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A sustainable approach to solve the routing problem for transportation services: a vehicle pollution assessment

Uma abordagem sustentável para solucionar o problema de roteirização em serviços de transporte: uma avaliação da poluição veicular

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ABSTRACT
This study addresses a complex issue in transportation service management, focusing on vehicle pollution within the Pollution Routing Problem (PRP) framework.It examines how direct fuel costs and greenhouse gas (GHG) emissions are influenced by travel distance, road slopes, and vehicle speed. The research centers on the urban solid waste (USW) collection service in Miraporanga, managed by Uberlândia, Brazil. Using GIS tools, the study evaluates waste collection routes to minimize GHG emissions. Due to the multifaceted nature of transportation costs and factors, an Analytic Hierarchy Process (AHP) was employed to rank the project variables effectively. The research compared two routing approaches: shortest path and flattest path, using a weighted implementation cost formula to determine which route is more sustainable. The findings reveal an 8% reduction in GHG emissions per collection. Additionally, applying the PRP showed a 16% decrease in fuel consumption by optimizing for distance, speed, and road slopes. This approach demonstrates a practical method for enhancing environmental sustainability in urban waste management.

RESUMO
Este estudo aborda uma questão complexa na gestão de serviços de transporte, com foco na poluição veicular dentro da estrutura do Problema de Roteirização da Poluição (PRP). Examina como os custos diretos de combustível e as emissões de gases de efeito estufa (GEE) são influenciados pela distância percorrida, declives da via e velocidade do veículo. A pesquisa concentra-se no serviço de coleta de resíduos sólidos urbanos (RSU) em Miraporanga, gerenciado por Uberlândia, Brasil. Utilizando ferramentas de SIG (Sistemas de Informação Geográfica), o estudo avalia rotas de coleta de resíduos para minimizar as emissões de GEE. Devido à natureza multifacetada dos custos e fatores de transporte, um Processo Analítico Hierárquico (AHP) foi empregado para classificar as variáveis do projeto de forma eficaz. A pesquisa comparou duas abordagens de roteirização: caminho mais curto e caminho mais plano, utilizando uma fórmula de custo de implementação ponderado para determinar qual rota é mais sustentável. Os resultados revelam uma redução de 8% nas emissões de GEE por coleta. Além disso, a aplicação do PRP mostrou uma redução de 16% no consumo de combustível ao otimizar a distância, a velocidade e os declives da via. Essa abordagem demonstra um método prático para aprimorar a sustentabilidade ambiental na gestão de resíduos urbanos.

1. Introduction

Most Brazilian municipalities face significant challenges in transportation and operational services, particularly in the collection and transportation of urban solid waste (USW). Efficient routing of USW collection must be integrated with Transportation Systems (TS), which involve multifactorial elements related to infrastructure, urban mobility, and operational network procedures (UN, 2022). In Brazil, USW collection often relies on outdated operational management, with limited tax and government incentives. The costs associated with USW collection and disposal represent 7% to 15% of the municipal budget (Detofeno & Steiner, 2010), with 77% to 95% of this budget allocated to operational stages, including collection and transportation. Notably, 50% of these costs are dedicated to collection and transportation, leading to high energy consumption and significant greenhouse gas (GHG) emissions.

The International Energy Agency (IEA) reports that global transportation accounts for 24% of direct emissions from fuel combustion, contributing 37% of global CO_2 emissions (IEA, 2020). Given this impact, applying the Pollution Routing Problem (PRP) to urban transport planning is essential (Lai *et al.*, 2024). This study examines the PRP in the context of USW collection in Miraporanga, MG, focusing on identifying the most sustainable routing options. By comparing the shortest and flattest routes, this research aims to determine the most sustainable path by minimizing fuel consumption and GHG emissions (Lai *et al.*, 2024).

The PRP is a comprehensive approach that seeks to reduce carbon emissions by considering various routing factors beyond just travel distance, such as speed, slope, payload, and distance (Ericsson, 2001). This study employs mathematical models and algorithmic iterations to optimize the route network, with the key indicators being driving speed, slope, payload, and travel distance. However, the study assumes constant ratios for driving speed and payload, applying them to both the shortest and flattest routes. To address the complex, multi-factorial nature of this problem, an Analytic Hierarchy Process (AHP) matrix was developed to evaluate the costs and penalties associated with each variable. Three scenarios were considered: the perspectives of the service provider and municipal office, an expert in transportation, and the current state of the art in PRP optimization.

2. Background

USW services face numerous challenges, including the need to optimize logistics mitigating its negative impacts on human health, the economy, and the environment. The Environmental Company of the State of São Paulo (CETESB) identifies motor vehicles as major contributors to air pollution, releasing a variety of harmful substances such as nitrogen oxides (NOx), hydrocarbons (HC), carbon monoxide (CO), sulfur oxides (SOx), particulate matter (PM), and non-methane volatile organic compounds (NMVOCs) (CETESB, 2021). In Brazil, the Vehicle Pollution Control Plan (VPCP) was established under Law No. 6938 of 1981, as part of the National Environmental Policy. This plan sets regulations and recommendations for monitoring and limiting pollutant emissions, particularly in response to greenhouse gases (GHG) from motor vehicle fuel combustion (MMA, 2014; CETESB, 2021)).

