diesel coolers played in Scenario A.1, as Gas Crisis Scenario is basing its choices in BioLNG and HVO100 trucks specially. This shift underscored the significant impact of a gas crisis on the model's outcomes, offering valuable insights for Ginobili to consider in future planning.

4.3.2.3 Macroeconomic and Policy Scenarios: LNG Ban

The potential for an LNG truck ban in urban areas across certain EU countries in the coming years was examined as a possible scenario for the European continent, particularly in light of the 2030 sustainability goals. This scenario was incorporated as a sensitivity test to assess the model's response in the event that LNG trucks are excluded from the optimal fleet mix within the feasible solution set. The effect of this possible resolution can be seen in figure 60.

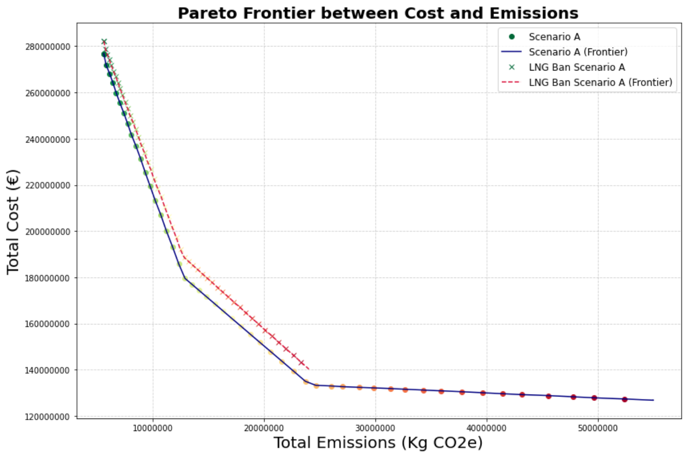

Figure 60: LNG Ban: Comparison of Pareto Frontiers

The Pareto frontiers in the graph showed that the LNG ban scenario incurred costs similar to Scenario A.1, though slightly higher across all points on the curve compared to the base case. The red curve, representing the LNG ban, had a smaller solution range, spanning emissions from 5,568,547 kg CO2 to 24,032,345 kg CO2, with its most cost-efficient solution at €140,281,405. The cost barrier in this scenario arose because the model, constrained by the LNG ban and risk management requirements, maximized BioLNG and HVO100 truck quantities up to their 50% limit in the final iterations. This sensitivity analysis highlighted that an LNG ban increased costs and complicated optimization. BioLNG and HVO100 served as the primary substitutes for LNG, offering relatively more economic alternatives, while electric trucks are the type that remains as a possible choice, that the model could use but it would represent a higher cost alternative. This whole situation creates a barrier for the model to seek more cost-optimal solutions.

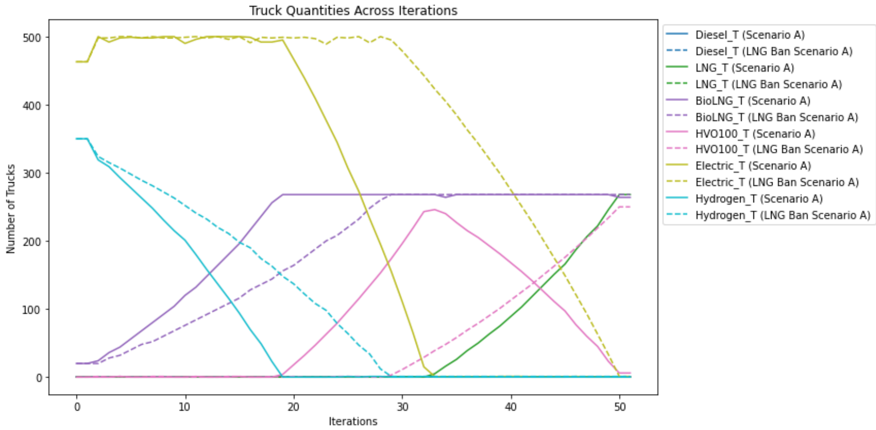

Figure 61: LNG Ban: Comparison of Truck Quantities

The truck quantities in Figure 61 highlighted how the model adapts to constraints such as the LNG ban, offering insights into the shifting fleet composition. In the environmentally focused solutions, Hydrogen trucks dominated alongside Electric trucks, with initial quantities of 350 and 463, respectively. As iterations progressed, the share of Hydrogen trucks declined steadily, reaching just one truck in cost-focused solutions. Electric trucks exhibited a similar pattern, starting at 463 in environmental scenarios and gradually decreasing as cost considerations became more prominent, ending with only one unit in the most economical solution.

BioLNG trucks displayed a clear upward trajectory throughout the iterations, reflecting their role as a stable and cost-effective alternative under the LNG ban. Starting with just 20 trucks in the initial solutions, their quantity raised steadily to 268 in cost-optimized scenarios. HVO100 trucks appeared sparingly in the environmentally focused iterations but gained prominence in later stages, increasing from negligible quantities to 250 in the most cost-driven solutions. This pattern demonstrated the model's prioritization of HVO100 trucks as a replacement for LNG in cost-sensitive contexts. By maintaining a constant number of BioLNG trucks and gradually phasing in HVO100 as costs dominated, the analysis highlighted the trade-offs and strategic adjustments necessary for Ginobili to navigate a potential LNG ban effectively. The actual geopolitical scenario, including many new environmental regulations taking effect in the future years is pretty much irregular, so considering a situation like this when investing on a new truck fleet is important for the decision-making process to take place.

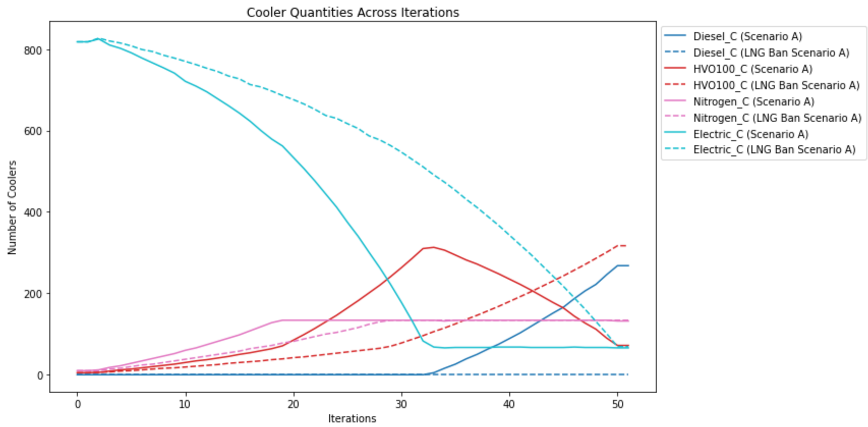

Figure 62: Comparison of Cooler Quantities

When studying the cooler quantities graph, it is possible to evaluate that the LNG Ban made the model choose Electric coolers the most (initially over 800), that were the ones that are used with Hydrogen and Electric trucks, following the information provided by the major supermarket company. These high quantity numbers that this type of coolers had relate to the choices made by the truck quantity model, by selecting high quantities of Hydrogen and Electric Trucks. An uprising trend looking forward to cost-effective solutions was made by HVO100 coolers, reaching in the last solutions a number of 317 coolers. Diesel coolers, used only with LNG trucks were obviously not selected by the optimization model. BioLNG cooler quantity remained constant.

This perception is valuable as part of the sensitivity analysis because in a possible LNG Ban, Electric and Hydrogen trucks would be undoubtedly considered in the most environmental approaches, while HVO100 and BioLNG coolers would be present in a constant trade-off for cost-efficient solutions.

4.3.2.4 Macroeconomic and Policy Scenarios: Renewable Content Mandates Increase

Considering that European mandates like the EU RED II might be updated or revised in the future, this analysis provides a realistic perspective for assessing the viability of the project within the context of evolving regulations.

For this scenario, two new inputs were used for the model to show an extreme situation of a possible revision made in the RED II mandate: the fleet's minimum renewable energy content was set at 25% and its minimum biofuel share was set to 7.5%.

The effect of a percentage increase in the renewables content could be seen in the figure 63 below.

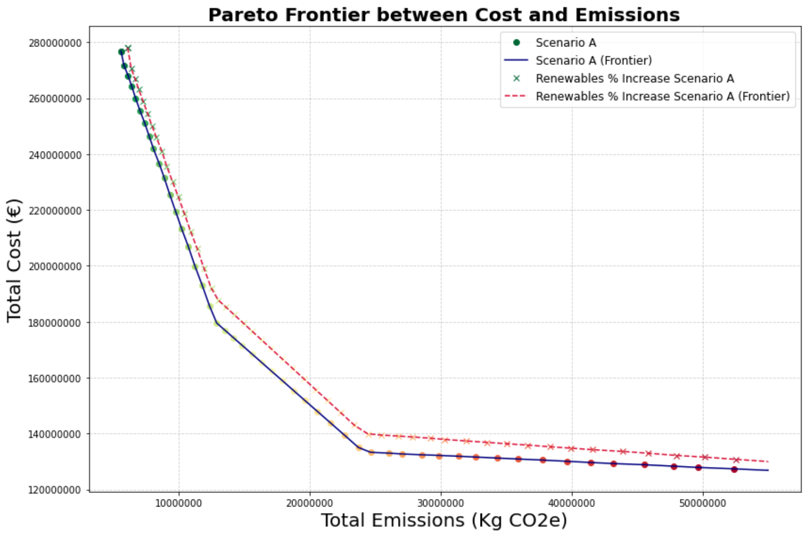

Figure 63: Renewable Content Mandates Increase: Comparison of Pareto Frontiers

The overview of the effect of a possible review of the EU RED II reflected that an increase in the renewables and biofuels percentage would shift the Pareto Frontier to the right with respect of the A.1 Scenario, representing price differences up to 3.5% in some of the cases, as it is possible to depict in the transition zone in the middle. Initially, in the environmental cases, the effect of the regulation only showed cost differences near to 1 or 2%, while this increase as the focus of the optimization included economical objective solutions. The overall takeaway for the decision-making process that Ginobili has to take, as part of the sensitivity analysis is that this regulation could only make them incur more costs, something to consider in a risk management approach before taking the investment decision.

The overview of the potential impact of a revision of the EU RED II suggested that increasing the share of renewables and biofuels would shift the Pareto Frontier to the right compared to Scenario A.1. This shift reflected price differences of up to 3.5% in some cases, particularly in the transition zone. In the initial environmental scenarios, the regulation's effect is relatively minor, with cost differences of around 1–2%. However, as the optimization incorporated economic objectives, these cost differences became more pronounced.

For Ginobili, the key insight from this sensitivity analysis is that the proposed regulation could lead to higher costs. This is an important factor to consider as part of a broader risk management strategy before making an investment decision.

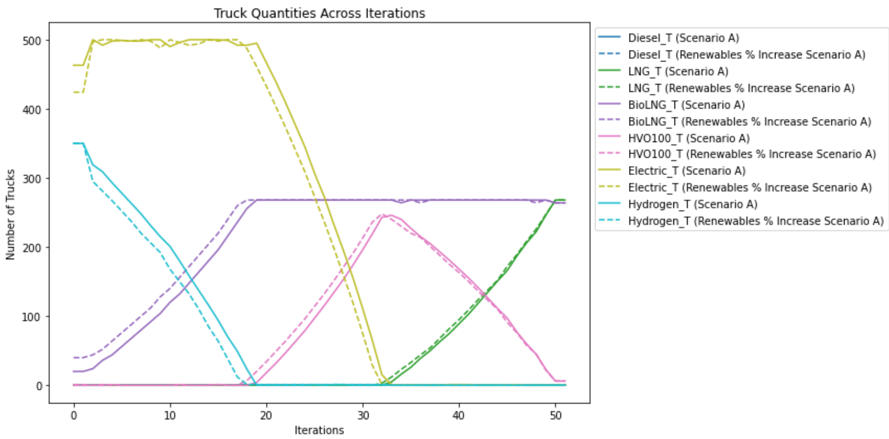

Figure 64: Renewable Content Mandates Increase: Comparison of Truck Quantities

The truck quantities curves as well exhibited shifts in figure 64. All of the curves shifted left in the trends for the truck types when comparing the increased renewables scenario (in the dotted lines) to the original Scenario A (solid lines). This leftward shift indicated an earlier adoption of greener alternatives such as BioLNG, Electric, and Hydrogen trucks.

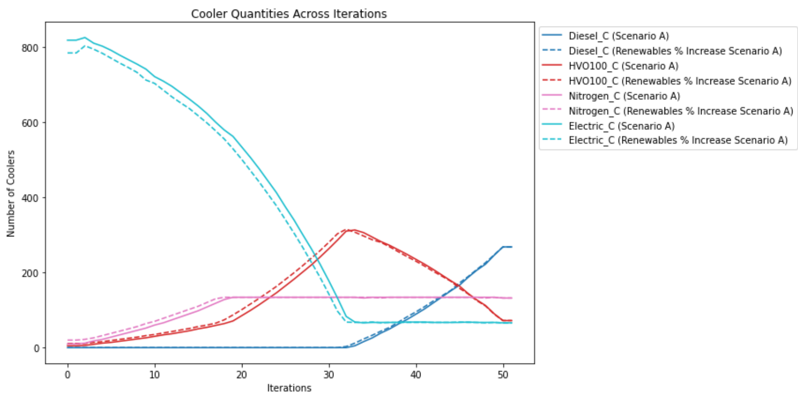

Figure 65: Renewable Content Mandates Increase: Comparison of Cooler Quantities

The cooler quantity curves, in figure 65, also reflected the same trend as the previous cases. All of the cooler curves shifted to the right, showing an earlier adoption of each cooler type, being these Diesel, HVO100, Nitrogen or Electric.

