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Multi-Objective Approaches for Solving Sustainable VRP with Multiple Power Sources and Accident Risk Considerations

Abordagens Multi-objetivo para Resolver VRP Sustentável com Múltiplas Fontes de Energia e Considerações de Risco de Acidente

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Dissertação apresentada a Faculdade de Ciências Aplicadas da Universidade Estadual de Campinas como parte dos requisitos exigidos para a obtenção do título de Mestre em Engenharia de Produção e de Manufatura, na Área de Pesquisa Operacional e Gestão de Processos.

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Resumo

Nesta dissertação, apresentam-se dois estudos derivados de pesquisas realizadas sobre problemas de roteamento de veículos, com foco em abordar preocupações multi-objetivo, incluindo riscos de acidentes, emissões de gases de efeito estufa (GEE) e custos logísticos. No primeiro estudo, foi introduzida uma abordagem para auxiliar na tomada de decisões no planejamento de rotas para uma empresa de transporte rodoviário de carga, com o objetivo de minimizar tanto os custos logísticos quanto os de risco. Dada a escassez de dados sobre acidentes, tornou-se imperativo desenvolver um método analítico baseado em estatísticas básicas e simulação de Monte Carlo para estimar os custos associados aos riscos de acidentes. Em seguida, foi selecionada uma abordagem bi-objetiva baseada nos métodos PROMETHEE II e método ϵ-restrito para lidar com os objetivos conflitantes inerentes a este problema de roteamento de veículos. Os resultados destacaram a eficácia das abordagens estatísticas e multi-objetivo na exploração dos trade-offs entre os custos logísticos e de risco em um cenário real de roteamento de veículos. Por fim, como uma sequência do primeiro, no segundo estudo, além de abordar riscos de acidentes e custos logísticos, foi introduzido o objetivo de minimizar as emissões de CO_2 , tornando o VRP tri-objetivo. Também explorou-se a consideração de uma frota heterogênea composta por veículos pesados movidos a diesel, gás natural comprimido e eletricidade, uma característica que foi relativamente pouco explorada na literatura. Neste cenário, o método Augmented Weighted Tchebycheff foi empregado para lidar com a natureza multi-objetiva do problema, enquanto uma heurística de algoritmo genético aprimorada foi utilizada para gerar soluções viáveis como incumbentes do processo de otimização exata. Os resultados revelaram que os veículos a diesel são mais economicamente viáveis; no entanto, os caminhões elétricos foram preferidos em cenários que priorizam preocupações ambientais, alcançando aproximadamente uma redução de 90% nas emissões de CO_2 . Contudo, resultaram em um aumento de 35% nos custos logísticos quando comparados a maneira tradicional de VRP que otimiza somente a dimensão econômica. As principais contribuições dessa dissertação foram o desenvolvimento de uma abordagem que resolveu instâncias do mundo real e facilitou a tomada de decisões no planejamento de rotas, considerando diversos objetivos conflitantes associados a dimensões de sustentabilidade como fatores ambientais, sociais e econômicos. Além disso, as abordagens demonstraram-se úteis e simples na geração de soluções apenas ajustando os pesos da função objetivo, possibilitando sua aplicação em diversos cenários.

Palavras-chave: VRP sustentável. Multi-Objetivo. Simulação de Monte Carlo. Risco de acidente.

Abstract

In this dissertation, two studies are presented stemming from research conducted on vehicle routing problems, with a focus on addressing multi-objective concerns including accident risks, greenhouse gas (GHG) emissions, and logistic costs. In the first study, an approach was introduced to aid decision-making in route planning for a road freight company, with the objective of minimizing both logistic and risk costs. Given the dearth of accident data, it became imperative to devise an analytical method rooted in basic statistics and Monte Carlo simulation to estimate the costs associated with accident risks. Then, a bi-objective approach based on PROMETHEE II and the ϵ-constrained method were selected to address the conflicting objectives inherent in this vehicle routing problem. The findings underscored the effectiveness of statistical and multi-objective approaches in exploring the trade-offs between logistic and risk costs in a real-world vehicle routing scenario. Finally, as a continuation of the first study, in the second study, in addition to addressing accident risks and logistical costs, the objective of minimizing CO_2 emissions was introduced, making the tri-objective VRP. This second study also delved into the consideration of a heterogeneous fleet consisting of heavy-duty vehicles powered by Diesel, Compressed Natural Gas, and electricity characteristic that has been relatively under explored in the literature. In this scenario, the *Augmented Weighted Tchebycheff* method was employed to address the multi-objective nature of the problem, while an enhanced genetic algorithm heuristic was utilized to generate feasible solutions as a precursor to the exact optimization process. The results revealed that Diesel vehicles are more economically viable; however, electricity-powered trucks were favored in scenarios prioritizing environmental concerns, achieving approximately a 90% reduction in CO_2 emissions. Nonetheless, this choice resulted in a 35% increase in logistics costs, when compared to the tradicional way of VRP that optimizes only the economic dimension. The primary contributions of this dissertation were the development of an approach that addressed real-world instances and facilitated decision-making in route planning, considering various conflicting objectives associated with sustainability dimensions such as environmental, social, and economic factors. Furthermore, the approaches demonstrated utility and simplicity in generating solutions merely by adjusting the weights of the objective function, enabling their application across diverse scenarios.

Keywords: Sustainable VRP. Multi-objective. Monte Carlo simulation. Accident risk.

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1 Introduction

Finding processes that ensure the needs of contemporary society, considering not only economic factors but also environmental and social aspects, is crucial to guarantee a safer world for future generations, while mitigating socio-environmental disasters resulting from human intervention.

According to the Sistema de Estimativas de Emissões e Remoções de Gases de Efeito Estufa (SEEG, 2021), Brazil was responsible for emitting approximately 2.4 billion tons of CO_2 in 2021, marking an increase of 8% compared to pre-pandemic levels in 2019, with the road freight sector accounting for 8.5% of Brazil's total CO_2 emissions, making it the third most polluting sector.

While in the social dimension, according to the World Health Organization (WHO), the costs of road accidents can reach up to 3% of a country's Gross Domestic Product (GDP), and deaths caused by traffic accidents are listed as the eighth leading cause of death worldwide.

In Brazil, according to a report from the Confederação Nacional de Transportes (CNT, 2022), there were 64,447 traffic accidents in 2022 solely on roads managed by federal agencies, with 52,948 of these accidents resulting in deaths or injuries, leading to an estimated total cost of 13 billion reais.

Given the absence of available data, it is likely that the figures provided for traffic accidents are even higher. Accidents occurring on roads managed by the states and within municipalities have not yet been taken into account, suggesting that the actual numbers could be significantly higher.

Therefore, there is significant pressure for efficient processes ensuring uninterrupted supply chain flow while minimizing negative socio-environmental impacts. It is essential for road freight companies to integrate socio-environmental considerations alongside economic factors in their decision-making process to plan routes.

In this dissertation, two studies were presented in the area of multi-objective Vehicle Routing Problems (VRP), with a focus on minimizing economic, social, and environmental impacts. The first study considered real instances obtained from a road freight company located in the state of São Paulo, Brazil, that wishes to optimize not only logistic costs but also the accidents risks (bi-objective VRP), as some loads can have high shipment commercial values, causing significant financial losses if an accident occurs.

As this study considered real instances and was concerned with seeking real data, a basic statistical approach and Monte Carlo simulation to estimate the risk costs of each arc proved necessary due to the limited data available on traffic accidents. Real instances known to the authors were proposed to compare the results obtained from the developed approach with those expected from reality. The primary data sources, freely accessible from government agencies, include the Confederação Nacional de Transportes (CNT, 2019), the Departamento de Estradas e Rodagem do Estado de São Paulo (DER-SP, 2021), and the Departamento Nacional de Infraestrutura e Transportes (DNIT, 2021).

Subsequently, the Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) II and ϵ-constrained methods were employed to address a bi-objective VRP, incorporating logistics costs and risks. Finally, the approach to estimate the risk cost proved to be coherent with what was expected from reality, and the Pareto-optimal solutions of the bi-objective model represent a consistent trade-off between logistic cost and accident risk, providing different results to the decision-maker. This initial study is detailed in Chapter 2.

As a continuation of the first study, the second study, detailed in Chapter 3, incorporated the environmental dimension resulting in a tri-objective VRP aimed at optimizing logistic costs, accident risks, and CO_2 emissions. The same approach used in Chapter 2 to estimate the risk was implemented in study of Chapter 3, and we also focused on working with a real instance, which was larger than the first. For this, we chose a large retail chain (Magazine Luiza) whose depot and stores are located in cities in the macro-region of Campinas, state of São Paulo, Brazil. A heterogeneous fleet was considered, including heavy-duty vehicles powered by diesel, Compressed Natural Gas (CNG), and electricity, each with varying costs, fuel consumption, and CO_2 emissions.

A scalarization method that would best handle a tri-objective problem was desired, and the objectives are weighted by easily adjustable parameters to generate various solutions, which decision-makers can evaluate to determine the ones most suitable for their process. Therefore, the multi-objective approach utilized in the second study was the *Augmented Weighted Tchebycheff* method, complemented by the insertion of an enhanced Genetic Algorithm heuristic to generate viable solutions for initializing the exact method, which struggles to find good initial feasible solutions.

The results of Chapter 3 indicated that electric trucks were the most selected in most scenarios, being less common only in scenarios where minimizing logistics costs was highly preferred. Compared to a traditional VRP, which minimizes only the economic dimension, significant reductions in CO_2 emissions and accident risks were achieved when the environmental and social dimension were highly preferred, respectively, causing a significant increase in logistic costs.

Finally, the main contribution of these studies was the implementation of multi-objective techniques to a VRP that could be applied to real instances of a road freight company, aiming to minimize not only logistic costs but also accident risks and CO_2 emissions. Important definitions of the techniques used in these studies are described to better guide the reader.

1.1 Multi-objective optimization

The multi-objective optimization problem is presented as follow:

$$\begin{aligned} &\textit{minimize} \quad \mathbf{z} = \{f_1(\mathbf{x}), f_2(\mathbf{x}), f_3(\mathbf{x}), ..., f_m(\mathbf{x})\} \\ &\textit{subject to}: \ \mathbf{x} \in S \end{aligned} \tag{1.1}$$

Where $f_m(\mathbf{x})$ represents each objective function m for $m \geqslant 2$ in which we want to optimize simultaneously, and the objective vector is $\mathbf{z}$. The variable vector $\mathbf{x} = (x_1, x_2, x_3, \ldots, x_m)^T$ belongs to a decision feasible space (S) and the objective vector $\mathbf{z}$ belongs to a objective feasible space (Z), as described in Figure 1 (MIETTINEN, 1998).

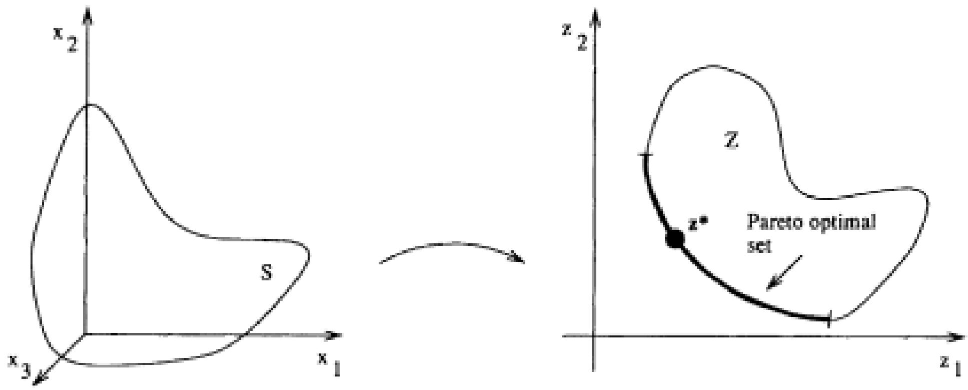


Figure 1 – The set S representing the decision feasible space (left), and the set Z representing the objective feasible space (right) (MIETTINEN, 1998).

$f_m(\mathbf{x})^I$ represents the ideal (minimum) solution when the objective m is minimized in a single-objective optimization. This concept is important because, in multi-objective problems, the objective functions $f_m(\mathbf{x})$ are often conflicting, e.g., if we prioritize the minimization of $f_1(\mathbf{x})$, we will achieve the smallest difference between $f_1(\mathbf{x})$ and $f_1(\mathbf{x})^I$. However, this will penalize $f_2(\mathbf{x})$ increasing the difference between $f_2(\mathbf{x})$ and $f_2(\mathbf{x})^I$, thus illustrating the conflict between the objectives $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$.

In contrast to single-objective optimizations, which generate only one optimal solution, multi-objective optimizations can generate a set of various optimal solutions, commonly called the Pareto optimal set or Pareto optimal frontier, as described in Figure 1. Thus, we are more interested in analyzing the feasible objective space Z over the feasible decision space S.

The Pareto frontier is composed of optimal objective vectors $\mathbf{z}^*$, where no component of this vector can be improved. In other words, for $\mathbf{z}^* \in Z$, $\mathbf{z}^*$ must be better than or equal to all objectives of another vector $\mathbf{z}$ such that $\mathbf{z}^* \leqslant \mathbf{z}$ and strictly better in at least one objective m where $f_m(\mathbf{x}^*) < f_m(\mathbf{x})$. Meeting these conditions, we can then say that $\mathbf{z}^*$ is a *non-dominated* vector, a very common term in the multi-objective optimization to express that $\mathbf{z}^*$ is a Pareto optimal solution.

There are several methods that deal with multi-objective optimization problems. The most common methods include the weighted method, the ϵ-constrained method, the weighted Tchebycheff method, and the augmented weighted Tchebycheff method.

Generally, these methods are classified as a posteriori, a priori, and interactive. In a posteriori methods, the entire Pareto optimal set is generated and then presented to the decision-maker, who selects the most preferred solution from the alternatives. In a priori methods, the decision-maker must specify their preferences before generating solutions, meaning the decision-maker participates in the search for solutions before the problem is solved. Finally, the interative methods in multi-objective optimization provide a structured way to incorporate decision-maker preferences progressively.

In conclusion, multi-objective optimization is an effective approach for solving problems with multiple conflicting objectives. In this dissertation, multi-objective optimization techniques were crucial in providing a set of Pareto optimal solutions. These solutions enable decision-makers to understand the trade-offs between economic factors, accident risks, and environmental dimensions, allowing them to make informed decisions based on their preferences.

1.2 Monte Carlo simulation

Monte Carlo simulation is a powerful computational technique used to estimate possible outcomes of uncertain events using random numbers. These random numbers are akin to those generated by a roulette wheel, similar to those found in the casinos of Monte Carlo, from which the method derives its name (ZIO, 2013).

Monte Carlo simulation involves generating random numbers from a probability distribution to make estimates, e.g, in this dissertation, we aim to estimate risk costs. This process typically includes the following steps: defining the probabilistic model, generating input random values according to their probability distribution functions, running the simulation for N iterations, estimating the mean value after N iterations, and analyzing the results to draw conclusions.(CRUSE, 1997).

One of the advantages of Monte Carlo simulation is that it relies on the principles of probability and statistical inference, making it particularly useful in fields where deterministic approaches are impossible due to the stochastic nature of the systems being studied. However, depending on the desired level of accuracy, the computational time to generate the results can be significantly high (ZIO, 2013).

Finally, Monte Carlo method proves to be an important technique for solving problems of a probabilistic nature. Thus, for this dissertation, Monte Carlo method was necessary to handle the input data on accident risks, which are inherently probabilistic, and to generate the output risk costs that could be used in a deterministic problem.

2 Bi-objective approaches to deal with accident risk and logistic costs in vehicle routing problems.

Vehicle Routing Problems (VRP) have been widely researched throughout history as a way of optimising routes by minimising distances and planning deliveries efficiently, but the issue of risk in VRP has received less attention over time. This is essential to increasing transport safety to avoid interruptions in supply chains and improve delivery reliability. Therefore, this first study aims to support decision makers to plan routes for road freight companies considering not only the logistics cost, but also travel safety due to road hazards. An analytical approach based on statistics was developed in which data of vehicle accidents and road features were used to estimate the risk cost by using the Monte Carlo simulation. A bi-objective approach based on PROMETHEE II and ϵ-constrained methods were used in the Capacitated Vehicle Routing Problem (CVRP) to analyse the conflict between the logistic cost and accident risk. Key contributions of this study are an analytical approach based on statistics, Monte Carlo simulation and multi-objective methods in a CVRP model to explore the trade-off between logistic costs and accident risk expressed by a risk cost. The outcomes of the first study show to be useful in practice to analyze transportation decisions in the VRP model involving route planning considering accident risk.

2.1 Introduction

In an increasingly globalised and connected world in which the population and urbanisation increase every year, the pressure for more efficient, sustainable and safe road freight has risen due to the greater demand for different types of products. Road freight plays a fundamental role in global logistics due to the flexibility of the infrastructure that this segment of transport offers, allowing a door-to-door service, which is not possible in maritime, air and rail transportation modes (ENGSTRÖM, 2016).

On the other hand, the reliability in road freight depends on some elements that can be the cause of many accidents, interrupting the supply chain and generating significant losses. According to data from the World Health Organization (WHO), road accidents cost on average around 3% of the Gross Domestic Product (GDP) of a country and lead to the death of 1.35 million people, and is the eighth leading cause of death all around the world.

Thus, reducing the accident rate of road freight is an important factor from a strategic and sustainable point of view, which aims to ensure logistical and economical development. When an accident occurs, financial losses can lead to large financial proportions, in addition to causing interruptions in the supply chain. From this point, the need to reduce losses in road transportation can be highlighted (ENGSTRÖM, 2016).

When a route is chosen for a vehicle that will leave a depot to deliver goods to other locations, not only the logistic costs and the distance should be considered, but also some route hazard measures should be added. Most of the VRP studies consider only the logistic cost in the models to solve the routing problem. Recently risk measurement was addressed in cash-in-transit problems through the VRP, which consisted of a model that aimed to minimise the distances travelled with the restriction that the risk value of robberies of heavy trucks during the transportation of money was limited by a risk threshold (TALARICO; SÖRENSEN; SPRINGAEL, 2015). More recently the route safety was also discussed in studies on hazardous materials transportation such as fuel, flammable materials, gases and others, aiming to reduce social and environmental impacts and increase transport safety by minimising the risk factor (HOLECZEK, 2021).

Despite the fact that the VRP has been widely studied throughout its sixty-year history, few studies have addressed different types of risk in the problem. As mentioned, some research has emerged in the areas of cash-in-transit and hazardous materials, but they did not consider accident risk due to road conditions in the models. This is likely because in most cases real data is difficult to find and a methodology to estimate the risks should be developed.

Therefore, verifying the applications of the subject risk in VRP and considering the lack of studies that address the accident risk due to characteristics of the routes (infrastructure, traffic etc.), this study intends to contribute to filling this gap by developing an analytical approach based on simple statistical calculations coupled with two multi-criteria methods in a CVRP model to analyse the trade-off between the logistics cost and accident risk measured by cost. The Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) II and the ϵ-constrained methods were selected to solve this conflicting bi-objective problem. Finally, the statistical approach to estimate risk cost was validated with experts in cargo insurance and the obtained solutions were interpreted knowing the characteristics of the roads well in the tested instance, indicating that the outcomes were compatible with those expected.

This study is organized in four sections, besides this introduction. Section 2.2 reviews and discusses key studies which address risks in VRP. In Section 2.3, the proposed analytical approach is presented in detail. Finally, the results (Section 2.4) are presented through the experimental studies and the conclusion is drawn in Section 2.5.

2.2 Literature related to risk in VRP

VRP have been extensively studied throughout their history to support real-life applications. Risk and travel safety in VRP have received greater attention in applications for road freight of hazardous materials, whose risk is associated with socio-environmental damage, and cash-in-transit, which is related to cargo theft (TALARICO et al., 2017).

Erkut & Ingolfsson (2005) cited eight risk models that were developed for the optimisation of hazardous materials transportation, whose three main ones are presented in Table 1. Considering a path r as a set of links $\{i_1, i_2, ..., i_n\}$, the first risk model IP_r is calculated through the probability of the undesirable occurrence event of each link p_i, while the second PE_r considers only the number of people exposed to risk D_i. In the traditional model, risk TR_r is a product between the probability of the undesirable event p_i and its measure of consequence C_i.

Table 1 – Risk assessment models. Adapted from Erkut & Ingolfsson (2005).

Model	**Equation**	
Incident Probability	$IP_r = \sum_{i \in r} p_i$	p_i = accident probability
Population Exposure	$PE_r = \sum_{i \in r} D_i$	D_i = population exposure
Traditional Risk	$TR_r = \sum_{i \in r} p_i.C_i$	p_i = accident probability C_i = measure of the consequence

To investigate the behaviour of these three risk models in VRP, Holeczek (2021) used mono-objective functions that minimise distance, accident risk and population exposure.

The results showed that the Traditional Risk TR_r generated the lowest total risk value when compared to the other models, however when considering the total distance obtained for the TR_r, the greatest deviation in relation to the minimum total distance can be observed.

The Incident Probability IP_r offers the best trade-off with an economical goal and it is most appropriate for problems where the consequences are uncertain. Regarding the Population Exposed PE_r, the data are more easily acquired and the results are evaluated more intuitively by the decision maker, but it can only be applied to problems that consider urban areas, because for an environment, such as rural areas, other factors must be considered.

The elements of each model such as accident probability, consequences, number of people exposed and others, are defined according to the case being studied. Androutsopoulos & Zografos (2012) and Carrese et al. (2022), for example, studied risks in hazardous materials transportation and they considered that the undesirable event would be the road accident whose consequence is related to the number of people exposed to risk. On the other hand, Talarico, Sörensen & Springael (2015) applied the risk in the *cash-in-transit* routing problem that they considered the probability of a robbery is proportional to the distance of the route and, as a consequence, the amount of cash transported in the truck.

In addition to those elements, the models also vary according to the risk approach used in VRP. Thus, Table 2 shows some key features in the risk calculations used by the authors.

Du et al. (2017), Pradhananga et al. (2014) and Wang et al. (2018) applied the concept of the traditional model, as proposed by Erkut & Ingolfsson (2005), in which the probability of an accident was used as an undesirable event and the exposed population as a consequence. Androutsopoulos & Zografos (2012) and Holeczek (2021) applied the traditional definition, however it was considered as *load dependent*, that is, the amount of load factor is added to the model and varies as deliveries are made. Carrese et al. (2022) was also addressed the traditional risk model, but two other factors that interfere in the driver's attention are added to the objective function: the Altimetric Index and the Planimetric Index. The first considers the ground elevations along the route while the second is introduced to take into account geometrical constraints related to the road radius.