To estimate these emissions, CETESB relies on methodologies outlined in the Intergovernmental Panel on Climate Change (IPCC) reference manual (Houghton *et al.*, 1997), particularly the bottom-up method. This approach calculates emissions by considering various factors, including the emission rate of specific pollutants, the type of fuel used, the distance traveled, and the characteristics of the vehicle. Equation 1 of the bottom-up method specifically integrates these variables to provide accurate estimates of pollutant output:

$$\text{Emission}_i = \sum(EF_{iab} \cdot Act_{ab}) \tag{1}$$

where EF = emission Factor (g/km); Act= energy input (expenditure) (TJ) or distance traveled (km); i = emissions of a gas, $i = NO_x$, CH_4, NMVOC, CO, N_2O, CO_2; a = type of fuel; and b = activity sector.

To calculate net CO_2 emissions, the process involves subtracting the carbon content of non-CO_2 gases from the total carbon emissions. This calculation utilizes the molar masses of carbon (12 g/mol) and oxygen (16 g/mol) to perform stoichiometric calculations based on fuel consumption and distance traveled, as outlined by the Houghton *et al.* (1997). For the other gases, emission factors provided by CETESB and the IPCC are used to estimate emissions as follows: CO = 0.144 g, CH_4 = 0.06 g, NO_x = 0.973 g, N_2O = 0.03 g, and NMVOC = 0.8 g. Further details on these calculations can be found in the Ministry of the Environment's report (MMA, 2014), which provides annual fuel consumption estimates by vehicle type. For example, the diesel consumption for trucks is estimated at approximately 0.4718 kg/TJ. These reports also outline the estimated annual consumption for primary pollutant gases, such as CO, CH_4, NO_x, N_2O, and NMVOC, which are 166 kg/TJ, 6.4 kg/TJ, 955 kg/TJ, 0.60 kg/TJ, and 76 kg/TJ respectively (MMA, 2014). For this analysis, data provided by the Ministry of the Environment (MMA, 2014) and the IPCC (Houghton *et al.*, 1997) estimate emissions by gas type, fuel, and vehicle category. For cargo vehicles using diesel fuel, the emission values are as follows: CO_2 is estimated at 79.217 Gg/year, CO at 176 Gg/year, CH_4 at 6.70 Gg/year, NO_x at 1,004.7 Gg/year, N_2O at 0.65 Gg/year, and

NMVOC at 82.3 Gg/year. These values are used in calculations where CO_2 is determined by subtracting the contributions of other gases from the total carbon emissions.

This approach directly connects to the Pollution Routing Problem (PRP), which focuses on optimizing vehicle routes to minimize fuel consumption, emissions, and overall costs. The PRP is crucial for integrating sustainability into transportation by reducing both environmental impact and operational expenses (Koç *et al.*, 2016). This problem is formulated to reduce carbon emissions resulting from fuel combustion, recognizing that greenhouse gas emissions are influenced by factors beyond just travel distance (Ericsson, 2001). According to Costa *et al.* (2018), fuel consumption in vehicles is not solely dependent on the distance traveled but is also significantly affected by variables such as speed, road gradient, traffic congestion, driver behavior, vehicle fleet composition, and payload. Road gradient, in particular, has a pronounced impact on fuel efficiency; for instance, a +6% grade can increase fuel consumption in light-duty vehicles by 15–20% (Barth & Boriboonsomsin, 2009). For heavy-duty trucks, even minor changes in road grade (1–4%) can lead to fluctuations in fuel economy exceeding 50% (Davis, Diegel & Boundy, 2016).

Suzuki (2011) expanded on this by developing a linear regression model that incorporates road gradient into the fuel consumption rate for heavy-duty trucks, building on the work of Davis, Diegel & Boundy (2016). This model is used to solve the Traveling Salesman Problem (TSP) with time windows, highlighting the importance of considering road gradient in route optimization. Further research into PRPs has introduced additional variables, such as typical traffic conditions, driving patterns, payload, and fleet size, resulting in a diverse array of solution methods (Xiao *et al.*, 2020). Evolutionary and genetic algorithms have been particularly effective in exploring interactions between these variables to find optimal solutions (Koç *et al.*, 2014). Moreover, hybrid approaches that combine exact and approximate methods are increasingly used to address PRPs, particularly when framed within the context of the Traveling Salesman Problem Tirkolaee *et al.* (2020).

The use of the TSP as a way to optimize routes can be determined by different applications, whether of exact or heuristic solutions. The latter can be established through cycle and circuit improvements, which for a graph network prioritize the studies of all nodes (points) of a network to be studied, in order to reduce the total distance traveled. The Traveling Salesman Problem can be represented as Equation 2:

$$TSP = (G, f, T) \tag{2}$$

where $G = (V, E)$ represents a complete graph; V is the set of vertices (nodes); E is the set of edges (arcs); f is a function $V \times V \rightarrow Z$ represents the cost function between pairs of vertices; and $t \in Z$ represents the maximum allowable route cost. Thus, a graph G containing a routing of the traveling salesman with cost, should not exceed t (Bowler, Fink & Ball, 2003).

The Dijkstra Algorithm is an algorithm for achieving the shortest paths between nodes in a graph network. The process is based on the principle that the most accurate arc values gradually replace an approximation of the correct distance until the shortest distance is reached (Equation 3):

$$O = |A| + |V| \log \log |V| \tag{3}$$

where O denotes the computational complexity of the algorithm; $|A|$ represents the number of arcs (edges) in the graph network; $|V|$ represents the number of vertices (nodes) in the graph network; and $\log |V|$ denotes the logarithmic factor associated with the number of vertices.