The effect, as part of the sensitivity analysis to be incurred, was that the impact would be the most on costs and not on trucks or cooler quantities, so Ginobili would have to evaluate their budget constraint of € 131,000,000 while considering the potential revision of the EU RED II regulation.

4.4 Discussion and Recommendation

Building on the analysis outlined in Section 4, this subchapter focuses on aligning the results with the company's current situation while providing a clear recommendation for their 2030 sustainability investment goals. Alongside environmental objectives, the company has also set a strict budget of €130,000,000. However, it is crucial to account for potential risks in this investment, including regulatory changes, geopolitical instability, and macroeconomic fluctuations. These uncertainties require a cautious approach to decision-making, ensuring that any recommendations remain viable under different future conditions.

To address this, the analysis was divided into three scenarios: a base case that assumes minimal changes in external factors (A.1 and B.1 solutions together) and a scenario driven by modelling techniques previously discussed, where it was possible for the model to select optimally the truck-cooler parameters (A.2 and B.2 solutions together). The C-series scenarios were not considered as part of the recommendations as the objective of this study was to examine the current situation of the company and matching the external factors that could affect the decision-making process as a whole and not to use the pre-imposed strategies of the company previous to perform the optimization model. The focus of the study relies in which is the optimal fleet mix with the current conditions of the company through different scenarios based on the data provided.

Within each of these scenarios, the most suitable solutions were evaluated from the feasible sets that align with the budget that the company provided, stated in section 3.2 and then order the solutions by emissions. In this way, a quantitative initial threshold is introduced as a financial burden for the choices to take and then these solutions are filtered by their emissions level. As well, the solutions have to comply with the EU RED II Directive, as this regulation acts for companies from 2023 on (European Commission, 2018) and also use the trucks that the Ginobili does actually have in their fleet.

For each scenario, two tailored solutions are presented: one prioritizing environmental impact and the other emphasizing cost-efficiency, grabbed from the pareto frontiers presented.

To provide further clarity, descriptive statistics such as the mean, standard deviation, and relevant quantiles were included for each alternative. This statistical analysis demonstrates the model's outputs and serves as a foundation for the recommendations.

Base Case Scenario

When combining the feasible solution sets for scenario A.1 and B.1 under Ginobili's budget, as determined by the optimization studies, a descriptive statistical analysis was conducted to assess the quantities of trucks and coolers selected by the model in all the possible outcomes of A.1 and B.1 Scenarios, shown in Table 4.4.1 below. This analysis provided valuable insight into the characteristics of the solutions generated, allowing for a better evaluation of their practicality and alignment with the company's goals. Detailed results of the combined feasible solution sets are presented in Appendix section 7.5 for reference.

Variable	μ	σ	25%	50%	75%
Diesel Trucks	0	0	0	0	0
LNG Trucks	209	40	177	209	242
BioLNG Trucks	267	3	268	268	268
HVO100 Trucks	57	35	27	57	86
Electric Trucks	2	2	0	2	3
Hydrogen Trucks	0	0	0	0	0
Diesel Coolers	209	40	177	209	242
HVO100 Coolers	124	36	94	124	153
Nitrogen Coolers	133	2	134	134	134
Electric Coolers	68	2	67	68	70
Cost	128,397,380	936,607	127,658,764	128,401,839	129,188,274
Emissions	48,190,033	4,599,318	44,355,314	48,130,928	51,921,300

Table 12: Base Case Scenarios under budget constraints (A.1 and B.1): Descriptive Statistics

Table 12 highlighted that the mean of the solutions under the budget constraint remained approximately €2 million below the limit, though the standard deviation indicates that some solutions could approach the maximum budget threshold. The table showed that the model frequently selected 268 BioLNG trucks, as evidenced by its low standard deviation, suggesting consistency in this choice across solutions. Conversely, the highest standard deviation was observed in the selection of LNG trucks, with 40 units, and HVO100 trucks, reflecting the model's tendency to alternate between different strategies to reach the objectives of the model in the feasible solution sets for A.1 and B.1 Scenarios.

For the coolers, Electric and Nitrogen coolers were consistently selected in nearly all alternatives, as demonstrated by their minimal standard deviation. On the other hand, Diesel and HVO100 coolers exhibited greater variability, indicating a trade-off situation where their selection depended more heavily on the specific scenario and solution.

When analysing the solutions provided that are under the major supermarket company budget, that can be found in Appendix 7.5, two solutions were selected to recommend to the company in a base case, depending in the approach the managers want to take. These solutions were selected from the list being evaluated in the criteria used both for A-series and B-series scenarios modelling, being useful to comply with future EU RED II directives and that also used in the solutions the trucks that the company does actually have in their fleet. With all this being said, two solutions from different parts of the pareto frontier were grabbed, from the under-budget side, one that had a lower number of emissions but a higher costs and another one with a higher emission value and lower costs.

Variable	Approach	
	Economic	Environmental
Diesel Trucks	0	0
LNG Trucks	269	159
BioLNG Trucks	256	268
HVO100 Trucks	11	102
Electric Trucks	3	3
Hydrogen Trucks	0	0
Diesel Coolers	269	159
HVO100 Coolers	75	169
Nitrogen Coolers	128	134
Electric Coolers	67	70
Cost	127,245,919	129,717,751
Emissions	55,227,486	42,328,791

Table 13: Base Case Scenarios under budget constraints (A.1 and B.1): Solutions Proposed

Understanding the economic approach in the base optimization case helps clarify how the model selects the most cost-effective fleet composition. The combination of LNG trucks and Diesel coolers emerges as the most economically efficient solution. BioLNG trucks follow as the second most viable option, while HVO100 trucks rank last due to their slightly higher costs. This outcome highlights the cost-effectiveness of biodiesel, showing that the marginally greater expense of HVO100 gives BioLNG the advantage in the economic trade-off.

In the environmentally optimized scenario, HVO100 trucks play a much more significant role, outperforming LNG trucks, which have the highest environmental impact. The shift in truck selection also influences the choice of coolers, leading to a more balanced distribution in the model.

Scenario with Optimal Cooler Parameters

When examining the feasible solution sets, it was crucial to account for the modelling procedure detailed in Section 4, in the advanced base case models considering optimal truck-cooler parameters and a non-linear process optimization. This process incorporated coefficients as decision variables to represent various truck-cooler combinations effectively. The results of scenarios A.2 and B.2, developed under Ginobili's budget as defined by the optimization studies, were combined to present a comprehensive solution for the major supermarket company and can be also visualized in Appendix 7.5.

Additionally, a descriptive statistical analysis was performed to evaluate the truck and cooler quantities selected by the model for all the possible outcomes of the A.2 and B.2 Scenarios, providing insights into the distribution and consistency of the solutions. The outcomes of this analysis were summarized in Table 4.4.2 below.

Variable	μ	σ	25%	50%	75%
Diesel Trucks	0	0	0	0	0
LNG Trucks	176	64	133	177	229
BioLNG Trucks	269	1	269	269	269
HVO100 Trucks	86	59	37	85	126
Electric Trucks	2	1	0	3	3
Hydrogen Trucks	0	0	0	0	0
Diesel Coolers	176	64	133	177	229
HVO100 Coolers	331	118	306	354	395
Nitrogen Coolers	24	78	0	0	0
Electric Coolers	2	1	0	3	3
Cost	127,787,869	1,501,594	126,699,464	127,927,739	128,981,247
Emissions	44,408,663	7,518,339	39,347,663	44,452,533	50,456,038

Table 14: Base Case Scenarios under budget constraints (A.2 and B.2): Descriptive Statistics

In the table 14 provided, the joint selection of under budget alternatives for the optimized parameter cooler-truck advancements approach were showed together with their statistical measures. At first, it is possible to see that BioLNG trucks stand out for their consistent inclusion, with a mean of 269 units and a negligible standard deviation of 1, indicating they were almost always chosen in the same quantity across all solutions. In contrast, LNG trucks exhibited significant variability, with a mean of 176 units and a standard deviation of 64, reflecting the model's tendency to adjust their selection based on the part of the curve that was iterating. This type of truck was selected in the economic-oriented part of the curve and then had a null value in the environmental-oriented part of the curve. HVO100 trucks also showed a notable range, suggesting they were included in some solutions but excluded in others, likely as part of a trade-off. Hydrogen trucks consistently remained unselected, indicating they were not competitive under the model's constraints. Electric trucks, while consistently included, are adopted in very low quantities, as demonstrated by their mean of 2.

For coolers, the model's choices showed a mix of consistency and variability. Electric coolers were consistently selected, in small numbers, with a mean of 2. In contrast, Diesel coolers and HVO100 coolers demonstrated significant variability, suggesting their inclusion depended heavily on the specific trade-offs required by the solution. Nitrogen coolers, while present in some solutions, showed high variability, indicating their selection is scenario-dependent and less favoured overall. From a cost perspective, the mean remained just below the budget threshold, at €127.8 million, but the standard deviation of €1.5 million suggested some solutions closely approached the limit that Ginobili provided, of €130 million.

With all of this being said, the solutions provided by the Pareto Frontiers were joined, and by maintaining the most important constraints considered in the solutions selection, complying with EU RED II Regulation and also using the current trucks available in the fleet, an environmental and an economical solution was presented.

Variable	Approach	
	Economic	Environmental
Diesel Trucks	0	0
LNG Trucks	269	62
BioLNG Trucks	262	269
HVO100 Trucks	5	191
Electric Trucks	3	3
Hydrogen Trucks	0	0
Diesel Coolers	269	62
HVO100 Coolers	5	460
Nitrogen Coolers	262	0
Electric Coolers	3	3
Cost	125,003,199	129,978,818
Emissions	56,091,472	31,189,040

Table 16: Base Case Scenarios under budget constraints (A.2 and B.2): Solutions Proposed

To make a comparison between the base case environmental and economic solutions presented in the last section and those generated under the parameter optimization model, key differences emerged in fleet composition, cooler selection, and overall efficiency. The introduction of optimized truck-cooler parameters influenced both cost and environmental performance in interesting ways.

In regard to the economic solutions, the model with optimized cooler parameters achieved costs nearly €2 million lower than the base case, demonstrating the impact of polishing the combination of BioLNG trucks and various cooler types. The selection of coolers changed, with only 5 HVO100 cooler units chosen compared to 75 units in the base case. To compensate for this shift, the model introduced nearly 100 additional Nitrogen coolers, prioritizing their cost-effectiveness. When left unrestricted in its selection, the parameter-optimized model assigned Nitrogen coolers exclusively to BioLNG trucks, reinforcing their economic advantage.

Following the environmental solutions, the parameter optimization model achieved a reduction of approximately 10 million kg CO_2 compared to the base case. This outcome highlights the effectiveness of refining fleet parameters to minimize emissions. The selection of HVO100 trucks increased by 89 units, emphasizing their role in reducing the fleet's overall carbon footprint. On the other hand, the base case relied more heavily on LNG trucks, despite being configured for an environmental approach. The optimization process also led to the complete elimination of Nitrogen coolers, which were prevalent in the economic scenario, and resulted in a substantial increase in HVO100 coolers to 460 units. The shift toward biodiesel-powered coolers also caused a notable reduction in the number of diesel and electric coolers, aligning with emissions reduction goals.

A useful consideration, given Ginobili's position as a major supermarket company, is the relationship between cost and emission reductions when comparing the economic and environmental solutions. The analysis shows that a 4% increase in costs can lead to a 44% reduction in emissions. Since supermarkets operate on tight margins, this trade-off becomes relevant. Moving from a purely economic approach to a strongly environmental one achieves significant CO_2 reductions, which could become valuable if ETS Trading Scheme prices rise, or regulatory requirements become stricter. Strategically planning for these potential shifts allows for better long-term decision-making, ensuring both compliance and operational efficiency.

With the optimization process that the model performs in both cases, it is useful to evidence that:

- Lower costs in the economic approach due to the optimized mix of BioLNG trucks and Nitrogen coolers.
- Increased presence of HVO100 trucks in the environmental scenario, reinforcing their role in emissions reduction.
- Shift from Nitrogen coolers to HVO100 coolers in the environmental approach, with a reduction in diesel and electric coolers.
- Cost-emission trade-off shows that a 4% cost increase results in a 44% emission reduction, a critical factor for future regulatory and financial planning, as supermarkets work in narrow business margins.