Bula et al. (2016) and Bula et al. (2019) also use the traditional risk which comprises the probability of an undesirable event p_i and population exposure as the measure of consequence C_i. They consider several aspects that play an important role in determining the likelihood of an undesirable occurrence. Therefore, the p_i is combined as a result of: accident probability related to the type of truck, probability of hazardous materials released in case of an accident, parameters that represent the characteristics of the materials and the amount of cargo carried, and also the length of arc in the route.

Chai et al. (2023) argue that many studies consider only issues such as accident probabilities, the population exposed and consequences for the environment, but it is also important to consider the driver's behavior as a main cause of accidents.

Thereby, Chai et al. (2023) introduce the driver's behavior as a factor that also influences the risk of accidents in the transport of hazardous materials. Some aspects that impact the driver risk were considered, such as: age, driving experience, educational background, gender, driving speed and driving habits.

As a variation of hazardous materials models, the *cash-in-transit* ones arise. Talarico, Sörensen & Springael (2015) and Talarico et al. (2017) proposed the traditional method to calculate the risk of robbery. As already mentioned, they considered the consequence as equivalent to the amount of value being transported. Ghannadpour & Zandiyeh (2020) also assumed the consequence as the same manner and the distance travelled is proportional to the risk of theft, but added to the model a factor relative to the frequency of using the same route and the ambushing probabilities to the vehicle and its success. The authors also state that the probability of a robber attack was estimated using game theory and a model minimizes the risk of cash-in-transit developed using multi-criteria decision-making approaches.

Talarico, Sörensen & Springael (2015) and Bula et al. (2016) used a mono-objective function in which the first authors minimised the distances and the second the accident risk. Androutsopoulos & Zografos (2012), Bula et al. (2019), Pradhananga et al. (2014), Ghannadpour & Zandiyeh (2020) and Wang et al. (2018) suggested bi-objective functions that analyse both logistics costs or distances and risks. Multi-objectives are presented by Carrese et al. (2022) and Zheng (2010) whereby the last one aimed to minimise the distance, weighted the risk by the traditional method (probability of accident and a consequence) adding the number of people exposed.

Milovanović (2012) developed a methodology to calculate road accident risks when transporting hazardous materials, which considers some elements that influence the accident probability, as well as elements that influence their consequences. These elements were measured from indirect interviews in which experts obtained numerical risk results for each route through this analysis. On the other hand, it did not use mathematical models of VRP to optimise routes and it did not consider statistical analysis.

Generally, the risk factor is analysed as an objective to be minimised, however Talarico, Sörensen & Springael (2015) considered it as a constraint in which the risk value is defined by a risk threshold and classified as the *Risk constrained Cash-in-Transit Vehicle Routing Problem (RCTVRP)*. Wang et al. (2018) restricted the condition that no vehicles of the same fleet should travel in echelon because when there are two or more vehicles using the same route at the same time, the consequences are considered to be greater whether or not an accident occurs between them.

Table 2 – Characteristics of risks in VRP studies.

Authors	Case Studied	VRP type	Objective Function	Risk Approach	Real data
Androutsopoulos & Zografos (2012)	Hazardous Materials	Vehicle Routing Problem with Time Windows	Travel time dependent and Implied hazard/risk related	accident probability * population exposure * load amount	No
Bula et al. (2016)	Hazardous Materials	Homogeneous Vehicle Routing Problem	Implied hazard/risk related	accident probability related to truck type * release probability * load characteristics * route length * load amount population exposure	No
Bula et al. (2019)	Hazardous Materials	Homogeneous Vehicle Routing Problem	Distance dependent and Implied hazard/risk related	accident probability related to truck type * release probability * route length * load characteristics * load amount * population exposure	No
Carrese et al. (2022)	Hazardous Materials	Vehicle Routing Problem with Time Windows	Travel time dependent and Implied hazard/risk related	accident probability * population exposure + altimetric index + planimetric index	Yes
Du et al. (2017)	Hazardous Materials	Multi-depot Vehicle Routing Problem	Implied hazard/risk related	accident probability * population exposure	Yes
Ghannadpour & Zandiyeh (2020)	Cash-in-Transit	Vehicle Routing Problem with Time Windows	Distance dependent and Implied hazard/risk related	robbery attack probability * theft success probability * route length * load amount * frequency of repeated use of a route	No
Holeczek (2021)	Hazardous Materials	Capacitated Vehicle Routing Problem	Distance dependent and Implied hazard/risk related	accident probability * population exposure * load amount	Yes
Pradhananga et al. (2014)	Hazardous Materials	Vehicle Routing Problem with Time Windows	Travel time dependent and Implied hazard/risk related	accident probability * population exposure	Yes
Talarico, Sörensen & Springael (2015)	Cash-in-Transit	Risk constrained Cash-in-Transit Vehicle Routing Problem	Distance dependent	arc length * load amount	No
Talarico et al. (2017)	Cash-in-Transit	Risk constrained Cash-in-Transit Vehicle Routing Problem	Distance dependent	arc length * load amount	No
Wang et al. (2018)	Hazardous Materials	Vehicle Routing Problem with Time Windows	Distance dependent and Implied hazard/risk related	accident probability * population exposure	No
Zheng (2010)	Hazardous Materials	Capacitated Vehicle Routing Problem	Distance dependent, Implied hazard/risk related and Others	accident probability * consequence + population exposure	No
Chai et al. (2023)	Hazardous Materials	Vehicle Routing Problem with Soft Time Window for Hazardous Materials	Distance dependent and Implied hazard/risk related	accident probability * population exposure * driving risk * load amount * arc length	Yes
This study	**Indistinct load type**	**Capacitated Vehicle Routing Problem**	**Distance dependent and Implied hazard/risk related**	**accident probability, road infrastructure and traffic, load value**	**Yes**

For risk measurement, some studies addressed how the data were explored, and according to Du et al. (2017), real historical data from accidents should be integrated and resort to big data in terms of formulating models to transport hazardous materials. Moreover, Talarico, Sörensen & Springael (2015) mention that there is lack of data available and Androutsopoulos & Zografos (2012) indicate there is no data exploration related to risk measurement due to its complexity and also states that future studies should deal with this issue.

Pradhananga et al. (2014) estimated accident rates using data collected from the *Institute for Traffic Accident Research and Data Analysis* (ITARDA) and the *Ministry of Land, Infrastructure, Transport and Tourism* (MLIT), both from Japan. For a future study, Pradhananga et al. (2014) proposed extensions of the model considering such characteristics for the hazardous materials routing problem using real-time traffic information and the effects of infrastructural characteristics of the road network.

Carrese et al. (2022) calculated the road accident probability using data obtained by the mobility agency in Rome, quantified population density through a *census data* and measured the infrastructure through the *Google Application Programming Interface (API).*

Although some studies still try to deal with using real data in their problems, the probabilistic view in data analysis is not addressed in more depth. This study aims to use the probabilistic approach of the accident occurrences in the model. Table 2 summarises the problem features such as the VRP type, objective function and real world-data with a VRP taxonomic discussed in Braekers, Ramaekers & Van Nieuwenhuyse (2016). It can be observed that the studies are concentrated in only two areas: hazardous materials and cash-in-transit. Regarding other segments of transport, there are few studies that take into account risks in VRP despite its importance as a result of damage when an accident occurs.

2.3 Analytical approach

In this section, a detailed description with an illustration of the workflow to apply the analytical approach is provided (Figure 2). Firstly, the parameters, variables and constraints of the model representing the Capacitated Vehicle Routing Problem (CVRP) were defined and the logistic costs (c_{ij}) were calculated by the online tool qualp, which considers fuel expenses, based on the vehicle's consumption, and tolls along the road if applicable.

The accident probability ($Paccident_{ij}$) was generated by a statistical calculation that considers historical records from Brazilian government agencies whose information is publicly available on the web and from a load insurance company. Among the government agencies, there are: the National Transport Confederation (CNT, 2019), the Department of Roads and Highways of the State of Sao Paulo (DER-SP, 2021) and the National Department of Transport Infrastructure (DNIT, 2021). Some characteristics that interfere in the accident probabilities were extracted by Milovanović (2012) and all collected and processed data used in this study is available at github.

The data were processed using the *Knime Analytic Platform* tool, which generated the accident probabilities for each arc. Then, from the probability results, the Monte Carlo simulation was implemented to obtain the risk costs (r_{ij}).

Two different methods were performed to deal with the bi-objective problem, e.g., the Preference Ranking Optimization Method for Enrichment Evaluation (PROMETHEE II) and the ϵ-constrained method. The CVRP and these two methods were implemented using *Python*, and the results were obtained by *Gurobi Optimization*.

The results from PROMETHEE II and ϵ-constrained methods were compared and analysed. The method used to calculate the r_{ij} will be explained and how the PROMETHEE II and ϵ-constrained method were used in the CVRP.

2.3.1 Calculating the accident risk cost

As already mentioned, the risk cost r_{ij} was generated for each arc connecting location i to location j. A location can be a city or centroid, for example. The arc (ij) may have more than one distinguished roads.

These calculations were performed by using the *Knime Analytics Platform*, according to the workflows represented in Figures 3, 4 and 5 and Equations (2.1) until (2.9). This approach to estimate r_{ij} was necessary particularly because there are little data available referring to road accidents.

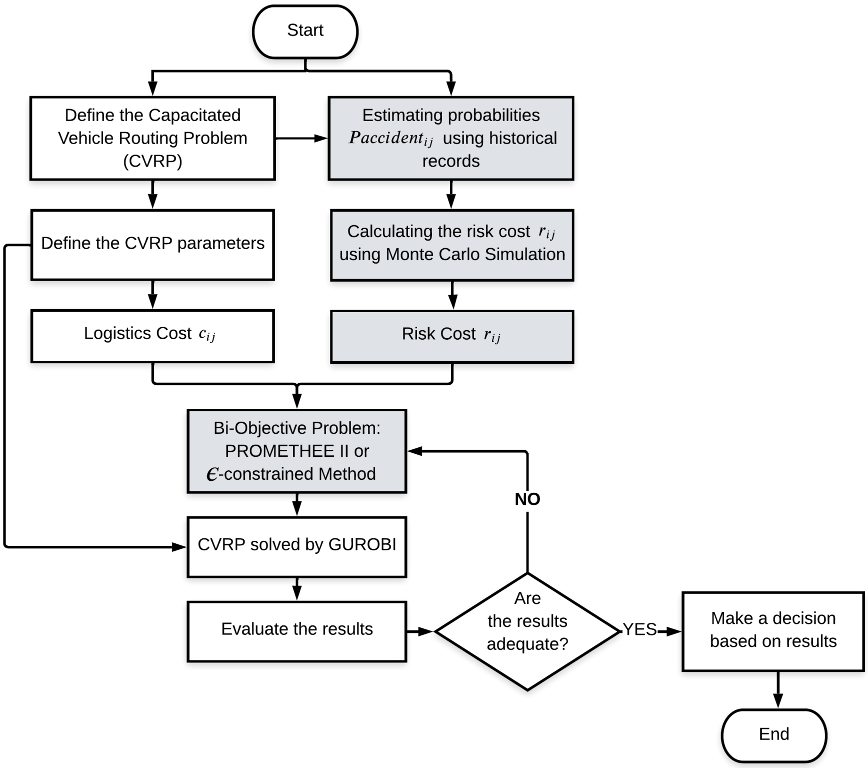


Figure 2 – Workflow of the analytical approach in this study.

A general probability of accidents ($Pgeneral$) occurring on any road in Brazil according to the workflow shown in Figure 3 was estimated. Data collected from DER-SP (2021) indicate the flow of all vehicles V_{sp} and heavy vehicles HV_{sp} in the State of Sao Paulo (sp). They were used to calculate the share of heavy vehicles P_{sp} that circulates in the roads of Sao Paulo State by Equation (2.1).

For the sake of simplicity and lack of specific data, it is assumed that P_{sp} is the same for all Brazilian Federal roads, therefore in Equation (2.2) the flow of heavy vehicles (HV) is calculated using the flow of all vehicles in Federal roads (V_{br}) – data extracted from DNIT (2021). Finally, $Pgeneral$ was generated by Equation (2.3) from the number of accidents in Brazilians' Federal roads ($N_{accidents}$), collected from CNT (2019), and HV from Equation (2.2).

$$P_{sp} = HV_{sp}/V_{sp} \tag{2.1}$$

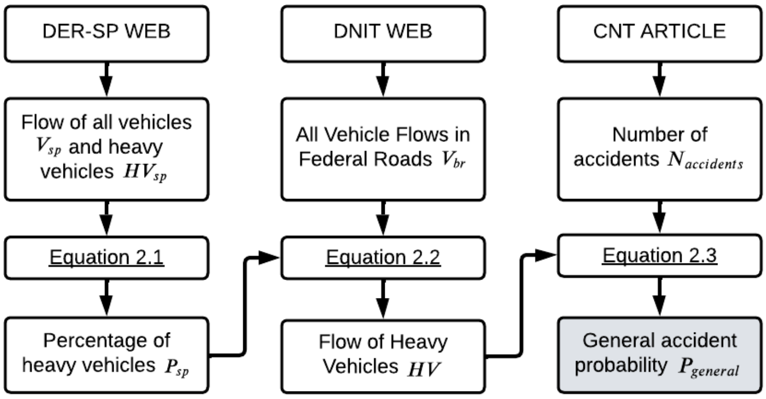


Figure 3 – Workflow to calculate $Pgeneral$.

$$HV = P_{sp}.V_{br} \tag{2.2}$$

$$Pgeneral = \frac{N_{accidents}}{HV} \; . \; 100\% \tag{2.3}$$

The elements considered for the calculation of r_{ij} are: the types of roads and the traffic of heavy vehicles. These elements were based on Milovanović (2012) and the first is considered because in Brazil there are several types of roads that demonstrate different safety levels. The Accident Panel Report prepared by CNT (2019) breaks it into five categories as presented by Table 3. The number of deaths per hundred of accidents extracted from this report is also shown, and is used in the calculations for accident risk.

Table 3 – Death rate per type of road (CNT, 2019).

Road type	**Death rate per 100 accidents**
Two-lane two-way road with central safety lane	12.3
Two-lane two-way road with central barrier	8.5
Two-lane two-way road with central line	18.0
Single-lane one-way road	11.9
Single-lane two-way road	22.3

The flow of heavy vehicles is obtained by speed radars installed along the roads (DER-SP, 2021) and it was considered as directly proportional to the accident probabilities as it was observed that two roads had the same infrastructure, distinguished only by the flow: the one with highest flow had more accidents, thus having greater probability of this occurrence.

Parameters it_h and iv_h represent the types of road (i.e. number of lanes, central barrier etc.) and the flow of heavy vehicles, respectively. These are calculated according to the workflow shown in Figure 4, where road h belongs to the problem roads of set H ($h \in H$) (CNT, 2019; DER-SP, 2021).

Initially, $\bar{x}$ and $\bar{y}$ must be calculated by Equations (2.4) and (2.5), which represent the average flow of vehicles x_h running in road h and the y_h the death rate of road type h. In the study, as there are 49 roads and five types of them, the parameter are $Nh = 49$ and $Nt = 5$.

Then, the parameters iv_h and it_h were calculated by Equations (2.6) and (2.7), which basically consists of a condition, i.e. if iv_h or it_h is greater than 1.0, the accident probability on road h will be greater than the general probability ($P_{general}$), otherwise the values are less than 1.0.

It is important to explain that two or more arcs comprising the same roads may present different risk costs according to the road distance in those arcs. For example, in a given arc, the vehicle would be on the more dangerous road for longer than the other arc in which a vehicle would travel for a short time on this same dangerous road.

$$\bar{x} = \frac{\sum_{h \in H} x_h}{Nh} \tag{2.4}$$

$$\bar{y} = \frac{\sum_{t \in T} y_t}{Nt} \tag{2.5}$$

$$iv_h = 1 + \frac{x_h - \bar{x}}{\bar{x}} \ , \ \forall \ h \in H \tag{2.6}$$

$$it_h = 1 + \frac{y_h - \bar{y}}{\bar{y}} \ , \ \forall \ h \in H \tag{2.7}$$

$$e_{ij} = \frac{\sum_{h \in H} iv_h.it_h.l_h}{l_{ij}} \ , \ \forall (i,j) \in E \tag{2.8}$$

$$Paccident_{ij} = Pgeneral.e_{ij} \ , \ \forall (i,j) \in E \tag{2.9}$$

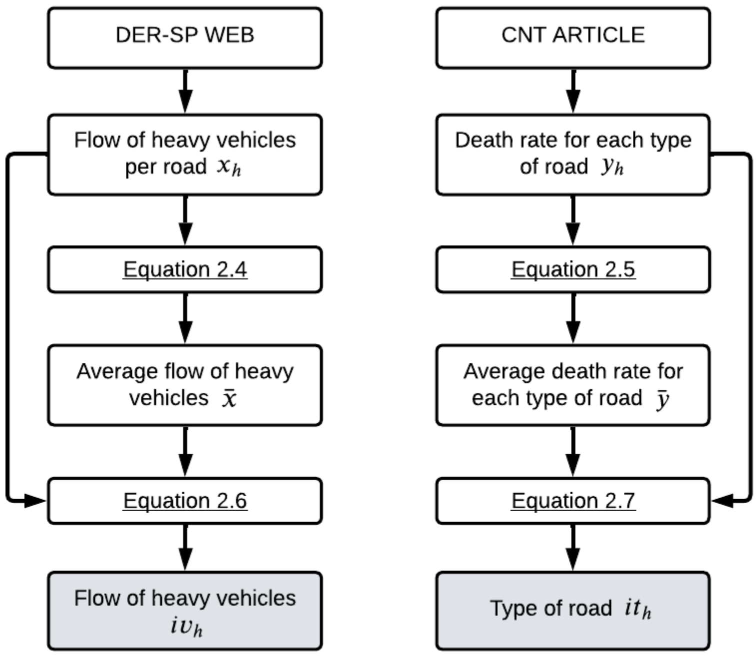


Figure 4 – Workflow to calculate parameters iv_h e it_h.

In some arcs, the vehicle may pass through more than one road (h), e.g., the arc Limeira to Cosmópolis has two roads: h_1 named SP330 and h_2 named SP133 whose flows and features are distinguished. Thus, a parameter named e_{ij} is needed, which is weighted by iv_h, it_h and l_h, and represented by Equation (2.8) as shown in the workflow of Figure (5). Where l_h is the length that the truck traverses each road h of the arc ij and l_{ij} represents the total length of the arc. Finally, Equation (2.9) describes the accident probability $Paccident_{ij}$ of the arc ij.

After finding the $Paccident_{ij}$, it is possible to estimate r_{ij} using the Monte Carlo simulation. This can be done using data provided by the cargo insurance companies, which collected the accident occurrences and the cargo losses involved (Table 4).

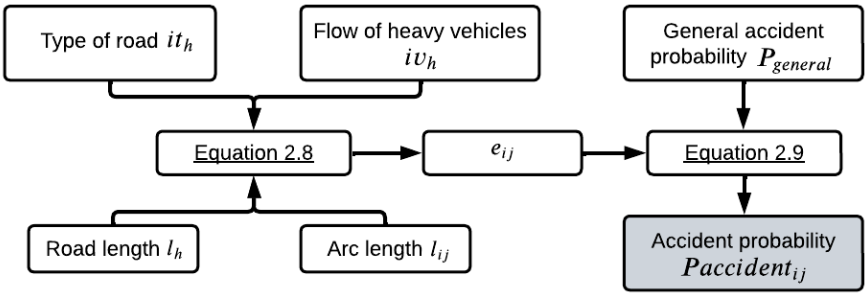


Figure 5 – Workflow to calculate e_{ij} and $Paccident_{ij}$.

Table 4 – Value involved in accident cargo transportation.

Range of values	**occurrence**
\$ 0.01 to \$ 200,000.00	37.91%
\$ 200,000.00 to \$ 300,000.00	24.17%
\$ 300,000.00 to \$ 500,000.00	19.91%
\$ 500,000.00 to \$ 1,000,000.00	16.11%
\$ 1,000,000.00 or more	1.90%

Figure 6 illustrates an example of how the probabilities are distributed. The maximum cargo value for each range and the cost to the road freight company is considered as being 1% of its value; a deductible that cargo insurances usually charge. Thus, in the occurrence of an accident in the range between \$0.01 and \$200,000.00, the value to be considered is always the highest of the range, which is in this case \$200,000.00, thus the deductible cost for the carrier should be \$2,000.00.

Figure 6 also shows the accumulated percentage values, between 0 and 1, for each accident cost on the right. This is important for the Monte Carlo simulation, which at each iteration selects a random value between 0 and 1 that corresponds to an accident cost. For example, according to Figure 6, each percentage range is equivalent to its cost, and therefore any value selected in the range between 0 and 0.990971 will correspond to an accident cost equal to \$0.00.

Thus, a number of 1,000,000 iterations are performed for each arc ij of the problem and the average risk cost of an accident r_{ij} is estimated and it is used in the objective function of the CVRP. This number of iterations was chosen because the accident probabilities are very low, and thus the values of r_{ij} presented a better

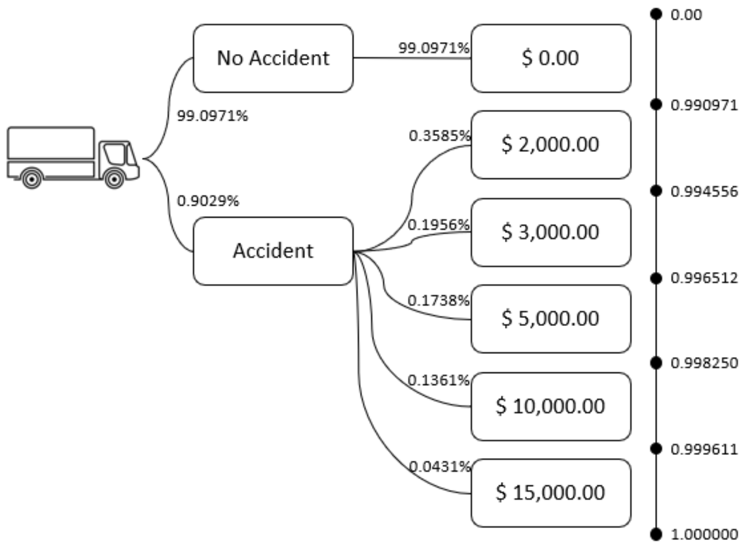


Figure 6 – Accident probabilities and their costs in the Monte Carlo simulation.

convergence. However, when the number of iterations is greater, the resolution time also increases, but r_{ij} results show few differences. Therefore, for this problem, the amount of 1,000,000 iterations was ideal.