The Dijkstra Algorithm and the "shortest path" algorithm in QGIS are both used to find optimal routes in a network but differ in their applications. The Dijkstra Algorithm focuses on finding the shortest path between nodes by minimizing distance or cost (Deng *et al.*, 2012). In contrast, QGIS's shortest path algorithm also considers additional factors like elevation and slope to determine the most efficient route between two points (Lai *et al.*, 2024). To use this algorithm effectively in QGIS, the network must be represented as a vector layer with attributes for elevation and length, allowing the algorithm to find the flattest path by minimizing elevation changes. To address the broader challenge of managing complex processes with multiple variables, the Analytical Hierarchy Process (AHP) is useful. AHP creates a matrix to evaluate various factors by assigning weights to each variable and converting these into a numerical scale from 0 to 1 (Saaty, 2001). Integrating AHP with routing algorithms like Dijkstra or QGIS's "shortest path" enables effective management of complex routing problems, balancing factors such as distance, cost, and environmental impact.

3. Study area

The study area is confined to the district of Miraporanga, located in the Brazilian city of Uberlândia (Figure 1). The first map (a) represents the district and the city in terms of national and state borders. The other map (b) graphically illustrates the geographical position of the district, which is located within the municipal perimeter of Uberlândia, lying at approximately 50 km from the urban area of the city (represented inside the red line on the map on the right).

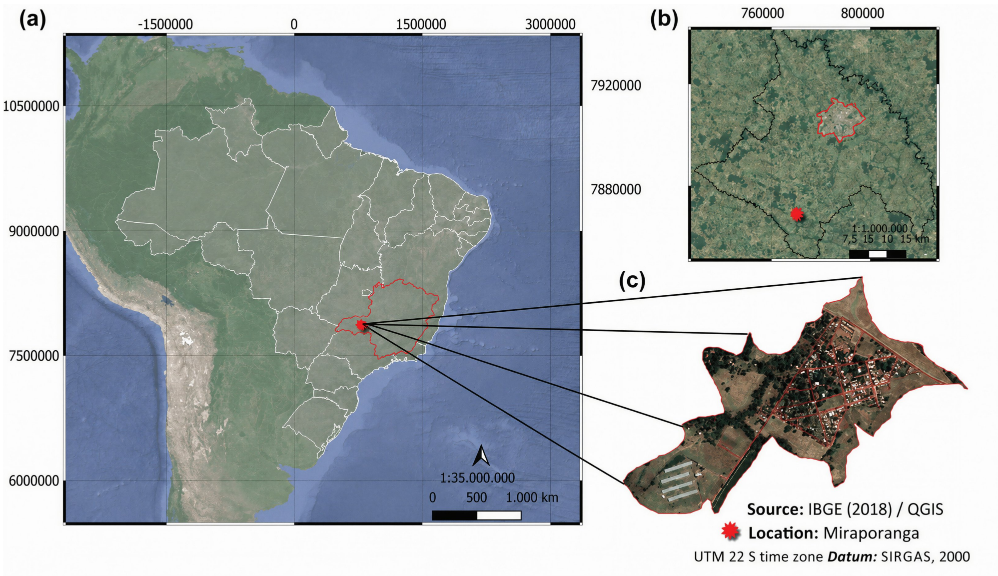

Figure 1 • (a) highlights the location of Minas Gerais and Uberlândia in Brazil. **(b)** shows the municipality of Uberlândia and highlights the district of Miraporanga. **(c)** presents an aerial view of the Miraporanga district only.

4. Materials and method

4.1. Analytic Hierarchy Process

To highlight the uniqueness of this research, an AHP tool was developed to identify the key variables impacting a routing process. The tool assessed 10 variables: Fleet Size; Distance; Road Inclination; Speed; Working Hours; Road Infrastructure; Demand; Typical Traffic; Vehicle Capacity; and Implementation Cost. Due to the complexity of these variables and their numerical ratios, three different scenarios were surveyed. These scenarios involved stakeholders from the USW collection company and the municipal body, the scientific community and current research, and a transportation engineering specialist. Once the weighting and scenarios were defined, a decision tree was constructed to analyze module correlations and grades.

4.2. Case study

In the Miraporanga district, the USW collection service starts at LIMPEBRAS headquarters in Uberlândia, where the vehicle fleet is based. Collection occurs twice a week, on Wednesdays and Saturdays, with the waste being transported to a landfill located at the same site as the company's garage.