5 Conclusion

5.1 Summary of Research

The analysis conducted in this thesis explored diverse optimal scenarios aimed at achieving the 2030 sustainable logistics objectives of a major supermarket company. With a multi-objective approach, a sustainable fleet-mix optimization process was performed through a mixed-integer programming method and epsilon-constraint technique combined with linear and non-linear optimization algorithms. To accomplish the goal of finding a fleet mix that meets both the budget and the emissions objectives for the company for 2030, evidence-based scenarios and possibilities were analysed in Pareto Frontiers, evaluating the whole possible range of fleet mix combinations that could be selected in the operational, financial and regulatory panorama.

The scenarios analysed considered potential regulatory changes by 2030, the current fleet composition of Ginobili, risk management perspectives, and time-series modelling to project price trends. Furthermore, the model considers the impact of exogenous events, such as fuel crises and resource scarcity, on decision-making. The study addressed the complex problem of fleet mix optimization, encompassing both truck and truck-cooler combinations, allowing technology and cost evaluation of LNG, BioLNG, HVO100, Electric and Hydrogen trucks combined with Diesel, Nitrogen, HVO100 and Electric coolers, including an innovative approach for the sustainable logistics problem. By leveraging data provided by the company, the analysis included scenarios with technological advancements that allowed for greater freedom in selecting optimal truck-cooler combinations to achieve superior results.

This work contributed to logistics decision-making processes by concurrently optimizing economic and environmental objectives, providing actionable insights for the supermarket's truck fleet investments in Italy. It came at a critical time, as EU countries transition away from diesel and fossil fuels toward renewable alternatives like biofuels, including BioLNG and HVO100, and emerging options such as hydrogen and electric technologies. The base case (A.1 and B.1 Scenarios) and optimized parameter scenarios (A.2 and B.2 Scenarios) results, taken from the respective Pareto frontiers, support the decision-making process of the company. Unlike prior studies that primarily focused on bus and sea fleet optimization, this research added valuable insights into truck fleets by addressing costs, emissions, and the potential influence of exogenous factors, including fuel bans and renewable energy mandates. The findings underscored the growing importance of biofuels for 2030, particularly BioLNG and HVO100, while highlighting the future potential of hydrogen trucks, despite current infrastructure challenges. For coolers, the study emphasized the transition from diesel to HVO100 and electric options, while balancing trade-offs with nitrogen-powered alternatives. Ultimately, it is useful to say that this research equips the supermarket company with a robust framework for navigating the complex landscape of fleet mix optimization in a rapidly evolving regulatory and technological environment.

5.2 Contributions

This thesis contributes to the literature by exploring fleet mix optimization for truck fleets in the food supply chain, an area that has received little attention. Unlike most studies, which focus on vehicle routing or fleet mix optimization in urban mobility systems like buses and maritime transport, this research introduces a new perspective by integrating truck and cooler combinations into the optimization process. Instead of relying on generic assumptions, the model as well incorporates real company data for both base parameters and their optimization, ensuring practical relevance.

A novel method was taking in account environmental policies such as the EU RED II Regulation, that represents the involvement of the new regulatory processes that sustainable logistics is facing, as this is applied from 2023 on (European Commission, 2018). From the start of the optimization process, the model factors in biofuel requirements and the percentage of sustainable-powered vehicles, including electric and hydrogen trucks, making the fleet mix compliant with actual and future regulations. These findings add a layer to decision-making, supporting companies in their long-term strategic planning.

A dedicated Fuel Price Prediction model enhances the cost analysis, integrating Guarantees of Origin costs into electricity pricing. This model also applies statistical forecasting methods with fuel-specific prediction variables, improving the accuracy of cost projections. The inclusion of Pareto Frontiers and epsilon-constraint techniques in the optimization process presents an innovative approach to sustainable logistics, offering valuable insights for future research.

Another key innovation lied in the incorporation of exogenous events, such as geopolitical conflicts and resource shortages, into the optimization model. This approach highlighted how these factors could influence fuel trends and regulatory changes, providing a realistic framework for future scenarios. The study as well accentuated the importance of considering structural costs alongside dynamic fuel price variations, offering a comprehensive methodology that accounts for both current fleet capabilities and future regulatory challenges. By addressing these multifaceted aspects, this research not only filled a critical gap in the literature but also established a foundation for further studies in truck fleet investment and optimization, particularly for industries requiring stringent cold chain management.

5.3 Limitations

The study faced several limitations, primarily due to data scarcity for emerging fuel technologies such as BioLNG, HVO100, and Hydrogen. These fuels were still in the early stages of adoption, with rapidly evolving trends influenced by regulatory developments and market dynamics. For example, the ongoing palm oil controversy in Asia significantly impacted the price structure of biofuels like HVO100, introducing considerable uncertainty and risk for long-term investment planning. Hydrogen fuel presented even greater challenges, as its supply chain remains underdeveloped, with limited historical data and insufficient infrastructure compared to in-house renewable energy sources like solar or wind. Furthermore, the Levelized Cost of Energy (LCOE) for hydrogen production and the associated transportation costs were not well-documented, making comprehensive evaluation difficult. These technological and market uncertainties represented key barriers to fully integrating these fuels into fleet investment decisions.

The volatile nature of fuel markets, exacerbated by geopolitical events like the Russia-Ukraine war, posed challenges for accurate price forecasting, further complicating the analysis. Despite these constraints, the model yielded strong results and actionable recommendations for the company, demonstrating its robustness and potential for addressing the complexities of fleet mix optimization in a challenging and evolving landscape.

5.4 Future Research Direction

Future research directions could focus on the integration of emerging technologies, which are now more advanced, into optimization models. This includes incorporating autonomous vehicles, advanced fuel technologies, and real-time decision-making systems to better address the evolving landscape of transport supply chains. Additionally, a more detailed analysis of the EU regulatory framework could provide insights into how specific policies and mandates impact fleet composition and operations in a rapidly changing environment. As well, a valuable integration to the study could be the incorporation of EU ETS carbon contract prices to account for the cost of emissions in the different alternatives.

Another promising avenue is the exploration of diverse loading strategies for trucks, aiming to reduce the number of trips and consequently lower emissions. Investigating heterogeneous fleet compositions instead of homogeneous fleets could open new possibilities, as it would allow for more tailored solutions based on varying demands and operational constraints. Further, optimizing truck load rates in conjunction with route planning could be an impactful area of study. Employing machine learning or AI techniques to analyse and improve load efficiency, while accounting for specific legal restrictions on various routes, could yield region-specific insights and enhance operational effectiveness across the country.

Simulation tools like AnyLogic could play a pivotal role in these studies. By introducing trucks as agents within a simulation, researchers could model their interactions with distribution centres, visualized through GIS maps. This approach could generate heatmaps to identify the required infrastructure for each fuel type in different regions, facilitating more strategic planning. Such analyses would not only benefit the specific company studied but also provide valuable insights for other transport operators across the EU, ultimately helping to optimize operations while minimizing environmental and social impacts.

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7 Appendix

7.1 Base cost structure

CATEGORY	Annual Cost	Years of Use	Annual KM	Cost per KM
PURCHASE				
Vehicle Purchase	110,000	6	140,000	0.13
Semi-Trailer Purchase	95,000	10	100,000	0.10
FUEL				
Diesel				0.60
MAINTENANCE				
Vehicle Maintenance	3,500	0.8	100,000	0.03
Semi-Trailer Maintenance	1,500		100,000	0.02
TIRES				
Tires for Vehicle and Semi-Trailer	5,000		100,000	0.05
ROAD TAXES				
Vehicle Road Tax	2,500		100,000	0.03
INSURANCE	5,000		100,000	0.05
DEPRECIATION				
Vehicle Depreciation	110,000	6	100,000	-0.18
Semi-Trailer Depreciation	95,000	10	100,000	-0.10
SALARY				
Base Salary	55,000	1.5	100,000	0.83
Overtime/Night/Holiday	3,500		100,000	0.04
TOLLS	19,000		100,000	0.19
STRUCTURE	6,000		100,000	0.06
FEES	8,000		100,000	0.08
TOTAL				€ **1.90**

Table 17: Cost structure for Diesel Trucks

CATEGORY	Annual Cost	Years of Use	Annual KM	Cost per KM
PURCHASE				
Vehicle Purchase	150,000	6	130,000	0.19
Semi-Trailer Purchase	95,000	10	100,000	0.10
FUEL				
LNG				0.42
MAINTENANCE				
Vehicle Maintenance	3,500	0.8	100,000	0.03
Semi-Trailer Maintenance	1,500		100,000	0.02
TIRES				
Tires for Vehicle and Semi-Trailer	5,000		100,000	0.05
ROAD TAXES				
Vehicle Road Tax	2,300		100,000	0.02
Towable Mass Tax	300		100,000	0.00
INSURANCE	8,500		100,000	0.09
DEPRECIATION				
Vehicle Depreciation	150,000	6	100,000	-0.25
Semi-Trailer Depreciation	95,000	10	100,000	-0.10
SALARY				
Base Salary	55,000	1.5	100,000	0.83
Overtime/Night/Holiday	3,500		100,000	0.04
TOLLS	19,000		100,000	0.19
STRUCTURE	8,000		100,000	0.08
FEES	7,000		100,000	0.07
TOTAL				€ **1.76**

Table 18: Cost structure for LNG Trucks

CATEGORY	Annual Cost	Years of	Annual	Cost per KM
PURCHASE				
Vehicle Purchase	150,000	6	130,000	0.19
Semi-Trailer Purchase	135,000	10	100,000	0.14
FUEL				
BioLNG				0.42
MAINTENANCE				
Vehicle Maintenance	3,500	0.8	100,000	0.03
Semi-Trailer Maintenance	1,500		100,000	0.02
TIRES				
Tires for Vehicle and Semi-Trailer	5,000		100,000	0.05
ROAD TAXES				
Vehicle Road Tax	2,300		100,000	0.02
Towable Mass Tax	300		100,000	0.00
INSURANCE	8,500		100,000	0.09
DEPRECIATION				
Vehicle Depreciation	150,000	6	100,000	-0.25
Semi-Trailer Depreciation	95,000	10	100,000	-0.10
SALARY				
Base Salary	55,000	1.5	100,000	0.83
Overtime/Night/Holiday	3,500		100,000	0.04
TOLLS	19,000		100,000	0.19
STRUCTURE	8,000		100,000	0.08
FEES	7,000		100,000	0.07
TOTAL				€ **1.80**

Table 19: Cost structure for BioLNG Trucks

CATEGORY	Annual Cost	Years of	Annual	Cost per KM
PURCHASE				
Vehicle Purchase	110,000	6	140,000	0.13
Semi-Trailer Purchase	135,000	10	100,000	0.14
FUEL				
HVO100				0.60
MAINTENANCE				
Vehicle Maintenance	3,500	0.8	100,000	0.03
Semi-Trailer Maintenance	1,500		100,000	0.02
TIRES				
Tires for Vehicle and Semi-Trailer	5,000		100,000	0.05
ROAD TAXES				
Vehicle Road Tax	2,500		100,000	0.03
INSURANCE	5,000		100,000	0.05
DEPRECIATION				
Vehicle Depreciation	110,000	6	100,000	-0.18
Semi-Trailer Depreciation	95,000	10	100,000	-0.10
SALARY				
Base Salary	55,000	1.5	100,000	0.83
Overtime/Night/Holiday	3,500		100,000	0.04
TOLLS	19,000		100,000	0.19
STRUCTURE	6,000		100,000	0.06
FEES	7,000		100,000	0.07
TOTAL				**€ 1.93**

Table 20: Cost structure for HVO100 Trucks

CATEGORY	Annual Cost	Years of Use	Annual KM	Cost per KM
PURCHASE				
Vehicle Purchase	400,000	5	70,000	1.14
Semi-Trailer Purchase	135,000	10	70,000	0.19
Incentives	24,000	5	70,000	-0.07
FUEL				
Electricity				0.14
MAINTENANCE				
Vehicle Maintenance	2,450	0.7	70,000	0.02
Semi-Trailer Maintenance	1,500		70,000	0.02
TIRES				
Tires for Vehicle and Semi-Trailer	2,500	2	70,000	0.07
ROAD TAXES				
Vehicle Road Tax	0		70,000	0.00
Towable Mass Tax	0		70,000	0.00
INSURANCE	9,000		70,000	0.13
DEPRECIATION				
Vehicle Depreciation	0	6	70,000	0.00
Semi-Trailer Depreciation	0	10	70,000	0.00
SALARY				
Base Salary	55,000	1.5	70,000	1.18
Overtime/Night/Holiday	2,450		70,000	0.04
TOLLS	13,300		70,000	0.19
STRUCTURE	7,700		70,000	0.11
FEES	13,300		70,000	0.19
TOTAL				**€ 3.36**