2.3.2 Bi-objective in the CVRP

The Capacitated Vehicle Routing Problem (CVRP) was used in a real problem of a freight transportation company located in the city of Limeira/SP. The connection among the cities in the region was represented by graph $G = (V, A)$, where $V = \{0, ..., n\}$ is the set of vertices representing the cities and A is the set of arcs between i and j. In the problem, there are k identical vehicles each one with capacity *cap*, and they start and finish at a depot in Limeira. The CVRP minimizing logistics cost (c_{ij}) and risk cost (r_{ij}) was also tested in four different instances in which the number of cities varied between 10 to 18 and the number of trucks ranged from 3 to 8, and this is because the number of cities increased, the demand also changed. The instances were named as follows: $n10 - k3$, $n12 - k4$, $n15 - k8$, $n18 - k8$.

The model is a *two-index vehicle flow formulation*, as described in Toth &

Vigo (2002), where X_{ij} is a binary variable which takes value 1 if a vehicle traverses an arc $(i, j) \in A$ and takes value 0 otherwise. The Mixed Integer Programming model was implemented in *Python* and used *Gurobi Optimizer* (version 10.0.0) to solve the CVRP.

2.3.3 The PROMETHEE II method

PROMETHEE II is a Multi Criteria Decision Making (MCDM) approach designed to deal with conflicting criteria. The method consists of ranking alternatives through a pairwise comparison by different weighted criteria and it comprises four steps, as discussed in Brans & Smet (2016).

- Step 1: A preference function $P_\omega(a_a, a_b)$ is built to compare functions $g_\omega(a_a)$ and $g_\omega(a_b)$ and takes 1 if the alternative a_a is preferable to a_b in a criteria ω, $(\omega \in \Omega)$, or 0 otherwise, as Expression (2.10).

$$P_\omega(a_a, a_b) = \begin{cases} 1, \text{ if } g_\omega(a_a) < g_\omega(a_b) \\ 0, \text{ if } g_\omega(a_a) \geqslant g_\omega(a_b) \end{cases} \tag{2.10}$$

- Step 2: The sum of preference (π) of each criteria ω weighted by w_ω is described by Expression (2.11)

$$\pi(a_a, a_b) = \sum_{\omega \in \Omega} P_\omega(a_a, a_b) w_\omega \ , \ \forall \ (a, b) \ \in \ M, \ a \ \neq \ b \tag{2.11}$$

- Step 3: The positive ranking flow (ϕ^+) and the negative ranking flow (ϕ^-) described by Expressions (2.12) and (2.13), respectively, represents how alternative a_a is ranked compared to all others. M is the set all alternatives.

$$\phi^+(a_a) = \frac{1}{|M| - 1} \sum_{b \in M} \pi(a_a, a_b) \ , \ \forall \ a \in M \tag{2.12}$$

$$\phi^{-}(a_a) = \frac{1}{|M|-1} \sum_{b \in M} \pi(a_b, a_a) \ , \ \forall \ a \in M \tag{2.13}$$

$$\phi(a_a) = \phi^{+}(a_a) - \phi^{-}(a_a) \tag{2.14}$$

- Step 4: Finally, the ranking flow $\phi(a_a)$ is a difference of $\phi^{+}(a_a)$ and $\phi^{-}(a_a)$ as shown in Expression (2.14) where the higher the $\phi(a_a)$, the better the alternative (a_a) compared to others.

In this study, a_a and a_b are the arcs of the problem and ω is the criteria related to logistics and risk costs. The weight $w_\omega \in [0, 1]$ and if w_1 increases as a proportion of p, then w_2 decreases $(1-p)$, once $\sum_{\omega \in \Omega} w_\omega = 1$. As the alternatives are the arcs and they are symmetric, one can change an alternative a_a $(\forall a \in M)$ to an arc (i, j) (i.e. $\phi(a_a) = \phi_{ij}$), thus ϕ_{ij} is used as the parameter in the objective function of the CVRP as described below:.

$$min \sum_{i \in V} \sum_{j \in V} \phi_{ij}.X_{ij} \tag{2.15}$$

$$\sum_{i \in V} X_{ij} = 1 \quad \forall \ j \in V \backslash \{0\} \tag{2.16}$$

$$\sum_{j \in V} X_{ij} = 1 \quad \forall \ i \in V \backslash \{0\} \tag{2.17}$$

$$\sum_{i \in V} X_{i0} = K \tag{2.18}$$

$$\sum_{j \in V} X_{0j} = K \tag{2.19}$$

$$U_i - U_j + cap.X_{ij} \leqslant cap - d_j \quad \forall \ (i, j) \in V \backslash \{0\} \ i \neq j \mid d_i + d_j \leqslant cap \tag{2.20}$$

$$d_i \leqslant U_i \leqslant cap \quad \forall\ i \in V \setminus \{0\} \tag{2.21}$$

$$X_{ij} \in \{0, 1\}\ \forall\ (i, j) \in V \tag{2.22}$$

$$U_i \in \mathbb{R}^+\ \forall\ i \in V \tag{2.23}$$

Expression (2.15) is the objective function that minimises the ranking flow (ϕ_{ij}). The objective function value is accounted for in the variable Z. Expressions (2.16) and (2.17) impose that for each vertex representing a location there is only one entry and one exit, respectively. Expressions (2.18) and (2.19) represent the depot where it receives and leaves a number of arcs equal to the number of vehicles k. Expressions (2.20) and (2.21) impose the capacity limit *cap* and the connectivity requirements along the route, where Constraints (2.20) guarantee the sub-tour elimination proposed by Miller, Tucker & Zemlin (1960) and adapted to CVRP. The continuous variable U_i represents the load of the vehicle after visiting customer i (TOTH; VIGO, 2002). The domain of the decision variables of the routes are described in Expressions (2.22) and (2.23).

2.3.4 ϵ-constrained method

The ϵ-constrained method optimises just one objective taking the others as constraints by limiting them to an upper bound, defined by parameter ϵ, in the case of a minimization problem. In the ϵ-constrained non-dominated efficient solutions can be produced and other advantages are the linearity preservation of the original problem.

In this study, the logistic cost is kept as the objective to be minimized and adds the risk cost as the constraint to be met. Therefore, the difference of this method with the previous one is that the objective function Eq. (2.24) only minimises $\sum_{i \in V} \sum_{j \in V} c_{ij}.X_{ij}$ and it is added to the set of the remaining constraints of the CVRP with the new one limited to the risk expressed by Eq. (2.25). A variation of ϵ is made within the range of feasible region to obtain different solutions.

$$min \sum_{i \in V} \sum_{j \in V} c_{ij}.X_{ij} \tag{2.24}$$

$$\sum_{i \in V} \sum_{j \in V} r_{ij}.X_{ij} \leqslant \epsilon \tag{2.25}$$

2.4 Experimental results

A freight transportation company in Limeira/SP collaborated in this study supplying real data. The set of all locations in the instance is shown on the map in Figure 7, where the depot in Limeira is identified by the letter "D".

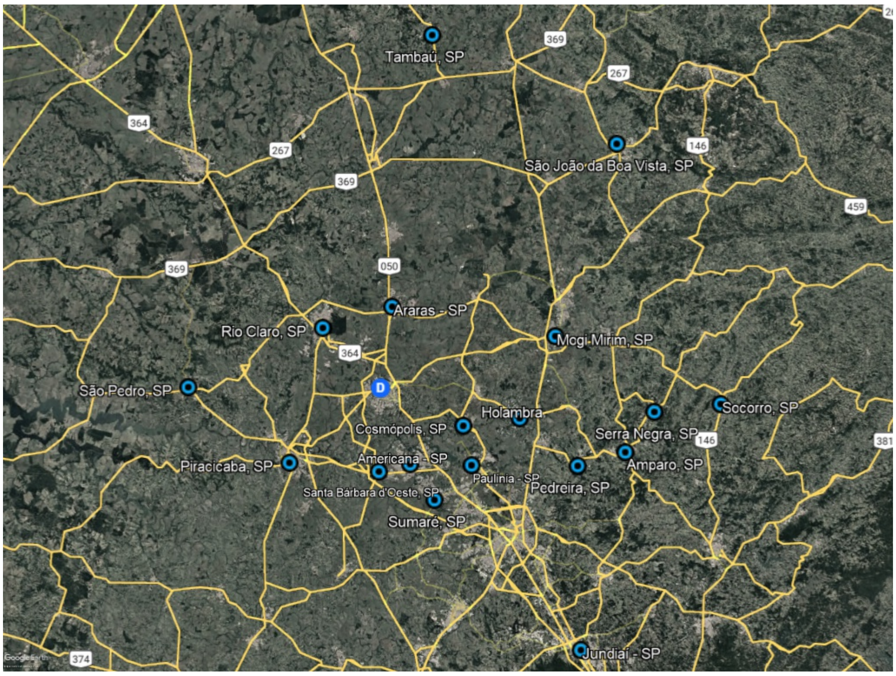


Figure 7 – Set of locations in all instances of this study.

2.4.1 Results of risk cost

The risk cost (r_{ij}) was obtained by the Monte Carlo simulation and a part of the results are shown in Table 5. It was observed that r_{ij} was obtained in line with what was expected. When comparing the arcs that have the same type of roads such as Piracicaba to Santa Barbara d'Oeste and Limeira to Mogi Mirim, the r_{ij} for the first arc is greater in the risk cost (r_{ij} = 1339.24) than the second (r_{ij} = 150.21), and it was expected because of the higher traffic (6,819 heavy vehicles) on the road h = SP304. On the other hand, the second arc is road h = SP147 where the heavy vehicle flow is only 757 making it a low-risk arc.

In the arcs, Mogi Mirim to Rio Claro (r_{ij} = 464.18) and Araras to Paulinia (r_{ij} = 859.05), the types of roads are equal for both, but in the first one, the truck goes by a longer distance (l_h = 47.6 km) on a safer road (h = SP147) whereas it is the opposite for the second arc. The same occurs when Limeira to Cosmópolis and Araras to Rio Claro are compared. On the second, the truck runs most of its way (l_h = 21.7 km) on a safer road (h = SP191) making the risk cost of this arc lower (r_{ij} = 345.60) than the first (r_{ij} = 1082.12), where the truck travels on two roads with high levels of risk.

When comparing arcs that present similar or nearly a vehicle flow such as Mogi Mirim to Araras and Limeira to Mogi Mirim, it is noted that r_{ij} for the first is greater than the second due to the Mogi Mirim to Araras arc, which is built by a road (h = SP191) single-lane two-way road, according to the nomenclature of CNT (2019), which has the highest death rate among all road types.

It can be observed that SP147 is a very safe road because of its road type, two-lane two-way road with a central safety lane, and the low flow of vehicles. When a vehicle travels long distances on roads such as the SP147, r_{ij} tends to be low and the arc is safe. On the other hand, roads SP304 and SP330 penalise the r_{ij} due to their high flow of vehicles.

Other analyses, such as this, were also carried out and the same conclusions were reached. Thus, it can be stated that the analytical approach followed to find r_{ij} was satisfactory as consistent results were found according to those expected.

The risk cost of using a road, that will be used for all arcs, obtained from the Monte Carlo simulation is presented in Table 5.

Table 5 – Risk cost (r_{ij}) obtained from Monte Carlo simulation.

Arcs (ij)	**c_{ij} (\$)**	**r_{ij} (\$)**	**h**	**Type of Road**	**Flow of heavy vehicles**	**l_h (km)**
Limeira – Cosmópolis	51.70	1082.12	SP330	Two-lane two-way road with central safety lane	4980	16.5
			SP133	Single-lane two-way road	3373	16.4
Holambra – Cosmópolis	50.76	418.44	SP107	Single-lane two-way road	1790	15.2
			SP332	Two-lane two-way road with central safety lane	1842	10.9
Limeira – Mogi Mirim	117.87	150.21	SP147	Two-lane two-way road with central safety lane	757	54.2
Limeira – Piracicaba	80.19	147.80	SP147	Two-lane two-way road with central safety lane	757	36.9
Limeira – Araras	72.11	971.9	SP330	Two-lane two-way road with central safety lane	4980	31
Limeira – Rio Claro	80.76	974.65	SP330	Two-lane two-way road with central safety lane	4980	12.5
			SP310	Two-lane two-way road with central safety lane	4950	24
Araras – Santa Bárbara d'Oeste	92.56	702.63	SP330	Two-lane two-way road with central safety lane	4980	14.3
			SP348	Two-lane two-way road with central safety lane	2490	38.7
			SP304	Two-lane two-way road with central safety lane	6819	5.9
Santa Bárbara d'Oeste – Sumaré	77.71	536.04	SP304	Two-lane two-way road with central safety lane	6819	4.7
			SP348	Two-lane two-way road with central safety lane	2490	24.9
Araras – Rio Claro	40.38	345.60	SP191	Single-lane two-way road	650	21.7
			SP330	Two-lane two-way road with central safety lane	4980	4
Mogi Mirim – Rio Claro	177.26	464.18	SP147	Two-lane two-way road with central safety lane	535	47.6
			SP330	Two-lane two-way road with central safety lane	4980	6
			SP310	Two-lane two-way road with central safety lane	4150	23.6
Piracicaba – Santa Barbara d'Oeste	44.78	1339.24	SP304	Two-lane two-way road with central safety lane	6819	28.5
Araras – Paulínia	163.00	859.05	SP330	Two-lane two-way road with central safety lane	4980	35.1
			SP147	Two-lane two-way road with central safety lane	535	16.5
			SP332	Two lane two-way road with central safety lane	1603	19.9
Piracicaba – Americana	77.47	1349.1	SP304	Two-lane two-way road with central safety lane	4980	49.3
Mogi Mirim – Araras	110.20	217.33	SP191	Single-lane two-way road	650	48.3
Jundiaí – Socorro	286.54	430.29	SP360-1	Single-lane two-way road	1458	22.0
			SP063	Single-lane two-way road	1267	40.0
			SP008	Single-lane two-way road	1301	47.0
Amparo – Jundiaí	128.06	327.31	SP360-2	Single-lane two-way road	585	40.0
			SP065	Two-lane two-way road with central safety lane	5780	4.4
			SP063	Single-lane two-way road	1267	9.5
			SP360-1	Single-lane two-way road	1458	19
Araras – São João da Boa Vista	222.20	498.75	SP330	Two-lane two-way road with central safety lane	4980	38
			SP225	Single-lane two-way road	880	50
			SP344-1	Single-lane two-way road	862	24
Cosmópolis – Amparo	106.39	610.90	SP332	Two-lane two-way road with central safety lane	1842	10.9
			SP107	Single-lane two-way road	1790	47.1
			SP95-2	Single-lane two-way road	1765	9.7

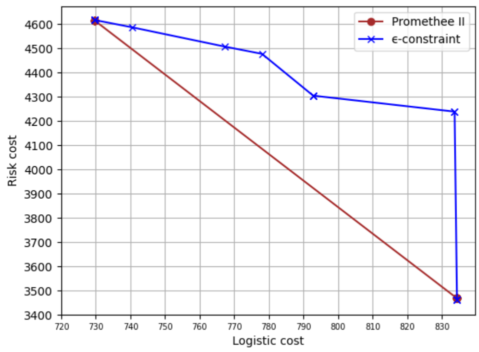
2.4.2 Solving the bi-objective function in the CVRP

The optimized results of the CVRP with the bi-objective methods are presented in Figure 8. Analysing the Pareto Frontier of each instance, the ϵ-constrained method resulted in more varied solutions than Promethee II as setting an upper bound for the constraints could lead to finding weak efficient solutions.

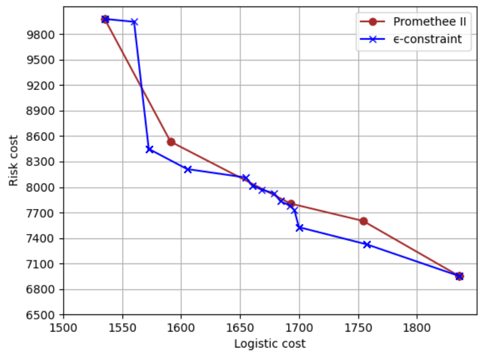
However, it is difficult to find an effective ϵ interval covering all possible feasible solutions, that is, the smallest value of ϵ should be found that still makes the solution feasible or a value of ϵ high enough covering all possible optimal solutions. Therefore, in the case of this study and according to Equation (2.25), the ϵ must be greater than the minimum risk value, otherwise the solution is unfeasible, or as high as the maximum risk to cover all possible optimal solutions.

Thus, the PROMETHEE II method can be used as a support to find the range of values of ϵ. For the results of instance n10-k3 according to Figure 8(a) and Table 6, when $w_\omega = 0$ the risk assumes the maximum value ($r_{ij}.X_{ij} = 4616.64$). On the other hand, when $w_\omega = 1$ the risk is minimum ($r_{ij}.X_{ij} = 3463.52$). Therefore, in instance n10-k3 when $\epsilon < 3463.52$, the solution is infeasible, and when $\epsilon = 4616.64$, it is large enough to cover all optimal solutions, making the ideal interval of ϵ equal to $3463.52 \leqslant \epsilon \leqslant 4616.64$.

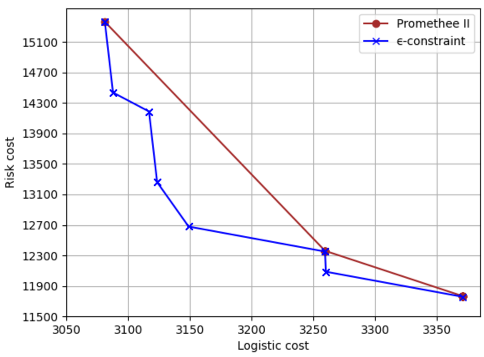
To detail the routes of each solution that compose the Pareto frontier of each instance, see Figures 9, 10, 11 and 12. The cost details of each route of each instance are explained in Tables 6, 7, 8 and 9, respectively.



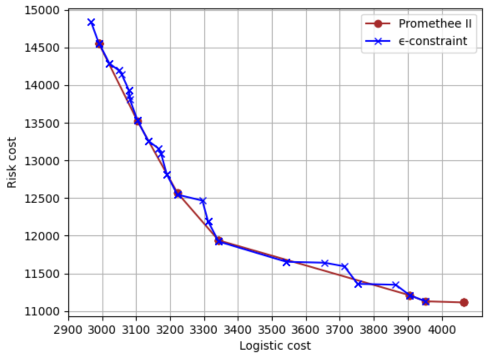
(a) n10-k3



(b) n12-k4



(c) n15-k8

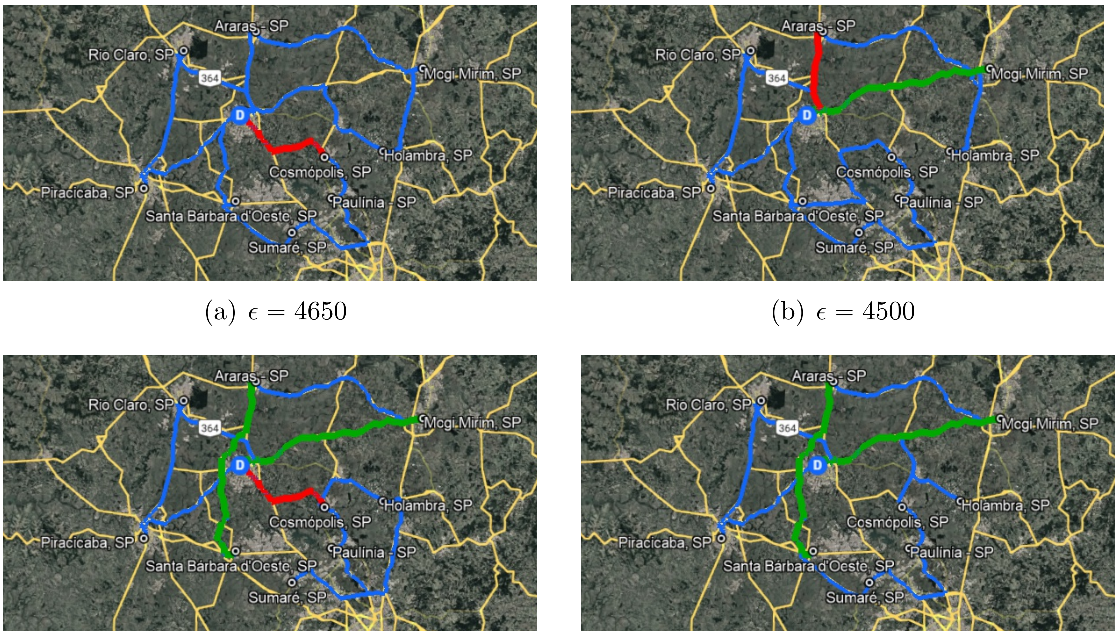


(d) n18-k8

Figure 8 – Pareto frontier from optimization with PROMETHEE II and ϵ-constrained methods.

2.4.3 Analysis of Solutions for instance n10-k3

Figure 9 presents the routes that correspond to optimal solutions that compose the Pareto Frontier for instance n10-k3 shown in Figure 8(a). The total risk cost, total logistic cost and which roads belong to each solution are shown in Table 6.



(a) $\epsilon = 4650$

(b) $\epsilon = 4500$

(c) $\epsilon = 4250$

(d) $\epsilon = 4100$

Figure 9 – Optimal solutions from Pareto-Frontier, for instance n10-k3.

Table 6 – Routes for each solution of instance n10-k3 presented in Figure 9.

Figure	ϵ	w_ω	$c_{ij}X_{ij}$ (\$)	$\Delta c_{ij}X_{ij}$	$r_{ij}X_{ij}$ (\$)	$\Delta r_{ij}X_{ij}$	Routes
9(a)	4650	0 to 0.45	729.69	-	4616.64	-	1)D–Holambra–Mogi Mirim–Araras–D 2)D–Piracicaba–Rio Claro–D 3)D–Santa Bárbara d'Oeste–Sumaré–Paulínia–Cosmópolis–D
9(b)	4500	-	778.01	↑ **6.62%**	4477.14	↓ **3.02%**	1)D–Santa Bárbara d'Oeste–Cosmópolis–Paulínia–Sumaré–D 2)D–Piracicaba–Rio Claro–D 3)D–Araras–Holambra–Mogi Mirim–D
9(c)	4250	-	833.67	↑ **14.25%**	4238.76	↓ **8.19%**	1)D–Mogi Mirim–Araras–Santa Bárbara d'Oeste–D 2)D–Piracicaba–Rio Claro–D 3)D–Cosmópolis–Holambra–Sumaré–Paulínia–D
9(d)	4100	0.5 to 1.0	834.36	↑ **14.34%**	3463.52	↓ **24.98%**	1)D–Mogi Mirim–Araras–Santa Bárbara d'Oeste–D 2)D–Piracicaba–Rio Claro–D 3)D–Sumaré–Paulínia–Cosmópolis–Holambra–D

In Figure 9(b), the green arc from Limeira to Mogi Mirim has been included in a VRP solution when the risk is relevant enough as compared to the initial solution for instances n10-k3 (Figure 9(a)). The inclusion of green arcs observed in Figures 9(b), 9(c) and 9(d) provided a greater reduction in the risk cost than the increase in the logistic costs (Table 6). Road SP147 plays an important role in the risk reduction as it is one of the safest roads in the problem.