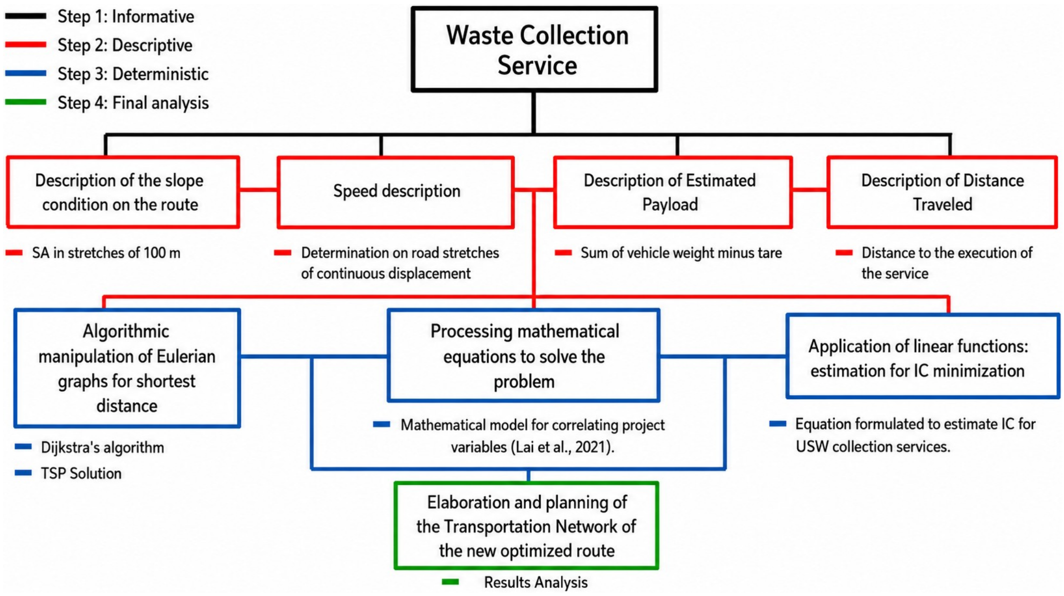

Figure 2 • Methodology used.

The methodology for this study is divided into four steps: informative, descriptive, deterministic, and enumerative (final analysis). Details of these steps are outlined in Figure 2.

The methodology unfolds through four distinct stages. The informative step involves reviewing and explaining existing data from work orders (WO) for the collection service. Following this, the descriptive step presents the quantitative data while classifying it into critical and acceptable ranges. The deterministic step then applies mathematical methods to precisely calculate the numerical data acquired earlier. Lastly, the final analysis compares the results obtained throughout the project to evaluate and analyze the outcomes.

4.3. Informative stage

As illustrated in Figure 2, the information stage involves collecting detailed data from work orders provided by the waste collection company, Limpebras, and the Solid Waste Directorate of the Municipal Water and Sewage Department (DGRS-DMAE). The methodology was developed using service evaluation techniques, which included personal interviews with the vehicle driver and document reviews detailing service execution. The collected data encompasses various aspects such as waste disposal, collection points, itinerary routes, speed, service duration and frequency, number of daily trips, vehicle capacity, and operational challenges. This information helps to understand the nature of the problem and estimate operating costs, particularly for fuel consumption. Key variables analyzed include vehicle payload, applied speed, and distance traveled. The consistency of the data was verified through questionnaires, completed forms, information from the Urban Planning Department of the Municipality of Uberlândia (SEPLAN), and documentation from DGRS-DMAE.

4.4. Descriptive stage

The spatial analysis utilized GIS for territorial analysis, employing high-resolution orbital images from Google Earth Professional (GEP) and QGIS. Access routes were mapped using vector layers with Open Street Maps (OSM) tools in QGIS. These layers, created in QGIS, reflect the morphological and topographic features of the road network within the study area. The analysis focuses on traffic intensity, travel directions, and the three-dimensional characteristics of access roads, including road grade, distance, and lane width. The goal is to establish longitudinal profiles of access roads. GEP was used to assess road slopes and average slope values for each route segment.

4.5. Deterministic stage

Using the methodology described, a comprehensive geospatial database was created in QGIS. The ORSTOOLS extension was selected for its precision, though other tools like Online Routing Mapper (ORM), PgRouting Layer, Qnet 3, Hqgis, and OpenTripPlanner were also tested for shorter travel distances. With ORSTOOLS as the chosen tool, two input vector layers were used: one for the USW collection points and one for the road network from the OSM database. To improve results, the road network lines were processed with the geometry closure tool to ensure a compact and accurate representation.

The Dijkstra's algorithm was applied using these layers, and the Traveling Salesman Problem was solved to find the shortest route starting and ending at a single point while visiting all nodes. The calculated route was saved in shapefile format (.shp). Further analysis in QGIS assessed traffic intensity, road dimensions, and flow direction. The road network was divided into 100 m segments to evaluate grade slopes, creating a new cost attribute for slope differences. Geocoded data, including key location addresses, were integrated with Google API and Open Route Service to study distance, slope, speed, traffic, and payload variables. The optimal speed was modeled considering both the shortest and flattest routes, adjusting for steep inclines to minimize mechanical stress and fuel consumption, and maintaining consistent speeds on flat sections. The legal speed limits adopted for each road segment (Table 1) were used as upper-bound constraints in the routing model. Operating speeds were subsequently estimated as a function of terrain slope, traffic intensity, road geometry, vehicle payload, and travel conditions, while ensuring compliance with the corresponding legal speed limits.