Table 21: Cost structure for Electricity Trucks

CATEGORY	Annual Cost	Years of Use	Annual KM	Cost per KM
PURCHASE				
Vehicle Purchase	990,000	5	100,000	1.98
Semi-Trailer Purchase	135,000	10	100,000	0.14
Incentives	24,000	5	70,000	-0.07
FUEL				
Hydrogen				1.04
MAINTENANCE				
Vehicle Maintenance	4,000	0.7	100,000	0.03
Semi-Trailer Maintenance	1,500		100,000	0.02
TIRES				
Tires for Vehicle and Semi-Trailer	2,500	2	100,000	0.05
ROAD TAXES				
Vehicle Road Tax	0		100,000	0.00
Towable Mass Tax	0		100,000	0.00
INSURANCE	23,000		100,000	0.23
DEPRECIATION				
Vehicle Depreciation	0	6	100,000	0.00
Semi-Trailer Depreciation	0	10	100,000	0.00
SALARY				
Base Salary	55,000	1.5	100,000	0.83
Overtime/Night/Holiday	3,500		100,000	0.04
TOLLS	19,000		100,000	0.19
STRUCTURE	11,000		100,000	0.11
FEES	19,000		100,000	0.19
TOTAL				**€ 4.76**

Table 22: Cost structure for Hydrogen Trucks

7.2 Base Case Scenario Results

	Methodology	Diesel Trucks	LNG Trucks	BioLNG Trucks	HVO100 Trucks	Electric Trucks	Hydrogen Trucks	Diesel Coolers	HVO100 Coolers	Nitrogen Coolers	Electric Coolers	Cost	Emissions
0	Environmental Single Objective	0	0	20	0	463	350	0	5	10	818	276,838,224	5,568,548
1	Multi Objective	0	0	20	0	463	350	0	5	10	818	276,838,224	5,568,548
2	Multi Objective	0	0	24	0	500	319	0	6	12	825	271,752,567	5,791,207
3	Multi Objective	0	0	36	0	492	309	0	9	18	810	268,048,212	6,106,915
4	Multi Objective	0	0	44	1	498	293	0	12	22	802	264,082,083	6,402,042
5	Multi Objective	0	0	56	0	499	278	0	14	28	791	259,829,051	6,692,500
6	Multi Objective	0	0	68	0	498	263	0	17	34	778	255,389,706	7,028,318
7	Multi Objective	0	0	80	0	498	248	0	20	40	766	251,181,866	7,370,721
8	Multi Objective	0	0	92	0	500	231	0	23	46	754	246,494,826	7,715,900
9	Multi Objective	0	0	104	0	500	215	0	26	52	741	241,815,881	8,053,106
10	Multi Objective	0	0	120	0	490	201	0	30	60	721	236,717,008	8,474,974
11	Multi Objective	0	0	132	1	496	180	0	34	66	709	231,348,265	8,884,236
12	Multi Objective	0	0	148	0	500	158	0	37	74	695	225,444,925	9,298,189
13	Multi Objective	0	0	164	0	500	137	0	41	82	678	219,363,367	9,749,530
14	Multi Objective	0	0	180	0	500	116	0	45	90	661	213,281,808	10,200,870
15	Multi Objective	0	0	196	1	500	94	0	50	98	643	207,005,842	10,705,543
16	Multi Objective	0	0	216	0	499	70	0	54	108	623	199,955,679	11,216,297
17	Multi Objective	0	0	236	0	492	49	0	59	118	600	193,206,497	11,761,661
18	Multi Objective	0	0	256	0	492	23	0	64	128	579	185,722,325	12,327,136
19	Multi Objective	0	0	268	4	495	0	0	71	134	562	179,546,949	12,881,837
20	Multi Objective	0	0	268	18	467	0	0	85	134	534	176,938,566	13,516,872
21	Multi Objective	0	0	268	32	439	0	0	99	134	506	174,330,184	14,151,908
22	Multi Objective	0	0	268	47	409	0	0	114	134	476	171,535,488	14,832,303
23	Multi Objective	0	0	268	63	377	0	0	130	134	444	168,554,479	15,558,058
24	Multi Objective	0	0	268	79	345	0	0	146	134	412	165,573,471	16,283,813
25	Multi Objective	0	0	268	97	307	1	0	164	134	375	162,227,931	17,092,314
26	Multi Objective	0	0	268	115	273	0	0	182	134	340	158,866,201	17,916,762
27	Multi Objective	0	0	268	134	233	1	0	201	134	301	155,334,348	18,770,623
28	Multi Objective	0	0	268	153	195	1	0	220	134	263	151,794,401	19,632,457
29	Multi Objective	0	0	268	174	155	0	0	241	134	222	147,873,732	20,592,983
30	Multi Objective	0	0	268	196	111	0	0	263	134	178	143,774,845	21,590,896
31	Multi Objective	0	0	268	219	65	0	0	286	134	132	139,489,645	22,634,169
32	Multi Objective	0	0	268	243	15	1	0	310	134	83	135,026,227	23,714,828
33	Multi Objective	0	5	268	246	1	0	5	313	134	68	133,306,249	24,640,542
34	Multi Objective	0	16	264	240	0	0	16	306	132	66	133,018,283	26,007,185
35	Multi Objective	0	26	268	227	0	0	26	294	134	67	132,698,345	27,081,441
36	Multi Objective	0	39	268	215	0	0	39	282	134	67	132,399,456	28,582,615
37	Multi Objective	0	50	268	205	0	0	50	272	134	67	132,189,119	29,861,843
38	Multi Objective	0	63	268	193	0	0	63	260	134	67	131,890,231	31,363,017
39	Multi Objective	0	75	268	181	1	0	75	248	134	68	131,590,426	32,701,273
40	Multi Objective	0	89	268	168	1	0	89	235	134	68	131,247,261	34,313,420
41	Multi Objective	0	103	268	155	1	0	103	222	134	68	130,904,097	35,925,566
42	Multi Objective	0	119	268	141	0	0	119	208	134	67	130,517,572	37,811,602
43	Multi Objective	0	135	268	126	0	0	135	193	134	67	130,085,856	39,645,694
44	Multi Objective	0	151	268	111	0	0	151	178	134	67	129,654,140	41,479,785
45	Multi Objective	0	166	268	97	0	0	166	164	134	67	129,266,700	43,202,904
46	Multi Objective	0	187	268	77	1	0	187	144	134	68	128,845,109	45,598,444
47	Multi Objective	0	206	268	60	0	0	206	127	134	67	128,325,758	47,817,398
48	Multi Objective	0	222	268	45	0	0	222	112	134	67	127,894,041	49,651,489
49	Multi Objective	0	246	268	23	0	0	246	90	134	67	127,384,816	52,431,892
50	Multi Objective	0	268	264	6	0	0	268	72	132	66	126,841,321	55,025,819
51	Economic Single Objective	0	268	264	6	0	0	268	72	132	66	126,841,321	55,025,819

Table 23: Scenario A.1 Results

	Methodology	Diesel Trucks	LNG Trucks	BioLNG Trucks	HVO100 Trucks	Electric Trucks	Hydrogen Trucks	Diesel Coolers	HVO100 Coolers	Nitrogen Coolers	Electric Coolers	Cost	Emissions
0	Environmental Single Objective	0	0	19	0	465	350	0	0	0	834	277,041,285	5,403,631
1	Multi Objective	0	0	19	0	465	350	0	0	0	834	277,041,283	5,403,631
2	Multi Objective	0	0	27	0	500	315	0	0	0	842	270,720,745	5,667,847
3	Multi Objective	0	0	40	0	500	298	0	0	0	838	265,779,083	5,944,982
4	Multi Objective	0	0	54	0	500	280	0	0	0	834	260,595,794	6,235,667
5	Multi Objective	0	0	68	0	500	261	0	0	0	829	255,159,063	6,540,567
6	Multi Objective	0	0	84	0	500	241	0	0	0	825	249,456,498	6,860,374
7	Multi Objective	0	0	100	0	500	220	0	0	0	820	243,475,100	7,195,819
8	Multi Objective	0	0	117	0	500	198	0	0	0	815	237,201,236	7,547,665
9	Multi Objective	0	0	134	0	500	175	0	0	0	810	230,620,605	7,916,716
10	Multi Objective	0	0	153	0	500	151	0	0	0	804	223,718,208	8,303,811
11	Multi Objective	0	0	172	0	500	126	0	0	0	798	216,478,311	8,709,835
12	Multi Objective	0	0	193	0	500	99	0	0	0	792	208,884,412	9,135,710
13	Multi Objective	0	0	214	0	500	72	0	0	0	786	200,919,202	9,582,410
14	Multi Objective	0	0	237	0	500	42	0	0	0	779	192,564,525	10,050,951
15	Multi Objective	0	0	260	0	500	12	0	0	0	772	183,801,338	10,542,403
16	Multi Objective	0	0	269	7	486	0	0	7	0	755	179,063,296	11,057,884
17	Multi Objective	0	0	269	19	462	0	0	19	0	731	176,842,450	11,598,570
18	Multi Objective	0	0	269	32	437	0	0	32	0	706	174,513,013	12,165,693
19	Multi Objective	0	0	269	45	411	0	0	45	0	680	172,069,677	12,760,547
20	Multi Objective	0	0	269	58	383	0	0	58	0	652	169,506,871	13,384,486
21	Multi Objective	0	0	269	73	354	0	0	73	0	623	166,818,754	14,038,934
22	Multi Objective	0	0	269	88	324	0	0	88	0	593	163,999,199	14,725,382
23	Multi Objective	0	0	269	104	292	0	0	104	0	561	161,041,779	15,445,394
24	Multi Objective	0	0	269	121	259	0	0	121	0	528	157,939,753	16,200,611
25	Multi Objective	0	0	269	138	224	0	0	138	0	493	154,686,050	16,992,756
26	Multi Objective	0	0	269	156	187	0	0	156	0	457	151,273,255	17,823,634
27	Multi Objective	0	0	269	176	149	0	0	176	0	418	147,693,587	18,695,138
28	Multi Objective	0	0	269	196	109	0	0	196	0	378	143,938,888	19,609,255
29	Multi Objective	0	0	269	217	66	0	0	217	0	336	140,000,599	20,568,069
30	Multi Objective	0	0	269	239	22	0	0	239	0	291	135,869,744	21,573,765
31	Multi Objective	0	0	269	250	0	0	0	324	0	195	133,639,230	22,628,636
32	Multi Objective	0	0	269	250	0	0	0	472	0	47	133,283,089	23,735,085
33	Multi Objective	0	7	269	243	0	0	7	513	0	0	132,997,648	24,895,635
34	Multi Objective	0	18	269	234	0	0	18	503	0	0	132,738,532	26,112,932
35	Multi Objective	0	29	269	223	0	0	29	493	0	0	132,466,746	27,389,750
36	Multi Objective	0	40	269	213	0	0	40	482	0	0	132,181,671	28,728,998
37	Multi Objective	0	53	269	201	0	0	53	470	0	0	131,882,657	30,133,731
38	Multi Objective	0	65	269	189	0	0	65	459	0	0	131,569,022	31,607,150
39	Multi Objective	0	79	269	177	0	0	79	446	0	0	131,240,052	33,152,612
40	Multi Objective	0	93	269	164	0	0	93	433	0	0	130,894,997	34,773,642
41	Multi Objective	0	108	269	150	0	0	108	419	0	0	130,533,069	36,473,933
42	Multi Objective	0	123	269	136	0	0	123	405	0	0	130,153,445	38,257,362
43	Multi Objective	0	139	269	121	0	0	139	390	0	0	129,755,259	40,127,994
44	Multi Objective	0	156	269	105	0	0	156	374	0	0	129,337,603	42,090,092
45	Multi Objective	0	174	269	88	0	0	174	357	0	0	128,899,526	44,148,128
46	Multi Objective	0	193	269	71	0	0	193	340	0	0	128,440,028	46,306,794
47	Multi Objective	0	213	269	53	0	0	213	322	0	0	127,958,062	48,571,011
48	Multi Objective	0	233	269	33	0	0	233	303	0	0	127,452,531	50,945,938
49	Multi Objective	0	255	269	13	0	0	255	283	0	0	126,922,281	53,436,990
50	Multi Objective	0	269	269	0	0	0	269	0	269	0	126,532,096	56,049,844
51	Economic Single Objective	0	269	269	0	0	0	269	0	269	0	126,532,096	56,049,844