Limeira to Cosmópolis (red arc in Figures 9(a) and 9(c)) is removed from the solution when $\epsilon = 4500$ due to the high-risk levels of roads SP330 and SP133. Although its logistic cost is low ($c_{ij} = 51.70$), the arc returned as a solution when $\epsilon = 4250$ and removed again when $\epsilon = 4100$ because the optimization in this case tends to prioritize safety instead of the logistic costs. The same happens for Limeira to Araras (red arc in Figure 9(b)) which is removed when $\epsilon = 4250$ and Araras to Santa Barbara d'Oeste (green one in Figure 9(c)) is considered due to the difference of their risk cost r_{ij}.

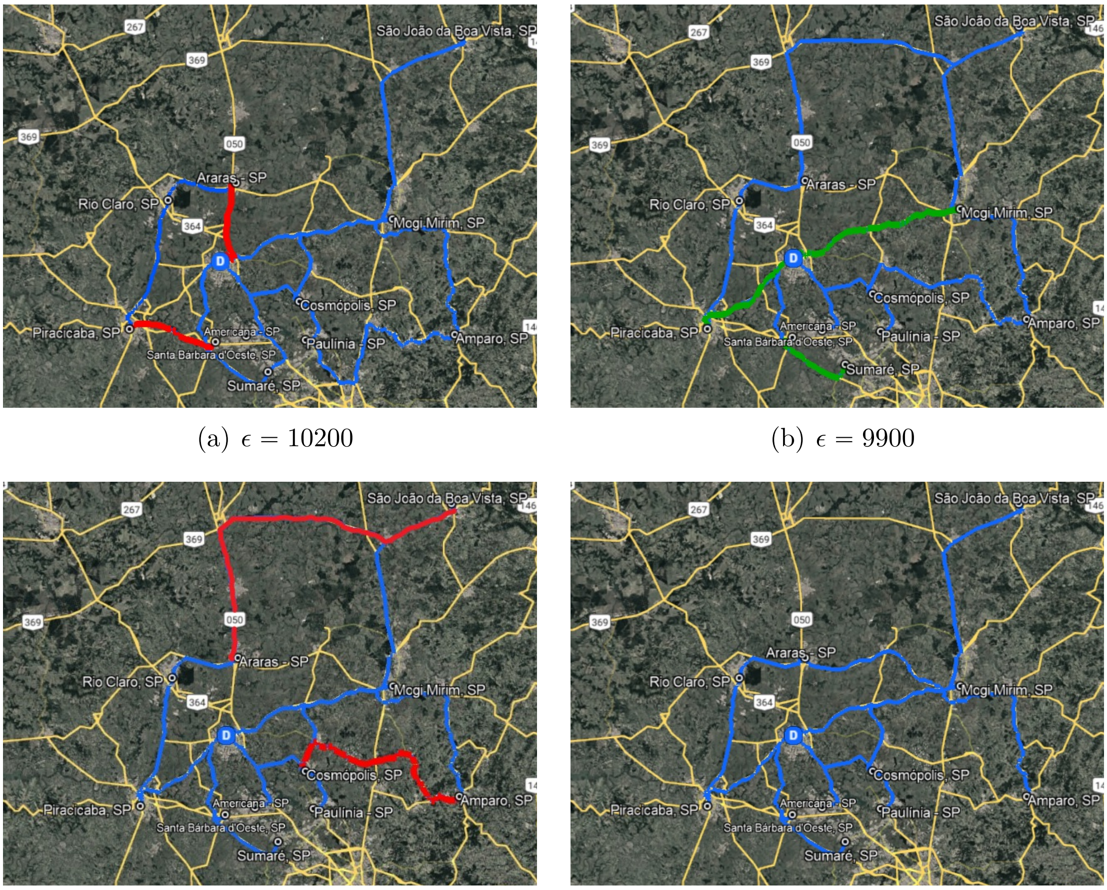
Road SP147 connects Mogi Mirim to Piracicaba, passing by Limeira. When $\epsilon = 4500$ (Figure 9(b)), the model selects this road for the vehicle to travel completely due to its high safety level. On the other hand, when the logistics cost is prioritized at $\epsilon = 4650$ (Figure 9(a)), a section of this road, the path from Mogi Mirim to Limeira, is not considered as a solution and the Holambra to Cosmópolis arc that comprises the SP107 and SP133 highways, is added.

The model also selects routes composed by SP348, which connects Araras to Santa Bárbara d'Oeste, from $\epsilon = 4250$ (Figure 9(c)) due to its low accident risk. Nonetheless, the SP133 that forms the Limeira to Cosmópolis and Santa Bárbara d'Oeste to Cosmópolis arcs, is excluded when the accident risk should be minimum (Figure 9(d)), as this road is a single-lane two-way road with high truck traffic.

The SP330 road is long and passes by several cities in the region, such as Limeira, Americana, Araras, Sumaré, and it is considered in the solutions only when the logistic cost is prioritized due to heavy traffic, similarly to SP133, which is shorter in distance and more risky for accidents. On the other hand, the SP147 and SP348 roads are preferred when the low accident risk is recommended.

2.4.4 Analysis of Solutions for instance n12-k4

Figure 10 presents the routes that correspond to optimal solutions that comprise the Pareto Frontier of instance n12-k4 (Figure 8(b)). Table 7 summarizes the key results.



(a) $\epsilon = 10200$

(b) $\epsilon = 9900$

(c) $\epsilon = 7750$

(d) $\epsilon = 7300$

Figure 10 – Optimal solutions from Pareto-Frontier for instance n12-k4.

The Limeira to Mogi Mirim, Limeira to Piracicaba and Santa Bárbara d'Oeste to Sumaré arcs are introduced as a solution when $\epsilon = 9900$ (green arcs in Figure 10(b)) and those are kept as solutions at $\epsilon = 7750$ and $\epsilon = 7300$. Limeira to Mogi Mirim and Limeira to Piracicaba are considered because these arcs are formed by the SP147 road, which is a very safe way, as already mentioned in the previous instance. Santa Bárbara d'Oeste to Sumaré are also included as the SP348 road that makes up this arc has low truck traffic and it is a two-lane two-way road with a central safety lane.

Table 7 – Routes for each solution of instance n12-k4 presented in Figure 10.

Figure	ϵ	w_ω	$c_{ij}X_{ij}$ ($)	$\Delta c_{ij}X_{ij}$	$r_{ij}X_{ij}$ ($)	$\Delta r_{ij}X_{ij}$	Routes
10(a)	10200	0.0 to 0.20	1535.16	-	9979.97		1)D–Santa Bárbara d'Oeste–Piracicaba–Rio Claro–Araras–D 2)D–Amparo–Paulínia–D 3)D–Cosmópolis–Mogi Mirim–São João da Boa Vista–D 4)D–Americana–Sumaré–D
10(b)	9900	-	1572.56	↑ **2.04%**	8449.35	↓ **15.34%**	1)D–Santa Bárbara d'Oeste–Sumaré–D 2)D–Cosmópolis–Amparo–Mogi Mirim–D 3)D–Piracicaba–Rio Claro–Araras–São João da Boa Vista–D 4)D–Americana–Paulínia–D
10(c)	7550	-	1696.06	↑ **8.77%**	7728.52	↓ **22.56%**	1)D–Santa Bárbara d'Oeste–Sumaré–D 2)D–Mogi Mirim–Cosmópolis–Amparo–D 3)D–Piracicaba–Rio Claro–Araras–São João da Boa Vista–D 4)D–Paulínia–Americana–D
10(d)	7300	0.55 to 1.0	1835.59	↑ **16.37%**	6953.59	↓ **30.32%**	1)D–Santa Bárbara D'Oeste–Sumaré–D 2)D–Mogi Mirim–Cosmópolis–São João da Boa Vista–D 3)D–Americana–Paulínia–D 4)D–Piracicaba–Rio Claro–Araras–Amparo-D

The Piracicaba to Santa Bárbara d'Oeste and Limeira to Araras arcs (red arcs in Figure 10(a)) have a low logistic cost, and thus are selected as a route when $\epsilon = 10200$. However, when $\epsilon = 9900$, $\epsilon = 7750$ and $\epsilon = 7300$, these arcs are excluded as a solution due to their high risk cost. The Piracicaba to Santa Bárbara d'Oeste and Limeira to Araras arcs are formed by roads SP304 and SP330, respectively, which have the highest accident risk among all the roads in the problem.

The Araras to São João da Boa Vista and Cosmópolis to Amparo arcs (red arcs in Figure 10(c)) do not have such a high accident risk as the Piracicaba to Santa Bárbara d'Oeste arc, and therefore they are selected as a solution for the routes at $\epsilon = 9900$ and $\epsilon = 7750$. However, when the safety level is even more prioritized at $\epsilon = 7300$, these arcs are eliminated.

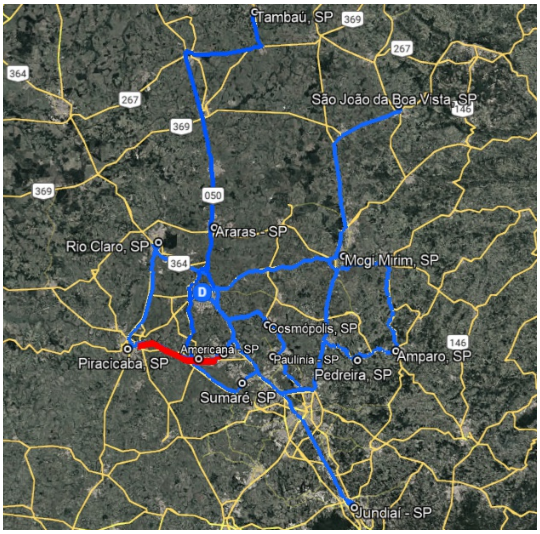
Thus, similarly as the previous solution for instance n10-k3, the routes with the SP147 and SP348 roads are preferable and the routes with the SP304 and SP330 roads are excluded when the safety level is prioritized.

2.4.5 Analysis of Solutions for instance n15-k8

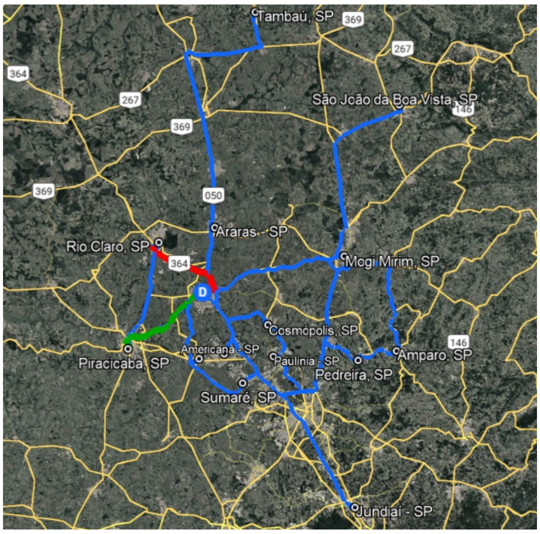
Figure 11 presents the routes that correspond to optimal solutions that compose the Pareto Frontier of instance n15-k8 (Figure 8(c)). Table 8 summarizes the key results.

Figure 11(a) displays the optimal solution with the lowest total logistic cost and consequently with a higher accident risk. This solution includes the Americana to Piracicaba arc (red arc in Figure 11(a)) which has a low logistic cost, but its accident risk is high due to the high traffic on road SP304. When the accident risk is reduced, other routes are configured as shown in Figures 11(b) and 11(c), where the safe roads are introduced (SP147 and SP191, respectively) as their logistical costs are not high.

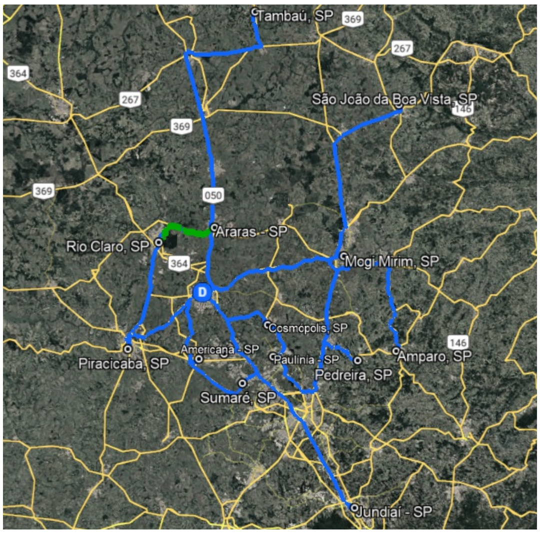
The Limeira to Rio Claro arc (Figure 11(b)) also has low logistics cost and high accident risk because it contains two roads that are dangerous shown by the data, SP310 and SP330. However, this arc is still considered as a solution when the accident risk starts to be prioritized at $\epsilon = 13300$. However, when the safety level is even more prioritized at $\epsilon = 12150$ and $\epsilon = 12000$, the model excludes this arc as a solution and selects a safer one, such as the arc passing by Araras to Rio Claro (Figure 11(c)).



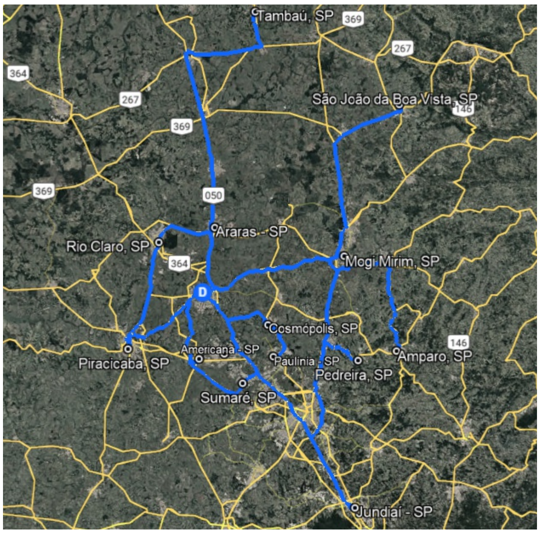
(a) ϵ = 15400



(b) ϵ = 13300



(c) ϵ = 12150



(d) ϵ = 12000

Figure 11 – Optimal solutions from Pareto-Frontier for instance n15-k8.

Table 8 – Routes for each solution of instance n15-k8 presented in Figure 11.

Figure	ϵ	w_ω	$c_{ij}X_{ij}$ (\$)	$\Delta c_{ij}X_{ij}$	$r_{ij}X_{ij}$ (\$)	$\Delta r_{ij}X_{ij}$	Routes
11(a)	15400	0.0	3081.24	-	15374.34	-	1)D–Mogi Mirim–D 2)D–Cosmópolis–D 3)D–Santa Bárbara d'Oeste–Tambaú–D 4)D–Sumaré–Amparo–D 5)D–Jundiaí–Araras–D 6)D–São João da Boa Vista–D 7)D–Paulínia–Pedreira–D 8)D–Americana–Piracicaba–Rio Claro–D
11(b)	13300	-	3123.56	↑ **1.37%**	13255.95	↓ **13.78%**	1)D–Tambaú–D 2)D–Mogi Mirim–D 3)D–Amparo–Sumaré–Santa Bárbara d'Oeste–D 4)D–Cosmópolis–D 5)D–Jundiaí–Araras–D 6)D–São João da Boa Vista–D 7)D–Paulínia–Pedreira–D 8)D–Americana–Rio Claro–Piracicaba–D
11(c)	12150	0.05 to 0.40	3260.07	↑ **5.80%**	12113.77	↓ **21.21%**	1)D–Tambaú–D 2)D–Mogi Mirim–D 3)D–Amparo–D 4)D–Americana–Jundiaí–D 5)D–Santa Bárbara d'Oeste–Sumaré–Cosmópolis–D 6)D–São João da Boa Vista–D 7)D–Paulínia–Pedreira–D 8)D–Araras–Rio Claro–Piracicaba–D
11(d)	12000	0.45 to 1.0	3370.42	↑ **9.39%**	11758.74	↓ **23.52%**	1)D–Tambaú–D 2)D–Mogi Mirim–D 3)D–Amparo–D 4)D–Americana–Paulínia–D 5)D–Santa Bárbara d'Oeste–Sumaré–Cosmópolis–D 6)D–São João da Boa Vista–D 7)D–Jundiaí–Pedreira–D 8)D–Araras–Rio Claro–Piracicaba–D

2.4.6 Analysis of Solutions for instance n18-k8

Figure 12 presents the routes that correspond to optimal solutions that compose the Pareto Frontier of instance n18-k8 (Figure 8(d)). Table 9 summarizes the key results.

The Limeira to Rio Claro arc (red arc in Figure 12(a)) is introduced as an optimal solution when $\epsilon = 14850$ due to its low logistics cost. However, when risk is prioritized in $\epsilon = 12550$, $\epsilon = 11700$ and $\epsilon = 11100$, this arc is excluded due to the high accident risk in SP330 and SP310, similarly as indicated in instance n15-k8. The Araras to Rio Claro arc (green arc in Figure 12(b)) is preferred as a solution when $\epsilon = 12550$, $\epsilon = 11700$ and $\epsilon = 11100$ as it has low risks of accident.

The Jundiaí to Socorro arc (red arc in Figure 12(a)) is selected as an optimal solution only in $\epsilon = 14850$. When the risk is prioritized, the routes obtained in $\epsilon = 12550$, $\epsilon = 11700$ and $\epsilon = 11100$ do not contain the Jundiaí to Socorro arc and the new solution introduces the Amparo to Jundiaí arc (green arc in Figure 12(b)) as option. This is because on the Amparo to Jundiaí arc, the vehicle travels mostly on the SP360-2 road, where the volume of vehicles is low, while on the Jundiaí to Socorro arc, the vehicle travels only on roads with high traffic. Thus, the risk cost for the Amparo to Jundiaí arc is lower and preferable as an optimal solution.

(a) $\epsilon = 14850$

(b) $\epsilon = 12550$

(c) $\epsilon = 11700$

(d) $\epsilon = 11100$

Figure 12 – Optimized routes for instance n18-k8.

Table 9 – Routing solution of instance n18-k8 presented in Figure 12.

Figure	ϵ	w_ω	$c_{ij}X_{ij}$ (\$)	$\Delta c_{ij}X_{ij}$	$r_{ij}X_{ij}$ (\$)	$\Delta r_{ij}X_{ij}$	Routes
12(a)	14850	-	2967.41	-	14836.43	-	1)D–Mogi Mirim–Araras-D 2)D–São João da Boa Vista–Tambaú–D 3)D–Cosmópolis–D 4)D–Santa Bárbara d'Oeste–Sumaré–Americana–Limeira 5)D–Piracicaba–São Pedro–Rio Claro–D 6)D–Paulínia–D 7)D–Pedreira–Amparo–Serra Negra–D 8)D–Jundiaí–Socorro–D
12(b)	12550	0.35 to 0.40	3221.46	↑ **8.56%**	12544.98	↓ **15.44%**	1)D–Mogi Mirim–Serra Negra–D 2)D–Tambaú–São João da Boa Vista–D 3)D–Jundiaí–Amparo–Socorro–D 4)D–Santa Bárbara d'Oeste–Sumaré–D 5)D–Piracicaba–D 6)D–Paulínia–D 7)D–São Pedro–Rio Claro–Araras–Pedreira–D 8)D–Cosmópolis–Americana–D
12(c)	11700	-	3542.54	↑ **19.38%**	12113.77	↓ **21.46%**	1)D–Mogi Mirim–Serra Negra–D 2)D–Tambaú–São João da Boa Vista–D 3)D–Jundiaí–Amparo–D 4)D–Santa Bárbara d'Oeste–Sumaré–D 5)D–Piracicaba–D 6)D–Paulínia–D 7)D–Pedreira–Araras–Rio Claro–São Pedro–D 8)D–Socorro–Cosmópolis–Americana–D
12(d)	11100	0.80	3951.87	↑ **33.18%**	11090.86	↓ **25.25%**	1)D–Mogi Mirim–Serra Negra–D 2)D–Americana–Cosmópolis–Socorro–D 3)D–Tambaú–Paulínia–D 4)D–Amparo–Jundiaí–D 5)D–São João da Boa Vista–D 6)D–São Pedro–Rio Claro–Araras–Pedreira–D 7)D–Santa Bárbara d'Oeste–Sumaré–D 8)D–Piracicaba–D

2.5 Final remarks

The need to consider accident risk in VRP is important because when an accident occurs not only are people exposed to risk, but the loss of transported goods can have major consequences such as: financial, interruptions in the supply chain and social-environmental impacts.

This study considered the issue of route safety in the VRP for a cargo transportation company to support decision-makers to choose the best routes that minimise both the logistics costs and accident risks.

Due to the limited data availability of road accidents, an analytical approach based on simple statistic calculations was developed to estimate the accident probabilities for each arc between locations, and the costs related to the accident were estimated through Monte Carlo simulations. The PROMETHEE

II and ϵ-constrained methods were implemented to deal with the bi-objective (i.e. tradeoff between logistic cost and accident risk cost) in the VRP. The obtained results were coherent for the analytical approach as a whole, converging to what was expected of the problem.

Analysing the results of instance n10-k3 presented in Table 6, the increase in logistic cost is greater than the risk cost reduction at $\epsilon = 4500$, but when the security level of the routes receives higher priority, the risk cost reduction is greater at $\epsilon = 4100$. On the other hand, in instance n18-k8 (results in Table 9), the opposite happened. In the first moment, the risk cost reduction is greater at $\epsilon = 12550$ and $\epsilon = 11700$, but the increase in logistics cost is greater when security is on the highest prioritization level ($\epsilon = 11100$). For instances n12-k4 (Table 7) and n15-k8 (Table 8), the risk cost reduction is greater than the increases in logistics costs for all safety levels.