Table 1 • Posted speed limits adopted as upper-bound constraints for each road segment

Road	Posted speed limit	Road	Estimated speed limit
1) Norte Ring Road	80 km/h	7) MGC 455 Highway	100 km/h
2) Taróis Street	60 km/h	8) Flamingos Street	50 km/ h
3) Juscelino Kubitschek Ave.	60 km/h	9) Aldo Borges Leão Ave.	60 km/h
4) Eucaliptos Ave.	50 km/h	10) St West Ring Road	80 km/h
5) Asp. Mega Ave.	60 km/h	11) MGC 497 Highway	100 km/h
6) Getúlio Vargas Ave.	50 km/h		

Associated with the mechanical effort and to the energy produced by the vehicle to carry the required demand load, we have estimated and calculated the amount of waste to be collected. The purpose of this calculation was structured to understand the demand for garbage to be collected, and consequently the total weight to be transported. The estimate used to calculate the produced waste was referenced from the local model of conjunctural socioeconomic variables expressed in Equation 4 (Dias *et al.*, 2012):

$$Y = -5 \times 10^{-8}x^2 + 6 \times 10^{-4}x + 2.848 \times 10^{-1} \tag{4}$$

where Y = daily USW production per capita (kg/person/day); and x = monthly per capita income in Brazilian reais (R$/month).

Data on per capita household income in the Miraporanga district were obtained from IBGE (2010). To align these data with service demand, additional information on collection frequency, vehicle load capacity, and fleet size was collected. The dataset was then linked to estimated greenhouse gas (GHG) emissions from diesel-powered waste collection vehicles, calculated using Equation 1. To address the Pollution Routing Problem (PRP), a logical function was applied to relate these variables to local operating conditions (Table 2). A mathematical cost model, adapted from Lai *et al.* (2024), was employed to analyze the results. CO_2 emissions were estimated using the Comprehensive Modal Emissions Model (CMEM) for light-duty vehicles, adapted for waste collection trucks by DMAE.

Thus, each arc e is discretized into a set of road segments of fixed length (100 m), denoted by S_e. Let d_{es} denote the length of segment $s \in S_e$, and x_{ke} the payload of vehicle k when traversing arc e, under a local road gradient φ_{es}. The total fuel consumption over arc e, denoted by FC_{ke}, is obtained by

Table 2 • CMEM variable parameters for light cargo vehicles, adapted from Barth & Boriboonsomsin (2009)

Symbol	Parameter	Values
F_k	Engine friction factor (kJ/rev/liter)	0.23
N_k	Engine speed (rev/s)	35
V_k	Engine capacity (liters)	3
A_k	Front surface area of a vehicle (m^2)	5
C_k^d	Aerodynamic drag coefficient	0.32
C_k^r	Rolling resistance coefficient	0.01
r_k	Vehicle acceleration (m/s^2)	0
W_k	Curb weight (kg)	2300
τ	Heating value for fuel (kJ/g)	45
ε	Vehicle efficiency parameter	0.4
η	Engine efficiency parameter	0.9
ξ	Fuel-air mass ratio	1
ψ	Grams to liter conversion factor	737
g	Gravity (m/s^2)	9.81
ρ	Air density (kg/m^3)	1.241

aggregating the contributions of all segments in S_e, as expressed in Equation 5:

$$FC_{ke} = \frac{\alpha_e^k}{\upsilon_k} + \beta_e^k(W_k + x_k^e) + \gamma_k^e \upsilon_k^2 \tag{5}$$

where

$$\alpha_e^k = \frac{\xi F_k N_k V_k \sum_{s\in S_e} d_{es}}{\tau\psi}, \tag{6}$$

$$\beta_e^k = \frac{\xi \sum_{s\in S_e} d_{es}(r_k + g\sin\varphi_{es} + gC_k^r\cos\varphi_{es})}{1000\varepsilon\eta\tau\psi} \tag{7}$$

$$\gamma_e^k = \frac{0.5\xi C_k^d A_k \rho \sum_{s\in S_e} d_{es}}{1000\varepsilon\eta\tau\psi}. \tag{8}$$

where FC_k^e represents the total fuel consumption of vehicle k over arc e; α_k^e is the model coefficient associated with engine friction effects; β_{ke} is the model coefficient associated with vehicle load and road gradient resistance; γ_k^e is the model coefficient associated with aerodynamic resistance effects; υ_k is the vehicle speed; W_k is the curb weight of vehicle k; x_k^e is the payload of vehicle k on arc e; S_e is the set of road segments associated with arc e; d_{es} is the length of segment s; φ_{es} is the road gradient of segment s; F_k is the engine friction factor; N_k is the engine speed; V_k is the engine capacity; C_k^d is the aerodynamic drag coefficient; C_k^r is the rolling resistance coefficient; r_k is the vehicle acceleration; ρ is the air density; τ is the heating value of the fuel; ε is the vehicle efficiency parameter; ξ is the fuel-air mass ratio; ψ is the grams-to-liters conversion factor; η is the engine efficiency parameter; and g is the gravitational acceleration constant.

After calculating fuel consumption using the parameters defined in Equations 5 to 8, speed adjustments were applied based on project requirements (Lai *et al.*, 2024). These adjustments include maintaining service time within specified limits, operating at a torque of approximately 1200 N·m at 2700 rpm, minimizing acceleration and deceleration phases, achieving higher constant speeds on slopes, and maintaining minimum constant speeds on flat terrain. Speed limits for the routes were then defined based on data from Table 1. Finally, a mathematical formulation was developed incorporating weighted averages derived from the Analytical Hierarchy Process (AHP) and the magnitudes of the analyzed variables. This formulation, presented in Equation 9 in the Results section, estimates the indirect cost of urban solid waste collection services for light-duty vehicles based on diesel consumption.