Table 24: Scenario A.2 Results

	Methodology	Diesel Trucks	LNG Trucks	BioLNG Trucks	HVO100 Trucks	Electric Trucks	Hydrogen Trucks	Diesel Coolers	HVO100 Coolers	Nitrogen Coolers	Electric Coolers	Cost	Emissions
0	Environmental Single Objective	0	0	52	5	394	350	0	18	26	757	269,871,155	6,527,783
1	Multi Objective	0	0	52	5	394	350	0	18	26	757	269,871,155	6,527,783
2	Multi Objective	0	0	52	5	492	281	0	18	26	786	260,052,404	6,814,525
3	Multi Objective	0	0	60	6	500	264	0	21	30	779	256,078,180	7,117,625
4	Multi Objective	0	0	72	5	500	250	0	23	36	768	252,064,748	7,406,695
5	Multi Objective	0	0	84	5	500	234	0	26	42	755	247,385,803	7,743,901
6	Multi Objective	0	0	96	5	499	219	0	29	48	742	242,946,458	8,079,719
7	Multi Objective	0	0	108	6	499	202	0	33	54	728	238,073,105	8,470,258
8	Multi Objective	0	0	124	5	494	186	0	36	62	711	232,912,850	8,856,128
9	Multi Objective	0	0	136	5	499	167	0	39	68	700	227,978,115	9,210,668
10	Multi Objective	0	0	152	5	498	147	0	43	76	683	222,136,157	9,660,620
11	Multi Objective	0	0	168	5	491	131	0	47	84	664	216,789,588	10,091,850
12	Multi Objective	0	0	184	5	490	111	0	51	92	647	210,947,630	10,541,803
13	Multi Objective	0	0	200	5	496	86	0	55	100	632	204,370,682	11,011,865
14	Multi Objective	0	0	216	5	499	63	0	59	108	616	198,041,429	11,472,567
15	Multi Objective	0	0	232	6	500	40	0	64	116	598	191,525,863	11,978,628
16	Multi Objective	0	0	252	6	500	14	0	69	126	577	184,041,691	12,544,102
17	Multi Objective	0	0	268	9	485	0	0	76	134	552	178,615,383	13,108,635
18	Multi Objective	0	0	268	22	457	1	0	89	134	525	176,201,409	13,690,338
19	Multi Objective	0	0	268	35	433	0	0	102	134	500	173,771,244	14,287,987
20	Multi Objective	0	0	268	49	405	0	0	116	134	472	171,162,862	14,923,023
21	Multi Objective	0	0	268	64	375	0	0	131	134	442	168,368,166	15,603,418
22	Multi Objective	0	0	268	79	345	0	0	146	134	412	165,573,471	16,283,813
23	Multi Objective	0	0	268	95	313	0	0	162	134	380	162,592,462	17,009,568
24	Multi Objective	0	0	268	112	279	0	0	179	134	346	159,425,140	17,780,683
25	Multi Objective	0	0	268	129	245	0	0	196	134	312	156,257,819	18,551,797
26	Multi Objective	0	0	268	147	209	0	0	214	134	276	152,904,184	19,368,272
27	Multi Objective	0	0	268	167	167	1	0	234	134	235	149,186,018	20,267,492
28	Multi Objective	0	0	268	186	131	0	0	253	134	198	145,637,975	21,137,299
29	Multi Objective	0	0	268	207	89	0	0	274	134	156	141,725,402	22,089,853
30	Multi Objective	0	0	268	229	45	0	0	296	134	112	137,626,515	23,087,766
31	Multi Objective	0	0	268	250	3	0	0	317	134	70	133,713,941	24,040,319
32	Multi Objective	0	9	264	245	3	0	9	311	132	69	133,469,335	25,133,072
33	Multi Objective	0	19	268	232	3	0	19	299	134	70	133,149,397	26,207,328
34	Multi Objective	0	30	268	222	3	0	30	289	134	70	132,939,060	27,486,557
35	Multi Objective	0	40	268	212	4	0	40	279	134	71	132,727,807	28,602,868
36	Multi Objective	0	51	264	206	3	0	51	272	132	69	132,439,841	29,969,511
37	Multi Objective	0	61	268	193	3	0	61	260	134	70	132,119,903	31,043,767
38	Multi Objective	0	75	268	180	3	0	75	247	134	70	131,776,739	32,655,914
39	Multi Objective	0	88	268	168	3	0	88	235	134	70	131,477,850	34,157,087
40	Multi Objective	0	101	268	156	3	0	101	223	134	70	131,178,961	35,658,261
41	Multi Objective	0	115	268	143	3	0	115	210	134	70	130,835,797	37,270,407
42	Multi Objective	0	129	268	130	3	0	129	197	134	70	130,492,632	38,882,554
43	Multi Objective	0	144	268	116	3	0	144	183	134	70	130,105,192	40,605,673
44	Multi Objective	0	159	268	102	3	0	159	169	134	70	129,717,751	42,328,791
45	Multi Objective	0	173	268	89	3	0	173	156	134	70	129,374,587	43,940,938
46	Multi Objective	0	194	268	69	4	0	194	136	134	71	128,952,997	46,336,477
47	Multi Objective	0	212	268	53	3	0	212	120	134	70	128,477,921	48,444,459
48	Multi Objective	0	229	268	37	3	0	229	104	134	70	128,001,929	50,389,523
49	Multi Objective	0	250	268	17	4	0	250	84	134	71	127,580,338	52,785,063
50	Multi Objective	0	269	256	11	3	0	269	75	128	67	127,245,919	55,227,486
51	Economic Single Objective	0	269	256	11	3	0	269	75	128	67	127,245,919	55,227,486

Table 25: Scenario B.1 Results

	Methodology	Diesel Trucks	LNG Trucks	BioLNG Trucks	HVO100 Trucks	Electric Trucks	Hydrogen Trucks	Diesel Coolers	HVO100 Coolers	Nitrogen Coolers	Electric Coolers	Cost	Emissions
0	Environmental Single Objective	0	0	52	5	393	350	0	5	0	795	269,836,470	6,139,590
1	Multi Objective	0	0	52	5	393	350	0	5	0	795	269,836,468	6,139,590
2	Multi Objective	0	0	52	5	490	283	0	5	0	824	260,382,266	6,423,129
3	Multi Objective	0	0	65	5	500	259	0	5	0	824	254,619,127	6,719,763
4	Multi Objective	0	0	80	5	500	240	0	5	0	819	249,085,504	7,030,096
5	Multi Objective	0	0	95	5	500	219	0	5	0	814	243,296,327	7,354,761
6	Multi Objective	0	0	111	5	500	198	0	5	0	810	237,239,793	7,694,419
7	Multi Objective	0	0	128	5	500	176	0	5	0	804	230,903,555	8,049,764
8	Multi Objective	0	0	146	5	500	153	0	5	0	799	224,274,697	8,421,519
9	Multi Objective	0	0	165	5	500	129	0	5	0	794	217,339,703	8,810,443
10	Multi Objective	0	0	184	5	500	103	0	5	0	788	210,084,437	9,217,328
11	Multi Objective	0	0	205	5	500	77	0	5	0	782	202,494,108	9,643,004
12	Multi Objective	0	0	226	5	500	49	0	5	0	775	194,553,240	10,088,338
13	Multi Objective	0	0	248	5	500	20	0	5	0	768	186,245,647	10,554,239
14	Multi Objective	0	0	269	7	486	0	0	7	0	756	179,129,951	11,041,656
15	Multi Objective	0	0	269	18	464	0	0	18	0	733	177,035,446	11,551,583
16	Multi Objective	0	0	269	30	440	0	0	30	0	710	174,844,213	12,085,060
17	Multi Objective	0	0	269	42	416	0	0	42	0	685	172,551,784	12,643,173
18	Multi Objective	0	0	269	55	390	0	0	55	0	659	170,153,485	13,227,062
19	Multi Objective	0	0	269	68	363	0	0	68	0	632	167,644,428	13,837,916
20	Multi Objective	0	0	269	83	335	0	0	83	0	604	165,019,497	14,476,980
21	Multi Objective	0	0	269	97	305	0	0	97	0	575	162,273,342	15,145,558
22	Multi Objective	0	0	269	113	275	0	0	113	0	544	159,400,363	15,845,012
23	Multi Objective	0	0	269	129	242	0	0	129	0	512	156,394,704	16,576,768
24	Multi Objective	0	0	269	146	209	0	0	146	0	478	153,250,237	17,342,319
25	Multi Objective	0	0	269	163	173	0	0	163	0	443	149,960,552	18,143,224
26	Multi Objective	0	0	269	182	136	0	0	182	0	406	146,518,942	18,981,116
27	Multi Objective	0	0	269	201	98	0	0	201	0	367	142,918,392	19,857,705
28	Multi Objective	0	0	269	221	57	0	0	221	0	326	139,151,560	20,774,776
29	Multi Objective	0	0	269	243	15	0	0	243	0	284	135,210,769	21,734,199
30	Multi Objective	0	0	269	248	3	0	0	346	0	174	133,861,620	22,737,931
31	Multi Objective	0	0	269	248	3	0	0	487	0	34	133,523,621	23,788,016
32	Multi Objective	0	8	269	242	3	0	8	511	0	3	133,264,558	24,886,598
33	Multi Objective	0	18	269	232	3	0	18	501	0	3	133,019,913	26,035,914
34	Multi Objective	0	28	269	223	3	0	28	492	0	3	132,763,969	27,238,307
35	Multi Objective	0	39	269	212	3	0	39	482	0	3	132,496,205	28,496,230
36	Multi Objective	0	50	269	202	3	0	50	471	0	3	132,216,075	29,812,247
37	Multi Objective	0	62	269	191	3	0	62	460	0	3	131,923,009	31,189,040
38	Multi Objective	0	75	269	179	3	0	75	448	0	3	131,616,407	32,629,416
39	Multi Objective	0	88	269	167	3	0	88	436	0	3	131,295,647	34,136,311
40	Multi Objective	0	102	269	154	3	0	102	423	0	3	130,960,073	35,712,799
41	Multi Objective	0	116	269	141	3	0	116	410	0	3	130,609,001	37,362,092
42	Multi Objective	0	131	269	127	3	0	131	396	0	3	130,241,716	39,087,553
43	Multi Objective	0	147	269	112	3	0	147	382	0	3	129,857,469	40,892,699
44	Multi Objective	0	163	269	97	3	0	163	366	0	3	129,455,477	42,781,211
45	Multi Objective	0	180	269	81	3	0	180	351	0	3	129,034,920	44,756,938
46	Multi Objective	0	198	269	65	3	0	198	334	0	3	128,594,940	46,823,908
47	Multi Objective	0	217	269	47	3	0	217	316	0	3	128,134,642	48,986,336
48	Multi Objective	0	236	269	29	3	0	236	298	0	3	127,653,086	51,248,629
49	Multi Objective	0	257	269	10	3	0	257	279	0	3	127,149,291	53,615,399
50	Multi Objective	0	269	262	5	3	0	269	5	262	3	126,947,212	56,091,472
51	Economic Single Objective	0	269	262	5	3	0	269	5	262	3	126,947,212	56,091,472

Table 26: Scenario B.2 Results

	Methodology	Diesel_T	LNG_T	BioLNG_T	HVO100_T	Electric_T	Hydrogen_	Diesel_C	HVO100_C	Nitrogen_C	Electric_C	Cost	Emissions
0	Environmental Single Obje	0	0	348	161	25	5	0	248	174	117	135,594,775	21,804,410
1	Multi Objective	0	0	348	161	25	5	0	248	174	117	135,594,775	21,804,410
2	Multi Objective	0	0	348	164	26	0	0	251	174	113	134,300,846	21,960,600
3	Multi Objective	0	0	348	169	16	0	0	256	174	103	133,369,281	22,187,398
4	Multi Objective	0	0	348	173	8	0	0	260	174	95	132,624,028	22,368,837
5	Multi Objective	0	1	348	174	4	0	1	261	174	91	132,207,126	22,570,529
6	Multi Objective	0	2	348	173	4	0	2	260	174	91	132,162,851	22,681,502
7	Multi Objective	0	4	348	172	3	0	4	259	174	90	132,119,491	22,955,392
8	Multi Objective	0	6	348	170	3	0	6	257	174	90	132,030,939	23,177,337
9	Multi Objective	0	8	348	168	3	0	8	255	174	90	131,942,388	23,399,282
10	Multi Objective	0	9	348	167	3	0	9	254	174	90	131,898,112	23,510,255
11	Multi Objective	0	9	348	167	3	0	9	254	174	90	131,898,112	23,510,255
12	Multi Objective	0	13	344	167	3	0	13	253	172	89	131,874,885	24,048,145
13	Multi Objective	0	16	348	160	4	0	16	247	174	91	131,819,686	24,293,648
14	Multi Objective	0	16	348	160	4	0	16	247	174	91	131,819,686	24,293,648
15	Multi Objective	0	19	348	158	3	0	19	245	174	90	131,732,051	24,678,510
16	Multi Objective	0	21	348	156	3	0	21	243	174	90	131,643,499	24,900,456
17	Multi Objective	0	23	348	154	3	0	23	241	174	90	131,554,947	25,122,401
18	Multi Objective	0	23	348	154	3	0	23	241	174	90	131,554,947	25,122,401
19	Multi Objective	0	23	348	154	3	0	23	241	174	90	131,554,947	25,122,401
20	Multi Objective	0	29	348	148	4	0	29	235	174	91	131,520,797	25,794,822
21	Multi Objective	0	30	348	147	4	0	30	234	174	91	131,476,522	25,905,794
22	Multi Objective	0	33	348	145	3	0	33	232	174	90	131,388,886	26,290,657
23	Multi Objective	0	35	348	143	3	0	35	230	174	90	131,300,334	26,512,602
24	Multi Objective	0	37	348	141	3	0	37	228	174	90	131,211,783	26,734,547
25	Multi Objective	0	37	348	141	3	0	37	228	174	90	131,211,783	26,734,547
26	Multi Objective	0	41	344	141	3	0	41	227	172	89	131,188,556	27,272,437
27	Multi Objective	0	44	348	134	4	0	44	221	174	91	131,133,357	27,517,940
28	Multi Objective	0	46	348	133	3	0	46	220	174	90	131,089,997	27,791,831
29	Multi Objective	0	48	348	131	3	0	48	218	174	90	131,001,446	28,013,776
30	Multi Objective	0	50	348	129	3	0	50	216	174	90	130,912,894	28,235,721
31	Multi Objective	0	51	348	128	3	0	51	215	174	90	130,868,618	28,346,693
32	Multi Objective	0	51	348	128	3	0	51	215	174	90	130,868,618	28,346,693
33	Multi Objective	0	57	348	122	4	0	57	209	174	91	130,834,468	29,019,114
34	Multi Objective	0	59	348	121	3	0	59	208	174	90	130,791,109	29,293,004
35	Multi Objective	0	62	348	118	3	0	62	205	174	90	130,658,281	29,625,922
36	Multi Objective	0	64	348	116	3	0	64	203	174	90	130,569,729	29,847,867
37	Multi Objective	0	65	348	115	3	0	65	202	174	90	130,525,454	29,958,840
38	Multi Objective	0	65	348	115	3	0	65	202	174	90	130,525,454	29,958,840
39	Multi Objective	0	72	348	108	4	0	72	195	174	91	130,447,028	30,742,233
40	Multi Objective	0	74	348	107	3	0	74	194	174	90	130,403,668	31,016,123
41	Multi Objective	0	76	348	105	3	0	76	192	174	90	130,315,117	31,238,068
42	Multi Objective	0	79	348	102	3	0	79	189	174	90	130,182,289	31,570,986
43	Multi Objective	0	79	348	102	3	0	79	189	174	90	130,182,289	31,570,986
44	Multi Objective	0	83	344	102	3	0	83	188	172	89	130,159,062	32,108,876
45	Multi Objective	0	86	348	95	4	0	86	182	174	91	130,103,863	32,354,379
46	Multi Objective	0	89	348	93	3	0	89	180	174	90	130,016,228	32,739,242
47	Multi Objective	0	91	348	91	3	0	91	178	174	90	129,927,676	32,961,187
48	Multi Objective	0	93	348	89	3	0	93	176	174	90	129,839,124	33,183,132
49	Multi Objective	0	93	348	89	3	0	93	176	174	90	129,839,124	33,183,132
50	Multi Objective	0	100	348	82	4	0	100	169	174	91	129,760,699	33,966,526
51	Economic Single Objective	0	100	348	82	4	0	100	169	174	91	129,760,699	33,966,526