Thus, a decision-maker could analyse the total logistic cost and risk of accidents, and one could plan the routes based on which safety level it wishes to operate, as the level of operational safety depends on some factors such as the cargo type and the cargo value.

It can be affirmed that the analytical approach worked coherently by representing the trade-off between logistics costs and the risk of accident due to more dangerous roads. According to the parameters that regulate the bi-objective approaches, the model may prioritize safer routes or the logistic costs, showing different solutions to the decision-maker.

The limitation of the study was the small amount of data and their types to estimate the risk cost in an even better way, as more data and different types of information on road hazards could be used to develop better risk models. For further studies, as presented in Chapter 3, the analytical approach will be extended to include more conflicting objectives to the logistical cost, such as environmental costs, making the VRP more multi-objective.

3 Augmented Weighted Tchebycheff for solving VRP considering accident risk and CO_2 emission using a fleet powered by diesel, electric, and CNG.

Multi-Objective Vehicle Routing Problems (MO-VRP) have attracted attention in the area of sustainability in which the objective is to optimize jointly the economic, environmental, and social dimensions. They have gained significant attention in sustainability studies due to their focus on optimizing economic, environmental, and social dimensions. As a continuation of Chapter 2, this study presents an application of MO-VRP to a real-case problem, aiming to minimize logistics costs, CO_2 emissions, and accident risks. The company employs a heterogeneous fleet with heavy-duty vehicles powered by various energy sources, including battery (electric vehicles), compressed natural gas, and diesel fuel. The MO-VRP was tackled using the *Augmented Weighted Tchebycheff* (AWT) method, and an enhanced Genetic Algorithm was employed as a heuristic to generate feasible solutions, which helped to warm-start the optimization process in the exact method when the model struggled to find solutions. To the best of our knowledge, few studies have applied the AWT approach to multi-objective and sustainable VRP, and limited research has been conducted on determining the optimal mix of vehicles using different energy sources. The results showed that diesel trucks were the most economically viable, but alternative fuel vehicles were preferred in scenarios prioritizing environmental considerations, achieving a nearly 90% reduction in CO_2 emissions. However, this led to an almost 35% increase in logistics costs. Additionally, some routes were consistently chosen across different scenarios due to their short distances and low accident risks. Routes with short distances but higher accident risks, though less frequently chosen, could become more viable if road conditions were improved. Finally, the analytical approach proved to be useful for the transportation company to make decisions when planning deliveries considering the three elements of sustainability as a result of its simplicity in generating solutions, either by changing the weights of the objective function or by allowing the model to be applied in several scenarios.

3.1 Introduction

The need for sustainable development has become increasingly urgent amid recent events such as rapid population growth, natural and social disasters, climate change, and many other reasons. Furthermore, sustainable development is important because the needs of the current generation must be met, but resources must also be guaranteed for the next generations (DÜNDAR; ÖMÜRGÖNÜLŞEN; SOYSAL, 2021). The Triple Bottom Line (TBL) approach supports the concept of sustainability by promoting a balance between economic, social, and environmental aspects (ELKINGTON, 2001). In the Vehicle Routing Problems (VRP), Dündar, Ömürgönülşen & Soysal (2021) and Reyes-Rubiano et al. (2020) claim that the economic dimension remains the most extensively explored, while Ferreira, Steiner & Junior (2020) and Qiao et al. (2020) observe that risk is often underrepresented.

The quantity of CO_2 equivalent in the atmosphere could be understood as an indicative of global warming. According to the Sistema de Estimativas de Emissões e Remoções de Gases de Efeito Estufa (SEEG, 2021), Brazil was responsible for the emission of approximately 2.4 billion tons of CO_2 equivalent in 2021, which represented an increase of 8% compared to 2019, the last year before the COVID-19 pandemic; and transportation sector contributed 8.5% of total CO_2 emissions in Brazil.

In the social dimension, Abdullahi et al. (2021) state that the risk of accidents is one of the most crucial social indicators in road transport. As mentioned by the Confederação Brasileira de Transportes (CNT, 2022), in 2022 road accidents accounted for 64,447 records only on Brazilian federal roads, resulting in 52,948 cases with deaths or injuries and an estimated total cost of approximately 13 billion Brazilian reais.

In addition to considering logistic costs and accident risks, road freight transport companies must integrate environmental considerations into their decision-making processes. This includes prioritizing the reduction of greenhouse gas (GHG) emissions and incorporating alternative fuel vehicles (AFVs) alongside traditional diesel vehicles in their fleets. Studies on sustainable VRP are less common compared to the extensive research on the general VRP topic. However, they have gained notable attention in recent years, as shown in the upcoming literature review.

This study did not focus on exploring VRP formulations or solution methods. Instead, it implemented a multi-objective approach based on the *Augmented Weighted Tchebycheff* method to find efficient, non-dominated solutions for a VRP that simultaneously considers logistics costs, environmental impact, and social criteria. We applied this approach to a real instance from a large retail chain in Brazil with a heterogeneous fleet, including diesel-powered trucks, compressed natural gas (CNG) vehicles, and electric trucks with battery power. The company seeks to identify the optimal mix of vehicles to use for deliveries, aiming to minimize carbon dioxide emissions and accident risks while maintaining efficient logistics and cost-effectiveness.

This study is organized in four sections, besides this introduction. Section 3.2 reviews existing research on VRP that addresses accident risk and sustainability, either together or separately. It also identifies gaps in the literature that this study seeks to reduce. Section 3.3 details the VRP model and outlines the equations used in our proposed analytical approach. Section 3.4 presents the results of computational experiments and discusses key findings. Finally, Section 3.5 offers concluding remarks, bringing some words about the limitations of our study, and suggests avenues for future studies on this topic.

3.2 Literature related to sustainable VRP

As stated in Section 3.1, the goal of sustainability in the vehicle routing problem is to optimize economic, environmental, and social aspects. In this literature review, we focused on papers that address accident risks and sustainable elements in multi-objective VRP. Table 10 highlights that most studies concerning the Triple Bottom Line approach in VRP have been conducted in recent years.

According to Ferreira, Steiner & Junior (2020), most studies on multi-objective VRP optimization focus primarily on economic factors such as costs and profits, as well as environmental aspects that are limited to greenhouse gas emissions and fuel consumption. Social considerations are less frequently explored, presenting an opportunity for contribution to the literature. Similarly, Dündar, Ömürgönülşen & Soysal (2021) note that social aspects continue to receive limited attention, while economic factors remain the dominant priority among the three pillars of sustainability.

Dündar, Ömürgönülşen & Soysal (2021) mention that in sustainable VRP, the economic dimension typically encompasses operating costs and profits, while the environmental dimension focuses on reducing greenhouse gas emissions, fuel consumption, and promoting the use of electric vehicles. The social dimension includes addressing accident risks, customer satisfaction, employee job satisfaction, punctuality in deliveries, and creating new job opportunities.

In terms of social considerations, research on risks and safety in road freight often centers on the transport of hazardous materials, where the risk involves potential socio-environmental disasters, and cash-in-transit transport, which is primarily concerned with theft (TALARICO et al., 2017). According to Carrese et al. (2022) and Holeczek (2021), the risk of damage is proportional to the probability of accidents and the number of people exposed to such risk. Additionally, Holeczek (2021), Abdullahi et al. (2021), and Reyes-Rubiano et al. (2020) highlighted the importance of considering the load amount as a significant factor in assessing accident risk. Besides these risk factors, Chai et al. (2023) add drive behavior as a relevant factor that affects the risk of hazardous materials transportation.

Talarico et al. (2017) and Ghannadpour & Zandiyeh (2020) applied their studies on cash-in-transit transport, focusing on the risk of robberies, which is directly proportional to the amount of monetary assets and the distance traveled. Ghannadpour, Zandieh & Esmaeili (2021) reduced the risk of hospital waste contamination by shortening collection times. Similarly, Lin, Musa & Yap (2023) minimized the risk of contamination by considering the number of people exposed during transport, the amount of waste being carried, and the probability of disease transmission.

Some studies have optimized social dimension factors beyond risks. For instance, Ouhader & kyal (2017) and Mondal & Roy (2021) focused on maximizing job creation as a social factor, while Ganji et al. (2020) aimed to minimize customer dissatisfaction by avoiding service during less-preferred time windows. The model outlined in Prajapati et al. (2022) aimed to minimize penalties from late deliveries and accident risks, both of which were directly connected to vehicle speeds. The model also emphasized the importance of speed control since higher speeds increase the probability of accidents, while lower speeds can result in delivery delays.

In the environmental dimension, Demir, Bektaş & Laporte (2014) assert that CO_2 emissions are directly related to the amount of fuel consumed by the vehicle. Authors such as Ouhader & kyal (2017), Molina et al. (2014), Mojtahedi et al. (2021), Abdullahi et al. (2021), Reyes-Rubiano et al. (2020), and Qiao et al. (2020) work to minimize CO_2 emissions, while Demir, Bektaş & Laporte (2014), Xu et al. (2019), Ghannadpour, Zandieh & Esmaeili (2021), and Kopfer, Schönberger & Kopfer (2014) focus on reducing fuel consumption. Consequently most authors prioritize minimizing both CO_2 emissions and fuel consumption.

There are several alternative methods for measuring the environmental dimension. For instance, Ganji et al. (2020) aimed to minimize carbon emissions by considering factors such as load amount, average arc speed, type of vehicle, distance between origin and destination, and arc-specific constants (related to acceleration and road angle). Similarly, Prajapati et al. (2022) reduced carbon emissions by accounting for carbon taxation costs based on fuel consumption and distance traveled. Meanwhile, Abdoli, MirHassani & Hooshmand (2017) and Niranjani & Umamaheswari (2022) minimize total GHG emissions considering a vehicle emission rate that is measured by the ratio between the mass of GHG generated due to the distance traveled.

In terms of multi-objective approaches, Table 10 displays that some Multi-Objective Evolutionary Algorithms (MOEAs) were the most commonly used method for tackling multi-objective problems, followed by scalarization methods such as the ϵ-constrained and the weighted sum approaches. Ferreira, Steiner & Junior (2020) also identified heuristics, the ϵ-constrained and the weighted method as the most prevalent multi-objective techniques applied in VRP, corroborating the bibliographic research. Regarding the *Augmented Weighted Tchebycheff* method, only Mondal & Roy (2021) employed it for addressing multi-objective sustainable VRP.

Dächert, Gorski & Klamroth (2012) claim that one of the advantages of the *Augmented Weighted Tchebycheff* method is that every non-dominated point of a multi-objective optimization problem can be generated by varying the weights of each criterion in a single optimization function. Additionally, Molina et al. (2014), Mondal & Roy (2021), Filho, Oliveira & Melo (2023) argue that another advantage of the AWT method is its ability to avoid weakly non-dominated solutions. Thus, this study explores these positive aspects to solve the multi-objective VRP.

When exploring the optimization approaches presented in Table 10, heuristic methods were implemented in most studies, with Particle Swarm Optimization (PSO) and Simulated Annealing (SA) algorithms being the most common. Ferreira, Steiner & Junior (2020) found that, concerning multi-objective vehicle routing optimization with environmental considerations, genetic algorithms were the most extensively studied, followed by PSO and SA. Souza (2023) argued that genetic algorithms do not perform well compared to other heuristics due to their more random nature in generating new individuals. This way, Souza (2023) enhanced a genetic algorithm to generate higher-quality solutions for a VRP with a mixed fleet, though they did not consider the multi-objective approach.

As Table 10 indicates, no papers considered the use of heuristic and exact methods simultaneously. Ferreira, Steiner & Junior (2020) highlighted the need for studies that seek a hybrid approach, where heuristic procedures are implemented to enhance the performance of an exact method. In this study, we aim to implement the enhanced Genetic Algorithm found in Souza (2023) with a multi-objective approach to initiate the exact method due to the significant computational effort required to find feasible solutions to the problem.

On the subject of fleets, Erdoğan & Miller-Hooks (2012), Abdoli, MirHassani & Hooshmand (2017), and Reyes-Rubiano et al. (2020) suggest for future work the addition of heterogeneous fleets with alternative fuels, such as electricity or CNG, to better represent reality. Only Abdoli, MirHassani & Hooshmand (2017) emphasize the implementation of an approach with vehicles powered by multiple energy sources, where the mono-objective function minimizes the total GHG emissions. In this case, they considered a homogeneous fleet with bi-fuel vehicles, each composed of two separate tanks, one containing petroleum-based fuel and the other containing an alternative fuel.

Asghari & Al-e-hashem (2021) note that despite the extensive literature in the field of green transportation, most publications considering AFVs assumed only a homogeneous fleet condition, as evident from Table 10, and did not consider the development of approaches for determining the optimal combination of vehicles powered by different fuels. Therefore, this study addresses this literature gap by minimizing the three dimensions of sustainability using a heterogeneous fleet with vehicles powered by batteries, CNG, and diesel fuel.

Table 10 – Multi-objective VRP with risks and sustainable considerations.

Authors	Objective function			Fleet			Multi-objective approach						Solution method	
	Env.	Social	Econ.	Het.	AFV	MES	WM	EC	WT	AWT	MOEA	OA	HE	EX
Abdoli, MirHassani & Hooshmand (2017)	✓				✓	✓							✓	
Abdullahi et al. (2021)	✓	✓	✓				✓	✓					✓	
Bektaş & Laporte (2011)	✓		✓											✓
Carrese et al. (2022)		✓	✓									✓	✓	
Chai et al. (2023)		✓	✓								✓		✓	
Demir, Bektaş & Laporte (2014)	✓		✓				✓	✓					✓	
Erdoğan & Miller-Hooks (2012)			✓		✓								✓	
Euchi & Yassine (2023)			✓		✓								✓	
Ganji et al. (2020)	✓	✓	✓	✓							✓		✓	
Ghannadpour & Zandiyeh (2020)		✓	✓								✓		✓	
Ghannadpour, Zandieh & Esmaeili (2021)	✓	✓	✓								✓		✓	
Kopfer, Schönberger & Kopfer (2014)	✓			✓										✓
Lin, Musa & Yap (2023)	✓	✓			✓						✓		✓	
Mojtahedi et al. (2021)	✓	✓	✓	✓				✓				✓	✓	
Molina et al. (2014)	✓		✓	✓					✓				✓	
Mondal & Roy (2021)		✓	✓	✓						✓				✓
Niranjani & Umamaheswari (2022)	✓	✓	✓	✓									✓	
Ouhader & kyal (2017)	✓	✓	✓					✓						✓
Prajapati et al. (2022)	✓	✓	✓	✓									✓	
Qiao et al. (2020)	✓	✓	✓										✓	
Reyes-Rubiano et al. (2020)	✓	✓	✓										✓	
Soleimani, Chaharlang & Ghaderi (2018)	✓		✓	✓										✓
Talarico et al. (2017)			✓										✓	
Xu et al. (2019)	✓	✓									✓		✓	
This study	✓	✓	✓	✓	✓	✓	✓			✓			✓	✓

AFVs: Alternative Fuel Vehicles, AWT: Augmented Weighted Tchebycheff, EC: ϵ-constrained, Econ.: Economic,Env.: Environmental, EX: Exact, Het: Heterogeneous, HE: Heuristic, MES: Multiple Energy Sources, MOEA: Multi-objective evolutionary algorithms, OA: Other Algorithms, WM: Weighted Method, WT: Weighted Tchebycheff.

3.2.1 Review of Literature gap

Based on the literature review of multi-objective and sustainable VRP, several gaps have been identified that this study aims to address. The following sections outline these gaps and explain how this study intends to tackle them.

- Ferreira, Steiner & Junior (2020) and Dündar, Ömürgönülşen & Soysal (2021) state that the risk dimension is less common in the literature. Therefore, a multi-objective VRP was developed to support decision-making in minimizing the three dimensions of the Triple Bottom Line: social, environmental, and economic.

- The simultaneous use of heuristic and exact methods to solve specifically multi-objective sustainable VRP optimization has not been explored before. Thus, this study aims to implement an enhanced Genetic Algorithm to generate good feasible solutions to initiate the exact method.

- To the best of our knowledge, few studies on multi-objective and sustainable VRP have addressed heterogeneous fleets, where vehicles are powered by multiple energy sources such as batteries, CNG, and diesel fuel. Therefore, this subject was added to make the problem more realistic, as costs, fuel consumption, and CO_2 emissions vary for each type of vehicle.

- Few papers have addressed the implementation of the *Augmented Weighted Tchebycheff* (AWT) method to deal with multi-objective VRP (MO-VRP). Thus, this study experimented with the use of the AWT method as a way to generate efficient non-dominated solutions, and also due to the ease of handling the weighted parameters for a decision-maker to find solutions for different scenarios.

3.3 Analytical approach

The mathematical approach used to solve the MO-VRP was divided into four phases, summarized in the workflow described in Figure 13. The highlighted processes represent the contributions of this study to the literature. The first phase consisted of defining the MO-VRP, assigning parameters and objectives to be minimized, grouping vehicles, and exploring the HVRP formulation.

Then, in Phase 2, the enhanced Genetic Algorithm developed by Souza (2023) was implemented to generate feasible solutions for use in Phase 3, which initiated the exact method. In Phase 3, the formulation of the *Augmented Weighted Tchebycheff* method was applied, where the initial *lexicographic Pareto optimal solutions* were identified using the VRPSolverEasy (ERRAMI et al., 2023) to normalize the objective functions. Subsequently, after finding the *lexicographic*

Pareto optimal solutions, the MO-VRP was solved using the *Augmented Weighted Tchebycheff* method with the commercial solver Gurobi 10.0.3.

The results obtained were analyzed in Phase 4. Considering the perspective of a decision-maker, it is necessary to validate whether the solution is suitable for the company's process. If it is suitable, the decision is made based on the obtained solution; otherwise, the weights are adjusted to generate new solutions. Therefore, this study analyzed solutions for several scenarios, with experiments conducted using different sets of weights to allow for the evaluation and comparison of outcomes.

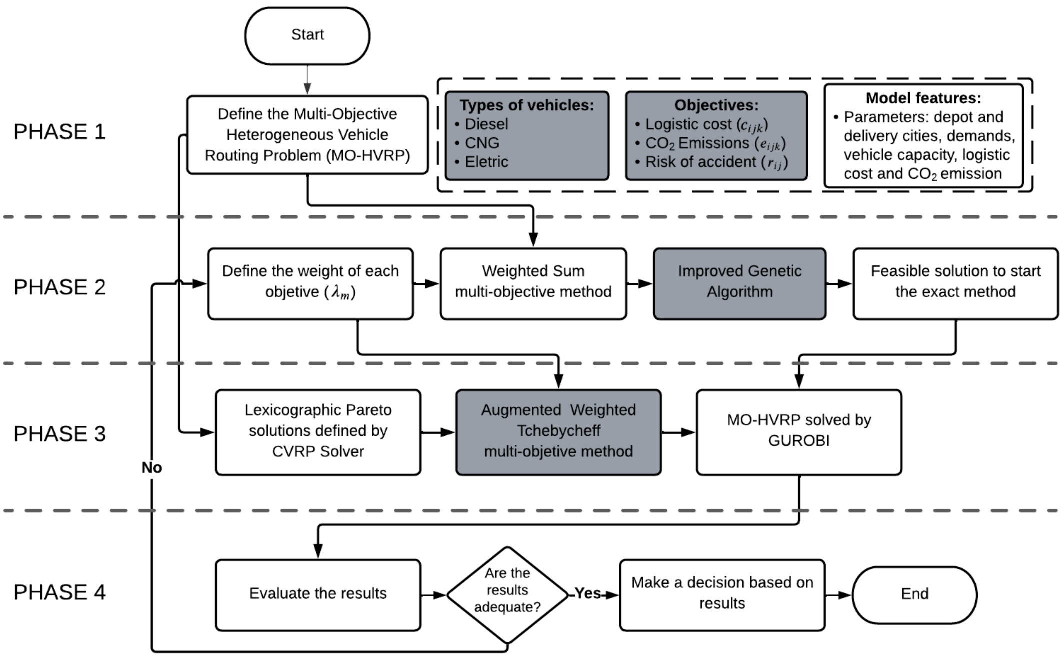


Figure 13 – Workflow of the analytical approach in this study.

3.3.1 Phase 1: Multi-Objective Heterogeneous Vehicle Routing Problem MO-HVRP

During Phase 1, primarily the MO-HVRP parameters were defined (Section 3.3.1.1) and then the mathematical formulation for the problem is presented

(Section 3.3.1.2).

3.3.1.1 Phase 1.1: Parameters of HVRP

Table 11 provides parameters such as the average consumption ($consu_k$), fuel price per volume ($cost_k$), and the CO_2 emission rate ($emiss_k$). The values for c_{ijk} and e_{ijk} were calculated using Equations 3.1 and 3.3, respectively. In this case, it was assumed that electric vehicles do not produce CO_2 , considering only the tank-to-wheel aspect, where CO_2 generation is attributed solely to fuel consumption for vehicle propulsion. The entire chain of fuel production and transportation was not considered. The fuel consumption and CO_2 emission parameters were collected from manufacturers producing these vehicle groups and were based on standard heavy-duty vehicles with a Gross Total Weight of 40 tons. The prices (in Brazilian reais – BRL) of the three fuel types were collected in July 2023 from fueling stations located on roads in São Paulo state, Brazil.

Due to the difficulty of finding information about fuel consumption and CO_2 emissions, these parameters were considered constant and do not change with variations in load amount. The speed of the vehicles is also constant and equal for all groups. The Alternative Fuel Vehicles (AFVs) were included in the problem, specifically electric vehicles and those powered by Compressed Natural Gas (CNG). The AFVs do not have restrictions on the distance they can travel, meaning the vehicles are sufficiently fueled at the depot to complete all deliveries and return.

Table 11 – Parameters of each group of vehicle.

	Diesel	CNG	Eletric
Fuel consumption	3.03 km/L	2.17 km/m^3	0.98 km/kWh
Fuel price (BRL)	\$ 4.59/L	\$ 3.89/m^3	\$ 1.95/KWh
Emission of CO_2 (Kg/Km)	2.03	1.76	-

Finally, the data used to calculate the risk of accidents, r_{ij}, for each arc ij, were collected from the CNT (2019), DER-SP (2021), and DNIT (2021). It was assumed that the factors influencing the risk of accidents include road infrastructure and the volume of heavy vehicle traffic traversing them. The r_{ij} values were considered to be the same for all vehicle groups and were presented in monetary losses ($), estimated by Monte Carlo simulations. The detailed procedure is described in Chapter 2.