5. Results

5.1. AHP

It was found that urban morphology, road network configurations, the load carried, and the geographic characteristics of the object of study directly influence the decision for a more sustainable path. Thus, the first expressed scenario regarding the application of the AHP, graphically represented in Table 3, describes the decision-making scenario regarding the evaluation of stakeholders.

Table 3 • Result of the multicriteria assessment of the project variables evaluated by stakeholders

Variables evaluated on the logistic routing process	Numerical results of the evaluated criteria
Fleet size	0.042
Distance	0.124
Road inclination	0.106
Speed	0.301
Working hours	0.011
Road infrastructure	0.032
Demand	0.029
Typical traffic	0.028
Vehicle capacity	0.067
Implementation cost	0.260

Table 4 • Result of the multicriteria assessment of the project variables evaluated by an expert

Variables evaluated on the logistic routing process	Numerical results of the evaluated criteria
Fleet size	0.031
Distance	0.019
Road inclination	0.093
Speed	0.071
Working hours	0.053
Road infrastructure	0.080
Demand	0.071
Typical traffic	0.068
Vehicle capacity	0.244
Implementation cost	0.270

The results of the evaluation of the second actor, namely a transportation specialist, are expressed in Table 4.

Finally, a last scenario was built (Table 5). This refers to the current state of the art on logistic routing problems inserted in the PRP (Koç *et al.*, 2014; Travesset-Baro, Rosas-Casals & Jover, 2015; Fukasawa, He & Song, 2016; Lai, Demirag & Leung, 2016; Savelsbergh & Van Woensel, 2016; Liu, Yamamoto & Morikawa, 2017; Raeesi & Zografos, 2019; Tirkolaee *et al.*, 2020; Xiao *et al.*, 2020; Brunner *et al.*, 2021; Lai *et al.*, 2024).

5.2. Current transportation results for the collection of USW

After analyzing and spatializing the Work Order (WO) provided by the executing company and reviewing typical traffic conditions using Google Maps Traffic within QGIS, it was determined that the entire route experiences a smooth, uninterrupted traffic flow with no congestion. The travel distance analysis revealed that the route is 164.059 km long, with 22 collection points along the highway leading

Table 5 • Result of the multi-criteria evaluation of the project variables according to the current state of the art

Variables evaluated on the logistic routing process	Numerical results of the evaluated criteria
Fleet size	0.020
Distance	0.142
Road inclination	0.197
Speed	0.152
Working hours	0.051
Road infrastructure	0.079
Demand	0.047
Typical traffic	0.043
Vehicle capacity	0.082
Implementation cost	0.187

to the district and 23 points within the Miraporanga district, totaling 45 designated waste collection points. Figure 3 visually represents this data, showing the service's start and end points, the route trajectory, and the specific geographic locations of the waste collection stops.

The three-dimensional characteristics of the road network used for waste collection indicate that all roads are bidirectional. The route has an average slope of 2%, with maximum uphill inclines reaching 6.8% and maximum slopes of 7.9%. The total distance traveled on the route is 164.059 km, with a total road elevation gain and loss of 1,864 meters each. Figure 4 illustrates the longitudinal profile of the entire route.

For clarity, Figure 4 presents the elevation profile along the traveled distance using a color gradient, in which darker colors, such as purple and blue, indicate higher elevations, while green and yellow represent lower elevations. The elevation along the route ranges approximately from 720 to 890 m. Based on the Work Order data, the average vehicle speed is 71 km/h, whereas the speed during waste collection operations in the district is constrained to a fixed range of 15–20 km/h. This speed range is predefined for collection operations and cannot be modified.