Table 27: Scenario C.1 Results

	Methodology	Diesel_T	LNG_T	BioLNG_T	HVO100_T	Electric_T	Hydrogen_T	Diesel_C	HVO100_C	Nitrogen_C	Electric_C	Cost	Emissions
0	Environmental Single Obje	0	0	350	158	26	5	0	158	0	381	136,248,191	19,143,040
1	Multi Objective	0	0	350	158	26	5	0	158	0	381	136,248,190	19,143,041
2	Multi Objective	0	0	350	163	23	0	0	163	0	373	134,642,581	19,384,104
3	Multi Objective	0	0	350	169	13	0	0	169	0	363	133,639,954	19,628,203
4	Multi Objective	0	0	350	173	3	0	0	177	0	349	132,729,370	19,875,376
5	Multi Objective	0	0	350	173	3	0	0	211	0	316	132,648,809	20,125,662
6	Multi Objective	0	0	350	173	3	0	0	245	0	282	132,567,233	20,379,099
7	Multi Objective	0	0	350	173	3	0	0	279	0	248	132,484,630	20,635,728
8	Multi Objective	0	0	350	173	3	0	0	314	0	213	132,400,987	20,895,588
9	Multi Objective	0	0	350	173	3	0	0	349	0	178	132,316,291	21,158,721
10	Multi Objective	0	0	350	173	3	0	0	384	0	142	132,230,527	21,425,167
11	Multi Objective	0	0	350	173	3	0	0	420	0	106	132,143,684	21,694,969
12	Multi Objective	0	0	350	173	3	0	0	457	0	70	132,055,748	21,968,168
13	Multi Objective	0	0	350	173	3	0	0	494	0	33	131,966,704	22,244,808
14	Multi Objective	0	1	350	173	3	0	1	523	0	3	131,882,960	22,524,931
15	Multi Objective	0	3	350	171	3	0	3	521	0	3	131,822,581	22,808,582
16	Multi Objective	0	5	350	168	3	0	5	518	0	3	131,761,442	23,095,804
17	Multi Objective	0	8	350	166	3	0	8	516	0	3	131,699,534	23,386,644
18	Multi Objective	0	11	350	164	3	0	11	514	0	3	131,636,846	23,681,146
19	Multi Objective	0	13	350	161	3	0	13	511	0	3	131,573,368	23,979,357
20	Multi Objective	0	16	350	159	3	0	16	509	0	3	131,509,091	24,281,322
21	Multi Objective	0	18	350	156	3	0	18	506	0	3	131,444,004	24,587,091
22	Multi Objective	0	21	350	154	3	0	21	504	0	3	131,378,098	24,896,710
23	Multi Objective	0	24	350	151	3	0	24	501	0	3	131,311,362	25,210,228
24	Multi Objective	0	27	350	149	3	0	27	499	0	3	131,243,786	25,527,694
25	Multi Objective	0	29	350	146	3	0	29	496	0	3	131,175,358	25,849,157
26	Multi Objective	0	32	350	144	3	0	32	494	0	3	131,106,069	26,174,669
27	Multi Objective	0	35	350	141	3	0	35	491	0	3	131,035,908	26,504,280
28	Multi Objective	0	38	350	138	3	0	38	488	0	3	130,964,863	26,838,042
29	Multi Objective	0	41	350	136	3	0	41	486	0	3	130,892,923	27,176,007
30	Multi Objective	0	44	350	133	3	0	44	483	0	3	130,820,077	27,518,227
31	Multi Objective	0	47	350	130	3	0	47	480	0	3	130,746,314	27,864,757
32	Multi Objective	0	50	350	127	3	0	50	477	0	3	130,671,622	28,215,651
33	Multi Objective	0	53	350	124	3	0	53	474	0	3	130,595,990	28,570,963
34	Multi Objective	0	56	350	121	3	0	56	471	0	3	130,519,405	28,930,750
35	Multi Objective	0	59	350	118	3	0	59	468	0	3	130,441,855	29,295,068
36	Multi Objective	0	63	350	115	3	0	63	465	0	3	130,363,329	29,663,973
37	Multi Objective	0	66	350	112	3	0	66	462	0	3	130,283,815	30,037,524
38	Multi Objective	0	69	350	109	3	0	69	459	0	3	130,203,299	30,415,779
39	Multi Objective	0	72	350	106	3	0	72	456	0	3	130,121,769	30,798,797
40	Multi Objective	0	76	350	103	3	0	76	453	0	3	130,039,212	31,186,638
41	Multi Objective	0	79	350	100	3	0	79	450	0	3	129,955,616	31,579,364
42	Multi Objective	0	83	350	97	3	0	83	447	0	3	129,870,967	31,977,035
43	Multi Objective	0	86	350	94	3	0	86	444	0	3	129,785,252	32,379,713
44	Multi Objective	0	90	350	90	3	0	90	440	0	3	129,698,457	32,787,463
45	Multi Objective	0	93	350	87	3	0	93	437	0	3	129,610,570	33,200,347
46	Multi Objective	0	97	350	84	3	0	97	434	0	3	129,521,576	33,618,430
47	Multi Objective	0	101	350	80	3	0	101	430	0	3	129,431,461	34,041,779
48	Multi Objective	0	101	350	80	3	0	101	325	105	3	129,404,893	34,470,458
49	Multi Objective	0	101	350	80	3	0	101	203	227	3	129,387,576	34,904,536
50	Multi Objective	0	101	350	80	3	0	101	80	350	3	129,370,041	35,344,079
51	Economic Single Objective	0	101	350	80	3	0	101	80	350	3	129,370,041	35,344,079

Table 28: Scenario C.2 Results

7.3 Fuel Price Forecast Scenario Cost Structure

LNG Mean Price [€/kg]	0.7221347
LNG per km [kg/km]	0.26

CATEGORY	Annual Cost	Years of Use	Annual KM	Cost per KM
PURCHASE				
Vehicle Purchase	150,000	6	130,000	0.19
Semi-Trailer Purchase	95,000	10	100,000	0.10
FUEL				
LNG				0.19
MAINTENANCE				
Vehicle Maintenance	3,500	0.8	100,000	0.03
Semi-Trailer Maintenance	1,500		100,000	0.02
TIRES				
Tires for Vehicle and Semi-Trailer	5,000		100,000	0.05
ROAD TAXES				
Vehicle Road Tax	2,300		100,000	0.02
Towable Mass Tax	300		100,000	0.00
INSURANCE	8,500		100,000	0.09
DEPRECIATION				
Vehicle Depreciation	150,000	6	100,000	-0.25
Semi-Trailer Depreciation	95,000	10	100,000	-0.10
SALARY				
Base Salary	55,000	1.5	100,000	0.83
Overtime/Night/Holiday	3,500		100,000	0.04
TOLLS	19,000		100,000	0.19
STRUCTURE	8,000		100,000	0.08
FEES	7,000		100,000	0.07
TOTAL				€ 1.53

Table 29: Quantitative scenario cost structure of LNG trucks

BioLNG Mean Price [€/kg]	0.77
BioLNG per km [kg/km]	0.26

CATEGORY	Annual Cost	Years of	Annual	Cost per KM
PURCHASE				
Vehicle Purchase	150,000	6	130,000	0.19
Semi-Trailer Purchase	135,000	10	100,000	0.14
FUEL				
BioLNG				0.20
MAINTENANCE				
Vehicle Maintenance	3,500	0.8	100,000	0.03
Semi-Trailer Maintenance	1,500		100,000	0.02
TIRES				
Tires for Vehicle and Semi-Trailer	5,000		100,000	0.05
ROAD TAXES				
Vehicle Road Tax	2,300		100,000	0.02
Towable Mass Tax	300		100,000	0.00
INSURANCE	8,500		100,000	0.09
DEPRECIATION				
Vehicle Depreciation	150,000	6	100,000	-0.25
Semi-Trailer Depreciation	95,000	10	100,000	-0.10
SALARY				
Base Salary	55,000	1.5	100,000	0.83
Overtime/Night/Holiday	3,500		100,000	0.04
TOLLS	19,000		100,000	0.19
STRUCTURE	8,000		100,000	0.08
FEES	7,000		100,000	0.07
TOTAL				€ 1.59

Table 30: Quantitative scenario cost structure of BioLNG trucks

HVO100 Mean Price [€/lt]	0.43
HVO100 per km [lt/km]	0.26

CATEGORY	Annual Cost	Years of	Annual	Cost per KM
PURCHASE				
Vehicle Purchase	110,000	6	140,000	0.13
Semi-Trailer Purchase	135,000	10	100,000	0.14
FUEL				
HVO100				0.11
MAINTENANCE				
Vehicle Maintenance	3,500	0.8	100,000	0.03
Semi-Trailer Maintenance	1,500		100,000	0.02
TIRES				
Tires for Vehicle and Semi-Trailer	5,000		100,000	0.05
ROAD TAXES				
Vehicle Road Tax	2,500		100,000	0.03
INSURANCE	5,000		100,000	0.05
DEPRECIATION				
Vehicle Depreciation	110,000	6	100,000	-0.18
Semi-Trailer Depreciation	95,000	10	100,000	-0.10
SALARY				
Base Salary	55,000	1.5	100,000	0.83
Overtime/Night/Holiday	3,500		100,000	0.04
TOLLS	19,000		100,000	0.19
STRUCTURE	6,000		100,000	0.06
FEES	7,000		100,000	0.07
TOTAL				**€ 1.45**

Table 31: Quantitative scenario cost structure of HVO100 trucks

Electricity Mean Price [€/kWh]	0.09
Electricity per km [kWh/km]	1.1

CATEGORY	Annual Cost	Years of Use	Annual KM	Cost per KM
PURCHASE				
Vehicle Purchase	400,000	5	70,000	1.14
Semi-Trailer Purchase	135,000	10	70,000	0.19
Incentives	24,000	5	70,000	-0.07
FUEL				
Electricity				0.10
MAINTENANCE				
Vehicle Maintenance	2,450	0.7	70,000	0.02
Semi-Trailer Maintenance	1,500		70,000	0.02
TIRES				
Tires for Vehicle and Semi-Trailer	2,500	2	70,000	0.07
ROAD TAXES				
Vehicle Road Tax	0		70,000	0.00
Towable Mass Tax	0		70,000	0.00
INSURANCE	9,000		70,000	0.13
DEPRECIATION				
Vehicle Depreciation	0	6	70,000	0.00
Semi-Trailer Depreciation	0	10	70,000	0.00
SALARY				
Base Salary	55,000	1.5	70,000	1.18
Overtime/Night/Holiday	2,450		70,000	0.04
TOLLS	13,300		70,000	0.19
STRUCTURE	7,700		70,000	0.11
FEES	13,300		70,000	0.19
TOTAL				**€ 3.32**