3.3.1.2 Phase 1.2: MO-HVRP Mathematical Model

The Multi-Objective Vehicle Routing Problem (MO-VRP) was applied to a large retail chain (Magazine Luiza) whose depot and stores are located in cities in the macro-region of Campinas, state of São Paulo, Brazil. The connections among the cities in the region were represented by a graph $G = (V, A)$, where $V = \{0, \ldots, n\}$ is the set of vertices representing the cities, and A is the set of arcs between vertex i and vertex j.

The problem involves a heterogeneous fleet, with the set $K = \{k_1, k_2, k_3\}$ composed of three vehicle groups: diesel fuel, CNG, and electric. An unlimited number of vehicles is available, all having the same capacity (*cap*), and starting and ending at the depot in Louveira. The MO-VRP was tested on an instance with 53 cities located in São Paulo state, as represented in Figure 14. The markers in blue represent the delivery cities, and the marker in red represents the depot.

The model employs a *three-index vehicle flow formulation*, which is a modification of the *two-index vehicle flow formulation* described in Toth & Vigo (2002). The sets, parameters, and variables are described as follows.

Sets:

V: set of all vertices representing the locations (delivery cities and the depot);

K: set of vehicle groups.

Parameters:

$fuel_k$: fuel price per unit volume for vehicle group k;

$consu_k$: fuel consumption of vehicle group k;

$dist_{ij}$: distance between city i and city j;

c_{ijk} : logistic cost of vehicle in the group k that traverses the arc ij;

$emiss_k$: CO_2 emission rate for vehicle in group k:

e_{ijk} : CO_2 emission of vehicle in the group k that traverses arc ij;

r_{ij} : accident risk cost between city i and j;

d_i : demand in city i;

cap : vehicle capacity (the same for all).

Variables:

X_{ijk} : binary variable that takes the value 1 if a vehicle from group k traverses arc $(i, j) \in A$, and takes the value 0 otherwise;

Y_k : integer variable representing the total number of vehicles from each group k used to make the deliveries;

U_{ik} : positive variable which account the cumulative load of vehicle k after visiting note i.

Each part of the objective function for the MO-VRP is described below.

Logistic costs: the logistic cost (c_{ijk}) was calculated using Equation (3.1), and the first part of the objective function representing logistic costs is given by Equation (3.2).

$$c_{ijk} = \frac{fuel_k}{consu_k} \; . \; dist_{ij} \quad \forall \; k \; \in \; K, \; \forall \; (i, j) \; \in \; V \tag{3.1}$$

$$f_1(\mathbf{x}) = \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} c_{ijk} \; . \; X_{ijk} \tag{3.2}$$

CO_2 Emission: the CO_2 emission (e_{ijk}) is calculated in Equation (3.3) and the second part of the objective function representing the total emissions are given by Equation (3.4).

$$e_{ijk} = emiss_k \ . \ dist_{ij} \quad \forall \ k \ \in \ K, \ \forall \ (i,j) \ \in \ V \tag{3.3}$$

$$f_2(\mathbf{x}) = \ \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} e_{ijk} \ . \ X_{ijk} \tag{3.4}$$

Risk of Accidents: the third part of the objective function that symbolizes risk of accidents (r_{ij}) are represented by Equation (3.5).

$$f_3(\mathbf{x}) = \ \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} r_{ij} \ . \ X_{ijk} \tag{3.5}$$

The Expression 3.6 represents complete objective function:

$$minimize: \quad \mathbf{z} = \{f_1(\mathbf{x}), f_2(\mathbf{x}), f_3(\mathbf{x})\} \tag{3.6}$$

The constrains of the MO-HVRP are described as follow.

$$\sum_{k\in K}\sum_{i\in V} X_{ijk} = 1 \quad \forall\ j \in V\backslash\{0\} \tag{3.7}$$

$$\sum_{k\in K}\sum_{j\in V} X_{ijk} = 1 \quad \forall\ i \in V\backslash\{0\} \tag{3.8}$$

$$\sum_{i\in V} X_{i0k} = Y_k \quad \forall\ k \in K \tag{3.9}$$

$$\sum_{j\in V} X_{0jk} = Y_k \quad \forall\ k \in K \tag{3.10}$$

$$\sum_{k\in K} Y_k \geqslant \frac{\sum_{i\in V} d_i}{cap} \tag{3.11}$$

$$\sum_{i\in V\backslash\{h\}} X_{ihk} - \sum_{j\in V\backslash\{h\}} X_{hjk} = 0 \quad \forall\ k \in K,\ \forall\ h \in V\backslash\{0\} \tag{3.12}$$

$$U_{ik} - U_{jk} + cap\ .\ X_{ijk} \leqslant cap - d_j \quad \forall\ (i,j) \in V\backslash\{0\}\ i \neq j \mid d_i + d_j \leqslant cap \tag{3.13}$$

$$d_i \leqslant U_{ik} \leqslant cap \quad \forall\ i \in V\ \backslash\{0\} \tag{3.14}$$

$$X_{ijk} \in \{0,1\}\ \forall\ (i,j) \in V,\ \forall\ k \in K \tag{3.15}$$

$$Y_k \in \mathbb{Z}^+\ \forall\ k \in K \tag{3.16}$$

$$U_{ik} \in \mathbb{R}^+\ \forall\ k \in K \tag{3.17}$$

Expressions (3.7) and (3.8) impose that for each vertex representing a location, there is only one entry and one exit, respectively. Expressions (3.9) and (3.10) represent the number of vehicles Y_k that depart from and arrive at the depot, respectively. We can also compute a lower bound on the number of vehicles needed, which is the sum of all demands divided by the vehicle capacity, as shown in Expression (3.11). This constraint is not necessary but usually helps to improve the performance of the model resolution process.

Expression (3.12) represents the flow at vertex h, where the same vehicle needs to arrive and depart from the nodes, with the exception of the depot. Expressions (3.13) and (3.14) impose the vehicle capacity and the connectivity requirements along the route. Constraints (3.13) ensure sub-tour elimination, as proposed by Miller, Tucker & Zemlin (1960) and adapted to MO-VRP. The domain of the decision variables for the routes is described in Expressions (3.15), (3.16), and (3.17) (TOTH; VIGO, 2002).

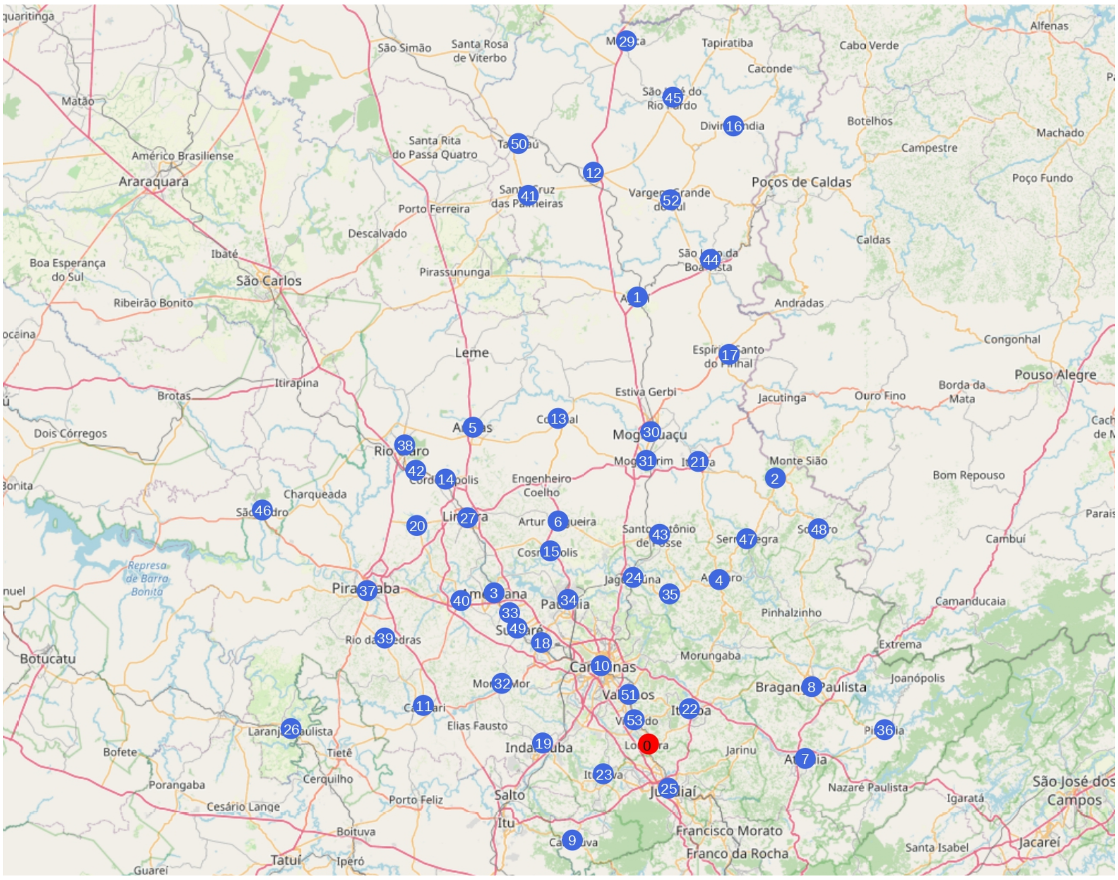


Figure 14 – Location of the cities in the problem.

Legend of Figure 14: 0: Louveira (depot), 1: Aguaí, 2: Águas de Lindóia, 3: Americana, 4: Amparo, 5: Araras, 6: Arthur Nogueira, 7: Atibaia, 8: Bragança Paulista, 9: Cabreúva, 10: Campinas, 11: Capivari, 12: Casa Branca, 13: Conchal, 14: Cordeirópolis, 15: Cosmópolis, 16: Divinolândia, 17: Espirito Santo do Pinhal, 18: Hortolândia, 19: Indaiatuba, 20: Iracemápolis, 21: Itapira, 22: Itatiba, 23: Itupeva, 24: Jaguariúna, 25: Jundiaí, 26: Laranjal Paulista, 27: Limeira, 29: Mococa, 30: Mogi Guaçu, 31: Mogi Mirim, 32: Monte Mor, 33: Nova Odessa, 34: Paulinia, 35: Pedreira, 36: Piracaia, 37: Piracicaba, 38: Rio Claro, 39: Rio das Pedras, 40: Santa Bárbara d'Oeste, 41: Santa Cruz das Palmeiras, 42: Santa Gertrudes, 43: Santo Antônio de Posse, 44: São João da Boa Vista, 45: São José do Rio Pardo, 46: São Pedro, 47: Serra Negra, 48: Socorro, 49: Sumaré, 50: Tambaú, 51: Valinhos, 52: Vargem Grande do Sul, 53: Vinhedo.

3.3.2 Phase 2: Enhanced Genetic Algorithm

The implementation of a heuristic procedure became necessary to improve the performance of the *Augmented Weighted Tchebycheff* multi-objective method optimized by a exact approach, which requires a large computational effort without the use of a heuristic.

Therefore, in this study, the Genetic Algorithm proposed by Souza (2023) was improved and implemented to generate feasible solutions to initiate the exact method using Gurobi. This was necessary because the solver took a long time to find an initial feasible solution, which always demonstrated a large gap relative to its lower bound.

The implementation followed the guidelines of Souza (2023), which employed two mechanisms to improve the performance of the genetic algorithm. One of these was the Split Algorithm proposed by Prins (2004), designed to handle a sequence of customers without route delimiters. Instead of considering the sequence 0-3-5-0-4-0-2-1-0, where 0 represents the depot and 1, 2, 3, 4, and 5 are delivery points, the algorithm considered only 3-5-4-2-1, removing the route delimiters (0). This increased the efficiency of the algorithm. According to Souza (2023), chromosomes with route delimiters complicate the code.

The second mechanism, developed by Blanton & Wainwright (1993), utilizes two crossover operations. These operations compare each gene of the parent chromosomes with a gene from a child precedence sequence and select the gene from either Parent 1 or Parent 2, depending on which appears first in the child precedence sequence. This explanation becomes clearer with the example represented in Figure 15.

In the first iteration, two individuals were randomly selected as parents to generate a new individual (child). Subsequently, the first gene for the child was chosen randomly from either parent 1 or parent 2. In this example, it was selected gene 2 from parent 1. Consequently, the gene with the same value from parent 2 was chosen and exchanged with the gene in the first position (same position of parent 1).

In the next step (Iteration 2), the genes in the second position of parent

1 and parent 2 were compared with the first gene of the child. Assuming that the distance between point 2 and point 5 is shorter than that between point 2 and point 4, the second gene from parent 2 was selected for the child, and the gene with the same value from parent 1 was exchanged with the gene in the second position.

In the Iteration 3, the genes of the third position of parents 1 and 2 were compared with the second gene of the child. In this case, the distance from point 5 to point 6 is shorter than form point 5 to point 1. Thus, the point 6 was selected as a new gene of the child.

This process was repeated successively, following the same procedure, until the child's chromosome was completed, representing a new individual and containing a new solution for the problem.

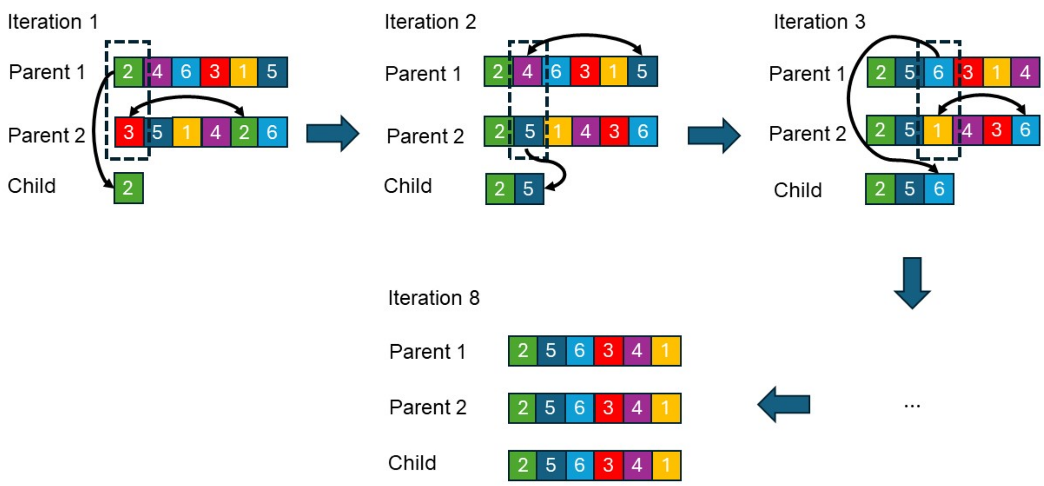


Figure 15 – Illustration of Blanton & Wainwright (1993) *crossover* operations.

The heuristic was adapted to address a MO-VRP with a heterogeneous fleet and was implemented in Python. Consequently, the Weight Sum method was applied solely to guide the feasible solution that initiates the exact method in Phase 3. Its implementation was simpler because it did not require adding constraints to the algorithm, and it did not alter the objective function.

The proposed weighted objective function in Expression (3.18) was defined as combination of three sustainability dimensions, aggregating the objectives into a single objective with priority weights, where z^* is the optimal solution obtained from the sum of the weighted objectives. In this way, λ_m represents the weights or the relative importance of dimension $m \in M$, where $M = 1, 2, 3$ denotes the set of three dimensions. We also have $0 \leqslant \lambda_m \leqslant 1$ and $\sum_{m \in M} \lambda_m = 1$.

$$minimize: \ z^* = \sum_{m \in M} \lambda_m \cdot f_m(\mathbf{x}) \tag{3.18}$$

Algorithm 1 is presented as pseudocode and returns the best solution among all generations. The initial population consisted of random individuals, with each solution calculated using Algorithm 2. The best solution was identified as the individual in this initial population that had the minimal objective value.

Subsequently, crossover operations were implemented, including the order crossover (OX) and two mechanisms proposed by Blanton & Wainwright (1993): one starting from the beginning of the chromosome and the other starting from the end. After performing the crossover operations and generating new individuals for the new population, mutation operations were carried out. Finally, an elitism function was added to replace a number of random individuals in the population with the best solution found so far. Each new individual's solution, generated by crossover and mutation operations, needed to be calculated using Algorithm 2.

3.3.3 Phase 3: *Augmented Weighted Tchebycheff* Method

In multi-objective optimization, techniques are needed to search for the set of Pareto solutions that represent the best trade-offs between conflicting objectives. Among the existing techniques, the Weighted Sum, ϵ-Constrained, and Tchebycheff scalarization methods are the best-known approaches for dealing with multi-objective problems.

Here, the *Augmented Weighted Tchebycheff* method was selected to generate solutions for the MO-VRP because this approach has the main advantage

Algorithm 1 : Enhanced Genetic Algorithm

Input: $TotalInd \leftarrow$ number of individuals in the population; $TotalGen \leftarrow$ number of population; $n \leftarrow$ number of delivery cities
Initial population with random individuals without route delimiters
array route[1 ... n].
while $i < TotalInd$ **do**:
    $Ind_i \leftarrow random.shuffle(route)$
    $Sol[Ind_i] \leftarrow SplitPrins(Ind_i)$
    $i \leftarrow i + 1$
end while.
$MinSol \leftarrow Sol[Ind_i]$
$BestSol \leftarrow MinSol$
while $Gen < TotalGen$ **do**:
    Crossover Operations
    Selects two random individuals to generate a child
    $SolChild \leftarrow SplitPrins(child)$
    if $SolChild < BestSol$ **then**:
        $BestSol \leftarrow SolChild$
    end if.
    Mutation Operations
    Selects a random individual
    Selects two random points of this individual
    Execute the mutation and generate a new individual
    $SolMut \leftarrow SplitPrins(NewInd)$
    if $SolMut < BestSol$ **then**:
        $BestSol \leftarrow SolMut$
    end if.
    Elitism selection
    Selects two random individuals of the population
    Change these two individuals for the best solution to date and generante a new individual
    $SolElit \leftarrow SplitPrins(NewInd)$
    if $SolElit < BestSol$ **then**:
        $BestSol \leftarrow SolElit$
    end if.
    Gen = Gen + 1
end while.
return: BestSol

Algorithm 2 : Split Algorithm for Mixed Fleet

Input: $S \leftarrow$ individual generated by enhanced Genetic Algorithm; $c_k \leftarrow$ variable cost of vehicle k; $l_{ij} \leftarrow$ length/distance between arcs ij; $e_k \leftarrow$ CO_2 emission rate of vehicle k; $cap \leftarrow$ vehicle capacity; $dem_i \leftarrow$ delivery demand of city i; $n \leftarrow$ number of delivery cities; $\lambda_m \leftarrow$ weight of objective m; $V_0 \leftarrow 0$.
for $i \leftarrow 1$ *to* n **do**:
    $V_i \leftarrow +\infty$
end for.
for $i \leftarrow 1$ *to* n **do**:
    $load \leftarrow 0$; $dist \leftarrow 0$; $risk \leftarrow 0$; $car \leftarrow 0$; $j \leftarrow i$
    repeat:
        $load \leftarrow load + dem_{Sj}$
        if $i = j$ **then**:
            $dist \leftarrow l_{0,S_j} + l_{S_j,0}$
            $risk \leftarrow r_{0,S_j} + r_{S_j,0}$
        end if.
        if $i \neq j$ **then**:
            $dist \leftarrow dist - l_{S_{j-1},S_j} + l_{S_j,0}$
            $risk \leftarrow risk - r_{S_{j-1},S_j} + r_{S_j,0}$
        end if.
        if $load \leqslant cap$ **then**:
            $Z_{ij} \leftarrow +\infty$
            $cost(diesel) \leftarrow c_{diesel} \,.\, dist \,.\, \lambda_1 + e_{diesel} \,.\, dist \,.\, \lambda_2 + risk \,.\, \lambda_3$
            $cost(gas) \leftarrow c_{cng} \,.\, dist \,.\, \lambda_1 + e_{cng} \,.\, dist \,.\, \lambda_2 + risk \,.\, \lambda_3$
            $cost(eletric) \leftarrow c_{eletric} \,.\, dist \,.\, \lambda_1 + e_{eletric} \,.\, dist \,.\, \lambda_2 + risk \,.\, \lambda_3$
            if $cost(diesel)$ is the minimum **then**:
                $car \leftarrow 0$
                $Z_{ij} \leftarrow cost(diesel)$
            end if.
            if $cost(cng)$ is the minimum **then**:
                $car \leftarrow 1$
                $Z_{ij} \leftarrow cost(gas)$
            end if.
            if $cost(eletric)$ is the minimum **then**:
                $car \leftarrow 2$
                $Z_{ij} \leftarrow cost(eletric)$
            end if.
            if $V_{i-1} + Z_{ij} < V_j$ **then**:
                $V_j \leftarrow V_{i-1} + Zij$
                $type\_car[j] \leftarrow car$
            end if.
            $j \leftarrow j + 1$
        end if.
        this
    until : $(j > n)$ or $(load > cap)$
end for.
return: V, type_car

of eliminating weakly efficient non-dominated solutions. Additionally, it does not interfere with the set of feasible solutions by avoiding the addition of constraints that limit the criterion space, which could make the use of exact methods more exhaustive (FILHO; OLIVEIRA; MELO, 2023).

Another important advantage of the Tchebycheff method is its ability to generate non-dominated solutions for a multi-objective optimization problem by appropriately varying the weights of each criterion in the objective function (DÄCHERT; GORSKI; KLAMROTH, 2012). This simplifies the decision-making process because varying the weight parameters for each criterion allows the generation of solutions for different scenarios, even if the objectives are conflicting.

To the best of our knowledge, studies addressing the MO-VRP with the *Augmented Weighted Tchebycheff* technique are less common. In this study, the implementation of the *Augmented Weighted Tchebycheff* method followed the guidelines and detailed explanations presented by Filho, Oliveira & Melo (2023), who applied the method for optimization with three conflicting objectives in the area of sugarcane cultivation.

The workflow described in Figure 16 represents the implementation of the *Augmented Weighted Tchebycheff* method, which was divided into two steps. In the first step, the lexicographic points were determined from the ideal and anti-ideal vectors. In the second step, the *Augmented Weighted Tchebycheff* method was used to identify the Pareto solutions through Expression (3.20).