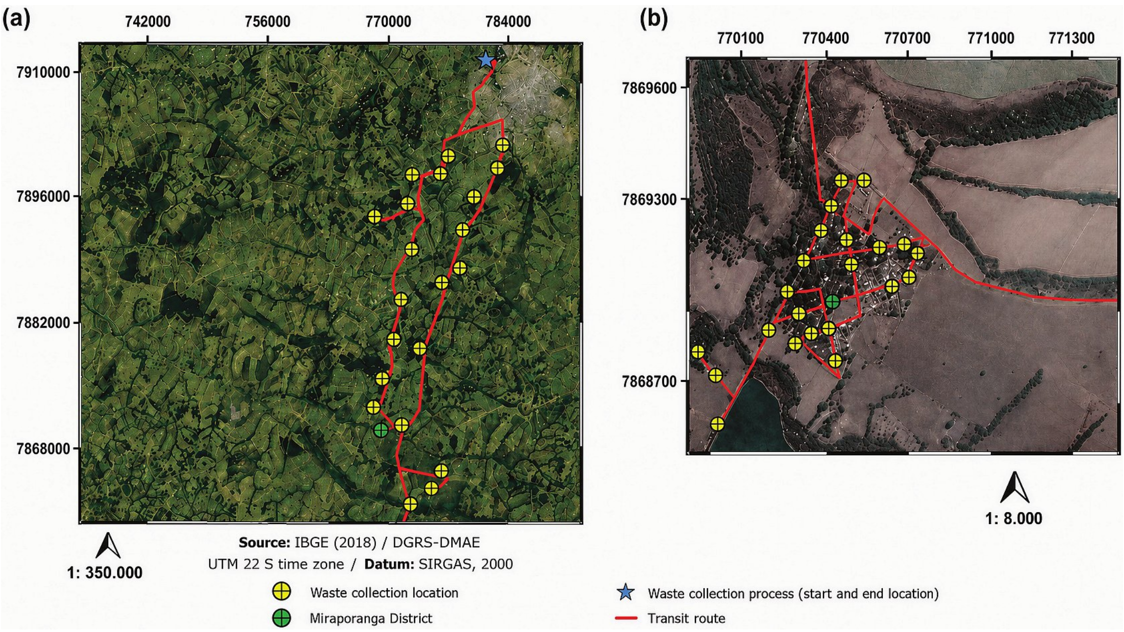

Figure 3 • Mapping and detailing the current garbage collection itinerary in Miraporanga-MG. (a) Represents the full waste collection route departing from Uberlândia and covering the Miraporanga district, showing the complete operational path and service coverage along the municipal network. (b) Zoomed-in view of Miraporanga district, illustrating only the local waste collection points, highlighting spatial distribution, service stops, and intra-district coverage patterns.

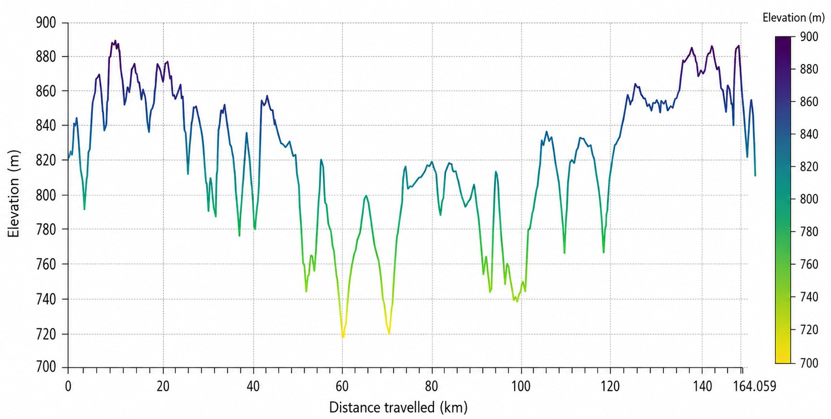

Figure 4 • Representation of the longitudinal profile of the current itinerary.

5.3. Shortest-path result

Using QGIS software, new route possibilities were modeled, taking into account all constraints related to time, days, and the 45 waste collection points to reflect current operational conditions. Although there were some changes in road access, the locations of the official collection points remained unchanged. By applying the TSP optimization in QGIS, the route distance was reduced by 8.3%, from 164.059 km to 150.438 km. This optimization also resulted in an 8.3% reduction in service execution time. The updated route has a total road elevation gain and loss of 1,791 meters each, with an average slope of 2%. Figure 5 illustrates the proposed shorter route.

5.4. Flattest path

Due to constraints at the collection points and restricted road access, the highway route with the flattest path ended up being the same distance as the shortest path (). However, the direction of travel influenced elevation changes: traveling in one direction involved a smoother climb, whereas the opposite direction encountered a steeper ascent. This difference in elevation is attributed to the curves and contour lines of the path. For the proposed model, there was a 1.4% reduction in total elevation gain and loss compared to the shortest path. The updated route covers a distance of 150.438 km, with a total road elevation gain and loss of approximately 1,766 meters and 1,765 meters, respectively and an average slope of 1.9%.

5.5. Final results

The optimal speed for the service, based on the correlation between time and operational cost, was determined to be 50.15 km/h. Table 6 presents the estimated GHG emissions for each route, calculated considering the vehicle's energy expenditure based on the distance traveled. This includes the journey from the garage, waste collection, and disposal at the landfill. The optimized route resulted in a reduction of 1,416.8 km over one year compared to the current service.