Table 32: Quantitative scenario cost structure of Electric trucks

7.4 Alternative Scenarios Results

	Methodology	Diesel Trucks	LNG Trucks	BioLNG Trucks	HVO100 Trucks	Electric Trucks	Hydrogen Trucks	Diesel Coolers	HVO100 Coolers	Nitrogen Coolers	Electric Coolers	Cost	Emissions
0	Environmental Single Objective	0	0	40	1	424	350	0	11	20	784	278,110,913	6,070,857
1	Multi Objective	0	0	40	1	424	350	0	11	20	784	278,110,913	6,070,857
2	Multi Objective	0	0	44	0	497	295	0	11	22	803	270,632,081	6,347,321
3	Multi Objective	0	0	52	1	500	281	0	14	26	794	267,054,706	6,633,086
4	Multi Objective	0	0	64	0	500	267	0	16	32	783	263,168,024	6,922,156
5	Multi Objective	0	0	76	0	499	252	0	19	38	770	258,857,809	7,257,974
6	Multi Objective	0	0	88	0	498	237	0	22	44	757	254,547,594	7,593,792
7	Multi Objective	0	0	100	0	500	220	0	25	50	745	250,023,494	7,938,971
8	Multi Objective	0	0	112	0	498	206	0	28	56	732	245,941,609	8,273,401
9	Multi Objective	0	0	128	0	488	192	0	32	64	712	240,917,236	8,695,270
10	Multi Objective	0	0	140	0	500	168	0	35	70	703	235,523,151	9,069,921
11	Multi Objective	0	0	156	0	496	150	0	39	78	685	230,071,008	9,510,512
12	Multi Objective	0	0	172	0	492	132	0	43	86	667	224,618,865	9,951,103
13	Multi Objective	0	0	188	0	494	110	0	47	94	651	218,738,952	10,410,416
14	Multi Objective	0	0	204	0	500	85	0	51	102	636	212,416,824	10,880,479
15	Multi Objective	0	0	220	1	498	64	0	56	110	617	206,327,262	11,377,179
16	Multi Objective	0	0	240	0	500	38	0	60	120	598	199,272,294	11,897,294
17	Multi Objective	0	0	260	0	500	12	0	65	130	577	192,022,122	12,462,768
18	Multi Objective	0	0	268	7	487	1	0	74	134	555	187,715,744	13,009,943
19	Multi Objective	0	0	268	20	461	1	0	87	134	529	185,178,105	13,599,619
20	Multi Objective	0	0	268	34	433	1	0	101	134	501	182,445,262	14,234,654
21	Multi Objective	0	0	268	49	403	1	0	116	134	471	179,517,217	14,915,049
22	Multi Objective	0	0	268	64	373	1	0	131	134	441	176,589,171	15,595,445
23	Multi Objective	0	0	268	80	341	1	0	147	134	409	173,465,922	16,321,200
24	Multi Objective	0	0	268	96	309	1	0	163	134	377	170,342,674	17,046,955
25	Multi Objective	0	0	268	114	273	1	0	181	134	341	166,829,019	17,863,429
26	Multi Objective	0	0	268	132	237	1	0	199	134	305	163,315,364	18,679,903
27	Multi Objective	0	0	268	151	199	1	0	218	134	267	159,606,507	19,541,737
28	Multi Objective	0	0	268	171	159	1	0	238	134	227	155,702,446	20,448,931
29	Multi Objective	0	0	268	191	119	1	0	258	134	187	151,798,385	21,356,124
30	Multi Objective	0	0	268	213	75	1	0	280	134	143	147,503,918	22,354,038
31	Multi Objective	0	0	268	236	29	1	0	303	134	97	143,014,248	23,397,310
32	Multi Objective	0	3	268	248	1	0	3	315	134	68	139,926,870	24,418,596
33	Multi Objective	0	12	268	240	0	0	12	307	134	67	139,453,110	25,469,295
34	Multi Objective	0	23	268	230	0	0	23	297	134	67	139,106,273	26,748,523
35	Multi Objective	0	33	268	220	1	0	33	287	134	68	138,769,789	27,864,834
36	Multi Objective	0	44	264	214	0	0	44	280	132	66	138,341,854	29,231,478
37	Multi Objective	0	54	268	201	0	0	54	268	134	67	137,891,266	30,305,734
38	Multi Objective	0	68	268	188	0	0	68	255	134	67	137,370,652	31,917,880
39	Multi Objective	0	82	268	175	0	0	82	242	134	67	136,850,037	33,530,026
40	Multi Objective	0	95	268	163	0	0	95	230	134	67	136,387,348	35,031,200
41	Multi Objective	0	109	268	150	0	0	109	217	134	67	135,866,734	36,643,346
42	Multi Objective	0	124	268	136	0	0	124	203	134	67	135,288,193	38,366,465
43	Multi Objective	0	138	268	123	0	0	138	190	134	67	134,767,579	39,978,611
44	Multi Objective	0	152	268	110	0	0	152	177	134	67	134,246,964	41,590,758
45	Multi Objective	0	172	268	91	1	0	172	158	134	68	133,621,570	43,875,325
46	Multi Objective	0	189	268	76	0	0	189	143	134	67	132,974,750	45,872,334
47	Multi Objective	0	208	268	58	0	0	208	125	134	67	132,164,506	48,039,343
48	Multi Objective	0	226	264	45	0	0	226	111	132	66	131,573,864	50,189,380
49	Multi Objective	0	247	268	22	0	0	247	89	134	67	130,776,440	52,542,864
50	Multi Objective	0	268	264	6	0	0	268	72	132	66	130,012,021	55,025,819
51	Economic Single Objective	0	268	264	6	0	0	268	72	132	66	130,012,021	55,025,819

Table 33: Results from HVO100 Scarcity Scenario

	Methodology	Diesel Trucks	LNG Trucks	BioLNG Trucks	HVO100 Trucks	Electric Trucks	Hydrogen Trucks	Diesel Coolers	HVO100 Coolers	Nitrogen Coolers	Electric Coolers	Cost	Emissions
0	Environmental Single Objective	0	0	20	0	463	350	0	5	10	818	386,192,412	5,568,548
1	Multi Objective	0	0	20	0	463	350	0	5	10	818	386,192,412	5,568,548
2	Multi Objective	0	0	24	1	455	349	0	7	12	810	383,246,835	5,709,320
3	Multi Objective	0	0	32	1	440	349	0	9	16	797	378,219,716	5,890,782
4	Multi Objective	0	0	40	1	424	350	0	11	20	784	373,206,797	6,070,857
5	Multi Objective	0	0	48	1	409	350	0	13	24	771	368,179,679	6,252,320
6	Multi Objective	0	0	56	1	394	350	0	15	28	758	363,152,560	6,433,783
7	Multi Objective	0	0	68	0	374	350	0	17	34	741	356,492,710	6,663,910
8	Multi Objective	0	0	76	0	359	350	0	19	38	728	351,465,592	6,845,373
9	Multi Objective	0	0	84	1	342	350	0	22	42	713	345,789,150	7,072,196
10	Multi Objective	0	0	92	1	330	348	0	24	46	701	341,196,641	7,263,020
11	Multi Objective	0	0	104	0	307	350	0	26	52	683	334,102,181	7,483,786
12	Multi Objective	0	0	112	1	290	350	0	29	56	668	328,425,739	7,710,608
13	Multi Objective	0	0	124	0	270	350	0	31	62	651	321,765,889	7,940,735
14	Multi Objective	0	0	136	0	249	349	0	34	68	632	314,442,516	8,217,610
15	Multi Objective	0	0	144	1	232	349	0	37	72	617	308,766,074	8,444,433
16	Multi Objective	0	0	156	1	210	349	0	40	78	598	301,456,902	8,719,920
17	Multi Objective	0	0	168	1	186	350	0	43	84	578	293,698,918	8,987,433
18	Multi Objective	0	0	180	1	164	350	0	46	90	559	286,389,745	9,262,920
19	Multi Objective	0	0	192	1	143	349	0	49	96	540	279,066,372	9,539,795
20	Multi Objective	0	0	204	1	122	348	0	52	102	521	271,742,999	9,816,670
21	Multi Objective	0	0	220	0	93	349	0	55	110	497	262,352,285	10,132,848
22	Multi Objective	0	0	232	0	72	348	0	58	116	478	255,028,912	10,409,723
23	Multi Objective	0	0	244	2	43	350	0	63	122	454	245,986,483	10,766,568
24	Multi Objective	0	0	260	1	18	348	0	66	130	431	237,016,179	11,093,495
25	Multi Objective	0	0	268	4	0	346	0	71	134	413	230,475,700	11,420,398
26	Multi Objective	0	0	268	10	1	337	0	77	134	405	228,304,002	11,731,389
27	Multi Objective	0	0	268	18	0	327	0	85	134	394	225,282,467	12,141,072
28	Multi Objective	0	0	268	25	1	316	0	92	134	384	222,433,045	12,500,199
29	Multi Objective	0	0	268	32	0	307	0	99	134	374	219,612,023	12,856,549
30	Multi Objective	0	0	268	40	1	295	0	107	134	363	216,562,088	13,269,008
31	Multi Objective	0	0	268	48	2	283	0	115	134	352	213,512,152	13,681,468
32	Multi Objective	0	0	268	56	2	272	0	123	134	341	210,476,417	14,092,539
33	Multi Objective	0	0	268	64	0	262	0	131	134	329	206,991,872	14,495,637
34	Multi Objective	0	0	268	73	2	248	0	140	134	317	203,727,224	14,962,817
35	Multi Objective	0	0	268	82	0	237	0	149	134	304	200,042,166	15,419,248
36	Multi Objective	0	0	268	91	2	223	0	158	134	292	196,777,518	15,886,429
37	Multi Objective	0	0	268	100	1	211	0	167	134	279	193,078,259	16,344,248
38	Multi Objective	0	0	268	110	1	197	0	177	134	265	189,164,288	16,856,787
39	Multi Objective	0	0	268	120	1	183	0	187	134	251	185,250,317	17,369,327
40	Multi Objective	0	0	268	130	1	169	0	197	134	237	181,336,345	17,881,867
41	Multi Objective	0	0	268	141	2	153	0	208	134	222	177,207,661	18,449,128
42	Multi Objective	0	0	268	152	0	139	0	219	134	206	172,644,366	19,007,028
43	Multi Objective	0	0	268	163	2	122	0	230	134	191	168,501,482	19,575,676
44	Multi Objective	0	0	268	175	1	106	0	242	134	174	163,723,474	20,188,297
45	Multi Objective	0	0	268	187	0	90	0	254	134	157	158,945,466	20,800,917
46	Multi Objective	0	0	268	199	0	73	0	266	134	140	154,153,259	21,414,926
47	Multi Objective	0	0	268	212	0	55	0	279	134	122	149,160,538	22,082,267
48	Multi Objective	0	0	268	225	1	36	0	292	134	104	144,153,617	22,750,996
49	Multi Objective	0	0	268	239	0	17	0	306	134	84	138,497,373	23,465,085
50	Multi Objective	0	1	268	250	1	0	1	317	134	68	134,356,321	24,196,651
51	Economic Single Objective	0	1	268	250	1	0	1	317	134	68	134,356,321	24,196,651