Step 1: Determining the lexicographic points

The first step involved dividing the problem into three sub-problems, as shown in Expression (3.19). Each sub-problem was minimized separately by prioritizing logistic costs ($f_1(\mathbf{x}) = \mathbf{z_1}$), CO_2 emissions ($f_2(\mathbf{x}) = \mathbf{z_2}$), and accident risks ($f_3(\mathbf{x}) = \mathbf{z_3}$). Here, $\mathbf{z_m} = \{s_{m1}, s_{m2}, s_{m3}\}$ represents the optimal solution vectors for each sub-problem $m \in M$, where s_{m1}, s_{m2}, and s_{m3} correspond to the solutions for logistic costs, CO_2 emissions, and accident risks, respectively.

$$
\begin{aligned}
&\textit{minimize}: \quad \mathbf{z_m} = f_m(\mathbf{x}) \quad m \in M \\
&\textit{subject to}: \quad \mathbf{x} \in S
\end{aligned}
\tag{3.19}
$$

The set M represents the three sustainability dimensions we aim to optimize, and the feasible decision space S is delimited by the constraints defined by Expressions (3.7) to (3.17). $\mathbf{z_m}$ is equivalent to the first three Pareto optimal solutions and determines the boundaries of the Pareto surface.

Each value of the objectives contained in the solution set $\mathbf{z_m}$ was compared to obtain the ideal ($\mathbf{v^I} = \{v_1^I, v_2^I, v_3^I\}^T$) and anti-ideal ($\mathbf{v^A} = \{v_1^A, v_2^A, v_3^A\}^T$) vectors, with the first symbolizing the best alternatives for each objective function and the second symbolizing the worst alternatives. For example, for the logistic cost, three different solutions were obtained: the first (s_{11}) was calculated when logistic cost was prioritized, the second (s_{21}) when CO_2 emissions were prioritized, and the third (s_{31}) when accident risks were prioritized. From this comparison, it is possible to obtain the minimum value, which represents the ideal point (v_1^I), and the maximum value, which represents the anti-ideal point (v_1^A).

The optimal solutions were generated by VRPSolverEasy (ERRAMI et al., 2023), a Python package that provides a simple interface for VRPSolver (PESSOA et al., 2020). VRPSolver is a Branch-Cut-and-Price algorithm specifically designed for VRPs. For instances with fewer than 100 customers, it often produces optimal solutions within a few minutes (PESSOA et al., 2020). In this case, it generated the optimal lexicographic solutions necessary for normalizing the objective functions in Step 2. The use of a solver specifically developed for VRPs was justified, as it solved the instance presented in this study with significantly lower computational effort compared to the commercial Gurobi solver. It is important to highlight that the feasible solutions obtained through the enhanced Genetic Algorithm were considered only in Step 2, not in Step 1.

Step 2: Determining efficient solutions

Using v^I and v^A obtained in Step 1, along with the feasible solutions generated by the enhanced Genetic Algorithm, new efficient solutions can be found

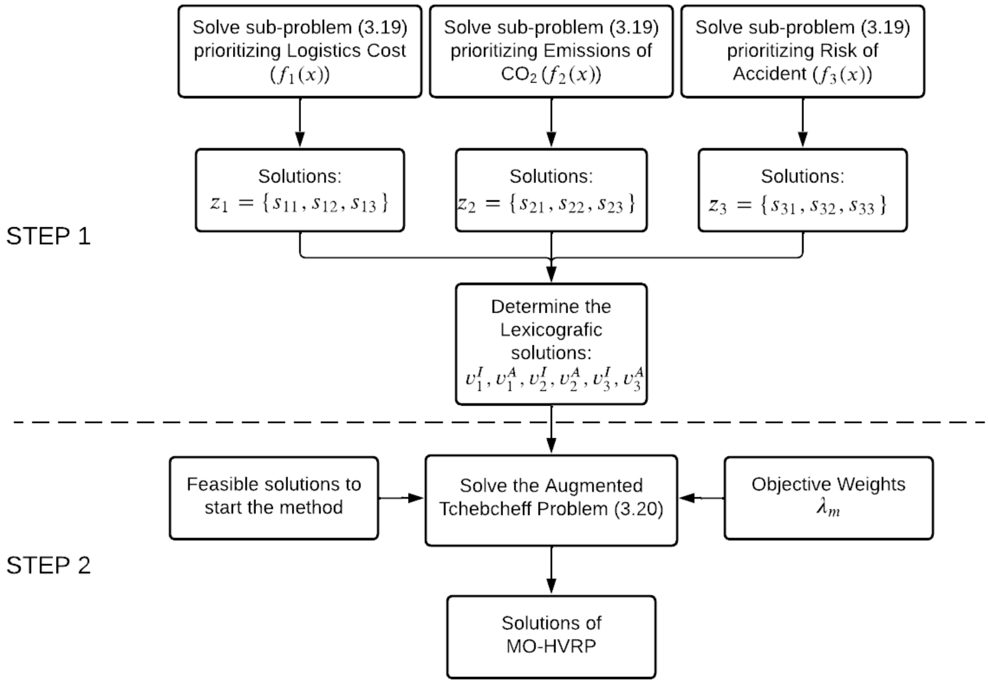


Figure 16 – Workflow of *Augmented Weighted Tchebycheff*

by minimizing the Expression (3.20).

$$\begin{aligned} &minimize: \quad \alpha + \rho \ . \sum_{m \in M} \bar{f}_m(x) \\ &subject\ to: \quad x \ \in \ S \\ &\qquad\qquad \lambda_m \ . \ \bar{f}_m(x) \ \leqslant \ \alpha \quad \forall \ m \ \in \ M \\ &\qquad\qquad \alpha \ \geqslant \ 0 \end{aligned} \tag{3.20}$$

Where: $0 \leqslant \lambda_m \leqslant 1$ and $\sum_{m \in M} \lambda_m = 1$. The normalized function $\bar{f}_m(x)$ is represented by Expression (3.21) and is obtained using v^I and v^A, found in Step 1. Normalization of the objective functions was necessary because each objective has a different order of magnitude.

An auxiliary variable α was considered to linearize the original *Tchebycheff* formulation while maintaining convexity. ρ is a sufficient small positive constant that makes part of the augmented term, which is added to balance the trade-off between the minimum deviation of each objective from its ideal point and the minimum of the deviations' sum of the objectives, achieving a well-distributed set of solutions and avoiding weakly efficient solutions.

Dächert, Gorski & Klamroth (2012) states that a very low ρ can cause problems because the augmented term in the objective function may lose significance. On the other hand, a very high ρ can make non-dominated points unreachable. Thus, Steuer (1989) suggests that ρ values between 0.01 and 0.0001 are normally sufficient.

$$\bar{f}_m(x) = \frac{f_m(x) - v_m^I}{v_m^A - v_m^I} \quad \forall\ m \in M \tag{3.21}$$

The final formulation of the *Augmented Weighted Tchebycheff* method for the MO-VRP problem was based on implementing Expression (3.20) along with Expressions (3.7) to (3.17). The Mixed Integer Programming model was executed in Python and utilized the Gurobi Optimizer (version 10.0.3) to solve the MO-VRP. The Gurobi solver was chosen because it offers the flexibility to construct objective functions and add new constraints. The alternative of using the VRPSolverEasy was not considered because it is restricted designed to a subset of VRP variants (ERRAMI et al., 2023), and does not allow for the addition of new constraints or modifications to the objective function as required by the *Augmented Weighted Tchebycheff* method.

3.4 Experimental results

The entire problem was based on a real instance from a large retail chain, where some parameters were adapted to simulate conditions under which the company could make decisions considering different sustainability dimensions. Different scenarios were created, with each objective receiving different weights, to analyze the solutions obtained for each scenario.

We started our analysis by presenting, in Table 12, the lexicographic solutions of each sub-problem defined in model (3.19). Prioritizing the minimization of logistic costs, the optimization yielded the lowest value for this objective ($v_1^I =$

5613.52), while resulting in the maximum values for CO_2 emissions ($v_2^A = 7506.13$) and risk costs ($v_3^A = 37534.72$). This outcome was achieved by selecting only diesel fuel vehicles due to their lower operational costs and prioritizing arcs with shorter distances.

When prioritizing CO_2 emissions and accident risks, only electric vehicles were selected for both sub-problems, as they do not emit CO_2 . This resulted in the minimum value for the CO_2 emission objective ($v_2^I = 0$). Finally, by prioritizing the minimization of accident risks, the optimization yielded the minimum risk cost ($v_3^I = 28254.20$) and the maximum logistical cost ($v_1^A = 12403.79$).

Table 12 – Lexicographic pareto optimal solutions obtained by VRPSolver.

Scenarios	Solution				Quantity of vehicles		
	CO_2 emission (kg)	(A) Logistics ($)	(B) Risks ($)	A + B ($)	Diesel	CNG	Electric
L1	7506.13	5613.52	37534.72	43148.24	14	0	0
L2	0.00	9315.23	29382.89	38698.12	0	0	14
L3	0.00	12403.79	28254.20	40657.99	0	0	14

Scenario L1: Prioritization of Logistic costs; Scenario L2: Prioritization of CO_2 emission; Scenario L3: Prioritization of Risks.

Based on the lexicographical solutions obtained, the MO-VRP was then solved using the *Augmented Weighted Tchebycheff* method. Seven additional scenarios were selected for this problem, as represented in Table 13. In each scenario, weights were assigned to each objective: λ_1 for logistic costs, λ_2 for CO_2 emissions, and λ_3 for minimizing accident risks.

The scenarios were designed to represent situations where evaluating and assigning weights to each criterion must be considered according to the levels of risk, CO_2 emissions, and logistic costs within which a company wishes to operate. In Scenarios S1 and S5, conditions were simulated where minimizing logistic costs is prioritized, such as in transport operations with low cargo values and fewer risks to the population in case of accidents. Conversely, if these risk factors need to be prioritized, Scenarios S3 and S7 were created to focus on this criterion.

Due to concerns about environmental aspects, Scenarios S2 and S6 simulated the prioritization of reducing CO_2 emissions over other criteria. Finally, Scenario S4 represents the condition where the three dimensions are equally weighted, assuming the decision-maker considers them equally important in the decision-process.

In the Appendix A contains detailed results, and Table 13 presents the solutions obtained for each scenario, including the number of vehicles from each group that should be used. Electric vehicles were selected in most scenarios where minimizing CO_2 emissions was a priority, as they emit 0 kg/km of CO_2 . Only in Scenario S1 were more diesel fuel trucks selected, as the importance of minimizing logistic costs was eight times greater than reducing CO_2 emissions.

Table 13 – Solutions obtained for each scenarios.

Scenarios	Weights	Solutions				Quantity of vehicles		
		CO_2 emission (kg)	(A) Logistics ($)	(B) Risks ($)	A + B	Diesel	CNG	Electric
S1	$\lambda_1 = 0.80$ $\lambda_2 = 0.10$ $\lambda_3 = 0.10$	5924.35	6279.89	35293.74	41573.63	10	0	5
S2	$\lambda_1 = 0.10$ $\lambda_2 = 0.80$ $\lambda_3 = 0.10$	283.39	8355.17	31987.89	40343.06	1	0	14
S3	$\lambda_1 = 0.10$ $\lambda_2 = 0.10$ $\lambda_3 = 0.80$	3694.60	9534.11	28959.97	38494.08	6	0	8
S4	$\lambda_1 = 0.333$ $\lambda_2 = 0.333$ $\lambda_3 = 0.333$	2623.77	7995.87	31499.25	39495.10	5	0	10
S5	$\lambda_1 = 0.50$ $\lambda_2 = 0.25$ $\lambda_3 = 0.25$	3675.72	7272.12	32746.57	40018.69	7	0	8
S6	$\lambda_1 = 0.25$ $\lambda_2 = 0.50$ $\lambda_3 = 0.25$	1260.02	8095.63	31615.70	39711,33	3	0	12
S7	$\lambda_1 = 0.25$ $\lambda_2 = 0.25$ $\lambda_3 = 0.50$	3387.66	8699.27	30365.55	39064.82	3	0	12

CNG vehicles were not selected for any of the scenarios because they have higher operational costs and emit only 15% less CO_2 compared to diesel vehicles. Although CNG vehicles have lower costs than electric vehicles, their CO_2 emissions are much higher. Consequently, when prioritizing the minimization of logistic costs, diesel vehicles were preferred, and when prioritizing the reduction of CO_2 emissions, electric vehicles were selected.

In this case, selecting more CNG trucks requires addressing technological improvements to reduce CO_2 emissions and fuel consumption. According to Seo, Kwon & Park (2020), technological advancements have the potential to reduce CO_2 emissions from CNG trucks by 28-35% in the near future and by 41-51% in the longer term.

New scenarios were made based on the assumption that CNG trucks emit 1.14 kg of CO_2 per kilometer, with a projected potential reduction of 35% in the near future, while diesel trucks maintain their current emission levels. The results indicated that in Scenarios S2, S5, S6, and S7, at least one CNG truck was utilized, whereas Scenario S3 included three CNG vehicles.

Regarding heavy-duty electric vehicles, according to Nykvist & Olsson (2021), they are currently not economically viable compared to diesel vehicles in terms of cost per distance. One factor that could enhance the viability of heavy-duty electric vehicles is the energy density of the battery, measured in watt-hours per kilogram (Wh/kg). Higher energy storage capacity in a battery results in a lighter battery, which improves the vehicle's autonomy. Consequently, in scenarios where logistic costs are prioritized, electric vehicles may become more preferable than diesel vehicles, also offering environmental benefits.

Analyzing the total logistic costs, CO_2 emissions, and accident risks presented in Table 13, the results demonstrated consistency with the weights assigned in each scenario. The *Augmented Weighted Tchebycheff* method proved suitable for the MO-VRP. For instance, when comparing the lexicographic solutions from prioritizing the minimization of logistic costs (Scenario L1) and Scenario S1, CO_2 emissions were reduced from 7506.13 kg to 5924.35 kg, and the risk cost decreased from $37534.72 to $35293.74. In Scenario S4, where the weights are equal, a balanced solution was achieved, avoiding extreme values for each objective and representing a satisfactory outcome for this scenario.

To compare the variation of the three dimensions in each scenario (S1, S2, S3, S4, S5, S6, and S7) relative to the lexicographic Scenario L1, commonly used in VRP for its focus on minimizing logistics costs, Figure 17 displays the variation in the three dimensions investigated. Among all scenarios, the environmental dimension exhibited significant negative variations due to the increased use of electric vehicles. Conversely, the logistics cost dimension showed considerable positive variations when prioritizing risk (Scenarios S3 and S7) and environmental concerns (Scenarios S2 and S6). In situations where the cargo type poses minimal risks to the population or has low commercial shipment value, operating under Scenarios S3 and S7 is not cost-effective due to their high costs. However, substantial technological improvements in the efficiency of heavy-duty AFVs, as discussed earlier, would lead to a significant reduction in logistics cost variations, making AFVs more economically viable.

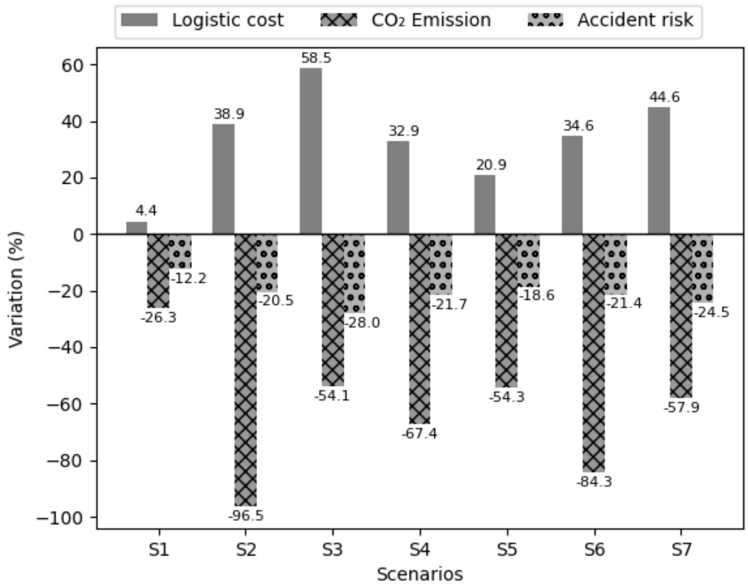


Figure 17 – Variation of each dimension comparing to scenario L1.

Regarding the routes presented in the solution sets of all scenarios, Table 14 ranks the most frequently used routes, indicating the scenarios in which they appear, the distances covered, and the associated risks of accidents. The most frequently used route appears in the solution sets of six scenarios and is listed at the top of Table 14. The other four routes appear in five scenarios each. These routes share common characteristics, including shorter distances and lower accident risks compared to the average distance ($\bar{d}$ = 311.49 km) and average risk ($\bar{r}$ = 2176.71) of all routes across the scenarios. Consequently, they are selected more frequently as optimal solutions.

The exceptions are the routes Louveira > Cabreúva > Itupeva > Jundiaí > Itatiba > Louveira, and Louveira > Tambaú > Santa Cruz das Palmeiras > Louveira. For the first route, although the risk was slightly above the average ($\bar{r}$ = 2176.71), the total distance covered was one of the shortest. For the second route, the distance was slightly above the average ($\bar{d}$ = 311.49) due to Tambaú and Santa Cruz das Palmeiras being farther from the depot. However, the risk of accidents for this route was significantly below the average risk ($\bar{r}$ = 2176.71).

The ranking was also performed for the least used routes, as shown in Table 15. These routes were characterized by either long distances or high accident risks. The route Louveira > Casa Branca > Sumaré > Mococa > Louveira, which appears in one scenario, required the vehicle to cover a distance of 715.50 km, significantly above the average ($\bar{d}$ = 311.49 km). The routes Louveira > Americana > Limeira > Iracemápolis > Santa Bárbara d'Oeste > Nova Odessa > Louveira and Louveira > Nova Odessa > Santa Gertrudes > Cordeirópolis > Iracemápolis > Santa Bárbara d'Oeste > Louveira had risks far exceeding the average ($\bar{r}$ = 2176.71). Despite their short distances, these last two routes have high accident risks. They could be candidates for selection in more scenarios if road conditions were improved. Enhancements to these roads would reduce accident risks, making these routes more viable in terms of safety.

Table 14 – Most frequently used routes.

Routes	Scenarios	Distance (km)	Risk cost ($)
Louveira > Cabreúva > Itupeva > Jundiaí -> Itatiba > Louveira	L3, S2, S3, S4, S5, S6	139.6	2317.57
Louveira > Serra Negra > Águas de Lindoia > Socorro > Louveira	L1, S1, S2, S5, S6	231.2	1280.72
Louveira > Artur Nogueira > Itapira > Louveira	L2, L3, S3, S4, S7	237.0	1395.15
Louveira > Atibaia > Piracaia > Bragança Paulista > Louveira	S1, S2, S4, S5, S6	165.7	2054.38
Louveira > Tambaú > Santa Cruz das Palmeiras > Louveira	S1, S2, S4, S6, S7	383.9	1551.25

Table 15 – Least frequently used routes.

Routes	Scenarios	Distance (km)	Risk cost ($)
Louveira > Americana > Limeira > Iracemápolis > Santa Bárbara d'Oeste > Nova Odessa > Louveira	L1	201.60	5635.29
Louveira > Americana > Nova Odessa > São Pedro > Santa Gertrudes > Pedreira > Louveira	S2	387.50	4231.00
Louveira > Nova Odessa > Santa Gertrudes > Cordeirópolis > Iracemápolis > Santa Bárbara d'Oeste > Louveira	S1	152.11	3904.08
Louveira > Casa Branca > Sumaré > Mococa > Louveira	L3	715.50	2141.53
Louveira > Conchal > Araras > Cordeirópolis > Santa Gertrudes > Louveira	L1	270.10	3732.40

3.5 Concluding remarks

Integrating procedures into road freight transport that consider financial factors alongside environmental and social impacts is becoming increasingly relevant. The primary objective of this study was to implement a sustainable Multi-Objective

Vehicle Routing Problem (MO-VRP) that minimizes logistic costs, CO_2 emissions, and accident risks. This approach includes a heterogeneous fleet consisting of diverse vehicle groups, such as Alternative Fuel Vehicles (AFVs) and diesel vehicles.

To address the MO-VRP, the *Augmented Weighted Tchebycheff* (AWT) method was implemented. Multiple scenarios were created by assigning different weights to the objectives, generating various solutions.

Given the complexity and computational demands of the problem when using the AWT method, both heuristic and exact methods were employed to generate solutions. The enhanced Genetic Algorithm produced feasible solutions to initiate the exact method, which helped to optimize performance.

The results indicated that in most scenarios, electric vehicles were the most utilized due to their significantly lower CO_2 emissions, despite higher costs. Conversely, CNG trucks were not used in any scenario because their emission rate was much higher than that of electric vehicles and only 13% lower than diesel, despite not having the highest cost. Thus, the findings suggest a need for technological advancements in heavy-duty AFVs to enhance their economic viability.

Additionally, the results showed that the optimization frequently selected certain routes across different scenarios due to their short distances and low accident risks. Some routes, which were less commonly selected, may become more viable in future solutions with improvements in road conditions to reduce accident risks.

One benefit of this analytical approach is that users can generate solutions for different scenarios by simply adjusting the weights of each objective, selecting a solution compatible with their operations. Each transport operation differs; for instance, some loads, such as hazardous materials and valuable cargo, require safer operations over cheaper ones, while other types of cargo may prioritize cost over risk. Similarly, if the user needs to focus on reducing environmental impact, they can adjust the parameters to prioritize this dimension.

Thus, road freight transport companies can plan deliveries based on sustainable aspects using the proposed analytical approach. By adjusting the parameters that regulate the multi-objective problem, multiple scenarios can be generated, providing different solutions for decision-makers.

A limitation of this study was the lack of real data related to road accidents and experimental data for CO_2 emissions and fuel consumption of heavy vehicles, which could contribute to more accurate and realistic results. Most electric heavy trucks are still in the testing phase, explaining the difficulty in finding data for this type of vehicle. For future work, we aim to incorporate more realistic elements into the problem, such as varying fuel consumption and CO_2 emissions according to load weight, and considering the value of the cargo and its insurance.

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APPENDIX

A Detailed results of Chapter 3

This appendix contains detailed results of the study described in Chapter 3.

Table 16 – Routes obtained for Scenario L1.