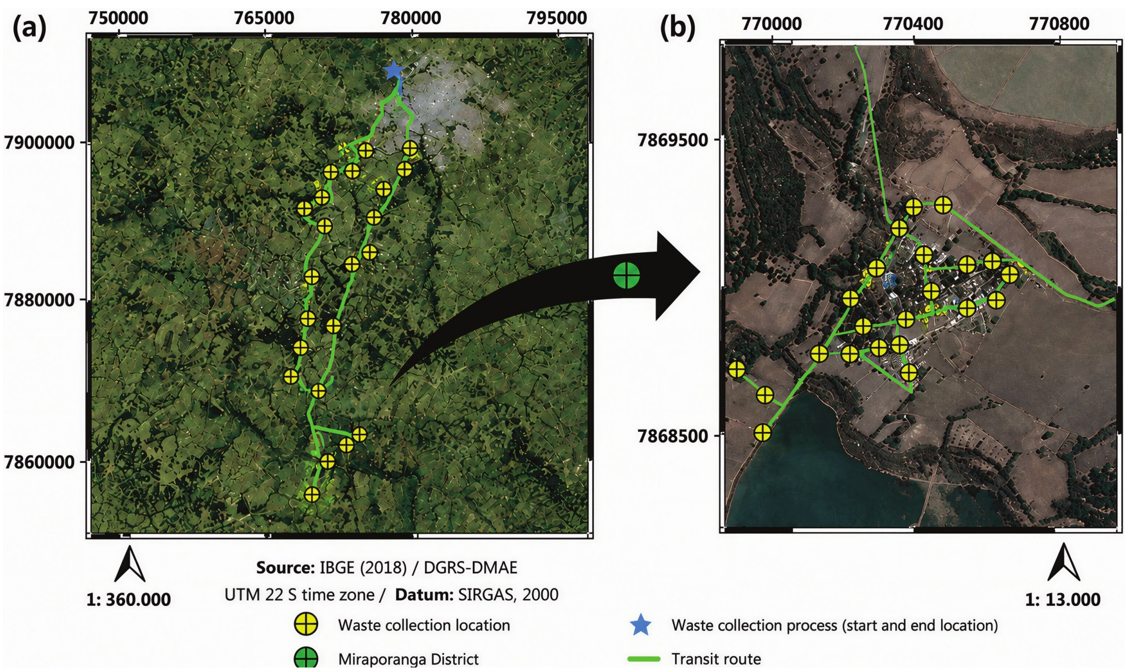

Figure 5 • Mapping and detailing the updated waste collection itinerary in Miraporanga (MG). (a) Represents the full waste collection route departing from Uberlândia and covering the Miraporanga district, showing the complete operational path and service coverage along the municipal network. (b) Zoomed-in view of Miraporanga district, illustrating only the local waste collection points, highlighting spatial distribution, service stops, and intra-district coverage patterns.

Table 6 • Estimated GHG emission results

Pollutants	Shortest itinerary	Flattest itinerary	Current itinerary
NO_x	15,223.07 g/year	14,994.7 g/year	16,601.52 g/year
CH_4	938.73 g/year	924.65 g/year	1,023.73 g/year
NMVOC	12,516.4 g/year	12,328.7 g/year	13,740.60 g/year
CO	2,252.95 g/year	2,219.16 g/year	2,456.96 g/year
N_2O	469.36 g/year	462.32 g/year	511.87 g/year
CO_2	12,047,035.00 g/year	11,867,329.50 g/year	13,137,894.00 g/year

Over the course of one year, the optimization of the waste collection service resulted in a savings of 566.72 liters of diesel, reducing CO_2 emissions by approximately 1,091,759 grams. Each collection transports about 7 tons of solid waste, reflecting the frequency of collection every 3 days. Based on the results discussed in this chapter, a mathematical formula was developed to estimate the implementation costs for executing the waste collection service. This formula incorporates weighted results from the Analytical Hierarchy Process (AHP) to evaluate the financial impact of various key variables involved in the collection process. The objective is to provide a clear understanding of the cost implications for the service planning. Equation 9 used for this purpose is as follows:

$$IC = \frac{\left(\sum \frac{d}{3}L + 0,017D + 0,013v\right)}{1} + 7.58h \tag{9}$$

where IC = implementation cost; d = distance traveled to perform the service (m); L = fuel cost per liter (light-duty diesel (logistic vehicle)) (R\$/L); D = altitude range (slope) of the route (m); v = average travel speed (m/s); and h = working hours of an employee (hours).

The analysis of the speed, travel distance, slope of each route section, and employee work hours reveals a 16.44% reduction in operating costs for the waste collection service. Additionally, this efficiency translates to an estimated monthly cost saving of R$ 3,173.63 for the service provider. This percentage reflects the cost difference between the current waste collection system and the more sustainable model proposed, which optimizes the route for the flattest path.

6. Conclusions

This study goes beyond basic route analysis, focusing on how route characteristics impact greenhouse gas (GHG) emissions. It reveals that the shortest path isn't always the most economical or sustainable. Instead, transportation variables like road slope, vehicle speed, and fuel consumption are crucial in determining the environmental and economic outcomes of logistics services. The research, aligned with global and national goals for sustainable urban transport, highlights the need for intelligent routing that considers more than just distance. For example, heavy-duty trucks are sensitive to factors like air density and gravity, and deviations from optimal speed limits (40–70 km/h) increase fuel consumption and emissions. The study also underscores the benefits of the Pollution Routing Problem (PRP) approach, which optimizes routes by considering multiple variables. This leads to better service execution, reduced distances, and lower elevation changes, resulting in both reduced GHG emissions and significant cost savings. The most sustainable route, therefore, is not necessarily the shortest but the one that effectively balances all relevant factors.

Although the comparison between the flattest and shortest paths yielded identical distances due to operational constraints, the flattest path emerged as the sustainable choice. Future studies could explore less restricted routing problems to pinpoint key decision-making factors with precision. Specifically, studies could investigate how varying road elevations, traffic conditions, and vehicle types influence GHG output in logistics operations. Researchers could also examine the impact of real-time traffic data and alternative fuel sources on emission reduction strategies.

CRediT authorship contribution statement

Gabriel Henrique Carvalho Rezende: Methodology, Data curation, Formal analysis, Writing – original draft. Raquel Naiara Fernandes Silva: Supervision, Writing – review and editing.

Use of artificial intelligence-assisted technology

The authors declare that no artificial intelligence tools were used in the research reported in this study or in the preparation of this manuscript.

Competing interests statement

The authors declare that there are no conflicts of interest to report.

Data availability statement

The datasets analyzed during this study are available in the institutional repository of the Universidade Federal de Uberlândia and are derived from the master's thesis entitled "Otimização logística da poluição de rotas de veículos no transporte de resíduos sólidos urbanos" (DOI:10.14393/ufu.di.2022.550).

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