Table 34: Results from Gas Crisis Scenario

	Methodology	Diesel Trucks	LNG Trucks	BioLNG Trucks	HVO100 Trucks	Electric Trucks	Hydrogen Trucks	Diesel Coolers	HVO100 Coolers	Nitrogen Coolers	Electric Coolers	Cost	Emissions
0	Environmental Single Objective	0	0	20	0	463	350	0	5	10	818	282,290,234	5,568,548
1	Multi Objective	0	0	20	0	463	350	0	5	10	818	282,290,234	5,568,548
2	Multi Objective	0	0	20	1	498	324	0	6	10	827	278,828,977	5,722,433
3	Multi Objective	0	0	28	0	498	315	0	7	14	820	276,298,109	5,897,368
4	Multi Objective	0	0	32	1	500	307	0	9	16	815	274,304,878	6,067,612
5	Multi Objective	0	0	40	0	500	298	0	10	20	808	271,774,009	6,242,547
6	Multi Objective	0	0	48	0	498	289	0	12	24	799	269,047,937	6,462,843
7	Multi Objective	0	0	52	1	500	281	0	14	26	794	267,054,706	6,633,086
8	Multi Objective	0	0	60	1	498	272	0	16	30	785	264,328,634	6,853,382
9	Multi Objective	0	0	68	0	498	263	0	17	34	778	261,797,766	7,028,318
10	Multi Objective	0	0	76	0	499	252	0	19	38	770	258,857,809	7,257,974
11	Multi Objective	0	0	84	0	500	241	0	21	42	762	255,917,853	7,487,631
12	Multi Objective	0	0	92	0	498	232	0	23	46	753	253,191,781	7,707,927
13	Multi Objective	0	0	100	0	500	220	0	25	50	745	250,023,494	7,938,971
14	Multi Objective	0	0	108	1	496	211	0	28	54	734	247,102,220	8,204,627
15	Multi Objective	0	0	116	1	500	198	0	30	58	727	243,948,378	8,443,644
16	Multi Objective	0	0	128	0	491	190	0	32	64	713	240,703,351	8,704,631
17	Multi Objective	0	0	136	0	499	174	0	34	68	707	237,107,295	8,954,398
18	Multi Objective	0	0	144	1	498	163	0	37	72	697	233,972,135	9,229,415
19	Multi Objective	0	0	156	0	499	148	0	39	78	686	229,857,123	9,519,873
20	Multi Objective	0	0	164	1	498	137	0	42	82	676	226,721,964	9,794,889
21	Multi Objective	0	0	176	0	499	122	0	44	88	665	222,606,952	10,085,347
22	Multi Objective	0	0	188	0	497	108	0	47	94	652	218,525,067	10,419,777
23	Multi Objective	0	0	200	0	489	98	0	50	100	637	214,870,951	10,735,485
24	Multi Objective	0	0	208	1	499	79	0	53	104	630	210,637,477	11,041,361
25	Multi Objective	0	0	220	1	498	64	0	56	110	617	206,327,262	11,377,179
26	Multi Objective	0	0	232	1	500	47	0	59	116	605	201,803,162	11,722,358
27	Multi Objective	0	0	248	0	491	34	0	62	124	587	197,202,322	12,097,479
28	Multi Objective	0	0	260	0	500	12	0	65	130	577	192,022,122	12,462,768
29	Multi Objective	0	0	268	3	495	1	0	70	134	563	188,496,557	12,828,504
30	Multi Objective	0	0	268	11	479	1	0	78	134	547	186,934,932	13,191,382
31	Multi Objective	0	0	268	20	461	1	0	87	134	529	185,178,105	13,599,619
32	Multi Objective	0	0	268	29	443	1	0	96	134	511	183,421,278	14,007,856
33	Multi Objective	0	0	268	39	423	1	0	106	134	491	181,469,247	14,461,453
34	Multi Objective	0	0	268	48	405	1	0	115	134	473	179,712,420	14,869,690
35	Multi Objective	0	0	268	58	385	1	0	125	134	453	177,760,389	15,323,287
36	Multi Objective	0	0	268	69	363	1	0	136	134	431	175,613,156	15,822,243
37	Multi Objective	0	0	268	79	343	1	0	146	134	411	173,661,126	16,275,840
38	Multi Objective	0	0	268	90	321	1	0	157	134	389	171,513,892	16,774,796
39	Multi Objective	0	0	268	101	299	1	0	168	134	367	169,366,659	17,273,753
40	Multi Objective	0	0	268	113	275	1	0	180	134	343	167,024,222	17,818,069
41	Multi Objective	0	0	268	125	251	1	0	192	134	319	164,681,786	18,362,385
42	Multi Objective	0	0	268	137	227	1	0	204	134	295	162,339,349	18,906,702
43	Multi Objective	0	0	268	150	201	1	0	217	134	269	159,801,710	19,496,377
44	Multi Objective	0	0	268	163	175	1	0	230	134	243	157,264,070	20,086,053
45	Multi Objective	0	0	268	176	149	1	0	243	134	217	154,726,431	20,675,729
46	Multi Objective	0	0	268	190	121	1	0	257	134	189	151,993,588	21,310,765
47	Multi Objective	0	0	268	204	93	1	0	271	134	161	149,260,746	21,945,800
48	Multi Objective	0	0	268	219	63	1	0	286	134	131	146,332,700	22,626,196
49	Multi Objective	0	0	268	234	33	1	0	301	134	101	143,404,654	23,306,591
50	Multi Objective	0	0	268	250	1	1	0	317	134	69	140,281,406	24,032,346
51	Economic Single Objective	0	0	268	250	1	1	0	317	134	69	140,281,406	24,032,346

Table 35: Results from LNG Ban Scenario

	Methodology	Diesel Trucks	LNG Trucks	BioLNG Trucks	HVO100 Trucks	Electric Trucks	Hydrogen Trucks	Diesel Coolers	HVO100 Coolers	Nitrogen Coolers	Electric Coolers	Cost	Emissions
0	Environmental Single Objective	0	0	40	1	424	350	0	11	20	784	278,110,913	6,070,857
1	Multi Objective	0	0	40	1	424	350	0	11	20	784	278,110,913	6,070,857
2	Multi Objective	0	0	44	0	497	295	0	11	22	803	270,632,081	6,347,321
3	Multi Objective	0	0	52	1	500	281	0	14	26	794	267,054,706	6,633,086
4	Multi Objective	0	0	64	0	500	267	0	16	32	783	263,168,024	6,922,156
5	Multi Objective	0	0	76	0	499	252	0	19	38	770	258,857,809	7,257,974
6	Multi Objective	0	0	88	0	498	237	0	22	44	757	254,547,594	7,593,792
7	Multi Objective	0	0	100	0	500	220	0	25	50	745	250,023,494	7,938,971
8	Multi Objective	0	0	112	0	498	206	0	28	56	732	245,941,609	8,273,401
9	Multi Objective	0	0	128	0	488	192	0	32	64	712	240,917,236	8,695,270
10	Multi Objective	0	0	140	0	500	168	0	35	70	703	235,523,151	9,069,921
11	Multi Objective	0	0	156	0	496	150	0	39	78	685	230,071,008	9,510,512
12	Multi Objective	0	0	172	0	492	132	0	43	86	667	224,618,865	9,951,103
13	Multi Objective	0	0	188	0	494	110	0	47	94	651	218,738,952	10,410,416
14	Multi Objective	0	0	204	0	500	85	0	51	102	636	212,416,824	10,880,479
15	Multi Objective	0	0	220	1	498	64	0	56	110	617	206,327,262	11,377,179
16	Multi Objective	0	0	240	0	500	38	0	60	120	598	199,272,294	11,897,294
17	Multi Objective	0	0	260	0	500	12	0	65	130	577	192,022,122	12,462,768
18	Multi Objective	0	0	268	7	487	1	0	74	134	555	187,715,744	13,009,943
19	Multi Objective	0	0	268	20	461	1	0	87	134	529	185,178,105	13,599,619
20	Multi Objective	0	0	268	34	433	1	0	101	134	501	182,445,262	14,234,654
21	Multi Objective	0	0	268	49	403	1	0	116	134	471	179,517,217	14,915,049
22	Multi Objective	0	0	268	64	373	1	0	131	134	441	176,589,171	15,595,445
23	Multi Objective	0	0	268	80	341	1	0	147	134	409	173,465,922	16,321,200
24	Multi Objective	0	0	268	96	309	1	0	163	134	377	170,342,674	17,046,955
25	Multi Objective	0	0	268	114	273	1	0	181	134	341	166,829,019	17,863,429
26	Multi Objective	0	0	268	132	237	1	0	199	134	305	163,315,364	18,679,903
27	Multi Objective	0	0	268	151	199	1	0	218	134	267	159,606,507	19,541,737
28	Multi Objective	0	0	268	171	159	1	0	238	134	227	155,702,446	20,448,931
29	Multi Objective	0	0	268	191	119	1	0	258	134	187	151,798,385	21,356,124
30	Multi Objective	0	0	268	213	75	1	0	280	134	143	147,503,918	22,354,038
31	Multi Objective	0	0	268	236	29	1	0	303	134	97	143,014,248	23,397,310
32	Multi Objective	0	3	268	248	1	0	3	315	134	68	139,926,870	24,418,596
33	Multi Objective	0	12	268	240	0	0	12	307	134	67	139,453,110	25,469,295
34	Multi Objective	0	23	268	230	0	0	23	297	134	67	139,106,273	26,748,523
35	Multi Objective	0	33	268	220	1	0	33	287	134	68	138,769,789	27,864,834
36	Multi Objective	0	44	264	214	0	0	44	280	132	66	138,341,854	29,231,478
37	Multi Objective	0	54	268	201	0	0	54	268	134	67	137,891,266	30,305,734
38	Multi Objective	0	68	268	188	0	0	68	255	134	67	137,370,652	31,917,880
39	Multi Objective	0	82	268	175	0	0	82	242	134	67	136,850,037	33,530,026
40	Multi Objective	0	95	268	163	0	0	95	230	134	67	136,387,348	35,031,200
41	Multi Objective	0	109	268	150	0	0	109	217	134	67	135,866,734	36,643,346
42	Multi Objective	0	124	268	136	0	0	124	203	134	67	135,288,193	38,366,465
43	Multi Objective	0	138	268	123	0	0	138	190	134	67	134,767,579	39,978,611
44	Multi Objective	0	152	268	110	0	0	152	177	134	67	134,246,964	41,590,758
45	Multi Objective	0	172	268	91	1	0	172	158	134	68	133,621,570	43,875,325
46	Multi Objective	0	189	268	76	0	0	189	143	134	67	132,974,750	45,872,334
47	Multi Objective	0	208	268	58	0	0	208	125	134	67	132,164,506	48,039,343
48	Multi Objective	0	226	264	45	0	0	226	111	132	66	131,573,864	50,189,380
49	Multi Objective	0	247	268	22	0	0	247	89	134	67	130,776,440	52,542,864
50	Multi Objective	0	268	264	6	0	0	268	72	132	66	130,012,021	55,025,819
51	Economic Single Objective	0	268	264	6	0	0	268	72	132	66	130,012,021	55,025,819

Table 36: Results from EU RED II Scenario

7.5 Discussion and Recommendation

Scenario	Diesel Trucks	LNG Trucks	BioLNG Trucks	HVO100 Trucks	Electric Trucks	Hydrogen Trucks	Diesel Coolers	HVO100 Coolers	Nitrogen Coolers	Electric Coolers	Cost	Emissions
A1	0	268	264	6	0	0	268	72	132	66	126,841,321	55,025,819
B1	0	269	256	11	3	0	269	75	128	67	127,245,919	55,227,486
A1	0	246	268	23	0	0	246	90	134	67	127,384,816	52,431,892
B1	0	250	268	17	4	0	250	84	134	71	127,580,338	52,785,063
A1	0	222	268	45	0	0	222	112	134	67	127,894,041	49,651,489
B1	0	229	268	37	3	0	229	104	134	70	128,001,929	50,389,523
A1	0	206	268	60	0	0	206	127	134	67	128,325,758	47,817,398
B1	0	212	268	53	3	0	212	120	134	70	128,477,921	48,444,459
A1	0	187	268	77	1	0	187	144	134	68	128,845,109	45,598,444
B1	0	194	268	69	4	0	194	136	134	71	128,952,997	46,336,477
A1	0	166	268	97	0	0	166	164	134	67	129,266,700	43,202,904
B1	0	173	268	89	3	0	173	156	134	70	129,374,587	43,940,938
A1	0	151	268	111	0	0	151	178	134	67	129,654,140	41,479,785
B1	0	159	268	102	3	0	159	169	134	70	129,717,751	42,328,791

Table 37: Joint results from A.1 and B.1 Scenarios

Scenario	Diesel Trucks	LNG Trucks	BioLNG Trucks	HVO100 Trucks	Electric Trucks	Hydrogen Trucks	Diesel Coolers	HVO100 Coolers	Nitrogen Coolers	Electric Coolers	Cost	Emissions
B2	0	269	262	5	3	0	269	5	262	3	125,003,199	56,091,472
B2	0	257	269	10	3	0	257	279	0	3	125,168,439	53,615,399
B2	0	236	269	29	3	0	236	298	0	3	125,676,104	51,248,629
B2	0	217	269	47	3	0	217	316	0	3	126,161,358	48,986,336
A2	0	269	269	0	0	0	269	0	269	0	126,532,096	56,049,844
B2	0	198	269	65	3	0	198	334	0	3	126,625,191	46,823,908
A2	0	255	269	13	0	0	255	283	0	0	126,922,281	53,436,990
B2	0	180	269	81	3	0	180	351	0	3	127,068,550	44,756,938
A2	0	233	269	33	0	0	233	303	0	0	127,452,531	50,945,938
B2	0	163	269	97	3	0	163	366	0	3	127,492,337	42,781,211
B2	0	147	269	112	3	0	147	382	0	3	127,897,416	40,892,699
A2	0	213	269	53	0	0	213	322	0	0	127,958,062	48,571,011
B2	0	131	269	127	3	0	131	396	0	3	128,284,614	39,087,553
A2	0	193	269	71	0	0	193	340	0	0	128,440,028	46,306,794
B2	0	116	269	141	3	0	116	410	0	3	128,654,719	37,362,092
A2	0	174	269	88	0	0	174	357	0	0	128,899,526	44,148,128
B2	0	102	269	154	3	0	102	423	0	3	129,008,487	35,712,799
A2	0	156	269	105	0	0	156	374	0	0	129,337,603	42,090,092
B2	0	88	269	167	3	0	88	436	0	3	129,346,638	34,136,311
B2	0	75	269	179	3	0	75	448	0	3	129,669,863	32,629,416
A2	0	139	269	121	0	0	139	390	0	0	129,755,259	40,127,994
B2	0	62	269	191	3	0	62	460	0	3	129,978,818	31,189,040

Table 38: Joint results from A.2 and B.2 Scenarios