Vehicle	Routes	Distance (Km)	Logistic Cost ($)	CO_2 (Kg)	Risk ($)
Diesel	Louveira > Santo Antonio de Posse > Itapira > Louveira	216.50	328.68	439.45	1658.45
Diesel	Louveira > Rio Claro > São Pedro > Louveira	299.50	454.67	607.98	2252.63
Diesel	Louveira > Casa Branca > Divinolândia > São João da Boa Vista > Louveira	420.60	638.53	853.82	1629.97
Diesel	Louveira > Paulinia > Artur Nogueira > Cosmópolis > Louveira	172.70	262.18	350.58	2163.91
Diesel	Louveira > Mococa > São José do Rio Pardo > Tambaú > Santa Cruz das Palmeiras > Louveira	482.00	731.75	978.46	2290.80
Diesel	Louveira > Itupeva > Cabreúva > Laranjal Paulista > Capivari > Monte Mor > Hortolândia > Louveira	288.60	438.17	585.86	3065.60
Diesel	Louveira > Serra Negra > Águas de Lindoia > Socorro > Louveira	231.20	351.00	469.33	1280.72
Diesel	Louveira > Campinas > Jaguariúna > Pedreira > Amparo > Itatiba > Louveira	153.00	232.28	310.59	3406.21
Diesel	Louveira > Indaiatuba > Rio das Pedras > Piracicaba > Sumaré > Louveira	230.10	349.33	467.10	3025.17
Diesel	Louveira > Conchal > Araras > Cordeirópolis > Santa Gertrudes > Louveira	270.10	410.05	548.30	3732.40
Diesel	Louveira > Mogi Guaçu > Mogi Mirim > Valinhos > Vinhedo > Louveira	195.70	297.10	397.27	2877.25
Diesel	Louveira > Bragança Paulista > Piracaia > Atibaia > Jundiaí > Louveira	187.30	284.35	380.22	2927.10
Diesel	Louveira > Americana > Limeira > Iracemápolis < Santa Bárbara d'Oeste > Nova Odessa > Louveira	201.60	306.06	409.25	5635.29
Diesel	Louveira > Espirito Santo do Pinhal > Vargem Grande do Sul > Aguaí > Louveira	348.70	529.38	707.861	1589.22
	Total	3697.60	5613.52	7506.13	37534.72

Table 17 – Routes obtained for Scenario L2.

Vehicle	Routes	Distance (Km)	Logistic Cost ($)	CO_2 (Kg)	Risk ($)
Eletric	Louveira > Artur Nogueira > Itapira > Louveira	237.00	471.58	0.00	1395.15
Eletric	Louveira > Nova Odessa > Monte Mor > Hortolândia > Rio das Pedras > Cordeirópolis > Serra Negra > Louveira	437.90	871.33	0.00	2625.98
Eletric	Louveira > Bragança Paulista > Piracaia > Socorro > Louveira	257.50	512.37	0.00	1285.98
Eletric	Louveira > Conchal > São Pedro > Araras > Pedreira > Louveira	437.40	870.33	0.00	2137.82
Eletric	Louveira > São João da Boa Vista > Divinolândia > Casa Branca > Louveira	420.60	836.91	0.00	1629.97
Eletric	Louveira > Laranjal Paulista > Limeira > Mogi Mirim > Louveira	368.40	733.04	0.00	1423.72
Eletric	Louveira > Mogi Guaçu > Cosmópolis > Campinas > Paulínia > Louveira	281.50	560.13	0.00	2381.24
Eletric	Louveira > Cabreúva > Piracicaba > Rio Claro > Capivari > Louveira	336.50	669.57	0.00	1949.08
Eletric	Louveira > Itupeva > Vinhedo > Valinhos > Santo Antonio de Posse > Louveira	195.10	388.21	0.00	2938.10
Eletric	Louveira > Mococa > São José do Rio Pardo > Santa Cruz das Palmeiras > Tambaú > Louveira	482.80	960.67	0.00	2280.31
Eletric	Louveira > Americana > Iracemápolis > Santa Bárbara d'Oeste > Sumaré > Indaiatuba > Louveira	240.10	477.75	0.00	3797.34
Eletric	Louveira > Espirito Santo do Pinhal > Aguaí > Vargem Grande do Sul > Louveira	385.80	767.66	0.00	1450.00
Eletric	Louveira > Jundiaí > Amparo > Louveira	179.60	357.37	0.00	1210.47
Eletric	Louveira > Águas de Lindoia > Santa Gertrudes > Jaguariúna > Louveira	421.30	838.30	0.00	2877.95
	Total	4681.50	9315.23	0.00	29382.89

Table 18 – Routes obtained for Scenario L3.

Vehicle	Routes	Distance (Km)	Logistic Cost ($)	CO_2 (Kg)	Risk ($)
Eletric	Louveira > Artur Nogueira > Itapira > Louveira	715.50	1423.70	0.00	1395.15
Eletric	Louveira > Casa Branca > Sumaré > Mococa > Louveira	464.00	923.26	0.00	2141.53
Eletric	Louveira > Laranjal Paulista > Santa Bárbara d'Oeste > Iracemápolis > Socorro > Louveira	440.40	876.31	0.00	1700.77
Eletric	Louveira > Serra Negra > Santa Gertrudes > Piracicaba > Mogi Guaçu > Louveira	343.10	682.70	0.00	1768.92
Eletric	Louveira > Capivari > Rio Claro > Amparo > Louveira	139.60	277.77	0.00	1052.59
Eletric	Louveira > Cabreúva > Itupeva > Jundiaí > Itatiba > Louveira	437.40	870.34	0.00	2317.57
Eletric	Louveira > Pedreira > Araras > São Pedro > Conchal > Louveira	620.60	1234.87	0.00	2137.82
Eletric	Louveira > Indaiatuba > Rio das Pedras > Hortolândia > Monte Mor > Nova Odessa > Divinolândia > Louveira	338.90	674.34	0.00	2651.40
Eletric	Louveira > Bragança Paulista > Piracaia > Águas de Lindoia > Atibaia > Louveira	316.00	628.77	0.00	2203.89
Eletric	Louveira > Jaguariúna > Cordeirópolis > Santo Antônio de Posse > Louveira	444.40	884.26	0.00	2296.84
Eletric	Louveira > Vargem Grande do Sul > Limeira > Mogi Mirim > Louveira	528.00	1050.61	0.00	1566.03
Eletric	Louveira > São João da Boa Vista > Aguaí > Americana > Espirito Santo do Pinhal > Louveira	471.50	938.19	0.00	2103.47
Eletric	Louveira > Santa Cruz das Palmeiras > Paulínia > Campinas > Cosmópolis > Louveira	737.30	1467.08	0.00	2405.04
Eletric	Louveira > Tambaú > Valinhos > Vinhedo > São José do Rio Pardo > Louveira	237.00	471.58	0.00	2347.18
	Total	6233.70	12403.79	0.00	28254.20

Table 19 – Routes obtained for Scenario S1.

Vehicle	Routes	Distance (Km)	Logistic Cost ($)	CO_2 (Kg)	Risk ($)
Diesel	Louveira > Aguaí > Casa Branca > Louveira	328.20	498.26	666.25	1633.36
Diesel	Louveira > Atibaia > Piracaia > Bragança Paulista > Louveira	165.70	251.56	336.37	2054.38
Diesel	Louveira > Capivari > Rio das Pedras > Piracicaba > Laranjal Paulista > Cabreúva > Louveira	322.80	490.06	655.28	1995.65
Diesel	Louveira > Conchal > Araras > Limeira > Americana > Louveira	256.10	388.80	519.88	3678.00
Diesel	Louveira > Mococa > São José do Rio Pardo > Divinolândia > Vargem Grande do Sul > São João da Boa Vista > Louveira	462.80	702.60	939.48	2262.33
Diesel	Louveira > Mogi Guaçu > Espirito Santo do Pinhal > Amparo > Louveira	294.00	446.34	596.82	1248.73
Diesel	Louveira > Mogi Mirim > Itapira > Louveira	214.80	326.10	436.04	1482.00
Diesel	Louveira > Nova Odessa > Santa Gertrudes > Cordeirópolis > Iracemápolis > Santa Bárbara D'Oeste > Louveira	258.90	393.05	525.57	4557.72
Diesel	Louveira > Serra Negra > Águas de Lindóia > Socorro > Louveira	231.20	351.00	469.34	1280.70
Diesel	Louveira > Tambaú > Santa Cruz das Palmeiras > Louveira	383.90	582.82	779.32	1551.25
Eletric	Louveira > Itatiba > Jundiaí > Itupeva > Louveira	90.50	180.08	0.00	1997.25
Eletric	Louveira > Paulínia > Cosmópolis > Artur Nogueira > Louveira	173.00	344.23	0.00	2075.72
Eletric	Louveira > Pedreira > Santo Antônio de Posse > Jaguariuna > Campinas > Indaiatuba > Louveira	206.40	410.69	0.00	3619.19
Eletric	Louveira > Rio Claro > São Pedro > Louveira	299.50	595.94	0.00	2252.63
Eletric	Louveira > Vinhedo > Valinhos > Hortolândia > Monte Mor > Sumaré > Louveira	160.00	318.37	0.00	3605.35
	Total	3847.80	6279.89	5924.35	35293.74

Table 20 – Routes obtained for Scenario S2.

Vehicle	Routes	Distance (Km)	Logistic Cost ($)	CO_2 (Kg)	Risk ($)
Diesel	Louveira > Cabreúva > Itupeva > Jundiaí > Itatiba > Louveira	139.60	211.93	283.39	2317.57
Eletric	Louveira > Aguaí > Divinolândia > São João da Boa Vista > Louveira	403.10	802.09	0.00	1601.40
Eletric	Louveira > Americana > Nova Odessa > São Pedro > Santa Gertrudes > Pedreira > Louveira	387.50	771.05	0.00	4231.00
Eletric	Louveira > Atibaia > Piracaia > Bragança Paulista > Louveira	165.70	329.71	0.00	2054.38
Eletric	Louveira > Capivari > Limeira > Piracicaba > Laranjal Paulista > Louveira	373.00	742.19	0.00	1477.65
Eletric	Louveira > Espirito Santo do Pinhal > Mogi Guaçu > Amparo > Louveira	294.90	586.79	0.00	1168.35
Eletric	Louveira > Mococa > São José do Rio Pardo > Vargem Grande do Sul > Casa Branca > Louveira	444.50	884.46	0.00	2038.23
Eletric	Louveira > Mogi Mirim > Artur Nogueira > Louveira	207.30	412.48	0.00	1512.06
Eletric	Louveira > Monte Mor > Hortolândia > Rio das Pedras > Iracemápolis > Santa Bárbara d'Oeste > Indaiatuba > Louveira	302.70	602.31	0.00	2791.04
Eletric	Louveira > Rio Claro > Araras > Conchal > Louveira	269.30	535.85	0.00	2131.24
Eletric	Louveira > Santo Antonio de Posse > Itapira > Louveira	216.50	430.79	0.00	1658.45
Eletric	Louveira > Serra Negra > Águas de Lindoia > Socorro > Louveira	231.20	460.04	0.00	1280.72
Eletric	Louveira > Sumaré > Cordeirópolis > Jaguariúna > Louveira	271.80	540.83	0.00	2669.93
Eletric	Louveira > Tambaú > Santa Cruz das Palmeiras > Louveira	383.90	763.88	0.00	1551.25
Eletric	Louveira > Vinhedo > Valinhos > Cosmópolis > Paulínia > Campinas > Louveira	141.10	280.76	0.00	3504.12
	Total	4232.10	8355.17	283.39	31987.89

Table 21 – Routes obtained for Scenario S3.

Vehicle	Routes	Distance (Km)	Logistic Cost ($)	CO_2 (Kg)	Risk ($)
Diesel	Louveira > Artur Nogueira > Itapira > Louveira	237.00	359.80	481.11	1395.15
Diesel	Louveira > Atibaia > Águas de Lindoia > Santa Gertrudes > Jaguariúna > Louveira	421.30	639.60	855.24	2877.95
Diesel	Louveira > Capivari > Rio Claro > Amparo > Louveira	343.10	520.88	696.49	1052.59
Diesel	Louveira > Itatiba > Jundiaí > Itupeva > Cabreúva > Louveira	139.60	211.93	283.39	2317.57
Diesel	Louveira > Santa Cruz das Palmeiras > São José do Rio Pardo > Casa Branca > Louveira	421.50	639.90	855.64	1738.85
Diesel	Louveira > Socorro > Piracaia > Bragança Paulista > Louveira	257.50	390.92	522.72	1285.76
Eletric	Louveira > Aguaí > São João da Boa Vista > Tambaú > Louveira	417.50	830.74	0.00	1678.97
Eletric	Louveira > Divinolândia > Espirito Santo do Pinhal > Vinhedo > Valinhos > Louveira	432.00	859.59	0.00	2327.44
Eletric	Louveira > Indaiatuba > Sumaré > Santa Bárbara d'Oeste > Iracemápolis > Americana > Louveira	240.10	477.75	0.00	3797.34
Eletric	Louveira > Mococa > Limeira > Piracicaba > Mogi Guaçu > Louveira	587.40	1168.81	0.00	1921.10
Eletric	Louveira > Mogi Mirim > Rio das Pedras > Hortolândia > Laranjal Paulista > Louveira	456.70	908.74	0.00	1654.63
Eletric	Louveira > Nova Odessa > Monte Mor > Campinas > Paulínia > Cosmópolis > Serra Negra > Louveira	354.70	705.78	0.00	2778.90
Eletric	Louveira > Pedreira > Araras > São Pedro > Conchal > Louveira	437.40	870.34	0.00	2137.82
Eletric	Louveira > Vargem Grande do Sul > Cordeirópolis > Santo Antonio de Posse > Louveira	477.10	949.33	0.00	1995.90
	Total	5222.90	9534.11	3694.60	28959.97

Table 22 – Routes obtained for Scenario S4.

Vehicle	**Routes**	**Distance (Km)**	**Logistic Cost ($)**	**CO_2 (Kg)**	**Risk ($)**
Diesel	Louveira > Atibaia > Piracaia > Bragança Paulista > Louveira	165.70	251.56	336.37	2054.38
Diesel	Louveira > Divinolândia > São João da Boa Vista > Aguaí > Louveira	405.50	615.61	823.16	1480.39
Diesel	Louveira > Indaiatuba > Rio das Pedras > Santa Gertrudes > Piracicaba > Capivari > Louveira	329.50	500.23	668.88	2319.76
Diesel	Louveira > Itatiba > Jundiaí > Itupeva > Cabreúva > Louveira	139.60	211.93	283.39	2317.57
Diesel	Louveira > Socorro > Águas de Lindoia > Louveira	252.20	382.88	511.97	1358.97
Eletric	Louveira > Artur Nogueira > Itapira > Louveira	237.00	471.58	0.00	1395.15
Eletric	Louveira > Conchal > Araras > Rio Claro > Nova Odessa > Louveira	288.00	573.06	0.00	2961.61
Eletric	Louveira > Cosmópolis > Paulínia > Campinas > Monte Mor > Hortolândia > Louveira	207.90	413.68	0.00	2856.55
Eletric	Louveira > Espirito Santo do Pinhal > Amparo > Louveira	294.90	586.79	0.00	1168.35
Eletric	Louveira > Laranjal Paulista > São Pedro > Cordeirópolis > Pedreira > Louveira	476.20	947.54	0.00	2363.28
Eletric	Louveira > Mococa > São José do Rio Pardo > Casa Branca > Vargem Grande do Sul > Louveira	450.30	896.01	0.00	1949.09
Eletric	Louveira > Santa Cruz das Palmeiras > Tambaú > Louveira	383.90	763.88	0.00	1551.25
Eletric	Louveira > Santo Antonio de Posse > Jaguariúna > Valinhos > Vinhedo > Louveira	152.00	302.45	0.00	3098.67
Eletric	Louveira > Serra Negra > Limeira > Mogi Mirim > Louveira	333.10	662.80	0.00	1261.63
Eletric	Louveira > Sumare > Santa Barbara d'Oeste > Iracemápolis > Americana > Louveira	209.00	415.87	0.00	3362.60
	Total	4324.80	7995.87	2623.77	31499.25

Table 23 – Routes obtained for Scenario S5.

Vehicle	**Routes**	**Distance (Km)**	**Logistic Cost ($)**	**CO_2 (Kg)**	**Risk ($)**
Diesel	Louveira > Artur Nogueira > Cosmópolis > Paulínia > Louveira	173.00	262.64	351.19	2075.72
Diesel	Louveira > Campinas > Jaguariúna > Santo Antonio de Posse > Louveira	151.60	230.15	307.75	2734.95
Diesel	Louveira > Capivari > Hortolândia > Monte Mor > Sumaré > Louveira	227.80	345.83	462.43	2243.68
Diesel	Louveira > Divinolândia > São João da Boa Vista > Aguaí > Louveira	405.50	615.61	823.16	1480.39
Diesel	Louveira > Itatiba > Jundiaí > Itupeva > Cabreúva > Louveira	139.60	211.93	283.39	2317.57
Diesel	Louveira > Mococa > São José do Rio Pardo > Tambaú > Santa Cruz das Palmeiras > Louveira	482.00	731.75	978.46	2290.80
Diesel	Louveira > Serra Negra > Águas de Lindóia > Scorro > Louveira	231.20	351.00	469.34	1280.72
Eletric	Louveira > Atibaia > Piracaia > Bragança Paulista > Louveira	165.70	329.71	0.00	2054.38
Eletric	Louveira > Espirito Santo do Pinhal > Mogi Guaçu > Amparo > Louveira	294.90	586.79	0.00	1168.35
Eletric	Louveira > Indaiatuba > Rio das Pedras > Piracicaba > Limeira > Pedreira > Louveira	331.10	658.82	0.00	2379.42
Eletric	Louveira > Itapira > Mogi Mirim > Louveira	214.80	427.41	0.00	1482.00
Eletric	Louveira > Nova Odessa > Rio Claro > Araras > Conchal > Louveira	288.00	573.06	0.00	2961.61
Eletric	Louveira > Santa Bárbara d'Oeste > Iracemápolis > Cordeirópolis > Americana > Louveira	231.10	459.84	0.00	3726.21
Eletric	Louveira > Santa Gertrudes > São Pedro > Laranjal Paulista > Louveira	393.80	783.58	0.00	2094.67
Eletric	Louveira > Vinhedo > Valinhos > Vargem Grande do Sul > Casa Branca > Louveira	353.80	703.99	0.00	2456.10
	Total	4083.90	7272.12	3675.72	32746.57

Table 24 – Routes obtained for Scenario S6.

Vehicle	Routes	Distance (Km)	Logistic Cost ($)	CO_2 (Kg)	Risk ($)
Diesel	Louveira > Artur Nogueira > Cosmópolis > Paulínia > Louveira	173.00	262.64	351.19	2075.72
Diesel	Louveira > Santo Antonio de Posse > Itapira > Louveira	216.50	328.68	439.49	1658.45
Diesel	Louveira > Socorro > Águas de Lindóia > Serra Negra > Louveira	231.20	351.00	469.34	1280.72
Eletric	Louveira > Atibaia > Piracaia > Bragança Paulista > Louveira	165.70	329.71	0.00	2054.38
Eletric	Louveira > Divinolândia > São João da Boa Vista > Aguaí > Louveira	405.50	806.86	0.00	1480.39
Eletric	Louveira > Itatiba > Jundiaí > Itupeva > Cabreúva > Louveira	139.60	277.78	0.00	2317.57
Eletric	Louveira > Jaguariúna > Mogi Guaçu > Espirito Santo do Pinhal > Louveira	263.50	524.31	0.00	1989.74
Eletric	Louveira > Mogi Mirim > Cordeirópolis > Amparo > Amparo	330.00	656.63	0.00	1419.24
Eletric	Louveira > Nova Odessa > São Pedro > Santa Gertrudes > Capivari > Louveira	354.00	704.39	0.00	2867.55
Eletric	Louveira > Pedreira > Limeira > Piracicaba > Rio das Pedras > Indaiatuba > Louveira	331.00	658.82	0.00	2379.42
Eletric	Louveira > Rio Claro > Araras > Conchal > Louveira	269.30	535.85	0.00	2131.24
Eletric	Louveira > Sumaré > Santa Bárbara d'Oeste > Iracemápolis > Americana > Louveira	209.00	415.87	0.00	3362.60
Eletric	Louveira > Tambaú > Santa Cruz das Palmeiras > Louveira	383.90	763.88	0.00	1551.25
Eletric	Louveira > Vargem Grande do Sul > Casa Branca > São José do Rio Pardo > Mococa > Louveira	450.30	896.01	0.00	1949.09
Eletric	Louveira > Vinhedo > Valinhos > Campinas > Monte Mor > Hortolândia > Laranjal Paulista > Louveira	293.10	583.21	0.00	3098.34
	Total	4215.70	8095.63	1260.02	31615.70

Table 25 – Routes obtained for Scenario S7.

Vehicle	Routes	Distance (Km)	Logistic Cost ($)	CO_2 (Kg)	Risk ($)
Diesel	Louveira > Aguaí > São João da Boa Vista > Divinolândia > Louveira	405.50	615.61	823.16	1480.39
Diesel	Louveira > Bragança Paulista > Piracaia > Amparo > Louveira	222.60	337.94	451.88	792.06
Diesel	Louveira > Paulínia > Cosmópolis > Campinas > Jaguariúna > Louveira	206.80	313.95	419.80	2676.77
Diesel	Louveira > Santa Cruz das Palmeiras > Tambaú > Louveira	383.90	582.82	779.32	1551.25
Diesel	Louveira > Serra Negra > Araras > São Pedro > Cabreúva > Louveira	450.00	683.17	913.50	1748.11
Eletric	Louveira > Artur Nogueira > Itapira > Louveira	237.00	471.58	0.00	1395.15
Eletric	Louveira > Conchal > Limeira > Mogi Guaçu > Louveira	312.30	621.41	0.00	1662.74
Eletric	Louveira > Itupeva > Jundiaí > Itatiba > Louveira	90.50	180.08	0.00	1997.25
Eletric	Louveira > Laranjal Paulista > Santa Bárbara d'Oeste > Iracemápolis > Rio das Pedras > Indaiatuba > Louveira	383.40	762.89	0.00	2108.26
Eletric	Louveira > Pedreira > Cordeirópolis > Mogi Mirim > Espirito Santo do Pinhal > Louveira	407.80	811.44	0.00	2358.86
Eletric	Louveira > Rio Claro > Piracicaba > Santa Gertrudes > Louveira	292.80	582.61	0.00	2544.25
Eletric	Louveira > Socorro > Americana > Águas de Lindoia > Atibaia > Louveira	510.10	1014.99	0.00	2551.78
Eletric	Louveira > Sumaré > Capivari > Hortolândia > Monte Mor > Nova Odessa > Louveira	270.00	537.24	0.00	3020.66
Eletric	Louveira > Vargem Grande do Sul > Casa Branca > São José do Rio Pardo > Mococa > Louveira	450.30	896.01	0.00	1949.09
Eletric	Louveira > Vinhedo > Valinhos > Santo Antonio de Posse > Louveira	144.50	287.53	0.00	2528.93
	Total	4767.50	8699.27	3387.66	30365.55